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Promoting Electric Vehicle Growth through Infrastructure and Policy: A Forecasting Analysis †

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Abstract: This study examines electric vehicle (EV) adoption in the United States, specifically the interconnected relationship between EV-promoting policies, EV charging infrastructure, and registrations of EVs. Gasoline-powered vehicles make up a significant portion of the US's carbon emissions, and increasing the use of EVs is a way to decrease this footprint. Over the past decade, there have been many incentives and policy-driven changes to propel electric vehicle adoption forward. The focus of this study is to identify if there a significant relationship between these three factors and the extent to which these factors are significant predictors for each other. To do so, we conduct several statistical tests to analyze the forecasting effect of changes in EV policies on EV infrastructure, and changes in infrastructure on EV registrations. We find that there are significant forecasting relationships between these factors. Furthermore, it is possible to accurately forecast changes in EV charging stations over time using the time-series data of previous EV charging stations and policies. There are many interconnected factors, but this strong forecasting relationship between EV incentive policies and the expansion of charging infrastructure provides valuable insights for policymakers, industry stakeholders, and researchers attempting to understand and promote EV adoption.

Keywords: time-series analysis; forecasting; vector autoregression; electric vehicles

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1. Introduction

Electric vehicles (EVs) have grown in popularity in the recent years. According to the Bureau of Labor Statistics, the number of electric vehicles increased from about 22,000 to more than 2 million across the United States in the decade from 2011 to 2021. This growth is significant, but EVs still make up less than 1% of vehicles on the road. Especially in light of the fact that the United States seeks to be carbon neutral by the year 2050, and that emissions from gasoline-powered vehicles made up 30% of energy-related CO_2 emissions, it is important to identify and understand the factors that contribute to the growth of EV consumption. Specifically, our goal is to analyze whether an increase in pro-EV legislative policies forecasts an increase in EV charging infrastructure, and whether the latter, in turn, forecasts an increase in EV use. We examine the past decade of charging station data across the board for all 50 states, as well as transportation policies enacted in these states. For each of our three general factors, we operationalize time and location.

1.1. Related Work

There is extensive prior work that attempts to model EV adoption from a number of lenses, especially for simulations that predict alternative future trends. A simulation-based study from MIT [1] modeled the impact of two different policies on EV sales over time: one where the government provided a USD 10,000 purchase incentive and installed

50,000 charging stations, and one where the government provided the same purchase incentive and installed 100,000 charging stations. For Scenario One, they found that after five years, sales of EVs declined because charging remains costly and stations are underutilized. After ten years, the number of stations declined because not enough stations were in use. On the other hand, when there were more policies promoting EV charging infrastructure, they found that sales of EVs were double the rate compared to Scenario One. After ten or even twenty-five years, the sales of EVs were higher and in turn, more charging stations were being installed. There was a positive feedback loop created between infrastructure and EV adoption where the initial investment into charging infrastructure had a strong positive impact in growing EV sales. This current study seeks to examine whether the real data for EV adoption matches these same trends.

Other work has investigated the urban planning and governmental factors affecting EV usage, again using simulation to model changes in electric vehicle charging infrastructure. Jenn and Highleyman analyzed how electric grid distribution affects the electrification of vehicles, and by extension, the feasibility of purchasing EVs [2]. The researchers used real-world feeder-circuit-level data in California from PG&E to measure the capacity of local feeders and modeled the adoption of electric cars to the census block. They were able to project the future loading on circuits throughout Northern California by adopting current vehicle charging data. In their largest simulation, which proposed an adoption of 6 million electric vehicles in California, they found that 20 percent of all Californian circuits would require upgrades, while only 19.8 percent of those have planned upgrades scheduled. Adding to the lack of feasibility for the Californian power-grid to sustain significant uptick in battery electric vehicles (BEV) consumption, the researchers tracked the stress of charging loads on distribution systems. They found that the effect of EV charging load on the network depends on how much additional stress the added demand places on the distribution network. The simulation showed that for every added million of added electric vehicles, there is significantly less headroom on the electrical grid, which is especially true in areas where a lot of electric vehicle adoption is expected. The more electric vehicles are added to the grid, the more feeder circuits will reach their maximum capacity, many of which will need significant upgrades as the study simulations indicate.

