The impact of the built environment on car parking duration

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Short summary

Parking regulation is a tool of choice in urban access regulation policies. However, this policy has many ripple effects and challenging to design and implement. This paper seeks to improve the understanding of parking demand by focusing on the link between the built environment and parking durations. The research leverages a unique dataset of parking payment transactions in Lyon, France. Using both unsupervised and supervised machine learning algorithms, the analysis quantifies the influence of spatio-temporal patterns and built environment characteristics. The findings highlight that parking durations are predominantly driven by parking design variables and that the other built environment dimensions are of least importance.
Keywords: built environment, duration, machine learning, parking, transactions

1 Introduction

Parking regulation is one of the oldest policies to regulate car use in urban areas (Desvergnes & Crest, 2000). Since its introduction, this regulation has continuously evolved to meet competing objectives, ranging from ensuring car access to city centers to mitigating the growing scarcity of available urban space (Russo et al., 2019). Today, car parking regulation is often presented as a key lever to mitigate car use in urban areas. However, this regulation has many ripple effects that go beyond car use to impact urban accessibility, city attractiveness, congestion, pollution, social and spatial equity, and city revenues. Consequently, the definition and implementation of a parking regulation is often challenging. A prerequisite for this implementation is understanding the demand for parking. The objective of this research is to investigate aggregate parking demand using unique data from parking meters in Lyon.

The demand for parking can be characterized by two main indicators: parking volumes and durations. Both indicators convey information on demand levels. Existing studies have predominantly examined parking volumes (Ghuzlan et al., 2016; Hunt & Teply, 1993), with limited attention to parking duration. However, this duration influences not only space availability but also parking turnover and revenue generation. Theoretically, the parking duration should be directly related to the activity duration of car users (implicit assumption). These activities should also be strongly correlated with the built environment around the parking location (implicit assumption). Therefore, we assume that the built environment has an influence on parking durations (main assumption). The influence of the built environment is evident in the case of parking volumes, but it remains to be demonstrated in the case of parking durations. This research aims to investigate this assumption.

The literature on the impact of the built environment on parking durations is very limited. Parmar et al. (2021) used neural networks to examine the impact of driver characteristics and land use on parking durations in Delhi, India. The authors highlighted the role of land use in shaping parking behaviors, noting that areas with many commercial activities tend to have shorter average parking durations than other zones. A recent study in Xi'an, China, also highlighted the importance of land use (Xie et al., 2024). The authors combined parking records and POI data to show that the presence of commercial facilities has a positive effect on parking duration on weekdays, but a negative effect on weekends (Xie et al., 2024). Building on this limited body of literature, this article aims to address the need to better understand urban parking duration and their interplay with the built environment. For this, this research uses unique data on parking transactions from Lyon.

Indeed, most studies on parking demand are based on survey data and stated preferences (Zong et al., 2019; Hilvert et al., 2012; Nurul Habib et al., 2012; Hensher & King, 2001). However, the recent development of transaction data from parking payment systems has enabled the emergence of data on revealed preferences. The literature suggests that these data sources hold significant promise to enhance the understanding of the determinants of parking choices (Zhou et al., 2024; Sonntag et al., 2021). In particular, they allow for exploring the impact of built environment and temporal factors on on-street parking demand. This research uses data from on-street parking transactions of 2023.

This paper differentiates itself from existing research in two main aspects. First, this paper is the first to assess the impact of the built environment on parking durations in a European context. Second, this article uses original data from parking meters on the location and duration of parking demand in Lyon. To bring the best out of these data and reveal the non-linear interactions with the built environment, machine learning is employed, specifically the XGBoost algorithm, to assess the impacts of different spatio-temporal factors on parking durations.

2 Methodology

Case study

Lyon is the main city of the metropolitan area of Lyon (here after ML). ML is the third most populous and the second largest economic hub in France. Most of ML population and economic activities are dependent on the city of Lyon. Consequently, the travel demand in relation to Lyon is important. According to the latest household travel survey (HTS), Lyon attracts each day 1,500,000 trips (Sytral Mobilités, 2015) and 80% of this demand is generated by the population of Lyon. Trips are mainly related to work (26%), leisure (24%), or shopping and services (22%). Most importantly, 39% of these trips were made by walking or biking, 30% by public transport, and 30% by private car. The share of car is of 43% among Lyon visitors (non-residents). Furthermore, 60% of households own at least one car, but only 44% have access to a private parking.

