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# Impact of the introduction of single-trip fare product on bikeshare usage and revenue: the Capital Bikeshare experience

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**Abstract**

Pricing plays a key role in policy and practice considerations at bikesharing systems. Yet, a notable gap exists in literature on studies related to the impact of changes in pricing policy on ridership and revenue. This paper presents results of the impact assessment of the introduction of a single-trip fare (STF) product (priced at $2 per trip) for casual users by Capital Bikeshare (CaBi), the public bikeshare system used in the Washington, DC metro area. Unique characteristics of the point of sale system in use at CaBi were leveraged for designing and executing a 'before-after' experiment. The experimentation allowed casual user revenues to be traced to individual stations, which further allowed comparing revenues and ridership 'before' and 'after' the launch of STF at the station-level, while controlling for other variables. Over 22 million records on individual bikeshare trips and revenue transactions for three years and 330 bikeshare stations were analysed. The results showed a statistically significant increase in ridership and a statistically significant decrease in revenue per ride for casual users after the introduction of STF. Furthermore, after STF was launched, an increase in growth rates of casual user ridership and a switch to negative growth rates from positive growth of casual user revenue were observed at common stations to the 'before' and 'after' periods. Statistical tests indicated that changes in both these growth rates might be attributable to the introduction of STF. The methods we used in this study are transferable and can be used for studying the impacts of bikeshare pricing policy changes on system usage and revenues at various public bikesharing systems.


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*Keywords:* Bike share; pricing; revenue; ridership; big data; price sensitivity

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## 1. Introduction

Exponential growth of shared mobility services such as carpooling/ridesharing, ride hailing (e.g. Uber, Lyft), carsharing (e.g. ZipCar) and bikesharing in recent years has taken the sustainable transportation concept by a storm. Even though bikesharing has been in existence since early 1960s, worldwide movement toward bikeshare is "off and running" since the 2007 launch of the third-generation bikeshare system Vélib' by the City of Paris (Goodyear 2018). In the decade since 2007, public bikeshare systems have caused major disruption to the landscape of urban transportation systems around the world. The fast-pace and large scales at which this disruption is taking place leaves researchers playing a catch-up in understanding this phenomenon's undercurrents such as demographic characteristics of users, causes and effects of changes in revenue, ridership and even the viability of bikeshare systems.

Public bikesharing programs typically serve three user groups—*members* (users with an annual or monthly membership); *casual users* (short-term bikesharing users who purchase a single trip or 24-hour or multiday passes); and *occasional members* (users with a special key to pay for a short-term pass) (Shaheen, Cohen & Zohdy 2016). Subscriptions from members provide a steady stream of revenue to bikesharing programs. Therefore, many bikesharing providers place an emphasis on catering to the preferences of members. On the other hand, for the year 2012 casual users of bikeshare programs in North America generate the largest source of revenue through membership and usage fees ranging from 44% to 67% of the programs total revenue (Shaheen et al. 2014). Casual users continue to account for a large percentage of total revenue (Venigalla et al. 2018).

Subscription products or 'fare products' and their pricing play a key role in policy and practice considerations at bikesharing systems. For, as in the case of a transit, the cost of ridership of a bikeshare trip plays a major role in mode choice behavior of users. To cater to the preferences of users, improve service and increase ridership, bikeshare providers routinely change pricing of existing fare products, introduce new products and alter the menu of pricing models for all user types. Despite the importance of pricing to bikeshare patronage, few studies focused on the impact of pricing on revenue and ridership (Venigalla et al. 2018, Kaviti et al 2018). The primary goal of this research is to examine the impact of changes made to bikeshare fare-products on bikesharing usage and revenue by analyzing large amounts of system wide data on revenue and ridership.

## 2. Motivation

The motivation to conduct this research came from the policy decision made by Capital Bikeshare (CaBi), the public bikeshare system in the Metro Washington DC area, to launch a single-trip fare (STF) product for its casual users. Overseen by the District Department of Transportation (DDOT), CaBi currently has over 500 stations and more than 4,000 bikes and is frequently expanding its coverage in the region (DDOT 2015). CaBi serves three types of users; casual users, occasional members, and registered members. The casual users and registered members combined constitute more than 98% of the bikeshare users (Venigalla et al. 2018). As of March 2018, subscription prices of prominent fare products offered by CaBi include the following.

Casual users:

- Single-trip fare (STF) for $2, for trips up to 30 min duration (introduced in June 2016)
- 24-hour pass for $8, for unlimited trips of 30-min duration or less in the 24-hour period after the pass is purchased
- 3-day pass for $17, for unlimited trips of 30-min duration or less in the 72-hour period after the pass is purchased

Registered members/occasional members:

- 30-day (monthly) pass for $28, for unlimited trips of 30-min duration or less that is valid for 30 days
- Annual pass for $85, for unlimited trips of 30-min duration or less that is valid for 365-days

In addition to the subscription fee, CaBi riders incur usage fees for trip durations exceeding 30 minutes.

CaBi added the STF product for casual users in June 2016, in conjunction with the first scheduled

SafeTrack, which is a track maintenance and safety rehabilitation initiative of the Washington Metropolitan Area Transit Authority (WMATA). During this rehabilitation process, metro rail had encouraged alternative travel options because of expected delays and capacity restrictions. CaBi's rationale for charging per-ride as opposed to offering only 24-hour and 3-day pass options for casual use was that fixed cost per ride could widen the appeal of Capital Bikeshare to new audiences seeking alternative travel options during SafeTrack beyond current subscriber base. The STF option was also aimed at potentially drawing new registered members towards regular bikeshare. Within a shorttime after its launch, STF has become a very popular fare option among the CaBi users (Venigalla et al. 2018). However, the potential effect of neither the price of STF, nor the timing of the launch on acceptance by CaBi users was studied before STF was introduced. A few months after the launch of STF, CaBi initiated this structured evaluation of the impact of STF on revenues and ridership at CaBi.

