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The effect of public transport disruption on bicycle usage. Evidence from a natural experiment in Budapest

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ABSTRACT

In this article we use a natural experiment to assess the effects of a public transport disruption on the bicycle sharing system ridership. We exploit maintenance work on a major tram line in Budapest. Fixed effects panel regressions are applied in a difference-in-difference setting. Our results show that bicycle sharing usage significantly increased on weekdays during the disruption, however, this effect is not substantial relative to the baseline usage of the tram service. These findings raise interesting policy questions.

KEYWORDS

bicycle sharing, multimodal transportation, public transport disruption, panel regression, placebo test

JEL CLASSIFICATION INDICES

C22, R41, R42

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1. INTRODUCTION

In recent years, bicycle sharing systems (BSS) have been expanded in large and mid-sized cities across the world. While these services are not always profitable (such as in the case of the Hungarian capital, Budapest, the subject of our study), many argue that they serve important policy goals. A prominent role that bicycles sharing could fill is being a substitute for motorised transport modes, including cars and buses. However, bicycle sharing can also serve as a substitute for other modes of public transport as well as walking. Also, the proponents of BSS claim that these services can become an integral part of local public transport as a part of a pattern of multimodal transportation. Our study intends to contribute to these policy discussions around bicycle sharing and public transport, in general.

There is a large number of literature that measure the cross-elasticities (price or time elasticities) between alternative transportation modes (see e.g., Fearnley et al. 2017, 2018; Wardman et al. 2019). A consistent finding in this literature is that passengers are particularly sensitive to changes in accessibility and waiting time while being somewhat less sensitive to the fare changes. Peak demand is also more responsive to changes than off-peak demand.

There is also a small but increasing body of research that examine the effects of exogenous transport disruptions on the use of different modes of transport. Most of this literature, however, use survey methods, while a significant minority uses hard data. Nguyen-Phuoc et al. (2018) used survey data to construct a model (prediction) for the effects of public transport strikes on passengers' behaviour. Their findings suggest that the largest percentage (43%) of users would switch to using a car in case of a disruption. Nazem et al. (2018) used smart card data to study the effects of disruptions (closures) of public transport on the users' behaviour. They find that even temporary disruptions can have long-term effects on the usage of different transportation modes, suggesting a role for habit formation.

Most of the literature analysed complementarity or substitution across traditional modes of public transport and cars. Less attention has been given to the effects on cycling and walking, in particular, effects of disruptions in public transport on the demand for BSS. For notable contributions to this topic, see e.g., Fishman et al. (2014) or Campbell – Brakewood (2017).

Our study contributes to this growing literature by exploiting a *quasi-natural experiment* in Budapest, namely, the disruption in the most heavily utilised tram service of the city, due to planned track maintenance and station refurbishments, and its replacement with buses. In our study, we aim to measure the effects of this disruption on the utilisation of the BSS stations along the tram line. Important for our empirical strategy is the fact that the maintenance works were done sequentially along the tram line, so the BSS stations along the line were differently exposed to the disruption. When measuring substitution or complementarity across transportation services, a researcher is usually concerned with elasticities. This paper cannot take this route as we are dealing with a disruption-induced change that is hard to express in terms of a percentage change in monetary or time costs. Instead, we can only demonstrate the existence and the nature of a relationship between a tram service and the bicycle sharing system and measure its magnitude. Our results suggest that a significant substitution occurs from the tram line toward BSS.

The paper is organised as follows. In the next section, we present the major facts concerning the BSS in Budapest, capital of Hungary. In Section 3 we describe our data and methodology, in Section 4 we present our results, while in Section 5 we draw some possible policy conclusions.

2. BSS IN BUDAPEST

The BSS system of Budapest (called MOL Bubi) was launched in September 2014 with 76 self-service terminals located in the inner city. The system was gradually expanded to reach 98 stations during the summer of 2015 and 112 stations at the end of 2016. Despite the expansive network, the BSS is not universally regarded as a success story in Budapest, in fact it is plagued by a decreasing usage trend (Bakó et al. 2020b). This may be partially attributed to the bulky design of the Bubi bicycles: as riding a Bubi requires substantial physical effort. Pricing may also contribute to this problem, however, as the BSS prices have not changed since launching, the service it is unlikely to be the culprit for the declining trend in the usage. Budapest is also regarded as one of the most car centric capitals in Europe with a car-friendly infrastructure, low parking fees and no congestion pricing. For these and perhaps for other reasons many argue that BSS has not yet become an integral part of the Budapest public transportation system. Even so, our results point to its potential in this regard.