These simulations are predicated on a variety of positive feedback relationships between charging infrastructure, policies, and eventual usage. However, there are a wide range of other factors that influence the usage of EVs or other vehicles in general. One example of more extended predictive analysis is a paper by Olgun Kitapcı et al., in which they examine the effect of economic policies in Turkey as one of a group of factors with an effect on automobile sales as a whole [3]. Using regression and neural networks as their mechanism for prediction, they found the features that most strongly predicted automobile sales were macroconomic factors like currency exchange rates, tax deductions, and the interest rate on vehicle loans. The fact that many of the crucial levers are within direct reach of policy supports the idea that effective policiy decisions can encourage specific effects in the market for vehicle purchases.

The question of how to predict the behavior of the purchase of EVs versus other vehicle types is also widely examined. A recent paper in *Nature* by Afandizadeh et al. [4] once again applies state-of-the-art machine learning models using LSTMs with attention to predict the performance of EV sales versus those of other vehicle types, with the motivation of understanding how best to promote EV sales and market penetration. The features their models identify as most important included Consumer Price Index, charging-equivalent MPG, search engine optimization performance, and the car price itself. This study also uses registration data as one of the key indicators of end EV adoption, an indicator we adopt in this study as well. There has also been research into which consumer profiles consumers tend to have a greater or lesser affinity for EVs over other vehicle types. Studies that investigate this question from an identity perspective [5] or a planned behavior perspective [6] have found a wide range of factors outside of infrastructure, policy, and economic factors that made consumers more likely to opt for EV purchases. These factors

included gender, education, number of cars owned, and a variety of personality factors including conservative versus non-conservative political tendencies.

The findings discussed in this section point to multiple sociological, socioeconomic, and physical factors that affect the increase in EV adoption in consumers. The sheer number of interconnected factors mean that the investigations of this paper are not causal ones. However, the extent to which changes in the key factors of stations, policies, and registrations forecast each other without an underlying assumption of causality can be examined, and understanding which are the strongest predictors remains a powerful tool for designing effective policy. Our current study seeks to use historical data to corroborate the underlying understanding of the interlinked forecasting relationship these prior studies make use of, especially as it pertains to predictive purposes.

1.2. Research Questions and Hypotheses

1. How does EV charging infrastructure vary across the United States and how has this changed over time? We want to understand the history of EV infrastructure and how charging infrastructure has developed over time. Hypothesis: The electric vehicle charging infrastructure will increase over time as well as the EV encouraging policy incentives. We predict that we can forecast the increase in EV charging infrastructure over time utilizing the EV policy time-series data.
2. What is the relationship between the increase in EV charging infrastructure and incentives or EV-encouraging policies? Is there evidence that EV policies have a significant influence on EV charging infrastructure? Does this hold across multiple states/regions across the US? Hypothesis: There is statistically significant connection between the increase in EV charging infrastructure and incentive policies for EV use. We predict that we will find a strong forecasting relationship between adoption of EV incentive policies and the amount of EV charging stations in every US state.
3. What is the relationship between EV registrations and EV infrastructure? We aim to forecast EV registration based on past EV registrations as well as time-series data for EV stations. Hypothesis: There is a statistically significant forecasting relationship between the establishment of charging infrastructure and the increase in registered EVs in a state on a month-by-month basis over time. The net change in EV-charging stations established significantly forecasts the net change in EV registrations within a state over time.

