PSL UNIVERSITÉ PARIS

THÈSE DE DOCTORAT
DE L'UNIVERSITÉ PSL

Préparée à l'Université Paris-Dauphine

The Integration of Digital Mobility Platforms in Multi-modal Transport Systems

Soutenue par
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Le 4 octobre 2024

Ecole doctorale n° ED 543
Ecole doctorale SDOSE

Spécialité
Sciences de Gestion

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To my lovely wife

Acknowledgments

"Dwarfs standing on the shoulders of giants" is one of the most meaningful metaphors in science, capturing the idea that every discovery is built on the work of previous minds. Modest as it may be, my work is built on the lessons of great minds, for whom I feel deep admiration and respect. I hope one day to fully understand the profundity of their visions. This thesis also played a role in my personal development. Even in the solitude of my thoughts searching for answers, I always felt the presence of wonderful friends who stood by me during the most challenging times. To all of you, thank you!

These are my giants:

> Alexandre Volle, Amélie Gabriagues, Andrea Ponce, Andrea Salvatori, Arturo Aguilar, Benjamin Levy, Brigitte Paquot, Bruno Chavez, Camille Hainnaux, Carine Staropoli, Carlos González, Carlos Lever, Cassandre Lebot, Christophe Benavent, Claudia Aburto, Daniel Herrera, de Callataÿ family, Dianzhuo Zhu, Diego Cebreros, Diego Domínguez, Edgar Jiménez, Edith Altamirano, Eduardo Luna, Eric Brousseau, *familia Banxico/FMP*, *familia* Cervantes Escamilla, *familia* Gómez Sánchez, *familias* Huerta Cruz *y* Cruz Chapa, Gabriela Lizarazu and family, Guillaume Monchambert, Joëlle Toledano, Jorge Barradas, José Carlos Romero, Juan Diego Luksic, Juan Ivars, Juan Montero Pascual, Julio Santaella, Louise Lecomte, Lucas Eustache, Maïté Stéphan, Mariana Reyes, María Teresa Aguilar, Marie-Hélène Caitucoli, Mario Sosa, Mauricio Herrera, *mi amada esposa, mi hermana, mi mamá, mi papá,* Nicolas Coulombel, Nour Kanaan, Olivier Caron, Qiming Zhang, Rami Benabdelkrim, Reyla Navarro, Romain Vacquier, Shahmeer Mohsin, Stéphanie Souche-Le Corvec, Surjasama Lahiri, Tadeo Ramírez, Tatiana Carrera, Timothée Mangeart, Vladimir Avetian, Wilfried Sand-Zantman, Xavi Bach, Zichuan Li, and a good cup of dark coffee.

I would like to express my deepest gratitude to Eric Brousseau for his invaluable guidance and professional advice throughout my PhD. I have always admired his extraordinary reading of the challenges faced by the organizations and institutions of our time and his vision on future societies. He embodies the essence of a social scientist. Although such a

personality can be intimidating in this profession, every moment spent learning from him and sharing a coffee has been a genuine inspiration. I am profoundly thankful for his belief in my ability to contribute, even in a small way, to the science he so passionately cherishes.

My warmest thanks to Stéphanie Souche-Le Corvec, Juan Montero Pascual and Christophe Benavent for accepting being part of the Jury. I deeply appreciate the time you have dedicated to reading my work and to providing me with insightful comments and suggestions. I would also like to extend special gratitude to Wilfried Sand-Zantman for accepting the role of referee. I am truly grateful for your thoughtful comments and suggestions, and for the invaluable opportunity to learn from such a distinguished scholar. Throughout my PhD journey, I have spent countless hours studying your work—first to learn, and later to find inspiration. It is an honor to have you as members of my Jury.

I am deeply grateful to Carine Staropoli—my advisor, coauthor, mentor, jury member, referee, and friend—to whom I owe my PhD. There are moments in life that define a clear before and after, and the day I walked into her office seeking an advisor for my master's thesis was one of those pivotal days. The extent of what I have learned from her and the admiration I hold for her passion and dedication is immeasurable. Thank you, Carine, for every minute you have gave me and for all the doors you have opened without expecting anything in return. I will be forever grateful.

To Arturo Aguilar, Carlos Lever, Claudia Aburto, and Diego Domínguez—I am eternally grateful for your mentorship and the countless opportunities you have gave me. I owe much of who I am today to you.

Special thanks to all my coauthors with whom I have spent countless hours asking questions, seeking answers, critiquing our work, dreaming, sharing joys and frustrations, and writing. In particular, I would like to express my gratitude to Nicolas Coulombel for our collaboration in the early stages of this journey. I learned a great deal about research from him, and I always try to apply his teachings in my work.

To my mom, dad, and sister —thank you for always supporting me in every decision I've made, without ever reproaching me for my mistakes. Instead, you've consistently encouraged me to work hard and keep moving forward. Though we don't share the same passion for academia, you have always nurtured my curiosity and intuition. Thank you for that, and for teaching me to dream.

To my wife—I will be forever grateful to have you with me on this journey. You know that I deeply admire your courage to make this dream come true. I know it was difficult at times, but I also know it would have been impossible without you. Despite the challenges, I wouldn't trade our memories from these past few years for an easier path. They hold a special place in my heart. I am deeply thankful for these wonderful years together! Though this journey has come to an end, there is so much more for us to accomplish… I am eager to see what is waiting for us in the future.

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Resumé

Au cours du siècle dernier, les voitures privées ont dominé l'industrie du transport, exerçant une influence profonde sur l'activité économique. Ce paradigme centré sur la voiture a entraîné des coûts substantiels, en raison de l'augmentation de la congestion routière et des émissions de carbone En conséquence, les gouvernements sont soumis à une pression croissante pour développer des systèmes de transport plus efficaces et plus durables, tout en favorisant la croissance économique. En réponse, les villes ont de plus en plus adopté de nouveaux services de mobilité, tels que le covoiturage, afin d'améliorer l'efficacité des transports et la qualité de vie.

Si certains de ces services existent depuis longtemps, la révolution numérique a considérablement accéléré leur expansion et leur adoption. S'appuyant sur les principes de l'économie de partage, les plateformes de mobilité numérique offrent un accès à court terme à divers moyens de transport. Ces plateformes cherchent à déclencher des effets de réseau en connectant des marchés fragmentés, tant du côté de l'offre que de la demande, créant ainsi de nouvelles places de marché. Ce modèle est attrayant car il favorise une utilisation plus efficace du capital et offre des alternatives plus propres à l'utilisation individuelle de la voiture.

Pour répondre efficacement aux enjeux liées au transport, les plateformes de mobilité numérique doivent respecter trois principes fondamentaux : réduire la dépendance à l'égard de la voiture, résoudre les dilemmes des voyageurs et favoriser les complémentarités avec les transports en commun. Cependant, ces innovations ont considérablement modifié le comportement des utilisateurs, perturbant le secteur et remettant en question les acteurs traditionnels. En outre, l'absence de preuves empiriques solides nous empêche de comprendre si les plateformes de mobilité numérique adhèrent à ces principes.

Par conséquent, la question de savoir comment intégrer efficacement les plateformes de mobilité numérique dans les systèmes de transport existants reste un sujet d'étude actuel et pertinent. L'idée centrale de l'intégration est de favoriser la coordination entre les différentes parties prenantes afin de créer des systèmes de transport multimodaux qui offrent une alternative viable à l'utilisation de la voiture. Cette thèse contribue à ce débat en quatre chapitres :

> **Chapitre 2** : S'appuyant sur la théorie de l'économie des plateformes, cette article développe une typologie de modèle d'affaire pour les plateformes de mobilité

numérique, en identifiant la proposition de valeur et les principaux avantages socio-économiques générés par chaque type de modèle. Il est essentiel de définir clairement la proposition de valeur, car elle influence directement l'intervention publique. En outre, cette recherche explore la manière dont ces modèles d'affaires remettent en question la régulation traditionnelle, qui s'est historiquement concentrée sur la gestion des économies d'échelle du côté de l'offre. L'article examine également comment les stratégies conçues pour générer des effets de réseau peuvent conduire à des défaillances du marché.

Chapitre 3 : Cette recherche étudie la dynamique du marché entre les transports en commun et les nouveaux services de mobilité. Dans ce chapitre, j'évalue de manière causale la substitution des transports en commun au partage de vélos à Mexico dans le contexte des perturbations du réseau de métro. Les résultats suggèrent une substitution importante au partage de vélos pendant les perturbations et une augmentation de la complémentarité par la suite.

Chapitre 4 : Le chapitre suivant est consacré à l'examen des aspects réglementaires de l'intégration des services de partage de scooters électriques. Il étudie l'efficacité et les conséquences non intentionnelles des changements réglementaires mis en œuvre pour lutter contre le stationnement abusif à Paris. En exploitant la relation spatiale entre les trottinettes électriques stationnées et les zones de stationnement désignées, les résultats suggèrent que les zones de stationnement désignées réduisent efficacement le stationnement abusif, mais qu'elles limitent également l'accessibilité.

Chapitre 5 : Cette étude explore la manière dont les systèmes de covoiturage interurbain peuvent contribuer à réduire les émissions de carbone. Le covoiturage offre un potentiel d'atténuation des émissions de carbone, mais il rend également les déplacements en voiture plus attrayants, ce qui a des répercussions incertaines sur l'environnement. Ce document développe un indicateur de base pour identifier l'efficacité du covoiturage dans l'atténuation des émissions de carbone et examine empiriquement l'impact de différentes politiques sur cet indicateur. Les résultats suggèrent que l'augmentation du coût des déplacements en voiture et l'incitation des conducteurs à se tourner vers les passagers sont des politiques prometteuses pour réduire les émissions de carbone.

En résumé, cette thèse vise à examiner l'introduction de plateformes de mobilité numérique et les défis politiques liés à leur intégration dans le mix de mobilité existant. En examinant ces questions, cette recherche vise à offrir des informations précieuses aux décideurs et aux praticiens. Par exemple, comprendre comment ces services complètent les transports en commun et évaluer les effets indésirables potentiels peut aider les gouvernements à concevoir un système de transport multimodal plus efficace et plus durable. L'élaboration de réglementations qui orientent la technologie vers des objectifs économiques et environnementaux est primordiale pour l'organisation future des sociétés.

Abstract

Over the past century, private cars have dominated the transport industry, representing a crucial lever for economic growth. However, this car-centric approach has also come with substantial costs, due to increasing traffic congestion and carbon emissions. As a result, governments are under growing pressure to develop more efficient and sustainable transportation systems, while fostering economic growth. In response, cities have increasingly adopted new mobility services, such as ride-hailing and carpooling, to improve transportation efficiency and enhance quality of life.

Though some of these services have existed for a while, the digital revolution have significantly accelerated their expansion and adoption. Leveraging the principles of the sharing economy, digital mobility platforms provide short-term access to various means of transport. These platforms seek to trigger network effects by connecting fragmented markets on both the supply and demand side, thereby creating new marketplaces. This model is appealing because it promotes more efficient use of capital and offers cleaner alternatives to individual car-usage.

To effectively address transport-related concerns, digital mobility platforms must follow three fundamental principles: reducing car-dependency, tackling travelers' dilemmas, and fostering complementarities with mass transit. However, these innovations have significantly changed users' behavior, disrupting the industry and challenging traditional players. Moreover, the lack of robust empirical evidence limits our understanding of whether digital mobility platforms adhere to these principles.

Therefore, the question of how to effectively integrate digital mobility platforms into existing transport systems remains an ongoing subject of scrutiny. The core idea behind integration is to foster coordination among various stakeholders to create multi-modal transport systems that offer a viable alternative to car usage. This thesis contribute to this debate in four chapters:

> **Chapter 2**. Building on the theory of platform economics, this paper develops a business model typology for digital mobility platforms, identifying the value proposition and the primary socio-economic benefits generated by each type. Clearly defining the value proposition is crucial, as it directly influences public intervention. Additionally, this research explores how these business models challenge traditional regulatory governance, which has historically focused on managing supply-side

economies of scale. The paper also examines how strategies designed to generate network effects might lead to market failures.

Chapter 3. This section studies the market dynamics between public transport and new mobility services. In this chapter, I causally assess public transport substitution to bike-sharing in Mexico City in the context of disruptions in the subway network. The findings suggests a substantial substitution to bike-sharing during disruptions and a rise in complementarity afterwards.

Chapter 4. The next chapter focuses on examining the regulatory aspects of integrating e-scooters sharing services. It studies the effectiveness and unintended consequence of regulatory changes implemented to address improper parking in Paris. By exploiting the spatial relation between parked e-scooters and designated parking zones, the findings suggest that designated parking zones effectively reduce improper parking, but they also limit accessibility.

Chapter 5. This study explores how intercity carpooling systems can contribute to mitigate carbon emissions. Carpooling holds potential for carbon mitigation, however, it also makes car travel more attractive leading to uncertain environmental impacts. This paper develops a baseline indicator to identify the effectiveness of carpooling in carbon mitigation and it empirically examines the impact of various policies on such indicator. The findings suggest that raising the cost of car travel and incentivizing drivers to switch to passengers are promising policies to mitigate carbon emissions.

In summary, this thesis aims to examine the introduction of digital mobility platforms and the policy challenges involved in integrating them with the existing mobility mix. By delving into these issues, this research seeks to offer valuable insights for decision-makers and practitioners. For instance, understanding how these services complement mass transit and assessing potential undesired effects can help governments to design more efficient and sustainable multi-modal transport system. Crafting regulations that guide technology toward economic and environmental objectives is paramount for the future organization of societies.

Chapter 1

Introduction

« L'homme est fou. Il adore un Dieu invisible et détruit une nature visible, inconscient que la nature qu'il détruit est le Dieu qu'il vénère »
Hubert Reeves (alleged)

—— ** ——

We stand at a pivotal moment in human history, where the long-standing paradigms for production and consumption have led to economic, social, and environmental degradation. This underscores the need for structural reforms in our current economic systems to build a better future. This transformation must enhance efficiency, improve quality of life, and move away from the anthropocentric worldview.

At the same time, the world is experiencing a technological revolution fueled by unprecedented advancements that are reshaping the way we live. However, if we fail to guide these innovations toward achieving socio-economic objectives, this process of creative destruction could result in significant social costs. Conversely, the digital revolution have the potential to deliver substantial welfare gains with the right regulatory policies and strong institutional frameworks in place.

This doctoral thesis examines the ongoing transformation in the transport sector, driven by the emergence of new mobility modes. Though some of these services have been around for a while, the digital revolution has significantly accelerated their expansion. Leveraging the principles of the sharing economy, digital mobility platforms connect fragmented markets on both the supply and demand side, creating new marketplaces. This model has been embraced globally for promoting more efficient use of capital and offering cleaner alternatives to individual car usage.

This transformation presents numerous opportunities, but it also requires a deep understanding of the disruptive forces at play to ensure that innovations are directed toward achieving common goals for a sustainable future. This humble work seeks to contribute to make decisions to make it better.

The structure of the thesis is outlined as follows. This Chapter 1 serves as an introduction, presenting the motivation, problematic, research question, and discussing the relevance of the research. Chapter 2 examines how the transformation of the industry is challenging the current regulatory policies and presents the main arguments for public intervention. The thesis' primary contribution to knowledge is presented in three standalone but interconnected papers in Chapters 3 to 5. The thesis concludes with a discussion on the policy implications associated to the findings presented along these Chapters.

1. Motivation

Private cars have dominated the transport industry for nearly a century, representing a crucial lever for economic growth. The early nineteenth century was marked by the invention of vehicles powered by internal combustion engines. However, it was after WWII that factors such as population growth, suburban expansion, and policies designed to stimulate consumption to transform war-time industries, led to a rapid rise in individual car ownership. This innovation reshaped cities layouts and commuting habits, offering flexibility, independence, and accessibility at affordable prices. As the twentieth century unfolded, most people lived in a car-dominated society.

However, this car-centric paradigm has incurred significant social and environmental costs, ultimately contributing to economic degradation. At the end of the last century, governments began to recognized the limitations of expanding physical capacity to deal with the pervasive use of individual vehicles. For instance, increasing road networks leads to higher traffic congestion resulting in highly inefficient investments, particularly in a world with scarcity of space.[1] As a matter of fact, the INRIX Global Traffic Scorecard estimates that traffic congestion cost the United States nearly 81 billion USD in 2022 (INRIX, 2023).[2] Moreover, using cars to commute is highly inefficient as they remained unmoved 95% of the time (Inci, 2015) and their occupancy rate is close to one almost everywhere.[3]

[1] Also known as the Braess paradox named after the work of Braess in 1968.
[2] According to the 2022 INRIX Global Traffic Scorecard, traffic congestion cost £9.5 billion for UK, and 3.9 billion € for Germany.
[3] For example, the car occupancy rate is 1.08 in France, 1.14 in the UK, and 1.13 in the US, according to the French Enquête Nationale Transports et Déplacements in 2008, the United Kingdom national travel survey in 2019, and the National Household Travel Survey from the US Department of Transport in 2009.

This time also marked the recognition of road transportation as one of the main sources of carbon emissions alongside growing awareness of the environmental damage and adverse health effects associated with car pollutants. Other issues such as security, violence, and social injustice are also associated to the car-oriented paradigm. According to the European Commission, the transport sector is responsible for 25% of total greenhouse gas emissions.[4] In addition, approximately 300,000 annual deaths globally are attributable to local pollutants such as $PM_{2.5}$ and O_3 emitted from cars (Xiong et al., 2022).[5] See Miner et al. (2024) for a compelling review of the harms caused by cars.

This scenarios has prompted the need of deep structural reforms to transform the industry. The main goal is to transform transportation into an efficient and sustainable mobility system that continues to contribute to economic growth while improving citizen's quality of life. Mobility has indeed become a priority on of public agendas worldwide. For instance, the European Green Deal targeted a reduction of 90% in emissions from the sector by 2050 and promoting new mobility is in the core of the initiative.[6]

In efforts to achieve such transition, cities have embraced the emergence of new mobility modes to complement other policies such as the promotion of electric vehicles, as they alone cannot effectively alleviate all transport-related concerns. Some examples of these new mobility modes are ride-hailing and carpooling.[7]

2. Digital mobility platforms: Preliminaries

Operating on the principles of the sharing economy, new mobility modes offer short term access to means of transport (Shaheen & Cohen, 2019; Botsman & Rogers, 2010). They are considered as an attractive model as they promote a more efficient use of capital as well as cleaner alternatives to individual cars. For example, they increase occupancy rates, the frequency of vehicle usage, and represent an alternative during highly congested

[4] See European Commission – Mobility and Transport website [Accessed: 4th September, 2023].
[5] $PM_{2.5}$ are particulate matter with aerodynamic diameters lower than 2.5µm and O_3 is surface ozone. Air polluted with these concentrations is associated with all-cause circulatory diseases, ischemic heart disease, lung cancer mortality, premature births, and in children it contributes to reduced lung volumes and increased risk of asthma and leukaemia (Miner et al., 2024).
[6] See European Commission – Green Deal website [Accessed: 4th September, 2023].
[7] In ride-hailing, people hires a personal driver while in carpooling (or ride-sharing) drivers share their rides with other users. The most representative companies are Uber for ride-hailing and BlaBlaCar for carpooling.

environments. Additionally, services such as bike-sharing offer vehicles powered by human effort or by electric engines providing cleaner options.

Nonetheless, the fragmentation of the market due to many distributed means of transport poses considerable restrictions to users as it requires large amounts of information to make decisions. This has led to the innovation of the so-called Mobility as a Service or MaaS, which central idea is the develop a single application for travelers to plan, book, and pay for a combination of multiple mobility modes (Hietanen, 2014; Hensher et al., 2020).

It is noteworthy that some of these services have existed for decades, however, the undergoing digital revolution has facilitate their expansion and adoption at large scale (Cohen & Kietzmann, 2014).[8] For instance, only 15% of US adults had ever used ride-hailing services such as Uber in 2015, but three years later that figure had risen to 36% (BCG, 2019). Moreover, according to the European Shared Mobility Annual Review 2023, the number of trips provided by vehicle sharing modes increased 144% since 2020 (from 245 to 600 million trips) and the fleet size more than doubled (from 450 to 930 thousand vehicles).[9]

One element of success of the sharing economy lies in the accumulation of substantial network effects (Montero & Finger, 2021). The central idea is that costumers derive positive benefits when other costumers consume the same good creating a network (Katz & Shapiro, 1985). As a result, the utility of each consumer increases with the number of users in the network. To manage network effects, these companies must function as a platform compensating users for the benefits they bring joining the network (Belleflamme & Peitz, 2021). However, when such transaction is costly, users may have no incentives to participate preventing any form of exchange.

The digital revolution has allowed mobility platforms to reduce these transaction costs, enabling efficient interactions between users that would otherwise be impossible. Additionally, digitalization enables economies of scope due to an efficient aggregation of demand and a rapid organization of various distributed means of production, which are key

[8] For instance, bike-sharing systems first appeared in Amsterdam on July 1965 with no success. Other small and unsuccessful programs were launch in Denmark, England, France, and Germany in the 90s. However, the first successful program was launch un Lyon, France in 2005 followed by the Vélib' system launched in 2007 in Paris (DeMaio, 2009).

[9] The Index encompasses shared bikes, scooters, mopeds and cars. Ride-hailing services (e.g. Uber, FreeNow), car-pooling (e.g. Klaxit, BlaBlaCar) and long-term rental services (e.g. Swapfiets) are not included. The survey was retrieved from the Fluctuo mobility enablement website [Accessed: 14th August, 2024].

elements in the sharing economy. Furthermore, digital mobility platforms collect and process large amounts of individual information to adjust supply and demand, thereby enhancing market efficiency.

3. Problematic and research question

Despite their seeming potential, it has being recognized that to effectively address transport-related concerns, digital mobility platforms must stick to three fundamental principles: reducing car-dependency (ITF, 2021; Goodwin, 1977), tackling travelers' dilemmas (Lesh, 2013; Shaheen & Chan, 2016), and improving accessibility (Shaheen S. et al., 2017).[10] In this context, it is crucial to foster complementarities with public transport to promote multimodality where users can combine two or more transport modes to complete their journeys without the need of private cars (Meng et al., 2020; Kenyon & Lyons, 2003; Ciari & Becker, 2017).

However, it remains uncertain whether these services align to these principles. For instance, the interaction between digital mobility platforms and public transport remains subject to debate due to contradictory results in empirical research (Cats et al., 2022; Hall et al., 2018). Additionally, the spatiotemporal usage of digital mobility platforms may differ from conventional services disrupting the current organizations of the public space (Reck et al., 2021; McKenzie, 2019; Younes et al., 2020; Brown et al., 2020). Furthermore, A better understanding on how users change their behavior in the presence of digital mobility platforms is crucial to prevent undesired outcomes, such as increased congestion and carbon emissions (Coulombel et al., 2019).

Another concern is related with the accumulation of strong positive network effects that occur when the value of the platform for each user increase as more users join the network (Belleflamme & Peitz, 2021). Consequently, platforms benefit from increasing returns, as users are often willing to pay more to be part of a larger network. Therefore, scaling up the number of participants in the platform is key to generate larger network effects.

[10] For travelers' dilemma, often exemplified as the first/last mile problem, refers to situations where the location of public transport lies beyond the comfort zone of travelers , individuals are more inclined to rely on their cars for transportation.

The increasing returns associated with these effects can incentivize companies to engage in aggressive competitive practices to rapidly attract participants and expand swiftly, potentially displacing established incumbents. Therefore, the presence of strong positive network effects may result in market dominance of a limited number of actors or even lead to the establishment of natural monopolies (Montero & Finger, 2021).

The rise of digital mobility platforms is driving the need for an evolution in regulatory governance due to the potential consequences for the presence of strong dominant players. This companies might be tempted to leverage their power to eliminate competition and to diminish consumer benefits without the risk of losing demand, ultimately harming social welfare. For example, digital mobility platforms might set predatory prices to deter competition and stimulate demand (Dubé et al., 2010) or to use big data and sophisticated algorithms to steer consumer decisions in ways that primarily serve the platform's interests.

Disruptions play a pivotal role in the transformation of the industry because it is central to the process of creative destruction. However, without appropriate policies to mitigate adverse effects or swiftly respond to unforeseen consequences, disruptions can lead to detrimental outcomes. Therefore, the question of how to effectively integrate digital mobility platforms into existing transport systems remains an ongoing subject of scrutiny. The core idea behind integration is to foster coordination among various stakeholders to create multi-modal transport systems that offer an efficient and sustainable alternative to private cars.

4. Relevance

Allocating resources towards addressing the aforementioned question is crucial because the choices we make today will lay the foundations for our future cities. The ecological transition in the mobility sector holds the promise of enhancing social welfare. The mobility system of the future must prioritize efficiency and quality of life by alleviating congestion, improving connectivity, enhancing spatial equity, an achieving zero carbon emissions. In the words of Sperling et al. (2018), humanity stands at a pivotal juncture, where “decisions today will strongly influence the path and speed of the change”.

This transition presents substantial challenges as urban density continues to rise. In 2007, the global urban population exceeded the rural population for the first time in history, according to The World Bank. By 2021, 56% of the world's population, or 4.4 billion people, lived in cities.[11] Projections suggest that by 2050, 7 out of 10 people will reside in urban areas.[12] Therefore, policy decisions today must prioritize the development of better spaces for people, the promotion of green mobility, and the enhancement of public transport systems (Banister, 2008).

Moreover, as any other network industry, transportation has historically been characterized by strong supply-side economies of scale. This has posed significant challenges for regulatory governance, as companies often leverage these economies of scale to dominate the market, leading to social welfare losses. The rise of digital mobility platforms introduces new challenges for public intervention, highlighting the need for an evolution in regulatory governance. However, governments may struggle to effectively address these challenges due to a limited understanding of how stimulating network effects can result in market failures.

5. Contribution

This doctoral thesis examines the rise of digital mobility platforms and the policy implications of their introduction. Through rigorous empirical analysis, it aims to enhance understanding of how to effectively integrate these platforms into multimodal transport systems while minimizing potential undesired effects. The insights provided here are essential for informed decision-making and the development of regulations that align with societal and environmental goals.

The main contribution of this thesis is developed in three papers comprising Chapters 3 to 5. These papers share several characteristics. First, they contribute to fill gaps in the literature of transport economics, public management, and organizational studies, focusing on: 1) market dynamics in relation to public transport, 2) the impact of regulation and public intervention, and 3) the efficacy of new modes to mitigate carbon. Second, all papers adopt a micro-level approach from the normative perspective, examining interactions between individual units and their respective environments. These units differ across papers and include individual e-scooters, bike-sharing journeys, and intercity carpooling itineraries.

[11] The World Bank: Urban population (% of total population) [Accessed: September 5th, 2023].
[12] The World Bank: Urban Development [Accessed: September 5th, 2023].

Third, econometrics techniques are predominantly employed to assess relevant hypotheses in each case. Lastly, all papers acknowledge the space as a key component in the analysis of transportation. For instance, the first and second papers leverage on the spatial relationship between the unit of study and the built environment, while the third paper considers geo-localized fuel-prices to ascertain trip costs in carpooling itineraries.

Besides the common grounds, each paper makes unique contributions to distinct areas of the literature. The first paper (Chapter 3) assess public transport substitution to bike-sharing in Mexico City. In this paper, I exploit an extemporaneous event that disrupted the city's subway system to causally identify modal shift to bike-sharing. By leveraging the spatial relationship between bike-sharing and subway stations, this study reveals a significant increase in bike-sharing usage during public transport disruptions. Furthermore, I present evidence of a subsequent rise in demand for bike-sharing following the restoration of subway services. Lastly, the paper investigates whether this surge in bike-sharing impacts subway ridership. The results suggests a rise in complementarity between the two systems. The evidence presented in this paper have important policy implications for designing resilient multimodal transport systems that align with sustainability objectives.

The second paper (Chapter 4) examines the regulatory aspects of integrating digital mobility platforms into existing multimodal transportation systems. It examines the introduction of dockless e-scooters in Paris and the regulatory changes implemented to address issues related to improper parking. The case study of Paris is particularly relevant due to the city's efforts to reallocate public spaces exclusively for e-scooter parking. By exploiting the spatial relation between parked e-scooters and designated parking zones, this paper proposes Key Performance Indicators to assess the impact of regulations on users behavior and accessibility. The findings suggest that designated parking zones effectively reduce instances of improper parking. However, they also limit e-scooter accessibility by constraining pick-up and drop-off points for users.

The last paper (Chapter 5) explores how carpooling systems can contribute to mitigating carbon emissions. Carpooling is considered as a promising innovation for carbon mitigation. However, its adoption makes car travel more attractive, leading to uncertain environmental impacts. This paper has two objectives. First, it aims to develop an indicator to assess the effectiveness of carpooling in mitigating carbon emissions. Second, it examines the impact of various policies on the baseline indicator. The findings suggest that the potential for carbon mitigation crucially relies on the occupancy rate, which reflects travelers' preferences over alternatives. Moreover, we argue that raising the cost of car travel through fuel price hikes is associated with increased supply and demand for carpooling. These responses vary depending on users experience, with novice users exhibiting more pronounced effects. Additionally, the research underscores the promising prospect of incentivizing drivers to switch to passengers, as this transition holds the potential for significant carbon mitigation outcomes. These findings offer valuable insights for designing effective policies aimed at promoting carpooling and reducing carbon emissions associated with individual vehicles.

I conclude the thesis with key policy recommendations based on the insights gained throughout these Chapters. As innovations continue to transforms the industry, it will be essential to strengthen the current regulatory governance to harness the benefits offered by digital mobility platforms minimizing potential adverse effects.

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Chapter 2

Pooled, Not Scrambled! Harmonizing Digital Mobility Platforms*

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Chapter outline

1. Introduction

From the introduction of the first mass transport service 150 years ago in France, the Omnibus,[1] governments have intervened to organize the industry with the aim of fostering economic growth. However, the introduction of new services such as ride-hailing and carpooling has disrupted such organization transforming the way transport services are provided. These innovative services function as platforms providing services under the principles of the sharing economy. Leveraging on efficiency gains due to the digital revolution, mobility platforms derive economic benefits managing network effects. This innovate business model approach is putting under pressure the historical regulatory governance developed to manage conventional economies of scale from the supply side.

As any other network industry, transportation has been historically marked by strong economies of scale from the supply side. In other words, transport companies experience a

[1] See Gourdon (1841) for a fascinated narrative on how the Omnibus changed the live of Parisians at the end of the 19th century.

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cost advantage by increasing the volume of service provision. Economies of scale poses significant challenges for regulators because companies typically used them to dominate the market resulting in social welfare losses. Over time, governments have learned how to regulate the industry to prevent such practices. For example, granting legal monopolies (state-owned or a regulated private company) ensures an efficient deployment and exploitation of transport infrastructures while maintaining affordability and universal access. Enforce competition, especially at the level of the service provision, is another policy strategy that lower prices and improve quality of service.

The past decade have witnessed the emergence of digital mobility platforms, innovations that have been embraced by governments due to their potential to improve the efficiency of transport systems easing traffic congestion, carbon emissions, and lack of access. Operating under the principles of a platform economics, they "bring together economic agents to actively manage the network effects between them" (Belleflamme & Peitz, 2021). Positive network effects occur when the value of the platform for each user increase as more users join the network. Consequently, the platform benefit from increasing returns, as users are often willing to pay more to be part of a larger network.

Additionally, these platforms leverage on the digital revolution to significantly reduce transaction costs, enabling the creation of new marketplaces that were previously unimaginable. They are capable of organizing a vast array of distributed means of production and efficiently aggregating demand, benefiting from economies of scope. By harnessing large volumes of data, digital mobility platforms can influence user behavior and swiftly adjust supply and demand, thereby enhancing market efficiencies. As a result, they develop highly effective coordination mechanisms that bridge fragmented market on both the supply and demand sides.

Network effects in digital platforms present significant challenges for regulatory intervention. The increasing returns associated with these effects can incentivize companies to engage in aggressive competitive practices to attract and retain consumers. This, in turn, may lead to highly concentrated markets where dominant players are tempted to leverage their power to eliminate competition and diminish consumer benefits without the risk of losing demand, ultimately harming social welfare. For instance, digital mobility platforms might set prices at very low levels, or even at zero, to stimulate demand (Dubé et al., 2010). Additionally, these platforms often utilize big data and sophisticated algorithms to offer personalized services, which can subtly steer consumer decisions in ways that primarily serve the platform's interests.

Overall, the rise of digital mobility platforms is driving the need for an evolution in regulatory governance. However, governments might not be prepared to address these challenges due to a limited understanding of the diverse business models employed by these companies. According to Snihur & Markman (2023), the way the value proposition is framed strongly influence the reaction of regulators. Therefore, a clear articulation of the value proposition of these platforms is essential to justify public intervention and to determine whether the practices used to stimulate network effects result in market failures.

The literature on digital platform business models is a relatively nascent trend in the literature, especially after the success of digital platforms such as Airbnb and Uber (Snihur & Markman, 2023). The study of platform business models in the mobility sector remains relatively underexplored, with the work of Cohen & Kietzmann (2014) standing out as one of the most relevant. In their research, the authors examine the key characteristics of various business models within the shared mobility. They also apply agency theory to analyze how differences among these business models, combined with the interests of local governments, lead to a misalignment of incentives, ultimately hindering efforts to address deficiencies in mass transit systems.

The literature on the regulation of digital mobility platforms is scarce. Scholars have recently explored the regulatory and institutional implications aimed at promoting app-based and integrated mobility services (Hensher et al., 2020; Wilson & Mason, 2020; Karlsson et al., 2020; Smith et al., 2018; Smith & Hensher, 2020; Lajas & Macário, 2020; ITF, 2023).[2] Similarly, studies about the regulation of online platforms constitute a nascent literature, with some reports examining key characteristics of digital platforms (Treasury, 2019; Scott-Morton et al., 2019; Crémer et al., 2019) and some papers focusing on the evolution of regulatory policies and institutional design (Cantero, 2017; Cusumano et al., 2021; OECD/KDI, 2021; Kerber, 2023).

Notable contributions to this field include the series edited by Finger & Audouin (2019) and the book by Montero & Finger (2021), which serve as excellent starting points for understanding this subject matter. These studies explore how digital mobility platforms disrupts markets and highlight the necessity of enhancing regulatory policies to keep pace with innovations.

[2] Integrated mobility, also referred to as Mobility as a Service (MaaS), is a one-stop access for users to combine multiple transport modes in their itineraries (Mukhtar-Landgren et al., 2016).

The key contribution of this paper is twofold. First, we clearly identify the nature of regulatory challenges posed by new digital mobility platforms. Governments have historically intervened in the market to manage supply-side economies of scale to prevent abusive practices from dominant players in the market. New services are challenging this view as they trigger network effects. Therefore, governments must evolve their regulatory governance following this logic. Second, this papers propose a business model typology for digital mobility platforms to better understand their value proposition from precisely from the perspective of the management of network effects. Furthermore, we identify practices followed by these platforms aimed at triggering network effects that could create market failures. We then characterize them following the economic theory.

The rest of this chapter is structured as follows. Section 2 briefly reviews the public intervention in the transport sector since the 19th century. It seeks to summarize different regulatory tools implemented to manage economies of scale. Section 3 focuses on recent innovations in the transport sector, framing new mobility within the platform and digital economy. The proposed business models' typology for digital mobility platforms is presented here. In Section 4, we relate platforms' practices and market failures and discuss various policy implications derived from our analysis. Finally, Section 5 offers concluding remarks.

2. Brief history of regulatory policies in mass transport

Public interventions in transport have existed for centuries aiming to organize the means of production and to manage the space for the use of multiple actors. However, it was not until the late nineteenth century that governments designed institutions and set regulatory frameworks with the goal of achieving social benefits and economic growth. By reflecting on the evolution of these interventions, we seek to better understand how recent innovations challenge the historical approaches to regulate transport services.

Mass transport originated in Nantes, France in 1826 when Stanislas Baudry introduced a shuttle service to transport customers from his bathhouse business to the city center.[3] This horse-powered carriage, with a capacity of sixteen passengers, rapidly caught attention from other residents who embraced it as a viable mean of transportation. Baudry saw a business

[3] The historical recapitulation of the Omnibus was mainly obtain from Gourdon (1841), RATP (2017) and from the blog Parisian Fields, The invention of the omnibus, consulted on August 20, 2023 from https://parisianfields.com/2014/05/11/the-invention-of-the-omnibus/.

opportunity and launched the first ever urban transport service named *Omnibus*.[4] It commenced operations in Paris in 1834 under the permission of authorities who mainly worried about congestion. Boudry's company, *Enterprise Générale des Omnibus*, along with two competitors, obtained license to operate, albeit with the city retaining control over routes, as well as the number and size of couches.[5]

Despite its popularity, the high maintaining costs of horses, low-demand in certain routes designed by the city, and tough competition, render the Omnibus an unprofitable venture. It wasn't until 1854 that the services became lucrative through the merger of all competitors establishing the *Compagnie Générale des Omnibus*. As congestion increased and demand grew, the city build railways and pressure the *Compagnie* to transit from horse-drawn carriages to horse-drawn trams. Eventually, around 1880, horses were replaced by electric motors. The last journey of an Omnibus in Paris occurred on January 11th, 1913, between La-Villette and St-Sulpice.

The history of the Omnibus reveals that the regulation of transportation fall under the power of local governments who were more aware and more capable of managing public space than national states.[6] However, the rapid industrialization and the emergence of national markets in the late nineteenth century led to an era of federalism marked by a strong interventionism from the national government. This intervention manifested through new institutional arrangements and regulatory frameworks designed to harness the benefits of industrialization (Johnson, 2009).

One fundamental part of the industrialized movement is the rapid expansion of interstate railroads. These companies enjoyed economies of scale and scope and wielded considerable economic power in national markets. Eliminating competition, either by setting predatory prices or by colluding with smaller counterparts, railroads established the first natural monopolies over specific regions. Nonetheless, it was their abuse of power over shippers and passengers that incited public indignation ultimately leading to the establishment of the first national regulatory intervention. The primary objective was to eliminate any form of discrimination by fostering competition (Hadley, 1886).[7]

[4] The Latin word Omnibus means "for all".
[5] In fact, the Omnibus was very popular all around the globe including cities such as London and New York.
[6] We acknowledge that the origins and influence of federalism is an open debate in political science. However, it is not open to discussion the fact that national states had no influence over the planning of urban transport systems at the end of the nineteenth century.
[7] For example, in the United States, the Interstate Commerce Act of 1887 make railroads subject to federal regulation and established the Interstate Commerce Commission (ICC). In contrast, the European approach predominantly favored state monopolies.

The beginning of twentieth century marked the advent of the internal combustion engine; an innovation that profoundly altered the organization of the transport industry facilitating the expansion of more flexible and accessible modes of transport such as private cars (Mom, 2014; Schrag, 2002). The strong competition faced by railroads lead to a significant contraction in the industry. Consequently, many private operators switched from tramways to fuel buses, a phenomenon known as the "motorization" of mass transport.[8]

In addition to technological evolution, rapid population growth exerted pressure to invest in railway-related projects.[9] However, due to low demand, escalating deficits, and declining service quality, public intervention were needed to protect such investment. Gaining legitimacy as efficient managers of primary goods and services during the WWI, governments nationalized the railway industry.[10] One relevant example is the consolidation of the National Company of the French Railways.[11]

These national monopolies were characterized by a strong vertical integration between operations and infrastructure management looking for efficiencies in the coordination costs over the entire supply chain.[12] Moreover, the rapid urban expansion after WWII required to increase mass transit capacity. However, this expansion proved costly and ineffective in

[8] In London, for example, horse-drawn buses were entirely replaced by motorized buses within just 14 years, and trams gradually vanished from urban landscapes (Yuzawa, 2014).

[9] Several notable projects exemplify this effort. In London, The Metropolitan Railway, inaugurated in 1863 the first underground line in the world known as "The Tube". Initially operated by steam locomotives before electrification in 1901. Similarly, In Paris, la *Compagnie du Chemin de fer Métropolitain de Paris (CMP)* completed the construction of the first metro line (*Ligne 1*), in 1900.

[10] During wartime, the efficient management of dense logistical networks for military movements and resource allocation necessitated technological and organizational advancements. This prompted the evolution of administrative structures and governmental agencies, fostering new forms of coordination and cooperation with civil society, the primary providers of these resources. These factors legitimized state intervention, facilitating state control over essential industries, including railroads (Purseigle, 2014).

[11] In France, the national *decree Décret-loi du 31 août 1937 portant réorganisation du régime des chemins de fer* consolidated all private companies operating the network into one entity, the *Société Nationale des Chemins de Fer Français (SNCF)*. Initially, the state owned 51% of the shares, allowing the companies to amortized their shares over 45 years until 1982. In the United Kingdom, the government assumed national ownership under the control of the British Transport Commission in 1947. In the United States, after numerous railway companies were bankrupt, the Rail Passenger Service Act of 1970 mandated the creation of the National Railroad Passenger Corporation, better known as Amtrak.

[12] Vertical integration constitutes a relevant topic in the literature of industrial organization. Please see Rey (2003), Vickers (1995), and Sappington (2006) for a comprehensive analysis on the economics of vertical integration, regulation, and advantages of vertical divestiture, relatively.

addressing issues such as congestion and coverage.[13] This period was also marked by the recognition of transport as one of the main sources of carbon emissions.[14]

The need to modernized the industry to promote a more efficient and sustainable transport sector prompted efforts for institutional and organizational changes to revitalize railroads. Reforms pursued liberalization introducing vertical divestiture with the aim of triggering redistribute productivity gains to final customers. Competition in service provision might lower prices, improve quality of service, and trigger innovation besides improves transparency, monitoring, and accountability.[15]

As a result of these policies, mass transit has experienced a genuine. According to the International Transport Forum, road transport is expected to grow at a lower annual average rate than rail transport between 2015 and 2050 (3.4% vs. 3.8%). A similar trend is expected for private cars and urban transport among OECD members (-0.2% vs. 2.2%) (ITF, 2019).[16] Nonetheless, liberalization have not fully taken off and incumbents maintain substantial market shares.

The history of regulation in mass transit reveals that strong economies of scale in the industry leads to a highly concentrated market with strong dominant players. Therefore, public intervention has aimed at preventing these companies to abuse their position guaranteeing affordable and universal access. More recently, regulatory measures seek to improve efficiency, reduce carbon emissions, and trigger innovation.

However, this mode-specific regulatory approach has failed to effectively coordinate various means of transport, preventing societies from reaching an inflexion point where a combination of multiple modes can provide travelers with sustainable solutions that prioritize flexibility and accessibility at affordable prices.

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[13] The seminal work of Braess (1968; 2005) revealed that increasing the capacity of road networks can paradoxically lead to higher congestion. Additionally, network expansion may induce demand, this effect is known as Downs-Thomson Paradox, The Pigou-Knight-Downs Paradox or the Lewis-Mogridge Position. See Arnott & Small (1994) for a comprehensive review.

[14] The United Nations Conference on the Human Environment, held in Stockholm in 1972, laid the groundwork for subsequent Conferences of the Parties (COP), including the Kyoto Protocol in 1997 (COP3) and the Paris Agreement in 2015 (COP21).

[15] One relevant example are the Railway Packages introduced by the European Commission intended to incrementally open up competition in the service provision and to establish a Single European Railway Area (For details please see https://transport.ec.europa.eu/transport-modes/rail/railway-packages_en).

[16] The scenario for non-OECD country member is 0.4%, 3.6%, and 12.4% for private cars, rail transit, and shared mobility, respectively.

3. Digital mobility platforms: A new era

Increasing recognition of inefficiencies in the industry and the urgent need to reduce carbon emissions have prompted governments to embrace new mobility services. Operated by private companies, digital platforms offer mobility services on the principles of the sharing economy, i.e. they facilitate short term access to transportation via smart applications (Shaheen & Cohen, 2019; Botsman & Rogers, 2010). These innovations are attractive as they represent a more efficient use of capital, offer cleaner alternatives to individual cars, and hold the potential to improve connectivity and accessibility. Therefore, digital mobility platforms have become key players in the process of developing an efficient and sustainable transport system.

