Closer, Cheaper, Better? Drivers of Electric Vehicle Charging Station Preferences

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I. Introduction

The global shift towards electrified transportation has become a strategic priority for many nations. At the COP28 climate summit, over 100 countries reaffirmed their commitment to accelerating electric vehicle (EV) adoption. COP28 CEO Adnan Z. Amin emphasized that " by 2050, electric vehicles would have to account for 80 percent of all road transport activity." Encouragingly, the EV market is already experiencing rapid growth: nearly one in five cars sold globally in 2024 was electric, and the total number of electric cars on the road reached 40 million, up from 14 million in 2023 (IEA, 2024[8]). Achieving long-term electrification goals, however, depends not only on technological progress but also on the availability of accessible and reliable EV charging infrastructure.

Governments worldwide have intensified efforts to develop public charging networks. For instance, China has mandated 100% EV-ready parking in new residential developments [4], the U.S. has allocated $521 million for expanding charging infrastructure (U.S. Department of Transportation, 2024[15]). China's development in the charging station market is particularly remarkable, it has built the world's largest public charging network (Wang et al., 2022[17]; Li et al., 2021[9]; Ma et al., 2019[11]), and announced to basically place

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in a high-quality charging infrastructure network by 2030 to support consumer's charging needs and new energy vehicles development. However, recent reports point to persistent issues in infrastructure layout, service quality, and uneven distribution across regions (State Council, 2023[12]). These challenges suggest that the current network may not fully align with consumer preferences, potentially reducing its effectiveness and limiting public satisfaction. Given the concentrated demand in urban areas (IEA, 2023[7]), optimizing the siting and characteristics of charging stations is essential to ensure infrastructure is both used efficiently and delivers value to EV users.

In this paper, we examine factors influencing consumer preferences for different EV charging station brands in China urban area. Prior research has studied EV user preferences across countries, focusing on factors such as price, charging speed, queuing time, use of renewable energy, and surrounding amenities ([1] [3] [13] [5][16]). However, many studies rely on stated preferences from surveys and do not incorporate real spatial or market data. In parallel, research in energy and GIS fields has explored optimal stations siting through spatial optimization models, but often without economic considerations such as price sensitivity or brand heterogeneity. Our study bridges these perspectives by combining geographic information system (GIS) analysis with economic modeling to estimate how factors like price and amenity proximity influence consumer choice in the EV charging station market.

To answer this question, we construct a unique panel dataset that combines economic and spatial data from multiple sources. We scraped required POIs (Point of Interests) from an online map platform for all provinces and administrative regions in mainland China, performed buffer analysis to quantify the proximity of amenities around charging stations. For price information, we scraped price information from 20 EV charging brands using WeChat Mini Programs across 31 provincial capitals, and simulated a time-series price dataset using monthly fluctuations in industrial electricity proxy rates. These data were then matched with brand-level usage and infrastructure data from the China Electric

Vehicle Charging Infrastructure Promotion Alliance (EVCIPA).

Analyzing based on multinominal logit model, our results show that consumers prefer charging stations near residential areas and restaurants, while business-area proximity appears to reduce consumer utility. We also find that larger firms face less elastic demand, and a counterfactual simulation shows that a merger among the five largest firms would further reduce price sensitivity to nearly unitary elastic. Our findings provide actionable insights for both charging station operators and policymakers seeking to improve infrastructure planning and promote broader EV adoption.

The remainder of this study is organized as follows. Section 2 reviews the existing literature on consumer preferences for EV charging infrastructure. Section 3 outlines the empirical framework used to study the drivers of consumers' choice among charging stations. Section 4 presents the data and processing procedure. Section 5 presents the result. Section 6 concludes the study with key insights and implications. Appendix A provides supplemental visualizations.

II. Literature Review

For charging stations to support EV adoption effectively, several key factors must be considered. One of the most prominent topics in EV charging station literature is location optimization, with research on this subject growing exponentially. Pinto et al. (2024)[14] conducted a systematic review reporting that a search of the Scopus database yielded 5,717 publications on EV charging station location selection as of February 2024. These studies employ advanced optimization techniques, such as multi-criteria decision-making (MCDM) and spatial network models, providing a robust foundation for aggregate electricity infrastructure planning and optimal station deployment. However, while these studies excel in optimizing locations from an engineering perspective, they often overlook consumer choice behavior and preferences, which are critical in economic analyses. This limitation reduces their applicability for understanding user-based decision-making and choice dynamics. Our study also incorporates spatial factors and surrounding amenities but takes a more user-oriented approach. We retrieve real-time spatial data from online maps and integrate it with consumer preferences to analyze the factors influencing consumers' choice for charging stations.

In addition to location optimization, understanding consumer preferences is crucial for ensuring the effective utilization of charging stations.A growing body of literature has explored factors influencing consumers' choice of charging stations and how consumers interact with and use this infrastructure. While the jury is still out on consumers' specific usage patterns and explicit preferences, a consensus has begun to form on a few key insights.

A key consensus is that the location and surrounding amenities of charging stations significantly affect their attractiveness. Charging stations located near homes, workplaces, and other public spaces are often prioritized (Hardman S., et al. (2018)[5], Visaria, A. A., (2022)[16], Yang, M., & Lin, B. (2024)[18]) to be the most ideal location for charging station, while the concept of "other locations" is vague and would be discussed later on. Hardman S., et al. (2018)[5] compared the importance of these three places using existing evidence and found them to be tiered as follows: home locations as the most important, workplaces second, and other public locations third. Visaria, A. A., (2022)[16] further conclude that these locations are more prominent within cities, while charging stations between cities for stops during long trips are also important. For specific publicly accessible locations, shopping malls, retail stores, highway service areas/motorway service stations, gas stations, restrooms, restaurants and sports center are potential candidates. (Lin, W., et al., (2024)[10], Yang, M., & Lin, B. (2024)[18], Visaria, A. A., (2022)[16], Philipsen, R.,et al., (2016)[13]). Nevertheless, existing literature has not integrated real charging station locations and their nearby amenities to empirically estimate their impact on users' choice. Instead, most studies rely on user surveys to infer the importance of these amenities. As a result, there is a clear need for real-time spatial data and rigorous spatial analysis to provide more robust insights into users' actual choices.

