CAUSALITY IN OREGON’S ELECTRIC VEHICLE MARKET

by

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A THESIS

Presented to the Department of Economics
and the Robert D. Clark Honors College
in partial fulfillment of the requirements for the degree of
Bachelor of Science

May 2022

An Abstract of the Thesis of

Aidan Potts for the degree of Bachelor of Science
in the Department of Economics to be taken June 2022

Title: Causality in Oregon's Electric Vehicle Market

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As the electric vehicle market matures in Oregon, examining successful policies and market dynamics is essential to maintain the healthy economic growth in this industry. Oregon has been a leader among other states in promoting electric vehicle adoption through various rebates, tax credits, initiatives, installing charging infrastructure, and expanding consumer awareness. I aim to critically analyze the specific causal impact that policy-driven charging initiatives have on electric vehicle demand in Oregon. As the electric vehicle market has grown, the various factors influencing consumer decision-making have become more complicated, and causality is not simply estimated. After analyzing the causal impact that chargers have on new electric vehicle purchases using a synthetic control model and a lagged OLS estimation, it appears that heterogeneity and indirect network effects have a significant impact on Oregon's electric vehicle market.

Acknowledgments

I want to thank Professors Ed Rubin, Corinne Bayerl, and Mike Urbancic for helping me thoroughly examine the specific topic and consider the various perspectives and contexts related to this subject matter. I would like to extend my deepest gratitude to Professor Ed Rubin for his patience and brilliant insight throughout my project. I also want to thank Professor Mike Urbancic for being a wonderful influence both at the university and on the Duck Store Board of Directors for all four years of my college experience. I had the privilege and excellent introduction to the CHC my freshman year from Professor Corinne Bayerl. I am grateful for those first seminar classes in Chapman that really ignited my passion for learning.

I would not have been able to complete this project were it not for my roommates and my friends Asher Savin and Kellie McSween, who through it all kept encouraging me and pushing me to be my best. Lady and gentlemen, thank you.

Finally, I would like to thank Professor Trond Jacobsen for his tireless support in teasing out my research topic and for the care he has for his students.

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Introduction

The United States electric vehicle market is a growing industry that combines the freedoms of car ownership with environmental consciousness. Before fully electric vehicles, the first mass-produced hybrid-electric vehicle was the Toyota Prius which first hit the global electric vehicle market in 2000. The US Energy Department would fund research and development around battery technology and charging infrastructure throughout the next decade in anticipation of fully electric vehicles being driven on US roads. A decade after the Prius' release in the US, the fully electric plug-in Nissan Leaf Chevrolet Volt emerged as the first plug-in hybrid-electric vehicle and generated great excitement in the electric vehicle industry. From 2014 to the current day, multiple car manufacturers have entered the market[1], bringing on healthy market competition and offering consumers different price points, styles, and performance options. Since its humble beginnings in 2010, the US electric vehicle market has grown to roughly $24.03 billion in 2020 and is forecasted by multiple private market researchers to exceed $120 billion by 2028[2].

Over the past decade, growth in the electric vehicle market has exhibited healthy economic growth in all aspects up to its current level. During that time, the US and state governments directly incentivized electric vehicle purchases using a variety of tax credits. They indirectly incentivized electric vehicle purchases via funding

[1] As of 2014, Chevrolet, Nissan, Tesla, Toyota, Ford, BMW, VW, Cadillac, Porsche, and Mercedes Benz offered plug-in EVs in the US. Other major and minor manufacturers have entered the market since then.
[2] Fortune Business Insights. (2022, February). U.S. Electric Vehicle Market Size, Share & COVID-19 Impact Analysis, By Vehicle Type (Passenger Cars, Commercial Vehicles) and Regional Forecast, 2021–2028.

technological research, providing loans to manufacturers, and creating plans to build out the charging network. Due to the range limitations of electric vehicles and long charge times, the issue of charger availability and charging speed has been central to the discussion of the electric vehicle market's path forward.

Discovering and analyzing the source of causality in a market enables policymakers and firms to make economically efficient and prudent decisions. Because of this, identifying the influence that charging infrastructure and other electric vehicle purchases have on new electric vehicle purchases reveals critical causal dynamics within the market. As Oregon's electric vehicle market grows, determining the causal effects of chargers and electric vehicle purchases can shape policy decisions and, ultimately, the future of electric vehicle use in Oregon.

Definitions and Abbreviations

1. **ARRA:** American Recovery and Reinvestment Act of 2009.
2. **Internal Combustion Engine Vehicles (ICEVs):** Automobiles powered by an internal combustion engine that uses gasoline as its fuel source.
3. **Electric Vehicles (EVs):** Automobiles propelled by one or two electric motors fed from batteries onboard the vehicle. In this thesis, this category of vehicles includes vehicles solely powered by electricity.
4. **NEVI:** The National Electric Vehicle Infrastructure Formula Program is outlined in President Biden's Infrastructure Bill of 2022.
5. **OLS:** Ordinary Least Squares is a linear least-squares method for estimating parameters in a linear regression model.
6. **Plug-in Hybrid Electric Vehicles (PHEVs):** Automobiles powered by an internal combustion engine and an electric motor. Electricity that powers the electric motor is obtained from an external charger and is stored in batteries on board the vehicle.
7. **SC:** An abbreviation for "synthetic control."
8. **Zero-Emission Vehicles (ZEVs):** This class of automobiles is identical to the EV subset of electric vehicles (defined above). For brevity and consistency, "EV" will be used in place of "ZEV".

