On the Chicken & Egg Problem in Transportation Electrification

Jason Hawkins Ph.D. Nicholas Aldridge

1 INTRODUCTION

Due to climate change causing rising global temperatures, countries around the world are starting to take action to fight these harmful effects. A big focus for climate scientists and policy makers alike is to reduce the amount of CO2 that is emitted into the atmosphere. One of the biggest contributors to CO2 emissions is the transportation system, which in the United States is responsible for 29% of the total CO2 emissions. The biggest reason for the high level of transportation system emissions is due to reliance of oil and gas, which power the majority of private vehicles in the United States. Producing oil and gas emits lots of CO2; the total amount of GHG emissions from the oil and gas industry is over 5 billion tons, which represents roughly 15% of the total energy sector emissions. These emission levels are exacerbated by driving patterns by citizens in the United States, which are much longer distances than other countries due to the geography and city planning trends that are common in the US. Because of the high amount of transportation system emissions due to the reliance on oil and gas, vehicle electrification is widely regarded as a critical tool for climate change mitigation in the transportation sector (Musti and Kockelman 2011). Researchers at Princeton University have worked to set aggressive targets to increase vehicle electrification in the United States, with some plans coming close to 95% of vehicles being electric (Larson et al. 2021). Less aggressive plans from the same researchers put the market share of electric vehicles around 60%. Despite this and the United States seeing an increasing share of electric sales, the pace of adoption remains well below the necessary level to mitigate climate change impacts. Electric vehicle adoption is driven by a number of factors related properties of the electric vehicles, such as price, driving range and charging time, and by factors outside of the vehicles, such as consumer characteristics, fuel prices, and government policy. The purchase price is one of the main properties that influences consumers to purchase electric vehicles. When surveyed about reason why they would choose to not purchase an EV, potential buyers cited the price as the biggest deterrent (Hidrue et al. 2011). Additional research has found that drastically increasing the battery size of the vehicle while not changing the price did very little to persuade buyers to purchase electric vehicles (**Adepetu2017?**). The least influential factor related directly to the vehicle properties is the charging time. One analysis found that reducing the charging time from 10 hours to 10 minutes while changing no other factors, buyers were still more likely to pick gas powered cars (Hidrue et al. 2011). There are many factors not directly related to electric vehicles that are influential in increasing EV adoption. The strongest of these factors is the price of fuel. One study found that an 10% increase in fuel prices resulted in an up to 90% increase in the market share of hybrid vehicles (Diamond 2009). In addition to fuel prices, the characteristics of consumers influences how electric vehicles are adopted. Characteristics like age and education are the most significant predictors in how likely a person is to purchase an EV (Hidrue et al. 2011). Another outside factor that affects the market share of EVs is government policy. Most government policy is targeted at reducing the price of EVs, but it can encompass many other strategies like creating a more robust charging infrastructure, which is the focus of this paper. The lack of charging infrastructure is another large barrier to widespread adoption (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 (Li et al. 2017). Governments are starting to utilize this knowledge when drafting spending policy; recently, the US Federal Government passed an infrastructure bill that allocates roughly $5 billion to creating a network of charging stations. The network of charging stations setup by this spending will be placed along designated roads, particularly the US Interstate System.The fact that government spending on charging station deployment can yield better results 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 (Zhou and Li 2018). 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 (Li et al. 2017). 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 (Sheldon, DeShazo, and Carson 2019). Knowing this information can allow policy makers to create subsidy programs that produce more effective outcomes.

2 THE ELECTRIC VEHICLE AND CHARGING STATION 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 (Granger 1969) and Rubin causality (Rubin 2005), 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. (Rosoł, Młyńczak, and Cybulski 2022) 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), neural net (NN), 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 (Hirano and Imbens 2005). Assuming a continuous treatment, the GPS is defined by

$$r(t, x) = f_{T|X}(t|x) \tag{1}$$

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 (Galagate 2016). The averaging used to construct the ADRF is based on weighting observations by the GPS using units within each basis function range.

3.3 Casual Mediation

A secondary question is the potential relationship between charging stations and other variables of interest. These relationships can be illustrated via a directed acyclic graph (DAG) as shown in **?@fig-dag** where X is a treatment variable, Z is a mediating variable, and Y is an outcome variable (Imai, Jain, and Ching 2009).