At the time of the analysis, the service was available through either passes or tickets. Pass holders could purchase a semi-annual or annual pass. Tickets were available in three different versions: 24-h, 72-h and 168-h tickets. Regardless of the fare type, users were able to rent the bicycles as many times as they wished during the validity period of their ticket/pass. The 24-h ticket cost around €1.6, [1] the 72-h one was €3.2, while for a 168-h ticket one had to pay €6.4. The price of the semi-annual pass was €40, the annual pass was around €60. The first 30 min per ride were free of charge. Renting a bicycle for longer than 30 min came with an additional variable fee that depended on the length of the usage. The additional variable fee was €1.6 per 30 min. Passes had two favourable features compared to tickets. First, a pass allowed the use of four bicycles at the same time, i.e., groups of people were able to buy only one pass together and share the related costs. Second, depending on the pass category, 15–25% of the price of the pass could be used to cover the variable fee that applies for a ride longer than 30 min. Tickets were mainly used by the *ad hoc* users (e.g., tourists), while the pass holders tended to be more frequent users.

The daily management and maintenance of the fleet was done by a third-party company. To ensure that the system is well managed and sufficient number of bikes are available at each station the operator was penalised based on the number of empty and full stations. This ensured that bicycles were almost always available at all the stations.

3. DATA AND METHODOLOGY

Our study aims to capture the effect of a temporal change in the public transport system on the usage of BSS. The temporal change was due to the partial refurbishment – including track maintenance and several station renovations – of the most heavily used tram line in Budapest. This tram line separates the inner city from the outer city and has an exceptionally high usage. The overhaul lasted from 21 March to 24 May 2015 – i.e., for about two months.

To identify the effect of the maintenance works on the BSS usage, we applied a difference-in-difference model setting. First, we separated the BSS stations based on their locations. Only

[1] All prices are expressed at the official HUF exchange rate.

stations located close (within 400 m) to the aforementioned tram line were assessed. Furthermore, three distinct areas were identified along the tram line (Figure 1):

- Maintenance area: this is the area of the tram line affected by the overhaul;
- Transfer area: this covers the part of the tram line where travellers had to change from the tram to the replacement bus;
- Full operation area: this is the area that was not impacted by the maintenance works at all.

We compared the BSS stations located within the area affected by the overhaul to those that were located in the full operation area. The intuition behind this is that passengers may use the BSS in lieu of the replacement bus service, thus generating additional demand for BSS. Moreover, we compared the period of the overhaul to the period after the maintenance.[2] With this technique, we aimed to identify the users who used the BSS service due to the absence of the tram service and would not have used it otherwise. This can capture the number of users that are willing to substitute public transport with BSS in certain circumstances. This information can help us estimate the cannibalization effect of public transport improvements on the BSS usage as well.

