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How the presence of public charging infrastructure can impact the adoption rate of electric vehicles in the UK

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Abstract. In the current work, the presence of public charging facilities and their impact on the adoption rate of Electric Vehicle (EV) are studied across 363 Local Authorities (LA) districts in the UK. This analysis is conducted utilizing the data from the UK government on the location of public electric vehicle chargepoints in various LAs as well as the EV ownership rate between years 2011 and 2021. Various rural, urban and extra urban (e.g. London) regions are analyzed to assess whether EV ownership has been impacted as the charging infrastructure is rolled out in these regions. The quarterly data on the number of licensed Ultra Low Emission Vehicles (ULEV) in each UK local authority is used to track EV ownership levels. The results indicate that the publicly available charging points stimulate the diffusion of EV adoption; however, this varies by region and saturation. The reverse effect of EV ownership on charging infrastructure rollout by Local Authorities cannot be entirely rejected; however, the positive stimulus of public infrastructure on adoption of EV is established. The findings can provide the UK policy makers with insight into the public charging infrastructure requirements and benefits in short to medium term to meet the committed emission reduction targets by 2035 and 2050.

1. Introduction

The increased environmental awareness among developed as well as developing economies in recent years and emergence of new and cost-effective renewable energy combined with a coordinated global effort to reduce carbon emission has distorted the global energy market significantly. According to U.S. Energy Information Administration, transportation is one of the biggest sectors of energy consumption (around 25%) globally[1]. Within the transportation sector itself, the light-duty vehicles are the biggest contributors to energy consumption. Electric Vehicles (EV) are one of the promising solutions that can drastically reduce the carbon footprint of transport industry and are shown to be a practical solution in fight against the climate change [1, 2]. With mass adoption of EVs, the transport sector-related CO_2 emissions are expected to drop significantly.

At the early years of competition for automobile market share, EV sales outnumbered internal combustion engines. However, besides technological superiority other factors such as marketing, political and social acceptance will have an impact on adoption of a new technology. As such, modelling the adoption rate of a new technology and its diffusion into the market should be

[1] U.S. Energy Information Administration, Transportation sector energy consumption 2016.

properly investigated and modelled. As pointed out by Diamond, and Graham-Rowe *et al* introduction of any new product into mainstream consumer markets commonly face similar hurdles: high cost, multiple decision makers, behavior change requirement, lack of knowledge and high risk, to name a few [3, 4]. One of the major considerations in choosing an EV over conventional Internal Combustion Engines (ICE) is the availability of convenient and affordable charging infrastructure. Home charging is the first and most straightforward method of EV charging. However, solely relying on home charging has its own shortcomings. Multiple short trips, an unusually long daily trip or starting the day with battery not at its full capacity can easily go beyond the vehicle battery range requiring some sort of publicly available charging facility. Lack of such options will limit the potential use case of electric vehicle to general public and makes electric vehicles only suitable for occasional journeys with limited purpose. Also, in many circumstances, a considerable portion of the population live in multi-family units without access to private or reserved parking space where a home charging unit can be installed. This is particularly true for dense and metropolitan areas in the UK and European countries [5]. Therefore, relying solely on home charging will result in a major barrier to transition to EVs. This further justifies the need for presence of a widespread, affordable and accessible public charging infrastructure to facilitate the adoption of electric mobility in mainstream society.

