Transportation Research Part A 133 (2020) 290–302

Contents lists available at ScienceDirect

Transportation Research Part A

journal homepage: www.elsevier.com/locate/tra

Does Uber affect bicycle-sharing usage? Evidence from a natural experiment in Budapest ☆

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ARTICLE INFO

Article history:
Received 12 November 2018
Received in revised form 4 January 2020
Accepted 15 January 2020

Keywords:
Bicycle-sharing
Uber
Complementarity
Substitution

ABSTRACT

In this article we exploit a natural experiment provided by the forced exit of Uber from Budapest to assess the effect of Uber on bicycle-sharing system (BSS) ridership. Our results show that banning Uber caused a significant decrease in usage among frequent users especially on weekdays, suggesting a complementary relationship between these services. On the other hand, our findings indicate that ad hoc users mainly use BSS and Uber as substitutes. These results shed light on some unintended consequences of banning ride-sharing services that are worth taking into consideration in future policy decisions.

1. Introduction

Bicycle-sharing systems (BSS) are gaining popularity in more and more cities throughout the world. There is substantial research concerning the utilization of these systems to better understand their success and failure factors. In this study we contribute to this discussion by analyzing the interplay among BSS and other transportation options in the case of Budapest. Recently, a number of changes have taken place in the transportation system of Budapest, e.g., launching a bicycle-sharing system, or the market entry and exit of Uber. These changes give us the possibility to analyze and understand the role Uber may play in local transportation. Specifically, we exploit a legal change that occurred in July 2016 in Hungary that caused the exit of Uber from Budapest to analyze the effect of Uber on BSS usage. From the point of view of our research the relevant question is whether Uber and bike-sharing are substitutes or complements. In case they are substitutes one would expect the exit of Uber to increase the demand for BSS, while if they are complements one would expect the opposite. Our findings suggest a complementary relationship. We find that Uber leaving the market decreased BSS usage overall. This effect comes from regular users of BSS who use the service with passes. For individuals using the service with single tickets the effect of Uber's exit has a positive effect, suggesting substitution across the two services. The results indicate that consumers who are more likely to buy bicycle-sharing passes use bicycle-sharing and Uber as parts of a multimodal way of transportation. Multimodal

☆ This research was supported in the Széchenyi 2020 program framework (EFOP-3.6.1-16-2016-00013) under the European Union project titled: "Institutional developments for intelligent specialization at the Székesfehérvár Campus of Corvinus University of Budapest". The authors thank the Center for Budapest Transport for access to the data and Péter Dalos for his helpful comments and suggestions. The first author gratefully acknowledges financial support from the Hungarian Academy of Sciences (MTA) through the Bolyai János Research Fellowship and from the National Research, Development and Innovation Office (FK-132343 and K-119930).

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https://doi.org/10.1016/j.tra.2020.01.010
0965-8564/

transportation is a transportation usage pattern characterized by users using a combination of different modes of transportation in a sequential manner (see e.g., Crainic and Kim, 2007). Thus, a person may use public transport, Uber and BSS in a complementary manner to reach the desired destination. However, if Uber is not available they may use their own car insted.

Our reasoning is supported by a number of previous findings. Several studies have found that BSS is popular mainly among young, urban, college educated and higher income individuals, who are not captive to public transport (see Raux et al., 2017; Goodman and Cheshire, 2014; Ricci, 2015). Raux et al. (2017) further finds that the majority of the users hold a driving license or otherwise have access to a private car. Similar demographic attributes have been found for Uber users as well (see e.g., Hall et al., 2017). Furthermore, these individuals in general tend to use the transportation system in a multimodal way as shown by Clauss and Döppe (2016) or Olafsson et al. (2016).

Based on these findings it is likely that a large number of individuals are able and willing to use both services. Moreover, Hall et al. (2017) shows that Uber can become an integral part of a multimodal transportation system. Taking away Uber as an option therefore might decrease the demand for other travel modes, including bike-sharing, since individuals might prefer to use their own car instead of choosing public transport as a substitute when Uber is no longer available. This line of reasoning is supported by Hampshire et al. (2017) who finds that after the suspension of Uber and Lyft services in Austin, TX, 45% of the population surveyed switched to the use of personal vehicles while only 3% shifted to public transport.

Our findings suggest that the nature of complementarity between ride-sharing and bike-sharing services is best characterized as a type of temporal complementarity. Many consumers use these two services at different times of the day, limiting substitution across them. To put it in a more intuitive manner, consider an individual who travels to the city center and wishes to stay there until late at night, perhaps to engage in "partying". If Uber is available, this city dweller can leave her car at home. She can use bike-sharing to reach her intended destination during the day and can use Uber late at night to get back home. However, if Uber is not an available service, she might use her own car to get in and, perhaps by hiring a driver, to get out of the city center. At least, this seems to be the case with many pass holders. For individual ticket holders, Uber and bicycle-sharing appear to be substitutes. Consider, for example, a tourist who ponders whether to buy a BSS ticket but then, perhaps out of convenience, orders Uber instead. A substitutory relationship in such cases seems intuitive.

Our findings of net complementarity receive further support from the fact that Uber has recently set up a bike-sharing service, JUMP (see www.uber.com). If ride-sharing and bike-sharing are substitutes, it would not be a profit-maximizing strategy from Uber's part, however if they are complements, it could be. Establishing complementary services increases demand for both services.

Uber has made it into the headlines many times since its launch. Besides its novel concept of transportation, most often the news has been about the controversy of "not playing by the rules". We are not aiming to take sides in this debate, however our results suggest that the presence of Uber (and Uber-like services) could have significant spillover effects on passengers' behavior related to other means of transportation. This may put the way we think about Uber in a different perspective that might be worth taking into consideration in future policy decisions.

The structure of the article is as follows. In Section 2 we provide some background on bicycle-sharing, Uber and similar ride-sharing services available in Budapest, as well as the Hungarian regulatory changes we have studied. In Section 3 we introduce our dataset and we present our empirical model. We discuss our results and draw policy implications in Section 4. The paper is concluded with a summary in Section 5.

2. Background

2.1. BSS in Budapest

The bicycle-sharing system of Budapest (called MOL Bubi) was established in September 2014. In the first round, 76 stations were opened. The system was expanded in three phases and reached 112 stations by the end of 2016 (see Fig. 1 for the geographical location of the stations). Currently, the system densly covers the inner area of the city.

