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Public EV charging infrastructure - why charging behaviours matter for placement, ownership and operations?

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Public EV charging infrastructure - why charging behaviours matter for placement, ownership and operations?

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Abstract

Sustainable uptake of electric vehicles will require efficient provision of public electric vehicle charging infrastructure for which it is essential to understand plug-in behaviors of electric vehicle users. Using plug-in data from 19 public charging stations and amenities in Durham, clustering, coupled with quantile regression analysis was used. Instead of focusing on the conditional average, we explain the effects of various factors, including availability of other amenities, on the entire distribution of the plug-in duration. Results show that both demand for charging and other amenities surrounding the charging station play an important role. More specifically, these effects are different at different quantiles of plug-in distribution.

1 Introduction

With the mission of providing affordable, reliable, accessible and secure electric vehicle (EV) network, UK government runs the *On-street residential charge-point scheme*, that invites local councils to apply for funding. This scheme provides councils grants to fund building and operation of EV charging station(s) (EVCS). Office for Zero Emission Vehicles (OZEV) has allocated £20 million for the year 2021-22 towards providing this grant. In many countries urban EV charging network is mainly the onus of local governments/councils. Apart from the reasons that are central to policy making, a more immediate (and yet connected) reason for this would be economic welfare and social inequality. Indeed, if all sections were to move to electric mobility, achieving this with purely private infrastructure may be a difficult objective to achieve. Hence, the push for governments to provide incentives for local governments to become primary drivers and stakeholders in developing EV infrastructure.

More generally, policy and strategy towards public EV infrastructure is not uniform across different countries, with some at a more mature state of play and others still in the process. In literature,

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the EVCS network formation is likened with chicken-and-egg dilemma, with users and operators at conflict with each other. While some theories are starting to emerge on deployment of a EVCS network, for example [Pardo-Bosch et al., 2021], there are no studies that provide guidance for long-term EV infrastructure strategy, [Shi et al., 2021]. We believe one reason for this is the lack of understanding of the human behavior towards EV evolution and their associated interactions with EV infrastructure. This is especially difficult when a majority of population are not EV-ready, in terms of existing driving and parking habits. A report published in March 2022 by UK department for Transport and OZEV ([DfT, 2022]) finds that a significant proportion of non-EV drivers think EVs would not fit well with their driving habits, and they are unlikely to use public charging spaces at night times unless close to their residence.

It is well-established that charging behaviours of EV users play a vital role in policy. For example, EVCS placement is a key policy question. In fact, in a number of studies policy decisions are almost synonymous to roll-out and placement decisions. Several studies provide arguments about how charging behavior traits or types should inform policy decisions. See for example [van der Kam et al., 2020, Helmus et al., 2020].

On the contrary, decisions such as ownership and operations are largely ignored policy decisions, likely due to their occurrence in downstream along the timeline of EV infrastructure maturity. Arguably, these decisions are also influenced by charging behaviours, hence the dearth of evidence of good models can be ascertained to lack of proper understanding of charging behaviors including users' interaction with EVCS. This forms the motivation for our work. Indeed, as our work shows charging behaviours can be used to understand the business models that are most likely sustainable. Our main aim is to establish a causal link between charging behaviors and ownership by connecting them to urban amenities. More specifically, transition to EVs is bound to have impact on urban planning. EVCS, seen as an amenity, will be utilized in tandem with other amenities, since charging EV (unless it is rapid DC charging) takes time. Hence, charging behaviors and EV users' interaction with charging infrastructure are fundamentally influenced by other amenities' locations, among other factors.

2 Literature on charging behavior

Understanding charging behavior using charging data is important to provide empirical basis to theories that prescribe charging and infrastructure policies, especially, for predicting what steady-state behaviours will emerge, if they emerge, over time. Below we review the studies published that focused on analyzing public charging behaviors at the time of this research.

Studies analyzing EV charging decisions have caught the attention of many researchers in recent times. More specifically, the charging decisions at public charge points are investigated by a number of researchers in last few years. The obvious motivation being an understanding of the charging behaviours is crucial to an optimal roll out of charging infrastructure.

Early studies on charging behavior focused on limitations on EV usage due to limited charging infrastructure. As EV adoption continues to grow in the last few years, studies emerged focusing on charging decisions in more evolved charging infrastructure environments. A number of studies focused on understanding users' interaction with charging infrastructure, general charging behavior (mostly at public charging facilities) and preferences. Many of these use either stated preference studies and/or GPS data, while a few use actual charging EVSE data. We first summarize a number of studies that use early observations in various countries.

Data from one of the early EV trials in Germany was analyzed by [Franke and Krems, 2013] which involve data from 6-month EV trial with 79 drivers. They develop measures for user-battery interaction style (UBIS) and show that UBIS and range anxiety influence the charging decisions of users. They use the framework of control theory and behavior self-regulation to explain the factors that lead to often observed heterogeneity in charging behaviors. [Yang et al., 2016] employ discrete choice models in stated preference setting to analyze combined route choice and charging decisions from survey data collected in Beijing, China and highlight the correlation between charging and route choice decisions and show that commuters prefer to choose routes with fast charging facilities. [Neaimeh et al., 2017] analyse the charging events from fast charging facilities in the UK. Using regression analysis they find that fast chargers could be instrumental in overcoming range barriers and making EVs attractive to future users. [Morrissey et al., 2016] analyse the charging data (primarily public charging points, and some home charging points) from Ireland, and find that chargers with access to home charging prefer to charge their EVs at home, while car parks were found to be the most favoured public charge points. They found that home chargers preferred to charge at peak time period. [Xu et al., 2017] study the charging mode and location choices using a mixed-logit model in revealed preference setting with EV usage data for both private and commercial vehicles in Japan. They find that choices made by private and commercial vehicles users are different. They highlight the endogeneity issue in using the night time charging choice as a proxy for lower electricity rate preference. They observe that the choice of night time charging not necessarily imply preference for lower rates but due to the unobserved effects such as comfort and convenience. They use a control function approach to include a suitable instrumental variable to correct for the endogeneity issue.