These platforms offer new types of mobility services characterized mainly by the mean of transport. Some of these services have existed for decades, however, recent technological advancements have facilitated their provision at extensive geographical regions representing true commercial ventures. It is noteworthy that the service type does not necessarily reflect the business model because it does not represent the value proposed by such companies. We extensively discuss this point in the next section. Some examples of these services are the following:

Bike-sharing**.** Typically operated by a single private entity under the agreement with local authorities, these companies provide short-term and affordable access to bicycles located in stations throughout the city. Societies have experimented with these services since the White Bikes in 1965.[17] Nevertheless, they have recently attracted the attention of citizens seeking cleaner and healthier transportation alternatives.[18]

E-scooters-sharing**.** Similar to bike-sharing services, these companies provide access to e-scooters "free-floating" across the city. Subscribers can pick-up and drop-off e-scooters using smart applications at any location within certain geographical boundaries. Introduced for the first time in the summer of 2017 in Santa Monica, California by the

[17] One of the first bike-sharing system was the White Bicycle Plan during the Provos movement in Amsterdam followed by many unsuccessful programs around Europe. It was not until 2005 that the company JCDecaux launched Velo'v in Lyon (France) that bike-sharing systems successfully sustained services offering. See DeMaio (2009) and Parkes et al. (2013) for details about the history of bike-sharing.

[18] Some of the largest bike-sharing systems, in terms of the number of bike available, are Hangzhou Public Bicycle in Hangzhou, China, Citi Bike in New York City, United States, Velib' in Paris, France, and Santander Cycles in London, England.

company Bird, e-scooter-sharing services expanded to European cities within a year. These companies innovated to introduced shared bikes also in free-floating.[19]

Car-sharing. These services have gained some popularity in recent years, although the market is not consolidated and various forms of approaches can be found. Some companies provide station-based services while others provide free-floating alternatives. Additionally, some companies offer their own cars while others facilitate transactions with private car owners.[20]

Ride-hailing. This service involves matching passengers with personal drivers willing to offered the ride to passengers' destination. Leveraging on geolocation technology, these companies offer drivers the benefit of hailed passengers from the streets on-demand. It is then considered an appealing modality for drivers to earn extra revenue monetizing their assets. Passengers also obtain benefits such as low search cost and security.[21]

Carpooling. Similarly to ride-hailing, other companies match connections between nonprofessional drivers willing to share the ride with multiple passengers that are willing to share the cost of the journey. The French company BlaBlaCar provides solutions for inter-city transportation and it is the market leader holding large market shares in most European cities.

Mobility as a Service. The multiplication of transport modes poses the structural challenge of coordinating multiple alternatives to provide flexible solutions. Mobility as a Service (MaaS) represents an innovation aimed at addressing this challenge. MaaS enables the combination of different transport modes through a single platform to provide a comprehensive transportation service. Travelers can plan, pay for, and access different modes using a single application (Smith et al., 2018). The first commercial MaaS service, Whim, was launched in Helsinki in 2017 by the company MaaS Global, whose CEO, Sampo Hietman, conceived the idea of MaaS in 2012.[22]

This rough categorization of new services overlooks the value proposed by these platforms and how they create value, which are key elements in conceptualizing business models. A clearer definition is then crucial for understanding how these platforms generate

[19] Within just two years of their debut, e-scooters sharing companies accounted for approximately 15% of the on-demand mobility market (BCG, 2019). Other relevant examples of companies are Lime, based in United States, and Voi, born in Sweden, both offers services all across Europe.

[20] Some examples of companies are Share Now | Free2move (Germany), Getaround (United States), Communauto (Canada), among many others.

[21] Companies such as Uber, Lyft, DiDi, or Bolt are leaders in the market.

[22] The literature related with MaaS has grown considerably in recent years, but the work by Hensher et al. (2020) is an excellent starting point.

revenue, deliver offerings, and interacts with direct and indirect stakeholders, such as regulators (Snihur & Markman, 2023). Therefore, well-defined business models are essential to enhance our understanding about the regulatory challenges posed by digital mobility platforms.

3.1. Digital mobility platforms and the sharing economy

Despite the fact that some digital mobility platforms are still in the process of consolidation, they have undeniably revolutionized the industry by overcoming historical challenges in the industry (Hadley, 1886).[23] The digital revolution has enabled these companies to leverage smart technologies leading to the development of the so-called sharing economy.

One element of success of the sharing economy lies in the accumulation of substantial network effects (Montero & Finger, 2021). The central idea is that costumers derive benefits from the consumption of services when other costumers consume the same good (Katz & Shapiro, 1985). In other words, the utility of each consumer increases with the number of users in the network. Therefore, scaling up the number of participants in the platform is key to accumulate positive network effects.

Network effects are classified as within-group or cross-group network effects. When two users play the same role in the interaction (e.g., passengers), they belong to the same group. On the one hand, when one additional user impact other users from the same group then one talks about within-group network effects. On the other hand, the impact of additional users joining one group (passengers) on users from other group (drivers) is referred to as cross-group network effects. Characterizing the various network effects is key to understand digital mobility platforms.

However, none of these concepts fully explain the proliferation of digital mobility platforms, which hinges on the their ability to “internalized” network effects. When users are not compensated for the benefits they bring to the network, they have little incentives to participate, making the transactions costly (Belleflamme & Peitz, 2021). In some cases, these costs can be so high that they prevent any form of exchange. The digital revolution has allowed mobility platforms to reduce these transaction costs, enabling efficient interactions between users.

[23] Fragmentation exists in both side of the market. Transport is a market with a heterogenous demand side in terms of activities, preferences, needs, etc. It is also fragmented in the supply side due to the large amount of transport modes, infrastructure, connectiveness, operators, etc.

Digital mobility platforms can lower transaction costs to such an extent that they can create new market places that would otherwise be impossible. Moreover, they effectively manage network effects among multiple actors, deriving significant benefits from this process. Digitalization also enables economies of scope due to an efficient aggregation of demand and a rapid organization of various distributed means of production, which are key elements in the sharing economy. Furthermore, digital mobility platforms collects and process large amounts of individual information to adjust supply and demand, thereby enhancing market efficiency.

3.2. Typology of business models

In the following section we introduce a new typology of business models that emphasizes the value proposition of various digital mobility platforms. The analysis focuses on how these business models generate and manage network effects among the different groups connected to the network. Additionally, we use the economic value created to each of these groups, as well as to society, to clearly delineate the boundaries of each business model. The findings of the analysis are presented in Table 1.

Data integrators are platforms that aggregate real-time data from multiple transport modes and provide it to customers in an organized and comprehensive manner. The information these platforms collect includes timetables, waiting times, routes, estimated arrival time, service interruptions, among others. These platforms typically help travelers to plan their journey in advance and to adapt in case of disruptions in the network. By centralizing information from various sources, they also enable travelers to seamlessly combine multiple modes of transport for door-to-door itineraries. Overall, these platforms reduce costs by optimizing travel time and contribute to better coordination among various transportation methods, leading to significant socio-economic benefits.

The value proposition of *B2Sharing* lies in offering fleets of transportation means for travelers to share over short periods of time. These transportation options are not limited to a specific type and can include bikes, e-scooters, trams, trains, autonomous vehicles, and more. Companies operating under this business model focus on managing within-group network effects, as they primarily influence the demand side. For example, in bike-sharing services, positive effects can occur if an increase in users leads to better redistribution of bicycles across the city. However, negative effects might arise if a surge in users results in system congestion.

By leveraging smart and geolocation technologies, these models allow users to access vehicles on demand, significantly reducing travel cost. They enhance travelers' flexibility by offering short-term access to vehicles tailored to their specific needs. In terms of the socio-economic values, geolocation technologies also contributes to a more efficient use of the public space. Furthermore, these platforms expand coverage by providing vehicles in time and zones where mass transit is unavailable. If they effectively complement mass transit, they could play a crucial role in reducing traffic congestion and carbon emissions.

P2P-Sharign models provide digital infrastructures to facilitate the connection among individual owners to share their assets with other travelers. Platforms following this business model typically facilitate the connection without directly matching users nor setting the conditions of the contract including prices. Instead, they restrict their intervention to ratings and recommendations as a way to actively manage cross-group network effects (Belleflamme & Peitz, 2021). [24] It is noteworthy that the pricing scheme in this business is defined for actors to share the cost of the trip.

Under these conditions, individual owners can decide whether to share their assets for the use of others or to become semi-professional drivers sharing their ride. Due to the cross-subsidy, the value individual owners obtained from the platform is a more efficient use of their assets.

The value obtain by passengers is the access to transport means at low cost as the price of the journey is typically lower than the alternative due to the cost-sharing condition. In addition, this business model may provide transportation services in regions uncovered by traditional means improving passengers' flexibility. These platforms serve for a better use of public space and hold potential to alleviate transport-related concerns by reducing solo-driving and improving connectivity to mass transit.

[24] For instance, the amount of information about drivers increases with the number of passengers allowing the platform to do better recommendations and improve the quality of the match between drivers and passengers. This is an example of a positive cross-group network effect .

Table 1. Business model typology for digital mobility platforms

Business model	Value proposition	Examples	Value to actors linked to the platform								
			Providers of means of transport[1] (supply)		Seamless services[2] (supply)	Passengers (demand)			Socio-economic value		
			Efficient use and/or investment in assets	Earn extra income	Low-cost access to networks	Reduce travel cost	Improve flexibility and certainty	Access to seamless services	Better coordination of distributed means	Better use of public space	Reduce pollution
Data integrators	Provide and organize real-time data collected from multiple transport modes.	Citymapper Transit				✓			✓		
B2Sharing	Provide fleets of transportation means to be shared among travelers in short periods of time.	Velib' Lime Europcar-on-demand				✓	✓		✓	✓	✓
P2P-Sharing	Facilitate the connection among individual owners to share their assets with other travelers.	BlaBlaCar Getaround	✓			✓	✓		✓	✓	✓
Super-intermediaries[3]	Allow individuals to hire transport services from owners of private vehicles setting the conditions of the contract.	Lyft	✓	✓			✓		✓		
Platform ecosystems[4]	Manage the connection of peripheral services to their core network generating strong complementarities.	Uber DiDi	✓	✓	✓		✓	✓	✓		
Mobility as a Service (MaaS)	Provide a plethora of digital services to manage transport systems.	MaaS-Global Whimp	✓	✓	✓	✓	✓	✓	✓	✓	✓

1. This column excludes means of transport provided by B2Sharing companies, because the Table aims to reflect the values added to actors linked to the platform. 2. Seamless services are peripheral services that are traditionally provided in a separate market, but they could belong to the same segment. For example, Uber providing delivery services or car rentals. 3. The name was taken from Montero & Finger (2021). 4. See the work of Jacobides et al (2018) for details on the theory of platform ecosystems.

S*uper-intermediaries'* value proposition is to allow individuals to hire transport services from owners of private vehicles. Contrary to *P2P-Sharing* models, *super-intermediaries* directly define the conditions of the contract and fully control the matching between users. Pricing in this model is designed to subsidize one group while charging a premium to the other group. The goal of such cross-subsidy scheme is to scale the size of subsidized users because they generate positive cross-group network effects. As a results users from the other side are willing to pay the premium in exchange for such benefit (Eisenmann et al., 2006).

This business model enable users to extract more value of their private assets, as drivers receive incentives to share them in exchange for a fee. The pricing and matching strategies inherent to this model allow drivers to generate additional income by monetizing their assets, potentially incentivizing them to invest in and acquire new ones. For passengers, these platforms offer benefits such as enhance security and predictability (Markman et al., 2021). However, there is not robust evidence to suggest that *super-intermediaries* provide low-cost trips. Despite this fact, the model creates socio-economic value by providing transport services to times and areas that traditional methods do not serve.

According to Jacobides et al. (2018), a *platform ecosystem* consists of an array of firms that offer seamless services connected to a central platform.[25] The value proposition of this model is to actively manage the connection between peripheral services and the core network to create strong complementarities. The platform leverage these complementarities to attract more consumers amplifying cross-groups network effects. For example, they often bundle services to create synergies across different segments of the network.[26]

Similarly to *super-intermediaries, platform ecosystems* enhance the efficiency of private assets and may encourage investment in new ones. In addition, they create economic benefits to peripheral firms, allowing them to access the platform's core network at a low cost. Passengers instead benefit by quickly accessing a wide range of complementary services through the platform. It is important to note that *platform ecosystems* can generate socio-economic value under certain conditions, such as improving the coordination of distributed means through the integration of related services. For example, Uber integrating e-scooter into its network could encourage multimodal behavior.

[25] Seamless services are peripheral services that are traditionally provided in a separate market, but they could belong to the same segment. For example, Uber providing delivery services or car rentals.

[26] For example, Uber offers complementary services such as Uber Cruises to navigate the Seine in a private Cruise.

As previously discussed, *Mobility as a Service (MaaS)* integrates various transportation modes into a single application allowing travelers to search for and book multiple services at once. Therefore, the value proposition of *MaaS* is to provide a plethora of digital services to manage transport systems. Similar to ecosystems, *MaaS* requires a digital infrastructure capable of integrating multiple services, leveraging complementarities among them.

The key difference is that *MaaS* must actively manage network effects to maximize socio-economic benefits by offering customers the most convenient combination of transportation modes. However, the exact mechanisms through which *MaaS* can generate these network benefits are not yet fully understood, though both pricing and non-pricing strategies together may certainly play a crucial role. Another significant distinction from *platform ecosystems* is that *MaaS* must generate socio-economic values by responding to the general interest, such as reducing traffic congestion and lowering carbon emissions.

4. Towards a new regulatory governance

Digital mobility platforms aim at creating network effects engaging in these efforts to increase the number of actors, scaling-up the size of the platform triggering further network effects. For example, platforms set individual prices, arbitrage over suppliers, collect large amounts of data from consumers and suppliers, and determine the conditions of the agreement between actors. This in turn raises considerable economic and societal challenges for sectorial and economic regulators because these efforts are often not within the scope of their power.

Nonetheless, research on this direction if still limited. In this section we characterize how various actions from digital mobility platforms conduct to market failures due to negative externalities, market power, information asymmetry or public goods. The main findings are summarized in Table 2.

Negative externalities. When the consumption of a good or service harms a third party is known as a negative externality.[27] In the case of transportation, the most important negative externalities are related with traffic congestion and pollution. The problematic regarding digital mobility platforms relies on the change of users' behavior in the presence of new alternatives. Due to cost-sharing schemes or to the possibility of earn extra income,

[27] The work by Pigou (2002) and Ronald Coase (1960) are probably the most iconic analyses on the topic of externalities.

digital mobility platforms makes car usage more efficient inducing car travel. Therefore, they might inadvertently increase congestion and carbon emissions by increasing the volume of cars on the streets or by inducing modal shift from cleaner alternatives (Olave et al., 2024).

Another concern is related to the use of public space. To manage this scarce resource, governments have traditionally organized transportation around stations with integrated car amenities. However, innovations in vehicle types, parking methods, and circulation modes may significantly diverge from this approach. Consequently, digital mobility platforms could lead a disorganized system, imposing substantial negative externalities on users, particularly when space is misused or when the infrastructure is incompatible.

A pertinent example is the introduction of free-floating modes like e-scooters. Issues such as improper parking, sidewalk obstructions, and fatal accidents illustrate some of these negative externalities. While better policies can help to effectively organize innovations, it us crucial to assess potential undesired effects that could lead to lower accessibility and higher congestion at transport hubs (see Chapter 4 for a detailed analysis).

Market power. To develop network effects, platforms must achieve scale, and the greater the scale, the more pronounced the network effect becomes. This positive feedback enable platforms to capture a significant portion of the market pulling away from their rivals, a phenomenon often referred to as tipping (Dubé et al., 2010). Moreover, platform ecosystems aims to generate strong complementarities across members to attract and retain consumers. Additionally, network effects may also raise barriers to entry as new companies may find difficulties attracting consumers from established networks (Katz & Shapiro, 1992).

Although robust evidence of these effects in new mobility is scarce, it is clear that companies such as BlaBlaCar and Uber hold high market shares.[28] There are some practical cases suggesting that new services represent a strongly competition to incumbents. See for example the case of Coach services and BlaBlaCar in Spain.[29]

[28] According to the mainstream media outlet CNN, Uber held approximately 74% of the market share in the United States in 2023, a significant lead over its competitor Lyft, which accounted for the remainder. This gap has widened over time, with Uber's market share standing at 62% in 2019, aligning with the predictions associated with the winner-takes-all effect. For details pleases visit https://edition.cnn.com/2023/03/29/tech/lyft-leadership-change/index.html (Accessed on 14th February 2024).

[29] In 2015, coach services suited BlaBlaCar in Spain for unfair competition. However, the Madrid Commercial Court dismissed the appeal because "Blablacar has not created a platform in order to provide a transportation service, but to put in contact individuals who want to make the same trip and share certain expenses… the activity is regulated by the Spanish Information Society Services and Electronic Commerce Act (SISSEC)."

Table 2. Market failures from digital mobility platforms

Failure	Description
Negative externalities	Platforms that make car travel more attractive by reducing travel costs may inadvertently change users' behavior, leading to negative outcomes such as: • Increased congestion, if they switch from mass transit, • Increased carbon emissions if they switch from cleaner alternatives. In the scarcity of space, innovations in vehicle types, parking methods, or circulation modes may impose significant negative externalities, especially when space is misused or the infrastructure is incompatible.
Market power	If digital mobility platforms concentrate large market shares, they may be tempted to exploit their dominant position, potentially harming social welfare. Two relevant cases include: • Predatory strategies to eliminate competition. • No benefit transfer to costumers. Business strategies aimed at building large ecosystems of complementary services increase market concentration and blur the boundaries of the relevant market.
Information costs asymmetries	Digital mobility platforms have access to large amounts of certain information at low or no cost, while the cost for users is considerably high. This asymmetry can lead to market failure if platforms manipulate the information for their own benefit.
Public goods	Digital mobility platforms may *free-ride* on transport infrastructure if there are no incentives to contribute. Even if these platforms increase mass transit ridership, their price does not internalize urban development.

The potential to tipping lead platforms to engage in aggressive practices exploiting their dominant position. One relevant case is predatory pricing. In other words, platforms set prices below cost or even zero to accumulate all demand eliminating competition. When prices are set below cost, competitors are unable to participate without making loss. Consequently, predatory pricing might harms future innovations.

Additionally, when companies hold a dominant position in the long run they might fail to share part of the benefits with costumers without the fear of losing them or to put aside the socio-economic value. Uber failing to improve drivers contractual agreements serves as an example. Another strategies could be the use data to lock-in consumers or to concentrate service provision in specific time/zones hindering universal accessibility.

To understand market dominance, one needs to define the relevant market to frame the boundaries of competition including products, geographic inference, and customers. However, the capacity of this platforms to integrate seamless services blurs the definition of the relevant market. *Platforms Ecosystems* quickly integrate numerous actors from various sectors without clear definition of the products they offer.[30] Moreover, *Platform Ecosystems* and *MaaS* may resemble "after markets" where the consumption of a primary product leads to the consumption of a secondary product. It is not clear whether both primary and secondary goods must be considered as a single or as a separate market.[31]

Overall, determining the relevant market in multi-sided platforms remains an ongoing debate within competition economics and law. Some advocate for defining each isolated side of the platform as a relevant market, while others propose considering all sides collectively as the relevant market. The question remains an open debate in the academic literature.[32]

Another key concern is related with the regulatory governance of *MaaS*.[33] While integration holds the promise of enhancing coordination among participants, it also implies a structural transformation of the industry with transport providers and passengers interacting through the platform. This organization will empower the platform may leverage its position to set entry conditions potentially hindering future innovation. The ultimate goal of the platforms must be to allocate efficiency gains derived from improved coordination and broader network effects (Montero & Finger, 2021). Therefore, imposing neutrality obligations on *MaaS* need to be set to guarantee universal access and to ensure equitable treatment.

Information cost asymmetries. Unbalances in the cost to access information among participants can lead to market failures if the party with superior knowledge abuse his

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[30] There are multiple examples of digital mobility platforms integrating other services. For instance, BlaBlaCar forged an agreement with the national railway company SNCF in 2019. BlaBlaCar also acquired Klaxit in 2023 to provide intra-city carpooling services, particularly focused on home-to-work commutes. Similarly, Uber has diversified with offers such as Uber Pool, Jump, Uber Eats, Uber Moto, Uber Cruise, among others. It has also partnered with Lime to enable users to locate and unlock shared e-scooters and e-bikes directly through its platform. More recently, Uber Rent allows users to rent cars from companies like Avis, Budget, or Europcar. Uber also provides advance technological solution for delivery logistics with Uber Freight.

[31] The relevant market in could be systemic, encompassing both primary and secondary together, multiple markets, comprising separate goods, or dual markets, consisting of one market for the primary good and another for the secondary good. Guidance to define relevant markets in this context has been recently revised by the European Commission in the draft notice on the definition of relevant markets in November 2022.

[32] The European Commission's recent draft Notice on the definition of relevant markets, published in November 2022, suggests that a market in multi-sided platforms may be defined either as a whole or as separate markets, depending on the case. The Commission recommends defining separate markets where significant substitution occurs across the platform's sides. Key factors in assessing whether such conditions exist include product substitution, product differentiation, users' decisions, and the nature of the platform. Additionally, the draft acknowledges that zero-pricing is intrinsic to multi-sided platforms and does not preclude the existence of a relevant market. The draft was retrieved from https://competition-policy.ec.europa.eu/public-consultations/2022-market-definition-notice_en on February 12th 2024.

[33] The literature on Mobility as a Service is extensive. Much of the research has primarily focused on identifying drivers and barriers for implementation (Audouin & Finger, 2018; Smith & Hensher, 2020; Smith et al., 2020; Van den Berg et al., 2022). Research to assess the impact of MaaS on key outcomes such as private car displacement and pollution is still limited.

position.[34] Digital mobility platforms collect large amounts of data from all actors at low or no cost with the aim of generating strong network effects. Conversely, consumers do not have access to such information because it is considerably high or even impossible.

This lack information raises concerns if platforms manipulate such information for their own benefit. For example, the lack of information about pricing and matching algorithms may induce them to pay higher prices. The possibility of comparing other services could help to solve such imbalances. Another example is the use of such information to *nudge* consumers, i.e. to influence their decisions towards options that are beneficial for the platform.

Another practice involves offering environmentally-friendly options to attract more users. Some digital mobility platforms offer eco-friendly rides, while others position themselves as a green alternative. However, consumers often lack sufficient data to make informed decisions. This information imbalance is critical because it can make car travel more appealing, potentially diverting users away from cleaner modes of transportation (Olave et al., 2024).

Public goods. Good considered as public are non-excludable and non-rivals, i.e., they are accessible to everyone and its consumption by one person does not limit the consumption of others.[35] The main problem related with these type of goods is the lack of private incentives to contribute to their production, resulting in their under-provision or degradation.

In the case of transportation, services are linked to the physical word through the construction of infrastructure and related amenities. Moreover, transport networks such as cycleways and roadways are considered as non-excludable. Mass-transit services also function under the principles of universal access. Consequently, private companies have no incentives to invest in infrastructure and it has been traditionally carried by the state through different sources of public contribution including traveler fares.

Yet, with the surge of digital mobility platforms displacing mass transit, the amount of fares collected from traditional players may significantly decreased pressuring the financing schemes for public investment (Finger et al., 2017). Additionally, digital mobility platforms free-ride on transport infrastructure and there no incentive in place for them to contribute.

[34] George Akerlof's paper, The market of lemons (1970), is probably the best reference to study the effect of asymmetric information on markets.

[35] The seminal work by Paul A. Samuelson (1955; 1954) are considered the basis of the modern theory of public goods.

Even in scenarios where platforms increases mass-transit ridership, their price does not internalize the use of public infrastructure. Therefore, it becomes imperative to devise policies that promote synergies with mass-transit to ensure sustainable urban development.

4.3. Policy implications

Digital mobility platforms have revolutionized our daily routines by offering novel and convenient transportation options as alternatives to private cars. While some studies have highlighted the positive impacts of these innovations, there are also disruptions that could potentially undermine social welfare. These platforms aimed at creating strong positive network effects extracting some economic benefit. To accomplish their purpose, they may engage in aggressive practices that requires further attention. In this section, we discuss some regulatory policies that could help regulators to accompany the integration of digital mobility platforms, thereby mitigating the risk of undesired effects.

Digital mobility platforms have been introduced without regulation mainly due to a lack of knowledge about their practices and their capacity to quickly evolve and adapt to changes in the market. In this context, defining a more adaptive and flexible regulatory policy in a broader urban environment is key. Flexible rules can help authorities to quicky adapt to different business models and innovations. Rules issued to manage urban transportation such as codes of circulation and parking, typically fragmented by the number of transport modes, need to be revised to develop a multi-modal regulatory framework. This must be coupled with a more active use of data to systematically assess the effects of regulatory intervention to keep pace with technological innovation. Moreover, enabling experimentation might improve predictability and stimulate innovation.

Investing in transport infrastructure and leveling the regulatory playing field between platforms and incumbents are also key principles. Better management of the public space to integrate platforms with traditional services is essential to trigger complementarities and to improve accessibility with the aim of tackling travelers dilemmas. Moreover, certain regulatory advantages in favor of platforms such as tax exemptions, no contributions for infrastructure investment, and no-charges for the use of the space may result in an under provision of infrastructure.

It is also important to promote the use of platforms to complement mass transit. Promoting business models to govern transport systems is a promising policy. Care must be taken to define obligations for universal service and neutrality to achieve policy objectives such as reduce congestion and carbon emissions. Other policies such as integrated transport benefits that covers multimodal mobility must be promoted.

The value proposed by digital mobility platforms is data-driven, therefore, it is necessary to improve regulatory capacity to better evaluate the influence of digital platforms on the market. Defining robust statistical methodologies to provide scientific evidence on how the presence of digital platforms affects congestion and emissions is a promising strategy. These methodologies should consider the presence of the platforms in a multi-modal environment from an holistic perspective to better understand the mechanisms behind their influence on transport-related concerns.

Moreover, it is crucial to promote data-driven regulation and define data-sharing obligations for platforms. Analyzing real-time data provided by platforms allows continuous monitoring, improves predictability, and ensures an effective and rapid intervention from regulatory authorities. To this end, it is crucial to set adaptative rules for data requirements, build open data standards, develop applications to collect real-time data from platforms, and build regulatory capacity to be able to process big data for better policy design and regulatory enforcement.

Additionally, multi-sided markets may create asymmetries of information. Promoting multihoming and defining obligations to platforms to reveal relevant information increases consumers' awareness and reduces platforms' potential abuses. Finally, for business models providing access to networks, it is crucial to better understand the effects of service integration in the definition of the relevant market. How the provision of network services influence competition and deter entry is a relevant question. Also, it is crucial to better understand how the use of data in one segment of the market might be used to influence actors' decisions over multiple segments.

5. Conclusion

Digital mobility platforms have been introduced because they hold potential to ease transport related concerns such as congestion and pollution. Contrary to traditional transport services, these platforms' value proposition is based on the management of network effects. Moreover, the digital revolution has allowed these companies to reduce transaction costs at the extent of creating new market places. In this paper, we propose a typology of the various business models following this logic. A better understanding of the value proposed by these companies help governments to adapt current regulatory policies to meet social, economic, and environmental objectives.

This analysis offers a typology of business models based on their approach to manage network effects. However, the literature on platform business models is still in its early stages, leaving many questions open for further research. A particularly important area of inquiry is how platforms define their business models and how these definitions evolve over time , which is crucial for understanding the rapid technological advancements within these companies. Another key question concerns the incentives for these companies to join a larger network. For example, it remains unclear whether larger platforms, which already generate strong network effects, would be willing to participate in a *MaaS* model.

Platforms managing network effects aimed at growing in size to amplify such effects, at the expense of attracting demand from incumbents. This *tipping* effect generates positive feedbacks that could result in high market concentrations. Therefore, digital mobility platforms engage in aggressive practices to *tip* the market towards their own benefits. This in turn prompt discussions about the necessity of public intervention. The potential to tipping may induce platforms to engage in aggressive competition practices including predatory pricing and personalized services to lock-in consumers eliminating competition.

Other key concerns are related with negative externalities–leading to higher congestion and carbon emissions, information cost asymmetries–leading to abuses to consumers, and the provision of public goods–resulting in an under provision and degradation of public infrastructure.

We also discuss various policy implications derived from our analysis. In summary, it is essential to develop a more adaptive and flexible regulation following an holistic approach. Similarly, improve space management to integrate and promote platforms to trigger complementarities to mass transit is crucial to reduce car dependencies. Promote digital mobility platforms that aim at governing transport systems is a promising policy, but care must be taken to define obligations for universal service and neutrality. Finally, it is essential to improve regulatory capacity and develop data-driven regulation to better evaluate platforms' practices and improve enforcement.

The evolution of regulatory policies must consider these conditions to fully unlock the potential benefits of technological progress. While societies benefit from such innovations, market concentration and coordination gaps may yield detrimental outcomes. Moreover, "these new solutions are disrupting the status quo and calling for the development of new organizational approaches" (Finger & Audouin, 2019). Indeed, the evolution of the regulatory governance becomes crucial to develop efficient coordination mechanisms among different stakeholders. We must not forget that technological evolution alone without the proper policies is an utopian vision (Yeung & Lodge, 2019). Instead, we must develop robust regulatory governance to steer innovations to address issues of general interest.

The ingredients are served, it is up to us to pooled them in an efficient and coordinated manner, rather than simply scramble them hoping for the best.

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Chapter 3

Fire bikes to the rescue!
Bike-sharing and public transport substitution

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Chapter outline

Abstract
Micromobility, particularly bike-sharing systems, have potential to ease environmental and social concerns by reducing car-dependencies and enhancing connectivity with public transport. However, the extent to which bike-sharing substitute public transport remains uncertain. This paper leverages an extemporaneous incident that disrupted Mexico City's subway system to causally identify public transport substitution to bike-sharing. By exploiting the spatial relationship between bike-sharing and subway stations, I characterize bike-sharing trips as substitutes or complements to public transport. The findings suggest a significant increase of public transport substitution to bike-sharing during disruptions. Furthermore, upon system restoration, the disruption is associated to a surge in bike-sharing ridership. Finally, this surge in ridership is related with an increase in the level of complementarity with public transport. These findings have crucial policy implications to design multimodal mobility systems resilient to disruptions capable of withstanding challenges related to the ecologic transition.

Keywords: *Sharing-mobility; Bike-sharing; Public transport substitution; Public transport disruption; Natural experiment.*
JEL classification: *D90, L92, R4, R41, R42.*

1. Introduction

The car-oriented paradigm that dominated urban transport during the last fifty years arose environmental and social concerns such as traffic congestion, pollution, territorial inequalities, and adverse health outcomes. In consequence, cities are welcoming new mobility services with the aim of solving these transport-related concerns. The so-called sharing mobility might help cities in their endeavor inasmuch as it reduces car-dependency (ITF, 2021; Asensio et al., 2022), tackles first/last mile dilemmas (DeMaio, 2009; Lesh, 2013; Shaheen & Chan, 2016), and improves accessibility (Shaheen & Cohen, 2019). In this regard, complementing public transport with new services is key to trigger multi-modal behavior stimulating non-car travel demand (Shaheen & Chan, 2016; Meng et al., 2020). Nevertheless, to what extend new mobility services substitute public transport is an open question in the literature which answer is key for the future organization of urban mobility.

I focus here on the station-based bike-sharing models which is a recent innovation that allows riders to borrow bikes from any dock and return them to any other dock near their destination. As any other shared mobility service, this mode enables users to have short term access to transport on an as-needed basis (Shaheen & Cohen, 2019). Furthermore, bike-sharing is growing in popularity among governments due to their potential to overcome the so-called last-mile dilemma by improving connectivity to public transport enhancing multimodal behavior (Shaheen & Chan, 2016). Nevertheless, the question on whether bike-sharing complements or substitutes public transport remains to be answered due to mixed results in empirical studies. Many have associated a larger public transport ridership due to the presence of bike-sharing, suggesting a complementary relationship (Ma et al., 2015; Ashraf et al., 2021; Radzimski & Dzięcielski, 2021). Others have found evidence of public transport substitution to bike-sharing, i.e., they have found evidence of a decrease in public transport ridership, especially in urban cores with high diversity of activities (Campbell et al., 2016; Campbell & Brakewood, 2017). Only a bunch of studies have explored the possibility of a dichotomic interaction where bike-sharing provides both: complementary and substitution journeys (Shaheen et al., 2011; Martin & Shaheen, 2014).

This paper provides empirical evidence in this regard by exploring an extemporaneous incident that shut down operations in Mexico City's subway network on January 9th, 2021. The purpose of the analysis is threefold. First, it seeks to causally identify to what extent bike-sharing substitutes or complements public transport by exploiting the spatial relationship between docking and subway stations. Second, it investigates the short and long-run effects of disruptions in the transport network on bike-sharing adoption. Third, it unravels whether an expansion in the adoption of bike-sharing displaces subway ridership.

The central hypothesis of this work is that docking stations highly integrated with public transport show a larger degree of substitution in comparison with stations outside the spatial coverage of the subway system. This is because commuters can fully substitute subway itineraries with bike-sharing when docking stations are located within the spatial coverage. In the case of disruptions in the system, those stations might help users to *bridge* disrupted connections in the network. Furthermore, disruptions might form habits among users towards cycling making intermodal journeys (bike-subway) more attractive affecting subway ridership in the long-run (Goodwin, 1977; Chen & Chao, 2011; Xin et al., 2019).

The Mexican context is particularly useful to assess the hypothesis. First, the extemporaneous variation in the supply of subway services allows a natural experimental setting to causally identify the impact of public transport disruption. Second, the bike-sharing model in Mexico City is integrated with the urban mobility system with docking stations located within the spatial coverage of the subway system. Third, subway lines unaffected by the incident remained open along the whole period of study. These feature, along with the fact that only a fraction of docking stations are located nearby disrupted subway stations, allow me to identify fluctuations in the degree of complementarity between both modes as a result of the network disruptions. Fourth, the data available allows the comparison of three relevant scenarios: before, during, and after disruption, which enables the assessment of time-varying effects. Fifth, information about bike-sharing in Mexico City is open source. The datasets collected provide information of every bike journey in an origin-destination format including the geo-location of docking stations. Thus, studying the spatial integration of bike-sharing with public transport is feasible. As a matter of fact, I exploited this spatial relationship to identify first/last-mile and substitute bike journeys using a methodology similar to Fan & Zheng, (2020).

My findings suggest that public transport disruption is associated with an increase in the demand for bike-sharing. On average, the number of additional bike journeys associated with disruptions is about 3,600 per week. This amount is equivalent to 30.4% of the total number of bike-sharing journeys in a common day and 6.4% of the number of journeys in a common week before disruption. Another interesting comparison is that the average number of additional trips each day after the incident is equivalent to 10.5% of the fleet-size (6,800 bikes). Regarding the level of integration, the evidence suggests that the effects are larger among docking stations within the spatial coverage of the public transport network. Notably, a decrease of 100m in the planar distance between any docking station and the closest subway station is associated with an increase in the daily average number of trips of 9.8% per docking station. I also explore the extent to which the effects vary with the degree of substitution and complementarity between bike-sharing and public transport. Results suggest that the number of trips substituting public transport increased in the weeks of disruption while the number of journeys complementing public transport decreased. The estimations do not change regardless of the type of complementary trip, i.e., first or last-mile connections. Overall, the evidence presented here suggests that commuters shifted towards bike-sharing to complete itineraries that, otherwise, could have been done using the subway network. In the same order of ideas, a lower degree of complementarity between both transport modes is reasonable due to a lower connectivity within the network.

Regarding the effects in the long-run, the estimates indicates that public transport disruption is associated with an overall increase of bike-sharing demand in the post-disruption period. In fact, the dynamics between both transport modes changed when the subway reopened operations in comparison with the scenario before disruption. The evidence suggests a higher degree of complementarity for all types of journeys (firs-mile and last-mile) as well as a higher number of bike-sharing journeys substituting subway itineraries (but at a lower extend than the scenario during disruption). Overall, these findings suggest that disruptions in public transport influenced modal shift to bike-sharing in a persistent way.

One concern with the interpretation of these findings is whether the effects are the result of commuters shifting from public transport to bike-sharing. It is important to point out that higher degrees of complementarities between public transport and bike-sharing are suitable to unlock multimodal behavior tackling car dependencies. However, disruptions in the network might detonate undesired modal shifts. To ease the interpretation of the results, I studied the association of bike-sharing on subway ridership displacement associated with disruptions in the network. Again, I exploited the spatial relationship between both modes to link bike-sharing and subway ridership. My findings suggest that expanding the number of bike-sharing journeys by 10% increases the inflow of subway passengers in integrated stations during disruption by 1.2%. Moreover, after the restoration of the system the positive associations is maintained, but the magnitude is reduced to 0.3%.

My findings are relevant for the public debate over the formation of multimodal transport systems. First, the evidence reveals that the relationship between bike-sharing and public transport is complex. A well-integrated bike-sharing system provides complementary journeys to public transit easing the first/last mile dilemma. In addition, it allows the substitution of some subway itineraries. What is more, this feature should not be considered as a detrimental factor because a certain degree of substitution is desirable to design resilient transport systems capable of facing disruptions. Thus, a well-integrated bike-sharing system serves to shield public transport from unexpected shocks. Second, cities could exploit the relevance of integrated docking stations to design a rebate system that promotes intermodal behavior.[1] Third, more policies that allow users to experience bike-sharing is another alternative to promote multi-modal behavior. For example, providing a test period free-of-charge might incentivize users to try the benefits of bike-sharing as an alternative to private cars. Finally, the evidence suggests that cycling infrastructure is key to improve the complementarities between bike-sharing and public transit.

The rest of the paper is organized as follows. Section 2 presents the related literature with a focus on the relationship between public transport and bike-sharing. Context about urban transportation in Mexico City and details on the incident that motivates this work are presented in Section 3. In Sections 4 and 5, I describe the data and the empirical strategy. Main results and robustness tests are reported in Sections 6 and 7. In Section 8, I provide additional evidence about the impact of disruption on the dynamics between both transport modes. Section 9 outlines the discussion and concludes.

2. Related literature

The findings presented in this article add to a nascent literature on new mobility modes, notably to the literature of station-based bike-sharing services (see Teixeira, et al. (2021) for a compelling review). The empirical evidence available falls in three categories: adoption

[1] Rebates in bike-sharing models are a common tool to help operators to rebalance the distribution of bikes across the city. For instance, the Velib' bike-sharing model in Paris offers "minutes bonus" to users who pick-up bikes from overcrowded stations or drop-off bikes in empty stations.

and modal shift, bike-sharing impact on transport-related concerns, and synergies with other modes of transport. This paper contributes to the latter strand as it aims to address to what extent bike-sharing substitutes public transport.

The evidence available so far shows mixed results. Some studies have found evidence of complementarities between both transport modes (Ma et al., 2015; Ashraf et al., 2021; Radzimski & Dzięcielski, 2021), others have found evidence of substitution (Campbell et al., 2016; Campbell & Brakewood, 2017), and a few have argued in favor of a dichotomic relationship, i.e., when bike-sharing complements and substitutes public transport (Shaheen et al., 2011; Martin & Shaheen, 2014). One of the very first studies exploring the dynamics between public transit and bike-sharing is the work by Martin & Shaheen (2014). Analyzing a survey data from Washington DC and Minneapolis and mapping geocoded home and work locations, the authors determine the conditions under which commuters shift towards and away from bus and rail using bike-sharing. They find that bike-sharing substitutes bus and rail transit in high density areas and complements it in suburban low-density areas, which, according to the authors, might be evidence of bike-sharing serving as a first/last-mile connection. In a subsequent work, Ma, et al. (2015) find a positive correlation between public transit and bike-sharing ridership after studying the Capital Bikeshare (CaBi) program in Washington, D.C. Moreover, the authors discuss to what extent the spatial integration between stations is a critical component to study dynamics between both modes of transport. They find that docking stations located close to subway stations produce more trips suggesting that public transport is an important feeder for bike-sharing. In contrast, Campbell & Brakewood (2017) are the first to causally identify a decrease in bus ridership associated with the introduction of bike-sharing in New York City. The authors exploit spatiotemporal differences in the construction of docking stations to estimate a difference-in-difference design comparing bus routes affected by the construction of docking stations with those not affected by the program. However, most of the evidence available is limited to stated preferences, short time coverage, and it is restricted to US cities. The unique analysis providing causal estimates focuses on the impact of bus ridership. The evidence presented in this paper is, to the best of my knowledge, the first to exploit a natural experiment to study subway substitution to station-based bike-sharing. In addition, I use origin-destination data at journey level to reconcile the dichotomic relationship between both transport modes identifying fluctuations in both complementary and substitution journeys. Furthermore, I study the evolution of the effects over time and discuss the role of habits for modal shift.

My methodology to distinguish complementary and substitution journeys is related to the paper by Fan & Zheng (2020). Estimating a difference-in-difference model, the authors find complementarities in the interaction between subway ridership and the intensity of use of dockless bike-sharing in Beijing. The authors collected data during two weeks after the introduction of the program in 2017. My paper differs in terms of the quasi-experimental design, the business model studied, and time coverage. I exploit as a natural experiment an extemporaneous shock in the provision of subway services to study the interaction between public transport and the station-based bike-sharing modes. Fan & Zheng (2020) instead, focus on dockless (or free-floating) bike-sharing services who exhibit different spatiotemporal patterns to those demonstrated by docked bike-share programs (McKenzie, 2019).

This paper is also informative about commuters behavior during public transport disruptions, a strand that has a long tradition in transport economics (van Exel & Rietveld, 2001; Zhu & Levinson, 2012; Anderson, 2014; Larcom et al., 2017); some recent research has focused on car-sharing (Tyndall, 2019) and carpooling (Yeung & Zhu, 2022). However, very few is known about the role of bike-sharing during network disturbances. Saberi, et al. (2018) conduct a spatial-temporal descriptive analysis to provide evidence of bike-sharing patterns before, during, and after the strike in the London Tube on July 8th – 10th, 2015. The authors find an increase in the number and duration of bike journeys during disruption. They also find a larger concentrations of highly used docking stations near the Tube and in London urban core. Younes, et al. (2019) study different rail transit closures in Washington, D.C. that happened between 2016 and 2017. The authors estimate an autoregressive Poisson time series model using journey level data to find that disruptions are associated with an increase in bike-sharing ridership in the vicinity of the affected subway stations. In addition, the authors discuss the possibility of bike-sharing as a first/last mile solution rather than as a substitute for public transit after inspecting the spatial distribution of journeys using a kernel density estimation. By analogy, I look at the impact of public transit disruption on bike-sharing ridership in an equivalent way. However, I provide robust empirical evidence estimating a quasi-experimental design exploiting an extemporaneous shock in public transport provision.

Finally, the results presented here provide evidence about public transit disruption management and the design of resilient transport networks (Zhu & Levinson, 2012; Zhang et al., 2021). Public transport disruptions are increasing in number due to the aging of subway systems around the world, forcing governments to find solutions to *bridge* disruptions using alternative transport modes. According to Zhang, et al., (2021), ride-sharing services could help by providing additional capacity to public transport. However, the role of new mobility services in disruption management is largely unknown. This paper contributes to fill this gap in the literature by identifying the effects of disruptions on bike-sharing journeys that served to replace subway itineraries.

