

CORVINUS UNIVERSITY OF BUDAPEST



MSc Economic Analysis

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The Impact of E-Scooter Services on Urban Bike-Sharing Usage in Budapest

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Abstract

This research analyzes the influence of e-scooter sharing services on the established bike-sharing system, BUBI, in Budapest. Specifically, the research measures the impact of the introduction of Lime on the usage of BUBI. In the context of increasing demand for flexible mobility solutions, the entry of Lime e-scooters provides an alternative method of transportation. The research is focusing on the peak usage months to assess how Lime's presence has affected BUBI's usage. Analyzing transactional data provided by BKK (the operator of BUBI), the research applies a Difference-in-Differences methodology complemented by an event study approach. The event study plays an important role to verify the parallel trend assumption, an indispensable assumption for Difference-in-Differences approach suggesting that the results of this study are causal. Therefore, any change in the use of bike-sharing services can be concluded to be due to the entry of e-scooters into the market. The question of the research is: *"How does the introduction of e-scooter sharing services affect the performance of bike-sharing systems in Budapest during peak usage months?"* The results gained from the research indicate that the introduction of e-scooter services have led to a statistically significant reduction in bike-sharing usage. This reduction is more visible among single ticket users, who tend to be tourists or occasional riders, compared to pass holders, who are predominantly using the service for commuting. Specifically, although there is a relatively similar impact of around 10.5% - 11.9% reduction on weekends, ticket users show a 8.7% decrease in daily bike-sharing trips per station on weekdays, nearly double the impact observed for pass holders, suggesting that e-scooters serve as a more attractive option for casual travel.

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1 Introduction

In modern times, the rapid expansion and urbanization of cities provide unique challenges for urban mobility. Essentially, urban mobility is the means of transportation from one point of a city to another. The means of transportation can be walking, taking public transportation, riding a car or riding bicycles. Urban mobility can be categorized into two sub categories, private and public mobility. Private mobility includes privately owned motorized or non-motorized vehicles. On the other hand, public mobility includes means of transportation that are widely accessible with low barriers to use. This research will mainly focus and compare public mobility services.

Over the past decade, public bike-sharing systems (BSS) were emerging as an innovative method of public urban mobility transformation providing an affordable, practical and environmentally friendly option for short-distance travel. These systems have become a prominent feature of the modern urban landscape. In Budapest, the first public bike-sharing system, BUBI, was introduced in 2014. The goal of introducing a bike sharing system in Budapest was not only to promote physical activity but to also help ease traffic congestion.

However, public mobility services in Budapest became more competitive in May 2019 with the introduction of e-scooters operated by Lime. Sharing the same eco-friendly properties as bicycles, e-scooters also offer flexibility and efficiency as they are not required to be returned to docking stations. This helps in bridging the last mile gap in urban transportation networks (e.g., Baek et al., 2021; Nawaro, 2021; Li et al., 2022) such as covering the distance between the transit of two public transport services. In practice, while BSS requires users to return bikes to fixed docking stations, e-scooter users do not need to find a docking station and can leave scooters more freely. Consequently, dockless e-scooters provide more flexibility than docked BSS. In addition, since e-scooters are powered vehicles, they also enable longer distances to be traveled with less physical effort. These features help to lower some of the obstacles related to bike-sharing systems (Yang et al., 2021). For the above mentioned reasons, this entry of Lime raises an important question: Are e-scooters a competitor or a complement to bike-sharing systems in Budapest? Will the introduction of e-scooters affect the performance of bike-sharing and to what extent?

The rest of the research is organized as follows. Section 2 provides an overview of literature review on bike-sharing and e-scooters. Section 3 describes the background as well as the data of the analysis. Section 4 presents the research design and

methodology used in this thesis. Section 5 presents the empirical results and the robustness check. Section 6 concludes and discusses limitations and future research.

2 Literature Review

In the research field, studies that measure modal change and competition between different forms of public mobility are continuously gaining attention. An increasing amount of research indicates that the use of e-scooters and bike-sharing systems has complicated relationships, which will be described in the literature review.

2.1 E-Scooter and Bike-Sharing Interactions

Recent studies indicate that e-scooters and bike-sharing systems often serve distinct yet overlapping urban mobility needs. Urban mobility needs cover several aspects, such as safety, convenience, ease of use, accessibility and speed of the means of mobility. Individual urban mobility needs define the usage pattern of a certain service. For example, whether the service is used for spontaneous journey or regular commuting, used for shorter trips or longer journeys, whether the user purchases pass or uses the service sporadically. Research done by Almannaa et al. (2021) and Bieliński & Ważna (2020) indicate that there are visible differences in usage patterns, that while e-bikes are favored for regular commutes, e-scooters are preferred for flexible, spontaneous journeys. According to Bieliński & Ważna (2024), these trends were further increased by the COVID-19 pandemic, which disrupted the micro-mobility market in Polish cities, leading to a significant rise in e-scooter usage as they were seen as safer and more convenient in order to avoid contagion.

2.2 Comparative Studies

The operational patterns, user behavior and mobility patterns were explored by McKenzie (2019), Younes et al. (2020) and Zhu et al. (2020). Firstly, McKenzie (2019) explores the spatiotemporal activity of scooter sharing and bike sharing platforms in Washington D.C., assessing the differences of their operational patterns. These operational patterns include whether the user must pick up and return to a fixed station or can leave the vehicle freely after reaching their destination. Operational patterns also include whether the user may purchase a single ticket or a pass (and essentially become a member) and the benefits of doing so. The analysis conducted by McKenzie helps in understanding how the scooter and bike sharing services fit into urban mobility ecosystems, with the assumption that dockless e-scooters offer a direct alternative to dock-based bikes.