## 3. Research objectives

The primary objective of the research work presented in this paper was to evaluate the impact of the introduction of this popular new fare product in the form of STF on revenue and ridership in the Capital Bikeshare system by conducting disaggregate analysis of revenue and ridership data. Specifically, this paper addresses the following research questions:

Research question 1:

a) Is there a statistically significant change in revenue from casual users of Capital Bikeshare after the launch of STF?
b) If the answer to 1.a were 'yes', the follow up question would be, is this change attributable to the launch of STF or is it simply an extension of the background trend that existed before the launch?

Research question 2:

a) Is the change, if any, in usage of Capital Bikeshare (trips and duration) by casual users significantly different after the launch of STF?
b) If the answer to 2.a were 'yes', the follow up question would be, is this change attributable to the launch of STF or is it simply an extension of the background growth that existed before the launch of STF?

The availability of large amounts ridership and revenue data at individual trip-level and transaction-level, respectively, provided an opportunity to accomplish this objective.

## 4. Literature review

Literature search was focused on two primary themes. First focus was on studies that employed disaggregate analyses of ridership and revenue data at the level of individual stations. Second emphasis on literature search was given to studies that examined the impact of pricing on bikeshare systems' ridership and revenues.

### *4.1 Station-level Analysis of Bikeshare Usage Data*

Rixey (Rixey 2013) studied the impact of demographic and built environmental characteristics on bikeshare ridership at station level for CaBi, Denver B-cycle, and NiceRide MN systems. The results indicated that bikeshare ridership has positive correlations with population and retail job density; presence of bikeways; and bike, walk, and transit commuters. The findings also showed that the minority population and days of precipitation have negative association with the station-level bikeshare ridership levels. El-Assi et al. (El-Assi et al 2017) conducted a similar study to identify factors affecting Toronto's bikeshare demand at the station level by developing trip generation models. The study further developed a station-pair regression model, which showed a positive correlation with the increase in infrastructure, decrease in number of intersections with major roads and negative correlation between distance and bicycle ridership. Ma et al. (Ma, Liu & Erdogan 2014) explored the linkages between bikeshare and transit at the station level and demonstrated that bike-sharing programs can help increase transit ridership. The analysis showed that Metrorail stations have been the source of important origin and destinations for Capital

Bikeshare trips and concluded that an increase in trips would also increase transit ridership.

A few studies discussed how regression models could be used to determine the bikeshare ridership at the station level. Zhang et al. (Zhang et al. 2017) developed multiple linear regression models to study the effect of built environment variables on trip demand and ratio of demand to supply (D/S) at station level for public bikesharing system in Zhongshan, China. The results showed that both trip demand and D/S were positively correlated with population density, length of bike lanes, and diverse land-use types near the station. The findings also suggest that adding a new station with additional capacity within a 300 meters (m) radius of an existing station can improve the D/S at the station level. Wang et al. (Wang et al. 2015) developed regression models to identify factors effecting bike station activity for Nice Ride Minnesota. The results showed that proximity to Central Business District, campuses and parks; access to off-street paths have the highest marginal effects on the station use whereas socio-demographic characteristics and economic variables have minimal marginal effects.

de Chardon and Caruso (de Chardon & Caruso 2015) compared various aggregation models to calculate daily trips at different public bikeshare systems. The study developed day-aggregation, interval aggregation and station aggregation models to estimate the number of daily trips for eight major bicycle sharing systems in Europe and North America. The results showed that the daily aggregate model provides the better estimates of trips compared to other models.

Research on comparative assessment of aggregate and disaggregate models for the prediction of bikeshare demand is sparse. Biehl et al. (2018) developed two Generalized Linear Models at station and community level to predict average annual daily bicyclists for Chicago's Divvy bikeshare system. The results show that the station-level analysis has superior predictive capacity than the community-level analysis and averaging of disaggregate results to represent community areas has better accuracy than aggregate model. This is because disaggregate model contain more information regarding the bikeshare system, built environment and socioeconomic factors that impact the bike usage.

### *4.2 Studies Related to Impact of Pricing on Usage*

Though numerous studies discussed factors affecting the bikeshare ridership, only very few studies included pricing as one of the factors (Kaviti 2018). Judrak (2013) analyzed the time-specific cost structure of the public bikesharing system of Boston and Washington, DC. The study observed that registered users exhibit higher cost sensitivity around the 30- and 60-minute pricing boundaries compared to the casual users. One of the recommendations of this study is that incentives should be provided to bikeshare users on specific congested roads with dynamic pricing based on the current traffic conditions. Goodman and Cheshire (2014) examined how the profile of income-deprived and women users changed in the first three years of operations at London Bicycle Sharing System (LBSS). The percentage of income-deprived users doubled as the LBSS expanded its system to areas with low-income populations and women users make a higher share of casual trips. However, these positive developments have been partially offset by increasing the then prevailing prices at LBSS by 50%. The study further argues that bikeshare fares should be in a reasonable range to maximize the bikeshare usage and to make the system more equitable to all the users.

