Do emission-based on-street parking charges work? Evidence from a natural experiment

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Short summary

Charging for on-street parking is a common policy instrument to regulate car use in cities, yet its effectiveness depends on drivers' responses to prices. We study an innovative policy reform, an emission-based parking prices implemented in Lyon in June 2024. Exploiting this natural experiment, we combine ten million parking transactions with vehicle registration data before and after the reform. We use a continuous DiD framework, building on recent econometric advances for heterogeneous treatment effects with continuous doses. Results show a significant and persistent reduction in parking demand. Responses are heterogeneous and increase with the magnitude of the price changes. More polluting vehicles are disproportionately exposed to higher price increases and account for a larger share of demand reduction. To our knowledge, this paper provides the first empirical evidence on emission-based parking pricing, suggesting it can curb high-emission vehicle use and mitigate environmental externalities.

Keywords: Parking demand; On-street parking fees; Emission-based pricing; Difference-in-Differences; Continuous treatment; Dose response

1 Introduction

Because all trips start and end with parking, parking management plays a central role in urban mobility and in mitigating its detrimental impacts (Shoup, 2005). Parking policies are at the intersection of major urban challenges, including congestion, public space occupancy, spatial justice, accessibility, transport-related environmental externalities, and urban attractiveness (Kim et al., 2022; Hagen & Tennøy, 2021; Mingardo et al., 2015). Consequently, urban planners and researchers have explored various strategies to provide parking supply and manage parking demand. Chief among them is on-street parking pricing (Vickrey, 1954; Verhoef et al., 1995; Hensher & King, 2001; Kirschner & Lanzendorf, 2020). In this context, a key challenge for policymakers when setting parking fees is to determine how users react to prices so that they can establish effective pricing levels. The existing literature has mainly focused on estimating demand elasticities and shows that higher prices reduce parking demand through adjustments in parking frequency, location choice, transport mode, or trip suppression (Kelly & Clinch, 2009; Ottosson et al., 2013; Feeney, 1989; Shoup, 2005). However, these estimates vary widely across studies, highlighting substantial heterogeneity in behavioral responses depending on the context, pricing design, or user characteristics (Lehner & Peer, 2019). Besides, most of this evidence is based on standard pricing schemes that rely on spatial differentiation (across zones), temporal variation (peak and off-peak tariffs), or demand-dynamic pricing (Wang et al., 2020; Yan et al., 2018; Pierce & Shoup, 2013; Pu et al., 2017).

More recently, a new generation of parking policies has emerged, linking parking prices to vehicle characteristics, in particular, their environmental impacts. These policies aim to align parking regulation with broader environmental objectives, such as reducing emissions by penalizing heavier or more polluting vehicles. Such policies were implemented in Madrid, Paris, Lyon, some boroughs of London, Bristol, or Birmingham (Kodransky & Hermann, 2011; Gonzalez et al., 2023). Despite the growing adoption of emission-based parking charges, there is currently no empirical evidence on how users respond to such environmentally differentiated pricing schemes and how this policy fosters the internalization of externalities generated by urban mobility. This research addresses this gap by evaluating the impact of such a policy on parking demand in the city of Lyon, France,

where an emission-based parking policy was implemented in June 2024.

Using a standard difference-in-differences estimator raises identification issues for causal effects. This study therefore rely on recent econometric developments (Callaway et al., 2024) to estimate both the average effect of the policy and its heterogeneity with respect to the magnitude of the price change. We address three main research questions: (i) how do users adjust their parking demand in response to individual price shocks induced by emission-based pricing? (ii) how does this response vary with the size of the price change? and (iii) does the policy induce larger reductions in parking demand among more polluting vehicles? To our knowledge, our results provide the first empirical evidence on behavioral responses to this new generation of parking policies. These results provide useful insights for policymakers, as many cities are currently considering or implementing similar pricing schemes.

2 Methodology

Case study

Lyon is France's second-largest metropolitan area. As such, it faces various challenges related to car use, public space availability, and parking demand management. Car ownership remains widespread in Lyon: around 60% of households own a car, yet only 44% have access to private parking, making on-street parking central. Parking demand is particularly high in central areas, generating congestion, cruising, and competition for space.