Secondly, expanding on McKenzie’s research, Younes et al. (2020) compares dockless scooter-sharing and station-based bike-sharing systems. The research dis-

covered that non-member bike-sharing users exhibit similar usage patterns to e-scooter users, indicating a general, but nuanced connection between usage patterns and specific membership types across the public mobility services. The research also investigated the influence of weather on user preferences in the research, indicating that scooter users demonstrated less sensitivity to weather conditions.

Lastly, Zhu et al. (2020) presented a study on the usage patterns of bike-sharing and scooter-sharing in Singapore. The research found that e-scooters outperform bike-sharing in terms of higher demands in areas like metro stations as well as higher sharing frequency and smaller fleet size. However, this also requires more maintenance due to the continuous need for repositioning of the fleet. Their analysis suggests potential for improving scooter shareability and offers policy recommendations for sustainable service development.

2.3 Micromobility’s Influence on Public Transit

Researches analyzing the broader impact of shared e-scooters reveal a complex relationship with public transportation. Ziedan et al. (2021) and Luo et al. (2021) provide empirical analyses from Louisville and Indianapolis, finding that shared e-scooters had an ambiguous impact on bus ridership. Ziedan et al. (2021) concluded that while e-scooters did not significantly reduce the number of bus passengers, but rather could potentially complement express bus routes as they serve the first and/or last mile of a trip. The results of Luo et al. (2021) show that there is a competitive relationship between e-scooters and buses if they are concentrated in downtown, but a complementary relationship also exists outside of downtown where the bus coverage is low.

On the other hand, these results are partly opposed to Campbell and Brakewood’s (2017) findings about how the introduction of bike-sharing in New York City impacted bus ridership. Their analysis suggests a significant decrease in bus trips along routes that are in the vicinity of bike-sharing docks, indicating that there is a substitution effect between bike-sharing and bus usage. Accordingly, Ma et al. (2019) also found that the introduction of a BSS can lead to reduction in bus ridership. Another analysis of Gebhardt et al. (2021) in Germany investigated the possibility of e-scooters replacing private urban mobility modes of transportation. The analysis took factors like trip length, purpose, and weather conditions and estimated that 10–15% single passenger motorized transport could be replaced by e-scooter trips.

2.4 E-scooter Impact on Bike-sharing

The effect of e-scooter sharing on bike-sharing usage was investigated in the paper by Yang et al. (2021) utilizing a Difference-in-Differences modeling approach with propensity score matching. The results showed that after the introduction of e-scooters, there was a significant decrease in bike-sharing usage. According to the results, there has been a reduction of 23.4 trips (10.2%) in weekly bike-sharing trips per station, with significant decreases in usage among both members (4.0%) and non-members (34.1%), and across different trip duration. Analyzing by gender, use by male members fell by 3.3 (3.1%), while female members saw a 2.0 (7.3%) trip reduction.

In another comprehensive urban mobility study by Cottam et al. (2023), the introduction of e-scooters has also been linked to a reduction in bike-sharing usage. At the University of Arizona, a no-ride zone was set up for e-scooters. This provided an opportunity for a natural experiment for the study. The results of the study revealed that there was a decrease of an average of 1.5 bike-sharing trips per station per day among BSS members where e-scooters were allowed and accessible. The results also underscored a preference for e-scooters over bicycles for non BSS members across all locations, and showed that e-scooters are preferred for spontaneous and leisure travel over BSS.

To summarize, there is a vast volume of research conducted on the relationship between e-scooter sharing and bike-sharing. However, there is a limited number of researches that investigate how the entry of e-scooters affects the usage of bike-sharing in magnitude. In Hungary, studies mainly focus only on bike-sharing systems or the relationship of bike-sharing with other means of transportation (e.g., Soltani et al., 2019; Bakó et al., 2020; Bucsky, 2020; Jaber et al., 2022) and there are almost no studies on e-scooters. In particular, research on the impact of e-scooters on bike-sharing, specifically focusing on the Budapest context, is absent, signaling a gap that this research addresses.

3 Data

3.1 Background

3.1.1 Bike-sharing system

Budapest’s public bike-sharing system, BUBI, was introduced in 2014 as an environmentally friendly urban transportation option. BUBI, which stands for “Budapest Bicycle,” began with 1100 bikes spread among 76 docking stations and were accessible all year round and 24 hours a day (BKK, 2014). It was designed to provide both citizens and tourists with a flexible, quick, and simple means of transportation.

Originally, the service offered a variety of ticketing choices, serving the needs of both visitors and regular commuters. These include 24-hour, 72-hour, and seven-day tickets, as well as longer-term passes for 180 or 365 days. Over time, BUBI evolved and experienced a transformation in 2021 in response to customer feedback, resulting in a significant redesign of the bicycles and price adjustment.

Subsequent to the redesign in 2021, BUBI had grown significantly with the number of docking stations nearly tripling to 208 and the number of bicycles having more than doubled, providing 2460 bicycles to users by 2024 (BUBI, 2024). This rapid growth reflects the success of the redesigned service, as evidenced by the achieving 6.6 million rentals recorded between 2014 and 2022, and a remarkable 3.4 million rentals in 2023 alone (BKK, 2022; MOL BUBI, 2024).

The current options for passes and tickets have been simplified: Monthly Pass, an Annual Pass as a membership option, and a Pay As You Go rate as a nonmembership option. The price of the Monthly Pass is HUF 1000 with the first 30 minutes of each ride free and an additional HUF 40/minute after that. The price for the Annual Pass is HUF 8500 with the same conditions. The Pay As You Go rate is HUF 40/minute and includes a 120 HUF bankcard registration fee covering the first 3 minutes of the first ride. The Monthly and Annual Pass are available only to customers with a home address in Hungary, while users with a foreign address can only use the Pay As You Go fare (MOL BUBI, 2024).