Another consensus is about pricing. Since one of the promising advantages of adopting EVs is their low operation fee compared to conventional gasoline cars (Hardman et al., 2018[5]), to keep this benefit, EV owners are not expecting to see a pricy charging rate. Furthermore, as the charging market gathers pace, overall EV charging cost have become more affordable (Chen, T., et al(2020)[2]). Consumers therefore become more resistant to any incremental changes of price as they have already acclimatized themselves to a low price. More specifically, Brückmann, G., & Bernauer, T. (2023)[1] showed that the probability of choosing a charging station will increase 0.15 percentage points if the charging price decrease by 1 CHF (Swiss Franc, equals to 8.16 CNY or 1.12 USD). However, interestingly, the development of charging infrastructure made consumers more accepting of price increases (Yang, M., & Lin, B. (2024)[18]), which implies consumers' demand elasticity of price may vary in cities with different development level and by time. For instance, China's cities are categorized into different tiers based on their level of development, and cities in US are often informally categorized into tiers based on their economic and real estate markets. And as time goes by, charging infrastructures are likely evolved. Hence how price affect users' choice remains an open question, inviting further exploration to address this gap in the literature.

While location and pricing are key factors influencing user preferences, understanding how these insights are derived is equally important. Existing studies employ various methodologies to explore these relationships, some common methods can be questionnaire surveys, interviews and modelling (Hardman et al., 2018)[5]. It is also common to see researchers integrate qualitative and quantitative methods Chen, Y., & Lin, B. (2022)[3] conducted a web-based survey in four of China's most developed first-tier cities, which have the highest EV adoption rates and the most developed charging infrastructure. They then applied an ordered logit model to analyze factors influencing consumer satisfaction. Visaria, A. A., (2022)[16]interviewed 11 EV owners in Facebook forum and conducted two stated-choice (SC) experiments to 558 EV users in Danish to collect data, and they analyze the data using mixed logit model to see how key factors of the charging process affect users' choice of charging stations. Yang, M., & Lin, B. (2024)[18] used an online questionnaire in first-tier cities in China to gather data, and then developed a series of logit models to analyze how consumer behavioral traits influence consumers' category preferences for charging infrastructure. Not hard to infer, logit models have quite promising analytical performance in consumers' choice analytics and surveys remain a popular method for data collection. However, few studies have utilized alternative data sources beyond surveys for user choice analysis. Survey data, while valuable, often suffer from limitations such as response bias and may fail to fully capture actual consumer behavior in real-world settings.

While consumer preferences and charging station choice are the primary focus of our study, competition and firm strategies offer valuable context for understanding market dynamics. Zhao et al. (2020)[20] explored price optimization and investment strategies for new entrants in the fast-charging station market, highlighting the competitive nature of for-profit investors. Similarly, Zavvos et al. (2021)[19] examined location and pricing strategies in a competitive setting. These studies provide important theoretical insights into firm behavior but often overlook the role of collaboration or mergers in improving profitability. Our model extends this discussion by estimating the potential impact of merger behavior on the charging station market, offering a broader perspective on firm strategies.

In summary, while existing literature has provided valuable insights into surrounding amenities, pricing, and methodologies for understanding consumer preferences, several gaps remain. First, the influence of specific amenities (e.g., residential areas, business zones, and food services) on charging station market share is not well quantified. Second, the sensitivity of users to charging prices in China market remains underexplored. Finally, most studies rely heavily on stated preferences, which may not accurately reflect real-world consumer behavior.

To address these gaps, our study uses real-world data from China's urban charging market combined with GIS-based spatial analysis to examine how amenities such as residential areas, business districts, and restaurants influence users' choice of charging stations. Additionally, we analyze price sensitivity and estimate the impact of merging behavior on the charging station market, providing actionable insights for policymakers and charging station operators to optimize infrastructure planning and decision-making.

III. Method

We employed the logit model to analyze how consumers choose between different electric vehicle charging station according to the features they possess. A common starting point for discrete choice models is the random utility maximization (RUM) framework. According to this framework, the utility that an individual h derives from choosing an alternative j can be expressed as:

$$U_{hj} = V_{hj} + \epsilon_{hj}$$

where V_{hj} represents the systematic component of utility that depends on the observed attributes of product j and the characteristics of the decision maker h (unobservale to researchers) and ϵ_{hj} is a random error term that captures unobserved factors and idiosyncratic preferences. The error term ϵ_{hj} is independently and individually distributed, assumed to be independent of the explanatory variables that enter through V_{hj}, and follows Extreme Value Type 1 distribution.

In our research, we model the utility function as follows:

$$\begin{aligned} U_j = \beta_o + \beta_1 \cdot log(Quantity_j) + \alpha \cdot P_j + \gamma_b Brand \\ + \beta_2 \cdot Business_j + \beta_3 \cdot Residence_j + \beta_4 \cdot Restaurant_j + \epsilon_j \end{aligned} \tag{1}$$

At this individual level, the variables can be explained as follows:

U_j: The (indirect) utility that a consumer derives from choosing a charging station j.

β_o: the constant term, refers to the baseline level of utility associated with the alternative when all explanatory variables are set to zero, relative to the chosen reference alternative

$Quantity_j$: The total number of electric vehicle charging piles owned by the brand to which station j belongs.

P_j: The average price charged by the brand that operates station j.

Brand: brand fixed effects, capturing unobserved, time-invariant brand characteristics that may influence consumer choices.

$Business_j, Residence_j, Restaurant_j$: Binary indicators for the amenities around charging station j. 1 if there is at least one corresponding amenity (a business building, residential area, or restaurant, respectively) within a defined proximity to that station, and 0 otherwise.

ϵ_j: idiosyncratic preference for charging station j, which is unobservable in data. It is i.i.d. distributed, follows a Type I Extreme Value distribution under the logit model.

