On the Chicken & Egg Problem in Transportation Electrification

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1 INTRODUCTION

Vehicle electrification is widely regarded as a critical tool for climate change mitigation in the transportation sector (Musti and Kockelman 2011). While the United States is seeing an increasing share of electric sales, the pace of adoption remains well below the necessary level to mitigate climate change impacts. One barrier to widespread adoption is the lack of charging infrastructure (Sullivan and Taylor 2021).

A common policy put forward to increase electric vehicle adoption is a federal income tax credit for EV buyers. However, spending similar amounts on increasing deployment of charging stations could yield more effective results (**Li2017?**). This is especially the case in the early stages of EV market penetration; EV markets that have critical-mass constraints have the most success in increasing market penetration with a subsidy policy that deals with indirect network effects (**Zhou2018?**). One of the indirect network effects on the EV market comes from the charging station market.

Subsidies for charging stations are found to be most effective because of the low-price sensitivity of early EV adopters (**Li2017?**). This is intuitive because early EV adopters are more eager to purchases EVs, which makes them more willing to pay for higher prices. The issue these consumers are concerned with is their ability to utilize this new technology, which is affected by the existing charging station infrastructure. Because of this, understanding consumer's preferences for charging station infrastructure is crucial. Consumers are willing to pay about 5 cents per mile for plug-in electric vehicles and about 10 cents per minute of wait time while refueling. Consumers are also willing to wait up to 8 minutes longer during refueling (**Sheldon2019?**). Knowing this information can allow policy makers to create subsidy programs that produce more effective outcomes.

Nick TO DO: - Expand discussion to focus on the need for EVs in climate policy in general (can draw from Net Zero America and Zero Carbon America studies and others) - Focus on what drives EV adoption according to literature - Talk about the infrastructure bill and its investment in charging stations

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  if LooseVersion(mpl.__version__) >= "3.0":
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  other = LooseVersion(other)
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2 THE ELECTRIC VEHICLE AND CHARGING STATION PROBLEM

Nick TO DO: - More of a technical focus on what's been done in the academic literature on the specific problem

Electric vehicle ownership is often referenced as exhibiting a "chicken and egg" behavior arising from the supply and demand relationship. Individual demand for electric vehicles is influenced by the available supply of charging points. Consumers are unwilling to purchase vehicles due to range anxiety and a perceived lack of charging stations. Suppliers are not incentivized to provide charging stations unless there is sufficient demand to warrant their cost. There is a clear role for public policy in such situations. The government deems electric vehicles as a solution to a public ill (i.e., climate change) and can incentivize either suppliers by providing installation subsidies or consumers by installing charging stations. While the problem has been recognized in the literature (Melliger, Vliet, and Liimatainen 2018), empirical analysis is minimal.

An important consideration to the analysis is how electric mobility system may differ from one based on fossil fuels. In the conventional private mobility model, the individual owns the vehicle and purchases fuel from centralized and privately owned refueling stations. In contrast, electric vehicles may be charged in the home using previously existing infrastructure. The presence of charging points in the home begs the questions 1) if (or to what extent) out-of-home charging stations are required for travel? and 2) to what extent is range anxiety a perception versus a reality?

According to the Bureau of Transportation Statistics, 98% of trips made in the US are less than 50 miles (Vehicle Technology Office 2022). Given that most battery-electric vehicles (BEVs) have a range greater than 200 miles (Elfalan 2021), it is feasible to make most trips on a single charge. However, long-distance trips (over 50 miles) comprise 30% of total vehicle-miles traveled (VMT) (Aultman-Hall 2018). There is clearly a need for out-of-home charging stations to accommodate these trips. Even if most trips can be accommodated by in-home charging, the vehicle purchase decision will be influenced by consideration of these longer trips that require charging stations (Silvia and Krause 2016). Additionally, Wolbertus et al. (Wolbertus et al. 2018) find that there is still a demand for charging stations in places where public daytime charging is the only option, such as at the workplace.

3 METHODS

We define two classes of causality which we termed as phasing causality and potential outcomes causality. These alternative forms of causality are often denoted by their principle developers: Granger causality (REF) and Rubin causality (REF), respectively. Both approaches are employed due to the (functionally) continuous nature of the two variables of interest. We detail each approach and its application to the present problem below.

3.1 Non-Linear Phasing Causality

Define two variables X_t and Y_t where subscript t denotes a time series process. Phasing causality seeks to identify whether the two time series exhibit a common pattern (or coherence). One variable may lead the other producing a time lag, but the series may also exhibit instantaneous *causality* whereby the current value of Y_t is better predicted when the current value of X_t is included in the model. In strict terms, phasing causality is defined by

$$\sigma^2(Y|U) < \sigma(Y|\overline{U-X})$$

#{eq:granger-causality}. There is also the potential for feedback, whereby X_t causes Y_t and Y_t also causes X_t. In the EV and charging station situation, this might mean that charging station installations encourage households in a county to purchase EVs, which then encourages further investment in charging station infrastructure. There are two key principles underling phasing causality: 1) that the cause occurs before its effect and 2) that the cause has unique information about the future values of its effect. Granger defines a simple test statistic for such causality using time series data using the F-test.

