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

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Abstract

The introduction of new mobility services, such as bike-sharing, has profoundly transformed urban mobility. These services have been adopted for their potential to improve efficiency, reduce congestion, and lower pollution by enhancing complementarities with public transport. However, the market dynamics between new services and public transport remains unclear. This study leverages a natural experiment based on an extemporaneous incident that temporarily shut down operations in Mexico City's subway network. Using geolocation data to analyze the spatial relationship between bike-sharing and subway stations, I identify bike journeys that substitute or complement public transport. The evidence suggests a substantial increase in the degree of substitution to bike-sharing during subway disruptions. Furthermore, following the restoration of subway service, both overall demand for bike-sharing and its complementarity with public transit increase. Lastly, I present evidence suggesting that this expansion is associated with a rise in subway ridership. These findings have important implications for the future of urban mobility, providing robust empirical insights for developing a resilient, efficient, and sustainable transport system.

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 has dominated urban transportation over the past seventy years has led to economic, social, and environmental costs associated with traffic congestion, both local and global pollution, and spatial inequalities. In response, cities are increasingly adopting new mobility services, such as ride-sharing and ride-hailing, to address these challenges. These services have potential to reduce car dependency by complementing public transportation, addressing first- and last-mile connectivity issues, and improving accessibility (Shaheen & Cohen, 2019; Shaheen & Chan, 2016; ITF, 2021; Meng et al., 2020). However, the extent to which these new mobility services may substitute public transport remains an open question in the literature, with significant implications for the future organization of urban mobility.

In this paper, I focus on station-based bike-sharing models—a recent innovation that allows riders to borrow bikes from docking stations and return them to any other dock near their destination. Like other shared mobility services, this model enables users to access transport on a short-term, as-needed basis (Shaheen & Cohen, 2019). Additionally, bike-sharing has gained popularity among governments due to its potential to address the "last-mile" problem by improving connectivity to public transport and encouraging multimodal travel behavior (Shaheen & Chan, 2016). However, the question of whether bike-sharing complements or substitutes public transport remains open, as empirical studies have produced mixed results. Many studies associate bike-sharing with increased public transport ridership, suggesting a complementary relationship (Ma et al., 2015; Ashraf et al., 2021; Radzimski & Dzięcielski, 2021). Conversely, some research points to public transport substitution, with findings of decreased public transport ridership, particularly in urban centers with a high diversity of activities (Campbell et al., 2016; Campbell & Brakewood, 2017). Only a handful of studies have explored the possibility of a dual relationship in which bike-sharing provides both complementary and substitutive journeys (Shaheen et al., 2011; Martin & Shaheen, 2014).

This paper provides empirical evidence by examining an extemporaneous incident that shut down operations in Mexico City's subway network on January 9, 2021. The analysis has three main objectives. First, it aims to causally determine the extent to which bike-sharing substitutes or complements public transport by leveraging the spatial relationship between docking and subway stations. Second, it examines the short- and long-term effects of transportation network disruptions on bike-sharing adoption. Third, it investigates whether increased bike-sharing adoption leads to a reduction in subway ridership.

The central hypothesis of this study is that docking stations located within close proximity to public transport stations exhibit a higher degree of substitution compared to those outside the subway system's spatial coverage. This is because commuters can fully replace subway trips with bike-sharing when docking stations are within easy reach of subway stations. In cases of service disruptions, integrated docking stations may enable users to *bridge* interrupted connections within the transit network. Additionally, research has shown that disruptions can encourage users to develop new habits, impacting subway ridership (Goodwin, 1977; Chen & Chao, 2011; Xin et al., 2019).

The Mexican context is particularly useful for assessing this hypothesis. First, the extemporaneous variation in the supply of subway services allows a natural experimental setting that allows for causal identification of the impact of public transport disruptions. Second, Mexico City's bike-sharing model is partially integrated with the urban mobility system, with docking stations located both within and beyond the subway system's spatial coverage. Third, subway lines unaffected by the incident remained operational throughout the study period. These factors, along with the fact that only a subset of docking stations is near disrupted subway stations, allow for analysis of changes in the degree of complementarity between the two modes in response to network disruptions. Fourth, the available data enables comparison across three relevant time periods: before, during, and after the disruption, facilitating assessment of time-varying effects. Finally, bike-sharing data in Mexico City is open source, providing detailed information on every bike journey, including the geolocation of docking stations. This data makes it feasible to study the spatial integration of bike-sharing with public transport.