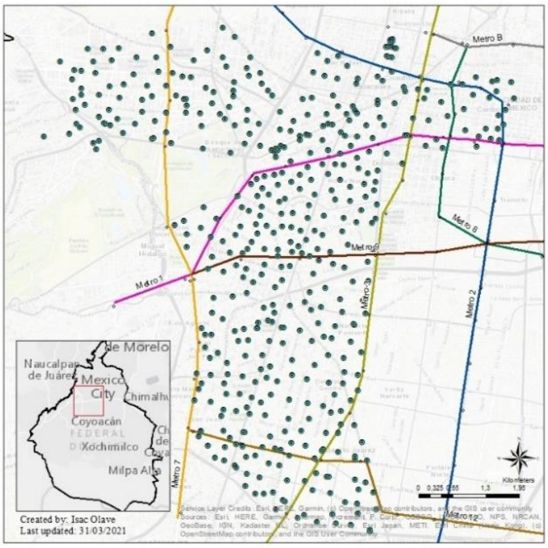
3. Case Study: Mexico City

Mexico City has a consolidated public bike-sharing system called ECOBICI where users undocked and docked bicycles in different stations distributed within a predetermine geographic region in the city (see Figure 1). The system was introduced in 2010 with the aim of complementing public transport providing more alternatives to commute. In 2021, ECOBICI managed 480 docking stations and a fleet-size of almost 6,800 bicycles (340 are electric). The profile of users is highly educated (86% bachelor of higher) young (40% have 25 to 35 years old) males (63%), as it is the case in other bike-sharing systems (SEMOVI, 2020). In order to use a bike, citizens must subscribe to one of the following plans: annual (27 USD[2]), weekly (20 USD), three day (12 USD), or one day (6 USD). Users are allowed to ride for 45 minutes (additional minutes cost extra fees). In the case of annual plans, the price allows users to access a low-cost transport service with a cost per trip close to 0.1 USD.[3] To the date covered in this study, there are more than 170 thousand users registered.

It is noteworthy that the city announced, at the end of 2021, a plan to expand the system adding 207 stations and 2,300 bicycles. Even if such expansion plan goes beyond the scope of this paper, it is important to point out the relevance of ECOBICI in the urban plannings for the city.

[2] Exchange rate used 1 USD = 19.5 MXN.
[3] Equal to 27 USD over 270 working days in a year.

Figure 1. ECOBICI's docking stations and Mexico City’s subway system



Note: The Figure reports the location of ECOBICIS’s docking stations (green dots) and their spatial relationship with Mexico City’s subway system (solid lines). The small square at the bottom shows the geographic coverage of ECOBICI.

Figure 2. Disrupted lines after the fire on January 9th, 2021

Note: The Figure reports the subway lines that stop operations after the fire in Mexico City’s subway headquarters on January 9th, 2021. Lines 4, 5, and 6, were restored 3 days after the incident. Lines 1, 3, and 2, reopened operations on January 25th, February 1st, and February 8th, 2021, respectively.

Mexico City’s backbone public transport is the subway network. It is formed by twelve lines connecting 195 stations and covering more than 226 km of tracks. The network serves more than 1.6 billion users annually (the second largest subway system in America after New York City). It is operated by Sistema *de Transporte Colectivo* (in Spanish), a public body decentralized from the local government. It is designed and managed in the basis of universality, therefore, the price per journey is relatively low (5 MXN, ≈0.25 USD) and no other pricing scheme exists.

A crucial point for this article is the dynamics between these two modes of transport. The survey conducted by ECOBICI in 2020 revealed that 45% of users complement their journey with the subway. Moreover, 11.9% would have completed the same itinerary in the absence of ECOBICI (SEMOVI, 2020).[4] Regarding the spatial relationship, as noticed in Figure 1, ECOBICI’s stations are located within a specific region of the city interacting with seven subway lines (1 to 3, 7 to 9, and 12). Those lines account for almost 74% of the daily traffic. In fact, 13% (63) of docking stations are located within 200m to the closest subway station and almost 50% within 500m (238 stations). In addition, some stations are integrated

[4] Being walking the first option in both cases: 65.1% and 37.3% respectively.

to important transport hubs such as the connection of lines 1, 7 and 9 (e.g., the Tacubaya station). Both transport modes are not only physically integrated, but they are also accessible using the same payment mode. The city launched in 2019 the intermodal mobility card (*Tarjeta de Movilidad Integrada*) as a payment method for different transport modes including subway and bike-sharing. The card costs 0.25 USD and works as a debit card, i.e., users can recharge it using specific modules distributed along the public transport network (since 2022, it is possible to recharge it using a mobile application). Concerning bike-sharing, such card allows users to unlock bicycles from stations.

3.1 Fire in subway's headquarters

On January 9, 2021, a fire caused by a short circuit struck Mexico City's subway headquarters shutting down operations in 6 out of 12 lines affecting 55% of the daily traffic (see Figure 2). Lines 4, 5, and 6 reopened operations only three days after the incident. However, lines 1, 3, and 2 where restored two (Jan 25th), three (Feb 1st), and four weeks (Feb 8th) later. As a result, the network remained disrupted for four consecutive weeks.

Mexico City's subway network disruption is suitable to be exploited as a natural experiment for the following reasons. First, it was an extemporaneous and unforeseeable event preventing operators and users to systematically modify their behavior beforehand. Second, ECOBICI is integrated into the disrupted lines, notably lines 1, 2, and 3. Furthermore, those lines are in fact the most demanded in the network accounting for almost 45% of daily traffic. Third, the network shut down partially, this in turn enables the possibility to study disruption effects on complementary bike journeys. Fourth, the network was disrupted for a sufficiently prolonged period (four consecutive weeks) to study the persistence of the effects over time and the formation of habits.

4. Data and descriptive statistics

To assess the disruption effects at hand, I created an original dataset combining diverse sources of information. First, I collected journey level data in an origin-destination format, which is publicly available from ECOBICI's website. The dataset includes, among other variables, docking stations' identifiers for the origin and destination, starting, and ending time, the type of station (e-bikes vs standard), zip code, and rider's age and gender. Second, I requested the geolocation of docking stations from the operator's API. Third, the total capacity, i.e., the total number of docks per station, was retrieved from ECOBICI's web application. Fourth, regarding subway data, I collected stations' geolocation as well as daily ridership at station level from the city's open data portal. Finally, this study also includes geo-data for biking infrastructure in the city, obtained again from the open data portal.

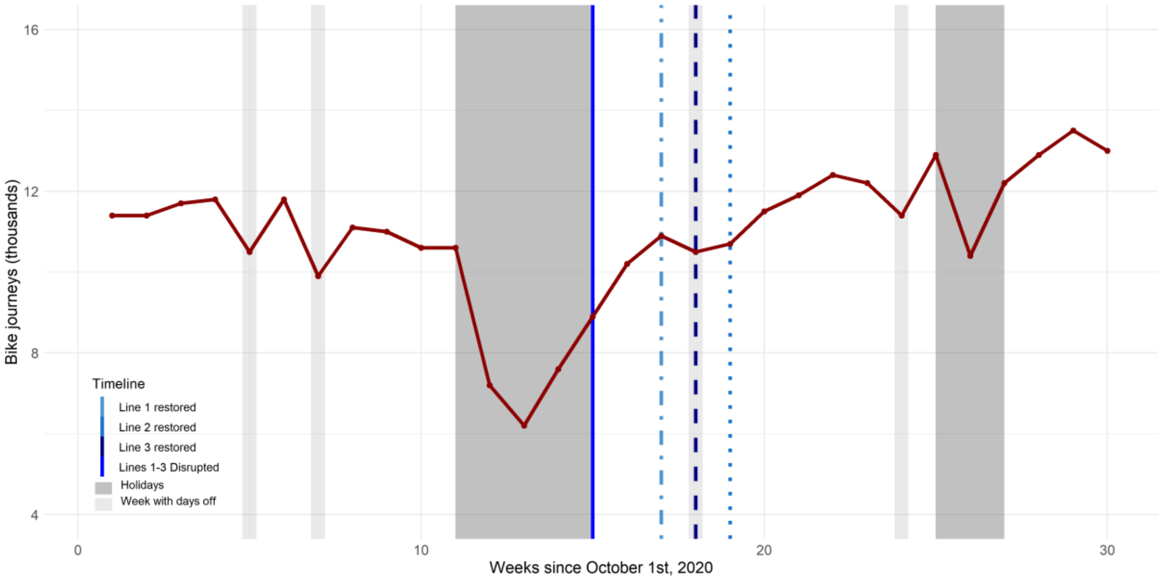
The period of study comprises the events between October 2020 and April 2021, i.e., before, during, and after the subway disruption.[5] It is worth mentioning that winter holidays in Mexico, during the period of study, started on December 21st, 2020, and ended on January 8th, 2021. Notice that, the day of the incident (January 9th, 2021) was the first Saturday after holidays. Therefore, I have dropped all the journeys during holidays. Consequently, the before-disruption scenario includes eleven weeks before December 21st, 2020, the during-disruption scenario starts on January 11th, 2021, and includes the next four weeks, and the after-disruption scenario considers the rest of the available weeks. This approach was taken to avoid confounding factors related with the end of school holidays. On the other hand, this strategy could threaten the empirical findings if riders use holidays to form habits, which I believe is implausible because people use bike during holidays mainly for ludic purposes. Nevertheless, I provided a robustness test to account for this caveat in section 7. Please referred to Figure 3 to see other holidays and days off in the time spam also dropped from the sample.

I winsorized the data using the distribution of journeys duration, inferred from the time at origin and destination, dropping the shortest and longest trips (0.5% of each extreme). This is because journeys lasting just a few seconds or more than two hours are not credible and might be considered as measurement errors. Furthermore, after analyzing travel patterns within any typical day, I dropped weekends and holidays. As noticed in Figure 4 and Figure 5, the intraday distribution of the number of trips is considerably different between working and nonworking days. As noticed, the travel pattern in a typical working day is characterized by two peak hours that coincides with entry to work (or school) and back-home time (≈9:00am and ≈19:00pm) and a third peak that coincides with lunch time in Mexico

[5] As expected, Covid-19 had an important effect on the transport system in the city. The second quarter of 2020 reported a bike-sharing ridership close to 20% of the total ridership in the same quarter of 2019, the lowest value observed during the crisis (see Figure A-2 for details). A similar behavior was observed in public transit ridership. The Figure by 2021 showed the first signs of recovery. By the second quarter of the year, bike-sharing and subway ridership were close to 45% of the levels observed in 2019-Q2. What is more, both systems have shown similar patterns.

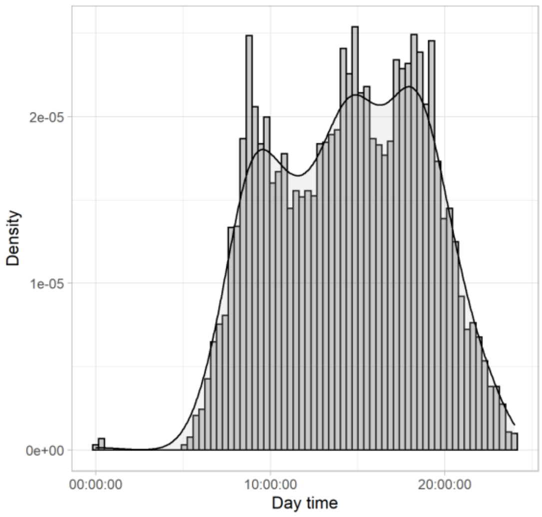
(≈15:00pm). In contrast, the volume of bike journeys during nonworking days is single peak around lunch time.

Figure 3. Daily average of bike journeys over time



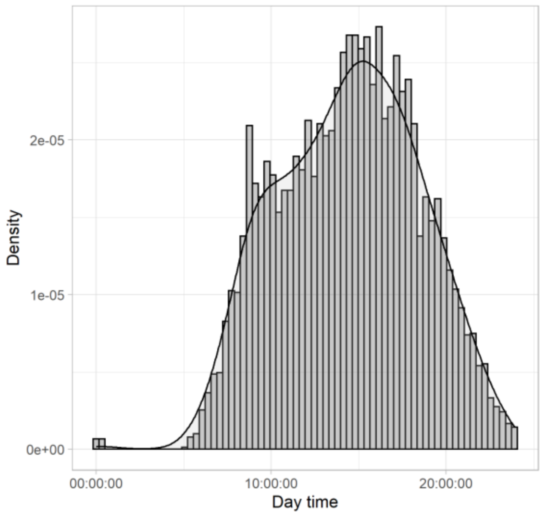
Note: The Figure reports the daily average of bike-sharing journeys each week since October 1st, 2020. Solid vertical line (in blue) shows the first week after the subway disruption on January 9th, 2021. Dashed lines show the progress restoring the network. Dark shaded regions show school vacations in Mexico due Christmas and the Holy Week. Light shaded regions indicate weeks with at least one day off.

Figure 4. Characteristic travel pattern of a working day



Note: The Figure reports the travel patterns of December 8th, 2020. This date was chosen to represent travel behavior during working days. It shows the density in the number of journeys by hour.

Figure 5. Characteristic travel pattern during holidays and weekends



Note: The Figure reports the travel patterns of December 21st, 2020. This date was chosen to represent travel behavior during nonworking days. It shows the density in the number of journeys by hour.

Afterwards, I have constructed two balanced panel data at the level of docking stations observed every week. The main difference between each other is the subject of study. The *origin-station* data base use characteristics of the docking station at the origin while the *destination-station* data exploits characteristics of the docking station used to complete the journey. Making this difference is relevant to dig deeper in the market dynamics between bike sharing and public transport. In a nutshell, bike sharing complement public transport connecting people to the service while substitution arise when bike is used to complete a similar subway itinerary.

The definitive samples are similar in many characteristics by construction such as the number of observations, contains close to 1.2 thousand observations for 480 stations and 25 weeks (11 before, 4 during, and 9 after disruption). The main outcome of interest is the number of bike journeys by docking station scaled by the number of working days in the week. During the period of study, on average 24.5 daily journeys were produced by docking station. In other words, almost 58,800 bike journeys were completed every week in the city.

The evolution of bike journeys over time is shown in Figure 6 (a), dots represent the daily average of bike journeys and shaded region represents the weeks during which the system remained disrupted. As noticed, the number of bike journeys during public transport disruption showed a clear change in the tendency increasing week after week. Moreover, the curve keeps its positive tendency even in weeks after the disruption. In addition to this Figure, a map with the daily average of the number of bike journeys by docking station is provided in Figure 7. As expected, there is heterogeneity in the intensity of use across stations represented in the Figure by the size of the circles. What is more, it is common to observe larger circles close to subway stations which is indicative of the importance of the level of spatial integration between both modes. As mentioned above, this stylized fact goes in line with previous studies (Ma et al., 2015; Ma et al., 2018; Ashraf et al., 2021).

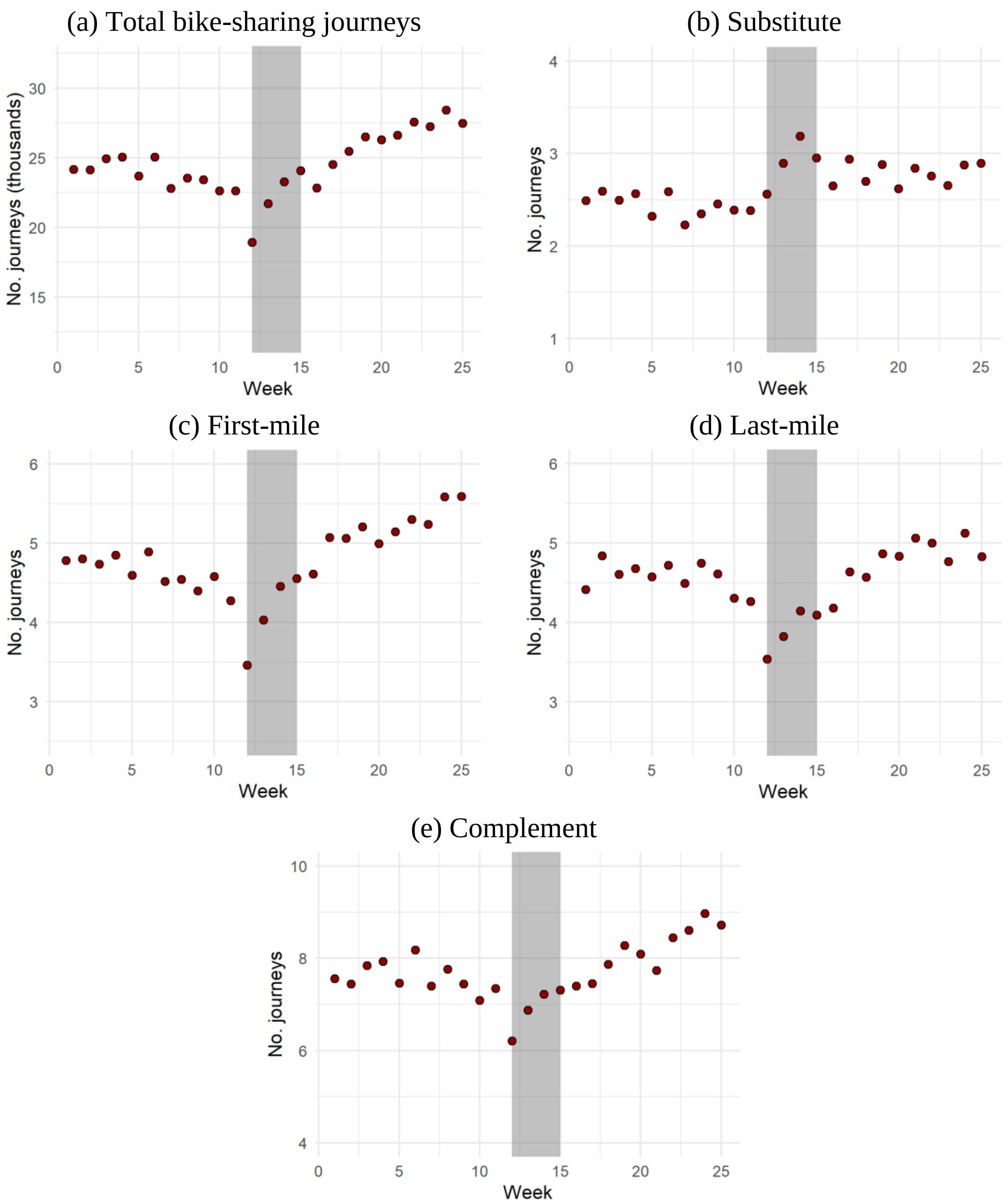
This paper sheds light on the dichotomic market dynamics between bike-sharing and public transport. To this purpose, I classified journeys making use of the geo-location information of the origin and destination docking station in the following way:

- *Substitute.* Bike journeys substituting subway trips are those that start and end within the spatial coverage of the subway. In other words, these types of itineraries could have been completed using the network.

- *First/Last-mile trips.* In this case, bike-sharing is complementing public transport by creating first/last-mile connections. Following the commuters dilemma stablished by Lesh (Innovative concepts in first-last mile connections to public transportation, 2013), a first-mile connection is defined here as a bike journey that starts beyond subway's spatial coverage and ends in a docking station near the subway. Consequently, a last-mile bike journey starts nearby subway stations and ends in uncovered areas.
- *Complement.* Bike-sharing can also serve to expand transport coverage, which is the case when journeys do not start or end within the spatial coverage of the subway system.

I used thresholds to define the subway's spatial coverage. Following Fan & Zheng (Dockless bike sharing alleviates road congestion by complementing subway travel: Evidence from Beijing, 2020), stations located closer to 300m (in planar distance) were considered to be within the spatial coverage of the subway system. On the other hand, stations located beyond 300m were considered as outside the range of public transport. The outcome of interest in these cases measures the daily average number of trips that falls in each one of the categories above.

Figure 6. Evolution in the number of bike journeys by type

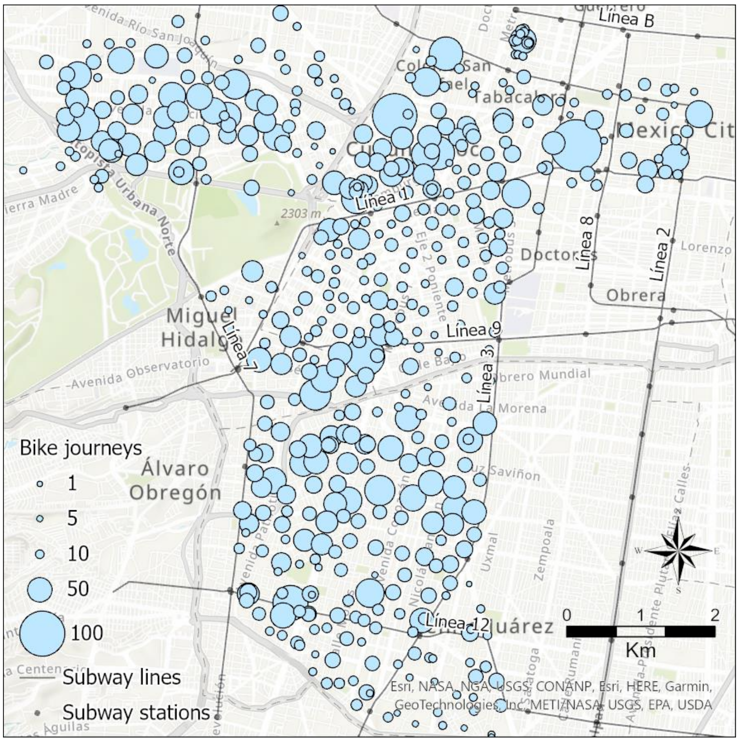


Note: The Figure reports the weekly average number of bike journeys in total and by type (in dots). Shaded region represents the weeks of subway disruption. Figure (a) pooled all the bike journeys together. Figure (b) is exclusive for substitute journeys defined as trips that start and end within the spatial coverage (300m) of the subway network. Figures (c) and (d) include first and last-mile journeys defined as trips that start/end beyond/within the spatial coverage (300m) of the subway and ends/starts within/beyond. Figure (e) refers to as complementary journeys, i.e., bike trips that does not start nor end within the spatial coverage of the subway system.

Figure 6 (b)-(e) reports the evolution of such outcomes during the period of study. Dots again represent the daily average, and the shaded region represents the weeks during which the system remained disrupted. As expected, the number of trips substituting public transport increased during disruption suggesting that riders used bike-sharing to *bridge* disrupted connections within the public transport network. In addition, first/last-mile journeys decreased significantly the first week of the disruption showing a constant recovery thereafter. This behavior could be explained by the fact that riders shift to private cars avoiding intermodal journeys or prefer to stay home when public transport is disrupted (Zhu & Levinson, 2012). However, the descriptive evidence suggests that such behavior changed in the following weeks, which might indicate that commuters considered bike-sharing as a viable alternative. A similar, and unexpected, behavior is observed for complementary journeys. One potential explanation for this is that the number of bikes available to make this kind of trips decreases because riders were using the system to *bridge* subway's disruption. Another intuition is that riders might have decided not to ride if they expected more congested and disturbed roads. Finally, it is relevant to point out that these Figures show evidence of an expansion of bike-sharing demand after the disruption, especially for complementary journeys of every kind. This in turn might indicate that public transport disruption had a long-lasting impact on modal shift to bike-sharing.

Other relevant variables for the analysis are the following. On average, the planar distance separating bike and subway's stations is about 590 meters. As mentioned, such distance is key to explain the spatial integration between both transport modes. An additional time-invariant characteristic of each docking station is their total capacity (26 docks on average). Including this variable is important specially when there are spatial heterogeneities among stations, i.e., when docking stations closer to the subway are also bigger in terms of the number of docks. I also control for the type of bicycle (electric vs standard). On average, only 5.8% of the stations in the city are electric. Moreover, cycling infrastructure has been found to be determinant of bike ridership. In this study, I followed a spatial approach estimating the planar distance to the closest cycleway (171 meters on average). Finally, it has been documented that the availability of bikes and/or of empty slots at destination might influence users' decisions to uptake the service. Nonetheless, this condition might be attenuated in areas with a larger density of docking stations. For instance, in the case where there are not available slots at destination, riders could find another station nearby. On the other hand, isolated (and congested) stations could increase travel time to a point of discouraging riders. Therefore, I have included the density measured as the number of docking stations within a radius of 300m (the average value is 2.9).

Figure 7. Number of bike journeys by docking station



Note: The Figure reports the geographical distribution in the daily average of bike journeys by docking station. Circles size represents the intensity of use of each docking station relative to the rest. Solid black lines and dots denote the location of subway lines and stations.

5. Empirical strategy

To examine changes in the demand for bike-sharing during disruptions relative to the level of integration with the network, I estimated the differences in the relationship between bike-sharing journeys and the distance to the closer subway station before, during, and after the disruption in the following way:

$$y_{i,t} = \gamma_1 during_t + \gamma_2 after_t + \beta_1 (d_i \times during_t) + \beta_2 (d_i \times after_t) + x'_{i,t}\Gamma + \mu_{i,t} \qquad (1)$$

where subindexes i and t stand for docking station and weeks since disruption. The outcome $y_{i,t}$ measures the number of bike journey staring (in the *origin-station* dataset) or ending (in the *destination-station* dataset) in a logarithmic scale. The dummy variable $during_t$ denotes the disruption treatment and take the value of one every week the system remained disrupted, $after_t$ is an indicator equal to one to every week after disruption. The vector $x'_{i,t}$ includes time and docking station fixed effects, square time trends of ridership per docking station as well as the covariates d_i. In addition, $x'_{i,t}$ includes a set of controls: an indicator for e-bikes stations, capacity, distance to the closest cycleway, and density of docking stations. Also, $\mu_{i,t}$ is the error term. The covariate d_i is a measure of the level of spatial integration between both transport modes. In the *origin-station* dataset, d_i is the inverse of the distance between the docking station at the origin and the closest subway station. In a complementary way, d_i refers to as the inverse of the distance within stations using the docking station at destination in the *destination-station* dataset. This procedure represents a first attempt to differentiate the effect depending on the type of bike journey (first or last-mile).

I estimated equation (1) using OLS applying cluster standard errors at docking station level. The estimates of β_1 and β_2 measure the disruption effects conditional on the spatial interaction between transport modes. Positive estimates are expected meaning that increasing the spatial integration between both transport modes is associated with larger bike-sharing rides during and after public transport disruption.

I detected the following menaces to the identification strategy. The first one relies on the city's response to manage disruption. For instance, if the city systematically relocates bicycles to support public transport, then the estimates would confound disruption effect with the operator' strategic behavior. To this regard, the corresponding authority published a daily report containing all the strategies the city implemented to manage the situation. Due to the size of disruption the city *bridged* the network by increasing the capacity and coverage of other modes of transport such as bus, bus rapid transit, and trolleybuses. What is more, no action was taken regarding the deployment and rebalancing of bicycles across stations. Second, the city offered a special six-month plan for 6 USD fee (instead of the annual plan at 27 USD) for new users subscribed between January 12th and January 31st. To isolate the potential influence of this subsidy I have controlled by the weekly number of new subscriptions. Third, one could argue that the limited capacity of docking stations might undermine the true effect if riders cannot find a bike at the origin or an empty dock at destination. Unfortunately, the dataset does not observe the number of bikes and docks available in stations at the origin and destination of each journey. Therefore, the results might only reflect a lower bound of the true effect. Nevertheless, in order to control for this potential bias, I used station's total capacity (i.e., the number of docks) and the density of additional docking stations within a radius of 300m. Finally, the underlying heterogeneity cause by variations in the weather was capture including time fixed effects.

In addition to the previous approach, I dig deeper on the effects depending on the market dynamics between both transport modes. As mentioned above, I classified each journey as substitute, complement, first-mile or last-mile depending on the spatial relationship of docking stations at origin or destination and the public transport network. Furthermore, thresholds on the distance between both stations were used to define the spatial interaction. Consequently, to measure changes in the complementarity and substitutability to bike-sharing during and after disruption, I estimated equation (1) using as outcomes the logarithm of the daily number of each type of journey by docking station. In addition, I dropped the covariate d_i because it is embodied in the definition of each outcome, and it does not provide any additional information for the estimation. The relevant coefficient in this case are the estimates of γ_1 and γ_2. They compare fluctuations in the number of bike-journeys by type during and after disruption with the scenario before the incident.

In addition to the estimates by period of event, I implement an analysis by week to study the time-varying effects. Instead of the $during_t$ and $after_i$ dummies used in equation (1), I include week dummies as follows:

$$y_{i,t} = \sum_{q=-11}^{13} \beta_q d_i \times week_q + x'_{i,t}\Gamma + \epsilon_{i,t} \tag{2}$$

Where q identifies the number of weeks elapse relative to the subway disruption ($q = 0$). The vector $x'_{i,t}$ still includes docking station fixed effects, trends, the covariate d_i as well as a set of controls. Again, when the outcome is computed as the number of trips by type of bike journey, the covariate d_i is excluded. This strategy allows to visually inspect the estimates of β_q as a function of time. I dummy out the indicator of one week before disruption to measure the effects with respect to this indicator. I used week $q = -2$ for the purpose of exposition. Results are not sensible to the selection of this indicator.

6. Results

6.1 Effects on bike-sharing adoption

The results of estimating equation (1) using the logarithm of the daily number of bike journeys as the outcome of interest are reported in Table 1. Columns (1)-(2) report disruption effects from the *origin-station* dataset that measures the inverse of the distance between the origin docking station and the closest subway station. Controls and fixed effects are included in both columns, however, only column (2) considers the square time trend of the outcome. Columns (3)-(4) repeat the analysis using the *destination-station* dataset to consider the inverse of the distance between the docking station at the destination and the closest subway station. Due to the fact that the outcome variable is log-transformed, the exponential of the estimates measures the percentage change in the daily number bike journeys by docking station of increasing the spatial integration to public transport network.[6] The marginal effects suggest that increasing the inverse of the distance between docking and subway stations by one unit increases by 3.5% the daily average of bike trips in both origin and destination stations during disruption. On the other hand, being closer to the public transport network is associated with a slight increase of 0.5%-1.0% in the number of bike journeys after disruption. Note that estimates are statistically different from zero almost everywhere. Moreover, the results are robust to the inclusion of the square trend time.

To ease the interpretation of the results in terms of the number bike journeys, I used the estimates from columns (2) and (4) from Table 1 to fit the daily number of journeys by docking station. The Table 2 shows the averages from the predicted values and prediction intervals by period (before, during, and after disruption) for groups of docking stations depending on their distance to the subway for both datasets, origin (Panel A) and destination (Panel B). As a mode of comparison, six additional groups are shown: docking stations within 100, 200, and 500m as well as beyond 1, 1.2, and 1.5km from the subway spatial coverage. As noticed from the Table, disruption is associated with a decreased of two daily

[6] By definition, the spatial integration decreases with the distance. Using the inverse of the distance between stations is a good measure of the spatial integration: the smaller the distance the larger its inverse reflecting a higher spatial integration.

bike journeys by station in both panels which is equivalent to a percentage decrease of -8.5%.

The result is not striking, as a matter of fact, the literature of commuters' behavior during disruption have largely documented that a fraction of citizens responds by staying home or shifting towards private cars (Zhu & Levinson, 2012; Zhang et al., 2021), which might explain the reduction in the total number of journeys. However, in line with the marginal effect, the reduction is heterogenous across groups decreasing in magnitude for those stations close to the subway. Docking stations at the origin located within 100m have a percentage increase of 2% in contrast to a decrease of -10% for docking stations located beyond 1.2km. Similarly, for stations at destination within the same range, the number of journeys increased by 3.3% while a decreased of -9.8% is found for distances beyond 1.2km. The panorama after disruption is also revealing. The number of journeys in both cases increased by 10.5% in comparison with the scenario before disruption. This amount is equivalent to 1.2 thousand journeys every day (almost 17.6% of the total fleet-size). Furthermore, stations in the close vicinity of the subway ($<$100m) produced between 18.7 and 22.2 more daily journeys than those beyond 1km. Moreover, these stations showed an increased in the number of journeys of about 13%-16% with respect to the scenario before disruption. I have also tested the null hypothesis of both $after_t$ and $d_i \times after_t$ jointly equal to zero, which is important for the validity and interpretation of the Table. The null hypothesis was rejected with a p-value lower than 0.001 in both cases suggesting that the number of bike journeys after the disruption was larger than the scenario before disruption.

Table 1. Public transport disruption effects on bike-sharing adoption

	Dependent variable:			
	ln(Bike journeys)			
	Origin-station		*Destination-station*	
	(1)	(2)	(3)	(4)
During*Distance	0.063	0.035***	0.055***	0.029***
	(0.006)	(0.005)	(0.009)	(0.006)
After*Distance	0.029	0.010***	0.024***	0.006**
	(0.007)	(0.002)	(0.005)	(0.002)
During	-0.040**	-0.007	-0.040**	-0.001
	(0.018)	(0.014)	(0.017)	(0.013)
After	0.102***	-0.126***	0.091***	-0.122***
	(0.023)	(0.021)	(0.023)	(0.021)
Distance	-2.822***	0.377***	-2.303***	0.248***
	(0.020)	(0.050)	(0.020)	(0.039)
Capacity	-0.059***	0.002**	-0.066***	0.001
	(0.0004)	(0.001)	(0.0004)	(0.001)
E-station	-2.987***	0.152***	-3.150***	0.053
	(0.004)	(0.051)	(0.004)	(0.050)
Distance to cycleway	-0.005***	0.0003***	-0.005***	0.0002**
	(0.00001)	(0.0001)	(0.00001)	(0.0001)
Density	-0.961***	0.023	-0.987***	0.009
	(0.003)	(0.016)	(0.003)	(0.016)
Subscriptions	0.003***	0.006***	0.003***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	8.093***	-0.826***	8.317***	-0.634***
	(0.038)	(0.149)	(0.037)	(0.140)
Stations FE	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes
Stations' trend	No	Yes	No	Yes
Observations	11,749	11,749	11,750	11,750
R^2	0.910	0.932	0.928	0.951
Adjusted R^2	0.906	0.929	0.925	0.949

Note: The Table reports the estimated impact of public transport disruption on bike-sharing adoption. Rows 2 and 4 show the estimates of β_1 and β_2 from equation (1), respectively. Columns (1) and (2) restrict the analysis to the *origin-station* dataset. Columns (2) and (3) restrict the analysis to the *destination-station* dataset. Distance refers to the inverse of the planar distance between subway and docking stations. Controls include e-bikes stations, station total capacity, distance to the closest cycleway, the number of docking stations in a radius of 300m (Density), and the number of new subscriptions. Stations' trend control for the quadratic approximation of outcome's trend. Cluster standard errors per docking station were applied. Significance levels are represented as follows: *p<0.1; **p<0.05; ***p<0.01.

Table 2. Daily bike journeys associated with public transport disruption by docking station

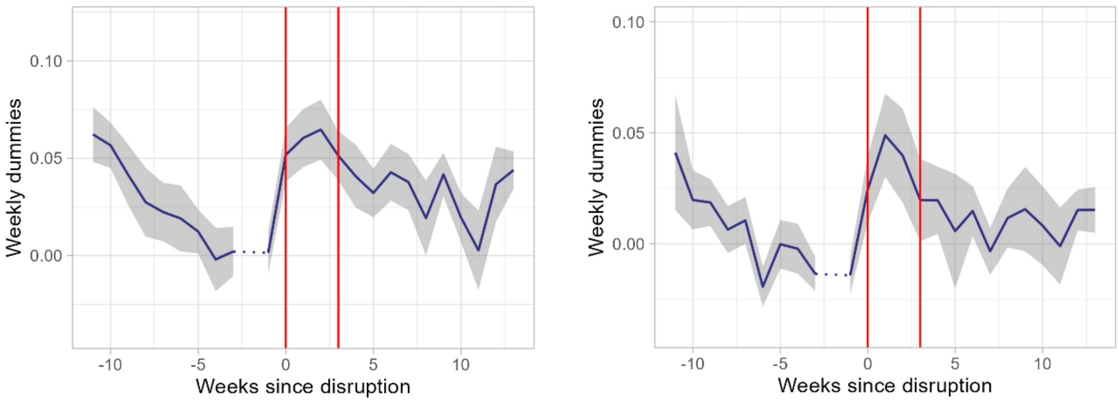
Group	Before	During	After	Differences	
				During-Before	After-Before
	(1)	(2)	(3)	(4)	(5)
Panel A: Docking stations at origin					
Pooled	23.6 (16.2, 34.5)	21.7 (14.9, 31.6)	26 (17.9, 38)	-1.9	2.4
By distance					
< 100m	32.8 (22.5, 47.9)	33.5 (22.9, 49)	37.2 (25.5, 54.3)	0.7	4.4
< 200m	32.1 (22, 46.8)	30.4 (20.8, 44.3)	34.4 (23.6, 50.1)	-1.7	2.3
< 500m	25.6 (17.6, 37.3)	23.8 (16.3, 34.6)	28.0 (19.2, 40.8)	-1.8	2.4
> 1km	16.3 (11.2, 23.8)	14.8 (10.1, 21.5)	18.5 (12.7, 26.9)	-1.5	2.2
> 1.2km	13.6 (9.3, 19.8)	12.4 (8.5, 18.1)	15.6 (10.7, 22.7)	-1.2	2.0
> 1.5km	12.0 (8.3, 17.5)	10.9 (7.5, 15.9)	13.8 (9.4, 20)	-1.1	1.8
Panel B: Docking station at destination					
Pooled	23.6 (16.9, 33.2)	21.8 (15.5, 30.5)	26.1 (18.6, 36.6)	-1.8	2.5
By distance					
< 100m	33.6 (24, 47.2)	34.7 (24.7, 48.8)	39.0 (27.8, 54.7)	1.1	5.4
< 200m	32.4 (23.1, 45.5)	30.9 (22, 43.4)	35.3 (25.2, 49.5)	-1.5	2.9
< 500m	25.9 (18.5, 36.3)	24.1 (17.2, 33.8)	28.5 (20.3, 40)	-1.8	2.6
> 1km	15.2 (10.8, 21.3)	13.7 (9.7, 19.2)	16.8 (12, 23.5)	-1.5	1.6
> 1.2km	12.2 (8.7, 17)	11 (7.9, 15.5)	13.4 (9.5, 18.8)	-1.2	1.2
> 1.5km	9.2 (6.6, 13)	8.2 (5.9, 11.5)	9.7 (6.9, 13.5)	-1.0	0.5

Note: The Table reports the daily average number of trips by docking stations before; during, and after public transport disruption (columns) conditional on the distance to the closest subway station (rows). It also reports the difference between the scenario during and before as well as the scenario after and before disruption. The values are computed from the fitted approximations of estimating equation (1). In other words, the values reported here are averages from the predicted values using the results shown in Table 1. The predicted interval at 95% confidence level is reported in parenthesis. Panel A refers to the estimates using the *origin-station* dataset only. Panel B refers to the estimates using the *destination-station* dataset only. Pooled includes all docking stations.

To show evidence of the evolution of the effects over time, Figure 8 displays the time dummies estimates (β_q) from equation (2). Zero in the x-axis represents the first week of disruption, the rest means the number of weeks elapsed since the incident. Solid red vertical lines indicate the week the disruption started and the week the system was fully restored. The gray region characterizes an interval confidence at 95% level around estimates. A dotted line was included instead of the dummy intentionally left out. Each one of the two sub-figures (a) and (b) presents respectively docking stations at origin and destination. It is important to remember at this point that positive estimates represent an increase in the number of bike journeys when the spatial integration between both transport systems also increases.

Figure 8. Persistence of the effects over time by type of docking station

(a) Origin docking stations (b) Destination docking stations

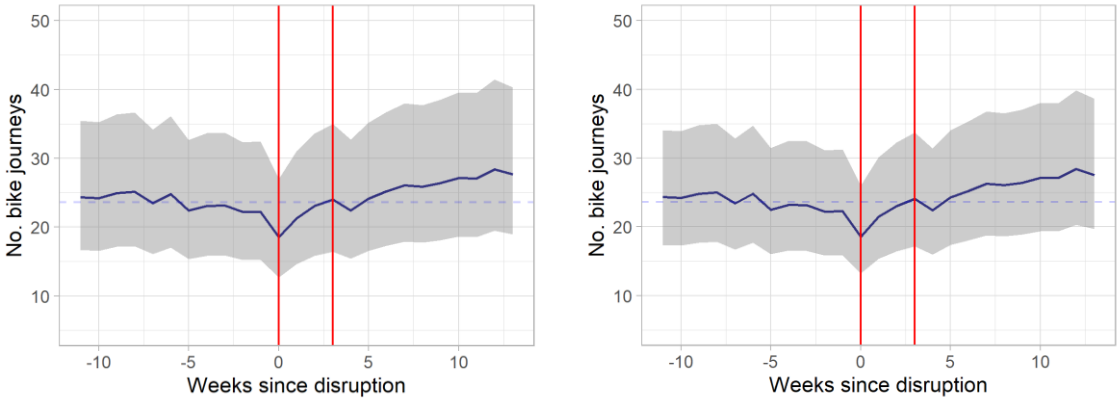


Note: The Figure reports the weekly dummy (β_q) estimates from equation (2). X-axis represents the number of weeks elapsed since the fire on January 9th, 2021. Therefore, the first week of disruption is in zero. Solid vertical lines indicate the week when disruption started and the week when the system was fully restored. Shaded regions denote an interval confidence at 95% level around estimates. The dotted line was included instead of the dummy intentionally left out from the regression. Figure (a) shows the effects from the *origin-station* dataset only. Figure (b) shows the effects from the *destination-station* dataset only.

The results are in line with what I described in the previous section, but the evolution week by week reveals additional information. For instance, note the spike in the magnitude of the coefficients during disruption suggesting an increase in bike-sharing demand in that period. In contrast, the pattern shows a decline in magnitude once the network is fully restored. What is more, the visual inspection suggests a change in the negative tendency shown in the weeks before disruption, especially for docking stations at destination. As noticed, these estimates represent changes in the daily number of bike journeys by docking stations conditional on their spatial integration to the network, which difficult the interpretation in terms of the total number of bike journeys. Therefore, to ease the interpretation, I compute the evolution in the daily average of bike journeys by docking station using the predicted values and intervals from equation (2). Figure 9 (a) and (b) report the results. The dotted blue line shows the average daily number of bike journeys before disruption. As noticed, the network disruption generated an abrupt decrease in bike-sharing demand (see Table 2 for details). Nevertheless, the negative tendency is immediately reverted and maintained along the rest of the weeks. The evidence suggests an expansion of bike-sharing demand associated with the disruption in the transport network.

Figure 9. Predicted number of trips over time by type of docking station

(a) Origin docking stations (b) Destination docking stations



Note: The Figure reports evolution in the daily average of bike journeys by docking station using the predicted values and intervals from equation (2). The dotted line (in light blue) shows the average before disruption. X-axis represents the number of weeks elapsed since the fire on January 9th, 2021. Therefore, the first week of disruption is in zero. Solid vertical lines indicate the week when disruption started and the week when the system was fully restored. Shaded regions denote an interval confidence at 95% level around the estimates. Figure (a) shows the estimates from the *origin-station* dataset only. Figure (b) shows the estimates from the *destination-station* dataset only.

6.2 Dichotomous effects

What I find in the previous section suggests that public transport disruption is associated with an increase in bike-sharing adoption, especially from docking stations nearby the subway system. However, it is not clear whether those journeys were used to substitute or to complement public transport. Table 3 reports the estimates of equation (1) for the outcomes that identify the number of bike journeys in each category: substitutes, complements, first-mile, and last-mile. It is important to point out that I exclude the covariate d_i in this case because it is used to classify each bike journey. It is noteworthy that some stations might not originate (or receive) specific types. For instance, no station beyond

300m can originate a substitute journey nor receive a first-mile journey by construction. Therefore, the number of observations is restricted accordingly. Docking stations, time fixed effects, and controls are included in every column. Panel A and B differs on the inclusion of square time trends in the number of total journeys by docking station. Moreover, columns (1) to (4) reports the results for docking stations at origin while columns (5) to (8) use stations at destination.