2. Dataset

2.1. Alternative Fueling Stations

This study uses the Alternative Fueling Station dataset provided by the National Renewable Energy Laboratory (NREL) via an accessible public API [7]. The data available in this API are stations in the US and Canada that provide alternative fuel sources from several different types of fuels, with the vast majority of the records being EV charging stations. The dataset consists of fueling stations across the US and Canada that provide alternative fuel sources, including electric, biodiesel, ethanol, and others. EV charging stations make up the majority of this dataset, at more than 79K of the total 90K records. We used this dataset as our record of when and where electric vehicle stations were established, which served as the outcome for our causal investigations. Source: The National Renewable Energy Laboratory. These data have numerous advantages: they are government-produced, frequently updated, and sufficiently dense; of the 90K cases in the dataset, more than 79K of them are EV charging stations, and of these, we found only 15 instances of duplicated stations. There are a few features we will be able to use for our investigations, but the most important ones for our purposes will be geographic data and the date the station in question opened.

2.2. Policies and Incentives

We also utilized datasets contaning various tax policies and incentives related to EVs. The NREL maintains a database of state and federal laws and incentives related to alternative fuels and vehicles, air quality, vehicle efficiency, and other transportation-related topics [8]. The dataset provides links for each of the policies to government managed websites that, in turn, have data on the amount of users impacted, demographics, and similar. We used the data from this API to understand what policies have been implemented across different states and at what points in time, as well as how these relationships vary depending on the policy categorizations the dataset provides.

From analyzing the Transportation Policy Data, we can see that the types of policy incentives available are alternative fuel operators/infrastructure building, EVs, tax incentives, rebates, grants, loans, and leases. The types of policies are separated into the following: (1) Federal Incentives: policies or programs offering financial advantages to encourage EV consumption enacted on the federal government level; (2) Laws and Regulations: legal enactments that govern transportation laws and practices; (3) Programs: organized initiatives or schemes, often with specific objectives related to transportation; (4) State Incentives: financial incentives provided at the state government level; (5) Utility/Private Incentives: incentives offered by utility companies or private entities.

In this dataset, the most common type and category are as follows:

- Most Common Type: "Laws and Regulations", with 592 occurrences.
- Most Common Category: "EVs" (Electric Vehicles), with 1306 occurrences.

As part of our exploration of this dataset, we examined how policy types and incentives vary per state to better understand how these are distributed. We examined what groupings of certain policies per region indicate about our data and which statistical analyses we can run. From this map, we can see that the top states ranked are those with higher records of EV use and ownership. These include New York (NY), California (CA), Washington (WA), and Texas (TX). We utilized the information from this initial analysis to focus on individual states in our research.

2.3. Registration Data

To analyze the above factors and the extent to which they can predict EV usage, we need a representation of end EV usage itself. We use registration data as an indicator of usage. The NREL also provides data on EV registrations by state, but the data are only at an annual granularity and only offer 5 years of data. Many states provide data on a more granular basis, but data intake on a per-state basis presents a significant challenge, especially with respect to normalization workload before starting analysis. This study uses a pre-collected, partially normalized collection of state registration data provided by Atlas Public Policy, an NGO promoting clean energy. The dataset includes registrations for 17 states on a variety of granularities. Of these 17, 4 provide monthly data: Colorado, Texas, New York, and Washington. A further six provide quarterly data: Maine, Minnesota, North Carolina, Oregon, Tennessee, and Vermont. Our analyses did not use any state with a granularity greater than quarterly. The fields we operationalize from this dataset are the registration date, the granularity in question for filtering, and the state in question. These choices allow this study to associate all three of our main areas both geographically and temporally.