A report by Venigalla et al. (2018) and research paper by Kaviti et al. (2018) discussed the impact of the launch of \$2/trip STF by CaBi on its revenue and ridership at jurisdiction level. These two studies examined the interrelationship of revenue and ridership with other system variables such as supply (as measured by number of stations and bike racks or docks), jurisdiction, seasonality, transit disruptions, day of week and precipitation. Aggregate analysis performed at the level of two urban (Washington DC and Arlington, VA) and two suburban (Alexandria, VA and Montgomery County, MD) jurisdictions showed significant increase in casual user ridership for the two identical 12-month periods before and after the introduction of STF. However, the study found that the analysis on the impact of STF on revenue from casual users before and after STF at jurisdiction-level was inconclusive. Though notable changes were observed in revenues aggregated at the jurisdiction level, the paper could not verify if the changes observed in revenues after the introduction of STF were in fact attributable to the introduction of STF. The analysis performed by Kaviti et al. (2018) was primarily based on ridership and revenue data aggregated by month and jurisdiction, which has no fidelity at the daily level and station-level. Furthermore, in normalizing revenues and ridership on a 'per-dock' basis, the analysis by Kaviti et al. (2018) not only included new stations with sparse ridership, but also diluted the true impact of the introduction of single-trip fare at stations that have high ridership. Therefore, disaggregate analysis of the data at station level (i.e. analysis of individual trips and revenue transactions by station) could provide additional valuable insights on the impact of STF.

Ahillen et al. (2016) compared the policies and ridership trends of the Washington, DC's Capital Bikeshare and Brisbane's Citycycle. The findings show CaBi had few changes in its pricing policy since its launch in 2010. However, Brisbane CityCycle reduced the daily subscription fees from $11 to $2, introduced weekly subscriptions and provided free helmets at each of the stations. The results show providing helmets, reducing subscription fees, and adding flexible subscriptions to users may have contributed to a 50% increase in Citycycle ridership in just six months. Kaviti et al. (2018) studied the impact of introducing Single-trip fare (STF) for $2 on CaBi ridership and revenue. The results showed that introducing this new fare option increased the monthly ridership for the first-time casual users and all casual users by 79% and 41% respectively.

### *4.3 Summary*

The literature review identified only limited research on station-level analysis and the benefits of using the disaggregate analyses over aggregate analyses in the public bikeshare system. Studies on impact on pricing changes on bikeshare ridership are scant. This study attempts to fill these gaps by analyzing the impact of a single-trip fare on the Capital Bikeshare ridership and revenue at the station level. Also, this research compares the disaggregate models with that of the aggregate models for the newly introduced fare product.

## 5. Data and methodology

### *5.1 Study Data*

The study employed two primary data sources, which include data on individual CaBi trips and revenue transactional data for every CaBi revenue transaction during the period January 2015 through May 2017.

- Dataset 1 - CaBi ridership data. This data contains information on anonymous individual trips and is available to public at http://www.capitalbikeshare.com/trip-history-data. The dataset contains detailed information on each trip, which includes start and end stations, start and end times, duration of trip etc.
- Dataset 2 - Revenue transactional data. This data includes information on each revenue recognition transaction, including refunds issued to customers. This dataset is obtained exclusively for this study and is not available for public. Variables included in the dataset are transaction date (includes time to the second), fare product (single trip, annual membership etc.), transaction amount, station at which the transaction occurred. To protect the security and identity of the users, DDOT (data provider) removed all personally identifiable data.

The ridership data (Dataset 1) identifies each trip-maker as only a casual or registered user. No details are available on the type of casual user (i.e. STF user, 24-hour / 3-day pass holder). This loss of detail handicaps the impact analysis of STF launch on other casual users. However, the details of casual user (e.g. type of casual user, time of purchase and station at which purchase is made) are present in revenue transaction data (Dataset 2), which could be successfully mapped into Dataset 1. Data fusion techniques outlined by Venigalla (2004) were employed to fuse datasets 1 and 2. This data-mapping exercise enabled further identification of each casual trip-maker as a single trip user; the first-time user of a 24-hour / 3-day pass; or a repeat user of a 24-hour / 3-day pass (Venigalla et al. 2018).

Additionally, for the purposes of analysis control, daily weather data were obtained from Weather Underground history data website (http://www.weatherunderground.com) which offers historical weather data for different regions. The two primary data sets combined contain over 22 million records.

### *5.2 Response Variables*

System usage and revenue are the primary response variables examined in the impact assessment analysis. The extent of system usage is reflected in the number of trips taken by users, and trip lengths or trip durations. However, trip length information is not available in the data. For this reason, only the trip duration variable was used as one of the three response variables. While total revenues are an indicator of the impact, true impacts on revenue may be captured only through revenue normalized for usage (or, revenue per trip). In summary, the set of response variables included in the analysis are the following:

- Ridership (number of trips)
- Usage (trip-length in minutes)
- Revenue (total revenue and revenue per trip)

The analysis was performed only on the casual user revenues and ignores revenues from registered members for two reasons. First, Kaviti et al (2018) established that the launch of STF has not impacted the ridership of registered users. Secondly, the revenue from registered users could not be sourced to individual stations where the registered users have made their trips.

### *5.3 Explanatory Variables*

Variations in response variables were examined as a function of the following explanatory variables and their two-way and three-way interactions.