[Helmus et al., 2020] provide a data driven typology of EV user types and charging sessions focusing on the public charge point usage data using a large dataset at multi-city population level in the Netherlands. [Wolbertus et al., 2018b] study the impact of policies on charging choices and future EV purchase decisions in the Netherlands. [Ge et al., 2018] study the existence of *gas anxiety* in PHEVs. They analyze charging choices of PHEVs using a stated choice experiment with a survey based in the United states. They find that PHEV owners do exhibit gas anxiety and prefer to charge at charging stations inspite of the high cost. [Chakraborty et al., 2019] explore the key demand factors that drive charging behavior at public charging facilities. They find that chargers prefer to charge at home when it costs less compared to elsewhere, moreover, charging choices are highly influenced by socio-demographic and vehicle technology factors. From the studies based in different countries, we find

that while there are some common factors, the charging behaviors and preferences vary considerably with location and may vary from country to country. We now shift our attention to studies that explicitly focus on public charging behavior analyses by connecting their findings to policy decisions such as rollout of EVCS network.

Roll-out of public charging infrastructure has been an active discussion area for many researchers with earlier works based on theoretical models. Many models have been presented for charge point placement. However, overall it is widely observed that charge point utilization rates are low in many places ([Pan et al., 2019],[van der Kam et al., 2020],[Hardman et al., 2018]). With the availability of more public charging data, some empirical research has been reported in the recent years.

[Wolbertus et al., 2018a] explore the factors that influence the connection times of EVs at public charging stations. Their study employs charging data from four Dutch cities and use logistic regression to understand the charging duration and factors driving the duration. It is highlighted that charge stations are rival goods. It is widely reported that charge station utilization is often poor due to poor placement of station and use of charge stations as parking spaces. To have an evidence based strategy for effective roll-out it is necessary to connect policy measures with goals. [van der Kam et al., 2020] provide a holistic view to map measures with goals by an empirical analysis of Dutch charging data. Different to the earlier works they also incorporate the neighbourhood factors in their analysis such as population, charge point density, etc.,. [Helmus et al., 2018] connect the performance of different roll-out strategies and find demand driven EVCS outperform compared to strategically placed EVCS.

[Kim et al., 2017] employ a heterogeneous hazard model to study charging transactions over a period of four years and highlights mixed behaviors including regular and random users. [Hu et al., 2019] use cumulative prospect theory to model the charging behavior and argue that risk attitudes play an important role in charging choices. Moreover, they also find that over time EV users may shift their charging needs to work and public EVCS. [Hardman et al., 2018] provide a review of consumer preferences and EVCS interactions highlighting the need for research to understand the level and type of EV infrastructure required. [Daina et al., 2017] evaluate the impact of smart charging services using a stated-preference study.

[Pan et al., 2019] highlight a high level of EVCS under-utilization. Using a web-based stated preference survey they develop choice models to show two classes - risk averse and risk seeking class of EV users. [Straka et al., 2020] illustrate the benefit of combining data from a wide ranging data sources for explaining energy consumption at slow EVCS. Like our study, in parallel, they also illustrate the use of data from OSM. However, our analysis differs fundamentally not only in terms of objectives but also in terms of scale with our study focused more at local level amenities. [Shahraki et al., 2015] illustrate the use the EV charging session data to determine optimal charging locations within an optimization model. Another aspect which is often more implicit (or sometimes not considered) in many studies is the choice of charging time, [Sun et al., 2015] study charging time choices of EV users and find that users prefer to charge at night to make use of lower tariff. A review

of application of machine learning algorithms to charging data is presented in [Shahriar et al., 2020].

2.1 Positioning and Contributions

The contribution of this paper towards the literature on EV charging behaviour and policy implications is two-fold:

1. Current studies highlight typologies of possible charging behaviors, but we attempt to also provide reasons for this behavior formation. Even when there are global (at multi-city population level) traits such behaviors can only be explained by taking local neighbourhood factors into account. [van der Kam et al., 2020] observe that *“policy makers responsible for public charging infrastructure should take neighbourhood-specific charging behavior into account for policy design”*. [Helmus et al., 2020] suggest that further research on understanding charging behaviors should take city or area perspective to arrive at a portfolio of behaviors. In our work we do this at a city level by connecting charging data with OSM data. Note that OSM data plays a role only at city or council level rather than at country level because amenities are strongly connected to local geography. Our approach differs from previous investigations which recognize the importance of neighbourhood characteristics, but encode these in an indirect way. Our approach directly encodes them by defining a distance-based approach to locating a number of different type of urban amenities. More importantly, role of amenities is time-dependent and is likely to impact the duration differently at different quantiles of distribution, hence our choice of methodology to combine clustering and quantile-regression methods. Our results shows a stark connection between charging behavior and location of amenities in close vicinity. Our results show that choice of charging station and time are largely dependent on amenities available in close vicinity.
2. Comparison of data sets: Our data set takes a city/council perspective as compared to recent empirical studies on charging behavior with real data, example, [Helmus et al., 2020, Wolbertus et al., 2018a]. Hence the scale of our data is incomparable to these studies when viewed purely from the scale viewpoint, however, as the metrics in Table 1 show they are comparable at per-station and per-month use statistics:

	charge sessions per station (CPS)	CPS per month
[Helmus et al., 2020]	≈ 822	≈ 22
Our data	≈ 550	≈ 11

Table 1: Data-set comparison statistics

3 Exploratory Data Analysis

We first give details of the data collected from the 19 EVCS in Durham and then present the data collected from OSM.

Variables	Data Type	Count of Data Points		
		Raw	Unique	Clean
Session ID	Categorical	10188	10188	9903
End Time	Date & Time	10188	10188	9903
Start Time	Date & Time	10188	10188	9903
User ID	Categorical	9968	1185	9683
EVCS site	Categorical	10188	19	9903
Car	Categorical	7894	38	7609
Total kWh	Numeric	10188	10188	9903
Charger type	Categorical (7kW, 3kW, Rapid)	10188	6	9903

Table 2: Summary of Durham County Council dataset

The Durham County Council data set is the collection of 10,188 charging events from 19 real public charging stations in Durham from 01/01/2015 to 11/07/2019. As is expected, charging rate in earlier years was very low. This data set has eight variables, as shown in the first column of Table 2. We derived car battery size from the car specification for all the users for which this information is available. There are a total of 38 different car types recorded in the data, not including the unknowns. Only a handful of sessions were recorded at Rapid stations. We have not considered them in our analysis. Roughly 84% of the charge points are 7kW type. Some stations were more busy than others and handful of stations account for more than 85% of the recorded sessions. Contrary to the popular belief, weekdays account for more sessions compared to the weekends.

