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Oldenburg Discussion Papers in Economics

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V – 450-25

March 2025

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Spatial Distribution of EV Charging Infrastructure in Germany:*

An Analysis of Determinants

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2025-03-26

This paper examines the determinants of the spatial distribution of electric vehicle charging infrastructure in Germany, a key element in the transition to a low-carbon economy. Using postcode-level geographic data and regression analysis, we investigate how factors such as population density, road networks, local amenities, the number of fuel stations, and electric grid infrastructure influence the placement of electric vehicle chargers. Our findings indicate that population density, the number of fuel stations, and intersections of the electric grid significantly impact charger placement, with fast chargers predominantly located along major transportation corridors. Additionally, the availability of local amenities and electricity supply plays a critical role in the placement of normal chargers. These findings highlight the importance of well-planned urban charging networks, strategic placement along transport routes, and strong public-private partnerships to enhance electric vehicle adoption.

Keywords: Electric Vehicles, Charging Infrastructure, Amenities, Geographic Data, Population Density, Road Networks

*We thank the participants of the 45th IAEE International Conference, Istanbul 2024 for their comments and suggestions. All errors remain our own.

1 Introduction

The growing urgency to combat climate change has heightened the need to reduce carbon emissions across all economic sectors, with the transportation sector being a critical focus area. Since road transport contributes a substantial share of global CO_2 emissions – amounting to three-quarters of emissions from the transport sector – it is evident that targeted interventions are necessary to curb this impact (Ritchie, 2020). For Germany, a global leader in climate initiatives, the transportation sector has, however, not progressed sufficiently toward meeting the national climate objectives. This sector accounts for about 21% of the country's total greenhouse gas (GHG) emissions and remains a significant challenge in achieving the goal of a 65% reduction in overall emissions by 2030 compared to 1990 levels (Die Bundesregierung, 2023). To bridge this gap, the German government established a national climate law in 2019, which was updated in 2021 to stipulate a 48% reduction in transport-related GHG emissions by 2030 (Bundesamt für Justiz, 2019).

The electrification of the transportation sector, with a particular emphasis on adopting Electric Vehicles (EVs), is central to Germany's plan to meet its climate targets. The country aims to decrease its dependency on fossil fuels and lower emissions from road transport by encouraging EV use and expanding the necessary charging infrastructure. However, the successful widespread adoption of EVs relies not just on advancements in vehicle technology but also on the availability of a comprehensive, reliable, and easily accessible charging network to accommodate the increasing number of EVs, overcome range anxiety, and enable seamless long-distance travel (Guo et al., 2024; Mohammad et al., 2024; Zeng et al., 2024).

Germany has outlined an ambitious plan to have 15 million EVs and approximately 1 million charging points by 2030 (BMVI, 2019). To achieve this, the government has introduced various incentives, such as purchase subsidies, which have significantly boosted EV sales. As a result, the number of battery electric vehicles has more than quadrupled to over 1.4 million between 2021 and 2024. Similarly, hybrid vehicle numbers have also more than tripled from 921,886 in 2021 to over 2.9 million in 2024 (Federal Environment Agency, 2024). In terms of overall new vehicle registrations, fully electric vehicles registrations accounted for 18.4%, surpassing diesel cars as of 2023 (Federal Environment Agency, 2024).

Despite the growing market share of EVs, internal combustion engine (ICE) vehicles still dominate new car registrations. Factors such as high upfront costs, limited driving range, and insufficient charging infrastructure continue to hinder widespread EV adoption, affect consumer choices and slow the transition to electric transportation. Existing literature has consistently shown that the availability of charging infrastructure plays a crucial role in influencing consumer decisions and adoption rates of EVs (Coffman et al., 2017; Sierzchula et al., 2014). As of early 2024, Germany has established around 103,226 normal charging points and 25,291 fast charging stations (Bundesnetzagentur, 2024). Although considerable progress has been made, reaching the target of 1 million public charging points remains a challenge. However, the growing use of workplace charging and advancements in fast and ultra-fast charging technology may alleviate the need for such a vast number of charging stations.

The uncertainty in achieving the 2030 target highlights the necessity of a strategy approach to placing and integrating EV chargers into everyday life. Effective integration of charging infrastructure into consumers' routines and ensuring the stability of the electric grid are critical for maximizing the impact of EV adoption and reducing emissions in the transportation sector. This paper explores the determinants that influence the distribution patterns of EV charging infrastructure. We use a geo-referenced dataset comprising 62,426 operational charging stations across Germany, combined with OpenStreetMap (OSM) data, which includes information on population, road networks, electricity supply, and local amenities at the postcode level. Our hypothesis is that these micro-level factors affect consumer demand and charging decisions, and ultimately shape how charging stations are spatially allocated across different areas. Our analysis shows that factors such as population density, highway accessibility, availability of amenities, presence of fuel stations, and local electric grid infrastructure significantly influence where charging stations are located. By identifying these determinants, this paper seeks to support evidence-based resource allocation and inform strategic interventions to advance the transition to electric mobility.

The structure of the remainder of the paper is as follows: Section 2 reviews the existing literature on the distribution of charging infrastructure and the integration of charging stations into the electric grid. Section 3 details the data sources, variables, and the empirical estimation strategy employed. The results are discussed in Section 4, and the paper concludes with insights and implications in Section 5.

2 Relevant Literature

This section reviews the relevant existing literature on factors influencing charging station distribution, the integration of EV chargers into the power grid, and the approaches used to optimize their placement.

2.1 EV Adoption and Distribution of Charging Infrastructure

The strategic placement and accessibility of EV charging infrastructure have been widely recognized as critical factors that influence the adoption and use of electric vehicles. While financial incentives, such as purchase grants and free complimentary home charger installations, have been shown to positively impact EV uptake (Liu et al., 2023; Qadir et al., 2024; Shang et al., 2024), the availability and distribution of charging stations are considered even more decisive, as they directly impact user convenience and mitigate range anxiety (Coffman et al., 2017; Fox, 2013; Hafezi & Morimoto, 2023; Hoffmann, 2018; Mersky et al., 2016; Sierzchula et al., 2014).

One of the main barriers to EV adoption is range anxiety, a psychological concern stemming from the limited driving range of EVs and the potential unavailability of charging facilities. Previous studies have shown that the presence of public charging infrastructure, especially fast chargers, significantly enhances the attractiveness of EVs by enabling users to cover long distances efficiently (Needell et al., 2016; Neubauer & Wood, 2014). The placement of charging stations at strategic locations, such as highways and urban centers, has been shown to alleviate this concern, thereby facilitating a smoother transition to electric mobility (Neaimeh et al., 2017). Besides range anxiety, the power output of chargers is also a crucial factor, with fast chargers drastically reducing charging times. Meintz et al. (2017) note that modern charging points delivering up to 400 kW can charge EVs for up to 320 km in just 10 minutes, nearing the refueling speed of ICE vehicles. Therefore, optimizing charger placement, differentiating between fast and normal chargers, and considering their impact on the electricity grid are vital steps in developing a robust, user-friendly charging network that supports the broader adoption of electric vehicles.

Several studies have used data-driven approaches to determine optimal charging station locations. For example, Yun et al. (2019) analyzed charging behaviors in Shanghai using GPS data from plug-in hybrid electric vehicles (PHEVs) and conclude that home and workplace charging were preferred over public charging stations. Choi (2020) developed a clustering algorithm to identify high-demand areas for charging infrastructure on Jeju Island, South Korea, concluding that proximity to tourist attractions and population density increased the effectiveness of charging stations. Shahraki et al. (2015) also utilized taxi driving data from Beijing to capture public charging demand and select the locations of public charging stations that maximizes the electrification of vehicle-miles-traveled, showing that the majority of optimal locations identified are situated in the inner city.