Then, by aggregating individual choice probabilities over a large population of consumers, we obtain the market share for each brand. In other words, the probability that an individual consumer selects a particular brand can be interpreted, at the aggregate level, as the market share that brand i attains in the overall market.

$$s_j = \frac{e^{U_j}}{1 + \sum_{i=1}^{k} e^{U_i}} \tag{2}$$

where k indicates totalling k brands in the market, and the denominator includes the outside option ($U_0 = 0$)

To estimate the model using linear regression techniques, we transform the market shares into log-odds form using the outside option s_0 as the baseline:

$$
\begin{aligned}
\ln(s_i) - \ln(s_0) = U_i& \\
&= \beta_0 + \beta_1 \cdot \ln(Quantity_i) + \alpha \cdot P_i \\
&\quad + \gamma_b \cdot Brand + \beta_2 \cdot X_{Business,i} \\
&\quad + \beta_3 \cdot X_{Residence,i} + \beta_4 \cdot X_{Restaurant,i} + \epsilon_i
\end{aligned} \tag{3}
$$

Notice that $X_{Business,j}$, $X_{Residence,j}$, and $X_{Restaurant,j}$ are not binary variables. These variables represent the proportion of a brand's charging stations that are located near amenities.

This is because when we model market shares instead of individual choices, we don't know exactly which station each consumer picks. We only have the market share for a brand, which is an average across many stations. In this case, we need to aggregate the station-specific characteristics to match this brand-level data. So, instead of saying that a single station has an amenity, we use the proportion of a brand's stations that are near amenities.

To make the transition clearer, when we move from individual stations to brand-level data, we combine the characteristics of all the stations to reflect the overall profile of the brand.

The same idea of utility applies whether we are looking at individual stations or market shares. At the individual level, U_j represents the utility of the consumer derives from choosing charging station j based on observable characteristics. When we move to brand-level market shares, we aggregate station-level characteristics (e.g. price or proximity to amenities) into brand-level averages or proportions, but the concept of utility stays the same. In this context, U_j reflects the average utility of a brand, based on all its stations, rather than just one. Despite this aggregation, the multinomial logit model remains applicable, as market shares still reflect the relative differences in utility across alternatives.

From the estimated coefficients, we can determine the directional influence of each factor on the choice of the station. Moreover, the own price elasticity of demand can be calculated by the following formula, so that we can observe how sensitive market shares are to price changes:

$$Elasticity_j = \frac{ds_j}{dp_j}\frac{p_j}{s_j} = -\alpha \cdot P_j \cdot (1 - s_j) \tag{4}$$

As in most discrete choice models, it is a natural way to utilize the ratio of coefficients to interpret the monetary value the consumers place on a characteristic. Specifically, we compute the marginal willingness to pay (WTP) as the ratio of the attribute's coefficient to the price coefficient:

$$WTP_j = \frac{\beta_j}{|\alpha|} \tag{5}$$

This ratio gives the average consumer's willingness to pay (in CNY) for a one-unit change in the attribute.

IV. Data

We compiled a comprehensive panel dataset from multiple authoritative sources to examine key factors influencing consumers' choice of charging stations. This dataset, spanning from October 2023 to October 2024, was constructed through a combination of Python-based web scraping techniques and manual data collection. The dataset includes monthly data on (1) the total charging volume of each brand (nationwide), (2) the number of charging piles owned by each brand (nationwide), (3) the average charging price of each brand (nationwide), and (4) the percentage of charging stations with nearby business buildings, residential areas, and restaurants.

The primary data sources are the China Electric Vehicle Charging Infrastructure Promotion Alliance (EVCIPA), a nonprofit organization under the guidance of the China

National Energy Administration; AMAP, a comprehensive navigation and travel platform developed by Amap Software; and the State Grid Corporation of China (SGCC). These data collectively provide a robust foundation for analyzing consumer preferences and charging station choices.

Price

The price variable is calculated as the average charging price of a brand across all cities in China for a given month. For price information, we collected data for 20 brands using their respective WeChat Mini Programs in September 2024. These mini-programs are lightweight applications that do not require installation, providing a convenient source for price data. While this method inherently excludes brands without online mobile services, we later matched these 20 brands with additional data from the Electric Vehicle Charging Infrastructure Promotion Alliance (EVCIPA) to obtain non-price-related information required for our analysis. Through this matching process, we observed that these brands collectively account for a dominant share of the Chinese charging station market. This outcome reinforces the representativeness of our sample and suggests that the risk of significant selection bias is limited, ensuring the reliability of our dataset.

We selected the capital cities of all provinces, autonomous regions, and municipalities in mainland China (22 provinces, 5 autonomous regions, and 4 municipalities) as representative locations. For each brand, we used the average of the highest and lowest prices within a province as its representative price. To mitigate potential biases from time discrepancies in data collection, which could artificially influence observed price fluctuations, we adopted a consistent methodology: using charging platform filtering functions to sort prices from highest to lowest during the peak time of 18:00–21:00. Deviations from this timeframe (e.g., 17:00–21:00 or 19:00–22:00) were normalized to align with the 18:00–21:00 period for consistency. For a visualization of price data, see Appendix A.

Due to the unavailability of actual monthly charging price data for different charging station brands, we adopted a simulation approach to construct a time-series dataset for analysis. This approach utilizes monthly fluctuations in proxy electricity rates for industrial and commercial users, published by the State Grid Corporation of China (SGCC), to estimate the variation in charging prices. By using the September 2024 charging price as the baseline, we projected monthly price levels based on observed market rate fluctuations, resulting in a continuous time-series dataset for charging prices.

The proxy electricity rates (proxy rates) are regulated and unaffected by market competition, ensuring consistency across different charging station operators. According to Southern Energy Watch,a journal overseen by China Southern Power Grid (another state-owned enterprise governed by the Chinese government), most charging station operators procure electricity through the grid enterprise's proxy-purchasing mechanism, making proxy rates a reasonable estimate of their electricity procurement costs. To simulate monthly charging prices, we collected proxy rates for all provinces, municipalities, and autonomous regions in mainland China from October 2023 to October 2024. The detailed methodology and assumptions are outlined below:

$$P_{itn} = P_{\mathrm{i,baseline,n}} + (\mathrm{Rate}_{tn} - \mathrm{Rate}_{\mathrm{baseline,n}}) \,, \tag{6}$$

where P_{itn} represents the simulated charging price for brand i in province n, month t, $P_{\mathrm{i,baseline,n}}$ is the baseline month's charging price, $\mathrm{Rate}_{tn}$is the proxy rate in province n, month t, $\mathrm{Rate}_{\mathrm{baseline,n}}$ denote the proxy rates for the baseline month, respectively.

