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## Harmonizing dockless E-scooters: insights from Paris

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### ABSTRACT

Improper parking is one of the most significant barriers to the adoption and acceptance of dockless shared e-scooters worldwide. This paper investigates the effects of mandatory parking regulations in Paris that require e-scooters to be parked in designated bays in the form of painted corrals. To assess the impact of these regulations and their unintended effects, we develop a novel multicriteria evaluation method around three principles: efficiency, accessibility, and compliance. Using a unique large-scale database that geolocates every parked e-scooter in the city at three-hour intervals, we find that designated parking bays improve mis-parking by reducing cluttering. However, they also unintentionally reduce accessibility. Furthermore, we provide insights into the persistence of mis-parking and the congestion of parking bays, two key factors that contributed to the ban of shared e-scooters in the city.

### 1. Introduction

The automobile-oriented paradigm that has dominated urban transport during the last fifty years has created social and environmental concerns due to traffic congestion, local and global pollution, inequalities, and adverse health outcomes. In consequence, cities welcomed new micromobility services designed to provide alternatives and reduce car dependency (ITF, 2021; Asensio, Apablaza, Lawson, Chen, & Horner, 2022), tackle travelers' dilemmas (Lesh, 2013; Shaheen & Chan, 2016; Cohen & Shaheen, 2018), and improve accessibility to public transit (Shaheen & Cohen, 2019; Ju, Martin, & Shaheen, 2024). Nevertheless, in most cases, these innovations were introduced without a proper regulatory framework, preventing communities from capturing all their potential benefits and hampering economic growth and development (Bağ, 2016; Gössling, 2020; Meng, Somenahalli, & Berry, 2020; Button, Frye, & Reaves, 2020). As a result, governments are issuing new rules and taking advantage of the digital revolution in an effort to better integrate these new services with the rest of the mobility mix.

Dockless shared e-scooters (also referred to as free-floating e-scooters) are a relatively recent innovation in urban mobility, where renters pick-up and drop-off vehicles at any location in the city within a predetermined geographic region. Like any other

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micromobility service, this innovation enables users to have short-term access to transport on an as-needed basis (Shaheen & Cohen, 2019). Many consider this mode of transport to be an innovative alternative with potential to overcome the so-called first/last mile dilemma by improving accessibility to public transport and enhancing multimodal behavior (Shaheen & Chan, 2016; Baek, Lee, Chung, & Kim, 2021). In fact, the *6t-bureau de recherche* (2019) conducted a survey in France among e-scooter users with the objective of understanding travel patterns. They found that 23 % of the trips were intermodal, i.e., users combine e-scooters with public transport (66 % of the cases) and walking (16 %).

Comparable results were obtained in other cities around the world (Eccarius & Lu, 2020; Laa & Leth, 2020). In addition, there is widespread demand for e-scooters across hundreds of cities worldwide and there is still potential for expansion. According to the *Boston Consulting Group* (2019), e-scooters will represent 15 % of market share for automotive-based on-demand mobility by 2025 with a value between 40 and 50 billion dollars. Altogether, these conditions make dockless shared e-scooters an attractive mobility mode for cities to alleviate transport-related concerns.

However, many have pointed out barriers to the provision of services that keep cities from unlocking all the benefits, especially in the absence of proper regulation (Button, Frye, & Reaves, 2020; Meng, Somenahalli, & Berry, 2020). In the specific case of dockless e-scooters, improper parking and cluttering (random parking) have been considered the main impediments to public acceptance, which is closely related to less adoption and demand (Klein, Brown, & Thigpen, 2023; Sobrino, Gonzalez, Vassallo, & de los Angeles Baeza, 2023; Brown, 2021; Brown, Klein, & Thigpen, 2021; Button, Frye, & Reaves, 2020). The issue is so serious that many cities, such as San Francisco, Barcelona, Miami, and, most recently, Paris, have decided to ban e-scooters, arguing that mis-parking interferes with the harmonization of urban transportation. Indeed, mis-parking imposes external costs on other users.

The trade-off between costs and benefits brought by the introduction of e-scooters has re-opened the debate about curb-space management (Shaheen & Cohen, 2019; Shaheen, Cohen, & Broader, 2021). Governments must rethink how public space is allocated among different users, including those who walk, park, or ride various types of vehicles. Echoing the words of Banister (2008), we must reconsider the concept of street as a space for people, green mobility, and public transport.

This paper in particular focuses on the introduction of dockless shared e-scooters in the city of Paris and the regulatory reforms implemented to counteract cluttering and improper parking. It seeks to investigate the effectiveness of the said regulations and potentially unintended effects. The case of Paris is relevant because the city decided to re-distribute conventional parking zones to the exclusive use of e-scooters. In 2019, the city announced the construction of 2,514 parking bays (in the form of painted corrals) and amended the regulation to mandate that users drop-off e-scooters inside parking bays before completing their journey. However, the benefits of these parking regulations are not obvious, and, to the best of our knowledge, they have not been empirically assessed in the literature.

The central hypothesis behind this work is twofold. On the one hand, parking bays are an effective way to reduce cluttering, improving the integration of this mode with the city's transport system. On the other hand, parking bays might have unintended effects by limiting pick-up and drop-off points which concentrate vehicles in certain spots. In other words, parking bays might improve the spatial distribution of e-scooters across the city, but regulations may have a negative impact on the accessibility of vehicles. As noted by Brown, et al. (2020), providing infrastructure for micromobility parking increases predictability, safety, and access for all sidewalk travelers. In contrast, according to the *6t-bureau de recherche* (2019), 63 % of users believe that these measures will decrease the frequency of use of e-scooters.

To assess various aspects of the regulation, we first develop a novel multicriteria evaluation method around three principles: efficiency, accessibility, and compliance. We then use an original administrative database that geo-locates Paris' whole fleet of e-parked scooters at three-hour intervals to provide robust empirical evidence for our method. This big dataset observes parked vehicles before and after the regulations adopted in the city, a feature that we exploit to compare changes in the spatial relationship between vehicles and parking bays over time. The first evaluation criterion is based on the Euclidean distance between vehicles and parking bays. At the end of 2019, before the regulation, the average distance between e-scooters and the virtual location of parking bays was close to 100 m, contrasting with a distance close to 20 m after their implementation. This change represents a percentage decrease of almost 80 %, therefore, the construction of parking bays effectively reduced cluttering.

Furthermore, we develop a criterion to measure congestion in parking bays. The evidence suggests that congestion skyrocketed in the last quarter of 2020, after the construction of parking bays. We find that almost 20 % of the vehicles parked in bays that exceeded capacity and that more than 30 % of parking bays were overcrowded by the end of the year. According to the evidence presented here, this trend shows no signs of abating. These findings suggest that regulation in Paris has a positive effect on harmonizing e-scooters by reducing cluttering, but it unintentionally creates congestion in specific parking bays.

Accessibility of vehicles is a key question for the adoption of e-scooters. The *6t-bureau de recherche* (2019) found that 59 % of users have experienced a lack of vehicles nearby and 24 % have given up on the usage of this mode for that reason. In a similar study, Sanders, et al., (2020) surveyed 1,256 university staff members in Tempe, AZ, to find that on average 40 % of riders indicate "not being able to find one when needed" as a barrier to riding e-scooters. On top of that, this option was chosen more often among regular riders (45 %). Therefore, to assess the effects of the regulation on accessibility, we exploit the location of parking bays to build maps (rasters) measuring the distance from any point in the city to the closest vehicle. Along the same lines, we create criteria to compare the situation before and after the regulation.

Our findings suggest that the average distance to find an e-scooter was about 180 m before construction of parking bays and 250 m afterwards, a percentage increase of almost 40 %. In other words, parking regulations in Paris had a negative effect on the accessibility of vehicles. Following a similar strategy, we develop a criterion to compare the concentrations of e-scooters across the city. The evidence documented here shows that regulations limit the concentration of vehicles in specific regions of the city and improve the provision of the service in uncovered areas. Additionally, we provide a regional comparison among the twenty districts in Paris. We

found heterogeneous effects that might help authorities better allocate resources to improve the provision of dockless e-scooters in the city.

We dig deeper into improper parking in the form of noncompliance with regulation, namely: not ending the trip within dedicated parking bays. Although the dataset used in this study does not allow for a detailed classification of individual users based on their behavior, by comparing the location of e-scooters with that of the parking bays, we can hypothesize that the co-existence of different user types—compliers, opportunistic, and unlawful—may help explain the observed effects in terms of compliance.

Finally, our findings also suggest that regulation is effective in incentivizing users to comply with the rules with close to 75 % of e-scooters parked within or near parking bays. However, unlawful users, those who never follow the rules, may represent a significant share of riders (13 % to 18 %). These results underscore the need for further research to better understand the determinants of mis-parking persistence, even in the presence of dedicated infrastructure. Parking behavior is not only shaped by regulation, cultural norms and cognitive biases may also play a role (Wang, Jia, Zhou, Charlton, & Hazen, 2021; Ralph & Delbosc, 2017). Therefore, considering the specific context of each city is essential for researchers and policymakers when evaluating the effects of new rules.

It is worth mentioning that, to the best of our knowledge, this is the first study that exploits big data analytics to study parking conditions of dockless micromobility modes. Furthermore, the methodology developed here represents a new framework to assess parking behavior not only for e-scooters but for any other type of mode with geo-localized information on vehicles such as bikes, cars, or mopeds. What is more, these methods are flexible, easily reproducible, and have many different applications in various contexts. We also wish to provide guidance for authorities to adapt our methodologies as smart-regulatory tools to monitor data-driven markets.

The rest of this paper is organized as follows. Section 2 presents the related literature with a focus on the impact of regulation on dockless micromobility modes, as well as our contribution to this literature. The case of dockless e-scooters in Paris is presented in Section 3. In Section 4 the data and its limitations are presented. We provide relevant definitions and the construction of the multi-criteria evaluation method in Section 5. The main results are reported in Section 6. Section 7 outlines the discussion and Section 8 concludes.

## 2. Related literature

Studying parking, especially for cars, has a long tradition in transportation and economics.<sup>1</sup> This trend in the literature has focused mainly on the economics aspects of parking such as price, quantity, and how market failures should be addressed to improve social welfare. However, new mobility modes have challenged this view by demanding redistribution of the public space to operate. Despite the growth rate of shared micromobility services, the academic literature is falling behind, and more research is required to address recent changes in urban mobility (Button, Frye, & Reaves, 2020).

While some shared micromobility modes, such as bike-sharing, have received relatively extensive attention in the literature (DeMaio, 2009), dockless e-scooters are still a minor topic despite their extensive adoption and potential to ease transport-related concerns.<sup>2</sup> One reason is because comprehensive datasets are not widely available yet. The literature on dockless e-scooters has focused on studying demand (Huo, Yang, Li, Zheng, Yang, & Wen, 2021; Nikiforiadis, Paschalidis, Stamatiadis, Raptopoulou, Kostareli, & Basbas, 2021; McKenzie, 2020; Eccarius & Lu, 2020; Laa & Leth, 2020; Sanders, Branion-Calles, & Nelson, 2020; Younes, Zou, Wu, & Baiocchi, 2020), mode choice and competition (Baek, Lee, Chung, & Kim, 2021; Krier, Chrétien, Lagadic, & Louvet, 2021; Reck, Haitao, Guidon, & Axhausen, 2021; Aarhaug, Fearnley, Hartveit, & Johnsson, 2023), and social perception and adoption as well as public intervention. Our paper contributes to different trends of the latter strand as we aim to address the effects of parking regulations.

First, this paper informs about mis-parking in the broad sense, including improper parking and cluttering. Ever since the earliest studies on e-scooter parking practices, various authors have found riders to be relatively well-behaved. For instance, Fang et al. (2018) photographed 530 parked e-scooters in downtown San Jose, California, and found that 90 % of them did not disrupt pedestrian traffic. Similarly, by collecting data on 606 parked e-scooters in Rosslyn, United States, James et al. (2019) found that only 16 % were improperly parked. Brown, et al. (2020) further provide empirical evidence to compare improper parking between different transport modes. They collected in-field data during three days from five US cities with a large micromobility mix in streets with significant levels of transportation activity. The authors find that improper parking among e-scooters happened in only 1.7 % of the cases, which is low compared to motor vehicles (24.7 %).

Second, our work provides empirical evidence about the efficiency of recent regulations in addressing mis-parking. The work by Karlsen et al. (2021) is among the first to assess the effectiveness of parking regulations. Using video and GPS data one e-scooter operator in Trondheim and Oslo, Norway, the authors evaluate parking behavior after the implementation of parking bays in the form of painted corrals. Their findings suggest a positive outcome, with over half of the e-scooter rides ending within or near designated bays. Klein et al. (2023) conduct experiments in Washington, D.C., United States, and Auckland, New Zealand, to assess three public interventions, including sidewalk decals, mandatory lock-to racks, and in-app messages. Their results suggest that the lock-to racks mandate is the most effective measure for improving parking conditions. Similarly, Brown et al. (2024) find that mandatory parking bays significantly improve parking behavior compared to regulations that only recommend their use.

Third, we seek to fill a gap in the literature related to the unintended effects of parking regulations. Parking rules may be detrimental to the adoption of the service by limiting pick-up and drop-off points; a topic closely related to the substitution of public spaces and curb-side management. Buehler et al. (2022) stands out among the few studies analyzing these issues. The authors surveyed riders

<sup>1</sup> See Inci (2015) for a compelling review.

<sup>2</sup> Research about parking conditions of dockless shared bicycles is also scarce. The paper by Wang et al. (2021) is one example.

before and after implementation of parking bays on Virginia Tech's Blacksburg campus and found a negative perception of the regulation, along with a 72 % decline in ridership due to poorly located infrastructure. Similarly, [Hurlet et al. \(2024\)](#) follow an agent-based approach to simulate and evaluate parking supply in the city of Lyon, France, and find a significant reduction of e-scooter ridership mainly due to increased walking and egress distances. We contribute to this literature by measuring the reduction in e-scooter accessibility using an observational dataset that covers the entire urban area.