Conventional causal mediation modeling takes the form of a linear structural equation model (SEM). Extending the above notation, M_t is a mediation variable. Following the potential outcomes framework, suppose we are interested in the mediating effect of charging station investments on grid decarbonization. In many cases, utility operators provide financial support for charging stations. Limited budgets mean that a private firm or government agency may need to balance investments in both infrastructures. Previously, the potential outcome depended only on the treatment variable but now depends on both the treatment and mediator variables as \$Y(t,m)\$. Also, assume there is no interference effect meaning that mediator values for one observation do not affect the treatment value for other observations, and vice versa. The causal mediation (indirect) effect for each observation is then given by

$$\delta(t) = Y(t, M(1) - M(0) \tag{2}$$

where $M(1)$ and $M(0)$ are the potential mediator variable values with and without the treatment. The mediation effect is interpreted based on the difference between $M(1)$ and $M(0)$ holding the treatment fixed at \$t\$. If $M(1) = M(0)$ - i.e., the treatment has no effect on the mediator variable - then the causal mediation effect is zero. Again, we use a generalized additive model (GAM) to test a nonparametric average mediation effect.

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 persons).

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 1 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

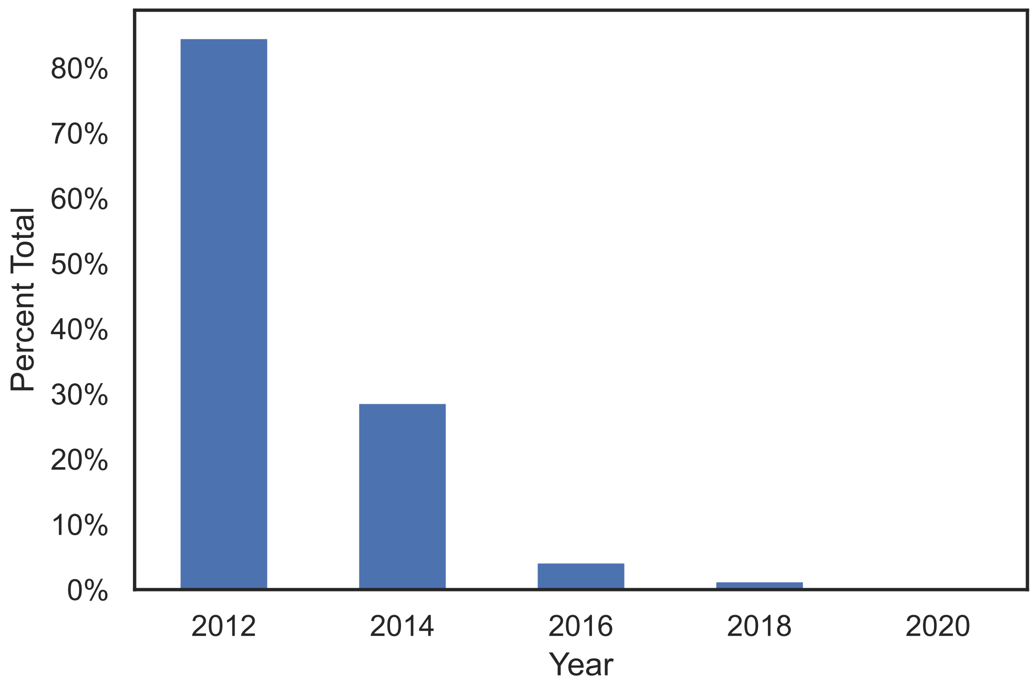

Figure 1: Counties with no PEV registrations by year

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 (**uscensusbureau2020?**). 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 persons) 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. This specification is termed a *spatial lag in X* model in the spatial econometric literature (**elhorst2017?**).

4.3 Model Specification

We use the causal-curve Python package developed by Kobrosly (**kobrolsly2020?**) for potential outcomes causal inference. This package uses a generalized linear model (GLM) to construct the GPS and a generalized additive model (GAM) to estimate the dose-response curve. 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). The model includes state-year fixed effects to account for unobserved policy variation and approxiamte autocorrelation between observations for the same county. Extensions to this model formulation are left for future work.