The findings presented here suggest that public transport disruptions are associated with increased demand for bike-sharing. On average, disruptions add approximately 3,600 bike-sharing trips per week, equivalent to 30.4% of daily bike-sharing journeys and 6.4% of weekly journeys prior to the disruption. Another noteworthy comparison is that the additional daily trip after the incident is close to 10.5% of the total bike-sharing fleet (6,800 bikes). Regarding integration with public transport, the evidence indicates that effects are stronger for docking stations within the spatial coverage of the transit network. Specifically, a 100-meter reduction in the distance between a docking station and the nearest subway station correlates with a 9.8% increase in the daily average trips per docking station.

Using geolocation data from origin and destination docking stations, I examined how the effects vary based on the degree of substitution or complementarity between bike-sharing and public transport. I identified substitution trips as bike-sharing journeys that both start and end within the spatial coverage of the subway network. In contrast, I identified complementary journeys as those that either start or end beyond the subway's spatial coverage. Results suggest that substitutional bike-sharing trips increased during the weeks of disruption, while trips complementing public transport decreased. This trend held constant for both first- and last-mile connections. Overall, the evidence indicates that commuters shifted to bike-sharing for trips that would have otherwise been completed by subway. Similarly, a lower level of complementarity between the two transport modes aligns with reduced network connectivity during the disruption.

In terms of long-term effects, estimates indicate that public transport disruptions are linked to a sustained increase in bike-sharing demand post-disruption. Following the subway's reopening, the relationship between bike-sharing and public transport showed a higher degree of complementarity for all trip types (first- and last-mile connections) and an increase in bike-sharing journeys substituting subway trips, although to a lesser extent than during the disruption period. These findings suggest that public transport disruptions led to a lasting shift toward bike-sharing.

One consideration in interpreting these findings is whether the observed effects truly reflect commuters shifting from public transport to bike-sharing. While higher levels of complementarity between the two modes can encourage multimodal behavior and reduce car dependency, disruptions might also trigger undesired modal shifts. To clarify this, I analyzed the relationship between bike-sharing usage and subway ridership displacement during network disruptions. Using spatial correlations between the two modes, my findings indicate that a 10% increase in bike-sharing journeys during disruptions raises subway inflow at integrated stations by 1.2%. After system restoration, the positive relationship persists, though the effect size decreases to 0.3%.

My findings contribute to the public debate on the development of multimodal transport systems. First, the evidence highlights the complex relationship between bike-sharing and public transport. A well-integrated bike-sharing system not only complements public transit by addressing the first- and last-mile dilemma, but it also offers a viable alternative for certain subway trips. Importantly, this substitutive capacity should not be seen as a drawback; a degree of substitution is desirable in designing resilient transport systems capable of handling disruptions. In this way, a well-integrated bike-sharing system helps safeguard public transport against unexpected shocks. Second, cities could leverage the importance of integrated docking stations to develop a rebate system that promotes intermodal travel. Third, policies that encourage users to try bike-sharing could further foster multimodal behavior. For instance, offering a trial period free of charge may incentivize users to experience bike-sharing as an alternative to private cars. Finally, the findings suggest that investment in the proper infrastructure is essential for enhancing the complementarity 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 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 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-sharing services (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 8^{th} – 10^{th}, 2015. The authors find an increase in the number and duration of bike journeys during disruption. They also find 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 filling 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). To use a bike, citizens must subscribe to one of the following plans: annual (27 USD[1]), 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.[2] 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 by 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.

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.

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[1] Exchange rate used 1 USD = 19.5 MXN.

[2] 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.

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).[3] 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 of the closest subway station and almost 50% within 500m (238 stations). In addition, some stations are integrated into 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

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

(since 2022, it is possible to recharge it using a mobile application). Concerning bike-sharing, such a 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 were 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 from systematically modifying 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