- Station: A single station or set of stations based on their location,
- Weekend/weekday: Whether or not the rides were taken on a week day where commute trip could be predominant, or on a weekend where recreation trips could be predominant
- Month: Month in which trips are taken to account for seasonality

### *5.4 Control Variables*

To enable a classical 'before-and-after' experimental set up for evaluating the true impact of STF on response variables, other variable that could potentially influence the outcomes must be controlled for. These controls and treatments for the experimental setup and evaluation included the following:

- The station-level disaggregate comparative analysis is conducted by pairing variables only at 330 stations that are common to the 12-month periods 'before' and 'after' the launch of STF. This direct comparison excludes stations that are open only for partial time in the 24-month analysis period and also eliminates the impact of seasonality.
- Days with precipitation are excluded from the analysis.
- No adjustments were made for temperature variations. However, by including calendar month as an independent variable, seasonal effects on ridership were controlled for.

## 6. Results

### *6.1 Before and After Analysis Results*

Descriptive statistics on the differences in response variables before and after the introduction of STF are presented and discussed in this section.

### *6.2 Casual User Revenues at Top 20-Common Stations*

Aggregate analysis based on monthly summaries of revenues presented in a prior study showed a decline in revenue from casual users (Venigalla et al. 2018). However, due to normalization by number of docks, the aggregate analysis did not adequately explain the impact of STF on revenue from casual users. To closely examine the STF at individual stations, revenues recognized from casual users at kiosks located at each of the 330 common stations were analyzed. Only the revenues that are marked as '*Product'* sales at a CaBi station (the designation indicates a sale at a station kiosk) are included in the analysis. Usage fees and refunds were excluded.

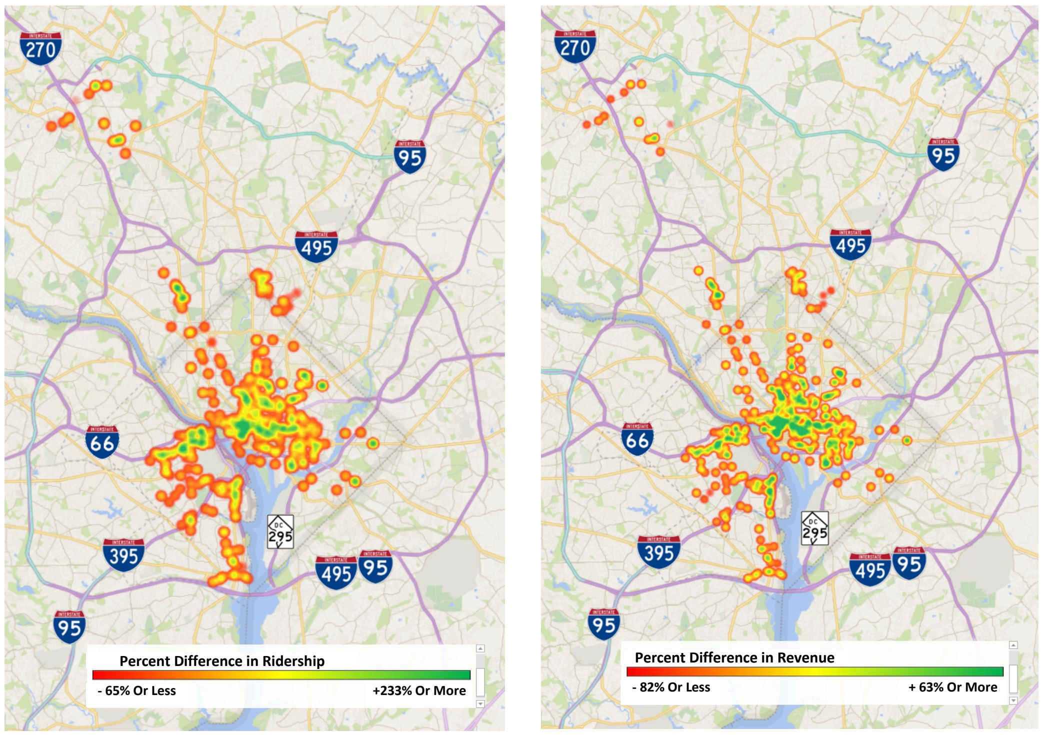
Casual user revenues recognized at kiosks located at the top 20 of the 330 common stations are presented in Table 1. The table indicates that the introduction of STF resulted in notable reduction in revenues at almost all 20 stations. The declines in revenues from 24-hour and 3-day passes are 42% and 34%, respectively, which indicates a shift in casual usage towards the STF product. After the launch of STF, revenues from all casual users at these stations declined by 21%, despite a 3.5% increase in ridership. A closer examination of revenues at individual stations indicates that all but two of the top 20 stations (Jefferson Memorial; and 14th & D St NW / Ronald Reagan Building) experienced decline in revenues. Declines in revenues at individual stations range from about 12% at Columbus Circle / Union Station to over 40% at 21st St & Constitution Ave NW (computations are not shown in the table). Statistical verification is needed if these changes could be attributed to the introduction of STF.

