Assessment of the Electric Vehicle Charging Station Incentive Program in the U.S. Electric Vehicle Market: The Case of Missouri

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Abstract

The paper evaluates the effects of incentives for installing electric vehicle charging stations on the number of charging stations installed. In turn, it also estimates the impact of the number of charging stations on the sales of plug-in electric vehicles. The first step is done using the synthetic control method, with Missouri as the treatment state. The synthetic control approach suggests that the percentage increase in charging stations will rise over time thanks to the incentive program. Compared to the number of stations in the counterfactual scenario where there was no incentive program, the real number of stations in Missouri is 151% higher in 2015 and 254% in 2016. We performed a regression model to find the relationship between EVs sales and the number of chargers, and found that for each 1% increase the total number of chargers, monthly EVs sales 12 months later will increase by 0.4%. These figures suggest that the charger incentive program of Missouri can increase the monthly sales of electric cars by 60.4% at the end of 2016 and 101.6% at the end of 2017. Using these figures and national data on costs of public charging stations, we estimated the cost of the incentive program for each additional EV sold as around $1,250, much lower than other EV incentives. Also, we explore the bi-directional causality between number of charging stations and number of EVs.

Keywords: Plug-in electric vehicle, charging stations, incentive program

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1. **Introduction**

In the US, petroleum remains the energy source for many industrial and commercial sectors. In 2016, 37% of total US energy use was from petroleum, and 92% of transportation energy came from petroleum (EIA, 2016). The extensive use of gasoline and diesel for transport also creates an oil dependency issue in the US. The use of petroleum products also increases air pollution. Therefore, decreasing the use of petroleum, especially in the transportation sector can significantly mitigate these two issues. Promoting the adoption of plug-in electric vehicles serves as one of the recent popular methods to achieve such a goal. The US government has launched multiple incentive programs to support potential consumers of electric cars. However, some of these incentives effectiveness have yet to be analyzed empirically using state level data, particularly the incentive to promote development of infrastructure.

This paper concentrates on the indirect incentive programs that aim to increase the number of Electric Vehicle charging stations for electric vehicles. This is due to the fact that without a sufficient charging station network, the plug-in electric car industry will struggle to grow. In this paper the synthetic control method is used to assess the effect of the incentive program on the number of charging stations over time. Then, the impact of the number of stations on the sales quantity of electric cars is estimated. While such an incentive program is available in a number of states, Missouri emerges as the ideal assessment target due to its unique features, which are discussed below. Finally, we provide conclusions and policy implications.

The paper is organized as follows: section 2 contains the literature review. Since the paper consists of two distinct steps – impact of charging station subsidies on number of charging stations and then impact of number of charging stations on EV sales, we will cover all the
analysis in each step in a separate section. In section 3, we present the methodology, data, and results of the charging station analysis, Section 4 contains the approach, data, and results for the second step of estimating the change in EV sales due to the increased availability of charging stations. Policy implications and conclusions are contained in section 5.

2. Literature review and contribution

2.1. Financial incentives

Multiple previous research has studied the impacts of regulations, financial incentive programs and socio-economic factors on the adoption of plug-in electric vehicle (plug-in EV henceforth), with a concentration on financial ones. Diamond (2009) has also found gasoline price as a significant factor in adopting hybrid electric vehicles (HEVs). A 10% increase in the gasoline price causes hybrid car share to increase 72-93% (but from a very low base). Nevertheless, direct financial incentives have little impact. On the contrary, Jenn et.al. (2013) found that for each dollar of incentive, HEV sales increase by 0.0046%, but gasoline price has little impact. Yet, Jenn et.al. and Diamond’s work are based on HEV rather than plug-in EV, and we thus cannot assume similar results for plug-in EV. Zhang et.al. (2013) studied the plug-in EV market in China, using survey methods and have found direct financial incentives to be a significant factor in the decision to purchase of plug-in EVs. However, among four factors: performance attributes, psychological needs, financial benefits and environmental awareness, financial benefits were ranked third in terms of the importance. Overall, most papers have found that direct financial incentives do have an impact on the quantity of plug-in EV sales.
2.2 \textit{Non-financial incentives and socio-economic factors}

Besides direct financial incentives, Langbroek et al. (2016) and Carley et al. (2013) have also studied other incentive programs and/or socio-economic factors. Their work has indicated a variety of significant factors in the adoption of plug-in EVs, such as the availability of HOV lane or free parking fee. Socio-economic factors such as age, gender and education also have an effect. Male, younger, and more educated people are more likely to adopt plug-in EVs than the counterparts. Thus, besides financial incentives, certain social features such as education or age can also bring consumers closer to the plug-in EV market. Jenn et al. (2018) evaluated the effects of multiple incentives and consumer awareness on EV adoption. They found that access to HOV lane plays an important role, and different levels in consumer knowledge of incentives, especially monetary incentives in different states can result in vast differences in the effects of those incentives. Essentially, if consumers are well educated about the availability of different types of incentives, the effects of those incentives will be much larger than if they are not aware of them.

2.3 \textit{The role of charging stations}

In addition to direct financial incentive schemes and socio-economic factors, several papers have also studied different topics regarding plug-in EV charging stations. Sierzchula et al. (2014) collected plug-in EV market share and other data from 30 nations to study the impact of various factors on plug-in EV adoption. The result has suggested that education, gasoline price and income do not have much of an impact on plug-in EV market share. Both direct, monetary incentives and indirect, non-monetary incentives, such as incentives for charging stations are significant factors. Importantly, while increasing incentive credit by $1000 only results in 0.06%
increase in EV market share, increasing one more charging station per 100,000 persons increases EV share 0.12%, twice the effect of the purchase incentive.