Table 3. Disruption effects by type of journey

	Dependent variable:							
	Origin-station				*Destination-station*			
	Substitutes	Complements	First-mile	Last-mile	Substitutes	Complements	First-mile	Last-mile
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: No time trend included								
During	0.051	-0.094**	-0.065	-0.037	0.093	-0.097**	-0.062	-0.085
	(0.079)	(0.038)	(0.050)	(0.053)	(0.066)	(0.040)	(0.051)	(0.054)
After	0.263***	0.261***	0.272***	0.161***	0.197***	0.265***	0.183***	0.227***
	(0.069)	(0.037)	(0.045)	(0.045)	(0.068)	(0.033)	(0.046)	(0.046)
Panel B: Controlling for time trend								
During	0.004	-0.119***	-0.091*	-0.079	0.050	-0.117***	-0.095*	-0.105*
	(0.075)	(0.036)	(0.051)	(0.049)	(0.067)	(0.039)	(0.050)	(0.054)
After	0.141**	0.158***	0.170***	0.050	0.083	0.182***	0.097**	0.147***
	(0.067)	(0.034)	(0.042)	(0.041)	(0.064)	(0.029)	(0.042)	(0.044)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Station FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,894	8,854	8,846	2,894	2,894	8,852	2,894	8,831

Note: The Table reports the estimated impacts of public transport disruption on bike-sharing adoption by each type of bike journey. Rows 1 and 2 show the estimates of γ_1 and γ_2 from equation (1) respectively. Columns (1) and (5) show the effects for substitute journeys defined as trips that start and end within the spatial coverage (300m) of the subway network. Columns (2) and (6) include complementary journeys, i.e., bike trips that does not start nor end within the spatial coverage of the subway system. Columns (3-4) and (7-8) include first and last-mile journeys defined as trips that start/end beyond/within the spatial coverage (300m) of the subway and ends/starts within/beyond. Columns (1) to (4) restrict the analysis to the *origin-station* dataset. Columns (5) and (8) restrict the analysis to the *destination-station* dataset. Controls include docking stations for e-bikes, station total capacity, distance to the closest cycleway, the number of docking stations in a radius of 300m (Density), and the number of new subscriptions into the program. Time trend in Panel B controls for the quadratic approximation of outcome's trend. Cluster standard errors per docking station were applied. Significance levels are represented as follows: *p<0.1; **p<0.05; ***p<0.01.

Different conclusions can be extracted from the Table. First, regarding substitution, the estimates are positive (columns (1) and (5)) suggesting that the degree of substitution to bike-sharing increased during disruption. Nevertheless, the estimates are not statistically different from zero because the expansion in the degree of substitution contribute to restore the before-disruption levels on average. On the other hand, after disruption, the degree of substitution is again positive and statistically significant suggesting a long-lasting effect. Furthermore, the direction of the effect is robust to the inclusion of square time trends. Second, disruption affected the degree of complementarity in the opposite direction during the event. Note that the marginal effects are negative for the three types of complementary trips (complement, first-mile, and last-mile), however the level of significance varies across specifications. What is more, the inclusion of the square time trend does not alter the results. As expected, disruption in the network limits intermodal trips decreasing the number of first and last-mile journeys. On the contrary, the results suggest and expansion in complementary after a fully restoration of the network. In this case, the estimates are positive and significant in almost every estimation. Finally, the estimates do not show a considerable variation between the *origin-station* and *destination-station* datasets.

Again, to interpret the results in terms of the number of journeys, the averages by groups using the predicted values from Panel B of Table 3 are shown in Table 4. The number of daily journeys by docking station that substitutes public transport itineraries increased during disruption between 5%-8%. Moreover, the number of all three types of complementary journeys fall during disruption. For instance, the daily number of last-mile and first-mile journeys in docking stations at origin and destination decreased both by -9.5%. On the other hand, the results suggest a generalized expansion in the service after full restoration of the network. Note that, substitute trips increased by 16%-18% in docking stations at the origin and destination, respectively. The expansion is similar for all complementary journeys. Overall, these findings show evidence of public transport substitution to bike-sharing during disruption. In other words, bike-sharing helped commuters to find alternative itineraries to public transport. After disruption, both substitutions and complementary journeys increased probably as a consequence of habit formation and modal-shift.

Table 4. Daily bike journeys as substitutes or complements to public transport

Group	Before	During	After	Differences	
				During-Before	After-Before
Panel A: Docking station at origin					
Substitutes	8.5 (4.9, 14.5)	9.0 (5.3, 15.4)	9.9 (5.8, 16.9)	0.5	1.4
Complement	16.1 (10.5, 24.7)	14.6 (9.5, 22.4)	17.7 (11.5, 27.1)	-1.5	1.6
First-mile	6.1 (3.4, 11.1)	5.6 (3.1, 10.2)	6.9 (3.8, 12.5)	-0.5	0.8
Last-mile	18.6 (12.6, 27.5)	16.8 (11.4, 24.9)	20.5 (13.8, 30.3)	-1.8	1.9
Panel B: Docking station at destination					
Substitutes	8.4 (5, 14.3)	9.1 (5.4, 15.4)	9.9 (5.8, 16.7)	0.7	1.5
Complement	16.1 (10.6, 24.5)	14.6 (9.6, 22.2)	17.7 (11.6, 26.8)	-1.5	1.6
First-mile	18.9 (12.9, 27.8)	17.5 (11.9, 25.8)	21.3 (14.5, 31.2)	-1.4	2.4
Last-mile	6.0 (3.2, 11.4)	5.5 (2.9, 10.3)	6.6 (3.5, 12.4)	-0.5	0.6

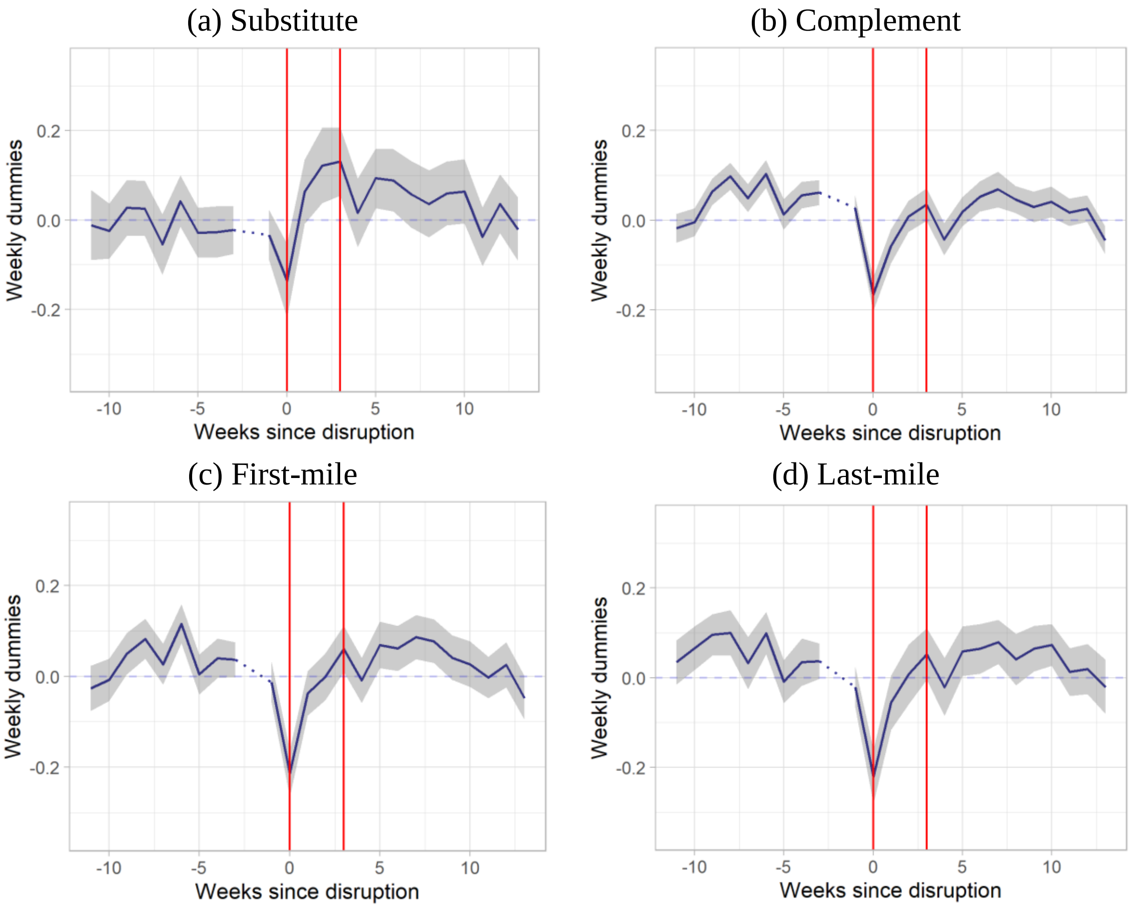
Note: The Table reports the daily average number of trips by docking stations before; during, and after public transport disruption (columns) for different type of journeys (rows). It also reports the difference between the scenario during and before as well as the scenario after and before disruption. The values are computed from the fitted approximations of estimating equation (1). In other words, the values reported here are averages from the predicted values using the results shown in Table 3. The predicted interval at 95% confidence level is reported in parenthesis. Panel A refers to the estimates using the *origin-station* dataset only. Panel B refers to the estimates using the *destination-station* dataset only. Pooled includes all docking stations. Substitute journeys are defined as trips that start and end within the spatial coverage (300m) of the subway network. First and last-mile journeys are defined as trips that start/end beyond/within the spatial coverage (300m) of the subway and ends/starts within/beyond. Complementary journeys are bike trips that does not start nor end within the spatial coverage of the subway system.

I show visual evidence of the evolution of the effects over time in Figure 10 and Figure 11. Figures display the time dummies estimates (β_q) from equation (2) for both, docking station at origin and destination, respectively. As above, the covariate measuring the distance to the closest metro station was not considered. Again, the x-axis represents the number of weeks elapsed since the incident. Solid red vertical lines indicates network disruption. The dummy-out is represented using a dotted line. Each one of the four panels (a) to (d), in both Figures, reports respectively the effects for Substitutes, Complements, First-mile, and Last-mile journeys. In contrast with the previous section, this time $100 * (e^{\hat{\beta}} - 1)$ represent the percentage change in the number of trips. Therefore, a positive coefficient is interpreted as an increase in bike-sharing demand.

The results are in line with the previous findings. However, the evolution week by week reveals additional information. In the case of Substitutes journeys, the evidence suggests a steep increase in the number of this kind of journeys since the first week of disruptions in the network. Furthermore, the positive tendency remained in the whole disruption period. Afterwards, once the system was fully restored, the degree of substitution decreased gradually until achieving levels similar to those before disruption. On the other hand, complementary journeys of every kind suffered a massive decrease just after disruption but recovered quickly in the coming weeks. What is more, the Figures show that such tendency was maintained for a couple of weeks after the system reopened operations in all the subway lines. Nonetheless, the Figures show an attenuation of the effects at the end of the period of study. The behavior is more accentuated in the case of first and last-mile journeys. The results are similar in both, docking stations at origin and destination.

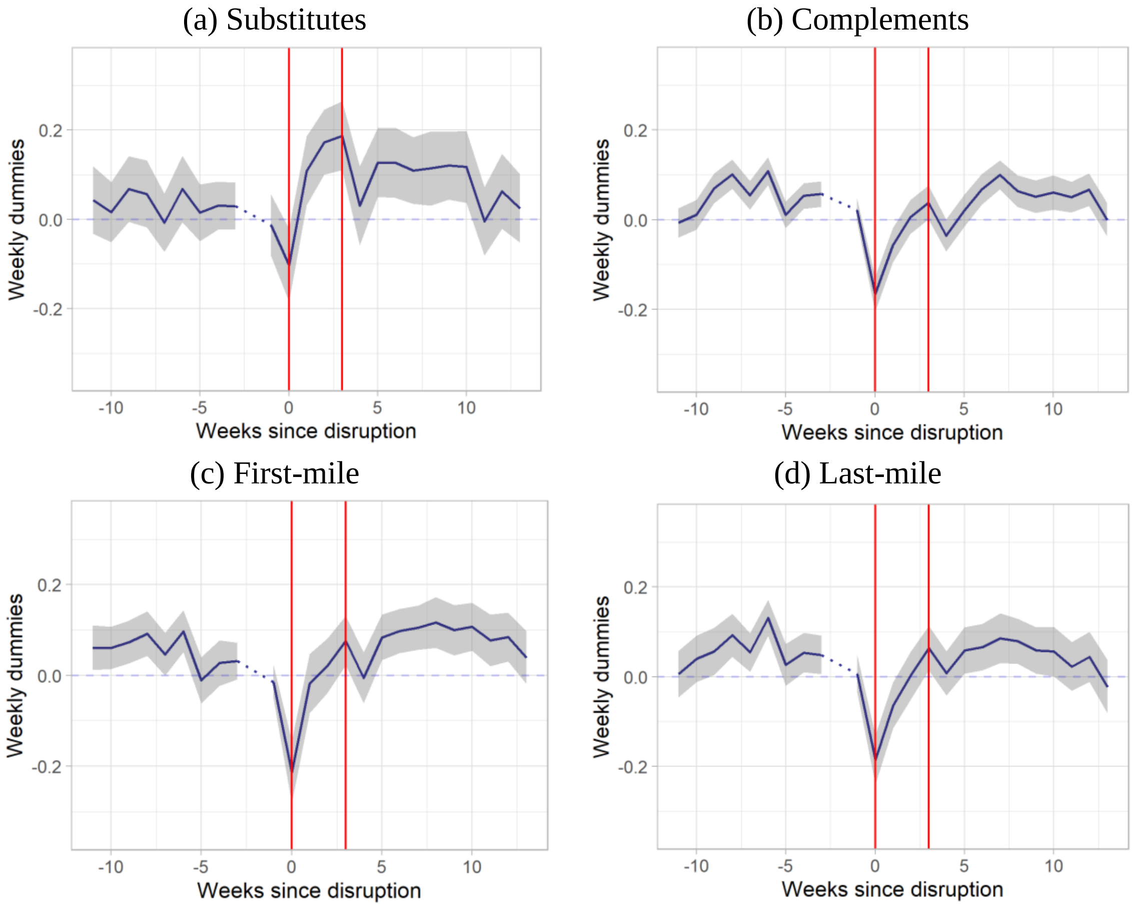
Overall, the findings presented here suggest that public transport disruption had a persistent effect on the degree of substitution and complementarity to bike-sharing. Although, the effect is vanished after a couple of months. However, as I show in the previous section, the attenuation of the effects has not been translated in a contraction of bike-sharing ridership. This in turn opens the question of whether the impact is a consequence of modal shift which might be possible due to the duration of the disruption. More evidence on this regard is presented in section 8.

Figure 10. Time-varying effects by type of journey, docking stations at origin



Note: The Figure reports the weekly dummy (β_q) estimates from equation (2) from the *origin-station* dataset only. X-axis represents the number of weeks elapsed since the fire on January 9th, 2021. Therefore, the first week of disruption is in zero. Solid vertical lines indicate the week when disruption started and the week when the system was fully restored. Shaded regions denote an interval confidence at 95% level around the estimates. The dotted line was included instead of the dummy intentionally left out from the regression. Figure (a) shows the effects for substitute journeys defined as trips that start and end within the spatial coverage (300m) of the subway network. Figures (b) and (c) include first and last-mile journeys defined as trips that start/end beyond/within the spatial coverage (300m) of the subway and ends/starts within/beyond. Figure (d) refers to as complementary journeys, i.e., bike trips that does not start nor end within the spatial coverage of the subway system.

Figure 11. Time-varying effects by type of journey, docking stations at destination



Note: The Figure reports the weekly dummy (β_q) estimates from equation (2) from the *destination-station* dataset only. X-axis represents the number of weeks elapsed since the fire on January 9th, 2021. Therefore, the first week of disruption is in zero. Solid vertical lines indicate the week when disruption started and the week when the system was fully restored. Shaded regions denote an interval confidence at 95% level around the estimates. The dotted line was included instead of the dummy intentionally left out from the regression. Figure (a) shows the effects for substitute journeys defined as trips that start and end within the spatial coverage (300m) of the subway network. Figures (b) and (c) include first and last-mile journeys defined as trips that start/end beyond/within the spatial coverage (300m) of the subway and ends/starts within/beyond. Figure (d) refers to as complementary journeys, i.e., bike trips that does not start nor end within the spatial coverage of the subway system.

6.3 Effects on bike journeys duration

A follow-up question is whether the increase in the degree of substitution was accompanied by an increase in the intensity of use of bikes during and after disruption. In this work, I focus on measuring the effects on the duration of journeys. It is not possible to observe in the data the actual trajectory taken by users, however, it does indicate the undocking and docking time of each journey, which allows me to compute a proxy of the actual travel time. To measure the effects of disruption on journeys duration, I have followed a different approach exploiting journey level data to estimate the following relationship:

$$ln(Duration)_{i,t} = \beta_1 during_t + \beta_2 after_t + substitute'_{i,t}\Upsilon + x'_{i,t}\Gamma + \mu_{i,t} \quad (3)$$

The vector $substitute'_{i,t}$ includes a dummy indicating the type of journey and the interaction terms with $during_t$ and $after_t$. On the other hand, the vector $x'_{i,t}$ includes a set of trip level controls (gender, age, and age^2), stations-level controls (same as above), outcome square time trend, number of new subscriptions, and a set of time fixed effects (week of the year, month of the year, day of the week, hour of the day) to capture time-varying conditions that affect duration such as whether, riding during peak vs off-peak hours, among others.

Estimates are shown in Table 5. Columns (1) to (3) exclude $substitute'_{i,t}$ and differ in whether fixed effects were included in the regression. Columns (4) to (6) add estimates for the covariates in $substitute'_{i,t}$. As can be seen from the Table, the results suggest that duration of bike journeys increased during disruption, every estimate is positive and statistically different from zero. The magnitude of the estimated coefficients suggests that disruption is associated with an increase in the travel time in between 8.2%-13.1%. This in turn represents an increase of 2 minutes with respect to the average journey duration (15.7 minutes). The effect after disruption is also positive and statistically significant, which might suggest that public transport disruption had a positive effect in the intensive margin of bike-sharing ridership in the long-run. Nevertheless, the magnitude of the effect is lower and ranges between 3.0% and 9.5% (i.e., close to 1.5 minutes with respect to the average).

Regarding the heterogenous effect by type of journey, the estimates in columns (4) to (6) in Table 5 suggest changes in the intensive margin of bike ridership across journey types during disruption. In fact, the duration of bike journeys as substitutes to the subway increased 16.4% with respect to the average duration of complementary journeys in the same period. On the other hand, comparing substitution trips during and before disruption, the duration of the trips suffered a percentage increase of 14.1% in contrast with the 12.1% comparing the scenarios before-after. A similar pattern is found for complementary trips which duration increased by 10.1% and 9.3%. Overall, these findings are in line with the usage of bike-sharing to *bridge* disruptions in the network. Riders are willing to do longer trips to complete their journeys as a consequence of a lack of connection inside the network.

Furthermore, as expected, no difference is found between substitutes and complementary journeys once the network is restored.

Table 5. Disruption effects on the bike journeys duration

	Dependent variable:					
	ln(Journey duration)					
	(1)	(2)	(3)	(4)	(5)	(6)
During	0.079***	0.077***	0.123***	0.076***	0.074***	0.117***
	(0.002)	(0.002)	(0.023)	(0.002)	(0.002)	(0.023)
After	0.030***	0.030***	0.091***	0.029***	0.029***	0.089***
	(0.001)	(0.001)	(0.015)	(0.001)	(0.001)	(0.015)
Substitutes				0.105***	0.140***	0.137***
				(0.003)	(0.004)	(0.004)
Substitutes*During				0.017**	0.014**	0.015**
				(0.007)	(0.007)	(0.007)
Substitutes*After				0.011**	0.006	0.007
				(0.005)	(0.005)	(0.005)
Constant	2.732***	2.647***	5.278***	2.727***	2.608***	5.154***
	(0.008)	(0.008)	(0.798)	(0.008)	(0.008)	(0.797)
Individual characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Station’s characteristics	No	Yes	Yes	No	Yes	Yes
New subscriptions	No	No	Yes	No	No	Yes
Week of the year FE	No	No	Yes	No	No	Yes
Month of the year FE	No	No	Yes	No	No	Yes
Day of the week FE	No	No	Yes	No	No	Yes
Hour of the day FE	No	No	Yes	No	No	Yes
Trend	No	No	Yes	No	No	Yes
Observations	1,280,729	1,280,729	1,280,729	1,280,729	1,280,729	1,280,729
R^2	0.005	0.027	0.032	0.007	0.029	0.035
Adjusted R^2	0.005	0.027	0.032	0.007	0.029	0.035

Note: The Table reports the estimated impacts of public transport disruption on the duration of the trip. Each row shows the estimates from equation (3). Substitutes is a dummy identifying substitute bike journeys defined as trips that start and end within the spatial coverage (300m) of the subway network. Columns differ in the inclusion of controls, fixed effects, and outcome quadratic time trend. Controls include user’s gender, age, age^2, distance to the closest subway station, docking stations for e-bikes, station total capacity, distance to the closest cycleway, and the number of docking stations in a radius of 300m (Density). Robust standard errors were applied. Significance levels are represented as follows: *p<0.1; **p<0.05; ***p<0.01.

7. Heterogeneity and robustness

7.1 Specification checks

Placebo analysis. One concern to the empirical strategy is that estimates are driven by random variations in the demand for bike-sharing over time. To show that the results are robust to this caveat, I replicate the analysis using a placebo sample with a different date that simulates public transport disruption. To produce a parallel sample, I take January 11th, 2020, as the first day of disruption (1 year before) and I count the same number of weeks before and during this placebo disruption scenario. Holidays and day-off were again dropped according to the schooling calendar. This placebo sample has the advantages that January 11th, 2020, is the first day after school holidays which allows us to reassure that the effect is driven by public transport disruption and not by seasonality in the school calendar. In addition, the sample is ideal to avoid any potential issues related with the global pandemic. It is relevant to clarify that the number of weeks after disruption in this placebo sample are reduced to avoid the first Covid-19 related lockdown in the city. As noticed in Table A-1, the corresponding coefficients are statistically not different from zero. To provide a visual inspection of the effects in this placebo sample, I estimate time dummies from equation (2). The results are summarized in Figure A-1 (a) and (b), which uses respectively the *origin-station* and *destination-station* samples. As expected, the Figures show a smooth behavior around both placebo time thresholds determining the during and after periods. Hence, the evidence presented here suggest that my findings are robust to the random variance of bike-sharing ridership over time.

Alternative threshold for the spatial integration. Even though some studies suggest that docking stations located within three hundred meters of the subway network might be considered spatially integrated with this transport mode, it is not clear whether this threshold reflects the specific case of Mexico City. Therefore, I reproduce the results for substitutes and complement journeys for a wide range of spatial thresholds. Details of these findings are discussed in Table A-2. The thresholds consider ranges from 200m to 1200m in a frequency of 200m, displayed in rows in the Table. Panels in the Table indicates the type of journey: substitutes (A), complements (B), first-mile (C), and last-mile (D). Notice that estimates of substitutes journeys, especially during disruption, are sensible to the choice of the distance. In fact, for a threshold of 400m and beyond, the results suggest a percentage decrease in the number of this type of bike journeys. Further research is needed to improve the identification of bike trips substituting the public network. On the other hand, estimates after disruption are robust to the choice of different thresholds. Regarding complementary trips, all the results are in line with the estimates presented in Table 3 regardless of the distance considered, the period of analysis (during or after), as well as the sample used (*origin-station* or *destination-station*). In other words, these results show that the number of complementary journeys decreased with the level of spatial integration during disruption but increased afterwards. Nonetheless, in terms of magnitude and significance, the effects are larger for short distances, especially in the case of first and last-mile journeys but vanish once larger distances are reached reassuring the intuition that those journeys serve as connections to public transport.

7.2 Heterogeneity across docking stations

In this section I explore heterogenous effects of public transport disruption for distinctive characteristics of docking stations. I replicate the main analysis for different subsamples as follows. Docking stations for e-bikes vs standard bikes. In the Mexican bike-sharing model e-bikes are only available in specific docking stations which, at the same time, cannot allocate standard bikes. This characteristic is identifiable in our sample. Docking station capacity, i.e., the total number of bikes that each docking station can support. I split the sample in two, low capacity between 10 to 23 bikes and high capacity between 24 and 36 docks (10 and 36 are the minimum and maximum capacity in the city). Docking stations connected with dedicated bike lines. I split again the sample in two: stations within and beyond 300m to the closest cycleway. Density of additional stations in a radius of 300m. This time I considered four different configurations: stations that share the space with exactly one additional station, where there are more than one, three or nine stations nearby.

Table A-3 summarizes all the results. The influence of e-bikes is irrelevant in this case (the estimates are mostly not significant) due to the small number of observations in comparison with standard stations (only 5.8% of docking stations are e-bikes). Regarding the size of the stations, it is irrelevant to determine the total effect. The effect is slightly larger in low-capacity stations contrary with the intuition. One could expect that riders prefer higher stations to decrease the uncertainty of finding available bikes at origin or empty docks at destination. However, it might be the case that users reduce such uncertainty by preferring denser regions in terms of number of stations. This strategic behavior might help them to reduce the expected travel time. In fact, this intuition is supported by the empirical evidence. As noticed, having at least one additional docking station nearby is relevant for users. What is more, during disruption, the density matter for users at origin and destination. However, under normal conditions, the estimates suggest that users value more denser areas at destination. Finally, the relationship with the proper infrastructure for cycling is also important for riders, the effects seem to arise from docking station with cycleways nearby before and after disruption. These results are in line with recent studies regarding the relevance of cycling infrastructure (Ashraf et al., 2021).

8. Influence on subway ridership

This article presents evidence of a dichotomic relationship between bike-sharing and public transport in Mexico City. It also shows how a disruption of the subway system affect the dynamics between both transport modes. The main findings suggest an increase in the degree of substitution during disruption and even after, when the network was fully restored. On the other hand, complementary bike journeys to public transport decreased during disruption, but the scenario after disruption shows an important recovery exceeding the levels observed before the incident. Nonetheless, a relevant question is whether the expansion of bike-sharing due to disruptions in the network has generated a modal-shift displacing subway ridership. Providing evidence in this regard is crucial for policy purposes because bike-sharing might represent a viable alternative to reduce car-dependency (to tackle transport related concerns) in as much as it complements public transport systems.

According to Goodwin (1977), habits prevent commuters to revise their choice set every time they travel limiting their capacity to notice changes in the attractiveness of new modes of transport. In addition, Goodwin argues that disturbances in the environment force commuters to deliberate among new alternatives. Disruptions in public transport is a well-documented case on how changes to the environment might alter commuters behavior (Zhu & Levinson, 2012; Tyndall, 2019; Yeung & Zhu, 2022). In the context of this article, disruption in the subway introduced bike-sharing into the choice set of different commuters increasing the number and intensity of use of this mode. Furthermore, the evidence presented here show long lasting effects suggesting that riders might have formed habits during the weeks of disruption putting bike-sharing as a viable option even under normal circumstances. This in turn might influence subway ridership by affecting the level of substitution between both modes.

Nevertheless, assessing modal-shift requires detailed information on commuters to be able to identify changes in their choice-sets and to observe their preferences among alternatives. This is important because modal shift does not necessarily come from public transport to bike-sharing. Affectations in the network disrupts other modes of transport by altering congestion on the streets and on other public transport services such as buses (Anderson, 2014). However, revealed preferences data from commuters is difficult to collect especially under the context of disruptions. In this paper instead, I proceed by studying the relationship between subway and bike-sharing ridership at three different levels of aggregation: at city, subway lines and subway stations level. This strategy helps me to identify to what extent bike-sharing adoption is associated with displacement in subway ridership.

To relate changes in subway ridership relative to the demand for bike-sharing as a consequence of the public system disruption, I estimate the following relationship:

$$lny_{i,t} = \theta_1(lnBr_{i,t} \times during_t) + \theta_2(lnBr_{i,t} \times after_t) + x'_{i,t}\Gamma + \mu_{i,t} \quad (4)$$

where subindex t represents days since disruption. Moreover, i stands for subway lines or stations depending on the level of desegregation. For the purpose of the exposition, I will consider i as the subway station in the description of the empirical strategy. The outcome $lny_{i,t}$ is the logarithm of the number of daily travelers entering in the network in station i. The vector $x'_{i,t}$ includes time fixed effects, subway line and subway station fixed effects, district fixed effects, square time trends by station as well as the covariates $during_t$ and $after_t$. This vector also includes a set of controls to the built environment such as the density of docking station nearby, an indicator for the type of subway station (transfer or intermediate station), distance to the closest cycleway, distance to district downtown, and distance to the city's downtown. Also, $\mu_{i,t}$ is the error term. The $lnBr_{i,t}$ is the logarithm of the number of bike journeys overall or by type (substitutes, complements, first-mile, and last-mile). As in the previous strategy, I exploited the spatial characteristics of both transport modes to relate subway and bike-sharing ridership assigning docking stations to the closest subway line/station in terms of the planar distance between each other. Therefore, the bike-sharing ridership associated to a specific subway line/station is generated from docking stations within the spatial vicinity. This strategy allows the classification of each bike journey by type.

I estimated equation (4) using OLS at city level. On the line/station disaggregation, I estimate a Poisson regression model because we are interested in the logarithmic relationship of the outcome. However, a simple logarithmic transformation is not viable because the flux of passengers in stations closed during disruption is zero. Furthermore, when I analyze the effects at stations level, I apply the hyperbolic sine transformation to the number of bike journeys by type. This is because some docking stations do not produce specific types of journeys. Cluster standard errors at the subject level (subway lines or stations) are considered.

Finally, the vectors of coefficients θ_1 and θ_2 measure the effects of increasing bike-sharing demand on subway ridership before, during, and after disruption. For instance, a negative coefficient is evidence that bike-sharing and public transport are substitutes. In other words, a percentage increase of one percent in bike-sharing ridership should be associated with a percentage decrease of subway ridership by the corresponding estimated coefficient. Moreover, if the expansion of bike sharing demand is not associated with subway ridership displacement, then we would expect to find positive estimates (statistically equal to zero) in the after-disruption scenario.

One important limitation in the analysis is that subway ridership is measured as the flux of commuters entering in each station which imposes important concerns to identify the relationship with last-mile journeys. A better approximation would be to use the flux of commuters leaving the station; however, I am restricted by the available information in the dataset. Nevertheless, a high correlation between the in/out flux by station is expected making the outcome a good approximation for the ideal measure. Another challenge is to separate the intensive and extensive margin regarding bike system. The expansion of bike-sharing demand might come as a consequence of an increase in the number of users (extensive margin) or due to an increase in the frequency of use of riders already registered in the system (intensive margin). Because I am only using information from working days, it is implausible that the effect comes from the intensive margin. Nonetheless, I estimated the effect of disruption to the number of new subscriptions adapting equation (3) to provide evidence about the expansion of bike-sharing in terms of the number of riders.

8.1 Results

This section's main results are reported in Table 6 and Table 7. Overall, the findings suggest that disruption is associated with an increase in the degree of complementarity between both transport modes. Nevertheless, the direction and magnitude of the effect differs between the level of aggregation. Restricting the analysis to subway lines integrated with bike-sharing shows evidence of subway substitution to bike-sharing. In other words, increasing the bike-sharing ridership is associated with lower subway ridership within those lines during and after disruption. Estimates suggest that increasing by 10% the number of bike-sharing journeys decreases by 3.3% and 0.4% subway ridership during and after disruption, respectively. However, more granular data shows the opposite results. When subway ridership is considered only in stations integrated with bike-sharing, both modes complement each other. According to the point estimates, increasing the number of bike-sharing journeys by 10% increases subway ridership by 1.2% and 0.3% during and after disruption.

Contradictory results in terms of the direction of the effect when more granular data is considered might be explained due to the spatial influence of bike-sharing system in the city. Due to physical restrictions, the influence of bike-sharing is limited to the location and distribution of docking stations. In contrast, the analysis at subway-line level considers users entering in stations not integrated with bike-sharing. In some extreme cases, bike-sharing is integrated in a small fraction of entire lines. Therefore, expanding the demand for bike-sharing should not influence the ridership in those stations specially when only inflow ridership is considered. Moreover, bike-sharing ridership might influence the outflow of passengers in outer regions. A more granular data in terms of the number of passengers exiting each subway station is suitable to fully explain this result.

Table 6. Bike-sharing influence on subway ridership

	Dependent variable:					
	ln(Subway ridership)		Subway ridership			
	OLS		*Poisson*			
	Aggregated		*Subway lines*		*Subway stations*	
	(1)	(2)	(3)	(4)	(5)	(6)
ln(Bike ridership)	0.125* (0.067)	0.124* (0.065)	0.247** (0.112)	0.246** (0.112)	0.122*** (0.024)	0.122*** (0.024)
During	-7.694*** (1.044)	-7.650*** (1.028)	1.491*** (0.289)	1.485*** (0.289)	-1.350*** (0.126)	-1.350*** (0.126)
After	-2.537*** (0.954)	-2.584*** (0.943)	-0.295** (0.125)	-0.301** (0.125)	-0.715*** (0.049)	-0.716*** (0.049)
ln(Bike ridership)*During	0.762*** (0.113)	0.756*** (0.112)	-0.334*** (0.051)	-0.334*** (0.051)	0.121*** (0.024)	0.121*** (0.024)
ln(Bike ridership)*After	0.228 (0.102)	0.232** (0.101)	-0.041*** (0.005)	-0.041*** (0.005)	0.032*** (0.006)	0.032*** (0.006)
Controls and FE	Yes	Yes	Yes	Yes	Yes	Yes
Output trend	No	Yes	No	Yes	No	Yes
Observations	121	121	968	968	6,403	6,403
R^2	0.986	0.986				
Adjusted R^2	0.984	0.984				
Log Likelihood (Mio.)			-9.490	-9.488	-6.117	-6.116
Akaike Inf. Crit. (Mio.)			18.980	18.975	12.233	12.233
Residual Std. Error	0.028	0.028				
F Statistic	496.5***	465.8***				

Note: The Table reports the estimated impact of bike-sharing on subway ridership during and after disruption. Columns report estimates at city level (1-2), subway line level (3-4), and subway station level (5-6). Regressions at aggregated level include new subscriptions, day of the week, and month as controls and fixed effects. Line fixed effects and the density of docking station nearby are added when subway lines are considered. For the analysis at station level, the type of subway station (transfer or intermediate station), district, zip code, distance to city downtown, distance to district downtown, and distance to closest cycleway are also included. Trend refers to the outcome quadratic trend. Cluster standard errors at subway line and station were applied in each case. Significance levels are represented as follows: *p<0.1; **p<0.05; ***p<0.01.

The estimates by type of bike-journey provide a more detailed information about the dynamics between both transport modes (see Table 7). As expected, considering only subway stations integrated with bike-sharing, increasing the number of bike-journeys that substitute subway itineraries is negatively associated with subway ridership during. Increasing by 10% substitution journeys diminishes on average subway ridership in those stations by 0.6%. It is noteworthy that the effect is sustained at a lower extend even after disruption. In this case, the response is reduced to 0.1%.

Complementary journeys, i.e., those that happened outside the spatial coverage of the subway system, show equivalent results. What is more relevant from the analysis is that this behavior even is sustained after fully restoration of the network. The case of first-mile bike journeys supports the previous evidence. Again, the direction of the effect is as expected, however, a larger effect after disruption in comparison with the scenario before suggests a larger degree of complementarity as a result of disruptions in the network. Last-mile trips on the other hand shows a negative and significant effect during and after disruption. The interpretation of these estimates is less evident. They suggest that improving connectivity for the last-mile, decreases the complementarity between both modes harming multimodal behavior. Nevertheless, as I mentioned above, interpreting these coefficients should be done with caution because subway ridership does not measure the number of users exiting the network. To accurately measure last-mile complementarities, stations' outflow is desired.

Previous findings are evidence on how disruption in the subway system changed the market dynamics with bike-sharing. Nevertheless, limitations in the data prevent us to disentangle whether the expansion of bike-sharing and its influence on subway ridership is consequence of more users shifting to bike-sharing (extensive margin) or an increase in the intensity of use of this mode (intensive margin). As a first attempt to study such difference, Table 8 reports the effects of disruption on the daily number of new subscriptions. As noticed, the results suggest that disruption is associated with an expansion in the number of citizens registered to ECOBICI. Nevertheless, caution interpreting these results its advised. Even if bike-sharing membership increased, the data does not allow to link it with the effective demand of those new members.

Table 7. Bike-sharing influence on subway ridership by type of journey

	Dependent variable:											
	ln(Subway ridership)	Subway ridership		ln(Subway ridership)	Subway ridership		ln(Subway ridership)	Subway ridership		ln(Subway ridership)	Subway ridership	
	OLS	*Poisson*		*OLS*	*Poisson*		*OLS*	*Poisson*		*OLS*	*Poisson*	
	Aggregated	Lines	Stations	Aggregated	Lines	Stations	Aggregated	Lines	Stations	Aggregated	Lines	Stations
	(1)	(2)	(3)++	(4)	(5)	(6)++	(7)	(8)	(9)++	(10)	(11)	(12)++
ln(Substitutes)*During	0.626*** (0.099)	-1.061*** (0.153)	-0.064*** (0.012)									
ln(Substitutes)*After	0.139 (0.064)	-0.118*** (0.008)	-0.016*** (0.004)									
ln(Complement)*During				0.753*** (0.120)	-0.204*** (0.029)	0.068*** (0.010)						
ln(Complement)*After				0.217** (0.097)	-0.024*** (0.003)	0.029*** (0.002)						
ln(First-mile)*During							0.732*** (0.124)	-0.246*** (0.034)	0.066*** (0.012)			
ln(First-mile)*After							0.225** (0.107)	-0.033*** (0.004)	0.031*** (0.003)			
ln(Last-mile)*During										0.762*** (0.145)	-0.471*** (0.078)	-0.030*** (0.011)
ln(Last-mile)*After										0.238** (0.101)	-0.070*** (0.009)	-0.010*** (0.003)
Observations	121	968	6,403	121	968	6,403	121	968	6,403	121	968	6,403
R^2	0.985			0.986			0.985			0.984		
Adjusted R^2	0.983			0.983			0.983			0.982		
Log Likelihood (Mio.)		-7.511	-6.146		-9.508	-6.105		-9.432	-6.129		-9.595	-6.147
Residual Std. Error	0.030			0.029			0.029			0.031		
F Statistic	424.8***			445.9***			437.8***			405.5***		

Note: The Table reports the estimated impact of bike-sharing on subway ridership during and after disruption by type of bike-sharing journey. Substitute journeys are defined as trips that start and end within the spatial coverage (300m) of the subway network. First and last-mile journeys are defined as trips that start/end beyond/within the spatial coverage (300m) of the subway and ends/starts within/beyond. Complementary journeys are bike trips that does not start nor end within the spatial coverage of the subway system. Bike journey were transformed using the inverse hyperbolic sine function (instead of the natural logarithm) in columns marked as ++. Regressions at aggregated level include new subscriptions, day of the week, and month as controls and fixed effects. Line fixed effects and the density of docking station nearby are added when subway lines are considered. For the analysis at station level, the type of subway station (transfer or intermediate station), district, zip code, distance to city downtown, distance to district downtown, and distance to closest cycleway are also included. Every model includes the outcome quadratic trend. Cluster standard errors at subway line and station are considered in each case. Significance levels are represented as follows: *p<0.1; **p<0.05; ***p<0.01.

Table 8. Impact on the number of new users

	Dependent variable:		
	ln(Daily No. of new subscriptions)		
	(1)	(2)	(3)
During	0.488**	0.524**	0.686***
	(0.207)	(0.210)	(0.233)
After	0.206	0.278	0.485
	(0.375)	(0.381)	(0.401)
Constant	3.456***	5.003***	5.743***
	(0.505)	(1.532)	(1.613)
Month of the year FE	Yes	Yes	Yes
Week of the year FE	Yes	Yes	Yes
Day of the week FE	Yes	Yes	Yes
Trend	No	Yes	Yes
Lag	No	No	Yes
Observations	120	120	119
R^2	0.754	0.757	0.764
Adjusted R^2	0.651	0.652	0.656
Residual Std. Error	0.268 (df = 84)	0.268 (df = 83)	0.267 (df = 81)
F Statistic	7.345*** (df = 35; 84)	7.185*** (df = 36; 83)	7.093*** (df = 37; 81)

Note: The Table reports the estimated impact of public transport disruption on the number of new subscriptions to the bike-sharing program. Each row shows the estimates from equation (1) excluding the covariate d_i. Trend refers to a quadratic approximation in the trend of daily new subscriptions and Lag is refer to the first lagged value of the outcome. Robust standard errors were applied. Significance levels are represented as follows: *p<0.1; **p<0.05; ***p<0.01.

9. Conclusion

This article investigates the impact of public transport disruptions on the adoption of bike-sharing. I exploit an extemporaneous event that shut down operations in 50% of the subway lines in Mexico City in a natural experimental setting to causally identify public transport substitution to bike-sharing. In addition, I provide empirical evidence on the spatial influence of subway networks to compare outcomes of docking stations with different degrees of spatial integration to public transport. Furthermore, using the spatial integration between both systems, I measure heterogenous effects by type of bike-sharing journeys including substitutes, complement, first, and last-mile connections. Finally, due to the amount of information available, I study the evolution of the effects over time.

Overall, my findings suggest an increased in the degree of substitution to bike-sharing associated to public transport disruption, especially in docking stations highly integrated with the subway network. Complementarity decreased during this period including both, first and last-mile journeys. This result was expected due to the lack of connectivity within the network. What is more, the empirical evidence suggests that disruptions were associated with an overall increase in the adoption of bike-sharing in the long-run. As a matter of fact, the number of bike journeys complementing and substituting public transport increased in the weeks after the restoration of the system. To ease the interpretation of these findings, I measure the influence of bike-sharing on subway ridership conditional on the network disruption. The estimates are positive during and after disruption when only subway stations integrated with the system are considered. These results suggest that disruptions in the network increased the degree of complementarity between both transport modes. Nevertheless, further research is needed to better understand whether the evidence found here is the consequence of modal shift from private cars.

The findings presented here might help policy makers to design multimodal mobility systems resilient to disruptions and compatible to face the current sustainable and environmental challenges. The dichotomic relationship between new mobility services and public transport is beneficial to face recent challenges such as disruptions and congestion while providing alternativities to reduce car-dependency. However, very few is known about this type of markets especially due to the recentness of such innovations and the limited availability of data. The introduction of these new modes challenged the traditional vertically integrated urban mobility and have given room to a more decentralized organization. This in turn raises new questions which answers will help societies to unlock the whole potential of an integrated multimodal mobility system.