The original applications of Granger causality were to economic variables that fluctuated over time. The test assumes that both X_t and Y_t are stationary time series, an assumption that will be shown to be violated in the present case. Several extensions have been developed to phasing causality that allow for non-stationary time series. We use the approach of Rosol et al (REF) with modifications to fit our application as detailed in the following section. Their approach compares the model median absolute error using both time series (Y_t and \$X_t\$)to that obtained using only the dependent time series (\$Y_t\$). The Wilcoxon signed-rank test is used to test for statistical significance - i.e., that X_t causes Y_t. The method is implemented as a Python package and includes multilayer perceptron (MLP), long short-term memory (LSTM), gated recurrent unit (GRU), and autoregressive integrated moving average (ARIMA) models. Model errors are calculated at each observation and the sum of their absolute values used in the statistical test. The method has the ability to measure changes in causality over time, but our time series is too short for its application.

3.2 Potential Outcomes Causality Via Propensity Score Matching

Potential outcomes causality begins from the definition that causal effects are a comparison between outcomes Y in response to differences in a treatment T on a common set of units. Unfortunately, such an analysis is not possible in reality since it would require the same unit (e.g., person) to simultaneously experience both the treated and untreated conditions. In observational studies, a common approach is to identify two sets of observational units that differ only in their exposure to a treatment variable of interest. A study interested in the effect of a new teaching strategy might compare two sets of schools that differ only in whether they adopted the strategy. A class of strategies to identify otherwise similar observational units (e.g., schools) is propensity score matching. Formally, the assumption is that $Y_t \perp T|X_t$, or that outcome Y_t is independent of the treatment conditional upon a set of X_t covariates. That is, treatment assignment is ignorable conditional on X_t. However, for the present problem the treatment (i.e., charging stations) is not binary. An observation unit may have any number of charging stations.

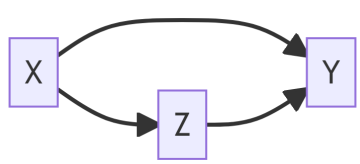
An extension to the standard propensity score, termed as generalized propensity score (GPS) matching, was developed by Hirano and Imbens (REF). Assuming a continuous treatment, the GPS is defined by

$$r(t, x) = f_{T|X}(t|x)$$

{eq-gps} where $t \in \tau$ is referred to as the unit-level dose-response function, X and T are random variables defined on a common probability space, and $r(t, x)$ is the GPS measure defining similarity between observational units. It can then be stated that $X \perp 1T = t|r(t, X)$, or that assignment to a treatment value t is independent conditional on its GPS.

The dose-response nomenclature is taken from pharmeutical research, where the interest is in the health response to a continuous drug dose. Each individual has a potential response at different doses, or treatment levels. The dose-response function that is an outcome of continuous GPS analysis is an average of the potential responses at each treatment level - an average dose-response function (ADRF). A challenge when transitioning from a binary to a continuous treatment is that a treated unit will not be available at every treatment level. The problem can be addressed by parameterizing the curve as a linear combination of a finite number of basis functions (REF Galagate). The averaging used to construct the ADRF is based on weighting observations by the GPS using units within each basis function range.

A secondary question is the potential influence of charging stations on other variables of interest.