Among 1185 recorded EV drivers in the dataset, about half of them, 522 EV drivers exactly, charged more than once. The other 557 EV drivers only charged once. The average charge frequency for EV drivers is 7.97. There are 133 EV drivers who charged more than 10 times, 20 EV drivers charged more than 100 times. Interestingly, no driver has connected multiple times in a single day, and multiple charging events of the same EV driver usually occur on different dates. For the 19 different charging sites, each has a different number of charging drivers. Some EV drivers prefer to charge in a fixed site, but some other have accessed multiple sites.

OpenStreetMap is an open source project that creates and distributes free geographic data for the world. It provides a comprehensive source for a range of data from roads, landmarks to amenities. Road junctions and key landmarks are represented by nodes, and roads (or road segments) are represented by edges. The position of each node is given by its latitude and longitude, and the length of each road (or road segment) is given in kilometres. We use OSMnx python library [Boeing, 2017] to extract the amenity information from OpenStreetMap (OSM). For the purpose of illustration, in Figure 1 we show the map of Durham extracted from OSM.

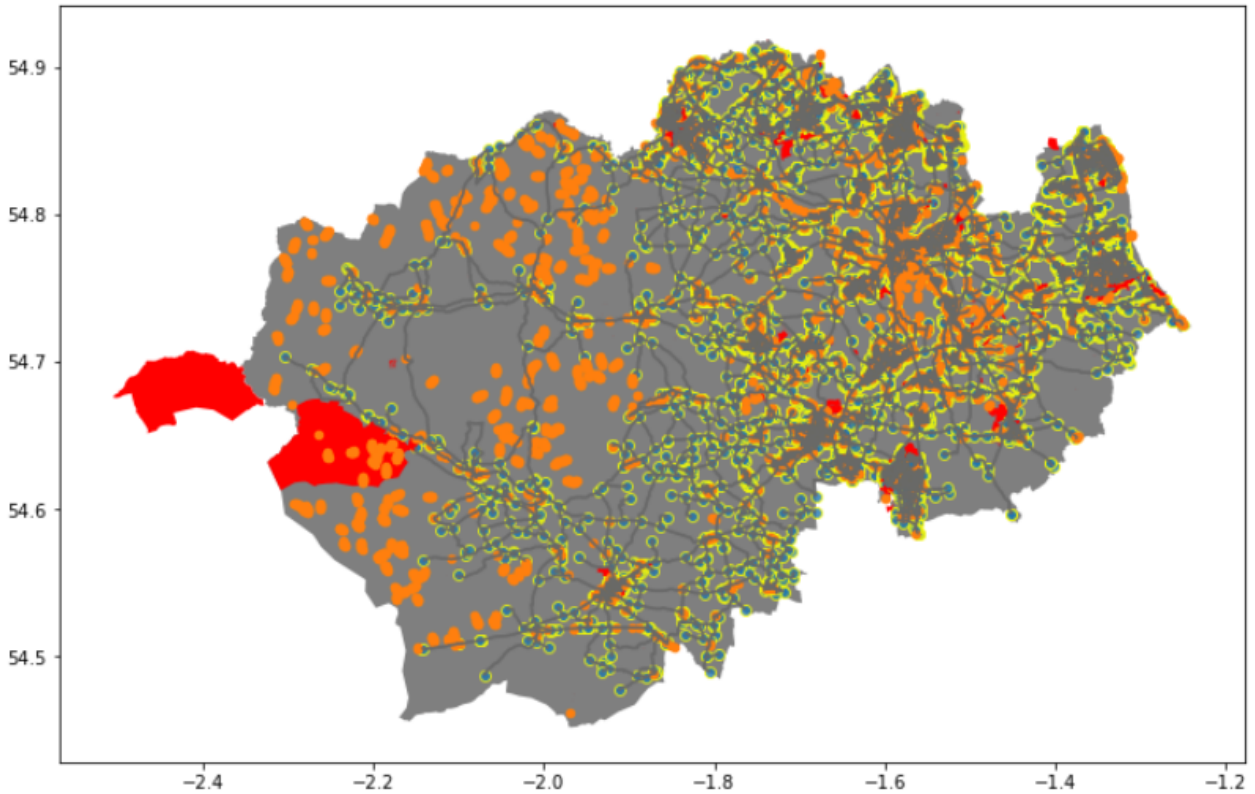


Figure 1: OSM Map of Durham

The black coloured area in the figure shows the entire area of the map (a close polygon). Dim-gray colour represent the drive ways (roads) around the county. Yellow colour represents nodes in the map, and there can be at least one tag associated with them. For example, a node might represent amenities, operator, traffic signal etc. Red colour shows the amenities and leisure data that will be used in our analysis.

In total we include seven amenity groups within our analysis, that we explain below:

- financial: ATMs, banks, currency exchange etc.,
- healthcare: general practitioner clinics, dentist, pharmacy etc.,
- education: schools, library etc.,
- entertainment: clubs, cinema theatres etc.,
- transportation: parking, train and bus station etc.,
- sustenance: restaurants, pubs etc.,
- leisure: parks, fitness centres etc.

Each of these amenity groups can have a number of amenities ranging from 10s to 100s in numbers. However, we chose amenities at group level rather than at individual or sub-amenity groups level, as the latter was found to be not significant in preliminary analysis, and we also wanted to avoid over-fitting of our results. We also omitted a general amenity group *Others* as it may contain wide heterogeneity which is difficult to explain. More information about these amenity groups can be found via the following Wikipedia pages: <https://wiki.openstreetmap.org/wiki/Key:leisure> and <https://wiki.openstreetmap.org/wiki/Key:amenity>.

As would be expected, the amenities that may influence the use of a certain EVSC are more likely to be the ones that are close, if not the closest. Therefore, we adopt a distance-wise approach to only consider amenities within a pre-specified distance from the EVSC under consideration. Using the GPS co-ordinates of the 19 EVSCs, for which we collected plug-in data, we calculate distances to all amenities within each of the seven aforementioned amenity groups using the Haversine formula [Gade, 2010],

$$d = 2r \times \arcsin\left(\sqrt{\sin^2\left(\frac{\phi_2 - \phi_1}{2}\right) + \cos(\phi_1)\cos(\phi_2)\sin^2\left(\frac{\lambda_2 - \lambda_1}{2}\right)}\right)$$

Here, d is the distance between two points in a geographical space with location, (longitude, latitude) (ϕ_1, λ_1) , (ϕ_2, λ_2) , and r is a constant, which, in our case, is equal to radius of Earth.