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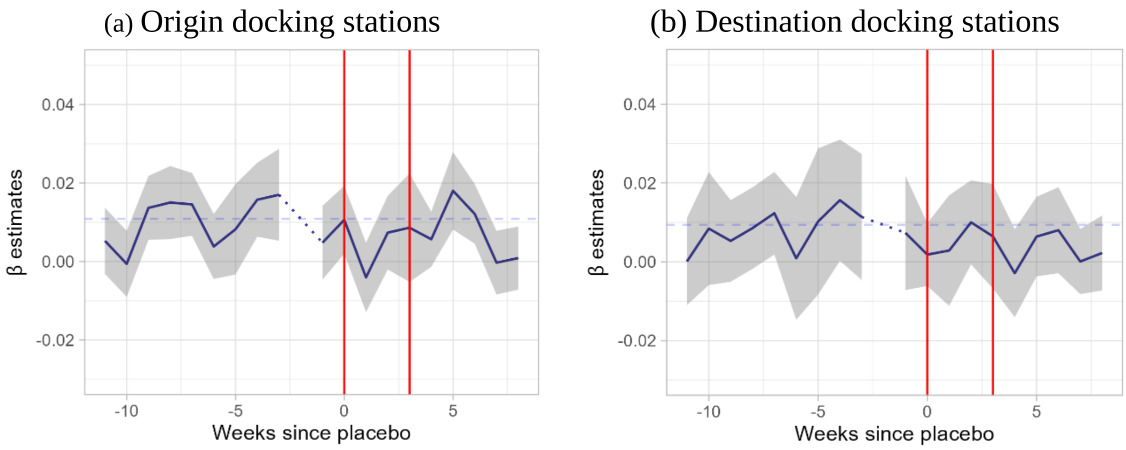
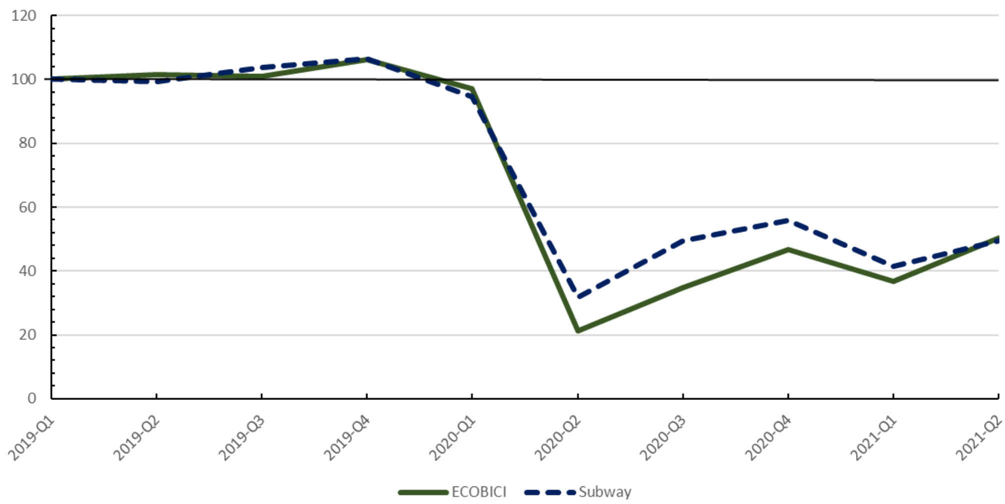
Appendix A. Robustness test and additional results

Figure A-1. Placebo analysis - Visual inspection



Note: The Figure reports the weekly dummy (β_q) estimates from equation (2) for the placebo sample. X-axis represents the number of weeks elapsed since the placebo date of disruption on January 11th, 2020. Therefore, the first week of disruption is in zero. Solid vertical lines indicate the week when disruption started and the week when the system was fully restored. Shaded regions denote an interval confidence at 95% level around estimates. The dotted line was included instead of the dummy intentionally left out from the regression. Figure (a) shows the effects from the *origin-station* dataset only. Figure (b) shows the effects from the *destination-station* dataset only. The analysis was restricted to 10 weeks after disruption to avoid the effects of the global pandemic Covid-19.

Figure A-2. Evolution of bike-sharing and subway ridership
(Index: 2019-Q1 = 100)



Note: The Figure reports the quarterly number of bike-sharing and subway ridership indexed to the first quarter of 2019. Series not seasonally adjusted.

Table A-1. Robustness test, disruption effects on a placebo sample

	Dependent variable:			
	ln(Journeys)			
	Origin-station		*Destination-station*	
	(1)	(2)	(3)	(4)
During*Distance	-0.005	-0.003	0.001	-0.002
	(0.003)	(0.004)	(0.003)	(0.002)
After*Distance	0.0004	-0.002	0.001	-0.005^{*}
	(0.006)	(0.002)	(0.003)	(0.002)
During	-0.040^{***}	-0.318^{***}	-0.034^{***}	-0.322^{***}
	(0.012)	(0.015)	(0.012)	(0.016)
After	0.023^{**}	0.062^{***}	0.035^{***}	0.056^{***}
	(0.010)	(0.006)	(0.010)	(0.007)
Distance	-82.922^{***}	2.274	-98.602^{***}	1.783
	(0.002)	(3.593)	(0.001)	(5.196)
Capacity	0.352^{***}	-0.009	0.323^{***}	-0.006
	(0.000)	(0.015)	(0.000)	(0.017)
E-station	-1.753^{***}	0.050	-1.588^{***}	0.030
	(0.000)	(0.076)	(0.000)	(0.084)
Distance to cycleway	-0.018^{***}	0.001	-0.019^{***}	0.0004
	(0.000)	(0.001)	(0.000)	(0.001)
Density	3.556^{***}	-0.105	2.954^{***}	-0.068
	(0.000)	(0.154)	(0.000)	(0.156)
Subscriptions	0.001	0.014^{***}	0.001	0.013^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	-2.182^{***}	-0.944^{***}	0.766^{***}	-0.951^{***}
	(0.103)	(0.113)	(0.095)	(0.127)
Stations FE	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes
Stations' trend	No	Yes	No	Yes
Observations	9,467	9,467	9,467	9,467
R^2	0.950	0.960	0.950	0.959
Adjusted R^2	0.947	0.957	0.948	0.956

Note: The Table reports the estimated impact of public transport disruption on bike-sharing adoption using the placebo dataset. Rows 2 and 4 show the estimates of β_1 and β_2 from equation (1), respectively. Distance is the planar distance between subway and docking stations. Controls include docking stations for e-bikes, station total capacity, distance to the closest cycleway, the number of docking stations in a radius of 300m (Density), and the number of new subscriptions into the program. Stations' trend control for the quadratic approximation of outcome's trend. The analysis was restricted to 10 weeks after disruption to avoid the effects of the global pandemic Covid-19. Cluster standard errors per docking station were applied. Significance levels are represented as follows: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table A-2. Sensitivity analysis to various levels of spatial integration

	Dependent variable: ln(Journeys)							
	During		After		During		After	
	Origin	Destination	Origin	Destination	Origin	Destination	Origin	Destination
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Panel A: Substitutes					*Panel B: Complement*			
200m	0.080 (0.110)	0.006 (0.112)	0.108 (0.098)	0.117 (0.090)	-0.101*** (0.030)	-0.102*** (0.033)	0.145*** (0.027)	0.162*** (0.027)
400m	-0.049 (0.058)	-0.023 (0.061)	0.117** (0.051)	0.063 (0.053)	-0.095** (0.042)	-0.117*** (0.043)	0.130*** (0.040)	0.172*** (0.033)
600m	-0.034 (0.039)	-0.046 (0.037)	0.091*** (0.035)	0.103*** (0.034)	-0.086 (0.065)	-0.067 (0.064)	0.146** (0.058)	0.199*** (0.050)
800m	-0.057* (0.032)	-0.067** (0.031)	0.114*** (0.028)	0.124*** (0.027)	-0.061 (0.091)	-0.097 (0.087)	0.111 (0.089)	0.159** (0.080)
1000m	-0.083*** (0.029)	-0.086*** (0.029)	0.130*** (0.025)	0.144*** (0.025)	0.033 (0.149)	0.016 (0.131)	0.076 (0.150)	0.083 (0.116)
1200m	-0.104*** (0.027)	-0.101*** (0.028)	0.136*** (0.023)	0.152*** (0.023)	0.212 (0.254)	0.101 (0.249)	-0.188 (0.290)	0.106 (0.196)
Panel C: First-mile					*Panel D: Last-mile*			
200m	-0.131** (0.063)	-0.047 (0.056)	0.180*** (0.051)	0.112** (0.048)	-0.039 (0.059)	-0.128* (0.070)	0.082* (0.049)	0.118** (0.058)
400m	-0.160*** (0.050)	-0.118** (0.056)	0.205*** (0.036)	0.148*** (0.045)	-0.040 (0.052)	-0.104** (0.051)	0.101** (0.045)	0.211*** (0.044)
600m	-0.211*** (0.054)	-0.204*** (0.057)	0.226*** (0.043)	0.165*** (0.047)	-0.141** (0.056)	-0.148** (0.058)	0.164*** (0.045)	0.202*** (0.046)
800m	-0.225*** (0.065)	-0.206*** (0.070)	0.265*** (0.055)	0.211*** (0.056)	-0.108* (0.059)	-0.129* (0.072)	0.182*** (0.053)	0.232*** (0.053)
1000m	-0.189** (0.092)	-0.196** (0.077)	0.243*** (0.075)	0.203*** (0.067)	-0.054 (0.077)	-0.110 (0.097)	0.151** (0.070)	0.159** (0.071)
1200m	-0.099 (0.112)	-0.102 (0.095)	0.182* (0.104)	0.188** (0.082)	0.058 (0.101)	-0.079 (0.122)	0.113 (0.088)	0.165* (0.099)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stations FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stations' trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: The Table reports the estimated impacts of public transport disruption on bike-sharing adoption by each type of bike journeys for different measures of spatial integration with subway system (from 200m to 1200m each 200m). Columns (1) and (2) report the estimates of β_1 while columns (2) and (3) reports β_2 estimates from equation (1). Columns (1) and (3) in each panel refer to the estimates using the *origin-station* dataset only. Columns (2) and (4) refer to the estimates using the *destination-station* dataset only. Panel A reports the effects for substitute journeys only defined as trips that start and end within the spatial coverage of the subway network that corresponds to the specified row. Panel B refers to complement journeys, i.e., bike trips that does not start nor end within the spatial coverage of the subway system. Panels C and D include first/last mile journeys defined as trips that start/end beyond/within the spatial coverage of the subway and ends/starts within/beyond. Controls include docking stations for e-bikes, station total capacity, distance to the closest cycleway, and the number of docking stations in a radius of 300m (Density). Stations' trend refers to a quadratic approximation in the outcome time trend by docking station. Cluster standard errors per docking station were applied. Significance levels are represented as follows: *p<0.1; **p<0.05; ***p<0.01.

Table A-3. Heterogenous effects

	Dependent variable:			
	ln(Journeys)			
	During*Distance		After*Distance	
	Origin-station	*Destination-station*	*Origin-station*	*Destination-station*
	(1)	(2)	(3)	(4)
E-stations	0.060	0.063	0.032***	0.035**
	(0.051)	(0.046)	(0.010)	(0.016)
S-stations	0.035***	0.028***	0.009***	0.005***
	(0.004)	(0.006)	(0.001)	(0.002)
Low capacity	0.146***	0.153***	0.048**	0.053***
	(0.030)	(0.030)	(0.019)	(0.014)
High capacity	0.031***	0.024***	0.008***	0.004***
	(0.004)	(0.003)	(0.001)	(0.001)
Cycleway nearby	0.079***	0.091***	0.026**	0.025***
	(0.025)	(0.027)	(0.010)	(0.009)
No cycleway nearby	0.033***	0.023***	0.009***	0.004***
	(0.004)	(0.003)	(0.002)	(0.001)
Station's density nearby				
One station	0.045*	0.033	0.054**	0.043***
	(0.025)	(0.024)	(0.022)	(0.016)
> One station	0.036***	0.031***	0.009***	0.006***
	(0.005)	(0.007)	(0.001)	(0.002)
> 3 stations	0.040	0.063*	0.018	0.029**
	(0.039)	(0.036)	(0.015)	(0.014)
> 9 stations	-0.403	-0.472	-0.771	-0.078
	(1.979)	(1.040)	(0.960)	(0.977)
Stations FE	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes
Stations' trend	Yes	Yes	Yes	Yes

Note: The Table reports the estimated impacts of public transport disruption on bike-sharing adoption for different subpopulations of biking stations. Columns (1) and (3) refer to the estimates using the *origin-station* dataset only. Columns (2) and (4) refer to the estimates using the *destination-station* dataset only. Distance refers to the inverse of the planar distance between subway and docking stations. Low capacity includes stations for less than 23 docks and high capacity those above 24 docks (10 and 36 are the minimum and maximum capacity). Cycleway nearby are docking stations connected to dedicated bike lines by no more than 300m. Density of additional stations in a radius of 300m consider four different alternatives: stations that share the space with exactly one additional station, where there are more than one, three or nine stations nearby. Stations' trend refers to a quadratic approximation in the outcome time trend by docking station. Cluster standard errors per docking station were applied. Significance levels are represented as follows: *p<0.1; **p<0.05; ***p<0.01.

Table A-4. Bike-sharing influence on subway ridership, alternative transformation of the independent variable

	Dependent variable:				
	Subway ridership				
	Poisson				
	(1)	(2)	(3)	(4)	(5)
ln(Bike ridership + 1)*During	0.121***				
	(0.024)				
ln(Bike ridership + 1)*After	0.032***				
	(0.006)				
ln(Substitutes + 1)*During		-0.072***			
		(0.014)			
ln(Substitutes + 1)*After		-0.018***			
		(0.005)			
ln(Complement + 1)*During			0.074***		
			(0.011)		
ln(Complement + 1)*After			0.031***		
			(0.003)		
ln(First-mile + 1)*During				0.071***	
				(0.013)	
ln(First-mile + 1)*After				0.035***	
				(0.003)	
ln(Last-mile + 1)*During					-0.028**
					(0.014)
ln(Last-mile + 1)*After					-0.010***
					(0.004)
Controls	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes
Trend	Yes	Yes	Yes	Yes	Yes
Observations	6,403	6,403	6,403	6,403	6,403
Log Likelihood (Mio.)	-6.116	-6.151	-6.108	-6.135	-6.152
Akaike Inf. Crit. (Mio.)	12.233	12.302	12.217	12.270	12.304

Note: The Table reports the estimated impact of bike-sharing on subway ridership during and after disruption. The analysis is restricted to subway stations. Substitute journeys are defined as trips that start and end within the spatial coverage (300m) of the subway network. First and last-mile journeys are defined as trips that start/end beyond/within the spatial coverage (300m) of the subway and ends/starts within/beyond. Complementary journeys are bike trips that does not start nor end within the spatial coverage of the subway system. Controls and fixed effects included are new subscriptions, day of the week, month, density of docking station nearby, type subway station (transfer or intermediate station), district, zip code, distance to city downtown, distance to district downtown, and distance to closest cycleway. Trend refers to the outcome quadratic trend. Cluster standard errors at subway station are considered. Significance levels are represented as follows: *p<0.1; **p<0.05; ***p<0.01.

Chapter 4

Harmonizing Dockless E-scooters: Insights from Paris*

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Chapter outline

Abstract
The auto-oriented paradigm that dominated urban transport during the last fifty years rose social and environmental concerns due to traffic congestion, local and global pollution, inequalities, and adverse health effects. In response, cities welcomed new micro-mobility services aiming to provide alternatives to reduce car-dependency, tackle travelers dilemmas, and improve accessibility while attaining economic growth. How to articulate these new services into a multimodal mobility system is an open debate in the literature far from over. This paper focuses on the introduction of dockless e-scooters in the city of Paris and the regulatory reforms that came along seeking to harmonize improper parking, considered for many as one of the most relevant drawbacks in the adoption and acceptance of this transport mode. The case of Paris is of relevance because the city decided to reallocate public spaces to exclusively park e-scooters. Leveraging on the spatial relationship of parked e-scooters and the location of parking zones, this paper proposes Key Performance Indicators to evaluate the effects of parking regulations on users' behavior and on the accessibility of e-scooters. We find that parking bays reduce cluttering and mis-parking, but, unintendedly, the regulation makes e-scooters less accessible to users by limiting pick-up and drop-off points.

Keywords: *Sharing-economy; E-scooters; Micro-mobility management; Big data analytics; Parking; Economic regulation.*
JEL classification: *: L91, L98, O38, R48, R52.*

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1. Introduction

The auto-oriented paradigm that dominated urban transport during the last fifty years rose social and environmental concerns due to traffic congestion, local and global pollution, inequalities, and adverse health outcomes. In consequence, cities welcomed new micro-mobility services aiming to provide alternatives for reducing car dependency (ITF, 2021; Asensio et al., 2022), tackle travelers dilemmas (Lesh, 2013; Shaheen & Chan, 2016), and improve accessibility (Shaheen & Cohen, 2019). Nevertheless, in most cases, these innovations were introduced without the proper regulatory framework preventing communities to capture all their potential hampering economic growth and development (Bąk, 2016; Gössling, 2020; Meng et al., 2020; Button et al., 2020). As a result, governments are issuing new rules, taking advantage of the digital revolution, in an effort to better integrate these new services with the rest of the mobility mix.

Dockless shared e-scooters (also referred to as e-scooters in free-floating) are a relative recent innovation for urban mobility where renters pick-up and drop-off vehicles at any location in the city within a predetermined geographic region. As any other micro-mobility service, this innovation enables users to have short term access to transport on an as-needed basis (Shaheen & Cohen, 2019). This mode of transport has been considered for many as an innovative alternative with potential to overcome the so-called first/last mile dilemma by improving accessibility to public transport and enhancing multimodal behavior (Shaheen & Chan, 2016; Baek et al., 2021). In fact, the 6t-bureau de recherche (2019) conducted a survey in France among e-scooters users with the objective of understanding travel patterns. They found that 23% of the trips were intermodal, i.e., users combine e-scooters with public transport (66% of the cases) and walking (16%). Similar results were obtained in other cities around the world (Eccarius & Lu, 2020; Laa & Leth, 2020). In addition, e-scooters have found an important demand across hundreds of cities worldwide and there is still a lot of potential for expansion. According to the Boston Consulting Group (2019), e-scooters will represent 15% of market share for automotive-based on-demand mobility by 2025 with a value between 40 to 50 billion dollars. Altogether, these conditions make dockless shared e-scooters an attractive mobility mode for cities to ease transport-related concerns.

However, many have pointed out barriers in the provision of services that prevent cities to unlock all the benefits, especially in the absence of proper regulation (Button et al., 2020;

Meng et al., 2020). In the specific case of dockless e-scooters, mis-parking and cluttering (random parking) have been considered as the main drawbacks for public acceptance, which is closely related to less adoption and demand (Brown A. , 2021a; Brown et al., 2021b; Brown et al., 2020; Gössling, 2020; Button et al., 2020; Sobrino et al., 2023). The problematic is so crucial that many cities such as San Francisco, Barcelona, Miami, and, most recently, Paris have decided to ban e-scooters arguing that both, mis-parking and cluttering, interfere with the harmonization of transportation. Indeed, mis-parking imposes external costs on other users. For instance, parking on sidewalks might block the use of the public space to pedestrians. The trade-off raised by the introduction of e-scooters re-opened the debate about curb-space management (Shaheen & Cohen, 2019). Governments must rethink how to distribute public spaces among different users including those who walks, parks, or rides different types of vehicles. Echoing the words of Banister (2008), one must reconsider the concept of street as a space for people, green mobility, and public transport.

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

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

To empirically assess our hypothesis, we use an administrative database unique of its kind that geo-locates the whole fleet of e-scooters in the city of Paris. This big dataset observes parked vehicles before and after the regulations adopted in the city. We exploit this data base to compare the spatial relationship between vehicles and parking bays before and after their construction. First, we develop a Key Performance Indicator based on the Euclidean distance between vehicles and parking bays. At the end of 2019, before the regulation, the average distance between e-scooters and the virtual location of parking bays was close to 100m, contrasting with a distance close to 20m after their implementation. This change represents a percentage decrease of almost 80%. Our finding proves that regulation in Paris have a positive effect harmonizing e-scooters by reducing cluttering.

Accessibility of vehicles is a key question for the adoption of e-scooters. The 6t-bureau de recherche (2019) found that 59% of users have experienced a lack of vehicles nearby and 24% have given up on the usage of this mode for that reason. In a similar study, Sanders, et al., (2020) surveyed 1,256 university staff in Tempe, AZ, to find that on average 40% of riders indicate "not being able to find one when needed" as a barrier to ride e-scooters. On top of that, this option was chosen more often among regular riders (45%). Therefore, to assess the effects of the regulation on accessibility, we exploit the location of parking bays to build maps (rasters) measuring the distance from any point in the city to the closest vehicle. Following the same direction, we create an index to compare the situation before and after the regulation. Our findings suggest that the average distance to find an e-scooter was about 180m before the construction of parking bays and 250m afterwards, a percentage increase of almost 40%. In other words, parking regulations in Paris had a negative effect on the accessibility of vehicles. Following a similar strategy, we develop a KPI to compare the concentrations of e-scooters across the city. The evidence documented here shows that regulations limit the concentration of vehicles ins specific regions of the city and improves the provision of the service in uncovered areas. Additionally, we provide a regional comparison among the 20 districts in Paris for all KPIs mentioned above. We found heterogeneous effects that might help authorities to better allocate resources to improve the provision of dockless e-scooters in the city.

Finally, we go in more detail about mis-parking persistence, i.e., improper parking in the presence of parking infrastructure. We identify three types of users based on how close they park to the corresponding infrastructure. We find that regulation is effective incentivizing users to comply with the rules. However, unlawful users, those who never follow the rules, still constitutes a significant share of riders (13% to 18%). furthermore, we develop an index to measure congestion in parking bays. The evidence suggests that congestion skyrocket in the last quarter of 2020, after the construction of parking bays. We find that almost 20% of the fleet-size parked in bays with exceeded capacity and that more than 30% of parking bays were overcrowded by the end of the year. The evidence shows no signs of deceleration. Our findings highlight the need for further research to better understand the determinants of mis-parking persistence even in the presence of infrastructure. Parking is not only related with regulation, cultural behavior and cognitive biases might also be relevant (Ralph & Delbosc, 2017). Therefore, taking into consideration each city context is important for researchers and policy makers to measure the effects of new rules.

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

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

2. Related literature

Studying parking, especially for cars, has a long tradition in transport and economic science.[1] This trend in the literature has focused mainly on the economics aspects of parking

[1] See Inci (2015) for a compelling review.

such as price, quantity, and how market failures should be addressed to improve social welfare. However, new mobility modes have challenged this view by demanding a redistribution of the public space to operate. Nevertheless, despite the growth rate of shared micro-mobility services, the academic literature is falling behind, and more research urges to address recent challenges in urban mobility (Button et al., 2020).

While some shared micro-mobility modes, such as bike-sharing, have received a relative extensive attention in the literature (DeMaio, 2009), dockless e-scooters are still a minor topic despite their extensive adoption and potential to ease transport-related concerns. One reason is because datasets are not widely available yet. The literature on dockless e-scooters falls in three categories: studies about users demand and behavior (Nikiforiadis et al., 2021; McKenzie, 2020; Younes et al., 2020; Laa & Leth, 2020; Sanders et al., 2020; Eccarius & Lu, 2020), mode choice and competition (Reck et al., 2021; Baek et al., 2021; Krier et al., 2021; Aarhaug et al., 2023), and social concerns and public intervention. Our paper contributes to the latter strand as we aim to address the effects of parking regulations.

The studies of Aarhaug et al. (2023) and Sobrino et al. (2023) discuss the need to accompany the introduction of dockless e-scooters with proper regulations to better integrate them with the existent transport system and meet specific public concerns. Gössling (2020) identifies what are the major social concerns before and after the introduction of this mobility mode in ten different cities including Paris. After collecting and analyzing information of news reports available online, the author finds that, the introduction of e-scooters raises concerns among citizens related with conflicts over space (including parking and riding), speed, and safety. Moreover, his findings suggest that more negative media headlines were published in cities where e-scooters were allowed without proper rules.

It is worth mentioning that, in contrast to conventional transport modes, two levels of mis-parking have been identified for e-scooters: improper parking and cluttering. The former comprises practices that block or reduce access to other road or sidewalk users (Brown et al., 2020). Notably, this term is mostly used to describe how vehicles are parked individually. Cluttering, in contrast, defines a disorganized distribution of parked vehicles across the city. This definition has been borrowed from the language-hearing science where cluttering is a syndrome characterized by an unclear and/or disorganized speech.[2] The literature very often treats both levels of mis-parking as synonyms mainly because they are

[2] See Ward (2017) for more details.

intrinsically related (e.g., a cluttered distribution of vehicles gives the idea of improper parking). Therefore, parking regulations for a better curb-space redistribution, such as dedicated parking zones, might improve cluttering and improper parking by limiting the space dedicated to pick-up and drop-off vehicles without interfering with other users.

This paper is informative about the current level of mis-parking in the broad sense, i.e., improper parking and cluttering. Brown, et al. (2020) provide empirical evidence to compare improper parking between different mobility modes including dockless e-scooters. They collected in-field data during three days from five US cities with a large micro-mobility mix in streets with high levels of transport activity. The authors find that improper parking among e-scooters happened in only 1.7% of the cases, which is relatively low compared to motor vehicles (24.7%). Although this study does not address the problem of cluttering, it discusses the relevance of providing infrastructure for micro-mobility parking to reduce mis-parking in general terms.

In addition, our work provides empirical evidence about the efficiency of recent regulations to address mis-parking. Moran, et al. (2020) study operators' responses to parking regulations in the city of Vienna. The municipal authorities clarified in 2019 their rules to defined where e-scooter may or may not be ridden and parked. Operators responded by designing virtual no-parking zones in the form of geofences. The authors track those zones among six operators once a week over 3 months. They find that no-parking zones vary significantly by operator mainly because the regulation did not clarify the spatial coverage of the service. Our paper differs from the work by Moran, et al. (2020) first, because they focus on responses from the supply-side (we focus mainly on users' behavior) and second, because we provide robust empirical evidence using observational data with a high spatial and time coverage. Many other studies review different parking policies around the world; however, they do not discuss their effectiveness to accomplish their goals (Brown A. , 2021a; Shaheen & Cohen, 2019).

Finally, we seek to fill a gap in the literature related with the unintended effects to parking regulations. First, parking rules may be detrimental for the adoption of the service by limiting pick-up and drop-off points; a topic closely related with the substitution of public spaces and curb-side management. There are few studies in this direction (Sanders et al., 2020; 6t-bureau de recherche, 2019), however the evidence is currently either restricted to stated preferences or limited by the low spatial extension and time depth of the collected dataset. It is important to highlight that this negative effect could be attenuated if new rules improve the integration the services with the transport system, a trade-off that, in our opinion, deserves further attention in the literature. Second, even in the presence of the proper rules, mis-parking behavior might persist among certain riders. As noted by Brown, et al. (2021b) a lack of knowledge or understanding of parking rules are relevant to incentivize proper parking. Other characteristics might also be relevant such as the cultural context, cognitive biases, land use, geography, access to other transport modes, demographics, among others. Therefore, a more detailed analysis to understand the conditions that determine mis-parking is suitable to evolve regulatory frameworks.

3. Case Study: Paris City

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

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

Moreover, in July (Arrêté No 2019 P 16391) and October 2019 (Décret No 20191082) the city issued a series of reforms to clarify the regulatory framework related to micro-mobility. These reforms determined, among other things, the rules to park e-scooters in public spaces and the type of data that the city will collect from operators. The new regulatory framework mandates that parking e-scooters outside designated zones is forbidden. Moreover, the decree was issued to establish the technical characteristics and rules to ride micro-mobility vehicles powered by non-thermic engines (or Engins de Déplacement Personnel Motorisé in French). At a national scale, France issued in December

2019 the Law of Mobility Orientation (or Loi d'Orientation des Mobilités in French) as a response of the challenges imposed by the ecologic transition in the transport sector. Regarding the specific case of dockless mobility, the Law provides the issuance of permits to operators to deploy transport services in a non-discriminatory manner after request to the local authorities.

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

Also noteworthy is the relevance of e-scooters in comparison with the rest of the mobility mix in the city, notably with respect to other micro-mobility services. Dockless shared e-scooters are similar to the station-based bike-sharing system in Paris called Vélib', the most important micro-mobility services in the city. Vélib' operates 1,400 stations and 20,000 bicycles (40% of them are electric). From the perspective of demand, dockless e-scooters found recognition among Parisians. In September 2020, the month where the demand for micro-mobility attained its historic maximum, Vélib' made on average 180,000 daily journeys (Vélib' Metropole, 2022), meanwhile 30,000 journeys were made using e-scooters (L'institut Paris Region, 2022). Finally, regarding the market for dockless mobility, e-scooters are the leaders with a share equal to 53% in 2020 and 59% in 2021. They are followed by mopeds (38%), bikes (6%), and cars (3%) (L'institut Paris Region, 2022). The case of Paris is also relevant at international level. As a matter of fact, Paris is one of the cities with the largest density of e-scooters in Europe per inhabitant with 6.9 vehicles per 1000 people. In comparison with other European capitals, the figures in Berlin and Brussels are 3.0 and 2.6 vehicles per 1000 people, respectively. What is more, the number of e-scooters in Paris is competitive even against cities less densely populated like Stockholm and Oslo (11.2 and 11.7 vehicles per 1000 people each) (Civity, 2019).

Despite the demand that e-scooters fund in the city and authorities' effort to harmonize the service with the transport system, the debate regarding misuse and security intensified due to congestion in parking bays and deadly accidents. Consequently, the city of Paris organized a referendum for citizens to decide whether to renovate e-scooters permits to circulate. On April 2nd, 2023, with an overwhelming majority of votes (89%), citizens decided to ban the circulation of e-scooters (Ville de Paris, 2023). The referendum did not happen without controversy either. For instance, only inhabitants of the city where allow to vote even if e-scooter were often used by citizens in the close neighborhoods. Additionally, the referendum showed a low participation with a turnout rate of less than 7.5% (Ville de Paris, 2023). Furthermore, according to the operators, only 33% of the young population (between 18 to 24 years old) were aware of the referendum in contrast to the 77% of adults (between 50 to 64 years old) (Le Monde, 2023).

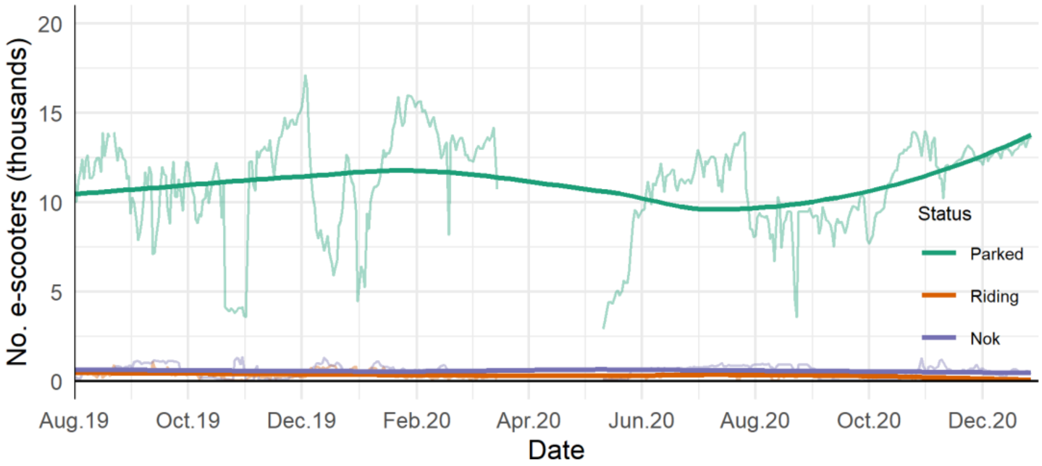
In summary, studying the case of Paris is relevant for the following reasons. First, e-scooters are a relevant mobility mode in urban cores, and they proved to be competitive with respect to other modes including the station-based bike-sharing models. Second, the Parisian case became an international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

4. Data

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

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

Figure 1. Fleet size over time by e-scooter status



Note: The Figure reports the evolution in the daily number of dockless e-scooters in the city of Paris by status. Dark lines show a smoothed patter applying the Locally Estimated Scatterplot Smoothing (LOESS) function. Nok refers to not-operational vehicles, i.e., those that are out of service or in maintenance. A blank space is intentionally introduced to identify the first national lock-down after the global pandemic.

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

Using this type of data for dockless micro-mobility studies is, to the best of our knowledge, a novelty. Many studies are restricted to the collection of data requesting information to APIs provided by operators. Although those formats have potential for further research, it usually needs to request information in high frequencies (each 1-5 minutes) to extract reliable information about the location and status of the vehicle. Consequently, the amount of computational resources oblige researchers to restrict the analysis to short periods of time (2-3 months). This in turn limits the possibility to capture changes in regulatory frameworks. In other cases, studies are restricted to the information available by a subsample in the number of operators or e-scooters. The data we use here is original and rich because it observes all the operators active in the market and because it covers large time and space span. However, working with a big dataset (45 million observations) with these characteristics required the programming of tools and models. Programs were coded to automatically clean and set-up hourly datasets, creates variables, compute indicators (see section 5), optimize memory use, and export the results for further analysis. Every dataset has flaws and ours is not the exception. The next paragraphs describe the limits to our data that we detected and how we addressed them.

GPS inaccuracies. Dockless e-scooters are provided with GPS devices to facilitate their location. Users use this information to locate e-scooters using their smart phones and operators can track locations while parking and riding. The same devices are used to report their location and status following the authority's mandate. However, GPSs are subject to inaccuracies due to different causes such as connectivity issues, limited resolution for angle measurements, noise, issues with the communications network, among others. These inaccuracies, properly referred to as User Equivalent Range Error (UERE), introduce uncertainties to the exact position of e-scooters. According to the European Space Agency, the UERE for Standard Positioning Services (SPS) ranges in between 7 and 33 meters. Nevertheless, we developed a methodology to infer confidence intervals from the data, which takes into consideration specific geographic characteristic of the city (see Appendix A for details). We concluded that a tolerance of 30 meters is a reasonably good range error in the case of e-scooters in Paris.

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

5. Methodology

5.1 Definitions

Mis-parking. For the purpose of this work, we approach mis-parking in the sense of cluttering. As we mentioned above, two types of mis-parking have been identified in the literature: improper parking and cluttering (Gössling, 2020; Brown et al., 2020). The former describes how vehicles are parked individually and the latter is used to describe a disorganized distribution of parked vehicles across the city. As noticed, our dataset does not observe improper parking at vehicle level. In contrast, the dataset allows the assessment of a cluttered distribution of e-scooters in a predetermined geographic region. Nonetheless, by studying the spatial relationship between parking bays and e-scooters we can provide insights about improper parking in the sense of compliance with the existing regulation. In other words, we could infer whether an e-scooter is properly parked by comparing its location and the location of parking bays.

Accessibility. Many definitions of accessibility exist in the transport literature (Páez et al., 2012). In this paper, we define it as the distance that any user must travel to find the closest e-scooter. This definition goes in line with the first/last mile dilemma; following Lesh (2013), any mobility mode is inconvenient when the starting or endings points are located beyond a comfortable distance for the user. Defining accessibility in the way we do here is convenient because dockless e-scooters are characterized by the possibility to pick-up and drop-off vehicles at any location in the city using smart technology. In other words, e-scooters are accessible to users without the need of docking stations (as it is the case in the station-based bike-sharing system). Therefore, the distribution of e-scooters across the city is crucial for users to find them when they need them (Sanders et al., 2020).

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

Type of users. We identify three different types of users depending on their level of compliance with parking regulations:

- Complier. Always comply with the rules regardless of the number of parking bays and the distance with respect to destination.
- Opportunistic. Any user that parks properly only when parking bays are close to their destination. Otherwise, they mis-park.
- Unlawful. Never follows the rules regardless of the number and location of parking bays.

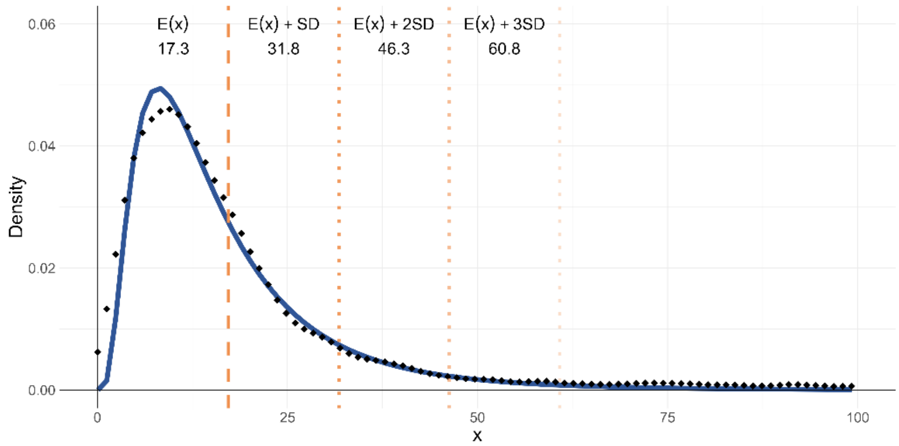
Following the principles of asymmetric information, the fundamental problem to study users' behavior is that their type is private information: each user knows their own type at the beginning of the trip and the information is revealed only when the trip is completed. Using the geo-location of parked e-scooters, presumably at the end of users' journeys, and their spatial relationship with parking bays, we obtain information about users' type. Afterwards, we use this information to provide insights about the effects of regulations on the level of users' compliance related with their types.

[3] We use a lognormal-decay function of the form:

$$D(x) = \frac{1}{x\sigma\sqrt{2\pi}} \exp\left(-\frac{(\ln x - \mu)^2}{2\sigma^2}\right)$$

Where x is the observed distance between e-scooters and parking bays. The parameters to estimate are σ and μ. It is important to point out that a lognormal distribution has expected value $E(x) = exp\left(\mu + \frac{\sigma^2}{2}\right)$ and variance $Var(x) = [\exp(\sigma^2) - 1]\exp\,(2\mu + \sigma^2)$.

Figure 2. Distance-decay function



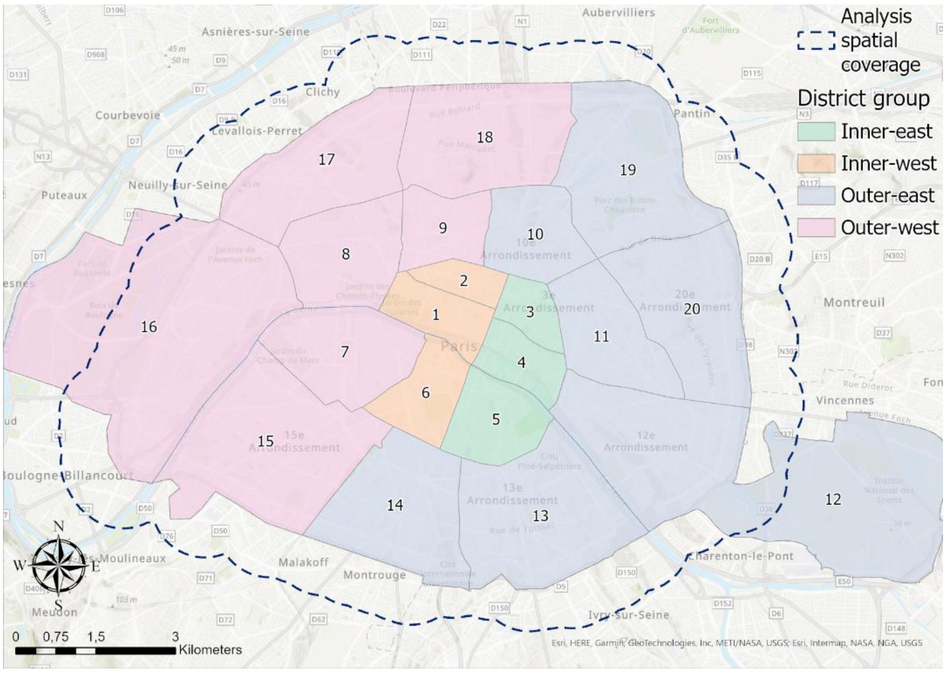
Note: The Figure reports the number of additional e-scooters by the size of the buffer around parking bays. Points describes the kernel density of the observed distribution. The solid curve in blue is the estimated lognormal-distance-decay probability density function of the form $D(x) = \frac{1}{x\sigma\sqrt{2\pi}} \exp\left(-\frac{(\ln x - \mu)^2}{2\sigma^2}\right)$. The parameters of the model were estimated using nonlinear weighted least-squares. The estimated parameters are $\mu = 2.58$ and $\sigma = 0.732$, resulting in an estimated expected value of $E(x) = 17.3$ and variance $Var(x) = 210.3$.

5.2 Spatial analysis

As mentioned above, this paper is based on the spatial relationship between vehicles and parking bays. The treatment of the data follows two different approaches: vector and rasters. Vector data allows to study the relationship between attributes of different features such as points (e.g., e-scooters location) and polygons (e.g., parking bays). Following this approach, we developed different Key Performance Indicators (KPIs) based on the geographical attributes of e-scooters and parking bays. To study the evolution of such KPIs, it is important to recall that parking bays were constructed at the end of 2019 and at the beginning of 2020. Therefore, we use the *virtual* location of parking bays, i.e., as if there were already built, in the construction of KPIs.

Raster data instead is defined as a collection of cells (or pixels) in the form of grids representing specific geographical regions. Each cell in the raster stores real-world information such as elevation, distance, etc. For the purpose of this paper, we produce high resolution rasters with cell size of 2 x 2 meters. Every raster was snapped (aligned cells) and masked (crop to the same extension) to a basic raster that covers a surface equal to the city extension. This last step is important to produce valid comparisons over time.

Figure 3. Spatial coverage and groups of districts



Note: The map reports the spatial coverage used in this analysis. Dashed line determines the extension of the analysis at the aggregate level. It covers an extension equal to 1km away from the last parking bay available at any direction in the city. Numbers are used to identified districts' names in Paris (1st district, 2nd district etc.). As noticed, the extension in districts 12th and 16th is larger than the city spatial coverage. This is because those areas are mainly forests and no parking bay has been constructed there. Moreover, it is not common to observed e-scooters parked in those areas.

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

5.3 Key Performance Indicators

We evaluate the efficiency of parking regulations and unintended effects through a set of KPIs developed using the spatial relationship between perked e-scooters and parking bays.

Planar distance to parking bays. Based on vector data, this indicator measures the Euclidean distance between parked e-scooters and parking bays and its evolution over time. First, we compute the distance for every e-scooter in the database. Then, we compute the mean to obtain an hourly panorama of the relationship between parking bays and e-scooters (remember that the location of e-scooters is available in a frequency of three hours). Afterwards, daily averages are obtained. Moreover, to provide comparable measures over time, we normalize every hourly mean using the methodology developed in Appendix B. The expected evolution of this KPI is the following: if parking regulations are effective, then the average distance between parking bays and e-scooters should decrease precisely because dedicated zones are concentrating vehicles in specific points.

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

Mis-parking. To assess the evolution of mis-parking in the city, we have classified e-scooters using the moments from the distance-decay function defined above:

A. *Properly parked*. If the distance to the closest parking bay is lower than the mean from the distance-decay function, i.e., when $distance < E(x) = 20m$. Regarding the type of users, we expect this classification to be mainly composed by compliers and opportunistic users.

B. *Mis-parked when parking bay nearby*. If the distance to closest parking bay is larger than the mean and lower than the mean plus two times the standard deviation, i.e., when $E(x) = 17.3m < distance < E(x) + 2SD = 46.3m$. This behavior is characteristic of unlawful users. We could expect to also observe opportunistic riders, but to a lower extend.

C. *Mis-parked when no parking bay nearby*. When the distance to closest parking bay is above the mean plus two times the standard deviation, i.e., when $distance > E(x) + 2SD = 46.3m$. This class should comprise unlawful and opportunistic users.

For the construction of this KPI we compute the daily share of e-scooters in each classification. Two types of conclusions can be obtained from this indicator. First, the share of *properly parked* vehicles is an additional indicator of how effective the regulations have been harmonizing parking behavior. On the other hand, separating the share of *mis-parking* as we do here help to disentangle what type of users are not complying with the regulation. For instance, if the share of *Mis-parked when parking bay nearby* is high, then more resources should be focused to better understand unlawful behavior. On the other hand, if the share of *Mis-parked when no parking bay nearby* is high, this could indicate that more infrastructure is needed to incentivize opportunistic users to comply with the rules. Overall, this KPI helps to identify flaws in the regulation that can be ameliorated in the future.

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

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

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

Planar distance to closest e-scooter. This indicator was constructed using raster data as follows. Every time the information is collected, we create a raster (with the same characteristics as the basic raster described in section 5.2) with cells' value equal to the planar distance to the closest e-scooter. Then, we compute the arithmetic mean using all the cells in the raster. Afterwards, to account for variations in the number of observations in different points in time, this value is scaled dividing by two times the square root of the number of parking vehicles (see Appendix B for details). Finally, we compute daily averages. Using this KPI, we expect to capture the unintended effects of regulations on accessibility. If parking bays effectively concentrates e-scooters in specific points, then the average distance to find an e-scooter should be distorted depending on the number and location of parking bays. In the case of Paris, we expect to see an increase in this indicator because parking bays were built without a careful assessment of this potential effect.

