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The case of Paris' shared e-scooter ban and its impact on mobility: a study with the difference-in-differences approach

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Abstract

The present thesis analyses the impact of the ban on shared e-scooters imposed by the City of Paris on traffic flows. This policy, implemented in September 2023, represents a unique case in the European shared mobility framework. Concerns about environmental impact, sidewalk occupancy, and safety led policymakers to impose restrictions, even though shared e-scooters are generally considered a sustainable alternative to cars.

This research uses multimodal flow data recorded by thermal cameras in the city of Paris and applies the difference-in-differences (DiD) technique to assess the impact of the policy. The technique involves the definition of a control and a treatment group in order to determine the significance of the results. The model shows that in central areas, the number of e-scooters decreased significantly while the number of bicycles increased, suggesting a substitution and competition dynamic between the two modes. On the other hand, the most peripheral stations didn't record any significant change after the ban, highlighting the predominance of privately owned scooters in this area.

The results suggest a limited impact of the policy on the total number of scooters in the city. Although safety was one of the reasons for the ban, scooters appear to have remained present or even increased, with a shift towards privately owned vehicles. The ban in central areas has changed transport choices, while in peripheral areas the effect has been minimal.

This research aims to contribute to the emerging literature on micromobility and provide insights for the regulation of shared mobility services in other cities.

Abstract (Italiano)

Titolo: Il caso del divieto dei monopattini condivisi a Parigi e il suo impatto sulla mobilità: uno studio con il metodo difference-in-differences.

La presente tesi analizza l'impatto del divieto dei monopattini in sharing imposto dalla città di Parigi sui flussi di traffico. Questa politica, attuata nel settembre 2023, rappresenta un caso unico nel quadro della mobilità condivisa europea. Critiche rivolte all'impatto ambientale, al parcheggio sui marciapiedi e alla sicurezza hanno portato a imporre restrizioni, anche se i monopattini in sharing sono generalmente considerati un'alternativa sostenibile alle automobili.

Questa ricerca utilizza dati di flusso multimodali registrati da telecamere termiche nella città di Parigi e applica la tecnica difference-in-differences (DiD) per valutare l'impatto della politica. La tecnica prevede la definizione di un gruppo di controllo e di un gruppo di trattamento per determinare la significatività dei risultati. Il modello mostra che nelle aree centrali il numero di monopattini è diminuito significativamente, mentre il numero di biciclette è aumentato, suggerendo una dinamica di sostituzione e competizione tra i due modi. D'altra parte, la stazione di conteggio più periferica non ha registrato alcun cambiamento significativo dopo il divieto, evidenziando la predominanza dei monopattini di proprietà privata in quest'area.

I risultati suggeriscono un impatto limitato della politica sul numero totale di monopattini in città. Sebbene la sicurezza fosse una delle ragioni del divieto, i monopattini sembrano essere rimasti presenti o addirittura aumentati, con uno spostamento verso i veicoli di proprietà privata.

Il divieto nelle aree centrali ha modificato le scelte di trasporto, mentre nelle aree periferiche l'effetto è stato minimo. Questa ricerca vuole contribuire alla letteratura emergente sulla micromobilità e fornire spunti per la regolamentazione dei servizi di mobilità condivisa in altre città.

Acknowledgements

First of all, I would like to express my sincere gratitude to Prof. Marco Diana for his constant supervision, as well as for the ideas and guidance he has consistently provided throughout this work. His contribution has been central and has served as a fundamental stepping stone in approaching research with rigor and critical thinking, and above all, for inspiring further curiosity and interest in the subject.

I am also grateful to all those who contributed, either with suggestions or by directing me to central material, both from the *Politecnico di Torino* and the *École Nationale des Ponts et Chaussées*. Thanks go to *Île-de-France Mobilités* to promptly answer questions related to this study, as well as *Citec* for the contacts provided in this regard.

Finally, my deeper thanks go to all the people who made this journey possible. My family, my friends, the people with whom I have shared ideas along the way, and especially Giulia.

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1 Introduction

The objective of this master's thesis is to demonstrate that the political decision of the City of Paris to ban all shared e-scooters has impacted the overall transportation trends within the city, even if to a limited extent. Paris's choice is of unique interest as it represents one of the first European cities to prohibit a transportation mode often labelled as "sustainable." This case provides an opportunity to study how the restriction of a shared micromobility service influences urban transport behaviours and modal preferences, against a backdrop where cities generally aim to expand rather than restrict such services.

Past research conducted on micromobility has already highlighted certain general trends regarding micromobility trips in the city, type of users, modal share and interaction with other transport modes, such as so called "last mile trips". On the other hand, the findings regarding the effect of restriction policies in micromobility, such as bans and restrictions, are relatively inconsistent and certainly deficient in quantitative terms. In this sense, the Paris decision represents a distinct case in Europe and warrants further investigation.

The expansion of shared transport modes is widely viewed as beneficial for urban sustainability and quality of life. Shared transport has the potential to reduce pollution and congestion if it serves as a substitute for private vehicles. Against this backdrop, the decision by Paris authorities to prohibit shared e-scooters raises questions about the policy's alignment with broader goals of sustainable urban mobility. This study seeks to assess the actual impacts of Paris's decision on transportation patterns, offering insight into the effects of such political reversals in the field of shared mobility.

Chapter 2 presents the current state of research, reviewing patterns and users of shared e-scooters, along with the impact of restrictive policies on micromobility and transportation. This chapter addresses a gap in existing literature: the lack of studies that evaluate the effects of removing shared transportation options, an approach this thesis aims to provide.

Chapter 3 introduces the methodology for analyzing the Paris case, specifically data cleaning activities, weighting attribution, time series analysis and difference-in-differences approach. These methods will be used to determine, in a structured approach, the impact of the policy on the broader flows of vehicles, isolating the effect of possible seasonal trends and comparing similar groups. In particular, through statistical approaches and under certain conditions, it will be possible to determine whether or not the results are statistically significant.

Chapter 4 presents transport trends in the Paris region and city, with a particular focus on shared scooter trends in terms of transport patterns, modal share and user typologies prior to the ban. It then presents the data set and the related preliminary activities, ranging from data aggregation to the results of data cleaning.

Chapter 5 provides the results of the case study and examines the rationale and surrounding discourse on the subject. The chapter analyses time series data, showing in central counting sites a relative decrease in e-scooter flows immediately following the ban and a corresponding, though smaller, increase in bicycle use. In contrast, in the less central counting station, the policy appears to have had no significant effect and globally is registered a general growth in scooter flows. Using difference-in-differences analysis, this study quantifies these trends.

In conclusion, the findings indicate that Paris's decision did indeed impact, even if in a relative measure, transportation patterns. This analysis suggests that the removal of shared e-scooters led users to opt for other available transport options in most central areas. The study demonstrates a mainly substitutive and competitive relationship between e-scooters and bicycles in most central areas, where the emergence of shared e-scooters is accompanied by a general increase in cycling. On the other hand, we demonstrate that the policy had a limited impact on the overall number of e-scooters, particularly in less central areas, where scooter usage remained constant, rather increased. This suggests that privately owned scooters continue to represent a significant share of transport flows and are even experiencing growth.

Our findings on this peculiar Parisian policy aim to contribute to the emerging literature on shared micromobility by providing insights into the concrete effects of a fully restrictive policy, using the difference-in-differences method. We show that this policy, implemented to minimise possible negative externalities of such transport modes, had a limited impact on total scooter flows. In addition, we have highlighted divergences in transport patterns, whether in the most central areas or in the more peripheral ones, indicating the need for a regulatory policy whether a ban is enforced or not. On the other hand, it suggests that tailored policies, different for central and peripheral areas, could be useful to regulate alternative transport.

2 State of the art

This second chapter is dedicated to a review of the scientific literature relevant to the subject of our research. The primary objective of this analysis is to explore the key issues surrounding shared e-scooters and their regulation. The goal is to identify significant developments in this field of study and potential research gaps that our work aims to address.

To begin, in Section *2.1,* we will define the concept of shared scooters and provide an overview of the current state of development of these systems on a global scale. This section will outline the extent of their adoption and quantify the size of these networks, offering a snapshot of their evolution in recent years.

In Section *2.2*, we will examine the impacts of shared e-scooters from multiple perspectives, including environmental, social, and their associated externalities. The purpose is to uncover the main arguments supporting restrictions (and, in some cases, outright bans) of these systems, identifying their underlying causes and connections. The aim is to provide a scientific and objective perspective on a debate that could be influenced by propaganda, misinformation, or distorted media narratives. We will explore how some of the concerns used to justify restrictions are valid (e.g., safety issues, negative environmental impact, sidewalk occupancy, etc.) but could be exaggerated by the media and policymakers who have decided to impose such restrictions or to ban shared e-scooters. Scientifically, there is no definitive answer regarding the environmental and social impact of shared e-scooters; rather, their effects must be evaluated on a case-by-case basis. This evaluation depends on factors such as modal patterns, substituted modes, applied economic models, and more. We will also highlight how, when used appropriately, these systems can contribute to transitioning from car-centric cities to more sustainable urban environments.

In Section *2.3*, we will provide an overview of the regulatory framework governing shared e-scooters on an international scale, with a specific focus on the French case. We will demonstrate how this framework has developed rapidly over the past few years in response to the rise of these systems. Importantly, we will show that no uniform approach exists across countries or authorities. While some nations or local authorities encourage the adoption of shared e-scooters with minimal regulation, others have opted for outright bans.

In Section *2.4*, we will analyse the literature on specific bans of shared e-scooters, as studied by researchers who have highlighted their impacts, from traffic patterns to accident rates. We will also examine additional studies on shared e-scooters that have assessed the causal impacts of their introduction on other modes of transport and urban mobility patterns in various cities.

In conclusion, Section *2.5* analyses the body of literature based on difference-in-differences models focusing on scooter-sharing. We will show how this emerging literature has delineated certain patterns related to the introduction of new scooter-sharing services and their impact on other modes of transport.

In conclusion, while the body of literature on the implications of introducing shared e-scooters has grown significantly in recent years, the same cannot be said for studies on their removal or regulation. This represents a notable gap in the existing research. Our study aims to contribute to this area by examining the consequences of such restrictions, offering insights into both the patterns and societal impacts of these measures. By focusing on the case of Paris, our research seeks to provide valuable input to the scientific community.

2.1 Definition and spread of shared e-scooter

This section seeks to define and categorise shared e-scooters within the broader context of the transportation field. It is important to establish clear boundaries for the subject under analysis in order to place it in the wider context of urban transport systems.

2.1.1 Categorisation of shared e-scooters

Firstly, this section defines and categorises shared e-scooters. The diversity of micromobility definitions reflects the relative novelty of this category of transportation modes.

The definition of micromobility by the International Transport Forum provides a useful basis for categorising this transport mode. This definition describes micro-vehicles as vehicles with a mass of no more than 350 kilograms (771 pounds) and a design speed no higher than 45 km/h. These vehicles may be human or electric powered. Examples of vehicles within this category include e-scooters, bicycles, e-bikes, and mopeds (Forum, 2020).

The correlation between weight and speed is significant as these two factors determine the kinetic energy of a vehicle. The ITF definition limits the kinetic energy of micro-vehicles to 27 kJ, which is one hundred times less than the kinetic energy of a compact car at top speed. There is a proportional correlation between vehicle kinetic energy and injuries sustained in vehicle accidents. Higher speeds and vehicle mass are statistically correlated with higher accident severity. (Khorasani-Zavareh et al., 2013). It can be seen that e-scooters are situated at the lower end of the category of kinetic energy micro-vehicles. The e-scooter can be considered to fit within this sub-category of micromobility vehicles, particularly given that they are capable of being powered up to 25 km/h and weigh less than 35 kg. (ITF, 2020).

Some other definitions of micromobility encompass solely electric-powered vehicles. For example the definition proposed by Maiti et al. (2019) that says "Micromobility is an umbrella term used to describe a novel category of transportation using non-conventional battery-powered vehicles, such as, electric- or e-scooters and e-skateboards". Alternative definitions put forward different characterisations based on a list of specific vehicles. For example, DuPuis et al. (2019) define this as "docked and dockless bikeshare systems, electric bikes and electric scooters."

In particular, it appears that researchers are increasingly inclined to define micro-mobility as encompassing e-scooters, e-bikes, and docked or free-floating vehicles. However, there is less consensus on the classification of other modes of transport, such as mopeds, vehicles with higher mass and maximum speed, and so on. Christoforou et al. (2021) propose a different categorization of vehicles based on their mass and passenger capacity. This approach, which excludes mopeds and other similar vehicles, introduces a new category termed "meso-mobility." Additionally, the categorization includes 'macro-mobility,' which encompasses larger vehicles such as automobiles, buses, and trains, representing modes of transport with higher passenger capacity and mass. Figure 1 presents the categorisation proposed by Christoforou et al. in 2021.

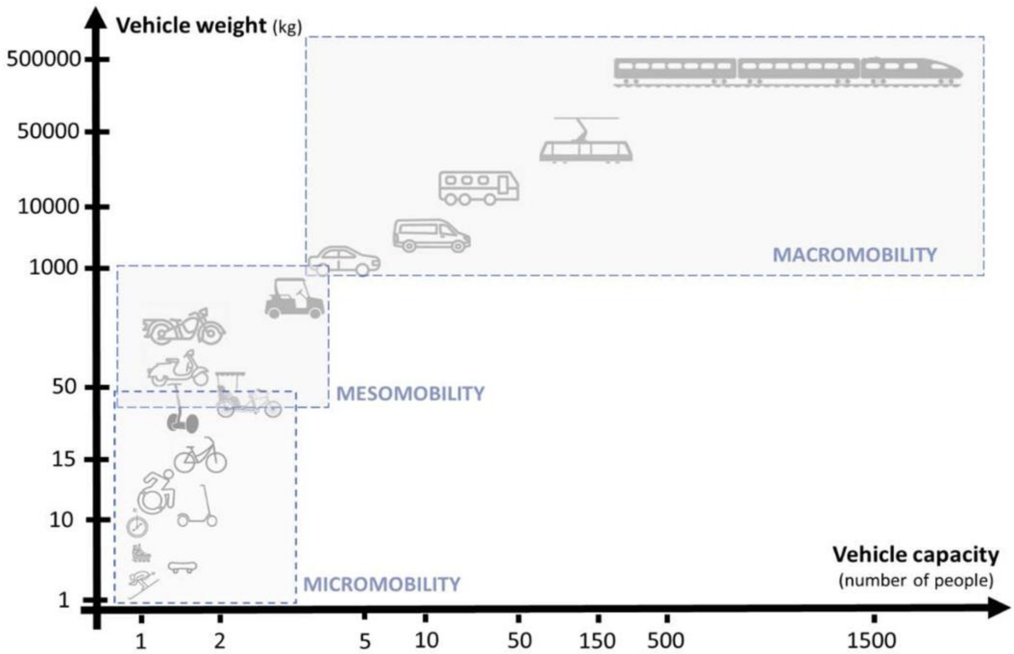

Figure 1: categorisation of micromobility, from Christoforou et al. (2021)

We will not elaborate further on this discussion, as it is not the focus of our research. The key takeaway is that there is consensus among researchers regarding the categorisation of e-scooters within the category of micromobility.

Building on the broader categorization of micromobility vehicles discussed earlier, free-floating e-scooters fall within this category and can be divided into specific subcategories. In particular, they represent a distinct subset of micromobility due to their shared-use nature and operational framework. Free-floating e-scooters, as the docked ones, are inherently shared vehicles, meaning they are sequentially used by multiple individuals over time. More specifically, they operate in a free-floating system, where users can pick up and leave vehicles within designated areas without relying on specific docking stations or collection points (Bretones et al., 2023; X. Yang et al., 2022). The concept of shared services is habitually closely linked to the concept of Mobility as a Service (MaaS), where one or more shared more are available via an app, necessary to book, lock and unlock the vehicles (Behrendt et al., 2022). Figure 2 represents this categorisation through a flow chart.

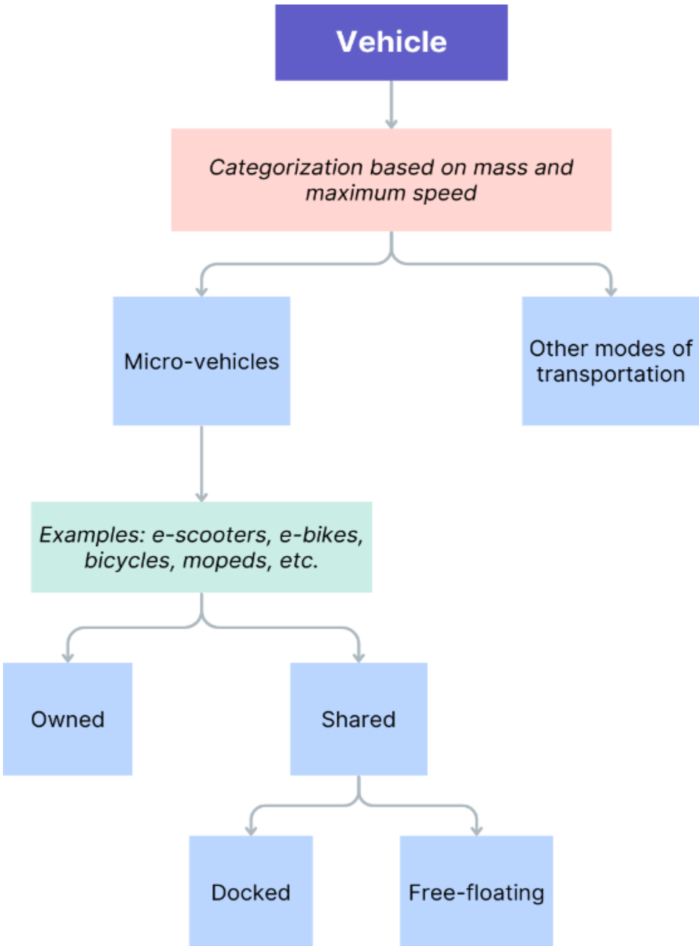

Figure 2: categorization of micromobility systems in the vehicles framework. Types and operational models (Source: own elaboration based on literature categorisation).

2.1.2 Distinction between shared and owned scooters

Much of the identified literature does not focus exclusively on shared scooters but also addresses privately owned scooters. In fact, much of the material, such as that related to accident rates or the modal shares of scooters in the total number of trips, also applies to privately owned scooters.

It is therefore crucial to make a clear distinction between these two modes of transportation, which characteristics and differences have just been discussed. Indeed, some variables at play are closely tied to the shared nature of scooters, which are generally managed by private companies. For example, the economic contracts between the user and the service provider are clearly specific to the latter. The same applies to certain aspects of parking, often criticized in journalism, where free-floating scooters can be parked in urban spaces without chains or physical locks but are automatically secured via an app (see *2.2.5 Safety issues of e-scooter*). Furthermore, certain aspects of the environmental impact differ: both types of scooters, shared and privately owned, follow more or less the same production cycles and have similar electric traction characteristics. However, their lifecycle usage differs, as shared scooters are, by nature, subject to a greater number of daily uses but also tend to have a shorter lifespan (see *2.2.4 Life cycle life assessment*).

Other variables are often analysed using samples of both owned and shared scooters without particular distinctions. For example, accident data generally refers to scooters as a whole, and even the severity of accidents is commonly aggregated (see *2.2.5 Safety issues of e-scooter*). The same can be said for national regulations, which typically apply equally to both shared and owned scooters, such as helmet requirements or the presence of an identification plate (see *2.3.1 Overview on national legislations*). Other regulations, often local, refer exclusively to shared scooters. For instance, some municipalities impose specific speed limits in pedestrian areas, which operators automatically apply to their fleet's scooters (see *2.3.2 Local limitation measures*). Similarly, traffic counts or modal shares of scooters are in some studies reported without distinguishing between owned and shared scooters (see *2.2.2 E-scooter replaced modes and purposes*).

In conclusion, the reader will encounter studies that are either specifically targeted or not at shared scooters or scooters in general. In each case, the presented studies will indicate whether they refer exclusively to shared scooters, to privately owned scooters, or to both types without distinction.

2.1.3 Shared e-scooter spread recent history

This section provides an overview of the global development of shared e-scooter systems, offering readers insight into the current stage of their evolution on a worldwide scale, based on the best available knowledge.

Shared e-scooters have gained significant popularity in recent years, experiencing rapid growth. For instance, in the United States, the number of e-scooter services increased from 149 in 2018 to 282 in 2019. The expansion of e-scooter systems now appears to have stabilized. In 2024, for example, there were 194 e-scooter systems operating in the United States (BTS, 2024).

In Italy, for instance, the inaugural e-scooter system emerged prior to the advent of the global pandemic in 2019. The e-scooter services experienced rapid growth, expanding to nearly 100 shared systems by 2022. However, their numbers declined to 53 by early 2024, driven by the tightening of local regulations and the conclusion of various pilot projects (Asperti, 2024). In France, the first shared e-scooter system was introduced in Paris in 2018. By the beginning of 2023, 58 cities had implemented a similar system (Trauchessec et al., 2023).

The COVID-19 pandemic and the resulting restrictions significantly disrupted the growth trajectory of shared mobility services. Reliant primarily on farebox revenues, these services encountered severe challenges due to the decline in travel demand and the implementation of mobility restriction policies.

As illustrated by Diana and Chicco (2022), in their study of Turin, varying levels of restrictions had a notable impact on the usage patterns of shared dockless e-scooters and bikes. E-scooters, in particular, exhibited greater variability in demand but demonstrated a faster recovery compared to shared bikes during periods when restrictions were eased.

In recent years, following the COVID-19 pandemic, shared e-scooter services have continued to operate in various cities worldwide, as previously exemplified, indicating a stabilization of these services.

It would appear that shared e-scooter systems have overcome the period of the global pandemic, although the rapid growth that was observed between 2018 and 2019 seems to have come to an end. These systems now seem to have reached a state of stabilization (Bert et al., 2020).

2.2 Shared e-scooters: debates on limitations and externalities

The rapid growth of shared e-scooters has sparked a global debate in recent years. This debate has led to significant regulatory responses from cities and governments worldwide, with some implementing restrictions or outright bans, such as Paris' decision, while others adopting policies to encourage their use. As a result, the regulatory landscape for e-scooters varies widely, reflecting contrasting views on their role in urban mobility.

On one hand, many cities have embraced these systems, citing their positive contributions to traffic congestion reduction, as a car trips substitution, and more efficient land use. These benefits position shared e-scooters as a promising solution for sustainable urban transportation.

On the other hand, some cities have implemented restrictive policies, highlighting challenges such as the limited car trip substitution rate, environmental scepticism surrounding their life-cycle impact, safety concerns related to high incident rates, and the obstruction of sidewalks caused by improper parking.

The inconsistencies in political decisions regarding shared e-scooters reflect a gap in the research field. There is a need for a more scientific and objective evaluation of the benefits and drawbacks of this mode of transport. On the other hand, it appears that certain political actors may be influenced by stereotypes and lobbying from the car industry, as suggested by Gössling (2020). Additionally, mainstream media have contributed to the negative perception of shared e-scooters, with a noticeable tendency to highlight their drawbacks. For instance, a study analysing coverage in the French mainstream press found a significant percentage of articles mainly focusing on the negative aspects of this transportation mode, resulting in a potentially biased narrative(Lipovsky, 2021).

This section aims to provide an overview of the arguments surrounding shared e-scooters and to examine the factors driving restrictive policies and bans. By critically analysing these dynamics, the objective is to bring more clarity and objectivity to a debate that has often been dominated by polarized views and inconsistent policy responses.

2.2.1 Shared e-scooters as a car trip substitute

One of the primary arguments in favour of shared e-scooters is their potential to substitute car trips. Many cities have adopted these systems as part of efforts to improve their transportation networks and promote more sustainable urban mobility.

Over the last decades, numerous studies have highlighted the issues associated with car-centred cities and emphasized the significant benefits of transitioning to diverse transportation modalities (Ceder, 2021). The rapid growth of the car market after World War II, driven by the affordability of automobiles, fundamentally reshaped urban landscapes, dedicating substantial public space to parking lots and major road infrastructures.

The negative externalities of car-cantered cities stem from localized issues such as noise, air pollution, road congestion, land usage, safety concerns, and the diminished quality of public spaces. These challenges are widely discussed in academic contexts, with a general consensus among researchers on the negative impacts of private mobility spread, particularly in densely populated areas.

In this context, shared micromobility has emerged in recent years, as outlined in the previous chapter, providing an alternative to private cars for trips within dense urban areas.

In densely populated areas where these systems are implemented, their advantages are particularly apparent. Compared to car trips, micromobility trips provide notable benefits in terms of reducing road congestion, land usage, fuel consumption, noise, air pollution, and safety. These advantages are closely tied to several factors, particularly the lower kinetic energy of these vehicles, which significantly reduces fuel consumption, noise, air pollution, and the severity of accidents. Additionally, the smaller physical size of these vehicles contributes positively to road congestion and land use compared to automobiles. These findings align with insights from a comprehensive literature review by Abduljabbar et al. (2021), which highlights the potential of micromobility to address urban transportation challenges effectively.

Moreover, shared vehicles have a lower impact on issues related to car ownership. By reducing the number of vehicles needed to meet travel demand, they increase the availability of urban space and help alleviate traffic congestion. Numerous studies and demonstrations highlight the sustainable potential of shared e-scooters in this context (Asensio et al., 2022; Bozzi & Aguilera, 2021; Félix et al., 2023; Lazer, 2023; Wang et al., 2023).

In conclusion, micromobility sharing generally represents a sustainable transportation solution. However, a more cautious approach should be taken when evaluating its impacts, particularly in relation to which modes it primarily substitutes.

2.2.2 E-scooter replaced modes and purposes

If shared e-scooters substitute automobiles, the cost-benefit is clear: e-scooter trips offer lower environmental impact, reduced land use, and other social advantages. However, a more cautious perspective is warranted when the replaced mode involves public transit, other micromobility modes, or walking. Furthermore, these evaluations should consider the ownership model of the e-scooter, distinguishing between privately owned and shared vehicles, and particularly between shared docked and dockless systems.

Many recent articles have explored this issue using various experimental or quasi-experimental approaches to address a key question: which modes of transportation do shared e-scooters replace? This question is crucial for understanding the social and environmental impacts of the growth of e-scooters.

Some studies suggest that shared e-scooters primarily replace car trips. For example, Wang et al. (2023) provide a review of the literature based mainly on US cities. In the American context, in the absence of shared e-scooter systems, users would have made their trips in cars and ride-hailing services (e.g. Uber). These findings indicate the potential of shared e-scooter systems to reduce car dependency.

On the other hand, different trends have been noticed in European cities. For instance, Kazemzadeh & Sprei (2024) analysed a case study in Sweden involving a survey of 805 users and non-users, comparing a control group with a treated group. They reviewed existing literature on modal shifts and identified contrasting patterns. Their study found that e-scooter users are more likely to use e-scooters for short trips, which could suggest a mitigated effect of e-scooters on social and environmental outcomes.

Weschke et al. (2022) conducted a nationwide user survey in Germany to determine mode substitution. Their results showed that the majority of shared e-scooter trips replaced walking, followed by public transport, with private bikes and private cars being replaced at a similar rate. The calculated net emission balance for shared e-scooters was negative, although the study suggested a pathway to achieving a positive effect.

Findings from Paris and other French cities align with these European trends. For example, Krier et al. (2021) investigated substituted modes toward dockless e-scooters in Paris using quantitative survey data from shared e-scooter users. Their research revealed that, for their most recent e-scooter trip, the majority of users would have walked or used public transport if e-scooters were not available. Only a small share of users would have relied on a car. The specific context of Paris and France will be further discussed in the next section (see *2.2.3 Replaced modes and purposes in France.*)

As a matter of fact, the literature highlights a clear discrepancy between Europe and North America regarding the modes of transportation replaced by shared e-scooters. In North America, a higher proportion of car trips are replaced compared to European case studies. Fearnley & Veisten

(2024), to examine which transportation modes shared e-scooters replace, conducted a global literature review about shared systems. Their findings indicate, in accordance with the broader literature corpus, that shared e-scooters replace more frequently car trips in North America and Oceania (36%) than in Europe (19%). Conversely, public transit trips are replaced more often in Europe (22%) compared to North America and Oceania (11%). Additionally, about 50% of shared e-scooter trips in the considered regions substitute active transport modes, such as walking or cycling, highlighting a significant share of trips previously made through these modes..

Similarly to bikesharing, the substitution patterns of e-scooters appear to be closely related to the local modal share. Several studies (Fishman et al., 2014; Teixeira et al., 2021) have highlighted this tendency for bikesharing, which helps explain the higher rate of car substitution by e-scooters in North America and Oceania compared to Europe.

A recent literature review by Badia & Jenelius (2023), "*Shared e-scooter micromobility: review of use patterns, perceptions and environmental impacts*", highlights a consistent trend in surveys regarding these shifts, offering valuable insights into user behaviour, perceptions, and the environmental implications of shared e-scooter systems. This review will be used to frame and analyse the discussion in this context.

In Europe, on the basis of data from the literature, shared e-scooter systems have demonstrated diverse patterns, with approximately 50% of trips replacing walking and only 20% coming from car trips. Unlike shared bicycle systems, e-scooter user patterns are less systematic and more reflective of occasional use. Many trips appear to be related to leisure or pleasure activities, rather than commuting. High pricing has emerged as a potential barrier, shaping user behaviour.

Figure 3 presents the purpose of trips made by shared e-scooters users in different cities, taken from the literature review by Badia and Jenelius (2023). The y-axis represents the different city patterns analysed in the literature across North America and Europe, while the x-axis represents the percentage share of trip purposes. The trip purpose categories are work/commuting, public transport connections, social/entertainment, fun/recreation, shopping/errands and other.

The general trend indicates that leisure-related purposes, which include social/entertainment and fun/recreation, dominate the use of shared e-scooters across most cities, often accounting for more than 50% of trips. Conversely, work-related trips and public transport connections consistently make up smaller proportions of usage. The confidence intervals across cities suggest that leisure purposes are reliably the most significant category, with minimal variation. In contrast, categories like shopping/errands and public transport connections show greater variability, reflecting localized differences in how e-scooters are integrated into urban mobility systems.

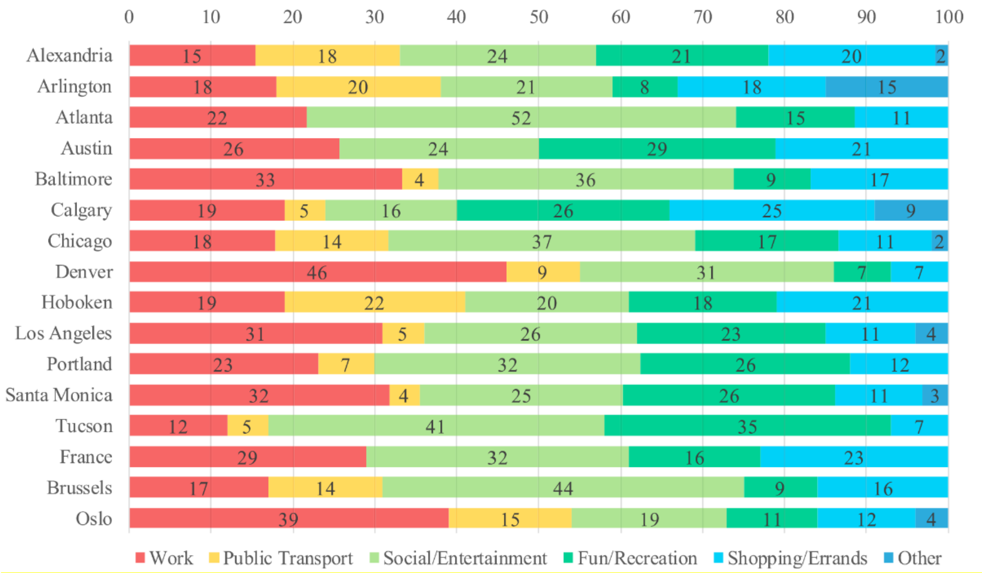

Figure 3: trip purposes for shared e-scooters across various cities, from Badia & Jenelius (2023)

The frequency of use is symmetrically presented in Figure 4 from the same literature review. Daily use is rare, with only a small fraction of riders reporting regular, everyday use; this is typically around 6% or less, as seen in cities like Alexandria and France. Weekly use is more common, although it varies significantly, with cities reporting between 20% and 40% of users riding e-scooters weekly. However, the dominant usage pattern is infrequent or occasional trips, with a large proportion of riders using shared e-scooters monthly or even less often. For example, in France, 47% of users reported rare usage, while in Oslo during the summer, this figure rose to 55%, indicating a seasonal dimension to e-scooter adoption.

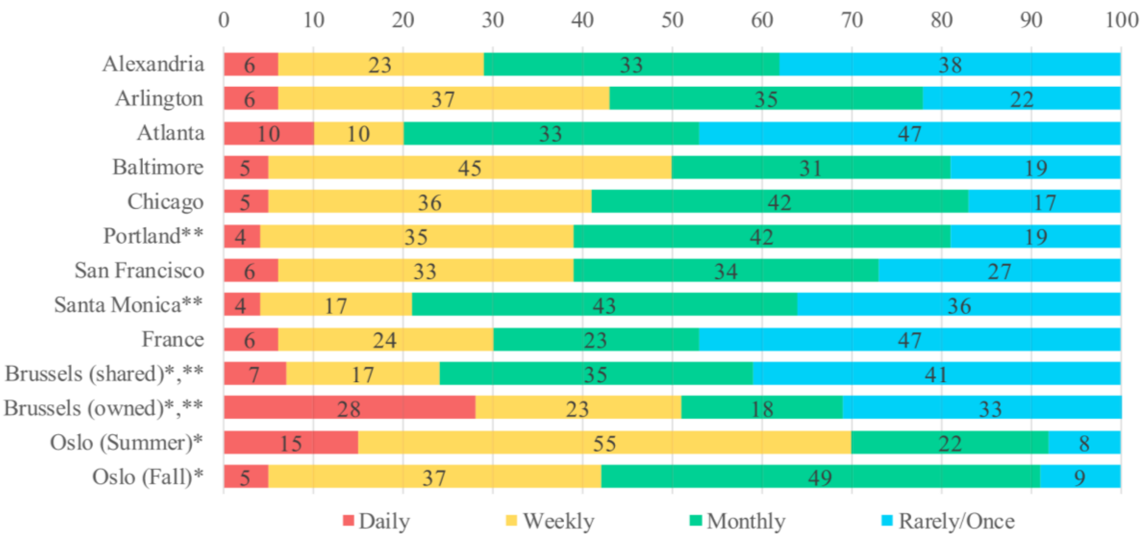

Figure 4: frequency of use for shared e-scooters across various cities, from Badia & Jenelius (2023)

In conclusion, the replaced modes by e-scooter are presented in analogous way in Figure 5 and illustrates that walking is the most commonly displaced mode across nearly all cities, with percentages often exceeding 30%. For instance, walking accounts for 62% of the displacement in Oslo and 56% in Calgary. In contrast, substitution of car trips, including private vehicles and ride-hailing, is less pronounced but varies between cities. In cities like Santa Monica and Portland, cars (yellow) account for 20% or more of the displacement. Public transport, on the other hand, is minimally affected in most locations, with percentages typically below 15%, except in Brussels, where it reaches 43%. Bicycle substitution is consistently low, rarely exceeding 10%.

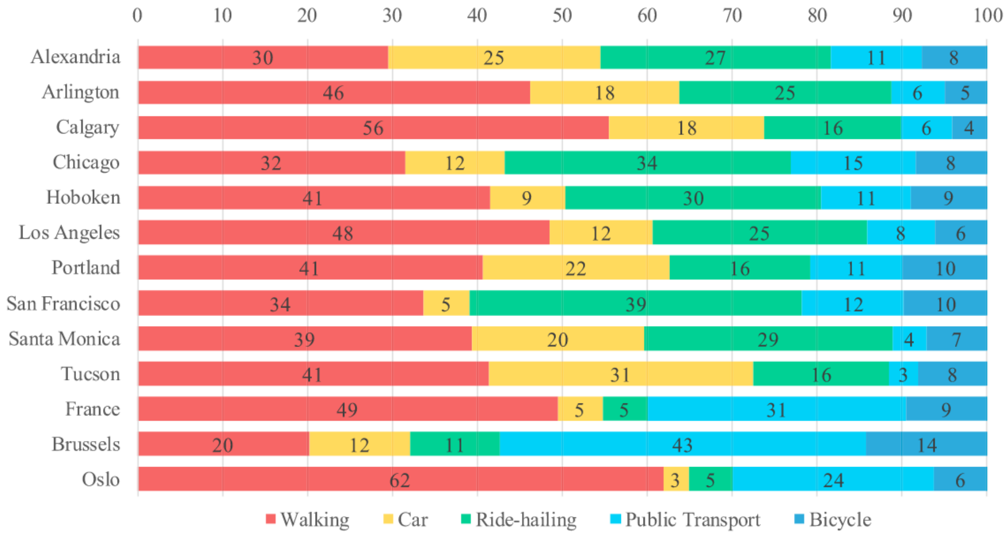

Figure 5: alternative transport mode in case an e-scooter is not available, from Badia & Jenelius (2023)

Additionally, numerous studies emphasize the role of shared micromobility in facilitating last-mile connections, particularly in areas that may otherwise lack access to public transit. Shared systems can promote new trips in previously isolated neighbourhoods and foster multimodal transportation behaviours. While the complementary relationship between public transport and shared mobility is recognized, the specific role of shared e-scooter systems remains a subject of debate among researchers. Badia and Jenelius (2023) discuss these dynamics in their review, noting that shared e-scooters often serve as a flexible but less predictable mobility option compared to bicycles, with varied impacts depending on local context and system design. The findings indicate that shared e-scooter users are more similar to non-systematic users of shared bike systems.

In conclusion, while the benefits of shared mobility are broadly acknowledged, a more nuanced evaluation is essential, considering modal alternatives, the specific characteristics of the shared system, and its interaction with the existing urban transportation landscape.

2.2.3 Replaced modes and purposes in France

The findings reviewed in the previous subsection about substituted modes were cited by the City of Paris as part of their justification for banning shared e-scooters, in particular based on a report commissioned to 6t-bureau de recherche (2019). The report provided a comprehensive analysis of the replaced modes and travel purposes associated with shared e-scooters in France, with a particular focus on Paris. It revealed that shared e-scooters often replaced more sustainable or active modes of transportation rather than automobiles. Specifically, 47% of trips substituted walking, 29% replaced public transport, and only 7% replaced car trips. The remaining percentage came from other modes, such as cycling or forgoing the trip altogether (6t-bureau de recherche, 2019, p. 108).

In terms of trip purposes, the study found that the majority of trips (44%) were leisure-related, such as recreational outings or sightseeing. Around 19% were linked to commuting to work or school, and 18% were associated with running errands or shopping. The remaining trips included various purposes, such as visiting friends or accessing public transport hubs.

These findings have been corroborated by a more recent national survey conducted in 2023 by ADEME, the French public agency for ecological transition. The survey, which sampled over 1,400 e-scooter users in France, reported similar trends. It found that 41% of trips replaced walking, 12% replaced bicycles, 24% replaced public transit, and 13% replaced motorized modes (Trauchessec et al., 2023, p. 50). This research also included e-scooter owners and highlighted significant differences in substituted mode and trip purposes between shared and privately owned e-scooters. For shared e-scooter users, the replaced modes largely came from sustainable transport modes, with leisure trips being overrepresented. In contrast, privately owned e-scooters were more often used as a substitute for motorised modes, accounting for 37% of the modal split, followed by public transit (20%), walking (15%), and bicycles (14%).

Table 1 presents data from the 2023 national survey in France on the replaced mode by e-scooters. The rows indicate the modes of transportation replaced by e-scooters, while the columns distinguish between shared and privately owned e-scooters.

The specific case of Paris and its context will be explored in greater detail in the chapter dedicated to the case study (see more at *4.2.2 Type of users and characteristics of e-scooter system before the ban).*

Replaced modes by e-scooter in France (2023)		
Mode of transportation	Shared e-scooters (%)	Owned e-scooters (%)
Walking	41%	15%
Bicycles	12%	14%
Public transit	24%	20%
Motorized modes	13%	37%
Other	10%	14%

Table 1: percentage of trips that would have been made using alternative modes if shared and owned e-scooters were not accessible in France, from Trauchessec et al.(2023)

2.2.4 Life cycle life assessment

The environmental impact of shared e-scooters is closely tied to the modes of transportation they replace. If the replaced modes primarily are walking or bicycles, the environmental benefits are less clear. Numerous studies have demonstrated that both walking and muscular bicycles have a significantly lower environmental footprint compared to e-scooters. In particular, walking has virtually no environmental impact, while traditional bicycles have a significantly low environmental footprint, taking into account the materials used in their manufacture and the recycling process. (Scott & Travers, 2023).

E-scooters, on the other hand, require electronic components and batteries, which contribute to a higher environmental footprint, either in the manufacturing phase or in the recycling processes. The consumption of electrical energy also leads to a higher footprint compared to the previous mentioned modes, even if the kinetic energy of e-scooters remains relatively low. Additionally, the number of uses per vehicle is a critical factor for shared e-scooter systems. Several studies have emphasized that the short lifespan of e-scooters can exacerbate their environmental impact, as their production and disposal are spread over a limited number of trips (de Bortoli & Christoforou, 2020; Weiss et al., 2015). This applies to both shared and owned e-scooters. In particular, studies have shown that shared e-scooters have a shorter lifespan than owned ones (Moreau et al., 2020).

To better understand the environmental impact of e-scooters, many studies have utilized Life Cycle Assessment (LCA) methodologies, some of which have been specifically designed for shared e-scooter. LCA is one of the most widely used approaches for evaluating the environmental impacts associated with a specific product, process, or system. This method assesses a wide range of environmental factors—not limited to CO2 emissions but also including impacts on biodiversity, land use, resource consumption, and more. The LCA framework examines the environmental footprint of the studied element throughout its entire lifecycle, from production and manufacturing to end-of-life disposal.

In a recent systematic review, Calan et al. (2024) conducted an in-depth analysis of the life-cycle environmental impacts of shared electric micromobility services, including shared e-scooters. The study highlights that the materials and manufacturing phase is the largest contributor to greenhouse gas emissions and environmental degradation. This phase encompasses the extraction and processing of materials used in the e-scooter's construction, particularly the batteries and electronic components. This is supported by many other studies designed shared e-scooter (de Bortoli & Christoforou, 2020; Moreau et al., 2020; Reis et al., 2023).

Another critical factor identified in the study is the operational phase, particularly the daily collection, recharging, and redistribution of e-scooters. These activities are often energy-intensive and involve vehicle emissions if fossil fuel-powered transportation is used. The study emphasizes that these operational logistics significantly affect the overall sustainability of shared e-scooter systems.

As highlighted in the review by Badia & Jenelius (2023), "There is the idea that shared e-scooters are an eco-friendly mode that would increase the sustainability of the transport system; although different concerns show a contrary opinion. Short lifetimes, low usage rates, and the emissions derived from collection and distribution tasks go against the original impression. Further, the new mobility service substitutes in a high degree walking trips, which is an unfavourable consequence."

Other studies report similar findings, often highlighting a generally negative impact on sustainability due to the modal shift associated with shared e-scooters. However, drawing definitive conclusions requires a case-by-case analysis of the modal split, as the outcomes can vary significantly depending on the specific urban context and travel patterns (Weschke et al., 2022).

2.2.5 Safety issues of e-scooter

Impacts of shared e-scooters on safety have been at the center of a widely developed debate in the previous years. Many researchers focused on this topic to understand if the negative impact on safety of e-scooter, reported by media and politicians, is supported by scientific arguments,

A recent systematic literature review by Burt and Ahmed (2023) delves into safety issues associated with shared e-scooters, emphasizing user behaviours, perceptions, and risk factors. The review highlights safety concerns, noting a slightly higher risk of injury compared to bicycles. This increased risk is attributed to several factors, including the inherent vulnerability of e-scooters due to their design, the low prevalence of helmet use among riders, and risk-prone behaviours often exhibited by users.

Compared to bicycles, e-scooters are generally associated with slightly higher injury rates. In particular, this seems to be related to their smaller wheels and lower stability. In addition, e-scooters have been associated with more risky riding behaviour, such as driving under the influence of alcohol or riding on the sidewalk.

The publication presents a lack of consistency on this issue, but the general tendency is to highlight a slightly higher risk on e-scooter trips than on bicycle ones. Most recent studies globally agree on the fact that the safety issues for e-scooters are strongly influenced by the type of infrastructure and traffic (Heydari et al., 2022; Jiao et al., 2021; Latinopoulos et al., 2021), suggests a slightly higher statistical index of crashes in relation to bicycle trips (Edwards et al., 2024), but above all a higher severity of e-scooter accidents in relation to bicycle ones (Kleinertz et al., 2021; Mair et al., 2021).

In conclusion, no clear consensus has emerged from the literature regarding the incident rate of e-scooters. However, it can generally be stated that e-scooter incident rates are similar to or slightly higher than those of bicycles. All studies emphasize that the primary factor influencing e-scooter safety is infrastructure quality. Lower incident rates are observed in areas with well-developed cycling paths (Cloud et al., 2023).

These findings align with broader conclusions about safety concerns for bicycles and pedestrians. This underscores the need for policymakers to transition from car-centric infrastructure to more sustainable, multimodal designs that prioritize safety for all road users. On the other hand, the arguments used to justify bans and restrictions on e-scooters, often citing safety concerns, appear, in light of current research, to be exaggerated and not fully aligned with reality.

2.2.6 Parking on sidewalks and other issues

In addition, the proliferation of e-scooters has raised concerns about their impact on public spaces, particularly regarding parking on sidewalks and potential obstructions. Research indicates that a significant proportion of e-scooters are not parked in compliance with regulations, leading to congested sidewalks and accessibility issues. For example, a study in Portland, Oregon named "Congested sidewalks: The effects of the built environment on e-scooter parking compliance" written by Hemphill et al. (2022) found that 76% of observed e-scooters failed to meet at least one parking compliance requirement, with 59% failing at least two.

On the topic of sidewalk occupation by shared e-scooters, the issue is significant but often linked to the availability of alternative parking spaces in the city, clear instructions for using designated parking areas, and public campaigns aimed at minimizing these negative externalities.

