How did the September 2010 introduction of the Capital Bikeshare system in Washington D.C. impact road accident rates?

Abstract

The last decade has led to the rapid emergence of bicycle-sharing programs around the world. Bicycles are a fun, less polluting, and cost-effective method of transportation which has given rise to its popularity. The Capital Bikeshare Program was launched in September 2010 in Washington D.C. and is a pioneer in enacting the benefits of bicycles. There is evidence suggesting that bicycles are a much safer way to commute than other forms of road transportation. In this study, we evaluate the effect of this program using a difference-in-differences modeling approach that utilizes pretreatment and post-treatment periods. We also divide Washington D.C. into two groups of wards where the wards with large amounts of bike sharing after the introduction of our program are our treated cohort, and the wards with low amounts of bike sharing are our control cohort. Our results indicate that the Capital Bikeshare Program is associated with more crashes, although it is possible that confounding variables could have caused this increase. Even so, our results emphasize the importance of creating safer infrastructure for cyclists because the other benefits laid out by bicycles continue to be relevant.

Introduction

The Capital Bikeshare Program was launched in September 2010 in Washington D.C. and was the largest bike sharing program at that time. The program was an initiative through the D.C. Department of Transportation and Arlington County. The main goals of the program were to make bicycles a part of the city transportation system, promote cycling and a healthy lifestyle, improve air quality, and increase peoples' movement around the city. The idea is simple: users can pay a daily, weekly, monthly, or annual fee to become a member and they are then granted access to borrow and ride a bike from any bike station around the city. With a fleet of 2,500 bikes and over 300 stations across the metro region, the program has been a resounding success in achieving its goals. But what impact does the program have on road safety?

It has been cited that bicycles are a much safer way to commute than motor vehicles due to its lower fatality rate. For example, within Illinois, 26 bicyclists were killed in the last year for which statistics were available, and 2,663 were injured, according to the Illinois Department of Transportation. Car crashes were responsible for 700 deaths that year, and 93,517 injuries. Further, bicyclist fatalities represented 2.1% of all traffic crash deaths, and bicyclists also represented 2% of all people injured in all traffic accidents. While this is already good news for the bicyclists out there, evidence suggests that bike-share users have lower accident rates than normal bicyclists. Additionally, the "safety-in-numbers" hypothesis suggests that more bike usage reduces vehicle usage and lowers collision chances (Martin et al., 2016).

To test these claims, we employ a difference-in-differences methodology to examine how bike sharing impacts road crash rates within the D.C. area. To do this, we study two distinct periods: pre-September 2010 and post-September 2010 to show the effect of the program. Further, we divide up DC into wards where the wards with large amounts of bike sharing after the introduction of our program are the treated cohort, and the wards with low amounts of bike sharing are the control cohort. For our analyses, we look at the daily crashes for each group in each of these periods respectively and examine the effects of the program on road accidents.

We hypothesize that the much greater use of the Capital Bikeshare program in the treatment wards in the post-treatment period is associated with a reduction in overall crashes in these wards. We hypothesized this because the program may have reduced the number of cars driving in treated wards more than in control wards, because people may ride bikes instead. Due to this, it may have also reduced the number of crashes occurring in the treatment wards compared to control wards, because bike usage may result in fewer crashes than car usage.

Methods

We used four data sets to create our final data set: Capital Bikeshare Trips, Capital Bikeshare Locations, Crashes in DC, and DC Wards from 2002. We obtained three of these datasets from the OpenDataDC website. The Capital Bikeshare Trips dataset was obtained from the Capital Bikeshare program website.

The Capital Bikeshare Trips dataset listed each trip taken using Capital Bikeshare bikes from September 20, 2010 to December 31, 2012. This dataset included the name of the starting and ending stations of each trip. The Capital Bikeshare locations dataset contained the Capital Bikeshare data to create a dataset with starting and ending coordinates for each bike trip. Using a spatial join in the ArcGIS program, the newly created trip coordinates dataset and the 2002 Wards dataset were combined to determine which ward each bike trip started and ended in. Then, we summarized the bike trips by ward and by date and created an overall trips variable, which is the average of trips started and trips ended in a ward on a given day.