**TABLE 1.** Revenues from Casual Fare Products at the Top 20 Stations

| Station | Before STF (June 2015 - May 2016) | | | After STF (June 2016 - May 2017) | | | |
|---|---|---|---|---|---|---|---|
| | 24-hour Pass | 3-Day Pass | Total Casual | 24-hour Pass | 3-Day Pass | Single Trip | Total Casual |
| Jefferson Dr & 14th St SW | $157,272 | $10,540 | $167,812 | $90,968 | $7,021 | $31,564 | $129,553 |
| Lincoln Memorial | $141,872 | $8,755 | $150,627 | $58,344 | $5,287 | $29,418 | $93,049 |
| Smithsonian-National Mall / Jefferson Dr & 12th St | $113,368 | $7,735 | $121,103 | $67,960 | $5,287 | $23,052 | $96,299 |
| 4th & C St SW | $48,440 | $5,253 | $53,693 | $28,392 | $3,060 | $9,222 | $40,674 |
| New York Ave & 15th St NW | $48,800 | $4,182 | $52,982 | $29,616 | $3,043 | $9,664 | $42,323 |
| Massachusetts Ave & DuPont Circle NW | $35,880 | $7,157 | $43,037 | $23,016 | $4,930 | $8,450 | $36,396 |
| Ohio Dr & West Basin Dr SW / MLK & FDR Memorials | $41,272 | $1,343 | $42,615 | $24,040 | $1,037 | $10,026 | $35,103 |
| Constitution Ave & 2nd St NW/DOL | $38,216 | $4,148 | $42,364 | $26,160 | $3,468 | $10,352 | $39,980 |
| Jefferson Memorial | $33,272 | $1,734 | $35,006 | $22,904 | $1,530 | $12,030 | $36,464 |
| 19th St & Constitution Ave NW | $33,072 | $1,921 | $34,993 | $14,184 | $1,122 | $5,688 | $20,994 |
| Columbus Circle / Union Station | $26,800 | $4,828 | $31,628 | $17,096 | $3,315 | $7,498 | $27,909 |
| 10th St & Constitution Ave NW | $28,392 | $2,414 | $30,806 | $18,704 | $1,275 | $6,584 | $26,563 |
| 17th & G St NW | $28,760 | $1,938 | $30,698 | $20,576 | $1,649 | $6,322 | $28,547 |
| 14th & D St NW / Ronald Reagan Building | $26,344 | $2,805 | $29,149 | $20,864 | $2,227 | $6,470 | $29,561 |
| Thomas Circle | $22,272 | $6,069 | $28,341 | $12,968 | $3,485 | $5,498 | $21,951 |
| USDA / 12th & Independence Ave SW | $25,032 | $2,414 | $27,446 | $16,400 | $1,156 | $5,006 | $22,562 |
| 21st St & Constitution Ave NW | $24,504 | $2,329 | $26,833 | $9,960 | $1,190 | $4,808 | $15,958 |
| Georgetown Harbor / 30th St NW | $23,912 | $1,581 | $25,493 | $14,120 | $884 | $7,332 | $22,336 |
| 7th & F St NW / National Portrait Gallery | $22,200 | $2,448 | $24,648 | $12,904 | $1,547 | $6,542 | $20,993 |
| Washington & Independence Ave SW/HHS | $20,904 | $2,176 | $23,080 | $12,104 | $1,156 | $4,786 | $18,046 |
| **Totals** | **$940,584** | **$81,770** | **$1,022,354** | **$541,280** | **$53,669** | **$210,312** | **$805,261** |
| **Percent change after STF** | | | | **-42%** | **-34%** | N/A | **-21%** |

### *6.3 Comparisons at All 330 Common Stations*

The comparison of metrics at the top 20 stations indicates that ridership and usage have increased after the launch of STF. After the introduction of STF, trips starting at the top 20 stations have grown by less than 1% and total trip hours increased by nearly 2%. In contrast, for all 330 common stations casual trips increased by nearly 20% and trip duration increased by 38%. Of the 330 stations, 282 (or 85%) stations recorded growth in trips and 266 (or 81%) recorded growth in trip durations. It is interesting to note here that the usage (both in terms of trips and trip-hours) by casual users increased at nearly twice as many stations as is the case for registered users. Despite such large increases in usage at common stations, it can be seen that the total revenue at 330 stations declined by 16% (over 21% decline at the top 20 stations). Figure 1 illustrates heat-maps of changes in ridership and revenue after the launch of STF.




(a) Change in Ridership (b) Change in Revenue

**Figure 1.** Heat Map of Changes in Ridership and Revenue after the Introduction of STF

*6.4 Hypotheses Testing*

A number of hypotheses tests were conducted to statistically verify if STF had caused the differences outlined above. Hypotheses tests were conducted on mean values of response variables, namely, number of trips, trip duration and normalized revenue, and the growth rates of ridership and revenue. Because of its simplicity and time-tested dependability in establishing statistical significance, paired z-test is determined to be the most appropriate hypothesis test for comparing the response variables 'before' and 'after' the introduction of STF. The generalized formulation of hypotheses tested using z-scores is shown below.

Null Hypothesis, $H_0$:

$$\left(\mu_{r,p}\right)_A - \left(\mu_{r,p}\right)_B = 0;$$

Alternate Hypotheses, $H_a$:

$$\left(\mu_{r,p}\right)_A > \left(\mu_{r,p}\right)_B \text{ (One-tailed)}$$

$$\left(\mu_{r,p}\right)_A < \left(\mu_{r,p}\right)_B \text{ (One-tailed); or}$$

$\left(\mu_{r,p}\right)_A - \left(\mu_{r,p}\right)_B \neq 0$; (Two-tailed)

Where:

$\left(\mu_{r,p}\right)_A$ - mean of response variable $r$ for the comparison pair $p$ - after the launch of STF; and