Studies in Europe and the United States have also examined the spatial distribution and utilization patterns of charging infrastructure. Dong et al. (2014) investigate EV charger location problems by analyzing the impact of public charging infrastructure deployment on increasing electric miles traveled. Utilizing a genetic algorithm based on GPS-based travel survey data collected in the Seattle metropolitan area in the USA, the authors show that electric miles and trips could be significantly increased by installing public chargers at popular destinations. Juhász & Hochmair (2023) analyzed public charging stations in the U.S., identifying economic activity, highway density, and local political preferences as key factors influencing station placement. In Germany, Jochem et al. (2016) focused on fast charger deployment along highways, finding that strategically placed chargers could cover significant distances and reduce range anxiety. Similarly, Hecht et al. (2020) conducted a comprehensive analysis of usage patterns, highlighting variations in charger utilization based on time and location.

Despite valuable insights from previous studies, there remains a need for comprehensive analyses that consider micro-level geographic data, such as population density, road networks, and electricity supply. This paper builds on this existing body of literature by utilizing detailed geo-referenced data to better understand the determinants of EV charging infrastructure distribution across Germany.

2.2 Vehicle Grid Integration (VGI)

Beyond the determinants of charger placement, the integration of EVs into the power grid, commonly referred to as Vehicle Grid Integration (VGI), presents both opportunities and challenges. As the number of EVs increases, their collective impact on the electricity grid becomes more pronounced, particularly during peak charging periods. Uncoordinated charging can strain the grid, leading to voltage imbalances, increased power losses, and potential instability in the distribution network (Masoum et al., 2012). Therefore, developing strategies to manage charging demand and integrate EVs effectively into the grid is crucial.

One of the key approaches to addressing these challenges is coordinated or smart charging, which manages the timing and intensity of EV charging to minimize grid disruptions. By shifting charging activities to off-peak hours, smart charging can reduce electricity costs, alleviate pressure on transformers, and prevent voltage deviations (Fairley, 2010; Masoum et al., 2012; Rangaraju et al., 2015). Moreover, advanced grid integration techniques, such as Vehicle-to-Grid (V2G) systems, allow bidirectional energy flow between EVs and the grid. This not only helps in balancing supply and demand but also provides ancillary services, such as frequency regulation and backup power (Richardson, 2013; Wu, 2013).

However, V2G integration is not without its drawbacks. Concerns include the potential for accelerated battery degradation and the need for substantial investments in grid infrastructure to accommodate bidirectional energy flow. Additionally, the existing distribution networks may not be equipped to handle large-scale VGI without significant upgrades (Das et al., 2020; Ul-Haq et al., 2015). As a result, careful planning and policy support are essential to realize the full benefits of VGI while ensuring grid reliability and stability.

Our analysis contributes to this area by examining the role of local electric grid infrastructure in the placement of EV charging stations. We investigate how grid characteristics, such as power line density and the presence of substations, influence the spatial distribution of charging infrastructure, thereby informing strategies for more effective VGI.

3 Data and Methods

This section describes the data sources, variables, and regression model employed to examine the factors that determine the placement of EV charging station at the postcode level in Germany.

3.1 Postcode and EV Charging Stations

To explore the factors influencing the placement of charging infrastructure at the postcode level, we obtained detailed geographic polygon data for all postcodes in Germany, along with corresponding population statistics. This data is essential for understanding the spatial distribution and potential demand for EV chargers.[1] In Germany, all public charging points are registered, and with the provider's consent, the geo-referenced data on the charging station are made publicly available by the Federal Network Agency (Bundesnetzagentur, 2024). The dataset is updated regularly and, as of March 1, 2024, comprises $62,426$ chargers, accounting for approximately 49% of all public chargers in Germany. The number of charging points available at these stations varies from a minimum of 1 to a maximum of 6, with an average of 2 charging points across all chargers. The dataset provides the location by coordinates, address (including postcode), provider, commencement of operation date, exact charging power, and maximum connections per charger. Chargers are categorized as normal with power output of 22 kW or less and fast chargers with power output exceeding 22 kW. Whether chargers are publicly disclosed is at the discretion of the provider; thus, the dataset does not entirely capture Germany's public charging infrastructure.

The dataset, spanning from 1992 to 2024, includes 50,899 normal charging stations and 11,527 fast charging stations, including Tesla superchargers. Given Tesla's significant market share in Germany (Kraftfahrt-Bundesamt, 2023) and its proprietary fast charging network (120 kW to 250 kW), these chargers are essential for a comprehensive analysis of the charging landscape. While there is no official publicly available dataset encompassing Germany's superchargers, we rely on a user-based website that aggregates all Tesla's superchargers across countries, and filter the chargers located in Germany.[2] The data shows that of the 194 Tesla superchargers in Germany, approximately 190 support charging other electric vehicles. The Tesla superchargers are added to the fast chargers in the Federal Network Agency dataset. While superchargers constitute merely a fraction of the charging infrastructure in Germany, our analysis aims to comprehensively cover the German charging landscape, which includes Tesla's supercharger network.

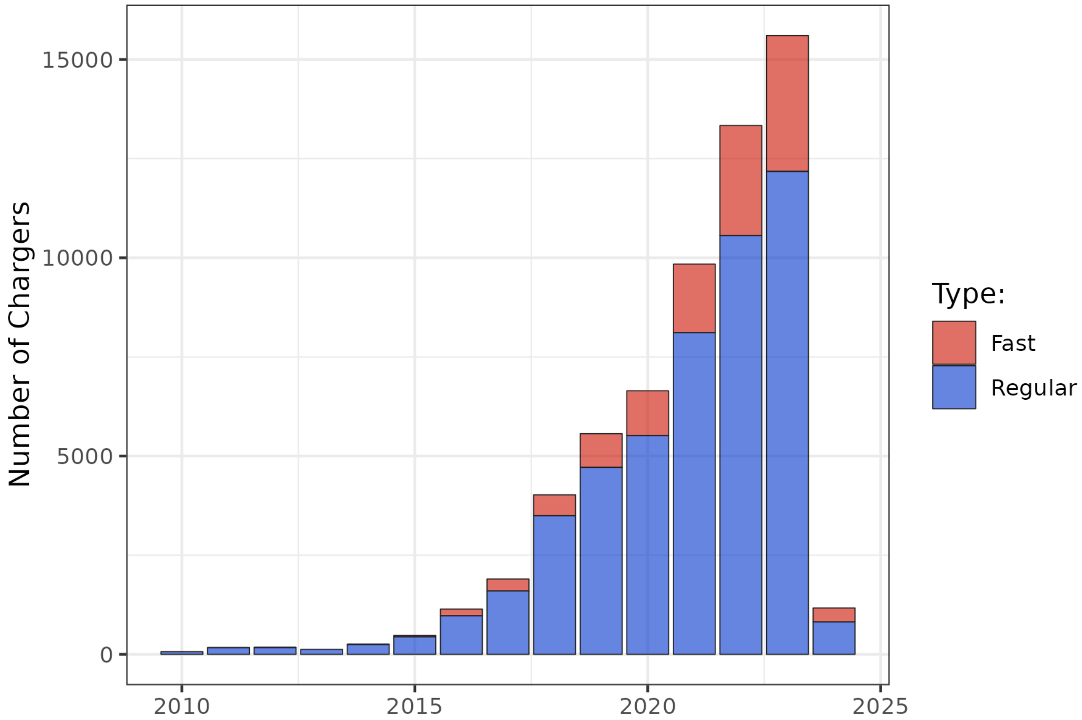
Figure 1 illustrates the evolution of charger installations from 2010 to 2024, encompassing both normal and fast chargers.[3] The count of normal chargers exhibits a gradual

[1]This data is sourced from https://www.suche-postleitzahl.org/.