2.4. Pre-Processing

The predictive analyses and tests our study entails rely on aligned, completely nonempty time-series data with matching granularity and timescale. We run each analysis on a per-state basis; so, we first filter down each dataset based on the state in question. Policies and station data are both day-granular time-series; so, to run our tests and modeling, we align the start and end of the period for which they share data then use the *merge_asof* merging strategy as provided by pandas. This strategy converts our individual records into date-associated cumulative sums of stations built to date and policies established,

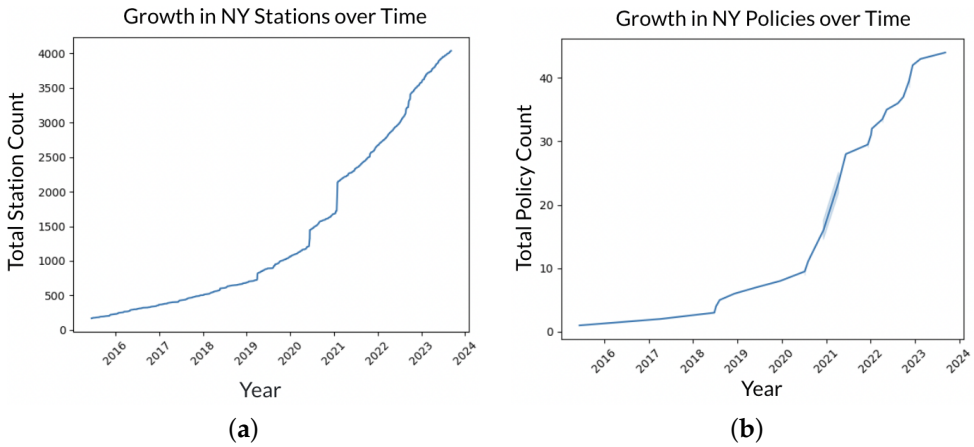
which guarantees that each date in the merged set is non-empty for both policy count and station count. In order to weight the difference in cumulative counts that each new record represents, we apply a percent difference transformation to ensure that our comparisons are normal across the entire date range and consistent for each of our per-state analyses. In order to perform similar analyses incorporating registration data, an additional pre-processing step is required for policy and station data. Depending on the granularity of the state's registration data, we group either by month or by quarter and use each quarter or month as the basis for our time-series instead of individual days. We employ the same "merge as of" strategy and used both difference or percent difference to normalize, depending on the analysis in question. The result for any such merged data is a time-aligned series with counts for registrations, policies, and charging stations with a consistent granularity, which we can use for our statistical tests and predictive modeling below. The datasets and code for this project can be found in the Appendix A.

3. Method and Evaluation

Our goal is to understand the relationship between EV incentives, charging infrastructure, and EV registrations. In order to analyze these relationships, we first performed explanatory data analysis investigating the patterns in our data. Then, we applied a variety of statistical tests to examine the relationship between these variables and test our hypotheses. Specifically, there are three main tests we utilized: (1) the Granger causality test, which determines the usefulness of one time-series dataset in forecasting another; (2) the cointegration test, which evaluates if there is a significant relationship between two or more time-related series; and (3) vector autoregression (VAR), which determines if we can forecast one variable based on past values of itself and the past values of another variable.

3.1. Policies and Station Growth: Initial Time-Series Modeling

To examine the relationship between policies enacted and stations built, we first examine the quantity of stations and policies in effect throughout the state as a function of time. We generated graphs to display the growth of policies and stations for all states that contained sufficient data for both measures. We display the graphs for New York in Figure 1a,b. As expected, both quantities are monotonically increasing. We will utilize these two time-series datasets when applying the Granger causality test and other tests like VAR to evaluate our hypothesis that policies are significantly related to EV charging infrastructure development.



(**a**) (**b**)

Figure 1. (**a**) Number of EV charging stations in New York (NY) over time; (**b**) number of EV-related incentive policies enacted in New York (NY) over time.