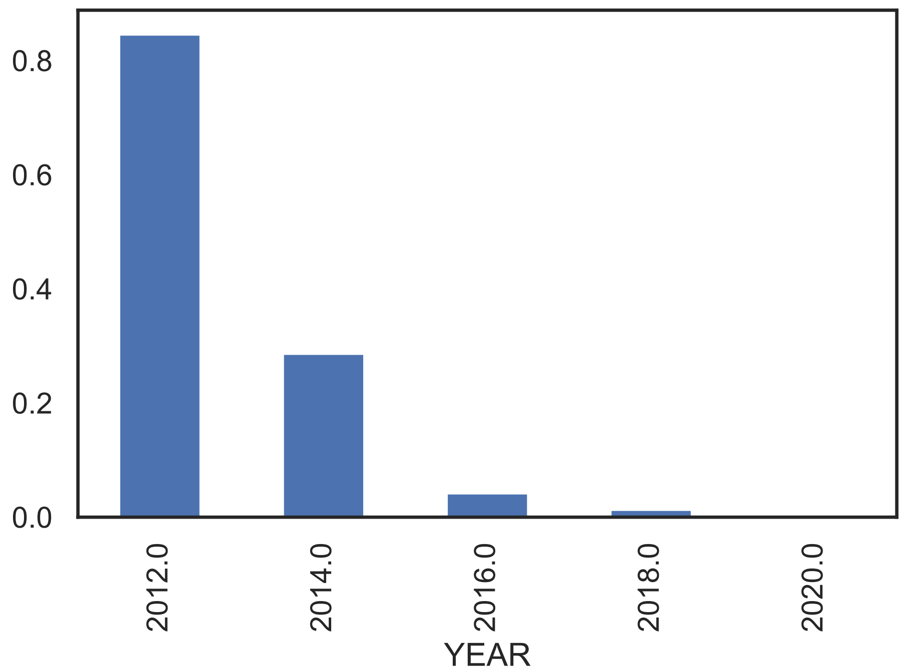
4 DATA AND MODEL SPECIFICATION

4.1 Treatment and Outcome Variables

The two key input datasets are charging station locations provided by the Alternative Fuel Data Center (AFDC) and electric vehicle registrations provided by Experian Inc. The vehicle registration dataset comprises a 10-year panel at 2-year intervals (2012, 2014, 2016, 2018, 2020). Total vehicle registrations are recorded by county, make, model, year, and other vehicle characteristics for the United States. The frequency and spatial resolution of the vehicle registration data define the analysis units. Our treatment and outcome variables are charging stations and EV registrations normalized by population (per 100,000 inhabitants).

Charging stations are geocoded and aggregated into annual cumulative totals by county. Only public charging stations are maintained for analysis. Further, the we make no distinction between charger port capacity (level 1, 2, or 3) when aggregating the number of charging ports per county. Such a distinction could be made as a sensitivity test but may reduce the effective sample size as not all counties with charging stations have all three charger port types.

After filtering out protectorates and other non-state locations, several county codes in the Experian data remain that are missing registration totals in a subset of years (117/3275, or about 4%). We remove county codes with more than one missing year, leaving 34 counties for which registration totals are interpolated from adjacent years. Many of these county codes are for remote areas with low populations (e.g., the Aleutian Islands in Alaska). Of the 3140 viable counties, it is found that 1406 lack EV registrations or public charging stations in any analysis year. These counties are excluded from analysis because they lack variation for model estimation. Figure **?@fig-missing** illustrates that a further 80% of the remaining counties did not have EV registrations in 2012. While kept in the dataset for analysis, the high proportion of zero-valued observations poses a significant challenge for statistical inference.



4.2 Covariates

Census data was compiled to construct county-level statistics for median income and racial composition. Five-year American Community Survey (ACS) data were used to approximate annual variation. We use the 2011-2015 ACS for years 2012 and 2014 and the 2016-2020 ACS for years 2016, 2018, and 2020. For the purposes of analysis, we define minority racial groups as Black and Hispanic based on an overrepresentation of poverty according to Census Bureau analysis (https://www.census.gov/library/stories/2020/09/poverty-rates-for-blacks-and-hispanics-reached-historic-lows-in-2019.html#:~:text=In%202019%2C%20the%20share%20of,share%20in%20the%20gene We also include American Indian and Alaska native, and Native Hawaiian and Other Pacific Island, and Other Race Not Specified in our definition.

To capture spatial spillover effects, a Queen contiguity matrix is constructed for charging station density (per 100,000 inhabitants) in adjacent counties. The rationale is that an individual may purchase an EV if there are charging stations in adjacent counties and charge at their residence when driving in their home county.

Nick TO DO: - Could help describe the data we used a bit

4.3 Model Specification

We use the causal-curve Python package developed by Kobrosly (REF). This package uses a generalized linear model (GLM) to construct the GPS and a generalized additive model (GAM). The GAM model takes as inputs the GPS, a treatment grid, and a number of splines. We use the default 100 unit grid and 30 splines (i.e., separating the GPS space using 30 basis functions).

5 Results

5.1 Descriptive Analysis

Figure @fig-us-totals provides a first validation of the research hypothesis. Registered plugin electric vehicles (PEVs) and public charging stations are normalized by population and plotted over the eight year analysis period for the United States. The two infrastructure show a similar exponential increase, suggesting there is a correlation between their adoption but giving no indication of temporal phasing or causality.

The classical Granger causality test assumes stationary data, which is not the case here based on visual inspection and confirmed by ADF and KPSS tests. Several non-linear extensions to Granger causality have been developed in recent years (REF). One challenge applying such methods to our application is that non-linear methods require a larger time series than the five annual totals purchased from Experian. We address this limitation by leveraging the multiple observations available in each year.