In a recent survey, Austmann provides a comprehensive overview of research on the predictive models to study the determinants of EV market by using actual data [6]. A variety of predictive methods have previously been employed to investigate incentives and socio-demographic/economic compositions to predict the adoption of EVs. These studies cover different regions/countries but mostly focused on the US and China and to some extent EU and the UK. The current research is motivated by extending the previous studies on adoption rate of EVs and the underlying barriers (e.g. charging infrastructure) in the UK using quantitative methods. One of the biggest concerns among EV owners or potential buyers is the so-called range anxiety. Franke *et al* provided a detailed description of range anxiety [7]. The range anxiety is more pronounced among EV owners/buyers mainly due to lower number of available public charging stations and higher charging times compared to corresponding gas station availability and fueling time of ICE. Neubauer and Wood studied the impact of charging infrastructure on range anxiety and concluded that the presence of non-private charging infrastructure greatly eliminates range anxiety [8]. Similar studies about the positive impact of public infrastructure on reducing range anxiety leads us to expect a measurable impact on adoption rate of EVs in presence of public infrastructure. Javid and Nejat studied the adoption of electric vehicles in California and the underlying factors driving consumer purchase decision [9]. They considered socioeconomic variables, travel habits, demographics, and infrastructure development in their Multiple Logistic Regression Analysis (MLRA) method and identified the charging station density as one of the major determinants of electric vehicle adoption in California.

Few studies however have focused specifically on the impact of charging infrastructure on adoption of EVs. How important is the public charging infrastructure to adoption of EVs? And is the massive investment in the infrastructure helping the cause? Considering governmental incentives and private sector investment, it is vital to assess the link between mass adoption of electric vehicles and public charging infrastructure. To the best of authors' knowledge, only a limited number of studies in the literature have focused on this topic. Illmann and Kluge studied the fundamental long-run relationship between EV registrations and availability of charging infrastructure in Germany [10]. They employed a cross-sectional augmented autoregressive distributed lag (CS-ARDL) and concluded a positive long-run relationship albeit at low scale. Mersky *et al* studied EV sales at Norwegian regional and municipal levels by cross analyzing location, demographic data and government incentives to establish the dominant factors affecting electric vehicle adoption rate [11]. Their work demonstrated that availability of charging infrastructure had one of the greatest predictive powers in adoption of EVs. One of the

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challenges in regressing the EV adoption rate to local charging infrastructure availability is the simultaneity bias. On one hand, we can argue that the availability of more charging points in all likelihood will increase local adoption. On the other hand, one can argue that charging points are predominantly set up in areas with high/growing demand from the electric vehicle consumers in the region. Solving this causality dilemma allows policy makers to make informed decision on whether to favor subsidizing charging infrastructure or looking for other avenues to stimulate EV sales directly. In the present work, we utilize the Difference-in-Differences event study framework proposed by Callaway and Sant'Anna [12] to assess the effect of presence of charging infrastructure on EV adoption rate in various regions in the UK.

2. Mathematical Framework

In order to estimate the treatment effects on the experiment outcome, the so-called class of event studies provide a popular tool for researchers (Heckman *et al* [13], Sun and Abraham [14] and Abadie [15]). These event study techniques are specifically effective when the treatment is non-random and the available panel data allows comparing the outcome trajectory before and after the onset of treatment, as well as across units treated at different times (Clarke and Tapia-Schythe [16]). The Difference-in-Differences (DiD) method with multiple time periods of Callaway and Sant'Anna [12] captures the effect of an event (treatment) on the outcome. The measured outcome is compared between the treated and non-treated sets across all treatment groups on all observed times to estimate the impact of the treatment. This way the causal effect of the treatment can be traced back to the performance of the measure outcome among the overall population of cases under study. For instance, consider the most basic setup with only two time periods and two group (one treated and one untreated group). In this setup, one group remains untreated throughout the observation window, while the event (treatment) happens to the other group in the second period. Further defining the measured outcome of unit i in period s as $Y_{is}(k)$ – where $k = 0$ corresponds to not participating in treatment and $k = 1$ for participating in treatment; the observed outcomes can be refactored as:

$$Y_{it-1}(0) \quad and \quad Y_{it} = D_i Y_{it}(1) + (1 - D_i) Y_{it}(0) \tag{1}$$

where $D = 1$ for the treated groups and $D = 0$ for untreated groups. This essentially yields the potential outcome for everyone in the first period (where neither group received treatment) and the potential treated outcome in second period for units that participated in the treatment. The so-called parallel trends assumption of DiD allows to utilize the observed path of untreated groups in estimating the impact of treatment on treated groups. A particularly interesting treatment effect parameter in DiD is the average treatment effect on the treated; ATT which is defined as:

$$ATT = \mathbb{E}\left[Y_t - Y_{t-1} | D = 1\right] - \mathbb{E}\left[Y_t - Y_{t-1} | D = 0\right] \tag{2}$$