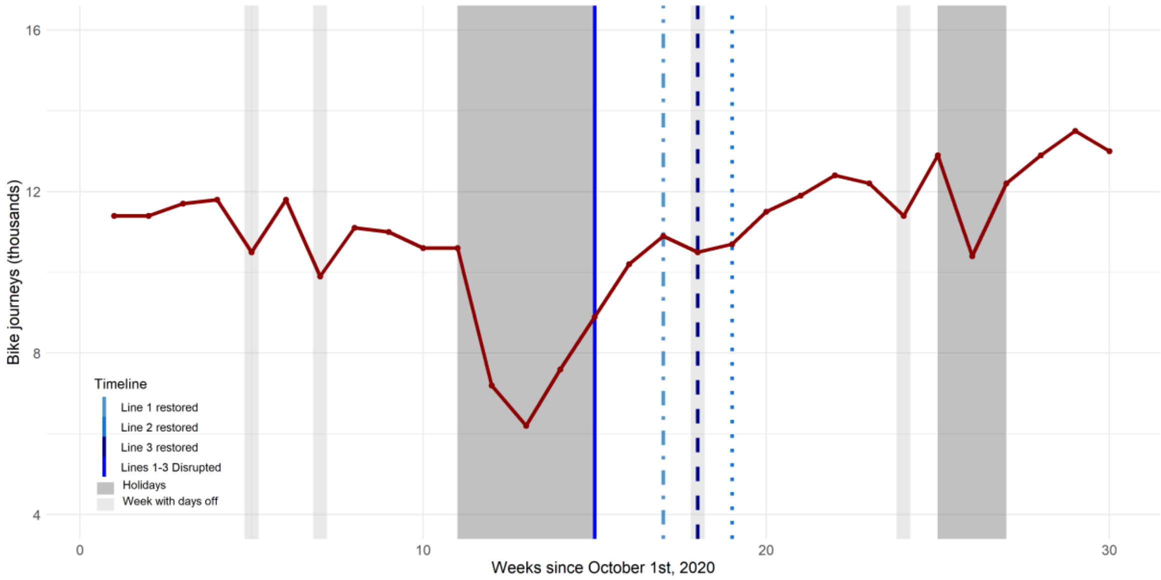
To assess the disruption effects at hand, I created an original dataset combining diverse sources of information. First, I collected journey level data in an origin-destination format, which is publicly available from ECOBICI's website. The dataset includes, among other variables, docking stations' identifiers 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.[4] 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 to 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 bikes 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 ($\approx$9:00am and $\approx$19:00pm) and a third peak that coincides with lunch time in Mexico ($\approx$15:00pm). In contrast, the volume of bike journeys during nonworking days is single peak around lunch time.

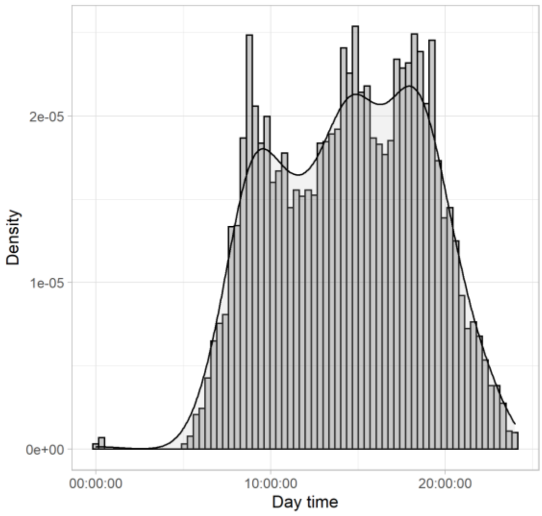
[4] As expected, Covid-19 had an important effect on the transport system in the city. The second quarter of 2020 reported a bike-sharing ridership close to 20% of the total ridership in the same quarter of 2019, the lowest value observed during the crisis (see Figure A-2 for details). A similar behavior 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.

Figure 3. Daily average of bike journeys over time



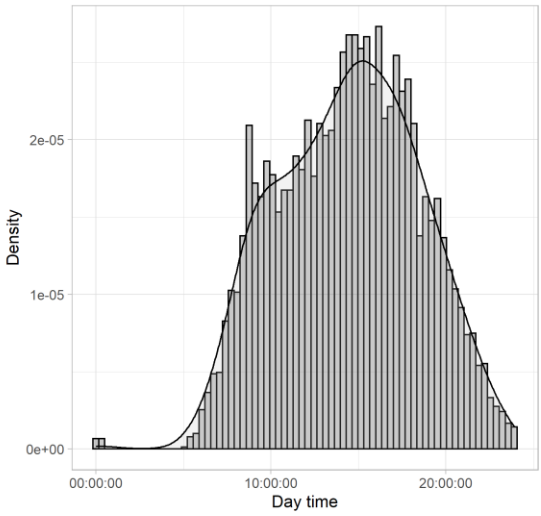
Note: The Figure reports the daily average of bike-sharing journeys each week since October 1st, 2020. Solid vertical line (in blue) shows the first week after the subway disruption on January 9th, 2021. Dashed lines show the progress restoring the network. Dark shaded regions show school vacations in 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



