

Smart Charging Diff-in-Diff Analysis

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Executive Summary

The objective of this study was to evaluate the effectiveness of a managed smart charging program in modifying the charging behaviors of electric vehicle owners to alleviate grid stress and costs during peak hours. We used a diff-in-diff approach to compare changes in energy consumption patterns between a control group and treatment group, both before and after the implementation of the managed charging program. Data was collected over a period from June to December 2023, covering a total of 600 electric vehicles. We found that the managed charging program shifted peak hours (6-9 PM) to off peak hours (10 PM - 8 AM) and reduced average energy costs by \$2.04 per day across all 600 vehicles. The analysis suggests that the benefits in terms of cost savings and grid stability can be scaled up with increased participation. We propose a pricing model which provides vehicle owners with monthly incentives to stay enrolled in the program as well as performance-based compensation for successful shifts in loads.

Introduction

The integration of electric vehicles (EVs) into the grid presents challenges as well as opportunities. As the adoption of EVs increases, so does the demand for electricity, especially during peak hours from 6-9 PM when drivers return home and plug in their EVs to charge for the next day. This can lead to grid instability and higher energy costs, as energy in peak hours is usually provided by expensive peaker plants to meet steep increases in demand. Managed charging programs for EVs offer a promising solution by shifting EV charging from peak to off-peak hours, thus improving grid management and reducing the costs of providing electricity. Providing demand side flexibility through managed charging programs can charge vehicles in the least cost manner, and return some of those benefits to EV owners enrolled in the program.

Part A: Effects of Smart Charging on Load Shapes

Naive Analysis

When examining possible grid overload on the demand side, we are in particular focused when peak load is highest which occurs between the times of 6 to 9 pm each night. Reducing load during peak hours through managed charging has the potential to significantly lower the risk of blackouts, and functions similarly to virtual power plant

softwares. We begin by plotting the monthly average charging power consumption for households in both the control and treatment groups over the course of 2023.

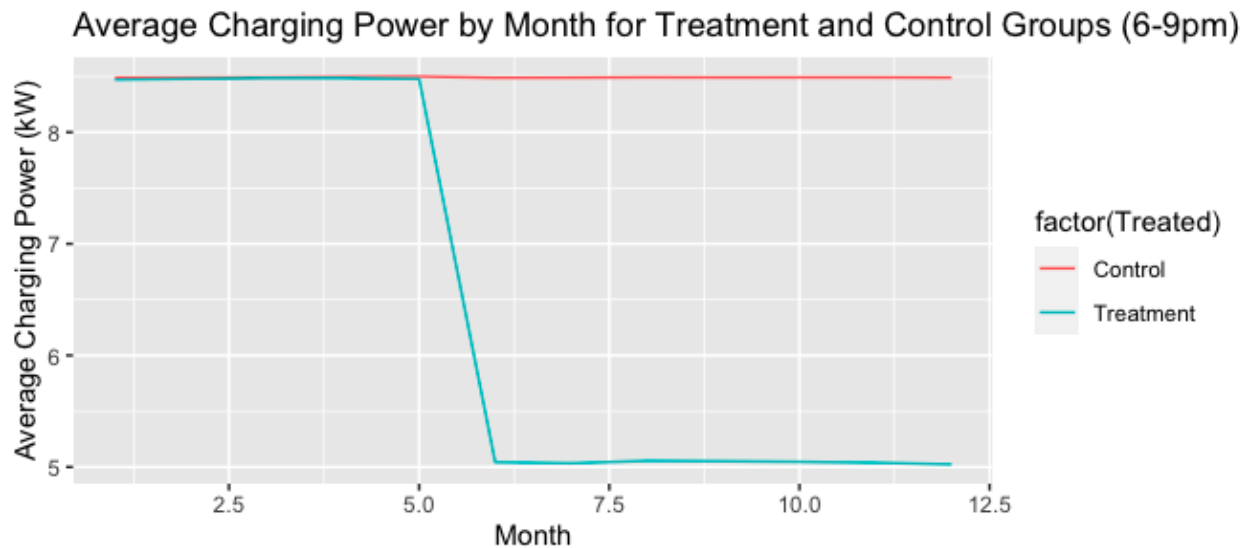


Figure 1

We see that promptly after the treatment group begins the managed charging program on June 1, 2023, that there is a significant decline in their average charging power by household when compared to the control group. Both the treatment and control group average about 8 kWh of charging power consumption per day before June 1. After June 1, the average charging power consumption of the control group remains constant at about 8 kWh but the treatment group sees their consumption decline to about 5 kWh on average.