3.2. Policies and Station Growth: Vector Autoregression (VAR)

Vector autoregression (VAR) is used in time-series research to study the relationships between variables. It is used when it is believed that the time-series data for two or

more variables influence each other. In our case, this applies since the number of EV charging stations over time may influence and be influenced by policies over time. The two sets of time-series data that we are analyzing are (1) percent change in station counts over time and (2) percent change in policy counts over time. We first perform a Granger causality test to confirm if these time-series data influence each other. As demonstrated in Figure 2, the results from the Granger causality test for New York (NY) showed a *p*-value for policy_counts and station_counts of 0.0065. This is less than 0.05, so we can reject the null hypothesis that there is no significant relationship between the increase in EV charging infrastructure and incentive policies for EV use. When the test was applied on other states, we found that the *p*-value was consistently less than 0.05. For example, the *p*-value for Washington (WA) was 0.0437. This means that the past values of the percentage change in policy counts provides predictive information that improves our ability to predict the percentage change in station counts. After the Granger causality test, we then perform a cointegration test to determine if there is a significant relationship between the two time-series data. The cointegration test showed that there is a statistically significant relationship between the percentage change in station_counts and the percentage change policy_counts with 95% confidence.

Granger Causality Test for New York (NY)

	station_counts_x	policy_counts_x
station_counts_y	0.9981	0.0078
policy_counts_y	0.0065	1.0000

Figure 2. Granger causality test between station counts and policy counts for New York (NY). The *p*-value is 0.0065, which is below 0.05, so we reject the null hypothesis. There is significant relationship between charging infrastructures and EV incentivizing policies.

Having shown that there is a significant relationship between the two variables, we can then fit the VAR model. The data are split into 80% training and 20% testing. We fit the VAR model on the training data and then use it to forecast (aka to predict) on the test data. The augmented Dickey–Fuller Test is also applied to ensure all time-series data are stationary. We trained the model and forecast on the test data and compared our findings to the actual values. Figure 3 shows the forecasting results for New York (NY). As can been seen in Figure 3, the forecast/predicted percentage change in station counts closely matches the actual test values. This helps confirm that we can build a VAR model and predict or forecast the future values of percentage change in station counts based on the past values of percentage change in station counts and the past values of percentage change in policy counts. We evaluate the forecasting results using mean absolute percentage error (MAPE) and other metrics such as correlation. The MAPE was very low at 0.0079, and the correlation was very high at 0.999, showing that the forecasting results are very close to the actual test data values. We also test whether this forecasting relationship holds across the US. As shown in Figure 4, we find that the VAR model accurately predicts percentage change in station counts for Washington (WA), Washington DC, Texas (TX), and New Jersey (NJ). Therefore, we conclude that our second hypothesis is fully supported: not only are EV stations and EV-encouraging policies significantly related, their relationship is also forecasting and can be used to predict future EV station counts.