Until June 2024, parking was charged in Lyon based on a zoning system. The *Presto* zone covered the city center, where demand is highest and tariffs are relatively high, while the *Tempo* zone covered the rest of the city with lower prices. In June 2024, the municipality introduced an emission-based parking pricing policy where fees depend on the weight of the vehicle and its energy type, aiming to better internalize the external costs of car use in terms of space occupancy, environmental impact, and road safety. This reform induces substantial and heterogeneous price changes across users, depending on their vehicle characteristics. Importantly, while the timing of the reform is common to all users, the magnitude of the price change varies across users. This feature provides quasi-experimental variation that we exploit to identify the causal effect of parking prices on demand. Figure 1 shows the spatial distribution of parking meters in Lyon, along with the pre-reform pricing zones, while Table 1 compares price levels before and after the reform, as well as the technical criteria used to assign cars to each pricing category.

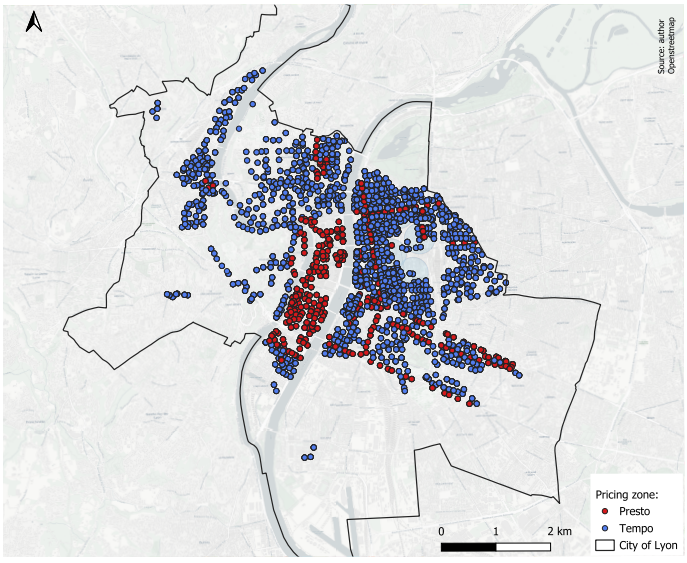


Figure 1: Parking pricing zones before the June 2024 reform in Lyon.

Table 1: Parking fees in Lyon before and after the June 2024 emission-based parking reform.

	Before reform		**After reform**		
	Tempo	**Presto**	**Reduced** EV < 2100 kg; PHEV < 1000 kg; Comb. < 1000 kg	**Standard** Comb. 1000–1525 kg; PHEV 1000–1900 kg	**Increased** Comb. > 1525 kg; PHEV > 1900 kg; EV > 2100 kg
Duration					
1 hour	1.20 €	2.00 €	1.00 €	2.00 €	3.00 €
2 hours	2.80 €	11.00 €	3.00 €	6.00 €	9.00 €
3 hours	4.00 €	23.00 €	6.00 €	10.00 €	15.50 €
Max (10 h)	35.00 €	60.00 €	35.00 €	55.00 €	80.00 €

Comb. = combustion engine; PHEV = plug-in hybrid electric vehicle; EV = electric vehicle.

Data

The econometric analysis is based on a large dataset of approximately 10 million parking transactions recorded between January 2023 and September 2025 across 1,550 parking meters in Lyon. Each transaction includes detailed information on the parking meter id, start and end parking times, price, user type (resident or visitor), and vehicle plate number. The latter information helps to track users/vehicles over time and construct a longitudinal dataset. Table 2 provides examples of raw parking transactions before and after the reform. We restrict the analysis to visitor transactions, as residents benefit from specific parking permits and are therefore differently and less affected by the pricing reform than visitors. The transaction-level data are then aggregated at the user-month level to construct the estimation sample. The outcome variable is defined as the number of parking transactions per user per month. This monthly aggregation helps smoothing short-term fluctuations in parking behavior, while ensuring sufficient variation for identification. Table 3 illustrates the resulting panel structure of the data.