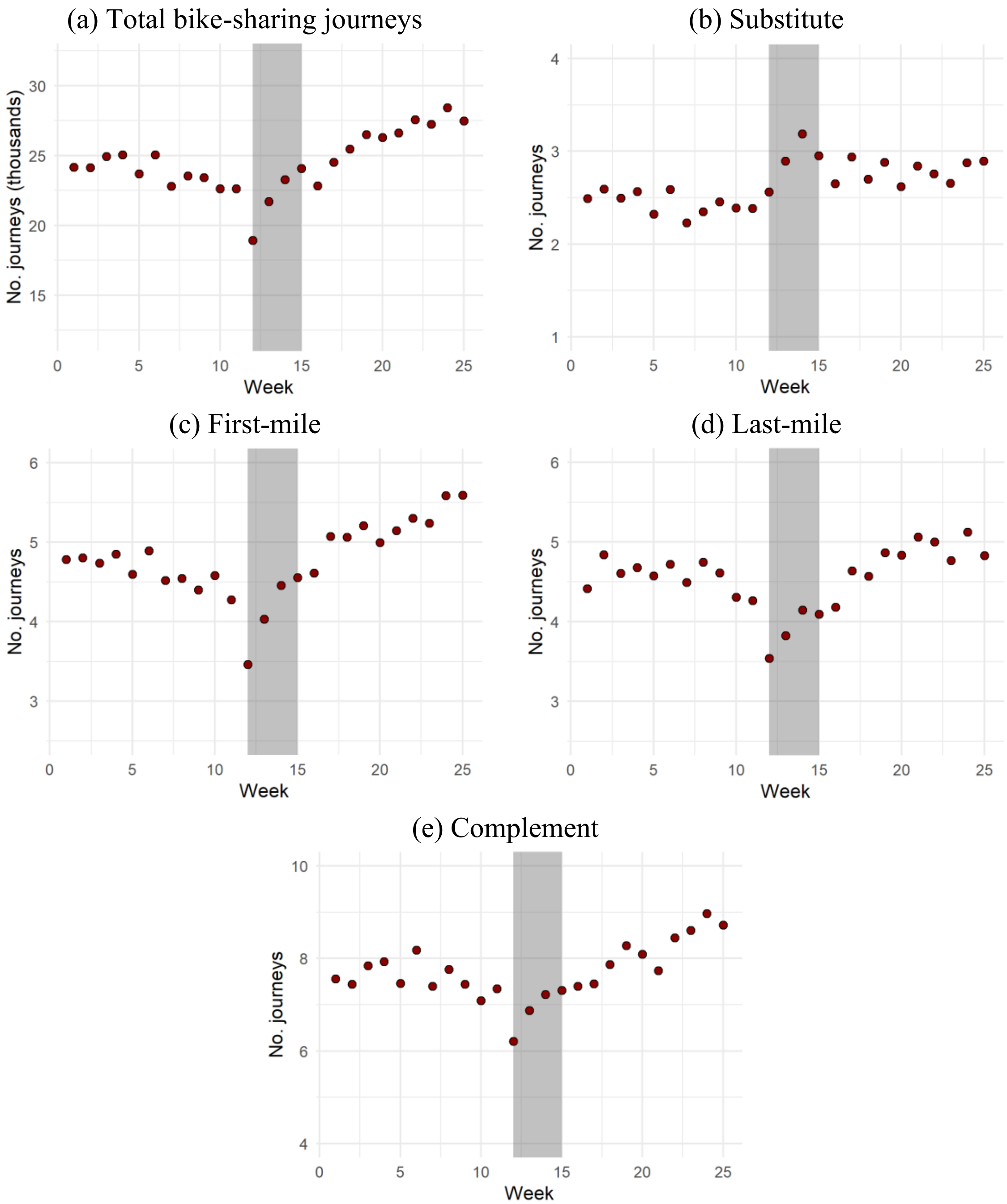
Note: The Figure reports the travel patterns of December 21st, 2020. This date was chosen to represent travel behavior during nonworking days. It shows the density in the number of journeys by hour.

Afterwards, I 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* database uses 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 into the market dynamics between bike sharing and public transport. In a nutshell, bike sharing complements public transport connecting people to the service while substitution arises 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).