Springel (2016) used an indirect network effect model to study the impact of subsidy schemes for purchasing and constructing charging stations. Her result has indicated that charging station incentives are more effective than direct purchasing subsidies. In particular, $12.39 million funding for charging stations can result in 835 more plug-in EVs. The same amount if spent on purchase subsidy only results in 387 more plug-in EVs. Li et.al. (2017) also found similar result, using a simulation method and vehicle registration data from 353 Metropolitan Statistical Areas from 2011 to the end of 2013. Their work has suggested that with a funding amount of $924.2 million, purchase subsidies will result in around 168,000 more EVs after 10 years, while if the same amount is spent on charging stations, the increase in EVs would be around 245,000 to 373,000. Zhu, Wang & Zhang (2019) have examined the importance of indirect network effects in China using three-level Stackelberg model, and suggested that incentives for charging stations would be more cost-saving and effective than direct purchase incentives. As such, we can observe that any incentive program which aims to increase the number of charging stations has a crucial role in promoting plug-in EVs.

This paper assesses the effectiveness of current and ongoing incentive programs for building plug-in EV charging stations, using US state level data. In the US, the federal government initiated a direct financial/purchasing incentive program in 2010, which is still in place now. The federal purchasing program is available in all states. However, state incentive programs for charging stations are only available in a number of states with different starting times. The purpose of this paper is to examine the effectiveness of an incentive scheme that includes both the federal EV purchasing incentive and a state-run charging station incentive
(double-incentive scheme), in comparison to a scheme that includes only the federal purchasing incentive (single-incentive scheme).

3. **The impacts of charging station incentive on the number of chargers – a synthetic control approach**

3.1. **Methodology**

Charging station incentive programs, either in the form of tax credit or rebate do not directly affect the quantity of plug-in EVs but rather the number of charging stations. Thus, In this section, we used the synthetic control method constructed and used by Abadie and Gardeazabal (2003) and Abadie, Diamond & Hainmueller (2010) to first evaluate the direct effect of the charger incentive program on the number of chargers, using Missouri as the treatment entity.

A conventional diff-in-diff method was also used. However, we decided to use synthetic control to explore the possibility of non-constant effects of the charger incentive program on the number of chargers overtime. Particularly, Li et.al. (2017) and Springel (2016) suggested that an increase in EVs will increase the number of chargers, and vice versa, since businesses wish to build chargers to attract customers. Hence, with more EVs in the future, more and more businesses will consider building chargers; and if an incentive for chargers exists, it will likely attract an increasing number of businesses who wish to build chargers. Additionally, due to the small sample size of treatment entity, there might be biased estimation of the policy effect in the diff-in-diff estimates. Also, the synthetic control method can allow for time-varying state-specific heterogeneity (McClelland & Gault, 2017). More information regarding the diff-in-diff results and model can be found in Table B-1 in Supplement Online Material (SOM) B.
The synthetic control method essentially enables us to use data from the control states in the dataset to empirically estimate what would have happened in Missouri in the absence of the charging station incentive program, compared to when a program exists. Treatment and control entities are US states.

Specifically, in this paper, the synthetic cohort of the treatment state (Missouri) gives us the number of charging stations in the state when there is no incentive program. This synthetic cohort is constructed using the information of the “donors”, which are the weighted values of the observed covariates of the control states. The assessment period extends from 2011 to 2016 because by 2011 every state had the federal purchasing incentive program available. Additionally, data is obtainable until 2016.

It is hypothesized that states with charging station incentive programs will see a larger increase in the number of charging stations compared to states without the incentive. For the treatment state, it is ideal to have a state with the incentive program starting at the beginning of the year, so that the policy can have full effect in that year. Additionally, the treatment state should not have more than one charging station incentive program or a state or utility purchase incentive, or the station number may be overestimated. The incentive program of the treatment state should also not have any gap during its enacted period, so that the effect of the policy in all years after the enacted date can be assessed appropriately.

The station incentive program of Missouri started in January 2015 and ended after 12/2016. It also has no gap during the enacted period and was the only state incentive program for charging stations during the time period 1/2015 - 12/2016. For those reasons, Missouri emerges as the perfect candidate to be the treatment state. The control states include 14 states.

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1 The charging station tax credit of Missouri is 20% of the total cost of making a station available to public.
that do not have either charging station incentives or state purchasing incentive programs during the assessment period, resulting in overall total of 15 states being assessed.