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

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

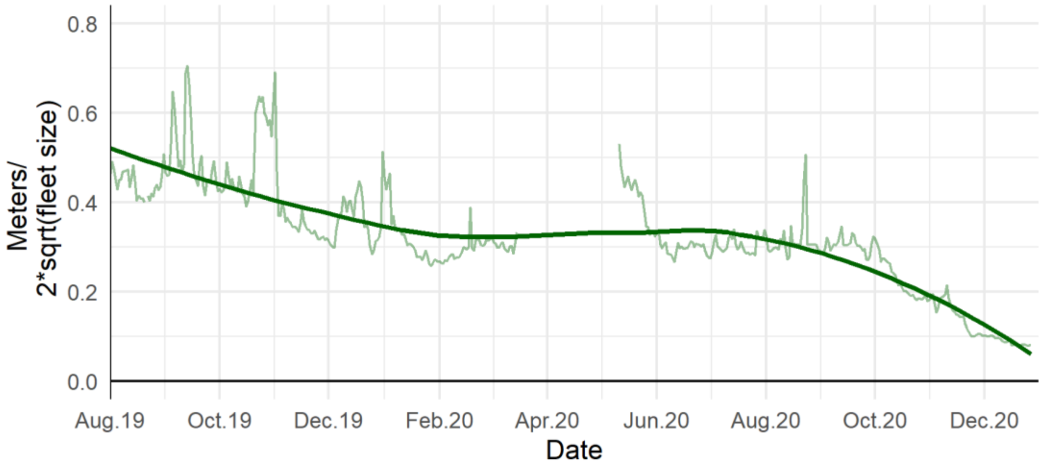
6. Results

6.1 Overall impact of parking regulations

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

Another way to assess the policy is studying the demand for parking bays. As observed in Figure 5, the evolution of this index goes in line with the previous KPI and with a positive effect of parking regulations. Considering a spatial tolerance of 30 meters (see Appendix A for a discussion about GPS accuracy), in August 2019 close to 25% of the space later used for parking bays had at least one vehicle inside raising up to almost 85% after their construction (60 pp. increase). In terms of coverage, in December 2020 parking bays allocated almost 85% of the fleet size. Note that this KPI could be capturing a random distribution of e-scooters in the city. To account for this caveat, we compare the evolution in the demand for parking bays between parked and non-parked (riding and not operational) e-scooters. If the evolution of this measure is related with the concentration of vehicles due to the construction of parking bays and not with the random spatial distribution, then the demand for parking bays for riding e-scooters must not change over time. This assumption is supported by the data as one might notice in Figure 6.

Figure 4. Normalized distance between e-scooters and parking bays over time



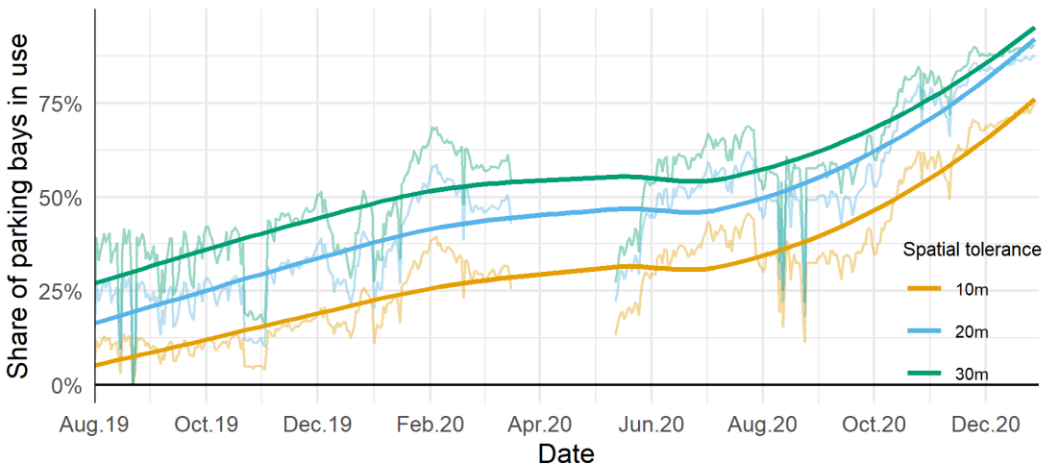
Note: The Figure reports the evolution in the distance from e-scooters to the closest parking bay normalized by the fleet size. For further details about normalization, please see Appendix B. Dark lines show a smoothed patter applying the Locally Estimated Scatterplot Smoothing (LOESS) function. A blank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

Additionally, we study the impact of parking regulations at district level. As mentioned above, time-series were built for four different district groups. Figure 7 shows the results for the planar distance between parking bays and e-scooters during the entire period of study. Moreover, to improve visualization,

Figure 8 restricts the period shown from October 2020 to December 2020. As noticed, the distance between parking bays and e-scooters follows a similar behavior in all four district groups. Furthermore, after comparing the levels, the evidence suggest that the regulation was effective homogenizing the behavior across regions achieving a convergence in terms of KPI performance. Note that in October 2020 (and in all previous months) there was a clear difference across districts. It is clear from

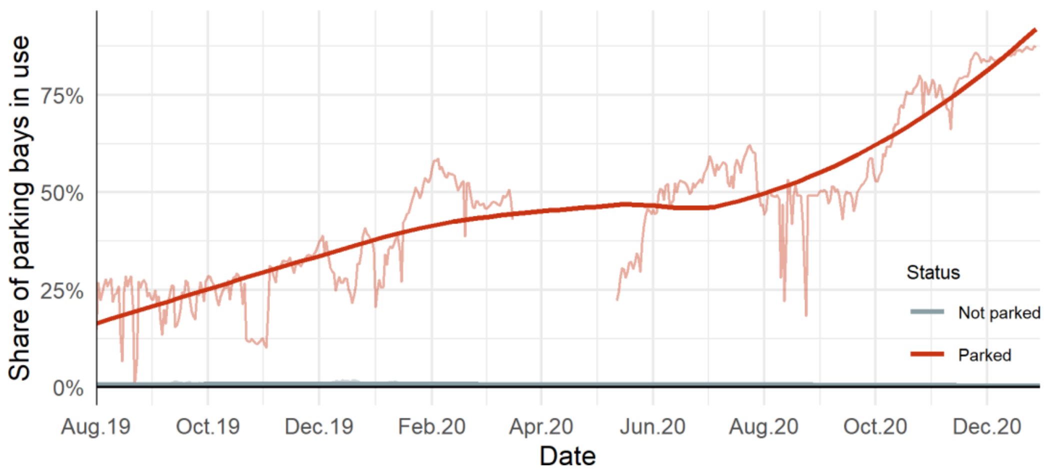
Figure 8 that e-scooters in the outer-east region were dropped-off farer away from parking bays than in the outer-west regions, which demonstrate a better performance. On the contrary, at the end of December 2020, three groups converged to the same level of performance, but still slightly higher than the indicator from the outer-west region.

Figure 5. Demand for parking bays over time



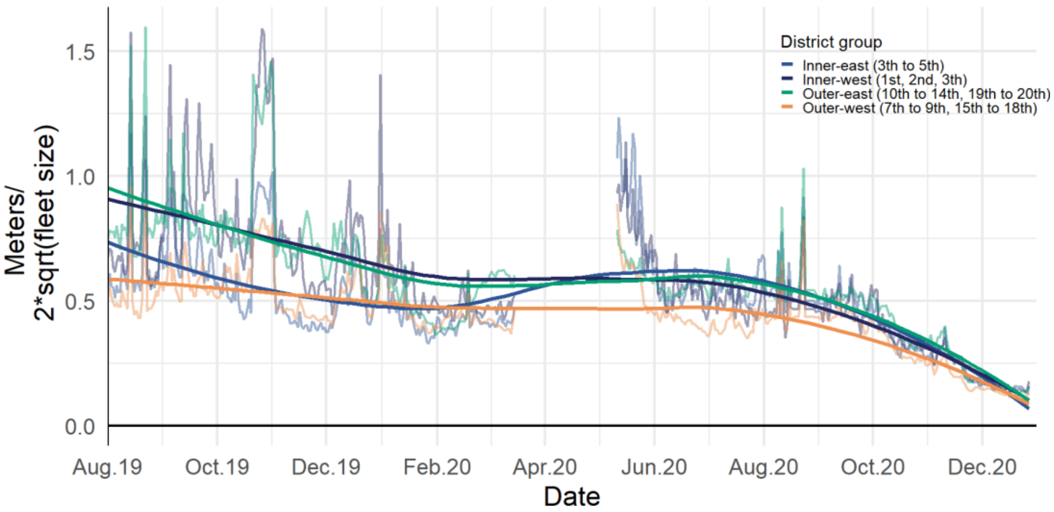
Note: The Figure reports the number of parking bays with at least one e-scooter within, measured as a share of the total number of parking bays. Spatial tolerance refers to the size of the buffer used to expand parking bays surface to account for potential GPS inaccuracy. For further details about GPS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

Figure 6. Demand for parking bays over time, parked vs. not parked e-scooters
Twenty meters of spatial tolerance



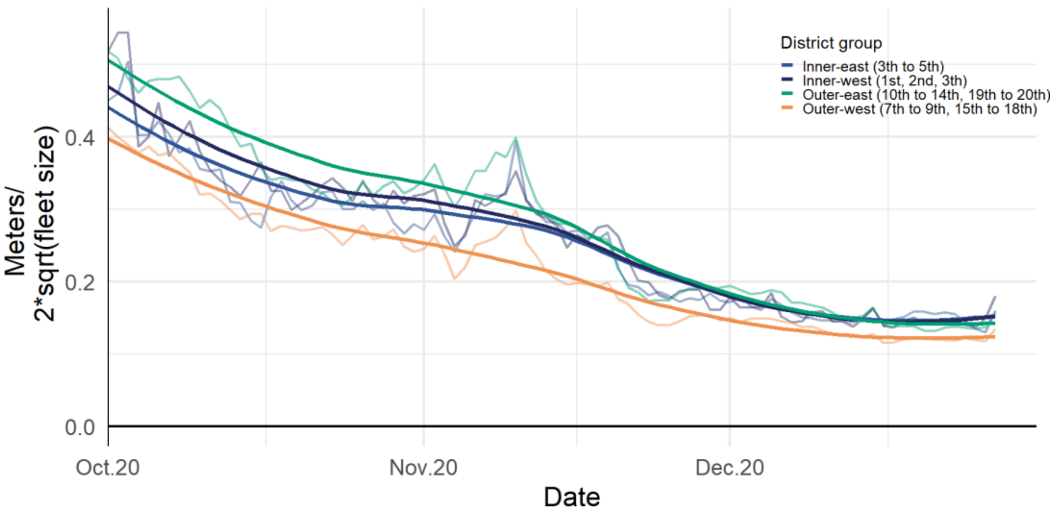
Note: The Figure reports the number of parking bays with at least one e-scooter within by status, measured as a share of the total number of parking bays. The status Not parked includes those in use (riding) and not operational (nok), i.e., out of service or in maintenance. A Spatial tolerance refers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

Figure 7. Distance between e-scooters and parking bays by district groups
August 2019 to December 2020



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

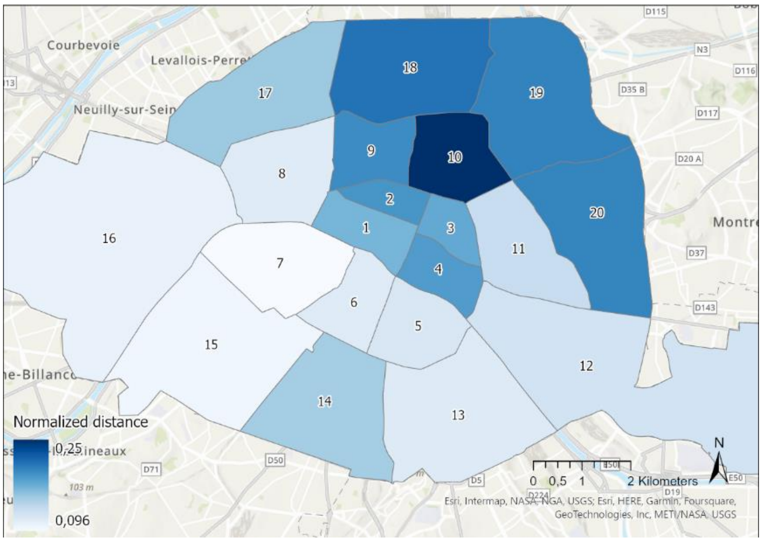
Figure 8. Distance between e-scooters and parking bays by district groups
October 2020 to December 2020



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

Finally, to provide insights about the heterogeneities among the twenty Parisian districts, we compute the monthly average of the normalized distance between e-scooters and parking bays in December 2020 (after regulation) per district. Afterwards, we display the results in the form of a map. The results are reported in Figure 9. It is clear from this analysis that there are some disparities across districts. For instance, it is noteworthy that all southern districts performed better than the northern ones except the fourteen district. This result is relevant to detect areas of improvement for future interventions.

Figure 9. District heterogeneities in the distance between
e-scooters and parking bays, December 2020



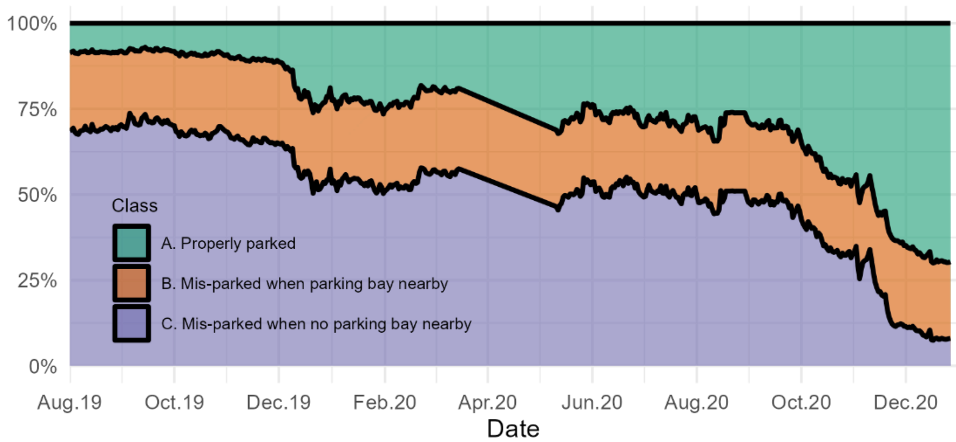
Note: The map reports the average distance from e-scooters to parking bays in December 2020 by district. The values shown are normalized by the fleet size. For further details about normalization, please see Appendix B. Numbers are used to identified districts' names in Paris (1st district, 2nd district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

6.2 Assessment of mis-parking

In this section we present evidence about the effects of parking regulations on mis-parking. In other words, we study the evolution over time on the classification of parked e-scooters as a function of the distance between the location of the drop-off point and the closest parking bay. Figure 10 shows the daily average share of the three classifications of e-scooters over time. The Figure clearly shows a re-composition in the share of vehicles across classes, especially after September 2020, i.e., after ending the construction of parking bays.

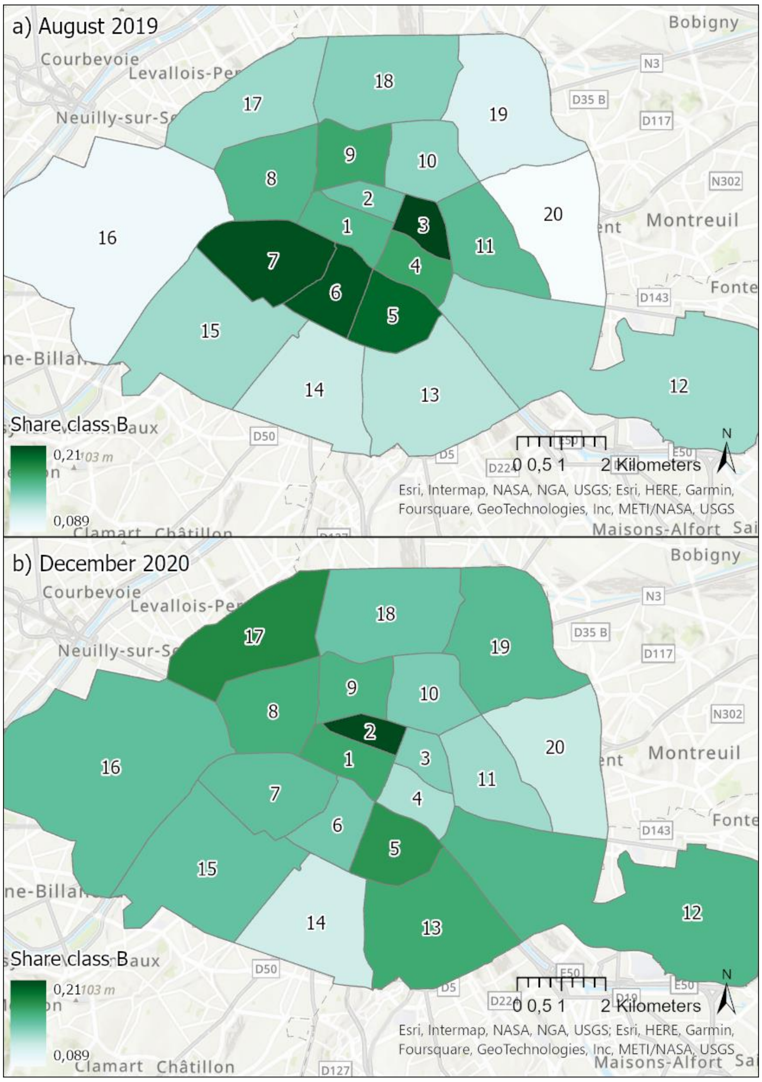
The main findings after analyzing this KPI are the following. First, the regulation has been effective incentivizing opportunistic users to comply with the rules. As we mentioned above, we have conjectured that opportunistic users should be distributed across classes A and C, *properly parked* and *mis-parked when no parking bay nearby* respectively. As noticed in Figure 10, the share of class C e-scooters passed from 55% in September 2020 to less than 10% at the end of December 2020. Nevertheless 10% still represents a considerable number of vehicles that deserves further attention. As a matter of fact, the performance of this indicator might improve even further with an optimal design in the number and location of parking bays. Second, at the end of the period, there was still an important share of e-scooters (almost 15%) *mis-parked when a parking bay is nearby* (class B). Class B is expected to be composed mainly of unlawful users, i.e., those who never follow the rules. In addition, the evidence does not show an improvement of this classification over the time span even if, overall, it does show a clear improvement for the other two classifications. Therefore, more studies should be conducted to understand this type of behavior and the means to incentivize these users to comply with the regulation.

Figure 10. Evolution in the composition of e-scooters according to its parking classification



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

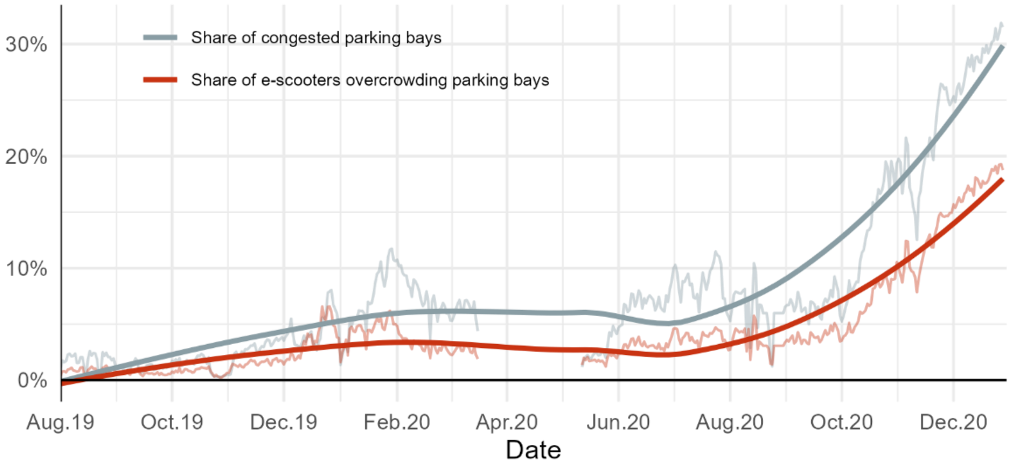
Figure 11. Share of class B e-scooters by district before
and after the implementation of parking regulations



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

Although the share of class B scooters shows to be constant along the period of study, it is still relevant to analyze differences across districts to provide empirical evidence about the distribution of mis-parking across the city. To this end, we measure the shared of class B e-scooters in each district before and after the regulation. We compute the average of this share in August 2019 as well as in December 2020. Then, we compare the results within and intra period. As it can be noted in Figure 11 a), in August 2019, class B e-scooters were mostly concentrated in downtown districts (1st to 7th). Other districts, such as the 16th and the 20th, showed extremely low number of class B e-scooters. On the other hand, in December 2020, the results show a more even distribution of this indicator across districts with only a few showing extreme values. This evidence, together with the conjecture about class B composition in terms of type of users, allows us to conclude that parking regulations had an effect on the spatial distribution of opportunistic behavior. Furthermore, it reveals that mis-parking remains a global issue that impacts the whole city.

Figure 12. Congestion in parking bays



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

Another crucial indicator regarding mis-parking is related with congestion in parking bays. Contrary to stations-based modes, designated parking bays in the form of painted corrals do not restrict users to drop-off the vehicles when the space reach its capacity. As a result, one could expect an excessive concentration of vehicles in specific parking bays. We document this effect in Figure 12. First, we show the evolution of the share of congested parking bays. As noticed, congestion raises with the construction of parking bays and the enforcement of the rules. In the first part of 2020 until approximately October, 10% of parking bays were congested. However, the index picked to a point were almost 30% of parking bays showed a sign of congestion in the last three months of the year. What is more, the index shows a clear positive tendency with no sign of deceleration at the end of the period. Second, we also show the share of e-scooters that overcrowd parking bays. The pattern is similar to the previous index along the period. In this case, the evidence suggests that almost 20% of vehicles (close to 3,000) are responsible for parking bays congestion. It is important to highlight that both indexes show different growth rates in the last quarter of the year. Congested parking bays growth at a rate of 500% versus 300% growth rate for the share of vehicles overcrowding parking bays.

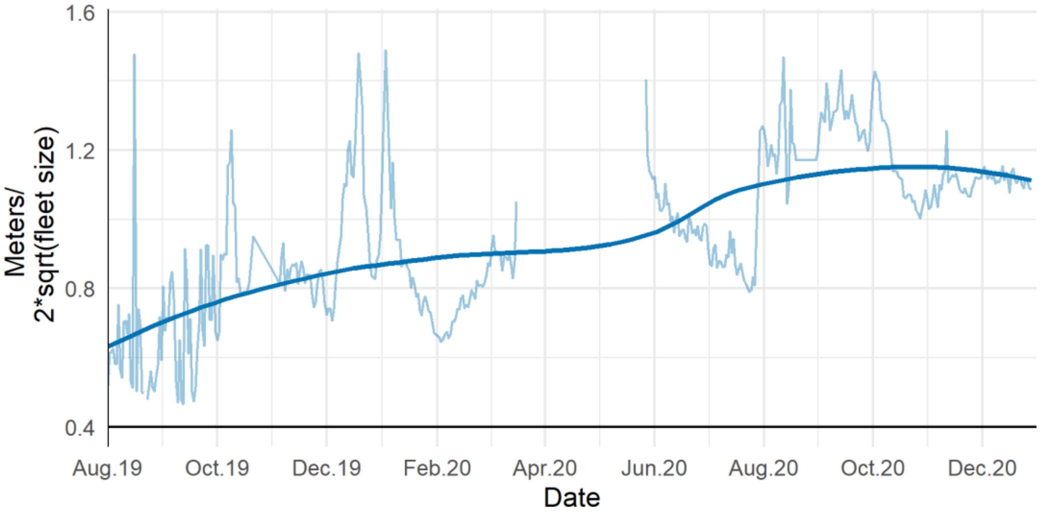
6.3 Effects on accessibility

The second research question that we address in this paper is related with the unintended effects of the regulation. Notably, parking bays accumulate e-scooters in specific spots in the city. Therefore, their location and distribution became relevant for the accessibility of vehicles. As a reminder, accessibility is defined here as the shortest distance that any users must commute to find the closest e-scooter. The results of the KPI develop for this purpose are documented in Figure 13. As before, the darkest curve shows the smoothed curve using a LOESS method and the blank space is the consequence of dropping observations due to the global pandemic. The evolution of this KPI shows that, in August 2019, the average distance to find the closest e-scooter in the city was about 120m (0.6 after normalization). Nonetheless, after the construction of parking bays in December 2020, this KPI reached a value close to 250m (1.2 after normalization), which represents a percentage increase of 108%.

The regional analysis reveals interesting results. To provide a before-after comparison, we compute the percentage change in this KPI by district. As can be seen in Figure 14, eight out of twenty districts (40%), show an improvement in the accessibility of e-scooters. In other words, the distance to find the closest e-scooter decrease as a consequence of the construction of the parking bays. Nevertheless, this improvement does not compensate the loss in accessibility in the other districts. Another relevant conclusion is related with the spatial redistribution of accessibility after the regulation. Note that inner-north districts (1st to 4th) are the one with the largest lost in accessibility with a percentage increase larger than 90% on average. In contrast, all the districts that showed improvements are located in the eastside of the city.

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

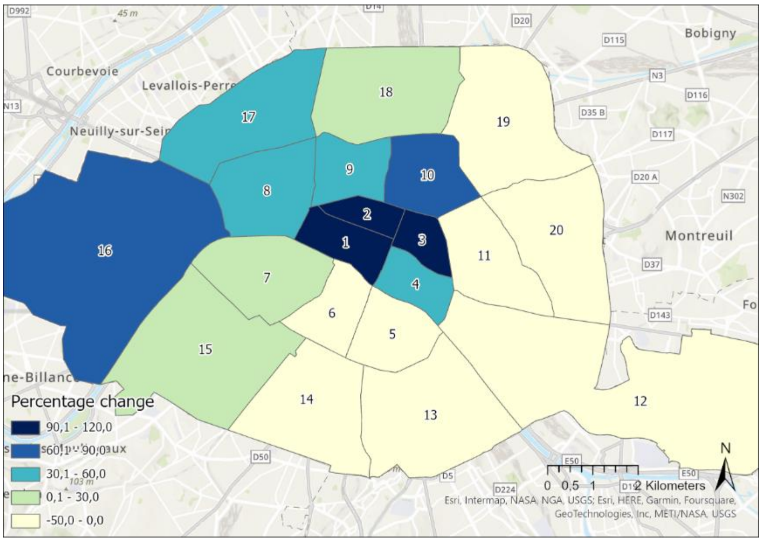
Figure 13. Average distance to the closest e-scooter



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

Another important concern is related with the potential impact of parking bays on the distribution in the number of vehicles across the city. The KPI develop to study this effect explores the distribution of the differences in the kernel density estimations between December 2020 and August 2019. First, we provide visual evidence of such estimations in Figure 15 a) and b). Both maps show zones in the city with high (in yellow) and low (in blue) concentration of e-scooters. Blank zones are excluded regions with density values lower than the mean. Moreover, a chart that reports the distribution of the kernel density estimation is included in each Figure. Although some differences are possible to identify from this visual inspection, computing the difference between both scenarios will allow to obtain analytical conclusions. The result of this exercise is documented in Figure 16. Note that the difference ranges from -0.51 to 0.62. Negative values (in red) represent regions where the density of e-scooters was higher in August 2019. Conversely, positive values (in blue) are zones where the density was higher in December 2020. Regions with low variation were intentionally left blank. These regions are spots that remained unchanged. In addition, the Figure includes a histogram that describes the distribution of all the values in the raster.

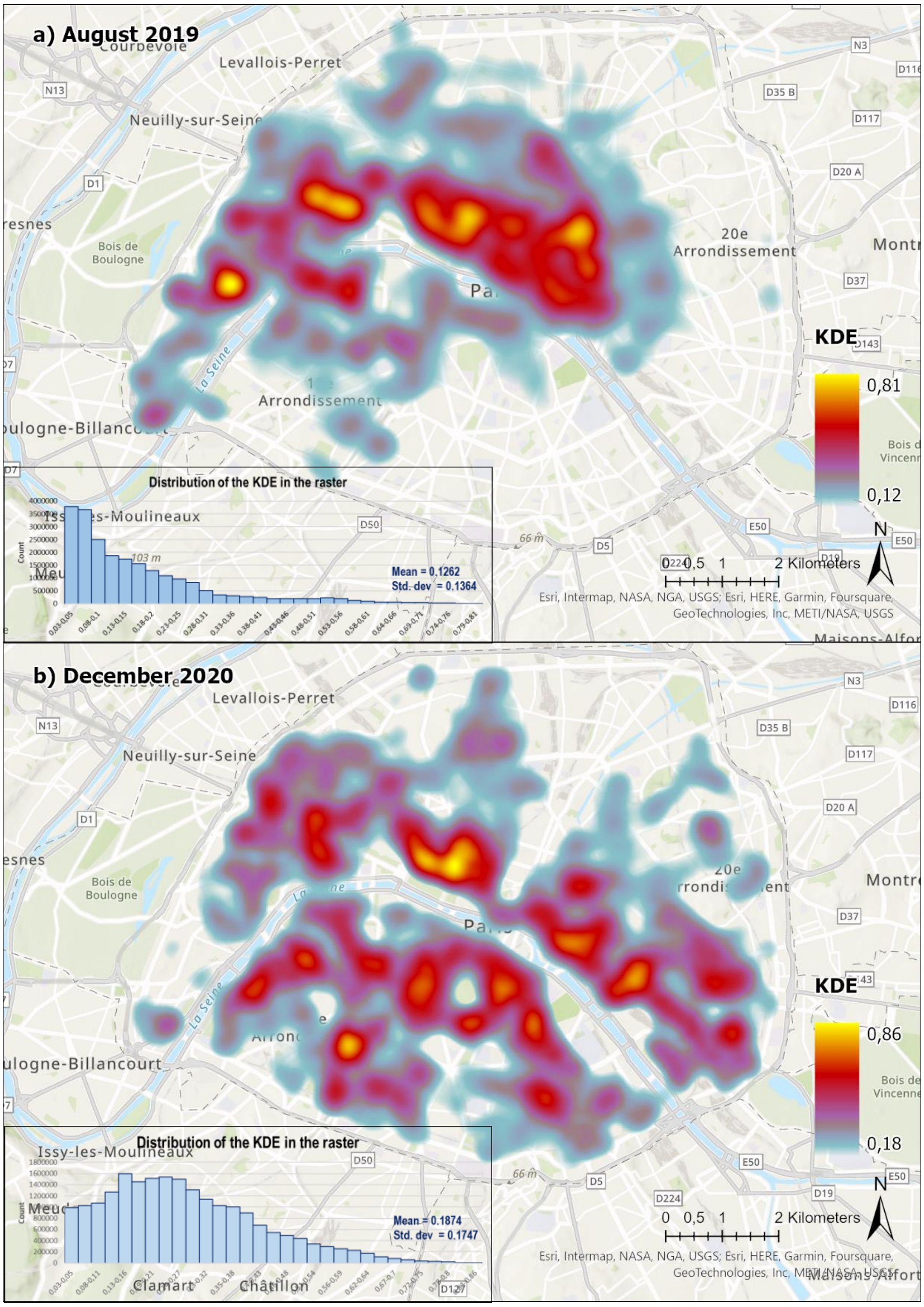
Figure 14. Difference in the average distance to the closest e-scooter before and after the regulations



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

Several findings might be obtained from the analysis. First, parking bays improved the spatial coverage related with the provision of the service. Figure 16 clearly shows a higher density of e-scooters beyond the periphery (the provision of e-scooters is restricted to zones within the periphery of the city) in August 2019. Therefore, the construction of parking bays might have helped the city to control the geographical boundaries for the operation of this service. Second, the distribution reflects differences in the density over time. A positive mean (0.06), a positive skewness (0.64), as well as the long tails of the distribution indicate that, overall, the density of e-scooters in the city changed due to the construction of parking bays. Finally, analyzing the spatial component of the difference in the density shows that parking bays augmented the number of e-scooters in the south-east regions of the city at the expense of reducing the density mainly in the south-west and downtown districts. Therefore, unexpectedly, parking regulations had an effect on the distribution of e-scooters in the city. This result is because the capacity of e-scooters in each parking bays is limited, which might force operators to considered other regions of the city to deploy their e-scooters.

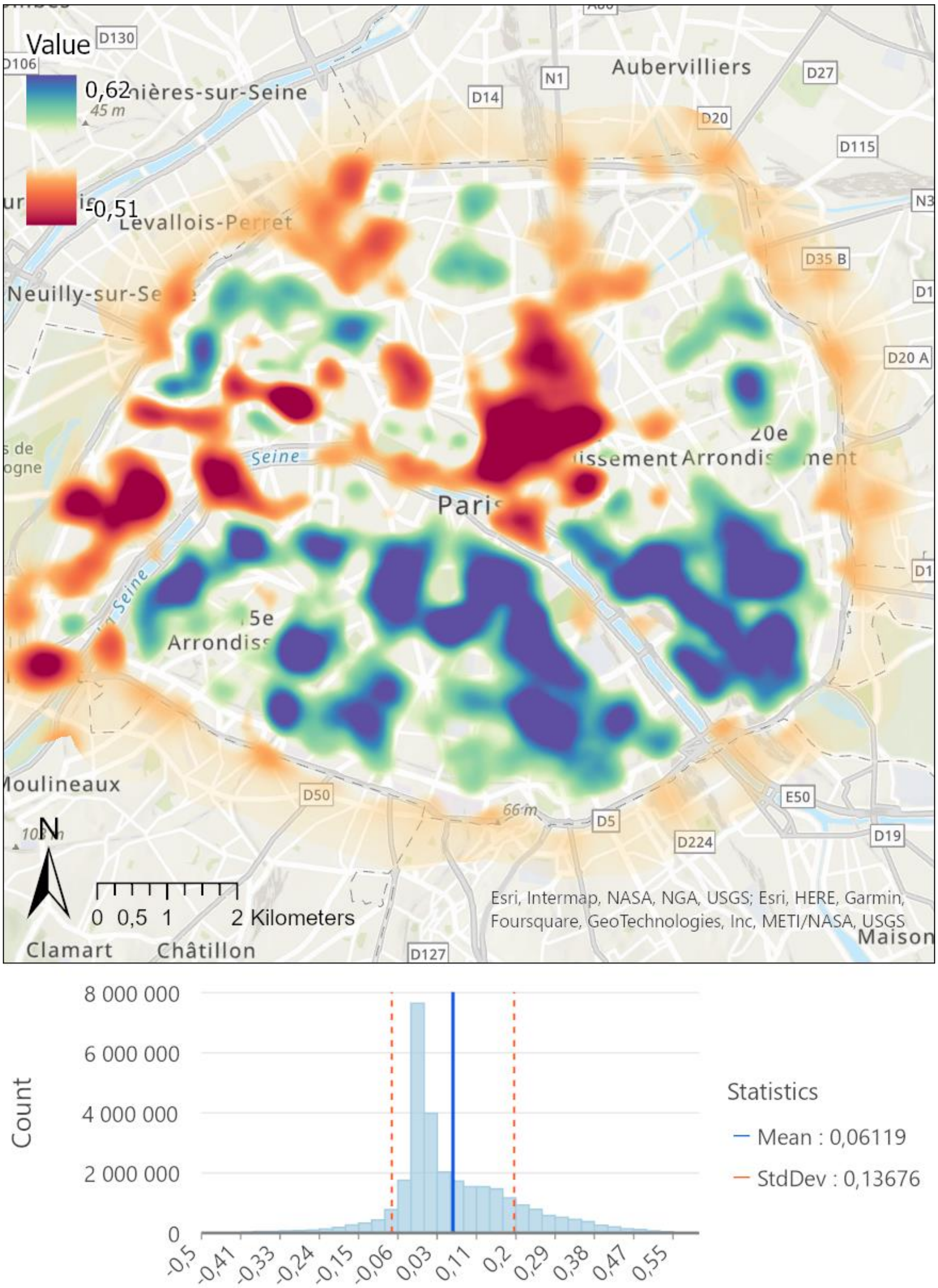
Figure 15. Comparison in the density of e-scooters across the city before and after the construction of parking bays



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

Figure 16. Differences in the density distribution of e-scooters

December 2020 relative to August 2019



Note: The map reports the difference in the concentration of e-scooters before and after the construction of parking bays. It shows the result of subtracting, cell by cell, the values in the heat-map for December 2020 from the vales observed in August 2019. Transparent regions represent locations in the city with low variation in the concentration of e-scooters. Regions in blue represent places in the city with a higher concentration of e-scooters in December 2020 in comparison with August 2019. Regions in red show the opposite results. The plot at the bottom shows the resulting distribution of the difference in the raster.

7. Discussion

This paper documents the effects of parking regulations implemented with the purpose of better integrate the deployment of dockless e-scooters in the city of Paris. The Key Performance Indicators developed and documented in this paper are limited to the availability of data and its structure. We acknowledge that parking regulations, namely in the form of parking corrals, might have additional effects worth to be analyzed.

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

Supply-side. Complying with the regulation impacts the provision of the services by increasing operators' costs. Suppliers must invest in technologies to monitor users' behavior. For instance, to complete the journey, users are mandated to send pictures of the e-scooter located inside parking bays. The app then uses artificial intelligence to determine whether the vehicle is properly parked. Other technologies include geofences to virtually design parking bays. Moreover, operators might incur on rebalancing cost due to a high concentration of vehicles in specific parking bays as we showed here. In addition, concentrating e-scooters in parking bays might trigger operators to compete for space. Finally, the spatial re-distribution of e-scooters creates supply in places where demand might not be guaranteed. As it is the case in other markets, increasing supply when demand is low might increase social costs resulting in welfare losses.

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

Finally, it is important to point out that a micro level analysis might be suitable to understand mis-parking behavior. Different factors influence citizens towards parking. Users might change behavior depending on the conditions of the environment and on specific characteristics of the ride. One might expect different behaviors between tourists and residents or between a commuting and a ludic ride. What is more, some of these factors are related with cultural and cognitive conditions specific of the region of study. Because many of these factors are often difficult to account for in empirical studies, we recommend researchers and politicians to be cautious interpreting results regarding mis-parking.

8. Conclusion

One of the main drawbacks for the adoption of dockless e-scooters is mis-parking. In the form of cluttering, i.e., the random parking of vehicles in the city, mis-parking of e-scooters has been considered for many as a mode unharmonized with the rest of the mobility mix. With the aim of improving the integration of this service, many cities have implemented different regulations that has received limited attention in the literature. The city of Paris, for instance, has built parking bays in the form of painted corrals where users are mandated to drop-off the vehicle at the end of their journey.

In this paper we propose a methodology to evaluate and monitor the impact of such parking regulations in the city of Paris. Exploiting the spatial relationship between the geolocation of parked e-scooters and parking bays, we constructed a set of Key Performance Indicators to evaluate the effectiveness of the regulation and to monitor unintended effects over time. Our findings suggest the following. First, we document that parking bays have being effective reducing cluttering by concentrating more than 85% of the total fleet size. As a matter of fact, the average distance between parking bays and e-scooters was only about 20m after the implementation of the regulation (almost equal to the average level of GPSs' inaccuracy, which is 20m approximatively).

Second, we found that the regulation has been effective incentivizing opportunistic users to comply with the rules reducing the number of mis-parked vehicles when no parking bay nearby. However, the share of overcrowded parking bays reached 30% and showed no sign of deceleration. Finally, we found evidence that parking regulations negatively impacted the accessibility of dockless e-scooters measured as the average distance to find the closest vehicle in the city. On average, the average distance increased 108% (from 120m to 250m) between August 2019 and December 2020, before and after implementing the rules. However, the regional analysis revealed that some districts benefited from the regulation. In particular, the scenario in the south-east districts showed an improvement of accessibility and a larger number of vehicles per surface unit.

This work has important policy implications for regulation and urban planning. The KPIs developed here could help regulatory bodies to implement data-driven regulatory practices to monitor the behavior of e-scooters operators. Furthermore, they might be modified to different contexts and to the different regulatory frameworks that have being implemented all around the globe. What is more, our findings might help policy makers to decide the optimal number of parking bays as well as their optimal location with the aim of finding a balance between harmonization and accessibility.

Finally, we raised new concerns and questions that deserved to be addressed in the future. Parking regulations should have other effects in addition to those addressed in this paper. We have identified the following: they might impact users' certainty to find an e-scooter, improve safety and security for other users of the public space, and improve public opinion about dockless micro-mobility services. This in turn might increase demand, however, it is important to consider spatial heterogeneities analyzing market dynamics to avoid unbalances that might lead to welfare losses. Additionally, considering the opportunity cost of the public space dedicated exclusively for dockless e-scooters is key to evaluate the welfare effects behind the public intervention.