3.1.2 E-scooter system

Starting on May 1st, 2019, Lime, an international company well-known for its e-scooter sharing system, started its operations in Budapest with a test phase. 200 e-scooters were made accessible to users during Lime’s test phase in Budapest (Budapest Business Journal, 2019). These could be located and unlocked through the

Lime app within a limited area (marked as green zone in the app’s map) that spanned certain sections along the Danube riverbanks and nearby areas. Unlike the bike-sharing system where the bikes must be picked up and returned to the docking stations, e-scooter users can drop them off anywhere within the designated service zone after use. The introduction of Lime into Budapest provides a natural experiment, particularly as it began with a geographically constrained test phase, to assess the effect of its entry on bike-sharing system ridership. The underlying assumption is that the unrestricted and flexible parking feature of e-scooters compared to the docking requirement for bike-sharing systems might influence user preference and transportation habits. The natural experiment offers an opportunity for research on this flexibility’s influence as well as changes in the users’ usage patterns.

3.2 Data description

3.2.1 Transactional data from BUBI

The BSS related data for this study was provided by my supervisor Bakó Barna, which includes detailed records of daily trip volumes from each bike-sharing station across the entire city. This valuable data set contains information on each bike trip, including the date, starting and ending time of the trip, starting point and destination, as well as the ticket type (pass or ticket), offering a clear picture of how the system is used throughout the city. In order to conduct a thorough analysis, these individual station data points are aggregated to the station level. This aggregation process results in a consolidated measure of daily bike-sharing usage, denoted as Q_{st} which represents the quantity of trips for station s on day t .

3.2.2 Weather data

Incorporating weather data into regression analysis is important for better understanding urban mobility patterns, where weather conditions significantly influence the number of bike-sharing trips (e.g., Bakó et al., 2020; Younes et al., 2020; Hosseinzadeh et al., 2021), acting as an important control variable that helps isolate the effects of e-scooter introduction. By controlling for weather conditions (temperature, precipitation, humidity, wind speed, and solar radiation), the analysis can more accurately attribute changes in BSS performance to e-scooters, beyond the natural fluctuations caused by weather. Since the effects of temperature and precipitation on the bike usage are not linear, therefore intervals of 5°C and 5mm were created for daily temperature and precipitation data, respectively (Bakó et al., 2020). Data on other weather conditions was used without any modification.

The data for weather conditions was collected from a publicly available database in Visual Crossing Weather.

3.3 Sample construction

This study focuses on the utilization patterns of BSS during the peak usage months from April to September, between the years 2018 and 2019. This period was specifically chosen to align with the findings of Jaber et al. (2022) and Bakó et al. (2022), who found a significant seasonal variation in BSS usage, with the highest activity observed during the summer months. The selection of this time period is further justified by the introduction of e-scooters in May 2019, offering a unique opportunity to assess their impact on BSS dynamics within an urban setting.

In accordance with the usage patterns reported in previous studies (e.g., El-Assi et al., 2017; McKenzie, 2019; Bakó et al., 2020; Ma et al., 2020; Yang et al., 2021), the analysis will also be divided into two subsamples: weekday and weekend. This breakdown addresses the different nature of BSS usage in Budapest as on weekdays, it primarily serves commuting purposes, while weekend usage is characterized by leisure and recreational activities (Bakó et al., 2020). Such a division enables a comparative analysis, recognizing the different motivations and patterns of BSS users across different days of the week. In addition, it is also important to split the data one more time into two subsamples: regular users (who buy passes) and casual users (who buy tickets). This distinction allows for a more detailed measurement of the changes in their usage pattern, which can differ significantly between weekdays and weekends, potentially revealing different trends and preferences after the entrance of e-scooters.

Table 1: Number of trips for summer months (2018-2019)

Ticket type	Weekday	Weekend	Total
Pass	307,864	80,615	388,479
Ticket	54,825	32,535	87,360
Total	362,689	113,150	475,839

Notes: Summer months include April – September.
District 5 was excluded from the dataset.

Following the cleaning of the data, the database contains 475,839 trips as shown in Table 1. District 5 has been removed from the dataset due to its questionable features, which will be explained in the next section. Apparently, pass users account for the majority of the trip volume (82%), while only 18% of the usage was associated

with ticket users. The utilization on weekdays is 3.2 times higher than on weekends, especially for pass users, who travel 3.8 times as frequently on weekdays compared to weekends. This is consistent with earlier research (e.g., El-Assi et al., 2017; McKenzie, 2019; Bakó et al., 2020; Ma et al., 2020; Yang et al., 2021) that the consumption of bikes is different between weekdays and weekends.

Table 2 summarizes the data used within the study. On average, there are more trips per station from pass users on weekdays, which can be attributed to commuting.