For example, if the Teld charging price in September 2024 in Szechuan Province is 2 CNY/kWh, the proxy rate for September 2024 in Szechuan Province is 1 CNY/kWh, and the proxy rate for August 2024 in Szechuan is 2 CNY / kWh, then the Teld charging price for August 2024 in Szechuan is simulated as:

$$2 + (2 - 1) = 3\,\mathrm{CNY/kWh}.$$

Our simulation methodology relies on several key assumptions. First, it is assumed that fluctuations in proxy electricity rates are linearly transmitted to charging prices, meaning that a 1 CNY change in the proxy rate corresponds to a 1 CNY change in charging price. Second, non-electricity costs such as service fees, operational expenses, and market-related factors are considered stable in the short term, ensuring that they do not significantly influence the observed price variations. Lastly, it is assumed that the effect of electricity cost fluctuations on charging prices is consistent across different regions and brands, allowing for uniform application of the simulation model.

Market Share and Quantity

We used monthly charging volume to represent each brand's sales, and market share for each brand was calculated by dividing its monthly charging volume by the total monthly charging volume across all brands. The ”outside option” refers to brands that have their charging volume data recorded by EVCIPA but do not have available price information. This lack of price data is primarily because these brands either do not have WeChat Mini Programs (which would allow us to scrape price data) or do not publish price datasets publicly. We used the total number of charging piles as a control variable to account for the potential scale effect on charging volume. We collected monthly charging volume data for 41 brands and total charging pile data for 37 brands from October 2023 to October 2024. This information was sourced from the China Electric Vehicle Charging Infrastructure Promotion Alliance (EVCIPA) and required manual aggregation to ensure its usability for analysis.

Spatial Data

Proximity was represented by the spatial relationship between charging stations and nearby amenities. Specifically, we defined proximity as the presence of amenities—such as restaurants, business buildings, and residential areas—within a predefined buffer zone around each charging station. Intuitively, in Fig. 1, the icon featuring a lightning bolt represents a charging station, while the orange circular region around it indicates the predefined buffer zone. Three restaurants, represented by the fork and knife icons, are located within this predefined proximity.

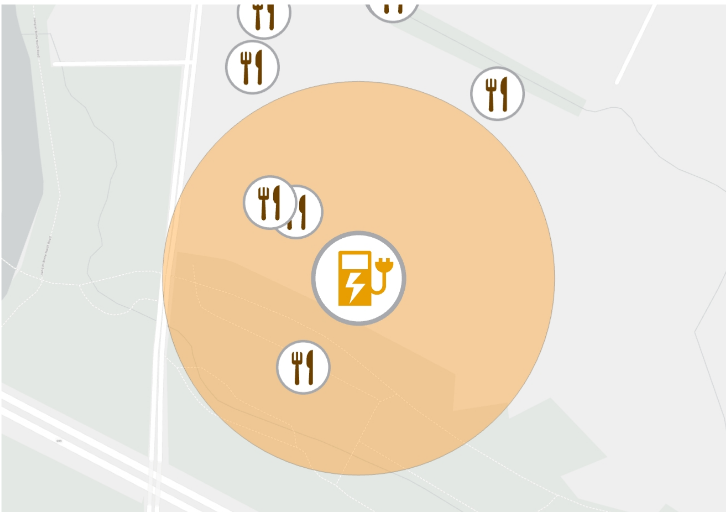

Figure 1: Proximity to Restaurants

Specifically, the defined proximity for restaurants is 200 m, and 1 km for residential area and business buildings. Initially, we planned to set a uniform 1-kilometer threshold for all amenities. This decision was based on the functionality provided by charging station brands' WeChat Mini Programs, which allow users to input a specific location (e.g., PwC Building) and filter charging stations within a selected distance, with options limited to 1 kilometer or greater. Since we focused on central urban areas with relatively compact spatial coverage, a 1-kilometer range was considered appropriate for capturing relevant charging stations within these regions.

However, upon further exploration, we discovered a different feature within the Mini Programs available on individual charging station detail pages. This feature displays nearby services, with the first category prominently being restaurants. If users do not select the option to "View All Restaurants," they are presented with only the ten closest restaurants, most of which are located within approximately 200 meters. Notably, this feature does not display nearby residential areas or business buildings. Based on this observation, we decided to apply a differentiated approach to distance thresholds. Specifically, we set the threshold for restaurants to 200 meters, reflecting the closer proximity commonly emphasized in the Mini Programs, while maintaining a 1-kilometer threshold for residential areas and business buildings to align with the search filtering functionality. We created a thematic map showing the proximity of EV charging stations to business buildings in a sample area. For details, see Appendix A.

Spatial data on amenities and charging stations were primarily obtained from AMAP. We scraped Points of Interest (POIs) for restaurants, business buildings, and residential areas (including villas, residential quarters, dormitories, and community centers), as well as charging stations within the central area of capital cities of all provinces, autonomous regions, and municipalities in mainland China (22 provinces, 5 autonomous regions, and 4 municipalities). The central area was defined as a rectangular region centered on the city's geographic coordinates.

Fig 2 provides an example. The orange-colored areas represent capital cities in China, with the larger highlighted area corresponding to Chengdu, the capital city of Sichuan province. The POI data points (depicted in orange-red) were retrieved from a rectangular area centered on the geographic coordinates of Chengdu.