However, the perception of e-scooter safety often differs from these statistics, exacerbating the negative factors. Public concerns frequently focus on the novelty of e-scooters and their integration into existing traffic systems, leading to debates that may be influenced more by subjective views and political agendas than by empirical evidence, as highlighted by different studies in many research sectors (Lipovsky, 2021).

While these sociopolitical factors are noteworthy, our research does not delve into the sociological or psychological aspects of these decisions. Therefore, we will not elaborate further on this topic.

2.2.7 Conclusion on the arguments on shared e-scooter and potential mitigation

Municipalities often impose restrictions on shared e-scooters, citing concerns such as road safety, public space management, and environmental impact. However, this debate needs to be objectively framed, as there is no one-size-fits-all answer for every city. The effectiveness of e-scooters largely depends on the specific urban context and the travel patterns of the population. If shared e-scooters are primarily used as a substitute for private car trips, the cost-benefit balance seems to be generally positive. Conversely, if they replace walking, cycling, or public transit trips, the environmental and societal benefits are mitigated or even absent. Compared to shared bicycles, e-scooters have the advantage of being accessible to individuals who might not wish to pedal, thus broadening their appeal.

Studies suggest several potential improvements to enhance the functionality and sustainability of these systems. For example, if e-scooters were used more systematically and with higher frequency, particularly as an alternative or complement to cars, their environmental and social impact on society could become more favourable. Properly conducted studies on travel patterns could help identify strategies to maximize the positive outcomes of these systems.

Currently, shared e-scooter systems are predominantly driven by private market dynamics. This results in high costs for users, sporadic use primarily for leisure purposes, and limited integration into broader urban transportation networks. However, if e-scooters were viewed as a complement to public transit and supported by funding mechanisms, they could play a significant role in addressing transportation gaps. For example, they could be instrumental in areas where public transport is absent or insufficient, providing quicker connections for last-mile trips and improving overall urban mobility.

Additionally, better travel pattern studies could inform a more efficient balance between supply and demand, helping to optimize these systems and make them more effective in meeting urban mobility needs.

In this research, we will focus on the impact of the ban on shared e-scooters in Paris to provide a comprehensive overview of the implications for travel patterns and the broader effects of such a policy. By examining the shifts in transportation modes, usage patterns, and urban mobility outcomes following the ban, we aim to offer valuable insights into the potential advantages and challenges associated with such measures.

2.3 Regulatory framework

As discussed in the previous sub-chapter, the role of shared e-scooters in urban mobility remains a topic of active debate. Public authorities have adopted various approaches to address the externalities associated with this mode of transport. Some cities have implemented targeted regulations, ranging from speed limits to designated parking areas or outright bans, to mitigate the negative impacts of shared e-scooters. This subsection examines the legislative frameworks governing shared e-scooters, providing evidence of contrasting policies adopted at both governmental and local levels. Additionally, we present a review of literature focused on case studies involving bans and reversal designs, highlighting the methods used and the results obtained.

2.3.1 Overview on national legislations

The rapid growth of e-scooter all over the world generated a rapid legislative response from the national and local authorities. This response, as said previously, hasn't been homogenous.

In Europe, for example, rules and restrictions are specific to each country. The European Transportation Safety council wrote a document on how to improve safety and they also summarise the legislation in each country ETSC (2023). We can summarise in big categories the current legislation, in 2024, of the countries in Europe, from the more restrictive to permissive.

Some countries impose *strict rules* on e-scooter use, often equating them to motorized vehicles or implementing significant restrictions on where and how they can be operated. For example, Germany requires e-scooters to meet strict type-approval standard and users need an insurance. In the Netherlands, e-scooters are classified as mopeds and need to be approved by the motor vehicle authorities. Similarly, the United Kingdom has banned private e-scooter use, only allowing limited trials of hire schemes with strict oversight.

Other countries imposed restrictions to a lesser extent. For instance, France allows e-scooter use but enforces speed limits (25 km/h), age restrictions (minimum age 14), and prohibits riding on sidewalks except at walking speeds (up to 6 km/h). In Italy, e-scooters are limited to roads with speed limits below 50 km/h and must include technical features like indicators and independent brakes. Countries like Spain and Slovakia also enforce moderate restrictions, including alcohol limits, designated areas for riding and for younger driver mandatory helmet.

In contrast, some countries adopt a more *permissive approach* to e-scooter regulation, treating them similarly to bicycles. Sweden and Finland, for instance, allow e-scooter use with minimal restrictions, such as a 20 km/h speed limit and no mandatory helmet requirements for adults. Riders are generally permitted to use bike lanes and are not subject to licensing requirements. Portugal also classifies e-scooters as bicycles, imposing few limitations aside from speed caps and basic safety requirements.

In the United States, e-scooters are generally allowed, although regulation is generally left to the states. Local authorities often impose specific restrictions, such as restricted riding areas and special operating rules.

Although China is the world's largest producer of e-scooters, the country faces a significant gap in national-level regulations (Song, 2024). E-scooters are often classified as "sliding tools," restricting their use to specific areas such as campuses, industrial parks, and scenic spots. In some regions, geofencing technologies are mandated to regulate "no-go zones," enforce speed limits, and designate safe riding areas.

Some studies have been conducted on e-scooter services in Taiwan (Huang, 2024) and Singapore (Cao et al., 2021; Zhu et al., 2020) highlighting similar set of rules of European cities, with specific area of services, highlighting a higher distribution of trips around the universities.

Concerning Japan, in Tokyo eight operators were authorized by the government to operate under a special set of rules (Imamura et al., 2024). In South Korea, shared e-scooters are well developed, primarily in Seoul. E-scooters are limited to a maximum speed of 25 km/h and are restricted to designated local zones, with certain inner areas being off-limits Kim et al. (2022).

2.3.2 Local limitation measures

Similarly, in many countries, local authorities have adopted tailored measures to address e-scooter use. These include localized prohibitions in pedestrian-heavy or central areas, restrictions on the total number of shared e-scooters allowed, speed limits in specific zones, and designated parking areas to reduce clutter. Some cities have implemented time-based restrictions, such as banning e-scooters during nighttime hours, while others, like Paris and some Canadian cities, have opted for complete bans on shared e-scooter.

These specific cases of e-scooter bans are central to our research. While some studies have examined the general effects of the legal framework on e-scooters, much less attention has been given to the complete ban of shared e-scooters. In this context, our study will focus on the case of the partial ban of shared e-scooters and will also explore similar studies conducted on bans affecting other micromobility modes.

2.3.3 French legislative framework

This subsection presents some general aspects of the French regulatory framework for e-scooters. In fact, the Paris decision to ban shared e-scooters represents a specific local regulation on a specific system, while the national regulations impose specific restrictions related to e-scooters in general.

The French traffic law named e-scooter as "Engins de déplacement personnel motorisés" (EDPm), and they are classified as motorized personal transport vehicles. This classification was introduced in October 2019 in the national traffic law, the so-called "*Code de la route*", and mainly deals with technical specifications on vehicle characteristics, road use and general specifications for users.

In terms of technical specifications, the regulation imposes specific dimensions for e-scooters, in particular a maximum width of 0.9 metres and a maximum length of 1.65 metres. Safety features such as front, rear and side reflectors and audible warning devices are also required.

As with bicycles, e-scooter users must use cycle lanes where they exist. Riders can use the road up to a speed limit of 50km/h in urban areas, must ride at a maximum of 6km/h in pedestrian areas, and must wear a helmet and reflective vest in extra-urban areas for roads that allow a higher maximum speed, such as 80km/h. Riding on sidewalks is generally prohibited in urban areas, and is allowed in extra-urban areas and smaller towns if the mayor doesn't decide otherwise. Parking on sidewalks is subject to local regulations, but generally users don't have to block the way for pedestrians. In some local contexts there are stricter rules, for example in Paris, where parking on the sidewalks is prohibited and punishable by a fine of 49 euros.

In addition, the "Code de la route" imposes a speed limit of 25 km/h for vehicles, and local authorities can impose more restrictive measures. Wearing a helmet is not compulsory in urban areas, but is generally recommended, especially for young riders. Riding an e-scooter with more than one user is strictly prohibited (*Circulation à trottinette électrique, rollers ou skateboard*, 2024).

2.4 Case studies on bans and their implications

Concluding the discussion on the regulatory framework for e-scooters, we now turn to the first studies examining the effects of bans on shared e-scooters. As previously noted, national policies often align with stricter local regulations and limitations. While many cities have opted to restrict e-scooter usage to designated areas or limit shared systems, others have chosen to implement outright bans. These bans range from time-restricted prohibitions, such as those enforced during specific hours, to comprehensive bans like the one introduced in Paris.

2.4.1 Atalanta ban case study

A notable example of a time-specific ban used to evaluate the impacts of micromobility policies is a study conducted in Atlanta. This research, led by Asensio et al. (2022), examines how restricting micromobility devices, particularly shared e-scooters, influences travel behaviour, traffic congestion, and environmental outcomes. The study provides valuable insights into the broader implications of micromobility restrictions and highlights the potential consequences of these policies for urban transportation systems.

The policy intervention in Atlanta prohibited e-scooter use during evening hours, specifically from 9:00 PM to 4:00 AM. The ban requires e-scooter service companies to deactivate the devices during restricted hours in order to achieve maximum compliance. The research on the ban was conducted using travel time data, with 47,000 observations of trips over a 90-day period. The researchers used normalised travel times per mile to understand the impact of the ban during peak hours and during major events.

The research used quasi-experimental models in order to achieve robust results. The first focused on recurring evening travel times in the city center, referred to as the Midtown Experiment. The second concentrated on transit hubs heavily used for last-mile connections, known as the MARTA Experiment. The third examined travel times during major sporting events at the Mercedes-Benz Stadium. Each of these approaches compared travel times in policy zones, where the ban was enforced, to non-policy zones. A triple-difference estimator was employed to control for biases related to population characteristics, weather, and other external factors, creating a counterfactual analysis to isolate the policy's effects.

The findings of the study were significant. The e-scooter ban led to a 9–11% increase in evening commute times in the city center, with travel times rising by 37% during major events, such as those at the Mercedes-Benz Stadium. The results showed that many users who had previously used e-scooters switched to cars or ridesharing services in the absence of the system, increasing congestion in the area. Furthermore, there was no relevant substitution effect from e-scooters to walking or public transport. The researchers point out that new patterns emerged after the ban and only stabilised after a week, indicating a temporary adaptation period.

The study also revealed substantial economic costs associated with the ban. The increased congestion translated into annual losses of up to $10.5 million for Atlanta alone. On a national scale, similar policies could result in economic losses of $536 million due to lost time value. Furthermore, the environmental implications of the policy were negative, as the substitution of e-scooters with cars increased emissions, given the higher carbon footprint of vehicles compared to micromobility devices.

2.4.2 Helsinki restriction case study

As mentioned above, the number of studies on the impact of bans and restrictions on shared e-scooters is small in the general research corpus. One of them is the one conducted by Dibaj et al. (2024) on Helsinki's partial ban on shared e-scooters. This study examined in particular the effects of the ban during late-night hours (midnight to 5 a.m. on weekends) and speed limit reduction at other times. The study provides insights into the relationship between policy and safety outcomes.

The results show that the number of e-scooter related injuries decreases by 64% after the implementation of the restrictions. However, the severity of injuries remains constant, with no particular changes. In addition, the research highlighted that accidents became more dispersed throughout the city and less concentrated in the city centre.

In fact, the study showed that drunk drivers were more likely to suffer serious injuries, even though the restriction appeared to reduce the number of alcohol-related incidents. In addition, the researchers highlighted that older drivers and those driving in the evening rush hour experienced higher rates of serious injury.

2.4.3 Canadian bans

Another city experimenting with some form of ban is Montreal, in Quebec. In February 2020, a few months after Lime and Bird were allowed to operate, the city decided to ban shared e-scooter systems (Bailey et al., 2024). The city's argument for the ban was mainly based on safety concerns and inappropriate parking. In particular, the city states that only 20% of shared e-scooters were parked in designated areas (Schneeweiss et al., 2021). As mentioned above, Montreal's experience is rather short, only a few months due to the winter interruption of services, and to the best of the author's knowledge there is a complete lack of literature on the subject.

The city of Toronto also decided to ban e-scooters, most notably extending the prohibition beyond shared models to include all e-scooters. After introducing shared e-scooters in 2019, the Toronto City Council voted in 2021 to prohibit their use on public streets, bike lanes, sidewalks, pathways, trails, and other public spaces (Bailey et al., 2024; Frisbee et al., 2022). The decision was based on concerns over safety, as e-scooters' high speeds, low noise levels, and ability to be parked anywhere were deemed to pose a disproportionate risk to seniors and individuals with disabilities. However, despite the ban, e-scooters continue to be used throughout Toronto (Jacobs & Dhaliwal, 2024).

No further literature appears to have been published on these specific Canadian cities with e-scooter bans, suggesting a gap in the research on this type of policy.

2.5 Difference-in-differences method applied to shared e-scooter studies

As highlighted in the previous sections, the last few years have seen an important proliferation of shared e-scooter systems. The growing body of literature on the subject focused on many aspects such as travel patterns, type of users or safety issues, but also tried to study the impact of the introduction of shared e-scooters confronting scenario where they were present and not. To do this, several studies use the difference-in-differences (DiD) technique.

The DiD methodology, which will be extensively discussed in this research (see *3.4 Difference-in-differences method*), involves comparing two scenarios: one where a "treatment" occurs—such as the introduction of a new mode of transport or a specific policy—and another where no such treatment is implemented. By comparing the changes in outcomes between the treated and untreated groups, DiD captures the causal effect of the policy and provides a clear, quantifiable measure of its impact.

In this section, we will examine several studies on shared e-scooters that utilize the DiD approach with pre- and post-treatment periods. This analysis will highlight the growing application of this technique in transportation research and showcase the concrete results obtained in the literature through this methodology. These examples will provide a foundation for understanding how DiD can be applied to evaluate the effects of policies, such as the shared e-scooter ban in Paris, which is central to this study.

Many studies utilizing the DiD methodology for shared e-scooters focus on their impact on other modes of transportation, particularly bikesharing systems. For instance, research on e-scooter impacts on bikesharing by H. Yang et al. (2021) and Meng & Brown (2024) employed operator data combined with propensity score matching within a DiD framework. These studies reveal a substitution effect, where e-scooters tend to reduce bikesharing trips, both docked and free-floating. In Chicago, Yang et al. reported a 10.2% decrease in bikesharing usage following the introduction of e-scooters. The entry of e-scooters also coincided with a significant rise in crashes (up by 56%) and crimes (up by almost 10%), highlighting important safety concerns.

However, Meng & Brown's research on the study cases of Chicago and Boston found that while bikesharing declined with the introduction of shared e-scooters, total micromobility trips, bikesharing and e-scooters, increased by 50% to 55% respectively. In particular, they focused on the areas with lower accessibility and services, the communities of concern, experienced an increase in bikesharing trips, improving mobility in these areas.

This theme of accessibility is also supported by Opitz et al. (2024), who analyzed e-scooter adoption in Santiago, Chile. In their paper they used GPS data and by applying urban clustering and DiD with binomial regression they showed different patterns depending on the relative area. On the one hand, the introduction of shared e-scooters reduced public transport trips in more central areas, on the other hand they increased them in peripheral regions, up to 80%. Through this study, they demonstrated a different role of shared e-scooter systems depending on the area, with a substitution and competition role with public transport in central areas, and a complementary role in peripheral areas with lower accessibility.

E-scooters' role as a last-mile solution further strengthens their complementarity with public transit (Weschke, 2023; W. Yang & Ewing, 2024). A study by W. Yang & Ewing (2024) focused on Los Angeles, employing a DiD model with propensity score matching, and found that e-scooters located near metro stations increased rail passenger numbers, reinforcing their value as a connector to public transportation. It suggests that e-scooter helps and have complementary with urban transit, in particular as last mile solution.

The complementarity role is highlighted by other studies as the Weschke (2023) one that employs a DiD approach based on European data to assess how the opening and closing of metro stations affect e-scooter usage, revealing that new stations increase e-scooter demand while closures decrease it, indicating a complementary relationship between e-scooters and public transit.

Similarly, Luo et al. (2021) utilize a DiD methodology to evaluate the competitive dynamics between e-scooters and bus services in Indianapolis, in the US, finding that approximately 27% of e-scooter trips potentially compete with bus trips, leading to a reduction in bus ridership. This is particularly in downtown areas, similarly as the results in Chile (Opitz et al., 2024). The 29% of complementarity trips are mainly located outside the downtown areas, where the bus coverage is low.

This suggests that shared e-scooter systems are functional in last mile solutions, as presented in Section *2.2.2, E-scooter replaced modes and purposes*. There is not only a fundamental difference in shared e-scooter patterns between cities and countries, but also differences between areas within the same cities, in particular between city centres and less accessible areas.

In addition to mobility impacts, DiD has been used to examine safety outcomes related to shared e-scooters. Cloud et al. (2023) conducted a study across six European countries, highlighting an 8% increase in traffic accidents following e-scooter adoption. The increase was observed primarily during warmer months, with no significant changes during winter. These results suggest that e-scooter accidents are mainly related to infrastructure characteristics and with seasonal variations. Cities with better cycling infrastructure experienced lower accident rates compared to other cities. This relationship between infrastructure and shared e-scooters is also highlighted by W. Yang & Ewing (2024) n their case study of Los Angeles. They highlighted that better cycling and pedestrian infrastructure increased the use of e-scooters.

This findings are in line with those presented in Section *2.2.5, Safety issues of e-scooter*. In particular, slightly higher accident rates compared to bicycles ones are associated with e-scooters, whether or not cycling infrastructure seems to be the most important variable to address the issue.

In conclusion, researchers in the field of transportation have increasingly utilized the DiD method in recent years to evaluate the impacts of shared e-scooter systems. This method has proven effective in quantifying the effects of introducing this mode of transport on various aspects of urban mobility. It is important to emphasize the novelty of this research area and the rapid growth in academic interest about shared e-scooters.

The results of the literature analysis indicate that the primary focus of research with DiD methodology is on the role of shared e-scooter schemes in relation to public transit and other shared systems. The analysis suggests that the introduction of e-scooters can substitute to a certain extent for bikesharing, despite a concurrent growth in both bikesharing and e-scooters. Notably, e-scooters have the potential to reach areas that are less accessible and previously underserved (Meng & Brown, 2024; H. Yang et al., 2021).

This is particularly evident in relation to the introduction of e-scooters and its impact on public transportation. A competition and substitution dynamic is observed in downtown areas, while in less accessible regions, e-scooters assume a stronger complementary role, particularly in last-mile trips (Luo et al., 2021; Opitz et al., 2024; Weschke, 2023; W. Yang & Ewing, 2024). In conclusion, it is suggested that e-scooters could play a significant role in linking suburbs or areas with limited public transportation coverage. In contrast, within urban centres, e-scooters have the potential to substitute for bicycle-sharing systems and public transit.

The existing literature further underscores the importance of infrastructure, particularly the presence of well-connected bicycle pathways and a pedestrian-friendly environment. These factors have been shown to contribute to a reduction in injuries (Cloud et al., 2023) and an increase in e-scooter utilisation (W. Yang & Ewing, 2024).

However, while numerous studies have focused on the introduction and expansion of shared e-scooter systems, there is a noticeable lack of research exploring the opposite scenario—the impact of their removal. Investigating the consequences of banning shared e-scooters presents a valuable opportunity to deepen our understanding of not only the rise of this transport mode but also the regulatory responses and resulting changes in mobility patterns. Such studies can shed light on how regulatory frameworks shape urban mobility and provide critical insights for policymakers aiming to balance innovation, sustainability, and public order in transportation systems.

2.6 Conclusion of the State of the art and research gap

The objective of this chapter is to provide a comprehensive overview of the current research landscape pertaining to shared e-scooters. In doing so, it seeks to examine the environmental and social impacts of this phenomenon, analyse usage patterns, and investigate the legislative frameworks established by national or local authorities to regulate it.

From an environmental and social standpoint, the debate surrounding shared e-scooters is complex. On one hand, these vehicles have the potential to reduce car dependency, alleviate congestion, and promote more sustainable urban mobility. If shared e-scooters primarily replace car trips, the cost-benefit balance is generally positive, with significant reductions in emissions, road space consumption, and noise pollution. On the other hand, their benefits are diminished when they substitute for walking, cycling, or public transit—modes that already have a low environmental footprint. This highlights the importance of analysing the specific impacts of shared e-scooter networks within their local context, particularly regarding replaced modes and usage patterns observed in each city. The effects of shared e-scooters vary considerably depending on local urban dynamics and transportation systems. On average, e-scooters appear to act as a substitute for other modes of transport, or for other types of transport in terms of modal share. In areas where public transit and cycling are more prevalent, shared e-scooters are more likely to replace sustainable modes. However, a significant proportion of the substituted modes are automobiles or improve accessibility to suburban zones in last-mile trips, as all the studies highlight.

In addition, the literature review highlights that safety concerns and sidewalk occupancy are genuine issues regarding shared e-scooters. However, based on the literature, no clear trend indicates a significantly higher risk compared to bicycle incident rates. In this context, it appears that media narratives and some arguments for restricting e-scooters are often exaggerated. Instead, improving cycling infrastructure could play a crucial role in enhancing the safety of e-scooter users.

Our review also revealed a limited yet growing body of research addressing the regulation of shared e-scooters, with particular attention to partial bans and restrictions. While several studies examine the general effects of legal frameworks on shared e-scooters, the literature on complete bans remains sparse. This is especially true for the case of Paris, where the ban on shared e-scooters offers a unique opportunity to study the effects of such a drastic policy decision. The reversal design of this policy is rare and has not been extensively analysed in the context of shared e-scooter systems. Existing studies on partial restrictions—such as hourly bans and geofenced zones—provide valuable insights but are not directly comparable to the comprehensive ban implemented in Paris.

Moreover, we observed an increasing application of quantitative methods, such as DiD, to evaluate the impacts of shared e-scooters on urban mobility and public safety. This technique, which relies on comparing outcomes before and after an intervention while controlling for trends in untreated groups, has proven effective in assessing the causal effects of policy changes. The extant literature highlights the DiD methodology, which demonstrates that the introduction of e-scooters in downtown areas exerts a competitive and substitutes effect, despite the concomitant increase in shared trips. Conversely, e-scooters are more likely to have a complementary role to that of bikesharing and public transit in less accessible and covered areas. However, its application to understanding the impacts of general e-scooter bans remains underexplored. This gap in the literature further underscores the novelty and relevance of our research, which aims to apply such methods to the Paris case study.

In conclusion, the literature on shared e-scooters is expanding rapidly, reflecting their growing prominence in urban mobility discussions. Nevertheless, significant gaps remain, particularly concerning the study of complete bans and their social, environmental, and mobility impacts.

Gaining a more precise understanding of these effects is crucial for providing a clearer perspective on similar policy measures.

3 Methodology

This chapter is devoted to an examination of the methodological framework employed in the analysis of the ban on shared e-scooters in Paris and its overall impact on mobility in the city. In particular, Sections *3.1*, *3.2* and *3.4* examine the principal methodologies that will be employed to examine transportation patterns within the city of Paris. In the present work we will mainly focus on repeated measures of flows related to different kinds of vehicles, as better explained in the next chapter. First of all, data cleaning methodologies and time series analysis are presented. Subsequently, difference-in-differences (DiD) methodology is presented, both in the basic version and then in the more advanced one. These methodologies will be used in order to determine the significance of the policy.

Section *3.1* introduces the basics of time series analysis, which is used to get an initial graphical view of the results and is useful for identifying general variations, seasonal trends and potential breakdowns in the data. In this way, it is possible to capture the first important trend that emerges from the data before moving on to more accurate and advanced methods.

Section *3.2* introduces the data cleaning methodologies applied to the above mentioned dataset. in fact, the dataset originates from real-world observations and contains raw data that include outliers, which may affect the reliability of our analysis. This section presents the elbow method, the technique employed to systematically identify and discard outliers while establishing robust thresholds for cleaner data.

Section *3.3* presents the weighting of the data on a daily basis. In particular, due to a lack of data, the representation of the day of the week on a monthly basis is not homogeneous, which introduces possible biases. By systematically normalising the daily data, it will be possible to obtain more robust and reliable results.

Section *3.4* transitions to the DiD methodology, an approach for evaluating policy impacts in non-experimental settings. By comparing outcomes between treated and control groups before and after the policy intervention, the DiD methodology provides a causal estimate of the ban's effect on flows. This section presents two different methodologies of DiD, their application using regression models, the key statistical indicators, and the assumptions required for their validity.

Section *3.5* introduces the application of the DiD methodology in the context of our transportation study. The section covers the implementation process, the key elements of the model, and the analysis coefficients, both input and output. Additionally, it presents the algorithm flow, including an explanation of the key functions used in the methodology.

3.1 Time series analysis

Time series data is one of the most common formats for presenting information when dealing with chronological data. A time series is a set of observations ordered by the time of collection. In this study we will use data from vehicle counting stations that operate continuously over different years, where the data are aggregated on an hourly basis.

This type of data collection equipment can use different methods, from manual counting to electronic systems. The time series provide a good basis for analysing variation over time to capture patterns and internal mechanisms, and is useful for predicting possible future trends.

3.1.1 Exploring methods for time series

As highlighted by Washington et al. (2011) in the book *Statistical and econometric method for transportation data analysis* the initial step in time series analysis is to explore the series by studying its trends and seasonal components. A trend in a time series refers to a gradual long-term change in the data. Common methods to analyse these trends include the least squares approach and moving averages, which help to identify and quantify the underlying direction of the series.

Seasonal components, on the other hand, refer to patterns that repeat at regular intervals over time. These patterns can occur annually, such as monthly variations due to weather or seasonal changes, or daily, for example, when forecasting traffic patterns throughout the day. To quantify these repetitive variations, a seasonal index is often calculated, using methods like the average percentage approach.

One of the most straightforward ways to observe trends and seasonal variations is through graphical visualization. Trends and seasonal effects can sometimes be directly identified by examining time series plots, such as histograms or scatter plots. To aid in visual interpretation, trends are often highlighted with fitted lines or smoothed curves superimposed on the graphical representation of the data.

Regarding methods for displaying data, the most common techniques include histograms, ogives, box plots, bar charts, and line charts. Among these, histograms are particularly prevalent for displaying data that is naturally grouped (Washington et al., 2011) A histogram is a type of chart consisting of bars of varying heights, where the height of each bar represents the frequency or count of outcomes for a particular variable. For time series data, the y-axis typically represents the measured values, while the x-axis represents time intervals (e.g., hours, days, or years), and each time point corresponding to its own bar.

Instead, pie chart are often used when handling nominal or categorical data. These kind of charts are characterised by a circle divided into proportional areas related to the categories percentage, providing a direct visualisation of the data distribution.

The choice of visualization technique depends on the type of data and the insights being sought. Histograms and bar charts are ideal for observing distributions and comparing frequencies, while pie charts are more suited to summarizing proportions in categorical datasets. For time series data, line charts are also commonly used to depict trends and variations over time, as they provide a continuous representation of changes.

In our research on the specific case study of the ban on shared e-scooters in Paris, we will utilize counting data to examine patterns and variations in vehicle usage. In Section *5.2*, we will plot this data to visually identify trends and seasonal variations, which will provide an initial understanding of the changes over time.

3.2 Data cleaning methodology

The reliability of the model's results is mainly related to the quality of the input data. In this particular instance, the utilisation of raw data obtained from a traffic counting station (*see 4.4 Dataset presentation*) necessitates the execution of a data cleaning analysis. This is necessary to address issues such as outliers, missing values, inconsistencies, and other concerns related to instrumental errors, flaws in the categorisation algorithms, and so on. It is important to note that such issues are inherent to real-world data, where the capture of actual flows can be influenced by a multitude of factors.

To address this issue, we adopt a straightforward and practical approach to handle missing data. Gelman & Hill, in their book *Data Analysis Using Regression and Multilevel/Hierarchical Models* (2006), dedicate Chapter 25, "Missing-Data Imputation," to explore a range of techniques for dealing with incomplete data. Among these methods, they also discuss the strategy of discarding missing or unreliable data, recognizing it as a valid approach in certain contexts. In our case, we chose to discard missing data and exclude days with flow values below a certain threshold. This decision aligns with the needs of our analysis, ensuring that the results remain interpretable and robust without introducing unnecessary complexity.

To address this solution, it is necessary to determine optimal thresholds for discarding outliers. Traffic counts in our dataset show relatively regular patterns due to hourly, weekly and seasonal variations, except for the presence of outliers, which exhibit significant deviations beyond a certain percentage. For this reason, identifying thresholds to eliminate these extreme values is essential.

The most efficient method individuated for finding these thresholds in our dataset is the so-called elbow method.

3.2.1 Elbow method

The elbow method is a technique, typically used to determine the optimal number of clusters, that involves plotting the number of clusters in decreasing order on the x-axis and the percentage of variance explained by the statistical model on the y-axis. This process generates the characteristic "elbow curve," which generally takes the shape of a concave function. The point of maximum variation in the angle of the curve is visually identified as the "elbow," from which the method derives its name.

This technique allows for a direct identification of the point at which a specific stabilization of numerical values occurs, thereby indicating a stable distribution. Increasing the number of clusters beyond this point does not significantly increase the explained variance. Consequently, the determined value ensures a sufficient explanation of the variance without unnecessarily increasing the number of clusters.

In our case, we decided to use this method to similarly determine the optimal threshold for identifying outliers, whether significantly above or below the mean flow values in a given section, for a given kind of vehicle. The identification of the threshold value is performed to define the range where the distribution of values does not present abrupt anomalies that deviate significantly from the mean.

To do this, we followed an approach analogous to the classical method for identifying the number of clusters. First, traffic counts are sorted in descending order and the mean value is calculated. Each outcome value is then divided by the mean value to create a new column containing the ratio of the count to the mean, expressed as a percentage.

This allows the elbow curve to be plotted, where the x axis shows the ordered traffic counts and the y axis the corresponding percentage variation relative to the mean. Two elbow points are normally visible. Subsequently, the analysis is divided into two parts: one for values greater than 100% of the mean value and the other for values less than 100%.

To identify the elbow point for the values, the perpendicular distance is calculated between the line connecting the maximum value and the minimum value and each point on the curve: respectively from maximum point to 100% and from 100% to minimum point. This perpendicular distance is calculated using Eq. 1 presented below.

$$d = \frac{|(y_2 - y_1) \cdot x_i - (x_2 - x_1) \cdot y_i + x_2 \cdot y_1 - y_2 \cdot x_1|}{\sqrt{(y_2 - y_1)^2 + (x_2 - x_1)^2}} \tag{1}$$

Where:

- The start point, the initial point of the line, is defined by the coordinates (x_1, y_1)
- The end point, the final point of the line, is defined by the coordinates (x_2, y_2)
- The coordinates of the i-th point under consideration, denoted as x[i] and y[i], are represented by the point (x_i, y_i).

In this way, the two elbow points can be identified: an upper one, corresponding to values significantly deviating as outliers above the norm, and a lower one, corresponding to values significantly deviating below the norm.

3.2.2 Elbow method implementation

This section presents the concrete implementation of this methodology. First, the code used for data cleaning, written in the R programming language, is provided. Additionally, a concrete example is presented, including charts of the elbow points as an illustrative reference.

The code below implements the function that will be called to calculate the distance for each point.

```
find_knee_point <- function(x, y) {
  start <- c(x[1], y[1])
  end <- c(x[length(x)], y[length(y)])
  # Perpendicular distance for every point
  distances <- sapply(1:length(x), function(i) {
```

```
        numerator <- abs((end[2] - start[2]) * x[i] - (end[1] - start[1]) * y[i] + end[1] * start[2] - end[2] * start[1])
        denominator <- sqrt((end[2] - start[2])^2 + (end[1] - start[1])^2)
        return(numerator / denominator)
    })

    # return index with maximum distance
    return(which.max(distances))
}
```

The function is applied for the first time to values exceeding 100% to identify outliers with excessively high values. By splitting the general array into a subset containing values greater than 100% of the mean, the data is plotted with blue dots. As an example, see Figure 6. The data is coming from a specific counting station of the Paris' city, the Sébastopol x Rivoli counting point (counting points will be presented in *4.4.2 Counting point location and characteristics*), for scooter from March 2022 to February 2024. A dashed red line is drawn between the maximum and minimum points, and the function is applied to identify the elbow point, highlighted in red.

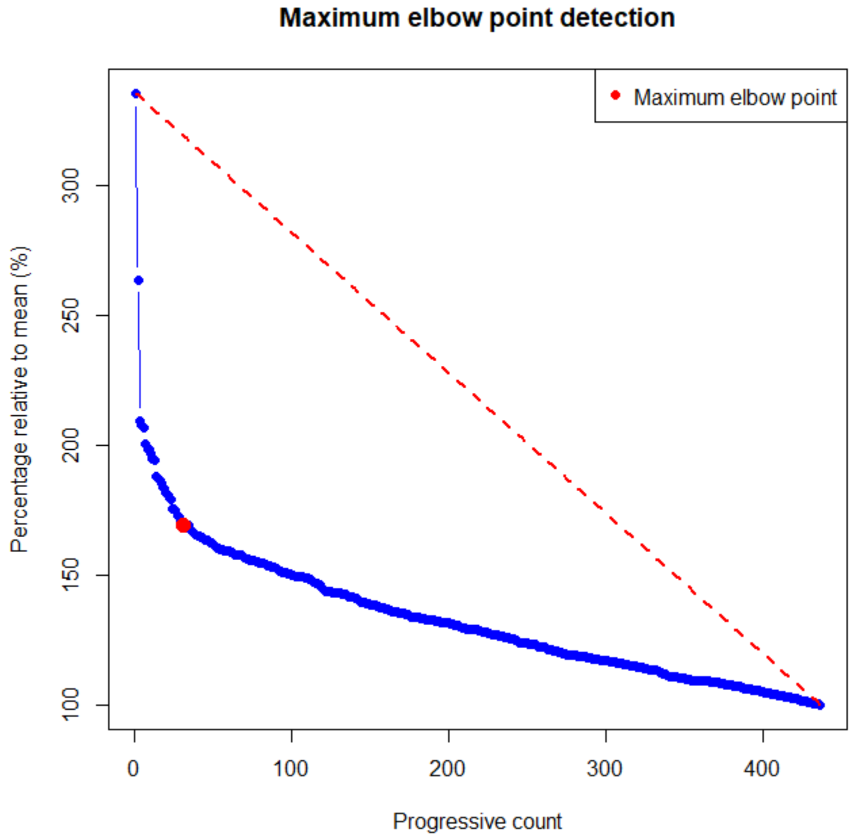

Figure 6: maximum elbow point detection, example from Sébastopol x Rivoli counting point

Similarly, the same method is applied to values below 100%. In this case, due to the specific shape of the curve, as previously discussed, the first curve is analysed to calculate the maximum distance point. Only the positive deltas between the curve and the line connecting the minimum and maximum points are considered.

An example is shown in Figure 7, again from the Sébastopol x Rivoli counting point for e-scooters, covering the period from March 2022 to February 2024 for all values below 100% of the mean count. Green dots represent the points of the elbow curve, while the dashed blue line connects the first and last points of the dataset under consideration. The elbow point is highlighted in red.

Particular attention is drawn to the relatively more complex nature of the elbow curve in this part of the graph, due to a higher distribution of points below 10%, which are concentrated in the lower section of the array.

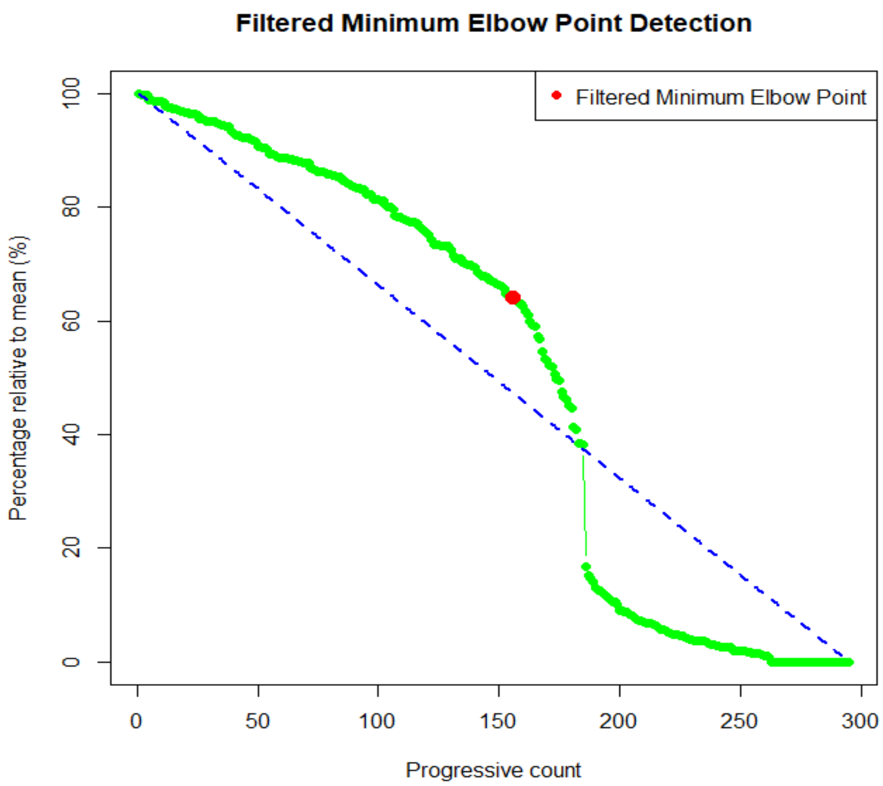

Figure 7: minimum elbow point detection, example from Sébastopol x Rivoli counting point

All elbow points will be graphically verified to ensure that the values have been correctly identified. If an error occurs and an incorrect value is chosen, as observed from a graphical perspective, a new elbow point will be added manually. The reader is invited to refer to *4.5.5*

Application of the elbow method for cleaning activities for the complete implementation on the dataset.

3.3 Day of the week normalisation

In our analysis we will use daily aggregated data and the DiD model will average the counts over specified periods, monthly or semestral. However, this monthly analysis may be unbalanced if certain days of the week are overrepresented or underrepresented. For example, a month may contain a higher number of weekends or have specific days missing due to data cleaning exclusion, leading to an uneven distribution of certain weekdays and potentially distorting the analysis. In order to ensure a balanced dataset, this section presents a day-of-week normalisation method to ensure consistency across the dataset, applying a specific weight used to ensure weighted averages in the model.

3.3.1 Weighting principles

In order to guarantee a balanced dataset and avoid distortions due to the under- or over-representation of certain days of the week, one of the most widely used methodologies is the weighting of dataset values (Gelman & Hill, 2006). This approach consists of applying a weight to the dataset values based on their frequency in the selected period. If a particular day is overrepresented, the coefficient reduces its impact, whereas if a day is underrepresented, the coefficient increases its weight.

For example, on a monthly basis, each day of the week is expected to occur at least four times. If a Sunday appears five times in a given month, this could distort the analysis. To correct for this, a normalization coefficient of $\frac{4}{5}$ is applied to each Sunday value of that month. Conversely, if a Monday appears only three times since a particular Monday in that month was excluded based on the above presented data cleaning activities, a coefficient of $\frac{4}{3}$ is applied to increase its representation. Finally, the models will calculate average values based on the sum of the coefficients. This methodology ensures a more uniform distribution of values in the dataset, controlling for potential distortions caused by unbalanced distributions.

Adding weights to the dataset has been shown to offer significant advantages in enhancing the robustness of the analysis. Primarily, it ensures that no particular day of the week is over- or underrepresented, thereby smoothing out potential biases associated with distorted distributions. By incorporating weights into each value of the dataset, a more accurate reflection of vehicle flows is achieved, thus obviating the need to rely entirely on potentially distorted data.

Furthermore, the weighting activity enables a more equitable comparison of analogous periods, such as months, by assigning greater weight to underrepresented days or, conversely, by giving less weight to overrepresented days. This allows for the comparison of similar periods as though they were completely analogous, without distortion attributable to real flows. Standardising the dataset ensures that a month and another are standardised on the same period, and any comparison between them is made without distortion. This is because the presence of a longer month is not distorted by a shorter one, for example. In this way, each day's weight aligns with its expected distribution.

This technique enables comparisons between regularized time periods without distortions that could otherwise compromise reliability. However, it is important to note that normalization assumes that the available dataset is representative of real-world conditions. If the data itself is already distorted, applying normalization coefficients may inflate these distortions. To mitigate this risk, we have implemented the above introduced data cleaning activities, histogram visualization, and statistical analysis to verify the regular distribution of data (see respectively *4.4.3, 5.2, 5.4* for their implementation). Based on these validations, we consider this key assumption to be robust and reliable.

3.3.2 Weighting implementation

As discussed in previous sections, some days may be missing due to outliers, missing values, or other data inconsistencies, while others may be overrepresented due to the configuration of the month. Furthermore, since a monthly basis is one of the most frequently used in our analysis (see *3.4* and *3.5*), we will apply monthly normalization. Eq. 2 presents the general rationale for daily normalization on a monthly basis:

$$C_d = \frac{N_{\text{expected}}}{N_{\text{observed}}} \tag{2}$$

Where:

- C_d is the normalisation coefficient for daily normalisation,
- N_{expected} is the expected number of occurrences of day d in a period (e.g. 4 occurrences per month),
- N_{observed} is the actual number of occurrences in the considered period.

Applying the normalisation coefficient to all the daily flows of the dataset it will be possible to make a balanced comparison between month, both for histograms visualisation and making our analysis. Consequently, the average values of the models are obtained by dividing the sum of the normalised values by the sum of the normalisation coefficients.

The coefficient is first calculated on a monthly basis, assuming that the expected number of occurrences (N_{expected}) for each day of the week is 4. Then, the actual number of observed days (N_{observed}) in the month is determined, and the corresponding coefficient is applied to adjust the values. If the expected number of days matches the observed number, the coefficient is equal to 1, and the values remain unchanged.

Not only can the number of days be distorted by irregular monthly distribution and data cleaning activities, but also completely missing days of the week within a given month can distort the analysis. In our analysis we start from the hypothesis that there are 4 occurrences of each weekday within a given month. In total, the base hypothesis implicitly taken as the expected number of occurrences is 20 weekdays and 8 weekend days within each month. If one day is completely missing, this basic assumption is deformed and could distort the analysis. In this way another weighting activity is added.

For example, if one day of the week is completely missing in a month, a weight of 20/16 is added to the other day of the week to take account of the new configuration and give a higher weight to the representation of the week. The weight applied is the same as in the previous Eq. 2, where the number of expected occurrences is 20 or 8 for weekday and weekend respectively, whether the number of observed days is the expected occurrences minus 4 multiplied by the number of missing days for weekday and weekend respectively. Months missing any weekend or weekday are discarded as unrepresentative. This technique makes it possible to compare months in a robust way.

In conclusion, this technique will be applied to the entire dataset, with further details provided in Section *4.6 Dataset weighting*.

3.4 Difference-in-differences method

Experimental randomised analysis is often the most direct way to demonstrate the effect of a treatment on a sample. For example, in medical trials, the most direct way to demonstrate the effectiveness of a drug is to have a control group and a treated group, with the first serving as the reference level and the differences with the second group demonstrating the effectiveness (or not) of the drug being tested.

This procedure, called a randomised trial, is not always possible for research purposes. For example, to continue with the previous statement, in medicine some randomised experiments can't be carried out for ethical or feasibility reasons. Similarly, in the social sciences, economics and engineering, it's almost impossible to do randomised experiments. Examples are studies on the impact of new policies, new laws and regulations. In these cases, it is impossible to study the impact of a policy on a random sample. For example, a government's decision to extend free health care to a population can't be studied on a random sample, but it can't be studied by any other method.

In this case, we are talking about an evaluation method in a non-experimental setting. One of the most common and widely developed technique for analysing the impact of a new policy, in this way, is difference-in-differences (DiD) analysis. This technique involves a combination of before-after and treatment-control group comparisons. The aim of the method is to estimate the causal effect of a policy on a treatment group relative to the untreated group.

Accordingly, the DiD approach represents a research design based on a comparison of four distinct groups. The groups can be distinguished by two main characteristics: firstly, whether they were analysed before or after the treatment; and secondly, whether they were the control group or the treated group. The assumption is that the two groups before treatment exhibited a similar trend, and that following treatment, the treated group will change in average in respect to the control group, which will follow its "natural" trend. The aim of the technique is to capture this difference.

DiD is a widely used method in a number of social science disciplines, management, clinical studies, engineering and, in particular, labour economics. It is employed for the analysis of the impact of policies, such as minimum wages, on the labour market. Notable examples are the papers published by Ashenfelter (1978) on the effect of training programs on earnings and Card & Krueger (1993) article that studied the impact of rising minimum wages in New Jersey on market labour. The two researchers were awarded the 2021 Nobel Prize in Economics (*The Sveriges Riksbank Prize in Economic Sciences in Memory of Alfred Nobel, 2021*) for their groundbreaking contributions, particularly exemplified in this study. With this research, they demonstrated that rising minimum wages don't have a significant impact on the labour market. To reach this result, they compared the employment rate in fast-foods before and after the policy in New Jersey and Pennsylvania, which didn't raise the minimum wage and thus served as a control group. In the last years this method widespread in policy impact studies (Fredriksson & Oliveira, 2019).

It should now be clear how the DiD method can contribute to our research on the impact of the shared e-scooter ban in Paris. By conducting an analysis before and after the implementation of this policy and selecting an appropriate control group, we can effectively evaluate the causal effect of the policy.

3.4.1 DiD method – 2 x 2 basic model

To elaborate on the DiD method, we aim to estimate the effect of a policy (the "treatment") by comparing outcomes between a treated group and a control group. The primary assumption underlying this method is that the groups exhibit similar trends before the treatment, an assumption known as the "parallel trend assumption." This assumption will be discussed in detail in subsequent sections. Graphically, the parallel trend assumption implies that the gap between the treated and control groups remains constant over time before the treatment. When the treatment is introduced, these trends diverge: the control group continues along its "natural trend," while the treated group experiences a change in slope. The DiD analysis captures this change in slope, providing a quantitative estimate of the policy's effect.