Our study is also related, to a minor extent, to broader trends in the adoption and perception of e-scooters. This is a major issue considering the striking divergence between the empirical evidence and public opinion towards parking behavior.

Few studies have focused on how to improve public perception. For instance, [Brown et al. \(2025\)](#) closely monitored a pilot project introducing e-scooters in the city of Eugene, United States. By surveying both riders and non-riders before, during, and after the pilot, the authors found that controlled exposure to the service can ease citizens' overall concerns—particularly among those who were more skeptical before their introduction. The work by [Klein et al., \(2023\)](#) stands out in the specific context of parking. The authors conducted intercept surveys of pedestrians in Washington, D.C., United States, and Auckland, New Zealand, to assess public perceptions regarding e-scooter parking. They found that citizens strongly associate organized parking—such as bike racks or designated parking bays—with proper e-scooter use, and that this sense of tidiness significantly improves public perception. A similar study was conducted by [Buehler et al. \(2021\)](#) to compare public perception before and after the introduction of e-scooters on Virginia Tech's campus in Blacksburg, VA. The authors found a more positive perception among non-riders after the launch of the system.

### 3. Case study: city of Paris

Dockless e-scooters circulated on Parisian streets for the first time in the summer of 2018. Initially twelve operators had permits to deploy vehicles in the city and the fleet size was close to 20,000 vehicles in total. They were not introduced without controversy. Some argued in favor of clean and ludic alternatives to commuting to alleviate transport-related concerns. Others highlighted the chaos and the lack of security mainly caused by irresponsible riding, mis-parking, and vandalism ([Gössling, 2020](#); [Dezobry, de Fontenelle, & Staropoli, 2020](#)).

In response, the city implemented a plan to harmonize the service with the rest of the mobility mix. First, in April 2019, the city announced the construction of 2,514 parking bays (in the form of painted corrals) for the exclusive use of e-scooters. According to the authorities, half were built in the last months of 2019 and the rest during 2020. Moreover, parking bays were located so that the average distance between them did not exceed 150 m and with a capacity reflecting fleet size.

Moreover, in July (Arrêté No 2019P 16391) and October 2019 (Décret No 20191082) the city issued a series of reforms to clarify the regulatory framework related to micromobility. These reforms determined, among other things, the rules for parking e-scooters in public spaces and the type of data the city will collect from operators. The new regulatory framework mandates that parking e-scooters outside designated bays is forbidden. Moreover, a law was passed to establish the technical characteristics and rules for riding micromobility vehicles powered by non-combustion engines (or *Engins de Déplacement Personnel Motorisé* in French). Nationwide, in December 2019 France enacted the Transport Omnibus Law (or *Loi d'Orientation des Mobilités* in French) as a response to the challenges posed by the ecological transition in the transport sector. Regarding the specific case of dockless mobility, the Law makes provision for issuing permits to operators to deploy transport services in a non-discriminatory manner after applying to the local authorities.

Subsequently, in July 2020, after a public tender, the city granted permits to Lime, Dott, and Tier to operate 5,000 e-scooters each for the next three years. Winners were selected on the promise of implementing sustainable and environmentally responsible business practices, improving user safety, and their ability to manage maintenance, removal, and mis-parking ([Sands, 2020](#)). Altogether, this government initiative represents the first regulatory framework incorporating dockless micromobility modes into the multimodal transport environment in the city of Paris. This work seeks to assess the overall effects of these rules, notably those related to improving parking behavior.

Also noteworthy is the prevalence of e-scooters in comparison with the rest of the mobility mix in the city, notably with respect to other micromobility services. Dockless shared e-scooters are similar to the station-based bike-sharing system in Paris called Vélib', the biggest micromobility service in the city. Vélib' operates 1,400 stations and 20,000 bicycles (40 % of them are electric). From the demand perspective, dockless e-scooters resonated with Parisians. In September 2020, the month where the demand for micromobility attained its historic maximum, Vélib' made an average of 180,000 daily journeys (Vélib' [Metropole, 2022](#)), meanwhile 30,000 journeys were made using e-scooters (L'institut Paris Region, 2022). Finally, regarding the market for dockless mobility, e-scooters are the leaders with a share equal to 53 % in 2020 and 59 % in 2021. They are followed by mopeds (38 %), bikes (6 %), and cars (3 %) (L'institut Paris Region, 2022). The case of Paris is also relevant at the international level. In fact, Paris is one of the cities with the largest density of rental e-scooters in Europe per inhabitant with 6.9 vehicles per one thousand people. In comparison with other European capitals, the figures in Berlin and Brussels are 3.0 and 2.6 vehicles per one thousand people, respectively. What is more, the number of e-scooters in Paris is competitive even against less densely populated cities, like Stockholm and Oslo (11.2 and 11.7 vehicles per one thousand people each) ([Civity, 2019](#)).

Despite the demand for e-scooters in the city and authorities' efforts to harmonize the service with the transport system, the debate regarding misuse and security intensified due to congestion in parking bays and fatal accidents. Consequently, the city of Paris organized a referendum for citizens to decide whether to renew e-scooter circulation permits. On April 2nd, 2023, with an overwhelming majority of votes (89 %), citizens decided to ban the use of e-scooters (Ville de Paris, 2023). The referendum was not without controversy, either. For instance, only inhabitants of the city were allowed to vote, even if e-scooters were often used by residents of the surrounding neighborhoods. Additionally, the referendum posted a low participation with a turnout rate of less than 7.5 % (Ville de Paris, 2023). Furthermore, according to the operators, only 33 % of the young population (between 18 to 24 years old) were aware of

the referendum in contrast to 77 % of adults (between 50 to 64 years old) (Le Monde, 2023).

In summary, the case of Paris is relevant for the following reasons. First, e-scooters are a relevant mobility mode in urban cores, and they have proved to be competitive with respect to other modes including station-based bike-sharing models. Second, the Parisian case became an international benchmark, especially in Europe. Third, authorities have intervened to regulate parking conditions in the city. This in turn allows us to compare the scenario before and after regulations to assess the effectiveness of the regulations and their potential unintended effects. Fourth, even though e-scooters will no longer circulate the streets of Paris, an in-depth examination of this case will help other cities better design and assess regulatory frameworks that facilitate the integration of e-scooters with the existent transport system and to catch up with the technological innovation.

#### 4. Data

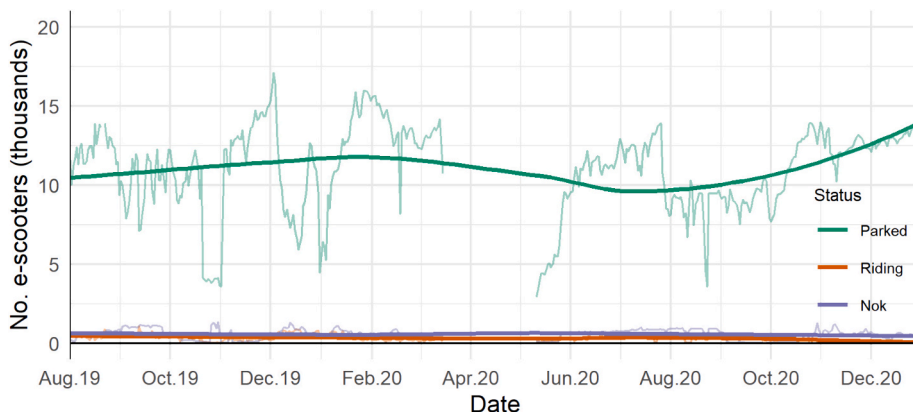
To investigate the effects of parking regulations in Paris, we use an original administrative dataset that geo-locates dockless e-scooters in the city. According to the corresponding regulations, operators are obliged to report daily the status and location of each vehicle with a frequency of three hours starting at 01:00hrs. Our dataset includes observations collected from August 2019 to December 2020. The vehicle's status includes the following: parking, riding, and not operational (out of service or in maintenance). On average, almost 12,000 vehicles are deployed every day in the city from which 92 % are parked, 3 % riding, and 5 % not operational. Nevertheless, the number of vehicles riding might not reflect the true demand for dockless e-scooters due to the low frequency in the collection of data.

Regarding evolution over time, Fig. 1 reports the daily average of the fleet size by status over time. Note that this Figure reveals a substantial variation in the number of parked vehicles over short periods of time. The maximum value observed was close to 17,000 attained in December 2019 (before the reduction in the number of permits and fleet-size). The minimum value is hard to estimate because of the global pandemic. The Figure also reveals that the number of riding and not operational vehicles remained more stable over time.

The geographical information of the polygons representing parking bays was collected from the city's open data website. The city constructed a total of 2,514 parking bays, which account for a surface close to 25,600 m<sup>2</sup>. It is noteworthy to mention that this amount of public space was designated to allocate the whole fleet (15,000 e-scooters) assigning to each vehicle an individual space of 1.7 m<sup>2</sup>. In addition, the average distance between parking bays is 141 m, which is commensurate with what the city announced before implementation of the policy (150 m). Nonetheless, there is no information available on the exact date of construction for each parking bay. In consequence, the empirical evidence that we present here focuses more on the before-after comparison (by comparing the initial situation in mid-2019 to the scenario by the end of 2020) than on the dynamics itself.

Using this type of data for dockless micromobility studies is, to the best of our knowledge, an innovation. Many studies are restricted to the collection of data in the form of information requests from operator's APIs. Although those formats have potential for further research, it is usually necessary to request information in high frequencies (each 1–5 min) to extract reliable information about the location and status of the vehicle. Consequently, the demand for computational resources obliges researchers to restrict this analysis to short periods of time (2–3 months). This, in turn, limits the possibility of capturing changes in regulatory frameworks. In other cases, studies are restricted to the information available by a subsample of the number of operators or e-scooters.

The data we use here is original and rich because it observes all the operators active in the market and because it spans a considerable reach of time and space. However, working with a big dataset (forty-five million observations) with these characteristics requires programming tools and models. Programs were coded to automatically clean and create hourly datasets, define variables, compute different criteria (see section 5), optimize memory use, and export the results for further analysis. Every dataset has flaws and



**Fig. 1.** Fleet size over time by e-scooter status *Note:* The Figure reports the evolution in the daily number of dockless e-scooters in the city of Paris by status. Dark lines show a smoothed pattern applying the Locally Estimated Scatterplot Smoothing (LOESS) function. Nok refers to non-operational vehicles, i.e., those that are out of service or in maintenance. A blank space is intentionally introduced to identify the first national lock-down after the global pandemic.

ours is no exception. The next paragraphs describe the limitations we detected in our data and how we addressed them.

**GPS inaccuracies.** Dockless e-scooters are provided with GPS devices to facilitate locating them. This information allows users to locate e-scooters with their smart phones and operators can track locations while parking and riding. In accordance with authority's mandate, the same devices are used to report their location and status. However, GPS systems are subject to inaccuracies for various reasons, such as connectivity issues, limited resolution for angle measurements, noise, issues with the communications network, among others. These inaccuracies, known as User Equivalent Range Error (UERE), introduce uncertainties in establishing the exact position of e-scooters. According to the European Space Agency, the UERE for Standard Positioning Services (SPS) ranges between 7 and 33 m. Nevertheless, we developed a methodology to infer confidence intervals from the data, which takes into consideration specific geographic characteristic of the city (see Appendix A for details). We conclude that a tolerance of 30 m is sufficient to account for potential GPS inaccuracies in the case of Paris. Furthermore, we include a range of values (10 m, 20 m, and 30 m) across various criteria to capture the maximum potential error of GPS devices.

**Normalization.** Variations in fleet size invalidate the comparison of different spatial measures over time (see Fig. 1). A clear example of this is the minimum distance between a predetermined point  $(x_0, y_0)$  and  $N$  different points located at random inside a cell of fixed size. In fact, the minimum distance will converge to zero at a decreasing rate of  $(2\sqrt{N})^{-1}$  (see the proof in Appendix B). The case of e-scooters in the city is the same, if we measure the distance from vehicles to the city center, we will observe variations as function of the number of vehicles deployed in the city. To avoid volume effects due to daily variations in fleet size, we normalize our measurements by a factor equal to  $(2\sqrt{N})^{-1}$ .

## 5. Methodology

### 5.1. Definitions

**Mis-parking.** Two types of mis-parking have been identified in the literature: improper parking and cluttering (Gössling, 2020; Brown, Klein, Thigpen, & Williams, 2020). The former refers to how vehicles are parked individually—blocking sidewalks, bus stops, lying on the ground, etc.—while the latter describes a disorganized distribution of parked vehicles across the city. For the purpose of this work, we approach mis-parking in two different ways:

- **In the form of cluttering**, by assessing the overall distribution of e-scooters within a predetermined geographic region. Cluttering is considered mis-parking because it gives the impression of a disorganized transport system that is not harmonized with the rest of the mobility mix (Klein, Brown, & Thigpen, 2023).
- **In the form of improper parking.** It is noteworthy that, *ex post*, according to the regulations, not ending a trip inside a designated parking bay is also considered improper parking. Failure to follow the rules is considered mis-parking in the same way that a car must be parked in zones designated for that purpose. The dataset used in this study allows for the assessment of this type of mis-parking at the vehicle level by examining the spatial relationship between parking bays and e-scooters. In other words, we infer whether an e-scooter is properly parked by comparing its location with that of the parking bays. Accordingly, this paper provides insights into improper parking in the sense of compliance with existing regulations. See, for instance, the work by Brown et al. (2024), Klein et al. (2023), and Karlsen et al. (2021).