[2]See: https://supercharge.info/data

[3]Notably, between 1992 and 2009, only 55 operational charging stations are documented in the dataset. Further note that the number of chargers in 2024 is only until March 1, 2024.

Figure 1: Yearly Normal and Fast Chargers



Source: Author's own illustration

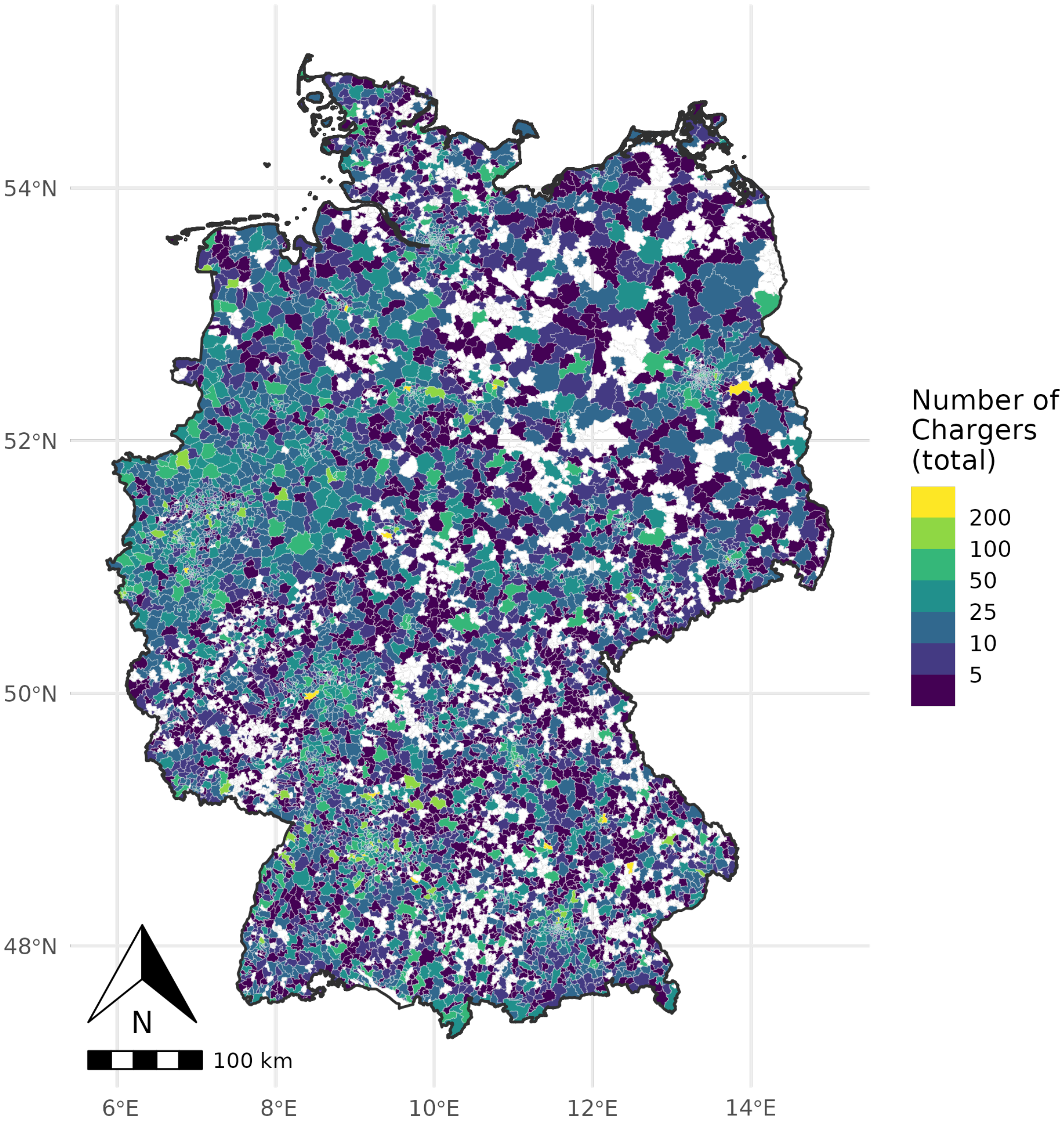
increase, particularly from 2013 to 2016, surging to about $1,130$ chargers. The upward trajectory persists, with about 42% average annual growth rate, leading to over $10,000$ normal chargers in 2023. Figure 1 also shows a steady increase in the number of fast chargers, particularly noticeable from 2016 onwards, indicating a growing presence of these types of chargers in Germany. Overall, the dataset reveals a consistent and exponential expansion in charger installations, highlighting Germany's advancement in EV infrastructure. Figure 2 shows the spatial distribution of chargers, illustrating distinct variations across postcode areas with some postcodes having over 200 chargers while others have no public chargers.

3.2 OpenStreetMap (OSM) Data

Much of the data required for this research was sourced from the crowdsourced OpenStreetMap (OSM), renowned for its highly detailed geographic data and global coverage. We rely mostly on database dumps from Geofabrik, as these compressed data file formats facilitate data utilization and eliminate the need to directly access OSM (Geofabrik, 2024). For data types that go beyond the pre-selected variables in the Geofabrik database dumps, we rely on requests from the Overpass API.[4] Based on these two data sources,

[4] https://wiki.openstreetmap.org/wiki/Overpass_API

Figure 2: Distribution of chargers across postcode area



Source: Author's own illustration

we compute several variables that are utilized in the regression analysis.

Population and Road Density

We evaluate population density and road density at the postcode level to reflect the degree of urbanization and infrastructure development. Population density is computed as the population per postcode area divided by the square kilometers of the postcode area. For road network representation, we calculate the density of two categories of roads: *motorway* and *other* roads including primary, secondary, tertiary, and residential roads. The road length per square kilometer is computed by aggregating the length of various road types within the postcode areas and dividing it by the area. Postcode areas with higher road density suggest higher demand for mobility and should generally feature a greater number of charging stations. Postcode areas with higher population and road densities indicate a heightened demand for charging infrastructure to adequately cover the postcode area, implying a positive relationship between these factors. As depicted in Figure 3, the spatial distribution of population and road density closely aligns, with postcode areas of higher population density typically exhibiting greater road density.[5] This trend is further reflected in the distribution of charging stations across Germany, as shown in Figure 2, where postcode areas with higher population and road densities tend to have more charging stations.

Amenity Variables

From the OSM data, we derive *amenity* variables that reflect how daily activities or trips to various POIs influence the placement of charging stations. We construct four groups of amenity variables to represent the diverse usage of different POIs. As the POIs are obtained as geographical point features, they are assigned and aggregated to their respective postcode areas using postcode borders. Table 4 in the Appendix lists all included locations per variable. Locations are grouped by their OSM label and classified into one of the four groups: *Errands*, *Food and Beverages*, *Shopping*, and *Daily Essentials*.

The group, labeled *Errands*, encompasses destinations integral to daily life but requiring minimal time, such as dropping off a package or using an ATM. Due to their short usage duration, the impact of these destinations on charger demand may be minimal, as the

[5]The road density here includes all roads from residential to motorway road.

dwelling time for EVs in these locations may be very brief. The *Food and Beverages* group includes locations like cafes or restaurants that offer opportunities for longer parking and charging periods from 20-30 minutes to several hours. Similarly, *Shopping* follows a similar intuition since these locations permits both shorter visits and extended stays. The last category comprises *Daily Essentials*, which carry significant importance as they are indispensable for nearly everyone on a weekly basis. This category includes supermarkets and pharmacies, which are frequently accessed via automobile.