Users can buy quarterly, semi-annual and annual passes or 24-h, 72-h and weekly tickets. Both the tickets and the passes allow unlimited number of bicycle hiring. The first 30 min of each rent is free of charge. Renting a bicycle for longer than 30 min comes with an additional variable fee that depends on the length of the usage.

The 24-h ticket costs around €1.6, while the price of the annual pass is around €60. The additional variable fee is €1.6 per 30 min. Passes have two favorable features compared to tickets. First, one pass allows the use of up to four bicycles at the same time, i.e., groups of people can buy only one pass together and share the related costs. Second, 15–25% of the price of the passes can be used to cover the variable fee (that applies for a rental lasting longer than 30 min). Prices have not changed since the launch of the system, therefore they could not influence the change of the usage patterns.

The daily operation of the BSS is managed by a third-party company. This company is penalized based on the number of empty and full stations. To be more precise, the penalty applies if there are less than two bicycles or less than two empty places available in any station, which, however, rarely happened according to the data.

2.2. Uber

Uber is a highly valued start-up company that provides taxi-like transportation services currently in more than 700 cities worldwide. Uber prices are significantly lower compared to taxi prices, however, prices depend on supply and demand and

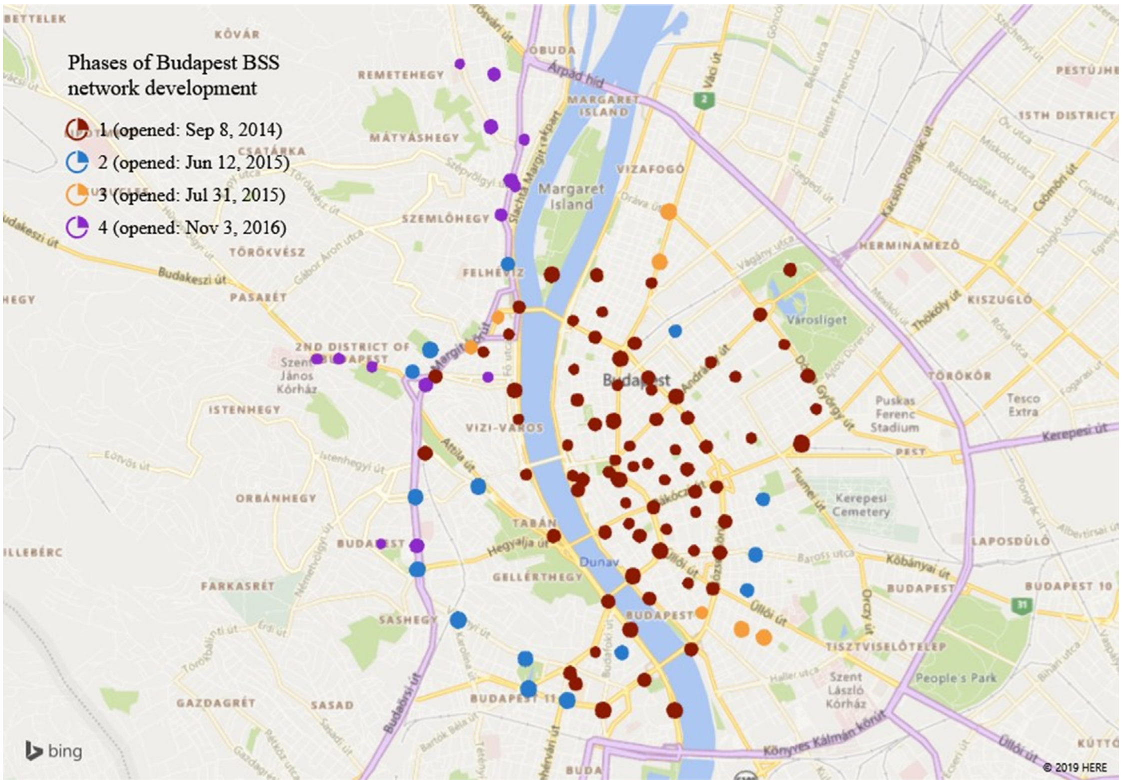

Fig. 1. BSS station development in Budapest (size of the dots represents number of bicycle docks at a given station).

this flexibility could cause very high prices in some peak periods (e.g., at New Years' Eve). The service can be ordered via a mobile application available for the three most widespread smartphone operating systems (iOS, Android and Windows Mobile). After downloading and registering for the application, potential passengers can check the location of the closest available Uber cars. They can see the ratings and reviews of the driver and decide which car they would like to order. The driver can also check the profile of the potential passenger and confirm the order. After the trip, payments are done via the mobile application, i.e., there is no cash transaction in the cars. Finally, both the passenger and the driver can evaluate each other to generate additional ratings and reviews. The system of Uber is considered an innovative one and this is a major factor behind its success in several cities.

Uber drivers are self-employed contractors using their own cars and driving whenever they want. Since this activity is mostly outside of the scope of taxi regulations, several protests have taken place against Uber's operation around the world. Protesting taxi drivers indicate unfair competition between unregulated Uber and regulated and licensed taxi services. This has prompted some cities to regulate more strictly the operation of Uber.

Uber was launched in Budapest in November 12, 2014, and, as was the case in most cities, drew much controversy. The main critics of the ride-sharing service came from local taxi driver associations that accused Uber of "not playing by the rules". There was truth in that accusation. In 2013 Budapest introduced a new taxi regulation. The most important part of it was the introduction of a mandated price. Uber provided similar services for, on average, less than half of that price. Lower prices caused fast penetration of Uber and triggered intense protest from taxi drivers against the company. The campaign, which featured demonstrations by taxi drivers, was at the end successful. The Hungarian parliament accepted a new law that made Uber's operation in Hungary (in essence Budapest) impossible. Uber quit the market on the day (July 24, 2016) the law came into force.