In order to generalize ATT to situations with multiple treatment groups and multiple times periods, Callaway and Sant'Anna extended the definition of ATT to include units who at a particular time period t are members of a particular group G and defined the group-time treatment effect as:

$$ATT(g, t) = \mathbb{E}\left[Y_t\left(g\right) - Y_t(0) | G = g\right] \tag{3}$$

As before, $Y_{it}(0)$ is unit i outcome in period t if it is not treated; $Y_{it}(g)$ is the outcome associated with unit i in period t if it is treated in period g; and G_i corresponds to the time period when unit i is first treated. In the present work, a considerable number of group-time treatment values are generated in DiD framework (large number of observations). A number of weighting schemes $w(g, t)$ can be used to aggregate the outcomes:

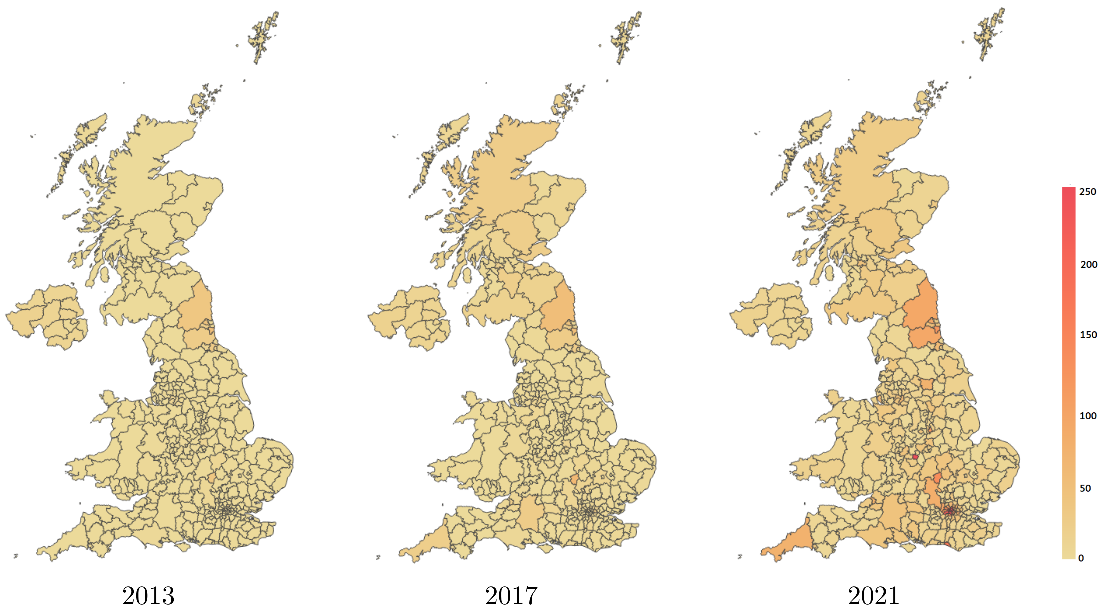

Figure 1. Evolution of number of EV charging points across UK LAs between 2013 to 2021

$$ATT_{agg}(g,t) = \sum_{g\in G}\sum_{t=2}^{\mathcal{T}} w(g,t) \times ATT(g,t) \tag{4}$$

Furthermore, utilizing the concept of event time e in definition of the weighting scheme $w(g,t)$, the impact of exposure length on treatment effect can be assessed. Denoting event exposure time $e = t - g$ as the amount of time passed since treatment was adopted, one can aggregate the average effect of participating in the treatment for the group of units that have been exposed to the treatment for exactly e time periods as below:

$$ATT_{agg}^{D}(g,t) = \sum_{g=2}^{\mathcal{T}} \mathbb{1}_{g+e\leq\mathcal{T}} \times ATT(g,g+e)P\left(G=g|G+e<\mathcal{T}\right) \tag{5}$$

where $\mathcal{T}$ is the total number of time periods.