To limit private car use, Lyon has implemented various measures, including parking regulation. The city has increased the coverage of its paid on-street parking from 15% in 2005 to nearly 100% today. The city has also implemented a zone-based pricing policy, distinguishing between two pricing zones: the city center (called hereafter *Presto*), where parking demand is high and parking costs €2 per hour and €11 for 2 hours, and the *Tempo* zone, priced at €1.20 per hour or €2 for 2 hours (Fig. 1). Parking is free on Sundays and during the summer holidays. Residents benefit from reduced rates, regardless of their parking duration.

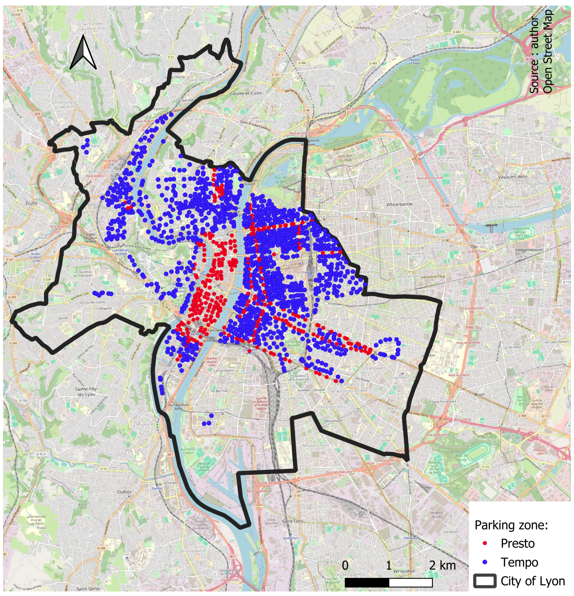


Figure 1: Map of on-street parking pricing zones in the city of Lyon

Data

The on-street parking records contain 3 million parking transactions registered by 1,550 parking meters between January and November 2023, and from Monday to Saturday. Each observation is a parking transaction characterized by the parking meter ID, date, parking duration, cost, and type (resident or visitor). Since residents are not charged based on the duration, only transactions from visitors are kept. Individual durations are aggregated to compute the average durations per parking meter. This duration is segmented by month, weekday, and arrival time interval: 9:00–12:00, 12:00–14:00, and 14:00–17:00.

To investigate the impact of the built environment on parking demand, land use around parking meters is characterized. For this, we adopt the 3D dimensions (density, diversity, and design) to characterize the built environment (Cervero & Kockelman, 1997). However, the theoretical link between these dimensions and parking durations is not evident. The density of amenities can encourage the possibility to take part in activities, which can influence the duration of parking. The nature of these amenities and their diversity can also influence the duration. The diversity of amenities encourages car drivers to carry out several activities in one place, which tends to increase the parking duration. Pedestrian-friendly design can also encourage drivers to chain different activities by foot once the car is parked, and thus increase parking duration. Neighborhoods with prohibitive parking restrictions, such as the *Presto* zone, can also influence the parking duration. Finally, accessibility to different alternative modes of travel can also encourage car drivers to park their vehicle at a location and continue using other means of transportation to reach their different activity locations which may influence the duration of parking.

To characterize the built environment around each parking meter, the population, employment (INSEE, 2023b), the number and nature of amenities (INSEE, 2023a), including firms, educational establishments, leisure facilities, and public services were collected (Tab. 1). The proximity to public transportation (tramway and subways stations) was also collected. Given these land use data, the density dimension was defined as the density of amenities (weighted by their number of jobs) and the ratio between population and jobs. The diversity dimension was defined as the relative share of amenities and their Shannon entropy. The design dimension was characterized by proximity to metro and tram stations, off-street parking, parking zone type (*Presto* and *Tempo*). The geographical coordinates of each parking meter were also included. To control for the temporal variability in parking durations, temporal factors such as month, weekday, and transaction arrival period were included.

Table 1: Amenity groups

Category	Types of POIs
Leisure & Entertainment	Arts, entertainment, restaurants, hotels
Commercial activities	Retail activities, wholesale trade, repair activities
Healthcare & Social services	Human health services, social health services
Teaching activities	Schools, colleges, universities
Back office & Non customer facing businesses	Specialized and technical activities, insurance and finance, transportation and storage, manufacturing, information and communication, water supply, electricity distribution
Administrative services	Administrative and support services, public administrations

Methods

Our research methodology follows a two-step approach. First, an exploratory analysis of parking demand is performed using two key indicators: volumes and durations. Then a confirmatory analysis is conducted to test the assumption on the impact of the built environment on parking durations.

Exploratory analysis:

The aim here is to understand parking demand in terms of durations and volumes. First, a descriptive analysis of parking durations is performed. Second, the daily profiles of the normalized stock of vehicles parked is clustered using the k-means method. This clustering helps to verify whether there is heterogeneity in the parking demand profiles within the city of Lyon and their correlation with the built environment. The optimal number of clusters was set to maximize the Silhouette score.