This graph visualizes what we are measuring with a diff-in-diff estimation strategy by illustrating the “difference” as the change in slope between the treatment and control groups after the treatment is implemented. For this analysis to hold, it must satisfy the parallel trends assumption. In this case, this assumption implies that in the hypothetical *absence* of the load management program, the treatment and control group consumption would have continued on their original trajectories. In this particular case, since the treatment and control not only demonstrate parallel trends but also parallel levels, we could additionally add that the assumption here is that the treatment group’s consumption level would have been unchanged relative to the control group in the absence of the program.

While the parallel trends assumption cannot be tested *directly*, we can examine the data for evidence in support of making this assumption. We plot the difference between the treatment group average power charging consumption and the control group.

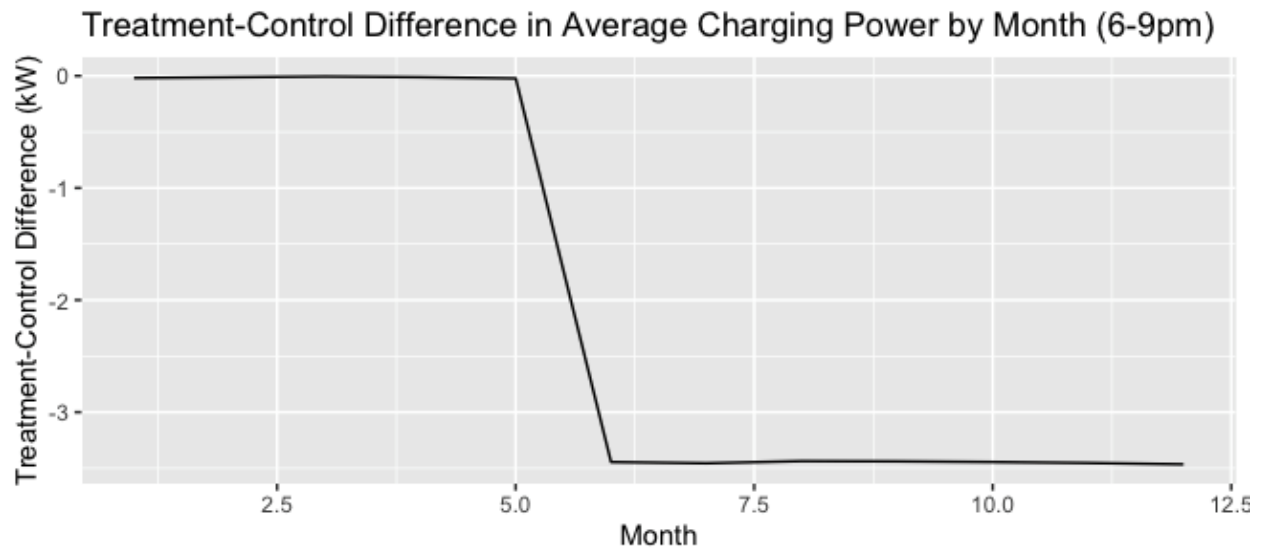


Figure 2

We see that the treatment minus control difference remains constant both before and after the managed charging program begins on June 1. Since both the parallel leads and lags are relatively constant, we can see that any difference between the groups is likely explained by the managed charging program and we proceed with our difference-in-difference analysis, having provided strong evidence in support of the parallel trends assumption.

Difference-in-Difference Analysis

We proceed by plotting the average charging load shape over the course of the day (split into 15 minute periods across the day) for each of the four groups in our analysis: control group pre-treatment, treatment group pre-treatment, control group post-treatment, and treatment group post-treatment. We not only want to observe differences in load shape between the treatment and control groups after the charging program, we are interested in the time differences as well both before and after June 1 since trends in consumption are seasonal. This is especially important since we are not running a randomized control experiment, and the groups could behave differently.