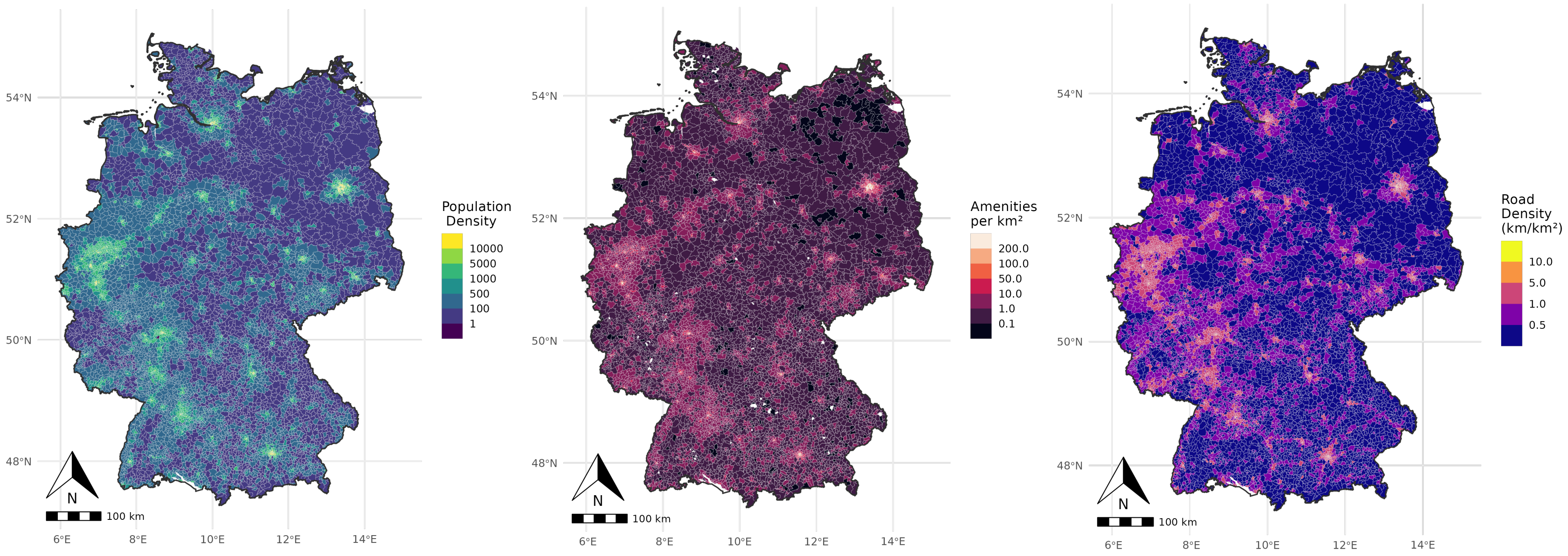
Generally, longer stays in POIs should create more charging opportunities and render such locations more attractive for potential charging points. In fact, previous studies such as Hecht et al. (2020) have highlighted increased demand for fast chargers during weekend recreational shopping. Utilizing time for daily activities or in between trips for charging could, therefore, alleviate the inconvenience of the charging process, seamlessly integrate EVs into users' daily routines, and reduce the disparity compared to ICEs. Figure 3 shows the distribution of all amenities across postcodes, with – as expected – higher number of amenities in densely populated areas as well as areas with higher road densities. Clearly, postcodes with higher amenities also have higher number of charging infrastructure.

Figure 3: Distribution of population and road densities and amenities per postcode area

(a) Population Density

(b) Amenities

(c) Road Density



Source: Author's own illustration

Infrastructure Variables

In addition to road densities, the presence of motorway links is considered crucial for charging opportunities off the highway, such as at motorway rest areas, which are essential for longer journeys. To address this, a dummy variable is introduced for motorway links, where a value of one signifies the presence of at least one motorway link within the postcode area, and zero otherwise. This approach prevents the overestimation of the influence of large motorway nodes and ensures that postcodes lacking links, and thus charging opportunities, are negatively correlated with the number of charging stations. It is worth noting that the number of fast chargers in areas with motorway links is expected to be higher, given their importance for longer journeys, as emphasized by Neaimeh et al. (2017).

To capture other aspects of the public transport network, retail fuel stations at the postcode level – often proposed as viable locations for EV chargers – are considered. These stations are expected to play an increasingly critical role in the future, especially if mandated by regulations to provide charging facilities. With their nationwide coverage and established usage patterns, such regulations could significantly facilitate the transition from ICE vehicles to EVs. We obtain the geographic locations of all fuel stations in Germany from Tankerkoenig[6] and aggregate the number of fuel stations at the postcode level.

Electric Grid Variables

It is worth mentioning that the robustness of EV charging infrastructure is reliant on the availability of electricity. To represent electricity supply in our analysis, we include variables that not only capture the number of power plants but also the number of electric grid intersections as well as power line density at the postcode level. We acquire data on power plants from the German public authority, which regularly updates this dataset.[7] This dataset encompasses power plants and renewable energy sources such as wind parks. The count of power plants and renewable energy sources are aggregated per postcode and used as a proxy for energy supply or availability, which is a pre-requisite for building charging infrastructure.

[6]https://dev.azure.com/tankerkoenig/_git/tankerkoenig-data

[7]https://www.bundesnetzagentur.de/DE/Fachthemen/ElektrizitaetundGas/Versorgungssicherheit/Erzeugungskapazitaeten/Kraftwerksliste/start.html

Data pertaining to the electric grid intersection is sourced from the OSM dataset. Intersections within the electrical grid are considered by tallying converter stations, substations, and transformers per postcode. This information denotes locations where electricity from high voltage transmission lines is redistributed to local distribution lines. We suggest that these intersections are ideal locations for EV charging points due to their ability to redistribute significant amounts of electricity, making them well-suited for charging EVs. Additionally, these grid intersections are valuable for improving coordinated charging and managing demand to prevent grid overload. To compute power line density, we aggregate the length of power lines within the postcode area and divide by the area's square kilometers. Overall, these variables are constructed to reflect the availability of electricity within a given postcode area.

3.3 Descriptive Statistics

Table 5 presents the descriptive statistics of the dataset. As highlighted in Section 3.1, normal chargers exhibit significant variability in their numbers across postcodes, with the highest overall average and per postcode area counts. Fast chargers are relatively scarce in Germany, and Tesla's superchargers constitute only a small fraction of the nationwide charging grid. These descriptive statistics underscore the diversity of German postcode areas, encompassing urban centers to remote rural regions. Note that the different amenity variables (Errands, Food and Beverages, Shopping, Daily Essentials) also vary considerably in their counts and reflect the diverse distribution of amenities across different areas. Moreover, the presence of up to 38 power plants in one postcode area is surprising, but this can potentially be explained by the inclusion of wind parks and offshore facilities.

3.4 Estimation

Charging station counts can be influenced by various factors such as population density, urbanization, infrastructure availability, and policy interventions. To investigate this relationship, our analysis is performed at the postcode level, with all variables aggregated accordingly to capture variations across cities or districts. We employ cross-sectional regression analysis because most of the variables are time-invariant, making panel regression analysis unnecessary.

Given the discrete nature of charger counts, we use a count-data model for estimation, specifically the negative binomial regression, which extends the Poisson regression model. Count data, such as the number of charging stations in a geographic area, often exhibit overdispersion, where the conditional variance exceeds the conditional mean. In such cases, negative binomial regression introduces an additional parameter to account for this overdispersion, making it a more suitable approach than Poisson regression, as it tends to produce narrower confidence intervals.