To apply vicinity based approach we encode the presence of an amenity of certain group only if it is located within a distance of 200 meters (0.2 km). This choice is mainly motivated by practical considerations and did not bear a particularly high sensitivity to our results. Instead of directly encoding distance to amenities within this distance we use dummy encoding for the presence of amenity within the distance as 1, and 0 otherwise. Table 3 presents the output of this encoding for each of the charging stations alongwith a count of the recorded sessions.

4 Clustering of charging sessions

Clustering is a useful technique to detect and distinguish the patterns within the choice of plug-in time during the day, especially, when drivers tend to plug-in only once a day at a public charging station. This is contrary to home charging where vehicles are plugged in and out several times a day. After experimenting with several clustering methods including hierarchical clustering, k -means clustering and Gaussian mixture model, we observed k -means clustering gave a more interpret-able outcome with duration, start time, etc., of the main variables.

All charging sessions of duration more than 24 hours (1440 minutes) were not considered in the analysis. Before clustering, data was normalized using min-max scaling as the start time data had a range from 0 to 24 hours and the total duration data had range of 0 to 1440 minutes. Then, euclidean distance was used to estimate the dissimilarity among two data points. k -means algorithm divides data into k mutually exclusive and exhaustive samples (say $\mathcal{C}_1, \mathcal{C}_2, \dots, \mathcal{C}_k$), each described by the mean, $\mu_t \in \mathbb{R}^2$ of the data points within these samples; also, known as clusters. Here, μ_t are

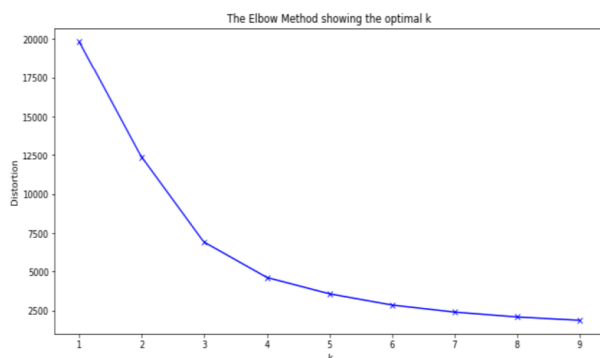
Site Name	Financial	Healthcare	Education	Entertainment	Transportation	Sustenance	Leisure	Freq
Bowlees Visitor Centre	0	0	0	0	1	1	1	43
Albert Road Car Park	1	1	0	1	1	1	1	820
Greencroft Centre	0	0	0	0	0	0	0	59
Comeleon House	0	0	0	0	0	0	0	38
Scott Street	0	0	0	0	1	1	0	356
Annand House	0	0	0	0	0	0	1	174
Meadowfield Depot	0	0	0	0	1	0	0	519
Sniperley Park and Ride	0	0	0	0	1	0	0	420
Durham County Hall	0	0	0	0	1	0	1	1282
Howlands Park and Ride	0	0	0	0	1	0	0	212
Riverside Car Park	0	0	0	0	1	0	1	267
Green Lane, Spennymoor	0	0	0	0	1	0	0	739
North Burns	0	1	0	0	1	1	0	746
The Sands Car Park	0	0	1	0	1	1	1	1958
Old Elvet	1	1	0	0	1	1	1	1560
Belmont Park and Ride	0	0	0	0	1	0	0	156
St John's Car Park	0	0	1	0	1	0	0	48
Terrace Green Carpark	0	0	0	0	1	1	1	344
Spectrum 8	0	0	0	0	1	0	0	162

Table 3: Vicinity based amenity labels and counts for all EVCS

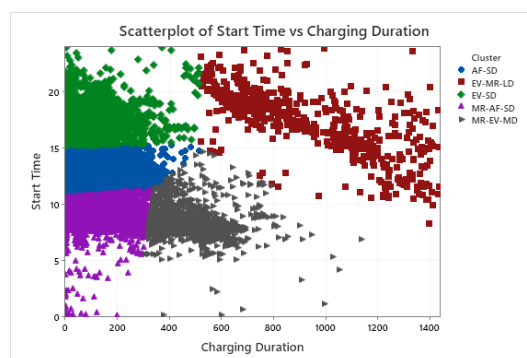
commonly understood as the “centroids”. The three step k -means algorithm (Lloyd’s algorithm) tries to minimise within-cluster sum-of-squares;

$$\sum_{i=0}^n \min_{\mu_t \in \mathcal{C}} (||\mathcal{D}_i^i - \mu_t||^2)$$

For validation, we employ both the visual and rule based approaches. Based on the knee-plot shown in Figure 2(a)) and spatial distribution of clusters in Figure 2(b)), five clusters were identified. Note that Figure 2(b) illustrates spatial distribution of the five clusters on start time-duration plot, that is, x -axis represents the duration of charging in minutes and y -axis represent the start time of



(a) Knee-Plot to find optimal k



(b) Multi-dimensional scaling for clusters

Figure 2: Cluster plots

charging in hours (for example, 15 means 3pm/mid-afternoon).

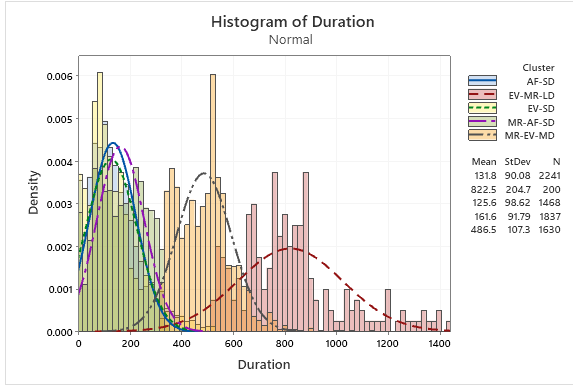
We now give characterisation of the five identified clusters. To make names of these clusters more meaningful we typify them based on start time, end time, length of charging sessions, and time of the day (i.e. MR - morning, AF - afternoon, EV - evening). There are three short duration (SD), one medium (MD) and one long (LD) duration clusters.