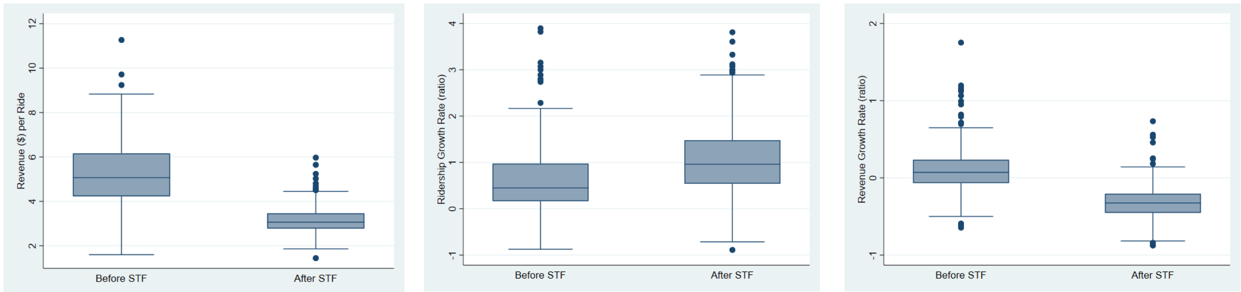
$\left(\mu_{r,p}\right)_B$ - mean of response variable $r$ for the comparison pair $p$ - before the launch of STF

Response variable set, $r$ represents the mean ridership (number of casual users); mean normalized revenue ($ per casual ride); mean growth rate in ridership; and mean growth rate in normalized revenue

Pair-level $p$ represents the paired levels of independent variables at which comparisons are made. (a) 330 individual stations (319 in the case of growth rate comparisons); (b) station and weekend/weekday (two-way interaction); (c) station and month (two-way interaction); and (d) station, month, and weekday/weekend (three-way interaction).

### *6.5 Tests for Normality*

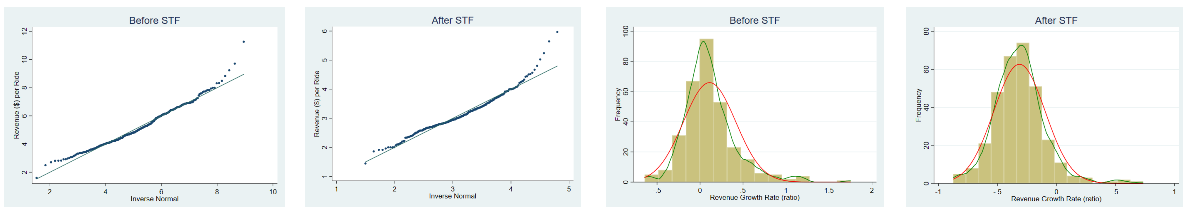
Z-test is applicable only to normally distributed variables. Therefore, to confirm if the response variables are normally distributed, mean values of ridership, normalized revenue ($ per trip) and growth rates of revenue and ridership were tested for Normality using descriptive (box plots) and theory-driven methods (quantile-quantile or Q-Q plots). Box plots (Figure 2) show that whiskers are evenly spread out around the boxes, and the median values are generally in the middle of the box – both of which are indicative of a Normal distribution of the variables. Box plots also indicate a sharp decline in revenue for casual ride and the associated growth rates (Figure 2 (a) and (c)), a noticeable increase in ridership growth (Figure 2 (b)). Q-Q plots and comparative histograms illustrating the distribution of response variables for all stations in the analysis are shown in Figure 2. Linearity of Q-Q plots and the histograms' approximation of Gaussian curve indicate that three response variables are normally distributed.



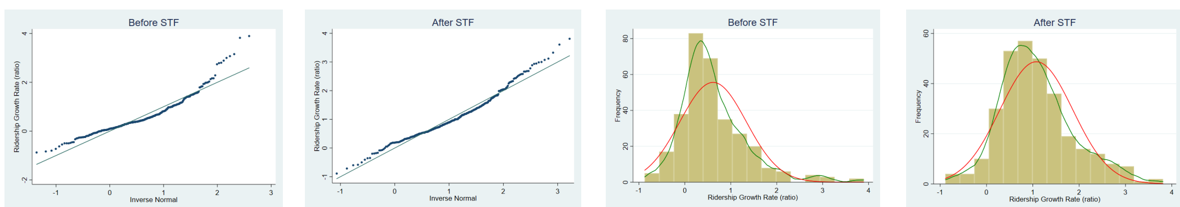

(a) Revenue per casual ride (n=330)

(b) Calendar month growth rates of casual user ridership (n=319)

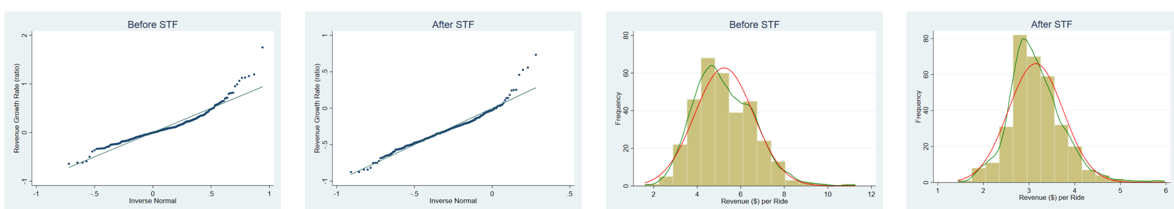
(c) Calendar month growth rate of revenue per casual user (n=319)




(d) Revenue per casual ride (n=330)




(e) Calendar month growth rates of casual user ridership (n=319)




(f) Calendar month growth rate of revenue per casual user (n=319)

Normal Kernel

**FIGURE 2.** Box plots and Q-Q Plots and Comparitive histograms with nNormal and Kernel Densities

The data preparation for hypotheses testing included the following steps:

1. Arranging 'before' and 'after' revenue, casual trips and trip-hours data aggregated by all possible combinations of station, month, and weekday/weekend.
2. Maintaining aggregation of paired observations of response variables by station, month, and whether the trip occurred on a weekday or a weekend. This grouping is chosen to verify if calendar month or weekday

status has any impact on the increase/decrease because it has been widely established in the literature that bikeshare ridership is dependent on these variables.

