How Demographics and Urbanization Affect EV Adoption in New York

Analysis Report – Mario Zacherl (23464824)

Disclaimer: This product uses the Census Bureau Data API but is not endorsed or certified by the Census Bureau. During the preparation of this report, I have used DeepL Write to assist me in the writing process to improve language, flow, and readability. After using this tool/service, I have reviewed and edited the content as needed and I take full responsibility for the content of the whole report.

1. Introduction

The adoption of electric vehicles (EVs) has been increasing globally, yet the rate of progress across regions has varied considerably. Understanding these differences is crucial for policymakers and manufacturers aiming to accelerate EV adoption to meet climate goals and reduce dependency on fossil fuels. This project aims to identify the factors influencing the adoption of EVs by correlating the demographic characteristics of counties in New York with their respective EV penetration rates.

New York was selected for its extensive demographic diversity, including both wealthy, highly urbanized areas such as New York City and sparsely populated rural regions within the Adirondack Park. The central research question addressed in this report is as follows: "Which demographic and geographic factors most strongly influence the adoption of electric vehicles in New York State?"

2. Data Sources

The analysis is grounded in vehicle registration data from the Department of Motor Vehicles (DMV) of the State of New York and demographic data from the US Census Bureau. The data from the DMV is available without attribution, whereas the terms of service of the Census Bureau require attribution. The attribution can be found in the above disclaimer.

The processing of these datasets is conducted through the implementation of an ETL (Extract, Transform, Load) pipeline, which yields the following column structure:

Column	Interpretation
County	County of New York
EV_Percent	Percentage of Electric Vehicle Registrations
Rural_Percent	Percentage of households classified as rural by the Census Bureau
Average_Education_Level	A continuous variable ranging from 1 (less than 9th grade) to 7 (graduate or professional degree)
Median_Age	Median age of the population of the county
Females per 100 Males	Gender ratio
Races (White/Black/Asian...) %	Do not add up to 1. Only include the most relevant ones.
Median Household Income	Amount of money that the median household in the given area makes.

Data Quality

The quality of the data is consistently high, as it is collected by government agencies. The accuracy of the registration data is guaranteed by its definition, and the demographic data is

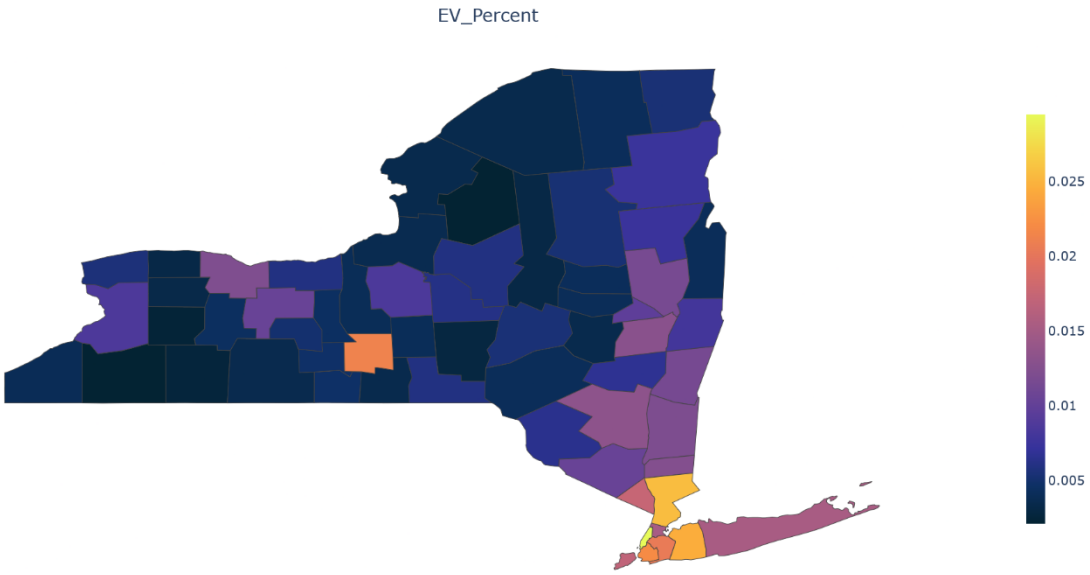
verified by the Census Bureau for its statistical accuracy. However, a limitation arises from the temporal mismatch between the datasets. The registration data is updated regularly and reflects the current situation, whereas the Census data is frozen as of 2022 unless manually updated. This discrepancy could introduce minor biases in correlational analyses.