Seems unlikely that interaction is occuring at a sub-annual basis given the time lag and information acquisition requirements between vehicle purchase and infrastructure construction. Granger: "Whether or not a model involving some group of economic variables can be a simple causal model depends on what one considers to be the speed with which information flows through the economy and also on the sampling period of the data used. It might be true that when quarterly data are used, for example, a simple causal model is not sufficient to explain the relationships between the variables, while for monthly data a simple causal model would be all that is required. Thus, some nonsimple causal models may be constructed not because of the basic pro- perties of the economy being studied but because of the data being used."

The Bipartisan Infrsatructure Act places a strong focus on equitable investment allocation. Equity can be explored both inter-regionally and intra-regionally by key demographic features. Figure 2 compares the distribution of charging stations for four representative cities. Omaha is located in the central Great Plains, a region that has received minimal exploration in the EV literature. Chicago and Detroit are large cities with well-documented histories of housing segregation (REF). San Francisco is included as an example of a large city in a progressive state. In all four cities, charging stations are concentrated in the central city. San Francisco does not show clear evidence of inequality, likely partially as a function of the overall high density

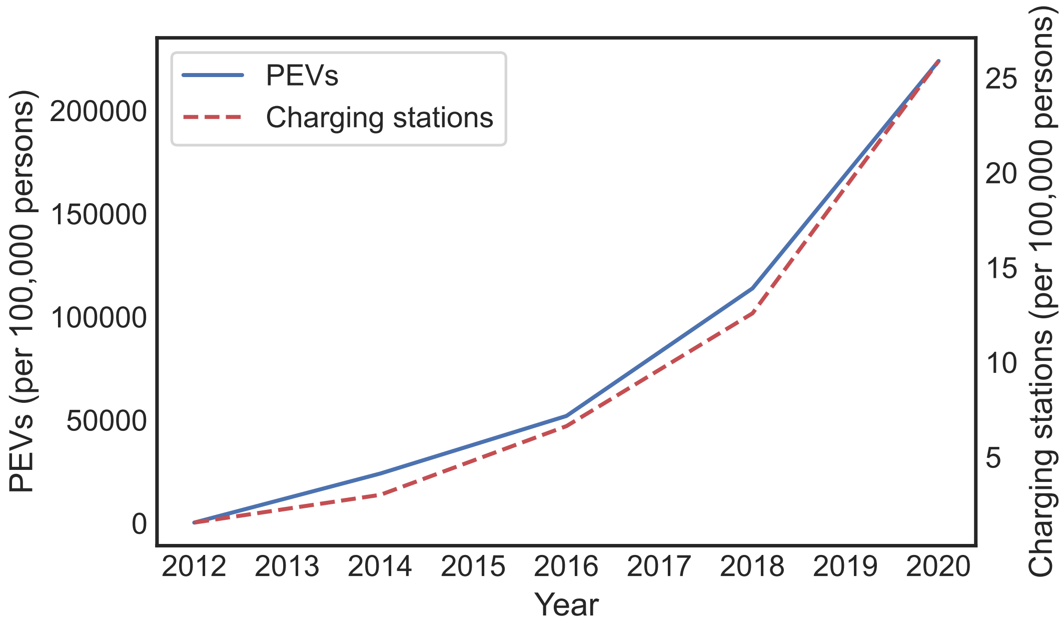


Figure 1: US BEV Registrations and Charging Stations

of charging stations. However, Chicago and Detroit both show clear patterns of low charging station density in their majority-minority communities and unexpectedly high station densities in low density suburban communities. While there are few charging stations in Omamah, those outside its downtown are located along an east-west axis along the I-80 corridor. There are few stations in north and south Omaha, which are enclaves of black and hispanic residents, respectively.

Another simple descriptive comparison between the PEV and charging station markets is shown in Figure 3. PEV sales market share is plotted against charging stations per thousand residents as of 2020. While there appears to be a positive correlation between these infrastructures, there are clearly other factors at play - e.g., observe the difference between California and Vermont.