In the sample, there are 15 states over \( t = 2011, 2012, 2013, 2014, 2015, \) and 2016 periods, with Missouri (which will be called state 1) is the only treatment state, and other 14 states are control states (donor states) (states 2 to 15). The charging station incentive program took place in January 2015 and affected only Missouri. The dependent variable of interest is the number of charging stations per 100,000 persons of each state. This is done in order to take into account the difference in the population of different states. States with higher population may have more chargers even without an incentive program, Let \( Y_{i,t}^{NT} \) be the number of charging stations per 100,000 persons in state \( i \) in year \( t \) that can be observed without the availability of the program. Similarly, let \( Y_{i,t}^{WT} \) be the number of charging stations per 100,000 persons in state \( i \) in year \( t \) that can be observed if the program is in place. Before the program is officially enacted, it has no effect on the number of chargers (there is no action taking place in anticipation of the program), since the tax credit only applies to chargers being built from January 2015 and onwards. Thus:

\[
Y_{i,t}^{NT} = Y_{i,t}^{WT} \quad \forall i, t \in \{2011, \ldots, 2014\} \tag{1}
\]

The goal is to estimate the causal effect of the incentive program on the number of chargers in Missouri, which is:

\[
\alpha_{1,t} = Y_{1,t}^{WT} - Y_{1,t}^{NT} \quad t \in \{2015, 2016\} \tag{2}
\]

where \( Y_{1,t}^{WT} \) is observable. \( Y_{1,t}^{NT} \), the number of charging stations per 100,000 of Missouri from 2015 and onwards without the program is not observable, and thus is a counterfactual value. Therefore, in order to obtain \( \alpha_{1,t} \), it is necessary to construct \( Y_{1,t}^{NT} \).

\( Y_{i,t}^{NT} \) follows a factor model \( \forall i \):
\[ Y_{i,t}^{NT} = D_t + \alpha_1 G_{i,t} + \alpha_2 Z_{i,t} + \epsilon_{i,t} \]  

where \( G_{i,t} \) is the vector of observed covariates unaffected by the incentive program. In this paper, it includes the log of income per capita per state in a given year, and log of population density per state in a given year. Income per capita per state is a predictor as EV demand increases with higher income (Li et al., 2017), and a larger stock of EVs will likely lead to more charging stations, and vice versa. Population density is a predictor since the demand for charging stations would be a function of the area to be served. It also includes the values of the number of charging stations per 100,000 before 2015, which will the elaborated later. \( Z_{i,t} \) is the vector of common unobserved factors. The \( \epsilon_{i,t} \) is the error term.

In order to estimate \( Y_{i,t}^{NT} \), the synthetic cohort of Missouri, we combine the data of \( G_{i,t} \) of the control states. In order to achieve this, the control states are each weighted, so that the weighted values of the covariates in \( G_{i,t} \) of those states when added up will produce the \( G_{i,t} \) vector of the synthetic Missouri. The values of the covariates of this synthetic cohort are expected to converge to those of Missouri. This will also result in an automatically matched \( Z_{i,t} \).

This whole process allows for heterogeneity of different states, and thus acts as a fixed effect model.

Let \( W = (w_2, w_3, \ldots, w_{15}) \) be the vector of weights of the control states, with \( w_i \geq 0 \ \forall i \).

For a given \( W \), the outcome of the combination of the control states, or the synthetic cohort at time \( t \) is:

\[ Y_{w,t} = \sum_{i=2}^{15} w_i Y_{i,t} = D_t + \alpha_1 \left( \sum_{i=2}^{15} w_i G_{i,t} \right) + \alpha_2 \left( \sum_{i=2}^{15} w_i Z_{i,t} \right) + \left( \sum_{i=2}^{15} w_i \epsilon_{i,t} \right) \]  

(4)
Suppose that $\exists W^* = (w_2^*, w_3^*, \ldots, w_{15}^*)$ such that the synthetic cohort matches Missouri in the years before the incentive program enacted, then:

\begin{align*}
\sum_{i=2}^{15} w_i^* Y_{i,t} &= Y_{1,t} \quad \forall t \in \{2011, \ldots, 2014\} \\
\sum_{i=2}^{15} w_i^* G_{i,t} &= G_{1,t} \quad \forall t \in \{2011, \ldots, 2014\}
\end{align*}

(5) 
(6)

Then for all $t > 2014$, we have:

$$
\mathbb{E} \left[ Y_{1,t}^{NT} - \sum_{i=2}^{15} w_i^* Y_{i,t} \right] \to 0
$$

(7)

As the number of pre-treatment periods grows large.

Therefore, $\sum_{i=2}^{15} w_i^* Y_{i,t}$ essentially acts as counterfactual $Y_{1,t}^{NT}$ that needs to be constructed. Thus the causal effect of the incentive program can be estimated as:

$$
\hat{\alpha}_{1,t} = Y_{1,t}^{WT} - \sum_{i=2}^{15} w_i^* Y_{i,t} \approx Y_{1,t}^{WT} - Y_{1,t}^{NT}
$$

(8)

which is the difference between the observed number of charging stations per 100,000 and the synthetic number from 2015 onwards.

Nonetheless, a $W^*$ that matches exactly the synthetic cohort with $Y_{1,t}^{NT}$ rarely exists.

McClelland and Gault (2017) suggested that as long as the assumption that the synthetic cohort approximates $Y_{1,t}^{NT}$, then the implementation of the synthetic control is valid. A set of predictors of the outcome variable is necessary to construct the data for synthetic Missouri. These
predictors are the covariates belong to $G_{t,t}$. McClelland and Gault (2017) indicated the importance of the lagged values of number of stations for some pre-treatment periods, which also belong to $G_{t,t}$.

With the dataset of quarterly observations of the number of chargers per 100,000 persons, there are sixteen pre-treatment periods (from 2011 quarter 1 to 2014 quarter 4), and eight post-treatment periods (from 2015 quarter 1 to 2016 quarter 4). As mentioned earlier, although the quarterly data for the number of charging stations is available, only yearly data for income and population density per state are available. The following predictors are included: log of income, log of population density, number of charging stations per 100,000 persons in 2011 quarter 4, 2012 quarter 4, 2013 quarter 4 and 2014 quarter 4, which results in a total of 6 predictors. The last quarters of each year are included since they will best represent the natural growth of new stations built over time. Additionally, 2014 quarter 4 is the last pre-treatment period. It thus is expected to be a good predictor of the outcome value in 2015 quarter 1. We decided to use all pre-intervention data for log of income and log of population density because unlike the number of chargers, these two variables are annual data, and thus in effect there are only 4 pre-intervention periods for them. The values of the predictors are averaged over the years before the incentive program was enacted, which is 2015.