Electric Vehicle Policy and Literature Review

Federal Policy and Market Analysis

Before the release of the next generation of electric vehicles in 2010, the American Recovery and Reinvestment Act (ARRA) of 2009 provided consumers up to $7,500 in the form of a tax credit for a newly registered plug-in electric vehicle (PEV) to help spur mass adoption of new EVs[3]. ARRA provided that a purchase of a new EV would grant the owner a base level of $2,500 tax credit and an additional $417 for each kilowatt-hour above five-kilowatt hours, up to $5,000[4]. Multiple amendments seeking to increase the amount provided in tax credits or rebates were proposed to congress, but most were not passed. However, in 2014, a provision was passed that increased the maximum tax credit for EVs and some qualified PHEVs to up to $10,000 but excluded luxury vehicles that exceeded an MSRP price of $45,000. Luxury vehicles maintained the $7,500 maximum tax credit as presented in ARRA.

ARRA also allocated funding to research and develop innovative battery, EV, and charging technology. Following President Obama's announcement of ARRA, roughly $400 million was devoted to improving battery and chagrining technology that was awarded on a competitive basis[5]. Early investment in the emerging EV market has decreased firms' battery production costs. These grants from the Energy Department

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[3] Matulka, R. (2014, September 15). The History of the Electric Car. Energy.Gov.

[4] American Recovery and Reinvestment Act, 26 U.S.C. § 30D (2009). https://www.govinfo.gov/app/details/PLAW-111publ5

[5] American Recovery and Reinvestment Act, 26 U.S.C. § 138 (2009). https://www.govinfo.gov/app/details/PLAW-111publ5

have also allowed more firms to enter the market, increasing competition and improving pricing options for consumers.

Due to the complex nature of determining specific causal impacts of subsidization in the EV market, the existing literature offers mixed conclusions on the best policy route for allocating subsidy funding. Often in economics, randomized control trials or experiments are the main methods of distinguishing causality from simple correlation. Holland et al. primarily focus on exporting the pollution from EVs and the uneven distribution of environmental impact (Holland et al., 2016). Their research found that EVs driven in metropolitan areas have a $0.01 per mile positive societal and environmental benefit, whereas EVs driven outside metropolitan areas have a -$0.017 per mile negative benefit[6]. Because the net effect of the $7500 federal tax credit was negative, Holland et al. argue that direct subsidization on a national level might not have positive beneficial societal and environmental effects. Furthermore, the critical piece of their research was the idea that while EVs are considered "zero-emission vehicles," they can create pollution during the electricity generation process. Because electricity is produced in different ways at the state, county, and city levels, where consumers receive their electricity is the main determining factor in their indirect carbon footprint of EV ownership. The net negative societal and environmental benefit calls into question the efficacy of an all-encompassing federal subsidy that lacks targeted and efficiently dispersed monies. Regardless of the ecological effects, Holland

[6] Holland et al. (2016) subsidies averaged between California EV benefits ($2,785) and North Dakota EV benefits (-$4,964) came to an average benefit of -$1,095. The dollar amount that Holland et al. attach to the subsidies or benefits is a combination of environmental factors that include electricity grid cleanness, greenhouse gas emissions from electricity generation, and overall social benefit. The negative "benefit" is due to the electricity generation that powers EVs predominantly from fossil fuels.

et al.'s research does provide insight into the abilities of subsidization policy to promote market growth and EV adoption.

Similarly to Holland et al.'s critiques of federal funding, critical findings in a 2018 report support state-level subsidies and estimated that for each additional $1000 in state EV policies (i.e., tax credits, rebates, etc.), there is a 5-11% increase in EV sales (Wee et al., 2018). However, this demand increase in response to subsidies is not uniform across all states implementing incentive programs. In Wee et al.'s research, several states witnessed peaks in new EV registrations after state subsidies had ended. At the same time, other states experienced a rise in demand during the financial support period, which adds some ambiguity to the causal relationship between direct subsidy and EV purchases. Gas prices must also be taken into consideration when assessing the value derived from an EV. Because gas prices vary from state to state, states may adjust their incentives accordingly, which further complicates the determination of causation within the market.

Another study published by the Journal of the Association of Environmental and Resource Economists from the University of Chicago displayed an ambiguous positive impact of subsidization on the national level. Li et al. discovered through counterfactual modeling that while direct incentives to consumers increase the purchase rate of new EVs, a policy with equal funding directed toward charging infrastructure investment could be twice as effective for EV adoption[7]. Their findings also indicate that both the federal and counterfactual subsidy policies generated demand and adoption. According

[7] Li et al. (2018) attribute their estimation of higher effectiveness in infrastructure policy to the "low price sensitivity of early adopters and strong indirect network effects."

to their research, EVs and EV chargers have demonstrated a positive feedback loop within the market, implying that any investment into the industry will yield positive results[8]. More specifically, the feedback loops within the EV market emerged from indirect network effects, which can be characterized by two sides of the market (EVs and EV chargers) being closely correlated, and a shock to one side of the market persistently affects both sides (Corts, 2010). Responsiveness within the EV market cannot be solely attributed to the feedback loop described by Corts (2010) and Li et al. (2018). The latter cites that policy effectiveness "hinges on the relative magnitude of indirect network effects on the two sides as well as consumer price sensitivity" (Li et al., 2018)[9]. The EV market responds positively to subsidization, regardless of which side of the market the subsidy is applied. Wee et al. (2018) suggest that the EV market is highly heterogeneous across the US and posit that there are likely more effective policies that target specific portions of the EV market from state to state.