Causal mediation is explored for two variables. First, we consider the mediating effect of charging stations on grid carbon intensity. We use state-level eGrid data available for each analysis year. The treatment variable in this case is state annual CO_2 equivalent output emissions measured in lbs per MWh. We hypothesize that public charging station access may not be as important to PEV adoption as perceived environmental benefit as measured by grid emissions output intensity.

Second, we use 2020 county-level presidential election results as a proxy for local political effects. Climate policies have been more strongly pushed by Democratic presidential administrations, including the recent legislation by the Biden Administration to support PEV charging station infrastructure. Climate policy is also set at the state-level, so gubernatorial election returns are an alternative political variable. However, consistent county-level data were not readily available from a single source. The causal hypothesis is that political affiliation is associated with a proclivity towards environmentally considerations when purchasing a vehicle. A change in charging infrastructure access is a mediating variable on higher Democratic affiliation (as a proxy for public sentiments about the need for climate change action) leading to PEV adoption.

5 Results

5.1 Descriptive Analysis

@fig-us-totals provides a first validation of the research hypothesis that there is a relationship between PEV adoption and charging station access. Registered 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. This initial plot also ignores regional variations, which will be important to understanding the drivers of the relationship.

The Bipartisan Infrastructure Act places a strong focus on equitable investment allocation. Equity can be explored both inter-regionally and intra-regionally by key demographic features. @fig-equity 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 (**menendian2020?**). 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 of charging stations. However, Chicago and Detroit both show clear patterns of

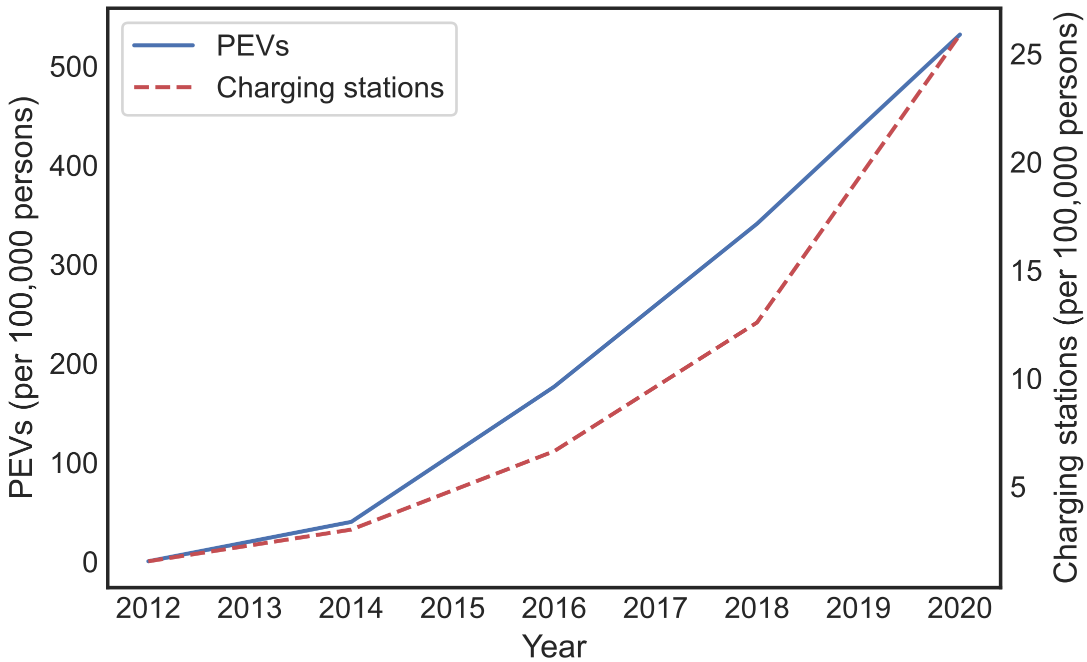

Figure 2: US PEV registrations and charging stations by year

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 Omaha, 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. Similar inequities have been observed across US cities for other transportation infrastructure investments, such as rail transit stations that map more closely to income than population density (**spieler2020?**).

Another useful descriptive comparison between the PEV and charging station markets is shown in Figure 4. 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. This comparison suggests that there are other factors that drive PEV adoption and it may not be sufficient to simply install charging stations.