2.1. Data

The UK National Chargepoint Registry database for electric vehicles in the UK is used to collect the location of public charging points. The data is visualized in Figure 1 where the number of charging point locations across UK LAs are shown between 2013 to 2021. As observed, the increase in the number of charging point locations is not homogeneous across the UK and some areas are increasing their charging infrastructure capacity faster than the rest of the country. The adoption of electric vehicle in each of UK LAs is retrieved from ownership data for ULEVs from 2011 Q4 within each UK Local Authority and is summarized in Figure 2 where the number of licensed Ultra Low Emission Vehicle (ULEV) are shown in all UK LAs between 2013 through 2021. As observed, in some LAs the change in number of licensed ULEVs follows a similar trend to that of public charging locations. However, there are some LAs with high public charging stations where the number of ULEVs has not caught up with the increased public charging infrastructure. This will be quantitatively further assessed in the subsequent section.

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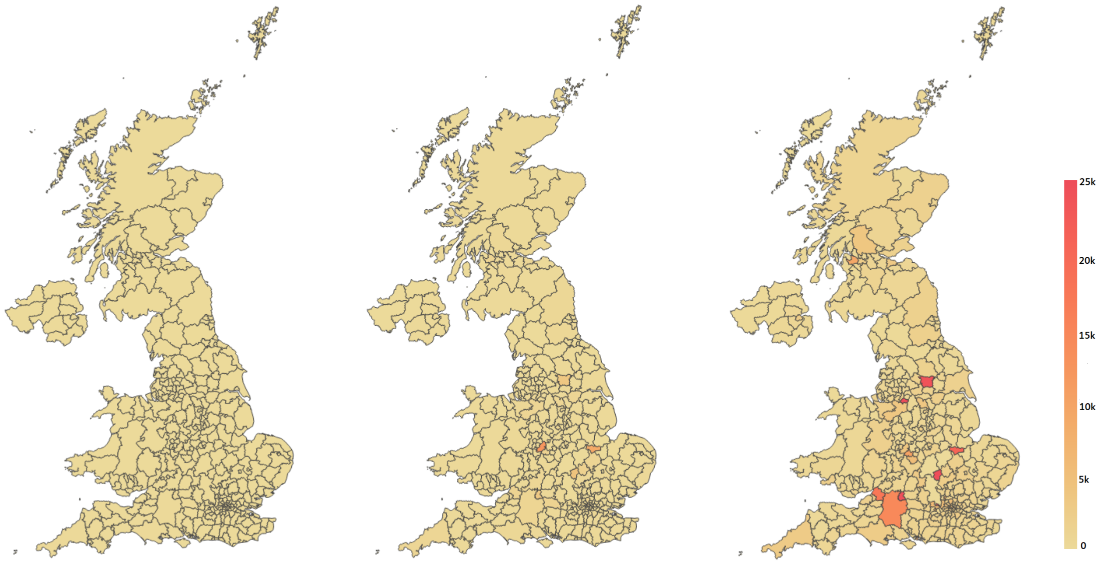
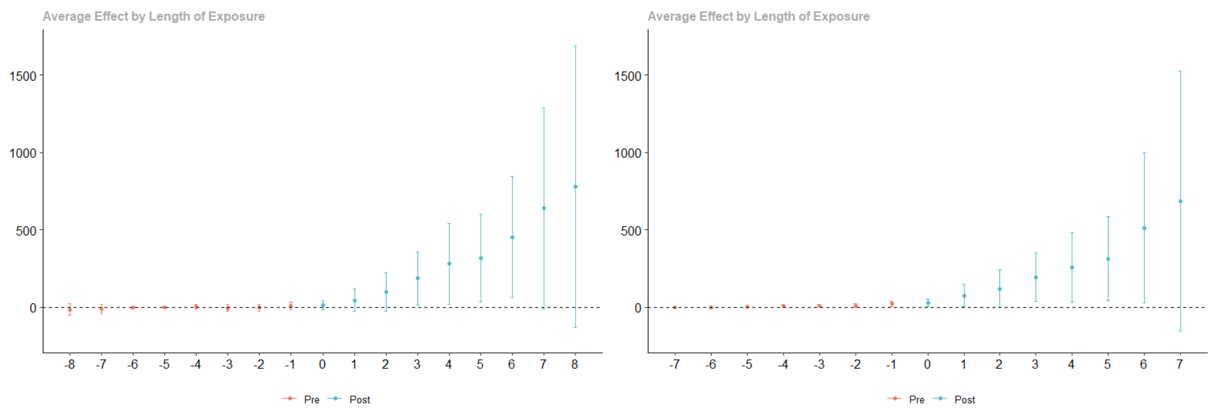