Therefore, we utilize the negative binomial regression model to capture the relationships between these determinants and the count of charging stations, while appropriately accounting for overdispersion. In addition to the negative binomial estimation, we also use traditional Ordinary Least Squares (OLS) estimation to assess the robustness of our findings across different estimation methods. Our negative binomial regression model is specified as follows:

$$\ln(C_{ij}) = \beta_1 \ln(P_{ij}) + \beta_3 \ln(M_{ij}) + \beta_2 \ln(R_{ij}) + \gamma_1 A_{ij} + \sum_{l=1}^{6} \lambda_l X_{ij} + \alpha_j + \epsilon_{ij} \quad (1)$$

In this cross-section negative binomial regression equation, C_{ij} is the dependent variable and denotes the expected count of charging stations in postcode area i within the municipality area j. P_{ij} denotes the population density, M_{ij} is the motorway road density and R_{ij} denotes road density for all other roads apart from motorway road network. In our baseline regression equation, A_{ij} represents the amenity variable, included as the sum of all four variables, i.e., shopping, food and beverages, errands, and daily essentials. In our subsequent specifications, the four different amenity variables are then included separately in Table 2. X_{ij} denotes all other variables, α_j represents municipality fixed effects and all other residual variation is captured in the error term ϵ_{ij}.

We estimate different variants of the regression equation to capture the different variables constructed. All specifications accounts for municipality-level unobserved heterogeneity through the fixed effects α_j. These fixed effects control for all time-invariant differences across municipalities, such as local policies, geographic features, or socio-economic factors that are constant within a municipality and also avoid omitted variable bias. To account for correlations within municipalities and address potential heteroskedasticity, we cluster standard errors at the municipality level. Our regression approach ensures a comprehensive analysis of factors influencing charging station placement, including population density, infrastructure, the availability of amenities, and characteristics of the electric grid or energy supply. By utilizing a variety of data sources and applying robust regression techniques, our analysis sheds light on the key determinants that influence the spatial distribution of charging infrastructure across Germany.

4 Results

Table 1 presents the results of the baseline municipality-level fixed effects negative binomial regression specified in Equation 1. Across all specifications, the results indicate significant over-dispersion, confirming the appropriateness of using the negative binomial estimation approach. The first specification (column 1) includes three density variables expressed in logarithmic form, to handle potential non-linear relationships. The coefficients or elasticities, which measure the percentage change in charger count in response to a 1% change in these variables, are all statistically significant at the 5% level and show the expected positive effects. Here, a 1% change in population density leads to *0.36%* change in the expected count of charging stations at the postcode level. Similarly, A 1% increase in road density corresponds to approximately *1.15%* change in the expected count of charging stations. The significant positive impacts of population and road densities – both considered proxies for the degree of urbanization within a postcode area – highlight the importance of charger placement in urban settings.

Road density generally serves as an indicator of infrastructure development, and areas with higher road density often correspond with higher population densities or increased urbanization. This suggests that urbanized areas are more likely to have greater demand for EVs, and consequently, a greater need for public charging infrastructure. The significant positive coefficient for motorway density suggests that areas with higher motorway density are more likely to have a greater number of public charging stations. This finding aligns with previous findings by of Jochem et al. (2016), highlighting the critical role of motorway-based fast charging infrastructure in facilitating long-distance EV travel and reducing range anxiety.

Note that motorway and other road densities lose their significance in subsequent specifications when the number of amenities is included, likely due to the correlation between amenities and road density (see Figure 3}). Nonetheless, the results consistently show a positive and significant effect of population density on charger placement. This emphasizes population density's critical role in the spatial distribution of charging stations, and further highlight the importance of accessibility and convenience for EV users. Clearly,

Table 1: Baseline Regression Results

	(1)	(2)	(3)	(4)	(5)	(6)
Log(Population Density)	0.359***	0.159***	0.183***	0.138***	0.139***	0.139***
	(0.070)	(0.052)	(0.049)	(0.045)	(0.046)	(0.045)
Log(Motorway Density)	1.148***	1.212***	0.184	0.198	0.222	0.227
	(0.169)	(0.160)	(0.241)	(0.216)	(0.213)	(0.206)
Log(Other Road Density)	0.342**	-0.216	-0.199	0.009	0.056	0.062
	(0.166)	(0.143)	(0.138)	(0.131)	(0.130)	(0.125)
Dispersion Parameter	1.441***	1.865***	1.934***	2.283***	2.317***	2.338***
	(0.059)	(0.151)	(0.159)	(0.163)	(0.166)	(0.162)
Amenity		0.010***	0.009***	0.005***	0.005***	0.005***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Motorway Link Dummy			0.529***	0.332***	0.310***	0.308***
			(0.076)	(0.070)	(0.070)	(0.066)
Fuel Stations				0.180***	0.165***	0.163***
				(0.017)	(0.015)	(0.015)
log(Power Line Density)					0.025	-0.012
					(0.065)	(0.064)
Grid Intersections					0.002***	0.002***
					(0.000)	(0.000)
Power Plants						0.048**
						(0.021)
Neighbor Power Plant						0.005
						(0.006)
Number of Postcode Areas	8170	8170	8170	8170	8170	8170
$R^2_{Adj.}$	0.081	0.121	0.126	0.146	0.148	0.149
FE: Municipality	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Constant term included but not shown. Robust standard errors are clustered at the municipality level and reported in parentheses. The dependent variable is the log-count of all EV charging stations.
*: Significant at the 10% level. **: Significant at the 5% level. ***: Significant at the 1% level.

charger placement strategies should be attuned to patterns of urbanization and road networks to effectively serve the needs of EV users across diverse geographical contexts.

In specifications (2) to (6) of Table 1, the variable *Amenity* represents a composite measure that captures the count of all four amenity categories: shopping, food and beverages, errands, and daily essentials. This composite variable consistently shows a positive and significant coefficient at the 1% level, emphasizing the importance of these locations in influencing the placement of charging stations. Across these specifications, the coefficient for *Amenity* suggests that a one-unit increase in the number of amenities in a postcode area leads to a 0.005 to 0.010 increase in the log count of charging stations, corresponding to an incidence rate ratio (IRR) between 1.005 and 1.010. This indicates that each additional amenity in a postcode area is associated with a 0.5% to 1.0% increase in the expected count of charging stations. The results suggest that the presence of amenities in a postcode area – typically indicative of a well-developed, convenient, and economically vibrant environment attractive to both residents and tourists – has a significant impact on the placement of charging stations, and further highlight the importance of considering local amenities in the planning and deployment of charging infrastructure to adequately meet the needs of EV users.

Specifications (3) to (6) include the dummy variable for motorway links. The dummy has the value 1 if a postcode has at least 1 motorway link area, and 0 otherwise. On average, postcodes with a motorway link have more chargers than those without, aligning with findings from previous studies (Hecht et al., 2020; Jochem et al., 2016; Neaimeh et al., 2017) that emphasize the importance of charging opportunities, especially fast charging, for longer journeys. Motorway links typically lead to areas with higher traffic and more active users, resulting in a greater number of chargers. Note, however, that the magnitude of the coefficient for motorway links decreases when the number of fuel stations in the postcode area is included (see, column (4)). Charging facilities close to highways, such as those found in highway service areas, are often provided by fuel stations to diversify their services to cater to the growing EV market. The positive correlation between the two variables potentially leads to the diminished magnitude of the motorway link dummy variable.

The results in Table 1 also show that the number of fuel stations in a postcode area is positively associated with the number of charging stations. The results show that a one-unit increase in the number of fuel stations in a postcode area increases the log count of chargers by between 0.163 and 0.180, corresponding to a 17.7% to 19.7% increase in the expected count of charging stations. This can be attributed to the fact that locations with existing fuel stations are already recognized as convenient spots for vehicle services, making them suitable candidates for hosting charging stations as well. Moreover, fuel stations are often located in areas with high vehicle traffic or significant transportation needs. With the increasing number of EVs, especially in urban and suburban areas, fuel stations offer regulators the opportunity to incentivize or mandate the installation of EV charging stations in conjunction with fuel stations as part of sustainability initiatives or regulatory requirements. In such cases, the presence of fuel stations could indirectly influence the proliferation of charging stations.