To formalise what has been said, we will present the general equation form for DiD and introduce more complex methods. The basic DiD has data from two groups and two time periods. These data could be repeated several times in a panel, for example. By taking the difference between the mean of the treatment group after and before the treatment, we capture the difference related to the time variation in that group. Then, by taking the difference between the two averages of the control group, we will do the same for the other group. The differences between the two differences will give us the effect of the treatment.

Introducing a mathematical term, we will calculate the average value of the four variables, as in Eq. 3:

$$DiD = \left(\overline{y}_{s=\text{Treatment},t=\text{After}} - \overline{y}_{s=\text{Treatment},t=\text{Before}}\right) - \left(\overline{y}_{s=\text{Control},t=\text{After}} - \overline{y}_{s=\text{Control},t=\text{Before}}\right) \tag{3}$$

Where:

- $\overline{y}_{s=\text{Treatment},t=\text{After}}$ represents the average outcome for the treatment group after the intervention.
- $\overline{y}_{s=\text{Treatment},t=\text{Before}}$ represents the average outcome for the treatment group before the intervention.
- $\overline{y}_{s=\text{Control},t=\text{After}}$ represents the average outcome for the control group after the intervention.
- $\overline{y}_{s=\text{Control},t=\text{Before}}$ represents the average outcome for the control group before the intervention.

This could be also seen in a graphical way, as shown in Figure 8, which plots the average values over time of control and treatment group. The figure illustrates the variables introduced earlier and the estimated DiD, interpreted as the change over time in the treatment group relative to the counterfactual value. The counterfactual represents the assumed value that would have followed a parallel trend over time in the absence of treatment.

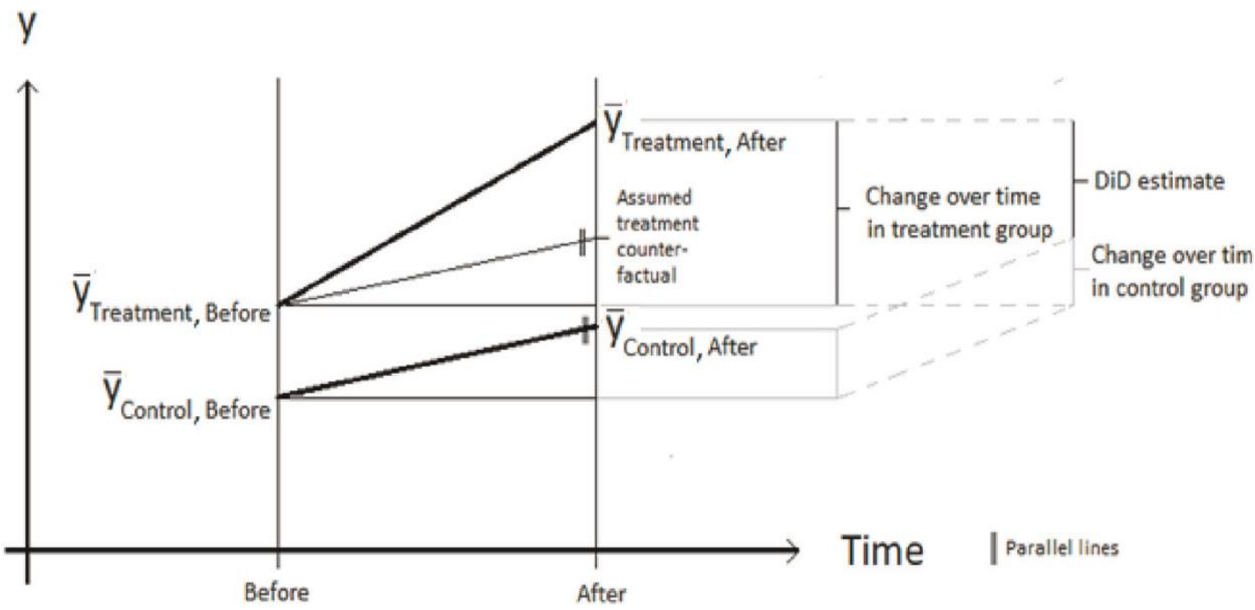

Figure 8: DiD method for a 2x2 model, from Fredriksson & Oliveira (2019)

This 2 x 2 model doesn't tell us anything about the statistical significance of the model. Regression analysis is generally used to provide this information and will be discussed in the next section.

The DiD model can be extended from its basic 2x2 form to more complex frameworks. One of the most relevant and widely used extensions is the so-called multiple time period analysis. In this approach, we no longer consider, *sic et simpliciter*, an average value for the periods before and after treatment. Instead, a DiD analysis is conducted for each analysed period in relation to the average pre-treatment values. This allows specific temporal trends to be identified and enhances the robustness of the model. This approach will be discussed in more detail in a dedicated section (see *5.4 DiD application: the temporal analysis approach).*

3.4.2 Rationale for using linear regression in DiD analysis

In the previous section, we presented the foundational framework of the DiD analysis. In our case, with a large dataset derived from traffic counting points, it is crucial to determine whether the calculated DiD coefficient reflects a causal impact of the studied policy or is merely the result of random variations or confounding factors.

In order to achieve this, one of the most straightforward and widely diffused approaches is the application of linear regression using the Ordinary Least Squares (OLS) method (Callaway & Sant'Anna, 2021; Card & Krueger, 1993; Fredriksson & Oliveira, 2019; Lechner, 2010). There are several reasons why OLS is particularly suitable for our analysis.

Firstly, linear regression enables us to explicitly include interaction terms between time and treatment groups, which form the basis of the DiD coefficient. Moreover, OLS provides statistical estimators for the evaluated coefficients, thus enabling the determination of the significance of the considered values. Subject to specific assumptions, the model captures whether variations are likely to be random or not. In addition, OLS provides statistical metrics, such as R^2 and adjusted R^2, which allow the evaluation of how well the model explains variations.

In conclusion, OLS serves as an appropriate tool for implementing the DiD methodology, enabling us to analyze our data rigorously. In the following sections, we will detail the OLS methodology and its application to our case study.

3.4.3 Application of OLS in DiD analysis

The main goal of the regression analysis, within an OLS framework, is to estimate the different coefficients of the general model equation. Eq. 4 presents such model, where the main dependent variable, y, represents the count of vehicles in our analysis, and the other coefficients are derived through estimation.

The β-coefficients are calculated from the following regression, where y_{ist} is the dependent variable, the output of the panel data at a given time and group. For example, in our analysis based on the recorded flows this value will be the number of vehicles counted in a specific point and on a specific time. A_s is the fixed effect for each group, the "base value" or "intercept", B_t is the before/after fixed effects, I_{st} is a dummy equal to 1 for treated observations in the after period and 0 for the other observations, and ϵ_{ist} is the error term:

$$y_{ist} = A_s + B_t + \beta I_{st} + \epsilon_{ist} \tag{4}$$

In this way we can get the expected value of y_{ist} present in the following expressions:

$E(\, y_{ist} \mid s = \text{Control}, t = \text{Before}\,) = A_{\text{s = Control}} + B_{\text{t = Before}}$
$E(\, y_{ist} \mid s = \text{Control}, t = \text{After}\,) = A_{\text{s = Control}} + B_{\text{t = After}}$
$E(\, y_{ist} \mid s = \text{Treatment}, t = \text{Before}\,) = A_{\text{s = Treatment}} + B_{\text{t = Before}}$
$E(\, y_{ist} \mid s = \text{Treatment}, t = \text{After}\,) = A_{\text{s = Treatment}} + B_{\text{t = After}} + \beta$

Estimating the coefficient of the regression in (4) through Ordinary Least Squares (OLS) and plugging the values in (3) we are able to calculate $DiD = \widehat{\beta}$.

Individual-level control variables can be added to this model to capture differences in the model due to other elements not directly related to treatment, such as weather, demographics, specific boundaries, and so on.

3.4.4 Key statistical indicators in OLS regression

As stated in Eq. 4, we present the general form for the linear regression model. In this section, we will examine the parameters estimated by the regression and discuss their implications. First, as previously mentioned, the parameters are calculated using the method of Ordinary Least Squares (OLS). This method seeks to minimize the sum of the squared differences between the observed values of the dependent variable (y) and the values predicted by the regression model.

The OLS method is based on the principle of least squares, where the error term (ϵ) is minimized. Mathematically, the goal is to minimize the objective function of Eq. 5:

$$\sum_{i=1}^{n} \epsilon_i^2 = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \tag{5}$$

Where:

- y_i is the actual observed value of the dependent variable
- $\widehat{y_i}$ is the predicted value from the model
- n is the number of observations

By solving this minimization problem, we obtain the estimated coefficients (β) that define the relationship between the independent variables (X) and the dependent variable (y) in the model.

Following the estimation of the parameters, the subsequent stage is to evaluate their statistical significance. This is achieved by calculating various parameters, including the standard errors, t-values, p-values and confidence intervals. These indicators are fundamental in determining whether the casual relationship is related to variation over the normal distribution assumption, or whether the distribution is related to randomness.

In a regression framework, the null hypothesis (H_0) and alternative hypothesis (H_1) often relate to the significance of a specific coefficient, such as β_1, which represents the effect of an independent variable (e.g., a policy or treatment) on the dependent variable.

$$H_0: \beta_1 = 0 \tag{6}$$

This states that the independent variable (e.g., the policy or treatment) has no effect on the dependent variable. In other words, there is no causal relationship between the variable of interest and the outcome.

$$H_1: \beta_1 \neq 0 \tag{7}$$

This suggests that the independent variable does have an effect on the dependent variable, meaning there is a causal relationship.

Under these specific hypotheses we can calculate the standard errors, the p-value, the t-values and the confidence interval. Here explained.

The standard error measures the variability of the estimated coefficient $\left(\widehat{\beta_1}\right)$ and indicates how much it is expected to fluctuate due to random sampling.

$$SE\left(\widehat{\beta_1}\right) = \sqrt{\frac{\sigma^2}{\sum(x_i - \bar{x})^2}} \tag{8}$$

Where:

- σ^2 is the variance of the residuals,
- x_i are the values of the independent variable,
- $\bar{x}$ is the mean of the independent variable.

Another key parameter is the t-value. This parameter is functional to determine whether $\widehat{\beta_1}$ is significantly different from zero. It is calculated as:

$$t = \frac{\widehat{\beta_1}}{SE\left(\widehat{\beta_1}\right)} \tag{9}$$

The value is then subjected to comparison with a t-critical value, the latter being related to the number of degrees of freedom of the model in question, as well as to the level of significance that has been chosen (which is generally set at 0.05).

The p-value represents the probability of observing a test statistic as extreme as (or more extreme than) the one calculated, under the assumption that the null hypothesis is true. It is derived from the t-distribution and is calculated as:

$$p = 2 \cdot P(T > |t|) \tag{10}$$

Where T follows the t-distribution with n−k degrees of freedom, n is the sample size, and k is the number of predictors.

If $p < \alpha$ (commonly 0.05), we reject the null hypothesis.

A confidence interval provides a range of values within which the true coefficient ($\beta 1$) is expected to lie, with a specified level of confidence (e.g., 95%).

$$CI = \widehat{\beta_1} \pm t^* \cdot SE\left(\widehat{\beta_1}\right) \tag{11}$$

In summary, the Ordinary Least Squares (OLS) method offers a robust approach for estimating the parameters of a regression model by minimizing the sum of squared residuals. By calculating standard errors, t-values, p-values, and confidence intervals, we can rigorously assess the significance and reliability of the estimated coefficients. Additionally, the null hypothesis framework applied to each coefficient allows us to determine whether independent variables, such as policies or treatments, have a statistically significant impact on the dependent variable. This methodology will be applied in the case study to analyse and interpret the effects of regulatory changes on urban mobility.

3.4.5 Parallel trend and other DiD assumptions

DiD design is quite a simple model to be implemented on a basic level. This characteristic in one hand explains its popularity, in the other hand we should notice that some key hypotheses have to be respected.

The assumption of this design approach are discussed in deep by Lechner (2010), which highlights firstly that the model should follow the standard assumption in micro econometric causal studies but also some specific hypothesis. Regarding the standard assumptions, Lechner emphasizes the necessity of the so-called Stable Unit Treatment Value Assumption (SUTVA). This assumption states that there should be no significant interaction between the members of the population, meaning that the treatment applied to one unit should not affect the outcomes of other units. In addiction, the covariates (indicate by X) have not to be influenced by the treatment.

Speaking about specific DiD assumption we introduce the so called “parallel trend” or “common trend”. The assumption has already been anticipated on the previous sections and is the core of the DiD approach. The main idea of this hypothesis is that in the pre-treatment period the treated and control groups had the same trend, a constant gap, and without the treatment the two groups would have experienced the same trend. Any variation in time of this trend will be attributed to the treatment, except some covariates applied.

The most straightforward way to demonstrate this hypothesis is from a graphical point of view, as presented, for example, by Courtemanche & Zapata (2014) in a research on the causal impact of universal coverage on health, applied on the case of Massachusetts. Figure 9 represents an example of visualisation of data with control and treatment group, with pre-treatment trends highlighted in order to visualise the parallel trend assumptions.

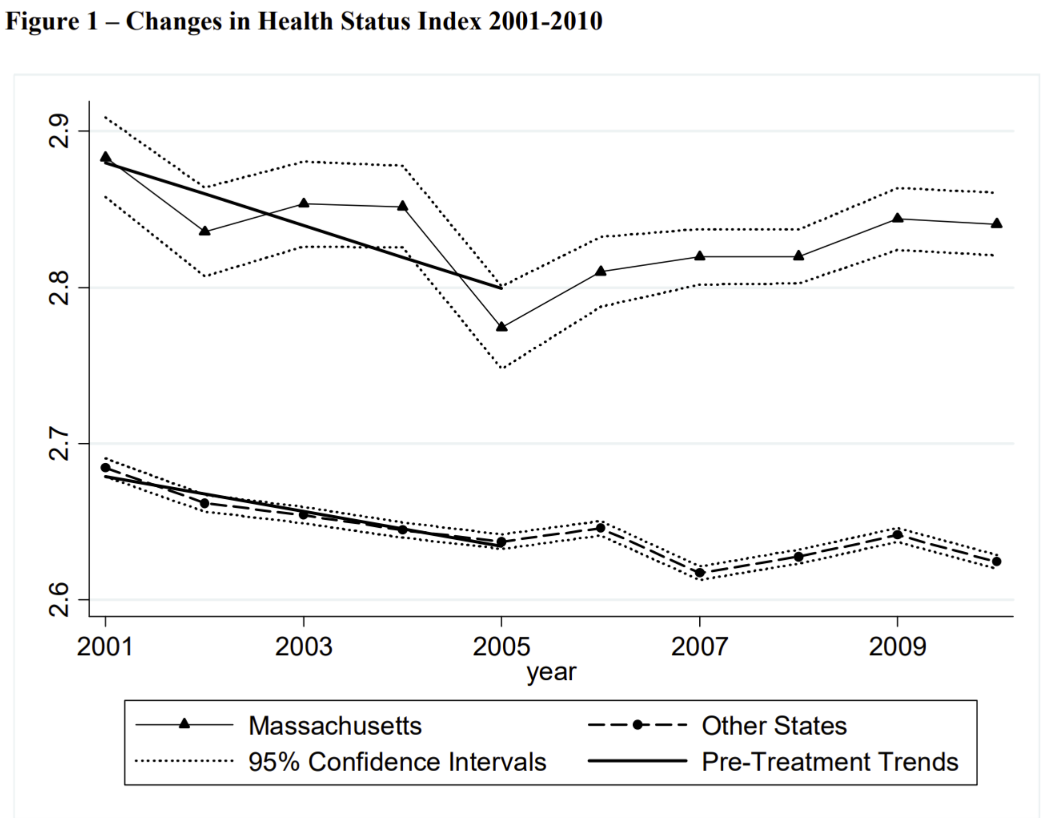

Figure 9: example of graphical validation of the parallel trend assumption from Courtemanche & Zapata (2014, p.40)

The more formal approach implies, for example, a DiD analysis to the pre-treatment model, a process known as placebo regression. The anticipated outcome, contingent upon the assumption being validated, is that no statistically significant effects should be observed in the groups before treatment (Fredriksson & Oliveira, 2019).

In our research, we will employ the direct evaluation of the DiD from periods preceding the treatment in relation to the average outcomes of the pre-treatment period. It is anticipated that no significant differences will be observed. This method, which will be discussed in greater detail in the following sections, is currently the most prevalent and widely used in the field of DiD with multiple time periods. It is particularly highlighted in the design approach proposed by Callaway & Sant'Anna, (2021), that will be used in our research.

3.4.6 Extended DiD with multiple time periods

The most prevalent 2x2 DiD model, as previously developed, can be upgraded to facilitate analysis of more complex nature, with greater robustness and higher levels of detail as output. In contrast to the previous model, which employed only "pre" and "post" periods, more advanced DiD methodologies rely on evaluating multiple periods in order to evaluate DiD in a repetitive manner over longer periods and study effects from one time to another. The employment of methodologies incorporating multiple time periods is instrumental in the capture of variation and the period-by-period fluctuations.

We focus on the methodology proposed by Callaway & Sant'Anna (2021), who developed a paper and accompanying code specifically for this DiD framework. The key parameter estimated is the ATT (Average Treatment Effect on the Treated), which measures the treatment's average effect on the treated subjects, comparing their observed outcomes to the counterfactual scenario in which they were untreated.

The outcomes of the model, as previously mentioned, are the ATT_i values, which compare the difference between the treatment and control groups at a specific time to the difference between the treatment and control groups at the previous time analysis.

This approach allows for the evaluation of two key factors:

1. Pre-Treatment ATT_i: these values assess whether the parallel trends assumption is satisfied. Specifically, they should be close to zero to indicate that the overall pre-treatment difference remains constant across time periods. Alternatively, the 95% confidence interval should include zero, which would also suggest that the parallel trends assumption holds.
2. Post-Treatment ATT_i: these values measure the effect of the policy. Post-treatment ATT_i values are expected to deviate further from zero. If the 95% confidence interval does not include zero, this indicates that the difference is statistically significant.

We can define the ATT count of the specific group if treated and untreated (g) and time (t) in the following way in Eq. 12:

$$ATT(g,t) = (E[Y_t|D = 1] - E[Y_{t-1}|D = 1]) - (E[Y_t|D = 0] - E[Y_{t-1}|D = 0]) \quad (12)$$

Where:

- $E[Y_t|D = 1]$ is the average outcome at time *t* for the treated group (D=1)
- $E[Y_{t-1}|D = 1]$ is the average outcome at time *t - 1* for the treated group (D=1); After the treatment period, this value becomes fixed as the baseline value, corresponding to the last period before the treatment t = *treatment t – 1*.
- $E[Y_t|D = 0]$ *and* $E[Y_{t-1}|D = 0]$ are, symmetrically, the average outcomes for the untreated group (D=0) at the analogous time points.

In conclusion, the methodology presented provides a more accurate understanding of monthly variations between treated and untreated groups. This analysis can be further refined and discussed using a linear regression model to evaluate the distribution of values, accompanied by 95% confidence intervals, standard deviation, and statistical significance.

Specifically, the model allows for the assessment of month-to-month variations in values with statistically significant results. Moreover, in the post-treatment period, relative to the baseline, the model facilitates the calculation of the average variation.

3.5 Did application

3.5.1 Data aggregation levels

When implementing the above technique, we must evaluate which type of data aggregation to consider, such as daily, weekly, or monthly values. The latter option, on a monthly basis, is certainly clear in terms of graphical visualisation but is not statistically appropriate. This is primarily because our assumptions regarding the normal distribution of the sample require a sufficiently large number of observations, and 5 or 6 values per analysed group are unlikely to exhibit a distribution suitable for assessing statistical significance. Additionally, monthly values are prone to significant variations due to the incompleteness of the dataset, as highlighted in the previous sections. While this issue could potentially be mitigated, for instance, by weighting values according to the number of available days (Gelman & Hill, 2006), this approach is not currently pursued for the aforementioned reason, namely the need for a sufficiently large sample size.

In conclusion, the most suitable option for aggregation in our analysis is the daily one, which will be discussed in greater detail in section *4.4.4 Data aggregation*.

3.5.2 2x2 DiD implementation

To analyse the causal impact of the policy treatment on transportation patterns, we apply a regression-based DiD framework, as outlined in the previous sections. The analysis is performed using R statistical software, which provides robust tools for regression modelling (see Section *5.1* for further details about software and coding). Below, we outline the regression setup, describe the variables included in the model, and explain the methodological steps taken to ensure accurate and reliable results.

The key dependent variable is the count of observations or measurements (e.g., traffic scooter flows) in both the control and treated groups. The model's independent variables include the *Intercept*, representing the baseline value for the control group before the treatment. The *time* variable is a dummy that indicates the post-treatment period and captures changes over time for the control group. The *treated* variable is another dummy that indicates if the observation belongs to the treated group, showing the pre-treatment difference between the treated and control groups.

The *did* term is an interaction between *time* and *treated* and measures the treatment effect by capturing how the treated group differs from the control group after the treatment. In order to capture variations in the dataset related to factors external to the policy treatment, we will include a covariate, referred to as *cov* coefficient. The utilisation of this covariate facilitates a more precise evaluation of the treatment, thereby isolating external influences such as weather conditions. Consequently, it enables the capture of variations exclusively related to the treatment, excluding any extraneous factors.

The model is then fit using the linear model function in R, which provides parameter estimates (coefficients) for each variable. The key coefficient is the *did* term, which shows the estimated causal effect of the treatment after accounting for differences in time and group characteristics.

In addition, the column *weight* contains the normalisation coefficient previously discussed in paragraph *3.3 Day of the week normalisation*.

The model's code follows the formula below, highlighting the nature of the various dummy variables mentioned earlier. ModelA is an example of model result.

```
modelA <- lm(count ~ time + treated + did, data = seb_d_trot, weights =
weight)
```

In this study, the coding for the DiD analysis and the detailed implementation steps will be presented in the *Appendix C* for reference and reproducibility.

3.5.3 Extended DiD implementation

The extended DiD analysis is implemented using the did package, developed by the aforementioned Callaway and Sant'Anna (2021). The package is invoked through a specific function and works with the following parameters, as indicated in the code below. The att_gt function returns the ATT values for each period. The function is presented and described below.

```
results <- att_gt(
  yname = "count",                # Outcome variable
  tname = "time",                 # Numerical time variable
  idname = "id",                  # Unit ID variable
  gname = "group",                # Period in which treatment occurs
  data = fla_att_trot,           # Dataset
  control_group = "nevertreated",
  panel         = FALSE,          # Use never-treated units as control
  weightsname = "weight",    # Column with weights
  est_method = "dr"               # Doubly robust estimation method
)
```

Where:

- **yname** is the outcome variable, in this case, the daily counts;
- **tname** refers to the time variable, representing the period in which the count falls. In our case, months will be marked in progressive order, from 1 to 12 (see *5.4 DiD application: the temporal analysis approach);*
- **idname** is the identifier variable for each unit. In our case, every unit will have a unique and progressive ID;
- **gname** represents the time unit in which treatment occurs. It is equal to zero for the untreated group and corresponds to the period when treatment occurs for the treated group. For example, it is set to 9 for September if the first month corresponds to 1;
- **data** is the input dataset;
- **control_group** specifies the control group with the value "nevertreated", indicating that it is never treated;
- **panel** indicates the use of never-treated units as the control group;
- **weightsname** is the column containing the weights;

- **est_method** applies the doubly robust method, which combines two independent models to estimate the final result with robustness.

In conclusion, the model returns an ATT value for each time period, along with the difference values, standard errors, and 95% Simultaneous Confidence Bands.

Since the value of ATT depends on the previous month, all results start from the second time period onward. Specifically, the results are presented graphically, with the x-axis representing the time period and the y-axis displaying the ATT value along with its 95% confidence bands.

This specific method will be used in the Case study (see *5.4 DiD application: the temporal analysis approach*)

4 Case study and related dataset

The focus of this thesis is on a specific case study: the decision of the City of Paris to remove all shared electric scooters. In this chapter, we analyse the context of this decision, its implications, both with literature and previous study. Then we present the data that will be used in the experimental part of the thesis. The structure and source of the data are first introduced. Readers can then access and review the structure of the collected input data, as well as the preprocessing activities and initial aggregation. Finally, an initial data cleaning process using the previously introduced elbow method is presented, highlighting the preliminary results of its application and the identified thresholds.

4.1 General context of the case study: transport trends in the city of Paris

The City of Paris presents quite peculiar trends in transportation, and in this section, we will analyse why these specific trends are interesting from a research point of view and which specificities could create discontinuities do not present in other cities around the world.

First, Paris and its region, administratively called Île-de-France, is the most populous region of France, with 12.32 million inhabitants and also one of the richest in the Eurozone. It generates approximately 30.6% of France's GDP, contributing around 765 billion euros in 2021. The region's GDP per capita is higher than the national average, reaching around 62,000 euros, compared to the national average of 37,000 euros. Additionally, Île-de-France is one of the most densely populated regions in Europe, with over 1,000 inhabitants per square kilometre. Within the administrative borders of Paris, the population density peaks at approximately 21,000 inhabitants per square kilometre, making it one of the most compact urban areas in the world (INSEE, 2024)[1].

[1] INSEE (Institut National de la Statistique et des Études Économiques), the French National Institute for Statistics and Economic Studies.

Every ten years, the public authority DRIEAT[2] publishes the Enquête Globale sur les Transports (EGT), a comprehensive transport survey aimed at understanding the travel behaviours and mobility patterns of the population. The survey collects detailed data on various aspects of transportation, such as the modes of transport used (e.g., public transit, walking, cycling, driving), trip purposes (e.g., commuting, leisure), trip distances, and travel times.

The last partial survey was published in 2020, covering the period from 2010 to 2018, and highlights some general trends. First of all, displacements are generally increasing in the Paris region due to the overall population growth, rising GDP per capita and changing travel behaviours. From 2008 to 2018, the population grew by around 460,000 inhabitants, and while manufacturing jobs decreased by approximately 60,000, the number of corporate executives increased by around 120,000, on a total of 5.7 million jobs. In this context, daily travels are also rising, with 43 million daily trips in 2018 compared to 41 million in 2010.

Focusing now on more recent statistics only dealing with the city of Paris itself (excluding its suburbs), we see the most significant peculiarities. In 2018, according to the EGT only 347,000 trips per day within the city was made by car out of 8,782,000 overall trips, thus representing 4.0% of modal split. The car trips made inside Paris in 2010 were 537,000 per day (6.7% of the overall 2010 trips), therefore the car market share lowered by 2.7%. About 26% of trips was made by public transportation in 2018, while 65% was made on foot (OMNIL, 2020). The use of bicycles has also seen relatively important growth since 2020. During the COVID-19 pandemic, the city of Paris implemented a set of temporary cycling infrastructures known as "*coronapistes*" to promote safe and sustainable mobility while reducing crowding on public transport. The establishment of these *coronapistes* in 2020 resulted in the formation of a 50 km network along the primary axis of the city. This initiative was taken mainly as a response to the health crisis, with the objective of providing alternatives to public transit in order to mitigate the congregation of crowds. From 2018 to 2022, the number of average daily number of bicycles counted on the 52 fixed points of the City of Paris has increased from 702 to 1870 (Observatoire Parisien des Mobilités, 2024, p. 19).

As an example of implementation of a *coronapiste* we consider one of the city's most central east-west axes, Rue de Rivoli, that experimented a meaningful change of use. In 2020, this street had a two-way cycle lane and two general traffic lanes. After 2020, the central lane was converted into a cycle lane, while the side lane was reserved for public transport, taxis, deliveries and bicycles or scooters. Today, Rue de Rivoli has a bi-directional cycle lane, approximately 7 metres wide, and a single, unidirectional general traffic lane (east to west), 3.5 metres wide, reserved for specific vehicles such as buses, taxis and deliveries (Ville De Paris, 2022). This main axis is also

[2] An acronym for Direction Régionale et Interdépartementale de l'Environnement, de l'Aménagement et des Transports, the French public authority responsible for implementing national policy on public transport.

equipped with some of the vehicle counting points of the city of Paris used for our experimental analysis, which are presented in the subchapter 4.4 Dataset presentation.

Figure 10 illustrates the modal share percentages from 2010 to 2018 within the Paris region, Île-de-France (OMNIL, 2021). The bar chart presents one bar for each year, representing the modal share percentage for each transport mode, with trends highlighted through distinct colours. The chart clearly shows a significant decline in car usage, while public transport, walking, and bicycles demonstrate growth over the same period.

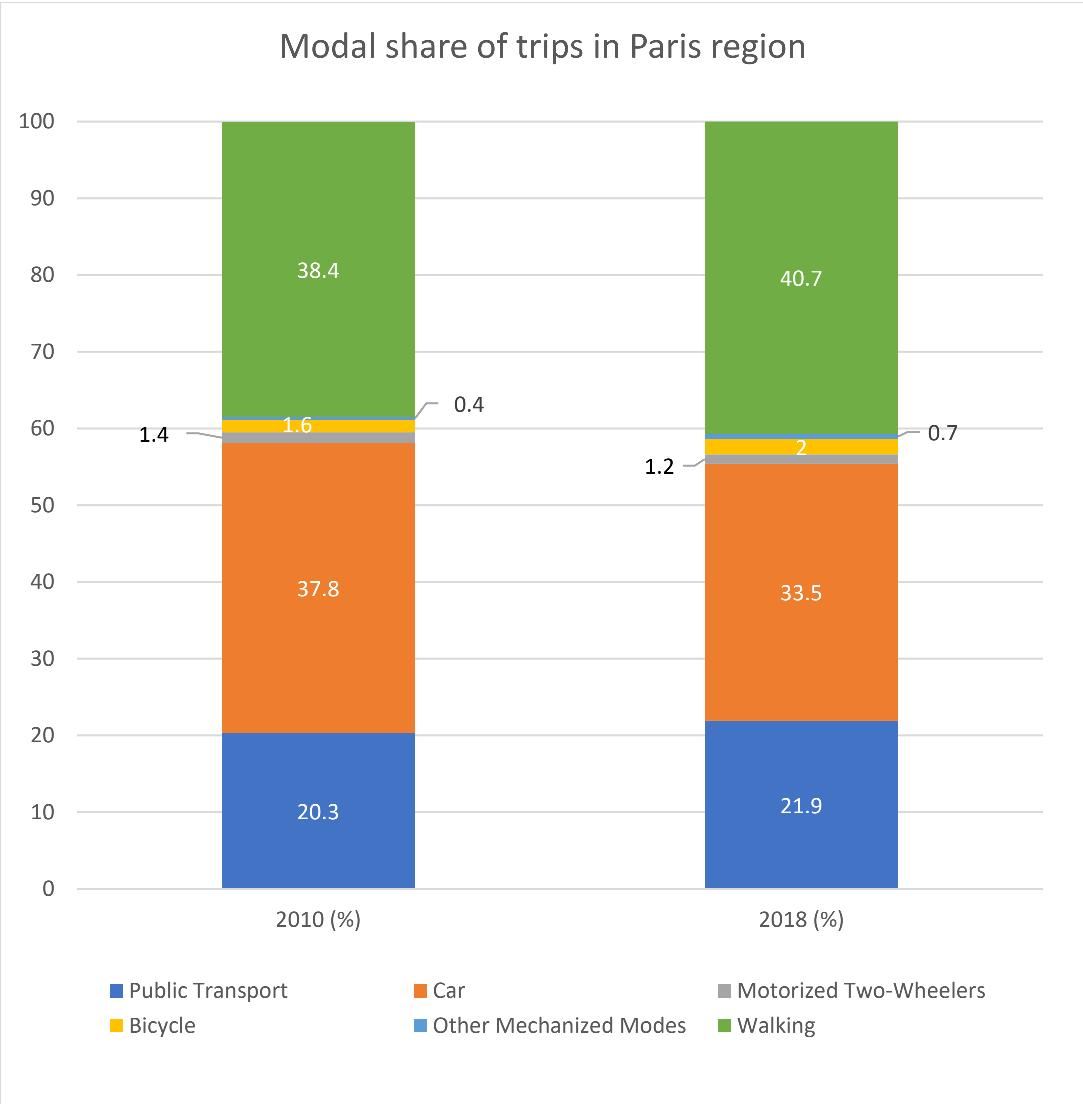

Figure 10: modal share of trips within the Paris region in 2010 and 2020, data (OMNIL, 2021)

From 2018 onwards, novel forms of urban mobility, such as scooters and shared electric scooters, became increasingly prevalent in the city of Paris. In the next subsection (see *4.2 The context of the shared e-scooters and the decision of the ban*) the topic of scooter sharing is dealt with in more detail, here we present some general elements in relation to the overall trends in the city of

Paris. The shared e-scooters were introduced in Paris in 2018 and have been a success in a first moment. As highlighted by a study developed by the DRIEAT entitled "Free floating services in 2019 in the Paris region" (DRIEAT Ile-de-France, 2020) that mentions APUR[3] data, in a few months the shared electric scooters reached approximately the number of 15,000 and they served 18.5 million of displacements in 2019. The major studies are in general agreement that the shared electric scooters displacements represented approximately the 0.6% to the 2.2% of all displacements within the city of Paris in 2019 (APUR, 2020).

This phenomenon has taken place in a more general Paris *intra muros* trend of diminution of the utilisation of the car and growing of more sustainable way of moving, such as bike and walk. As highlighted by APUR in a recent study, named "Evolution des mobilités dans le Grand Paris (APUR, 2021), in a general trend where displacements are increasing and transport offer remain constant and congested, more or less, new ways of moving inside the city of Paris are growing.

Those very Paris specific trends, of general growing of public transit, walking, cycling, and going in scooters are not only related to the COVID-19 pandemic but they are strongly related to the public policy in France and of the city council of Paris, as highlighted by APUR. In 2019 the government approved the Mobility Orientation Law (LOM) which set ambitious goals, such as reducing greenhouse gas emissions from road transport by 50% by 2030 compared to 2010 levels, and in parallel the city of Paris implemented new intervention for improve pedestrian zones, bicycle lanes and car restrictions, such as the increase of the parking tax for SUV.

In conclusion, the City of Paris is experiencing a shift toward sustainable transportation, with a significant decrease in car use. This change is especially visible within the city itself, where public transport, walking, cycling, and electric scooters have all grown in popularity and are the main modes of transportation, as highlighted by Figure 11, where we can see the modal split of the 2010 and 2018 inner-city travel in Paris. As previously stated, the modal split within the city is trending towards a greater reliance on sustainable modes of transportation. The red area represents the walking modal part, which has experienced a growth over the past ten years. The orange area denotes the public transit modal part, which has not undergone a notable change, primarily due to the congestion of the infrastructure network. As previously stated, automobile trips represent a minor proportion of the total number of trips. Bicycle trips, on the other hand, have remained relatively constant. However, it should be noted that this data is not available for the most recent years, during which time bicycle trips have increased significantly, as evidenced by the findings of the more recent studies referenced above.

[3] Atelier parisien d'urbanisme, set up by the City of Paris to study urban issues and help the city council make decisions on urban planning and transport.

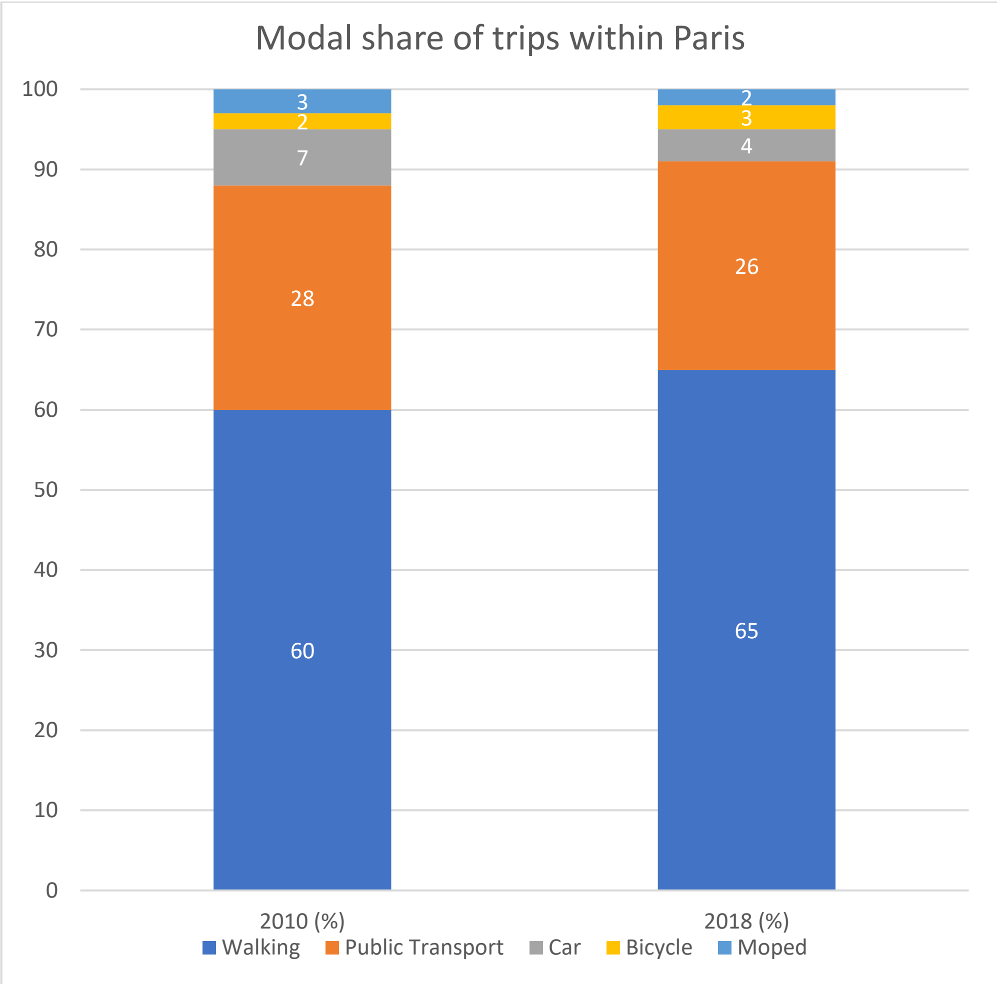

Figure 11: modal share of trips within the Paris city in 2010 and 2020 (OMNIL, 2021)

This shift toward sustainable transportation is not only happening in Paris. Many other large cities in Europe, such as Milan, Barcelona, and Berlin, are seeing similar trends with more people choosing bikes, walking, or public transport over cars. In this way, Paris is one of the European big cities with highest sustainable transportation modal split making it an interesting case study that could be replicated in other contexts (Deloitte, 2018).

4.2 The context of the shared e-scooters and the decision of the ban

In this chapter, we will examine the historical context of shared scooters deployment in Paris, from their introduction to prohibition. In the present section, we will examine the extant literature on the topic, with a view to defining the typical user before the ban, the characteristics of the trips and the main characteristics of the system. This analysis will be useful in determining specific patterns to the Paris situation, and in providing clarity in the evaluation of the data.

4.2.1 The rise and regulation of shared mobility in Paris

As demonstrated in the preceding section (see *4.1 General context of the case study: transport trends in the city of Paris*), the number of individuals using a personal car for their daily commutes is on the decline in the City of Paris. Instead, there has been a notable increase in the utilisation of more sustainable modes of transportation. Since the year 2000, there has been a proliferation of shared options, with the development of bicycle, automobile and scooter sharing services.

The city of Paris was the inaugural location for a bike-sharing service, namely the dockless bicycle-sharing scheme known as "Velib’" This was initiated by the municipal administration in 2007 and has since expanded to 1,475 stations across the Île-de-France region, comprising 19,000 bicycles and 390,000 one-year registered users (Vélib’ Metropole, 2022). The Velib' service has demonstrated a number of positive trends over time, with predictable peak usage during commuting hours. This illustrates effective integration with other public transport systems, such as the Paris Metro (Miller-Hooks et al., 2012) .

The first free-floating, dockless shared system was launched in Paris in 2016 by the Cityscoot company, which provides shared electric mopeds. The first dockless bicycle-sharing operator commenced operations in 2017. During the peak of the shared mobility expansion, before the Covid-19 pandemic in 2018, the number of scooters and bicycles in shared was around 40,000 (APUR, 2021).

Figure 12 illustrates the evolution of the shared service in relation to the various modes of transport, including scooters, bicycles (with a focus on the Velib' system) and mopeds, from their introduction to 2021. As can be observed, the general trend is for a decrease in 2019-20 due to the impact of the pandemic and subsequent restrictions on mobility. However, the number of vehicles is growing in the subsequent period (2021). The only type of vehicle that continues to decrease is the scooter, due to the progressive limitations on these vehicles imposed by the city of Paris, which will be discussed in further detail below.

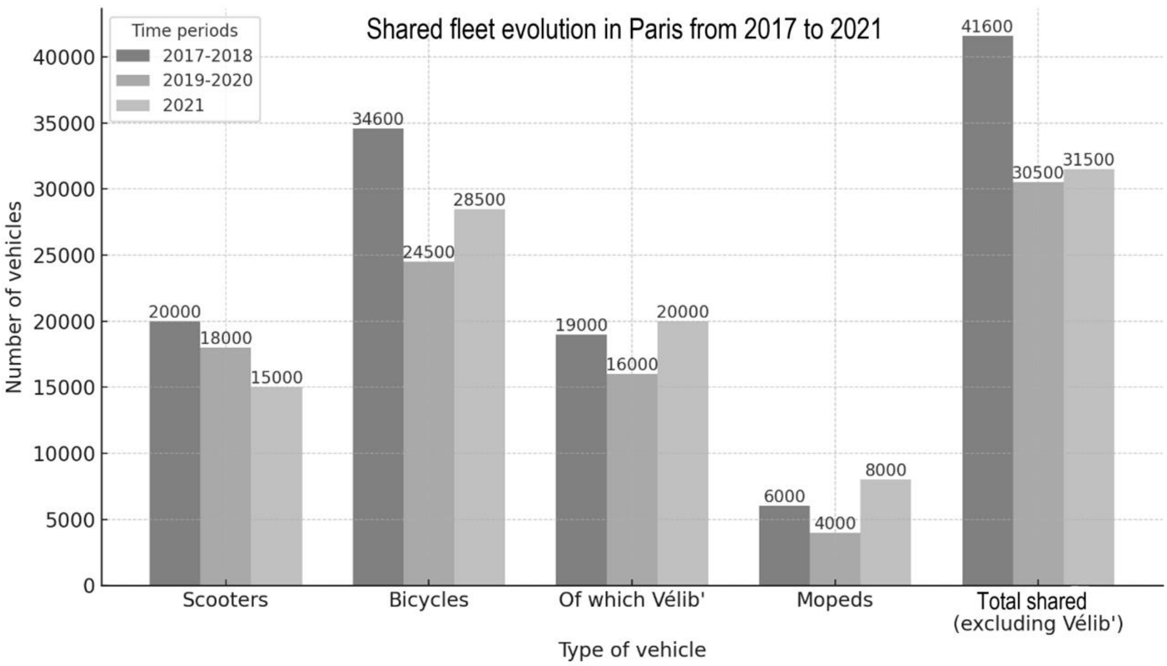

Figure 12: evolution of the shared fleet in Paris from 2017 to 2021, data from APUR (2021)

Indeed, situation changed in 2020 due to the call for projects initiated by the municipal authority, the number of operators permitted to operate electric scooters has been restricted to three. The number of scooters has been restricted to a maximum of 15,000, with an equal distribution between the three operators chosen by the City of Paris: Lime, Dott and Tier.

This policy choice was made by the municipality of Paris based on a number of arguments, first of all to define a regulatory framework for scooter sharing. The presence of numerous operators in the city made it difficult for the municipality to interface with service providers and apply a policy of controlling the vehicles in public space. In addition, the municipality reported numerous safety issues for citizens related to the presence of scooters in public space, such as parking on sidewalks or numerous traffic offences (de Bortoli & Christoforou, 2020; Latinopoulos et al., 2021).

In contrast, the operator Lime published a paper in 2022 that addressed safety issues associated with electric shared scooters (Lime, 2022). This paper utilized data obtained from the company's service, spanning from January 2020 to June 2022. In this paper, the authors argue that 0.01% of trips had incidents, with 87% of these incidents being minor, necessitating no medical attention. In their report, the company argues that scooters have a fatality rate of 5.36 per 100 million trips, which is similar to that of bicycles (5.48 per 100 million trips). Furthermore, they suggest that the number of incidents is more correlated to the type of infrastructure. Indeed, they found that streets without dedicated infrastructure for cyclists had three times more incidents than other streets, with 36 incidents per million km compared to 11 incidents per million km (Lime, 2022).

Another argument of the City of Paris for limiting e-scooters is their environmental impact. Although the rise of shared e-scooters—and shared mobility in general—has been seen as a positive shift away from car-centric transportation, which generates negative outcomes such as noise, pollution, and congestion, concerns remain regarding the sustainability of e-scooters themselves (Moreau et al., 2020). The city of Paris advanced the argument that the environmental impact of shared e-scooters could be negative, citing the life cycle of the materials, the recharging of the batteries during the night and the short operational life as particular concerns. This position is supported by a number of studies (Hollingsworth et al., 2019; Reis et al., 2023). Therefore, the arguments against the electric scooter in Paris said that the main users of the services were tourists, and non local people, that could easily use alternatively walk or public transport. This last argument will briefly be analysed in the next subchapter (see section *4.2.2*).

4.2.2 Type of users and characteristics of e-scooter system before the ban

As seen in the previous section, the number of e-scooter in Paris grew in time, with a decrease solely related to the Covid period. Since the introduction of e-scooter in Paris many studies have been conducted on the kind of service proposed, on the pricing model, the covered areas and kind of users.

The majority of the literature on the subject concurs on the matter of the good predisposition of Paris for sharing micro-mobility. In particular the high density of the city and the tendency to make short trips of both Parisians and tourists have made Paris an excellent market for e-scooter companies (APUR, 2020; Latinopoulos et al., 2021).

In the period from 2019 to 2020, several studies have been carried out in order to describe the number and type of e-scooters trips in Paris, the type of users and the main patterns. The studies are mainly from research groups related to public authorities, such as the previously presented in Section *4.1*, "Free floating services in 2019 in the Paris region" (DRIEAT Ile-de-France, 2020) This research collect data from the general transport survey of 2018. On the other hand, some private research groups have conducted analyses in this sense, such as *6-t bureau de recherche* in Paris, an independent research and consultancy firm. On the behalf of the ADEME[4], the French agency for ecological transition, 6-t bureaux de recherche has conducted a study entitled “Usages et usagers des trottinettes électriques en free-floating en France” (6t-bureau de recherche, 2019) through a survey on 4000 people in Paris, Lyon and Marseille in order to map the type of users and the use of shared e-scooters at the French national level.