The Crashes in DC dataset was summarized by ward and by date, so that each observation represented the number of crashes in a ward on a specific day. After both the Bike Trips and Crashes in DC datasets were summarized by ward and date, they were merged to create the final dataset which includes data for crashes and bike trips in each ward on each date between May 20, 2008 and December 31, 2012. We created a variable based on the date which represents the number of days after Capital Bikeshare was introduced (treatment), which is negative for dates before the program's introduction.

A difference-in-difference method was used to examine the effect of bike sharing on crashes. In this case, the control group consisted of wards 1, 2, and 6, that have consistently very few bike trips taken (see Appendix C). The treatment group consisted of wards 4, 7, and 8, which have consistently high amounts of bike trips taken (see Appendix C). In this type of model, there are also pre-treatment and post-treatment periods defined by the starting date of Capital Bikeshare, which is September 20, 2010. Neither the control or treatment group is subject to the bike sharing treatment before this treatment start date, and this pre-treatment period is used to demonstrate that the trends for crashes in the control wards are similar to the trends for crashes in the treatment wards, as is shown in Appendix A. These common trends between the treatment and control groups in the absence of treatment are important to establish because they form the basis of the comparison in the post-treatment period. In the model, there is an assumption that the crashes in the post-treatment control group serve as a counterfactual for what would have occurred in the treatment group had the treatment not been applied, so common trends in the pre-treatment period are established to show that this is a reasonable assumption.

For the difference-in-difference regression, a linear regression was modeled using three main predictors for crashes in a ward on a date. One predictor, *treatment group*, is a dummy variable representing if the ward is a treatment ward, and another predictor, *post period*, is a dummy variable representing whether the date was in the post-treatment period. The main effect of interest is captured by the *post* $\times$ *treatment* predictor, which is a dummy variable corresponding to true only in the post-treatment period in treated wards. Additional variables were included to control for potential confounding of the main predictor, including *days after treatment* to control for a citywide long-term trend, and dummy variables to control for variation in seasons, as there is some variation among seasons (Appendix D).

Results

In our difference-in-difference linear regression model, the main coefficient of interest *post* $\times$ *treatment* is 1.388, the *treatment group* coefficient is 1.143, the *post period* coefficient is -2.212, and the *days after treatment* coefficient is 0.00382. The coefficients for all of these variables are supported by a low p-value of $< 2*10^{-16}$ respectively.

Discussion

The main coefficient of interest, *post* $\times$ *treatment*, was found to be very significant with an estimate of 1.388 and a p-value that is lower than $2*10^{-16}$, the lowest possible value. This estimate indicates that we expect the daily crash rate for a ward significantly affected by the Capital Bikeshare program to have 1.388 more crashes than a ward that was not significantly impacted by the program. This is the opposite of what we hypothesized and indicates that the Capital Bikeshare program is actually associated with more crashes. This result is inconsistent with the safety-in-number hypothesis that more bikes would reduce crashes. However, the association found here is not direct and there could be many other confounding variables that happened to increase crashes in the treatment wards more than the control wards.

Because higher bike sharing usage may be associated with higher crash rates, our research suggests it is important to create a safer road environment for cyclists. With 33% to 40% of bicycle crashes involving another roadway user in the United States (Martin et al., 2016), the promotion of dedicated bike lanes could be very beneficial. Research also suggests that bike sharing riders were less likely to be aware of protected routes compared with regular cyclists. As such, including features that indicate safe bike routes for bike share users on apps or at bikeshare stations can be beneficial (Kealy & Wu, 2021). Overall, while the introduction of bike sharing in Washington, D.C. is associated with higher crashes, it may still be worthwhile to overcome barriers to grow bike sharing since they can provide urban residents with a convenient, environmentally friendly and time-saving travel mode. If executed with the correct infrastructure and utilized to a high degree, bike-sharing could dramatically decrease traffic, reduce energy consumption, decrease harmful gas emissions, improve public health generally, and promote economic growth (Qui & Ling-Yun, 2018). Further research on the safety of bike sharing programs in different cities of varying bike-friendliness would help in order to develop a more optimal approach to the success of bike sharing.