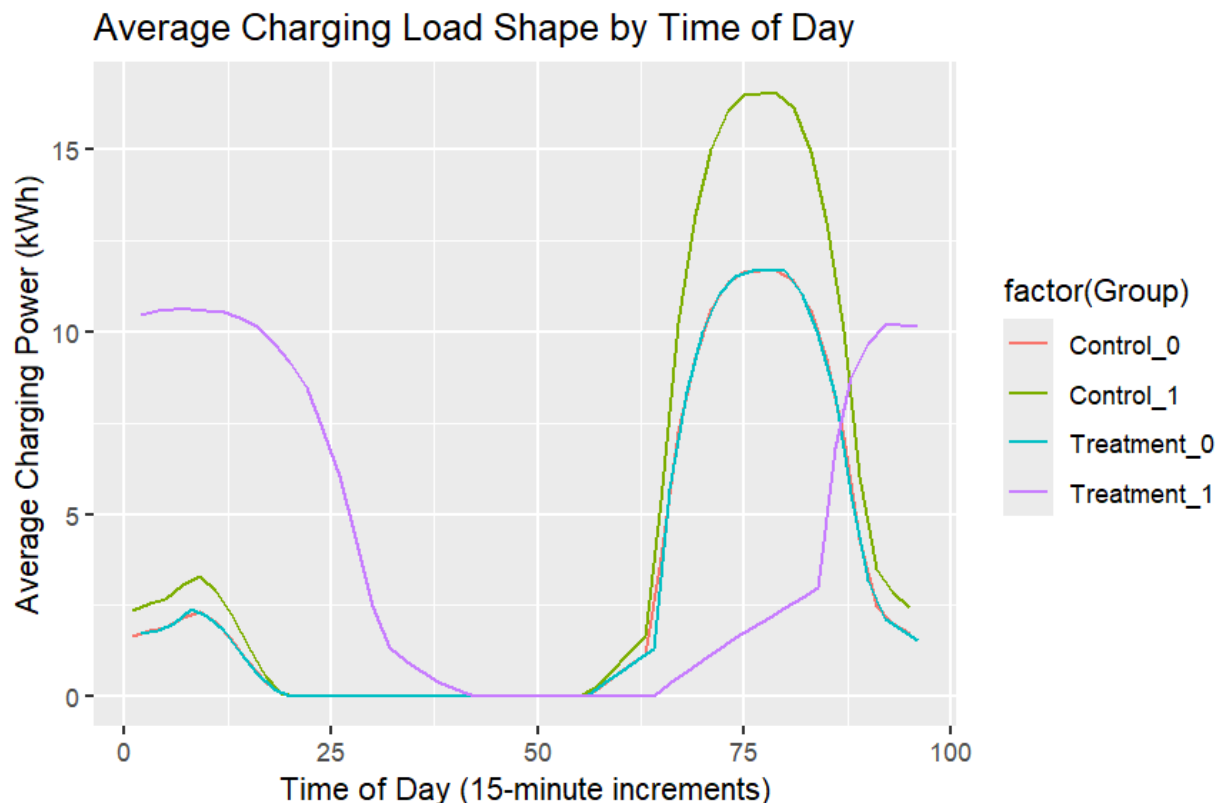


Figure 3

We see the load shape for the treatment and control groups before June 1 is the same. Although not required for a difference-in-difference analysis, it does suggest the treatment and control group behave not only in parallel but similarly as we saw before in our naive analysis. After June 1, we see significant differences not only between the control and treatment group, but between the control group before and after June 1 as well. The control group before and after treatment follows similar patterns, with a small increase in average charging power occurring in the middle of the night, but a concerning large increase during 6 to 9 PM peak hours. The treatment group after June 1 shows the managed charging program significantly shifts load shape from peak hours to the middle of the night when grid load is low, while also ensuring people's cars are charged for the morning when they go to work.

We can use Figure 3 to construct a difference-in-difference estimate of the managed charging program by capturing the difference in changes over time between the treatment and control groups. To calculate the estimate for each 15-minute period throughout the day, we use the following formula for each period i of the day:

$$(AvgkWh_i[treatment_post] - AvgkWh_i[treatment_pre]) -$$

$$(AvgkWh_i[control_post] - AvgkWh_i[control_pre])$$

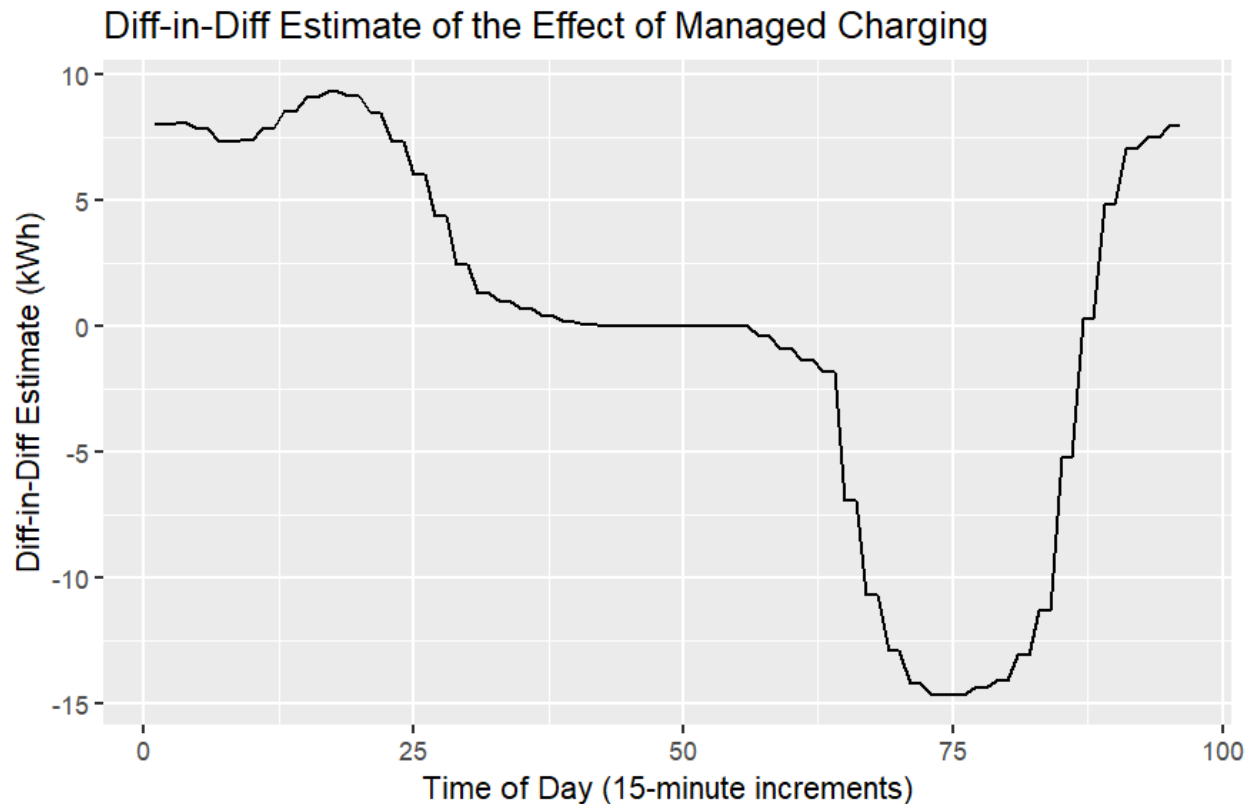


Figure 4

Figure 4 is the difference-in-difference estimate of the managed charging program throughout the day, plotted every 15 minutes. We see the estimate of the managed charging program suggests average power charging consumption decreases by almost 15 kWh around 6:45 PM (during the middle of peak hours). The difference-in-difference estimate suggests charging consumption load is instead shifted to night hours from 10 PM to about 8 AM the next morning, all of which are non-peak hours.

Part B: Energy Cost Savings

The general idea of a demand response program is to shift load from higher to lower demand times, which eases stress on the grid and can provide cheaper electricity for the consumer. Figure 5 indicates that during peak demand hours, around 6-9 pm, the average hourly price doubles from around \$50/MWh to \$100/MWh.