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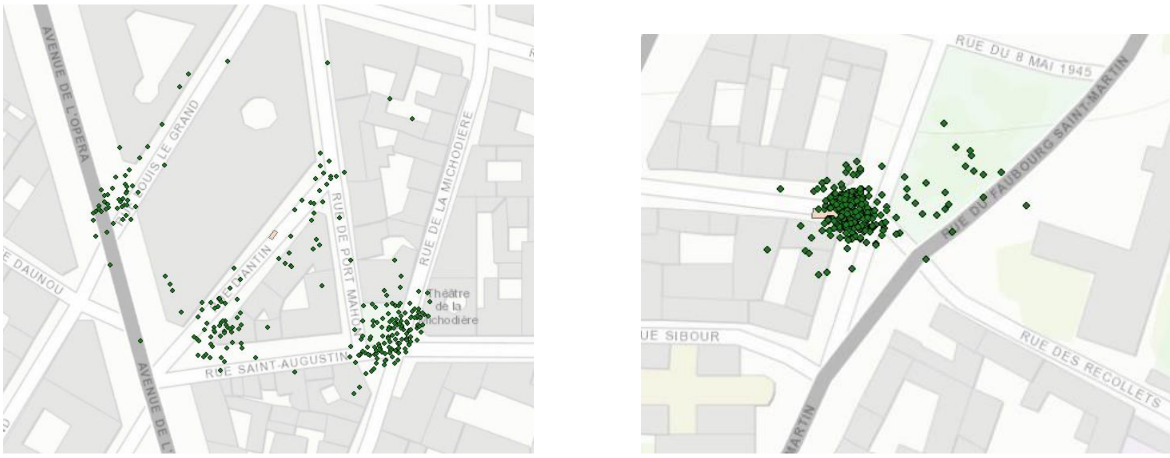
Appendix A. GPS inaccuracy analysis

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

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

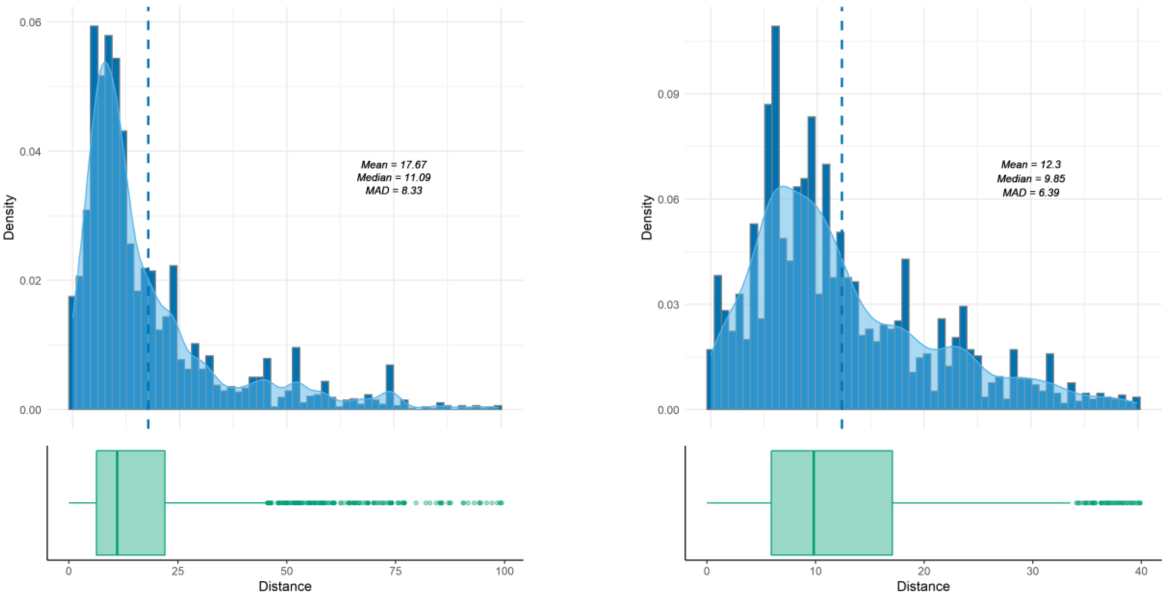
Figure A-1. Example of parking bays dropped and kept for the analysis



a) Dropped b) Kept

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

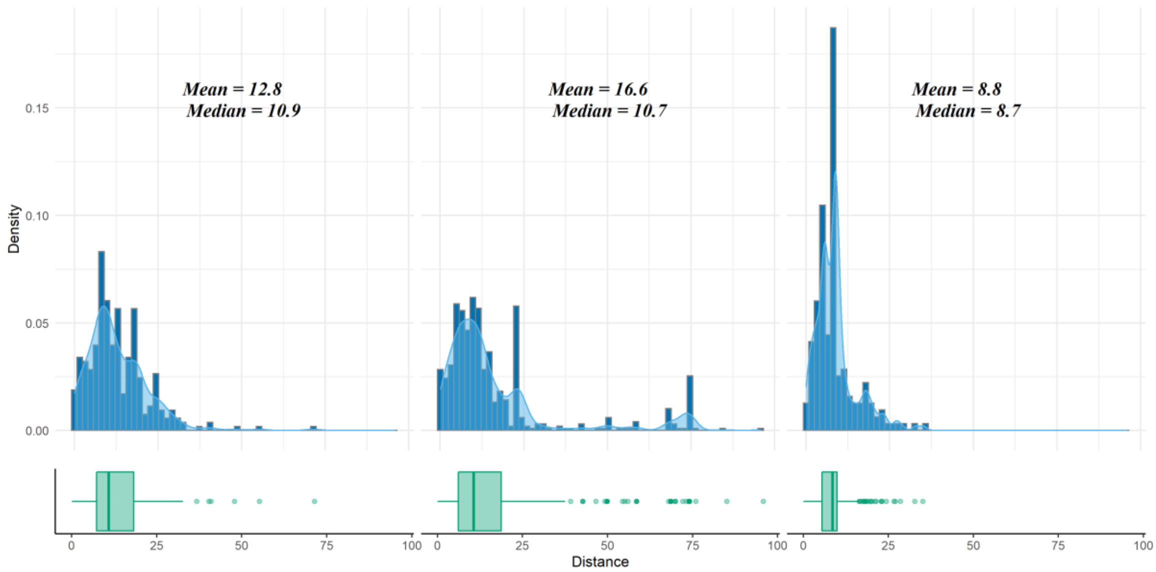
Figure A-2. GPS inaccuracy estimation



a) Buffer: 100m b) Buffer: 40m

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

Figure A-3. GPS inaccuracy estimation from selected parking bays



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

Appendix B. Normalization

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

$$\int_0^1\int_0^1\int_0^1\int_0^1 \sqrt{(x_2-x_1)^2+(y_2-y_1)^2}\,dx_1dx_2dy_1dy_2 = 4\iint_0^1 \sqrt{x^2+y^2}\,(1-x)(1-y)dxdy$$

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

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

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

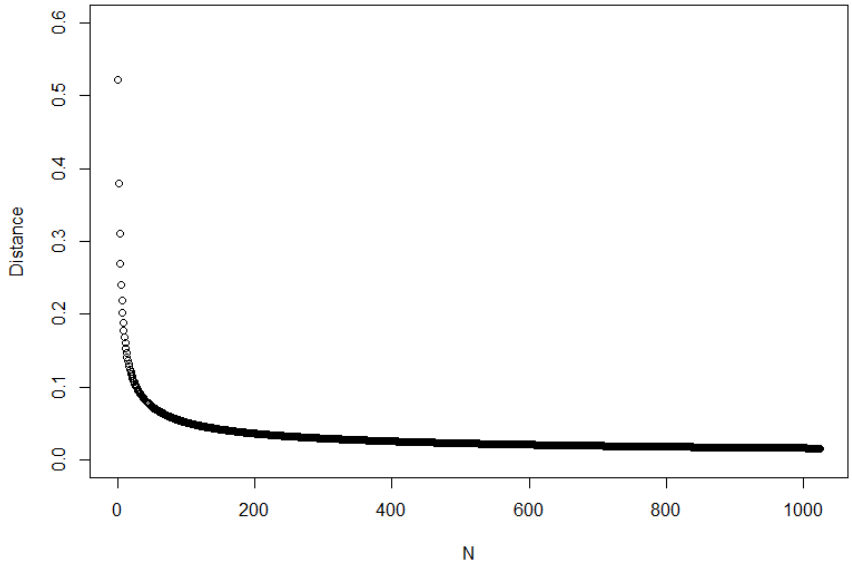
The result for $N = 1{,}024$ is documented in Figure B-1. As expected, the minimum distance when $N = 2$ is close to 0.521.

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

$$\log(distance) = \beta_1 \log(N) + \mu_n$$

We estimate the equation using OLS. We find that $\widehat{\beta_1} = -0.61$ (SD = 0.001 and $R^2 = 0.99$). Hence, the closest distance between a point (x_0, y_0) and N points randomly located in the grid is $\approx \frac{1}{2\sqrt{N}}$.

Figure B-1. Closest distance to N points randomly located in a cell



Note: The Figure reports the minimum distance between N points randomly drawn in a box of size 1x1.

Chapter 5

Improving Carpooling Carbon Mitigation: Insights from France*

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Chapter outline

Abstract

Road transportation is one of the most carbon-emitting sectors in the economy, urging the implementation of strategies to facilitate the ecological transition. Carpooling is considered a promising innovation for carbon mitigation. However, its adoption may make car travel more attractive, leading to uncertain environmental impacts. This paper devise an indicator to assess the effectiveness of carpooling in mitigating carbon emissions. Moreover, it leverage on a unique dataset to examine the impact of various policies on the baseline indicator. We argue that the potential of carpooling for carbon mitigation crucially depends on the occupancy rate, which encompasses travelers' preferences for alternative modes of transport. Regarding the mechanisms, our findings suggest that raising the cost of car travel through fuel price hikes is associated with increased supply and demand for carpooling. We then calibrate the potential impact of the French carbon tax. Furthermore, our research underscores the promising prospect of incentivizing drivers to switch to passengers, as this transition holds the potential for significant carbon mitigation outcomes. These findings offer valuable insights for designing effective policies aimed at mitigating carbon emissions.

Keywords: *Carbon Mitigation, Carpooling, Climate Change.*

JEL classification: *H23, R41, Q54.*

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This research benefits from the PIA fund of the French Ecological Transition Agency (ADEME) under the BlaBlaModes project. Any opinion, finding, conclusion, or recommendation expressed in this material are those of the authors and do not necessarily reflect the view of ADEME or BlaBlaCar.

1. Introduction

Reducing emissions from road transport is paramount to achieve climate goals. According to the French Ministry of Ecological Transition, road transport stands as the main emitting sector, contributing with 28.7% of all emissions in 2020. Notably, more than half of these emissions originate from individual vehicles, highlighting the urgency of implementing comprehensive strategies that go beyond merely improving motor engine efficiency.[1] Ride-sharing, also known as carpooling, emerges as a promising innovation for carbon mitigation by providing users with on-demand access to transport services at a reduced cost. However, carpooling may inadvertently increase the attractiveness of car travel, resulting in uncertain environmental impacts. Consequently, significant uncertainty persists regarding the conditions under which carpooling effectively mitigates carbon.[2]

Carpooling is a relatively recent innovation in intercity transportation that involves a platform connecting individuals traveling by car with others willing to share the same route. By sharing the journey, travelers jointly bear the expenses such as fuel costs and tolls. This transport mode is often regarded as environmentally friendly since it allows two (or more) separate private drivers to reduce their carbon emissions by sharing a single vehicle. However, the environmental impact of carpooling is not solely determined by the number of occupants in the vehicle, in fact, it relies on the potential alternatives of all travelers involved. The cost sharing condition may attract travelers from cleaner alternatives such as trains. This *modal shift effect* may diminish the environmental benefits of intercity ride-sharing.[3]

This paper delves into intercity carpooling in France as an strategy for carbon mitigation. The analysis serves two main objectives. First, it seeks to establish an indicator to determine the effectiveness of carpooling in mitigating carbon emissions, taking into account the modal shift effect. We rely on the short-term distribution of stated preferences from carpooling riders regarding alternative transport modes, along with the corresponding carbon emissions

[1] International organizations such as the Environmental European Agency (EEA) have emphasized this urgency. In fact, this organization has recently stated that "*in road transport, higher occupancy rates are needed, for example through ride-sharing*" EEA Website [Accessed 21/08/2023].

[2] Recently pointed out by the Intergovernmental Panel on Climate Change in the Sixth Assessment Report, Climate Change 2022: Mitigation of Climate Change (IPCC, 2022).

[3] Consider the following example. If two train travelers, a low-emission mode of transport in France, switch to carpooling, then the car journey would result in an increase in carbon emissions.

for each alternative. The indicator is expressed in terms of the occupancy rate, representing the minimum number of travelers in a ride required to mitigate the emissions of an average car journey. The central premise is that a higher occupancy rate indicates a greater probability of carbon mitigation.

Second, leveraging a unique dataset from the leading carpooling platform in France, we delve into the impact of various mechanisms on our baseline indicator and, ultimately, on the potential of carpooling for carbon mitigation. Our analysis focuses on two primary levers that align closely with common policies aimed at reducing CO2 emissions: fluctuations in the cost of car travel due to fuel price volatility and incentives for drivers to travel as passengers, a behavior that we denominate *switchers*. In particular, we combine the city of origin of each ride with geolocated data on filling stations to measure travelers' responses to fuel price fluctuations. Additionally, we calculate carbon emissions under different scenarios of drivers switching to passengers to examine the potential effects of promoting this behavior.

Our analysis reveals that carpooling effectively reduces carbon emissions when two travelers share a ride, comprising one driver and at least one passenger. This phenomenon stems from notable disparities in the transportation choices of alternative modes of drivers and passengers. Notably, solo driving is significantly more common among drivers, with 66% opting for this mode in the absence of carpooling, compared to only 16% of passengers (see Table 1 for details). This contracts in solo driving among travelers significantly influence the outcome. Additionally, increasing the occupancy rate further diminishes emissions from car-journeys. These findings motivates the importance of investigating mechanisms to promote higher occupancy rate in carpooling.

Initially, we explore the impact of car travel costs on the behaviors of carpooling participants. Particularly, we analyze the fuel price elasticity of both offering and requesting seats for journeys. The former denotes the supply side, while the latter reflects the demand side for carpooling services. Our findings suggest that a 10% rise in fuel prices corresponds to approximately a 3.6% increase in seats offered and roughly a 4.8% increase in seats requested. This increase in supply and demand in response of fuel price hikes translates to an approximately 5.2% increase in the total number of confirmed seats. Furthermore, we examine how these effects vary among users with differing levels of experience on the platform. We observe that novice users, defined as those with fewer than 5 seats offered or requested, exhibit a more pronounced elasticity compared to their more experienced counterparts. This discovery holds significant policy implications, suggesting the potential efficacy of policies aimed at attracting new users to the carpooling service.

Building upon the aforementioned findings, we study the phenomenon of drivers switching into passengers, which presents a promising strategy for mitigating carbon emissions. This approach is particularly relevant given the tendency of drivers to opt for solo car usage in the absence of carpooling. We draw several scenarios involving *switchers*, including two benchmark cases. The results reveal that if all empty seats were fill by current drivers, the resulting emission reduction would be equivalent to approximately 9.3 cars traveling 500km daily. Furthermore, in an scenario where no incumbent drivers switch and all empty seats were occupied by newcomers, the emissions saved would be comparable to those of 11.3 cars.[4] Finally, we discuss further policy implications derived from our findings, including the implications regarding the stagnation of the French Carbon Tax and the subsidies offered to new carpooling users through the 'Certificat d'économie d'énergie'.

Our research contributes to the existing literature on individual strategic responses within the transport sector to increases in fuel and road pricing (Sagner, 1974; Bomberg & Kockelman, 2007). The main responses include reducing discretionary driving and decreasing driving speeds (Wolff, 2014). Davis and Kilian (2011) highlight the considerable promise of these responses in terms of their environmental impact, particularly in their assessment of the introduction of a carbon tax aimed at reducing emissions in the transportation sector in the United States. Additionally, some studies indicate that drivers consistently react to gasoline prices by reducing car ownership (Klier & Linn, 2010), their annual vehicle miles traveled (Sipes & Mendelsohn, 2001) and, to a lesser extent, by increasing public transport ridership (Spiller, Stephens, Timmins, & Smith, 2014).

This paper contributes to the ongoing debate about the effect of road transport policies on the environment. For instance, Fu and Gu (2017) assess the effects of toll fee removal on congestion and air pollution in China. However, there remains a dearth of research examining the cost of car travel and its potential for carbon mitigation through carpooling, with an exception being the study by Bento, Hughes, and Kaffine (2013). Focusing on commuting in High Occupancy Vehicles lines in Los Angeles, the authors find that a 10% increase in fuel price is associated to 10 more carpoolers per hour on those lines. In contrast, our

[4] Based on the average emissions of a new thermal car in 2019 equal to 112 gCO2/km.

paper focuses on the relationship between car travel costs and individual responses for inter-city journeys. Furthermore, we extend this analysis to explore the environmental impact of carpooling, a research avenue that has traditionally received less attention.

We explore individual traveler characteristics, including their experience using the carpooling platforms. Hence, our study contributes to the existing literature that investigates the influence of socio-demographic factors on carpooling behavior. Current research in this area typically examines factors such as age, gender, and income. For instance, studies have shown that younger individuals are more prone to carpool (Shaheen, Stocker, & Mundler, 2017; Bulteau, Feuillet, & Dantan, 2019; Monchambert, 2020), while women exhibit a greater willingness to participate in carpooling compared to men (Bulteau et al., 2019). Additionally, female drivers tend to prefer having two passengers rather than one, whereas male drivers often prefer sharing the ride with only one passenger (Monchambert, 2020). Concerning income, Shaheen et al. (2017) find that high-income members of carpooling platforms are more likely to offer seats, whereas low-income members tend to request seats more frequently.

The structure of this paper is organized as follows: Section 2 establishes the baseline indicator for carbon mitigation. Section 3 studies the effect of car travel cost on the occupancy rate. This section describes the database, outlines our primary empirical strategy and presents our key findings. Policy implications are discussed in Section 4, followed by concluding thoughts in Section 5.

2. Baseline indicator for carbon mitigation

To determine a baseline indicator for carpooling to mitigate carbon it is crucial to take into account the modal shift effect to internalize the emissions of travelers opting for alternative modes of transport. In a nutshell, carpooling mitigates carbon when the emissions from the carpooling journey are lower than the combined emissions of all travelers who would have otherwise used alternative transportation modes.

Denoting E_c as the total CO_2 emissions of a carpooling (c) journey and E_{nc} as the combined emissions af all travellers opting for an alternative transport mode (nc), carpooling mitigates carbon when

$$E_{nc} - E_c \geq 0 \tag{1}$$

Note that E_c is equal to the distance of the ride d (in km) times the vehicle emission coefficient, e_v, measured as grams of carbon emissions per kilometer (gCO_2/km). On the contrary, E_{nc} should be computed taking into account the alternative modes of both drivers and passengers. Assuming that one driver is matched with n homogeneous passengers, E_{nc} is then equal to the sum of driver e_{nc}^D and passengers e_{nc}^P emissions from the alternative transport modes.[5]

$$E_{nc} = d \times (e_{nc}^D + n \times e_{nc}^P) \tag{2}$$

From both equations (1) and (2), we can determine the occupancy rate n, defined as the number of passengers in the ride, that balances the emissions from carpooling with the emissions of all travelers using alternative transportation modes:

$$\begin{aligned} e_{nc}^D + n e_{nc}^P \geq & \quad e_v \\ n \geq & \quad \frac{e_v - e_{nc}^D}{e_{nc}^P} \end{aligned} \tag{3}$$

The key metric of achieving carpooling carbon mitigation is to increase the number of passengers in each ride. This result is rather intuitive because some travelers would have opted for a less-polluting transport mode such as trains. It is important to point out that additional passengers do not increase carbon emissions from the carpooling journey. In fact, e_v is not conditional on the number of travelers. In contrast, carpooling may help to mitigate the emissions from the alternative transport mode.

It's important to recognize that the profiles of travelers vary between drivers and passengers, both would likely have opted for different modes of transportation with differing probabilities considering factors such as car ownership. Therefore, equation (3) must be adapted to take this fact into account. Denoting by w_j^D the probability of a driver of opting for the alternative mode $j \in m$ with an emission coefficient e_j, and w_j^P the equivalent probability for passengers, E_{nc} may be restated as

[5] Note that here we use gCO_2/km/person as the definition of the emission coefficients of alternative modes, while for the vehicle emission coefficient, we only use gCO_2/km for simplicity because the total emissions of the ride are (roughly) the same no matter the number of people in the car. We could have written the equation as $E_c = d \times 1 \times e_v$, where e_v would be gCO_2/km/person. For alternative modes, especially mass transit, it is important to assess both the total emissions per ride and the occupation rate to attribute emissions per person using the mode.

$$E_{nc} = d \times \sum_{j=1}^{m} e_j \left(w_j^D + n w_j^P\right) \tag{4}$$

Several assumptions must be taken into account to ensure the validity of our baseline indicator. First, we assume that the emission coefficient of transport modes remain stable over time. Specifically, if cars become less polluting (e_v decreases), the occupancy rate threshold for mitigating carbon would diminish. Second, we assume travelers' preferences over alternatives remain unchanged. Changes in the distribution of travelers' preferences, capture by the weights w_j^D and w_j^P directly influence E_{nc}. Lastly, we assume there are no significant market variations across alternative transport modes. This implies that transport mode prices remain steady, as any changes would impact travelers' preference distributions.

2.1. A case study of the occupancy rate

In this section we use real data on carbon emissions and the distribution of travelers preferences to assess the carbon mitigation potential of carpooling. We collected car emissions data by mode from the European Environmental Agency (EEA) and the French Agency for Ecological Transition (or ADEME).[6] We then combine this data with vehicles' models in carpooling following the methodology outline in Appendix A. We successfully matched 80% of the vehicles modes reported in the carpooling dataset (see subsection 3.1 for details). However, because only 50% of drivers report the model of their vehicle, we rely on the average vehicle emission coefficient of all rides the remaining 50%. [7] Concerning emissions for other transport modes, we only use ADEME standard as it is tailored to the French case.

Two distinct sources were used to address potential caveats. For instance, the EEA standard enables differentiation based on vehicles models, but it lacks accuracy in reflecting fuel consumption for intercity trips, as it only estimates a low-speed scenario (0-30 km/h). In contrast, the ADEME standard offers a more realistic estimation in terms of speed, but it provides only a single emission coefficient for all vehicle models.

To estimate travelers' preferences over alternative modes, w_j^D and w_j^P, we use the follow-

[6]EEA website [Accessed 15/04/2023]
[7]ADEME website[Accessed 21/07/2023].

ing two surveys. The first survey, conducted by ADEME in 2015, includes responses from 1,393 BlaBlaCar users. The second survey, conducted in 2018 by BlaBlaCar in collaboration with the consulting company Le BIPE, includes 1,064 respondents.[8] For the purpose of our study, we focus on the question concerning the alternative mode travelers would opt for when carpooling isn't available. Furthermore, the question identifies whether the travelers is usually a driver or a passenger. Both surveys specifically target carpooling participants and offer insight into the distribution of their preferences regarding alternative transport modes.

Table 1: Carbon emissions and carpoolers' preferences over transport modes

	Thermal cars	Train		Thermal bus	Airplane	Subway	No Travel
		High-speed	Regional				
Panel A. Carbon emissions coefficient (gCO2/km/person)							
ADEME (e_v, e_j)	192	1.73	24.8	104	229.6	2.5	0
EEA Average (e_v)	114.2						
Panel B. Alternatives to carpool from ADEME							
Passenger (w_j^P)	16%	27%	42%	2%	1%	Not asked	12%
Driver (w_j^D)	66%	10%	14%	1%	1%	Not asked	8%
Panel C. Alternatives to carpool from Le BIPE							
Passenger (w_j^P)	12%	24%	34%	15%	1%	1%	13%
Driver (w_j^D)	78%	7%	5%	1%	4%	0%	5%

Notes: In Panel A. ADEME and EEA stand for the European Environmental Agency (EEA) and the French Agency for Ecological Transition (ADEME). The emissions coefficient for airplane only includes short-distance flights since we focus on alternatives to domestic rides. Panels B and C reports the results of two different surveys regarding the question about the alternative mode travelers would opt for when carpooling isn't available. The survey conducted by ADEME in 2015 includes responses from 1,393 BlaBlaCar users. The survey conducted in 2018 by BlaBlaCar in collaboration with the consulting company Le BIPE includes 1,064 respondents.

The distribution of travelers' preferences alongside the carbon emission coefficients of different transport modes are presented in Table 1. Panel A of the table excludes emissions during the construction phase of vehicles. Electric vehicles are omitted due to their low representation, with only around 2% of users offering seats in these cars. Notably, there is a distinction in emission coefficients between high-speed and regional trains, attributable to the cleaner engines of the former and their higher passenger capacity.[9] Concerning airplanes,

[8]ADEME commissioned 6t, a company specialized in transportation studies, to run the survey. Initially, the survey was sent to four carpooling platforms. However, the other three collected very few responses. 6t decided to only analyze data collected from BlaBlaCar users. The data on the published BIPE survey contains responses from 6884 BlaBlaCar users from eight countries. We collected data directly from BlaBlaCar staff for data from the 1064 French respondents. The ADEME survey [Accessed 21/07/2023], page 6 of the synthesis and page 69 of the full report. The Le BIPE survey[Accessed 21/07/2023], page 9.

[9]High-speed trains in France are powered by electric motors, which is not the case for regional trains.

we consider emissions for short-distance flights since we focus on alternatives to domestic rides. As for public transport, we use the carbon emissions from the subway as a proxy. [10]

Regarding travelers' preferences, presented in Panels B and C, the Table highlights the heterogeneity across different modes of transportation. As expected, a significant share of drivers, between 66% and 78%, show a preference for car travel when carpooling isn't available. Trains are the second most favored choice among travelers. Conversely, other modes exhibit comparatively lower attractiveness. Notably, not traveling is a noteworthy option, particularly among passengers, with percentages ranging from 5% to 8% for drivers and 12% to 13% for passengers. Additionally, it's observed that 12% to 16% of passengers would opt for using their own car to complete the journey.

Note that the Le BIPE survey shows an increase in the use of buses for passengers. This surge can be attributed to France's market liberalization in September 2015 (only for journeys over 100km). This deregulation on the supply side stimulated demand, positioning bus operators as significant competitors in the market. Given that Le BIPE survey is more recent in capturing current market dynamics, we prioritized it over the ADEME survey.

Using the aforementioned data, we computed the occupancy rate n from Equations (3) and (4). The results are reported in Table 2, considering various combinations of surveys and emissions sources. However, we advise caution in interpreting results based on the EEA emissions standard, as it tests vehicles at low speeds, potentially leading to inaccuracies for intercity journeys.[11] Additionally, the Le BIPE survey is preferable over ADEME because it reflects more recent market dynamics. Thus, according to our preferred estimation, the minimum occupancy rate for carpooling to effectively mitigate carbon is equal to 0.61. It is important to point out that the heterogeneous distribution of alternative modes to carpooling contributes to a relatively high dispersion of the occupancy rate. This underscores the

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According to the report of the French Transportation Regulation Authority (ART) on the opening up to competition of the regional trains, in 2017, 18% of the regional trains are with diesel engine. Also, according to data provided by ART, the occupancy rates of the classic regional train, TER, from 2017 to 2022 is 25%, 26%, 27%, 21%, 23%, 29% respectively. For high-speed trains, the rates are 67%, 67%, 72%, 59%, 65%, 74% respectively.

[10]Public transport is not a viable alternative for most intercity journey. However, using the emissions form the subway as a proxy diminish any potential bias. Note that public transport is not an option in the ADEME 2015 survey. In the BIPE 2018 survey, only 1% of passengers selected it. These passengers may come from shorter rides that have public rail transportation connections like tramways, train segments, or regional express. The metro emission coefficient would be the most appropriate in these cases.

[11]The results could be a good benchmark for urban carpooling.

complexity involved in estimating the carbon mitigation potential of carpooling.

Table 2: Minimum occupancy rate for carpooling to effectively mitigate carbon

Source for travelers' preferences	Source for carbon emissions	Occupancy rate (n)
Le BIPE	ADEME	0.61
ADEME	ADEME	1.26
Le BIPE	EEA	0.33
ADEME	EEA	0.95

Notes: The Table reports the occupancy rate computed from Equations (3) and (4). See Table 1 for details about travelers' preferences over alternatives transport modes alongside their carbon emissions coefficient.

The results described above present a promising outlook, showing that any journey with at least one passenger contributes to mitigating carbon emissions. To dig deeper into this question, we explore several scenarios that take into account the heterogeneity in travelers' preferences over alternative mode, as well as other potential biases in the surveys (see Appendix B for detailed results). Our findings suggest that shifting the distribution towards cleaner modes, such as high-speed rail, while reducing the preferences towards buses and flights, can increase the occupancy rate above one. On the contrary, efforts to reduce carbon emissions coefficients of cars, such as through the transition from thermal to electric engines, may diminish the value of our baseline indicator. Hence, the evidence presented here shows the relevance of carpooling as a strategy for carbon mitigation; however, it also emphasizes the necessity of implementing policies to boost the occupancy rate.

3. The effects of increasing the cost of car travel

Carpooling relies on the premise of sharing the journey's cost among travelers which may result in lower carbon emissions. As our previous findings show, carpooling proves effective in mitigating carbon emissions when the occupancy rate remains sufficiently high. Therefore, studying the impact of the cost of car travel on the occupancy rate becomes relevant for policy-making purposes. In this section we use a unique data set to empirically measure fuel price elasticity of both offering and requesting seats in carpooling journeys.

3.1. Data

To conduct the empirical analysis we collect two main datasets: observable intercity carpooling rides, fuel prices at filling station level, and tolls fees by route. We obtain BlaBlaCar data from direct research collaboration with the company. The rest of the data is publicly available.

Carpooling rides. BlaBlaCar is the leading intercity carpooling platform in Europe. This company allows millions of travelers to share long-distance journeys. Even thought drivers are not professional, they are compensated with the purpose of splitting the cost of the journey.

Our dataset includes ride-level observations spanning from January 2017 to May 2022 encompassing 96 round-trips routes. These routes represent around 75% of the most popular routes in the platform marketplace.[12] We focus on the French market, which is one of the most consolidated market worldwide. The dataset contains information including departure and arrival city, departure date, and trip distance. It also includes information on the number of seats offered by the driver, seats requested by potential passengers, seats booked, and the price set by the driver. Additionally, user-related data such as travelers' experience with the platform when the ride takes place is included. Two measures of experience are available, representing previous participation as drivers or passengers. An additional unique aspect of the dataset is the information about vehicle brand and model, which is voluntarily declared by drivers. 40% of the rides contain this information.

This dataset is, to the best of our knowledge, the most comprehensive data used for studying supply and demand dynamics in carpooling. Furthermore, this data enables the exploration of relevant features, including behavioral responses conditional on users' experience.

Cost of car travel. To evaluate the effects of car travel cost, we collect additional data at route level. These variables allow us to investigate the impact of car travel cost on the occupancy rate.[13] We collect fuel price data by filling stations for each city observed in the carpooling

[12] See Appendix H for the complete route list. See Appendix D for a detailed discussion on data representativity. Due to confidentiality concerns of BlaBlaCar, data is only shared when the route-date combination has more than 10 rides offered.

[13] For electric vehicles, we ignore the cost of electricity and set the fuel cost at zero. The bias should be negligible as EVs only count for around 2% of all rides.

rides dataset. Prices are then aggregated by day at city level.[14] Our dataset includes diesel and 95 octanes gasoline prices because those are the most consumed fuel types in France.[15]

Concerning tolls, it is noteworthy that highways in France are managed by various concessionaires, who possess the authority to establish toll fees. They can adjust these fees annually, in February. Although data on toll fees is publicly available, it is dispersed across different sources, including concessionaires' websites. We systematically collect toll fee data from 2017 to 2022 for every route included in our analysis.

Some important variables are absent from our dataset, including the value of time, typically quantified as the hourly wage. Notably, we omit vehicle depreciation due to the complexities involved in approximating this coefficient for individual journeys. We address this potential confounding effects by controlling for route and time-fixed effects. Certain assumptions were made in our analysis. For instance, we assume uniform fuel consumption for all drivers on the same route. Consequently, only fuel prices influence the total fuel cost of the journey. Additionally, we presume that drivers consistently refuel their tanks at the city of departure.

Other relevant variables. We collect other relevant variables to serve as controls in our regression analysis. Initially, we focus on the primary competing modes of intercity travel: buses and trains. Trimester-route level bus frequency data is obtained from the website of the French transport regulator. [16] As for trains, due to the unavailability of historical data, we manually collect the direct train frequency as of September 2022 and assume consistent frequency throughout the entire data period. Dummy variables are then computed for direct trains and direct high-speed trains along the same route. Other control variables include departure city population and holidays.

[14]Fuel data source[Accessed 19/10/2022]. The raw data documents every change in price at every service station, leading to different numbers of observations per day for different service stations. We simply compute the mathematical mean for the daily city-level fuel price.

[15]According to the French Ministry of Transportation, in January 2022, diesel cars still occupy 55.5% of the market, while gasoline cars occupy 42.2%.

[16]Bus data source [Accessed 16/11/2022].

3.2. Descriptive Statistics

Table 3 presents summary statistics of the main variables of interest regarding carpooling rides, car travel costs, and control variables. The data is aggregated at the route-day level.[17] As observed from the table, the number of supplied seats more than doubles the number of seats requested. Additionally, they are nearly five times the number of seats booked, resulting in an occupancy rate of 0.5. If we narrow our focus to rides with booked seats only, the occupancy rate rises to 1.5. This contrast is particularly noteworthy as it underscores the potential to improve the occupancy rate. It is important to point out that the occupancy rate shown in Table 3 does not represents BlaBlaCar's occupancy rate because additional passengers may be sharing the same car for intermediate journeys. Finally, novice users, defined as those with less than five interactions with the platform, represent 31% of travelers.

Figure 1 illustrates the evolution of diesel and gasoline prices over time. Unsurprisingly, prices experienced a decline at the onset of the COVID-19 outbreak. Furthermore, they have shown a rapid increase since the end of 2021, attributed to the Russo-Ukrainian war. Additionally, the figure depicts the trend of booked seats over time, revealing the impact of the global pandemic on carpooling. This effect persists into mid-2022. We exclude from our analysis the initial lockdown period in France (March 17 to May 11, 2020), as carpooling activity nearly ceased during this time. The subsequent lockdowns were less stringent, allowing carpooling to continue operating to some extent. It's important to note that Figure Figure 1 does not establish a causal relationship between fuel prices and carpooling. Instead, by conducting an econometric analysis controlling for time-fixed effects, we aim to address potential biases.

[17] In this paper, we consider supplied rides for the same route on the same day homogeneous. This simplistic view is certainly not perfect, but not unrealistic. Passengers for long-distance, inter-city carpooling rides are more flexible in adjusting their departure time of day and departure locations compared to urban commuters.

Table 3: Summary statistics

Variable	Description	Mean	SD	Min	Max	Count
Supply	Daily seats offered by route	232.8	217.7	10	2845	116,511
Demand	Daily seats requested by route	93.5	149.9	0	8199	116,511
Booked (Q*)	Daily seats booked by route	45.9	69.3	0	1482	116,511
Occupancy rate	Average no. of passengers per ride	0.47	0.34	0	2.42	116,511
Occupancy rate (bis)	Average no. of passengers per ride with bookings	1.54	0.34	1	4	114,658
Novice	$= 1$ if the driver has offered or requested seats less than 5 times, $= 0$ otherwise	0.309	0.462	0	1	116,511
Ride price	Average price set by drivers (€ of 2015)	7.3	5.2	0.0	74.0	116,511
Gasoline	Real price of gasoline 95% octane (€ of 2015/litre)	1.83	0.66	0.70	5.47	116,109
Diesel	Real price of diesel (€ of 2015/litre)	1.73	0.68	0.62	5.26	116,133
Distance	Average route distance (km)	173.75	107.97	40.93	689.84	116,511
Toll fee	Toll fee by distance (€/km)	0.07	0.03	0.0	0.16	116,511
Train freq.	Daily No. of direct trains in the route	20.09	9.95	2.0	58.0	116,511
Bus freq.	No. of direct buses by trimester in the route	453.60	576.41	0.0	4533.0	116,511
Population	Population in city of origin (thousands)	451,466.3	664,841.3	24,475.0	2,165,423.0	116,511

Notes: All variables are grouped by route-day without distinguishing round trips.

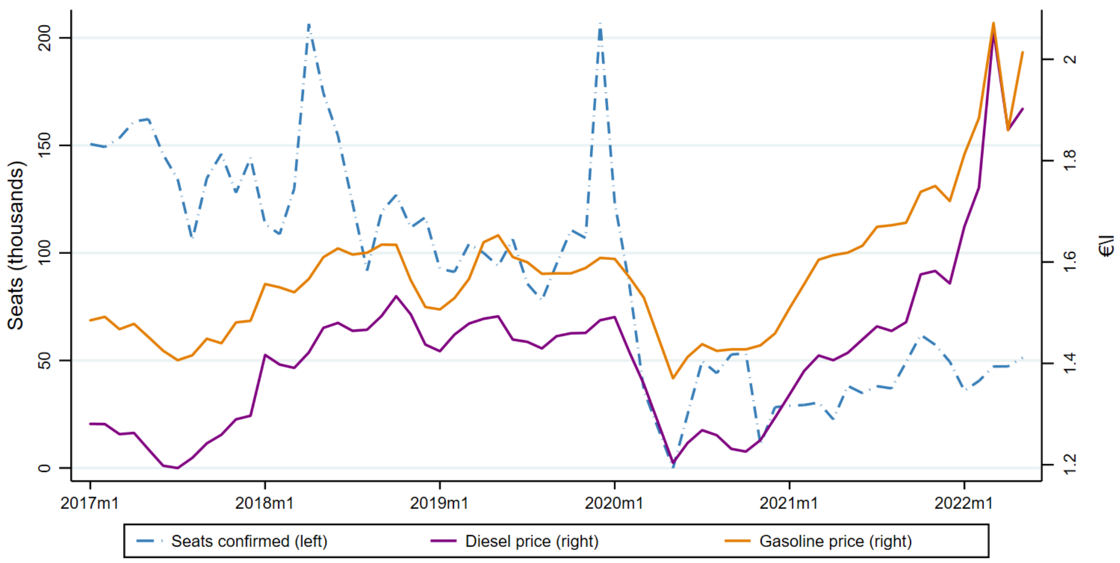

Figure 1: Monthly number of confirmed seats (left), shown together with the monthly average of fuel prices (right). January 2017 to May 2022.

3.3. Empirical Strategy

To examine changes in carpooling supply, and demand relative to variations in the observable cost car travel, we estimate the fuel prices elasticities as follows:

$$\ln(Q_{it}) = \beta_0 + \beta_1 \ln(G_{it-1}) + \gamma X_{it} + FE_i + FE_t + \epsilon_{it} \tag{5}$$

The variable Q_{it} is a carpooling outcome on the route i at day t. The outcomes considered include the quantity of seats offered (supply), seats requested (demand), and seats booked (traded quantity denoted as Q*). The vector G_{it-1} denotes the fuel price at day $t-1$ in the city of origin of route i. We assume that drivers and passengers are better informed of fuel prices at the start of their trip. The vector X_{it} comprises a set of variables suspected to influence carpooling supply and demand. These variables may include toll fees by itinerary, the frequency of buses and trains, and city-specific characteristics such as population. Also, X_{it} includes times dummies to account for well-known seasonality factors like the day of the week and holiday seasons in the city of departure. Furthermore, it includes the one-period-lagged average price set by drivers as a market-relevant variable.

The vector FE_i corresponds to a set of route fixed effects, which effectively filter out all time-invariant route characteristics and control for unobserved heterogeneities. Additionally, FE_t is a set of monthly dummies designed to capture all time-varying factors influencing carpooling and fuel prices. These determinants may include variations in economic activity, advertising campaigns related to carpooling, and other seasonal effects. To ensure the consistency of the error term, we employ clustered standard errors at the route level. Not clustering the standard errors may pose challenges when comparing larger cities, which might exhibit higher levels of carpooling activity, with smaller cities.

The coefficient of interest in Equation 5 is denoted as β_1. This coefficient is interpreted as follows: an increase of 10% of fuel price is associated with a change of $10 \times \beta_1\%$ in the number of seats offered, requested, or booked. We estimated Equation 5 using a Negative Binomial regression because outcomes are in fact counting variables that may assume a zero-value for some itineraries at a certain point in time.

3.4. Results

Fuel price elasticities. We begin by estimating the fuel price elasticity of carpooling. Table 4 reports the results of estimating Equation (5) for diesel prices. All the estimations reveal a positive association between diesel prices and carpooling activity in France. Our findings suggest that, between 2017 and 2022, an increase of 10% in diesel prices is related with approximately a 3.6% rise in seats supplied (column 1), a 4.8% increase in seats requested (column 3), and approximately a 5.1% increase in the total number of seats booked (column 5). The relatively smaller reaction in seats supplied can be attributed to specific characteristics of carpooling, where supply may transition into demand. An increase in fuel prices might prompt individuals to switch from driving to becoming passengers, potentially offering even lower travel costs. Additionally, column (7) shows the estimations using the ratio of the number of seats booked to the number of seats supplied as the outcome variable. Notably, the coefficient is positive and statistically significant suggesting that the additional supplied is compensated by the rise in booked seats. Table 14 in Appendix F depicts the results for gasoline prices.

A more surprising finding is the lack of statistically significance between carpooling activity and toll fees. This could be due to several factors, including the infrequent variation in toll fees, which typically occur only once a year, as well as the relatively small magnitude of these variations. On average, toll fees increased by 2.2% year-on-year in 2019 and by 4.1% in 2022. In 2021, only two routes experienced a price increase as part of a policy to recover from the effects of the global pandemic. Furthermore, the positive coefficients associated with alternative transport modes such as trains and buses suggest that travelers consider potential demand shocks rather than engaging in a straightforward substitution effect. Operators tend to increase frequencies in response to anticipated increases in demand.

To ease the interpretation of the log-log model we compute the marginal effects across different segments of the fuel price distribution on the number of effective seats booked (Q*). Figure 2 reports these effects derived from the findings presented in column (6) of Table 4 and Table 14 in Appendix F. Notably, a diesel price of 1.5€/l corresponds to approximately 45 daily booked seats per route. Furthermore, a 50 cents increase in fuel prices yields to three additional daily booked seats per route. This comparison is relevant due to the substantial

Table 4: Fuel price elasticity of carpooling activity

	Dependent variable						
	ln(supply) OLS	supply NegBin	ln(demand) OLS	demand NegBin	ln(Q*) OLS	Q* NegBin	Q*/supply OLS
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$ln(\text{Diesel price})_{t-1}$	0.359***	0.259***	0.482***	0.383***	0.506***	0.564***	0.0448***
	(0.0713)	(0.0698)	(0.113)	(0.0994)	(0.111)	(0.110)	(0.0151)
$ln(\text{Average seat price})_{t-1}$					0.015***	0.014***	0.0009*
					(0.0043)	(0.0047)	(0.0005)
Toll price/Distance	-3.070	-3.459	8.243*	8.052*	6.674	6.356	-0.957
	(4.654)	(4.401)	(4.693)	(4.361)	(4.829)	(4.609)	(0.749)
Train frequency	0.290*	0.349*	0.402*	0.413*	0.338*	0.331	-0.0103
	(0.162)	(0.198)	(0.214)	(0.248)	(0.196)	(0.223)	(0.0142)
Bus frequency	0.011	0.012*	0.019	0.018	0.022*	0.023*	0.0027
	(0.0074)	(0.0069)	(0.014)	(0.012)	(0.013)	(0.012)	(0.0020)
Dep. Var. mean	5.1	232.7	3.9	93.5	3.1	45.9	0.17
Dep. Var. sd	(0.835)	(217.73)	(1.212)	(149.94)	(1.222)	(69.347)	(0.124)
Observations	116,511	116,511	115,994	116,511	114,658	116,511	116,511
R-squared	0.780		0.743		0.769		0.667
Axis FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Holidays	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day of the week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Monthly FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table reports the results of interest after estimation of Equation 5. Diesel price and ride price are log-transformed and lagged one day. Toll fees refer to as the toll fee by kilometer, and it is transformed using then inverse hyperbolic sine function. The frequency for the train service is daily, as for the bus, the frequency is quarterly. The difference in the number of observations is explained by the zero-value in the outcome that is always accounted in the negative binomial estimation. Robust standard errors clustered at the route level are shown in parentheses. Statistical significance: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

rise in fuel prices following the onset of the Russo-Ukrainian war at the end of 2021, as illustrated in Figure 1.

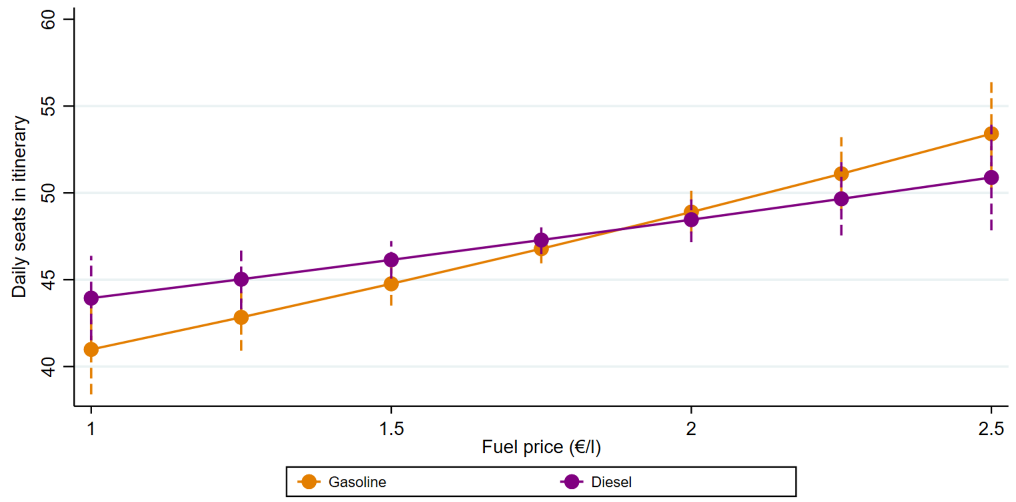

Figure 2: Predicted number of daily booked seats per route across various diesel and gasoline prices.

We further explore travelers' responses to persistent changes in diesel prices following the methodology proposed by Bento et al. (2013). We use the moving average of fuel prices four weeks before the departure date to estimate Equation 5. The results reported in Table 5, column (2), show a positive and significant effect. These findings confirm that a persistent increase in fuel prices is relevant in the carpooling market. Moreover, it is expected to observe a smaller effects when examining longer timeframes.

Finally, our main estimations are based on the assumption that travelers offering seats are informed about fuel prices the day before the departure date. However, our analysis revealed that, on average, travelers tend to offer seats six days before departure. Consequently, we conducted a revised analysis, employing fuel prices lagged by six periods. The outcomes are depicted in column (4) of Table 5. Notably, these results exhibit a significant but reduced effect, thereby supporting our hypothesis and previous findings.