References

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Appendix A: Difference-in-Differences Regression

.Coefficient	Estimate	Std. Error	t-value	p-value
post $\times$ treatment	1.388	0.114	12.191	$< 2*10^{-16}$ ***
treatment group	1.143	0.0777	14.714	$< 2*10^{-16}$ ***
post period	-2.212	0.128	-17.219	$< 2*10^{-16}$ ***
days after treatment	0.00382	0.000125	30.622	$< 2*10^{-16}$ ***
spring	0.457	0.0823	5.554	$2.87*10^{-8}$ ***
summer	0.00425	0.0790	0.054	0.957
winter	-0.106	0.0827	-1.278	0.201
intercept	4.499	0.0958	46.976	$< 2*10^{-16}$ ***

Table A1. Difference-in-differences regression coefficients

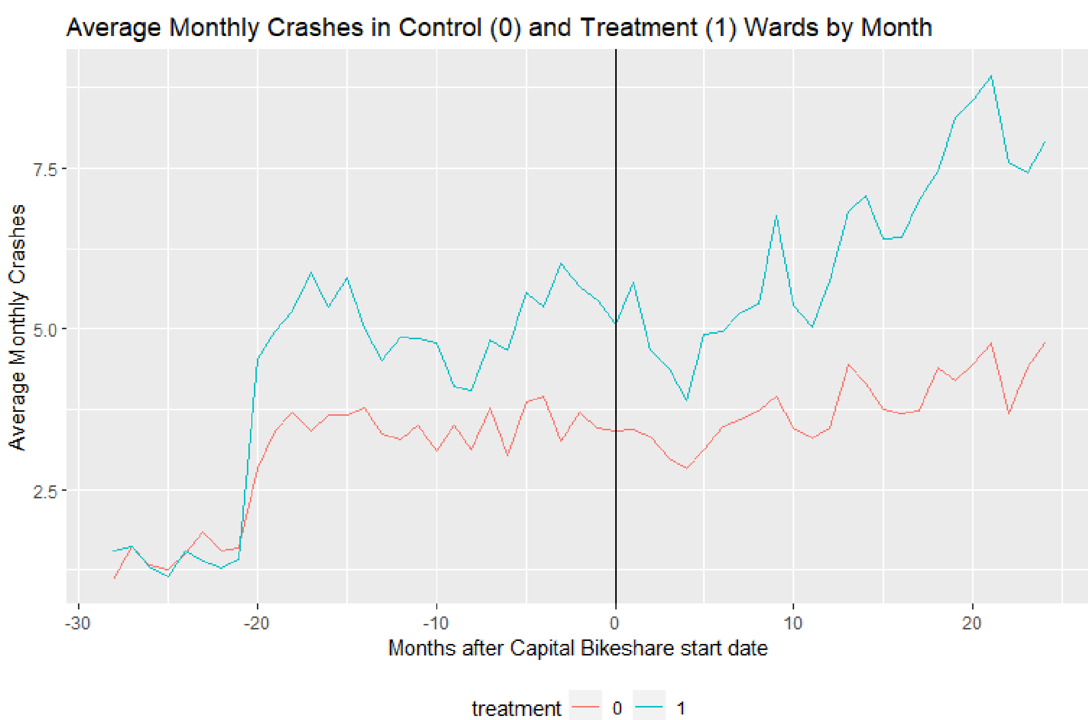

Figure A1. Average monthly crashes in control and treatment wards by months after Capital Bikeshare start date. This demonstrates common trends.