AF-SD cluster contains those charging sessions, which start and end in the afternoon. Figure 4 indicates that a typical charging session starts between 11:00-3:00 pm, end between 1:00-4:00 pm, and duration of a charging session is less than four hours for most data points in this cluster. The mean start time of charging sessions is at 1:02 pm, mean end time is at 3:13 pm, and mean duration of charging sessions is around 132 minutes (2 hours and 12 minutes). Table 3 shows that an average user in this cluster plugs-in at EVSC approximately 3.97 times (mean) on weekday and 2.29 times on a weekend. This cluster contains 31% of the observed charging transactions, and 65% of total users (individual user identified by user-id) available in the Durham county council data-set (Table 3). Similar observations can be made for the remaining four clusters and Table 3 and Figure 4 provide all the relevant details.

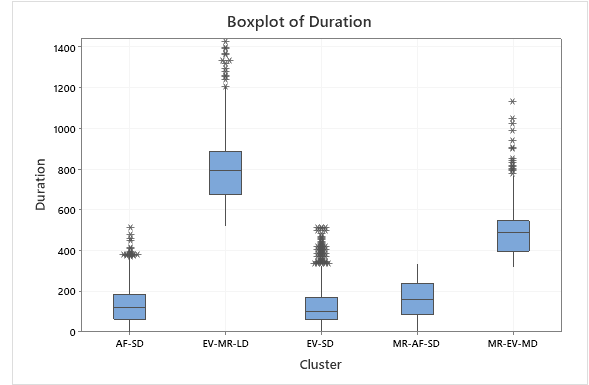
We make two further observations. Firstly, in EV-SD cluster, the high number of sessions per user on weekdays might be suggesting that these drivers have used charging station to park their vehicle while being on workplace (assuming weekend as most likely to be non-work days); thus, they utilised charging station as parking spot in addition to charging station as a pre-defined tactic, something also noted by [Helmus et al., 2020]. Secondly, in case of EV-MR-LD cluster, the charging sessions could be seen as overnight charging session, similarly observed in [Helmus et al., 2020]. It is highly likely that these sessions are more parking in nature than fulfilling the charging needs, which is also observed in [Helmus et al., 2020]. We remark that similar, though not exactly same, typology was observed in charging data analyses in the literature [Helmus et al., 2020, De Gennaro et al., 2014].

Cluster	Weekday	Weekend	% Charging Session	% Individuals	Total
AF-SD	3.969112	2.292566	31.11%	64.77%	3.947575
EV-MR-LD	9.538462	3.2	6.28%	6.11%	8.444444
EV-SD	3.742268	1.819383	19.26%	42.19%	3.752515
MR-AF-SD	5.268362	2.305419	24.09%	39.13%	5.060738
MR-EV-MD	13.91667	3.611111	19.26%	12.48%	12.68707
Total	8.518644	3.355243	100.00%	100.00%	8.219864

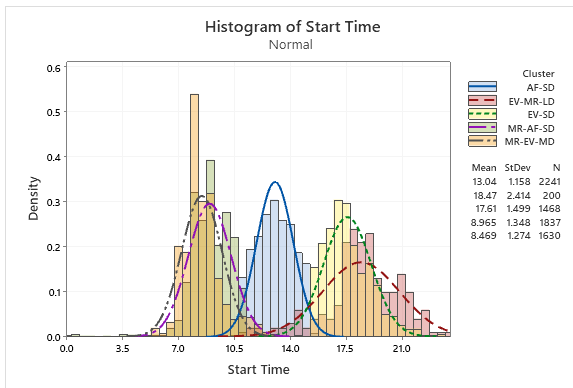
Figure 3: Cluster-wise charging statistics



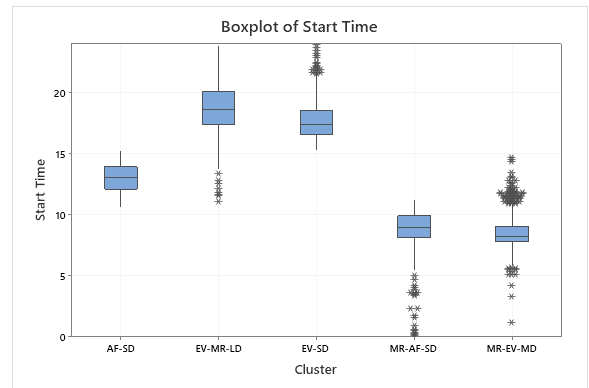
(a) Histogram of Charging Duration



(b) Box-plot of Charging Duration



(c) Histogram of Start Time



(d) Box-plot of Start Time

Figure 4: Box-plot & Histogram of Charging Duration, Start Time, and End Time

5 Regression modelling

We start with a quick comment about choice of models. While there are aspects of data which possibly can make space for dynamic models the issues such as possibility of users charging at other venues (outside of recorded stations and/or home/work), very large charging sessions sometime recorded as multiple sessions etc makes it hard to apply such models. We use consumed kWh (Total kWh) as a proxy to the demand or State of Charge (SOC) of the car user. Since our main aim is to establish a causal link between connection times and factors that influence these times this does not lead to look-ahead bias. However, these models cannot be used to make predictions for the same reason.

The rate of recurring usage is different among different users with some using more frequently than others. If EV users depend (critically) on public EVCS then their connection times must depend on their frequency, that is, a more frequent user is more likely charge habitually. We include a count variable that keeps count of how many times the user has connected the vehicle before the said

charging session as a dependent variable to explain connection times, named *Previous.Charge*.

We start with an OLS model. Table 5 shows the estimates of an OLS model. Except transportation all other amenities are seen to have significant effect on connection times. Similarly, other factors such as demand proxy, previous.charge, and days also affect times. However, it is difficult to offer an explanation for the sign and magnitude of the effect for any of the factors hence we focus on cluster-wise quantile regressions which we motivate below.