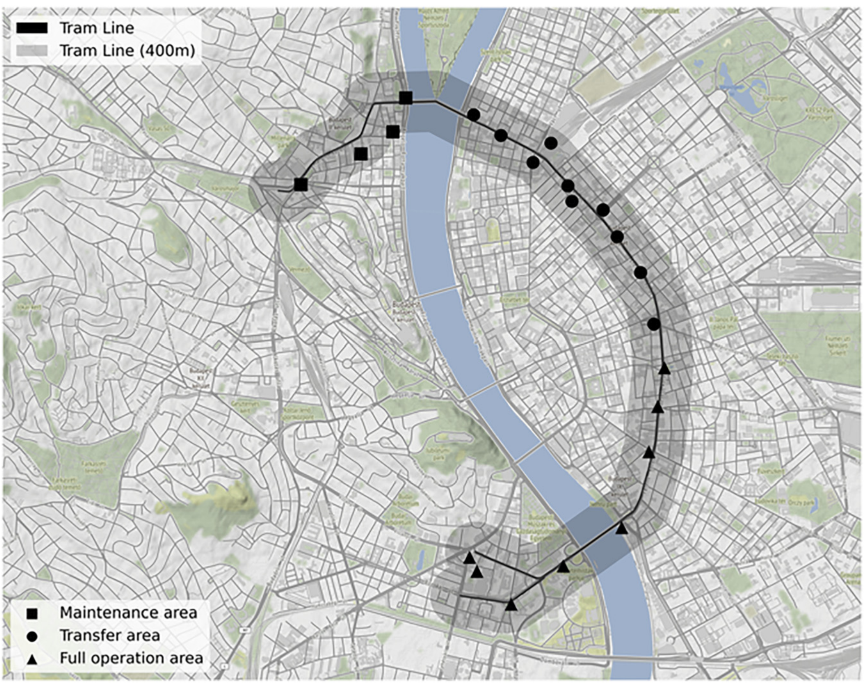

Fig. 1. BSS stations along the considered tram line

[2]We did not consider the pre-maintenance period since BSS usage is markedly lower in the winter period (see Fig. 2).

This approach requires a further validation step to examine whether the estimated change in the BSS ridership is directly a result of the tram maintenance. If trip generation of the two types of stations shows parallel trends before the intervention, we can infer that the change was a result of the intervention. Since the BSS usage is highly seasonal, analysing the peak period of the preceding year would be called for. However, in our case, this is not possible as the BSS was launched only in September 2014. Therefore, we analysed the trip generation trends and applied a placebo event study test, as discussed in Angrist – Pischke (2009), for the peak period of the subsequent year. Thus, we estimated the same model for 2016. It is important to stress that in that year no tram maintenance was undertaken along this tram line (except for two weekends). If the relationship we uncovered is a causal one, we should not see any significant effect for 2016.

The general form of the estimated model was the following:

$$y_{it} = a + \beta_1 D_{mntnc} + \beta_2 D_{mntnc} \times D_{close} + \Gamma X_{it} + c_i + u_{it}, \quad (1)$$

where y_{it} refers to the number of trips generated by station i on day t, D_{mntnc} refers to the time of the maintenance and D_{close} refers to the stations located in the maintenance area of the tram line (it only appears in the interaction term as the fixed effects already capture the direct station-specific effects). Control variables are captured by X_{it}, while station-specific fixed effects by c_i and u_{it} is the error term. The model was estimated by a fixed effects panel model to take into consideration the panel structure of the data. The main variable of interest is β_2 that shows the impact of the maintenance works on the number of trips generated by stations close to the refurbished tram line.

The control variables were identified based on prior literature. There is a consensus (e.g., Saneinejad et al. 2012; Gebhart – Noland 2014; El-Assi et al. 2017; de Chardon et al. 2017; Bakó et al. 2020a) that weather conditions (temperature, wind speed and precipitation) have major effects on the BSS usage. Weather data were obtained from the European Climate Assessment & Dataset provided by the European Climate Support Network. This includes daily average, minimum and maximum temperature, daily total precipitation and daily average wind speed. The effect of temperature on bicycle usage is not linear (Bakó et al. 2020a), therefore 5°C intervals were created from the daily average temperature data. Regarding precipitation, we used a dummy variable indicating whether it was raining on the given day. Wind speed data was used without any manipulation.

The size of the BSS network is another important factor (e.g., Gebhart – Noland 2014; Campbell – Brakewood 2017), therefore we also controlled for this in the regression. Several studies showed that natural and built environments affect the utilisation of a BSS station (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. 2017). However, environmental conditions are stable in the short run, thus these effects are captured by the station fixed effects. Finally, pricing also affects usage (e.g., Goodman – Cheshire 2014; Fishman 2016; Lin et al. 2017). Yet, neither the BSS prices nor the public transportation prices have changed in the analysed time period. Moreover, taxi and public transportation prices did not change in 2015 either, while the fuel price changes were negligible in the relevant time interval. Thus, we did not include any price related data in our analysis.