The treatment variable captures the individual price shock induced by the reform. It is defined as the change in the hourly parking price for the first hour of parking faced by each user, which depends on the tariff class assigned to the vehicle after the reform (Eq. 1).

$$D_i = p_{i,a} - p_{i,b} \tag{1}$$

Where $p_{i,b}$ and $p_{i,a}$ are the hourly parking price faced before and after the reform by user i. Since pre-reform tariffs depend on parking zones, the latter is computed as a weighted average of zone-specific prices (Eq. 2).

$$p_{i,b} = \pi_i^{Tempo} \times P_{Tempo} + \pi_i^{Presto} \times P_{Presto} \tag{2}$$

Where π_i^{Tempo} and π_i^{Presto} are the shares of user i's transactions in each zone before the reform. P_{Tempo} and P_{Presto} are the hourly prices of the first parking hour in the *Tempo* and *Presto* zones, respectively.

This yields a time-invariant of treatment intensity for user i, which reflects the heterogeneous exposure of users to the pricing reform. Combined with the panel structure of the data, this allows us to exploit within-user variation over time while accounting for differences in treatment intensity across users. In practice, the econometric analysis focuses on positive price changes, while observations with non-positive values of D_i are used as a comparison group.

It is noteworthy that this pricing policy effectively targets more polluting vehicles. Treatment intensity is positively correlated with vehicle CO_2 emissions in g/km ($\rho = 0.35$, $p < 0.001$), and vehicles above the median CO_2 emission level face significantly higher average price increases (€0.81 vs. €0.51; $p < 0.001$). Overall, treatment intensity exhibits substantial variation in the full sample, with a mean of €0.66, a median of €0.76, and an interquartile range from €0.27 to €0.80, with a right tail extending up to €2.1. Users who did not experience a price increase are assigned a treatment intensity of zero, ensuring a clear distinction between treated and untreated users.

79.7% of users are thus considered treated under this framework.

Table 2: Examples of raw on-street parking transactions. PMID: parking meter ID. V = visitors; R = residents.

PMID	Plate	Type	Lon.	Lat.	Arrival	Departure	Price (€)	Zone	Tariff class	Policy period
1	AB-1111	V	4.83	45.76	2023-09-15 10:06	2023-09-15 12:06	11.00	Presto	–	Before
2	AC-3333	V	4.80	45.77	2024-10-11 11:41	2024-10-11 12:41	6.00	Presto	Standard	After
3	AC-3333	V	4.80	45.77	2025-01-05 11:58	2025-01-05 17:58	16.00	Tempo	Standard	After

Table 3: Example of the user-month panel used in the estimations. Each row corresponds to one user (vehicle plate) observed in one month.

Plate	Month	nb_tx	$\Delta prix$	$post_pol$	t_rel_month
AC-3333	2024-04	1	0.80	0	-2
AC-3333	2024-05	2	0.80	0	-1
AC-3333	2024-06	1	0.80	1	0
AC-3333	2024-07	0	0.80	1	1
AB-1111	2024-04	0	0.00	0	-2
AB-1111	2024-05	4	0.00	0	-1
AB-1111	2024-06	4	0.00	1	0
AB-1111	2024-07	3	0.00	1	1

Notes: nb_tx denotes the number of parking transactions per user and month. $\Delta prix$ is the individual treatment intensity, defined as the change in hourly parking price induced by the reform. $post_pol$ is an indicator equal to one after the policy implementation. t_rel_month denotes event time, measured as the number of months relative to the reform date ($t = 0$).

Methods

To estimate the causal effect of user-specific price shocks on parking demand, we use a difference-in-differences (DiD) framework. Three DiD models are estimated depending on the causal effect of interest. First, a DiD model is run to measure the relative impact of the new parking policy on the different tariff classes (Standard, Reduced and Increased). This model informs about how different user groups were impacted by the policy. A second model leverages the continuous dose design to estimate average impact and dose-response function of treated users. Third, an event study is conducted to ass how the impact on parking demand evolved over time and to partially check the pre-trend assumption needed by the DiD framework.