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



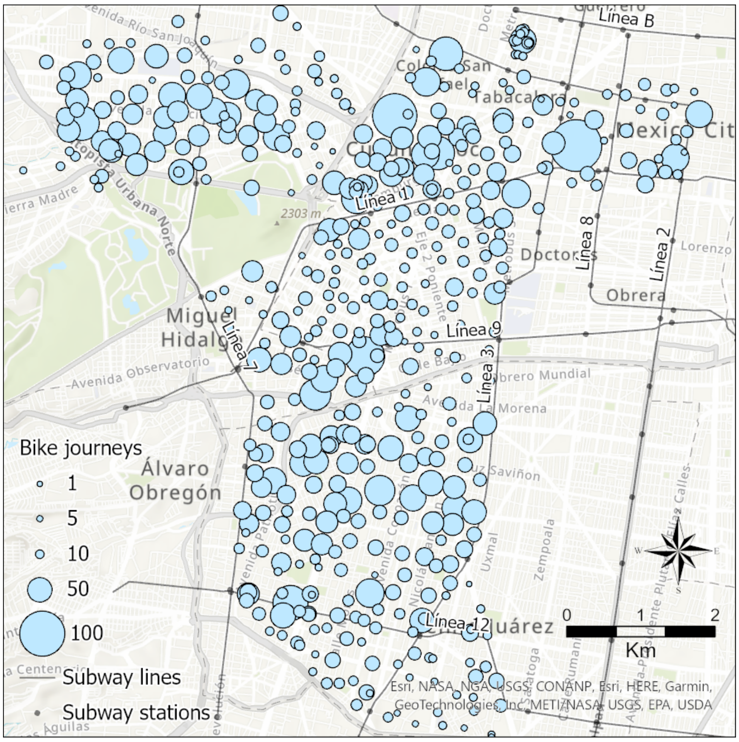
Note: The Figure reports the weekly average number of bike journeys in total and by type (in dots). The shaded region represents the weeks of subway disruption. Figure (a) pooled all the bike journeys together. Figure (b) is exclusive for substitute journeys defined as trips that start and end within 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.

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 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 (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 in 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.

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. The circle 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.

Other relevant variables for the analysis are the following. On average, the planar distance separating bike and subway stations is about 590 meters. As mentioned, such distance is key to explaining 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 especially 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 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 their 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).

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-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 control for 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, to control for this potential bias, I used the 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 caused by variations in the weather was captured including time fixed effects.

In addition to the previous approach, I dig deeper into 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

Table 1 reports the estimates of equation (1) using the logarithm of the daily number of bike journeys as the outcome of interest. 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.[5] 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. Table 2 reports 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 decrease of two daily bike journeys by station on both panels which is equivalent to a percentage decrease of -8.5%.

[5] 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.

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

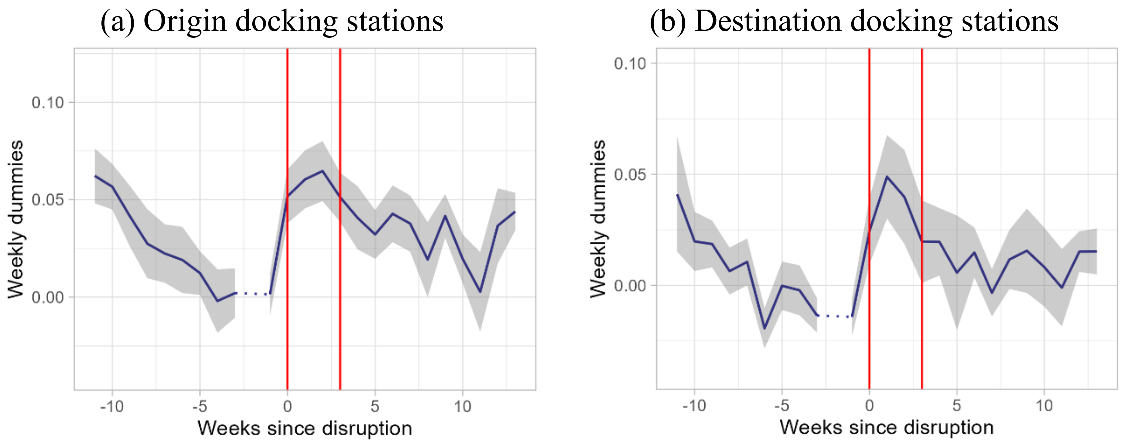
Note: The Table reports the daily average number of trips by docking stations before, during, and after public transport disruption (columns) conditional on the distance to the closest subway station (rows). It also reports the difference between the scenario during and before as well as the scenario 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.