BSS related data were provided by the system operator company, Centre for Budapest Transport. The dataset contains start date, end date, start station, end station, and ticket type (pass or ticket) for all trips occurring in 2015. The dataset allowed us to separate users based on the ticket types, i.e., differentiate regular users (who are using the system with passes) from *ad hoc* users (who are using the system with tickets). Some data cleaning was required to eliminate the invalid entries. Once a trip was not longer than 1 min or the start station was missing, the trip was deleted from the database. The original dataset contained 669,519 observations. After data cleaning, 656,743 trips remained in our database. The majority (88%) of the usage was generated by regular users, and only, 12% was connected to tickets. Furthermore, data indicates that the network is more heavily used on weekdays. Trip data were summarised into number of trips by day, generating station and ticket type.

Station data shows that station utilisation varies heavily. While the average daily trip generation was 20.8 per station in the analysed period, it was ranging from 0 to 202 trips per day. Previous studies (e.g., Faghih-Imani – Eluru 2015; El-Assi et al. 2017) indicated that weekdays and weekends show different usage patterns. On weekdays usage is more connected to commuting, while weekend usage is more about leisure and recreation. Therefore, we separated the data into weekend and weekdays subsamples.

Usage patterns show significant seasonality (Figure 2). The system is much less utilised during the winter and usage picks up in the spring. Controlling for weather conditions does not eliminate seasonal effects completely: a user who does not buy a pass for the winter period might not use the BSS even on a mild winter day. Figure 2 also reveals that the peak season of the BSS is from April to September, hence the model was estimated only for this period. This left us with 483,415 trips in total (74% of the total trips made in 2015) out of which 61,402 trips were generated by the stations situated along the tram line we are concerned with. 93% of the trips analysed in this study were rented via passes and only 7% via tickets.

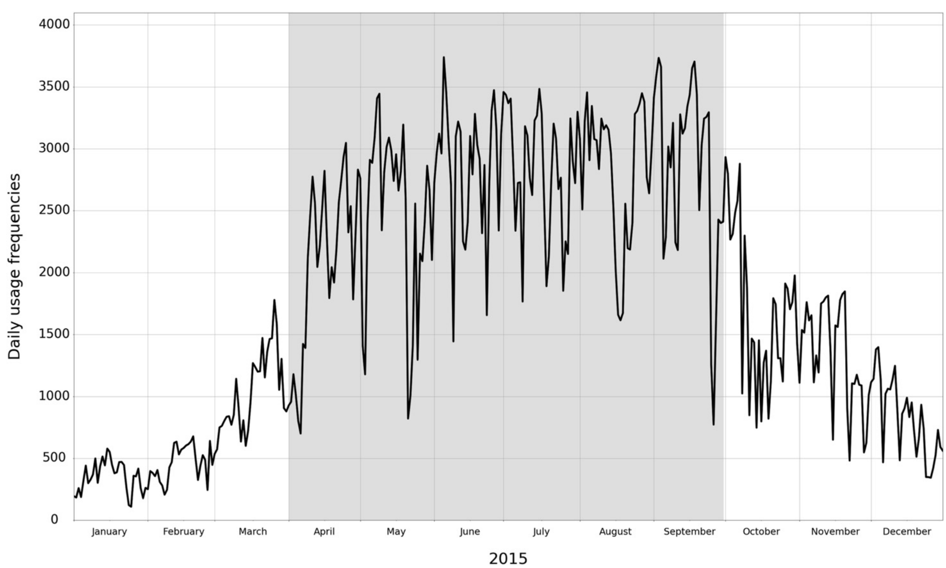

Fig. 2. Daily usage frequencies of the Budapest BSS in 2015
Note: The dark shaded area indicates the peak period (April – September).

Table 1 reports summary statistics of the dataset used. It shows that the regular users use BSS more often on the weekdays, which can be attributed to commuting. On the other hand, the *ad hoc* users are more 'on the go' on weekends, their usage on weekdays being more sporadic.