Table 4 gives mean and standard deviations for each of the clusters for recurring users with battery information available. Since most charging sessions are short duration most variance is also observed in these clusters. We note that high density clusters AF-SD, EV-SD and MR-AF-SD have high variance. Hence focusing on averages obscures the opportunities to understand the causal factors affecting tails of the duration distribution. For example, the uncertainty in other amenity directly affects duration times, that is, if at a particular time of the day users are more likely to avail a particular amenity nearby whose service times are highly uncertain then impact of this is different at 80th quantile compared to 20th quantile of plug-in distribution. For this reason we employ quantile regression, which is well known to be robust against outliers in high variability data and is able to estimate effects of independent variables on plug-in times (see [Koenker and Hallock, 2001]). Moreover, quantile regression offers a huge benefit of not requiring to have Gaussian error structure and the relative independence of the bootstrapped standard errors to the heteroskedastic errors. However, the results should be interpreted carefully, since quantile regression does not address omitted variable bias and violation of linearity assumption.

Given that major proportion are short duration (SD) (average duration of 2 hours) we focus our analysis on these clusters. In all SD clusters, SOC-proxy (Total kWh) is significant factor which highlights that EV users account for availability of EVCS to fulfill their charging needs. Moreover, in all SD cluster no day variables were significant in OLS model. Hence these were not taken for the respective QR models. Previous.charge variable is significant for AF-SD users which implies users in this clusters are habitual and strategic. However, this is not the case for EV-SD cluster, while for MR-AF-SD this is only the case for higher quantiles, see Figure7. Battery size inversely affects connection times indicating that small battery EV users are most likely benefactors of public EVSCs compared to large battery EV users. A probable explanation for this could be larger battery cars are typically more expensive and are likely owned by people with home and work charging availability. Indeed, different population level battery mix evolution can have different impact on public EVSC usage.

All SD clusters are affected by amenity categories, albeit, in different manner across the quantiles. Leisure, among all, is significant in three SD clusters. In non evening clusters, it is negative effect, which can explained by the fact that people are less likely to visit at these time. Using a similar explanation presence of leisure facilities is likely to result longer connection times at evening times with this effect along the quantiles. Note that in OLS model leisure has a negative effect in contrast to different effects at different clusters which highlights the importance of cluster-wise modeling.

Interestingly, healthcare, as an amenity category, when significant, has always a negative slope indicating inverse relationship with connection times when all other factors are held constant. A likely explanation here time duration at healthcare facilities such as clinics and pharmacies are very short within an hour and does not allow EV users enough time to plan for charging.

Sustenance and transportation show effects only at certain quantiles which, for example, captures effects such as EV users planning trips to restaurants (EV-SD) and charging while a short train or bus travel (upper quantiles MR-AF-SD).

Cluster	Mean	Std. dev
AF-SD	140.61	94.71
EV-MR-LD	806.49	195.48
EV-SD	130.78	101.37
MR-AF-SD	167.58	91.64
MR-EV-MD	487.94	107.84

Table 4: Cluster-wise summary statistics for recurring chargers

6 Policy implications

EVCS placement is an important policy decision and have been widely discussed in the literature. Here we revisit the implications on placement decisions of our results. We found that two key factors (among many) that heavily influence charging decisions at public EVCS are amenities and demand. Moreover, charging sessions are more likely short duration (averaging a couple of hours). While a city or council level there are several amenities that may influence each other, seen as an amenity itself, EVCS usage ties with specific amenities at specific times. This indicates that EVCS placement should focus around those amenities (eg., parks, fitness centres) which are more likely ones to be used by EV users while charging and not the ones which underlie very short durations (like healthcare). It is important to see the connection with amenities in conjunction with recurring users, since we found that users exhibit recurring behavior that strongly reinforces that they do depend on public EVCS for fulfilling their charging needs.

Equally important, but not discussed enough, are ownership and operation (including management) policy decisions. The significance of other amenities within the urban landscape pose interesting and important future infrastructural implications for councils. From an ownership viewpoint, councils may explore a joint ownership within a public-private partnership model that makes local businesses important stakeholders. Given that EVCS deployment comes with considerable set-up costs this can lead to manageable risk sharing with councils not having to take all the risk. When local businesses that manage other amenities partner with councils in EVCS operations this could lead to increased utilization. For example, the following medium and long term effects are very likely in view of our

sqrt(Duration)	estimate
(Intercept)	5.42***
sqrt(Total.kWh)	3.41***
Previous.Charge	0.01***
Battery size	-0.03***
Charge type (3 or 7 kW)	0.10
Financial	4.80***
Healthcare	-1.54***
Education	2.77***
Entertainment	-3.27***
Transportation	-0.70
Leisure	-1.49***
Monday	0.47*
Saturday	-0.59*
Sunday	-1.32***
Thursday	0.50*
Tuesday	0.15
Wednesday	0.79***
R^2	0.49

Table 5: OLS full model for chargers who have charged more than once. *** : $p \leq 0.0001$, ** : $0.001 < p \leq 0.01$, * : $0.01 < p \leq 0.05$, · : $0.05 < p \leq 0.1$

results. With considerable EV uptake in medium term, businesses may use deploying EVCS as a tactical move to increase sales. Such practices are already common practice in urban parking management. In longer term, businesses may offer perks such as discounts on charging prices to boost their sales. Our argument for this to improve utilization rate is because charge station hogging is more likely in a centrally owned scenario where only councils own and operate EVCS. In a shared ownership scenario, other amenities are more likely to interact with users directly hence utilization is more directly observable and likely controllable. In a similar vein community financed and shared EV infrastructure is recently proposed in [Azarova et al., 2020].

Commercial fleet charging solutions are quickly emerging such as battery swapping and mobile charging units. However, such solutions are difficult to implement for personal users. Those can be extended to personal users when local businesses join within PPP models where charging cars comes as a package deal for this customers. There is very little discussion on future business models for EV infrastructure expansion with aspects such as risk and revenue sharing between partners still need to be fully understood. From councils' point of view there are several aspects which make the case for an active partnership. Significant of these factors include: (a) usage of EVCS in combination with

	Quantiles			
	0.2	0.4	0.6	0.8
(Intercept)	50.42***	81.85***	115.10***	159.90***
Total.kWh	9.87***	11.10***	11.04***	10.39***
Previous.Charge	0.26***	0.30***	0.39***	0.37***
Battery size	-0.67***	-0.87***	-0.95***	-1.41***
Financial	12.10*	36.45***	34.36***	52.69***
Healthcare	-9.93*	-30.93***	-19.62***	-9.76
Education	0.29	-0.75	-3.26	10.80
Transportation	-22.81**	-15.64	-20.70	3.69
Sustenance	8.86*	12.40	5.13	-17.97*
Entertainment	7.66	1.14	-10.08	-33.47**
Leisure	-9.62*	-30.12***	-25.09***	-18.92**

Table 6: Quantile regression results AF-SD

other urban amenities presents the opportunity for more effective urban and city planning including better congestion control, (b) high volume of data generated from charging transactions can hold a wealth of information for councils to enable better social welfare, (c) last but not least EV charging holds a key revenue source which councils can use to be less dependent on federal funds.