The result is not striking, as a matter of fact, the literature on 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 destinations within the same range, the number of journeys increased by 3.3% while a decrease 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 increase in the number of journeys of about 13%-16% with respect to the scenario before disruption. A final word on the level of significance. I have 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 results. 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 overall.

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

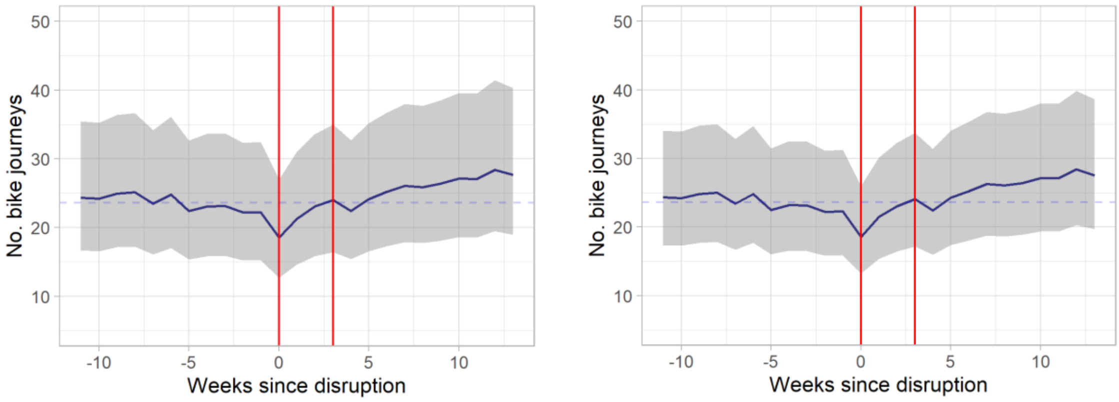


Note: The Figure reports the weekly dummy (β_q) estimates from equation (2). X-axis represents the number of weeks elapsed since the fire on January 9th, 2021. Therefore, the first week of disruption is zero. Solid vertical lines indicate the week when disruption started and the week when the system 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 throughout 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 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 near 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 differ on the inclusion of square time trends in the number of total journeys by docking station. Moreover, columns (1) to (4) report 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 do 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 contributes 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 expansion in complementary after a full 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.

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

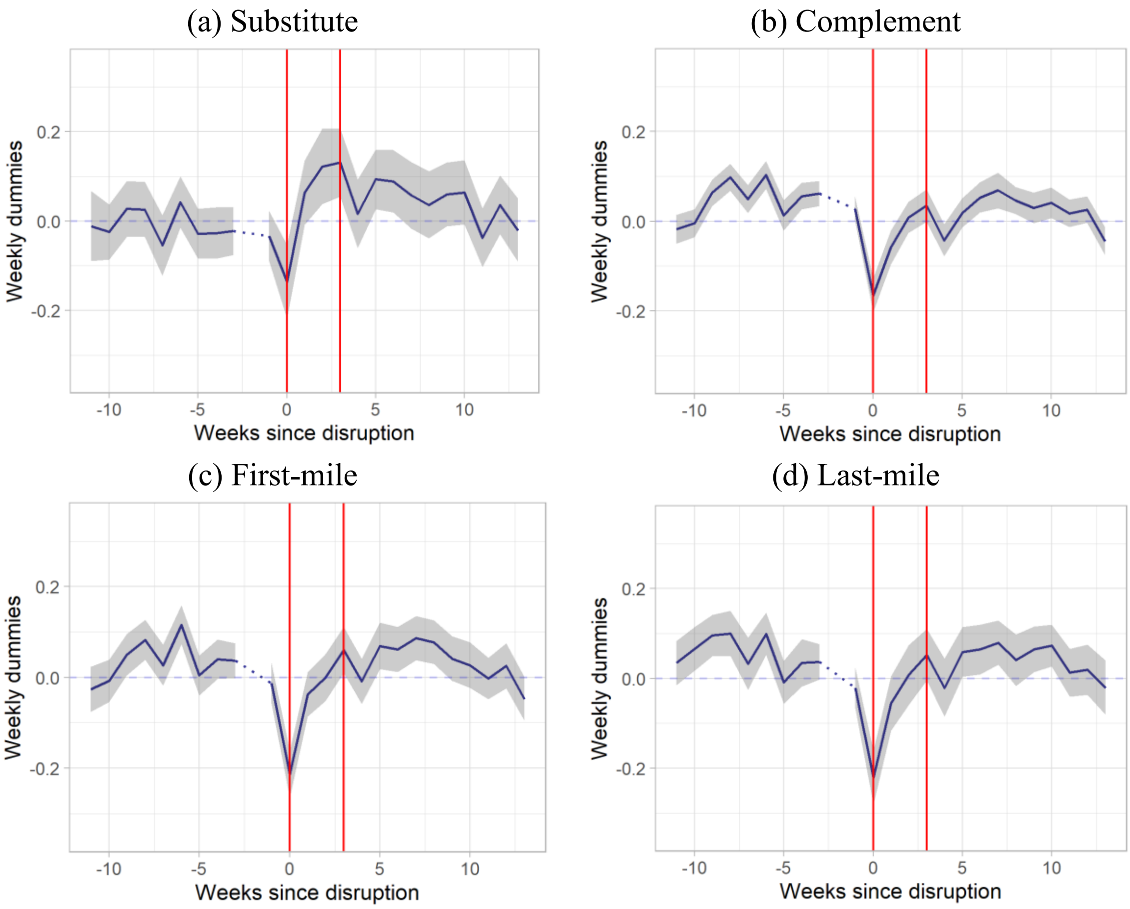
Note: The Table reports the daily average number of trips by docking stations before, during, and after public transport disruption (columns) for different types of journeys (rows). It also reports the difference between the scenario during and before as well as the scenario after and before disruption. 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 do not start nor end within the spatial coverage of the subway system.