[4] Acronyme standing for Agence de l'Environnement et de la Maîtrise de l'Énergie

Those researches have then been integrated in the document "Emerging forms of mobility, scooters and bikeshare" (APUR, 2020), prepared by this public entity linked to the City of Paris, which also collects data directly from the operators.

The results of these studies are consistent in saying that the modal share of e-scooters within Paris, in the period before the Covid-19 pandemic, was estimated to be between 0.8% and 2.2%. Based on operators' data, the APUR study concluded that the modal split for e-scooters was around 0.6%, representing around 18.5 million trips by year. More recent data concur with this analysis. From the annual report of the City of Paris about transport and trips (Ville de Paris, 2022) it appears that the total annual trips declared by the operators have been 16,464,997 in 2022.

From the same report, the average distance of rentals in 2022 was of 2.62 km and the average rental time in 2022 was 14.3 minutes. Those values are consistent with those considered from the above-mentioned reports, that highlight that the high majority of trips are made under 5 km (54% of the trips are in this category according to APUR). The researchers concur on the fact that those trips are similar in length and time to those normally made with own bicycles or docked shared bicycles, such as Velib' in Paris (APUR, 2020).

In order to understand the rapid growth of shared e-scooters in Paris, it is useful not only to highlight the type of trips but also the type of users. In the article "Who is using e-scooters and how? Evidence from Paris" (Christoforou et al., 2021, p.24), the results of a face-to-face survey are presented, which collected 459 interviews with e-scooter users in Paris. The findings indicate that most users were young adults aged 18-29, with high educational levels. The majority of respondents were men (68%), and the most represented social categories were students and executives. The main purposes for e-scooter trips included leisure, commuting and visits to friends or family. About 35% of users shifted from walking, and 37% from public transportation for their e-scooter trips, 16% a motorised mode, 7% private or shared bicycles, and 6% would not have made the trip.

Similarly, in the 2020 APUR research, a non-mandatory survey was conducted among e-scooter users via the associated application, gathering 11,200 responses. The findings reveal that shared micromobility services primarily attract young, active, and predominantly male users, with a significant portion identified as professionals or executives. In terms of modal shift, shared e-scooters and other micromobility options often replaced trips that would otherwise be taken by public transport (69%), walking (59%), or cycling (30%). Notably, about 38% of users indicated they would have chosen motorized modes, such as cars, taxis, or motorcycles, if these shared services were not available (APUR, 2020).

The 6-t study from 2019, previously cited, focused on shared e-scooter users in Paris, Lyon, and Marseille gathering data through an online questionnaire. This survey involved responses from various user groups, highlighting that 58% were locals, 33% were foreign tourists, and 9% were French visitors. The study found that the majority of users were male, comprising about two-thirds of respondents. Users were notably wealthier and younger compared to the general population, with over half being under 35 years of age and an average age of 36. Students were slightly over-represented, accounting for 19% of participants compared to 13-17% in the general population. Executives were significantly over-represented, comprising 53% of the sample, much higher than the general rate of 44% in Paris.

The survey revealed that 38% of respondents reported using a scooter at least once a week, while 42% stated that they used it up to three times a day. It was observed that approximately 20% of trips were made as a single use for the user. The primary reason for scooter use among locals was time saving, while visitors preferred to use them for recreational reasons. The predominant limitations cited by users pertain to cost, safety concerns, and inclement weather. Moreover, 59% of users reported difficulties in locating available scooters, while 27% subscribe to multiple services offered by different companies to enhance their probability of finding a scooter. With regard to alternative means of transportation that would have been utilised in the absence of scooters, the most frequently cited options were travelling on foot (47%), utilising public transportation (29%), bike-sharing services (7%), and employing personal bicycles (2%). Additionally, respondents identified potential alternatives such as taxi services or similar rental services with drivers (5%), personal vehicles (3%), and motorbikes (1%) in the event that scooters were not available. Notably, 3% stated they would not have made the trip at all (6t-bureau de recherche, 2019, p. 108).

In conclusion, the primary demographic of users of shared e-scooters in French main cities was young, male, and wealthy. This description is consistent with that observed in other studies conducted in other cities (see *2.2 Shared e-scooters: debates on limitations and externalities*) and is strongly related to the nature and purpose of the trips. The principal motivation for undertaking these journeys appears to be the saving of time, particularly for those who reside in the area. As evidenced by the majority of studies, shared e-scooter have a relatively higher cost in comparison to alternative transportation options, including bicycles, public transportation, and, obviously, walking (APUR, 2020; DRIEAT Ile-de-France, 2020). This suggests that users of shared e-scooters should be people willing to spend relatively more money in order to save time, and this should be related to a higher time value of the users (such as executives) or for a strong time saving on the trip.

Figure 13 displays the percentage distribution of transportation modes replaced by shared scooters across the three previously mentioned studies: Christoforou et al. (2021), APUR (2020), and 6t bureau de recherche (2019) . Each bar represents the percentage breakdown of modes previously used by scooter users, categorized as public transportation, walking, cycling, motorized modes, "not made trip," and others. The APUR, 2020* study refers to the previously mentioned APUR survey, which allowed multiple responses. However, the percentages have been scaled to 100% to enable a direct comparison with the other studies. The 6-t study was involved in about 50% of the responses about Parisians, therefore it is reasonable to make comparison between each of these studies.

All the researches indicate that the primary modes replaced by shared e-scooters are public transportation and walking. This finding suggests that e-scooters may often substitute trips that were already considered "sustainable." It is important to note that these rebound effects must be scaled in relation to the overall modal split of e-scooters. The *6-t bureau de recherche* 2019 study highlighted that if the modal split of e-scooters is close to 0.8% to 1.9% of total trips, a substitution rate of 30% related to public transport should be almost unnoticeable and marginal (6t-bureau de recherche, 2019).

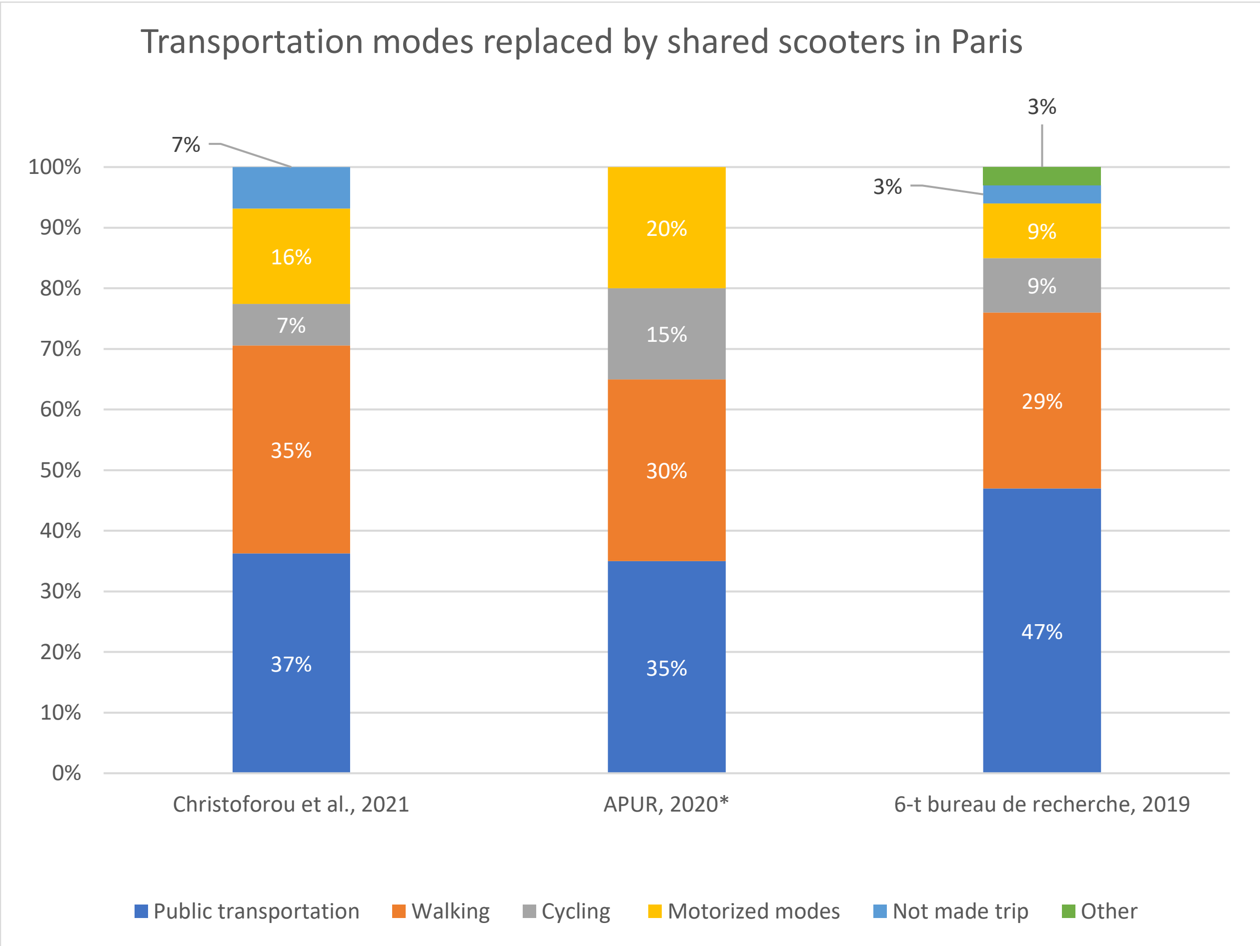

Figure 13: replaced modes by shared e-scooters in Paris, in percentage from different studies

4.2.3 The ban of shared e-scooter

With similar arguments to those reported in Section *4.2.1 The rise and regulation of shared mobility in Paris* the mayor of Paris decided in 2023 to call a non-binding referendum for the Paris citizens, to decide to maintain or to ban the shared electric scooters. The election was called for the 2 April 2023 and the Parisians answered to the question “For or against free-floating scooters” in one of the 203 polling station. With an electoral participation of 103,084 voters out of approximately 1.38 million registered voters, resulting in a turnout of about 7.46%, 89% (around 92,745 people) were in favour of banning shared e-scooters (Ville de Paris, 2023).

Considering the non-binding vote, the city of Paris has taken the decision to prohibit the operation of shared scooters with effect from 1st September 2023. This is the inaugural decision in a European country to prohibit a specific mode of transportation, which had heretofore been regarded as a "sustainable mode of transportation." In this way, this decision, which is distinctive within the European context, represents a significant case study, particularly in light of the prevailing international trend of implementing alternative transportation options in lieu of the automobile, especially in urban areas. The decision of Paris, in this sense, represents a distinctive outcome of a broader European and international discourse about shared mobility (Angiello, 2023).

4.3 Exchange with public authorities about shared scooters

Île-de-France Mobilités (IDFM) is the public authority responsible for coordinating and financing public transport across the Île-de-France region. It is one of the main actors in determining public transport policies in the region and also includes the supervision of studies and evaluation of transport policies. After being contacted, IDFM responded through Ms. Arantxa JULIEN (Urban Transport Plan Project Manager Île-de-France). Through the exchange with the institution, it was possible to outline some evaluations. In particular, IDFM representatives emphasised that their interest in sharing scooters is mainly related to safety and parking regulation considerations.

According to IDFM representatives, shared scooters represent less than 1% of the global transport survey. This particularly low percentage of total travel in the region makes it difficult to assess a concrete and real effect on transport flows, e.g. trains, buses and metro.

As a supplementary resource, IDFM representatives referred to an older study conducted by 6t for ADEME, examining shared scooter usage patterns (see *2.2.3 Replaced modes and purposes in France*).

The city of Paris was also contacted in order to have a mutual exchange on the topic. Unfortunately, no response was received. This absence of an exchange with such a leading body in the policy of removing sharing scooters is certainly a limitation, as the municipality is definitely considered to have an analysis of the impact of this policy, as regulators of traffic and management of the city's roads.

4.4 Dataset presentation

The data used in the present research comes from the City of Paris and is open source (for license references see *Appendix A. Counting stations characteristics.*). The City of Paris is responsible for the management, maintenance, and development of road infrastructure such as roads, cycle paths and car parks. To monitor and make improvements, the City of Paris collects a wide range of data on the road system.

4.4.1 On-site equipment and data format

In particular, our study uses data from multimodal counts carried out with fixed thermal cameras installed in some central points in the city of Paris. The system works by taking images without being able to define faces or number plates, and through an algorithm it can automatically define what type of vehicle it is. This algorithm is also able to define where the vehicle is, whether it is on a road lane or a cycle path, and in which direction it is travelling (Ville de Paris, 2024).

An example of image captured by a thermal camera is presented in Figure 14, where we can see the different lanes of the road and how the system works to understand the direction and position of the vehicles, in function of the enter and exit point of the registered area.

Appendix A presents the thermal camera views for all the counting points that we will consider, providing a clear understanding of the infrastructure and the functioning of the thermal camera system's algorithm.

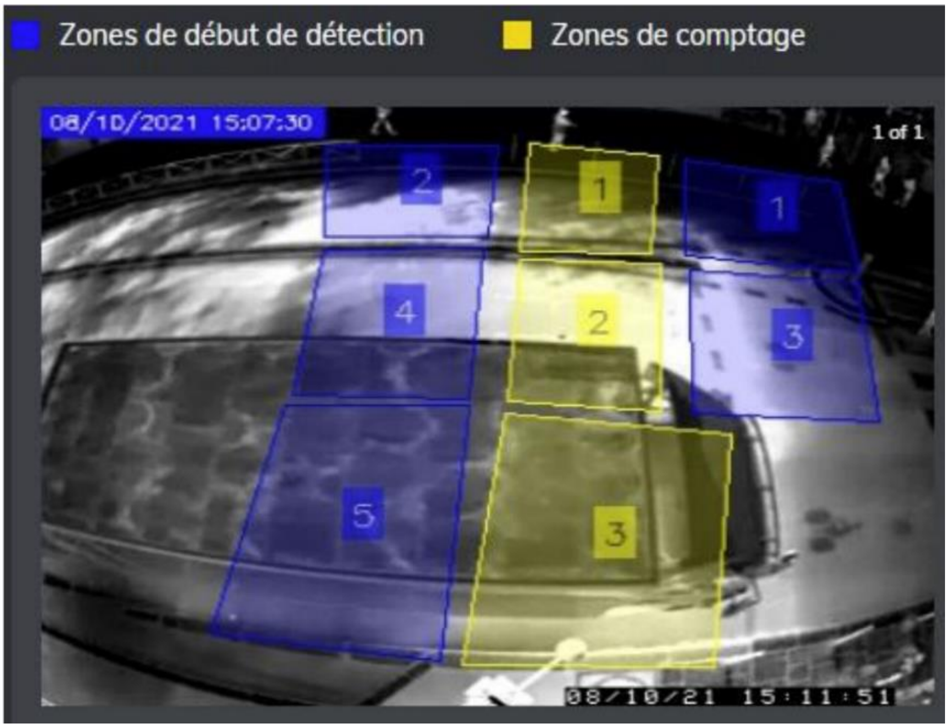

Figure 14: example of an image captured by the thermal cameras of the City of Paris, from Ville de Paris (2024)

The data are aggregated on an hourly basis, in function of the type of vehicle, of the trajectory, of the site name and have the structure shown in Table 2 (Ville de Paris, 2024). In the first column, the vehicle trajectory can be identified, i.e. from which area of the roadway the vehicle is arriving and to which direction it is heading, followed by the site identification code and the site name. The fourth column refers to the date and time of the count, followed by the column indicating the type of vehicle (light vehicles <3.5t, heavy vehicles >3.5, bicycles, scooters, bicycles+scooters, motorbikes, buses and coaches), the number of counts in the hour, the carriageway location where the count takes place (cycle lane, general traffic lane, coronapiste), the direction of traffic as a function of the geographic coordinates, the trajectory identification code for the algorithm and the geographic coordinate of the site.

Path identifier	Site identifier	Site name	Date and time	Mode	Counts	Track type	Direction of traffic	Trajectory	Geographical coordinate
10004_5 -> 3	10004	[Paris] Rivoli x Nicolas Flamel	01/11/2021 01:00:00	Heavy vehicles> 3,5t	1	General traffic lane	E-O	5 -> 3	48.858273, 2.349109
10004_4 -> 2	10004	[Paris] Rivoli x Nicolas Flamel	01/11/2021 04:00:00	Bikes	34	Cycle track	E-O	4 -> 2	48.858273, 2.349109

Table 2: example rows of the main data set of the multimodal counting of the City of Paris

4.4.2 Counting point location and characteristics

The counts, that took place at 9 locations within the city of Paris, are shown in the map in Figure 15. Those counting sites have specific peculiarities in terms of kind of infrastructures and geographic position. The main data collection, i.e. 4 collecting point out of 9, occurs along Rue de Rivoli.

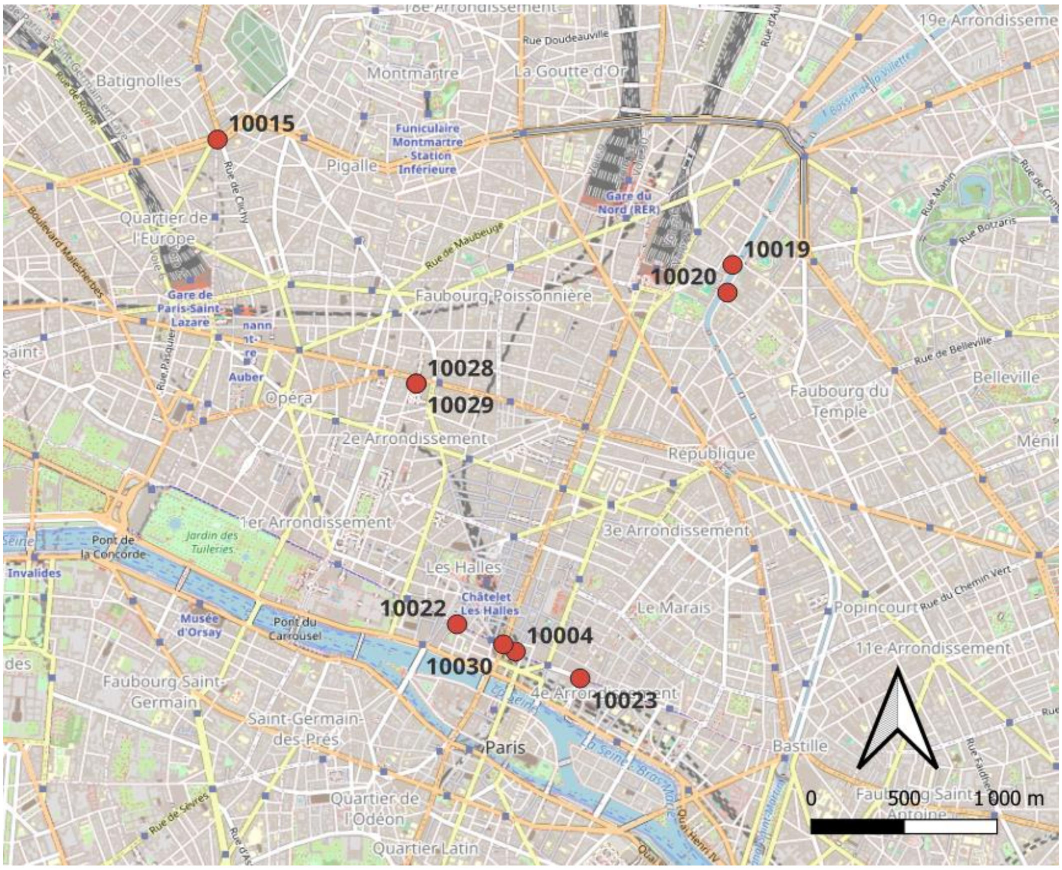

Figure 15: map of counting points in the city of Paris (own production based on data from the City of Paris)

In terms of infrastructure, the counting points along Rue de Rivoli have two bidirectional bicycle paths, each measuring 7.5 metres in width, and one general circulation lane, measuring 3.5 metres in width. However, this is not the case for the counting point located at the intersection of Rue de Rivoli and Boulevard de Sébastopol, which is situated within Boulevard Sébastopol. The counting point on Rue de Rivoli and Boulevard de Sébastopol features a bidirectional bicycle lane of 3.5 m in width and two general circulation lanes of 7 m. Similarly, the counting point on Boulevard Poissonnière has two general circulation lanes of 7 m in width and one directional bicycle path of 2.5 m. Quay de Valmy and Quay de Jemmapes have each on a monodirectional bicycle path, 2.5 m wide, and a monodirectional general lane. Rue d'Amsterdam and Boulevard de Clichy counting point has only a monodirectional general traffic lane, 4 m wide.

Table 3 provides a comprehensive overview of the aforementioned information. Each row is related to a counting site and has provided a geographical coordinate and detailed information regarding the infrastructure characteristics, including the width of each lane and the purpose of the traffic. The latter has been classified as follows: general traffic, for all urban traffic; reserved for specific vehicles (public transit, delivery, bicycles, motorcycles, residents); and a cycling path reserved for bicycles, scooters, and other similar vehicles. The number of lanes pertaining to the cycle path is also contingent upon the direction of the cycle path. For instance, if the cycle path is bidirectional, two lanes are calculated.

Indeed, out of the total of nine counting points, not all of them are functional for our analysis of the decision by the City of Paris to remove the shared scooters. Firstly, the algorithm used to identify the type of vehicle is not present in the same way at all the counting points. In three counting points - Quai de Jemmapes, Quai de Valmy, Boulevard Poissonnière and Boulevard Montmartre (East) - the algorithm applied on these cameras isn't able to distinguish between bicycles and scooters, so on these points the two types of transportation mode are aggregated. For this reason, data coming from these counting stations will not be used in our analysis.

Rue de Rivoli and Avenue de la Bourdonnais, Rue de Rivoli and Rue Lobau and Boulevard Poissonnière and Boulevard Montmartre (West) will only distinguish between bicycles and scooters from November 2022. Therefore, our research will only use data from these stations from that date onwards.

For the remaining three counting points - Rue de Rivoli and Boulevard de Sébastopol, Rue de Rivoli and Rue Nicolas Flamel - the data is complete, with a distinction between bicycles and scooters from the start of the counts for each of these counting points.

The conclusion of the dataset is defined as December 4, 2024, marking the last day of operation for the thermal cameras at the above introduced counting stations. From this date onward, the City of Paris has relocated these cameras to other axes within the city. Additionally, the counting station located on Boulevard de Sébastopol ceased operation earlier, in September 2, 2024.

Site identifier	Counting site name	Geographical coordinates	General traffic N. lane	General traffic Width (m)	Reserved lane N. lane	Reserved lane Width (m)	Cyclable path N. lane	Cyclable path Width (m)	Counts start	Counts end	Distinction between bicycles and scooters
10004	Rue de Rivoli and Rue Nicolas Flamel	48.858273, 2.349109	-	-	1	3.5	2	7	07/07/2020	04/12/2024	Yes
10015	Rue d'Amsterdam and Boulevard de Clichy	48.883513, 2.327263	1	4	-	-	-	-	19/10/2020	04/12/2024	No, bicycles and scooters aggregated
10019	Quai de Valmy	48.877338, 2.365016	1	3.5	-	-	1	2.5	19/10/2020	04/12/2024	No, bicycles and scooters aggregated
10020	Quai de Jemmapes	48.875967, 2.364635	1	3.5	-	-	1	2.5	13/11/2020	04/12/2024	No, bicycles and scooters aggregated
10022	Rue de Rivoli and Avenue de la Bourdonnais	48.859617, 2.344817	-	-	1	3.5	2	7	13/11/2020	04/12/2024	Yes, from 24th November 2022
10023	Rue de Rivoli and Rue Lobau	48.856949, 2.353837	-	-	1	3.5	2	7	15/12/2020	04/12/2024	Yes, from 24th November 2022
10028	Boulevard Poissonnière and Boulevard Montmartre (East)	48.8714843, 2.3418311	2	7	-	-	1	2.5	15/12/2020	04/12/2024	No, bicycles and scooters aggregated
10029	Boulevard Poissonnière and Boulevard Montmartre (West)	48.8714843, 2.341831	2	7	-	-	1	2.5	23/05/2020	04/12/2024	Yes, from 24th November 2022
10030	Rue de Rivoli and Boulevard de Sébastopol	48.858628, 2.348208	2	7	-	-	2	3.5	07/07/2020	02/09/2024	Yes

Table 3: counting points and characteristics

From this point forward, to improve text readability, the counting sites will also be referred to by the two streets that define their intersections in the following abbreviated form:

- Rue de Rivoli and Rue Nicolas Flamel: **Rivoli x Flamel**
- Rue d'Amsterdam and Boulevard de Clichy: **Amsterdam x Clichy**
- Quai de Valmy: **Valmy**
- Quai de Jemmapes: **Jemmapes**
- Rue de Rivoli and Avenue de la Bourdonnais: **Rivoli x Bourdonnais**
- Rue de Rivoli and **Rue Lobau: Rivoli x Lobau**
- Boulevard Poissonnière and Boulevard Montmartre (East): **Poissonnière x Montmartre (East)**
- Boulevard Poissonnière and Boulevard Montmartre (West): **Poissonnière x Montmartre**
- Rue de Rivoli and Boulevard de Sébastopol: **Rivoli x Sébastopol**

It should be noted by the reader that the two counting points are located at the intersection of Boulevard Poissonnière and Boulevard Montmartre. It is important to note that only the Poissonnière x Montmartre West makes a distinction between bicycles and scooters (as shown in Table 3). Consequently, uniquely this counting point will be used in future analyses. In order to enhance simplicity and reliability, it will be referred to as Poissonnière x Montmartre, without the term "West", as presented in the previous list.

Additionally, the reader will find this counting station presented, for example, in figures without accent marks—so Sébastopol will appear as Sebastopol, and Poissonnière as Poissonniere. This is related to encoding simplicity, as many of these characters are not recognized by certain packages and could interfere with output readability.

In conclusion, the counting points that are useful for a clear comparison between scooters and overall trips are only the ones that distinguish between bicycles and scooters. Therefore, five out of nine, and all of them only after 24 November 2022.

4.4.3 Preprocessing and filtering activities

As previously stated, not all the data from the City of Paris dataset is always useful, and some information is redundant or unnecessary. Before starting our analysis, it is essential to apply a preprocessing and selection phase to retain only the most relevant information. This ensures that the dataset remains as light as possible and easy to handle. In this subsection, we present this initial preprocessing activity, which serves as a reference for the filtered and relevant data used in the analysis.

Firstly, the site identifier is redundant when compared to the site name or its geographic coordinates (see Table 2), so only the former one will be used. Secondly, details such as vehicle trajectories (entry and exit directions) or whether vehicles use the roadway or the cycle lane are not relevant to our specific focus.

In conclusion, firstly we discarded columns redundant (e.g. geographical coordinates of counting site) or with non useful material (e.g. trajectories of the vehicles).

The input dataset for our analysis will be structured in four columns, as presented in Table 4, compared with the initially downloaded Table 2.

Site	Date and time	Mode	Counts
Rivoli x Lobau	01/01/2022 18:00	Scooters	12

Table 4: example of pre-processed dataset configuration

In addition, in our analysis based on Paris' decision to ban shared scooters, we need a clear assessment of this mode of transport. Therefore, the counting stations that do not distinguish between scooters and bicycles, as presented in Table 3, are not useful for our analysis and will be discarded. We will retain only the data from the five counting stations that provide a distinction between bicycles and scooters.

As a reminder, the counting stations that do not separate bicycles and scooters, and are therefore maintained in this preprocessing step, are:

- Rivoli x Flamel
- Rivoli x Bourdonnais
- Rivoli x Lobau
- Poissonnière x Montmartre
- Rivoli x Sébastopol

Additionally, the starting date of operation for each counting station varies. Some stations began collecting data during the COVID period, when significant mobility restrictions were in place. In our analysis, we are particularly interested in examining what happened after the ban on shared e-scooters. As a reminder, the ban took effect on September 1, 2023, and we aim to compare this period with the previous one. For this reason, in the preprocessing phase, we have decided to retain only data from January 1st, 2022. This provides a dataset covering more than one year and six months before the ban, nearly equivalent to the period after the ban (from September 1, 2023, to December 2024), allowing for a well-grounded comparison before and after the policy change.

The final filtering step concerns the selection of transport modes. As presented in Subsection *4.4.1 On-site equipment and data format*, the Paris dataset includes counts for light vehicles (<3.5t), heavy vehicles (>3.5t), bicycles, scooters, motorbikes, buses, and coaches. For our analysis, we have retained only scooters, bicycles, and light vehicles, as these are the most relevant in terms of modal shifts. Conversely, buses, coaches, and heavy vehicles are linked to public transit services and specific logistics demands. In our hypothesis, the e-scooter ban does not have a direct causal effect on these vehicle categories. Motorbikes have also been excluded due to their relatively minor modal share in Paris trips (see *4.1 General context of the case study: transport trends in the city of Paris*), although they could be considered in future research.

In conclusion, the preprocessing phase has focused on filtering and selecting only the necessary data for analysis: retaining five out of nine counting stations, data from January 1, 2022, onward, and only the modes of transport most relevant to our study—scooters, bicycles, and automobiles.

4.4.4 Data aggregation on a daily basis

The analysis we aim to perform spans a time period of many months; therefore, an hourly granularity, as presented in the dataset, is excessively detailed and heavily influenced by time-specific fluctuations. On the other hand, monthly aggregations would result in a granularity that is too coarse and significantly affected by missing daily data in the dataset. For this reason, the data aggregation in our analysis is conducted on a daily basis across the entire dataset. From this point forward, all references to the collected counts will refer to daily aggregated counts.

Below, in Table 5, the different sub-datasets used to conduct the analyses are presented, along with the initial number of hourly records downloaded from the City of Paris, and the number of records remaining after daily aggregation. This counting activity is conducted for the entire dataset from 1st January 2022 and maintaining distinction between sites and modes. The table indicates the start and end dates of the considered counting period, according to the previous discussion, and breaks it down by the modes analyzed: scooters, bicycles, and automobiles.

Counting site data - daily aggregation records									
Site identifier	Counting site name	Start date	End date	Scooters		Bicycles		Automobiles	
-	-	-	-	No. initial records	No. aggregated records	No. initial records	No. aggregated records	No. initial records	No. aggregated records
10004	Rivoli x Flamel	01/01/2022	04/12/2024	83245	920	109150	920	42548	920

10030	Sebastopol x Rivoli	01/01/2022	02/09/2024	79800	824	90524	824	48607	824
10022	Rivoli x Bourdonnais	01/01/2022	04/12/2024	53981	636	69141	635	49892	932
10023	Rivoli x Lobau	01/01/2022	04/12/2024	52594	621	63296	615	54362	911
10029	Montmartre x Poissonnière	01/01/2022	04/12/2024	29967	594	37344	593	58595	887

Table 5: counting site data - first aggregation records

As the reader can observe, the number of aggregated days is consistent across the Rivoli x Flamel and Sébastopol x Rivoli counting stations. This consistency is due to the fact that anomalies in vehicle counting—likely caused by malfunctions, maintenance, or other external factors—are uniform for each counting station and equally affect all counts from the same station. However, this is not the case for the other three stations, where the distinction between scooters and bicycles began only in November 2022, with some gaps in data collection between the two modes. As a result, the data from November 2022 will not be used in future analyses as a comparison month due to this irregularity in the starting dates.

In addition, the initial number of recorded data points differs between transportation modes at the same station. This is due to the hourly aggregation method employed by the City of Paris' algorithm. Specifically, the algorithm attributes a unique count to each specific hour, counting site, transportation mode, trajectory, and lane used (see Table 2). Each count represents a single row, presented in the previous Table 5 under the column *No. of Initial Records*. If no occurrences are recorded for a specific condition (hour, mode, trajectory, and lane), the algorithm does not generate a row or assign a value of zero; instead, the row is simply absent.

This approach adds complexity to our data, as it makes it difficult to distinguish between missing data and an actual zero hourly flow. This issue will be discussed subsequently in paragraph *4.5 Data cleaning activities.*

4.5 <u>Data cleaning activities</u>

A cleansing of the above introduced dataset was preliminary carried out with a removal of possible errors due to the way the data was counted and recorded. These steps are detailed below.

Upon initial plotting of the values it became evident that not every day was represented, and that there were some outliers or missing data. This issue is related to the initial dataset exported from the City of Paris and is likely due to instrumental issues or biases in the basic aggregations. This issue has been widely reported in scientific literature with respect to localised counting points (Lam et al., 2018).

It is crucial to adopt a comprehensive approach to missing data in order to construct robust models that are not influenced by any potential bias associated with incongruent data, outliers, or values These factors have the potential to significantly impact the outcomes of our analysis, and we will delve deeper into this topic in the subsequent chapters.

This paragraph focuses on the data cleaning activities, as outlined in the methodological framework in Section *3.2 Data cleaning methodology*. We will discuss the nature of the outliers, their distribution, the methodology applied for cleaning the data, and the results of this process.

4.5.1 Outliers in the dataset

The dataset imported from the city of Paris exhibits clear missing values and incompleteness. A simple histogram of daily flows for a counting station, with the chronological days on the x-axis and the flows on the y-axis, reveals that entire periods are absent from the data. These periods are not the only instances of this phenomenon, as simple occurrences also appear to deviate significantly from the mean values, either by being considerably lower or higher than expected. This suggests the potential for the presence of outliers.

Figure 16 presents the histogram of bicycle records at the Rivoli x Flamel counting station from January 1, 2023, to December 4, 2024. It is evident that relatively long periods are missing, such as June and July 2023 and June 2024. Additionally, single days are also absent from the dataset.

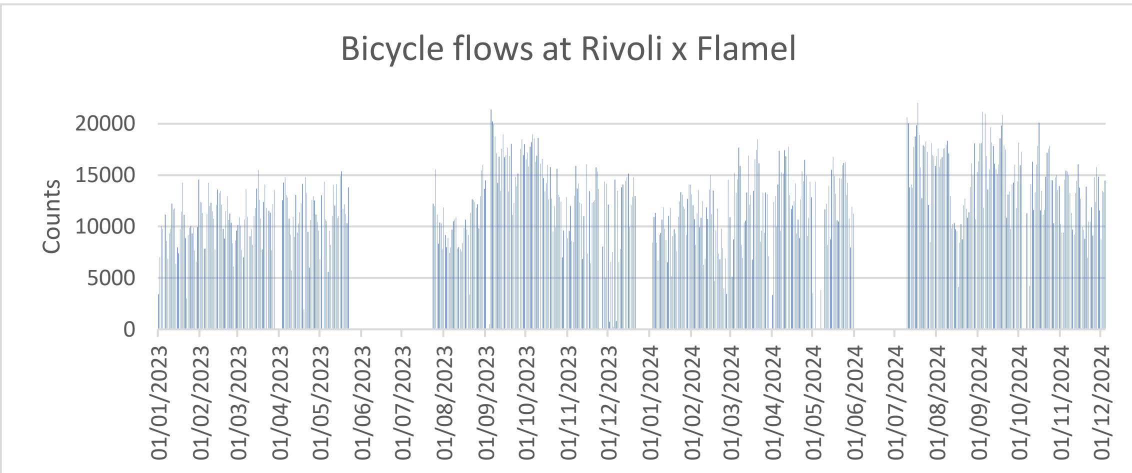

Figure 16: bicycle flows at Rivoli x Flamel counting station from January 1, 2023, to December 4, 2024

This graphical representation allows for the identification of two types of outliers: those characterized by missing or very low values, and those with exceptionally high values that exceed the mean by several magnitudes. These outliers are typical of real-world datasets in the field of transportation and beyond. Unlike an idealized or controlled domain, the data collected from sensors can vary significantly and may skew conclusions if not addressed, even though these values do not reflect actual phenomena.

Such anomalies often stem from instrument errors—faults in detection devices, sudden malfunctions—or from the algorithms used to classify the types of vehicles detected, such as incorrectly identifying e-scooters as bicycles in this case. It is, therefore, crucial in this initial stage to identify these outliers, understand their nature, and apply a methodical, replicable, and robust technique to ensure that the results correspond accurately to reality.

4.5.2 Data gaps and low-value outliers

For the first type of outliers, those with missing or significantly lower values than the mean, it is plausible to hypothesize equipment malfunctions. These data points often appear clustered over several hours or days, with the lack of detection common across all modes of transport during the same period. This absence of data can reasonably be attributed to electrical failures, network issues in data transmission, or optical obstructions of the cameras. These values are thus highly likely to result from such errors, and it is implausible to assume that null or near-zero values reflect an actual absence of vehicles on a given day. Consequently, these values do not represent real-world observations and will be discarded based on the methodology explained later.

It is worth noting that these missing values occur not only in the daily data but also significantly affect the hourly values. A close examination of the hourly data reveals that certain hours are not consistently present. This phenomenon may be attributable to both instrumental issues and the absence of vehicles detected during those hours, along specific lanes and trajectories. The city of Paris dataset, however, does not record flows equal to zero but instead represents them as missing, thereby introducing ambiguity to the analysis of the dataset.

In conclusion, the dataset exhibits a high level of missing data, making it difficult to determine whether the absence of values is due to missing data or the actual lack of vehicle counts. From this point onward, we will assume that the data cleaning process effectively identifies and removes days with structured anomalies, while the absence of counts will be considered part of "normal days."

It is important to recall that the cleaning activities and in particular the elbow method (see 3.2.1 Elbow method) discards values with high variance from the average using a graphical approach.

For the application of the elbow cleaning method, the reader can refer to Section *4.5.5 Application of the elbow method for cleaning activities*. However, even if we consider this assumption valid, the dataset may still be affected by missing counts, potentially leading to an underestimation of some values.

4.5.3 High-value outliers

For the second type of outliers, characterized by values significantly above the mean, another plausible explanation emerges. These values, often three to four times higher than the mean, were analyzed in relation to events occurring on the corresponding dates.

A clear correlation was identified between these elevated values and large-scale cultural, political, or social events, such as political demonstrations, cultural festivities, or sporting events. On these occasions, vehicle traffic in the affected streets was interrupted, and tens of thousands of people crossed the areas monitored by the counting devices. The cameras thus detected an abnormally high number of vehicles on these dates. Below, the main outliers identified are listed along with their corresponding explanations.

The list of outliers of this second kind include:

- 7 February 2023: Strike and demonstrations in Paris (Tuesday)
- 11 February 2023: Strike and demonstrations in Paris (Saturday)
- 13 April 2023: Strike and demonstrations in Paris (Thursday)
- 21 June 2023: Fête de la Musique (Wednesday)
- 7 April 2024: Paris Marathon (Sunday)
- 10 August 2024: Amateur marathon for the Olympics (Saturday)

As said before, the outliers in our dataset are numerous and arise from various factors. This occurrence is closely tied to the nature of the data, which originates from a real-world application domain and is subject to significant biases, as previously discussed. In order to address this issue, it is necessary to undertake a thorough cleansing of the dataset, thereby ensuring that the data accurately reflects reality.

Furthermore, it is imperative to acknowledge that the high-value outliers identified by the Paris dataset are associated with errors in the categorisation system employed for the recognition of vehicles. This may result in pedestrians being erroneously classified as vehicles. This bias raises questions about the accuracy of the data categorization system, as such a recurring issue could potentially affect the entire dataset over time.

4.5.4 Field visit in Paris and extemporary check of the dataset through a manual count

As part of this analysis, a field visit was conducted on December 2, 2024, to inspect the counting cameras installed on Rue de Rivoli (see *4.4.2 Counting point location and characteristics*). During the visit, the number of e-scooters and bicycles passing the counting station was manually recorded at Rivoli x Flamel counting station between 11:00 and 11:30 AM, resulting in approximately 28 e-scooters and 206 bicycles counted on the bike lane. This figure aligns with the corresponding data counts published by the City of Paris, that was subsequently checked. Figure 17 represents the photo of Rue de Rivoli at the Rivoli x Flamel counting point, location of the manual count of December 2.

Figure 17: photo of Rue de Rivoli at the Rivoli x Flamel counting point, taken on December 2, 2024

Although this analysis is not carried out on all counting stations and over a particularly short period, it also provides a counter-example to the results, giving us greater confidence in them. In addition, the City of Paris verifies and ensures the proper functioning of these counts, and they are used in the city's annual traffic reports.

In conclusion, we can say that it is reasonable to assume that the data set is reliable and that the counts reflect the real traffic flows, net of outlier and malfunctions. From this point on, our analysis will be based on the idea that, if the data are clean, they are reliable and reflect reality.

For a more detailed analysis and to make our work more robust, it would be useful to further investigate the functioning of the algorithm used by the City of Paris, to identify other methods of measurement and, finally, to have a greater variety of forms of measurement in order to ensure greater overall robustness and resilience.
For the purposes of this thesis, we will regard the available data as reliable. However, a more extensive and detailed investigation could serve as the basis for future research.

4.5.5 Application of the elbow method for cleaning activities

For data cleaning and the identification of optimal thresholds, the elbow method was selected, as detailed in the respective methodology chapter (see *3.2 Data cleaning methodology*). Specifically, the data cleaning process was carried out using a custom R function, designed and implemented for all subsets of the dataset aggregated for the specific analyses conducted. This approach ensures consistency and accuracy across all datasets.

In the next chapter, statistics and figures will exclusively pertain to datasets that have undergone this preliminary cleaning process.

The elbow points, minimum and maximum, are identified with the specific function and the cleaned dataset, the minimum and maximum values held, the percentage of rows held and the graphical representation of the entire dataset with the two points of maximum and minimum are returned (the reader is invited to refer to *3.2.2 Elbow method implementation).*

These two points are visually evident in Figure 18 for the counting station at Rivoli x Lobau where they are highlighted in red (see for more detail *4.4.2 Counting point location and characteristics*), only for automobiles of the previously pre-processed dataset.

For values above the mean, we can visually observe a significant distribution of values that exceed the mean, with stabilization occurring only for values around 120% of the mean, location of the first elbow point. For values below the mean we can identify another elbow point around 70% of the mean. After this value a sharp decline is noticeable. We can therefore identify two elbow points on the graph: the first corresponding to the concave curve for higher values and the second to the convex curve for lower values.

The values that will be excluded from our analysis are thus the extreme ones: those exceeding the upper elbow point, corresponding to the higher outliers, and those below the lower elbow point, corresponding to the lower outliers.

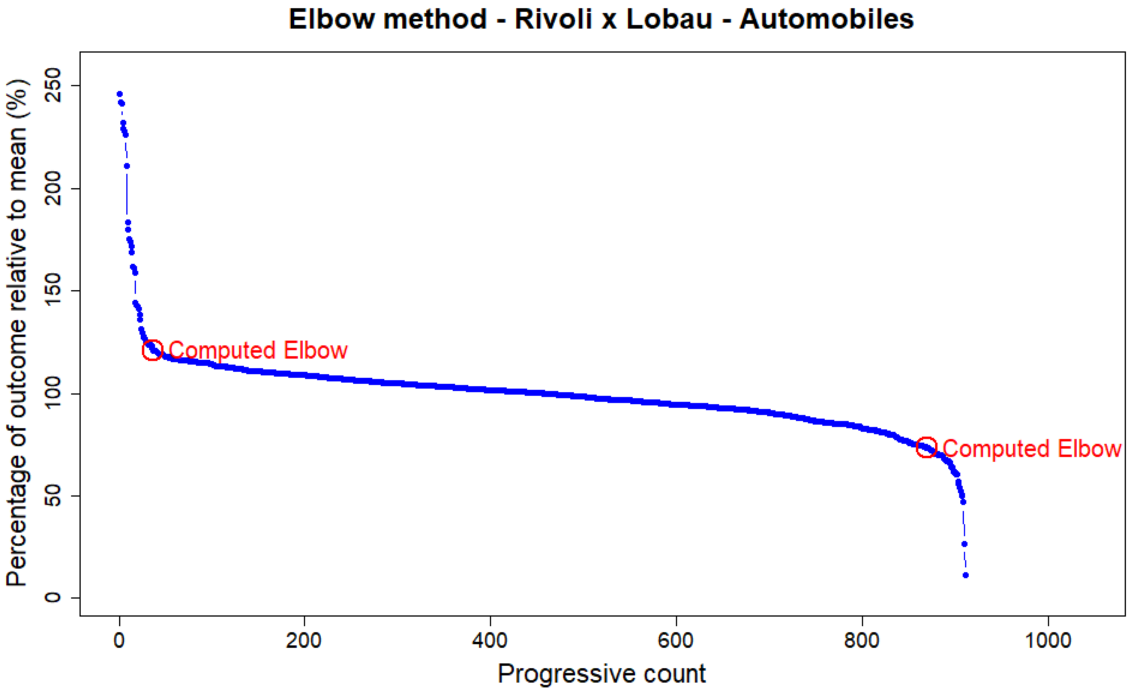

Figure 18: elbow curve for Rivoli x Lobau counting point for automobiles

The methodology for identifying the elbow points is performed using an algorithm that determines the maximum perpendicular distance from the line connecting the mean value (100% of the outcome) to the extreme values (see *3.2.2 Elbow method implementation*). However, some extreme values can distort the analysis, creating irregular shapes in the elbow curve and causing the elbow points to deviate from the actual ones. For this reason, once the algorithm computes the elbow points, they are verified graphically. If the computed elbow points deviate significantly from the true graphical representation, the elbow points are manually adjusted to match the real values.

An example of this is shown in Figure 18,which represents the elbow curve for automobile flows at the *Montmartre x Poissonnière* counting point. In the figure, the computed elbow points are displayed in red, while the forced, or manually adjusted, elbow points are shown in green.

It is evident that, without this manual correction, the data cleaning process could discard important upper values that clearly follow a continuous trend with the curve. Conversely, lower values might include data with already missing information. An important observation about the lower part of the curve is the rapid decrease from 90% to 0%, which is attributable to partially missing data. As discussed earlier in Section *4.5.2 Data gaps and low-value outliers*, several small gaps in hourly values can distort some days' data. These incomplete data points are discarded during the cleaning process.