Given the demonstrated positive effects of policy at the federal and state level, it becomes clear that government subsidization in various forms has produced positive results in market growth. Within President Biden's infrastructure bill, $5 billion has been devoted to building out the nation's EV charging network over the next five years[10]. The National Electric Vehicle Infrastructure Formula Program (NEVI) will oversee the implementation of chargers on the interstate system and in rural areas that have not had access to charging infrastructure. States must submit an EV Infrastructure

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[8] Li et al. (2018) and Corts (2010) analyze the persistent shocks within the automotive alternative fuel market.

[9] Concerning chargers, Li et al. found that early adopters of charging technology (consumers and suppliers) have low price sensitivity.

[10] The US Energy Department also announced that grants would be awarded on a competitive basis to private firms in the EV charger industry.

Deployment Plan prior to receiving the funding outlined in the NEVI program. Implementation of this plan will take place over the next five years and is expected to expand upon the existing Alternative Fuel Corridors.

Given the dynamics of feedback loops and low price sensitivity in the young EV market, growth due to policy intervention is relatively sure. Regardless of the magnitude of the effect, and according to the existing literature, there will be growth in the EV market from the NEVI program. What remains to be seen is the effectiveness of the NEVI plan, which combines the financial might of the federal government and the targeted approach of state-level policy.

Oregon Policy (2009-2017)

Since 2009, Oregon has displayed promising flexibility and adaptability in creating policy directed toward EV adoption. In this section, I will outline the significant policies in Oregon since 2010 that have affected Oregon's EV market.

In 2009, Oregon passed House Bill 2180, which ended the $1500 tax credit provided for non-plug-in hybrid vehicles and instead offered that tax credit to plug-in hybrid-electric vehicles (PHEVs)[11]. Because the first widely available EVs (the Nissan Leaf and Chevrolet Volt) were not available until 2010, this amendment gracefully anticipated the release of a new generation of EVs and PHEVs and reallocated the incentivization policy accordingly. According to the Oregon Department of Transportation, from 2010 to 2013, there were less than 5,000 registered EVs in the

[11] House Bill 2180, ORS 469.160 § 2, 3, 6 (2009)

state, which complicates the determination of this policy's direct effect on Oregon's EV market. This investment has likely positively impacted demand for EVs and their charging infrastructure based on the recent research mentioned above.

As newly registered EVs hit the road, the policy objective of Oregon's government began to shift focus to the charging network. In 2009, Oregon joined the West Coast Electric Highway initiative with California and Washington to create an "electrified highway" network of chargers along the Interstate-5 corridor and the US-101. The vision of this initiative was that a US citizen could drive from British Columbia to Baja California in an EV[12]. Additional project benefits include job creation, increased demand for EVs, and reduced ecological impact from the transportation sector[13]. This plan required frequent charging stations to accommodate short-ranged EVs, specifically fast-charging stations. The West Coast Electric Highway has spurred considerable demand for fast chargers, increasing EVs and pulling in more investment from the public and private sectors. Because this project was recently completed, aggregated data from western states are likely, not complete and ready for cost-effectiveness analysis.

From 2009 to 2016, multiple published studies identified new guiding principles in EV adoption that would take hold in state governments seeking to increase EV ownership. Perhaps one of the most pivotal studies of the early 2010s, Gyimesi & Viswanathan (2011) conducted interviews and surveys that determined that consumer

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[12] Charging connector standards are not unified currently between North America and Japan's type 1 connector and the EU's type 2 connector. Further, the speed of chargers (via their output of DC electricity) is also in different stages across the connector types.
[13] West Coast Green Highway (2014). http://www.westcoastgreenhighway.com/electrichighway.htm

knowledge of EVs was meager[14] and that most consumers are more willing to absorb the higher costs of emerging technology if they were more knowledgeable. Their findings supported the emerging idea that consumers maintain low buy-in to a new technology until they understand it. A 2013 study done by Krause et al. also found that an astounding level of unawareness of incentives and policies existed in the market. According to their surveys, 95% of respondents were unaware of their state's policies and benefits for EV ownership (Krause et al., 2013). The lack of consumer EV familiarity led more states to increase the awareness of EV technology and incentives via EV showcases, driving experiences, and other promotional campaigns. Following a series of state and federal incentives, showcases, and demonstrations of EVs, Vergis et al. (2014) explored the social, economic, and policy factors that influence the EV market. One critical finding from the research details the vast array of influential factors in the EV market and how a single variable cannot guide the market. Instead, Vergis et al. suggest that a combination of social, economic, and policy factors determine market behavior.

The research published by Gyimesi & Viswanathan (2011), Krause et al. (2013), Vergis et al. (2014), and others have provided crucial insight and guided policy decisions on the national and state level. Based on research published years prior, 2016 was a significant year for EV market development in Oregon. Multiple state-sponsored shows and programs were implemented to increase consumer understanding of EVs, increasing market participation (Krause et al., 2013). Furthermore, as detailed in Oregon Senate Bill 1547, the state legislature called for increased availability of EV

[14] Gyimesi & Viswanathan (2011) found that 45% of surveyed drivers knew little to nothing about EVs.

charging, offered better prices to expand market reach to lower-income communities, and directed electric companies to create programs to accelerate transportation electrification[15]. Additionally, just before Oregon passed SB 1547, the state removed the sunset option of the Clean Fuels Program, which continued to promote alternative fuels within the state. Because SB 1547 was an instrumental piece of legislature for Oregon's EV charging network, 2016 was used as my treatment year in my economic analysis.