5.2 Phasing Causality

Before conducting the phasing causality tests, we applied Augmented Dickey-Fuller (ADF) and Kwiatkouski-Phillips-Schmidt-Shin (KPSS) tests for stationarity to the aggregated US time series and its first differenced analogue. In both cases, it was found that the time series is

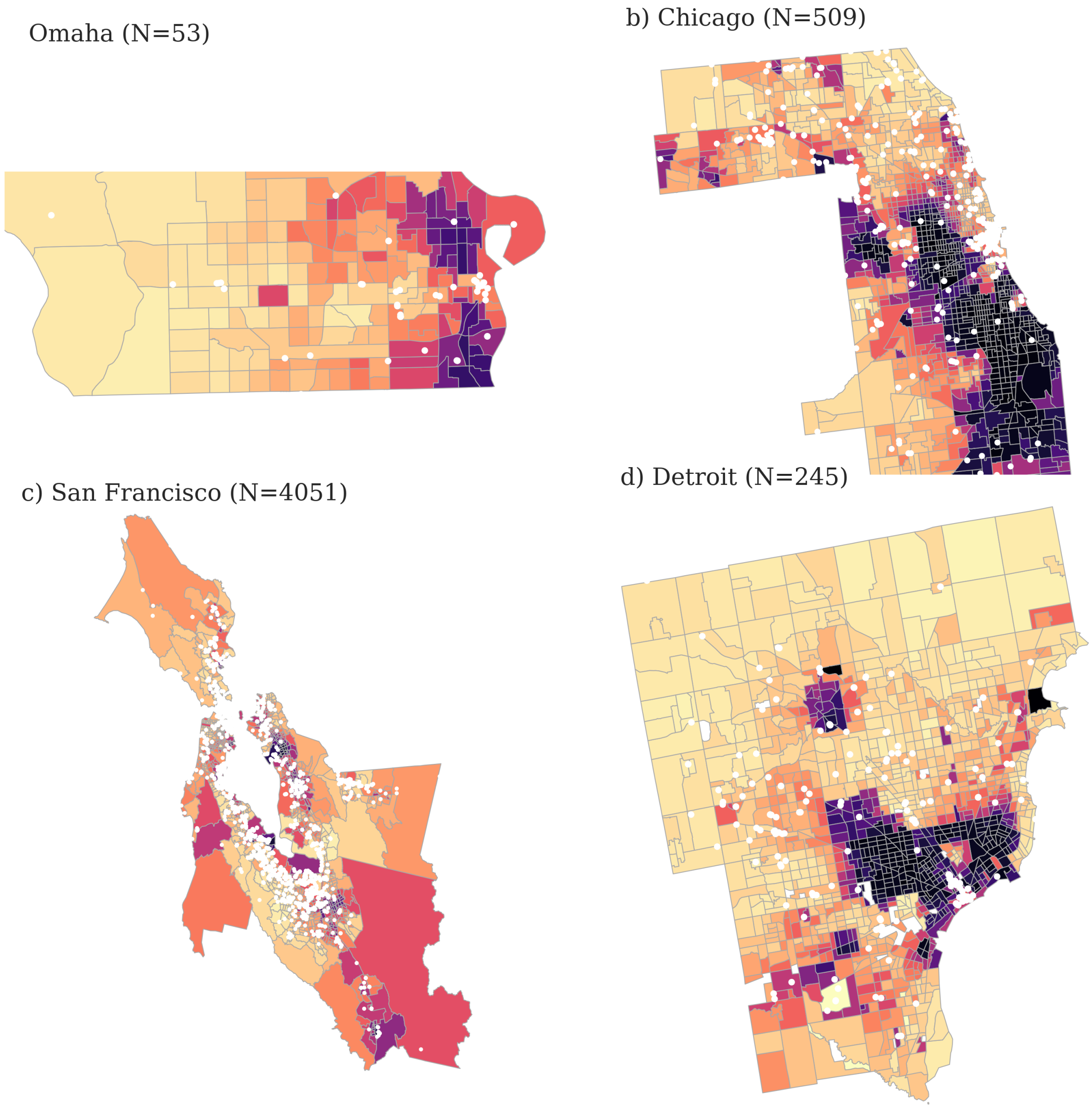

Figure 3: Charging station locations for four metropolitan regions

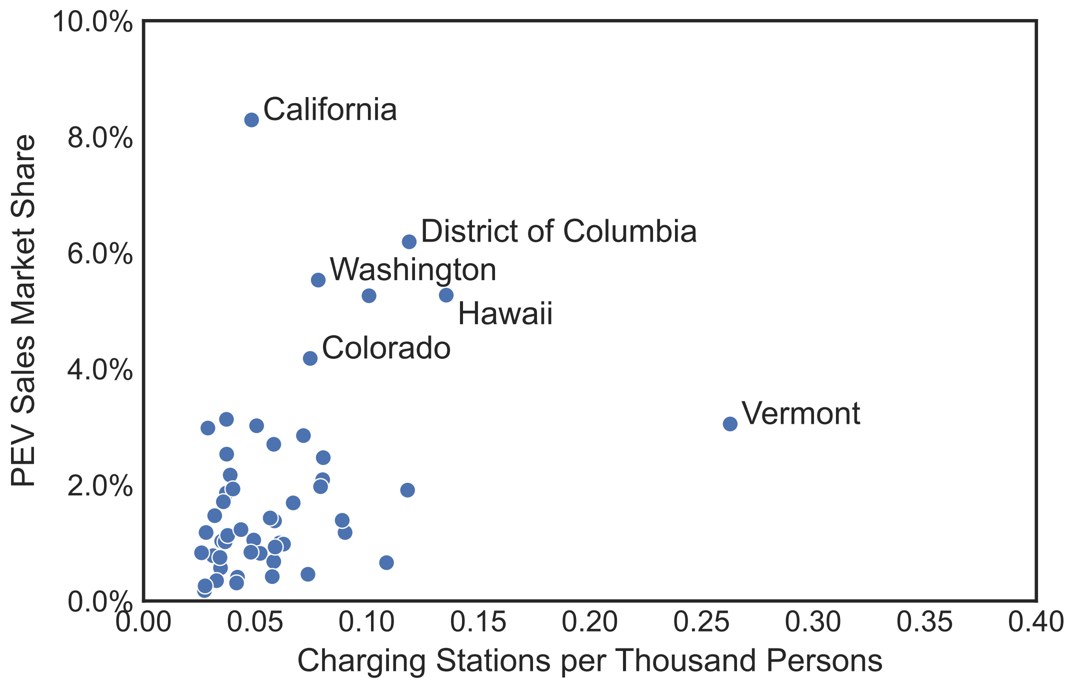

Figure 4: Charging stations and PEV sales by state in 2020

non-stationary. ADF and KPSS tests were also iteratively applied to each county time series with similar 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, as we found to be the case here. Five annual data points 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 observations) plus an instantaneous effect (the 2020 observation). Figure 5 illustrates the concept for five randomly selected counties.

We perform the non-linear causality tests using MLP, LSM, GRU, and ARIMA models, with resulted summarized in (**tab-phasing-tests?**). 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 station totals causing PEV registrations in the five available years, then add 2021 station totals and consider PEV registrations as causing charging station deployments. None of these analyses