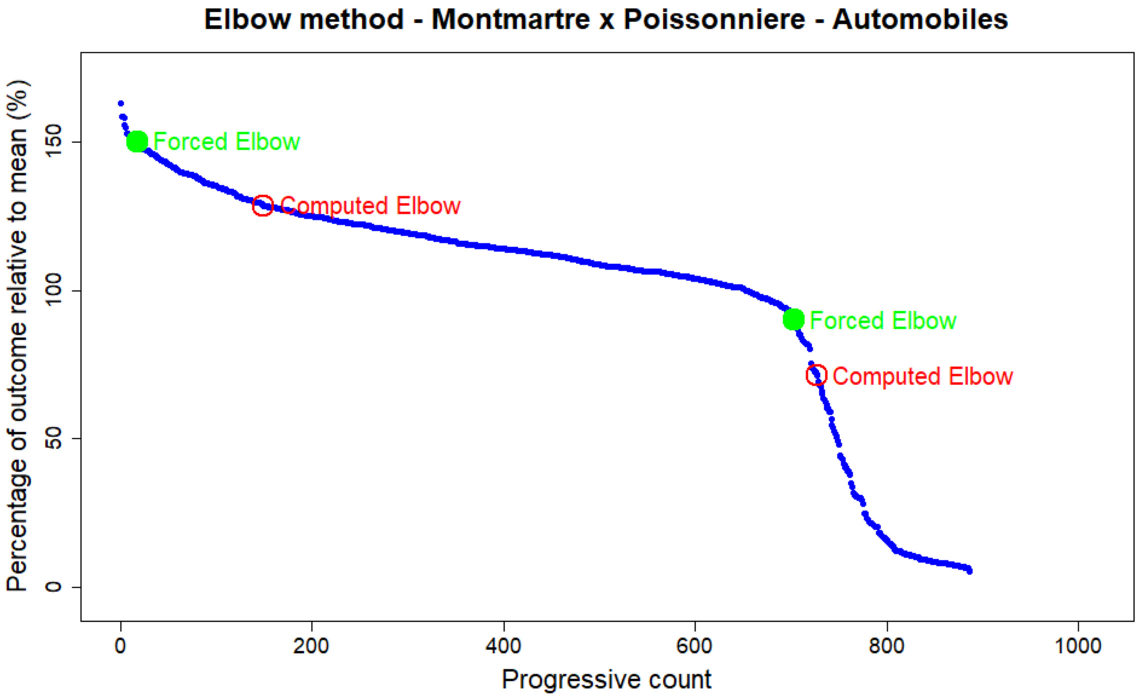

Figure 19: elbow curve for Montmartre x Poissonnière counting point for automobiles

In conclusion, the cleaning activity using the elbow method has been applied to each of the five datasets for the three modes of transport, resulting in a total of 15 sub-datasets analysed and cleaned. The data cleaning process was conducted over the entire period previously selected, from January 1, 2024, to the end of the counts. The reader can find the forced elbow values and the initially computed values in Table 6.

Adjusted elbow points				
Site	Mode	Elbow Type	Computed value (% of mean)	Forced value (% of mean)
Rivoli x Bourdonnais	Automobiles	Max	120.2	135
Rivoli x Bourdonnais	Bicycles	Max	130.4	150
Rivoli x Bourdonnais	Bicycles	Min	59.0	45
Rivoli x Bourdonnais	Scooters	Min	47.4	30
Rivoli x Flamel	Automobiles	Max	116.1	130
Rivoli x Flamel	Bicycles	Max	142.3	150
Rivoli x Flamel	Bicycles	Min	65.2	50
Rivoli x Flamel	Scooters	Min	49.3	30
Rivoli x Lobau	Bicycles	Max	137.0	150
Sebastopol x Rivoli	Bicycles	Max	140.9	155

Sebastopol x Rivoli	Scooters	Min	64.3	30
Montmartre x Poissonnière	Automobiles	Max	128.5	150
Montmartre x Poissonnière	Automobiles	Min	71.2	90

Table 6: adjusted elbow points

The next chapter will present the complete results of the elbow method applied to each sub-dataset. To ensure full reproducibility and to provide clear evidence of the graphical identification of the elbow points, detailed graphical results are included in *Appendix B* for each counting station and mode.

4.5.6 Results of the cleaning activities

The cleaned subsets, in function of counting site and mode, are presented below, following the elbow point analysis, along with the values for retained days, removed days, the corresponding percentage of retained days, and the minimum and maximum values kept relative to the dataset's mean value.

Table 7 presents the data for all scooters at the counting stations and for the periods previously introduced. Retained values of the sub-datasets are closely to 80 to 95% of the values. Additionally, it was verified that days with particularly high values corresponding to events or demonstrations were correctly removed (see *4.4.2 Counting point location and characteristics*).

Counting site data - cleaning activity - scooters									
Site identifier	Counting site name	Start date	End date	Initial records	Excluded days	Retained days	% retained	Min. % of average	Max. % of average
10004	Rivoli x Flamel	01/01/2022	04/12/2024	920	41	879	95.54	30	203
10030	Sebastopol x Rivoli	01/01/2022	02/09/2024	824	36	788	95.63	30	157.8
10022	Rivoli x Bourdonnais	01/01/2022	04/12/2024	636	18	618	97.17	30	197.4
10023	Rivoli x Lobau	01/01/2022	04/12/2024	621	60	561	90.34	48.1	192.5
10029	Montmartre x Poissonnière	01/01/2022	04/12/2024	594	116	478	80.47	38.2	204.3

Table 7: counting site data - results of cleaning activities for scooters

In a similar manner, the results of the cleaning activities for the bicycle sub-database are presented in Table 8. As was the case with the preceding results, data is retained from a range of 75% to 90%.

Counting site data - cleaning activity - bicycles									
Site identifie r	Counting site name	Start date	End date	Initial records	Exclud ed days	Retaine d days	% retained	Min. % of average	Max. % of average
10004	Rivoli x Flamel	01/01/2022	04/12/2024	920	100	820	89.13	50	150
10030	Sebastopol x Rivoli	01/01/2022	02/09/2024	824	86	738	89.56	59.96	155
10022	Rivoli x Bourdonnais	01/01/2022	04/12/2024	635	56	579	91.18	45	150
10023	Rivoli x Lobau	01/01/2022	04/12/2024	615	89	526	85.53	63.8	150
10029	Montmartre x Poissonnière	01/01/2022	04/12/2024	593	143	450	75.89	49.7	159.2

Table 8: counting site data - results of cleaning activities for bicycles

Finally, as illustrated in Table 9, the results for cleaning activities involving the elbow method for automobiles are presented in a comparable manner. In instance, the values retained range from 78% to 92%.

Counting site data - cleaning activity - automobiles									
Site identifie r	Counting site name	Start date	End date	Initial recor ds	Exclude d days	Retaine d days	% retained	Min. % of average	Max. % of average
10004	Rivoli x Flamel	01/01/2022	04/12/2024	920	123	797	86.63	80.1	130
10030	Sebastopol x Rivoli	01/01/2022	02/09/2024	824	142	682	82.77	87.6	113.7
10022	Rivoli x Bourdonnais	01/01/2022	04/12/2024	932	96	836	89.7	74.1	135
10023	Rivoli x Lobau	01/01/2022	04/12/2024	911	76	835	91.66	73.2	121
10029	Montmartre x Poissonnière	01/01/2022	04/12/2024	887	200	687	77.45	71.2	150

Table 9: counting site data - results of cleaning activities for automobiles

In conclusion, the cleaning activities highlighted a significant number of discarded days, representing outliers in the dataset, ranging from around 5% to 20% of the total values. This underscores the presence of a considerable number of missing values or exaggerated flow counts generated by the algorithm used by the City of Paris. The elbow method, applied consistently across all sub-datasets, ensures robustness in the cleaned data by filtering out anomalous values while preserving realistic daily records. From this point onwards, we will assume that the sub-datasets most accurately reflect the actual vehicle flows.

4.6 Dataset weighting

As presented in *3.3 Day of the week normalisation*, the presence of a varying number of weekdays in each month, along with the data cleaning activities that led to the exclusion of entire days, results in an unbalanced dataset. Some weekdays are either underrepresented or overrepresented on a monthly basis, which could distort our analysis. This section focuses on the normalization of the dataset to balance the outcomes and mitigate potential distortions.

4.6.1 Day of the week normalisation

To calculate the weight of each value, the methodology presented in the previous chapter is applied to the entire dataset. First, each counting site is considered separately, mode by mode. Using a specific function, the corresponding day of the week is assigned to each date, and within each month, the number of occurrences of each specific weekday is calculated.

A new column is then added to the dataset reporting the weights, which will be used in the analysis, that are computed as the ratio of the number of occurrences of the weekday in the month over the expected value (4 – see Section *3.3* for details). Our analysis will be conducted using average values calculated over months or longer periods. In this way, the averages will be weighted, eliminating the underrepresentation or overrepresentation of specific weekdays in the dataset.

Furthermore, the processed weights are based on the assumption that there are 28 days within the month. However, it is also true that it can happen, either because of gaps in the dataset or because data cleaning removes some occurrences, that some days of the week are completely missing from the dataset. Let us assume, for example, that Mondays are completely absent in a given month, then the weights attributed to the other days of the month will be disproportionate, giving greater weight to weekends in this particular case. Consequently, it seems obvious to add further balancing to the dataset, i.e. a modification of the weights if a weekday is absent in the given month.

This addition of the weights, as presented in Section *3.3.2* follows the assumption that the basic weekdays are 20 and the weekend days are 8 in all. If a day is completely missing in the month then this hypothetical base will have to be scaled based on the new number of occurrences. For example, if all Mondays are missing in a given month, the number of weekdays in that month will no longer be 20 but 16. Consequently, a weight of 20/16 will be applied to all weekdays in the respective month. Similarly, if there are no Saturdays in a given month, then the weight to be applied to all remaining weekend days in the month, i.e. Sundays, is 8/4.

If no weekday or even a weekend day is found in the month, the month is automatically discarded. Below in Table 10 are the months deleted in the dataset because not a single weekend day or weekday is found.

Discarded months due to low occurrences					
Year	Month	Site	Mode	Initial rows	Final rows
2022	November	Rivoli x Bourdonnais	Scooters	618	614
2024	September	Sebastopol x Rivoli	Scooters	788	787
2022	November	Montmartre x Poissonnière	Scooters	478	474
2022	November	Rivoli x Bourdonnais	Bicycles	579	576
2024	June	Rivoli x Lobau	Bicycles	526	522
2022	November	Rivoli x Lobau	Bicycles	526	522
2022	November	Montmartre x Poissonnière	Bicycles	450	442
2024	August	Montmartre x Poissonnière	Bicycles	450	442
2024	August	Rivoli x Bourdonnais	Automobiles	836	829
2024	July	Sebastopol x Rivoli	Automobiles	682	680
2022	February	Montmartre x Poissonnière	Automobiles	687	669
2022	September	Montmartre x Poissonnière	Automobiles	687	669
2024	August	Montmartre x Poissonnière	Automobiles	687	669

Table 10: discarded months due to low occurrences

To provide clarity, the average weight for each site and mode is reported in Table 11. As expected, all the coefficients are higher than one, ranging from around +10 to +50%, because the missing values are presents in higher number than the overrepresentation due to strikes or other exceptional events.

Mean daily weight coefficients		
Site	Mode	Mean normalisation coefficient
Montmartre x Poissonnière	Automobiles	1.30
Montmartre x Poissonnière	Bicycles	1.52
Montmartre x Poissonnière	Scooters	1.48
Rivoli x Bourdonnais	Automobiles	1.18
Rivoli x Bourdonnais	Bicycles	1.22
Rivoli x Bourdonnais	Scooters	1.14
Rivoli x Flamel	Automobiles	1.23
Rivoli x Flamel	Bicycles	1.20
Rivoli x Flamel	Scooters	1.11
Rivoli x Lobau	Automobiles	1.21
Rivoli x Lobau	Bicycles	1.29
Rivoli x Lobau	Scooters	1.30
Sebastopol x Rivoli	Automobiles	1.28
Sebastopol x Rivoli	Bicycles	1.21
Sebastopol x Rivoli	Scooters	1.14

Table 11: mean weight by mode and site

In conclusion, from this point onward, all references to the dataset will pertain to weighted average values.

4.7 <u>Defining control and treatment groups</u>

The initial essential inquiry, in order to setting up the dataset for the difference-in-differences analysis, is to define the control group and the treatment group (methodological references in *3.4 Difference-in-differences method*). In the present case, the range of possible assumptions is limited. If, for example, the previously cited economists Card and Kruger demonstrated the impact of minimum wages by comparing two American states (Card & Krueger, 1993), it is challenging to conduct a similar analysis in our case. Firstly, the data in question are point counts, and identifying a similar type of count with the same characteristics in another city is a challenging undertaking. Furthermore, even if such counts could be sourced from another city, comparing the data taken with the method of the city of Paris (with the previously mentioned thermal cameras) with other cities using completely different methods is a highly complex endeavour.

In light of the aforementioned considerations, we elected to utilise a sample of the same array from the city of Paris as a control group, albeit over a different period, thereby ensuring an accurate comparison of vehicles counted at identical points and employing the same methodological approach. For these reasons, we will compare data from the same counting station across different years. Therefore, we will define the treated group as a one-year period surrounding the treatment (including several months before and after) and the control group as the corresponding period in the previous or following year, also divided into control and treated sub-periods.

This type of subdivision allows us to analyse the causal effects in a more robust manner, as the counting data originates from the same stations, maintaining identical infrastructure and characteristics, thereby minimizing fluctuations related to instrumental variations. The key hypothesis of this methodology is that the period considered as the control group should experience no changes after the treatment period, while the period defined as the treated group should exhibit the causal effects of the policy (or not).

For instance, the treatment date is set for September 1st, when the Paris City decision officially took effect. While the formal ban date is September 1st, it is reasonable to assume that the shared e-scooter companies began removing vehicles gradually before this date. This assumption is also supported by reports in the media (À Paris, les trottinettes en libre-service disparaissent des rues, 2023).

In the next sections, the definition of the control and treated groups for both the 2x2 and temporal approach models, along with their specific implementation on the dataset, will be presented.

4.7.1 Setting up the dataset for the DiD 2x2 basic model

The 2x2 model (see *3.4.1 DiD method – 2 x 2 basic model*) requires four distinct groups: the control and treated groups, each divided into pre-treatment and post-treatment periods. In this section, we will identify these four periods and the corresponding counting stations to define the new time periods and the configuration of the respective sub-datasets.

As previously mentioned, we will define the treated group as the data from the year surrounding the treatment, for example, six months before and six months after the intervention, to capture the causal impact of the policy. The key hypothesis underlying this one-year period is that it provides a sufficient timeframe to study the policy and its impact—long enough to account for latency effects, but not so long as to be influenced by broader transportation trends. Additionally, the comparison between two different years allows us to account for seasonal variations, which are likely to be symmetric from one year to the next.

However, the data from the year following the treatment is insufficient to implement the DiD analysis, as data collection at all counting stations ended by December 4, 2024. In this context, the only counting stations that distinguished between scooters and bicycles in the year prior to the intervention (2022) are *Sebastopol x Rivoli* and *Rivoli x Flamel*. Therefore, we have decided to initially conduct the 2x2 analysis using data from these two counting stations.

Finally, we will utilise the counts from March 2022 to February 2023 as a control group with start of the treatment on 1st September 2022, following the assumption that no impact should be noticed on the treated period of the control group.

The same period but one year later, from March 2023 to February 2024, will be considered as treatment group. The start of the treatment is located on 1st September 2023 for the treated group. This allows the model to compare the 'natural' development of the year 2022/23 with the 'changed' development of the year in which the treatment took place.

Table 12 summarizes the definition of the control and treated groups, indicating the data range for each group and period.

Definition of control and treated group – DiD 2x2			
	Period	From	To
Control group	Pre-treatment	March 2022	August 2022
	Post-treatment	September 2022	February 2023
Treated group	Pre-treatment	March 2023	August 2023
	Post-treatment	September 2023	February 2024

Table 12: definition of control and treated group for DiD 2x2 model

This subdivision will be used to create sub-datasets for the two counting stations, *Sébastopol x Rivoli* and *Rivoli x Flamel*, across each of the three modes of analysis—scooters, bicycles, and automobiles—resulting in a total of six sub-datasets.

Table 13 presents, for each sub-dataset, the initial number of rows and the final number of rows after filtering the date range for the creation of the sub-dataset used in the DiD 2x2 analysis.

Data filtering results for 2x2 DiD basic model					
Site	Mode	Initial days	Group	Days	Total days
Rivoli x Flamel	Automobiles	797	Control - Pre	126	552
			Treated - Pre	112	
			Control - Post	162	
			Treated - Post	152	
	Bicycles	820	Control - Pre	166	572
			Treated - Pre	110	
			Control - Post	156	
			Treated - Post	140	
	Scooters	879	Control - Pre	169	606
			Treated - Pre	113	
			Control - Post	168	
			Treated - Post	156	
Sébastopol x Rivoli	Automobiles	680	Control - Pre	151	533
			Treated - Pre	133	
			Control - Post	136	
			Treated - Post	113	
	Bicycles	738	Control - Pre	166	564
			Treated - Pre	149	
			Control - Post	130	
			Treated - Post	119	
	Scooters	787	Control - Pre	171	590
			Treated - Pre	157	
			Control - Post	122	
			Treated - Post	140	

Table 13: results for data filtering activities for 2x2 basic model dataset

For each sub-dataset, a new column called treat will be added, indicating whether the data belongs to the control group or not, with a dummy variable equal to 1 if it is part of the control group. Another dummy variable will be added in a new column called time, indicating whether the data is from the pre-treatment period (dummy equal to 0) or the post-treatment period (dummy equal to 1). The interaction of these two dummies will create a new dummy variable in a column called did, which will equal 1 only for the treated group during the post-treatment period.

Additionally, a dummy variable for seasonal effects on the covariate will be added in a new column called cov, equal to 1 for the winter months: December, January, and February. This decision is based on the hypothesis that winter months experience a decline in the use of scooters and bicycles due to colder temperatures, shorter daylight hours, and increased adverse weather conditions such as snow or rain.

For a more detailed analysis, one could also include rainfall events; however, this was avoided here to maintain simplicity. It should also be noted that Paris's rainfall characteristics, primarily influenced by its Atlantic climate, typically consist of moderate to low-intensity precipitation, which does not significantly hinder the use of bicycles and scooters

For more background information on the implementation of the model, the reader is invited to refer to *3.5.2 2x2 DiD implementation.*

4.7.2 Setting up the dataset for the DiD temporal analysis

In the following part of the research, the DiD analysis will be conducted by comparing several periods, trough the temporal approach that calculates the Average Treatment on Treated (ATT) (see *3.4.6 Extended DiD with multiple time periods*). Unlike the 2x2 model, this methodology impose fewer temporal restrictions. In order to do that, all five counting stations that distinguish between bicycles and scooters will be used, except for the *Sébastopol x Rivoli* station, which ceased operations in September 2024, making a full-year comparison impossible. Consequently, only the four counting stations with complete data for the entire period will be included in this analysis.

As done previously, we need to define a control group and a treated group. In this scenario, the year following the treatment will serve as the control group, while the year during the treatment will serve as the treated group. Data is available only until December 4, 2024, for all counting stations. Therefore, the last complete month available for analysis is November 2024. For the control group, data from December 2023 to November 2024 will be used, with the treatment period starting in September 2024. For the treated group, data from December 2022 to November 2023 will be used, with the treatment period starting on September 1, 2023. This approach implies that the treatment period is limited to the last three months .However this model provides a longer baseline period, which, under our hypothesis, should not show significant changes, allowing us to test the robustness of the model.

Table 14 summarizes this definition of control and treated groups.

Definition of control and treated group – DiD temporal analysis			
	Period	From	To
Control group	Pre-treatment	December 2023	August 2024
	Post-treatment	September 2024	November 2024
Treated group	Pre-treatment	December 2022	August 2023
	Post-treatment	September 2023	November 2023

Table 14: definition of control and treated group for DiD ATT model

Consequently, the sub-datasets are created for each of the four counting stations and for each of the three modes, resulting in a total of 12 sub-datasets.. The following data has been filtered to remove superfluous information. The analysis will be limited to the period of interest. In addition, only months with a corresponding month in the other year of confrontation are retained, since both months are necessary for the comparison between the two years and for the temporal analysis. In fact, some months have been discarded because of too few occurrences (see Table 10).

Table 15 shows the results of the data filtering activities, confronting for each sub-dataset the initial days, the filtered days and the respective categorisation of the latter in each control or treatment group. It also shows the number of months available for analysis. Each monthly occurrence is related to the same month in two different years in order to perform the DiD analysis.

Data filtering results for temporal analysis model								
Site	Mode	Initial rows	Filtered rows	Control - Pre	Treated - Pre	Control - Post	Treated - Post	No. Months
Montmartre x Poissonnière	Automobiles	669	464	120	201	73	70	11
Montmartre x Poissonnière	Bicycles	442	415	123	192	43	57	11
Montmartre x Poissonnière	Scooters	474	470	111	230	67	62	12
Rivoli x Bourdonnais	Automobiles	829	539	178	207	84	70	11
Rivoli x Bourdonnais	Bicycles	576	572	212	219	79	62	12
Rivoli x Bourdonnais	Scooters	614	612	221	237	82	72	12
Rivoli x Flamel	Automobiles	797	547	185	197	87	78	11
Rivoli x Flamel	Bicycles	820	519	189	188	73	69	11
Rivoli x Flame	Scooters	879	563	198	199	85	81	11
Rivoli x Lobau	Automobiles	835	549	173	225	86	65	12
Rivoli x Lobau	Bicycles	522	496	182	175	77	62	11
Rivoli x Lobau	Scooters	561	549	191	226	85	47	12

Table 15: results for data filtering activities for temporal analysis model dataset

For the implementation of the model (see *3.5.3 Extended DiD implementation*), a progressive number for the period needs to be defined. This will be added in a column named period, where December is assigned a value of 1, January is assigned 2, and so on until November, which is assigned 12.

Another column, treat, provides information about the treated group. This column is set to 10 for all values of the treated group corresponding to the treatment period (September). Additionally, each daily occurrence is assigned a specific ID, a progressive integer starting from 1 and reinitialized for each month of the years considered, stored in the id column.

In conclusion, the final sub-datasets have been prepared and configured for the DiD analysis. The results of the conducted analysis will be discussed in the next chapter.

5 Results

The chapter starts by briefly outlining the computational tools used and the potential limitations of the above introduced dataset. Then, we use the methodology presented in Chapter 3 to highlight some key results.

5.1 Tools and software

5.1.1 Programming environment

In order to proceed with the analysis of the results, from data cleaning activities to regressions, the analysis is developed using the R profiling language. In particular, several packages inherent to the R language are used to carry out the analysis. These libraries are open source, which guarantees full reproducibility of the work.

The following R packages were employed during the analysis:

- **fixest**: this package was employed for linear regression modelling. The main functions used in this work include the basic regression model for 2x2 analysis, and this library allows the calculation of regression coefficients and relative statistical indicators.
- **did**: this package, developed by the aforementioned Callaway and Sant'anna, makes it possible to use the DiD technique with different study periods and calculate the relevant ATT values. In particular, this package allows the calculation of ATT values for all periods considered, evaluates their confidence intervals and also gives a graphical result that will be used in this work.
- **dplyr**: is the library used for data manipulation, including filtering, summarizing, and restructuring datasets to prepare them for analysis.
- **ggplot2**: for creating data visualizations, used to generate and charts that complement the analysis.

The most significant portions of the R code are provided in *Appendix C* to ensure full reproducibility of the analysis.

5.1.2 Data management

The initial dataset of the municipality of Paris allows it to be filtered before being downloaded. Nevertheless, it remains very heavy, taking into account that the occurrences are of the order of a million, having to download a dataset with hourly flows, several counting stations and several modes, over a period of almost 3 years. For this reason, the files were first downloaded in CSV format and filtered using an Excel Query tool. In addition, the use of Excel was useful for first visualisations through a quick graphical format.

In particular, time and date columns were separated to facilitate the initial date aggregation using pivot tables. Once pre-processed, the data was exported in CSV format and imported into R for further cleaning, analysis, and processing.

5.2 Observed trends in the dataset

This section focuses on the analysis of time series (as introduced in the methodology, see *3.1 Time series analysis*) to visually explore the data, identify trends, and detect seasonal or infrastructure-related variations.

5.2.1 Quarterly trends

In this subsection, we present the first histograms illustrating the quarterly trends of the datasets for the three main modes of analysis: scooters, bicycles, and automobiles.

First, we use the complete dataset, as discussed in the previous chapter, covering the period from January 1, 2022, to the end of data collection. However, as previously mentioned, not all counting stations began recording data in January 2022, and some stations only started distinguishing between bicycles and scooters in November 2022. This explains why certain counting stations appear later in the plots.

The histograms display the quarterly mean flows for each mode. It is important to note that these flows are weighted averages, adjusted for the number of weekday occurrences, and have been cleaned of outliers and missing values. The histograms are presented separately for each counting site.

Each bar represents the daily average flow for the respective quarter, with all values weighted as explained in the previous chapter. Each quarter is labelled in the format YYYY-QX, where YYYY represents the year (e.g., 2022) and QX denotes the quarter (e.g., Q1). Figure 20 illustrates the corresponding histogram for scooters. The third quarter of 2023 is presented in red, as is the first quarter during which the prohibition of e-scooters comes into effect.

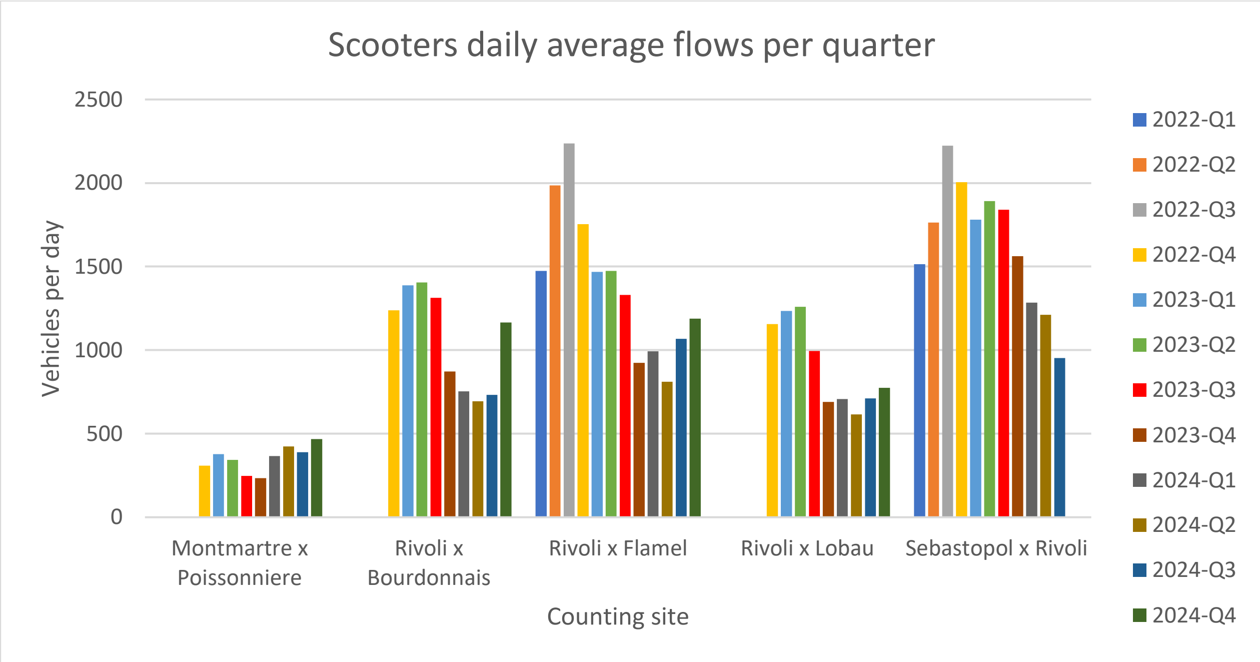

Figure 20: scooters daily average flows per quarter

From the graph, the first noticeable element is that the average flows after the ban varies depending on the counting station. Generally, a decline in flows immediately following the ban is observed in almost all stations, or at least no station continues the growth trend that was typically visible before the ban in a consistent manner. This growth trend is particularly evident at Rivoli x Flamel, Rivoli x Lobau, and Sébastopol x Rivoli. The first two are located along Rue de Rivoli, as previously mentioned, and the latter on Boulevard de Sébastopol. The fourth quarter of 2023 shows a significant decline in flows across all stations.

In conclusion, a decline in scooter counted is observed immediately following the ban. However, this decrease is not as sharp as one might have expected. Flows decrease by approximately one-third at the aforementioned stations, but without an abrupt interruption. Additionally, in the last quarters of 2024, a rise in values is noted. This increase could be explained by a growing trend of private scooter purchases, which appears to be on the rise.

In addition to what has been said, the station at Montmartre x Poissonnière presents a contrasting trend. This station, located in less central areas compared to the other four, even shows an increase in scooter counts in the quarters following the ban. While the flows are smaller compared to other counting stations, this might suggest that in less central areas, the ban on shared scooters did not lead to a decrease in scooter usage overall. This analysis suggests the insight that the ban on shared scooters did not necessarily affect all areas of Paris equally, but that more central and peripheral areas experience different trends, as also suggested by the literature (see *2.5 Difference-in-differences method applied to shared e-scooter studies)*. This point will be explored further in the following sections.

Figure 20 illustrates the corresponding histogram for bicycles.

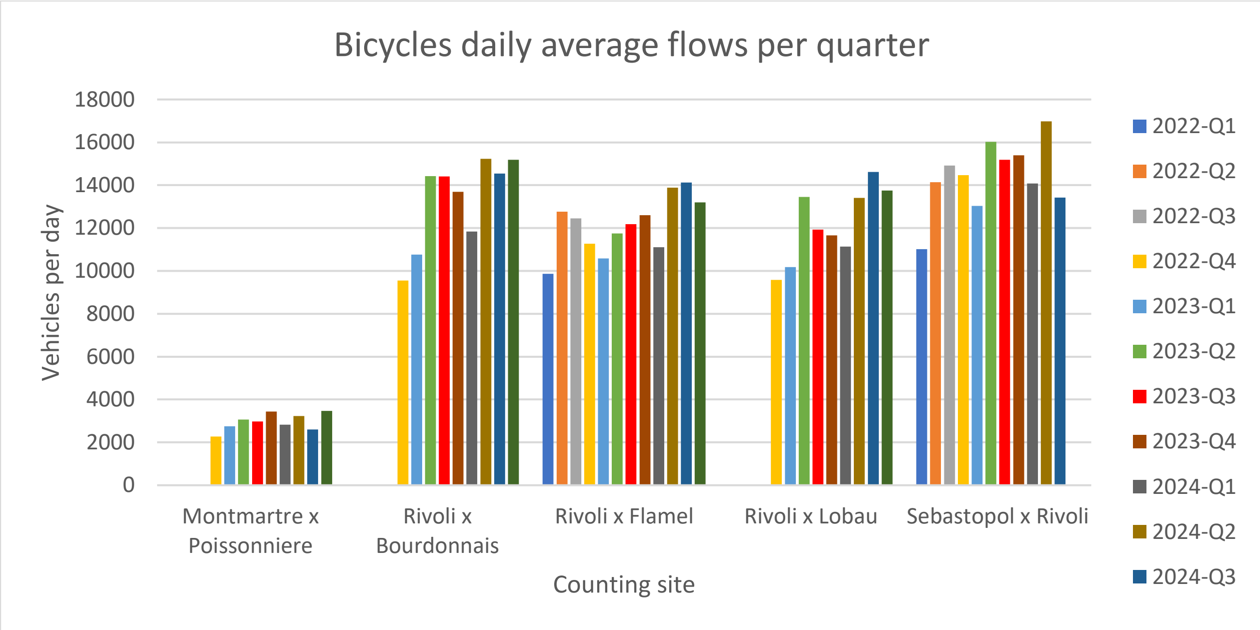

Figure 21: bicycles daily average flows per quarter

The reader can clearly see how the number of bicycle flows is strongly influenced by infrastructure and proportional to previous scooter flows. The magnitudes of the four centrally located stations with more extensive bike lanes are similar, while Montmartre x Poissonnière exhibits lower counted vehicles. This demonstrates that areas with better bicycle infrastructure, such as more and wider bike lanes, have higher flows. The greater offer of infrastructure is clearly linked to higher counts. In addition more central areas exhibits higher flows. This occurs similarly for both scooters and bicycles.

Regarding bicycles, no particularly notable trends are immediately apparent, except for a general growth. This overall increase aligns with broader transportation trends observed in the city of Paris (see *4.1 General context of the case study: transport trends in the city of Paris*). On the other hand, some seasonality in the counts is also evident, with lower flows during some winter quarters, likely due to weather conditions (particularly in the first quarters of each year). This aspect will be considered in the application of specific covariates in our model.

Figure 22 represents the daily average car flows per quarter, similarly to the previous ones.

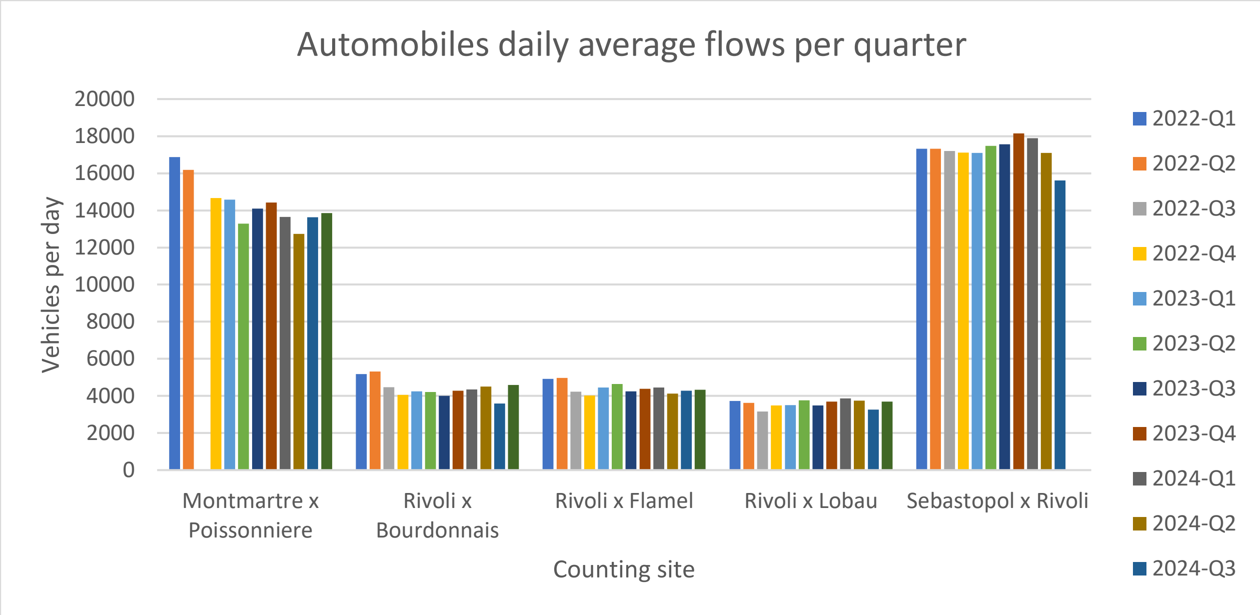

Figure 22: automobiles daily average flows per quarter

In this case as well, it is evident how differing infrastructure availability influences flows, although the results are different. The axes of Sébastopol x Rivoli and Montmartre x Poissonnière show counts of an order of magnitude higher compared to the stations along Rue de Rivoli. This is expected, as the first two axes are open to through traffic, while Rue de Rivoli has lower values since it is a single-lane axis reserved for residents, taxis, and other authorized vehicles.

From a graphical perspective, no particularly notable trends emerge, except for a slight decrease in flows on the main traffic axes. This decrease seems to align with the general transportation trends of the city. The Montmartre x Poissonnière counting station has no data available for the third quarter of 2022. This is due to significant gaps in the dataset, to data weighting and to data cleansing activities, resulting in the absence of information for effective comparison during this period (for detail on discarded months see *4.6 Dataset weighting*).

In conclusion, when comparing the above mentioned plots, it is important to emphasize the influence of infrastructure characteristics at the various counting sites, which significantly affect the results. For example, the number of bicycles recorded is considerably higher on the Rue de Rivoli axis, a key thoroughfare in Paris that has been redesigned to prioritize sustainable modes of transport, as highlighted in the Section *4.4.2 Counting point location and characteristics*, with the exception of the corner with Boulevard de Sébastopol, which is a main road axis with two lane dedicated for general traffic. A contrasting pattern is observed at the intersection of Boulevard Poissonnière and Boulevard Montmartre. Each of these two axes has two lanes designated for general traffic, and the cycle lanes are bidirectional and only 3.5 metres wide. In this area, the number of cars is significantly higher, with an average of approximately 3,000 bicycles per day compared to around 14,000 automobiles per day.

5.2.2 Monthly trends

The main interest is to spot traffic flow trends through comparable time periods across different years. Therefore, data will now be analysed on a monthly basis using time series analysis, commencing from 1 December 2022 until November 2024, the last month entirely available on 4 over 5 stations. We postponed the starting point of the analysis compared to the previous section because this date marks the point at which complete data was available from five counting stations within the municipality of Paris, as previously outlined.

However, the Sébastopol x Rivoli counting station is not available from September 2024. To ensure a sufficiently long observation period and to maintain consistency in comparisons, we will exclude this counting station from the monthly histograms. In a certain sense, a portion of the data is missing. However, the ability to graphically visualize the entire dataset — which will be analysed in greater detail in the following sections — remains of primary importance.

The data will be plotted in histograms showing the average daily flows per month (note that the averages are weighted, for more information see *4.6 Dataset weighting*), summed across all the four aforementioned counting stations: Rivoli x Flamel, Rivoli x Lobau, Rivoli x Bourdonnais, Montmartre x Poissonnière. In this way, each bar in the plot represents the summed average daily flow recorded for each of the four counting stations on monthly basis.

Figure 23 represents the average daily flow of scooters recorded across the four previously mentioned counting stations. According to the DiD framework presented in the previous chapter, the treatment month (September 2023) is highlighted in red. The x-axis represents the corresponding month, while the y-axis shows the average number of vehicles recorded daily.

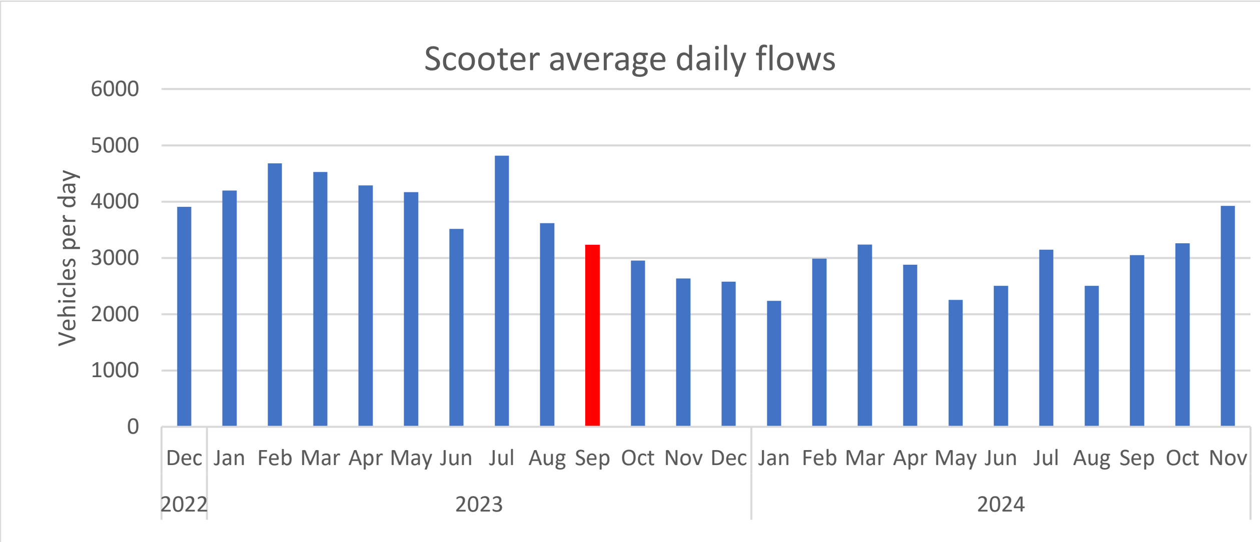

Figure 23: scooters daily average flows per month

From the previous histogram, we can observe that immediately following the ban on shared e-scooters, the overall number of recorded scooters has decreased for about four consecutive months. This decline appears to be consistent, but it does not indicate a total disappearance of this mode of transport. On the contrary, the reduction is relatively moderate. Then, from February 2024 onwards, an upward trend is observed.

Going into details, it seems that the decline began before the ban, already in August 2023. This is likely due to the operators progressively removing scooters from the streets of Paris ahead of the official ban date, in order to relocate them to other operational cities (see Chapter 4). Additionally, the decrease in scooter numbers remains noticeable until January 2024. However, from February 2024 onwards, an increase can be observed. Despite fluctuations throughout 2024, there appears to be an overall upward trend, with scooter levels in November 2024 returning similar to those recorded before the ban. This could suggest a tendency towards private scooter ownership, indicating an increase in personally owned scooters in Paris. This latter point will be analysed in further detail in section *5.4 DiD application: the temporal analysis approach*.

There is also a spike in the month of July in 2024, especially when compared to the trends in 2023. This is probably due to the Olympic Games and the relative change in traffic flows. Notably, the City of Paris launched a campaign encouraging the use of alternative transportation modes instead of public transit to mitigate overcrowding caused by the influx of tourists and visitors attending the Olympics. A plausible explanation for this peak is that a higher number of Parisians opted for privately owned scooters during this period as a substitute for public transit.

Figure 24 represents the average daily flows for bicycles, similarly to the previous histogram.

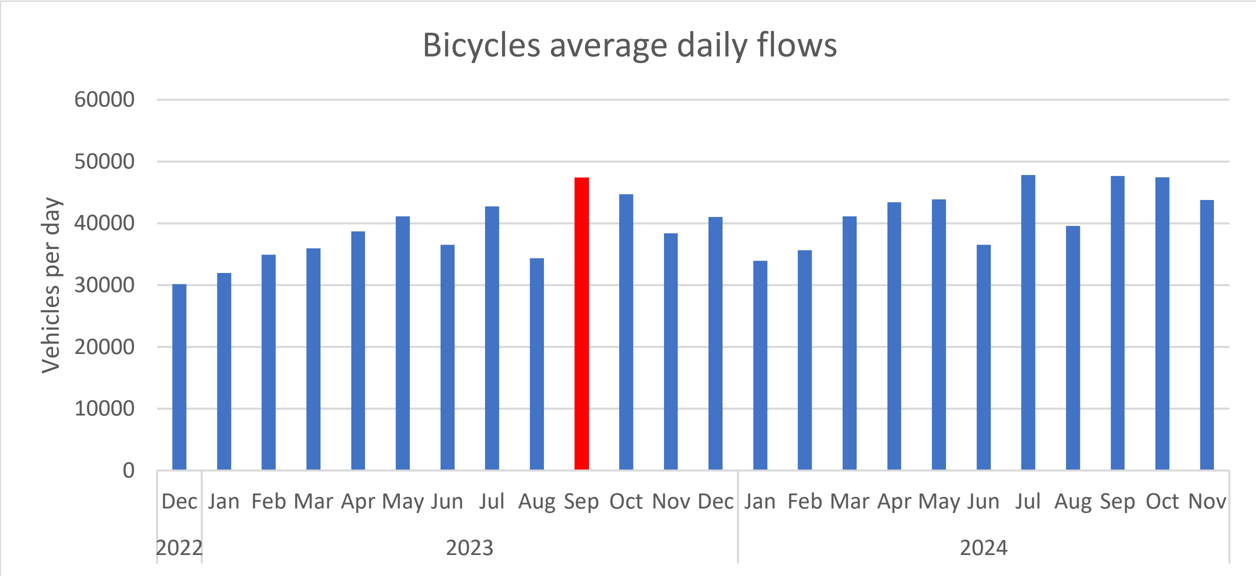

Figure 24: bicycles daily average flows per month

The trend of bicycles across all counting points appears to show an overall upward trend, with some seasonal variations. In particular, high peaks are observed in the middle of the year, notably in July. A decline is noticeable during the winter months, such as January and February. Despite these seasonal variations, the general trend is one of growth, ranging from a few thousand to several tens of thousands of units. These seasonal patterns will be analysed in detail in the following sections.

Figure 25 represents the average daily flows for automobiles, with same characteristics of the previous graphs.

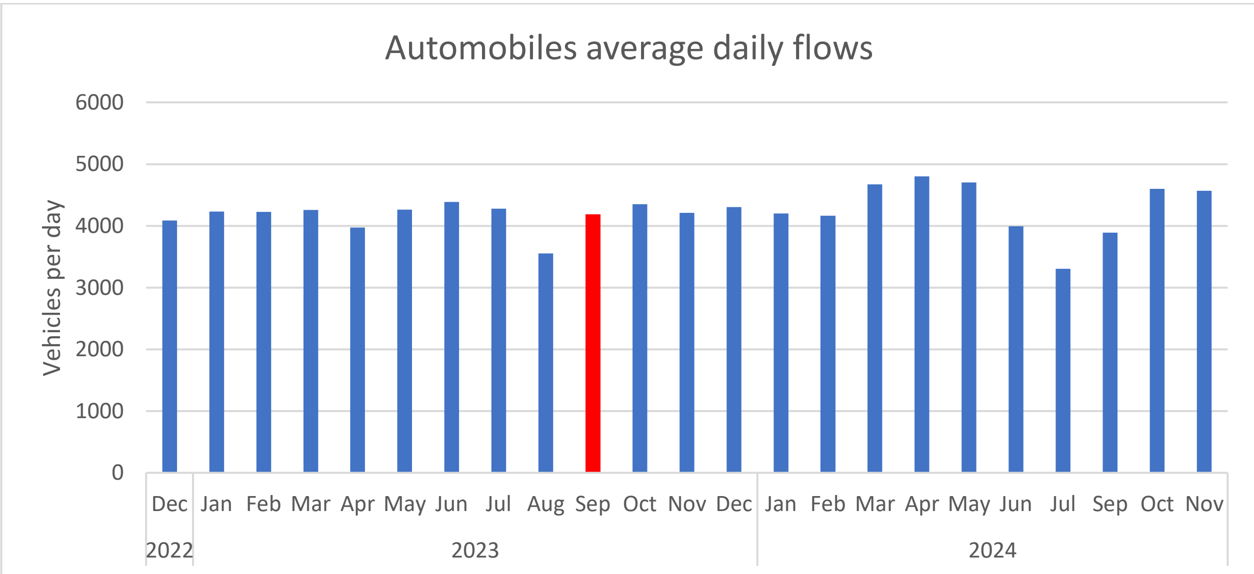

Figure 25: automobiles daily average flows per month

From the last histogram, we can observe a slight increase. However, it is important to note that three out of the four counting points in this graph are located on an axis reserved for specific vehicles, such as taxis, residents, and delivery services.