In the following year, Governor Kate Brown released executive order no. 17-21, which set the statewide goal of at least 50,000 registered EVs on Oregon's roads by 2020. This executive order intended to increase all aspects of the EV market, from charger access, EV access, and awareness of state programs to the general understanding of EVs and their environmental benefits. Numerous policies have been implemented since 2017, but this economic analysis focuses on the middle of the past decade.

[15] Senate Bill 1547, ORS 757.600 § 20 (2016)

Research Question and Hypothesis

Research Question

My research aims to determine the causal influence of one aspect of the EV market. Specifically, I want to ascertain the impact of government policy on the demand for electric vehicles. To guide my thesis, I ask: do new installations of electric vehicle chargers positively influence consumers' willingness to buy an electric vehicle, and if so, by how much?

Hypothesis

Before beginning my research, I believed that installing more EV chargers would directly influence consumers' likelihood of purchasing an EV. I was aware of the limited ranges of earlier EVs and thought that consumers would derive more utility from the car and justify its purchase if there were more chargers on the road. During the early stages of the EV market, if we assume that consumers are rational, purchasing an EV would not make sense with limited range and charging capabilities. Despite any desire of consumers to buy a new EV purely from an environmental standpoint, range limitations were a significant barrier. That barrier would likely be removed once range limitations are addressed with better battery technology or more access to chargers. I hypothesized that a government policy implementing an improved charging station network would increase the number of EVs purchased in the following years. Initially, I wanted to compare two states' EV market data to test my hypothesis. It became clear after comparing data sets that my research might yield better results from a weighted average of multiple states in the US.

Methodology

Model Selection

I believed that a Difference-in-Difference (diff-in-diff) model would work well to test my hypothesis. This form of economic and statistical modeling works by comparing the trends of a control group and a treatment group before and after treatment. We can infer that the treatment affected the treatment group if the control and treatment groups followed similar trends before treatment and then diverged. In this quasi-experimental model, the treatment effect is determined by comparing the observed trend from the treatment group to a counterfactual trend the treatment group would have maintained were it not for the treatment. The most critical assumption in diff-in-diff estimation is the "Parallel Trend Assumption," which holds that for the model to be valid, the difference between the treatment and control group over time must be the same in the absence of treatment (Schwerdt et al., 2020). The diff-in-diff approach would work well comparing two states, but because many of the states' EV markets moved in different ways, they did not provide adequate control group trend behavior.

Instead, I use a synthetic control (SC) model to test my hypothesis. Abadie and Gardeazabal (2003) used this statistical modeling method when determining the causal effect of political conflict on GDP[16]. The SC model replicates the quasi-experimental nature of the diff-in-diff model. A treatment and control group are analyzed before and

[16] Abadie & Gardeazabal (2003) analyze the effects of terrorism on GDP in the Basque region of Spain by creating a "synthetic" Basque region without terrorism. It was comprised of a weighted average of other Spanish provinces.

after treatment, and their difference after treatment is the behavior of interest. The key factor that makes the SC method popular in the field of economics and statistics is the allowance for multiple control units to represent the single control unit from a diff-in-diff model. Essentially, a control group is created by taking a weighted average of control units that fit the similar trend of the treatment group. SC estimation does not require the "Parallel Trend Assumption" that the diff-in-diff estimator does, but SC assumes the existence of weights and a stationary process. Stationarity is how changes in a function's trend remain constant over time. In simple mathematical terms, if the slope of a line is x^2, the values of x will change over time, but the way in which x changes is constant, so it is stationary.

Treatment Selection

In my research, I use EV registration and charger data from California, New York, Colorado, and Vermont to create my synthetic control group. Oregon's EV registration and charger data are used as the treatment group. Another critical factor in both diff-in-diff estimation and SC estimation is the treatment.

For this, I use policies implemented in the year 2016. I chose this year because when analyzing the EV charger data from Oregon, I noticed a spike in 2016. This led me to review policies that were implemented during that year. After being drafted in 2015 and passed in 2016, Oregon Senate Bill 1547, with its comprehensive advancement of charging stations and charging technology, serves as the treatment in my experiment. When selecting my treatment, I could not use Governor Brown's 2017 executive order because it called for improvements in many different areas of the EV market, complicating the causal impacts of only chargers on EV purchases.