The influence of the electric grid or electricity supply on the placement of chargers is also shown in Table 1. Power line density is used as a proxy for electricity availability and accessibility within the postcode. Interestingly, the findings suggest that this variable is statistically insignificant across all specifications. However, the number of intersections such as converters, substations, and transformers within the electric grid appears to induce more charger placement. These intersections are ideal locations for EV charging points due to their strategic position where multiple transmission lines or distribution networks converge. This convergence enables the redistribution of significant amounts of electricity, making these sites particularly well-suited for supporting the high power demands of EV charging, including fast charging services.

Additionally, these grid intersections are valuable for enhancing coordinated charging and demand-side management, allowing for better load monitoring and distribution, which is crucial for preventing grid overload, especially during peak usage times. Overall, the results show that these intersections appear to offer favorable opportunities for charger placement in the postcode area. The results also show that the number of power plants serving as electricity supply sources appears to stimulate charger infrastructure, although the existence of power plants in a neighboring postcodes – *Neighbor Power Plant* – appears to have a statistically insignificant effect. The highly significant coefficients for the number of local grid intersection and power plants highlight the importance of electricity supply – a prerequisite for charger installation – via the grid in determining the placement of EV chargers.

In Table 2, we disaggregate amenity into its various components – *Shopping*, *Food and Beverages*, *Errands*, and *Daily Essentials* and explore whether the expected log count of the number of chargers increases more noticeably for some amenity variables than others. From column (2) to (5), we include these variables individually and in column (6), we incorporate all amenity variables. All *Amenity* variables in columns (2)-(5) exhibit significance at the 1% level and demonstrate the expected positive influence. When comparing the magnitude of the amenity variables, it is evident that the expected log count of the number of chargers increases more noticeably for a unit increase in points of interests – including supermarkets, greengrocers, pharmacies, butchery – categorized as *Daily Essentials* compared to the other amenity variables.

Specifically, for a unit increase in the number of *Daily Essentials*, the expected log count of the number of chargers rises by 0.046, suggesting that POIs that could offer longer dwell time appear to have a larger effect on charger placement than other amenities. Additionally, the *Errands* category also tends to increase the placement of EV chargers in the postcode area more than the *Shopping* and *Food and Beverages* categories. Overall, the findings highlight the importance of amenities as determinants of charging station counts, and suggest that proximity to POIs that offer essential services and other amenities with regular usage stimulates demand for charging infrastructure. These results suggest the need to incorporate local amenities and consumer behavior into charging infrastructure planning. Note that when all amenity variables are simultaneously included in column (6), only the *Errands* and *Daily Essentials* – the amenities with the largest coefficients in columns (2)-(5) – exhibit statistically significant positive effects at the

Table 2: Regression Results: Amenity Variables

	(1)	(2)	(3)	(4)	(5)	(6)
Log(Population Density)	0.193***	0.156***	0.160***	0.140***	0.108**	0.121***
	(0.049)	(0.046)	(0.047)	(0.042)	(0.045)	(0.043)
Log(Motorway Density)	0.033	0.147	0.186	0.235	0.178	0.259
	(0.195)	(0.196)	(0.210)	(0.196)	(0.205)	(0.206)
Log(Other Road Density)	0.483***	0.190	0.080	0.222*	0.282**	0.165
	(0.135)	(0.130)	(0.132)	(0.128)	(0.122)	(0.123)
Motorway Link Dummy	0.325***	0.327***	0.315***	0.284***	0.316***	0.285***
	(0.067)	(0.066)	(0.066)	(0.067)	(0.069)	(0.067)
Fuel Stations	0.207***	0.184***	0.184***	0.135***	0.154***	0.132***
	(0.009)	(0.010)	(0.014)	(0.011)	(0.012)	(0.010)
log(Power Line Density)	-0.161**	-0.083	-0.031	-0.009	-0.086	0.003
	(0.063)	(0.062)	(0.068)	(0.060)	(0.062)	(0.064)
Grid Intersections	0.003***	0.003***	0.003***	0.001***	0.002***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Power Plants	0.050**	0.053**	0.047**	0.046**	0.047**	0.045**
	(0.022)	(0.021)	(0.021)	(0.021)	(0.022)	(0.021)
Neighbor Power Plant	0.007	0.007	0.005	0.004	0.006	0.004
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Dispersion Parameter	2.149***	2.259***	2.288***	2.394***	2.287***	2.404***
	(0.124)	(0.141)	(0.160)	(0.152)	(0.149)	(0.159)
Shopping		0.016***				-0.004
		(0.002)				(0.004)
Food and Beverages			0.008***			0.002
			(0.002)			(0.003)
Errands				0.024***		0.018***
				(0.002)		(0.002)
Daily Essentials					0.046***	0.015***
					(0.006)	(0.005)
Number of Postcode Areas	8170	8170	8170	8170	8170	8170
$R^2_{Adj.}$	0.137	0.143	0.146	0.151	0.146	0.152
FE: Municipality	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Constant term included but not shown. Robust standard errors are clustered at the municipality level and reported in parentheses. The dependent variable is the log-count of all EV charging stations.
*: Significant at the 10% level. **: Significant at the 5% level. ***: Significant at the 1% level.

1% level. This may be attributed to the positive correlation among the variables – see Figure 5 in the Appendix for the correlation matrix.

Previous studies such as Flammini et al. (2019) and Hecht et al. (2020) reveal distinct demand and usage patterns of EV chargers depending on the power output of the charger. Neaimeh et al. (2017) in particular, highlight the importance of fast chargers for longer journeys, while Flammini et al. (2019) note that chargers with low power output near highways are among the least utilized chargers. To explore the disparity in the distribution as well as factors that influence the locations of different charger types, we estimate a variant of Equation 1, where the dependent variable is categorized into *normal* chargers (22 kW power output or less) and *fast* chargers (more than 22 kW power output). Note that Tesla's superchargers are included in the fast charger sample since a large majority of these chargers can be used by other EVs.

Table 3 presents the estimates for *normal* and *fast* chargers, reflecting the distinct roles these types of chargers play within the overall charging infrastructure. The dependent variable in columns (1) through (5) is the count of normal chargers, while in columns (6) through (10), it is the count of fast chargers in the postcode area. For columns (1) and (6), amenities are incorporated as a composite variable, as done in Table 1.

In these specifications, the coefficients for both *normal* and *fast* chargers are significant at the 1% level, although the magnitude is consistently larger for normal chargers. This pattern persists even when the amenity variable is disaggregated into its sub-categories. Specifically, while all coefficients for the amenity variables in both the normal and fast charger regressions are positive and statistically significant at least at the 5% level, the estimates indicate that the coefficients are consistently larger in the normal charger regressions compared to the fast charger regressions.

This suggests that the presence of amenities in a postcode area has a stronger influence on the placement of normal chargers than on fast chargers. One plausible explanation for this difference is that normal chargers are more likely to be located in areas where people spend more time, such as shopping centers or residential areas, where the convenience of a slower charge is less of a concern. In contrast, fast chargers are often positioned along highways or in transit hubs, where the primary need is for quick charging, making their placement less dependent on the density of local amenities.