Table 2: Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max
No. of trips per station for passes (weekdays)	10.59	8.613	1	82
No. of trips per station for passes (weekends)	7.409	7.099	1	87
No. of trips per station for tickets (weekdays)	4.223	4.657	1	53
No. of trips per station for tickets (weekends)	5.422	6.191	1	103
Holiday (dummy)	.033	.179	0	1
Temperature ($^{\circ}\text{C}$)	19.676	4.541	6.6	27.6
Humidity (%)	66.438	11.003	35.7	96.9
Precipitation (mm)	1.818	5.981	0	61.357
Wind Speed (kph)	10.285	3.427	4.7	27.7
Solar Radiation (W/m^2)	217.696	73.682	24.1	343.2

4 Research Design and Methodology

The methodological approach used in this thesis is the Difference-in-Differences (DID) estimation, which is one of the most widely used methods for assessing the impact of policy and business interventions using observational data. The DID method compares the changes in outcomes over time between a treatment group that receives an intervention (in this case, the introduction of e-scooters) and a control group that does not. In this study, it examines how the use of bike-sharing changed before and after e-scooters were introduced. By applying the DID approach, the study aims to isolate the impact of e-scooters on BSS performance from other confounders. Assuming that both groups would have followed similar trends in the absence of the treatment, any changes in BSS performance in the treatment group relative to the control group can be attributed to the introduction of e-scooters.

This methodology allows for a robustness check on the causal effect of e-scooters on BSS, assuming that the parallel trends assumption (PTA) holds - that is, in the absence of the introduction of e-scooters, the BSS performance would have followed a similar trend in both treatment and control groups. Later in this thesis, findings from this method and additional robustness check will be conducted to ensure our assumptions hold true. This is important to confirm that the results are robust and reliable.

Two distinct groups, a treatment group and a control group were set up within the study, categorized based on the presence of e-scooters and BSS in specific stations:

Treatment Group: This group includes bike stations within a 50-meter radius of the green zone on Lime’s app map, indicating the presence of e-scooters. The presence of e-scooters in these stations is considered the “treatment” because the study is interested in observing the impact of this new transportation method on the existing BSS. The 50m location restriction ensures that the treatment group is confined to locations where the choice between using a bicycle and an e-scooter is most apparent, thereby allowing for an in-depth analysis of behavior changes and the potential substitution between bikes and e-scooters. Specifically, the stations in the treatment group belong to districts 1, 5, 9, and 11. However, the study excludes District 5 from the treatment group, as it later, while still within the summer period of the study, became a red zone where e-scooter usage is heavily restricted. This elimination is necessary to ensure the integrity of the analysis, as regulatory changes in District 5 could bias the assessment of the impact of e-scooters on BSS usage. Therefore, the regression model will be more robust when run the regression without

data from this district.

Control Group: This group consists of stations from districts where only the BSS operates and no e-scooter services are present. These districts include 2, 3, 6, 7, 8, 12, 13, and 14. The control group serves as a benchmark to understand the performance of BSS without the influence of e-scooters.

In this thesis, the impact of e-scooter entry on BSS performance is examined through a regression framework, employing two outcome variables to capture different dimensions of BSS utilization across stations over time. The first outcome variable, Q_{st} , represents the actual count of daily trips in each station s on day t . This variable allows for an assessment of the absolute impact of e-scooter presence on BSS trip frequency, providing a direct measure of changes in usage volume. The second outcome variable, $\log(Q_{st})$, is the natural logarithm of the daily trip count. The logarithmic transformation stabilizes the variance of trip counts and normalizes their distribution, enabling the use of a log-linear regression model. In this model, the coefficients can be interpreted as the proportional effect of the independent variables on BSS usage, particularly useful for understanding the relative change due to e-scooter introduction.

The baseline regression specification is thus defined as:

$$Y_{st} = \alpha_s + \beta Entry_{st} + \gamma X_{st} + \delta_s + \mu_t + \varepsilon_{st} \quad (1)$$

where s and t indicate station and day, respectively; Y_{st} is the outcome variable, measured as either Q_{st} or $\log(Q_{st})$ depending on the model; $Entry_{st}$ is the key regressor of interest that equals 1 if e-scooters are operational in station s on day t , capturing the treatment effect; X_{st} encompasses control variables, including weather conditions and other relevant factors, to account for additional influences on BSS demand; δ_s and μ_t represent station and time fixed effects, respectively, controlling for unobserved heterogeneity and temporal patterns; ε_{st} is the error term. This regression will be run for all subsamples of the study.

The fixed effects capture station-specific characteristics and broader temporal trends, such as year and month variations as well as holiday effects, ensuring that the model accurately isolates the impact of e-scooters from these confounding factors. The differentiation between the samples of weekday - weekend as well as regular - casual users addresses the potential for distinct usage behaviors of different types of customers on these days, allowing for a more detailed analysis.

The primary variable of interest, β , captures the marginal effect of e-scooter entry on the number of BSS trips, providing crucial insights into the competitive

or complementary dynamics between these two modes of urban transportation. By analyzing both absolute and relative changes through Q_{st} and $\log(Q_{st})$, the thesis offers a robust evaluation of e-scooter entry's implications for urban mobility and BSS performance.

5 Results and Discussions

5.1 Regression results

Table 3 presents the results of a regression analysis on the impact of e-scooter entry on daily bike performance in Budapest among all users, where the number of trips and the natural logarithm of trips are the outcome variable, with separate models for weekdays and weekends. The coefficient on *Entry* captures the impact of the introduction of e-scooters on the number of BSS trips. The significant negative coefficients in all models suggest that the entry of e-scooters lead to a decrease in bike-sharing trips.

While controlling for only station effects, for both weekdays and weekends (Models 1 and 2), the *Entry* coefficient is negative and statistically significant at the 1% level. In numbers, the entry of e-scooters resulted in a decrease by 7.34 and 6.35 daily bike trips per station during weekdays and weekends, respectively. In Models 3 and 4, additional controls are included to account for seasonal trends and other temporal variations in bike performance. Despite these additional controls, the negative impact of e-scooter entry on BSS trips still persists but smaller in magnitude, with an average decrease of about 3.38 daily trips per station during weekdays and 3.01 daily trips on weekends.