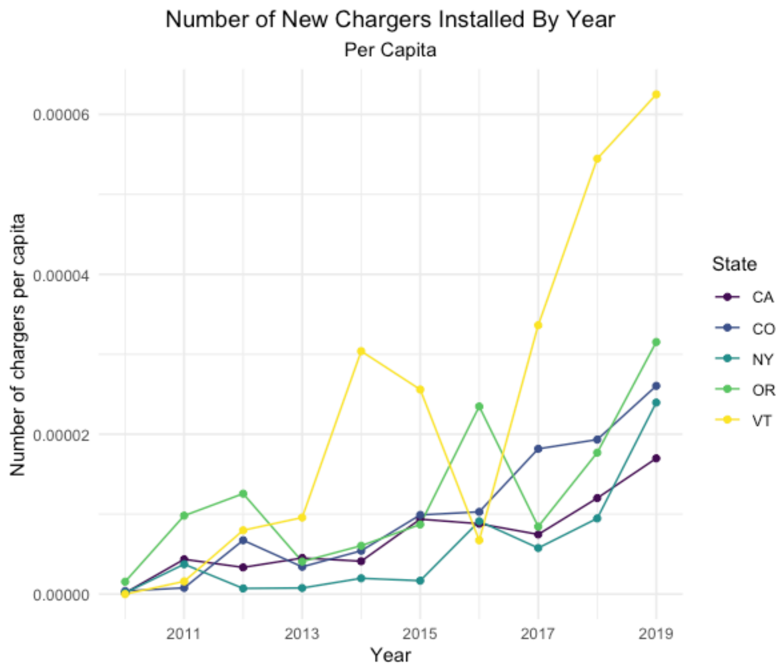

Figure 1: Number of New Chargers Installed By Year Per Capita

This graph can also be interpreted as the number of chargers per 100,000 people. E.g., in 2016, there were just above 2 EV chargers per 100,000 Oregon citizens.

The 2016 spike in Oregon EV charger installation per capita was noticeable based on the graph I generated from the EV charger data. I confirmed the abnormality by comparing Oregon's population to Colorado's, the state closest to Oregon in terms of population. To be thorough, I also looked for a similar spike in the charger data when not adjusted for the population.

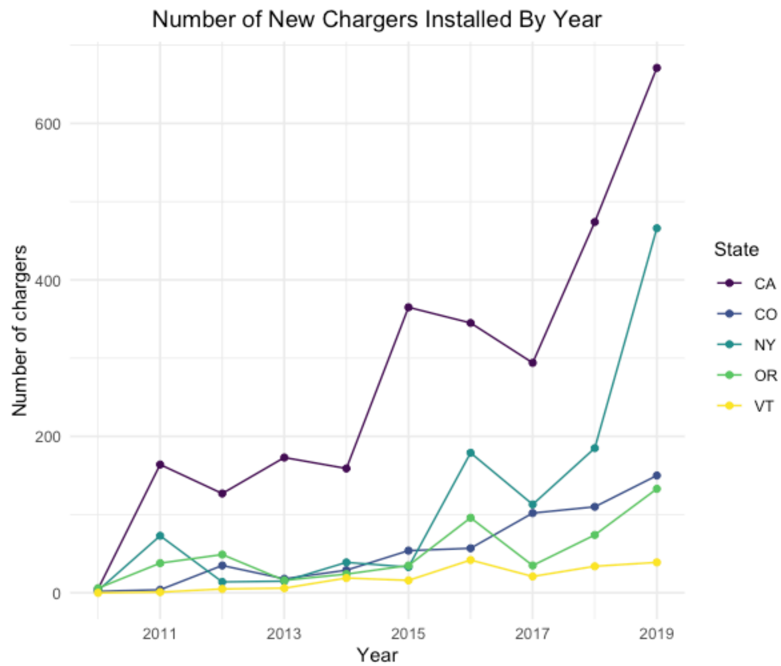

Figure 2: Number of new Chargers Installed By Year

While Oregon's 2016 is not as pronounced when the data is presented in levels, the spike still exists compared to itself in years before and one year after. I suspected that the unusual spike in EV chargers was prompted by state policy in Oregon. Because of this, I use SB 1547 as my treatment.

Regression Model

In addition to the SC model, I also analyze the correlation between EVs and EV chargers using a standard ordinary least squares (OLS) estimation. I only analyze the EV market in Oregon for this estimation. The model that I use for estimating the effects follows the OLS model specification but with lags to account for delayed effects:

$$y_t = \beta_0 + \beta_1 x_t + \beta_2 x_{t-1} + \varepsilon_t$$

In the standard OLS model with lags, the variables stand for:

- y_t: The dependent or outcome variable at time t. When there is a change in x, y will change according to the parameters.
- β_0: The intercept value. When time t = 0, the intercept would be the only variable explaining the dependent variable, y
- $\beta_1 x_t$: The coefficient, β_1 dictates how much y is affected from a change in x
- $\beta_2 x_{t-1}$: The lagged independent variable. This term allows y to also be affected by the most recent previous period of x.
- ε_t: The error term representing the influences imparted on y that are not from x.

I define my lagged OLS model as follows:

$$Number\ of\ EVs\ registered_{OR,t} = \beta_0 + \beta_1 Number\ of\ chargers_{OR,t} + \beta_2 Number\ of\ chargers_{OR,t-1} + \varepsilon_t$$

I chose to add a lag on "Number of chargers" because I want to test for a lag in charger installation affecting EV purchases. Using this simple regression model, I quantify the influence that the installation of new chargers has on new EV purchases in Oregon. Additionally, it is important to recognize one of the main assumptions in OLS, which is strict exogeneity to maintain unbiasedness. Due to the close relationship between EVs and EV chargers, this assumption is not completely fulfilled, but this regression analysis serves to test that assumption.

Software

I use RStudio, an integrated development environment (IDE) for the R computer language, to run my analyses. Within RStudio, I run my SC analyses and my OLS regression analysis.

Data

All my data is publicly available registration and charging network data. I sourced the individual state EV registration from the Atlas EV Hub[17], an online platform that collects public data and collects and distributes market data for free. Atlas has worked "with NGOs, companies, and public officials" since 2017. Charger network data was sourced from the US Department of Energy's Alternative Fuels Data Center (AFDC).

The years that encompass my analysis are 2010-2019. I use these years because SC requires some time (not clearly defined) before the treatment to establish a trend and time post-treatment to see the potential effects. 2010 is the earliest year that all states have available data. Due to data constraints, I could not include data past 2019 because not all states in my synthetic control group had available data.