3. Data and methodology

BSS related data were provided by the system operator, Centre for Budapest Transport. The dataset contains start date, end date, start station, end station, and ticket type (pass or ticket) for all the trips occurred in 2015 and 2016. Usage patterns show significant seasonality (see Fig. 2), BSS is much more utilized during summertime. Since the exit of Uber happened in the middle of summer (July 24, 2016), we decided to use the summer periods only, i.e., from June 1 to August 31 for both years. This shorter sample makes it possible to analyze the most utilized periods. Additionally, the shorter period enables a regression discontinuity-type of analysis that is often used in treatment effect identifications (O'Keeffe and Baio, 2016) to mitigate the unobservable changes that might occur in a larger time window.

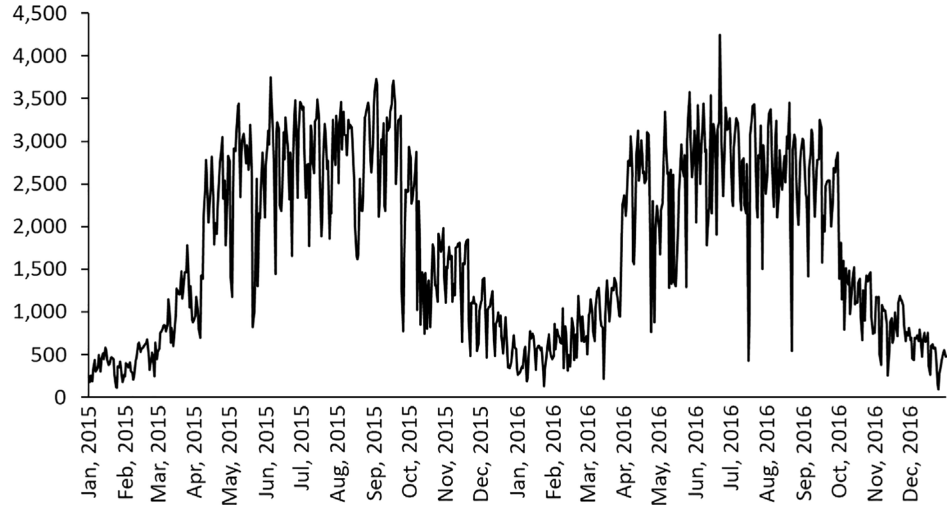

Fig. 2. Daily usage frequencies of the Budapest BSS (total number of trips per day).

The dataset allowed us to separate users based on ticket types, that is, to differentiate regular users (who are using the service with passes) from ad hoc users (who are using the service with tickets). Some data cleaning was required to eliminate invalid entries. If a trip was no longer than 1 min or either the start or the final station was missing, the trip was deleted from the database. After this cleaning, 511,539 trips remained in our database. The majority (85%) of the usage was generated by regular users and only 15% was connected to tickets. Furthermore, the service is more frequently used on weekdays, and only 25% of the total usage is connected to weekends (Saturdays and Sundays) (see Table 1). This is in line with previous findings (see e.g., El-Assi et al., 2017; Faghih-Imani and Eluru, 2015), that indicate that weekdays and weekends might show different dynamics and usage patterns. Usage on weekdays is more connected to commuting, while weekend usage is more about leisure and recreation. The dataset was, therefore, separated into weekday and weekend subsamples. The utilization of the stations varies heavily. While the average trip generation was 29.3 per station per day, it is ranging from 0 to 148. Trip data were summarized into number of trips by day, generating station and ticket type.

Table 2 reports summary statistics of the data used. It shows that regular users use BSS more often on weekdays, which can be attributed to commuting to work. On the other hand, ad hoc users use the service more frequently during weekends.

To identify the causal effect of Uber on BSS usage, a control and a treated group need to be compared. However, there is no natural control group available, and therefore, it was required to construct a counterfactual. In this study, we exploit the fact that Uber was available in the whole summer of 2015, but its service was terminated in the middle of 2016. We use the data of 2015 as a counterfactual for 2016. The first half of the summer of 2016 enables us to identify the usage differences between the two summers, and thus, estimate the impact of Uber as a treatment effect. We created the difference between the 2015 and 2016 data to analyze the changes between the two summers. More specifically, since subtracting the same day (e.g., July 1, 2015 from July 1, 2016) might cause a bias in comparing a weekday to a weekend day, we always subtracted the same types of days from each other (i.e., a Sunday was subtracted from the closest Sunday a year before). In this way we captured the changes in trip generation by station, day of week and ticket type between the two summers.

To account for the differences between the two consecutive years, we control for the most important variables affecting BSS usage based on prior literature. There is a consensus (see e.g., Saneinejad et al., 2012; Gebhart and Noland, 2014; El-Assi et al., 2017; de Chardon et al., 2017) that weather conditions (e.g., temperature, wind speed and precipitation) have major effects on BSS usage. We use Physiological Equivalent Temperature (PET) scores in order to capture the effect of thermal related weather conditions on BSS usage. PET is one of the most commonly used thermal indicator for assessment of the thermal conditions (mean radiant temperature, air temperature, humidity and wind speed) of the human body (see Matzarakis et al., 2007; Matzarakis et al., 2010). We used RayMan 1.2, developed by the Meteorological Institute, University of Freiburg, Germany, which is a micro-scale model to calculate radiation changes in different environments, to calculate the PET scores. We set geographic longitude at 19°2' and latitude at 47°30', altitude at 105 m and time zone at UTC+2.0 representing the geographic parameters of Budapest. Furthermore, the average weight was set to 83 kg and height to 176 cm (the average weight and height of Hungarian males[1]; HCSO, 2018). Physiological parameters were constant with an internal heat production of 80 W and a heat transfer resistance of the clothing of 0.9 clo. Since precipitation is not considered in the calculation of PET scores, we control for it separately. The effects of thermal conditions and precipitation on bicycle usage are not linear, therefore several intervals were created from PET scores and precipitation data. Weather data were obtained from the European Climate Assessment & Dataset provided by the European Climate Support Network.

[1] The predominant user group of the BSS.

Table 1
Number of trips for the summers of 2015 and 2016.

Ticket Type	Weekday	Weekend	Total
Pass	336,400	98,334	434,734
Ticket	49,771	27,034	76,805
Total	386,171	125,368	511,539

Table 2
Summary statistics.