2013 2017 2021

Figure 2. Number of licensed Ultra Low Emission Vehicles in UK between years 2013 to 2021



(a) Base line **(b)** Including control variable

Figure 3. The presence of charging infrastructure and its effect on adoption of electric vehicles in the UK, before and after introduction of first public charging point in local authorities in the presence of mean disposable household income covariate.

3. Results and discussion

First, the effect of public charging points addition on adoption of electric vehicles are estimated without incorporating any control variables. The effect of introducing the first public charging point on the change in the number of licensed ULEVs is illustrated in Figure 3a. In order to better visualize this impact, the group-time average treatment effects are aggregated for all treated groups in this figure. The red points in this plot correspond to the pre-treatment group-time (average) treatment effects and blue dots represent the post-treatment effect. They can be interpreted as the effect of policy (introduction of public charging infrastructure) on the adoption rate of electric vehicles.

The effect begins almost immediately after the introduction of treatment at $t = 0$ and can be seen to remain statistically significant in the following years. The expected mean of the number of registered ULEVs in the 8 years before installation of first public charging station at $t = 0$ is virtually equal to zero; whereas post intervention the expected mean of the number of registered ULEVs (represented by blue dots) steadily keeps rising over time. This is broadly in line with the expected impact of charging point infrastructure on the adoption of electric vehicles, as was implied in regional maps of Figure 2. Furthermore, in order to include the control variable in DiD regression to separate out its additional effect on the outcome, the change in the mean Gross Disposable Household Income (GDHI) of UK local authorities are included in the subsequent results. The data is sourced from Nomis (UK's largest independent producer of official statistics) which is a service provided by Office for National Statistics ONS in the UK. The dataset used in the present work spans from 2011 through 2019. Similar to the base results in Figure 3a, the effect of treatment on the change in the number of licensed ULEVs by including GDHI covariate is illustrated in Figure 3b. As suggested by the results, the increase in ULEV registration after treatment is not influenced by demographic variables such as household income.

4. Conclusions

In the present work the impact of presence of public charging infrastructure on adoption of Electric Vehicles in various UK local authorities is assessed. Detailed data of charging points for ultra-low emission vehicles (ULEV) in the UK and electric vehicle registrations across 363 UK local authorities (LA) are employed. Using an event study approach of Difference-in-Difference (DiD) method, we found that the introduction of first establishment of a charging point subsequently increases diffusion of electric vehicles considerably. The effect of treatment (introduction of first public charging point) on the change in the number of licensed ULEVs begins immediately after treatment and its effect remains to be statistically significant in the following years. Furthermore, in order to include the control variable in DiD regression to separate out its additional effect on the outcome, the change in the mean Gross Disposable Household Income (GDHI) of UK local authorities are included in the analysis. Similar to the base results, the effect of treatment on the change in the number of licensed ULEVs by including the mean household income covariate is studied in the present work. The results suggest that the increase in ULEV registration after treatment is not influenced by demographic variables such as household income.

5. References

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