3. Normalizing station-level revenue per casual trip (as opposed to total revenue) to smooth wide variations in total revenue among stations
4. Removing data points on days with precipitations as precipitation has its own impact on bikeshare ridership. However, no attempt was made to control for temperature such as eliminating data points on extremely cold or hot days.
5. Computing background growth rates using available data for the 5-months prior to the launch of STF so as to compare these rates to the growth rates after the launch of STF. Such comparison would establish whether or not the background growth itself has changed due to the launch of STF, there by confirming or negating the impact of STF on trips and revenue by casual users.

### *6.6 Pairwise Comparisons*

A series of pairwise comparisons were made to verify the following two primary one-tailed alternative hypotheses:

Hypothesis 1: Casual user revenues decreased significantly after the launch of STF product. i.e., $\left(\mu_{r,p}\right)_A < \left(\mu_{r,p}\right)_B$

Hypothesis 2: Casual user ridership increased significantly after the launch of STF product, i.e. $\left(\mu_{r,p}\right)_A > \left(\mu_{r,p}\right)_B$

Presented in Table 2(a) are the results of z-tests at various levels of aggregation for hypothesis 1. The table shows that the mean values of revenue per ride 12-months before and 12-months after STF for each combination of 330 stations, 12 months and 2 weekday/weekend possibilities are \$5.05 and \$3.11, respectively. These mean values indicate that before the launch of STF, on average casual users paid \$5.05 per trip. This amount declined to \$3.11 per trip after the STF launch. The total possible number of paired observations for these combinations would be 7,920 (330 stations, 12 months and 2 weekend/weekday designations). Statistics presented in the table show that the decline in mean revenue is statistically significant at 5% level of significance as indicated by a z-score of 59.9 and a p-value of near zero. Likewise, pairwise comparisons of mean values of revenues aggregated at station and month; and station and weekday/weekend combinations indicate statistically significant decline in revenues after STF launch.

Table 2(b) presents analysis for change in casual ridership (trips) in a month before and after the launch of STF. As the table shows, average number of trips for each combination of 330 stations, 12 months and 2 weekend/weekday possibilities before and after STF are 90.5 and 101.1, respectively. The difference is indicative of an increase in ridership after STF launch. The z-score (-2.545) and p-value (0.005) denote statistical significance to this increase. Similarly, pairwise comparisons aggregated at all possible combinations of station and month indicate a statistical significance to the ridership increase at each station by month. The p-value of 0.276 for the difference in average trips at the station level (151.7 vs. 169.4) indicates that there is a relatively weaker evidence of station-level aggregate increase in trips after the launch of STF. Pairwise comparison for casual user ridership was not examined for dataset aggregated by station and weekday/weekend because the casual user ridership in a month was considered in the analysis. A closer examination of the data indicated that station-level aggregation might have been skewed by a few outliers that saw dramatic reductions in ridership. However, for consistency, no attempt was made to remove those outliers. For example, in the CaBi service area the March 2017 was unusually colder when compared to March 2016. This resulted in dramatic drop in ridership in March 2017 over March 2016 (Venigalla et al. 2018).

**TABLE 2.** Pairwise Comparisons of Revenue and Ridership

(a) Revenue per Casual Ride

| Pair-level (p) | N | Observation pair: Mean revenue ($) per casual ride | | z-test | | |
|---|---|---|---|---|---|---|
| | | 12-months Before STF $\mu_B$ | 12-months After STF $\mu_A$ | $H_a$ (Alternative hypothesis) | z-score | P-value |
| Station, Month and Weekday/Weekend | 6,635 | 5.046 | 3.113 | $\mu_B > \mu_A$ | 59.96 | 0.00 |
| Station and Month | 3512 | 5.131 | 3.127 | $\mu_B > \mu_A$ | 49.91 | 0.00 |
| Station and Weekday/Weekend | 655 | 5.214 | 3.147 | $\mu_B > \mu_A$ | 33.16 | 0.00 |
| Station | 330 | 5.236 | 3.147 | $\mu_B > \mu_A$ | 25.63 | 0.00 |

(b) Casual User Ridership

| Pair-level (p) | N | Observation pair: Mean monthly casual user ridership (trips) | | z-test | | |
|---|---|---|---|---|---|---|
| | | 12-months Before STF $\mu_B$ | 12-months After STF $\mu_A$ | $H_a$ (Alternative hypothesis) | z-score | P-value |
| Station, Month and Weekday/Weekend | 6,635 | 90.54 | 101.09 | $\mu_B < \mu_A$ | -2.54 | 0.005 |
| Station and Month | 3,512 | 171.05 | 190.98 | $\mu_B < \mu_A$ | -1.82 | 0.034 |
| Station | 330 | 151.70 | 169.37 | $\mu_B < \mu_A$ | -0.59 | 0.276 |

Thus, the common stations have experienced generally significant increase in ridership and decisively significant decline in revenue after the launch of STF. It is not known if the launch of STF itself caused these changes or if the changes were due to the continuation of a trend that was in existence from months prior to the launch. Additional pairwise z-tests were performed to verify if the growth trends in revenues and ridership have significantly changed after STF.