5.3 DiD application: 2x2 model

In this experimental section, we will attempt to demonstrate, through the difference-in-differences method, whether the ban on shared e-scooters has impacted transport patterns in Paris.

In order to examine the impact of removing scooters in Paris, we will first employ a difference-in-differences (DiD) analysis, previously presented in a 2x2 format with a linear regression (see *3.4.1 DiD method – 2 x 2 basic model* , to ascertain its statistical significance. In particular, the model that we are going to use estimates the mean values of the different groups involved in the pre- and post-periods and studies whether the pre- and post-difference is statistically significant on the given sample.

The following subsections will present the results for the two selected locations in this initial analysis: Sébastopol x Rivoli and Rivoli x Flamel counting points, covering the period from March 1, 2022, to February 29, 2024. It is important to note that all values presented are based on aggregated, cleaned, and weighted data. For further details on the selected time periods, data formulation, and all preprocessing steps leading to the results, please refer to Chapter 4.

5.3.1 Results– Sébastopol x Rivoli counting point

First, this subsection presents the results of the 2x2 DiD analysis for the Sébastopol x Rivoli counting station.

Table 16 shows the results of our first OLS regression analysis. The results are obtained from the code presented in section *3.5.2 2x2 DiD implementation.*

The *Intercept* coefficient of about 1890 vehicles counted per day represents the baseline value in the control group before the treatment. The DiD coefficient indicates a significant decrease of approximately -467 vehicles per day after the treatment, which corresponds to a 23.8% reduction in the number of scooters counted after the treatment on the treated group. This result is statistically significant at the 0.001 level (***), indicating that the observed reduction is unlikely to be due to random variation. The confidence levels of the estimated parameters are indicated by the * symbols, respectively *** for $p < 0.001$, ** for $p < 0.01$, * for $p < 0.05$.

The time coefficient recorded an increase of about +76 vehicles per day, indicating a slight increase for the control group in the months following the ban. The treated group showed a decrease of around -8 units compared to the control group, a low value indicating that there are no significant differences between the control and treatment groups. The p-value of the last two coefficients are not statistically significant, this is not the focus of our analysis, but it should validate the baseline of our model: variation in time and from treated to untreated group does not vary with statistical significance, so this variable doesn't affect the number of scooters at this count point.

DiD regression results summary – Scooters at Sébastopol x Rivoli				
Coefficients	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	1890.08	34.19	55.275	< 2e-16***
Time	75.64	48.36	1.564	0.118
Treated	-8.08	48.36	-0.167	0.867
Did	-466.69	68.39	-6.824	2.21E-11***
Confidence levels: *** p < 0.001, ** p < 0.01, * p < 0.05				

Table 16: DiD regression results summary for scooters at Sébastopol x Rivoli counting point

Table 17 presents additional metrics related to the 2x2 analysis of the Sébastopol x Rivoli counting point, useful to provide more information on the statistical significance of our model, as presented in the section *3.4.4 Key statistical indicators in OLS regression.*

In particular, the analysis highlights a rather low value of R-squared, which should be explained by the nature of the data, with a high value of variances related to external variables and a significant variation in the count from day to day.

Supplementary metrics	
Residual standard error	443.2
Multiple R-squared	0.167
Adjusted R-squared	0.163
F-statistic	39.23

Table 17: DiD regression supplementary metric for scooter ad Sébastopol x Rivoli counting point

This analysis is replicated for bicycles and cars. The complete set of coefficients and metrics can be found in the *Appendix D*. Here, we focus on the key coefficients relevant to our analysis.

Table 18 summarizes the base value, the DiD coefficient, the confidence interval, the number of observations analysed, and the percentage variation, providing a concise overview of the main findings about the main transport modes: scooters, bicycles and automobiles.

The results for this counting station suggest a possible trend following the treatment, namely the prohibition of shared scooters. First of all, as expected, the magnitude of the daily counts differs across vehicle types. The average daily flow for the untreated group before the treatment is approximately 13,697 bicycles per day and 17,308 automobiles per day.

The DiD coefficients, indicating the causal impact of the treatment, highlight a -23.8% decrease in scooters, as expected, with a particularly low p-value, indicating high statistical significance. Regarding bicycles, the DiD coefficient is particularly small, revealing substantial continuity between the pre- and post-treatment periods. Moreover, the coefficient is not statistically significant, suggesting no causal effect of the policy on this group.

Finally, the result for automobiles shows an increase of approximately +4,8%, with a highly significant p-value. This seems to indicate a high probability of a causal effect of the policy on traffic. However, it is worth noting that the magnitude of the increase in automobiles per day (about +819) is larger than the decrease in scooters (-467), pointing to the possibility of other factors, and possibly local conditions, contributing to the rise in automobile traffic. Furthermore, this increase runs counter to the general trend of declining vehicular traffic in Paris (see *4.1 General context of the case study: transport trends in the city of Paris).*

Sébastopol x Rivoli DiD summary results			
Variable	Scooters	Bicycles	Automobiles
Intercept	1890.08	13696.8	17308.05
Time	75.64	640.4	-178.13
Treated	-8.08	1149.6	68.26
Did	-466.69	-292.8	819.39
Did p-value	2.21E-11***	0.60614	2.11E-05***
Percentage variation	**-23.8%**	**-1.9%**	**+4.8%**
Confidence levels: *** p < 0.001, ** p < 0.01, * p < 0.05			

Table 18: Sébastopol x Rivoli DiD summary results

The results of this initial analysis provide us with weighted averages over different periods of interest: before and after the ban on shared scooters, for both the control and treatment groups.

The first observation we can make is that a substantial decrease in scooter use is noticeable on average after the policy implementation, as was already apparent from the trend analysis with the dataset plots. This decrease, while substantial and statistically significant, is however not representing the disappearance of these vehicles. A 23.8% reduction in daily scooter flows suggests that, while there was indeed a decrease, it was not drastic.

On the other hand, the stagnation in bicycle flows and a slight increase in car flows may suggest that the policy had no particularly significant effect on bicycle usage and caused only a slight increase in car usage. However, the increase in car traffic on an axis like Boulevard Sébastopol (considering the characteristics of the site) can likely be attributed to a general recovery of more intense car traffic following the COVID period or other variables.

In conclusion, the results of the DiD analysis for the Sébastopol x Rivoli counting station indicate a significant decrease in the number of scooters and an increase in the number of automobiles counted on Boulevard de Sébastopol, which is a major north-south traffic axis in the hypercenter of Paris (see *4.4.2 Counting point location and characteristics*). However, these findings need be explored further in subsequent analyses.

5.3.2 Results – Flamel x Rivoli counting point

The same analysis was replicated for the Flamel x Rivoli counting station. Table 19 presents the results in a summarized format, as in the previous case. Readers can find the full results in Table 23 in *Appendix D*.

Once again, the magnitude of the different modes of transport varies significantly. Bicycles are the most represented mode at this location on the Rue de Rivoli axis, where a significant portion of the roadway is dedicated to bicycles on the east-west axis. As a result, cars are less represented, precisely because this axis is mainly dedicated to bicycles, while motorists can only enter if they are residents, taxis or other specific categories.

In particular, the results of the Did coefficient highlight a statistically significant decrease in scooters by -16.7%. Bicycles increased by +16.3%, and automobiles by +11.5 %. All results are statistically significant, pointing to a causal effect of the policy on the treated groups.

Flamel x Rivoli DiD summary results			
Variable	Scooters	Bicycles	Automobiles
Intercept	2040.66	12077.1	4730.7
Time	-320.09	-633.9	-544.46
Treated	-574.59	-856.7	-268.77
Did	-191.26	1724.1	449.97
Did p-value	0.00318**	0.000213***	1.42E-11***
Percentage variation	**-16.7%**	**+16.3%**	**+11.5%**
Confidence levels: *** p < 0.001, ** p < 0.01, * p < 0.05			

Table 19: Flamel x Rivoli DiD summary results

The results suggest a pattern similar to that observed at the Sébastopol x Rivoli station. The increase in bicycle usage is significant and statistically meaningful; however, is not drastic, and the number of scooters remains substantial. Car usage appears to increase again; however, it is worth noting that Rue de Rivoli is restricted to taxis, residential vehicles, and other authorized users. Therefore, these flows must be interpreted in the context of the specific traffic regulations for this axis.

In conclusion, the results confirm the decrease in scooters at both counting stations. On the other hand, cars and bicycles show significant increases, seemingly supporting the hypothesis of a substitution effect from scooters to other means of transport, such as bicycles and taxis in this case. These hypotheses will be further explored in the following analyses.

5.3.3 Inclusion of seasonal effects as covariate

This section introduces covariates into the 2x2 linear regression model, and the results are analysed. The covariates are introduced to account for seasonal effects during the winter months, specifically December, January, and February (see *4.7.1 Setting up the dataset*).

Table 20 presents the updated analysis results with the introduction of the covariate for the different modes of transport at the Sébastopol x Rivoli counting station. The covariate coefficient is highly significant, showing a statistically significant decrease in scooters and bicycles, as expected. The use of these modes during winter months is lower compared to the rest of the year. Automobiles, on the other hand, remain constant, with no statistically significant variation.

The DiD coefficient remains almost unchanged compared to the previous results, with a slight decrease in absolute value for scooters and bicycles, showing an approximate decrease of -21% scooters.

Sébastopol x Rivoli DiD summary results			
Variable	Scooters	Bicycles	Automobiles
Intercept	1890.08***	13696.8***	17308.05***
Time	338.06***	2190.0***	-233.21
Treated	-8.08	1149.6**	68.26
Did	-466.69***	-292.8	819.39***
Covariate: season (summer is the base)	-524.84***	-3099.2***	110.15
Did p-value	9.71E-14***	0.58579	2.12E-05***
Percentage DiD variation	**-21.0%**	**-1.7%**	**+4.8%**
Confidence levels	*** p < 0.001, ** p < 0.01, * p < 0.05		

Table 20: Sébastopol x Rivoli DiD 2x2 summary results with covariates

Table 21 similarly presents the results for Flamel x Rivoli. Here too, the covariates highlight a statistically significant decrease in the number of scooters and bicycles during the winter months. In this case, automobiles show an increase, which is statistically significant.

Compared to the model without covariates, the variation in the DiD coefficient remains nearly unchanged, confirming the robustness of the previously developed model.

Flamel DiD summary results			
Variable	Scooters	Bicycles	Automobiles
Intercept	2040.66***	12077.1***	4730.7***
Time	-125.86**	821.9*	-662.25***
Treated	-574.59***	-856.7**	-268.77***
Did	-191.26**	1724.1***	449.97***
Covariate: season (summer is the base)	-388.45***	-2911.7***	235.58***
Did p-value	0.00162**	6.31E-05***	4.58E-12***
Percentage DiD variation	**-14.3%**	**+14.3%**	**+11.8%**
Confidence levels	*** p < 0.001, ** p < 0.01, * p < 0.05		

Table 21: Flamel x Rivoli DiD 2x2 summary results with covariates

For the complete results, the reader can refer to *Appendix D*.

Notably, the inclusion of covariates leads to an increase in the adjusted R^2 values for some models, reflecting an improvement in the explanatory power of the regression. Below in Table 22, we discuss key results and comparisons of adjusted R^2 values before and after the introduction of covariates for different datasets.

The improvement in adjusted R^2 values is particularly notable for scooter models. This highlights the importance of adding variables to capture variations that aren't related to the policy. The values of R^2 have increased, in particular for scooters and bicycles, but are still in the range of around 0.1 to 0.5, highlighting the fact that the model only explains a portion of the variations.

This fact is closely linked to the actual structure of the data, which reflects that of numerous real-world variables that are difficult to explain altogether with a basic mathematical model.

Adjusted R^2 comparison covariate model		
	Adj. R^2	Adj. R^2 cov
Sébastopol scooters	0.163	0.3301
Sébastopol bicycles	0.02221	0.1247
Sébastopol automobiles	0.08016	0.07958
Flamel scooters	0.5108	0.5718
Flamel bicycles	0.01992	0.162
Flamel automobiles	0.2136	0.2516

Table 22: Adjusted R^2 comparison covariate model

5.3.4 Results and limits of the 2x2 case

In conclusion, the results of this section study highlight a significant reduction in the number of scooters following the political decision by the City of Paris to ban shared e-scooters. Based on data from two key counting points located in the hyper-center of the city, this reduction is quantified at approximately **-14-21% of scooter flows,** compared to the natural trend. The statistical significance of this decrease has been demonstrated, confirming that the treatment (the ban) had a causal impact on the number of scooters.

However, this decrease is not considerable as a complete breakdown of this mode of transport. Indeed, as highlighted previously in the monthly trend (see *5.2.2 Monthly trends*), the scooter flows remain in the same order of magnitude after the ban. In the center of Paris, on the two central axis of the city, the decrease in scooter flow is noticeable, but the consistent flows continued after the Paris policy signify that a substantial part of scooter flows are owned vehicles.

Conversely, **bicycles** experienced differing trends across the two locations following the ban. At Rivoli x Flamel, there was an increase of up to **+14%** after the policy was implemented. This increase is consistent with the values indicated in the studies on potential used modes in the absence of shared scooters (see *4.2.2 Type of users and characteristics of e-scooter system before the ban*). This suggests that shared e-scooter users may have changed to cycling in the absence of this mode of transport.

However, Sébastopol x Rivoli counting station did not show any significant change in bicycle usage after the policy. This suggests that the observed decrease of approximately 500 daily scooters recorded at this location after the policy was not offset by an increase in bicycle usage. These trips may have instead been completed on foot, through other modes of transport, or potentially not taken at all.

The study also highlights an approximate **+4-11% in automobile counts**, suggesting a possible causal impact of the policy banning shared scooters on car flows. Notably, the absolute increases in car and bicycle flows during the treatment period far exceed the reduction in scooter counts. This observation indicates that a portion of the increased traffic might be induced or newly generated. This is particularly evident for bicycles at Rivoli x Flamel, aligning with the broader trends in the city, as discussed in the previous chapter (see *4.1 General context of the case study: transport trends in the city of Paris*).

The regression model applied in this study proved instrumental in evaluating the statistical significance of these values across a broad dataset. However, it is important to note that the 2x2 DiD model operates based on average values and does not account for temporal variations within the study period. As a result, the analysis cannot determine whether the observed reduction in scooters occurred immediately after the ban or whether, over time, the number of scooters began to increase again—possibly due to users shifting to privately owned scooters instead of shared ones.

This latter point—whether the decline in shared e-scooters was fully offset by an increase in bicycle usage, as suggested by the initial findings, or whether there was a shift toward privately owned scooters—is a critical question that warrants further investigation. Subsequent section adopt a temporal analysis approach to better capture dynamic changes in transportation patterns and provide a more nuanced understanding of the long-term impacts of such policies.

5.4 <u>DiD application: the temporal analysis approach</u>

This section is dedicated to experimental analysis using the temporal analysis method. Unlike the previous 2x2 case, where it was not possible to specifically determine the temporal trend of the variation in the counted vehicles, this more advanced methodology enables such analysis (for the methodology see *3.4.6 Extended DiD with multiple time periods*).

The initial decision was made to implement the model for all four counting stations with an activation date following November 22, 2022 and working until November 2024 (see *4.4.2 Counting point location and characteristics*).

The counting stations considered are thus as follows:

- Flamel x Rivoli, as previously analysed
- Poissonnière x Montmartre
- Rivoli x Bourdonnais
- Rivoli x Lobau.

The reader will find all references regarding the dataset, the data cleaning processes applied, the weights integrated based on the number of weekday occurrences, and other relevant details in Chapter 4.

In particular, it is important to note that the temporal analysis outputs the Average Treatment Effect on the Treated (ATT) for each specific period. The ATT values are essentially DiD estimates, calculated either with respect to the previous period or, in the treated period, compared to the last untreated period. The selected periods are structured on a monthly basis, covering December 2022 to November 2024, with the control group consisting of the last 12 months and the treatment group covering the first 12 months. Period 1 corresponds to December, January is period 2, and so forth, with November being period 12. Period 1 does not appear in the results, as it serves as the baseline month for calculating the ATT of period 2. All the references mentioned here are explored in further detail in Section *4.7.2 Setting up the dataset for the DiD temporal analysis* .

The results will be presented for each counting station individually as well as in an aggregated format.

5.4.1 Evolution of scooter flows – Temporal analysis

The analysis was first developed for scooters across the four counting stations. The results are presented in both tabular and graphical forms. Specifically, each month is assigned an ATT value along with its 95% confidence interval. In the graphical representation, the y-axis displays the ATT value, which can be either positive or negative depending on the result, while the x-axis represents the corresponding month. The red values correspond to the months prior to the ban on shared scooters, ranging from January (month 2) to August (month 9). The blue values indicate the treated months, from September (month 10) to November (month 12).

The zero ATT value is indicated with a dashed line; if the 95% confidence interval does not intersect zero, the result is statistically significant. If the pre-treatment values are not statistically significant (i.e., the confidence interval includes zero), this reinforces the parallel trend assumption, indicating that the model is more accurate.

The graphical results are presented below, while the tabulated values are provided in *Appendix D.2 Temporal analysis results* for reference.

The results are briefly discussed as follows.

- **Flamel x Rivoli** (Figure 26): the parallel trend assumption is validated for 5 out of 7 periods, as the confidence intervals include zero. In July (month 8), a decrease is observed This decrease is likely attributed to the fact that July 2024 (control period) experienced an increase in alternative transportation modes due to the Olympics, as highlighted in the monthly trend discussion (see *5.2.2 Monthly trends*). During the post-treatment period, the results indicate a significant reduction, with an average ATT of -475 This corresponds to a **-36.4%** compared to the baseline value (period 9). The reader should notice that period 7 is missing. This is because June data are missing due to cleaning activities.

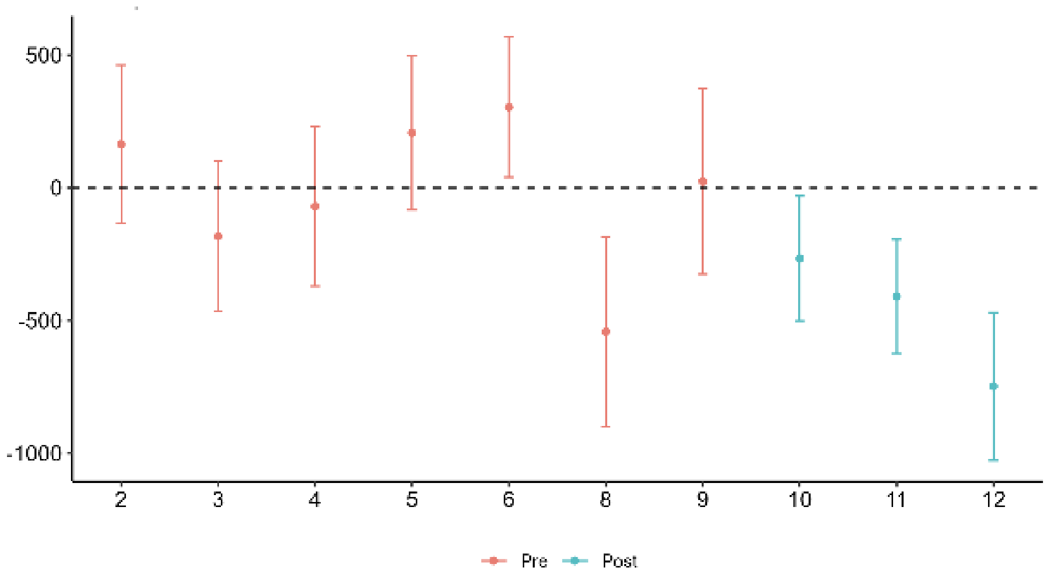

Figure 26: ATT - Scooters at Flamel x Rivoli counting point

- **Rivoli x Bourdonnais** (Figure 27): The parallel trend assumption holds for 8 out of 8 months. ATT values for the treated period are statistically significant in 2 out of 3 months (excluding September). On average, the post-treatment ATT is -572, representing a **-48.3%** compared to the baseline.

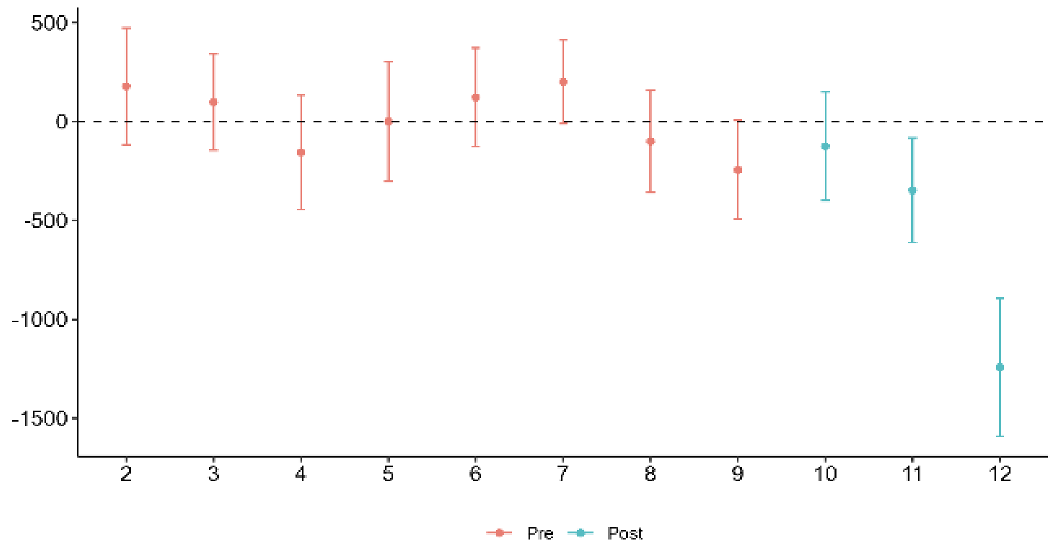

Figure 27: ATT - Scooters at Rivoli x Bourdonnais counting point

- **Montmartre x Poissonnière** (Figure 23): results indicate that the parallel trend assumption is satisfied for out of 6 pre-treatment ATT. The post-treatment results are not statistically significant for any period. The average post-treatment ATT is equal to -122 units, equating to a **-56.7%** from the baseline. The high value for July is probably due to variation within the dataset, the reader should note that June 2024 has only 3 records which may inflate the variations.

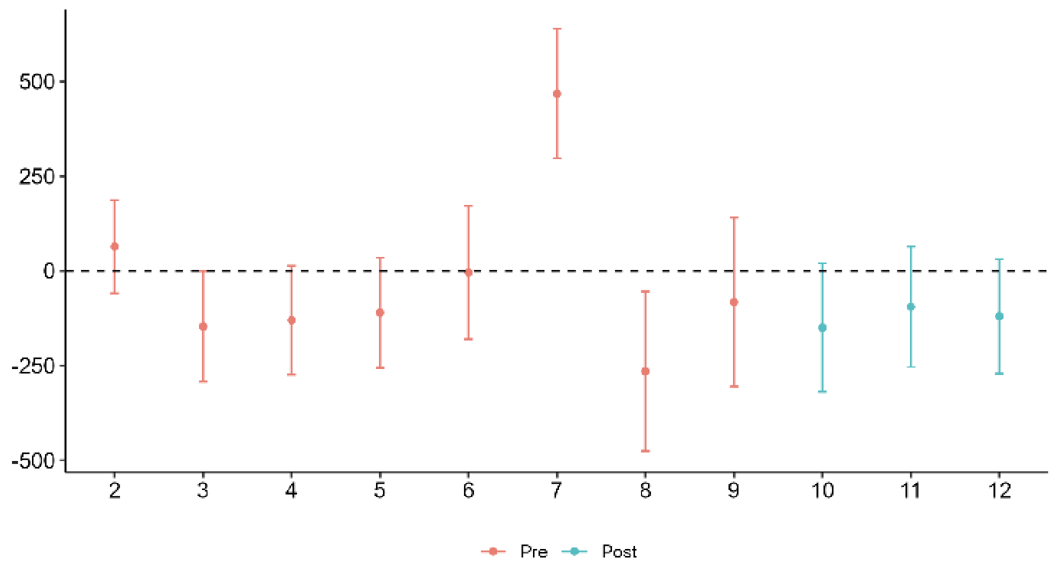

Figure 28: ATT - Scooters at Montmartre x Poissonnière counting point

- **Lobau x Rivoli** (Figure 29): results indicate that for 6 out of 8 pre-treatment months, the values are not statistically significant, ensuring robustness. In the post-treatment period, there is a clear reduction, with all results being statistically significant. The average ATT during this period is -121, corresponding to a **-46.1%** decrease compared to the baseline.

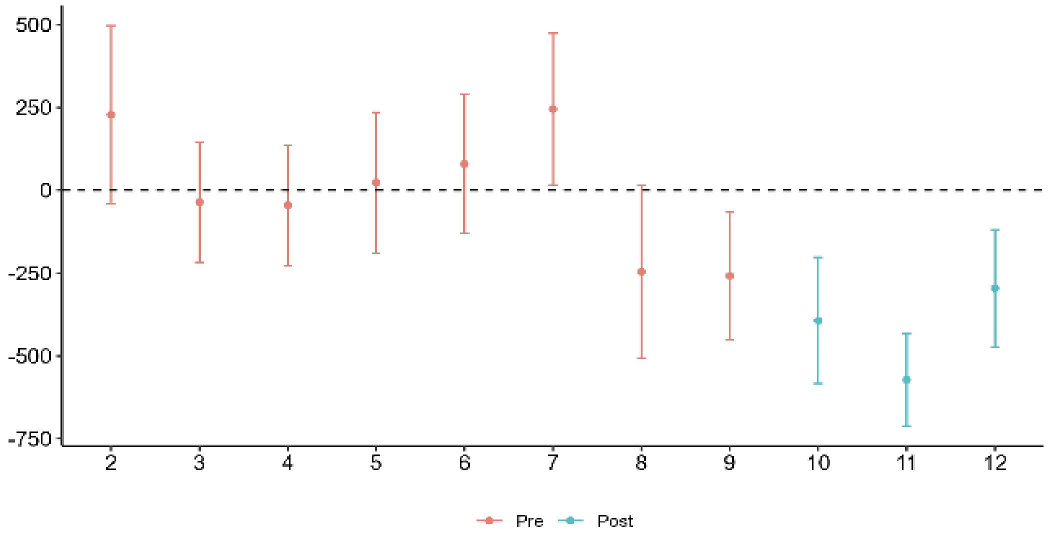

Figure 29: ATT - Scooters at Lobau x Rivoli counting point

In conclusion, in 3 out of the 4 case studies, a statistically significant decrease in the number of scooters is observed, as expected from the policy of banning shared scooters. The decrease appears to have already started in the month of August, highlighting the early removal of scooters prior to the official enforcement date of September 1, 2023.

It is particularly significant that the three stations recording a statistically significant reduction in scooter flows are all located along the Rivoli axis. In these central counting stations, a significant decrease of approximately one third has been observed in comparison with the levels recorded in July or June, which are regarded as the pre-treatment period. This finding is consistent with those obtained from the 2x2 model. The higher results obtained in this analysis can be primarily attributed to the monthly variations, where seasonal trends exacerbate the existing variations.

Conversely, scooter flows remained consistent post-ban, indicating a significant number of scooters in circulation. However, the model is not able to capture variations in subsequent months, which could have provided a more precise understanding of the resurgence in growth observed in the months following the ban, as previously seen in the monthly trends.

Nevertheless, a divergent outcome is observed at the Montmartre x Poissonnière counting station. This station is situated in a less central area in the north-west of Paris, where cycling infrastructure is considerably less developed than along the Rivoli axis. The absence of statistically significant changes in scooter flows at this location indicates that, from one year to the next, or when comparing treated and non-treated years, no substantial variations occurred. This suggests that the removal of shared e-scooters had no impact on scooter usage in this less central axis of Paris.

Several factors could explain these findings. First, it is possible that before the ban, shared scooters were predominantly used in more central areas, such as Rue de Rivoli, compared to Boulevard Montmartre. If shared scooters were more concentrated in the central zone, it would naturally explain why their removal led to a more pronounced decline in scooter flows in that area.

Additionally, another hypothesis could be linked to the substitution effects associated with e-scooters. As highlighted in Section *2.5 Difference-in-differences method applied to shared e-scooter* studies, researchers have identified different relationships between shared e-scooters and other modes of transport. In particular, usage patterns vary depending on the area of the city. In central areas, shared e-scooters primarily replace other transport modes, such as cycling or public transit, whereas in less central areas, they tend to serve mainly as complementary modes of transport.

This distinction suggests that after the ban, the significant decline observed in central areas was likely absorbed by other modes of transport, as former e-scooter users shifted to alternative mobility options. Conversely, in less central areas, where shared e-scooters played a less substitutable role, users may have opted to switch to privately owned e-scooters instead. This hypothesis will be further examined in relation to the results observed for other modes of transport.

Finally, the aggregated results are presented in Figure 30, showing the data consolidated by mode rather than by individual site. The pre-treatment results indicate that in 5 out of 8 cases, the confidence intervals intersect with zero, validating the parallel trend assumption. In addition, the 3-month period from September to November are statistically significant, demonstrating a clear decline in the number of units, with an average daily decrease of **-490 units** and a corresponding decrease of **-46.8%** compared to August.

However, it is crucial to acknowledge the fact that three out of four counting stations that contributed significantly to this decrease are located on the same axis, and the Montmartre x Poissonnière counting station recorded comparatively limited flows in relation to the others. Furthermore, it has been observed that the decline in the utilisation of scooters commenced in July and August, indicating that operators initiated the retirement of shared e-scooters prior to the imposition of the ban, as previously mentioned.

In conclusion, the overall number of scooters in circulation decreased following the implementation of the ban, as demonstrated by the statistical model that was employed to analyse the impact of the policy on the overall number of e-scooters. However, as previously mentioned, the decline is not absolute, with consistent numbers of scooter flows continually recorded in the month subsequent to the ban. Consequently, it can be concluded that the decision of the City of Paris to ban shared e-scooters has led to a significant reduction in the number of recorded scooters on one of the city's main central axes, although this overall effectiveness is moderate due to the continued use of privately owned scooters, particularly in the less centralised counting point where no decrease was noticed.

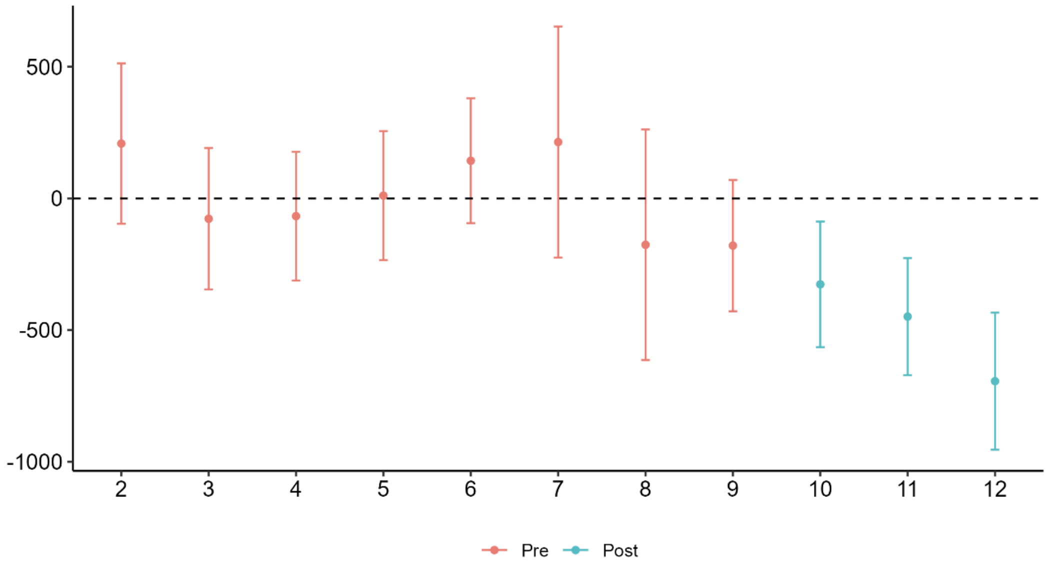

Figure 30: ATT - Aggregated results for scooters

5.4.2 Evolution of bicycle flows – Temporal analysis

The analysis of bicycles for the various counting stations is presented as follows.

- **Flamel x Rivoli** (Figure 31): all values prior to September intersect with zero, indicating no statistically significant variation. For the post-treatment period, there is a statistically significant increase in the number of bicycles for 1 out of 3 periods, however a general upward tendency is noticeable. The average ATT post-treatment is of +2956 units per day, corresponding to a **+28.7 %** to the baseline value. Period 7 is missing due to the lack of data for June, as presented in the previous chapter.

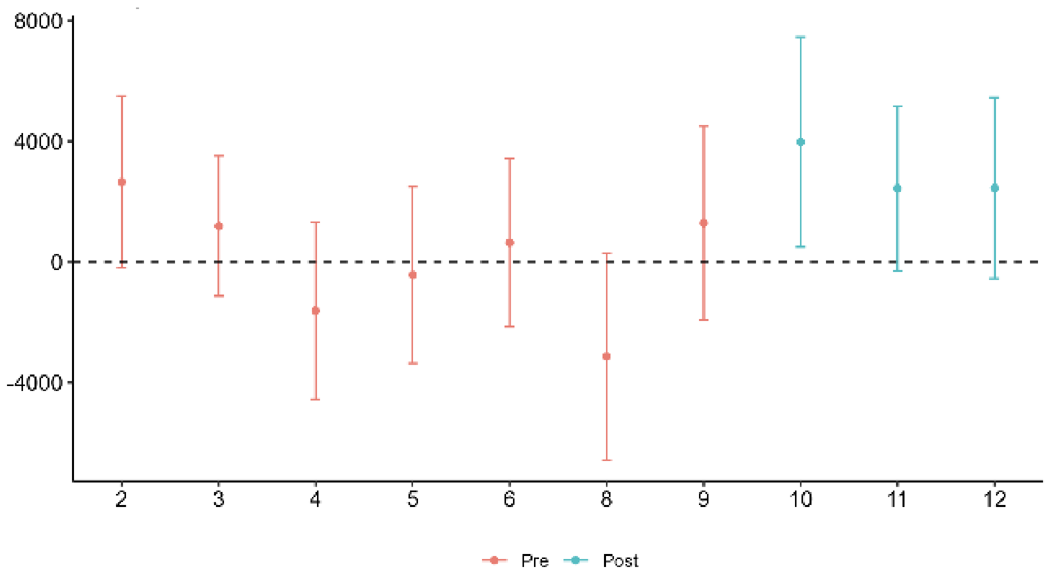

Figure 31: ATT - Bicycles at Flamel x Rivoli counting point

- **Rivoli x Bourdonnais** (Figure 32): one value is statistically significant in the post-treatment period. The average ATT post-treatment is of +1580 units per day, corresponding to a **+14.0 %** to the baseline value, demonstrating a general upward tendency.

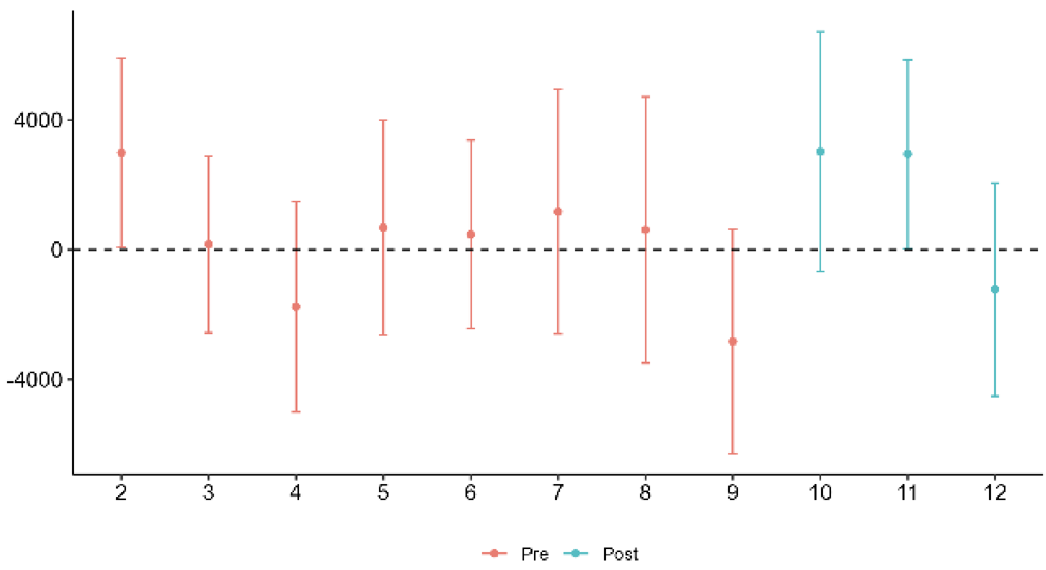

Figure 32: ATT - Bicycles at Bourdonnais x Rivoli counting point

- **Poissonnière x Montmartre** (Figure 33): the values are not statistically significant. The average ATT post-treatment is of -75 units per day, corresponding to a **-2.6 %** to the baseline value. In fact, no particular changes can be detected from this station. Period 9 is missing due to a lack of data for August.

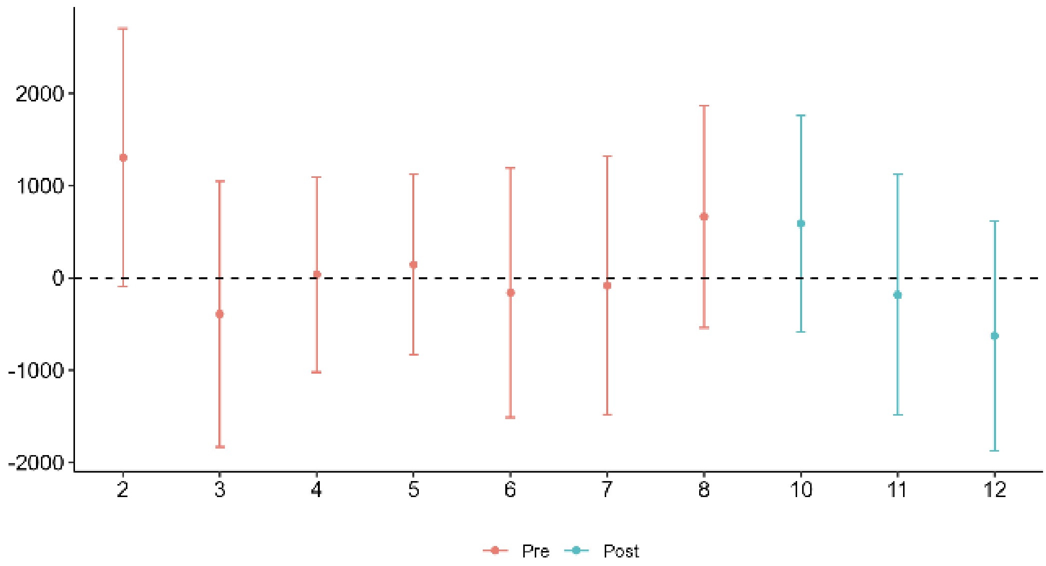

Figure 33: ATT - Bicycles at Montmartre x Poissonnière counting point

- **Rivoli x Lobau** (Figure 34): the values are not statistically significant. However, there is a more pronounced increase in bicycle counts for December. The average ATT post-treatment is of -46 units per day, corresponding to a **-0.4 %** to the baseline value, highlighting a overall stable tendency. Period 7 is missing due to lack of data.

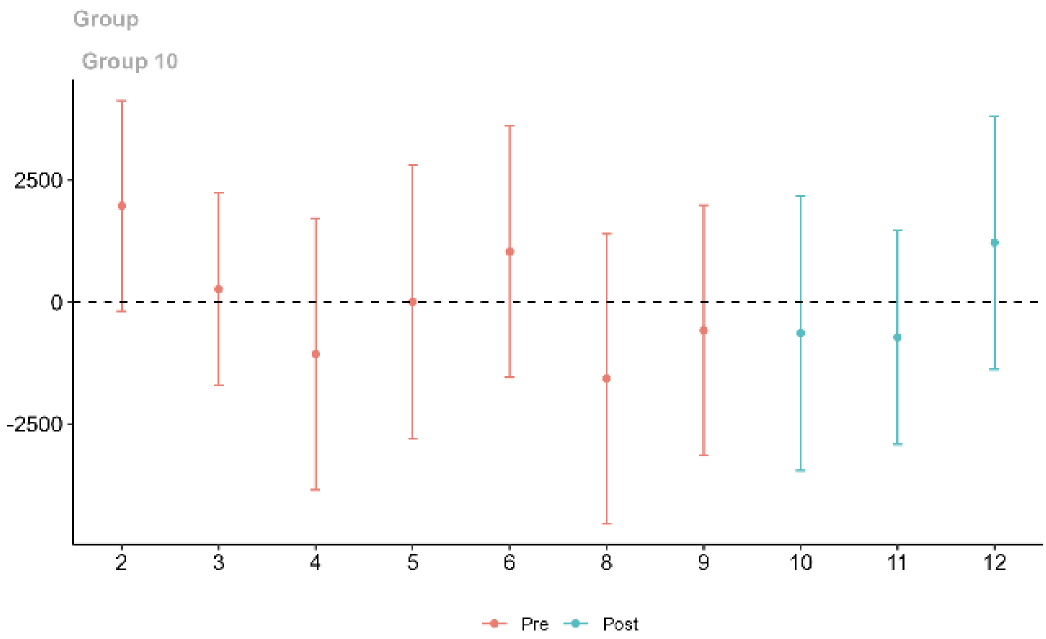

Figure 34: ATT - Bicycles at Lobau x Rivoli counting point

In conclusion, the variations in bicycle counts appear to be less pronounced and more challenging to detect. Overall, there is a general trend of increased bicycle usage, with one counting station—Flamel x Rivoli—showing a significant increase. The other three stations do not present clear trends, apart from a slight overall increase that is more noticeable compared to any specific decreases. While the values are not always statistically significant, they suggest an upward trend in bicycle usage during the post-treatment period.

In particular, the low values observed in periods 9 and 8 (corresponding to August and July, respectively) are likely influenced by the Olympics, as discussed in the section on monthly trends. The upward trend observed in the summer of 2024, which serves as the control group in our analysis, results in a lower estimated reduction during the treatment period.

As demonstrated in the scooter case study, a discernible discrepancy emerges in the comparison of the Rue de Rivoli and Boulevard de Montmartre counting points. Specifically, an upward trend is observed in the former, though it is not in every case statistically significant. In contrast, the Montmartre counting point, situated in less central areas, reveals that the ban appears to have no discernible impact on the number of bicycles, which remains relatively constant compared to the control year, indeed, decreasing. This finding lends support to the hypothesis that shared e-scooters were primarily utilised along the Rivoli axis. Consequently, the ban likely forced users to shift to alternative modes, such as cycling. In the most central areas, a noticeable substitution effect between e-scooters and bicycles can be observed.

Conversely, at the Montmartre counting point, which is located in a less central area with limited cycling infrastructure, bicycle flows do not appear to have been significantly affected by the policy.

Figure 35 presents the aggregated results for cycling across the four counting stations. The results indicate an average ATT of **+1,508**, corresponding to a **+13.8%** increase compared to August. The upward trend along the Rue de Rivoli axis is clearly evident, although none of the values are statistically significant. This is likely due, on the one hand, to the relatively small number of e-scooters compared to bicycle flows. On the other hand, the ban on shared e-scooters may have influenced other transportation modes in the area in a less consistent manner.

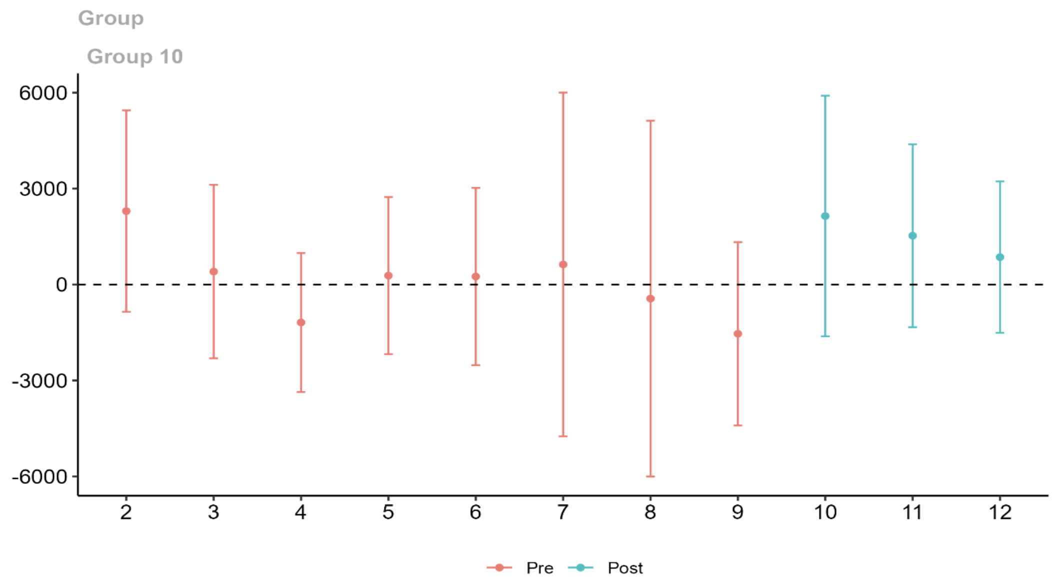

Figure 35: ATT - Aggregated results for bicycles

5.4.3 Evolution of automobile flows – Temporal analysis

The analysis concludes with the evaluation of automobile counts.