Variable	Obs.	Mean	Median	Standard deviation	Min	Max
Number of trips per station with pass on weekdays	12,496	26.9	23	16.9	0	144
Number of trips per station with pass on weekends	4,950	19.9	16	16.2	0	148
Number of trips per station with ticket on weekdays	12,496	4.0	2	5.8	0	61
Number of trips per station with ticket on weekends	4,950	5.5	2	7.6	0	69
Number of stations	184	95.2	98	5.4	76	99
PET scores (hourly data)	4,416	18.4	17.5	6.7	5.7	36
Total daily precipitation (mm)	184	2.5	0	7.8	0	66

Naturally, ticket and pass prices also affect usage (see e.g., Goodman and Cheshire, 2014; Fishman, 2016; Lin et al., 2017). Yet, these prices have not changed since the launch of the BSS service. Moreover, taxi prices and public transportation prices did not change either in the analyzed period, thus, we did not include any price-related data in our analysis.

Another important factor that might influence usage is the size of the BSS network (see e.g., Gebhart and Noland, 2014; Campbell and Brakewood, 2017). Therefore we also controlled for this factor in our regression. Furthermore, several studies suggest that changes in natural and built environment, in public transportation routes, temporary traffic constraints, etc. might affect the utilization of a BSS station (see e.g., Nair et al., 2013; Fishman et al., 2015; Mateo-Babiano et al., 2016; Wang et al., 2016; Noland et al., 2016; Gonzalez et al., 2016; Faghih-Imani et al., 2017b). To account for these changes, we included station-specific fixed-effects in the regression. Finally, to account for the between-day variations, we included day of week dummy variables in the model.

Our model can be written in the following general form:

$$\Delta y_{it} = \beta \Delta Uber_t + \Gamma \Delta x_{it} + c_i + u_{it} \tag{1}$$

where y_{it} is the total number of trips generated by station i on day t; $Uber_t$ is a dummy variable taking the value of 1 if Uber was available in Budapest on day t and 0 otherwise; x_{it} contains all the control variables and c_i captures station-specific effects. The unexplained random error term is represented by u_{it}. The model was estimated using fixed effect panel regression. We assumed AR(1) error term in the fixed effect regressions in the weekday subsamples. This is because our dataset contains daily observations that can cause autocorrelation in the dependent variable. However, for weekends, normal fixed effect model was used, as autocorrelation is not relevant in that case, since the weekend subsample contains only two consecutive days per weekend.

4. Results and discussions

The analysis is divided into three parts. First, we look at the average temporal trends of the network (Section 4.1); second, we analyze the differences of the two summers using panel regression methods (Section 4.2); finally, we divide the sample into five time periods to capture the daily temporal differences using a panel regression framework (Section 4.3).

4.1. Usage patterns

We begin our analysis by considering the unconditional changes that happened after the exit of Uber. Fig. 3 and 4 depict the average trip generation per station for different ticket types during weekdays and weekends when Uber was present in Budapest and after its exit. The figures show data for the summer of 2016 (June 1-August 31). Since no new station was added to the network in this period, network expansion does not bias the data.

The figures reveal some interesting patterns. Pass-holders mainly use BSS on weekdays, especially during the morning and afternoon peak periods, which may be connected to commuting. Following the exit of Uber there is a significant decline in BSS usage, mainly during the afternoon commuting peaks. Changes in early morning and midday usage are less sizeable. Some usage reduction is also observable in evenings and late-nights. Furthermore, usage distributions indicate differences in

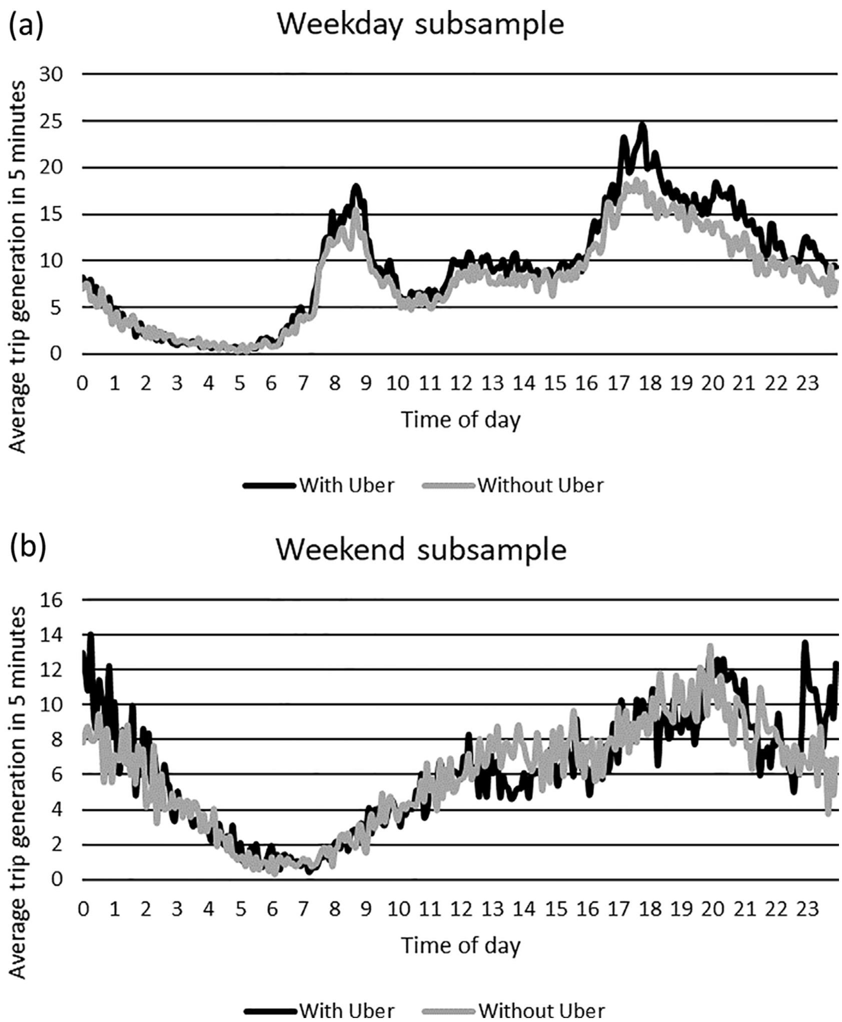

Fig. 3. The distributions of temporal trip generation of regular BSS users before and after Uber's exit (summer of 2016).

usage during weekdays and weekends. While BSS is more frequently used during the commuting peak periods on weekdays, usage is the lowest during the morning period and it is mainly concentrated in the evening and night periods on weekends.