4. RESULTS

Figure 3 illustrates the average trip generation by the pass holders for the treated (maintenance area) and for the control (full operation area) stations in the analysed time period. The graph reveals that trip generation was nearly identical on average during the overhaul, and it started to diverge after the maintenance works ended. This difference persisted in the long-run. This observation suggests that an increase in the BSS usage occurred during the maintenance period that declined after the tram was in operation again.

Equation (1) was estimated using BSS data for April-September 2015. Results are presented in Table 2. Column 1 shows the key results, since 93% of the trip in the dataset were generated by the pass holders who mainly use BSS on weekdays.

Our results are in line with the literature regarding the impact of weather conditions on BSS usage. Not surprisingly, rainy weather and higher wind speed discourage users from riding a bike. Moreover, the results show that the effect of temperature is not linear, neither very cold, nor very hot weather is comfortable for cycling. According to the results, the highest usage is associated with a daily average temperature between 20°C and 25°C, higher and lower temperatures are associated with lower BSS usage.

As one can see from Table 2, the period of the maintenance is not significant in any of the regressions. This confirms that no significant occurrences took place affecting the usage during this period.

Table 1. Summary statistics

Variable	Obs.	Mean	Median	Standard deviation	Min.	Max.
Number of trips per station with pass on weekdays	1,524	28.98	26	14.95	0	92
Number of trips per station with pass on weekends	672	19.57	18	12.18	0	74
Number of trips per station with ticket on weekdays	1,524	1.56	1	2.34	0	20
Number of trips per station with ticket on weekends	672	2.54	1	3.32	0	22
Number of stations	183	86.79	91	8.93	76	96
Average daily temperature (°C)	183	19.33	19	5.66	4.8	29.8
Average daily wind speed (m s^{-1})	183	2.33	2	0.99	1	6.2
Total daily precipitation (mm)	183	1.82	0	6.42	0	66

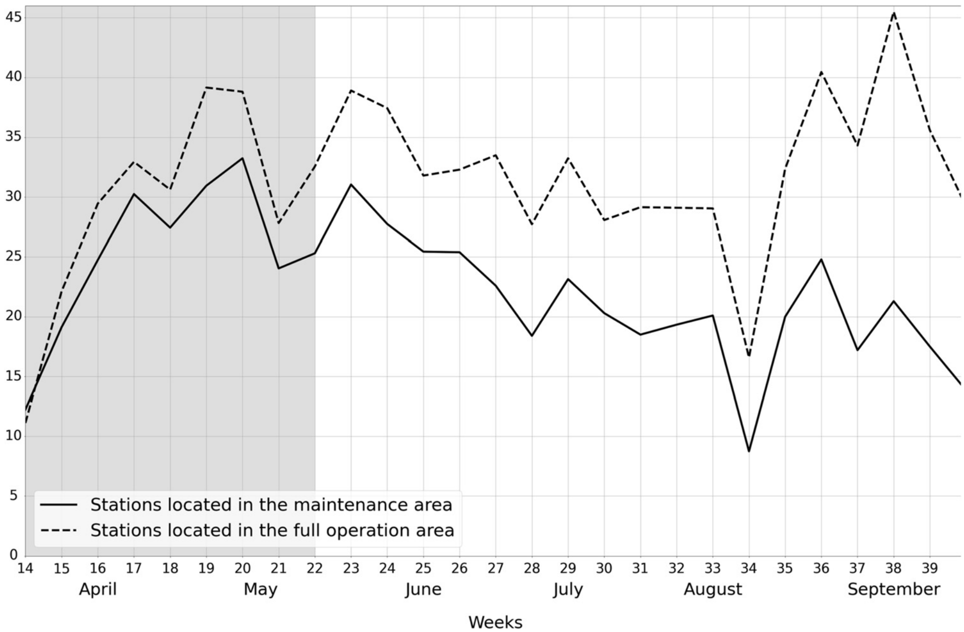

Fig. 3. Daily average trip generation of the analysed stations by pass holders (April – September 2015, weekdays only)
Note: The dark shaded area indicates the period of the maintenance.