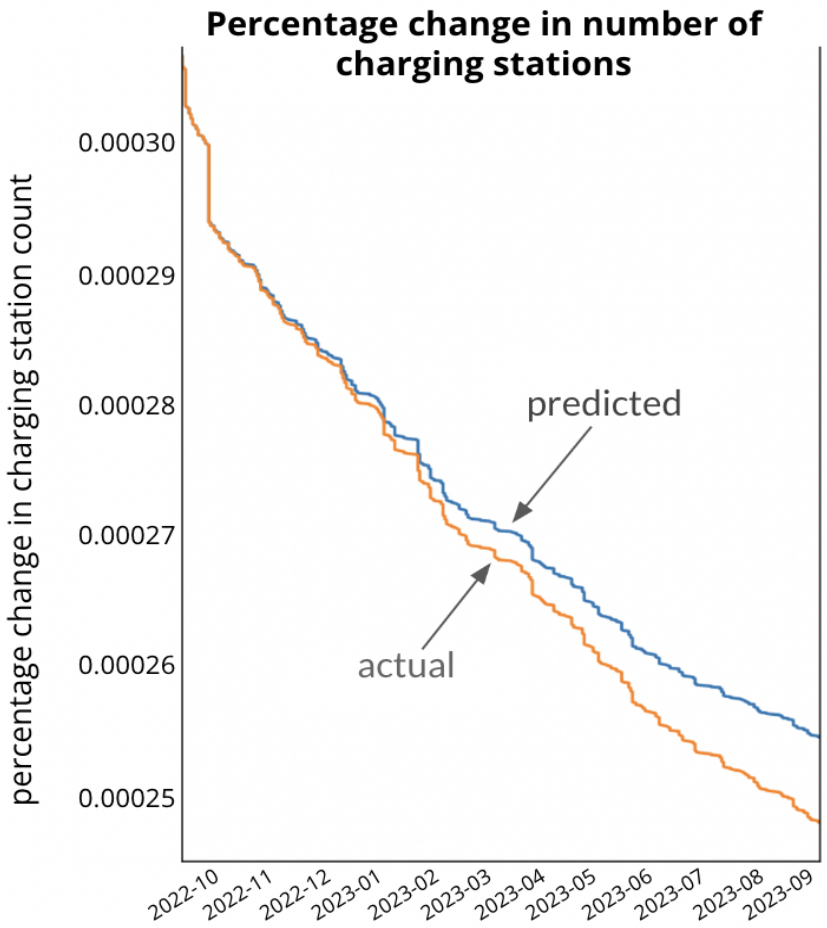


Figure 3. VAR results for New York (NY). Forecast percent change in station counts over time vs. actual percent change in station counts over time.

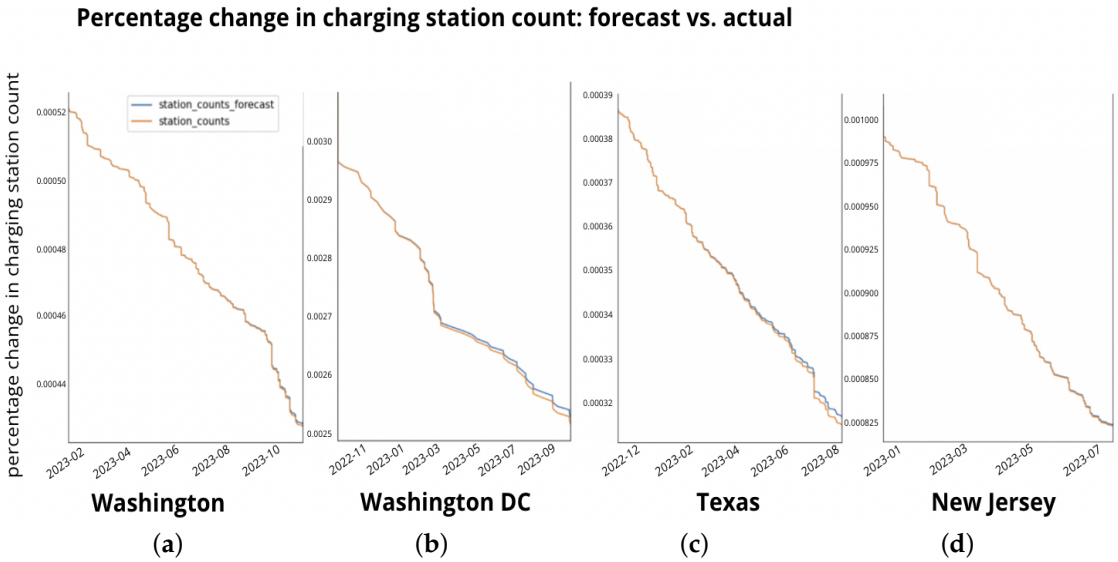


Figure 4. VAR results for other states. Forecast vs. actual percent change in station counts over time for (**a**) Washington, (**b**) Washington DC, (**c**) Texas, and (**d**) New Jersey.