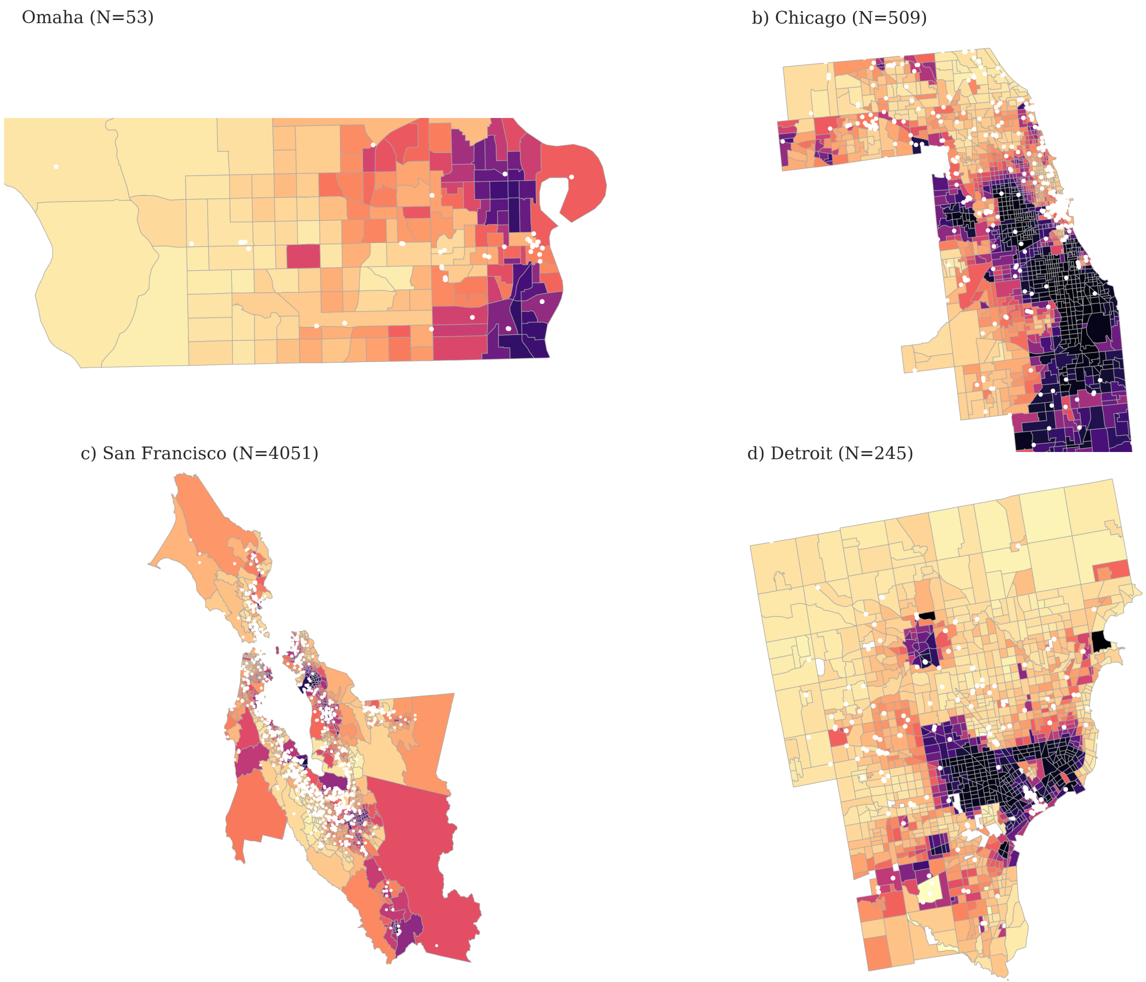
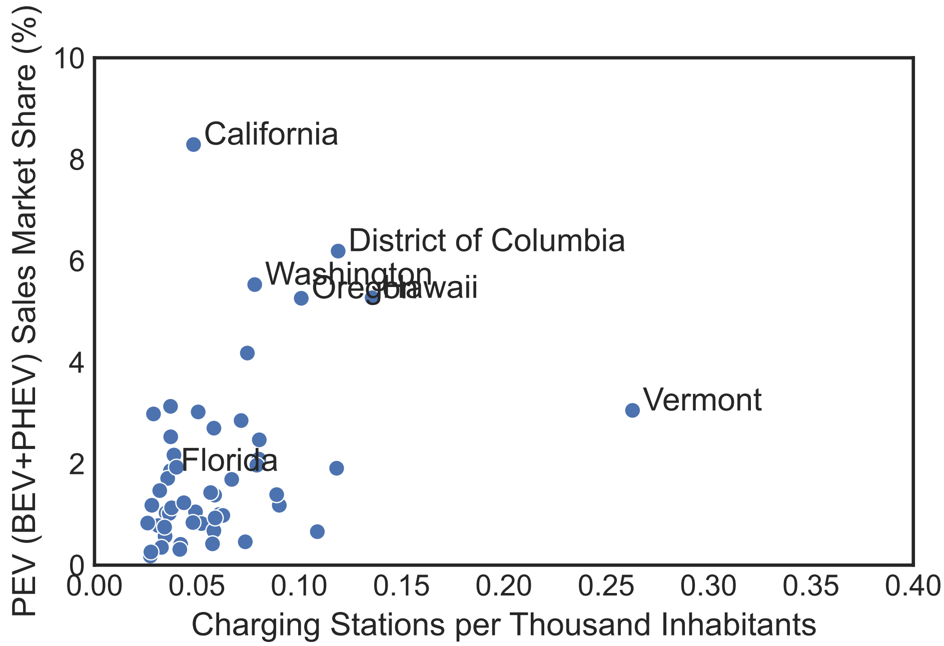


Figure 2: Equity plot



5.2 Phasing Causality Analysis

Before conducting the causality testing, we use Augmented Dickey-Fuller (ADF) and Kwiatkouski-Phillips-Schmidt-Shin (KPSS) tests for stationarity tests were applied to the aggregated US time series and its first differenced analogue. In both cases, it was found that the time series is non-stationary. ADF and KPSS tests were also iteratively applied to each county time series with simiar results.

