# 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

- C:\Users\jhawkins17\Anaconda3\envs\geo\_env\lib\site-packages\seaborn\rcmod.py:400: Deprecation
  if LooseVersion(mpl.\_\_version\_\_) >= "3.0":
- C:\Users\jhawkins17\Anaconda3\envs\geo\_env\lib\site-packages\setuptools\\_distutils\version.pg
  other = LooseVersion(other)

# 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

# 3.1 Non-Linear Granger Causality

### 3.2 Potential Outcomes Causality Via Propensity Score Matching

#### 4 DATA

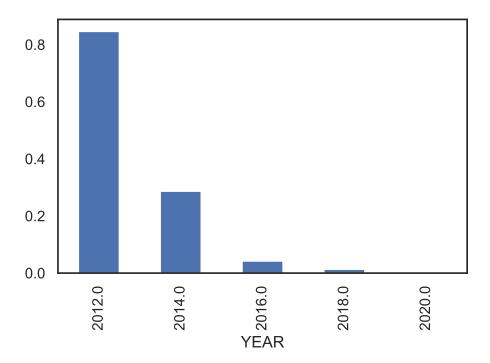
We use a combination of open-source and purchased data in our analysis. The two key input datasets are charging station locations provided by the Alternative Fuel Data Center (AFDC) and electric vehicle registrations provided by Experian Inc. The vehicle registration dataset comprises a 10-year panel at 2-year increments (2012, 2014, 2016, 2018, 2020). Total vehicle registrations are recorded by county, make, model, year, and other vehicle characteristics for the United States.

After filtering out protectorates and other state-state locations, several county codes in the Experian data remain that are missing registration totals in a subsset of years (192/3172, or about 6%). We remove county codes with more than one missing year, leaving 186 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 and much of Idaho).

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

To capture spatial spillover effects, a Queen contiguity matrix is constructed.

# 5 Results



(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.

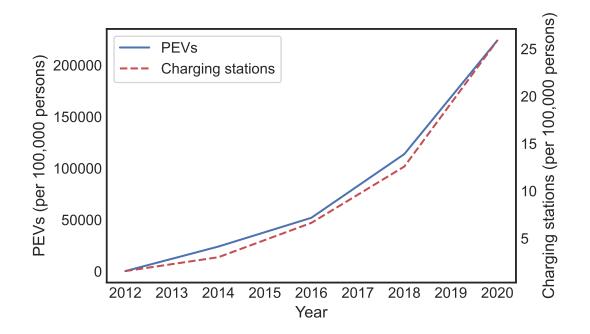
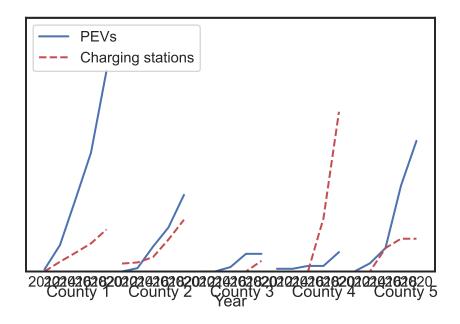


Figure 1: US BEV Registrations and Charging Stations



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. 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 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.

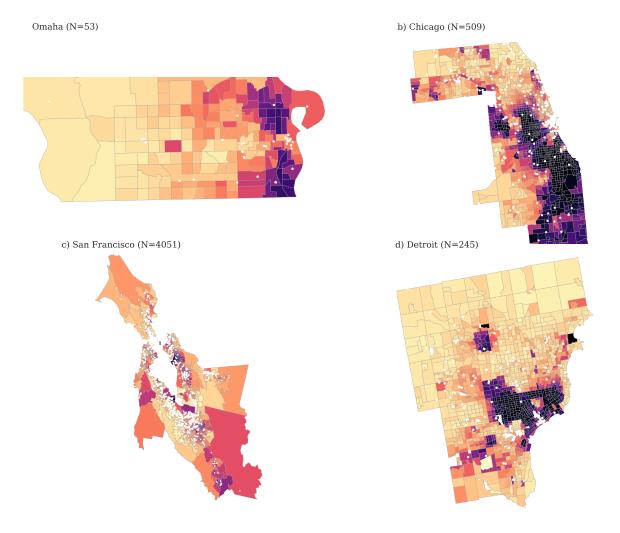
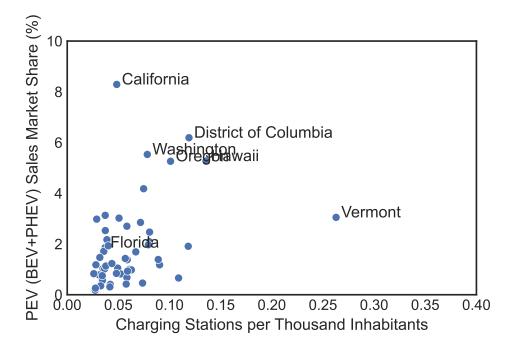


Figure 2: Equity plot

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.



Both ADF and KPSS tests indicate that the BEV and charging station data are non-stationary. Therefore, we will difference the data, as required by the Granger causality test.

The differences didn't help and we don't have a long enough time series to use a longer lag. Let's take a look at it by state.