Ticket buyers' usage distribution is similar on weekdays and weekends, indicating that they might use BSS for purposes other than commuting. Their usage was altered significantly less than that of pass-holders' after the exit of Uber. There is some increase in the usage on weekdays and weekends. However, as we have mentioned earlier, only a minority of users use the service with tickets and the majority is using it with pass. Thus, the impact of the former subsample should be down-weighted when considering the total impact of Uber's exit on BSS usage.

4.2. Regression results

The previous section revealed some interesting patterns regarding BSS usage. Yet, the changes in usage patterns might not solely be driven by the presence or absence of Uber, but be influenced by many other factors as well. As we have argued in the previous section weather conditions, network size and station-specific characteristics might impact the usage of BSS, therefore a more thorough analysis in which we control for these variables is necessary to determine the impact of Uber. More specifically, a fixed effects panel model is estimated for the regression expressed in Eq. (1). Table 3 summarizes the estimation results.

As we have mentioned earlier, pass-holders predominantly use the BSS on weekdays, while ticket-buyers use it more often on weekends (see Table 1). For this reason we concentrate our attention on the effects generated in these cases.

Estimation results for regular users (pass holders) are shown in the first two columns of Table 3. The first column of the table indicates that Uber had a positive effect on BSS usage during weekdays. The results suggest that the market exit of Uber caused a decrease of around 1.74 trips on average per weekday per station. Considering that the average trip generation of a station on weekdays was 26.9 (see Table 2), this shows an approximate 6.5% decrease in trip generation. Given that there

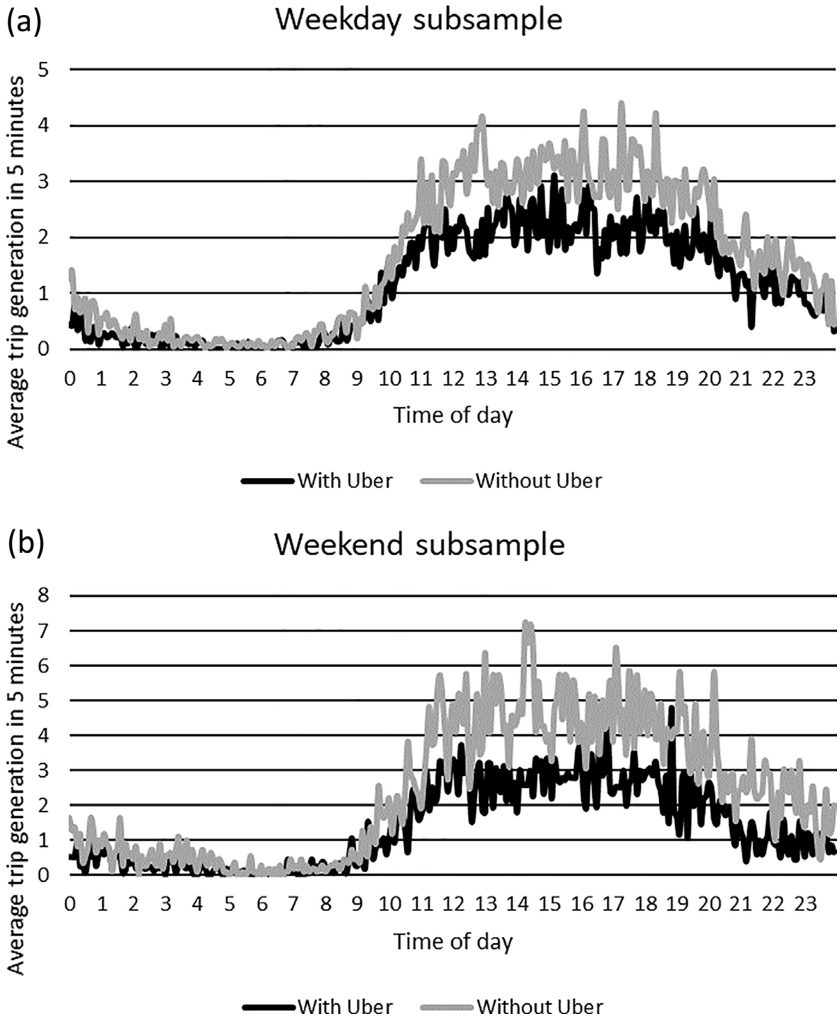

Fig. 4. The distributions of temporal trip generation of ad hoc BSS users before and after Uber's exit (summer of 2016).

were 96 BSS stations in Budapest in the time frame considered, the exit of Uber *ceteris paribus* caused a decrease of around 167 rentings per weekday. These results suggest a complementary relationship between the two services.

The third and fourth columns of Table 3 show the results for ad hoc users, who are using BSS with tickets. Results are exactly the opposite of the ones we observed for regular users. The presence of Uber had a significant negative effect on weekend usage. In numbers, the exit of Uber resulted in a 1.26 increase in average daily trip generation for a given station during weekends. This is rather substantial since it shows an approximate 23% increase is BSS usage. These results indicate that ad hoc users use the BSS as an alternative to Uber during weekends.

The negative effect of the network size, even though is not significant, might be surprising. This might be the case because the popularity of BSS did not increase with the expansion of the network. Since the new stations were added on the outskirts of the city centre they were naturally less attractive, and less frequently used.

Not surprisingly, if thermal conditions deviate from the ideal, BSS usage generally decreases. Since no thermal stress is the reference category in the regression, the estimated parameters indicate that BSS usage is *ceteris paribus* lower for less favorable PET categories. For example, if there is a slight cold stress, BSS usage is lower by 0.97 trips per station per day on weekdays among pass holders. Similarly, BSS usage is lower by 5.05 trips per station per day on weekdays among pass holders if there is a moderate heat stress.

Precipitation is also negatively impacting BSS usage in general. Results indicate that a light rain during the day reduces BSS usage by 3.36 trips per station per day on weekdays among pass holders. However, there are some surprising results, namely that the effect of relatively light rain is stronger than that of a heavier rain during weekends. This can be caused by two effects. First, there were only 5 weekend days with precipitation above 5 mm. Additionally, we used daily averages, therefore, it is possible that it was raining at dawn or late night on these days, yet it did not affect BSS usage during the whole day that much.