Table 1 shows the weight of 14 control states in the synthetic control. Table 2 shows the comparison between Missouri and its synthetic cohort. The “Missouri” column shows the average values of log density and log income over the years 2011 to 2014, and the number of charging stations per 100,000 persons in 2011, 2012, 2013 and 2014, quarter 4 for Missouri. The “synthetic” column shows these values for the synthetic version of Missouri. The pre-treatment
Root Mean Squared Prediction Error for the estimation of the synthetic Missouri reported by Stata is 0.029.

<table>
<thead>
<tr>
<th>State</th>
<th>Weight</th>
<th>State</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>AL</td>
<td>0.001</td>
<td>ND</td>
<td>0.117</td>
</tr>
<tr>
<td>AR</td>
<td>0.311</td>
<td>NE</td>
<td>0.132</td>
</tr>
<tr>
<td>IA</td>
<td>0</td>
<td>NM</td>
<td>0</td>
</tr>
<tr>
<td>ID</td>
<td>0</td>
<td>SD</td>
<td>0</td>
</tr>
<tr>
<td>KY</td>
<td>0.171</td>
<td>WI</td>
<td>0.14</td>
</tr>
<tr>
<td>MS</td>
<td>0</td>
<td>WV</td>
<td>0.127</td>
</tr>
<tr>
<td>MT</td>
<td>0</td>
<td>WY</td>
<td>0</td>
</tr>
</tbody>
</table>

Table 1. Weight of each state in the synthetic control

<table>
<thead>
<tr>
<th>Predictors</th>
<th>Missouri</th>
<th>Synthetic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ln_density</td>
<td>4.475</td>
<td>3.957</td>
</tr>
<tr>
<td>Ln_income</td>
<td>10.648</td>
<td>10.638</td>
</tr>
<tr>
<td>station (2011q4) (per 100,000)</td>
<td>.299</td>
<td>.299</td>
</tr>
<tr>
<td>station (2012q4) (per 100,000)</td>
<td>.598</td>
<td>.597</td>
</tr>
<tr>
<td>station (2013q4) (per 100,000)</td>
<td>.794</td>
<td>.794</td>
</tr>
<tr>
<td>station (2014q4) (per 100,000)</td>
<td>1.089</td>
<td>1.088</td>
</tr>
</tbody>
</table>

Table 2. Comparison between Missouri and Synthetic Missouri (variable station is the number of stations per 100,000 persons)

3.2 Data

2 We tested different sets of predictors and found that they yield similar values for the synthetic cohort of Missouri (in both pre and post treatment periods), although they may result in different weights for each state.
The data for the open dates and locations (state and address) of all charging stations in the US was obtained from the US Department of Energy (DoE) in the form of Excel worksheet. We then calculate the quantity of stations per 100,000 persons in each year using this data, which is the dependent variable. The information regarding the availability of state charging station incentive programs of 14 control states comes from the Alternative Fuels Data Center, Federal and State Laws and Incentives section of the DoE. The details of the sources of charging station incentive programs information can be found in Table A-1 in SOM A. The availability, timeframe and end date of the incentive program in Missouri was obtained from the DoE and Missouri Statutes Title X, §135.710. The data for state yearly income comes from the US Bureau of Economic Analysis (BEA). Finally, the data for yearly state population and state land area (for calculation of population density) was acquired from the US Census Bureau. The method will use panel data with quarterly observations of the number of stations and annually observations of state income, population and land area. This is done due to the lack of quarterly data for state income and population. It is also assumed that state income and population vary little during the year.