Regarding the other regressors, the results indicate that while the signs of the coefficients across all specifications generally align with the benchmark results in Table 1, there are a

Table 3: Regression Results: Normal vs. Fast Chargers

	Normal Chargers					Fast Chargers				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log(Population Density)	0.127**	0.145***	0.150***	0.130***	0.093*	0.267***	0.281***	0.281***	0.254***	0.243***
	(0.049)	(0.050)	(0.052)	(0.046)	(0.049)	(0.047)	(0.049)	(0.048)	(0.048)	(0.050)
Log(Motorway Density)	0.141	0.061	0.098	0.147	0.093	0.381	0.318	0.352	0.431*	0.358
	(0.216)	(0.211)	(0.221)	(0.208)	(0.217)	(0.235)	(0.228)	(0.235)	(0.229)	(0.233)
Log(Other Road Density)	0.022	0.154	0.046	0.198	0.249*	0.136	0.236*	0.158	0.166	0.242*
	(0.137)	(0.143)	(0.144)	(0.139)	(0.134)	(0.134)	(0.132)	(0.139)	(0.131)	(0.138)
Motorway Link Dummy	0.098	0.118	0.106	0.068	0.100	0.996***	1.006***	1.000***	0.978***	1.005***
	(0.072)	(0.072)	(0.072)	(0.072)	(0.074)	(0.078)	(0.078)	(0.078)	(0.078)	(0.078)
Fuel Stations	0.133***	0.155***	0.156***	0.103***	0.121***	0.296***	0.308***	0.306***	0.272***	0.289***
	(0.016)	(0.010)	(0.015)	(0.012)	(0.013)	(0.018)	(0.016)	(0.017)	(0.017)	(0.017)
log(Power Line Density)	-0.025	-0.105	-0.047	-0.025	-0.108	0.114	0.071	0.099	0.146	0.085
	(0.071)	(0.067)	(0.076)	(0.065)	(0.067)	(0.114)	(0.114)	(0.113)	(0.115)	(0.116)
Grid Intersections	0.002***	0.003***	0.003***	0.001***	0.002***	0.003***	0.003***	0.003***	0.002***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Power Plants	0.054**	0.060***	0.054**	0.053**	0.054**	0.010	0.012	0.010	0.009	0.009
	(0.023)	(0.023)	(0.023)	(0.022)	(0.023)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Neighbor Power Plant	0.005	0.008	0.006	0.004	0.007	-0.001	0.000	-0.001	-0.002	-0.000
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)
Amenity	0.005***					0.002***				
	(0.001)					(0.001)				
Dispersion Parameter	2.182***	2.105***	2.127***	2.237***	2.141***	0.837***	0.832***	0.834***	0.847***	0.834***
	(0.165)	(0.141)	(0.161)	(0.155)	(0.152)	(0.047)	(0.047)	(0.047)	(0.048)	(0.047)
Shopping		0.017***					0.005***			
		(0.003)					(0.002)			
Food and Beverages			0.008***					0.003**		
			(0.003)					(0.001)		
Errands				0.025***					0.015***	
				(0.002)					(0.002)	
Daily Essentials					0.052***					0.024***
					(0.007)					(0.006)
Number of Postcode Areas	8170	8170	8170	8170	8170	8170	8170	8170	8170	8170
$R^2_{Adj.}$	0.146	0.140	0.143	0.148	0.143	0.123	0.122	0.123	0.125	0.123
FE: Municipality	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Constant term included but not shown. Robust standard errors are clustered at the municipality level and reported in parentheses.
The dependent variable is the log-count of EV charging stations, i.e., Normal (columns 1-5) and Fast (columns 6-10).
*: Significant at the 10% level. **: Significant at the 5% level. ***: Significant at the 1% level.

few notable differences for certain variables. First, the *Motorway Link Dummy* remains consistently insignificant when *normal* chargers are used as the dependent variable (see columns (1) through (5)), but it is statistically significant at the 1% level in the case of fast chargers as the dependent variable. This suggests that motorway links have a significant impact on the placement of fast chargers, highlighting their strong association with the highway network, where quick charging is essential. In contrast, the insignificant effect of motorway links on normal chargers may be attributed to normal chargers being commonly found in locations where users spend longer periods, such as residential areas or commercial centers, rather than along major highways.

For electricity supply variables, the number of power plants is significant in the case of *normal* chargers but not for *fast* chargers. This implies that the presence of power plants in a postcode area is more likely to influence the placement of normal chargers. One possible explanation is that normal chargers, which typically operate over longer periods, may be more dependent on a stable and accessible electricity supply, making proximity to power plants more relevant for their placement. In contrast, fast chargers, which require high power for short bursts, may rely on specialized infrastructure or grid connections that are not as closely tied to the number of nearby power plants.

Despite all regression results indicating significant overdispersion in the count of chargers and justifying the use of the negative binomial estimation approach, we also conducted the analysis using the OLS estimation technique as a sensitivity check. The OLS results, as shown in Table 6, are largely consistent with the negative binomial regression, with only a few exceptions. Notably, population density remains statistically insignificant across all specifications in the OLS models, contrasting with its significance in the negative binomial approach. This suggests that while population density may play a role in the presence of overdispersion, which the OLS method might not capture effectively.

Motorway road density shows statistical significance only in the case of fast chargers, reinforcing the idea that fast chargers are closely associated with major highways where quick access is crucial. In contrast, other road density remains generally significant across models, unlike the results in Table 1, suggesting its influence on charger placement when overdispersion is not accounted for. Overall, the OLS results are largely consistent with those from the negative binomial regression, indicating the robustness of the findings. However, the few differences observed, such as the insignificance of population density in the OLS models, highlight the importance of addressing overdispersion when analyzing count data, as effectively done by the negative binomial model.

5 Conclusion

In the effort to decarbonize the economy and combat climate change, EVs have emerged as a crucial component for reducing emissions in the transport sector. Yet, the successful and widespread adoption of EVs depends heavily on the presence of a well-developed charging infrastructure, which helps mitigate range anxiety and accommodates the increasing number of EVs on the road. In this paper, we analyse the factors that affect the spatial distribution of EV charging stations across all postcode areas in Germany. Our results highlight the importance of population density, road networks, local amenities, fuel stations, and electric grid infrastructure in influencing charger placement, emphasizing their essential role in strategic planning and policy formulation.

Our analysis shows a strong positive relationship between population density and the number of charging stations, highlighting the importance of prioritizing infrastructure development in urban areas, where demand is highest. This finding implies that urban planners and policymakers should focus on densely populated regions when allocating resources for charging infrastructure to ensure sufficient access for EV users. Furthermore, the strategic positioning of chargers along major transportation routes, such as highways and motorway links, proves to be essential. Specifically, our results indicate that while proximity to major highways is especially relevant for fast chargers, it holds less significance for normal chargers. This distinction underscores the need to place fast chargers near highways to facilitate long-distance travel and reduce range anxiety.

The analysis also reveals the relationship between amenity variables and the distribution of charging stations, highlighting how local amenities drive demand for charging infrastructure. Our findings show that the presence of amenities like shopping centers, food and beverage outlets, and daily essentials have a positive impact on the placement of chargers, particularly normal chargers. This suggests that policymakers should factor in the proximity of essential services when planning charger placement, especially in residential neighborhoods and areas with high consumer traffic. In this regard, collaborating with supermarkets, retail outlets, and fuel stations could increase accessibility and convenience for EV users while offering potential revenue opportunities for these businesses.

Furthermore, the statistically significant effect of electric grid infrastructure highlights the necessity of ensuring local electricity availability and strong grid connectivity when determining charger placement. Our findings suggest that while the presence of power plants significantly influences the distribution of normal chargers, it does not have the same impact on fast chargers. This indicates that proximity to power sources is more critical for sustained, slower charging. Policymakers should tailor infrastructure development to these differing needs: prioritizing normal chargers for overnight charging in residential areas and focusing on fast charging infrastructure along major transportation routes, where rapid, high-power charging is essential.

While our analysis offers insights into the factors that influence the placement of EV charging infrastructure, we acknowledge certain limitations. First, our focus is primarily on the determinants of existing charging infrastructure. The rapidly evolving nature of EV adoption and advancements in charging technology may shift these factors over time. Future research could investigate the impact of emerging technologies, such as wireless charging or ultra-fast chargers, on infrastructure planning and explore how these innovations might be seamlessly integrated into urban development strategies.