Table 3
Estimation results.

Variable	Pass		Ticket	
	Weekday (1)	Weekend (2)	Weekday (3)	Weekend (4)
Uber	1.742***	0.456	-0.404	-1.264***
	(0.569)	(0.655)	(0.251)	(0.375)
Network size	-0.035	-0.107	0.036	-0.054
	(0.056)	(0.075)	(0.025)	(0.043)
PET: Moderate Cold	-5.853***	−5.553***	-0.960***	-2.037***
	(0.562)	(0.788)	(0.250)	(0.451)
PET: Slight Cold	-0.971***	-1.665***	-0.340***	0.133
	(0.291)	(0.340)	(0.130)	(0.195)
PET: Moderate Heat	-5.050***	-0.950	-1.214***	0.181
	(0.425)	(0.638)	(0.189)	(0.365)
Precipitation: 0–5 mm	-3.356***	-1.926***	-0.346**	-1.431***
	(0.365)	(0.406)	(0.163)	(0.232)
Precipitation: >5 mm	-7.384***	−1.308**	-1.062***	-0.600
	(0.357)	(0.649)	(0.159)	(0.371)
Tuesday	4.056***		0.989***	
	(0.494)		(0.220)	
Wednesday	1.824***		0.901***	
	(0.593)		(0.263)	
Thursday	0.832		0.753***	
	(0.638)		(0.282)	
Friday	0.696		1.119***	
	(0.653)		(0.288)	
Sunday		0.657		-0.066
		(0.464)		(0.265)
N (sample size)	5,907	2,380	5,907	2,380
R^2	0.273	0.257	0.053	0.113

Notes: reference category for PET is No Stress, for precipitation is 0 mm and for the day of week dummies Monday and Saturday. Standard errors are in parenthesis.
$^{*}p<0.1$; $^{**}p<0.05$; $^{**}p<0.01$.

The day of week dummies indicate that Tuesdays and Wednesdays became more important in BSS usage. Thursdays and Fridays do not differ from Mondays in the pass subsample, but there is a difference in the ticket subsample. The significant day of week variables in the ticket model indicate that ticket-based usage can change patterns across years. However, it is important to note that ticket buyers mainly use BSS on weekends, therefore, the significant estimates rely on relatively small number of trips. Furthermore, there is no significant difference between Saturdays and Sundays based on the weekend models.

Table 4 shows summary statistics about station-specific fixed effects for the 96 stations in use. The station-specific fixed effects capture all the changes that occurred in the average usage of a station from 2015 to 2016 apart from the exit of Uber, thermal conditions and precipitation. The average values of the fixed-effects indicate that there is a slight increase in usage, mainly among pass holders. Usage with tickets did not change considerably.

The minimum and maximum values indicate that some pattern changes occurred in the analyzed period. Some stations gained popularity while others lost some from 2015 to 2016. This might have been caused by the extension of the network in 2015 (15 new stations were opened in June 12, 2015 and 7 new stations in July 31, 2015). As the network size variable shows, the extension did not increase the overall usage of the system but affected the usage patterns of the existing users. However, the interquartile range of the fixed-effects is between -3 and $+3$ in all cases and the decrease was never above 50% of the average number of trips generated by a station during the summer of 2015 suggesting that the majority of the network was unaffected.

4.3. Regression results by time periods

Since the daily distribution of trips is uneven, we also investigated the effect of Uber in different time periods of the day. This method enabled us to capture the temporal differences in usage and shed light on how users combined Uber and BSS within a day. We identified five time periods: dawn (1:00–7:00), morning peak (7:00–10:00), midday (10:00–16:00), afternoon peak (16:00–20:00) and night (20:00–1:00) based on the usage distribution of BSS trips within a day (see Figs. 3 and 4) and on prior literature (see Faghih-Imani et al., 2017a and El-Assi et al., 2017).

Results are summarized in Table 5. Control variables were eliminated from the table to reduce its size. More detailed results are presented in the Appendix (see Tables 6–9). The results shed light on the following patterns. For pass holders, Uber and BSS appear to be complements especially in the afternoon commuting periods on weekdays. The exit of Uber caused a significant reduction in BSS usage during the afternoon peak period and at night for these users. These findings support our conjecture that the presence of Uber might encourage commuters to leave their cars at home and use a combination

Table 4
Summary statistics for station-specific fixed effects.

Subsample	Average	Standard deviation	Min	Max
Pass – weekday	0.23	5.87	−15.38	21.69
Pass – weekend	0.16	5.75	−41.33	11.29
Ticket – weekday	-0.03	1.19	−3.88	5.76
Ticket – weekend	0.01	1.57	−3.17	8.02

of other transportation modes, including BSS, instead. For ticket buyers, Uber and BSS appear to be substitutes, and this relationship is statistically significant throughout the day except at dawn and morning. This appears to be convincing since a considerable share of the ticket users are tourists, who are likely to start their city tour later during the day and may use either BSS, Uber, taxi or public transport to travel within the city without having a plan to combine these transportation modes. If Uber is not available, BSS obviously will get a higher share. The more detailed results presented in the Appendix reveal somewhat counter-intuitive effects for the control variable in some cases. In particular, slight or moderate cold stress seem to have a positive effect on BSS usage especially in the afternoons and at nights. One can speculate that these thermal conditions might be even conducive to cycling on summer evenings.