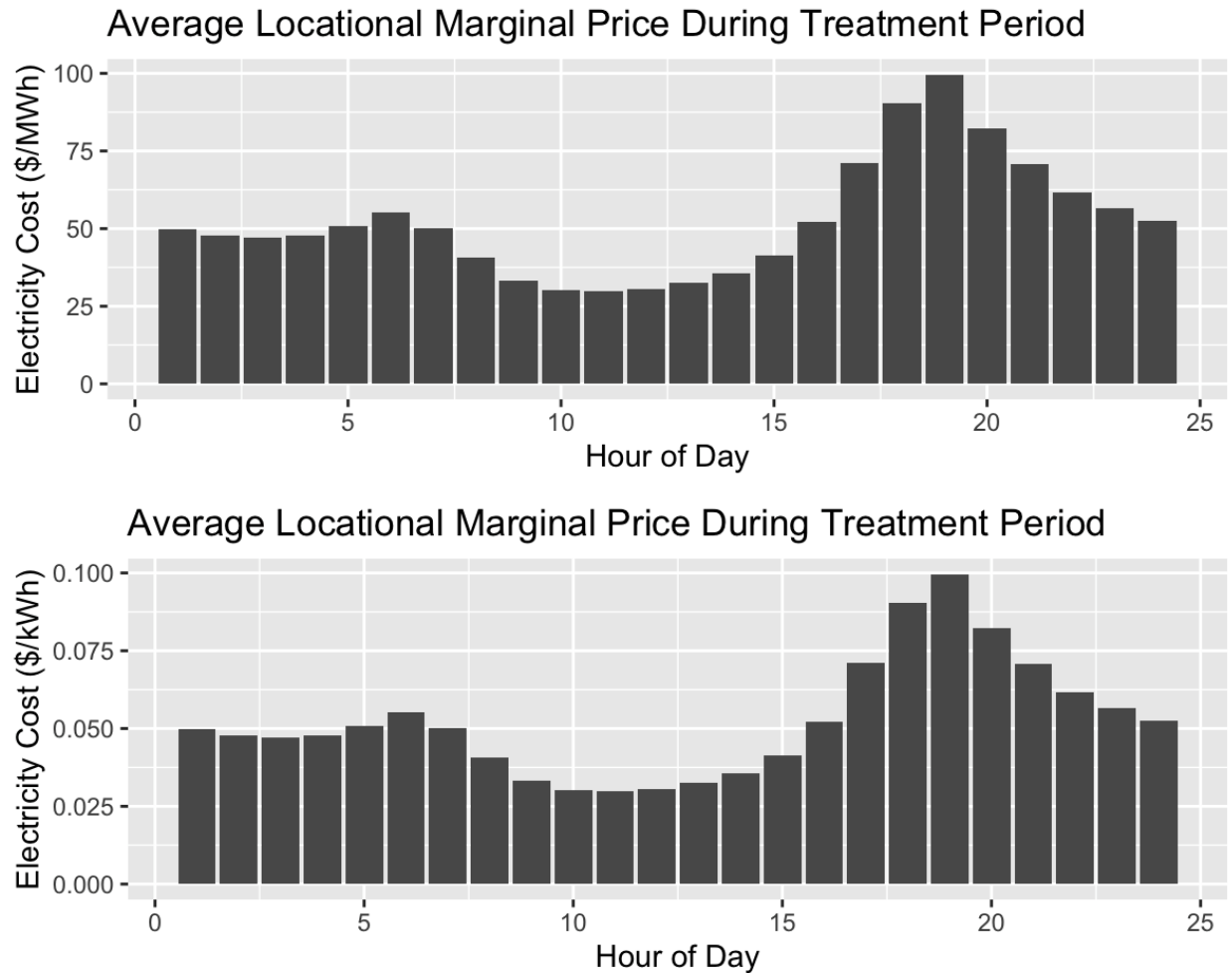


Figure 5

To determine energy cost savings, we'd want to know what the average daily expenditure is on electricity under a non-managed scenario, then take the difference between that amount and what would be spent under a managed scenario. This is precisely how we can interpret figure 4: by multiplying the positive or negative *change* in kWh consumed in at a given time of day by the price of electricity (in kWh, accounting for the unit change) at that same time of day, we effectively derive the difference between the managed and unmanaged scenarios. Theoretically, the additional hours demanded in off-peak hours will be offset by substantial demand reduction in peak hours. If this figure is negative, this would be net savings, and vice versa were it positive.

Since our diff-in-diff estimate is taken across the entire treatment period, we took average lmp prices across the same period. These data are only available by the hour, while our diff-in-diff estimates are every 15-minute period throughout a day. So we collapsed every four 15-minute periods into their corresponding hour, then multiplied that *change* in demand (treatment - control) by the average lmp price for that corresponding hour, in the same time period (June 1 to December 31, 2023). So note that a negative value implies *savings*, since control cost was greater than treatment cost.

Figure 6 below highlights that during peak hours from 6-9 pm, there are substantial cost savings caused by demand reductions, passing that demand over to less expensive hours in the day. Again, a negative value implies savings, because the control demand*cost was *greater* than the treatment demand*cost.