A limitation to the machine learning-based causality tests is that they require large datasets to perform inference on a highly non-stationary time series. Five annual datapoints is insufficient to run the tests. We overcome this barrier by leveraging the spatio-temporal nature of our dataset. The strategy is to consider each county as a slice of a spatio-temporal series. We select only the 2020 data and assume that charging stations and EV registrations in that year may be affected by their corresponding observations in previous years but not observations in other counties. This approach effectively defines a spatio-temporal series with a maximum lag of four units (lagged 2018, 2016, 2014, and 2012) plus an instantaneous effect (2020). Figure Figure 3 illustrates the concept for five random counties.

We perform the non-linear causality tests using MLP, LSM, GRU, and ARIMA models. Given that charging station data can be aggregated to annual totals in every year, we also test both one and two year lags alternatively considering charging stations and EV registrations as the causal impetus. That is, we consider 2012, 2014, 2016, 2018, and 2020 station totals and 2011, 2015, 2017, and 2019 totals causing EV registrations in the five available years, then add 2021

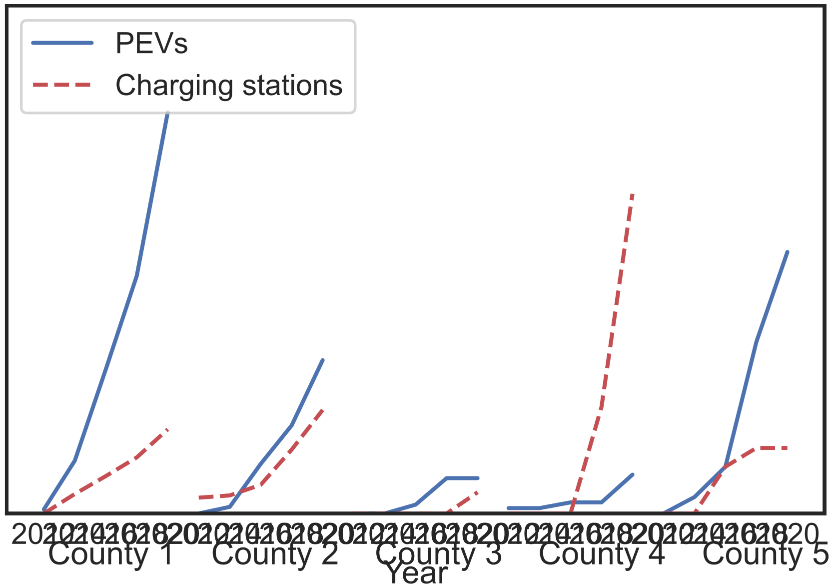


Figure 3: Lags plot

station totals and consider EV registrations as causing charging station deployments. In neither case are definitive results found to support either causal mechanisms. These results indicate a feedback relationship between the two variables of interest. While our spatio-temporal approach allows us to perform these statistical tests, it does not allow us to test for feedback effects because the underlying time series remains too short.

model	lag	cohens_d_pc	cohens_d_cp	cohens_d_pcl	cohens_d_cpl
ARIMA	1	0.012	0.031	0.027	0.030
ARIMA	2	0.010	0.029	0.026	0.026
ARIMA	3	0.013	0.018	0.025	0.031
ARIMA	4	0.005	0.025	0.016	0.024
ARIMA	5	0.000	0.018	0.010	0.005
GRU	1	0.131	0.199	0.156	0.258
LSTM	1	0.240	0.231	0.133	0.035
LSTM	2	0.211	0.157	0.101	0.357
LSTM	3	0.196	0.069	0.145	0.062
LSTM	5	0.144	0.094	0.102	0.264
MLP	2	0.253	0.433	0.627	0.164
MLP	3	0.120	0.511	0.414	0.526
MLP	4	0.197	0.522	0.371	0.210
MLP	5	0.008	0.506	0.574	0.100
NN	1	0.160	0.007	0.003	0.136

model	lag	cohens_d_pc	cohens_d_cp	cohens_d_pcl	cohens_d_cpl
NN	3	0.155	0.044	0.097	0.020
NN	4	0.053	0.064	0.036	0.049

5.3 Dose-Response Results

With inclusive phasing causality results, we maintain the assumption that charging stations cause EV registrations in the dose-response analysis.