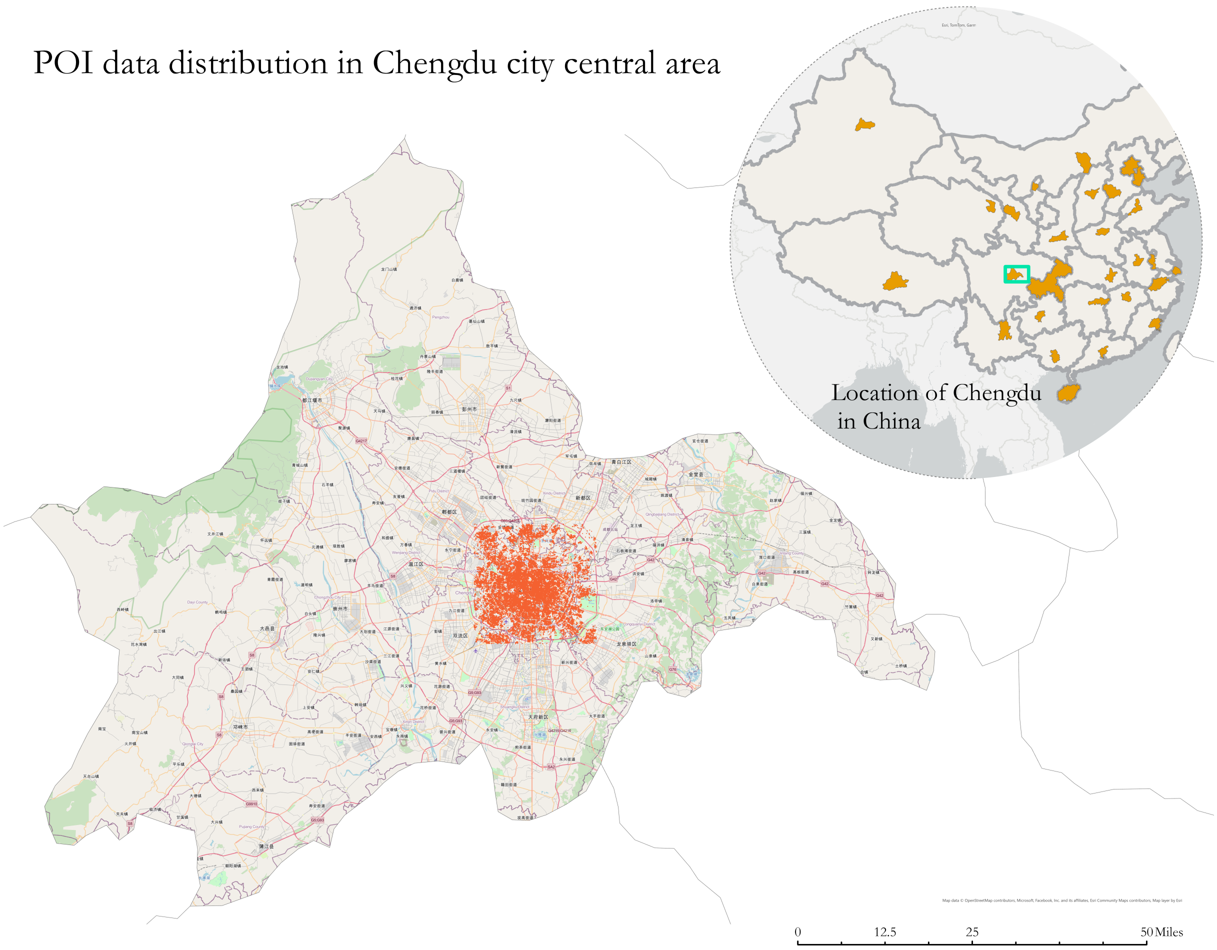

Figure 2: Map for POIs in Chengdu

We used the standardized China base map for spatial alignment and analysis and ArcGIS Pro to integrate and visualize the data.

Summary Statistics

In summary, we collected monthly electricity price data across provinces and regions, totaling 390 observations; monthly sales and quantity data, totaling 470 observations; and POI data comprising approximately 600,000 records, including details on restaurants, business areas, residential areas, and charging stations.

Through data merging and transformation, we produced a cleaned and consistent dataset comprising 193 observations for the regression analysis. Summary statistics for the key variables are presented in table 1 below:

Table 1: Summary Statistics

Variable	Mean	Std. Dev.	Min	25%	50%	75%	Max
Quantity	151,088.98	210,686.02	3,068	13,296	36,320	163,328	671,023
Sales	25,290.95	34,373.71	107	1,959.25	7,109	44,284.25	122,011
Price	1.28	0.12	1.01	1.20	1.28	1.33	1.56
Business Percent	0.84	0.17	0.33	0.84	0.89	0.94	1.00
Residence Percent	0.78	0.17	0.08	0.71	0.85	0.85	1.00
Restaurant Percent	0.80	0.17	0.33	0.76	0.85	0.89	1.00

Notes: Business Percent is the percentage of charging stations in our dataset that have at least one business building within 1 km distance. Other ”Percent” variables follow the same idea. For more detailed variable definitions, refer to the main text.

The usage of charging piles shows a significant variation, with a mean of 151,088.98 kWh, ranging from a minimum of 3,068 kWh to a maximum of 671,023 kWh. This disparity is largely due to the market dominance of the three largest brands—Teld, StarCharge, and YKC—which collectively own over 50% of the total charging piles in China, with each holding nearly 20%. In contrast, the next three largest competitors each account for around 5% of the market, while smaller firms hold less than 3% of the charging piles. Sales, represented by charging volume data, exhibit similar variability. The average charging volume is 25,290.95 kWh, with a standard deviation of 34,373.71 kWh, spanning from a minimum of 107 kWh to a maximum of 122,011 kWh. This variation reflects the uneven scale of firms within the charging station market, where the three largest brands—Teld, StarCharge, and YKC—dominate approximately 75% of the market.

Given that charging volume tends to increase with the number of charging piles, there is a concern that market share may primarily capture the scale effect rather than the impact of other variables of interest. Figure 3 illustrates the positive correlation between the number of charging piles (quantity) and the charging volume (sales)as well as the huge difference between big businesses and smaller firms. Therefore, we control for the quantity of charging piles in our model to account for scale effects.