**Types of user.** To better explain the results observed in terms of compliance with the regulations, we hypothesize that three types of users co-exist among e-scooter riders:

- **Complier.** Always complies with the rules regardless of the number of parking bays near the destination.
- **Opportunistic.** Parks properly only when parking bays are near the destination; otherwise, mis-parks.
- **Unlawful.** Never follows the rules, regardless of the number and location of parking bays.

It is important to clarify that a more detailed dataset would be required to classify individual users based on their behavior. However, for the purposes of this study, we assume that the co-existence of various user types could help explain the patterns observed in the data regarding improper parking of vehicles *ex post* implementation of the regulations.

Following the principles of asymmetric information, the fundamental challenge in studying user behavior is that user type constitutes private information: each user knows their own type at the beginning of the trip, and this information is only revealed when the trip is completed. By analyzing the geo-location of parked e-scooters—presumably marking the end of users' journeys—and their spatial relationship with parking bays, we can hypothesize how the co-existence of different user types helps explain the effects observed in terms of compliance.

**Accessibility.** Many definitions of accessibility exist in the transport literature (Páez, Scott & Morency, 2012). In this paper, we define it as the distance that any user must travel to find the closest e-scooter. This definition corresponds to the first/last mile dilemma. Following Lesh (2013), any mobility mode is inconvenient when the start or end points are located beyond a comfortable distance for the user. Defining accessibility in the way we do here is convenient because dockless e-scooters are characterized by the possibility that vehicles can be picked up and dropped off at any location in the city using smart technology. In other words, e-scooters are accessible to users with no need for docking stations (as is the case in the station-based bike-sharing system). Therefore, the distribution of e-scooters across the city is crucial for users to find them when they need them (Sanders, Branion-Calles, & Nelson,

2020).

**Distance-decay function.** We estimate a distance-decay function to study the evolution of mis-parking behavior over time. It describes the relationship between the distance from an e-scooter to the location of the closest parking bay. In other words, it determines the likelihood that a user chooses to park inside parking bays. We use the location of e-scooters during the second week of December 2020 when the distance to parking bays reached its minimum value. Studying this period allows us to estimate a decay-function that describes a scenario where parking bays and rules are being implemented. To estimate moments of the distance-decay distribution, we fit a log-normal decay probability density function using nonlinear weighted least-squares.<sup>3</sup> The results are documented in Fig. 2. The estimated distance-decay function has an expected mean of 17.3 m and variance 210.3.

## 5.2. Spatial analysis

As mentioned above, this paper is based on the spatial relationship between vehicles and parking bays. The data is processed using two different approaches: vector and rasters. Vector data allows the study of relationships between attributes or features, such as points (e.g., e-scooter locations) and polygons (e.g., parking bays). Raster data is defined as a collection of cells (or pixels) in the form of grids representing specific geographical regions. Each cell in the raster stores real-world information such as elevation, distance, etc. For the purpose of this paper, we produce high resolution rasters with cell sizes of  $2 \times 2$  m. Every raster was snapped (the cells aligned) and masked (cropped to the corresponding extent) to a basic raster that covers a surface equal to the extent of the city. This last step is important to produce valid comparisons over time.

Following this approach, we develop a novel multicriteria evaluation method based on the geographical attributes of e-scooters and parking bays. To study the evolution of such criteria, it is important to recall that parking bays were constructed at the end of 2019 and in early 2020. Therefore, the aforementioned scenario uses the virtual location of parking bays, i.e., as if they were already built.

Regarding the spatial coverage of this work, we provide empirical evidence at the city and district level. See Fig. 3 for a visual description. E-scooter operators have permits to deploy vehicles within the boundaries of Paris (In French: La Ville de Paris) and its twenty districts. In consequence, the 2,514 parking bays are also confined within the same boundaries. Therefore, our analysis covers a surface up to 1 km from the farthest parking bay in every direction. Regarding the district comparison, we have grouped the 20 Parisian districts in four big groups based on the geographical and economic characteristics of the city. The inner-west includes 1st, 2nd, and 6th districts; inner-east includes 3rd, 4th, and 5th districts; outer-west comprises 7th to 9th districts, and 15th to 18th; outer-east the rest.

## 5.3. Multicriteria evaluation method

To evaluate various aspects of parking regulations, we develop a multicriteria evaluation method based on three principles: efficiency, accessibility, and compliance. The criteria for each principle are described below.

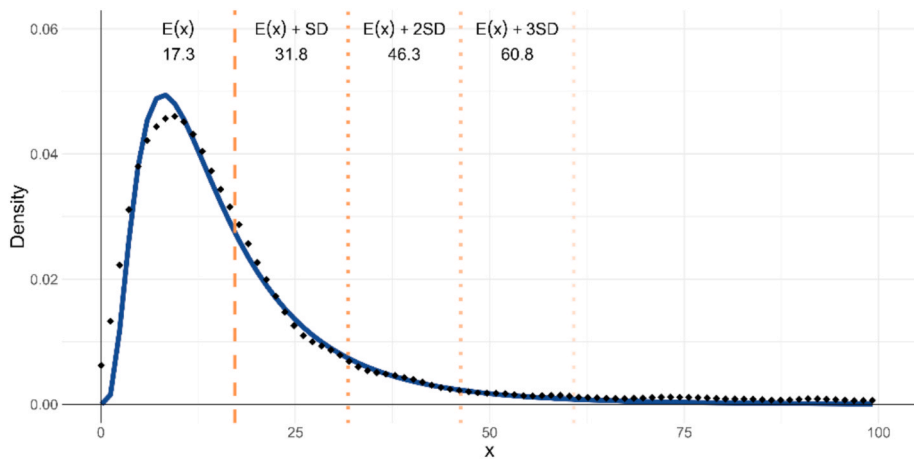
## 5.4. Efficiency

**Planar distance to parking bays.** Based on vector data, this criterion measures the Euclidean distance between parked e-scooters and parking bays and its evolution over time. First, we compute the distance for every e-scooter in the database. Then, we compute the mean to obtain an hourly panorama of the relationship between parking bays and e-scooters (remember that the location of e-scooters is available in a frequency of three hours). Afterwards, daily averages are obtained. It is noteworthy that the distance between e-scooters and parking bays depends on fleet size, as explained in Section 4. Therefore, we propose normalizing this criterion to limit the influence of daily fleet size variations, as documented in Fig. 1. Details about the normalization method can be found in Appendix B. The expected evolution of this criterion is the following: if parking regulations are effective, the average distance between parking bays and e-scooters should decrease precisely because dedicated zones are concentrating vehicles on specific points.

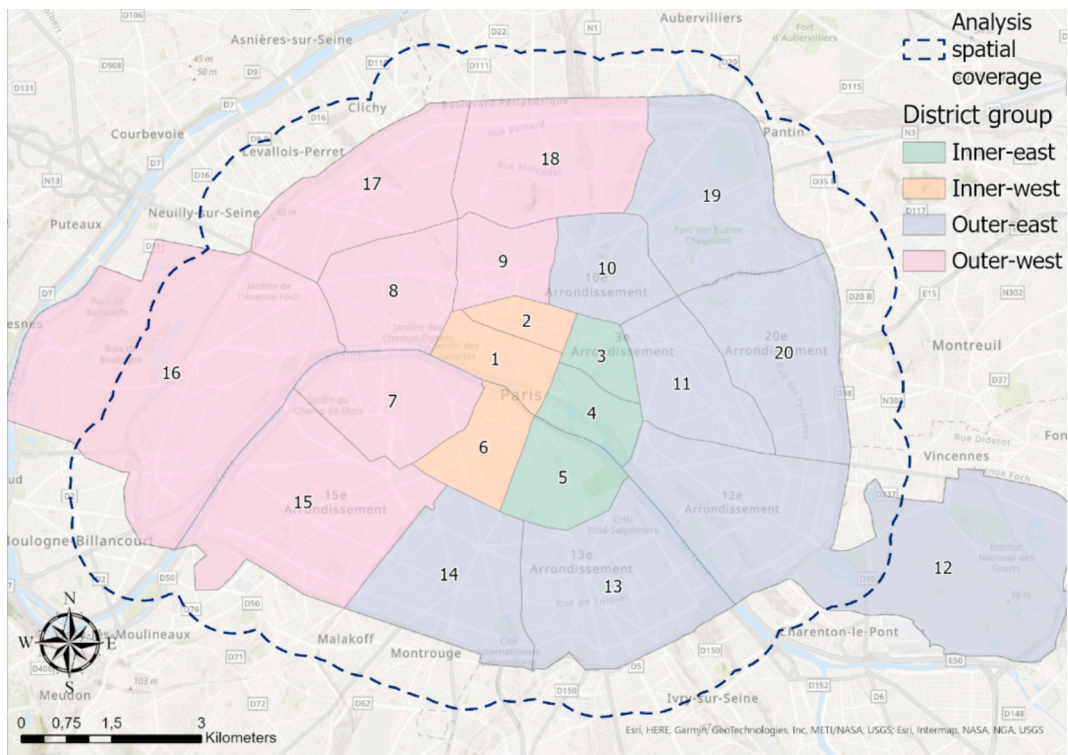
**Demand for parking bays.** Using the same logic as before, if this concentration follows new regulations, then the surface (or the space) delimited by such parking bays should be demanded more often. In other words, we expect to see more e-scooters parking inside dedicated parking bays. To capture this performance, we define a dichotomic variable equal to one if the space delimited by parking bays had at least one e-scooter nearby. Therefore, after computing the daily average as we did before, this criterion measures the evolution in the share of parking bays in use. As noted, defining the vicinity is crucial to correctly classifying parking bays. Using the results from the analysis of GPS inaccuracies (see Appendix A for details), we show three degrees of spatial tolerance to determine vicinity boundaries: 10, 20, and 30 m around parking bays.

An alternative measure is to count the number of e-scooters parked inside parking bays as a share of the daily fleet size. These measures are complementary and reflect the demand for parking bays. However, our preferred criterion is the dichotomous measure,

<sup>3</sup> We use a lognormal-decay function of the form:  $D(x) = \frac{1}{x\sigma\sqrt{2\pi}} \exp\left(-\frac{(\ln x - \mu)^2}{2\sigma^2}\right)$  Where  $x$  is the observed distance between e-scooters and parking bays. The parameters to estimate are  $\sigma$  and  $\mu$ . It is important to point out that a lognormal distribution has expected value  $E(x) = \exp\left(\mu + \frac{\sigma^2}{2}\right)$  and variance  $Var(x) = [\exp(\sigma^2) - 1] \exp(2\mu + \sigma^2)$ .



**Fig. 2.** Distance-decay function *Note:* The Figure presents the number of additional e-scooters by the size of the buffer around parking bays. Points describe the kernel density of the observed distribution. The solid curve in blue is the estimated lognormal-distance-decay probability density function of the form  $D(x) = \frac{1}{x\sigma\sqrt{2\pi}} \exp\left(-\frac{(\ln x - \mu)^2}{2\sigma^2}\right)$ . The parameters of the model were estimated using nonlinear weighted least-squares. The estimated parameters are  $\mu = 2.58$  and  $\sigma = 0.732$ , resulting in an estimated expected value of  $E(x) = 17.3$  and variance  $Var(x) = 210.9$ . (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)



**Fig. 3.** Spatial coverage and groups of districts *Note:* The map presents the spatial coverage used in this analysis. The dashed line determines the extent of the analysis at the aggregate level. It covers an area equal to 1 km from the last parking bay available in any direction in the city. Numbers are used to identify districts' names in Paris (1st district, 2nd district etc.). As observed, the extent of the 12th and 16th districts exceeds the city's spatial coverage. This is because those areas are mainly forests and no parking bay has been constructed there. Moreover, it is not common to observe e-scooters parked in those areas.

as it also helps to detect unused parking bays (see Figure C-1 in Appendix C for the results on the share of e-scooters properly parked).

**Congestion in parking bays.** One of the most crucial unintended effects of parking regulations in Paris is related to congestion, i. e., an excessive accumulation of vehicles in each parking bay. To assess congestion, we first measure the maximum capacity of each parking bay. According to the regulation, the 2,514 parking bays were designed to allocate exactly 15,000 e-scooters, thus, each vehicle occupies  $1.7 \text{ m}^2$ . Afterwards, we compute the maximum capacity of each parking lot by dividing its surface by  $1.7 \text{ m}^2$ . Finally, we compute the following two criteria:

- *Share of congested parking bays:* Number of parking bays in excess capacity over the total number of parking bays. In other words, it is the number of parking bays with at least one vehicle above capacity.
- *Share of e-scooter overcrowding parking bays:* In this case, we count the number of e-scooters exceeding the capacity of parking bays as a share of the daily fleet-size.

As above, we compute the criteria by hourly observations to compute daily averages, and we show their evolution over time. Considering the sequences of events, notably the arguments behind the referendum, we expect to see an increase in both criteria along the period of study.

It is important to note that the space attributed to one e-scooter in this analysis is based on the city's objective of distributing the fleet across parking bays. Therefore, even if e-scooters might use space more efficiently within parking bays, the criteria used here reflect parking bay congestion taking into consideration the city's goal of harmonizing the distribution of vehicles throughout the city.

### 5.5. Accessibility

**Planar distance to closest e-scooter.** This criterion was constructed using raster data as follows. Every time the information is collected, we create a raster (with the same characteristics as the basic raster described in section 5.2) with cell values equal to the planar distance to the closest e-scooter. We therefore compute the arithmetic mean using all the cells in the raster. Finally, we compute daily averages. This criterion is also dependent on fleet size, as it naturally decreases as the number of e-scooters in the city grows (see Section 4 for details). To limit the influence of fleet-size variations, we propose normalizing this criterion using the methodology described in Appendix B. We expect to use this criterion to capture the unintended effects of regulations on accessibility. If parking bays effectively concentrate e-scooters in specific points, then the average distance to find an e-scooter should be distorted depending on the number and location of parking bays. In the case of Paris, we expect to see an increase in this criterion because parking bays were built without a careful assessment of this potential effect.