The log-transformed specifications from models 5 to 8 allows the coefficients to be interpreted as percentage changes. The coefficient of the *Entry* variable still remains negative and statistically significant at 1% level across all specifications. Since the outcome variable is in logarithm, this indicates that the introduction of e-scooters ($Entry = 1$) is associated with a decrease in the natural logarithm of bike-sharing trips by approximately 0.422 in model 5. To express this effect as a percentage change, a transformation $\exp(-0.422) - 1$ is applied, which yields a 34.42% decrease in daily bike-sharing trips per station due to the entry of e-scooters for weekdays. This significant negative coefficient signifies a competitive relationship where e-scooters likely substitute some bike-sharing usage. The impact is relatively similar on weekends (model 6), with a 37.75% decrease in the number of trips. However, when controlling for time fixed effects and other confounders (model 7 and 8), BSS usage is lower by approximately 6.01% and 12.1% in the number of daily trips per station on weekdays and weekends, respectively. Notably, after adding more control variables, the impact of e-scooter entry on bike-sharing is more significant on weekends when the number of bicycles used per station on weekends decreases by 12.1%, which is double than the decrease on weekdays.

Table 3: Regression results for all users

VARIABLES	Number of Trips				Log(Trips)			
	(1) Weekday	(2) Weekend	(3) Weekday	(4) Weekend	(5) Weekday	(6) Weekend	(7) Weekday	(8) Weekend
Entry	-7.337*** [0.242]	-6.347*** [0.382]	-3.381*** [0.226]	-3.014*** [0.366]	-0.422*** [0.016]	-0.474*** [0.031]	-0.062*** [0.015]	-0.129*** [0.031]
Holiday			-1.711*** [0.295]	-0.585 [0.424]			-0.277*** [0.024]	-0.103*** [0.034]
Temperature 5 – 10°C			-4.535*** [0.245]	-5.285*** [0.491]			-0.515*** [0.024]	-0.467*** [0.049]
Temperature 10 – 15°C			-2.195*** [0.142]	-3.278*** [0.278]			-0.159*** [0.013]	-0.299*** [0.027]
Temperature 15 – 20°C			0.060 [0.098]	-0.134 [0.192]			0.034*** [0.008]	-0.010 [0.016]
Temperature ≥ 25°C			-1.500*** [0.115]	-0.555*** [0.193]			-0.109*** [0.010]	-0.027 [0.022]
Humidity			-0.065*** [0.005]	-0.070*** [0.009]			-0.006*** [0.000]	-0.005*** [0.001]
Precipitation 0 – 5mm			0.357*** [0.088]	-0.189 [0.161]			0.041*** [0.008]	0.026 [0.016]
Precipitation ≥ 5mm			-1.214*** [0.172]	-0.770*** [0.253]			-0.146*** [0.017]	-0.089*** [0.027]
Wind speed			-0.129*** [0.010]	-0.091*** [0.018]			-0.009*** [0.001]	-0.007*** [0.002]
Solar radiation			0.011*** [0.001]	0.009*** [0.002]			0.001*** [0.000]	0.002*** [0.000]
Tuesday			0.785*** [0.106]				0.094*** [0.009]	
Wednesday			1.069*** [0.105]				0.120*** [0.009]	
Thursday			1.203*** [0.104]				0.131*** [0.009]	
Friday			1.141*** [0.106]				0.116*** [0.010]	
Sunday				-0.820*** [0.116]				-0.087*** [0.011]
Constant	33.532*** [0.678]	27.122*** [1.048]	36.868*** [0.735]	34.908*** [1.322]	3.504*** [0.030]	3.288*** [0.050]	3.696*** [0.046]	3.718*** [0.095]
Observations	29,204	11,164	29,204	11,164	29,204	11,164	29,204	11,164
R-squared	0.617	0.610	0.708	0.686	0.542	0.531	0.666	0.626
Station Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	No	No	Yes	Yes	No	No	Yes	Yes

Notes: Time fixed effects include month and year fixed effects. Reference category for daily temperature is 20°C - 25°C interval, for precipitation is 0 mm. Robust standard errors in brackets.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

This pronounced divergence could be attributed to different travel patterns. A higher decline on weekends could reflect a change in usage pattern, in which there is a greater shift to e-scooters for leisure activities or as part of a recreational experience.

Table 4 presents regression results specifically for pass holders of a bike-sharing system to assess if their usage pattern changed due to the introduction of e-scooters. The *Entry* variable, shows a significantly negative coefficient in all model specifications at 1% level, similar to the combined user group in table 3. However, the magnitude of the decrease in trips and $\log(\text{trips})$ among pass holders is smaller compared to the combined group, indicating that regular users may be slightly less influenced by the availability of e-scooters than casual users.

In the models with control variables, results show that the presence of e-scooters resulted in a 2.98 on weekdays and 2.12 on weekends decrease in the average daily bike-sharing trips per station among regular holders. This translates to a decrease by about 5.16% and 10.5% in the number of daily trips per station for weekdays and weekends, respectively. Similarly, the effect among pass holders also experienced a doubled effect on weekends, indicating a shift to e-scooters for leisure activities.

The consistently significant negative coefficients across all specifications indicate that the introduction of e-scooters is associated with a reduction in bike-sharing usage among pass holders, albeit less than that observed in the all users' sample. This suggests that while e-scooters do present competition to bike-sharing systems, however, pass holders, who may represent more committed or habitual users, are not as readily substituting bike-sharing with e-scooter use.