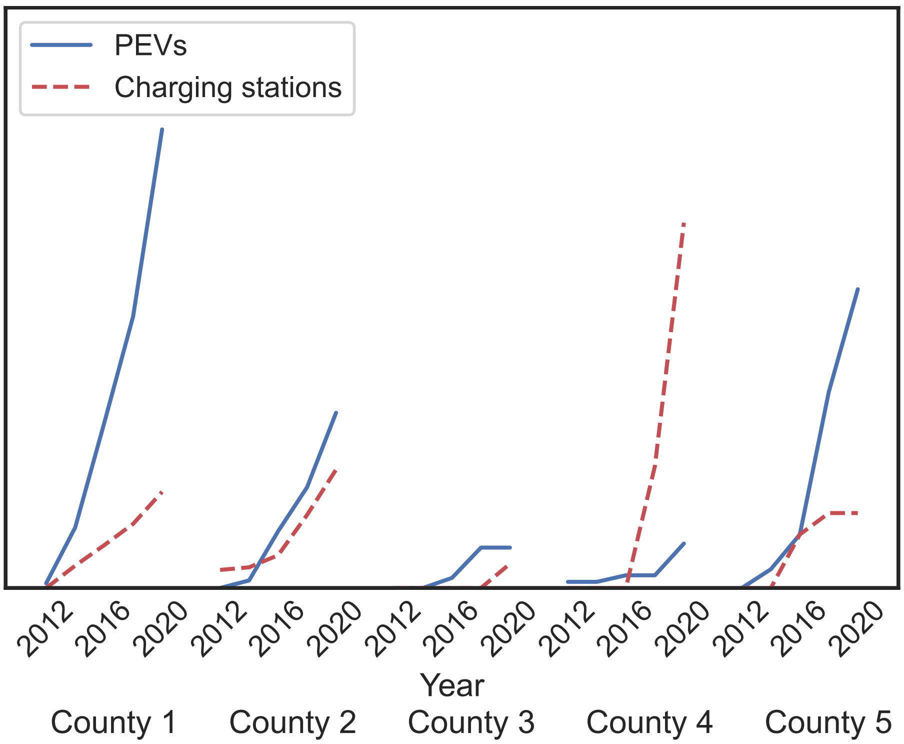

Figure 5: Spatio-temporal lag illustration for five random counties

gives definitive support for 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.

Granger (Granger 1969) notes that the speed of information flow is an important factor in causal phasing, as well as the data sampling frequency. He suggests that results may differ depending upon if analysis is conducted at an annual, quarterly, or monthly frequency. However, the electric transportation market does not change fast enough pace for sub-annual variation to be significant. Two pertinent factors to consider are that vehicles tend to be kept for many years and a single charging station is unlikely to incentive widespread EV purchases in a county. As such, it is unlikely that individuals respond to charging station investments at a sub-annual frequency and this frequency is deemed acceptable.

Model	Lag	(1)	(2)	(3)	(4)
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
NN	3	0.155	0.044	0.097	0.020
NN	4	0.053	0.064	0.036	0.049

5.3 GPS-Based Potential Outcomes Causality

Given the inconclusive phasing causality results, we maintain the assumption that charging stations cause PEV registrations in subsequent analysis. This section first presents the GPS model results that are input into the GAM dose-response model. We then provide the dose-response results, followed by mediation model results.

5.3.1 GPS Model Results

The GPS model includes spatially lagged charging stations per 100,000 persons in adjacent counties, the portion of the population that identifies as a minority, median household income in $10,000, and state-year fixed effects (omitted from (**tab-gps-results?**)). As expected, we find that charging stations in adjacent counties are correlated with more charging stations in the home county. Counties with higher minority population shares tend to have lower charging station access. Income is found to have a negative effect on charging station access. At first glance, this is an unintuitive result because we tend to see more amenities in higher income communities. However, it is supported by past research (REF). A plausible reason for this result is that higher income counties tend to have larger homes in which residents can charge their vehicles, thus reducing the need for public charging stations. As illustrated in Figure 3, charging stations are concentrated in urban counties that tend to have lower median incomes than their surrounding suburban counties.

	est.	t-stat
Lagged charging stations	0.019	13.10
Percent minority	-7.3	-1.28
Household income ($10,000)	-0.28	-4.75

5.4 Dose-Response Model Results

Figure 6 confirms the hypothesis that charging station access encourages individuals to purchase PEVs. However, the encouragement tends to become less effective at higher charging station penetration rates. In fact, it becomes negative in the region around 100 charging stations per 100,000 persons when controlling for other covariates. This result fits our finding in Figure 4 that California has the highest PEV sales market share despite several other states having more charging stations per capita.