**Spatial distribution of vehicles.** This criterion was constructed using raster data as well. The main idea behind the criterion is to determine whether parking regulations had an effect on the spatial distribution of parked e-scooters in the city. To this end, we estimate a two-dimensional Kernel Density raster with the same spatial characteristics as the basic raster described in section 5.2. Each cell in the raster measures the number of e-scooters within a predefined radius. We compute one raster every three hours (the frequency of observations in the dataset). Each resulting raster is normalized using the min-max methodology. This normalization allows us to create a raster representing the average monthly density for August 2019 and December 2020. These rasters represent the scenario before and after parking regulations. Afterwards, following McKenzie (2020), only the values above the *core* (arithmetic mean) in each raster are kept. As the author suggests, this mechanism allows comparison between both rasters, ignoring the effect of volume, i. e., the number of e-scooters in the city. Finally, to visually inspect the impact of the regulation, we produced a raster with the difference between the two. In addition, it is possible to study the distribution of all the values in this final raster. For instance, a non-skewed leptokurtic distribution with mean equal to zero would indicate that the spatial density distribution of e-scooters in December 2020 is similar to that in August 2019. In this case, we do not expect to find any difference between the two scenarios because parking regulations should not impact users' travel behavior in terms of routing and destinations.

It is important to mention that every criterion developed here can be produced at various levels of spatial coverage. In this paper, we show the results at an aggregate level covering the whole City of Paris and at a different regional level: for the 20 Parisian districts or for four different groups of districts (see Fig. 3 for details).

**Table 1**

Classification of e-scooters based on their distance to parking bays.

Class	Name	Definition using the moments of the distance-decay function	Co-existence of users' type
A	<i>Properly parked</i>	If the distance to the closest parking bay is lower than the mean from the distance-decay function: $distance < E(x) = 20m$	Composed mainly of compliers and opportunistic users
B	<i>Mis-parked when parking bay nearby</i>	If the distance to the closest parking bay is larger than the mean and lower than the mean plus two times the standard deviation: $E(x) = 17.3m < distance < E(x) + 2SD = 46.3m$	Characteristic behavior of unlawful users; to a lesser extent, we could also expect this behavior from opportunistic riders
C	<i>Mis-parked when no parking bay nearby</i>	When the distance to the closest parking bay is above the mean plus two times the standard deviation: $distance > E(x) + 2SD = 46.3m$	Unlawful and opportunistic users

*Note:* The Table reports the methodology used to classify e-scooters using their distance to parking bays. The moments of the distance-decay function are estimated in section 5.1.

## 5.6. Compliance

**Improper parking.** To assess the evolution of mis-parking in the form of improper parking *ex-post* regulations, we have classified parked e-scooters based on their distance to parking bays. As noted, *ex post* implementation of the regulations, not ending a trip inside a designated parking bay is also considered improper parking. Parked vehicles are classified based on the estimated moments of the distance-decay function defined in [section 5.1](#). The classification is presented in [Table 1](#). For construction of this criterion, we compute the daily share of e-scooters in each classification.

This criterion allows us to hypothesize about the type of users that compose each class. Compliers must only be present in Class A (*properly parked* vehicles), while unlawful users must be present in Classes B and C (*Mis-parked when parking bay nearby* and *Mis-parked when no parking bay nearby*, respectively). Additionally, opportunistic users may be found mostly in Classes A and C, and to a lesser extent in Class B. Therefore, these hypotheses are informative about parking behavior. For instance, a high share of Class A vehicles is a good indicator of the presence of compliers, while a high share of Classes B and C indicates a higher degree of unlawful and opportunistic behavior.

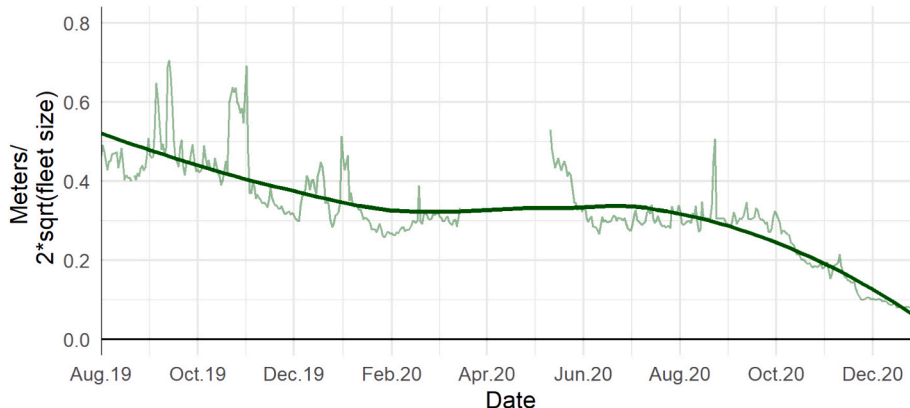
Our assumptions about the types of users that compose each class are also informative regarding the effectiveness of the regulation and provide insights for developing better policies. For instance, the share of properly parked vehicles serves as an additional indicator of how effective the regulations have been in harmonizing parking behavior. On the other hand, separating the share of improper parking—as we do here—helps to disentangle which types of users are not complying with the regulation. For example, if the share of *mis-parked with a parking bay nearby* is high, then policies targeting unlawful behavior could be implemented. Conversely, if the share of *mis-parked with no parking bay nearby* is high, it could indicate that additional infrastructure is needed to encourage opportunistic users to comply with the rules.

## 6. Results

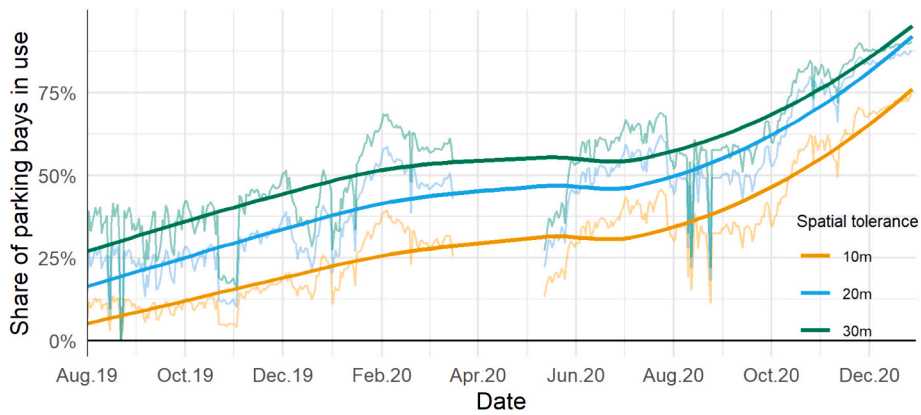
### 6.1. Overall impact of parking regulations

Parking regulations in Paris had a positive effect on harmonizing dockless e-scooters in the city. [Fig. 4](#) shows the evolution of the daily average distance over the whole time span normalized by the daily fleet size. The dark line shows a smooth curve using LOESS. During the first national lock-down—a consequence of the global pandemic—the provision of the service was interrupted resulting in a considerably small number of vehicles deployed in the city. Therefore, to avoid presenting misleading results, we dropped those observations, represented as a blank space in the time-series. The evolution of this criterion shows that the average distance between e-scooters and parking bays decreased considerably after implementation of the regulation: In August 2019, the average distance was close to 100 m (0.5 after normalization, see [section 5.3](#) for details), once they were all built in December 2020 this value falls to around 20 m (0.08 after normalization, see [section 5.3](#) for details) which represents a percentage decrease of 80 %. Overall, the evolution of this measure shows that the policy has been effective in harmonizing dockless e-scooters in terms of mis-parking.

Another way to assess the policy is to study the demand for parking bays. As observed in [Fig. 5](#), the evolution of this index goes in line with the previous criterion and with the positive effect of parking regulations. Considering a spatial tolerance of 30 m (see [Appendix A](#) for a discussion about GPS accuracy), in August 2019 close to 25 % of the space later used for parking bays had at least one vehicle inside, rising to almost 85 % after their construction (a 60 pp. increase). In terms of coverage, in December 2020 parking bays allocated almost 85 % of the fleet size. Note that this criterion could indicate a random distribution of e-scooters in the city. To account for this caveat, we compare the evolution in the demand for parking bays between parked and non-parked (riding or not operational) e-



**Fig. 4.** Normalized distance between e-scooters and parking bays over time *Note:* The Figure reports the evolution in the distance from e-scooters to the closest parking bay normalized by fleet size. For further details about normalization, please see [Appendix B](#). Dark lines show a smoothed pattern applying the Locally Estimated Scatterplot Smoothing (LOESS) function. A blank space is intentionally introduced to identify the first national lock-down after the global pandemic.



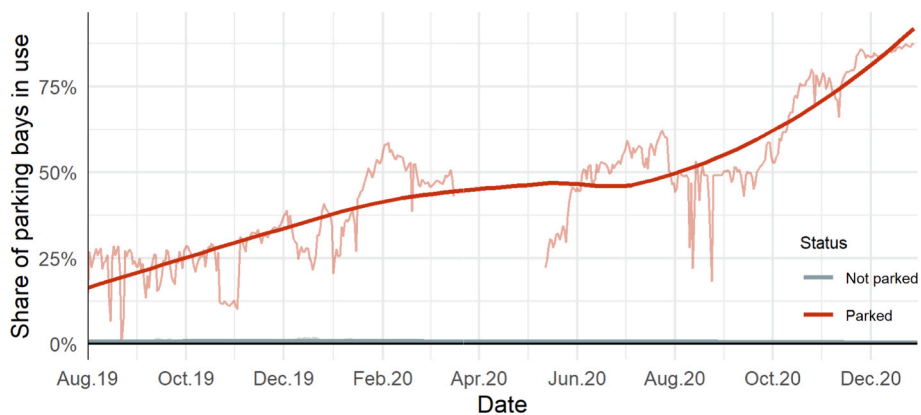
**Fig. 5.** Demand for parking bays over time *Note:* The Figure reports the number of parking bays with at least one e-scooter within, measured as a share of the total number of parking bays. Spatial tolerance refers to the size of the buffer used to expand parking bay surfaces to account for potential GPS inaccuracy. For further details about GPS inaccuracy, please see Appendix A. Dark lines show a smoothed pattern applying the Locally Estimated Scatterplot Smoothing (LOESS) function. A blank space is intentionally introduced to identify the first national lock-down after the global pandemic.

scooters. If the evolution of this measure is related to the concentration of vehicles due to the construction of parking bays and not to the random spatial distribution, then the demand for parking bays for in-use (riding) e-scooters must not change over time. This assumption is supported by the data, as one might notice in Fig. 6.

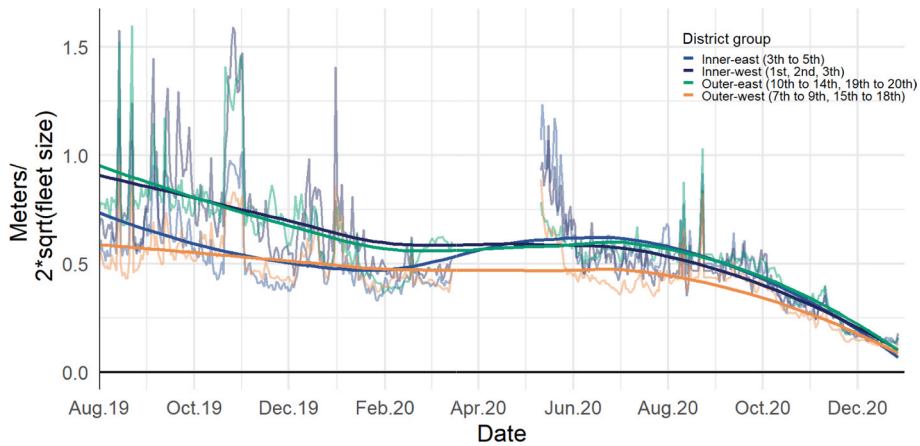
Additionally, we study the impact of parking regulations at the district level. As mentioned above, the time-series were built for four different district groups.

Fig. 7 shows the results for the planar distance between parking bays and e-scooters during the entire period of study. Moreover, to improve visualization, Fig. 8 restricts the period shown from October 2020 to December 2020. As noticed, the distance between parking bays and e-scooters behaves similarly in all four district groups. Furthermore, after comparing the levels, the evidence suggests that the regulation was effective for homogenizing the behavior across regions, achieving a convergence in terms of performance. Note that in October 2020 (and in all previous months) there was a clear difference across districts. It is clear from the Figure that e-scooters in the outer-east region were dropped farther from parking bays than those in the outer-west regions, which demonstrate a better performance. On the contrary, at the end of December 2020, three groups converged to the same level of performance, but still slightly higher than the criterion from the outer-west region.

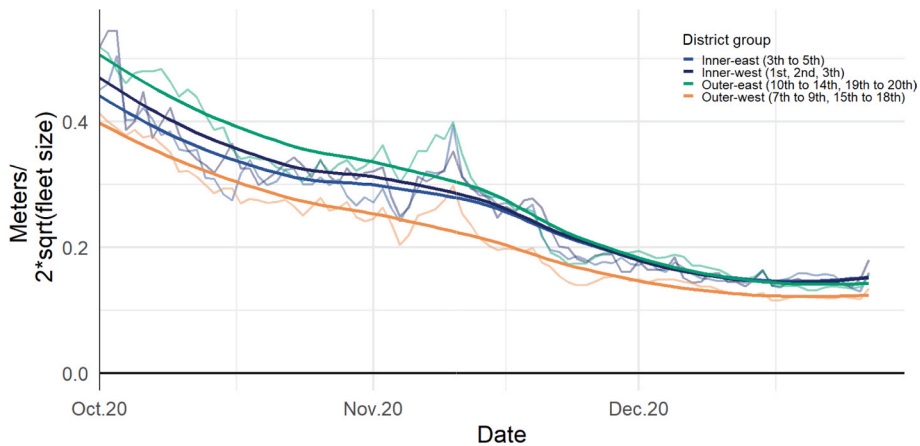
Finally, to provide insights about the heterogeneous nature of the twenty Parisian districts, we compute the monthly average of the normalized distance between e-scooters and parking bays in December 2020 (after regulation) per district. Afterwards, we display the results in the form of a map. The results are reported in Fig. 9. It is clear from this analysis that there are disparities between the districts. For instance, it is noteworthy that all southern districts performed better than the northern ones except the fourteenth district.