Appendix B: Crashes per Year

0 stands for control and 1 stands for treatment. Our treated groups are wards 1, 2, and 6, while our control group are wards 4, 7, and 8.

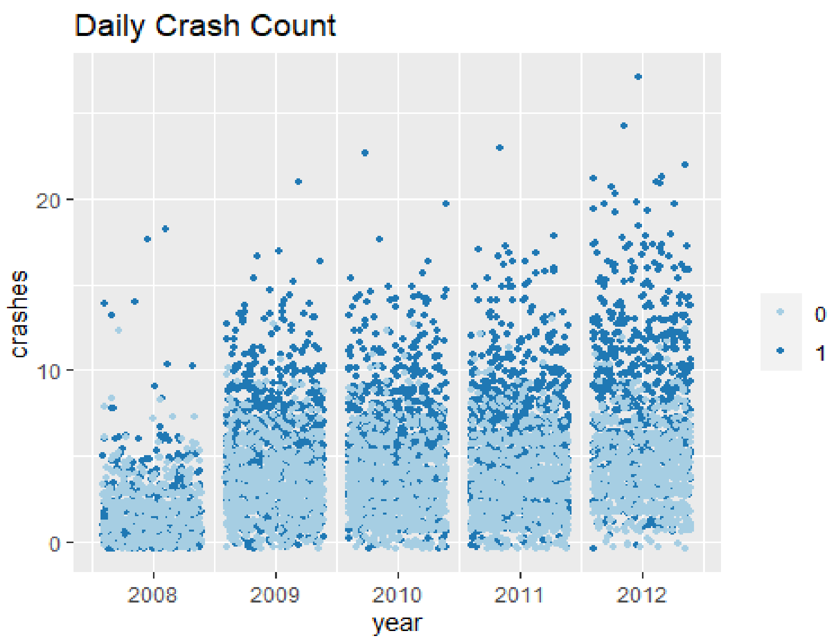

Figure B1. Crashes per year by treatment and control group in Washington DC with each point representing a day.

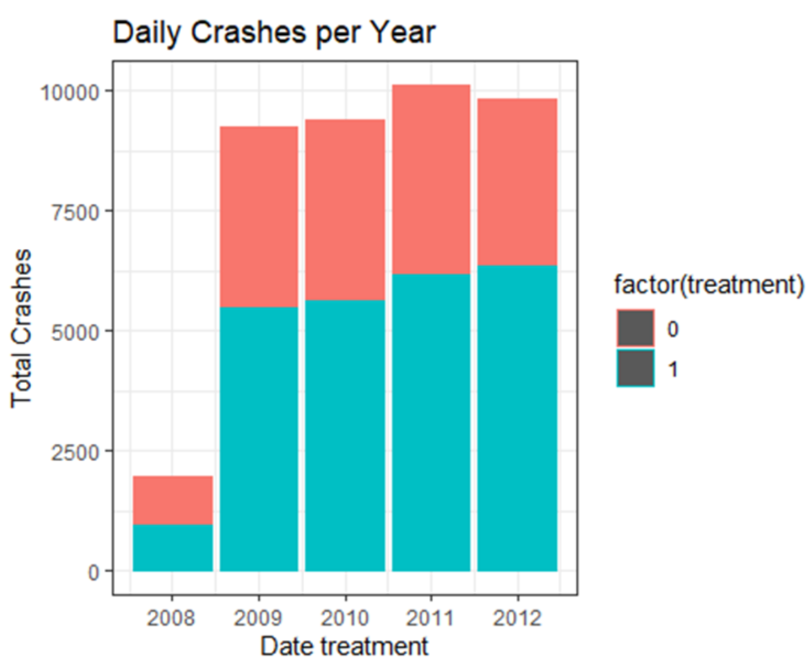

Figure B2. Crashes per year by treatment group and control group.

Appendix C: Trips per Year

0 stands for control and 1 stands for treatment. Our treated groups are wards 1, 2, and 6, while our control group are wards 4, 7, and 8.