Second, although our analysis emphasizes variables like population density, road networks, amenities, and grid infrastructure, it does not fully address the behavioral dimensions of EV users, such as their charging preferences and travel habits. Understanding these behavioral patterns is vital for optimizing charger placement. Future research could incorporate survey-based insights or real-time usage data to provide a more nuanced understanding of user behavior. Lastly, our analysis reflects a policy landscape that is subject to change, providing a snapshot based on current regulations and incentives. Future studies should account for how evolving policies might reshape the accessibility and distribution of charging infrastructure. By addressing these limitations to complement our analysis, policymakers and urban planners can more effectively support the transition to electric mobility and contribute to broader environmental and sustainability goals.

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6 Appendix

Table 4: Amenities

Variable	Included Amenities (OSM Labels)
Errands	bakery, post_box, kiosk, atm, post office
Food and Beverages	cafe, restaurant, beverages, biergarten, fast_food, pub, bar
Shopping	mobile_phone, garden_centre, books, computer, toys, Florist, shoe, Bicycle,
-	jeweller, sports_shop, department_store, optician
Daily Essentials	greengrocer, pharmacy, butcher, supermarket

Table 5: Descriptive Statistics of Variables

Variables	N	Mean	SD	Min	Max
Chargers: Total	8170	7.64	17.59	0	524
Chargers: Normal	8170	6.23	16.54	0	523
Chargers: Fast	8170	1.41	3.11	0	53
Density: Population	8170	923.6	2228	0	26646
Density: Other Roads	8170	0.73	0.93	0	11.77
Density: Motorway Roads	8170	0.11	0.24	0	2.6
Amenities: All	8170	54.54	70.1	0	1122
Amenities: Errands	8170	18.56	17.99	0	202
Amenities: Shopping	8170	23.14	37.5	0	778
Amenities: Food and Beverages	8170	7.01	13.15	0	162
Amenities: Daily Essentials	8170	5.82	6.67	0	61
Motorway Link	8170	0.27	0.45	0	1
Fuel Stations	8170	2.36	2.12	1	18
Power Line Density	8170	0.24	0.33	0	3.75
Grid Intersections	8170	41.79	53.9	0	625
Power Plants	8170	0.25	1.32	0	38
Neighbor Power Plants	8170	1.57	3.5	0	46

Figure 5: Correlation among variables

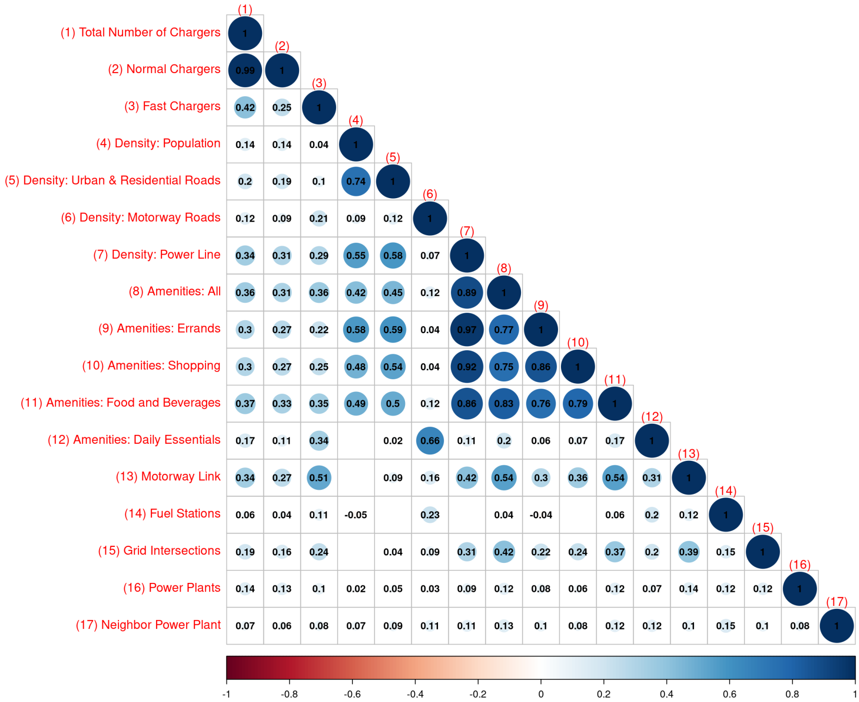

Table 6: Regression Results: OLS Estimation – Normal vs. Fast Chargers

	All	Normal Chargers					Fast Chargers				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	
Log(Population Density)	0.134	0.086	0.228	0.285	0.113	-0.220	0.048	0.062	0.063	0.035	0.040
	(0.305)	(0.279)	(0.262)	(0.280)	(0.265)	(0.310)	(0.047)	(0.047)	(0.047)	(0.047)	(0.048)
Log(Motorway Density)	4.562	3.606	2.903	3.279	3.574	3.130	0.955**	0.896**	0.926**	0.999**	0.904**
	(3.597)	(3.536)	(3.472)	(3.549)	(3.498)	(3.494)	(0.451)	(0.447)	(0.451)	(0.450)	(0.447)
Log(Other Road Density)	2.714*	2.243	2.956*	2.589*	3.634**	3.718**	0.471***	0.548***	0.510***	0.513***	0.598***
	(1.515)	(1.487)	(1.536)	(1.471)	(1.657)	(1.536)	(0.178)	(0.178)	(0.174)	(0.184)	(0.184)
Motorway Link Dummy	1.474	0.285	0.446	0.362	0.072	0.348	1.188***	1.200***	1.194***	1.163***	1.195***
	(1.024)	(1.010)	(1.008)	(1.009)	(1.014)	(1.006)	(0.134)	(0.134)	(0.134)	(0.134)	(0.134)
Fuel Stations	1.702***	1.089***	1.222***	1.268***	0.882***	0.915***	0.612***	0.624***	0.625***	0.584***	0.608***
	(0.189)	(0.178)	(0.142)	(0.165)	(0.136)	(0.159)	(0.029)	(0.028)	(0.028)	(0.029)	(0.029)
log(Power Line Density)	0.235	0.205	-0.267	-0.002	0.126	-0.268	0.030	-0.011	0.010	0.055	-0.014
	(0.774)	(0.739)	(0.702)	(0.750)	(0.713)	(0.741)	(0.152)	(0.153)	(0.151)	(0.154)	(0.153)
Grid Intersections	0.013**	0.010*	0.016***	0.015***	0.002	0.009*	0.002**	0.003***	0.003***	0.001	0.002**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Power Plants	0.994**	0.957**	0.998**	0.948**	0.955**	0.946**	0.036	0.039	0.036	0.036	0.036
	(0.413)	(0.400)	(0.403)	(0.400)	(0.399)	(0.399)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)
Neighbor Power Plant	-0.011	-0.011	0.005	-0.010	-0.016	-0.003	0.000	0.001	0.000	-0.001	0.001
	(0.073)	(0.070)	(0.070)	(0.070)	(0.069)	(0.070)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Amenity	0.049***	0.045***					0.003***				
	(0.012)	(0.011)					(0.001)				
Shopping			0.171***					0.010***			
			(0.032)					(0.004)			
Food and Beverages				0.067***					0.004***		
				(0.024)					(0.002)		
Errands					0.201***					0.019***	
					(0.025)					(0.004)	
Daily Essentials						0.485***					0.026**
						(0.094)					(0.010)
Number of Postcode Areas	8170	8170	8170	8170	8170	8170	8170	8170	8170	8170	8170
$R^2_{Adj.}$	0.254	0.205	0.199	0.201	0.204	0.202	0.341	0.340	0.341	0.343	0.341
FE: Municipality	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Constant term included but not shown. Robust standard errors are clustered at the municipality level and reported in parentheses.
The dependent variable is the log-count of EV charging stations, i.e., All (column 1), Normal (column 2-6), and Fast Chargers (column 7-11).
*: Significant at the 10% level. **: Significant at the 5% level. ***: Significant at the 1% level.

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