Model 1: Causal effect on tariff classes volumes

The first model consists in comparing the relative effect of the pricing strategy between the tariff rates (R) (Tab. 1). A Two Way Fixed Effect (TWFE) model with a discrete treatment representing the three classes Standard, Reduced, Increased is estimated using the Standard rate as the reference group. The identification of this model relies on the common parallel trends assumption stating that the outcome evolution of all tariff rates would have been the same in the absence of the policy. It should be noted that the TWFE estimand identifies the relative impact of the policy between tariff rates, i.e. $\mathbb{E}[Y_{i,a}(R1) - Y_{i,a}(R2) \mid i \in R1]$, where a and b denote the post- and pre-policy periods, respectively, and $\mathbb{E}[Y_{i,a}(R2) \mid i \in R1]$ represents the counterfactual post-policy outcome for user i had she instead been subject to tariff rate $R2$, given that she actually faced $R1$. Since Y_i is a count variable, the model is estimated using a Negative Binomial specification with a log-link function and dispersion parameter θ to account for over-dispersion in Y_{it} (i.e. $Var(Y_{it} \mid \cdot) > \mathbb{E}[Y_{it} \mid \cdot]$). In this case, $Y_{it} \mid \alpha_i, \lambda_t \sim \text{NB}(\mu_{it}, \theta)$, where $\mu_{it} = \mathbb{E}[Y_{it} \mid \alpha_i, \lambda_t]$ and θ denotes the dispersion parameter (Eq. 3).

$$\mathbb{E}[Y_{it} \mid \alpha_i, \lambda_t] = \exp\left(\alpha_i + \lambda_t + \sum_c \beta_k(Post_Pol_t \times R_i(c))\right) \tag{3}$$

Where α_i are user fixed effects, λ_t are time fixed effects, $Post_Pol_t$ is an indicator equal to one after the reform, and $R_i(c)$ is equal to 1 is user i falls within tariff class c (reduced, increased), with the standard category as the reference group, and 0 otherwise.

Model 2: Continuous Treatment and Dose-Response Effects

To better understand how parking demand reacts to different parking prices, a continuous DiD model is estimated. In this case, the treatment is the magnitude of the price increase experienced by user i, denoted D_i (D for dose; see Equation 1). The outcome $Y_{i,a/b}$ is the number of parking transactions made by user i before (b) and after (a) the introduction of the policy.

With continuous treatments, the TWFE estimand generally does not recover an accurate average treatment effect (Callaway et al., 2024; de Chaisemartin et al., 2024). A causal interpretation of TWFE coefficients relies on comparisons between users exposed to different treatment intensities, which in turn requires a strong assumption known as *strong* parallel trends, stating that, for any dose d, users exposed to that dose would have followed the same outcome trend as users exposed to other doses in the absence of treatment. In our context, this assumption is unlikely to hold, as price changes are not randomly assigned. Besides, TWFE estimates rely on implicit weighting schemes that may not reflect the distribution of treatment intensity (Callaway et al., 2024; de Chaisemartin et al., 2024).

We therefore focus on dose-specific effects, namely $ATT(d \mid d)$, which captures the average effect of a price shock of magnitude d for users exposed to that level of treatment (Eq. 5). Identification of this effect relies on a common parallel trends assumption (Eq. 4):

$$\mathbb{E}[Y_{i,a}(0) - Y_{i,b}(0) \mid D_i = d] = \mathbb{E}[Y_{i,a}(0) - Y_{i,b}(0) \mid D_i = 0] \tag{4}$$

Under this assumption, the average treatment effect for users exposed to a price change of magnitude d can be identified as in Eq. 5.

$$\begin{aligned} ATT(d \mid d) &= \mathbb{E}[Y_{i,a}(d) - Y_{i,a}(0) \mid D_i = d] \\ &= \mathbb{E}[Y_{i,a}(d) - Y_{i,b}(0) \mid D_i = d] - \mathbb{E}[Y_{i,a}(0) - Y_{i,b}(0) \mid D_i = 0] \end{aligned} \tag{5}$$

Model 3: Dynamic Treatment Effects

The previous model is complemented with an event-study framework to (i) assess the plausibility of the parallel trends assumption and (ii) investigate the dynamic effects of the treatment over time. We estimate dynamic treatment effects at event time $k = t - e$, where e denotes the policy implementation month (June 2024), t the month of observation, and k the difference between them. The treatment variable D_i captures the magnitude of the price change (normalized for event-study estimation). Coefficients are interpreted relative to the omitted reference period $k = -1$, corresponding to the month preceding the reform:

$$ATT(k) = \mathbb{E}[ATT(k, D_i)] \tag{6}$$

The absence of systematic differences in pre-treatment periods ($k < 0$) provides support for the parallel trends assumption, while post-treatment estimates ($k \geq 0$) capture the dynamic response to the price change.