- **Flamel x Rivoli** (Figure 36)**:** none of the values after treatment are statistically significant, although a slight increase is observed during the post-treatment period. The average ATT post-treatment is of + 79 units per day, corresponding to a **+ 2.0%** to the baseline value. The reader should note that period 7, June, is missing due to lack of data. In addition, the low peak in July, as in the bicycle analysis, should be related to the impact of the Olympic Games.

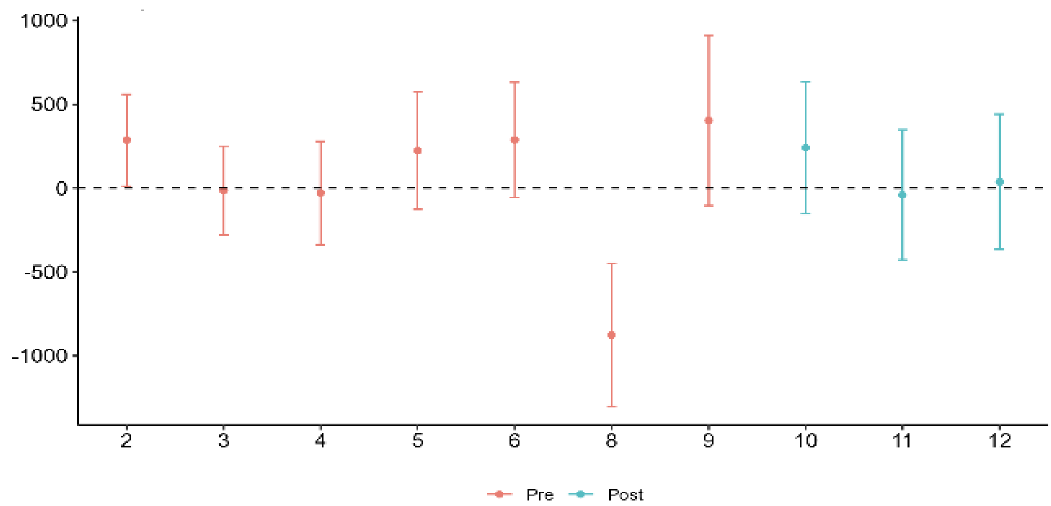

Figure 36: ATT - Automobiles at Flamel x Rivoli counting point

- **Rivoli x Bourdonnais** (Figure 37)**:** three over seven ATT values in the pre-treatment period satisfy the parallel trends assumption, indicating notable variations during the summer months, potentially related to the Olympics. The average ATT post-treatment is of -1079 units per day, corresponding to a **-25.2%** to the baseline value, with 3 ATT values over 3 statistically significant. Period 9 is missing due to lack of data.

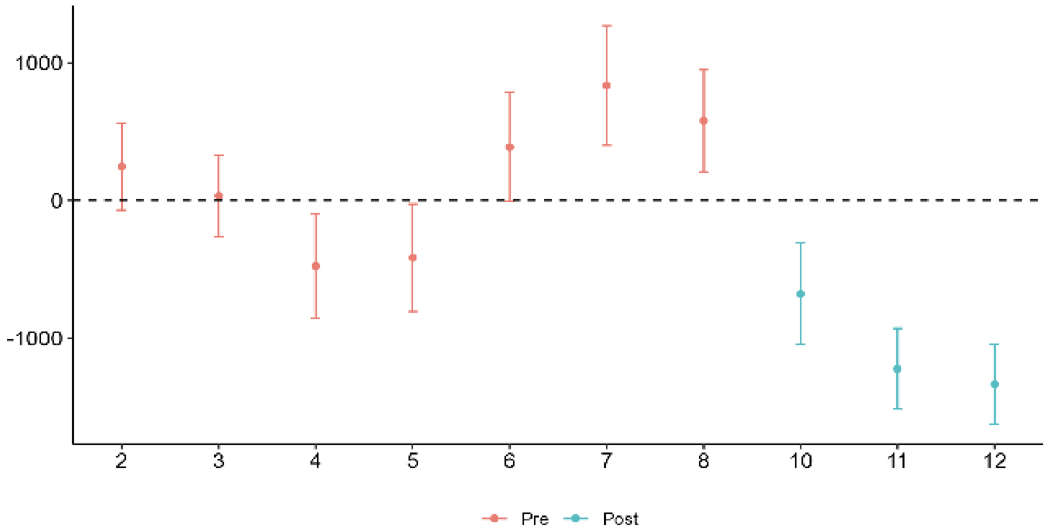

Figure 37: ATT - Automobiles at Bourdonnais x Rivoli counting point

- **Montmartre x Poissonnière** (Figure 38)**:** in the post-treatment period, a decrease in automobile flows is observed, and it is statistically significant in 2 out of 3 periods. The average ATT post-treatment is of -1274 units per day, corresponding to a **-8.7 %** to the baseline value. Periods 9 is missing due to lack of data, which is particularly relevant for this specific analysis.

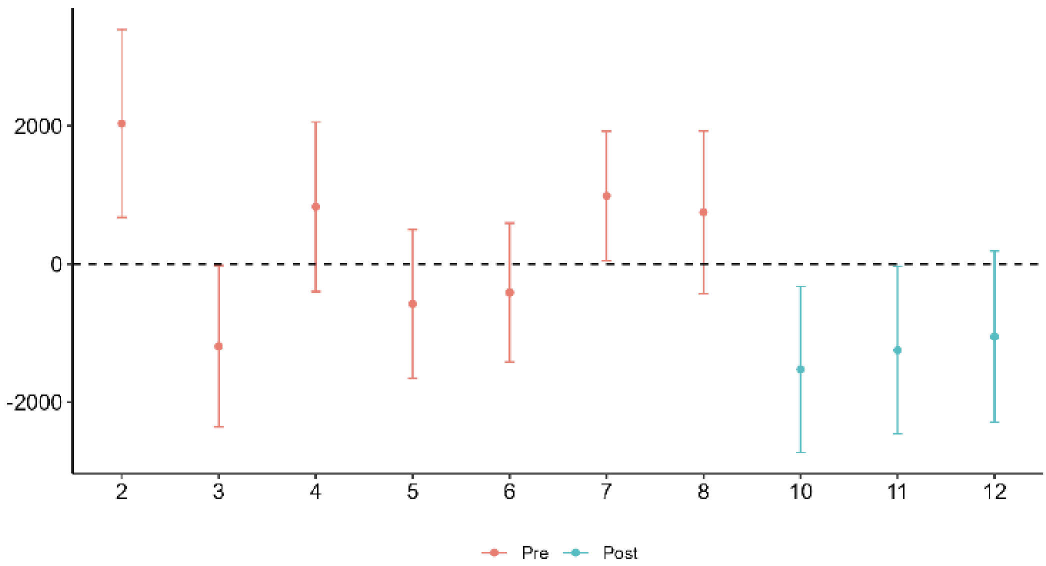

Figure 38: ATT - Automobiles at Montmartre x Poissonnière counting point

- **Lobau x Rivoli** (Figure 39)**:** there is a general tendency to decrease from the treatment periods, with 2 out of 3 ATT values not intercepting zero, indicating statistical significance. e The average ATT post-treatment is of -638.1 units per day, corresponding to a **-18.1 %** to the baseline value.

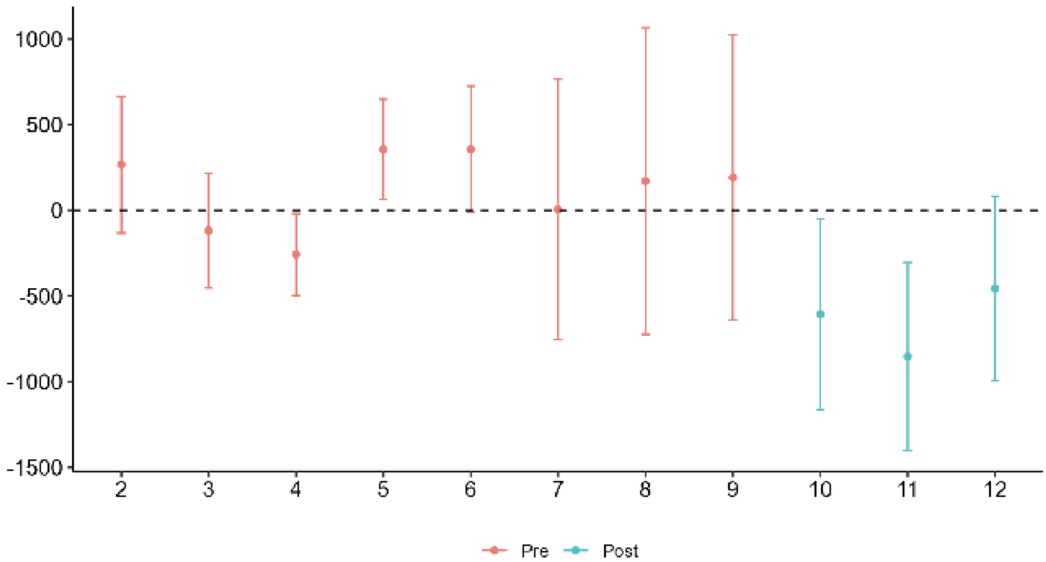

Figure 39: ATT - Automobiles at Lobau x Rivoli counting point

The results for automobiles are more challenging to interpret, as significant variations occur across different months without a clear trend. It is important to recall that access to Rue de Rivoli is restricted to certain vehicles, such as taxis, residents, and a few other authorized users. Additionally, as highlighted in the monthly trends, Rue de Rivoli served as an open lane for Olympic athlete vehicles during the Games. A general decrease on automobile flows can be observed along stations, albeit without particular consistent trends.

In Boulevard Montmartre, which we recall is a major road axis in Paris with relatively high vehicle flows, there is a general decrease in the latter, although again the results are not statistically significant.

Figure 42 presents the aggregated results for automobiles. They show a decrease of **-606 vehicles** in average, equivalent to **-7.3%**, yet none of these values reach statistical significance. This suggests that the ban on shared e-scooters had no significant impact on automobile flows. Several factors could explain this outcome.

First, the substitution effect between shared e-scooters and automobiles appears to be minimal. As highlighted in Chapters 2 and 4, in European cities with well-developed public transportation networks and relatively low car dependency, shared e-scooters typically do not replace car trips to a significant extent. Additionally, prior to the ban, user surveys in Paris indicated that only a very small percentage of shared e-scooter riders would have opted for a car in the absence of this service.

Moreover, the data from Rue de Rivoli is highly specific due to its access restrictions, making it difficult to draw generalizable conclusions about automobile usage patterns. Lastly, the relatively low modal share of shared e-scooters within the overall transportation system in Paris further complicates the identification of clear trends. In conclusion, no distinct causal impact of the policy on automobile flows has emerged. However, this result is strongly influenced by the unique characteristics of central Paris, where sustainable modes of transport already dominate the modal share.

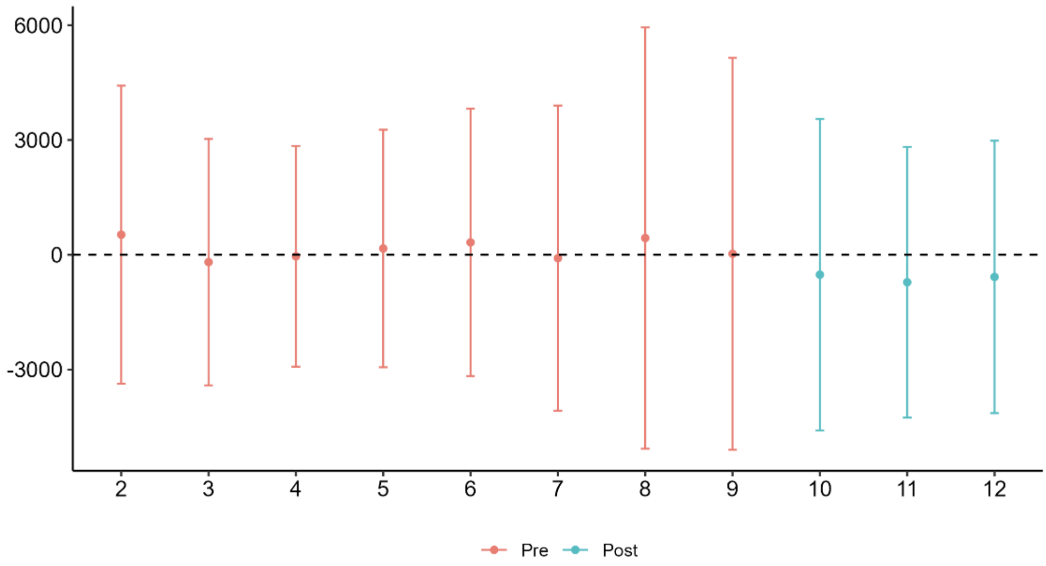

Figure 40: ATT - Aggregated results for automobiles

5.4.4 Results and limits about the temporal analysis approach

The ATT results have shown an overall decrease in scooter daily flows, with a reduction attributed to the policy. This decrease is evident at the Rue de Rivoli counting station, a central axis of the city in the hypercenter dedicated mainly as a cycle path. In this axis, the reduction of daily weighted flows is in the order of -36% to -57%.

Meanwhile, these counting stations noticed a slight increase in bicycle counts. On one hand, the growth in bicycle usage may be partially explained by seasonal variations and the general trend of increased bicycle adoption in Paris. However, the parallel trend assumption (values before treatment) indicates no significant variation in bicycle counts prior to the policy's implementation. Post-treatment, the counting stations recorded an anomalous increase in bicycle counts, exceeding the typical pre-treatment variations. Notably, Rivoli x Flamel observed a 28.7% increase, while Rivoli x Bourdonnais saw an 14,0% rise in bicycle counts. However, Rivoli x Lobau recorded a minimal change of -0.4%.

In conclusion, the aggregated findings highlight an anomalous increase in bicycle counts after the treatment, suggesting a causal effect of the policy on the rise in bicycle usage. This indicates that the ban on shared scooters may have contributed to a modal shift toward bicycles in the main central areas of the city.

However, a different trend emerges from the Montmartre x Poissonnière counting station, located in a less central area of the city and with lower infrastructure dedicated to cycle paths compared to automobiles. From this counting station, no significant variations are noticed both for scooters and bicycles, with an increase of scooters and a decrease for bicycles. The decrease in scooters whether important in percentage (around 56% of the baseline) no statistical significance has been noticed, indicating a relative impact of the policy, whether a possible seasonal impact. The non-statistically significant results for this more peripheral counting station may suggest that the policy impacted different areas of the city in distinct ways.

One possible explanation is related to the higher presence of shared scooters in central areas, like Rue de Rivoli, suggesting that their usage was more concentrated in the main city center prior to the ban, and former users shifted to other modes of transport such as bicycles. Another explanation is related to transport patterns and the substitution effect, as highlighted in Chapter 2. In most central areas, e-scooters have a competitive role with other modes of transport, such as bicycles and public transit. In less central areas, the role of e-scooters is more related to complementarity. In this way, another hypothesis is the tendency of former shared e-scooter users to own private scooters, as emerged from the trend.

Automobile analysis has yielded contradictory results across various counting stations, with the findings generally failing to reach statistical significance. Rivoli x Bourdonnais and Lobau x Rivoli counting station exhibited a decrease in daily weighted flows, both statistically significative. This support the idea of a potential reduction in car usage in this area. In contrast, Flamel x Rivoli showed slight increases in automobile counts, but these were not statistically significant. Montmartre x Poissonnière showed a marginal decrease that was also not statistically significant.

In summary, the policy banning shared scooters appears to have effectively reduced immediately following the ban scooter counts in the treated areas, with reductions exceeding 50% in some locations. Aggregated results show a -46.8% reduction in scooters, a +13.8% increase in bicycles, and a -7.3% decrease in automobiles. Simultaneously, the upward trend in bicycle counts suggests a partial shift toward sustainable transportation modes.

The findings indicate a decline in scooter usage in central areas concomitant with a increase in bicycle usage in relation to the ban. Conversely, less central areas do not exhibit a significant decline in scooter usage, suggesting that the policy may have had a limited impact in these locations. Notably, the prohibition on shared e-scooters has had a substantial effect on scooter usage, though not to the extent of a complete cessation. A significant proportion of users appear to have transitioned to private scooters, with a modest increase observed at select measurement points.

It is important to note the limitations of this analysis. In particular, apart from strong trends directly affecting scooters, no clear and general trends emerged from the analysis. There are many reasons for this. First of all, the limited scope of the policy on scooter but also general traffic flows. In addition, the real-world data and the limited quantities related to shared e-scooters in other traffic flows.

Moreover, while the analysis highlights interesting trends, the results are influenced by the granularity and scope of the available data. For instance, the data lacks detailed insights into individual behaviours, such as trip purposes or modal preferences, which could provide a more nuanced understanding of the observed trends.

6 Conclusions

This thesis focused on studying the impact of the City of Paris' decision to ban shared e-scooters starting from September 1, 2023. Specifically, our analysis centred on open-source data provided by the City of Paris regarding vehicle counts at some key locations within the French capital.

Through an analysis of these data trends and with the support of the difference-in-differences (DiD) technique, which allowed us to robustly and replicably compare pre- and post-ban data, several significant trends were identified. First, the reduction in the number of scooters, with decreases ranging from 10% to 50% of the daily weighted flows, highlights the substantial contribution of shared e-scooters to the overall population of scooters in circulation. Nevertheless, this decrease is not as drastic as expected, and statistically significant decreases were observed mainly in central counting stations, whether a general increase was observed by quarterly trends for 2024. In contrast, the less central counting station showed a lower impact from the policy, with no significant change in scooter numbers and even an increase.

The analysis also observed an increase in bicycles at the same counting stations located in most central areas, ranging from slight increments to up to around 30% at certain location. The results were statistically significant for some stations, and even where not, the values were still higher than the average. This finding suggests that the policy banning shared e-scooters prompted an increase in bicycle flows, with a strong likelihood of causality for at least part of the observed changes in central areas. This result—that users without access to shared e-scooters likely turned to bicycles (presumably also in shared systems)—supports literature demonstrating that, in the absence of shared e-scooters, a percentage of users would switch to bikesharing. A substitution effect with bicycles emerged in central areas, where the transport network is dense, and general traffic roads are limited.

Conversely, in less central areas, the policy had no significant impact, indicating that shared e-scooters were less prevalent, and users tend to rely more on private scooters—a trend that continues to grow. These findings are generally consistent with the existing literature, which highlights substitution effects in highly central areas, proportional to the presented modal share, and a more complementary role in less central areas, where shared e-scooters may have been used for last-mile trips. This could explain why, in central Paris, e-scooters were partially replaced by bicycles, whereas in less central areas, this substitution effect did not occur.

In this regard, the decision to ban shared e-scooters did not fully achieve the municipality's objectives. While the number of shared scooters has decreased, the overall scooter flows in the analysed counting stations continues to rise.

On the other hand, no clear trend emerged for automobiles, with contradictory results across different counting stations. On average, there was a slight decrease in automobile counts, but these results were not statistically significant and may be due to random variation. One possible avenue for further research could involve better understanding the relationship between e-scooter users and vehicular traffic.

In conclusion, the analysis of Paris' open-source vehicle data revealed a decline in e-scooter usage in central areas, quantifying a significant reduction in the number of shared e-scooters in circulation. The model showed that in central areas the number of e-scooters decreased while the number of bicycles generally increased, suggesting that former users switched to other alternatives. The results also show local patterns, particularly between more central and more peripheral counting stations. The policy appears to have a mitigating effect on the impact of the e-scooter, which can be attributed to the relatively high number of owned e-scooters. Furthermore, the policy appears to have a relatively low impact on the overall transportation trends. The increase in bicycle usage, which has been observed, can be partly attributed to the ban, despite the fact that this shift occurs in the main city centre, where the number of other shared options remains particularly high. Such a dynamic, however, depends on the presence of robust cycling infrastructure, as found in the center of Paris.

Some limitations of this study do not allow for broader or sharper conclusions. First and foremost, the number of counting stations with useful data is very low, therefore they could not be fully representative of the entire network, thus capturing only local trends within the city. Moreover, these results must be interpreted in light of variations in other modes of transport, as there is no clear distinction between shared and private modes, no inclusion of pedestrian counts, and no detailed differentiation of the counting stations. Additionally and more broadly speaking, the unique case of Paris, with its specific urban transport policies, city size and travel demand characterised by the high share of tourists and visitors, may not guarantee replicability in contexts with smaller urban areas or different transportation dynamics.

Ultimately, this analysis provides valuable insights into the changes in transportation patterns following the ban of a transport mode, offering tools for analysing similar cases and contributing to the discourse on this unique international example of prohibition. Numerous avenues for further research remain open. A broader database would allow for access to more detailed and comprehensive data across the network. Investigating the long-term effects of the ban, including potential increases in the use of privately owned scooters, is another important topic. Additionally, comparing Paris to other international cities that have terminated shared services or implemented similar restrictive policies would provide further insights. The DiD technique has proven to be a robust tool for such comparative studies.

This analysis can also be expanded to address environmental impacts, effects on safety and accident rates, infrastructure-related issues, and the relationship between shared and public transport systems. Such extensions could provide a more comprehensive understanding of the interplay between shared mobility systems and urban environments.

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Appendix A. Counting stations characteristics.

The following section shows some frames taken by the thermal cameras installed for each of the vehicle counting points mentioned in the Section *4.4.1 On-site equipment and data format*.

The images presented in this section, alongside the primary data used in this study, are provided as part of the open-source material released by the City of Paris. The dataset is referenced as follows: Ville de Paris. (2024). Comptage multimodal (Vélo, Trottinette, 2RM, VL, PL, Autobus-car)—Comptages—Paris Data. https://opendata.paris.fr/explore/dataset/comptage-multimodal-comptages/information/).

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Figure 41 represents a thermal camera picture from the Poissonnière x Montmartre counting point. The starting detection zone is highlighted in blue, while the counting zone is indicated by the yellow rectangle. The 1, 2 zones are general traffic lanes, and the 3 zone is the designated cyclable path.

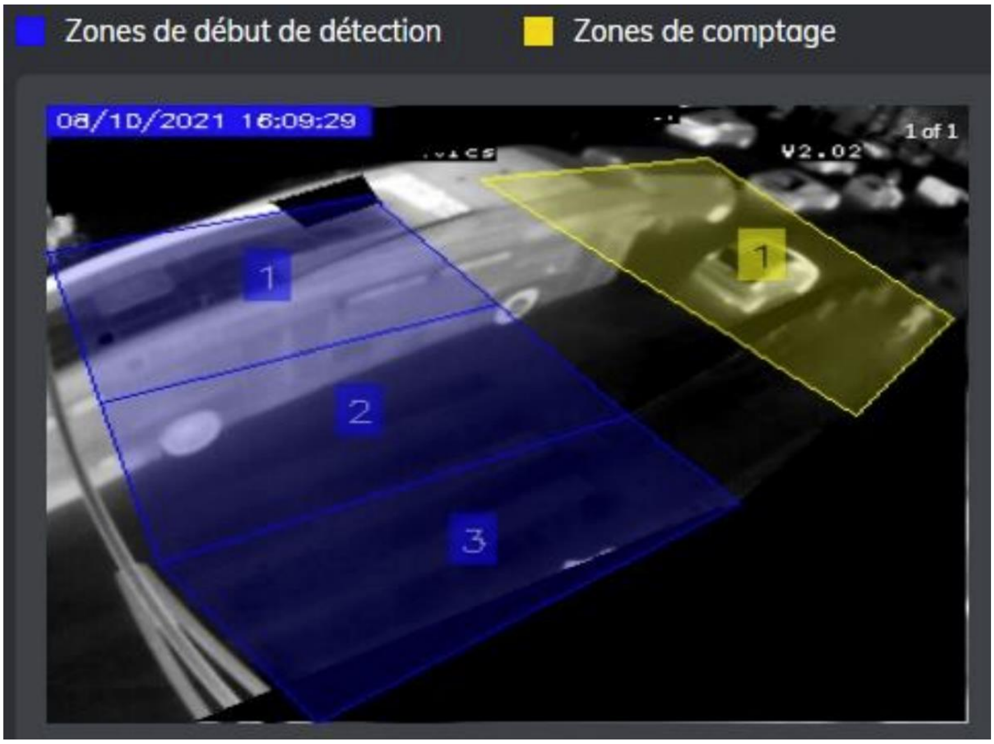

Figure 41: Poissonnière x Montmartre counting site. From Ville de Paris (2024).

The Figure 42 is a frame of the Rivoli x Bourdonnais counting site The yellow quadrilateral elements represent the counting zones. The number 1 is the general traffic lane, the number 2 is a cycle path, called a "coronapiste" due to its creation during the period of the coronavirus pandemic (see *4.1 General context of the case study: transport trends in the city of Paris*), and the other lane of the cyclable path.

Figure 42: Rivoli x Bourdonnais counting site. From Ville de Paris (2024).

In the same way of the previous figure, the Figure 43 represents the Rivoli x Nicolas Flamel counting site, with the cyclable path (number 1 and 2) and the reserved lane for authorized cars busses, delivering vehicles, etc. In Figure 44 is presented a frame of Rivoli x Lobau counting point, with the same infrastructure configuration of the previous figure.

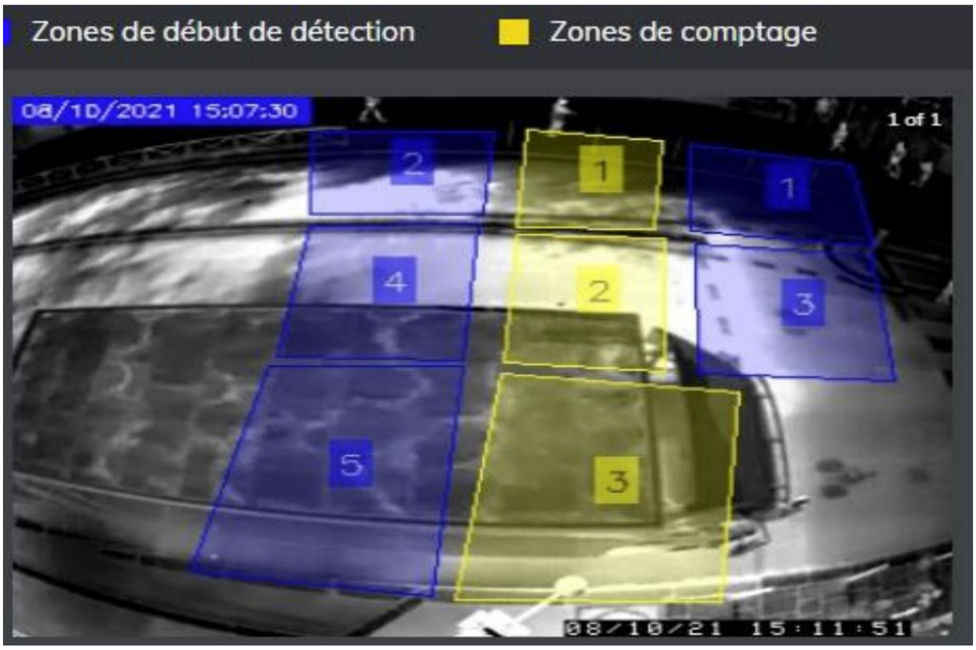

Figure 43: Rivoli x Flamel counting site. From Ville de Paris (2024).

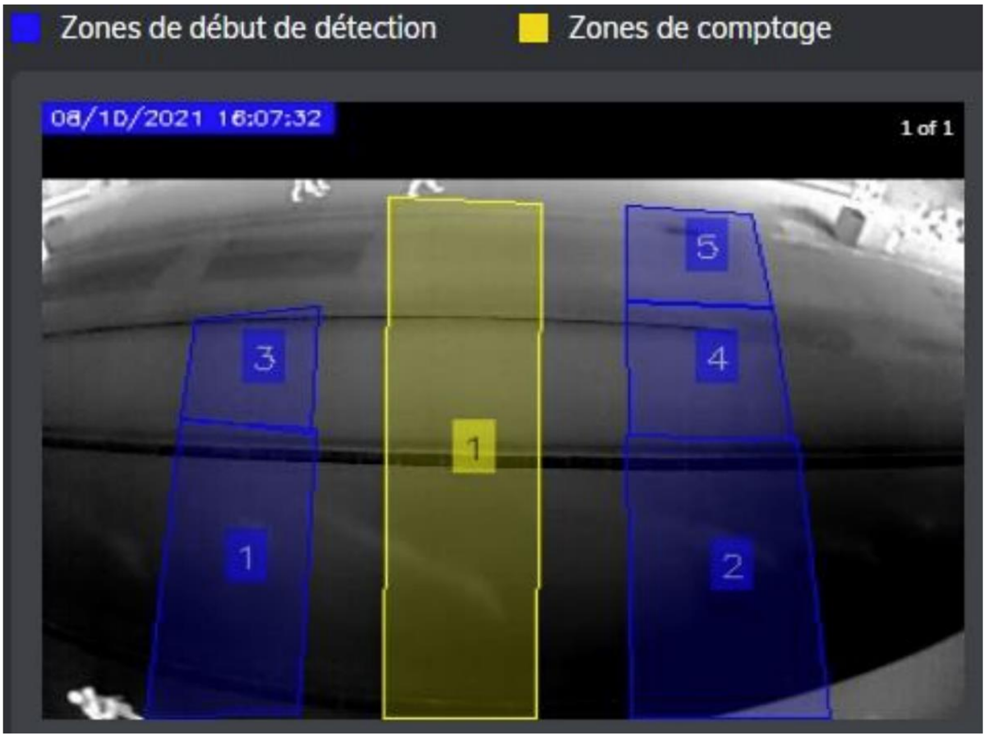

Figure 44: Rivoli x Lobau counting site. From Ville de Paris (2024).

The last image, Figure 45, is a frame captured from Rivoli x Sébastopol counting point, with a unidirectional cyclable path, number 2 in yellow, and two general traffic lanes, number 1 in yellow.

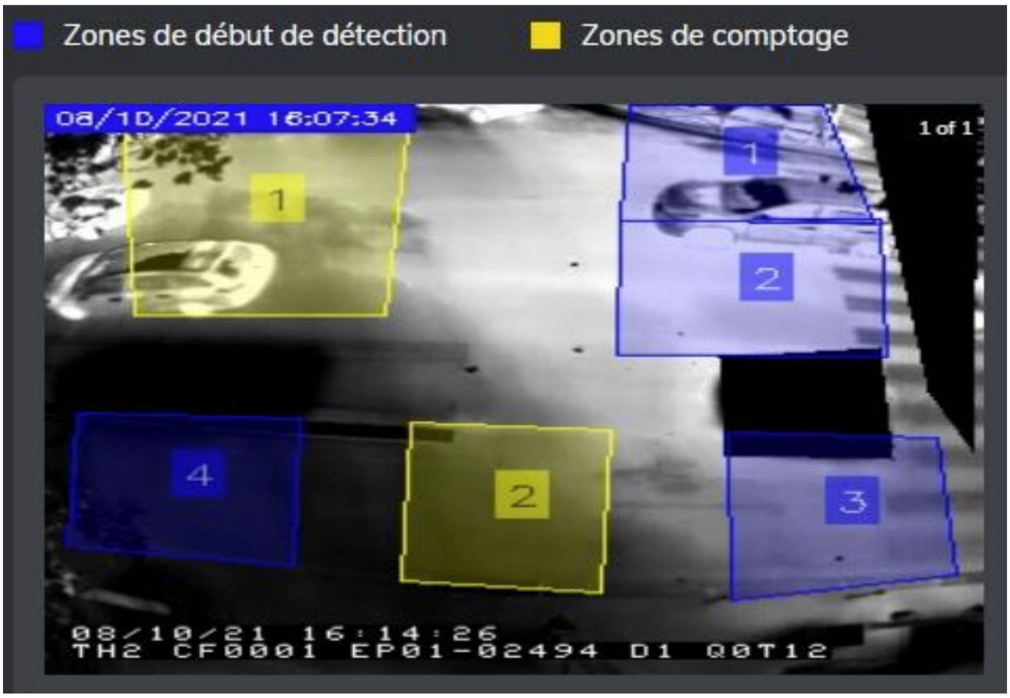

Figure 45: Rivoli x Sébastopol counting site. From Ville de Paris (2024).

Appendix B. Elbow method complete results.

Appendix B is dedicated to the presentation of the results of the data cleaning activities, using the Elbow method (*see 3.2 Data cleaning methodology* and *4.5.5 Application of the elbow method for cleaning activities*). Figure 46 represents the elbow graph results for Monmartre x Poissonnière counting station for automobiles. Respectively: Figure 47 for Monmartre x Poissnnière bicycles; Figure 48 for Montmartre x Poissonnière scooters; Figure 49 for Rivoli x Lobau automobiles; Figure 50 for Rivoli x Lobau for bicycles; Figure 51 for Rivoli x Lobau scooters; Figure 52 for Sébastopol x Rivoli automobiles; Figure 53 Sébastopol x Rivoli bicycles; Figure 54 Sébastopol x Rivoli scooters; Figure 55 Rivoli x Bourdonnais automobiles; Figure 56 for Rivoli x Bourdonnais bicycles; Figure 57 for Rivoli x Bourdonnais scooters; Figure 58 for Rivoli x Flamel automboiles; Figure 59 for Rivoli x Flamel bicycles; Figure 60for Rivoli x Flamel scooters.

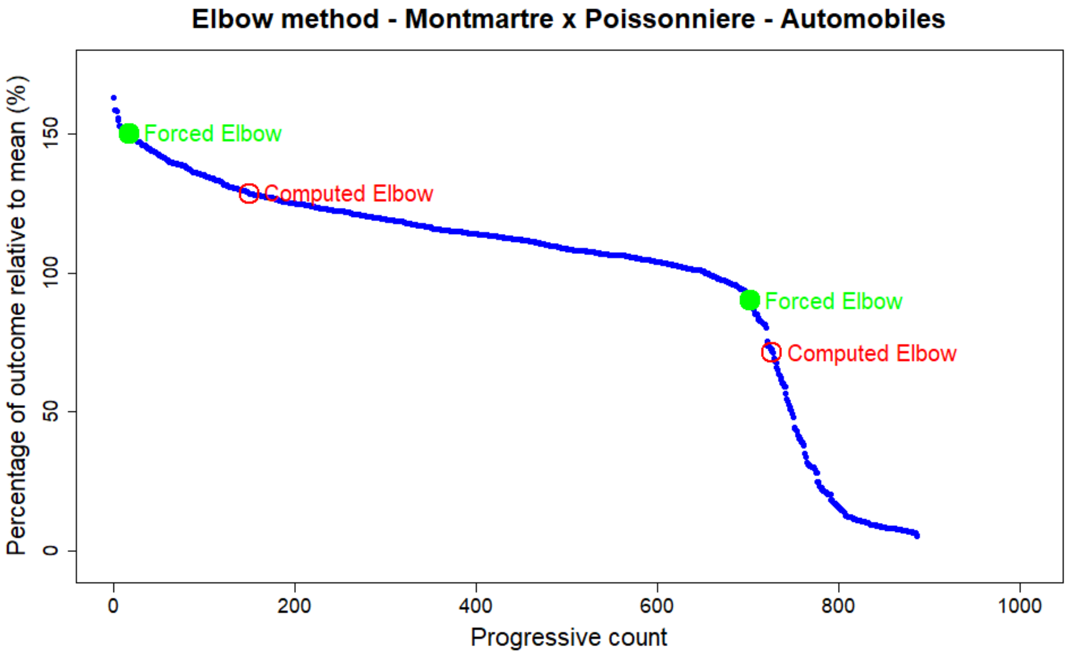

Figure 46: Elbow method analysis applied for daily flows at Montmartre x Possonnière for automobiles

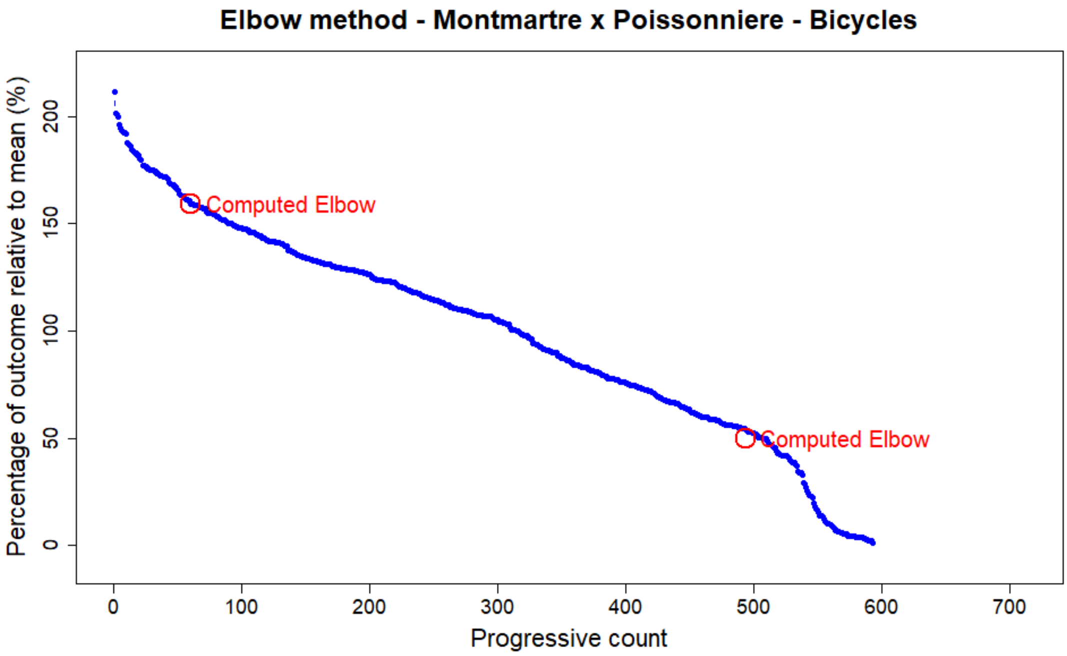

Figure 47: Elbow method analysis applied for daily flows at Montmartre x Possonnière for bicycles

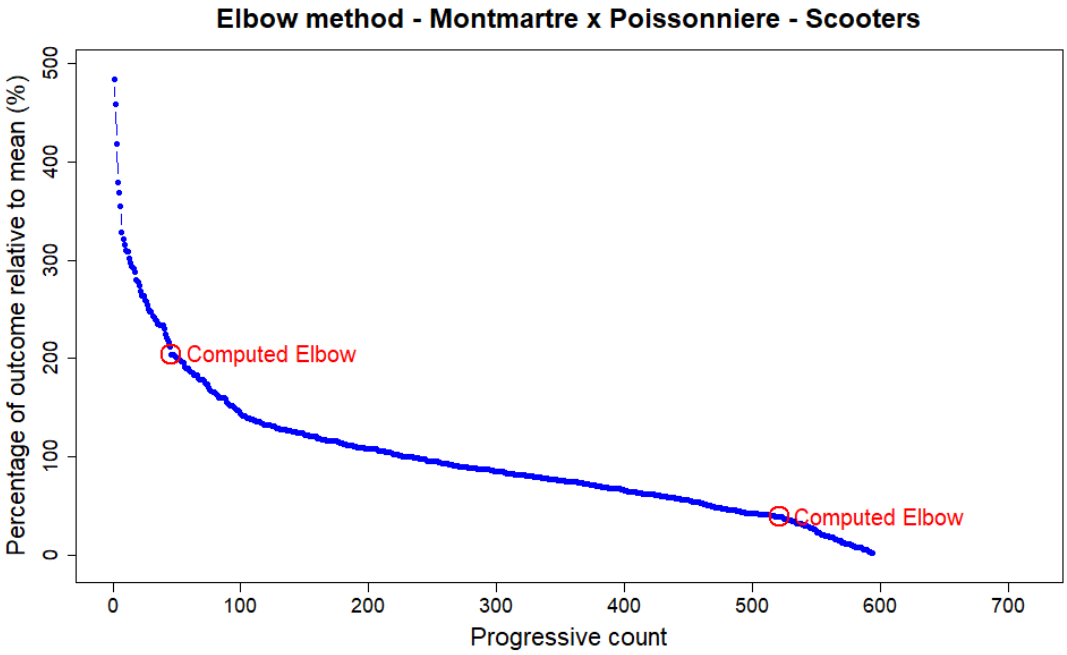

Figure 48: Elbow method analysis applied for daily flows at Montmartre x Possonnière for scooters

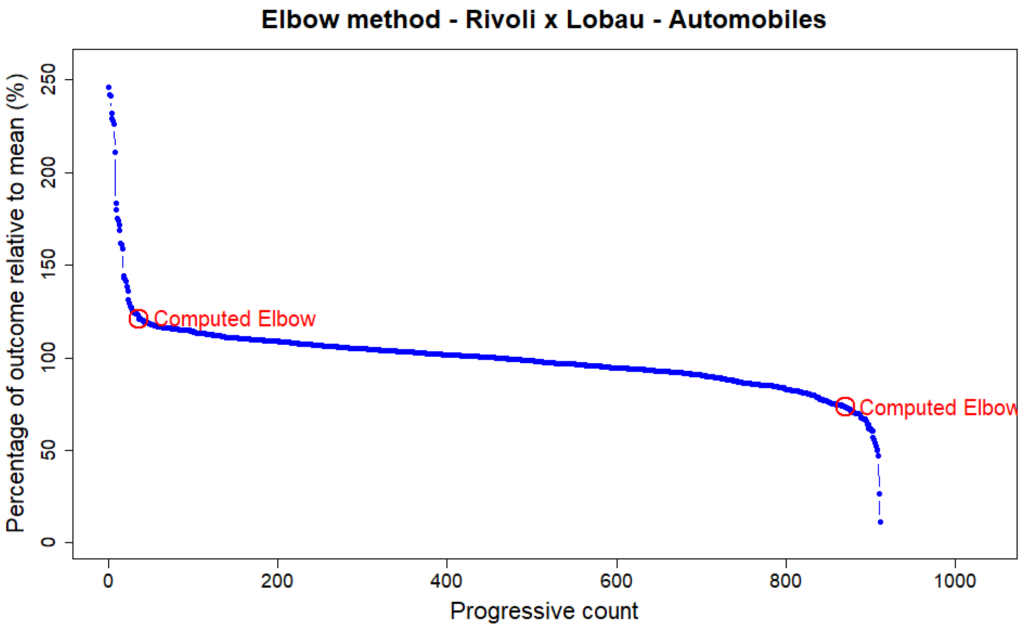

Figure 49: Elbow method analysis applied for daily flows at Rivoli x Lobau for automobiles

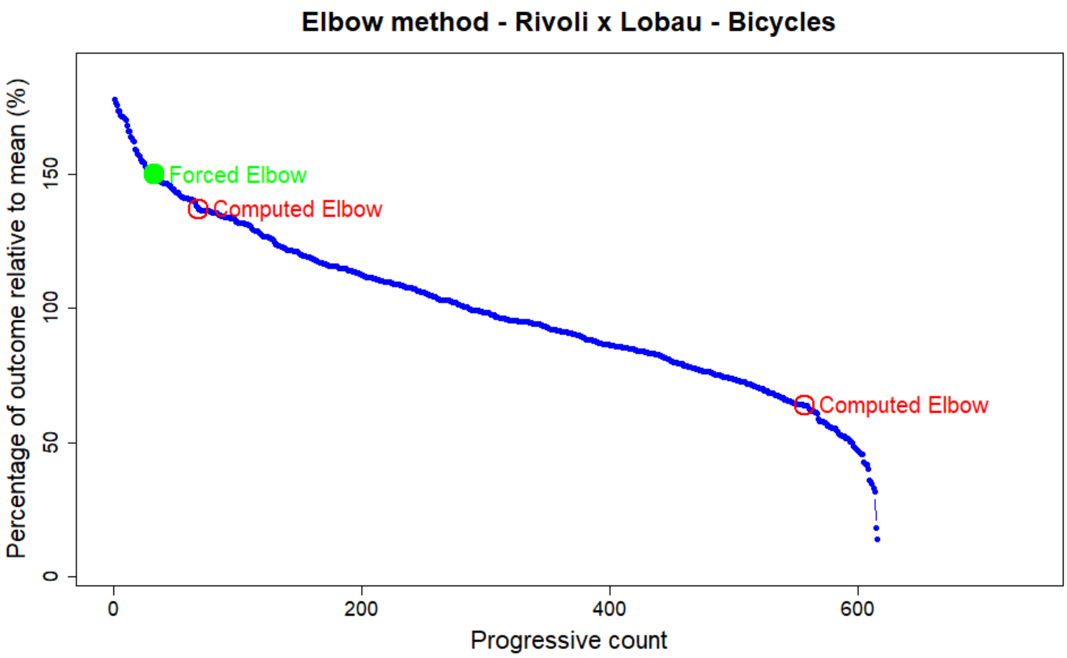

Figure 50: Elbow method analysis applied for daily flows at Rivoli x Lobau for bicycles