3.3. Policy Categories: Granger Causality

To examine which policy categories are able to forecast charging station growth in a statistically significant manner, we decided to examine the types of policies based on

the existing categorization in the Transportation Policy Data dataset. The study used a Granger causality matrix on the two time-series data, i.e., EV charging stations and EV policies grouped by category, to see whether the policy data can be used to forecast the charging station data. Each of the policy categories—Federal Incentives, Laws and Regulations, State Incentives, and Private Incentives—were considered a predictor variable, while the measured variable was the number of new charging stations. The results of the Granger causality test (displayed in Figure 5) showed that each of the policy types was highly statistically significant, with *p*-values below the 0.05 threshold. Specifically, Federal Incentives had a predictor *p*-value of 0.0486, Laws and Regulations had a predictor value of 0.005, State Incentives had a predictor value of 0.0385, and Private Incentives had a predictor value of 0.0054. As such, we see that Private Incentives and Laws and Regulations are the policy categories with the highest predictive power for charging station growth. Hence, although all policy incentive types are successful at incentivizing charging stations given their *p*-values, we see that Private Incentives and Laws and Regulations are most significant in doing so.

Granger Causality Table for Predictive Power of Policy Types on New Charging Stations

	New Stations	Federal Incentives	Laws and regulations	State incentives	Private incentives
New Stations	1.0000	0.0486	0.0050	0.0385	0.0054

Figure 5. *p*-values representing predictor ability for each of the policy types on new charging stations.

3.4. EV Registrations and Station Growth: Vector Autoregression (VAR)

For our final research question, we wanted to understand the relationship between EV charging stations and EV infrastructure. Our hypothesis was that there is a significant relationship between these two variables. In order to test said hypothesis, we used the time-series data for registrations and the time-series data for electric charging stations. The registration data collected from Atlas are less granular; thus, we only had access to monthly data. The goal is to forecast the net change in EV registrations using the registrations and stations time-series data. We first performed a co-integration test; the test showed that the two datasets had a statistically significant relationship. We then performed a vector auto regression (VAR). As can be seen in Figure 6, the forecast predictions are not completely accurate, but the model does match some of the increases and decreases that are seen in the true data. One reason for why the VAR was not as accurate is because it was fit on monthly data, resulting in a smaller size training dataset. We can conclude that our third hypothesis is partially supported: there is evidence of a significant relationship between stations and registrations, but there is still more work needed to determine if this is a forecasting relationship.

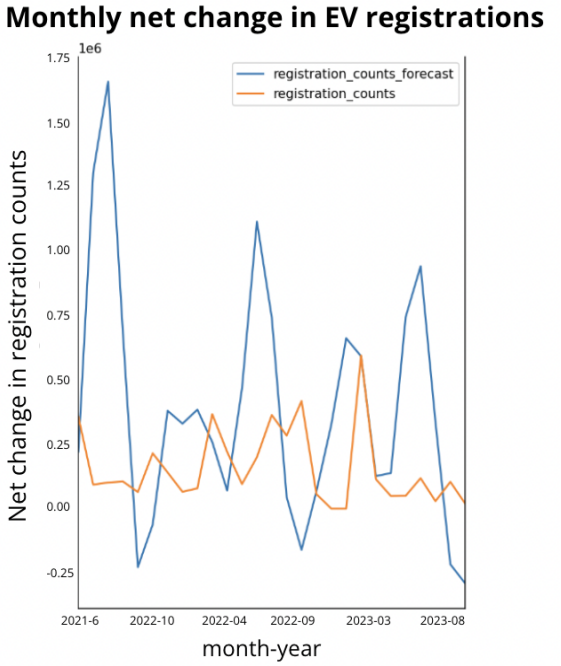


Figure 6. Forecast net change in registrations counts over time vs. true net change in registration counts over time for New York (NY).