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 because of habit formation and modal-shift.

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 indicate 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 $100 * (e^{\widehat{\beta}} - 1)$ 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 like 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.

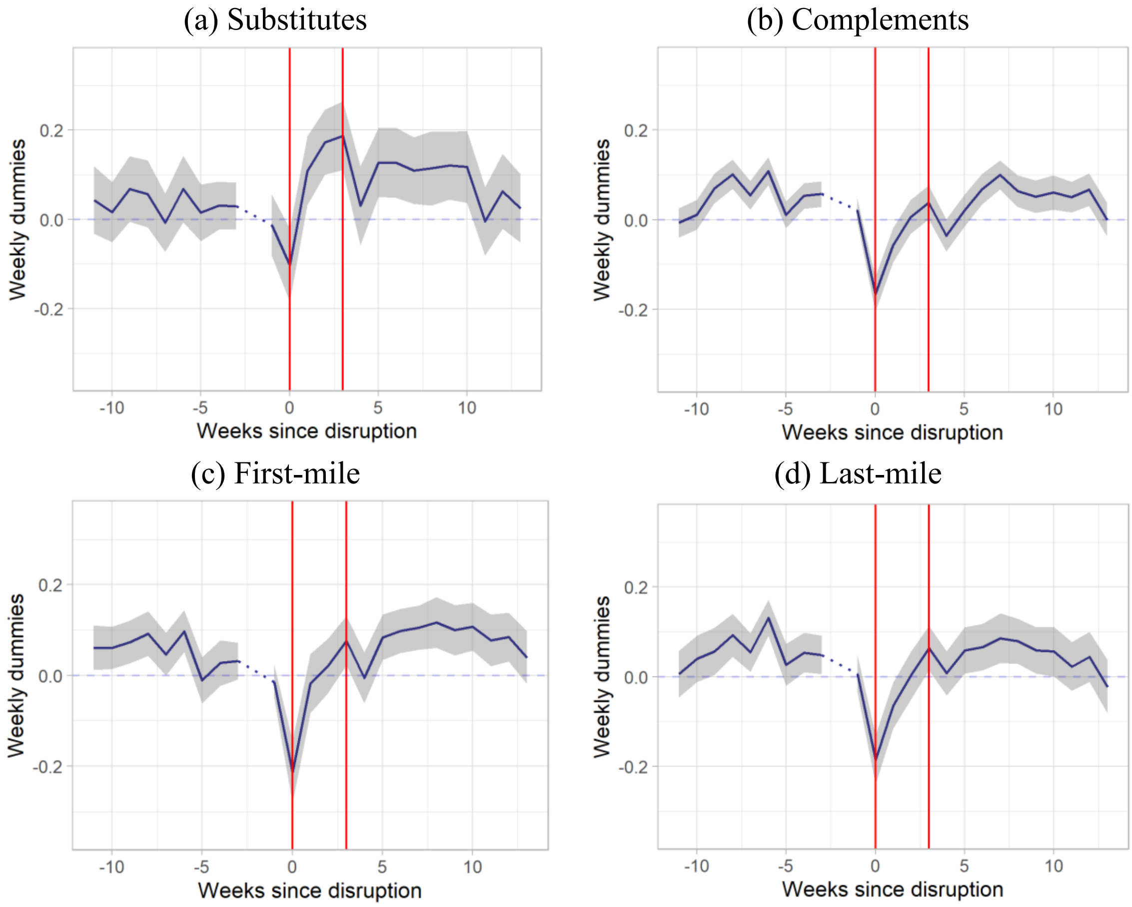
Figure 10. Time-varying effects by type of journey, docking stations at origin



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 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.