Models 2 and 3 are estimated using the `contdid` estimator (Callaway et al., 2025)[1]. For model 3, this package computes group-time effects from outcome changes and aggregates them across time and doses.

Overall environmental impact of the policy

To assess how the effects of the pricing reform vary across vehicles with different environmental performances, we aggregate the estimated dose-response function (Model 2) using group-specific exposure to treatment intensity. This approach allows us to evaluate whether the policy effectively

[1]See `https://bcallaway11.github.io/contdid/` for documentation of the `contdid` package.

targets more polluting vehicles in terms of its overall impact. We split vehicles into two groups based on whether their CO_2 emissions (in g/km) are above or below the sample median. Let $\widehat{ATT}(d \mid d)$ denote the estimated dose-response function obtained from the continuous DiD estimator. For each group $g \in \{\text{Higher-emission vehicles, Lower-emission vehicles}\}$, we construct the empirical distribution of treatment intensity, $\hat{f}_g(d)$, and define the group-specific aggregate effect as:

$$\widehat{ATT}_g^{agg} = \sum_{d \in \mathcal{D}} \hat{f}_g(d)\, \widehat{ATT}(d \mid d) \tag{7}$$

This aggregation captures differences in exposure to the policy across groups, while holding the underlying dose-response function fixed. In particular, it provides a direct assessment of whether the pricing reform disproportionately affects more polluting vehicles.

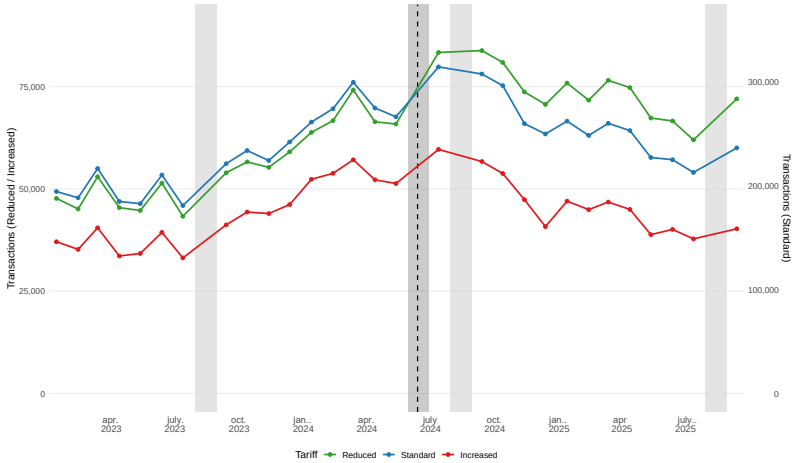
3 Results and discussion

Exploratory analysis

Figure 2a shows the evolution in time of the total number of parking transactions and the number of active users, i.e., users with at least one transaction in a given month. Both series exhibit a clear upward trend prior to the reform, followed by a decline afterwards. However, there is heterogeneity across tariff classes (Fig. 2b): users benefiting from reduced tariffs have the strongest increase in parking demand. Overall, this descriptive analysis suggests that parking demand was on an upward trend across all tariff categories prior to the reform, which the policy appears to have disrupted. In the next section, we formally estimate the causal effect of this disruption using a difference-in-differences framework.



(a) Aggregate parking demand evolution



(b) Aggregate parking demand evolution by tariff class

Figure 2: Evolution of parking volumes over time. Grey shaded areas correspond to either free parking periods or missing data. The vertical dashed line indicates the introduction of the new pricing.