4.4. Discussion

Policy discussions about Uber are quite widespread, with the sharing service generating a lot of controversy (for an overview, see e.g., Taylor, 2017). While other taxi service providers and some critics charge Uber with "not playing by the rules" and "exploiting" their workers, many economists have emphasized the social welfare increasing effects of Uber: the ride-sharing service could increase competition in local taxi markets, providing cheaper and higher quality and quantity service. Uber also has a system of surge pricing that, according to studies conducted by Cramer and Krueger (2016), is effective in balancing supply and demand. There seem to be large direct benefits from allowing Uber to operate, particularly in terms of consumers' surplus (see Cohen et al., 2016), although some raise questions regarding the viability of Uber's business model and the long-term welfare effects (see e.g., Horan, 2017). All in all, open questions remain regarding the right regulatory framework with respect to Uber. However, less attention has been given to the policy implications of indirect effects caused by substitutory or complementary relationship between Uber and other local transportation services. Our findings suggest that many users of Uber have a preference for multimodal urban transport use. This means that if Uber is banned from a city, it might depress the use of other local transportation services, including BSS.[2]

Regarding bicycle-sharing, Fernandez-Heredia et al. (2016) found that convenience (flexibility and efficiency) and pro-bike attitudes have an impact on the demand for BSS. Thus faster and more flexible transportation (especially for commuting) seems to be a factor in BSS usage. Faghih-Imani et al. (2017a) showed that BSS is competitive in terms of travel duration with taxis in the inner city of New York. This is particularly true during peak times and for some specific routes where cars have to make a longer trip due to e.g., one-way roads or traffic jams. Not surprisingly, results by Campbell and Brakewood (2017) show that there is substitution between public bus usage and BSS usage in New York, however, the size of the substitution effect is rather small. These results indicate that BSS is an effective way of commuting in dense cities and could act as a substitute to cars. To adjudicate the policy implications from all this, we also need to take into account externalities from BSS use. *Ceteris paribus*, greater reliance on bicycles may contribute to decreased pollution levels (see Johansson et al., 2017) and furthermore, bicycle usage has numerous health benefits (although we do not count this among the externalities). In the light of our findings, therefore, we believe that expelling Uber might, apart from the first-order welfare effects, adversely affect some other policy goals. Naturally, the generalizability of our results obtained for Budapest is in question. However, we would again refer to the findings of Hall et al. (2017) who find a complementary relationship between public transport and Uber, suggesting that consumers prefer multimodal transportation in general. Thus, our results might be relevant for several medium-large cities and these findings may provide a useful contribution to the debate on ride-sharing services by empirically verifying and measuring the impact of Uber on BSS ridership on a medium sized city.

5. Conclusion

In the past few years, several innovations were introduced in local transportation. In this article, we analyzed the interaction between two new services, Uber and bicycle-sharing. BSS is getting more and more widespread and nowadays middle size and even small cities are setting up their own networks. Uber is currently present in more than 700 cities worldwide with an explicit aim to further expand its business and geographical footprint.

In this article we exploit the fact that Uber exited from the Budapest market after a regulatory change in the middle of 2016. This natural experiment makes it possible to estimate the impact of Uber on BSS ridership. Our results suggest that regular BSS users combine bicycle-sharing with Uber to commute, and, therefore, banning Uber caused an around 6.5%

[2] Hall et al. (2017) showed this to be true, under certain conditions, to traditional modes of public transport, while our study points to complementarities between bicycle-sharing and Uber.

Table 5
Effect of Uber on BSS usage by time periods.

Variable	Pass		Ticket	
	Weekday (1)	Weekend (2)	Weekday (3)	Weekend (4)
Dawn	0.024	0.459*	0.018	-0.031
	(0.108)	(0.246)	(0.034)	(0.064)
Morning	0.132	-0.170*	-0.012	0.014
	(0.133)	(0.096)	(0.036)	(0.052)
Midday	-0.275	-0.358	-0.105	-0.547**
	(0.201)	(0.267)	(0.149)	(0.236)
Afternoon	1.298***	-0.112	-0.131	-0.395**
	(0.252)	(0.281)	(0.117)	(0.187)
Night	0.745**	0.686*	-0.120	-0.350***
	(0.290)	(0.364)	(0.091)	(0.135)

Notes: Fixed effect panel regression results (with an AR(1) error term in the weekday subsamples) using network size, PET scores and precipitation as control variables. Standard errors are in parenthesis.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

decrease in BSS usage on weekdays among regular users. On the other hand, ad hoc users mainly use BSS and Uber as substituting services, especially during weekends and the exit of Uber caused a 23% increase in BSS usage among these users on weekends.

The net effect of Uber on BSS thus depends on the usage frequencies of the two groups (regular and ad hoc users). Not surprisingly, the majority of the trips was generated by regular users, hence, the exit of Uber caused an overall decrease in BSS usage. This finding draws attention to some unintended consequences that are worth taking into consideration in future policy decisions. Our results also provide valuable insights into commuters' preferences for combining different transportation modes, yet further research on this topic is needed.

Appendix A

See Tables 6–9.

Table 6
Estimation results (Pass holders' weekday usage).

	Dawn	Morning	Midday	Afternoon	Night
Uber	0.024	0.132	−0.275	1.298***	0.745**
	(0.108)	(0.133)	(0.201)	(0.252)	(0.290)
Network size	0.022**	0.009	0.012	−0.065**	−0.009
	(0.011)	(0.014)	(0.020)	(0.025)	(0.029)
PET: High Cold Stress	−0.564***				−1.716***
	(0.132)				(0.366)
PET: Moderate Cold Stress	−0.429***			0.147	−0.157
	(0.084)			(0.245)	(0.241)
PET: Slight Cold Stress	−0.153*	−0.396***	−1.485***	0.812***	1.064***
	(0.088)	(0.089)	(0.235)	(0.158)	(0.245)
PET: Moderate Heat Stress		0.095	0.030	−1.156***	
		(0.081)	(0.129)	(0.231)	
PET: High Heat Stress		−0.502***	−0.626***		
		(0.112)	(0.135)		
PET: Very High Heat Stress			−2.264***		
			(0.337)		
Precipitation: 0–5 mm	−0.143**	−0.927***	−0.743***	−1.412***	−1.427***
	(0.072)	(0.094)	(0.143)	(0.189)	(0.198)
Precipitation: > 5 mm	−0.027	−0.497***	−1.233***	−3.008***	−3.291***
	(0.075)	(0.093)	(0.147)	(0.182)	(0.206)
Tuesday	−0.119	0.179	1.004***	1.260***	1.015***
	(0.102)	(0.120)	(0.195)	(0.243)	(0.275)
Wednesday	−0.191	−0.149	0.413*	0.584**	0.873***
	(0.121)	(0.152)	(0.232)	(0.286)	(0.312)
Thursday	−0.341***	0.366**	0.591**	-0.497*	-0.495
	(0.123)	(0.156)	(0.235)**	(0.290)	(0.330)
Friday	−0.539***	0.253	0.735***	-0.062	-0.246
	(0.124)	(0.161)	(0.240)	(0.302)	(0.342)
N	5,907	5,907	5,907	5,907	5,907

Notes: reference category for PET is No Stress, for precipitation is 0 mm and for the day of week dummies Monday. Standard errors are in parenthesis.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 7
Estimation results (Ticket buyers' weekday usage).