My experiment's main variables of interest are EV registrations and EV chargers. I use EV registrations as the variable for a new EV associated with the year it was first registered from the state datasets. I define a new charger as a charging station in association with its open date, as defined in the original dataset from the AFDC. In

[17] https://www.atlasevhub.com/materials/state-ev-registration-data/

addition to EV registration data and charger data, I also include the population of each state each year so that my estimates are not skewed by state population size.

Using those two variables, I created a master data frame named "full_df" that includes state, year, number of EVs newly registered, the number of new charging stations opened, and the states' population (rounded to the nearest thousand). The format of my data frame is as follows.

State	Year	Number of newly Registered EVs	Number of new charging stations opened	State population
CA	2010	754	5	37270000
CA	2011	5857	164	37640000
CA	2012	18356	127	37950000
…	…	…	…	…
VT	2019	116	39	623989

Table 1: Data frame format

Finally, I did not include Vermont during my synthetic control analysis because it heavily skewed the results. In the synthetic control portion of my research, I adjust the data to the population of each state so that the potential causal relationship between EVs and chargers is only dependent on chargers and not population. I do not see this as problematic because Vermont skewed the data to the point where the experiment's validity was questionable.

Results

Synthetic Control Results

This section aims to determine whether installing EV chargers will cause an increase in the number of EVs purchased. Figure 3 illustrates the SC results of testing only for chargers' causal influence on EV purchase. The results indicate that Oregon and "synthetic Oregon" follow similar trends before the treatment, but synthetic Oregon diverges unexpectedly after the treatment. Determining a single factor to be causal among various other factors, especially in a market setting, is very difficult. As prior research indicates, synthetic controls, diff-in-diff, and other quasi-experimental procedures produce insightful results regarding causality.

However, the first synthetic control analysis results suggest that policy promoting the installation of new charging infrastructure has a negative causal relationship with new EV purchases and registrations. Before treatment, the gap between Oregon and synthetic Oregon is relatively small—at most, only straying about 0.001 EV per capita units away from its synthetic counterpart. Despite controlling for population differences, Oregon trends downward after increasing chargers in 2016. Oregon continues along with the trend before the treatment, only seeing an approximate 100% increase in EVs per capita after the treatment. Alternatively, synthetic Oregon, which did not receive the treatment, experienced over a 300% increase in EVs per capita.

These results raise several questions about the EV market in the US:

1. How much do EV markets vary from state to state?
2. How closely correlated are new chargers and new EV purchases in Oregon?
3. Because the first SC analysis adjusted for population, is Vermont an outlier that could be skewing the results due to having the highest EV per capita rates out of the other states?

To answer the third question, I remove Vermont from the SC analysis and use only California, New York, and Colorado for the weighted average of synthetic Oregon. Figures 5 and 6 show the SC results without Vermont.

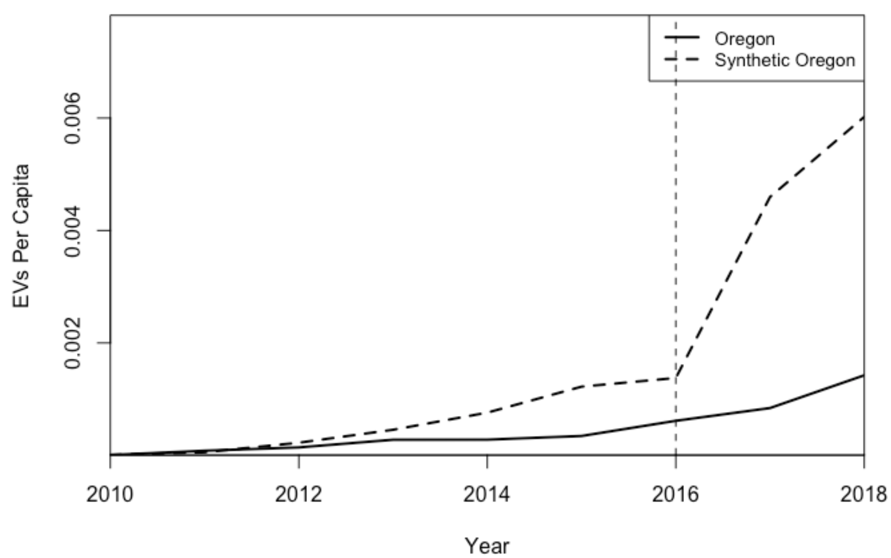

Figure 3: Synthetic Control Results Per Capita [path]