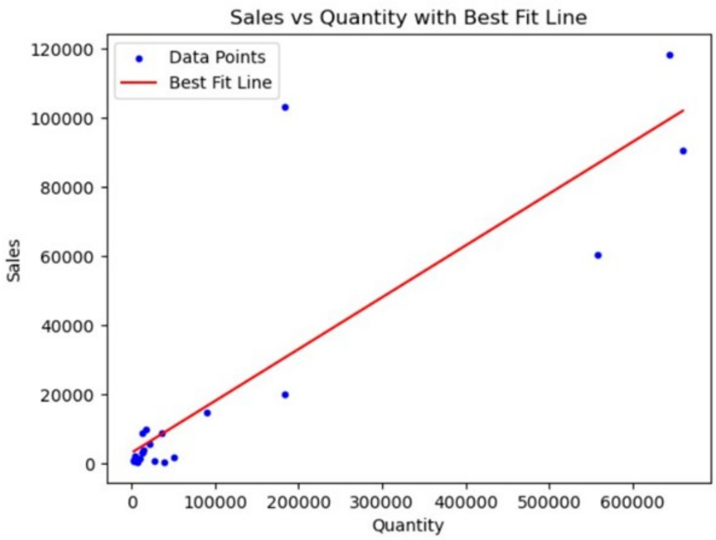

Figure 3: Quantity-Sales

The charging price, standardized as a national average, has a mean of 1.28 CNY/kWh with a relatively small standard deviation of 0.12 CNY/kWh. Prices range from 1.01 to 1.56 CNY / kWh, indicating a limited price variation between charging stations.

In terms of proximity to amenities, the business percent variable indicates that, on average, 84% of charging stations are located near business areas, with values ranging from 33% to 100%. Similarly, the restaurant presence variable shows comparable results, with an average of 80% and a range from 33% to 100%. In contrast, residential presence averages 78%, slightly below the 80% level, with a noticeably smaller minimum of 8%, compared to the former two types of amenities.

These percentages reflect the general accessibility of facilities near charging stations, suggesting that most brands recognize the importance of proximity to these amenities in attracting consumers. Specifically, the preference for locations near business buildings and restaurants may stem from the belief that these areas provide greater access to potential customers. Hence, it is reasonable to hypothesize a positive relationship between the presence of amenities and market share.

V. Results

In this section, we present the estimation results for factors influencing consumers' choices among EV charging station brands, as well as the relationship between market share and own-price elasticity of demand. We use the logit model (3) to estimate how brand-specific attributes affect market share, and extend the model to a counterfactual experiment in which the five largest firms merge, jointly capturing 80% of the market. Table 2 reports the baseline effects of price and non-price characteristics on consumer choice, and table 3 shows 17 brands' market share and own-price elasticity. For comparison, Table 4 displays both the original estimates and the results from the counterfactual merger scenario.

Table 2: Regression Results

Dependent variable:	$\ln(s_j - s_0)$
business	-4.013***
	(0.957)
const	-9.180***
	(2.133)
log_quantity	1.111***
	(0.190)
price	-3.496*
	(1.583)
residence	3.854***
	(0.457)
restaurant	0.825***
	(0.240)
Observations	192
R^2	0.972
Adjusted R^2	0.969
Residual Std. Error	0.313 (df = 173)
F Statistic	332.022 (df = 18; 173)

Note: *p<0.1; **p<0.05; ***p<0.01
This table excludes brand fixed effect variables to focus on key predictors.

Proximity to residential areas and restaurants positively correlates with market share. According to our WTP estimates, a consumer is willing to pay approximately 1.10 CNY more for a charging station located near a residence than for one that is not, and 0.24

CNY more for a charging station located near a restaurant than for one that is not. This aligns with our hypothesis and literature that electric car users prefer charging stations with restaurants and/or other amenities([16],[1]). The stronger correlation for residential areas likely reflects the EV users preference for charging near home at night([16]). Interestingly, proximity to business buildings shows a negative relationship with market share. Consumers require a 1.15 CNY price discount to choose a charging station near business buildings. Business areas may imply limited parking availability, higher congestion, or restricted access during certain hours especially peak time at night, all of which may reduce the perceived utility of these charging stations. Further research is needed to better understand this result.

Price exhibits a strong negative relationship with market share, confirming that higher prices deter consumers and reduce utility. Table 3 reports the market shares and own-price elasticities for the major EV charging station brands in our sample. The three largest brands together account for over 60% of the market, with relatively inelastic demand (e.g., -3.603 to -3.863). In contrast, smaller brands such as South Grid and Weilankuaichong face significantly more elastic demand (e.g., -5.344 to -5.677). Although price elasticity varies for firms with smaller market shares, it generally increases with market share.

To further explore market dynamics, we simulated a counterfactual scenario where the five largest firms merge, collectively occupying 80% of the market share. The newly merged firm's price was calculated as the weighted average of individual firms' prices, with sales and quantities summed across firms. Proportions for residential, business, and restaurant proximity were computed as quantity-weighted means. Table 4 shows that comparing to the real market, the price coefficient remains negative and statistically significant (–3.788), though its magnitude increases slightly. In contrast, the amenity-related variables display extremely large and statistically insignificant coefficients, with standard errors exceeding 500 for restaurant proximity and nearly 900 for business areas. A possible explanation is that in the counterfactual market, the model is no longer able to reliably identify the

Table 3: Market Share and Price Elasticity

Brand	**Market Share**	**Price Elasticity**
Teld	0.239	-3.603
Xiaojuchongdian	0.196	-3.854
StarCharge	0.183	-3.863
YKC	0.115	-4.265
Weijingyun	0.036	-4.695
South Grid	0.027	-5.344
Weilai	0.018	-5.087
Wanmaaichong	0.018	-4.405
Jingchong	0.017	-5.042
GAC Energy	0.011	-4.399
Jingneng	0.007	-3.966
Kaimaisi	0.007	-4.918
Zhonghehuitian	0.004	-4.542
Weilankuaichong	0.004	-5.677
Jinzhuang	0.002	-3.907
Yichongwang	0.001	-4.177
Joycharge	0.001	-5.017

marginal utility of specific amenities. Because the merged firm owns a large and diverse network of stations, it is no longer easy to say whether a consumer chose it because of restaurant proximity or despite business district location. Those spatial features become too averaged or widespread to matter — they don't help distinguish choices across brands anymore. Despite the loss of amenity interpretability, the model fit remains relatively strong.