Causal analysis

Model 1: Causal effect on tariff classes volumes

Table 4 reports the estimated effects from the Negative Binomial model with discretized tariff categories, using the standard tariff as the reference group (see Equation 3). The results confirm substantial heterogeneity across tariff categories. Relative to the reference group, users exposed to higher prices significantly reduce their parking demand, while those benefiting from lower tariffs significantly increase their usage. The estimated effects are economically meaningful, with an increase of about 11% for reduced tariffs and a decrease of about 5% for increased tariffs.

We then examine the temporal dynamics using an event-study specification. Figure 3 shows that pre-treatment coefficients are close to zero, although some deviations appear for the group facing price increases. After the reform, parking demand rises for users with reduced tariffs and declines for those facing higher prices. These effects persist over time and tend to increase in magnitude, suggesting gradual behavioral adjustment.

	DID NegBin
Reduced tariff	0.1112***
	(0.0048)
Increased tariff	-0.0507***
	(0.0049)
Unit FE	Yes
Time FE	Yes
Cluster	Plaque level
Observations	17,109,623
Pseudo R^2	0.160
Over-dispersion (θ)	0.695

Table 4: Effect of tariff changes on parking demand

Notes: Estimates from a Negative Binomial DiD specification. The reference category is the standard tariff. Standard errors clustered at the plaque level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

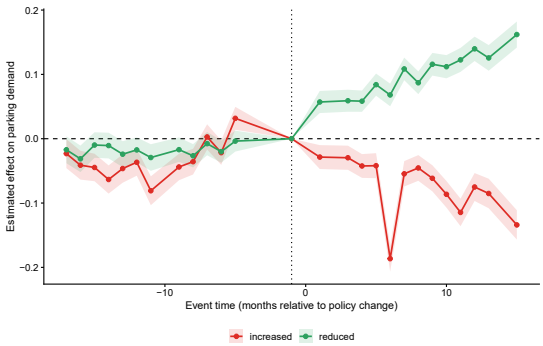


Figure 3: Event-study estimates of the effect of tariff changes on parking demand

Model 2: Continuous Treatment and Dose-Response Effects

While informative, this discrete approach abstracts from the continuous nature of price changes, which vary in magnitude across users. As a result, it may mask important heterogeneity in behavioral responses, which motivates the use of a continuous treatment framework to estimate dose-specific effects.

Table 5 reports the estimated average treatment effects of the pricing reform on parking demand using the continuous DiD estimator. The results indicate a significant negative causal effect of price increases on parking demand. The overall ATT is -0.140 (SE $= 0.0066$), implying that treated users ($D_i > 0$) make about 0.14 fewer parking transactions per month relative to the counterfactual. This corresponds to a reduction of approximately 23% compared to the average pre-policy level among treated users. Among those exposed to a price increase, the average price rise is about 64%, implying an average price elasticity of approximately -0.36. Consistent with treatment effect heterogeneity, Figure 4 presents the dose-response relationship, i.e. the evolution of $ATT(d \mid d)$ with respect to treatment intensity. Each point compares users exposed to a price increase of magnitude d to those with zero treatment. The effect is negative across all intensities and becomes more pronounced at higher doses, indicating that larger price increases lead to stronger reductions in parking demand.

Table 5: Main continuous DiD results: effect of price increases on parking demand

	(1) Main specification
ATT	-0.140
	(0.0066)
Outcome	Number of transactions
Treatment variable	Individual price increase
Control group	Users who did not experience a price increase
Cluster	User level
Observations	17 114 988