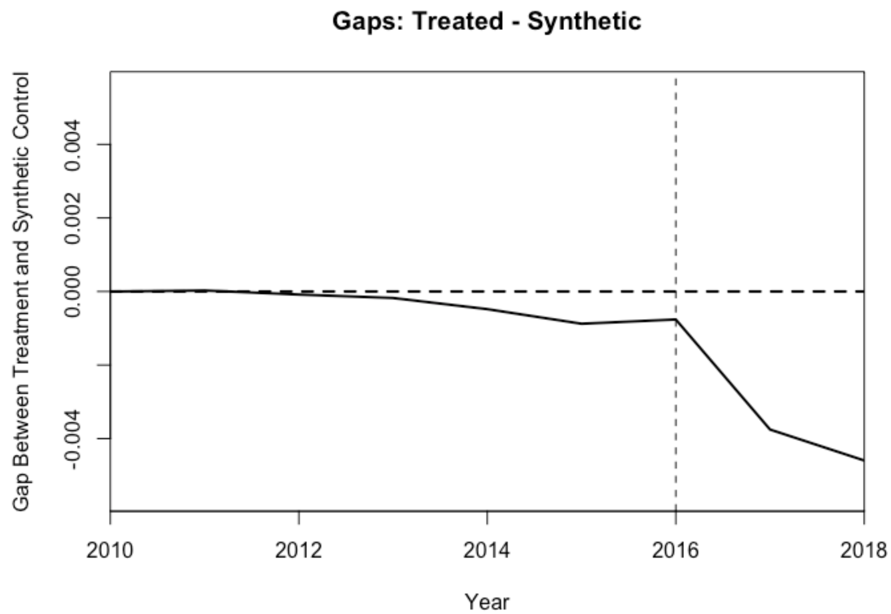

Figure 4: Synthetic Control Results Per Capita [gap]

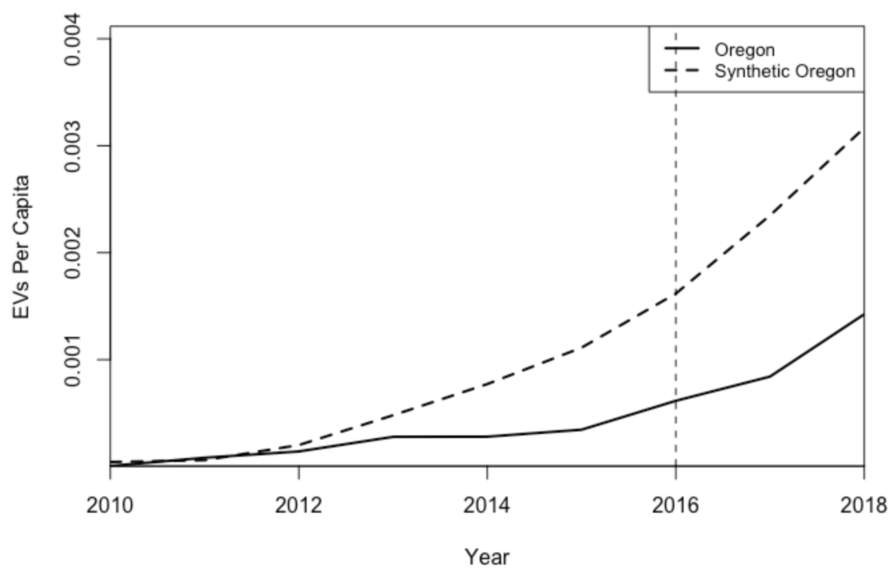

Figure 5: Synthetic Control Results Per Capita [path] [Omitting Vermont]

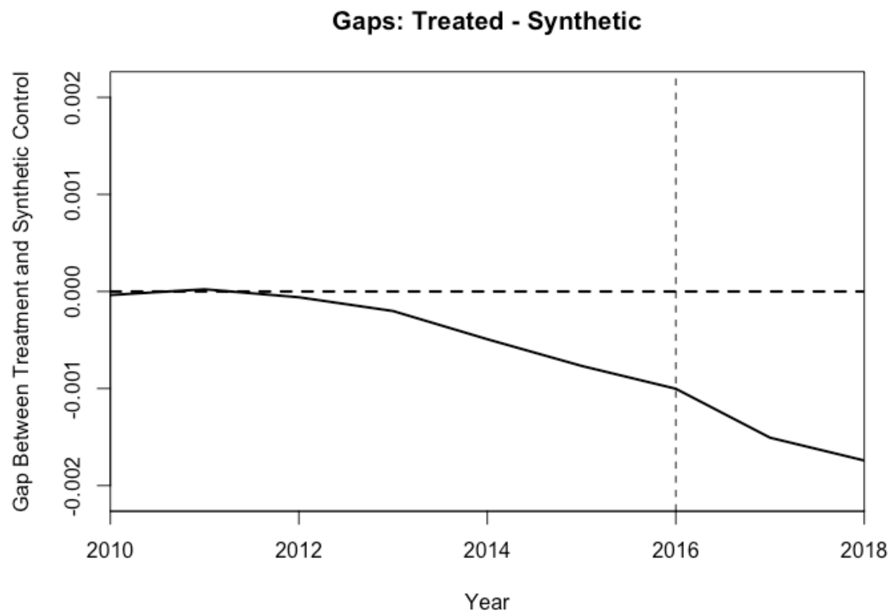

Figure 6: Synthetic Control Results Per Capita [gap] [Omitting Vermont]

The two graphs of the path and the gap appear different from the SC analysis without Vermont, but they are somewhat similar. By omitting Vermont from synthetic Oregon, the upper bound in Figure 5 and the magnitude of the gap in Figure 6 have decreased. The results shown in Figures 5 and 6 do not clarify the strange behavior from Oregon post-treatment. Still, it does answer the question about Vermont skewing the results from its abnormally high EV per capita rate.

One of the challenges that emerged after running the SC analysis is the issue of fit between the states that compose synthetic Oregon. Due to the heterogeneity of EV markets across states, their trends of EV purchases and installation of chargers differ from Oregon's. Because of this, the fit of synthetic Oregon is workable but not ideal before treatment.

Based on the synthetic control analysis results, there is insufficient evidence that new EV chargers cause new EVs to be purchased. Instead, I theorize several points that might explain this behavior.