Presented in Table 3(a) are the pairwise comparisons of revenue and ridership growth rates for 5-months before and after the launch of STF, respectively. The 5-month period (as opposed to 12-month period) was chosen due to limited availability of data. The mean revenue growth rate of 0.162 (column labeled $\mu_B$) indicates that before the launch of STF an average growth rate in casual user revenue of 16.2% was recorded for each combination of 319 stations, five calendar months and two weekday or weekend designates. Its counterpart after STF (column labeled $\mu_A$) registered about 29% decline in revenues after the launch of STF. That is, trends in revenue growth changed from positive growth to negative growth after STF launch. On the other hand, as Table 3(b) shows, mean year-over-year growth rates of the casual user ridership for comparable calendar months have accelerated after the introduction of STF from about 66% to about 119% (station level). The pattern is similar for other levels of aggregation. Thus, the statistical measures presented in Table 3 establish statistical significance to the decline in revenue growth and increase in ridership growth after the launch of STF.

**TABLE 3.** Pairwise Comparisons of Growth Rates

(a) Casual User Revenue

| Pair-level (p) | N | Observation pair: Mean growth rates of casual user revenue (ratio) | | z-test | | |
|---|---|---|---|---|---|---|
| | | 12-months Before STF $\mu_B$ | 12-months After STF $\mu_A$ | $H_a$ (Alternative hypothesis) | z-score | P-value |
| Station, Month and Weekday/Weekend | 2407 | 0.162 | -0.287 | $\mu_B > \mu_A$ | 18.79 | 0.00 |
| Station and Month | 1319 | 0.171 | -0.289 | $\mu_B > \mu_A$ | 15.94 | 0.00 |
| Station and Weekday/Weekend | 622 | 0.168 | -0.308 | $\mu_B > \mu_A$ | 15.34 | 0.00 |
| Station | 319[&] | 0.165 | -0.314 | $\mu_B > \mu_A$ | 12.66 | 0.00 |
| [&] Only 319 of the 330 stations which existed during January – May 2015 are used in growth rate analysis | | | | | | |

(b) Casual User Ridership

| Pair-level (p) | N | Observation pair: Mean growth rates of casual user ridership (ratio) | | z-test | | |
|---|---|---|---|---|---|---|
| | | 12-months Before STF $\mu_B$ | 12-months After STF $\mu_A$ | $H_a$ (Alternative hypothesis) | z-score | P-value |
| Station, Month and Weekday/Weekend | 2407 | 0.662 | 1.194 | $\mu_B < \mu_A$ | -8.82 | 0.00 |
| Station and Month | 1319 | 0.734 | 1.262 | $\mu_B < \mu_A$ | -6.99 | 0.00 |
| Station and Weekday/Weekend | 622 | 0.617 | 1.288 | $\mu_B < \mu_A$ | -7.91 | 0.00 |
| Station | 319[&] | 0.648 | 1.332 | $\mu_B < \mu_A$ | -5.82 | 0.00 |
| [&] Only 319 of the 330 stations which existed during January – May 2015 are used in growth rate analysis | | | | | | |

Since trip duration and ridership tend to be highly correlated, pairwise comparisons were not performed on trips duration as response variable.

## 7. Conclusions, recommendations and discussion

This research examined the impact of the launch of a single-trip fare (STF) product on Capital Bikeshare ridership and revenue by analysing large amounts of system wide data. The analysis presented in this paper employs 'big data' on individual bikeshare trips and revenue transactions at station-level. The revenue and ridership datasets combined contain over 22 million data records. The unique characteristics of the point of sale system at Capital Bikeshare are leveraged for designing and executing a controlled experiment. The experiment allowed revenues to be sourced to individual stations, which further allowed comparing station-level revenues and ridership before and after the launch of STF.

Statistical tests were performed on casual user revenue and casual user ridership for 12-month period before and after the introduction of STF at the 330 common stations. The results showed a decrease in casual user revenue per ride and an increase in monthly casual user ridership after the introduction of the STF. Furthermore, calendar-month growth rates for ridership and revenue were compared for periods before and after the launch of the new fare product for a five-month period at hundreds of common stations. The study has established statistical evidence that the launch of STF has significantly decreased revenues and increased ridership at CaBi. Additionally, trends in revenue growth changed from positive growth to negative growth after the launch of STF. However, it should be noted that it is not practical to identify and control for all possible variables that could have caused the decline. This study also demonstrates that the disaggregate analysis conducted at the station level has superior accuracy and helps in better understanding of the data than the community-level analysis performed by Kaviti et al (2018).

It is possible that the results and findings may be unique to Capital Bikeshare. However, the controlled nature of the experiment and the analysis shed light on the fundamental nature of the impact of change in fare structure on revenues and ridership. Bikeshare providers who are considering making changes to fare product line and their pricing could benefit from the findings of this study. In cases where changes have already been made, the methods used in this research may be employed to evaluate the impact of those changes on ridership and revenue at those systems. For example, other cities have introduced single trip fair products as well: Metro Bike (Los Angeles) in 2017, and Divvy (Chicago) and Citi Bike (New York) in 2018 have introduced single trip fare products ($3/trip at Divvy and Citi Bike; and $3.50/trip at Metro Bike). The methods discussed in this paper are flexible enough to study the impact of STF on ridership and revenue at these systems.

Most importantly, this paper fills a notable gap in literature related to the impact of introducing new fare options on bikeshare ridership and revenue. It should be noted that this study only examined the impact of pricing change on usage and did not investigate the user behavioural factors that may have influenced the changes in usage. Studies focused on examining inter-relationship between pricing and user sensitivity to pricing such as developing price elasticities, logit models etc., can further advance this research.

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