5.5 Mediation Effect Results

Mediation plots are shown in Figure 7 and Figure 8 for grid CO_2e intensity and Democratic vote share, respectively. The mediation plots show the proportion of the effect from each treatment variable that is caused by the mediating effect of charging stations. In the case of CO_2e emissions rate, charging stations account for roughly 18% of the effect for most states. However, in the states with the highest emissions intensities there are either very few registered PEVs (no effect from either charging stations or grid CO_2e intensity) or PEV registrations are driven by charging stations investments despite a high CO_2e emissions intensity state grid. These results suggest that lowering grid emissions tends to increase PEV registrations, but it is

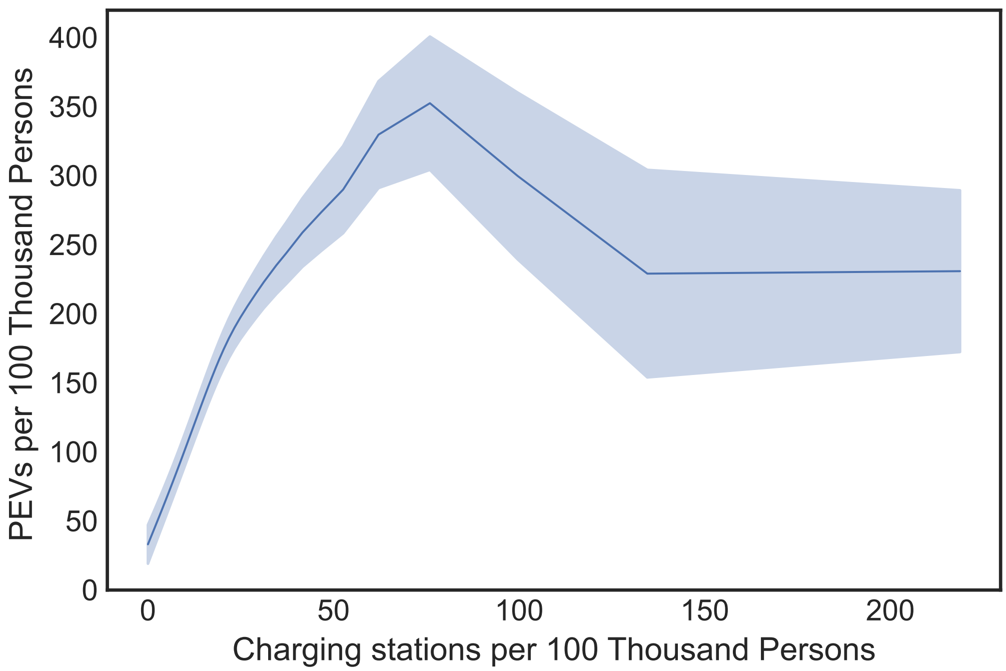

Figure 6: Dose-response curve for charging stations and PEV registrations

also feasible to encourage minimal PEV adoption with a highly emitting grid via investments in charging station infrastructure.

Democratic vote share is mediated by charging station infrastructure only in the lowest share range. Similar to highly emitting grids, it appears that charging stations investments can mediate the effect of political affiliation on PEV registrations. However, the PEV adoption rates tend to be low in these counties.

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.