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Please do not make inferences based on these values!

Collaborate on a solution, and stay up to date at:
github.com/dswah/pyGAM/issues/163

  self.gam_results.summary()
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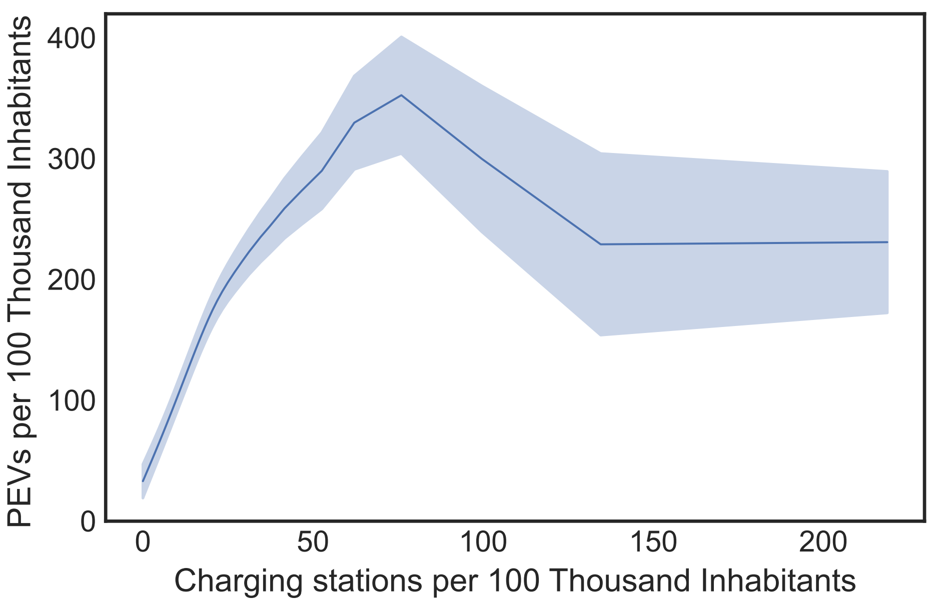
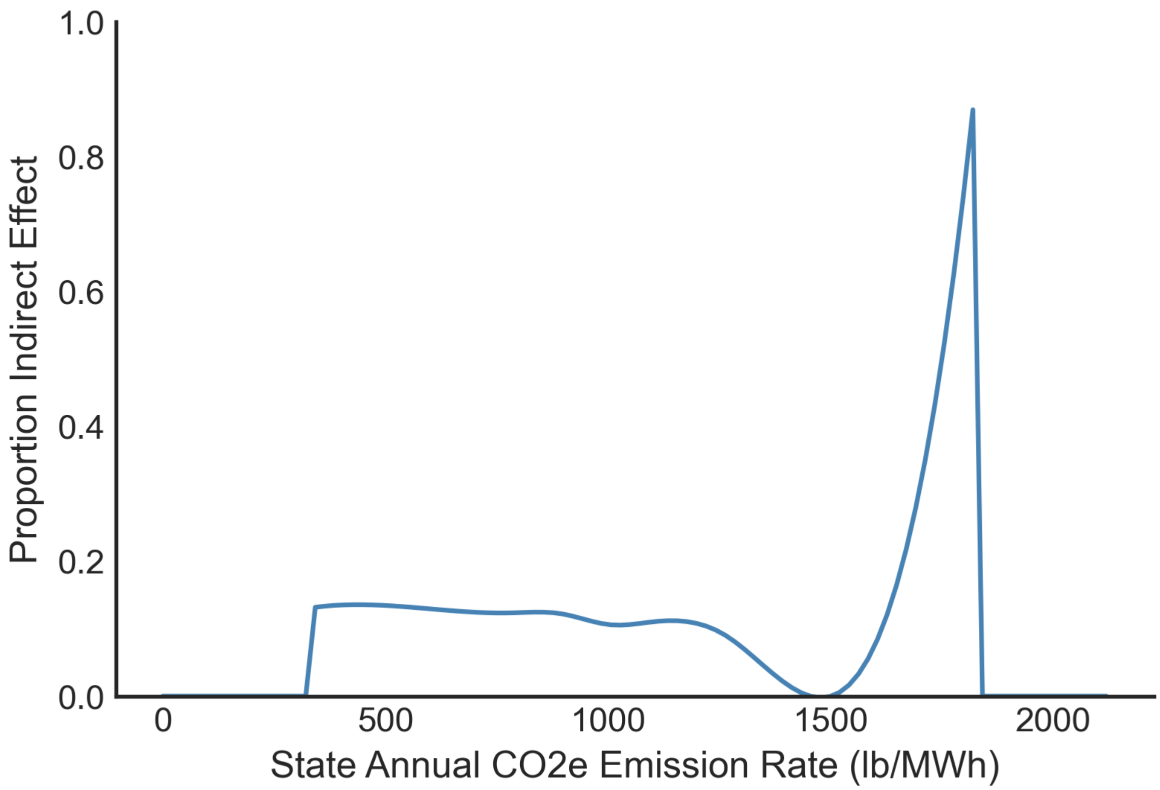
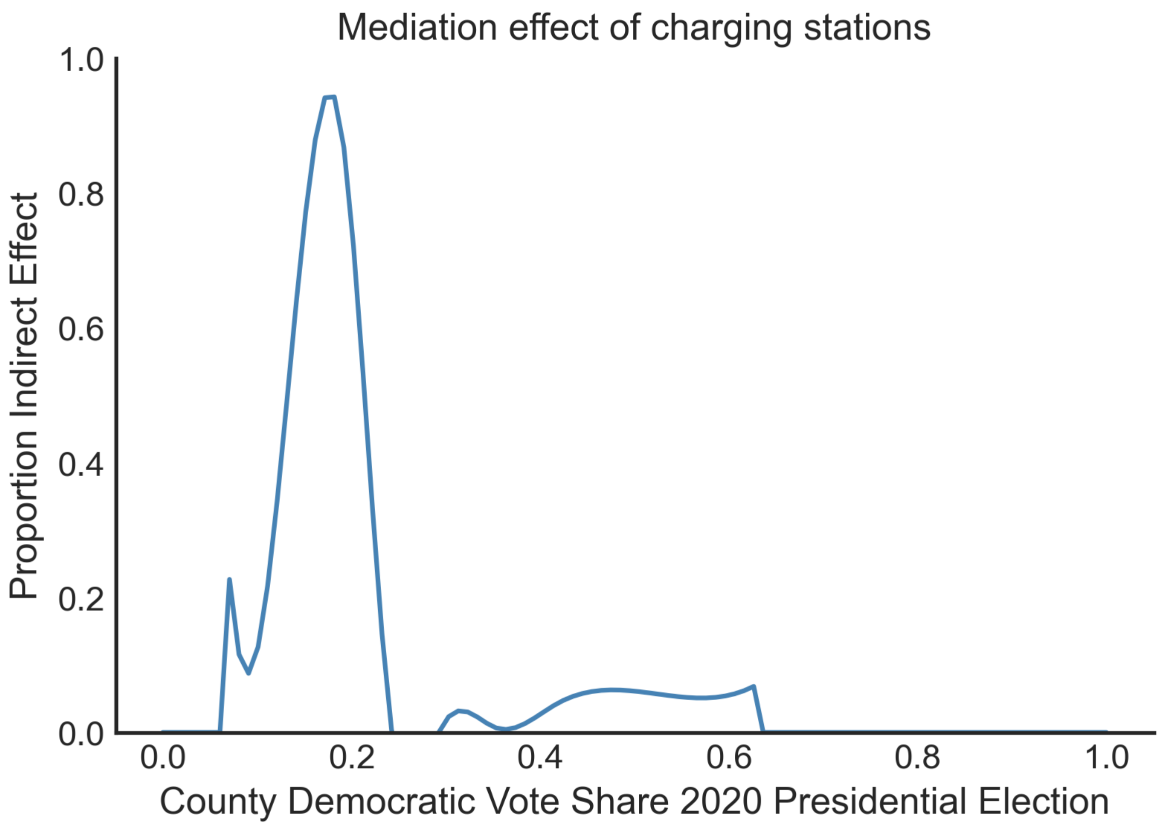


5.4 GPS Model Results

	est.	t-stat
xW	0.019	13.10
Percent_Minority	-7.3	-1.28
ABDPE001	-0.28	-4.75

5.5 Mediation Effect Results





6 Discussion and Conclusions

The results presented herein are preliminary and do not consider a key dataset – vehicle registrations. We will expand our analysis to a more robust inferential study in the coming months. Our causal question is what effect public charging stations have on electric vehicle registrations at the county-level. The treatment variable is continuous over the study period. We propose three causal identification approaches. The first approach is a difference-in-differences approach that is identified off state-level investments in charging stations by year. The second approach is generalized propensity score matching using federal election results, state-level greenhouse gas (GHG) emissions factors, and demographic characteristics (e.g., racial composition, median income, and population density) as inputs to the propensity score.

The final causal inference approach, Granger causality, differs in that it focuses on the temporal phasing of charging station installations and PEV registration, whereas the other two approaches rely on Rubin's potential outcome assumption (Reich et al. 2021). Granger causality relies on the assumption that past treatment knowledge reduces predictive uncertainty. It is a form of time series causal inference that would fit the current context well.

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