Currently, there is lack of studies that inform medium and long term policy on EVCS ownership and management and the role of councils in the same. We hope our analysis sheds light on the role councils may want to play in the long term, especially, with EVs expected to change the dynamics of urban planning.

7 Limitations and Future research

Our results are based on dataset specific to Durham. There may be confounding factors which are specific to Durham which are not accounted for in our analysis. Generalization should be done with care. However, our approach does illustrate, albeit not at estimate level, but at general level on effect of amenities on charging behaviors that can be argued to be largely true for a typical urban scenario.

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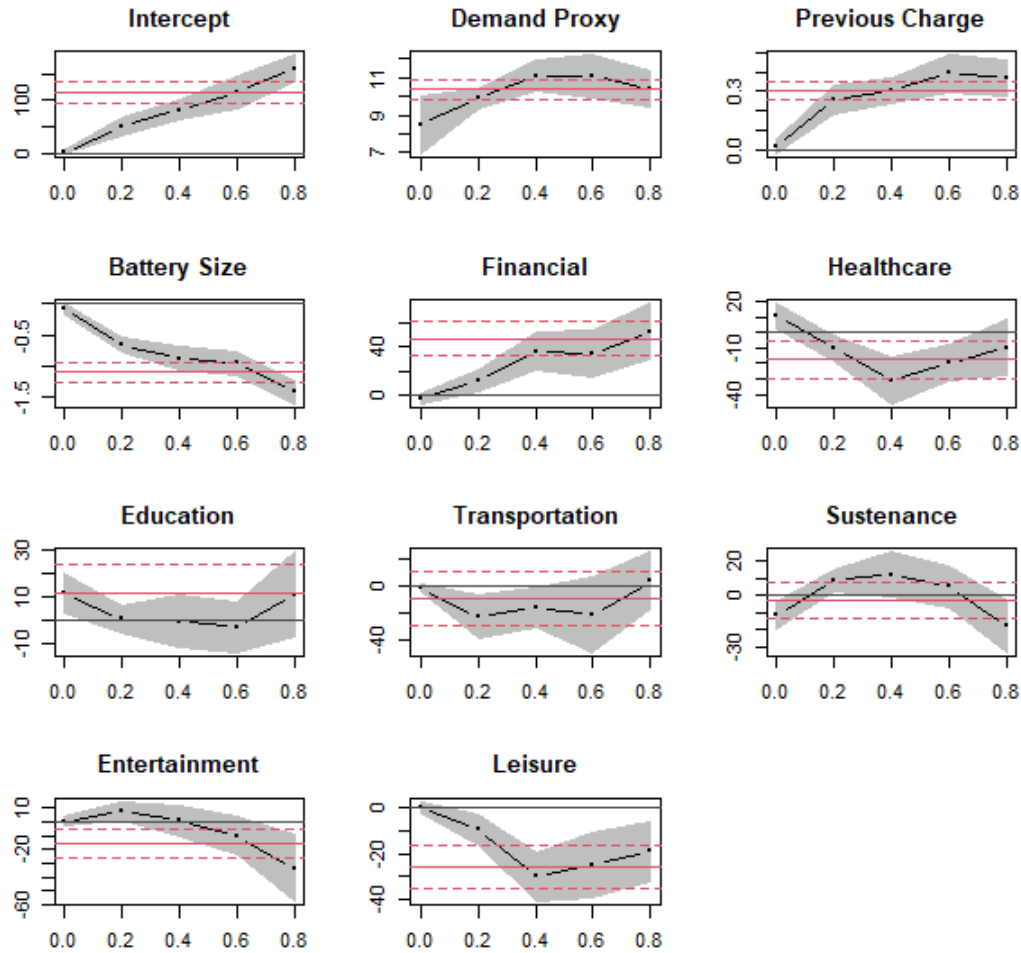


Figure 5: Quantile regressions plot AF-SD

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	Quantiles			
	0.2	0.4	0.6	0.8
(Intercept)	14.01***	15.78*	24.97*	33.39
Total.kWh/ Demand proxy	9.57***	10.59***	12.59***	14.75***
Previous.Charge	0.06	0.08*	0.07	0.21*
Battery Size	-0.41***	-0.51***	-0.64***	-0.55***
Financial	6.80	11.01	3.48	-25.97
Healthcare	-4.45	-19.53*	-18.26**	-9.97
Education	2.40	-2.29	-0.48	0.34
Transportation	-7.82	-4.12	-0.85	-4.17
Sustenance	10.16	27.53***	23.74***	17.68
Entertainment	-4.52	-10.74	-1.12	-10.55
Leisure	7.93***	11.49	19.49***	48.54***