In Table 5, the regression results for ticket users also reveal a significantly negative effect of e-scooter entry on bike-sharing performance among all specifications. The reduction in average daily trips per station is much smaller in magnitude compared to the results for pass holders, with just around 1 trip reduced per station per day. In terms of the percentage reductions, the results indicate a considerable decline on weekends by 11.93%, while on weekdays the trip volume reduces by approximately 8.7% per station per day. The larger effect on weekends also suggests that ticket users are substituting bike-sharing with e-scooters more during their leisure time than during weekdays.

It should be noted that the impact of 8.7% is nearly double compared to the weekday effect for pass holders, which is about 5.16%, suggesting that ticket users, who may predominantly be tourists or occasional riders, are more likely to switch to e-scooters than regular users. This could be due to the convenience and flexible

Table 4: Regression results for pass holders

VARIABLES	Number of Trips				Log(Trips)			
	(1) Weekday	(2) Weekend	(3) Weekday	(4) Weekend	(5) Weekday	(6) Weekend	(7) Weekday	(8) Weekend
Entry	-6.630*** [0.214]	-4.875*** [0.302]	-2.982*** [0.198]	-2.122*** [0.290]	-0.432*** [0.016]	-0.482*** [0.033]	-0.053*** [0.016]	-0.111*** [0.033]
Holiday			-2.911*** [0.245]	-2.643*** [0.262]			-0.415*** [0.025]	-0.350*** [0.036]
Temperature 5 – 10°C			-3.388*** [0.202]	-3.091*** [0.368]			-0.449*** [0.024]	-0.405*** [0.054]
Temperature 10 – 15°C			-1.505*** [0.122]	-2.266*** [0.211]			-0.127*** [0.013]	-0.278*** [0.029]
Temperature 15 – 20°C			0.263*** [0.085]	0.181 [0.144]			0.046*** [0.008]	0.021 [0.017]
Temperature ≥ 25°C			-1.028*** [0.099]	-0.129 [0.152]			-0.084*** [0.011]	-0.019 [0.023]
Humidity			-0.053*** [0.004]	-0.036*** [0.007]			-0.006*** [0.000]	-0.002** [0.001]
Precipitation 0 – 5mm			0.309*** [0.077]	0.029 [0.126]			0.039*** [0.008]	0.028* [0.017]
Precipitation ≥ 5mm			-1.094*** [0.147]	-0.756*** [0.199]			-0.136*** [0.017]	-0.136*** [0.028]
Wind speed			-0.114*** [0.009]	-0.047*** [0.014]			-0.009*** [0.001]	-0.004** [0.002]
Solar radiation			0.009*** [0.001]	0.007*** [0.001]			0.001*** [0.000]	0.001*** [0.000]
Tuesday			0.948*** [0.090]				0.118*** [0.010]	
Wednesday			1.245*** [0.089]				0.151*** [0.010]	
Thursday			1.289*** [0.089]				0.157*** [0.010]	
Friday			0.818*** [0.089]				0.112*** [0.010]	
Sunday				-0.476*** [0.091]				-0.069*** [0.012]
Constant	26.781*** [0.556]	17.104*** [0.709]	29.329*** [0.603]	21.320*** [0.974]	3.262*** [0.031]	2.787*** [0.054]	3.428*** [0.046]	3.031*** [0.102]
Observations	29,071	10,881	29,071	10,881	29,071	10,881	29,071	10,881
R-squared	0.593	0.490	0.698	0.593	0.510	0.432	0.645	0.548
Station Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	No	No	Yes	Yes	No	No	Yes	Yes

Notes: Time fixed effects include month and year fixed effects. Reference category for daily temperature is 20°C - 25°C interval, for precipitation is 0 mm. Robust standard errors in brackets.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 5: Regression results for ticket users

VARIABLES	Number of Trips				Log(Trips)			
	(1) Weekday	(2) Weekend	(3) Weekday	(4) Weekend	(5) Weekday	(6) Weekend	(7) Weekday	(8) Weekend
Entry	-0.772*** [0.165]	-2.123*** [0.291]	-0.467*** [0.171]	-1.232*** [0.300]	-0.147*** [0.030]	-0.264*** [0.042]	-0.091*** [0.031]	-0.127*** [0.045]
Holiday			1.691*** [0.210]	2.573*** [0.452]			0.316*** [0.032]	0.318*** [0.045]
Temperature 5 – 10°C			-1.964*** [0.244]	-3.176*** [0.513]			-0.351*** [0.051]	-0.340*** [0.075]
Temperature 10 – 15°C			-1.081*** [0.138]	-1.471*** [0.283]			-0.160*** [0.025]	-0.192*** [0.041]
Temperature 15 – 20°C			-0.398*** [0.092]	-0.531*** [0.183]			-0.066*** [0.016]	-0.050*** [0.025]
Temperature ≥ 25°C			-0.831*** [0.106]	-0.757*** [0.187]			-0.153*** [0.020]	-0.094*** [0.033]
Humidity			-0.025*** [0.004]	-0.054*** [0.009]			-0.004*** [0.001]	-0.007*** [0.001]
Precipitation 0 – 5mm			0.110 [0.081]	-0.311* [0.163]			0.020 [0.015]	-0.029 [0.026]
Precipitation ≥ 5mm			-0.080 [0.171]	0.077 [0.247]			-0.042 [0.035]	0.033 [0.039]
Wind speed			-0.025** [0.010]	-0.056*** [0.017]			-0.004** [0.002]	-0.010*** [0.003]
Solar radiation			0.003*** [0.001]	0.002 [0.002]			0.001*** [0.000]	0.000 [0.000]
Tuesday			-0.319*** [0.099]				-0.055*** [0.018]	
Wednesday			-0.395*** [0.099]				-0.083*** [0.019]	
Thursday			-0.298*** [0.099]				-0.069*** [0.018]	
Friday			0.448*** [0.102]				0.077*** [0.018]	
Sunday				-0.565*** [0.109]				-0.084*** [0.017]
Constant	7.347*** [0.344]	10.549*** [0.615]	9.208*** [0.536]	16.079*** [1.101]	1.736*** [0.051]	2.152*** [0.075]	1.978*** [0.096]	2.879*** [0.152]
Observations	12,981	6,001	12,981	6,001	12,981	6,001	12,981	6,001
R-squared	0.426	0.511	0.466	0.552	0.404	0.462	0.444	0.496
Station Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	No	No	Yes	Yes	No	No	Yes	Yes