**Fig. 6.** Demand for parking bays over time, parked vs. not parked e-scooters *Twenty meters of spatial tolerance* *Note:* The Figure reports the number of parking bays containing at least one e-scooter by status, measured as a share of the total number of parking bays. The status Not parked includes those in use (riding) and not operational (Nok), i.e., out of service or in maintenance. Spatial tolerance refers to the size of the buffer used to expand parking bays surface to account for potential GPS inaccuracy. For further details about GPS inaccuracy, please see Appendix A. Dark lines show a smoothed pattern applying the Locally Estimated Scatterplot Smoothing (LOESS) function. A blank space is intentionally introduced to identify the first national lock-down after the global pandemic.



**Fig. 7.** Distance between e-scooters and parking bays by district groups August 2019 to December 2020 *Note:* The Figure presents the evolution in the distance from e-scooters to the closest parking bay by groups of districts. The values shown are normalized by fleet size. For further details about normalization, please see Appendix B. Dark lines show a smoothed pattern applying the Locally Estimated Scatterplot Smoothing (LOESS) function. A blank space is intentionally introduced to identify the first national lock-down after the global pandemic.



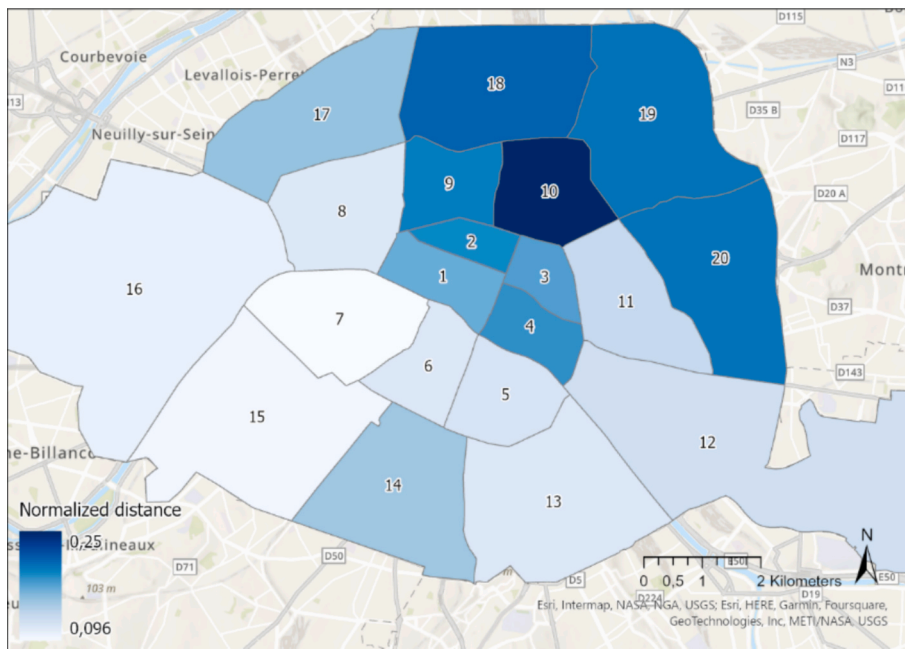
**Fig. 8.** Distance between e-scooters and parking bays by district groups October 2020 to December 2020 *Note:* The Figure reports the evolution in the distance from e-scooters to the closest parking bay by groups of districts in the fourth quarter of 2020. The values shown are normalized by the fleet size. For further details about normalization, please see Appendix B. Dark lines show a smoothed pattern applying the Locally Estimated Scatterplot Smoothing (LOESS) function. A blank space is intentionally introduced to identify the first national lock-down after the global pandemic.

This result is relevant to detect areas of improvement for future interventions.

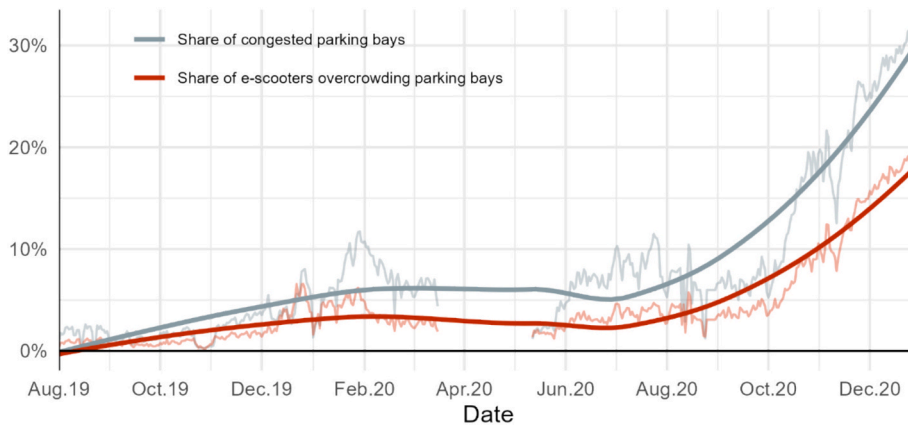
Another crucial criterion regarding the efficiency of the regulation is related to congestion in parking bays. Contrary to station-based modes, designated parking bays in the form of painted corrals do not limit users to dropping off the vehicles when the space reaches its capacity. As a result, one could expect an excessive concentration of vehicles in specific parking bays. We document this effect in Fig. 10. First, we show the evolution of the share of congested parking bays. As noted, congestion rises with the construction of parking bays and enforcement of the rules. In the first part of 2020 until approximately October, 10 % of parking bays were congested. However, the index picked up by a point where almost 30 % of parking bays showed signs of congestion in the last three months of the year. What is more, the index shows a clear positive trend with no sign of deceleration at the end of the period. Second, we also show the share of e-scooters that overcrowd parking bays. The pattern is similar to the previous index throughout the period. In this case, the evidence suggests that almost 20 % of vehicles (close to 3,000) are responsible for parking bay congestion. It is important to highlight that both indexes show different growth rates in the last quarter of the year. Congested parking bays grow at a rate of 500 %, versus a 300 % growth rate for the share of vehicles overcrowding parking bays.

## 6.2. Effects on accessibility

The second research question that we address in this paper is related to the unintended effects of the regulation. Notably, parking bays accumulate e-scooters in specific spots in the city. Therefore, their location and distribution became relevant to the accessibility of



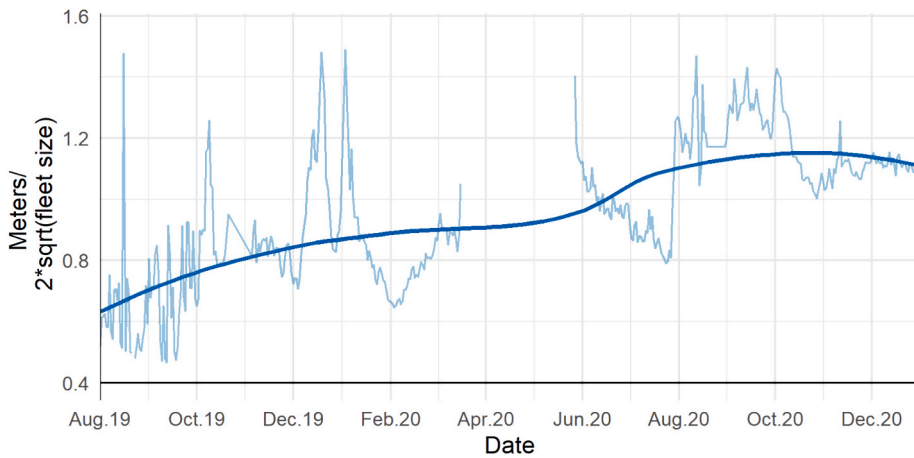
**Fig. 9.** District heterogeneities in the distance between e-scooters and parking bays *Note:* The map reports the average distance from e-scooters to parking bays in December 2020 by district. The values shown are normalized by the fleet size. For further details about normalization, please see Appendix B. Numbers are used to identify districts’ names in Paris (1st district, 2nd district etc.).



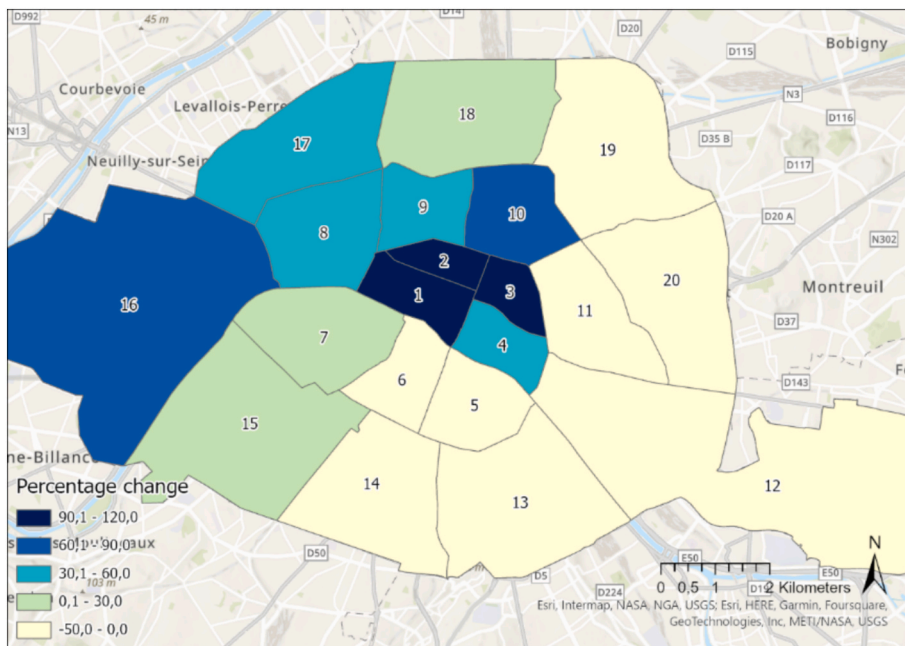
**Fig. 10.** Congestion in parking bays *Note:* The Figure reports the evolution in the indices related to congestion in parking bays. The *Share of congested parking bays* refers to the number of parking bays exceeding capacity as a proportion of the total number of parking bays in the city. The *Share of e-scooters overcrowding parking bays* is the number of e-scooters overcrowding parking bays, i.e., the number of vehicles above capacity as a proportion of the fleet-size. Dark lines show a smoothed pattern applying the Locally Estimated Scatterplot Smoothing (LOESS) function. A blank space is intentionally introduced to identify the first national lock-down after the global pandemic.

vehicles. As a reminder, accessibility is defined here as the shortest distance that any user must commute to find the closest e-scooter. The results of the criteria developed for this purpose are documented in Fig. 11. As before, the darkest curve shows the smoothed curve using a LOESS method and the blank space is the consequence of dropping observations due to the global pandemic. The evolution shows that, in August 2019, the average distance to find the closest e-scooter in the city was about 120 m (0.6 after normalization, see section 5.3 for details). Nonetheless, after construction of parking bays in December 2020, this value rose to nearly 250 m (1.2 after normalization, see section 5.3 for details), which represents a percentage increase of 108 %.

The regional analysis reveals interesting results. To provide a before-after comparison, we compute the percentage change in this criterion by district. As can be seen in Fig. 12, eight out of twenty districts (40 %), show an improvement in the accessibility of e-scooters. In other words, the distance to the closest e-scooter decreased because of the construction of the parking bays. Nevertheless, this improvement does not compensate for the loss of accessibility in the other districts. Another relevant conclusion is related to the



**Fig. 11.** Average distance to the closest e-scooter *Note:* The Figure reports the evolution in the average distance from any location in the city to the closest parking bay normalized by fleet size. This index is computed using rasters, where the location of each cell represents one location in the city and the value of the cell measures the distance to the closest e-scooter. For further details about normalization, please see Appendix B. Dark lines show a smoothed pattern applying the Locally Estimated Scatterplot Smoothing (LOESS) function. A blank space is intentionally introduced to identify the first national lock-down after the global pandemic.