Table 7: Quantile regression results EV-SD

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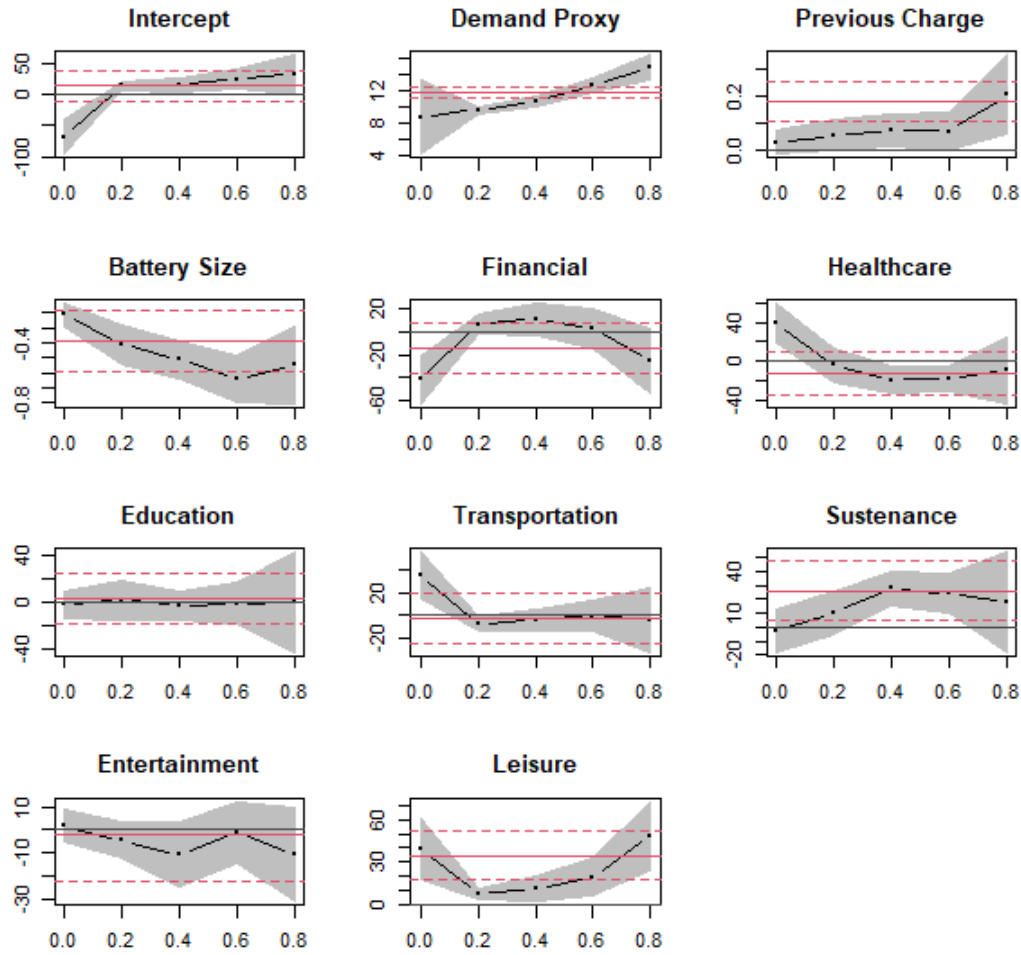


Figure 6: Quantile regressions plot EV-SD

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	Quantiles			
	0.2	0.4	0.6	0.8
(Intercept)	65.08***	104.32***	106.45***	150.02***
Total.kWh/ Demand proxy	10.35***	10.72***	10.27***	7.80***
Previous.Charge	0.06*	0.13*	0.17***	0.17***
Battery size	-0.99***	-1.00***	-0.81***	-0.65
Financial	31.60***	68.21***	63.02***	71.95***
Healthcare	-23.97***	-36.74***	-43.28***	-35.65
Education	5.31	11.27	-9.49	-17.74
Transportation	4.43	8.86	32.29***	52.49***
Sustenance	-10.09	-28.72***	-25.74***	-20.56
Entertainment	-1.80	-11.94	-5.41	-22.15
Leisure	-24.25***	-44.28***	-36.08***	-40.38***

Table 8: Quantile regression results MR-AF-SD

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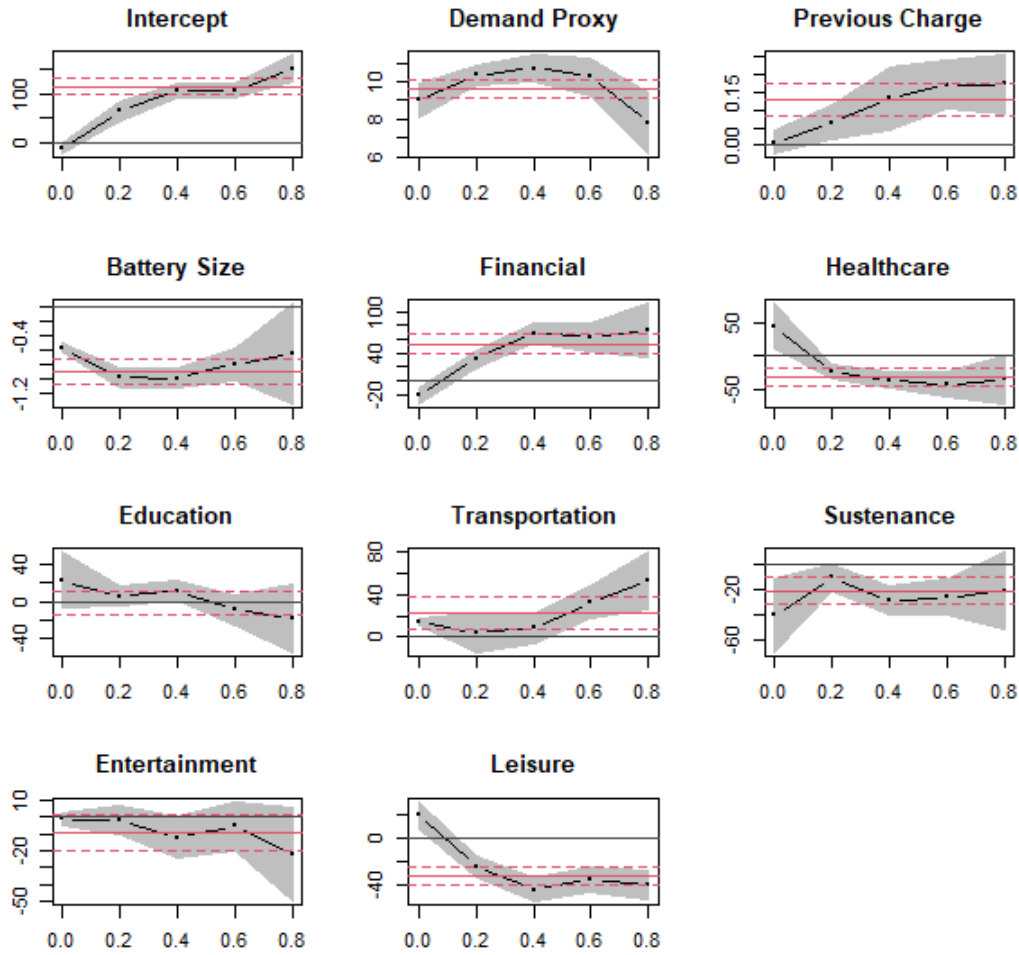


Figure 7: Quantile regressions plot MR-AF-SD

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