	Dawn	Morning	Midday	Afternoon	Night
Uber	0.018	−0.012	−0.105	−0.131	−0.120
	(0.034)	(0.036)	(0.149)	(0.117)	(0.091)
Network size	0.001	0.003	0.008	0.010	0.012
	(0.003)	(0.004)	(0.015)	(0.012)	(0.009)
PET: High Cold Stress	−0.043				0.122
	(0.042)				(0.115)
PET: Moderate Cold Stress	−0.040			0.123	0.130*
	(0.027)			(0.119)	(0.076)
PET: Slight Cold Stress	−0.010	−0.058**	−0.384**	0.101	0.267***
	(0.028)	(0.026)	(0.163)	(0.076)	(0.077)
PET: Moderate Heat Stress		−0.018	0.195**	−0.198*	
		(0.023)	(0.091)	(0.112)	
PET: High Heat Stress		−0.035	0.065		
		(0.032)	(0.097)		
PET: Very High Heat Stress			−0.305		
			(0.238)		
Precipitation: 0–5 mm	−0.005	−0.022	−0.195*	−0.264***	−0.149**
	(0.023)	(0.028)	(0.100)	(0.093)	(0.062)
Precipitation: > 5 mm	−0.052**	0.020	−0.531***	−0.350***	−0.248***
	(0.024)	(0.028)	(0.103)	(0.090)	(0.065)
Tuesday	0.014	0.032	0.127	0.405***	0.206**
	(0.032)	(0.035)	(0.137)	(0.118)	(0.087)
Wednesday	−0.006	0.046	0.113	0.447***	0.172*
	(0.038)	(0.043)	(0.167)	(0.136)	(0.098)
Thursday	0.028	-0.006	0.132	0.190	0.123
	(0.039)	(0.043)	(0.171)	(0.136)	(0.104)
Friday	0.036	0.030	0.272	0.406***	0.135
	(0.040)	(0.044)	(0.176)	(0.140)	(0.108)
N	5,907	5,907	5,907	5,907	5,907

Notes: reference category for PET is No Stress, for precipitation is 0 mm and for the day of week dummies Monday. Standard errors are in parenthesis.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 8
Estimation results (Pass holders' weekend usage).

	Dawn	Morning	Midday	Afternoon	Night
Uber	0.459*	−0.170*	−0.358	−0.112	0.686*
	(0.246)	(0.096)	(0.267)	(0.281)	(0.364)
Network size	0.002	0.033***	−0.061**	−0.029	0.055
	(0.028)	(0.011)	(0.027)	(0.032)	(0.043)
PET: High Cold Stress	−1.140***				−1.596***
	(0.333)				(0.406)
PET: Moderate Cold Stress	−0.804***	-0.514***		−0.712**	−0.744**
	(0.216)	(0.197)		(0.337)	(0.315)
PET: Slight Cold Stress	−0.293	−0.313***	−2.177***	−0.037	1.771***
	(0.252)	(0.091)	(0.336)	(0.144)	(0.411)
PET: Moderate Heat Stress		0.129**	−0.883***	−1.069***	
		(0.053)	(0.169)	(0.286)	
PET: High Heat Stress		0.142	−0.515***		
		(0.107)	(0.177)		
PET: Very High Heat Stress			−1.621***		
			(0.333)		
Precipitation: 0–5 mm	0.218	−0.199***	−0.529***	−0.826***	−1.315***
	(0.148)	(0.059)	(0.155)	(0.173)	(0.238)
Precipitation: > 5 mm	0.590**	−0.013	0.012	−0.882***	−1.241***
	(0.240)	(0.096)	(0.266)	(0.277)	(0.363)
Sunday	−0.177	0.125*	-0.247	0.033	1.076***
	(0.168)	(0.072)	(0.189)	(0.201)	(0.264)
N	2,380	2,380	2,380	2,380	2,380

Notes: reference category for PET is No Stress, for precipitation is 0 mm and for the day of week dummies Saturday. Standard errors are in parenthesis.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 9
Estimation results (Ticket buyers' weekend usage).

	Dawn	Morning	Midday	Afternoon	Night
Uber	−0.031	0.014	−0.547**	−0.395**	−0.350***
	(0.064)	(0.052)	(0.236)	(0.187)	(0.135)
Network size	−0.015**	−0.002	−0.026	−0.012	0.015
	(0.007)	(0.006)	(0.024)	(0.021)	(0.016)
PET: High Cold Stress	0.016				−0.462***
	(0.086)				(0.151)
PET: Moderate Cold Stress	−0.031	-0.141		0.567**	−0.141
	(0.056)	(0.107)		(0.224)	(0.117)
PET: Slight Cold Stress	−0.060	−0.071	−1.426***	0.091	0.055
	(0.065)	(0.049)	(0.298)	(0.096)	(0.153)
PET: Moderate Heat Stress		0.003	−0.353**	−0.209	
		(0.029)	(0.150)	(0.190)	
PET: High Heat Stress		0.095	0.077		
		(0.058)	(0.157)		
PET: Very High Heat Stress			−1.621***		
			(0.333)		
Precipitation: 0–5 mm	0.002	−0.066**	−0.865***	−0.268**	−0.376***
	(0.038)	(0.032)	(0.138)	(0.115)	(0.088)
Precipitation: > 5 mm	−0.044	0.029	−0.387	−0.116	−0.147
	(0.062)	(0.052)	(0.236)	(0.184)	(0.135)
Sunday	−0.011	-0.069*	-0.350**	0.210	0.002
	(0.044)	(0.039)	(0.168)	(0.134)	(0.098)
N	2,380	2,380	2,380	2,380	2,380

Notes: reference category for PET is No Stress, for precipitation is 0 mm and for the day of week dummies Saturday. Standard errors are in parenthesis. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Appendix B. Supplementary material

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.tra.2020.01.010.

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