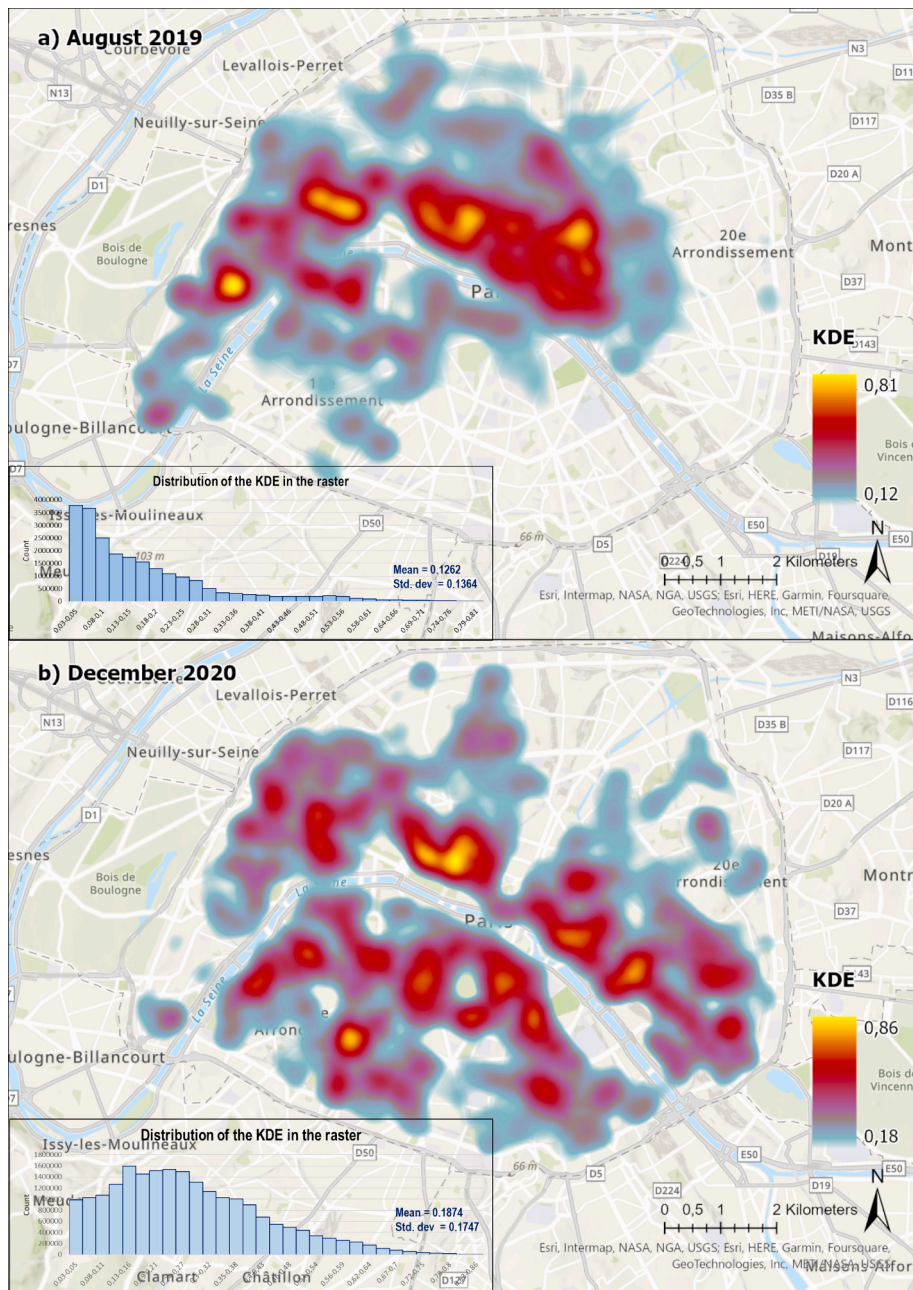


**Fig. 12.** Difference in the average distance to the closest e-scooter before and after the regulations *Note:* The map reports the percentage change in the Planar distance to the closest e-scooter between August 2019 and December 2020. A monthly average of daily measurements was used. Numbers are used to identify districts' names in Paris (1st district, 2nd district etc.).

spatial redistribution of accessibility after the regulation. Note that inner-north districts (1st to 4th) are the ones with the largest loss in accessibility with a percentage increase larger than 90 % on average. In contrast, all the districts that showed improvements are located on the east side of the city.

In a nutshell, the findings suggest that parking regulations in Paris have a negative effect on the accessibility of e-scooters by increasing the average distance to the closest vehicle. However, the effect is heterogeneous across districts. In fact, in 40 % of them (representing 47 % of the city's total surface) accessibility improved after provision of parking infrastructure.

Another important concern is related to the potential impact of parking bays on the distribution in the number of vehicles across the city. The criterion developed to study this effect explores the distribution of the differences in the kernel density estimations between December 2020 and August 2019. First, we provide visual evidence of such estimations in Fig. 13 (a) and (b). Both maps show zones in

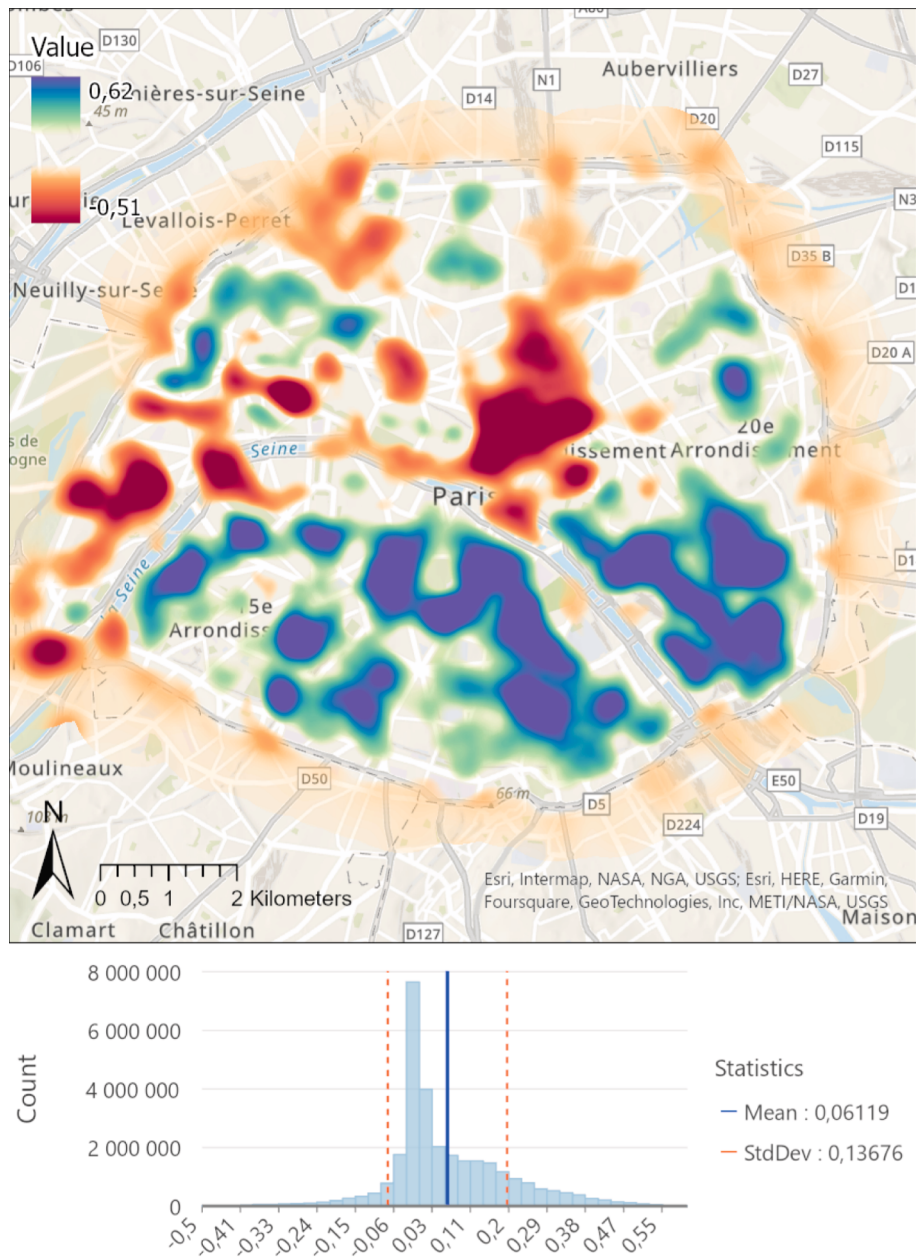


**Fig. 13.** Comparison of e-scooter density across the city before and after construction of parking bays Note: The map reports heat-maps representing the concentration of e-scooters in the city before (Panel a) August (2019) and after (Panel b) December (2020) regulation. A kernel density estimation (KDE) was used to measure concentration. To be comparable across time, each heat-map was normalized using the min–max methodology. Following McKenzie (2020), only values above the mean are considered to avoid volume effects. Plots at the bottom left corner show the distribution of the kernel density in rasters before truncation.

the city with high (in yellow) and low (in blue) concentration of e-scooters. Blank zones are excluded regions with density values lower than the mean. Moreover, a chart that reports the distribution of the kernel density estimation is included in each Figure. Although some differences can be identified from this visual inspection, computing the difference between both scenarios will allow us to obtain analytical conclusions.

The result of this exercise is documented in Fig. 14. Note that the difference ranges from  $-0.51$  to  $0.62$ . Negative values (in red) represent regions where the density of e-scooters was higher in August 2019. Conversely, positive values (in blue) are zones where the density was higher in December 2020. Regions with low variation were intentionally left blank. These regions are spots that remain unchanged. In addition, the Figure includes a histogram that describes the distribution of all the values in the raster.

## December 2020 relative to August 2019



**Fig. 14.** Differences in the density distribution of e-scooters *December 2020 relative to August 2019* Note: The map presents the difference in the concentration of e-scooters before and after construction of parking bays. It shows the result of subtracting, cell by cell, the values in the heat-map for December 2020 from the values observed in August 2019. Transparent regions represent locations in the city with low variation in the concentration of e-scooters. Regions in blue represent places in the city with a higher concentration of e-scooters in December 2020 in comparison with August 2019. Regions in red show the opposite results. The plot at the bottom shows the resulting distribution of the difference in the raster. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Several results might be obtained from the analysis. First, parking bays improved the spatial coverage related to the provision of the service. Fig. 14 clearly shows a higher density of e-scooters beyond the periphery (the provision of e-scooters is restricted to zones within the periphery of the city) in August 2019. Therefore, the construction of parking bays might have helped the city to control the geographical boundaries for the operation of this service. Second, the distribution reflects differences in the density over time. A positive mean (0.06), a positive skewness (0.64), as well as the long tails of the distribution indicate that, overall, the density of e-scooters in the city changed due to the construction of parking bays. Finally, analyzing the spatial component of the difference in the

density shows that parking bays augmented the number of e-scooters in the south-east regions of the city at the expense of reducing their density in the south-west and downtown districts primarily. Therefore, unexpectedly, parking regulations had an effect on the distribution of e-scooters in the city. A potential explanation is each parking bay's limited capacity for e-scooters, which might force operators to deploy their e-scooters in other areas of the city. Nevertheless, a causal empirical strategy is needed to assess the validity of this mechanism.

### 6.3. Assessment of compliance

In this section we present evidence about the effects of parking regulations on mis-parking in the form of improper parking *ex post* the regulation. In other words, we study the evolution over time on the Classes of parked e-scooters as a function of the distance between the location of the drop-off point and the closest parking bay (see Table 1 for details). Fig. 15 shows the daily average share of the three Classes of e-scooters over time. The Figure clearly shows a re-composition in the share of vehicles across Classes, especially after September 2020, i.e., after the construction of parking bays.

The main findings stemming from the analysis of this criterion are the following. First, the regulation has been effective incentivizing opportunistic users to comply with the rules. As mentioned above, we hypothesized that opportunistic users are mostly distributed across Classes A and C (*properly parked* and *mis-parked when no parking bay nearby*, respectively). As shown in Fig. 15, the share of Class C e-scooters dropped from 55 % in September 2020 to less than 10 % by the end of December 2020. Nevertheless, a 10 % share of this Class still represents a considerable number of vehicles and deserves further attention. The performance of this criterion could improve even further with an optimal design in the number and location of parking bays.

Second, at the end of the period, there was still a significant share of e-scooters (almost 15 %) *mis-parked when a parking bay is nearby* (Class B). Class B is expected to be composed mainly of unlawful users, i.e., those who never follow the rules. In addition, the evidence does not show any improvement over time. Therefore, further studies should be conducted to better understand this type of behavior and explore effective ways to incentivize these users to comply with the regulation.

Although the share of Class B scooters appears to remain constant throughout the study period, it is still relevant to analyze differences across districts to provide empirical evidence about the spatial distribution of mis-parking across the city. To this end, we measure the share of Class B e-scooters in each district before and after the regulation. Specifically, we compute the average of this share in August 2019 and in December 2020. The results are presented in Fig. 16. They show an uneven distribution of this criterion across districts. Moreover, unlawful behavior appears to be concentrated across Districts 2, 17, and 5. Therefore, the analysis reveals that, although improper parking remains a citywide issue, efforts focused on a few districts could have a significant impact on reducing unlawful behavior.

## 7. Discussion

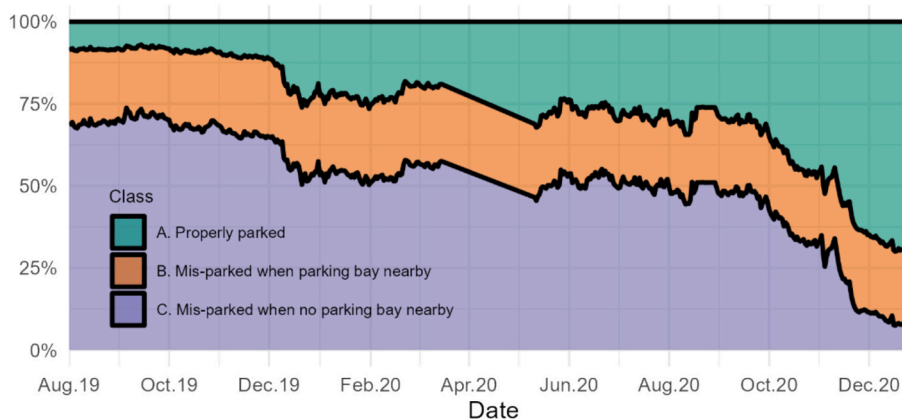
One of the main drawbacks of adopting dockless e-scooters is mis-parking as it creates a mode of transport that is not harmonized with the rest of the mobility mix. In order to improve the integration of this service, many cities have implemented different regulations that have received limited attention in the literature. In this paper we have investigated the effects of building dedicated parking bays in the form of painted corrals in the city of Paris.