3.3. Results

Figure 1 shows the graphical comparison between the number of charging stations per 100,000 persons of Missouri and its synthetic cohort. We can observe that the synthetic cohort fits Missouri very well for years before 2015, which indicates a good fit and validation of the synthetic control. This may well suggest that any noticeable difference between Missouri and its synthetic cohort is not generated coincidentally by the synthetic control. We can also observe that Missouri detaches from its synthetic cohort beginning in 2015.
Since planning and building a station often takes several months, the number of stations in the first quarter of 2015 is not significantly different from that of the last quarter of 2014. We therefore witness a difference from Missouri and the synthetic cohort beginning from 2015 quarter 2. From Figure 1, it is apparent that the gap between Missouri and its synthetic cohort is noticeably large, and increases in size over time. This may partially be due to positive network effects, which will be discussed further in section 4. Also, businesses and other non-profit entities may not be aware of the program at first, and take advantage of it later. The effect of the incentive program is computed as the difference between the number of charging stations per 100,000 persons of Missouri and its synthetic cohort. This difference over time is reported over eight quarters from 2015, which is summarized in the column “Difference” in Table 3. The counterfactual total number of stations of Missouri is also computed for each quarter using the number of stations per 100,000 persons of the synthetic cohort, which can also be found in Table 3.
<table>
<thead>
<tr>
<th>Period</th>
<th>Stations per 100,000 persons (Counterfactual)</th>
<th>Stations per 100,000 persons (Real values)</th>
<th>Difference</th>
<th>Total number of stations (Counterfactual)</th>
<th>Total number of stations (Real values)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2015Q1</td>
<td>1.15</td>
<td>1.23</td>
<td>0.089</td>
<td>70</td>
<td>75</td>
</tr>
<tr>
<td>2015Q2</td>
<td>1.29</td>
<td>1.83</td>
<td>0.536</td>
<td>78</td>
<td>111</td>
</tr>
<tr>
<td>2015Q3</td>
<td>1.36</td>
<td>2.12</td>
<td>0.766</td>
<td>83</td>
<td>129</td>
</tr>
<tr>
<td>2015Q4</td>
<td>1.48</td>
<td>3.72</td>
<td>2.24</td>
<td>90</td>
<td>226</td>
</tr>
<tr>
<td>2016Q1</td>
<td>1.66</td>
<td>4.27</td>
<td>2.61</td>
<td>101</td>
<td>260</td>
</tr>
<tr>
<td>2016Q2</td>
<td>1.84</td>
<td>5.04</td>
<td>3.20</td>
<td>112</td>
<td>307</td>
</tr>
<tr>
<td>2016Q3</td>
<td>1.91</td>
<td>5.93</td>
<td>4.02</td>
<td>116</td>
<td>361</td>
</tr>
<tr>
<td>2016Q4</td>
<td>2.05</td>
<td>7.27</td>
<td>5.22</td>
<td>125</td>
<td>443</td>
</tr>
</tbody>
</table>

Table 3. Difference between Missouri and its synthetic cohort, in numbers

The column “total number of stations (counterfactual)” in the table presents the total number stations available in Missouri in a given quarter without the incentive program. Based on the synthetic control results, the counterfactual number in 2015 quarter 4 is 90, while the real number of stations reached 226, which constitutes a difference of around 151%. The counterfactual for 2016 quarter 4 is 124, and the observed amount of stations was 443, which results in a difference of around 254%.

3.4. **Testing significance by using placebo test and post-pre RMSPE ratio**

In order to test the significance of the estimates, McClelland and Gault (2017) and Abadie, Diamond & Hainmueller (2010) suggested the use of the placebo test. First, the synthetic control method is applied to each of the 14 control states, as if each of them was the state that has the incentive program enacted in 2015.
Then, the post-treatment gap between each control state and its synthetic cohort is compared to that of Missouri. Since those control states do not have the incentive program, their number of charging stations per 100,000 persons should be close to that of their synthetic cohort in both pre and post-treatment periods. In other words, if the gap between Missouri and its synthetic cohort is the largest among all states, then there is evidence that the program is effective. McClelland and Gault (2017) suggested that a significant estimate should be interpreted as the acceptance of the alternative hypothesis (the treatment does have an effect on the outcome variable), rather than a rejection of the null hypothesis.

Figure 2 summarizes these gaps overtime. The gaps for all 15 states were sufficiently small for pre-treatment periods. These gaps began to widen beginning in the first quarter of 2015. It is clear that the gap between Missouri and its synthetic cohort is positive, and is the largest among 15 states. This suggests that the incentive program does have a positive effect on the number of charging stations in Missouri.

Figure 2. Number of stations per 100,000 persons gaps in Missouri and placebo gaps in 14 control states

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Another set of predictors was used, which gave similar results.
Alternatively, Abadie, Diamond & Hainmueller (2015) documented a method to estimate p-values. Essentially, if the ratio of post and pre RMSPE for Missouri is large enough, then there is evidence of the effectiveness of the incentive program. We found that the RMSPE ratio for Missouri is about 64.5, which is the highest among all states in the sample. The second highest ratio is 30.3, which belongs to North Dakota. North Dakota’s high RMSPE ratio is likely due to the fact that even though its GDP per capita is relatively high (around $64,000 in 2016), it is not a state which embraces EVs. If a state in the sample is picked randomly, the chances of obtaining a ratio as high as that would be \( \frac{1}{15} = 0.07. \)

4. **Plug-in EV adoption and charging stations analysis**

4.1. **Methodology**

In this section, the effect of the number of chargers on the quantity of plug-in EVs sold is estimated. Our hypothesize is that more stations will lead to more plug-in EV adoption. Importantly, there exists positive network effects between the number of charging stations and the quantity of plug-in EVs (Springel, 2016; Li et.al., 2017). This means that the quantity of plug-in EVs and charging stations will determine each other simultaneously, thereby creating the issue of reverse causality, which will be discussed later. A lagged value of the quantity of charging stations and the quantity of current plug-in EVs can also determine each other, as an expectation of more plug-in EV purchasing in the near future may induce more construction of charging stations now. Any incentive program that promotes constructing charging stations is expected to affect EVs sales only through the effect it has on the number of stations. It is therefore necessary to also obtain the relationship between the number of chargers and EVs sales.
With the size of the relationship between chargers and the quantity of plug-in EVs in hand, the size of the effect of the charging station subsidy on plug-in EV adoption can be estimated. For example, if the subsidy program increases the quantity of stations by 70%, and each 1% increase in stations will increase the quantity of plug-in EVs by 2%, then the effect of the station subsidy on plug-in EV adoption will be 70*2 = 140% increase in the quantity of plug-in EVs.