The fig. 4 shows our estimation for their market share and price elasticity. The merged company owns nearly 80 percent of the market, and its elasticity is nearly unitary elastic, while aligns with multinomial logit model. This substantial decline indicates that the merged firm would face much weaker competitive pressure and could raise prices with minimal loss in market share.

Table 4: Regression Results: Real Market and Counterfactual Market

Real Market			Counterfactual Market		
Variable	Coef.	Std. Error	Variable	Coef.	Std. Error
Constant	-9.180***	(2.133)	Constant	94.773	(338.629)
log_quantity	1.111***	(0.190)	log_quantity	1.235***	(0.250)
price	-3.496**	(1.583)	price	-3.788*	(1.919)
residence	3.854***	(0.457)	residence	-35.521	(153.481)
restaurant	0.825***	(0.240)	restaurant	198.100	(514.559)
business	-4.013***	(0.957)	business	-282.192	(892.094)
Observations	192		Observations	140	
R^2	0.972		R^2	0.964	
Adj. R^2	0.969		Adj. R^2	0.959	
Residual Std. Err	0.313 (df=173)		Residual Std. Err	0.366 (df=123)	
F Statistic	332.022 (df=18; 173)		F Statistic	205.570 (df=16; 123)	

VI. Conclusion

In this study, we examined the factors influencing consumer choices for electric vehicle charging stations in China, leveraging a logit model to uncover the relationships between prices, amenities, station availability, and market share. We found that proximity to residential areas and restaurants may significantly enhance a charging station's attractiveness, while the presence of business buildings nearby shows limited positive impact on consumers utility. These findings suggest that, for operators, siting stations near residential and dining areas could be an effective strategy for expanding market share. For policymakers, increasing coverage in high-density residential and dining zones may help meet consumer charging demand and promote EV adoption more broadly.

We also find that price is negatively associated with market share, consistent with economic theory. Within the prevailing pricing range of 1 to 2 CNY per kilowatt hour, we observed a high price elasticity. Specifically, a 1 CNY increase in price leads to a notable decline in market share, underlining the sensitivity of consumers to price changes in the real market.

Furthermore, large firms demonstrate lower price elasticity compared to smaller firms,

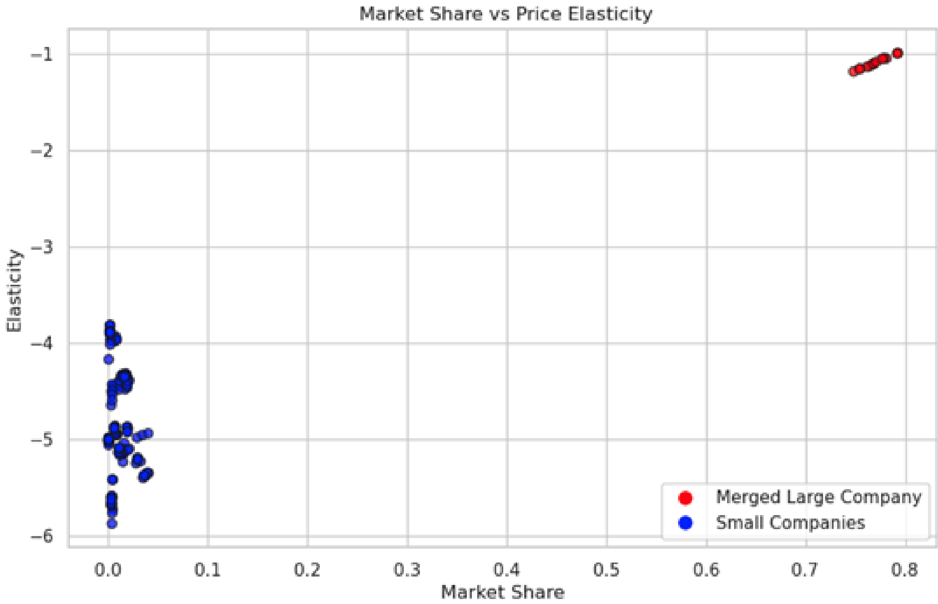

Figure 4: Highly Concentrated market

reflecting their market power and ability to sustain higher prices without significant loss in market share. This advantage becomes even more pronounced in a counterfactual scenario where the five largest firms merge into a single entity with 80% market share and their elasticity approach unit elasticity.

Overall, our findings highlight the critical role of strategic pricing, thoughtful spatial planning, and infrastructure scaling in shaping consumer behavior and market dynamics. These insights can help charging station operators optimize location strategies, pricing policies, and expansion plans while assisting policymakers in formulating targeted interventions to support the sustainable growth of China's EV charging infrastructure.