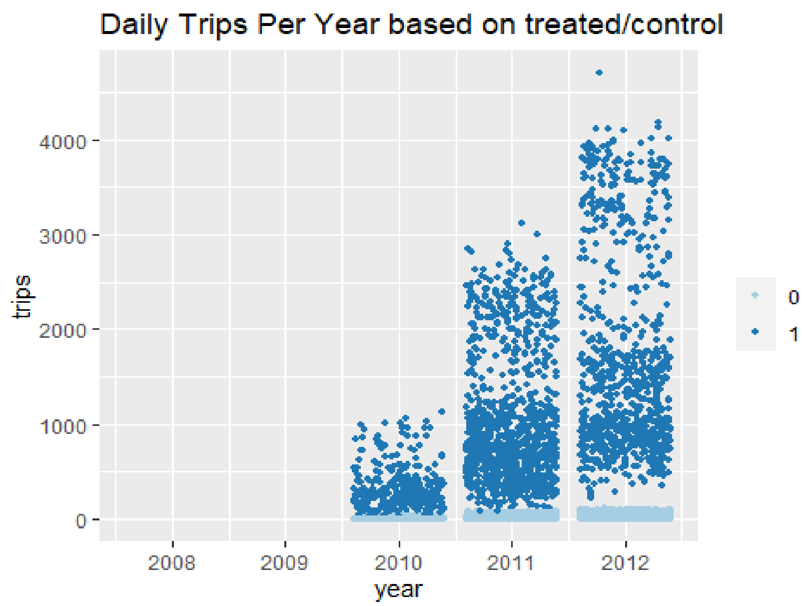

Figure C1. Trips per year by treatment and control group in Washington DC with each point representing a day.

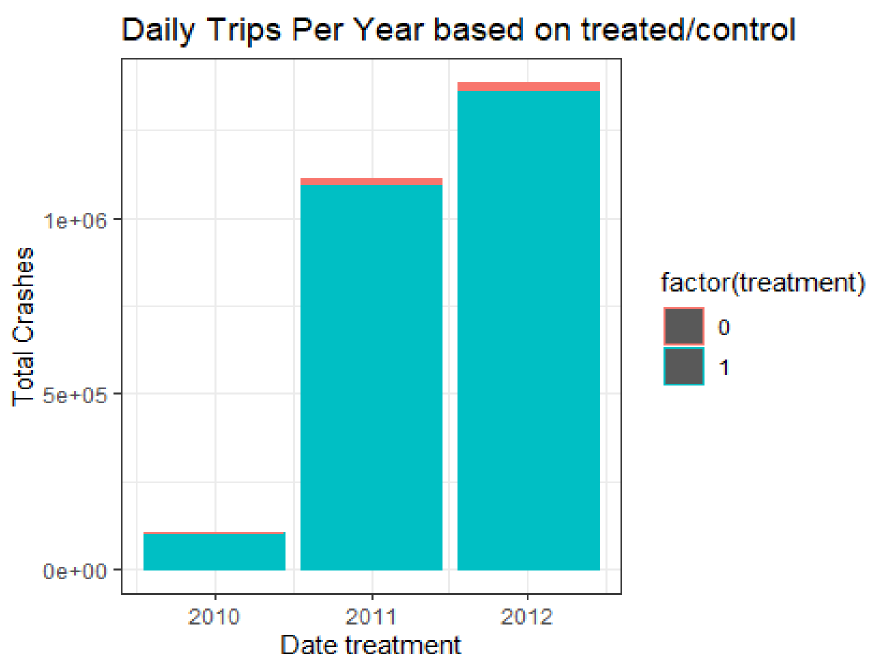

Figure C2. Trips per year by treatment group and control group.