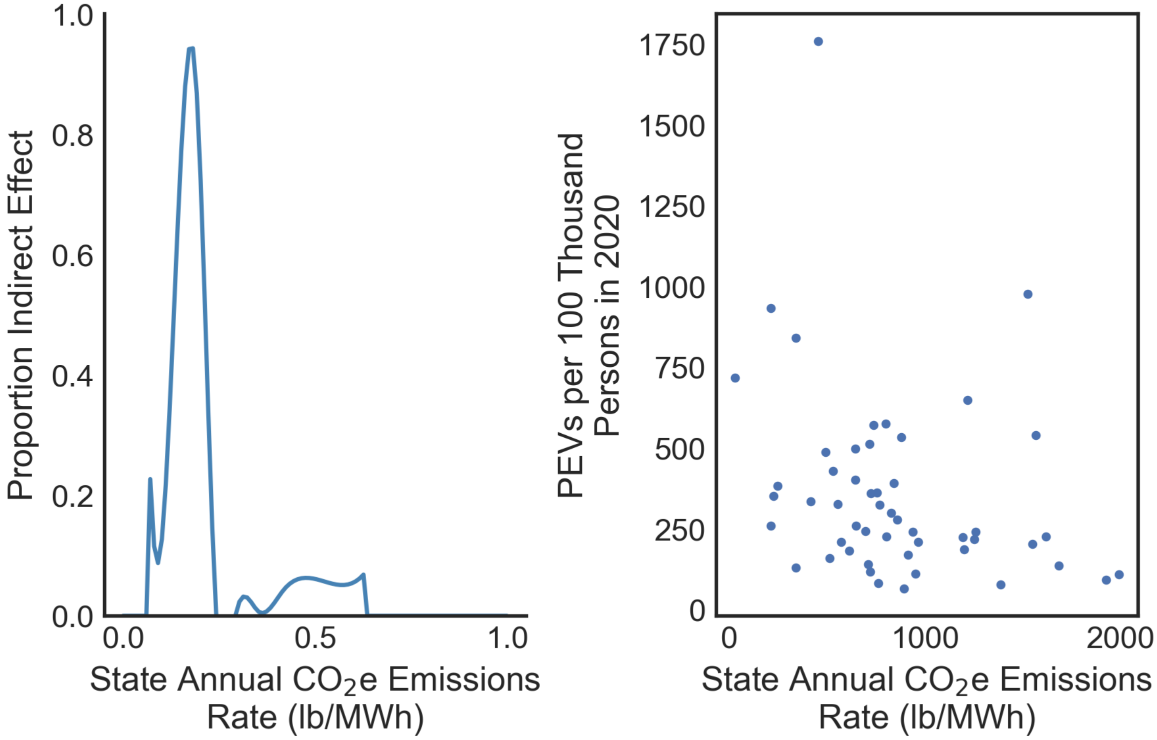

Figure 7: Mediation results for CO2

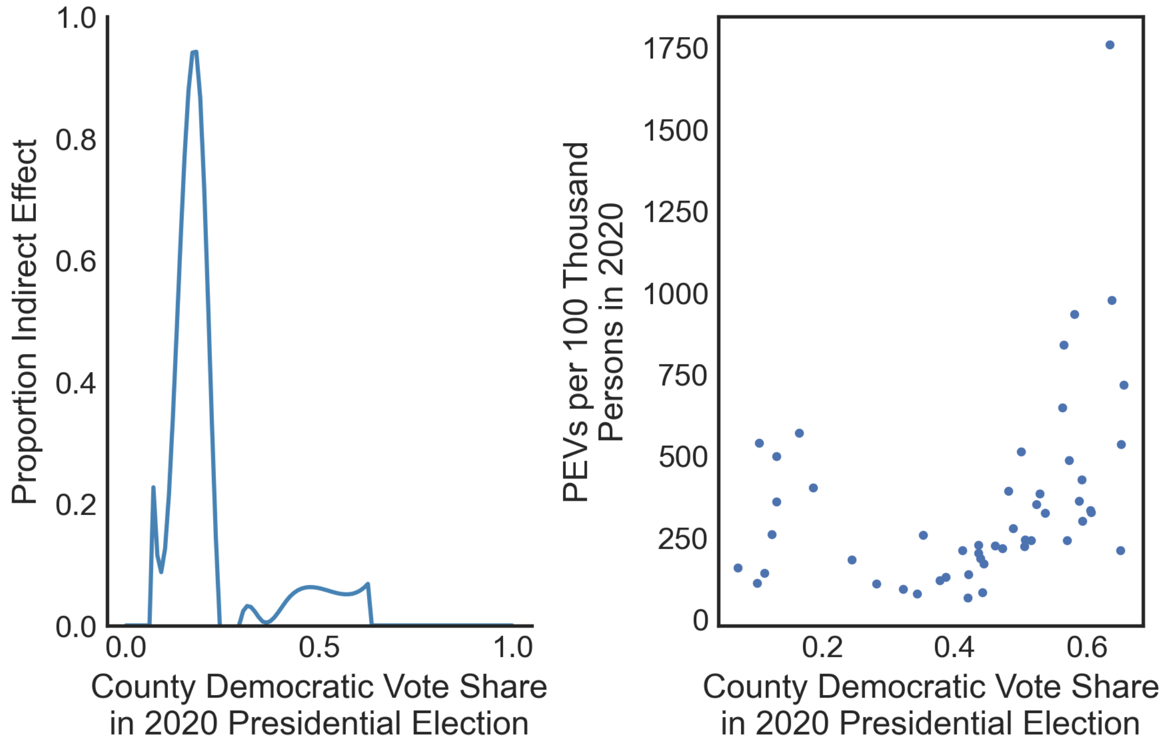

Figure 8: Mediation results for 2020 presidential election returns

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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