The study of e-scooter parking has received limited attention in the literature and the few studies available have found relatively low rates of mis-parking in U.S. cities; however, they primarily focus on individual parking behavior and rely on small sample sizes (Brown, Klein, Thigpen, & Williams, 2020; James, Swiderski, Hicks, Teoman, & Buehler, 2019; Fang, Agrawal, Steele, Hunter, & Hooper, 2018). Our study differs in two ways. On the one hand, the administrative dataset we use enables a comprehensive analysis of cluttering across the entire deployment zone instead of individual incidents, such as blocking sidewalks. On the other hand, our dataset covers the full fleet of e-scooters at high frequency intervals, which allows us not only to examine spatial patterns at the urban scale, but also to analyze temporal dynamics.

The specific case of parking regulations in the form of parking bays has already been explored by Brown et al. (2024), Klein et al. (2023), and Karlsen et al. (2021). These studies found that parking regulations in the form of parking bays effectively improve parking conditions. We contribute to this trend by providing a more complete geographic picture. This paper confirms the effectiveness of mandatory parking bays in reducing cluttering. Our findings suggest that parking bays have been effective in reducing cluttering by concentrating more than 85 % of the fleet. In fact, the average distance between parking bays and e-scooters was only about 20 m after the implementation of the regulation (almost equal to the average level of GPS inaccuracy, which is approximately 20 m).

Regarding compliance, while such studies argue that infrastructure and regulations are key to incentivizing proper e-scooter parking, we emphasize the need to consider these issues on a broader scale. We find that the regulation has been effective regarding compliance by reducing the number of mis-parked vehicles when there is no parking bay nearby. However, we also observe that almost 25 % of parked e-scooters remain non-compliant, and that Paris experienced persistent unlawful behavior, with 13–18 % of riders regularly ignoring rules after implementation of the regulation. Furthermore, our study highlights the need for improved parking infrastructure design to enhance compliance rates, aligning with findings from recent literature (Meng, Brown, Klein, Thigpen, Haydu, & Stout, 2024; Berg Wincent, Jenelius, & Burghout, 2023).

Additionally, our study contributes to the growing body of evidence on the unintended effects of parking regulations, which have mainly focused on public perceptions of parking bays, reduced ridership, and increases in egress walking distance (Hurllet, Manout, & Diallo, 2024; Berg Wincent, Jenelius, & Burghout, 2023; Buehler, Broaddus, White, Sweeney, & Evans, 2022). This paper reveals significant unintended consequences neither addressed nor observed in previous studies.



**Fig. 15.** Evolution in the composition of e-scooters according to parking classification *Note:* The Figure reports the number of e-scooters in each parking classification as a share of the fleet size. Values add up to one because e-scooters can only belong to one class by design. E-scooters are classified according to their likelihood to be parked inside a parking bay. *Class A. Properly parked* are vehicles located at a distance below or equal to the expected mean of the distance-decay function. *Class B. Mis-parked when parking bay nearby* are e-scooter but less than three times the standard deviation. Therefore, *Class C. Mis-parked when no parking bay nearby* are those located at a distance beyond three times the standard deviation. Straight lines were intentionally introduced to identify the first national lock-down after the global pandemic.

Our findings suggest that the share of overcrowded parking bays reached 30 % and showed no sign of decline. Moreover, we found evidence that parking regulations negatively impacted the accessibility of dockless e-scooters measured as the average distance to find the closest vehicle in the city. On average, the mean distance increased 108 % (from 120 m to 250 m) after implementing the rules. However, the regional analysis revealed that some districts benefited from the regulation. In particular, the scenario in the south-east districts showed an improvement in accessibility and a larger number of vehicles per surface unit.

The introduction of e-scooters has raised significant concerns among citizens, particularly regarding safety, reckless riding, and improper parking. Based on the results presented in this paper, we argue in favor of adopting proper regulations to harmonize e-scooter use, rather than banning them from circulation. In addition to reducing clutter and improving public perception, parking regulations may also help lower the risk of accidents. Furthermore, a well-designed supply of parking spots could support governments in their goal of fostering complementarities with other transport modes. Finally, the novel multidimensional criteria proposed in this paper may assist cities in developing agile regulations to better monitor and manage the deployment of e-scooters in urban areas

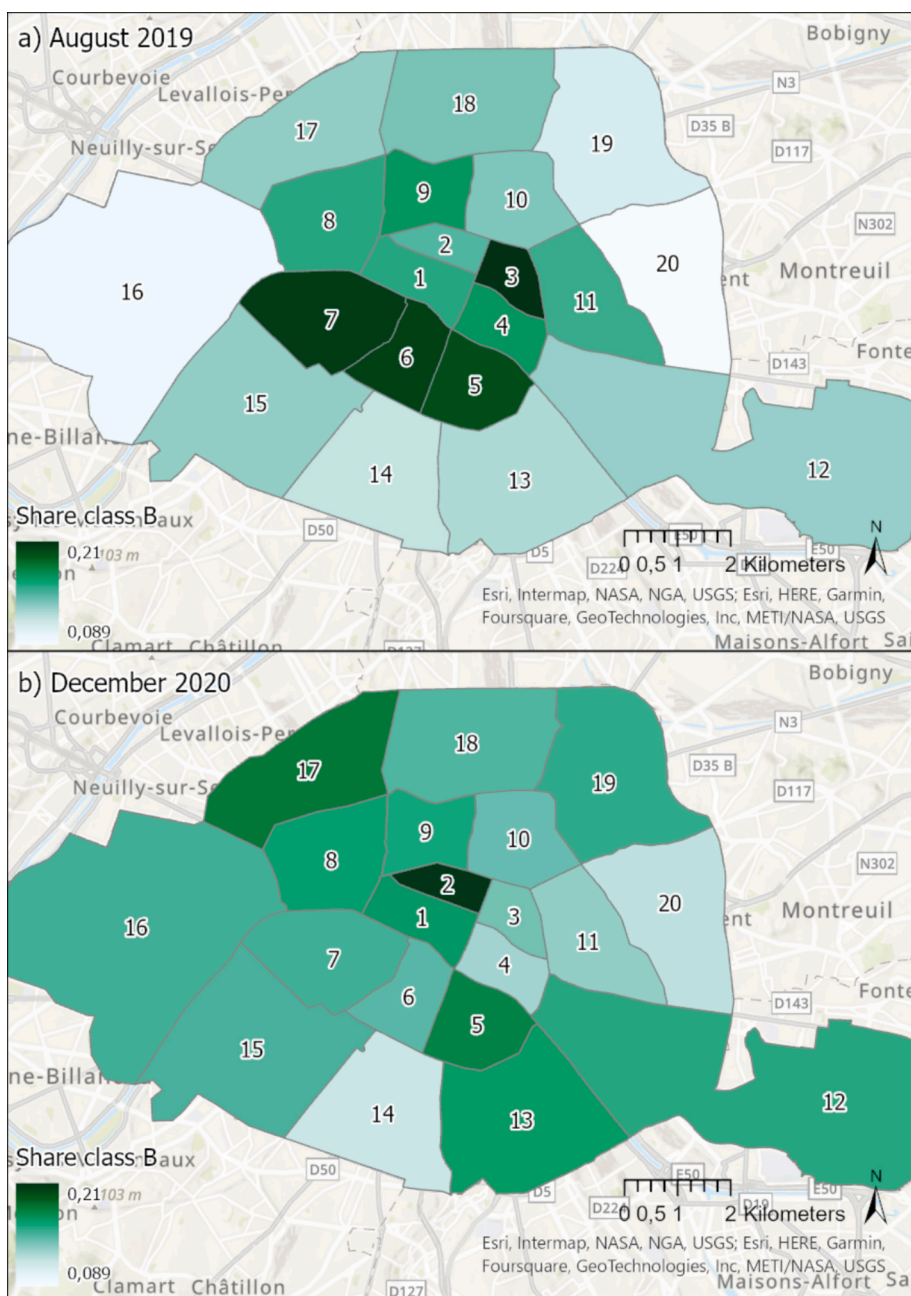
We acknowledge that parking regulations may have additional effects on various stakeholders that are worth exploring in future research to deepen our understanding of their overall impact.

**Demand-side.** On one hand, as we documented here, parking bays move e-scooters away from users, decreasing the attractiveness of free-floating. On the other hand, parking bays force operators to better distribute e-scooters across the city. This in turn might increase demand by attracting uncovered users before the regulations. Moreover, parking bays might reduce users' uncertainty regarding finding a ride. As is the case with station-based transport models, commuters are aware of the location of stations and direct themselves to those points to pick up vehicles. Free-floating instead requires users to use their phones to locate the closest vehicle. As noted, the effect of parking regulations on demand for e-scooters is ambiguous and require further analysis.

**General interest.** Parking regulations might have effects beyond the market for e-scooters. For instance, a well-designed parking system might have positive effects in terms of intermodal behavior. Parking bays closer to public transit might trigger users to complete their journey complementing both transport systems. Another effect is related to security. Defining parking bays reduces the likelihood of finding e-scooters lying in the middle of sidewalks, improving security conditions for other users. However, congestion in parking bays might have the opposite effect. An excessive concentration of vehicles in specific parking bays might block sidewalks and streets, undermining security and increasing citizens' perception of a chaotic system. Taking into consideration the opportunity cost of land use is also of general concern. On the one hand, parking bays reduce space for private parking, which might have a positive impact if it reduces car usage. On the other hand, leasing space to private companies might not be beneficial if there are other alternatives that include the general public. In addition, it raises questions about the administration of the resources collected by authorities.

**Limitations.** It is noteworthy that the multicriteria evaluation method developed and documented in this paper presents the following additional limitations. First, the methodology we propose provides valuable empirical insights into the impact of parking bay construction on clutter reduction, vehicle accessibility, and parking compliance. Nonetheless, further analysis is needed to causally identify the mechanisms driving this kind of effect. Second, it is important to point out that a micro level analysis might be suitable to the understanding of mis-parking behavior. Several factors influence citizens attitudes towards parking. Users might change behavior depending on the conditions of the environment and on specific characteristics of the ride. One might expect different behaviors between tourists and residents or between commuting and a casual jaunt. What is more, some of these factors are related to cultural and cognitive conditions specific to the region of study. Because many of these factors are often difficult to account for in empirical studies, we recommend caution to researchers and policy makers interpreting results regarding mis-parking.

**Supply-side.** Parking regulations also affect the supply side of the market. Although this aspect is not covered in the present



**Fig. 16.** Share of class B e-scooters by district before and after implementation of parking regulations *Note:* The maps present the average number of e-scooters in *Class B. Mis-parked when parking bay nearby* in each district as a share of the fleet size. Panel (a) only includes e-scooters deployed in August 2019 and Panel (b) only includes vehicles deployed in December 2020. Numbers are used to identify districts' names in Paris (1st district, 2nd district, etc.).

analysis, it is important to highlight several relevant concerns. First, compliance with the regulation impacts the provision of the services by increasing operators' costs. Suppliers must invest in technologies to monitor users' behavior. For instance, to complete the journey, users are mandated to send pictures of the e-scooter located inside parking bays. The app then uses artificial intelligence to determine whether the vehicle is properly parked. Other technologies include geofences to virtually design parking bays. Additionally, concentrating e-scooters in parking bays might incentivize operators to compete for space. Furthermore, the spatial re-distribution of e-scooters creates supply in places where demand might not be guaranteed. As is the case in other markets, increasing supply when demand is low might increase social costs resulting in welfare losses.

One relevant concern is related to rebalancing measures, that is the relocation of vehicles to optimize demand at lower operating costs. The construction of parking bays might help companies reduce rebalancing costs by improving predictability. Conversely, a

spike in parking bay congestion might hamper cost savings, as operators may need to rebalance the system more frequently to avoid a high concentration of vehicles in specific parking bays. Therefore, the potential effect of parking regulations on rebalancing is a relevant research question that deserves further attention. It is important to point out that inferring rebalancing requires an extension of the dataset used in this paper, allowing the identification of changes in the position of the same vehicle over time. What is more, not accounting for rebalancing does not affect the criteria presented in this article, as our data is collected at a frequency (every three hours) that limits the influence of rebalancing by capturing changes in vehicle locations made by riders during the day.

## 8. Conclusion

In this paper we have investigated the effects of e-scooter parking regulations, proposing a novel multicriteria evaluation method around three principles: efficiency, accessibility, and compliance, using an original database that geolocates parked e-scooters in the city of Paris. Our findings show that parking bays effectively reduce cluttering, concentrating more than 85 % of the fleet. However, 30 % of parking bays became overcrowded after the construction of parking bays. Parking regulations also reduced accessibility, with average walking distances to e-scooters more than doubling. Nonetheless, some districts, particularly in the southeast of Paris, saw improvements. Finally, we found that the regulation has been effective in reducing the number of mis-parked vehicles when there is no parking bay nearby, which may indicate a decrease in opportunistic behavior among riders. This work has important policy implications for regulation and urban planning. The multicriteria evaluation method developed here could help regulatory bodies implement data-driven regulatory practices to monitor the behavior of e-scooter operators. Furthermore, they might be modified to different contexts and to the different regulatory frameworks that have been implemented all around the globe. What is more, our findings might help policy makers decide the optimal number of parking bays, their optimal location, and congestion goals using objective measures with the aim of finding a balance between harmonization and accessibility.

Finally, we raised new concerns and questions that deserve to be addressed in future research including their impact on demand, multimodality and rebalancing costs. Additionally, considering the opportunity cost of using public space exclusively for dockless e-scooters is key to evaluating the welfare effects behind this public intervention.