Notes: Time fixed effects include month and year fixed effects. Reference category for daily temperature is 20°C - 25°C interval, for precipitation is 0 mm. Robust standard errors in brackets.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

nature of e-scooters, which may better serve the needs of tourists when exploring the city.

In summary, there is a clear difference in the behavior change between the two groups, while pass holders exhibit a smaller decrease in usage, likely because their travel purpose is more likely linked to commuting patterns that may not be easily replaced by e-scooters. On the other hand, ticket users exhibit a larger decrease, suggesting a higher degree of substitution effect between e-scooters and bike-sharing for non-regular rides. This finding is consistent with the finding of previous studies that e-scooter sharing has a competitive relationship with bike-sharing, especially for ticket users (Younes et al., 2020; Yang et al., 2021; Cottam et al., 2023). In addition, the finding that the introduction of e-scooter has the largest impact on weekends for ticket users (11.93% reduction) and the lowest impact on weekdays for pass holders (5.16% reduction) also suggest that the main purpose of e-scooter usage are more likely for recreational use instead of commuting (Caspi et al., 2020; Reck et al., 2021; Yang et al., 2021).

5.2 Event Study

DID relies on the assumption of parallel trend assumption (PTA), which assumes that, absent the intervention, the average outcome in treated group will change in the same way as in untreated group. However, the PTA’s verification requires the counterfactual outcome - what would have happened without the intervention, which is inherently unobservable. To infer the validity of the PTA, researchers often examine pre-treatment trends. If outcomes in both treated and untreated groups follow similar paths before the intervention, it gives an indirect evidence that PTA holds, suggesting that observed post-treatment differences can be attributed to the intervention. This comparison is typically operationalized through an event-study regression (e.g., Jacobson et al., 1993; Li et al., 2016; Cao et al., 2021), in which the pre-treatment trends can be tested through the following equation:

$$Y_{st} = \alpha_s + \beta_{-k} \sum_{k=1}^{28} A_{sk} + \gamma X_{st} + \delta_s + \mu_t + \varepsilon_{st} \quad (2)$$

where A_{dk} is a set of dummies ($A_{dk} = 1$) indicating that date t is k days before the entry day of e-scooters into station s . An interval of 28 days is set as a cutoff (e.g., Cao et al., 2021) and all days greater than 4 weeks prior to Lime’s entry will be pooled together as $k = 28$. The omitted time category is the day of entry ($k = 0$). Additional controls X_{st} as well as station (δ_s) and time fixed effects (μ_t) are also

included to allow for more flexible specification. The parameter of interest β_{-k} is the effect of the introduction of e-scooters k days up to 4 weeks before its occurrence. If the two groups of stations (treatment and control groups) follow similar time trends at least 28 days before the Lime's entry, none of the parameters β_{-k} should show any statistically significant value.

Figure 1 and 2 reports the estimation results from the event study. The first figure shows the coefficients for the average daily trips per station, while the second one displays the coefficients in terms of percentage change. Both graphs plot these coefficients for the days prior to the entry of e-scooters, with the reference referring to the day e-scooters were introduced ($k = 0$). Point estimates of β_{-k} ($k = 1, 2, 3, \dots, 28$) are plotted on the horizontal axis, and the vertical lines represent the 95% confidence intervals for each coefficient estimate.

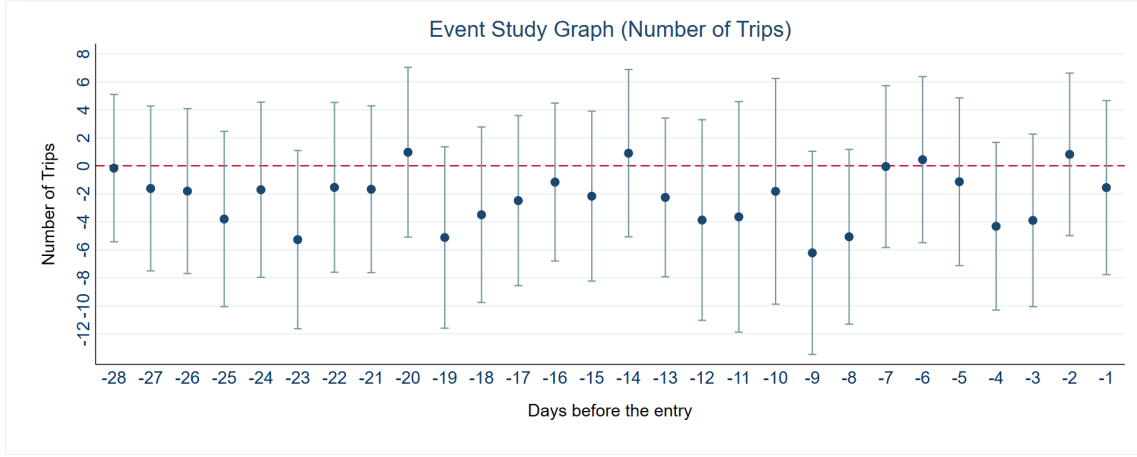


Figure 1: Parallel Trend Assumption Test (Number of Trips)