As discussed earlier, the number of plug-in EVs and of charging stations will determine each other. This results in the structural model with two regressions:

\[
\ln_{PEV_i} = \text{const} + \beta_1 \ln_{\text{STATION}}_{i,t-p} + \beta_2 \ln_{\text{income}}_{i,t} + \beta_3 \ln_{\text{population}}_{i,t} + \beta_4 \ln_{\text{gas}}_{i,t-q} + \beta_5 \text{subpch}_{i,t} + \sum_{i=1}^{12} (\omega_i \text{month}_i) + \epsilon_{it} \tag{9}
\]

\[
\ln_{\text{STATION}}_{it} = \text{const} + \gamma_1 \ln_{\text{PEV}}_{i,t-z} + \gamma_2 \text{subst}_{it} + \mu_{it} \tag{10}
\]

where model (9) is the PEV demand model, and model (10) is the charging station model. \( \ln_{PEV_i} \) is log of the monthly sales of plug-in EVs of state \( i \) at time (month) \( t \). \( \ln_{\text{income}}_{i,t} \) is log of yearly income of a state. Similarly, \( \ln_{\text{population}}_{i,t} \) is log of population. \( \text{subpch}_{i,t} \) is the dummy variable for state purchasing incentive availability, which will equal 1 if the state has additional purchasing incentive program(s) besides the federal tax credit. \( \ln_{\text{gas}}_{i,t-q} \) is the lag of log of gasoline price. The lag of gasoline price is included since it is likely that people will not respond to a change in gasoline price by buying a plug-in EV right away. Jenn et.al. (2013) used
the gasoline prices with 6 months lagged when analyzing the impact of gasoline prices and other factors on EV sales. Therefore, in this analysis, we also use a lag of 6.

\( \ln_{STATION_{i,t-p}} \) is the lag of log of the number of charging stations. Consumers’ decision to purchase a plug-in EV will likely depend partially on both the total number of charging stations available and the change in the number of new charging stations being built. If they observe an insignificant but rapidly growing number of stations, they will also be more eager to purchase a plug-in EV. Thus, two versions of the model are assessed. In the first version, the effect of the cumulative/total number of stations (variable \( \ln_{cumSTATION} \)) on the quantity of plug-in EVs is estimated. In the second version, the effect of the number of newly-built stations (variable \( \ln_{newSTATION} \)) is assessed.

Similar to a change in gasoline price, consumers will not be likely to respond to an increase in the number of stations by purchasing plug-in EV immediately. We chose a lag of 12 to account for this consumer adjustment period. A lag of 3, 6 and 9 were also tested and gave much larger coefficients of \( \ln_{STATION_{i,t-p}} \) relatively to the coefficient given by the lag of 12. Those large coefficients may be overvalued, given that the plug-in EV market is still expanding slowly (Linke, 2017). Thus, the lag of 12 was chosen to best represent consumer behavior. It should be noted that plug-in EV includes two types: PHEV (plug-in hybrid EV) and BEV (battery EV).

To take into account some degree of time fixed effect, the dataset includes the set of dummy month variables \( \sum_{i=1}^{12} (\omega_i \cdot month_i) \). The regression results of these month dummy variables were not included in the paper, but they can be found in the Appendix. Also, states vary greatly in terms of unobservable characteristics, such as culture, rules and laws, or political perspective, which will be taken into account using the fixed effect option in STATA. The
variable subst in (10) is the dummy variable for the availability of an incentive/subsidy program for charging stations, be it governmental or utility/private run. Finally, to solve for the endogeneity issue of reverse causality, instrument variables (IVs) are used. IVs are needed for both the number of charging stations in (9) and the number of plug-in EVs in (10). Subst will be the IV for $\ln_{STATION_{i,t-p}}$ in (1), and subpch will be the IV for $\ln_{PEV_{i,t-z}}$ in (10). For $ln_{PEV_{i,t-z}}$, we use a lag of 6, as businesses and other organizations/entities may respond to the increase in plug-in EV quantity much more quickly than consumers respond to the increase in charging stations quantity. A lag of 3 and 9 were also tested and gave similar results to the lag of 6.

An IV needs to be relevant and meets the exclusion restriction requirement. In order to test the relevance of station subsidy availability as an IV for the number of charging stations, the first stage is performed by regressing the log of total number of charging stations (variable $ln_{cumSTATION}$) on the dummy for station subsidy availability and included control variables in (1). Similarly, the log of number of newly-built stations (variable $ln_{newSTATION}$) was regressed on the dummy for station subsidy availability and the control variables. The results can be found in Table 4. They showed that the coefficients of the station subsidy availability dummies in both regressions are significant at 1% level, which confirm the relevance of station subsidy as an IV for the number of stations.

Regarding the exclusion restriction requirement, the availability of a charging station incentive program does not likely have a direct effect on the sales of EVs for 2 reasons. First, information on the laws/incentive programs that support charging stations is not widely available. Rather, they can only be found on state statutes websites. If consumers are not aware of the incentives available, their decisions will not likely be affected (Jenn et.al., 2018).
<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1) total station (ln_cumSTATION)</th>
<th>(2) new station (ln_newSTATION)</th>
</tr>
</thead>
<tbody>
<tr>
<td>subst</td>
<td>1.151*** (0.0605)</td>
<td>0.684*** (0.0441)</td>
</tr>
<tr>
<td>Constant</td>
<td>-11.52*** (1.412)</td>
<td>-10.47*** (1.031)</td>
</tr>
<tr>
<td>Observations</td>
<td>2,880</td>
<td>2,880</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.614</td>
<td>0.348</td>
</tr>
</tbody>
</table>