## CRedit authorship contribution statement

**Eric Brousseau:** Writing – review & editing, Supervision, Conceptualization. **Etienne Côme:** Writing – review & editing, Formal analysis, Conceptualization. **Nicolas Coulombel:** Writing – review & editing, Supervision, Methodology, Formal analysis, Conceptualization. **Isac Olave-Cruz:** Writing – review & editing, Project administration, Methodology, Formal analysis, Data curation, Conceptualization.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

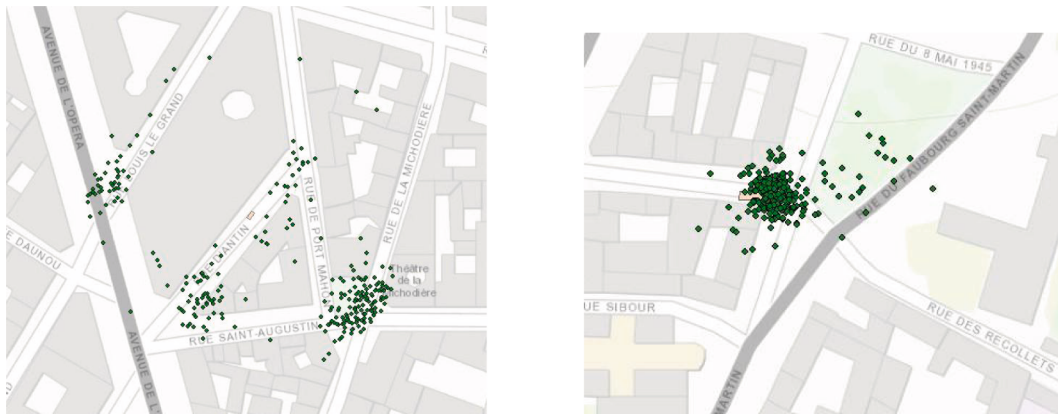
## Acknowledgements

We thank Christophe Benavent, Wilfried Sand-Zantman, Stéphanie Souche-Le Corvec, Juan Montero Pascual, Guillaume Monchambert, and Carine Staropoli, as well as the participants of hEART 2022, the Réseau ELUE seminar, the Management and Regulation seminar, the TrEnCE working group, and the Governance and Regulation Chair seminar for their helpful comments. We are indebted to two anonymous referees and the editor for their insightful remarks. We are also grateful to the City of Paris for granting us access to the database and for the valuable discussions.

## Appendix A. GPS inaccuracy analysis

The inaccuracy of the GPS devices used in dockless e-scooters was estimated as follows:

1. Select twenty-five parking bays at random.
2. Select all the vehicles within a buffer of one hundred meters.
3. Collapse the data set to observations after the construction of parking bays. We collapsed the data to observations from December 7th to 13th, 2020. This week was selected to avoid holidays or other non-working days.
4. Drop all the vehicles inside parking bays.
5. Compute the distance in meters between the remaining vehicles and parking bays.
6. Drop parking bays with very noisy information (see Figure A–1 for an example). Compute descriptive statistics (see Figure A-2 for an example).
7. To estimate the boundaries of GPS accuracies, we have produced descriptive statistics selecting parking bays with high accuracy. See Figure A–3 for the results.



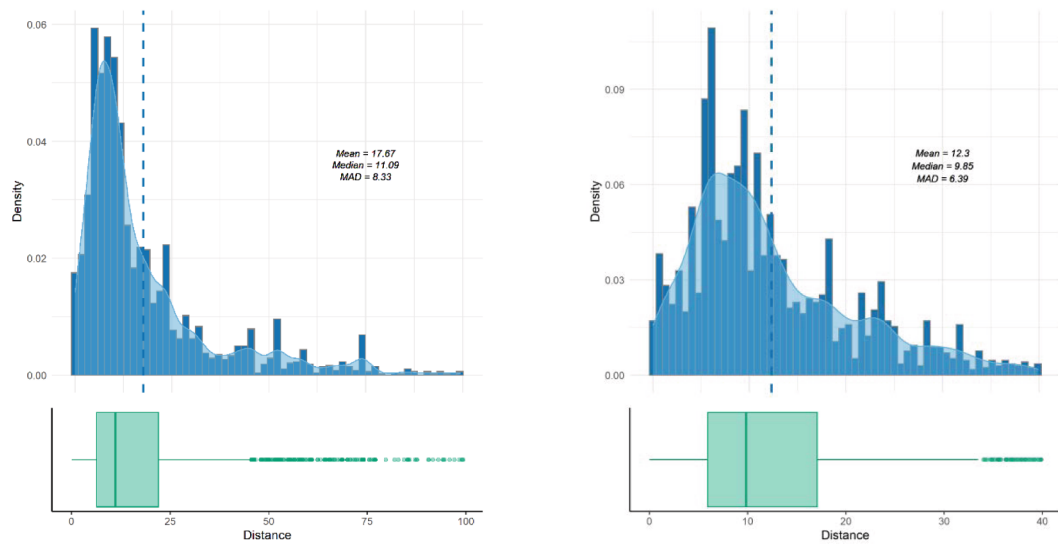
a) Dropped

b) Kept

Note: The Figure shows, in dots, the location of e-scooters around selected parking bays, in light pink.

**Fig. A1.** Example of parking bays dropped and kept for the analysis

Note: The Figure shows, in dots, the location of e-scooters around selected parking bays, in light pink.



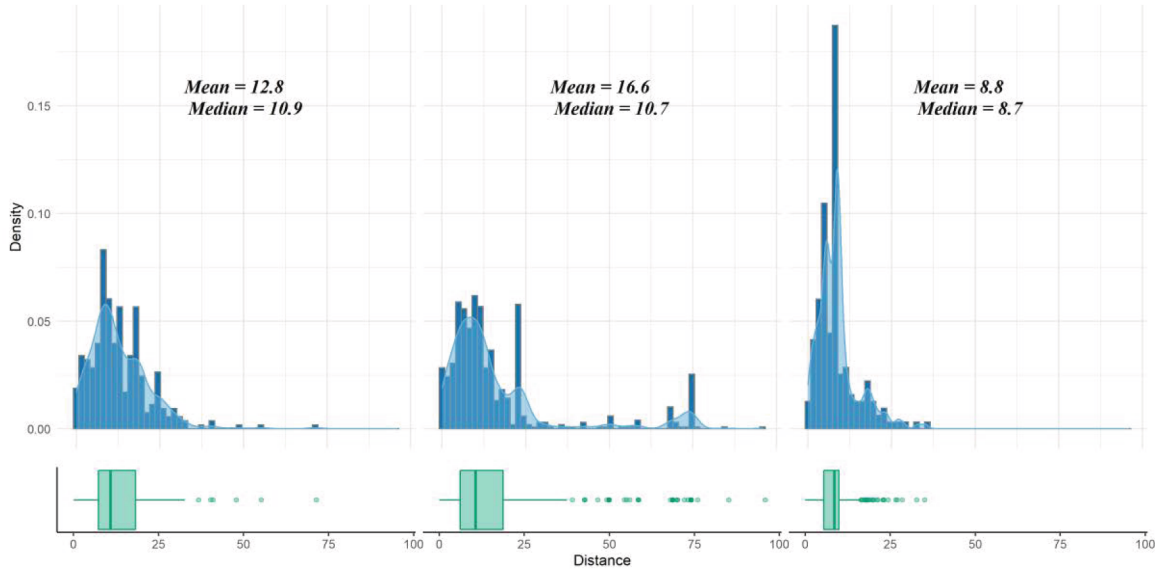
a) Buffer: 100 m

b) Buffer: 40 m

Note: The Figure presents different descriptive statistics of the distance from e-scooters to parking bays after the selection of parking bays. Panel (a) shows the results for the maximum distance considered in the analysis. Panel (b) restricts the analysis to e-scooters located within 40 m to the closest parking bay. MAD refers to the Mean Absolute Deviation which is a robust measure to the presence of outliers.

**Fig. A2.** GPS inaccuracy estimation

Note: The Figure presents different descriptive statistics of the distance from e-scooters to parking bays after the selection of parking bays. Panel (a) shows the results for the maximum distance considered in the analysis. Panel (b) restricts the analysis to e-scooters located within 40 m to the closest parking bay. MAD refers to the Mean Absolute Deviation which is a robust measure to the presence of outliers.



Note: The Figure presents different descriptive statistics of the distance from e-scooters to highly accurate parking bays, i.e., parking bays with a low GPS uncertainty. Selection was done after visually inspecting the data.

Fig. A3. GPS inaccuracy estimation from selected parking bays

Note: The Figure presents different descriptive statistics of the distance from e-scooters to highly accurate parking bays, i.e., parking bays with a low GPS uncertainty. Selection was done after visually inspecting the data.

## Appendix B. Normalization

The problem of solving the average distance of two random points  $(x_1, y_1)$  and  $(x_2, y_2)$  in a grid cell of size  $1 \times 1$  is a relatively well-known problem of analytic geometry. It is the result of solving the following integral:

$$\int_0^1 \int_0^1 \int_0^1 \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} dx_1 dx_2 dy_1 dy_2 = 4 \int_0^1 \int_0^1 \sqrt{x^2 + y^2} (1-x)(1-y) dx dy$$

where  $x_i$  and  $y_i$  are random points from a uniform distribution. Therefore, the distance  $x = |x_2 - x_1|$  has triangular distribution with a p.d.f.  $f(x) = 2(1-x)$ . After some computations, it is possible to show that the value of this integral is approximately 0.521.

We modified this problem to measure the closest distance between a point  $(x_0, y_0)$  and  $N$  points randomly located in the cell. We can think of this exercise as an abstraction of the problem of measuring the distance between a predetermined point in the city and the closest e-scooter. We simulate the problem following the next steps:

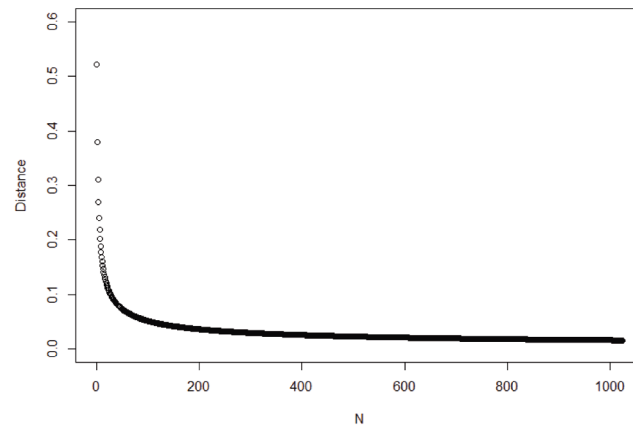
1. Assuming a cell of size  $1 \times 1$ , we simulate  $10^6$  different random (uniformly distributed) locations of the point  $(x_0, y_0)$  in the cell.
2. For every  $(x_0, y_0)$  we compute the distance to a random point (i.e.,  $N = 1$ ) uniformly distributed.
3. We compute the average of such distance and store it.
4. We redraw the location of  $(x_0, y_0)$  and re-compute the distance to a random point (i.e.,  $N = 2$ ) uniformly distributed.
5. Then, we compare pairwise (i.e., for each of the  $10^6$  locations) the result in step 2 with step 4 and keep the smallest value, i.e., the closest distance. Afterwards, we recompute the average between the  $10^6$  distances and store it.
6. It is possible to repeat  $N$  times the step number four and compare the result with the  $N - 1$  scenario.

The result for  $N = 1,024$  is documented in Figure B-1. As expected, the minimum distance when  $N = 2$  is close to 0.521.

Finally, we approximate the rate of decay when  $N$  increases assuming the following relationship between distance and the number of points in the cell:

$$\log(\text{distance}) = \beta_1 \log(N) + \mu_n$$

We estimate the equation using OLS. We find that  $\hat{\beta}_1 = -0.61$  (SD = 0.001 and  $R^2 = 0.99$ ). Hence, the closest distance between a point  $(x_0, y_0)$  and  $N$  points randomly located in the grid is  $\approx \frac{1}{2\sqrt{N}}$ .

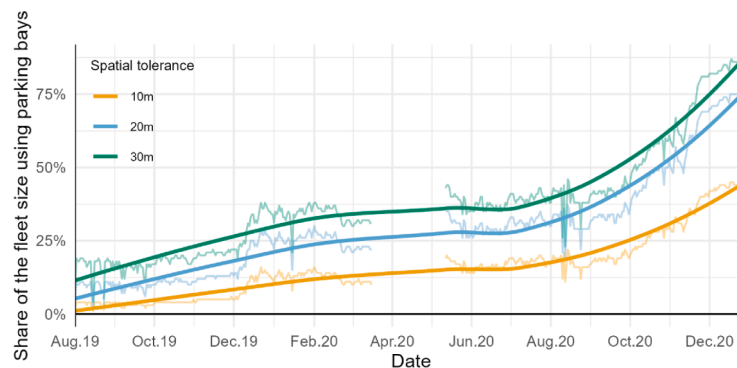


Note: The Figure presents the minimum distance between  $N$  points randomly drawn in a box of size one-by-one.

**Fig. B1.** Closest distance to  $N$  points randomly located in a cell

Note: The Figure presents the minimum distance between  $N$  points randomly drawn in a box of size one-by-one.

### Appendix C. Complementary criteria



Note: The Figure presents the number of e-scooters parked inside parking bays as a share of the fleet size. Spatial tolerance refers to the size of the buffer used to expand parking bays surface to account for potential GPS inaccuracy. For further details about GPS inaccuracy, please see Appendix A. Dark lines show a smoothed pattern applying the Locally Estimated Scatterplot Smoothing (LOESS) function. A blank space is intentionally introduced to identify the first national lock-down after the global pandemic.

**Fig. C1.** Demand for parking bays over time

Note: The Figure presents the number of e-scooters parked inside parking bays as a share of the fleet size. Spatial tolerance refers to the size of the buffer used to expand parking bays surface to account for potential GPS inaccuracy. For further details about GPS inaccuracy, please see Appendix A. Dark lines show a smoothed pattern applying the Locally Estimated Scatterplot Smoothing (LOESS) function. A blank space is intentionally introduced to identify the first national lock-down after the global pandemic.

### Data availability

The data that has been used is confidential.

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