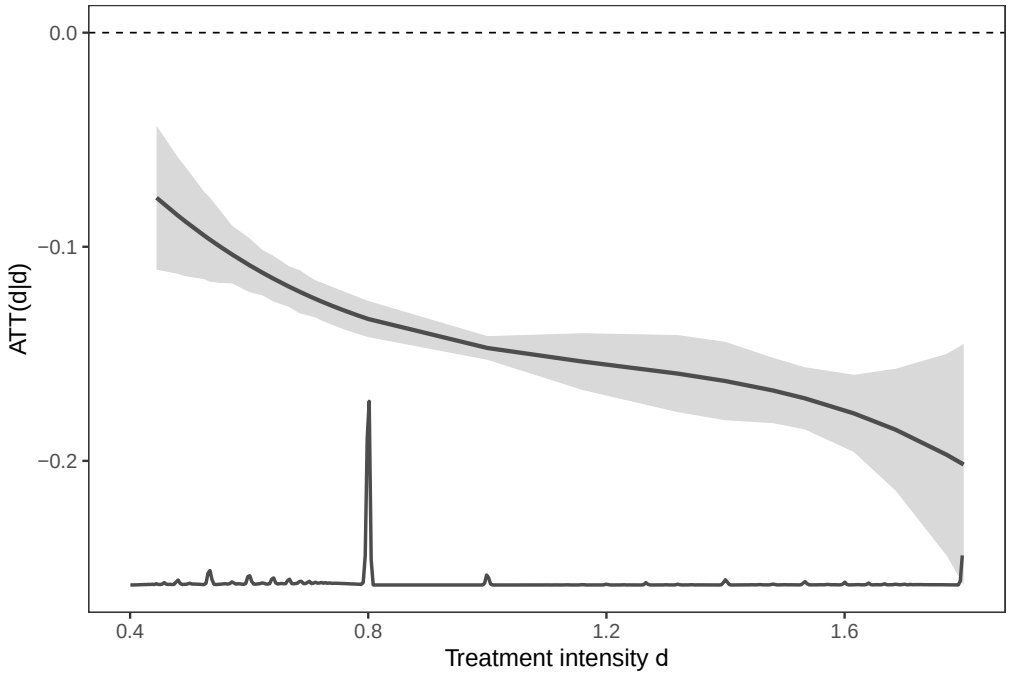


Figure 4: Dose-response relationship between price increases and parking demand

Notes: The figure reports the estimated dose response function $ATT(d \mid d)$ from the continuous DiD framework. The shaded area indicates 95% confidence intervals. The density of treatment intensity is displayed at the bottom of the figure.

Model 3: Dynamic Treatment Effects

To further investigate the impact of the policy, we estimate an event-study to examine how the treatment effect evolves over time (Figure 5). The event-study shows that before the reform, all users exhibit similar outcome dynamics, which supports the parallel trends assumption. Following the reform, parking price increases lead to an immediate decline in parking demand, with coefficients turning negative as soon as the policy is implemented. This immediate shift suggests that the tariff changes were quickly internalized by users, consistent with a clearly communicated reform. The effect remains relatively stable over the 12 months following the reform and appears to increase in magnitude toward the end of the study period, suggesting gradual behavioral adjustment and a persistent reduction in parking usage.