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4. IV relevance

4.2. Data

The data for monthly sales of plug-in EVs, both PHEV (plug-in hybrid EV) and BEV (battery EV) was collected from Auto Alliance website, beginning from 1/2011 to 12/2016. The data for the monthly quantity of stations is the same as that used in the synthetic control analysis. The yearly data for income and population from the BEA and the Census Bureau are still used. The yearly data for gasoline price was collected from the DoE, due also to the unavailability of monthly data. The information for the state purchasing rebate/tax credit and charging station incentive program was gathered from different sources, which can also be found in Table A-1 in SOM A. Due to the unavailability of information regarding the exact enacted date and end date the sample size will include 40 states rather than all US states,

4.3. Results

As discussed earlier, two versions of regression of the PEV demand model (model (9)) are estimated: the first version evaluates the effect of the 12 month lag of total number of stations on the plug-in EVs monthly sales. The second version estimates the effect of the 12 month lag of the number of newly-built stations in a month on the plug-in EVs monthly sales, using the same
set of control variables\textsuperscript{4}. For each version, both OLS and 2SLS methods were used. However, due to bi-directional causality and endogeneity issues, only the results of 2SLS are used, while OLS results are for reference only. The regression results for the first version can be found in Table 5, while the results and discussion of the second version can be found in Table C-1 in SOM C. Column (1) reports the results for the OLS estimates, while column (2) reports the results for the 2SLS estimates.

---

\textsuperscript{4} This version is done to examine the effect of the flow of stations (new stations built in a month) on the quantity of plug-in EVs in addition to the first version, which examines the stock of stations. While the first version will be used for analyzing of the effect of the station incentive program, the second version is used to help promote additional understanding of the EV market only.
**Dependent variable: ln PEV**

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1) total station</th>
<th>(2) total station</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>OLS</td>
<td>2SLS</td>
</tr>
<tr>
<td>Ln_cumSTATION (12th lag)</td>
<td>0.142***</td>
<td>0.400***</td>
</tr>
<tr>
<td></td>
<td>(0.0104)</td>
<td>(0.0814)</td>
</tr>
<tr>
<td>Ln_newSTATION (12th lag)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ln_population</td>
<td>7.681***</td>
<td>2.573</td>
</tr>
<tr>
<td></td>
<td>(0.961)</td>
<td>(1.926)</td>
</tr>
<tr>
<td>Ln_gas (6th lag)</td>
<td>0.0395</td>
<td>0.407***</td>
</tr>
<tr>
<td></td>
<td>(0.0728)</td>
<td>(0.141)</td>
</tr>
<tr>
<td>subpch</td>
<td>0.212***</td>
<td>0.147***</td>
</tr>
<tr>
<td></td>
<td>(0.0398)</td>
<td>(0.0492)</td>
</tr>
<tr>
<td>Ln_income</td>
<td>-0.841</td>
<td>-6.014***</td>
</tr>
<tr>
<td></td>
<td>(0.701)</td>
<td>(1.796)</td>
</tr>
<tr>
<td>Constant</td>
<td>-105.3***</td>
<td>26.97</td>
</tr>
<tr>
<td></td>
<td>(14.83)</td>
<td>(44.51)</td>
</tr>
<tr>
<td>Observations</td>
<td>2,400</td>
<td>2,400</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.278</td>
<td></td>
</tr>
<tr>
<td>Number of state1</td>
<td>40</td>
<td>40</td>
</tr>
</tbody>
</table>

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 5. PEV regression result

The coefficient of the 12 month lag of log of total number of stations is positive and significant at 1% level for both OLS and 2SLS regressions. The value of the coefficient of the 12 month lag of log of total number of stations using 2SLS is 0.4. This indicates that if the total number of stations increases by 1%, the sales of plug-in EVs twelve months later will increase by 0.4%. This estimate is smaller than that of the GMM estimate in the EV demand model of Li et.al. (2017), although their EV demand model did not utilize a lag. The difference might come
from possible downward bias in the 2SLS, or from the differences in the nature of the data in terms of timeline and observational units. Based on this estimate, a station incentive program such as one in Missouri that increases the number of stations by 151% by the end of 2015 can result in an increase of plug-in EV monthly sales by around 60.4% at the end of 2016. As an illustration, plug-in EV sales in Missouri in 12/2015 was 44 vehicles. Thus, an increase in monthly sales by 60.4% twelve months later translates to $44 \times 1.604 \approx 70$ vehicles in 12/2016, or an increase of 26 vehicles due to the charging station incentive program. If the program increases the number of stations by 254% in 2016 then plug-in EV monthly sales will expect to increase around 101.6% at the end of 2017.

The coefficient of the 6 month lag of log of gasoline price is positive and significant at 1% in the 2SLS regression. This implies that an increase in gasoline price has a positive impact on plug-in EV sales as a whole. Gasoline still remains the main fuel for most plug-in hybrid EV models. Hence, it may be the case that consumers generally purchase plug-in hybrid EV as a substitute for an ordinary all-gasoline vehicle, and fuel the car mostly with gasoline to take advantage of purchase subsidies, which are not granted to all-gasoline vehicles. On the contrary, battery EV adopters fuel their vehicle with only electricity, and gasoline price may be a more important deciding factor for them.