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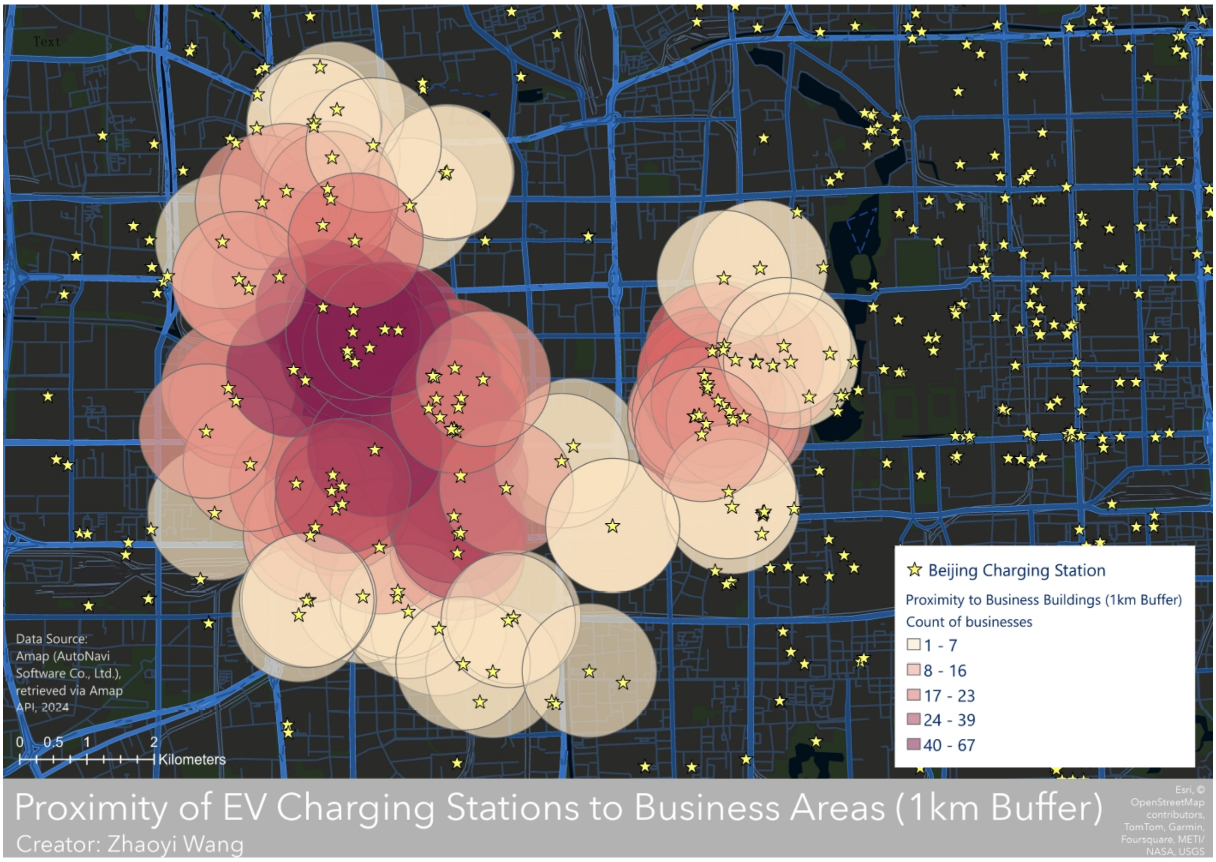
Appendix A: Supplemental Visualizations



The thematic map shows a sample area within central Beijing, illustrating the proximity of EV charging stations to business buildings. Each yellow star represents a charging station, with a 1-kilometer buffer applied to identify surrounding business buildings. The increase in business building density is represented by darker shades of pink, i.e. light tones indicate fewer nearby business buildings and deeper pink reflects higher concentration.

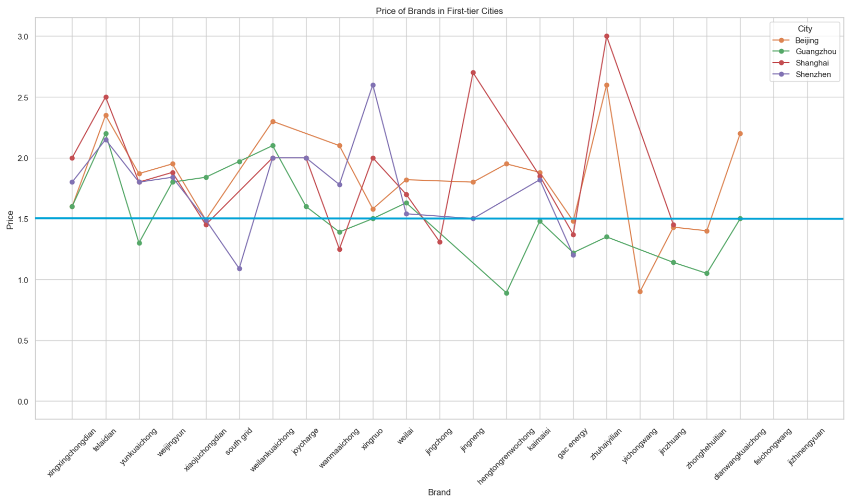


Figure 5: first tier

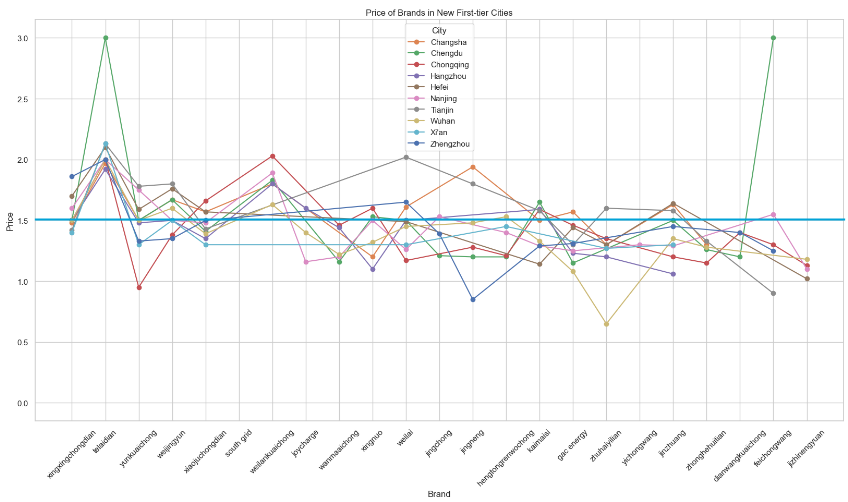


Figure 6: new first tier

We compared the pattern for prices in different cities citing a commonly accepted classification mechanism proposed by Yicai Research Institute (2023)[6], which labels cities in China as first-tier, new first-tier, second-tier, third-tier, and fourth-tier. By synthesizing concentration of commercial resources index, city as a hub index, urban residents' activity index, lifestyle diversity index, and future potential index, this mechanism is highly credible and is commonly cited in government reports. Fig 5 and fig 6 compared charging price of each brand in first-tier cities, which are the most well-developed metropolises across China and new first-tier cities, which are relatively less well-developed.

The price of each kWh of electricity is higher in more developed cities. Using the price of

1.5CNY/kWh as a threshold, we observe that in first-tier cities, 68.18% of the prices are set above this level, while the distribution is approximately 45.57% above the threshold and 54.42% below in new first-tier cities.