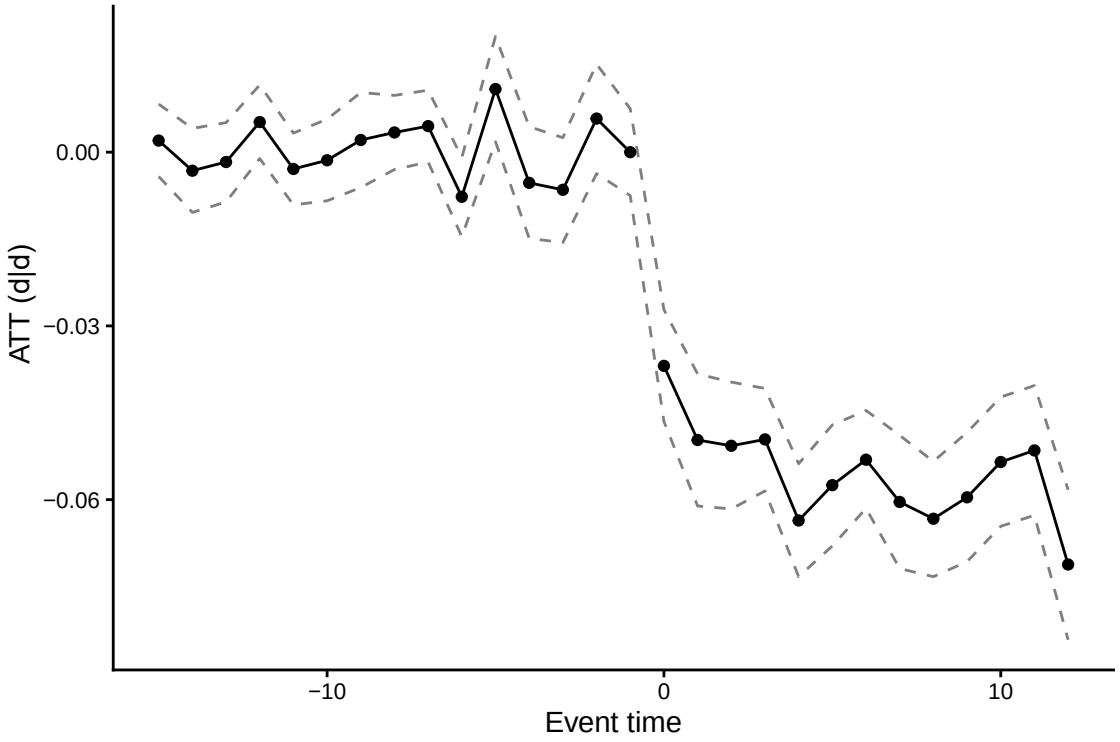


Figure 5: Dynamic effects of price increases on parking demand

Notes: Each point compares users exposed to a price increase to the rest of users at a given month. The shaded area indicates 95% confidence intervals.

Overall environmental impact of the policy

Although the above results show a decline in parking demand, it remains to be determined whether this translates into a reduction in pollution, which we proxy by changes in parking transactions among the most polluting vehicles. Note that we already examined whether more polluting vehicles are disproportionately exposed to higher price increases (see section 2).

Modeling outcomes show that the reduction in parking demand is greater for high-emission vehicles than for low-emission ones. On average, parking demand decreases by -0.10 (SE $= 0.010$) for lower-emission vehicles and by -0.13 (SE $= 0.006$) for higher-emission vehicles. These findings suggest that Lyon's parking policy effectively targets and reduces the parking demand of more polluting vehicles. To quantify the economic magnitude of these effects, we translate them into aggregate changes in parking volumes. For each group g, we compute:

$$\Delta_g = \widehat{ATT}_g^{agg} \times N_g^{post},$$

where N_g^{post} denotes the total number of user-month observations in group g over the post-reform period. This corresponds to aggregating the average treatment effect per user-month across all treated observations. In terms of aggregate volumes, this implies a reduction of about 403,000 parking transactions for lower-emission vehicles (SE 40,071) and about 469,000 for higher-emission vehicles (SE 22,080) over the post-reform period (from July 2024 to September 2025). This corresponds to an average monthly reduction of approximately 31,000 and 36,100 transactions, respectively. Expressed relative to pre-reform parking volumes, this corresponds to a decrease of about 15% for lower-emission vehicles and 19% for higher-emission vehicles, for groups of similar size defined around the median level of emissions.

4 Conclusions

This paper provides causal evidence on how an emission-based parking policy affects parking demand by exploiting a natural experiment from Lyon. Our two main findings are the following. First, price increases induce a statistically significant and persistent decline in parking demand: treated users reduce their monthly transactions by 0.14 on average, i.e., about 23% relative to pre-reform levels. Event-study estimates indicate that this effect is immediate, sustained, and not driven by differential pre-trends. Second, demand reaction is proportional with the treatment intensity: the dose-response function is strictly decreasing, with larger price increases generating stronger demand reductions. Beyond these average effects, our results show that the policy is effective at reducing demand for more polluting vehicles compared to less polluting ones. More polluting vehicles face higher price increases and, consequently, account for a larger share of the aggregate reduction in parking demand, both in absolute terms and relative to the baseline usage. Taken together, these findings provide strong support for emission-based parking charges as an effective instrument to curb the negative externalities associated with urban car use.

Overall, this paper demonstrates that vehicle-based pricing schemes differentiated by weight and engine type can effectively influence behavior while targeting environmental goals, making them a promising tool for urban policy. However, an analysis assessing the distributive effects across user characteristics, such as income, place of residence, and vehicle age, should complement this evaluation. The analysis will also assess the impact of this pricing scheme on local air pollution. The effect of the policy on municipal revenues will also be scrutinized. Most of these results are expected to be available by the hEART 2026 conference.

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