First, as observed by Wee et al. (2018)[18], "even in states with similar incentive programs, the per capita sales of EVs can differ quite drastically." Heterogeneity in the US EV market is stark, and while neighboring states might join a coalition with the same goal and implementation, the effects in each state are likely different. An example of this is the West Coast Green Highway. Furthermore, factors such as population density are likely playing a role in EV adoption nationwide. Solely offering tax credits, rebates, or charging vouchers still might not be enough to prompt a speculative individual to make a sizeable purchase on an EV. Because awareness of incentives and understanding of EV technology varies significantly from state to state, heterogeneity will continue to play a significant role in EV market analysis.

As for the downward trend after installing new chargers in Oregon, I suspect other factors carry more weight in consumer decision-making in Oregon than new chargers. Based on graphs depicting the growth of EVs and chargers in Oregon, I posit that the two are correlated, but correlation does not point to causation.

Lagged OLS Regression Results

The goal of this section is to interpret the lagged regression results from analyzing the correlation between EVs and chargers. In spirit with my research question and hypothesis, the dependent variable is the number of EVs registered each year. The

[18] Wee et al. (2018) found that heterogeneity between states can vary as much as 62% regarding EV incentives.

dependent variables are the number of chargers installed each year and a one-year lag of the number installed. After running the initial regression outlined in the methodology, only one of the dependent variables was statistically significant at the 95% confidence level.

Coefficients:	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	-475.405	1112.146	-0.427	0.68188
Number of chargers (by year)	55.194	15.418	3.580	0.00898 **
One year lag of number of chargers (by year)	1.298	4.433	0.293	0.77823

Table 2: Lagged OLS regression results

Because of the lack of statistical significance from the lag of the number of chargers and the risk of non-stationarity negatively affecting the estimation, I tried to control for the year fixed effects. The fixed effects model holds time constant, which removes the impact of non-stationarity. If the standard model exhibits non-stationarity, the variables in our estimation can have a spurious relationship, which means that two variables appear to be correlated due to coincidence or some unseen factor or variable. The new model is defined as:

$$Number\ of\ EVs\ registered_t = \beta_0 + \beta_1 Number\ of\ chargers_t + \beta_2 Number\ of\ chargers_{t-1} + \beta_3 Unobserved\ _t + \ \varepsilon_t$$

Based on the first lagged OLS estimation results, the only statistically significant variable is the coefficient on "number of chargers" (n_chargers). Because n_chargers' coefficient is significant at the 1% level, we are 99% confident that the coefficient is not zero.

Because both variables are not a dummy or binary variables, they are both continuous. This means that for every one-unit increase in the number of chargers in a year, we can expect to see 55.2 more EVs purchased in that given year. This interpretation makes logical sense when looking only at the regression results, but after reexamining the data, it appears to be an overestimation.

Overestimating a variable's effect signifies potential omitted variable bias (OVB). There are a few ways to combat OVB, but the best method is to include as many variables and data points as possible. This was a relatively simple analysis of Oregon's EV market, so I suspected there would be bias issues. Another problem with this model that might be present is reverse causality, which causes bias in estimates. Functionally like the indirect network effects described by Corts (2010) and Li et al. (2018), reverse causality is present when the dependent and independent variable(s) influence each other. The standard causal relationship dictates that one variable causes another, but estimates will be biased and inaccurate when reverse causality is present. I believe that is what is occurring within my lagged OLS model.

In conclusion, my lagged OLS model provides inadequate evidence of a strong correlation, given one out of three coefficients being statistically significant. Still, my model's estimation does support the idea of indirect network effects within the EV market.

Conclusions

Causality remains a deceivingly challenging relationship to ascertain clearly in a market setting. In our highly connected and globalized society, there is always a myriad of factors that dictate the behavior of consumers, prices, or even our general wellbeing. It is no surprise that economists are fascinated with the concept of unearthing the source of causality whenever possible.

Oregon's EV market is not impervious to the intricacies that make causal analysis challenging. Despite my hypotheses being difficult to demonstrate, there are important policy implications within the research that I have completed.

First, I have confirmed the idea that the US EV market is highly heterogeneous. The extension of this is staggering when neighboring states of similar political leanings have very different incentives and programs to promote EV adoption. Even states engaged in plans and initiatives that transcend state borders have wildly different markets for EVs and EV chargers. Following Wee et al. (2018), it is in any state's best interest to monitor their state's market health and responsiveness to policy to achieve the highest effectiveness and market efficiency.

Secondly, I have found evidence in support of the indirect network effects. The results from the lagged OLS estimation show signs of reverse causality and omitted variable bias. While my evidence is not as strong as that of Corts (2010) and Li et al. (2018), my results support the idea of indirect network effects via reverse causality. In theory, this causal relationship means that any investment into the EV market will yield positive results. It is difficult to estimate how much new chargers would increase EV purchases or vice versa.

Finally, my policy recommendation to Oregon or other states is this: investment into the EV market creates jobs, works toward greater sustainability, and nurtures innovation. I urge policymakers to incentivize, fund, and promote electric vehicles as much as possible. Although many EVs on the road obtain their electricity from fossil fuel-related sources, greener solutions will emerge over time as technology advances. Policymakers cannot speed up time, but they can get close by allocating funding to the right places. Even if my research shows that EV chargers have little effect on new EV purchases, Oregon's multi-pronged approach to mass EV adoption seems to be working. Let us continue to seek data-driven solutions that our policymakers can support and reach a greener future.

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