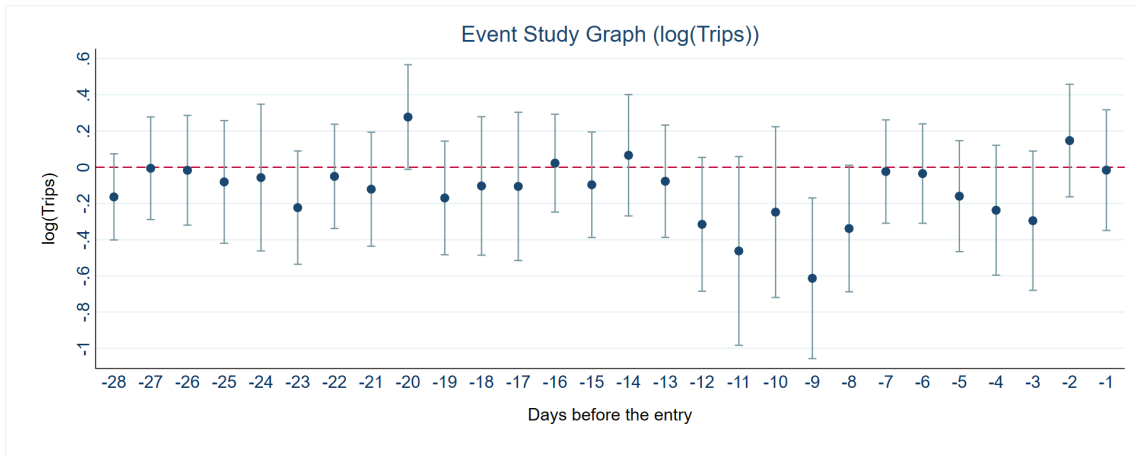


Figure 2: Parallel Trend Assumption Test (Log of Trips)

In figure 1, none of the pre-event coefficients appear to be statistically significantly different from zero, as the 95% confidence intervals cross the dashed zero line, suggesting that the treatment and control groups followed similar trends before the intervention. The figure 2 for $\log(\text{Trips})$ also shows the similar outcomes as almost all estimates are statistically indistinguishable from zero at 95% confidence intervals.

In summary, both graphs serve as a pre-test to prove that the PTA required for DID approach holds, showing that before the introduction of e-scooters, there was no significant difference in the trend of bike-sharing usage between treatment and control groups. The stability of the pre-event coefficients suggests that any post-event deviations from zero can be attributed to the entry of e-scooters rather than other unobserved factors.

6 Conclusion

This thesis measured the impact of the introduction of e-scooters Lime on the performance of Budapest’s bike-sharing system, MOL BUBI. The study employed a Difference-in-Differences methodology to isolate the effects of e-scooters entry from other variables and found a statistically significant reduction in bike-sharing usage. The event study serves as a robustness check to conclude that the introduction of e-scooters did have a causal effect on the reduction in bike-sharing trip volume but not just a negative correlation. Results show that e-scooters created substitution for bike-sharing for both pass holders and ticket users, as well as on weekdays and weekends. However, the magnitude of the effect in each category is different. The smallest negative impact was for pass users using BUBI on weekdays (5.16%) but appeared to be the most pronounced among ticket users on weekends (11.93%). A potential explanation for this difference can be derived from the fact that weekday pass holders are primarily commuters, while ticket users are often tourists or infrequent riders. To ticket users, e-scooters offer a more flexible and appealing option for casual and recreational travel. It should be noted that the presence of e-scooters also led to a decline in trip volume among BSS ticket users on weekdays, however, the effect was lower compared to weekends by 3.23 percentage points

Although this study provided new insights into the impact of e-scooter entry on bike-sharing ridership in Budapest, there are still some limitations within the research giving the opportunity for further research in this topic.

Firstly, this study currently analyzes e-scooter impact on a daily level but does not consider the specific times of day when users might prefer one part of the day over another due to factors such as commuting purposes, leisure activities, special events, or personal time preference. Typically, it is visible that the number of bike-sharing trips late at night is always significantly lower than in the afternoon or evening. To address this, future research could employ more detailed temporal segmentation within the analysis. This can be conducted by dividing the day into multiple time intervals, such as morning peak, midday, evening peak, and late-night, then repeating the same regression model for all of these subsamples. This direction allows us to explore how usage patterns shift within these parts of the day.

Another limitation of this research is the focus on the impact of only the first e-scooter provider (Lime) in Budapest but does not consider the entry of the second and third competitor such as Bird and Tier, respectively. Future studies could examine the effects of subsequent entries of new e-scooter brands and possibly, build a theoretical model about sequential game related to these entries. This research

would assess whether the appearance of Bird and Tier leads to further reductions in bike-sharing usage, remains neutral, or even improves bike-sharing performance. On the other hand, analyzing the competition among multiple e-scooter providers would also be attractive, since it is questionable whether the entrants (Bird and Tier) expand or steal the market of the incumbent (Lime). Such studies are related to the sustainability of impacts, which require a longer time horizon of data collection.

In conclusion, the entry of e-scooters into Budapest has reshaped the landscape of urban mobility, offering a substitute to bike-sharing for certain user groups and occasions. In addition, by expanding the scope of research to include detailed temporal analysis and the impacts of multiple e-scooter entries, future studies could provide more nuanced insights that help to develop more adaptive and sustainable transport strategies.

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