4. Discussion

Our first hypothesis is focused on studying the relationship between EV incentive polices and the number of EV charging stations. According to the Granger causality matrix, we find that there is a significant relationship between the time-series data for percent change in the number of stations over time and the data for percent change in the number of polices over time. Given that the time-series data influence each other, we performed vector autoregression (VAR). Our VAR results show that we can accurately forecast the percent change in number of EV stations over time based on its past values as well and the EV policies time-series data. We conducted a 80/20 train/test split and fit the model on the training data; we then applied the VAR model to predict the percent change in the number of EV policies over time on the test data. As shown in Figures 3 and 4, the forecast results are very accurate and close to the true values. This is verified across many states, including New York, California, Washington, Washington DC, Texas, and New Jersey. Therefore, we can conclude that there is a significant connection between EV stations time-series data and the policies time-series data. Utilizing the policy time-series data allows us to better model and predict the growth in EV stations over time. The robustness of our findings is supported by a comprehensive analysis of individual state-level data. We used vector autoregression (VAR) to delve deeper into the predictive capabilities of our model, demonstrating its effectiveness in forecasting the future trajectory of EV stations based on historical data. The consistency of our findings across diverse regions strengthens our ability to generalize our conclusions, suggesting that the observed connection is not confined to specific local conditions but extends to a broader context.

Our second research question delves deeper into what specific policy types are most effective at predicting charging station growth. The Granger causality test shows that all policies are statistically significant in predicting new station counts; as shown in Figure 5, the p-values for all policies are below the 0.05 threshold. As such, our initial hypothesis of Laws and Regulations being the only statistically significant policy type to successfully predict charging station emergence was effectively disproved. The implications of demonstrating that all of these incentive types are significantly successful in promoting charging station growth extend to future legislative and manufacturing decision making. Legislators,

consumers, and EV manufacturers alike will be aware that these policies are all highly effective and will be more encouraged to implement them to aid EV adoption.

Finally, our third research question looked at the relationship between EV stations and EV registrations. The co-integration test showed that the two variables have a significant relationship. The vector auto regression (VAR) showed preliminary signs of forecasting, but more work would be needed to confirm this. The implications of these findings is that building EV infrastructure could potentially have a positive impact on the adoption of electric vehicles. This is especially important for city planning and ensuring that the charging infrastructure is in place to support electric vehicles.

5. Conclusions

Our research examines the relationships between EV-related policies, charging infrastructure, and EV registrations. We discovered compelling evidence for there being a significant relationship between EV incentive policies and the growth of charging infrastructure. The vector autoregression (VAR) shows that time-series data for EV stations and EV policies can be utilized to successfully forecast percentage change in EV stations over time. These results demonstrates the practical utility of utilizing policy time-series data in modeling and predicting the evolution of EV stations over time. Furthermore, we also analyzed on a policy category basis and found that laws/regulations, as well as private incentives, were the most significant for forecasting. These findings can be especially useful in the development of future policies to further encourage EV adoption. In terms of the relationship between EV stations and EV registrations, we found that the two variables do have a significant relationship, but more work is needed to determine if it is a forecasting relationship. Overall, our research examined the dynamics between policies and charging infrastructure and their overall impact on EV registration. We hope that our research can contribute to future work to promote the adoption of electric vehicles.

6. Future Work

In this paper, we have performed statistical testing for examining the relation between EV charging stations, EV policies, and EV registrations. There are many potential future directions that would be worth investigating. For example, we believe more work can be conducted to test hypothesis 3 in forecasting EV registrations. Our preliminary results show that there is a statistical connection between EV registrations and EV station counts, but the VAR was not as accurate. One approach is to see if we can gather more data to train the VAR. This may help increase the accuracy of the forecasting model. Another future direction is exploring the effects of EV policies on an intra-state level. For example, we could perform a case study within one state of choice to see how regional factors, such as socioeconomic background and political identification, amongst other demographic information, influence EV adoption patterns. Finally, we could explore EV incentivizing policies on a more global scale and examine how policies of more climate-focused governments, such as the European Union, compare to those of the United States. We have come across a similar sentiment in our preliminary research on the difference in policies between the two and how this has led to fundamentally different outcomes in EV adoption patterns within their respective municipalities.

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Appendix A

Code and data for this project can be accessed at https://github.com/brennan913/empirical-methods (accessed on 1 December 2023).

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