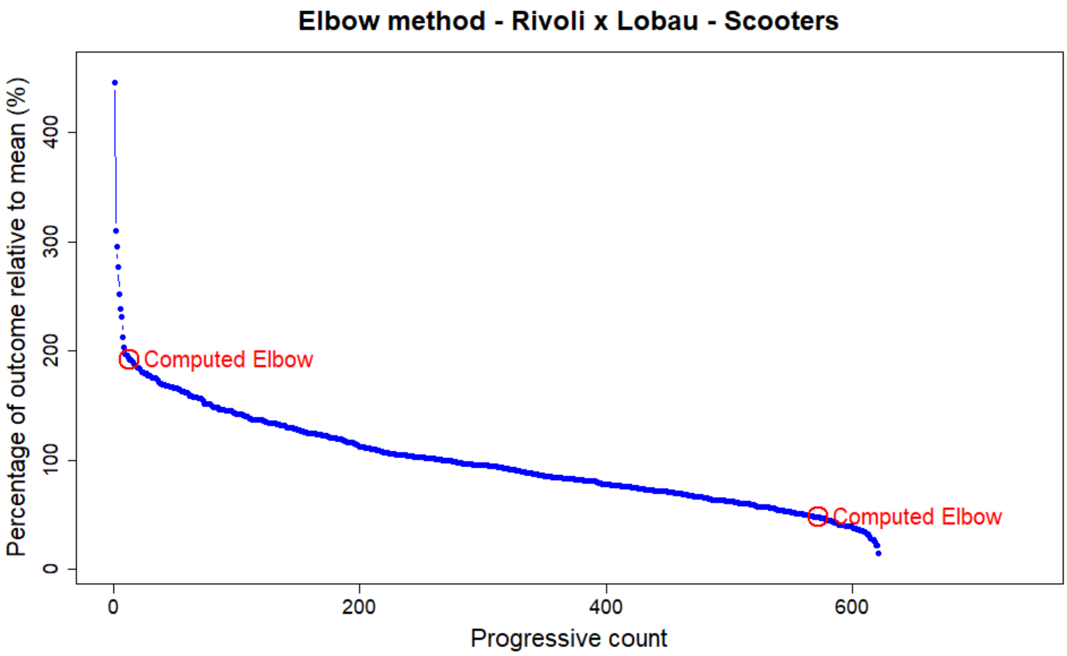

Figure 51: Elbow method analysis applied for daily flows at Rivoli x Lobau for scooters

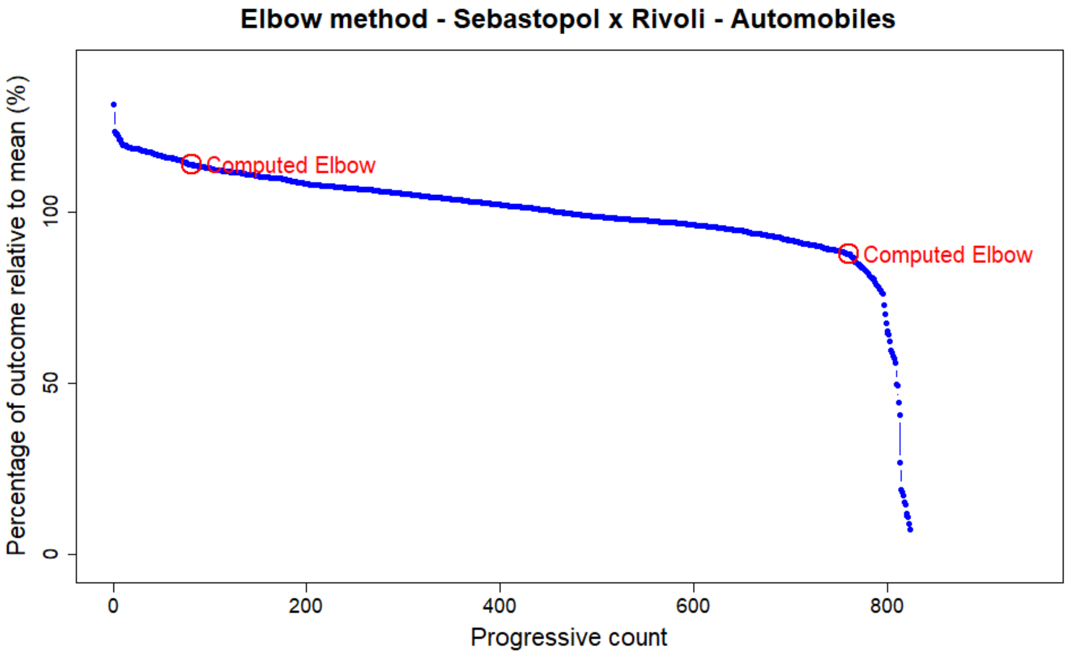

Figure 52: Elbow method analysis applied for daily flows at Sébastopol x Rivoli for automobiles

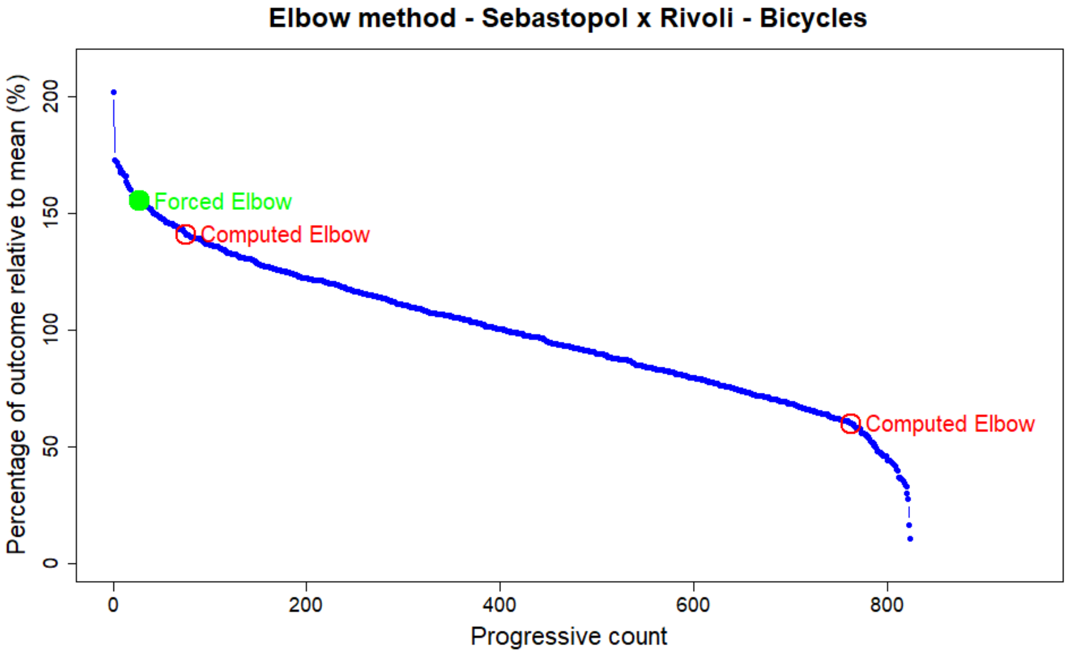

Figure 53: Elbow method analysis applied for daily flows at Sébastopol x Rivoli for bicycles

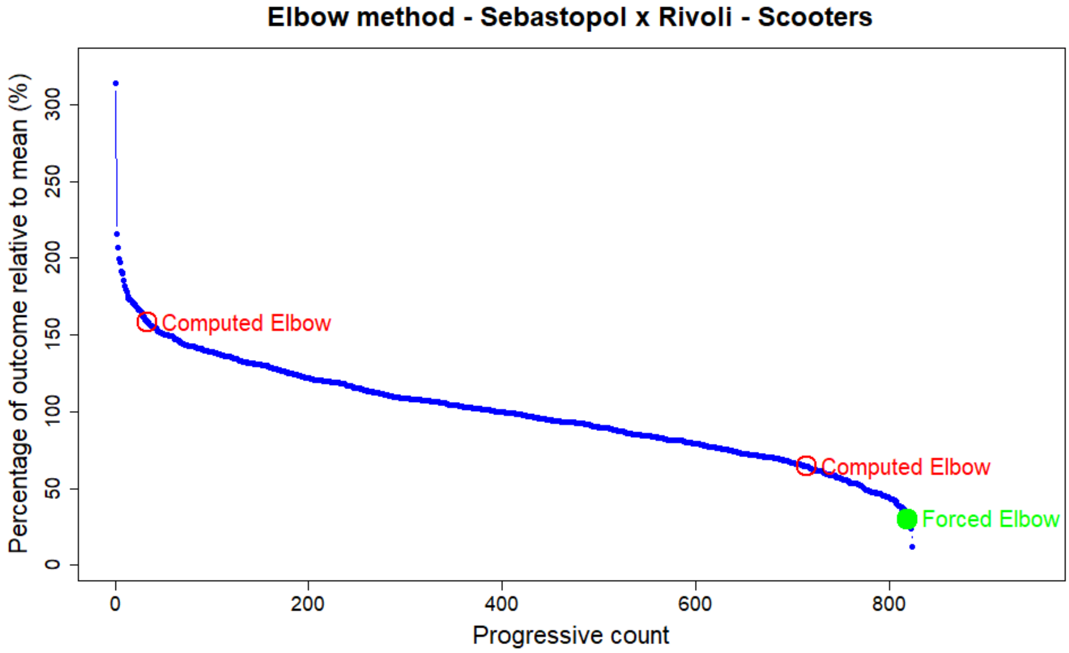

Figure 54: Elbow method analysis applied for daily flows at Sébastopol x Rivoli for scooters

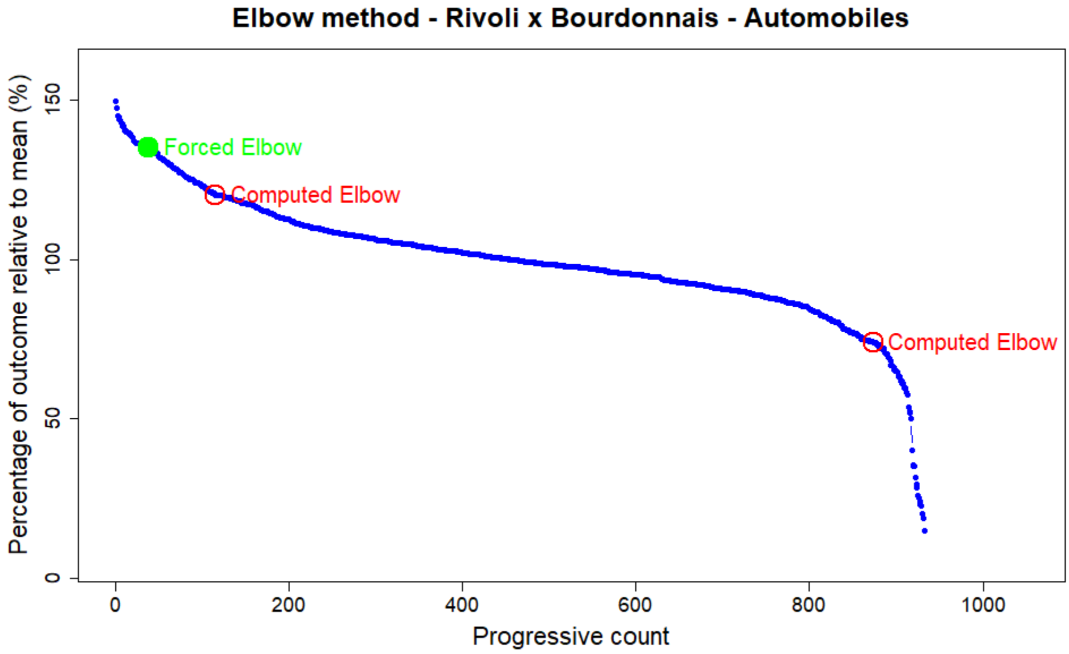

Figure 55: Elbow method analysis applied for daily flows at Rivoli x Boirdonnais for automobiles

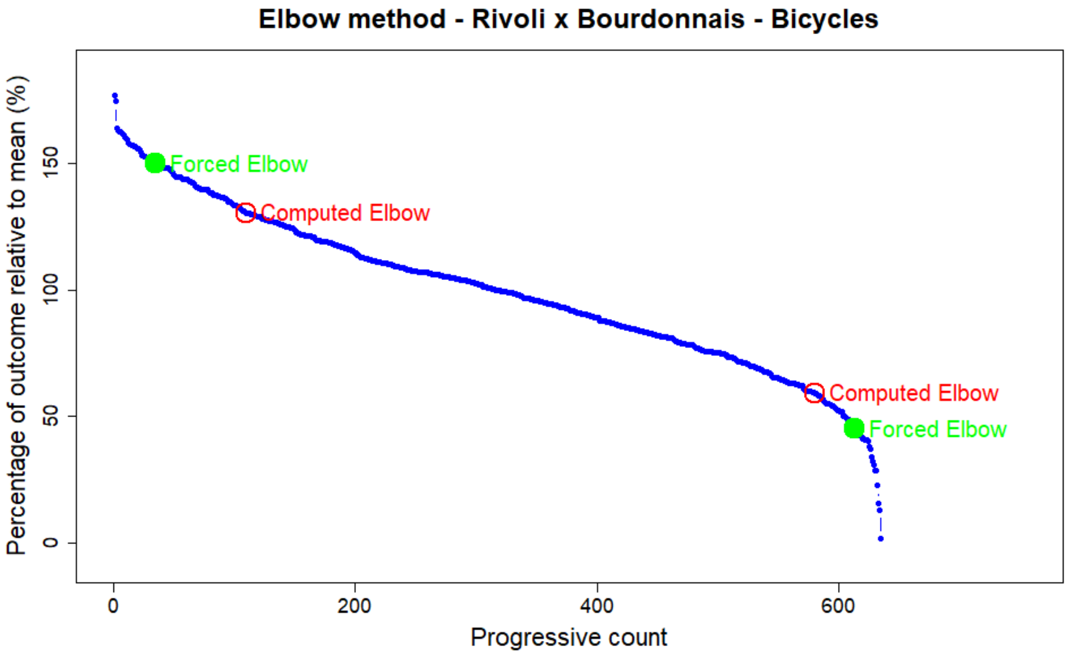

Figure 56: Elbow method analysis applied for daily flows at Rivoli x Boirdonnais for bicycles

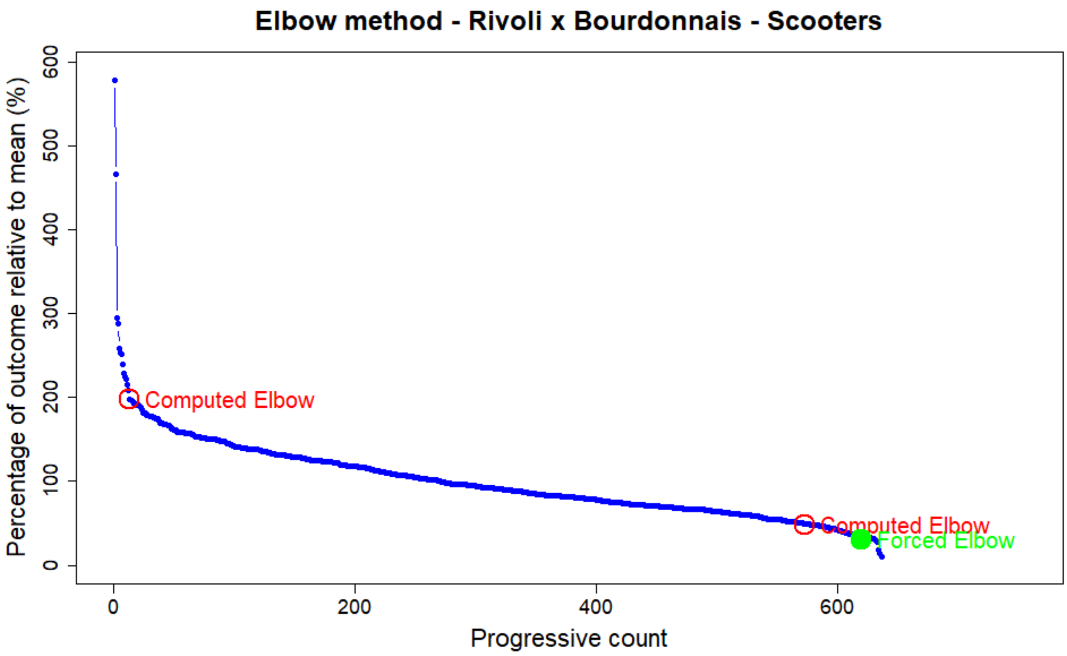

Figure 57: Elbow method analysis applied for daily flows at Rivoli x Boirdonnais for scooters

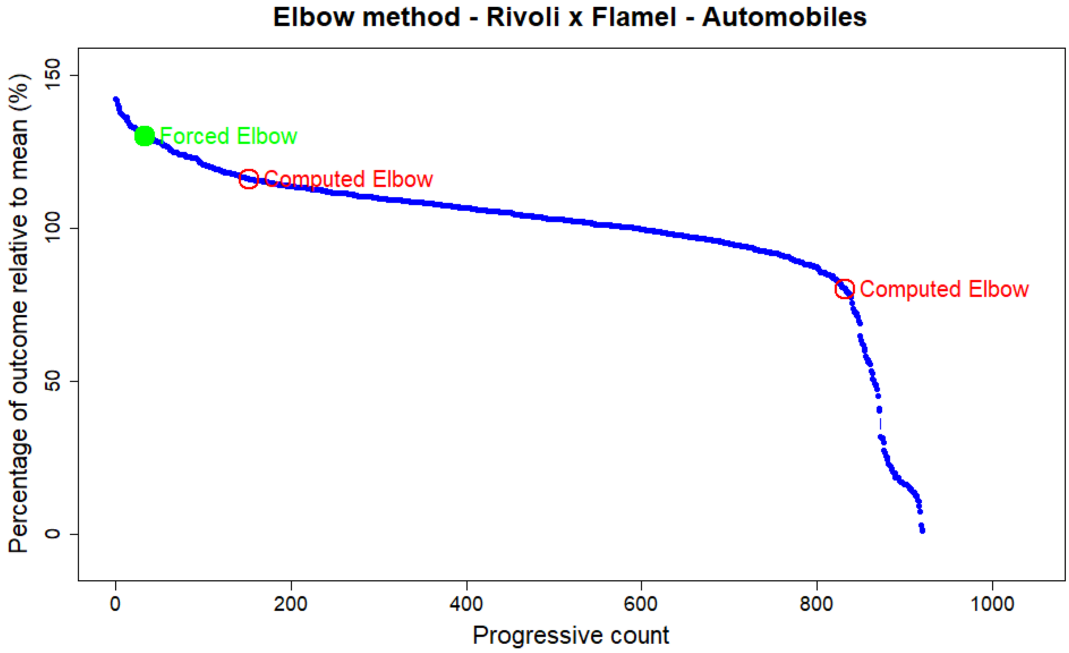

Figure 58: Elbow method analysis applied for daily flows at Rivoli x Flamel for automobiles

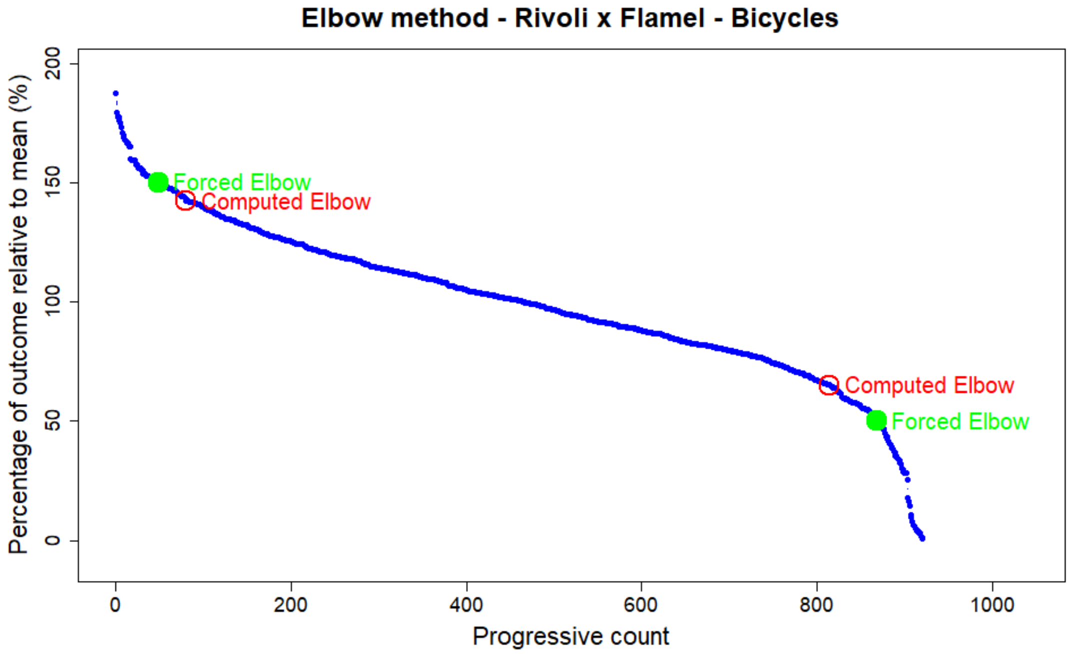

Figure 59: Elbow method analysis applied for daily flows at Rivoli x Flamel for bicycles

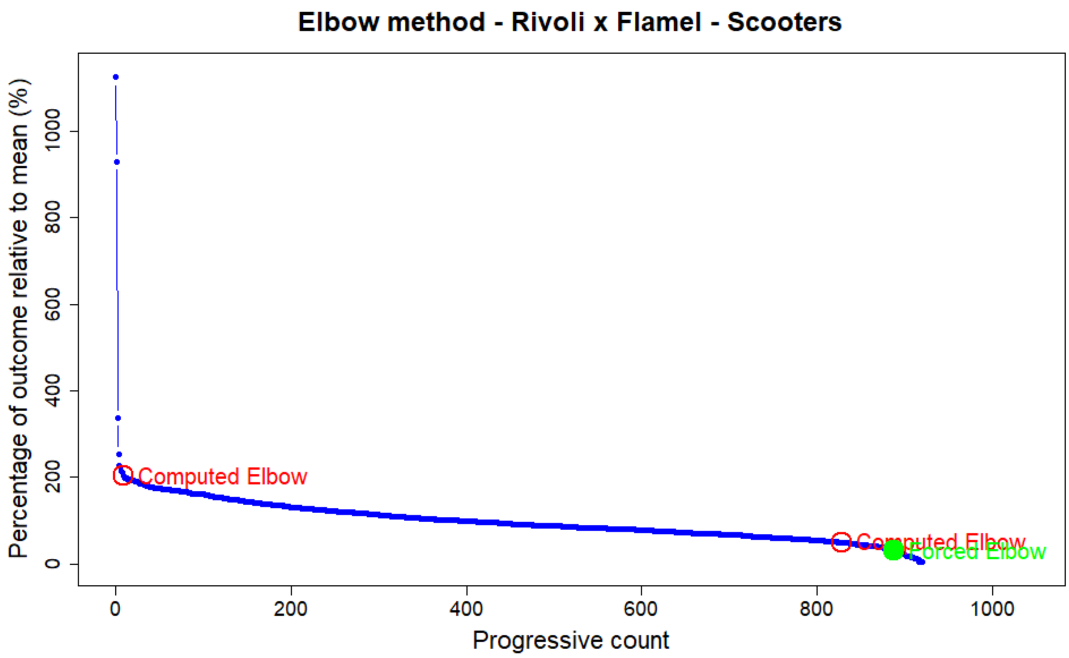

Figure 60: Elbow method analysis applied for daily flows at Rivoli x Flamel for scooters

Appendix C. Data processing code.

C.1 Data cleaning code

This section presents the R code used to perform the data cleaning procedures. The included functions streamline the processing of raw data, apply the elbow method for outlier detection and filtering.

```
# Function to find the elbow point
find_knee_point <- function(x, y) {
  start <- c(x[1], y[1])
  end <- c(x[length(x)], y[length(y)])

  # Compute perpendicular distances from each point to the line
  distances <- sapply(1:length(x), function(i) {
    num <- abs((end[2] - start[2]) * x[i] - (end[1] - start[1]) * y[i] +
end[1] * start[2] - end[2] * start[1])
    den <- sqrt((end[2] - start[2])^2 + (end[1] - start[1])^2)
    return(num / den)
  })

  return(which.max(distances))  # Return index of max distance (elbow point)
}

df <- read.csv("graph/csv_cleaned.csv", sep = ";", header = TRUE,
stringsAsFactors = FALSE)

# Count initial rows before aggregation
```

```
initial_counts <- df %>% group_by(Site, Mode) %>% summarise(Initial_Rows =
n(), .groups = "drop")

# Aggregate data by date, site, and transport mode
df_daily <- df %>%
  group_by(Date, Site, Mode) %>%
  summarise(Count = sum(Count, na.rm = TRUE), .groups = "drop")

# Count rows after aggregation
aggregated_counts <- df_daily %>% group_by(Site, Mode) %>%
summarise(Aggregated_Rows = n(), .groups = "drop")

# Merge initial and aggregated row counts
merged_counts <- merge(initial_counts, aggregated_counts, by = c("Site",
"Mode"), all.x = TRUE)
merged_counts$Aggregated_Rows[is.na(merged_counts$Aggregated_Rows)] <- 0  #
Replace missing values with 0

# Apply Elbow Method for data cleaning
cleaned_datasets <- list()
cleaning_stats <- data.frame()

for (site in unique(df_daily$Site)) {
  for (mode in unique(df_daily$Mode)) {
    sub_data <- df_daily %>% filter(Site == site, Mode == mode) %>%
arrange(Date)

    if (nrow(sub_data) == 0) next  # Skip empty datasets

    # Compute percentage of mean
    mean_y <- mean(sub_data$Count, na.rm = TRUE)
    sub_data$percent_of_mean <- (sub_data$Count / mean_y) * 100

    # Sort data in descending order of percentage
    data_sorted <- sub_data[order(-sub_data$percent_of_mean), ]

    if (nrow(data_sorted) < 2) next  # Skip if dataset is too small

    # Identify left (upper) and right (lower) elbow points
    left_data <- data_sorted[data_sorted$percent_of_mean >= 100, ]
    right_data <- data_sorted[data_sorted$percent_of_mean <= 100, ]
```

```
    left_knee_value <- if (nrow(left_data) > 1)
find_knee_point(1:nrow(left_data), left_data$percent_of_mean) else NA
    right_knee_value <- if (nrow(right_data) > 1)
find_knee_point(1:nrow(right_data), right_data$percent_of_mean) else NA

    # Apply tresholds
    forced_thresholds <- list(
      "Montmartre x Poissonniere_Automobiles" = c(150, 90),
      "Rivoli x Bourdonnais_Automobiles" = c(135, NA),
      "Rivoli x Bourdonnais_Bicycles" = c(150, 45),
      "Rivoli x Bourdonnais_Scooters" = c(NA, 30),
      "Rivoli x Flamel_Automobiles" = c(130, NA),
      "Rivoli x Flamel_Bicycles" = c(150, 50),
      "Rivoli x Flamel_Scooters" = c(NA, 30),
      "Rivoli x Lobau_Bicycles" = c(150, NA),
      "Sebastopol x Rivoli_Bicycles" = c(155, NA),
      "Sebastopol x Rivoli_Scooters" = c(NA, 30)
    )

    key <- paste(site, mode, sep = "_")
    if (key %in% names(forced_thresholds)) {
      forced <- forced_thresholds[[key]]
      left_knee_value <- if (!is.na(forced[1])) forced[1] else left_knee_value
      right_knee_value <- if (!is.na(forced[2])) forced[2] else
right_knee_value
    }

    # Filter data within elbow point range
    cleaned_data <- subset(data_sorted, percent_of_mean >= right_knee_value &
percent_of_mean <= left_knee_value)

    # Save dataset
    cleaned_datasets[[key]] <- cleaned_data

    # Store cleaning statistics
    cleaning_stats <- rbind(cleaning_stats, data.frame(
      Site = site,
      Mode = mode,
      Initial_Rows = nrow(df[df$Site == site & df$Mode == mode, ]),
      Aggregated_Rows = nrow(sub_data),
      Cleaned_Rows = nrow(cleaned_data),
      Percent_Kept = round((nrow(cleaned_data) / nrow(sub_data)) * 100, 2)
    ))
```

```
  }
}
```

C.2 2x2 DiD code

This section presents the R code used to perform the 2x2 method, presented in *3.5.2 2x2 DiD implementation.*

```
# Load dataset
data <- read.csv("final_cleaned_norm.csv", sep = ",", header = TRUE,
stringsAsFactors = FALSE)

# Convert Date to date format
data$Date <- as.Date(data$Date, format = "%Y-%m-%d")

# Apply date filtering (1st March 2022 - 29th February 2024)
data <- data %>%
  filter(Date >= as.Date("2022-03-01") & Date <= as.Date("2024-02-29"))

# Filter only useful sites
data <- data %>%
  filter(Site %in% c("Sebastopol x Rivoli", "Rivoli x Flamel"))

# Create time variables
data <- data %>%
  mutate(year = as.numeric(format(Date, "%Y")),
         month = as.numeric(format(Date, "%m")),
         weekday = weekdays(Date),
         period = ifelse(month >= 3, month - 2, month + 10),
         time = ifelse(month %in% c(9, 10, 11, 12, 1, 2), 1, 0),
         treated = ifelse(Date >= as.Date("2023-03-01"), 1, 0),
         cov = ifelse(month %in% c(12, 1, 2), 1, 0),
         did = time * treated)

# Run TWFE models for each site and mode
for (site in unique(data$Site)) {
  for (mode in unique(data$Mode)) {

    subset_data <- data %>% filter(Site == site, Mode == mode)
```

```
    if (nrow(subset_data) > 0) {
      model_with_cov <- lm(Count ~ time + treated + did + cov, data =
subset_data, weights = weight)
      model_without_cov <- lm(Count ~ time + treated + did, data =
subset_data, weights = weight)
          }
  }
}
```

Appendix D. DiD complete results.

D.1 2x2 analysis results

This appendix is dedicated to presenting the complete results of the 2x2 method analyses, which were summarized in the main body of the text. Table 23 presents the complete results with specific statistical coefficients.

Dataset	Intercept (Estimate ± SE)	time (Estimate ± SE)	treated (Estimate ± SE)	did (Estimate ± SE)	Adj. R^2	Residual SE	F-statistic (p-value)
Sébastopol x Rivoli - Scooters	1890.08 ± 34.19***	75.64 ± 48.36	-8.08 ± 48.36	-466.69 ± 68.39***	0.163	443.2	39.23 (< 2.2e-16)
Sébastopol x Rivoli - Bicycles	13696.8 ± 283.8***	640.4 ± 401.4	1149.6 ± 401.4**	-292.8 ± 567.6	0.02221	3679	5.263 (0.00138)
Sébastopol x Rivoli - Automobiles	17308.05 ± 95.47***	-178.13 ± 135.01	68.26 ± 135.01	819.39 ± 190.94***	0.08016	1237	16.45 (3.092e-10)
Flamel x Rivoli - Scooters	2040.66 ± 31.51***	-320.09 ± 44.56***	-574.59 ± 46.74***	-191.26 ± 64.58**	0.5108	408.4	211.5 (< 2.2e-16)
Flamel x Rivoli - Bicycles	12077.1 ± 225.7***	-633.9 ± 319.2*	-856.7 ± 334.8***	1724.1 ± 462.5***	0.01992	2925	4.869 (0.002369)
Flamel x Rivoli - Automobiles	4730.7 ± 31.81***	-544.46 ± 44.99***	-268.77 ± 47.18***	449.97 ± 65.19***	0.2136	412.3	50.89 (< 2.2e-16)
Confidence levels: *** p < 0.001, ** p < 0.01, * p < 0.05							

Table 23: 2x2 DiD analysis complete results

Table 24 represents similar results, to the previously presented, with the introduction of the covariate for treating the seasonal effect (see *5.3.3 Inclusion of seasonal effects as covariate*).

Dataset	Intercept (Estimate ± SE)	time (Estimate ± SE)	treated (Estimate ± SE)	did (Estimate ± SE)	cov (Estimate ± SE)	Adj. R^2	Residual SE	F-statistic (p-value)
Sébastopol x Rivoli - Scooters	1890.08 ± 30.59***	338.06 ± 48.37***	-8.08 ± 43.26	-466.69 ± 61.18***	-524.84 ± 43.26***	0.3301	1890.08 ± 30.59***	338.06 ± 48.37***
Sébastopol x Rivoli - Bicycles	13696.8 ± 268.5***	2190.0 ± 424.6***	1149.6 ± 379.8**	-292.8 ± 537.1	-3099.2 ± 379.8***	0.1247	13696.8 ± 268.5***	2190.0 ± 424.6***
Sébastopol x Rivoli - Automobiles	17308.05 ± 95.50***	-233.21 ± 151.00	68.26 ± 135.06	819.39 ± 191.00***	110.15 ± 135.06	0.07958	17308.05 ± 95.50***	-233.21 ± 151.00
Flamel x Rivoli - Scooters	2040.66 ± 29.48***	-125.86 ± 46.61**	-574.59 ± 43.72***	-191.26 ± 60.41**	-388.45 ± 41.69***	0.5718	2040.66 ± 29.48***	-125.86 ± 46.61**
Flamel x Rivoli - Bicycles	12077.1 ± 208.7***	821.9 ± 330.0*	-856.7 ± 309.5***	1724.1 ± 427.7***	-2911.7 ± 295.1***	0.162	12077.1 ± 208.7***	821.9 ± 330.0*
Flamel x Rivoli - Automobiles	4730.7 ± 31.03***	-662.25 ± 49.06***	-268.77 ± 46.03***	449.97 ± 63.60***	235.58 ± 43.89***	0.2516	4730.7 ± 31.03***	-662.25 ± 49.06***
Confidence levels: *** p < 0.001, ** p < 0.01, * p < 0.05								

Table 24: 2x2 DiD analysis complete results with covariates

D.2 Temporal analysis results

This section of the appendix presents the complete results of the Average Treatment Effects on the Treated (ATT) for each counting point and mode of transport. Each row corresponds to a specific time period (month) and includes the ATT, which is calculated as a function of the group and time. Additionally, we report the standard error (Std. Error), the lower and upper bounds of the 95% confidence interval, and the significance of the result. A result is considered significant if the confidence interval does not include zero, indicating a measurable effect.

ATT results Montmartre x Poissonnière						
Time	Vehicle Type	ATT(g,t)	Std. Error	95% Confidence Lower	95% Confidence Upper	Significance
2	Scooters	64.2619	47.571	-58.8521	187.3759	
3	Scooters	-146.5667	56.4753	-292.7252	-0.4081	*
4	Scooters	-130.131	55.4981	-273.7603	13.4984	
5	Scooters	-110.3095	56.166	-255.6674	35.0483	
6	Scooters	-4.3214	67.8419	-179.8966	171.2537	

7	Scooters	467.8976	66.2247	296.5077	639.2875	*
8	Scooters	-265.2619	81.511	-476.2129	-54.3109	*
9	Scooters	-82.4667	86.0567	-305.1818	140.2485	
10	Scooters	-149.8833	65.5504	-319.5283	19.7616	
11	Scooters	-94.9762	61.5537	-254.2776	64.3252	
12	Scooters	-119.7167	58.5187	-271.1635	31.7302	
2	Bicycles	1305.7214	494.1599	-6.021	2617.4638	
3	Bicycles	-391.8405	541.4788	-1829.1904	1045.5095	
4	Bicycles	36.869	426.3608	-1094.9015	1168.6396	
5	Bicycles	144.6905	391.3831	-894.232	1183.613	
6	Bicycles	-161.369	489.888	-1461.7719	1139.0338	
7	Bicycles	-83.1524	534.8969	-1503.0308	1336.726	
8	Bicycles	663.7619	416.671	-442.2871	1769.8109	
10	Bicycles	587.4738	429.9179	-553.7388	1728.6865	
11	Bicycles	-183.0103	467.204	-1423.1986	1057.1779	
12	Bicycles	-629.1929	451.8658	-1828.6661	570.2804	
2	Automobiles	2034.2881	496.8012	674.2641	3394.3121	*
3	Automobiles	-1191.5048	426.4035	-2358.8106	-24.1989	*
4	Automobiles	828.2905	448.6132	-399.8159	2056.3968	
5	Automobiles	-578.5167	392.8501	-1653.968	496.9347	
6	Automobiles	-412.7857	367.8568	-1419.8165	594.2451	
7	Automobiles	984.9929	342.5676	47.1927	1922.793	*
8	Automobiles	748.9095	429.8139	-427.7325	1925.5516	
10	Automobiles	-1525.5881	438.7687	-2726.7447	-324.4315	*
11	Automobiles	-1247.2286	443.3189	-2460.8415	-33.6156	*
12	Automobiles	-1051.8714	452.9035	-2291.7227	187.9799	

Table 25: ATT results Montmartre x Poissonnière

ATT results Flamel x Rivoli						
Time	Vehicle Type	ATT(g,t)	Std. Error	95% Confidence Lower	95% Confidence Upper	Significance
2	Scooters	164.1429	111.465	-142.3992	470.6849	
3	Scooters	-182.631	110.7324	-487.1585	121.8966	
4	Scooters	-69.9786	108.2325	-367.6308	227.6737	
5	Scooters	206.6476	105.8259	-84.3863	497.6816	
6	Scooters	303.4786	92.6264	48.7447	558.2124	*
8	Scooters	-542.0595	139.9399	-926.9111	-157.2079	*
9	Scooters	24.469	132.6028	-340.2047	389.1428	
10	Scooters	-266.181	84.8235	-499.4559	-32.906	*

11	Scooters	-409.3786	79.4279	-627.815	-190.9422	*
12	Scooters	-748.0214	108.025	-1045.1031	-450.9398	*
2	Bicycles	2650.3452	999.6475	-71.4814	5372.1719	
3	Bicycles	1193.0857	835.7114	-1082.3778	3468.5493	
4	Bicycles	-1618.3833	963.6272	-4242.1345	1005.3678	
5	Bicycles	-432.2786	1063.0544	-3326.7486	2462.1914	
6	Bicycles	637.0548	991.2338	-2061.8631	3335.9726	
8	Bicycles	-3135.0214	1272.6084	-6600.0623	330.0195	
9	Bicycles	1289.3119	1259.9725	-2141.3241	4719.9479	
10	Bicycles	3974.75	1184.837	748.692	7200.808	*
11	Bicycles	2443.3929	1086.5485	-515.0467	5401.8324	
12	Bicycles	2450.4643	1080.4831	-491.4605	5392.3891	
2	Automobiles	286.6929	101.5224	17.9536	555.4321	*
3	Automobiles	-14.9048	102.7884	-286.9952	257.1856	
4	Automobiles	-28.7667	106.8046	-311.4883	253.955	
5	Automobiles	222.4952	136.1948	-138.0252	583.0156	
6	Automobiles	287.1095	128.1143	-52.021	626.2401	
8	Automobiles	-875.569	157.7262	-1293.0851	-458.053	*
9	Automobiles	403.3595	186.5011	-90.3264	897.0455	
10	Automobiles	241.2905	148.259	-151.165	633.746	
11	Automobiles	-40.9857	139.904	-411.3246	329.3532	
12	Automobiles	37.2524	143.372	-342.2667	416.7715	

Table 26: ATT results Flamel x Rivoli

ATT results Lobau x Rivoli						
Time	Vehicle Type	ATT(g,t)	Std. Error	95% Confidence Lower	95% Confidence Upper	Significance
2	Scooters	228.319	101.977	-44.8965	501.5346	
3	Scooters	-35.8357	65.9659	-212.5707	140.8993	
4	Scooters	-45.1357	69.1406	-230.3763	140.1049	
5	Scooters	23.0357	79.4745	-189.8914	235.9628	
6	Scooters	79.8952	80.217	-135.0211	294.8115	
7	Scooters	245.3238	96.0641	-12.0499	502.6976	
8	Scooters	-245.969	99.0683	-511.3917	19.4536	
9	Scooters	-258.1929	64.3864	-430.6959	-85.6898	*
10	Scooters	-393.2143	69.2011	-578.617	-207.8116	*
11	Scooters	-572.2833	47.9891	-700.8551	-443.7116	*
12	Scooters	-296.0476	72.675	-490.7576	-101.3376	*

2	Bicycles	1969.381	831.9344	-283.4409	4222.203	
3	Bicycles	265.631	827.2733	-1974.5689	2505.831	
4	Bicycles	-1066.3619	964.4445	-3678.012	1545.288	
5	Bicycles	8.0667	974.5955	-2631.0715	2647.205	
6	Bicycles	1034.969	938.6436	-1506.8141	3576.752	
8	Bicycles	-1568.1643	1117.7173	-4594.8667	1458.538	
9	Bicycles	-577.6286	1018.2609	-3335.0099	2179.753	
10	Bicycles	-634.6167	988.0745	-3310.2553	2041.022	
11	Bicycles	-720.2714	891.7286	-3135.0118	1694.469	
12	Bicycles	1216.9238	945.9264	-1344.5805	3778.428	
2	Automobiles	266.6524	140.4879	-88.8622	622.167	
3	Automobiles	-118.581	123.3333	-430.6846	193.5227	
4	Automobiles	-257.5405	98.5665	-506.9699	-8.111	*
5	Automobiles	356.4619	113.7484	68.6136	644.3102	*
6	Automobiles	356.5071	152.4345	-29.2391	742.2534	
7	Automobiles	4.669	296.6711	-746.0781	755.4162	
8	Automobiles	171.3286	355.5319	-728.3702	1071.0273	
9	Automobiles	191.4125	296.2955	-558.3842	941.2092	
10	Automobiles	-606.4268	237.7331	-1208.0273	-4.8263	*
11	Automobiles	-852.0292	227.9309	-1428.8245	-275.2338	*
12	Automobiles	-455.9054	229.6545	-1037.0622	125.2515	

Table 27: ATT results Lobau x Rivoli

ATT results Bourdonnais x Rivoli						
Time	Vehicle Type	ATT(g,t)	Std. Error	95% Confidence Lower	95% Confidence Upper	Significance
2	Scooters	178.219	103.1173	-102.3616	458.7997	
3	Scooters	97.4071	89.4761	-146.056	340.8702	
4	Scooters	-155.9667	108.4358	-451.0189	139.0856	
5	Scooters	0.081	123.9784	-337.2624	337.4243	
6	Scooters	122.1619	98.9256	-147.0132	391.337	
7	Scooters	200.7	81.1687	-20.1587	421.5587	
8	Scooters	-100.8833	93.1901	-354.4522	152.6856	
9	Scooters	-243.6429	96.0398	-504.9658	17.6801	
10	Scooters	-125.0929	105.1217	-411.1275	160.9418	
11	Scooters	-348.3095	92.6648	-600.4491	-96.17	*
12	Scooters	-1242.3738	135.8051	-1611.8973	-872.8503	*
2	Bicycles	2988.2548	1056.9934	70.7946	5905.715	*
3	Bicycles	166.7333	979.6549	-2537.2612	2870.7278	

4	Bicycles	-1758.7881	1170.2184	-4988.7664	1471.1902	
5	Bicycles	678.5476	1047.1018	-2211.6103	3568.7056	
6	Bicycles	470.3548	1092.0246	-2543.7967	3484.5063	
7	Bicycles	1172.1321	1348.5137	-2549.9679	4894.2322	
8	Bicycles	609.9036	1429.3018	-3335.1838	4554.9909	
9	Bicycles	-2830.2833	1306.5976	-6436.6885	776.1218	
10	Bicycles	3020.119	1395.3438	-831.2391	6871.4772	
11	Bicycles	2949.4071	1110.2999	-115.187	6014.0013	
12	Bicycles	-1230.069	1217.3037	-4590.0097	2129.8716	
2	Automobiles	247.2238	120.3253	-70.6503	565.0979	
3	Automobiles	34.5381	114.6505	-268.3444	337.4206	
4	Automobiles	-476.4881	137.0097	-838.4387	-114.5375	*
5	Automobiles	-414.8071	137.1936	-777.2436	-52.3707	*
6	Automobiles	388.3	131.826	40.0435	736.5565	*
7	Automobiles	835.9643	153.3793	430.7686	1241.16	*
8	Automobiles	579.2238	130.7887	233.7077	924.7399	*
10	Automobiles	-679.0357	129.4255	-1020.9507	-337.1207	*
11	Automobiles	-1223.0381	106.8761	-1505.3821	-940.6941	*
12	Automobiles	-1334.681	112.8026	-1632.6816	-1036.6803	*

Table 28: ATT results Bourdonnais x Rivoli

ATT aggregated results						
Time	Vehicle Type	ATT(g,t)	Std. Error	95% Confidence Lower	95% Confidence Upper	Significance
2	Scooters	208.4152	110.7301	-96.3019	513.1323	
3	Scooters	-77.2643	97.6121	-345.8819	191.3534	
4	Scooters	-67.3329	88.7899	-311.6728	177.0071	
5	Scooters	10.6514	88.944	-234.1125	255.4154	
6	Scooters	143.0633	86.22	-94.2045	380.3312	
7	Scooters	213.9269	159.4647	-224.9023	652.7561	
8	Scooters	-176.0979	159.1738	-614.1265	261.9308	
9	Scooters	-179.1724	90.6283	-428.5715	70.2268	
10	Scooters	-326.253	86.7189	-564.8939	-87.6121	*
11	Scooters	-448.897	80.7801	-671.1949	-226.5991	*
12	Scooters	-694.2	94.5977	-954.5226	-433.8774	*
2	Bicycles	2296.1967	1163.8793	-954.1703	5546.564	
3	Bicycles	404.681	990.6097	-2361.796	3171.158	
4	Bicycles	-1186.5533	854.7126	-3573.5102	1200.404	

5	Bicycles	280.139	868.3325	-2144.8541	2705.132	
6	Bicycles	251.149	982.6145	-2492.9997	2995.298	
7	Bicycles	627.331	1910.5914	-4708.38	5963.042	
8	Bicycles	-440.3006	1970.3832	-5942.9921	5062.391	
9	Bicycles	-1539.655	923.426	-4118.508	1039.198	
10	Bicycles	2141.1637	1286.1399	-1450.6407	5732.968	*
11	Bicycles	1526.6117	1009.8227	-1293.5212	4346.745	
12	Bicycles	856.2637	936.6676	-1759.569	3472.096	
2	Automobiles	525.4857	1475.963	-3369.246	4420.217	
3	Automobiles	-191.6795	1219.962	-3410.881	3027.523	
4	Automobiles	-39.9529	1093.134	-2924.487	2844.581	
5	Automobiles	164.1305	1176.585	-2940.611	3268.872	
6	Automobiles	324.2671	1323.745	-3168.795	3817.33	
7	Automobiles	-88.5118	1511.717	-4077.591	3900.567	
8	Automobiles	437.3476	2086.431	-5068.272	5942.967	
9	Automobiles	26.4313	1941.006	-5095.443	5148.306	
10	Automobiles	-520.1784	1541.862	-4588.803	3548.447	
11	Automobiles	-718.5587	1340.593	-4256.08	2818.963	
12	Automobiles	-579.0397	1349.169	-4139.191	2981.111	

Table 29: ATT aggregated results