Heterogeneity analysis. A key question related to fuel price elasticities concerns heterogeneous behavioral responses due to a high concentration of seat offered among a reduced number of users. As we document in Figure 3 from Appendix G, the distribution of offered seats shows a long right tail. Additionally, our dataset reveals that roughly 42% of suppliers offer less than five seats throughout the entire timeframe, with only 19% offering more than twenty seats. Similarly, the distribution of requested seats mirrors this pattern, with 64% of

Table 5: Fuel price elasticity to different timeframes

	Dependent variable			
	ln(Q*)	ln(Q*)	ln(Q*)	ln(Q*)
Variable	(1)	(2)	(3)	(4)
$ln(\text{Diesel price})_{t-1}$	0.506***			
	(0.111)			
$ln(\text{Diesel price})_{\text{4-weeks MA}}$		0.285***		
		(0.0911)		
$ln(\text{Diesel price})_{t}$			0.716**	
			(0.327)	
$ln(\text{Diesel price})_{t-6}$				0.142**
				(0.0654)
Observations	114,280	114,658	114,512	113,569
R-squared	0.769	0.769	0.769	0.769
Controls	Yes	Yes	Yes	Yes
Axis FE	Yes	Yes	Yes	Yes
Holidays	Yes	Yes	Yes	Yes
Day of the week FE	Yes	Yes	Yes	Yes
Monthly FE	Yes	Yes	Yes	Yes

Notes: The Table reports the results of interest after estimation of Equation 5, column (6), for a 4 weeks moving average (4-weeks MA) of diesel prices. Controls includes the covariates in Table 4: $ln(\text{Average seat price})_{t-1}$, toll fees corrected by distance, train and bus frequency. Robust standard errors clustered at the route level are shown in parentheses. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

users requesting less than two seats. This observation suggests that more experienced users may exhibit reduced sensitivity to fluctuations in journey costs.

To asses this hypothesis we estimated Equation 5 distinguishing between novice and experienced travelers based on their level of interaction with the platform. Specifically, we create a binary variable identifying travelers with five or fewer interactions with the platform as novices. In other words, novices are travelers who have offered or requested seats five times or less. We then estimate the disparity in fuel price elasticity of supply and demand between novice and experienced users by introducing and interaction term between this dummy and the fuel price. The results, as shown in Table 6, indicate a difference in fuel price elasticity for offered and requested seats of 0.28% and 0.19%, respectively. Remarkably, novice users

Table 6: Fuel prices elasticities for novice and experienced travelers

	(1) ln(supply)	(2) ln(demand)
$ln(\text{Diesel price})_{t-1}$	0.223***	0.298***
	(0.0718)	(0.0964)
Novice	-1.048***	-1.247***
	(0.0371)	(0.0415)
Novice × $\ln(\text{Diesel price})_{t-1}$	0.282***	0.192***
	(0.0320)	(0.0251)
Observations	212,014	206,786
R-squared	0.747	0.702
Controls	Yes	Yes
Axis FE	Yes	Yes
Holidays	Yes	Yes
Day of the week FE	Yes	Yes
Monthly FE	Yes	Yes

Notes: The table reports the estimation of Equation 5 with the term Novice × $\ln(\text{Diesel price})_{t-1}$. Novice is a binary variable that takes the value of 1 for users with 5 or less interactions with the platform. Controls includes the covariates in Table 4: toll fees corrected by distance, train and bus frequency. Robust standard errors clustered at the route level are shown in parentheses. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

exhibit greater responsiveness compared to experienced users.

A complementary approach to the previous question involves identifying heterogenous effects among different types of travelers based on their roles within the platform. travelers who exclusively offer or request seats, and users who engage in both offering and requesting seats. Table 7 presents the results of estimating fuel price elasticities for these traveler types. In this context, the outcome of interests it the logarithm of the number of seats offered or requested. The findings suggest that fluctuations in fuel prices lead to increased supply and demand from both types of users, not solely from those with a singular role. Furthermore, when combining the first type with our experience indicator, it becomes evident that novice users who solely offer seats (column 3) demonstrate a higher response to fuel price variations. In contrast, experienced users who exclusively requests seats (column 8) exhibit a larger elasticity than novice users of the same type.

Table 7: Fuel price elasticity by travelers type

	Dependent variable:							
	ln(supply)				ln(demand)			
			Driver only				Pax only	
Variables	Driver only (1)	Driver/Pax (2)	Novice (3)	Experienced (4)	Pax only (5)	Pax/Driver (6)	Novice (7)	Experienced (8)
$ln(\text{Diesel price})_{t-1}$	0.467***	0.302***	0.401***	0.374***	0.477***	0.365***	0.381***	0.576***
	(0.0764)	(0.0809)	(0.0877)	(0.0875)	(0.117)	(0.119)	(0.113)	(0.116)
Toll price/Distance	-6.070	7.362*	-15.72**	-16.63**	7.789	3.499	4.718	7.650
	(5.146)	(4.128)	(6.663)	(6.771)	(4.852)	(4.524)	(4.986)	(5.125)
Train frequency	0.303*	0.251	0.447**	0.470**	0.374*	0.314**	0.348*	0.176
	(0.180)	(0.153)	(0.209)	(0.207)	(0.214)	(0.152)	(0.209)	(0.219)
Bus frequency	0.0143*	0.0100	0.0101	0.0104	0.0189	0.00427	0.0140	0.0212
	(0.00853)	(0.00723)	(0.0113)	(0.0113)	(0.0139)	(0.00724)	(0.0104)	(0.0151)
Observations	116,504	116,484	116,011	115,849	115,645	102,059	110,999	113,753
R-squared	0.730	0.783	0.663	0.657	0.724	0.613	0.615	0.702
Axis FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Holidays	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day of the week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Monthly FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table reports the results of interest after estimation of Equation 5 for various outcomes depending on travelers type. Driver only and Pax only denotes travelers who solely offered or requested seats, respectively. Driver/Pax and Pax/Drivers are users who have experienced offering and requesting seats. Novice is a binary variable that takes the value of 1 for users with 5 or less interactions with the platform. Diesel price and ride price are log-transformed and lagged one day. Toll fees refer to as the toll fee by kilometer, and it is transformed using then inverse hyperbolic sine function. The frequency for the train service is daily, as for the bus, the frequency is quarterly. Robust standard errors clustered at the route level are shown in parentheses. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

4. Policy implications

The subsequent section delves into different economic policies and their influence on the occupancy rate. As previously highlighted, the occupancy rate embodies travelers' preferences towards alternative modes and serves as a pertinent indicator to the *shifting mode* effect and, consequently, to the efficiency of carpooling in mitigating carbon emissions. In a similar vein, comprehending the diverse mechanisms affecting the occupancy rate is pivotal for devising appropriate policies in line with environmental goals. In this paper we focus on three key factors: the implementation of a carbon tax, subsidies targeting new travelers, and the transition of drivers to passengers.

4.1. Carbon tax

The widely accepted carbon tax is viewed as a viable solution for addressing environmental concerns, particularly those pertaining to the transportation sector (Nordhaus, 2019). Specifically, in the context of intercity car travel, the introduction of a carbon tax could motivate travelers to adjust their behavior to decrease fuel consumption. Furthermore, our research indicates a substantial association between fuel prices and the number of seats exchanged in carpooling. Notably, larger fuel prices increases the supply and demand for seats, along with an increased in the total volume of booked seats. higher fuel prices stimulate both the supply and demand for seats, resulting in an overall increase in the volume of seats booked. This raises questions regarding the impact of the carbon tax on the carpooling market, given its tendency to elevate fuel costs

In France, the government implemented a carbon tax, known as the *Contribution Climat-Energie*, aimed at reshaping energy policies toward sustainability. This tax is a market-based instrument that operates on the Pigouvian principle, where the polluter bears the cost. Originally, the plan was to gradually increase the tax from 7€/tCO_2 to 100€/tCO_2 by 2030 to achieve emissions reduction targets. However, following the Yellow Vest Movement in 2018, the government opted to stop the increase, fixing the rate at 44.6€/tCO_2, which is translated into 11.2 and 11.9 centimes per liter of gasoline and diesel, respectively. While this tax has broad political and redistributive implications (Chiroleu-Assouline, 2022), our focus here is its impact on the carpooling market.[18]

To assess the impact of the carbon tax on carpooling, we use the estimates derived from Equation (5) to predict the volume of booked seats under the carbon tax in place (outlined in column 1 of Table 8). Subsequently, we estimate the following two scenarios. Initially, we construct a fuel price vector by deducting the annual carbon tax for both fuel types used in this analysis. By comparing these outcomes with the primary findings, we can directly correlate carpooling participation with the effect of the carbon tax on fuel prices. Second, we construct an vector of prices including the carbon tax originally planned by the government for the years after 2018. This approach enables us to estimate the potential number of confirmed seats if the policy had been upheld. The results for both scenarios are reported in Table 8, using the models in column (6) from tables Table 4 and Table 14.

Table 8: Daily booked seats by route under various scenarios of the French carbon tax

Fuel type	Current policy	Price excluding tax		Tax policy envisaged	
		Value	Diff	Value	Diff
	(1)	(2)	(3)	(4)	(5)
Diesel	42.74	41.24	1.5	43.01	-0.27
	(68.57)	(66.25)		(68.83)	
Gasoline	42.75	41.55	1.2	42.95	-0.20
	(68.56)	(66.68)		(68.72)	

Notes: The table reports the predicted daily volume of booked seats by route under three different scenarios of the French Carbon tax. Predicted values for diesel and gasoline were obtained using column (6) of Table 4 and Table 14, respectively. Column (1) shows the results for the tax policy in place. Columns (2) and (3) present the predicted values deducting the carbon tax to fuel prices and the difference in seats with the tax policy in place. Columns (4) and (5) reports the predicted values including the carbon tax originally planned by the government and the difference in seats with the tax policy in place. Standard errors are shown in parentheses.

The findings suggest that the existing carbon tax leads to an average increase of nearly 1.5 additional seats per route on a daily basis. In essence, over the entire timeframe, this translates to more than 260 thousand booked seats. Conversely, the failure to enforce the original policy results in an average loss of 0.3 daily seats, almost 53 thousand seats between 2019 and 2022. Rather than focusing solely on numerical figures, it is crucial to underscore the potential repercussions of delaying carbon pricing within a pivotal sector.

[18] See Appendix C for details on the envisioned rates from 2017 to 2022.

4.2. Drivers switching to passengers

A promising strategy for carpooling to reduce carbon emissions is the transition of drivers into passengers, a phenomenon we defined as the *switchers effect*. As illustrated in Table 1, travelers offering seats often opt for more carbon-intensive alternative modes compared to those requesting seats as passengers. Hence, policies aimed at balancing the driver-passenger match, such as incentivizing drivers to become passengers, are crucial. Notably, in the database we use here, this phenomenon is significant, with 43% of users offering seats also request seats as passengers.

To assess the impact of *switchers*, we quantified the emission saved under two benchmark scenarios: filling empty seats with existing unmatched drivers on the platform and filling those seats with new users. In the first scenario, the algorithm ranks drivers based on the number of seats they offer. Those with the fewest offered seats are converted into passengers first. After filling the seats of the highest-ranked drivers, the algorithm proceeds to the next rank order. This process continues until all eligible drivers have been converted into passengers.

On the contrary, in the second scenario, no driver switch, and all seats are filled by new users. However, in this case, it is crucial to consider the alternative transport mode these new users would have used instead of carpooling. We examine two alternatives: new users shifting from private cars and new users shifting from trains. These options were chosen as they represent extreme cases of carbon emissions, with the former being a more effective means of reducing carbon emissions.

Table 9: Carbon emissions saved from *switchers*

Scenarios to fill empty seats	Mean (gCO_2)	SD	Min	Max	Count
Unmatched drivers	519,366	550,580	0	14,305,542	229,895
New users from cars	630,569	874,602	0	30,090,450	229,895
New users from trains	61,747	89,105	0	1,120,497	229,895

Notes: The Table reports the summary statistics of the carbon emissions saved in gCO_2 by drivers becoming passengers, or *switchers*. Estimations are aggregated at route-day level. Three scenarios are considered: filling empty seats with existing unmatched drivers on the platform, filling empty seats with new users shifting from private cars, and filling empty seats with new users shifting from trains.

The results of the estimations are displayed in Table 9. This Table presents the summary statistics of each scenario aggregated at the route-day level. To facilitate interpretation, we compare these emissions with the the average emissions of a new thermal car in 2019 which is $112gCO_2$ per km according to ADEME. The findings suggest that filling empty seats with unmatched drivers translates to saving 4.6 thousands km of car travel. Likewise, filling vacant seats with new users from cars results in saving 5.6 thousand kilometers. Notably, policies aimed at boosting the *switchers effect*, such as showcasing the option to book a similar trip to users offering seats, could lead to significant reductions in carbon emissions. Furthermore, it's crucial to emphasize the importance of understanding the preferences for alternative modes among new carpooling users.

4.3. Subsidies for new travelers

Another crucial implication from our findings pertains to the heterogeneous response patterns between novice and experienced users. Similar to other digital platforms, carpooling is heavily skewed, with a minority of users accounting for the bulk of offered seats, as it is shown in Figure 3 in Appendix G. The finding presented here show that novice travelers are more sensitive to the cost of car travel. In addition, attracting new users to fill empty seats may result in significant reductions in carbon emissions. These findings resonate with a recent subsidy scheme implemented by the French government under the *Certificat d'économie d'énergie* designed to attract new users. New users completing, as drivers, three trips above 80km whithin three months receive a subsidy of €100.

This policy was introduced mainly to offset the continuous rise in fuel prices and to protect the purchasing power of households. Our findings support this policy choice, suggesting that incentives targeting individuals who are more sensitive to such changes could effectively prompt people to try carpooling and, eventually, make it their preferred mode of transportation. Also, our findings contribute to the design of policies with environmental objectives in mind. According to our research, a subsidy program aimed at attracting new passengers or promoting *switchers* aligns well with these environmental goals.

5. Conclusion

Carpooling is considered as a promising innovation to reduce carbon emissions from roads, a sector notorious for its significant emissions worldwide. However, robust empirical evidence is crucial to confirm this hypothesis, as making car travel more appealing could could potentially draw travelers away from cleaner modes of transportation, such as trains, limiting the effectiveness of carpooling to mitigate carbon emissions. As shown in this paper, this trade-off is embodied in the occupancy rate, measured as the number of passengers in each trip. This is because the occupancy rate takes into account travelers' preferences over alternative modes of transport. Therefore, policies aimed at improving such indicator are in line with environmental objectives.

In this regard, we delve into the impact of two mechanisms on the occupancy rate: variations in the cost of car travel and incentives for drivers to travel as passengers. Our findings suggest that users consistently react to fluctuations in fuel prices. Moreover, novice users showed a larger response in comparison with more experienced users. In addition, our results show that enhancing the *switchers* effect may entail a significant reduction in carbon emissions.

The results discussed here have substantial implications for designing policies aimed at promoting carpooling as en environmental policy objective. For instance, implementing carbon pricing mechanisms and offering targeted subsidies for new passengers could prove to be effective strategies in boosting occupancy rates in carpooling and mitigating individual carbon footprints. Moreover, our study opens new avenues for future research. In this paper we focus on a short-term perspective without considering dynamics. Additionally, the influence of fuel prices on the distribution of preferences among alternative transport modes needs further investigation.

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Appendices

A. EEA Vehicle Emission Data Assessement

Our primary pollution indicator is derived from CO_2 emissions per kilometer (g/km), ascertained via the NEDC protocol. Although this protocol has faced criticism for its limitations, it provides a valuable benchmark for assessing a particular combination of vehicle models and brands. Since 2017, the European Commission has shifted towards the more realistic WLTP protocol and is mostly left empty before. This shift presents a trade-off for our research; while we aim for a comprehensive representation of car models spanning the period from 2017 to 2022, the resultant emission data may not fully reflect real-world conditions. Consequently, we interpret our results with caution, treating them as a lower boundary for actual emissions.

Given that our carpooling database only contains the vehicle's model name, as reported by the driver, and lacks detailed specifications concerning the engine, we calculate pollution indices by matching the reported model name to the weighted mean emissions for that model. This approach factors in the total number of sales in France between 2011 and 2021.

For example, if ten new Peugeot 208 were sold, nine of which had combustion engines that emit $200g/km$ and one with an electric motor that emits $0g/km$, the aggregated emission for Peugeot 208 in our database would be $180g/km$. Note that there may be significant intra-model variations across different years. Thus, we apply the weighted mean across our period of study, incorporating these variations into our calculations.

B. Carbon Mitigation Threshold Simulation

Table 10: Carbon Mitigation Passenger Number Threshold Under Different Scenarios of Alternative Mode Shares

Scenario of alternatives	Profile	Weights of alternative modes without carpooling					Passenger threshold	
		Car	Train	Bus	Flight	No Travel	ADEME	EEA
Current mode share, only high-speed rail	Passenger	0.16	0.69	0.02	0.01	0.12	1.7	1.5
	Driver	0.66	0.24	0.01	0.01	0.08		
Current mode share, only regional rail	Passenger	0.16	0.69	0.02	0.01	0.12	1.1	0.7
	Driver	0.66	0.24	0.01	0.01	0.08		
No flight, replaced by high-speed rail	Passenger	0.16	0.7	0.02	0	0.12	1.9	1.7
	Driver	0.66	0.25	0.01	0	0.08		
No flight nor bus, replaced by high-speed rail	Passenger	0.16	0.72	0	0	0.12	2.0	2.0
	Driver	0.66	0.26	0	0	0.08		
No flight nor bus, replaced by regional rail	Passenger	0.16	0.72	0	0	0.12	1.2	0.9
	Driver	0.66	0.26	0	0	0.08		
All the non-travels go to car + only regional rail	Passenger	0.28	0.69	0.02	0.01	0	0.5	0.4
	Driver	0.74	0.24	0.01	0.01	0		
All the non-travels go to car + only high-speed rail	Passenger	0.28	0.69	0.02	0.01	0	0.8	0.7
	Driver	0.74	0.24	0.01	0.01	0		
Current mode share, 25% cars are EVs + only high-speed rail	Passenger	0.16	0.69	0.02	0.01	0.12	1.6	1.3
	Driver	0.66	0.24	0.01	0.01	0.08		
Current mode share, 50% cars are EVs + only high-speed rail	Passenger	0.16	0.69	0.02	0.01	0.12	1.4	1
	Driver	0.66	0.24	0.01	0.01	0.08		
50% less car dependence, replaced by high-speed rail	Passenger	0.08	0.77	0.02	0.01	0.12	5.9	4.9
	Driver	0.33	0.57	0.01	0.01	0.08		
50% less car dependence, replaced by regional rail	Passenger	0.08	0.77	0.02	0.01	0.12	2.9	1.8
	Driver	0.33	0.57	0.01	0.01	0.08		
0 car dependence, replaced by high-speed rail	Passenger	0	0.85	0.02	0.01	0.12	32.0	18.7
	Driver	0	0.9	0.01	0.01	0.08		
0 car dependence, replaced by regional rail	Passenger	0	0.85	0.02	0.01	0.12	6.5	3.5
	Driver	0	0.9	0.01	0.01	0.08		

Notes: We calculate the carbon mitigation minimum number of passengers per ride threshold under different scenarios of weights of alternative modes. Our baseline weights are those of the ADEME questionnaire. We assume that drivers and passengers are always under the same scenario. Our scenarios are non-exhaustive but they allow us to observe the sensitivity of the threshold under heterogeneous user preferences. The first and second scenarios would be reasonable for routes that are mainly/only served by one rail type, knowing that high-speed rails are less polluting. The third to fifth scenarios would apply to routes without flights. The sixth and seventh scenarios allow all users to travel. Logically, it will lower the threshold. We chose the cleanest alternative modes to lower the threshold the least. The eighth and ninth scenarios assume 25% and 50% market shares of electric vehicles with zero pollution while driving, which *de facto* reduces the overall vehicle emission coefficient and lowers the threshold. The last four scenarios are extreme cases where the polluting car alternatives are partially or completely replaced by clean rail transport. In reality, these scenarios would be unlikely at the current stage, nor would promoting carpooling be logical under such scenarios. However, we find it interesting to report the extreme cases.
We report thresholds of both the ADEME emission standards and the EEA emission standards. Intuitively, the EEA thresholds are always below the ADEME threshold because EEA attributes a lower vehicle emission coefficient. Unless the car dependency would drastically reduce as an alternative, especially for drivers, changing the weight of alternatives would not modify too much the scale of the threshold (the highest is 2).

Table 11: Carbon Mitigation Passenger Number Threshold Under Ongoing Targets for Newly Registered Vehicles Emissions in the EU

Scenario of alternatives	Profile	Weights of alternative modes without carpooling					Passenger threshold
		Car	Train	Bus	Flight	No Travel	
Current mode share,	Passenger	0.16	0.69	0.02	0.01	0.12	0.82
EEA goal of 93.6 g CO_2/km [2025-2029]	Driver	0.66	0.24	0.01	0.01	0.08	
Current mode share,	Passenger	0.16	0.69	0.02	0.01	0.12	0.42
EEA goal of 49.5 g CO_2/km [2030-2034]	Driver	0.66	0.24	0.01	0.01	0.08	

*Notes: On 19 April 2023, the European Parliament and the Council adopted Regulation (EU) 2023/851 amending Regulation (EU) 2019/631 to strengthen the CO_2 emission performance standards for new passenger cars and new light commercial vehicles in line with the European Union's increased climate ambition (European Commission source [Accessed 10/11/2023]).*Since 2021, the emission targets for manufacturers are based on the WLTP (Worldwide harmonized Light vehicles Test Procedure).

C. Carbon Tax Rate Envisioned by the French Government

Table 12: Annual carbon tax rate envisioned by the French government in centimes per litre

Type of fuel	2017	2018	2019	2020	2021	2022
Gasoline 95	7.7	11.2	13.8	16.4	19.0	21.6
Gasoline 98	7.7	11.2	13.8	16.4	19.0	21.6
Diesel	8.1	11.9	14.7	17.5	20.2	23.0

D. Data Representativity

One key question regarding the external validity of our findings is how well our data sample represents the French carpooling market. To answer this question, we requested BlaBlaCar data on the aggregate number of seats supplied, requested, and booked by route by year for the entire French market, together with the route distance, the population of the departure city, and an indicator that shows whether the route is included in our sample. [19] These routes are ranked by frequency, i.e. the total number of seats supplied (requested, or booked) on the route i year t as a share of the total number of seats supplied (or booked) in the entire French market that year. We then compute the cumulative frequencies from the most to the least popular route. In this way, we are able to identify the top x routes that count for $y\%$ of the French carpooling market. We compute the same indicators for our sample to draw comparable statistics with the whole marketplace. For each year, we calculate the average

[19] Due to industry secrets, we cannot see the city names of the routes, only anonymized IDs.

number of seats supplied, requested, booked, route distance, and departure city population, taking into account all routes in our sample. We then compute the average of the yearly averages, both for the entire market and for our sample.

Table 13 compares our sample (column 1) with the top routes that represent 75%, 85%, and 95% of the entire French market (columns 2 to 4). We can see that in key market indicators (supply, request, booking), our sample resembles the top 75% routes. Distance and population comparisons are also satisfactory. It is not surprising to see a sharp decline in market indicators for the last 25% market share, due to the long tail of all possible routes. Although our sample is not representative of the *entire* French market, we are representative of the *most frequent* routes that constitute 75% of the supply and demand.

Table 13: Data representativity of the French carpooling market

Variable	Sample	Top Routes Constituting X% Cum. Freq.		
		75%	85%	95%
	(1)	(2)	(3)	(4)
Panel A. Supply				
No. of seats	6 763.8	6 140.7	3 081.3	967.2
	(35 715.8)	(18 349.8)	(12 515.7)	(6 764.3)
Distance (km)	276.9	220.7	240.9	279.2
	(141.6)	(156.9)	(167.4)	(186.2)
Population (thousands)	112.0	122.4	106.2	85.8
	(160.756)	(293.456)	(264.459)	(235.499)
Panel B. Request				
No. of seats	1 794.6	1 602.8	570.7	107.4
	(11,370.6)	(6,585.5)	(3,757.3)	(1,556.2)
Distance (km)	276.9	251.9	271.4	316.9
	(141.6)	(160.6)	(171.5)	(193.3)
Population (thousands)	112.0	163.5	125.3	80.2
	(160.756)	(356.616)	(301.675)	(226.915)
Panel C. Booking				
No. of seats	1 216.1	1 035.6	323.2	55.0
	(8,103.5)	(4 596.3)	(2 451.9)	(963.9)
Distance (km)	276.9	254.8	278.1	326.8
	(141.6)	(161.7)	(174.1)	(197.1)
Population (thousands)	112.0	156.1	120.5	75.2
	(160.756)	(341.704)	(292.083)	(218.078)

E. Carbon Mitigation Condition at Route Level

Individual rides may be very heterogeneous in terms of bookings. It is more interesting to look at the carbon mitigation condition aggregated at the route-day level. The result is parallel to the ride level:

$$\frac{N_{prt}}{N_{rt}} \geq \frac{\overline{e_{vrt}} - e_{ncd}}{e_{ncp}} \tag{6}$$

Where N_{prt} is the total number of passengers of route r on date t, N_{rt} is the total number of rides offered on route r date t, and $\overline{e_{vrt}}$ is the average vehicle emission coefficient on route r date t.

From Equation 6, we draw similar conclusions as in the individual case. In the short run, the key indicator for carpooling to be carbon mitigation is for each route-day pair to attain the minimum average number of passengers per ride (left-hand side). In the middle and long run, we could work on the right-hand side of the equation. For example, to lower the average vehicle emission coefficient of the entire fleet $\overline{e_{vrt}}$, or to lower the rebound effect of carpooling (to increase e_{ncd} and e_{ncp}), so that fewer participants who would have used cleaner modes would have been attracted to carpooling.

F. Results for Gasoline 95

Table 14: Gasoline price elasticity of carpooling activity

	Dependent variable						
	ln(supply)	supply	ln(demand)	demand	ln(Q*)	Q*	Q*/supply
	OLS	NegBin	OLS	NegBin	OLS	NegBin	OLS
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$ln(\text{Gasoline price})_{t-1}$	0.280*	0.270**	0.450***	0.445***	0.458***	0.590***	0.0480*
	(0.146)	(0.121)	(0.123)	(0.105)	(0.122)	(0.109)	(0.0254)
$ln(\text{Average seat price})_{t-1}$					0.0143***	0.0138***	0.0009
					(0.0042)	(0.0047)	(0.0005)
Toll price/Distance	-3.060	-3.468	8.248*	8.037*	6.682	6.339	-0.958
	(4.629)	(4.373)	(4.685)	(4.351)	(4.824)	(4.602)	(0.751)
Train frequency	0.293*	0.351*	0.405*	0.416*	0.341*	0.336	-0.0101
	(0.162)	(0.198)	(0.214)	(0.248)	(0.196)	(0.223)	(0.0141)
Bus frequency	0.011	0.012*	0.019	0.018	0.022*	0.023*	0.003
	(0.0074)	(0.0069)	(0.014)	(0.012)	(0.013)	(0.012)	(0.002)
Dep. Var. mean	5.1	232.7	3.9	93.5	3.1	45.9	0.17
Dep. Var. sd	(0.835)	(217.73)	(1.212)	(149.94)	(1.222)	(69.347)	(0.124)
Observations	116,511	116,511	115,994	116,511	114,658	116,511	116,511
R-squared	0.780		0.743		0.769		0.667
Axis FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Holidays	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day of the week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Monthly FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table reports the results of interest after estimation of Equation 5. Gasoline here is referred to as the price of gasoline 95 octanes. Gasoline and ride price are log transformed and lagged one day. Toll fees refer to as the toll fee by kilometer, and it is transformed using then inverse hyperbolic sine function. The frequency for the train service is daily, as for the bus, the frequency is quarterly. The difference in the number of observations is explained by the zero-value in the outcome that is always accounted in the negative binomial estimation. Robust standard errors clustered at the route level are shown in parentheses. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

G. Distribution of seats offered

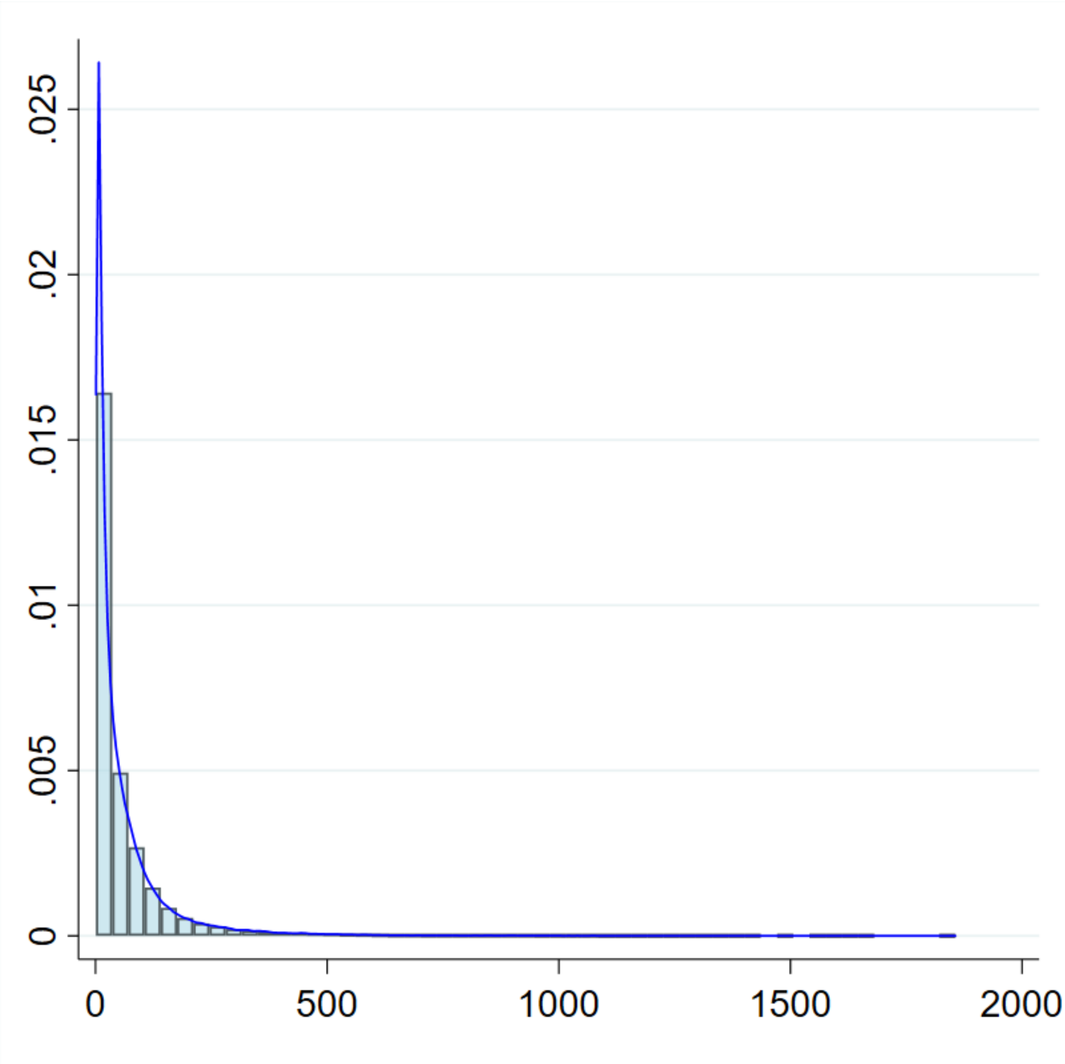

Figure 3: Distribution of the number of seats offered from 2017 to 2022.

H. Routes Included in the Database

Table 15: Inventory of itineraries

Origin	Destination	Distance (km)	Toll fee in 2022 (€)	Toll(€)/km
Lille	Arras	52	0	0.00
Nancy	Metz	55	0	0.00
Charleville-Mézières	Reims	92	0	0.00
Brive-la-Gaillarde	Limoges	96	0	0.00
Nantes	Rennes	107	0	0.00
Limoges	Châteauroux	122	0	0.00
Clermont-Ferrand	Le Puy-en-Velay	129	0	0.00

Table 15 – *Continued*

Origin	Destination	Distance (km)	Toll fee in 2022 (€)	Toll(€)/km
Caen	Rennes	188	0	0.00
Clermont-Ferrand	Rodez	246	0	0.00
Toulouse	Albi	86	1.6	0.02
Vierzon	Montauban	418	14.2	0.03
Clermont-Ferrand	Béziers	344	11.7	0.03
Paris	Beauvais	105	3.9	0.04
Paris	Compiègne	90	3.6	0.04
Saint-Etienne	Roanne	86	4	0.05
Grenoble	Annecy	106	5	0.05
Paris	Rouen	138	6.8	0.05
Toulouse	Montauban	55	3	0.05
Paris	Amiens	163	9.3	0.06
Paris	Dunkerque	301	17.3	0.06
Toulouse	Tarbes	154	9	0.06
Limoges	Montauban	240	14.2	0.06
Paris	Auxerre	169	10	0.06
Pau	Tarbes	45.6	2.9	0.06
Nemours	Nevers	167	10.8	0.06
Toulouse	Pau	195	12.8	0.07
Marseille	Avignon	103	7.2	0.07
Lille	Compiègne	159	11.2	0.07
Toulouse	Bayonne	296	21.8	0.07
Marseille	Montélimar	168	12.4	0.07
Caen	Rouen	127	9.5	0.07
Calais	Arras	112	8.4	0.08
Marseille	Orange	116	8.7	0.08
Lyon	Mâcon	72	5.4	0.08
Paris	Lille	230	17.3	0.08
Paris	Arras	190	14.3	0.08
Lyon	Valence	105	8	0.08
Dijon	Mâcon	127	9.7	0.08
Clermont-Ferrand	Brive-la-Gaillarde	180	13.9	0.08
Mulhouse	Besançon	141	10.9	0.08
Paris	Mâcon	397	30.7	0.08
Bayonne	Pau	113	8.8	0.08
Paris	Lyon	465	36.5	0.08
Bordeaux	Agen	140	11.1	0.08
Nantes	Niort	145	11.5	0.08
Reims	Metz	191	15.2	0.08
Paris	Reims	145	11.6	0.08
Lyon	Marseille	315	25.4	0.08
Bordeaux	Montauban	217	17.5	0.08
Bordeaux	Toulouse	245	19.8	0.08
Paris	Metz	332	26.9	0.08
Angers	La Roche-sur-Yon	138	11.2	0.08
Le Mans	Tours	102	8.4	0.08
Lyon	Montélimar	150	12.4	0.08
Paris	Orléans	131	10.9	0.08
Angers	Tours	133	11.1	0.08
Paris	Strasbourg	488	40.9	0.08
Reims	Troyes	125	10.5	0.08
Reims	Strasbourg	347	29.2	0.08
Angers	Cholet	65	5.5	0.08
Marseille	Valence	213	18.1	0.08
Metz	Strasbourg	164	14	0.09
Toulouse	Carcassonne	96	8.3	0.09
Bayonne	Tarbes	148	12.8	0.09
Lyon	Auxerre	302	26.4	0.09
Clermont-Ferrand	Périgueux	245	21.9	0.09
Lyon	Avignon	230	20.6	0.09
Lyon	Orange	202	18.5	0.09
Le Mans	Laval	87	8	0.09
Toulouse	Agen	115	10.6	0.09
Toulouse	Narbonne	154	14.3	0.09
Orléans	Clermont-Ferrand	299	28.7	0.10
Lyon	Clermont-Ferrand	167	16.3	0.10
Paris	Bordeaux	584	57.2	0.10
Lyon	Bordeaux	553	55.5	0.10
Paris	Tours	237	24.1	0.10

Table 15 – *Continued*

Origin	Destination	Distance (km)	Toll fee in 2022 (€)	Toll(€)/km
Angers	Nantes	90	9.2	0.10
Paris	Caen	241	25.4	0.11
Tours	Poitiers	105	11.3	0.11
Grenoble	Lyon	112	12.2	0.11
Caen	Le Mans	163	17.8	0.11
Paris	Poitiers	339	37.2	0.11
Orléans	Poitiers	218	24.3	0.11
Valence	Grenoble	93	10.4	0.11
Tours	Orléans	116	13	0.11
Lyon	Chambéry	108	12.2	0.11
Marseille	Toulon	65	7.6	0.12
Paris	Calais	197	23.4	0.12
Troyes	Orléans	216	29.2	0.14
Rouen	Tours	309	42.1	0.14
Pau	Bordeaux	216	29.6	0.14
Rouen	Le Mans	212	32.6	0.15

Conclusion

This doctoral research analyses the rise of digital mobility platforms in the context of profound structural transformations prompted by the digital revolution and the ecological transition. These technological innovations bring both opportunities and challenges. This thesis underscores the importance of understanding the disruptive forces behind such innovations to effectively unlock their benefits and mitigate potential negative impacts. The primary contribution of this research lies in its comprehensive analysis of the integration of digital mobility platforms in multi-modal transport systems. Through empirical studies presented in Chapters 3 to 5, this research offers valuable insights into the interaction between different relevant actors including authorities, public transport, and digital mobility providers. In addition, the thesis delves into the regulatory implications needed to direct innovations towards a more efficient and clean transport system.

The insights gained from this research have several important policy implications. As cities continue to grow, innovations continue to disrupt the industry, and the climate change continue to urge the ecological transition, better policy interventions will be essential to maximize the benefits of digital mobility platforms while minimizing potential adverse effects. Key policy recommendations include the following:

- Promoting Multimodal Integration: One of the primary goals to reduce car-dependencies is to promote multimodal behavior. This involves fostering complementarities between public transport and digital mobility platforms to enhance accessibility ant tackle the first/last-mile dilemma. Policymakers should focus on developing integrated mobility platforms that allow users to plan, book, and pay for trips involving multiple modes through a single application. Additionally, better urban design requires investment in infrastructure that enhances the physical integration of multiple modes.
- Designing Effective Regulatory Frameworks: Effective regulation is critical to manage the integration of digital mobility platforms into existing transport systems. This includes setting clear rules for the operation of shared mobility services, implementing policies to encourage the use of environmentally friendly modes of transport, implementing flexible rules to adapt to technological advancements and evolving user behaviors, and investing in infrastructure to promote multimodality. Additionally, policies that discourage the use of private cars, such as congestion

pricing and parking restrictions, can help shift travel behaviors towards more sustainable options.

- Enhancing Public Awareness and Acceptance: Public acceptance of new mobility services is crucial for their success. Policymakers should invest in public awareness highlighting the benefits of multimodality and addressing any concerns related to safety, accessibility, and environmental impact. Engaging with communities and stakeholders in the planning and implementation process can also help build trust and support for new initiatives.

Despite the promising potential of new mobility services, several challenges remain that require further research. Digital mobility platforms can disrupt existing spatial and temporal patterns of transport usage. First, future research should explore better strategies to distribute these services more evenly across urban areas and ensure complementarities with the current urban layout and public transport. Second, the introduction of emerging services can have unintended consequences, such as increased congestion or higher carbon emissions when they displace cleaner modes. More research is needed to develop robust methodologies for assessing the environmental and social impacts of these services. Third, ensuring equity and accessibility is a critical consideration in the design and implementation of transport policies. Future mobility systems should be accessible to all segments of the population, including those currently in underserved areas. This question remains considerable understudied and more robust empirical evidence is needed to understand whether these services exacerbate existing inequalities. Finally, regulatory authorities must keep pace with the rapid technological advancements and be able to adapt regulations accordingly. Research in this direction should consider this challenges to propose better regulatory governance.

As we stand at a pivotal moment in human history, the choices we make today will lay the foundations for our future cities. The ecological transition and the digital revolution holds the promise of enhancing social welfare for a better urban life. However, this vision requires a coordinated effort from policymakers, practitioners, and researchers. The integration of digital mobility platforms into transport systems presents a unique opportunity to address longstanding challenges and to create a more sustainable and equitable future. By leveraging the insights gained from this research, authorities can make informed decisions that promote the effective integration of these services, ultimately leading to mobility systems that prioritize people's quality of life.

RÉSUMÉ

Au cours du siècle dernier, les voitures privées ont dominé l'industrie du transport, exerçant une influence profonde sur l'activité économique. Ce paradigme centré sur la voiture a entraîné des coûts substantiels, en raison de l'augmentation de la congestion routière et des émissions de carbone. En réponse, les villes ont de plus en plus adopté des plateformes de mobilité numérique pour améliorer l'efficacité des transports et la qualité de vie. S'appuyant sur les principes de l'économie de partage, les plateformes de mobilité numérique offrent un accès à court terme à divers moyens de transport. Ce modèle est attrayant car il favorise une utilisation plus efficace du capital et offre des alternatives plus propres à l'utilisation individuelle de la voiture. Pour répondre efficacement aux enjeux liées au transport, elles doivent réduire la dépendance à l'égard de la voiture, résoudre les dilemmes des voyageurs et favoriser les complémentarités avec les transports en commun. Toutefois, l'absence de preuves empiriques solides nous empêche de comprendre si les plateformes de mobilité numérique adhèrent à ces principes. Par conséquent, la question de savoir comment intégrer efficacement les plateformes de mobilité numérique dans les systèmes de transport existants reste un sujet d'étude actuel et pertinent. Cette thèse contribue à ce débat par le biais de quatre articles. Le chapitre 2 s'appuie sur la théorie de l'économie des plateformes pour développer une typologie de modèle d'entreprise pour les plateformes de mobilité numérique et identifier la nature de l'intervention publique. Le chapitre 3 explore la dynamique du marché entre les transports publics et le vélopartage, révélant des complémentarités après de longues périodes de perturbation du réseau. Le chapitre 4 évalue les règles de stationnement pour les e-scooters. Les résultats suggèrent un effet positif sur le stationnement abusif, mais un effet négatif inattendu sur l'accessibilité. Le chapitre 5 étudie le potentiel de réduction des émissions de carbone du covoiturage et explore les politiques visant à améliorer la réduction des émissions de carbone. Dans l'ensemble, cette thèse fournit des indications aux décideurs et aux praticiens pour concevoir des systèmes de transport multimodaux plus efficaces et plus durables. Il est primordial pour l'avenir d'élaborer des réglementations qui orientent la technologie vers des objectifs économiques et environnementaux.

MOTS CLÉS

Plateformes numériques, Régulation, Mobilité, Systèmes de transport multimodaux, Modèles économiques, Transition écologique.

ABSTRACT

Over the past century, private cars have dominated the transport industry, profoundly shaping economic activity. However, this car-centric approach has also come with substantial costs, due to increasing traffic congestion and carbon emissions. In response, cities have increasingly adopted digital mobility platforms to improve transportation efficiency and enhance quality of life. Leveraging the principles of the sharing economy, digital mobility platforms provide short-term access to various means of transport. This model is appealing because it promotes more efficient use of capital and offers cleaner alternatives to individual car-usage. To effectively address transport-related concerns, they must reduce car dependency, address travelers' dilemmas, and fostering complementarities with mass transit. However, the lack of robust empirical evidence limits our understanding of whether digital mobility platforms adhere to these principles. Therefore, the question of how to effectively integrate digital mobility platforms into existing transport systems remains an ongoing subject of scrutiny. This thesis contribute to this debate in four papers. Chapter 2 builds on the theory of platform economics to develop a business model typology for digital mobility platforms and identify the nature for public intervention. Chapter 3 explores the market dynamics between public transport and bike-sharing, revealing complementarities after long periods of disruption in the network. Chapter 4 evaluates parking regulations for e-scooters. The findings suggest a positive effect on improper parking, but an unexpected negative effect on accessibility. Chapter 5 investigates carpooling's potential for carbon emission reduction, and explore policies to improve carbon mitigation. Overall, this thesis provides insights for decision-makers and practitioners to design more efficient and sustainable multi-modal transport systems. Crafting regulations that guide technology toward economic and environmental objectives is paramount for the future.

KEYWORDS

Digital Platforms, Regulation, Mobility, Multi-modal transport systems, Business models, Ecological transition.