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 vanished after a couple of months. However, as I show in the previous section, the attenuation of the effects has not been translated into 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.

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 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 days 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 to 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 suggests 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 indicate 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 journey. Further research is needed to improve the identification of bike trips by 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 into 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 to 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 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 their destination. Finally, the relationship with the proper infrastructure for cycling is also important for riders, the effects seem to arise from docking stations 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 affects 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 shows 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 because 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 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 especially when only inflow ridership is considered. Moreover, bike-sharing ridership might influence the outflow of passengers in outer regions. 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*	0.124*	0.247**	0.246**	0.122***	0.122***
	(0.067)	(0.065)	(0.112)	(0.112)	(0.024)	(0.024)
During	-7.694***	-7.650***	1.491***	1.485***	-1.350***	-1.350***
	(1.044)	(1.028)	(0.289)	(0.289)	(0.126)	(0.126)
After	-2.537***	-2.584***	-0.295**	-0.301**	-0.715***	-0.716***
	(0.954)	(0.943)	(0.125)	(0.125)	(0.049)	(0.049)
ln(Bike ridership)*During	0.762***	0.756***	-0.334***	-0.334***	0.121***	0.121***
	(0.113)	(0.112)	(0.051)	(0.051)	(0.024)	(0.024)
ln(Bike ridership)*After	0.228	0.232**	-0.041***	-0.041***	0.032***	0.032***
	(0.102)	(0.101)	(0.005)	(0.005)	(0.006)	(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 lines 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 extent 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 show 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 of 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 is advised. Even if bike-sharing membership increased, the data does not allow us 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 do not start nor end within the spatial coverage of the subway system. Bike journeys 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 refers 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

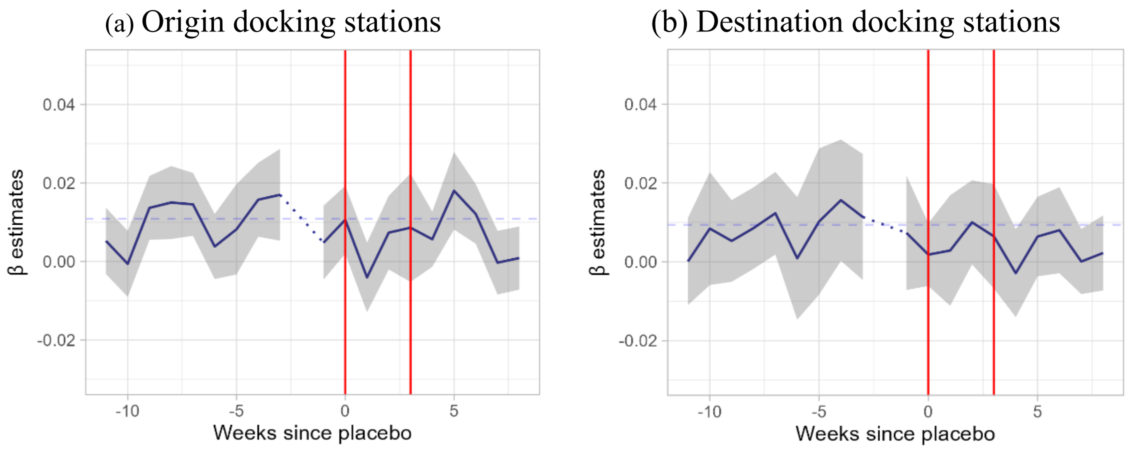
This article investigates the impact of public transport disruptions on the adoption of bike-sharing. I exploit an extemporaneous event that shut down operations in 50% of the subway lines in Mexico City in a natural experimental setting to causally identify public transport substitution to bike-sharing. 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 increase 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. In 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 market, 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 has 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.

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 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 do 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)
> Three stations	0.040	0.063^{*}	0.018	0.029^{**}
	(0.039)	(0.036)	(0.015)	(0.014)
> Nine 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 do 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 stations are considered. Significance levels are represented as follows: *p<0.1; **p<0.05; ***p<0.01.

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