Confirmatory analysis:

The confirmatory analysis examines the impact of the built environment on parking durations using XGBoost. XGBoost is a sequential ensemble learning approach introduced by Friedman (2001). It iteratively builds decision trees, progressively correcting errors from previous iterations. It is particularly renowned for its high performance, especially for time series forecasting (Fafalios et al., 2020; Chen & Guestrin, 2016). Recent studies suggest that decision-tree-based methods, such as XGBoost, can outperform econometric models in modeling parking behaviors, as they better handle the numerous non-linear interactions (Zhu et al., 2023).

For the XGBoost configuration, a grid search procedure was used to identify the optimal parameters including the maximum tree depth, minimum child weight, regularization term, number of trees, learning rate, subsampling ratio, and feature sampling fraction per tree. The model is then trained on a random sample of 70% of the observations. The remaining 30% are used to test the model. To interpret the modeling outcomes, the SHAP values (Shapley additive explanations) were calculated. SHAP values, based on game theory, are used to evaluate the relative contribution of each variable to predictions. This method will be used to rank variables according to their relative importance.

3 Results and discussion

Exploratory analysis

The average parking duration in Lyon is 1.7 hours (Std 2.1 h). This average is influenced by the parking design (*Presto and Tempo*), the day of the week (Saturday vs. working day), and the hour of the day (Fig. 2). The average duration is 1.1 h (Std 1.1 h) in the *Presto* zone and 1.8 h (Std 2.2 h) in the *Tempo* zone. The average duration increases on Saturdays (2.3 h) vs. weekdays (1.5 h). The average duration is also high at 9 am, 12 pm, and 3 pm, particularly in the *Tempo* zone. The increase during the morning and end of day is likely driven by overnight parking behaviors.

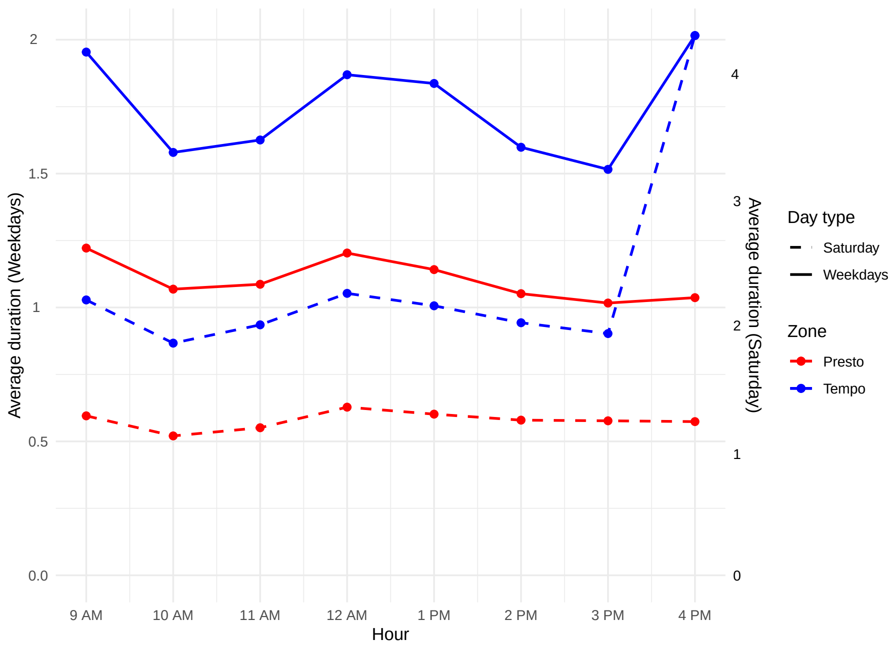


Figure 2: Average parking durations according to the parking zone, day type (right and left axis) and hour (X axis).

The clustering reveals three demand profiles (Fig.3): a morning peak cluster (C3) representing 43% of the parking meters, a midday peak cluster (C1) representing 31% of the parking meters, and an afternoon peak cluster (C2) representing 26% of the parking meters.