Appendix D: Seasonal Variation

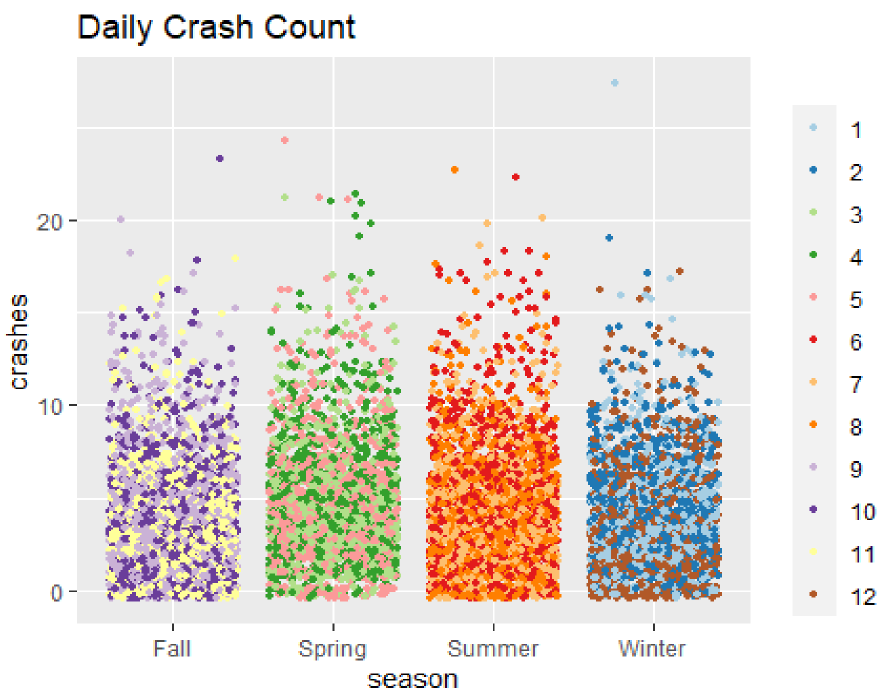

Figure D1. Crashes per year by season.

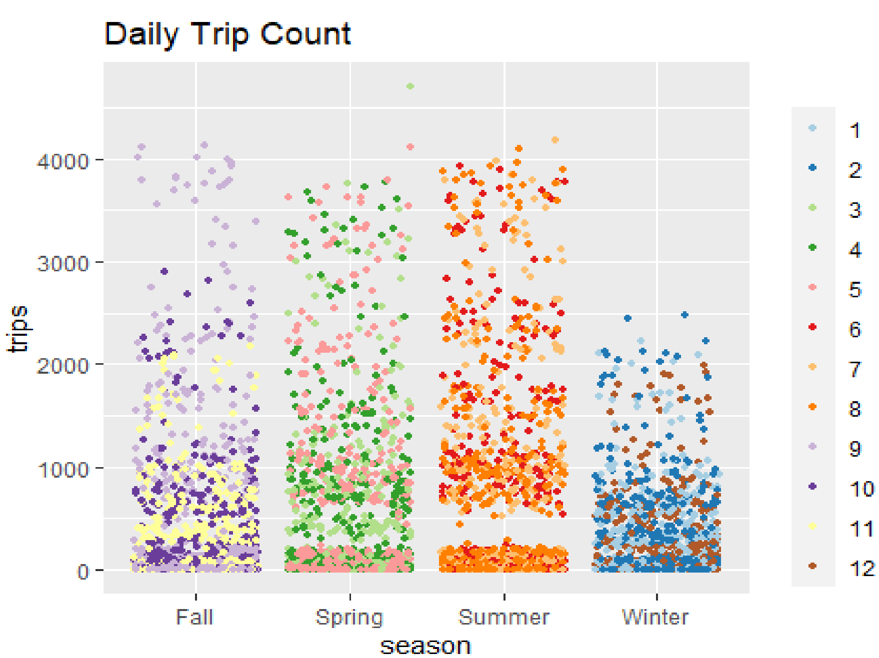

Figure D2. Trips per year by season.