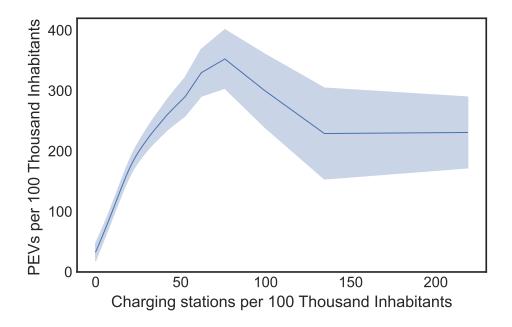
Let's try a non-linear causality analysis from Rosol et al.

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

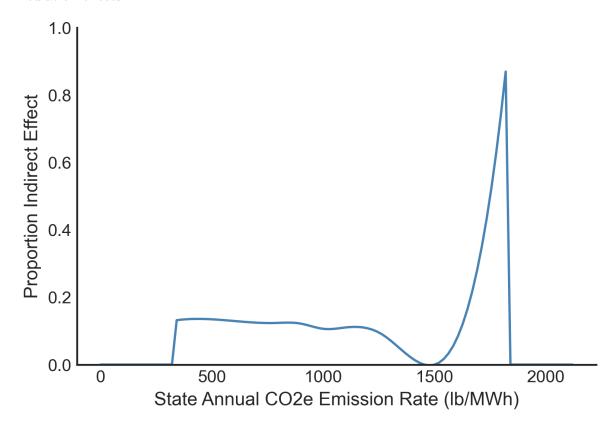
model	lag	cohens_d_pc	cohens_d_cp	$cohens\_d\_pcl$	cohens_d_cpl
MLP	2	0.253	0.433	0.627	0.164
MLP	3	0.120	0.511	0.414	0.526
MLP	4	0.197	0.522	0.371	0.210
MLP	5	0.008	0.506	0.574	0.100
NN	1	0.160	0.007	0.003	0.136
NN	3	0.155	0.044	0.097	0.020
NN	4	0.053	0.064	0.036	0.049

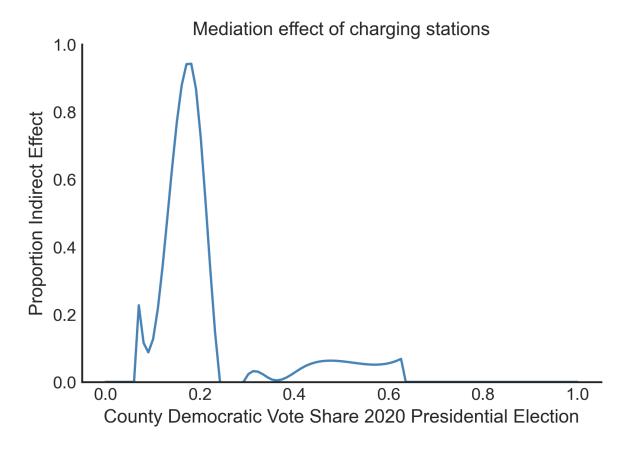
Using the following params for GPS model:

```
'gps_family': None,
              'lower_grid_constraint': 0.01,
              'max_iter': 100,
              'n_splines': 30,
               'random_seed': None,
              'spline_order': 3,
               'treatment_grid_num': 100,
               'upper_grid_constraint': 0.99,
               'verbose': True}
Determined the outcome variable is of type continuous...
Must fit `normal` GLM family to model treatment since
                                                      treatment takes on zero or negative values...
Saving GPS values...
Fitting GAM using treatment and GPS...
Calculating many CDRC estimates for each treatment grid value...
                                         Generating predictions for each value of treatment grid,
                                         and averaging to get the CDRC...
C:\Users\jhawkins17\Anaconda3\envs\geo_env\lib\site-packages\causal_curve\gps_core.py:452: Users\jhawkins17\Anaconda3\envs\geo_env\lib\site-packages\causal_curve\gps_core.py:452: Users\jhawkins17\Anaconda3\envs\geo_env\lib\site-packages\notation\geo_env\lib\site-packages\notation\geo_env\lib\site-packages\notation\geo_env\lib\site-packages\notation\geo_env\lib\site-packages\notation\geo_env\lib\site-packages\notation\geo_env\lib\site-packages\notation\geo_env\lib\site-packages\notation\geo_env\lib\site-packages\notation\geo_env\lib\site-packages\notation\geo_env\lib\site-packages\notation\geo_env\lib\site-packages\notation\geo_env\lib\site-packages\notation\geo_env\lib\site-packages\notation\geo_env\lib\site-packages\notation\geo_env\lib\site-packages\notation\geo_env\lib\site-packages\notation\geo_env\lib\site-packages\notation\geo_env\lib\site-packages\notation\geo_env\lib\site-packages\notation\geo_env\lib\site-packages\notation\geo_env\lib\site-packages\notation\geo_env\lib\site-packages\notation\geo_env\lib\site-packages\notation\geo_env\lib\site-packages\notation\geo_env\lib\site-packages\notation\geo_env\lib\site-packages\notation\geo_env\lib\site-packages\notation\geo_env\lib\site-packages\notation\geo_env\lib\site-packages\no
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()
```



# Mediation effects





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

# 6 Discussion

# 7 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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