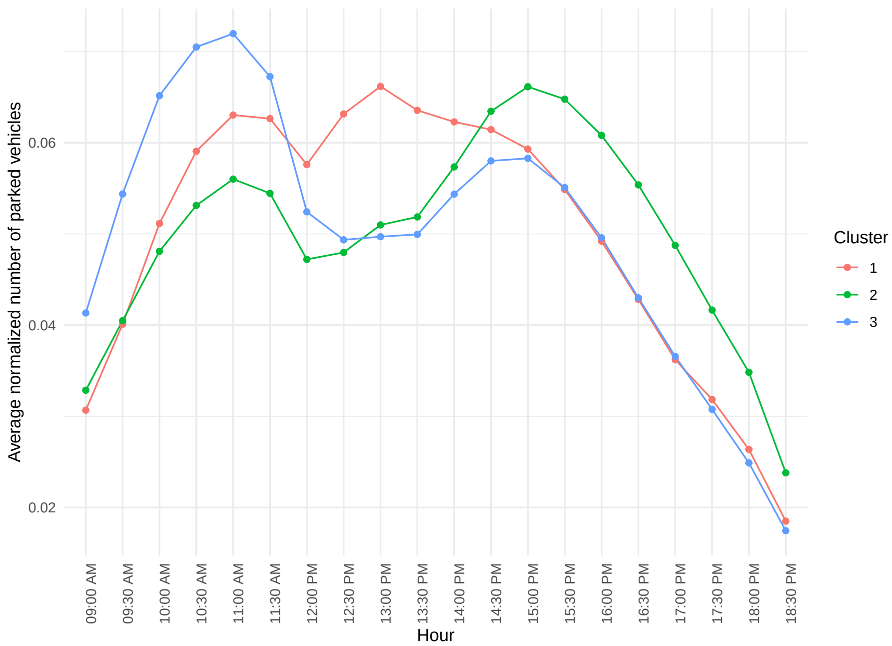


Figure 3: Average normalized profiles of parking demand per cluster according to the hours of the day(Monday to Saturday data)

Cluster 3 is characterized by the longest parking duration and the smallest share of commercial activity. This cluster has also the highest share of parking meters located in the *Tempo* zone (83%). Cluster 1, by contrast, represents parking meters with short durations, averaging 1 hour and 56 minutes, and a lower resident-to-job ratio (Tab.2). However, this clustering analysis shows that the link between the built environment and parking durations is not straightforward. The next section will adopt a machine learning approach to better investigate this relation.

Table 2: Cluster statistics.

Statistic	Cluster 1	Cluster 2	Cluster 3
Average parking duration (hour)	1.9	2.05	2.08
Standard deviation of parking duration (hour)	0.48	0.58	0.52
Average percentage of commercial activities	12%	13%	11%
Average percentage of teaching activities	7%	7%	8%
Average percentage of back office & non-customer-facing enterprises	37%	35%	36%
Average percentage of administrative services	21%	22%	24%
Average percentage of leisure & entertainment activities	12%	13%	13%
Average percentage of healthcare & social services	8%	7%	9%
Average number of inhabitants per job	0.58	0.61	0.62
Average Shannon entropy	1.52	1.52	1.49
Proportion of *Presto* parking meters	25%	26%	17%

Confirmatory analysis

The XGBoost model achieved an RMSE of 41 minutes in the training set and 43 minutes in the test set, with an R-squared of 0.26 on the test set. Among the built environment variables, the parking zone type, which is considered as a design variable, has the highest impact on the parking duration (Fig. 4). Parking prices vary depending on the zone type, and, as expected, parking duration decreases as the price increases. Parking durations are also longer on Saturdays, all else being equal. This is likely for two reasons: visitors conduct longer activities on Saturdays than working days, and the free parking on Sundays leads to extended parking durations (Fig.5a). Another time-related factor is the time of day: parking in the morning tends to result in shorter durations compared to the rest of the day (Fig. 5b). Commercial activity also plays an important role. In areas with higher relative commercial activity, users tend to park for shorter durations, as these areas are typically associated with shorter activity durations compared to residential areas (Fig. 5c). However, the effect is reversed for parking meters in the Presto zone: an increase in commercial activity is linked to longer parking durations. This could be explained by the specific dynamics of city center zones, where activities are more likely driven by shopping purposes, and a higher concentration of businesses tends to extend the duration of these activities (Fig. 5d). While the relatively low R-squared value is not entirely satisfactory for a data-driven model of this type, improving the model's performance is an ongoing focus of our research.