The coefficient for the main variable of interest (maintenance period × maintenance area, i.e., $D_{mntnc} \times D_{close}$) indicates that the overhaul increased BSS usage in the area of maintenance by around 7.3 trips per station per day for the pass holders on weekdays. This increase is equivalent to a 25.2% increase in the average usage of the BSS stations located in the closed tram area (29 trips per station). However, no effect was found for the pass holders on weekends and for the ticket holders irrespective of the day of the week. One reason behind these results can be that traffic usually is less congested during the weekends, thus time saving from using BSS instead of the replacement bus is lower in general. As for the ticket holders, many of them are tourists with limited knowledge about temporary traffic changes.

We complemented the results with analysing future usage trends and applying a placebo test. First, we examined the usage patterns of the analysed stations for 2016. Figure 4 indicates that the difference that was observable after the tram maintenance in 2015 remained unchanged in the peak period of 2016. The average daily difference in trip generation between the control and treated stations was 4.1 in the maintenance period in 2015 and 11.4 afterwards (difference was significant at every common significance level). In 2016, these were 10.1 and 12.0, respectively (difference was not significant at 5% level). These clearly show that the observed difference after the tram started to operate full-length persisted in 2016.

Estimating the placebo event study regression for 2016 reinforced this conclusion. The placebo variable of interest was found to be insignificant ($P = 0.301$ in the pass/weekday

Table 2. Regression results for the peak season (April – September 2015)

Variable	Pass		Ticket	
	Weekday	Weekend	Weekday	Weekend
Maintenance period	–1.460	–0.855	0.370	–0.046
	(1.417)	(0.994)	(0.269)	(0.370)
Maintenance period × maintenance area	7.334***	2.169	0.367	0.342
	(1.801)	(1.303)	(0.275)	(1.535)
Network size	–0.157	–0.224*	0.028	–0.042***
	(0.118)	(0.107)	(0.016)	(0.009)
Temperature 0–5°C	–	–19.952***	–	–1.563**
		(2.628)		(0.689)
Temperature 5–10°C	–16.099***	–10.925***	–0.739***	0.038
	(2.030)	(1.446)	(0.217)	(0.453)
Temperature 10–15°C	–3.638***	–3.039**	–0.448***	–0.049
	(0.833)	(1.083)	(0.100)	(0.247)
Temperature 20–25°C	1.518**	–0.479	0.131	–0.383
	(0.575)	(0.582)	(0.160)	(0.251)
Temperature ≥25°C	–5.319***	–3.099***	0.482	–0.421
	(1.173)	(0.735)	(0.298)	(0.335)
Precipitation (dummy)	–6.674***	–5.019***	–0.354**	–0.051
	(0.852)	(0.854)	(0.118)	(0.293)
Wind speed	–0.958***	–0.673**	–0.088	0.055
	(0.263)	(0.283)	(0.050)	(0.100)
Constant	48.296***	44.421***	–0.721	6.248***
	(10.890)	(9.816)	(1.363)	(1.014)
N	1,524	672	1,524	672
R^2 (between)	0.189	0.097	0.082	0.122

Notes: Fixed effects panel regression with station-clustered standard errors – reference category for average daily temperature is 15–20°C, for precipitation no rain.
* $P < 0.1$, ** $P < 0.05$, *** $P < 0.01$.

subsample, and also, insignificant in all other cases) indicating that the higher usage of the BSS stations along the tram line during the maintenance works was indeed caused by the maintenance and not by other factors reoccurring in the same period of the year.