In addition to the plug-in EV regression model, we also performed a regression of model (9) with the dependent variable being the log of monthly sales of only battery EVs (variable ln_BEV) to study the possible different effect of gasoline price and the number of charging stations on battery EV sales than on plug-in hybrid EV sales. The results showed that the number

\[\text{Sales of EVs in Missouri in 12/2016 was 113 vehicles. The fact that this number is bigger than 70 may likely be due to other factors besides the charger program, such as the increase in popularity of EVs overtime.}\]
of chargers and gasoline price have a much bigger impact on the sales of battery EVs. Higher gasoline price leads to a much higher sales of battery EVs, compared to the results of the regression that includes both battery EVs and plugin hybrid EVs. These results fit quite well with the findings of Zhao, Doering and Tyner (2015). In examining the economic competitiveness of battery EV when being compared with combustion engine vehicles, they found that the economic competitiveness of battery EV is most influenced by the vehicle price, followed by fuel price. Therefore, long run monetary saving earned from using electricity can be an important incentive for consumers to purchase battery EVs. The details of this regression model can be found in Table C-2 in SOM C.

4.4. Illustration of the cost effectiveness of charging station subsidy program

There are three types of charging stations: levels 1, 2 and 3. Level 1 stations are mainly installed in private residential property, while public stations include mostly level 2 and level 3, with the majority of public stations being level 2. Smith and Castellano (2015) estimated that unit cost range per level 1 station is $300-$1,500, for a level 2 station is $400-$6500, and for a level 3 station is $10,000-$40,000. Installation cost range for a level 1 station is $0-$3,000; the average installation cost per level 2 station is $3,000, and $21,000 for a level 3 station. EVAdoption has reported that nationwide, in 2017, 5% of public stations were level 1, 80% were level 2 and 15% were level 3. We assume the national pattern for Missouri’s network of public stations and thus estimate the average cost of a public station as $12,180. Since Missouri offers a tax credit of 20% of the total cost, the credit for each public station in Missouri would be $12,180 * 0.2 = $2,436.

There were a total of 66 stations in Missouri in 2014, and 226 stations in 2015, which
means that 160 new stations were built in 2015. Thus, the total subsidy that Missouri paid for public stations in 2015 was around $389,760, assuming average cost for a station. From section 6.1.1, we know that the increase in plug-in EV sales in 12/2016 thanks to the program was 26 vehicles. Hence, the program cost for an increase of one EV being sold per month is \( \frac{389,760}{26} \approx \$1,250 \) (approx). This is the incremental sales beyond what is achieved by the federal tax credit of maximum \$7,500. While this is only an illustration, it does show that adding charging stations is an important component of a set of policies designed to achieve greater EV market penetration.

As discussed above, the monthly sales of plug-in EVs is affected by both the quantity of newly-built stations and the stock of available stations. However, the decision to construct new stations will likely be determined more by the change in monthly sales of plug-in EVs rather than both monthly sales and the cumulative sales of plug-in EVs. Since station providers are businesses, they will only invest in stations should they anticipate an increasingly growing plug-in EV market. Therefore, past and future monthly sales of plug-in EVs will likely have a causal effect on the number of newly-constructed stations. In the next section, we will discuss the effect of past monthly sales of plug-in EVs on the number of the newly-built stations in a given month.

It should be noted that possible consumer anticipation of more chargers being available may have an impact on their EV adoption choice. However, we had no basis for estimating consumer expectations and did not include them in the analysis.

For the charging station model (model (10)), the dependent variable will be the log of number of newly-built stations in a month (ln_newSTATION), while the independent variable will be the 6 month lag of log of plug-in EV monthly sales (ln_PEV-6th lag). Intuitively, the number of newly-built stations in a month should depend, at least partially, on the monthly sales
of plug-in EVs. To estimate this model, the first stage regression was first performed to examine
the relevance of the IV purchasing subsidy availability. The results of the first stage regression
indicate the relevance of the IV. The details of the first stage regression results can be found in
Table D-1 in SOM D.

The results of the charging station model shows that each 1% increase in the monthly
sales of plug-in EVs leads to an increase in 0.389% in the number of new stations being built,
and those new stations will be available for public charging six months later. This suggests the
presence of the indirect network as reported in previous work (Springel, 2016; Li et.al., 2017).
Details of the results of this model can be found in Table D-2 in SOM D.

5. **Conclusions and policy implications**

The paper examined the relationship between the change in charging stations to the
change in the sales quantity of plug-in EVs. The cost for an increase of one EV being sold per
month is approximately $1250. This is the incremental sales beyond what is achieved by the
federal tax credit of maximum $7,500. Adding charging stations is an important component of a
set of policies designed to achieve greater EV market penetration.

The number of monthly sales plug-in EV affects the number of newly-built stations
nearly as much as the latter affects the former. This can be a sign that potential station owners
are becoming increasingly involved and reactive to the plug-in EV market. Given the effect of
the station incentive program on the number of new stations being built, policy makers can
effectively leverage the plug-in EV market by designing and enacting policies aimed at taking
advantage of the positive network externality. For example, Zhu, Wang & Zhang (2019)
suggested that incentives aim to increase the number of chargers would be more cost effective
and yield better results than direct monetary incentives. However, Springel (2016) also reported
that the effects on EVs adoption of subsidies for chargers taper off more quickly than direct monetary incentives when subsidy amount increases. Hence, a policy that initially supports construction of chargers, and later on subsidizes buyers might be an option for policy makers.
References


Linke, R. (2017, August 3). The real barriers to electric vehicle adoption. *MIT Management*