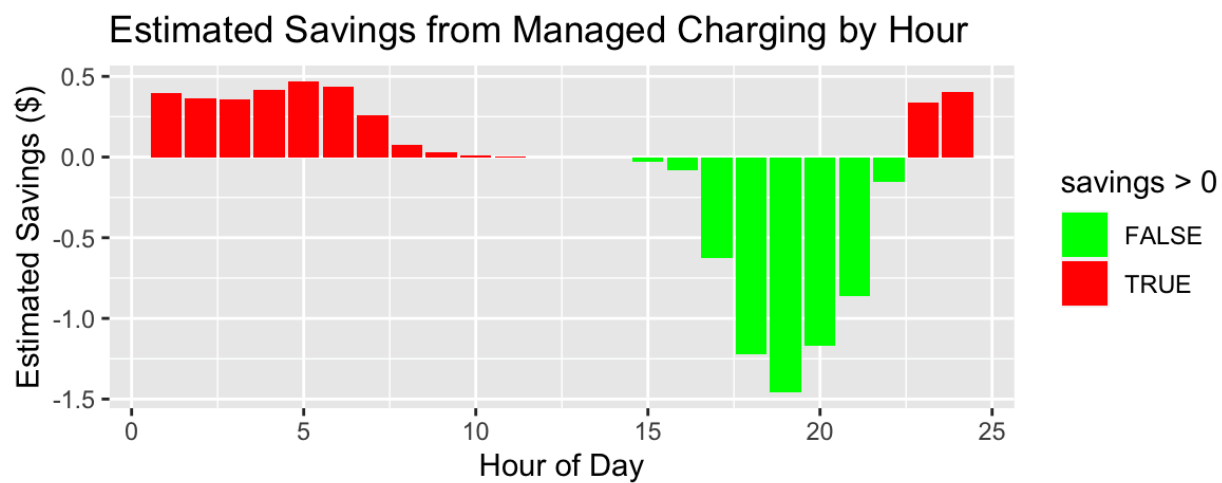


Figure 6

In aggregate, the *average daily savings*, derived by summing the product of the average difference between treatment and control groups and average lmp across all hours of a day, is \$2.04, just for the 600 vehicles in the experiment.

Part C: Business implications

In order to determine a successful pricing structure for the managed charging program, utilities should evaluate all of the benefits of the program, including grid stability. We can see from the results of part A that the charging program significantly shifts demand loads from peak hours to off peak hours, reducing the risk of blackouts

and grid stress. From part B, we determined that this shift provides substantial savings during peak hours from 6-9 PM, and an average daily savings of \$2.04 across all 600 vehicles in the experiment, or approximately \$1.24 per vehicle per year. However, in times where reducing demand is critical to preventing blackouts, this could result in a much higher cost savings, as loss of load events in California could cost industrial and commercial customers \$2 billion¹. Additionally, there is potential to close expensive peaker plants, or dispatching peaker plants less often, and potential for congestion and transmission costs to significantly decrease. These benefits are not included in our analysis of part B, which means this is likely an underestimate of benefits, and there is room for further analysis.

There should be an incentive structure to keep vehicles enrolled in the program in case blackouts are imminent, but also which allows utilities and the operators of the managed charging program to maintain a portion of the cost savings. Our recommended pricing structure involves a fixed monthly payment to vehicle owners at \$.05-.13 per month, the latter value being the maximum projected cost savings per vehicle per month. We also propose charging the utility additional performance based incentives based on the ability of the program at reducing peak demand at a rate of .05 - .8 per kWh during the hours of 6-9 when cost savings are highest, and paying vehicles \$.02-.05. Assuming that the energy savings are approximately equal to .025 kWh per day per vehicle if all vehicles provide equal energy storage services, this would mean vehicles would get paid \$.18-.46 per year for the performance based incentive.

The program as it stands with this pricing structure may not be financially promising enough to get electric vehicle owners to enroll and stay enrolled in the program. We recommend further research into the other additional benefits of the program, primarily in avoided transmission and congestion costs, as well as the avoided infrastructure costs for providing electricity during peak demands i.e. closing of peaker plants, transmission infrastructure, etc. in order to align the bottom lines of our smart charging program with utilities' and provide maximum benefits to participating vehicle owners.

Conclusion

The evaluation of the managed smart charging program through a difference-in-difference analysis provided insights to the benefits of programs such as this and

¹ <https://www.cnbc.com/2019/10/10/pge-power-outage-could-cost-the-california-economy-more-than-2-billion.html>

addresses challenges posed by integrating electric vehicles to the grid. The study found that there are substantial benefits which mitigate peak demand and shift charging to off-peak hours. There are cost savings averaging \$2.04 per day across 600 vehicles, underscoring potential cost savings to utilities which can be transferred to enrolled participants. Our proposed pricing structure leaves room for both utilities and participants to share the benefits, where utilities also stand to gain from reduced reliance on peaker plants and improved grid stability. The true value of managed charging programs likely extends beyond this analysis, and further research should be conducted on reduced transmission and congestion costs, avoided infrastructure investments, and decreasing GHG emissions. This paper supports the scalability and cost effectiveness of managed charging programs as a strategic response to EV integration.