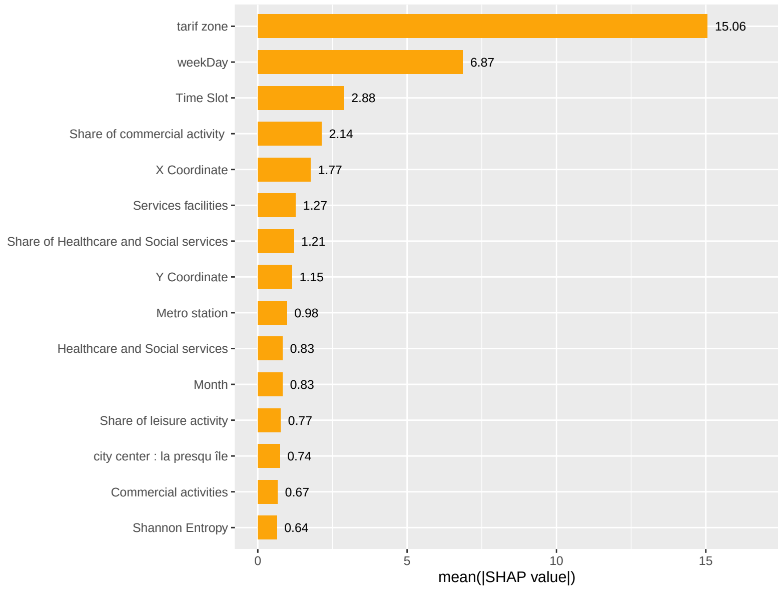
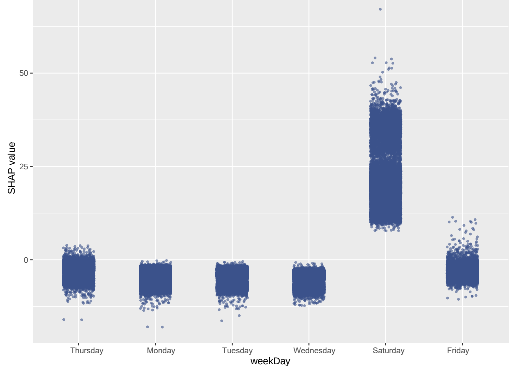
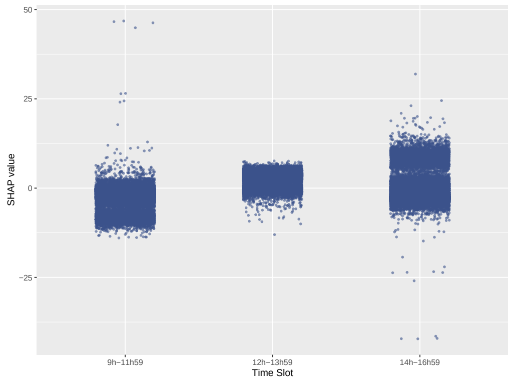


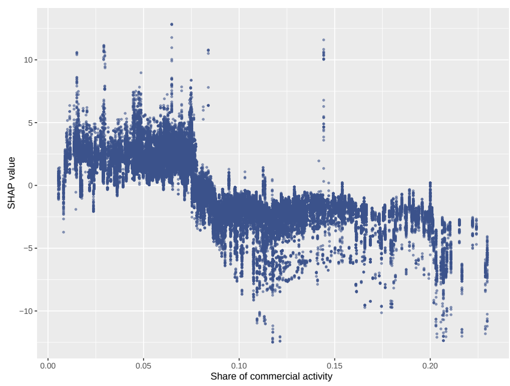
Figure 4: SHAP features importance of the 15 most important variables



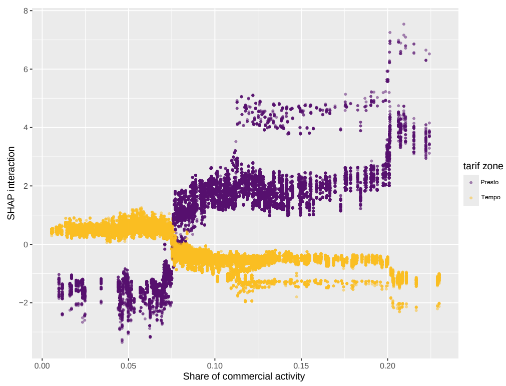
(a) Impact of weekdays on average parking durations



(b) Impact of arrival time slot on average parking durations



(c) Impact of the share of commercial activities on average parking durations



(d) Interaction effect between the share of commercial activities and parking zone on average parking durations

Figure 5: SHAP dependence plots

4 Conclusion and future research

This research investigates the relation between the built environment and parking durations using parking meter data from Lyon. In theory, one can expect that the density, diversity and design neighborhoods should influence parking durations. First results suggest that this influence is not straightforward for all considered built environment dimensions. The most impacting variable is related to the design of parking zones. As expected, zones with high pricing discourage long parking durations. The share of commercial activities also influences these durations. The interaction effects show that the effect of commercial activity is moderated by the parking zone type: commercial concentration tends to reduce parking durations in the more peripheral and less dense zones, but increases them in the city center.

Ongoing research now focuses on further improving the prediction model (XGBoost), and analyzing the interaction effects of the built environment.

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