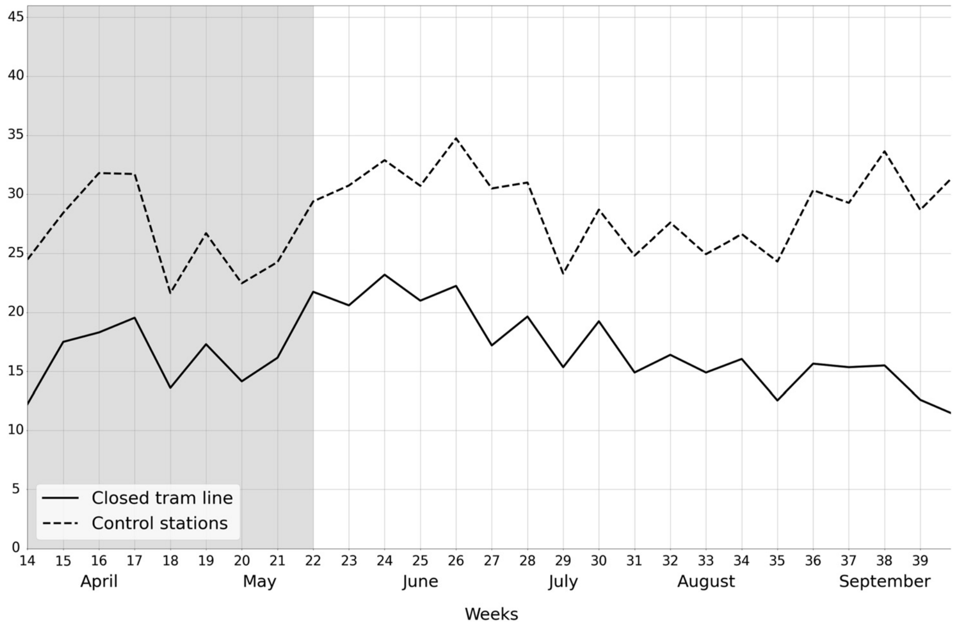

Fig. 4. Daily average trip generation of the analysed stations by pass holders (April – September 2016 weekdays only)

Note: The dark shaded area indicates the period when the tram was under maintenance in 2015.

5. DISCUSSION AND CONCLUSION

Earlier research, such as that of Fishman et al. (2014) suggested that there can be a substantial substitution from car use toward BSS. Jin et al. (2019) conducted a case study of bicycle sharing usage in Beijing and found that within 2 km, there is mostly substitution between public transport and BSS, while above that threshold, these services are mostly complements. Yang et al. (2018) found that BSS can in fact increase the efficiency of the local transportation system by decreasing travel time. Furthermore, a study by Campbell – Brakewood (2017), investigating the substitution between bus services and BSS found a 2.42% decrease in bus trips per thousand docks along a bus route. All in all, these studies suggest that there is a significant substitution between public transport and BSS. While confirming these effects, our study paints a more nuanced picture. The results suggest that the effect of tram line refurbishment on the bicycle sharing usage is substantial, however, when compared to the total usage of the tram line, the effect might not be that considerable given the much greater baseline usage of the tram service.

The normative implications of our findings are not straightforward. Bicycle-sharing is often subsidised with the aim of providing an alternative to motorised commute, potentially contributing to a reduction in greenhouse gas emissions and air pollution. Subsidising bicycle use is, of course, not a first-best way of internalising externalities, but nevertheless, if more direct and efficient policies, such as congestion charges or carbon taxes are, for some reason, not politically feasible, encouraging BSS usage could be a second-best efficient policy choice.

However, trams, like bicycles, are a relatively environmental friendly mode of transportation, so if users substitute the tram service for BSS, they do not decrease environmental externalities at the margin, except if the effect persists in the long run, that is, users develop a habit of bicycle use, which could mean that they use not only the tram service, but for e.g., bus services less. Unfortunately, our results cannot shed light on such possible effects, as we have only focused on the effect of disruption in the tram service. As for any cannibalization effect, as we have mentioned above, compared to the baseline traffic generated on the tram line, substitution away from it toward BSS is rather small. This may suggest that BSS is not yet a prominent and integral part of the public transportation system in Budapest. Another implication we can draw from our findings is that a number of passengers switch to bicycles during tram maintenance largely because they find the tram replacement bus too slow due to traffic congestion. On weekends, when there is less congestion, we found passengers to be less likely to substitute the replacement bus service for BSS. This might imply that it could be useful to set up temporary BSS stations along public transport lines under maintenance. Moreover, the user base of BSS is similar to the user base of ride-sharing services and that both services could be substitutes to using one's own car. If that were indeed true, this, combined with a relative lack of cannibalization *vis-à -vis* the tram service, would mean that the BSS contributes to a decrease in environmental externalities. However, for the time being, these claims and suggestions can only be tentative. Understanding the relationship between BSS and other modes of transportation therefore remains a fruitful area of further research.

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