3. Analysis

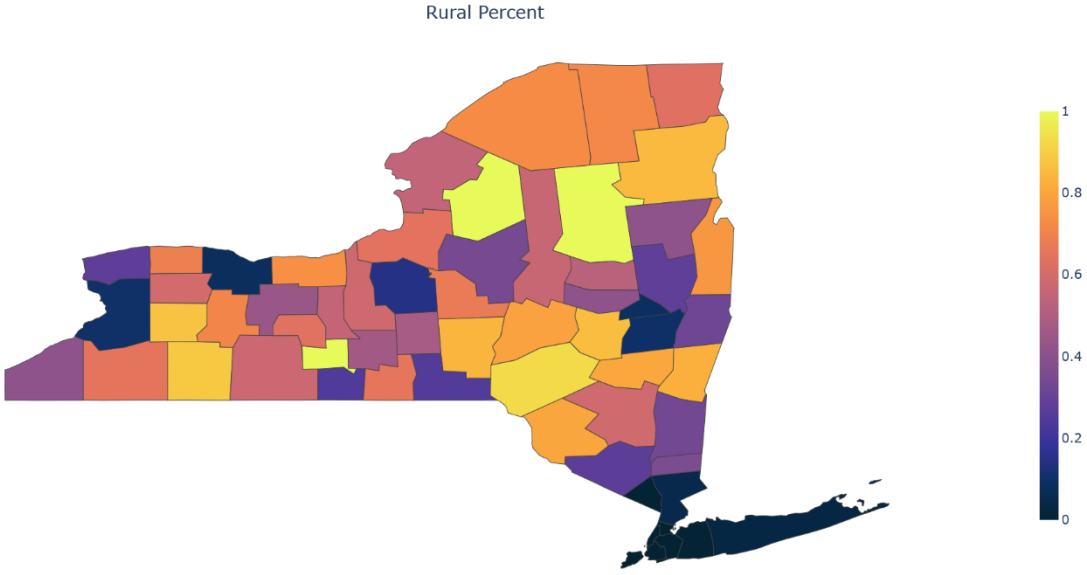
Exploratory Data Analysis

In order to gain an initial understanding of the data, exploratory data analysis can be employed, whereby the distribution of the data is investigated. Given that the data is geospatial in nature, a choropleth map will be utilized for this purpose.

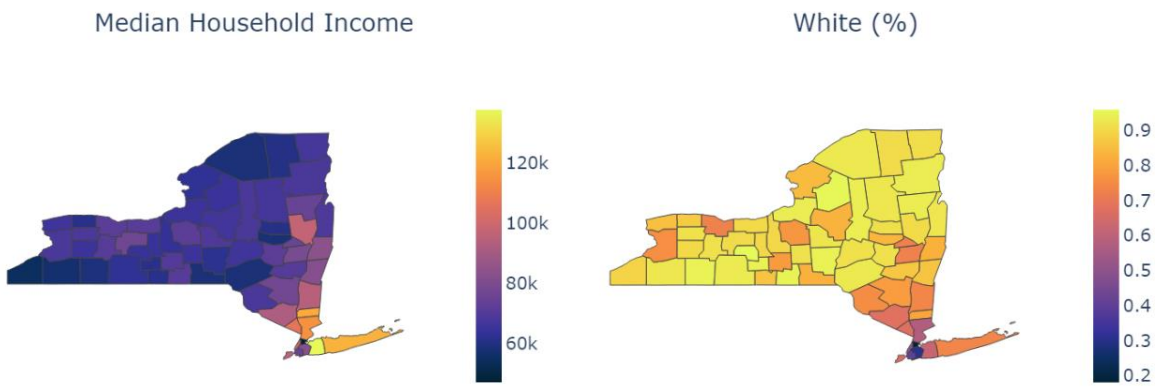
The following figure illustrates the distribution of electric vehicles.:



As illustrated, electric vehicles are predominantly concentrated in and around New York City, with higher concentrations observed in other major metropolitan areas. This phenomenon is further validated by the percentage of rural households depicted in the subsequent figure:

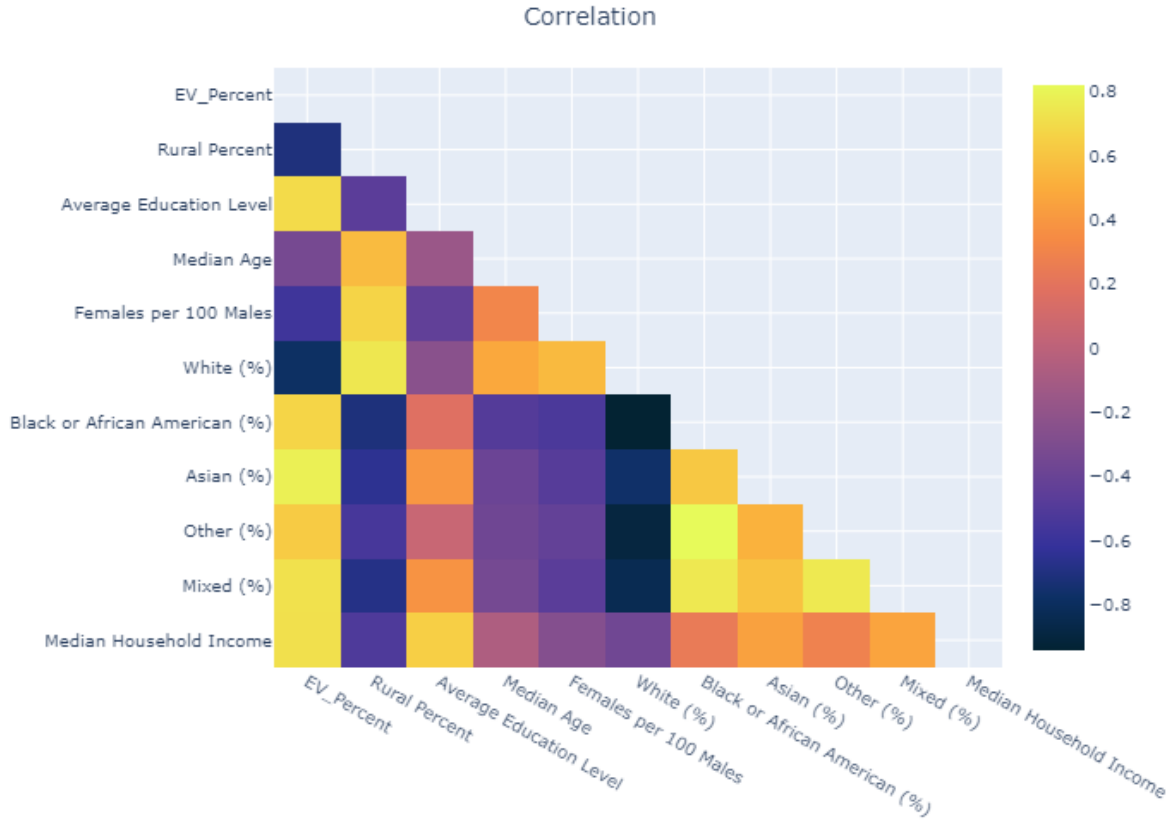


Other noteworthy observations include the presence of a high concentration of non-white individuals in and around New York City, as well as the highest median income in the states surrounding New York City, excluding the city itself.



Correlation Analysis

An examination of the correlation matrix reveals a significant correlation between the percentage of electric vehicles and the majority of the other metrics:



Median Household Income:

A correlation coefficient of 0.71 indicates a high degree of influence of income on the number of electric vehicles.

Rurality:

A value of -0.71 was obtained for the correlation between the percentage of rural households and the EV percentage, which indicates that electric vehicles are more prominent in more densely populated areas.

Average Education Level:

A coefficient of 0.69 has been calculated, suggesting a strong relationship between education level and the number of electric vehicles.

Race:

A robust negative correlation was identified between white ethnicity and the percentage of electric vehicles, with a correlation coefficient of -0.78. In contrast, a positive correlation was observed among other racial groups, with coefficients ranging from 0.62 to 0.77.

It is important to note that these correlations do not establish causation; for example, the observed link between income and EV adoption may be influenced by intermediary factors such as access to charging infrastructure.

4. Conclusion

Our analysis demonstrates a clear correlation between the adoption of EVs and a variety of factors, thereby confirming numerous commonly held beliefs. A frequently held stereotype is that EVs are primarily owned by wealthier individuals, and our analysis supports this stereotype. This might be partially attributed to the limited availability of used EVs.

A noteworthy finding is the correlation between ethnicity and the adoption of electric vehicles. This may be partially explained by the higher percentage of non-white residents in New York City compared to the rest of the state. However, this correlation persists when New York City is excluded from the analysis, suggesting that non-white individuals may exhibit a greater openness to progressive trends.

Our findings indicate that EVs may not yet be considered optimal for long-distance travel, as evidenced by a robust negative correlation between the rurality of an area and its EV density. However, it is plausible that this dynamic may change in the future.

It appears that a higher level of education may also influence the decision of people to purchase an electric vehicle. This could be due to increased awareness of environmental issues or greater familiarity with technological advancements.

Advanced statistical techniques such as regression analysis or machine learning could help disentangle overlapping correlations and provide deeper insights. Additionally, factors such as government incentives or the presence of local EV dealerships could also influence EV adoption but are not captured in the available data.

Future research should address these limitations by incorporating additional data, such as localized charging station availability, incentives, and consumer sentiment surveys, to further refine our understanding of EV adoption dynamics.