

# Could Value-Based Pricing Improve Economic Sustainability of Bikeshare?

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## ABSTRACT

We scrutinize the reactions of casual users of bikesharing services to fare menu, product pricing, and promotion. We hypothesize that by introducing value-based pricing into the fare-option mix, revenues can be increased and therefore enhance the economic sustainability of the bikesharing system. We conducted a controlled experimental survey of 157 current and potential bikeshare users across six cities in the United States. The survey registered the respondents' choice of fare options in two groups: one with a binary choice set (control group) and the other with an additional value-priced choice (experimental group). Evidence points to users' perception of value in bikeshare fare options would contribute to variations in revenues for the same ridership levels. Revenue projections and statistical tests showed that the introduction of value-based pricing options could lead to significant revenue increases. Furthermore, how the fare options are presented to the user would have an impact on users' reception to the value-based pricing options in the product mix. The study results could be useful for numerous bikeshare systems in re-examining their product mixes and how they are presented to the users on websites, mobile apps and kiosk locations.

**Keywords:** *decoy pricing, value-based pricing, behavioural economics, bikeshare, pricing, micromobility, shared mobility, revenue, ridership*

## 1 INTRODUCTION

Like transit fare, the cost of the ridership of a bikeshare trip plays a significant role in the mode choice behaviour of users and the system's economic sustainability. While subsidies are important, a healthy farebox recovery is the most essential ingredient for the economic sustainability of transportation services that are operated in the public interest (such as transit and bikesharing services). To this effect, bikeshare service providers routinely make changes to pricing structure and fare menus for all user-types.

When making changes to bikeshare pricing or introducing a new fare option, it is important to consider users' perceptions of the economic value of the new product on its own and in relation to the prices of other products in the 'product line' [1]. Very few studies addressed the infrastructure and pricing policy implications on general cycling usage [3]. Despite the importance of pricing to bikeshare patronage, only a limited number of studies focused on the impact of a well-defined pricing strategy on revenue and ridership [1,2,5-8].

### 1.1 Objective

In the marketing parlance, the essential elements of a marketing plan, namely: *product, price, place, and promotion* (known as 4Ps of the marketing mix), help develop marketing strategies and tactics [9]. We theorize that choices of bikeshare users, like that of consumers of any other commercial product, are influenced by perception of value and behavioural economics. In this research, we focus on service options (products), pricing, and presentation of public bikesharing systems.

We hypothesize that, by introducing value-based pricing options into the product mix, bikesharing revenues can be increased. We test this hypothesis by conducting a controlled experimental survey of 157 current and potential bikeshare users across six cities in the United States. We also examine the promotional aspects of bikeshare fare options by testing the revenue impacts of user choices when the same product menus are presented in different formats.

## 2 MOTIVATION

Bikeshare fare options and subscription plans for casual users (temporary users with no long-term commitment) and members (also known as subscribers) vary from system to system. They also change over time. The fare options for these two prominent user types represent the 'product' in the 4P-concept as applied to bikesharing. The market share of ridership and revenue for members and casual users varies across systems. For example, members account for 72% of ridership and 29% of the revenue at Capital Bikeshare (CaBi), while casual users account for only 28% ridership and yet 71% of its revenue [8]. Similarly, the revenue split between members and casual users for Citi Bike (NY) is 32.3% and 67.7% [10].

Consumer behaviour in transportation mode-choice was first modelled in the early 1970s [11,12]. Though consumer-pricing research shows that product(s) and pricing mix is an essential determinant of customer patronage and revenues, consumer-oriented research in pricing bikesharing services is rare. A non-scientific polling of three bikeshare providers in the USA indicated that decisions related to bikeshare product lines and pricing are often arbitrary, have minimal or no scientific basis, and based

on local political considerations. At the time of conducting this research, scooter-sharing is in the nascent stages of deployment and its impact on bikesharing was not considered.

For this research, we define value-based pricing as the strategic process of pricing a product or service that offers economic value to consumers. The value may be absolute or relative to other products in the choice set, and it may be real or perceived. Because it considers the customer perspective, value-based pricing increases the likelihood of maximizing revenues from the same set of customers simply by altering their product-selection from the given product mix [13].

Table 1 presents bikeshare product lines and their prices (fare options) at the seven largest bikeshare systems in the United States. The websites of all these systems emphasize that the annual membership is the “best value” option for users. However, only two systems offer a 3-day pass (valid for 36-hours after purchase), and the monthly pass option is not available at two of the systems. Although casual users account for a significant share of revenues [2,8], none of these systems appear to be emphasizing a “best value” option for casual users.

These observations led us to asking the following questions:

1. Does the product-mix itself have an impact on which option bikeshare consumers (especially casual users) choose and, therefore, on system-wide revenues?
2. If product-mix has an impact, what would be a value-based pricing strategy and the optimal product mix for bikeshare services?

Kaviti et al. partially addressed these issues in their study on the impact of the launch of a single trip fare (STF) product for \$2/trip on the revenue and ridership of CaBi at the jurisdiction level in the metro Washington DC area [5]. The study showed a significant increase in casual user ridership after the introduction of STF. In an analysis conducted at individual station-level, Venigalla et al. observed that the introduction of STF led to a significant increase in casual user ridership, coupled with a positive growth rate; and a significant decrease in revenue per ride with a negative growth rate [1]. The research presented in this paper builds on the studies by Kaviti et al. [5] and Venigalla et al. [1].

### 3 REACTIONS TO VALUE-BASED PRICING

A notable gap exists in literature with respect to understanding user behaviour towards bikeshare product pricing. Literature in consumer product pricing presents numerous examples of how to expose the relative value through such behavioural economics considerations as decoy pricing [22-24], value-based pricing, and menu-engineering [25,26]. For example, restaurants design their wine menu based on a widely known discovery that the second lowest-priced wine is usually the best seller on the wine list [27]. Ariely illustrated that by introducing a decoy option within the product mix might increase revenues [28]. Ariely’s experiment (Table 2) divided the subscription options for The Economist magazine into two choice sets (ACS1 & ACS2). Two separate groups of 100 students at Massachusetts Institution of Technology were asked to select a subscription from one of the choice sets given to them.

As the results of the Ariely’s experiment indicate, the hypothetical revenue from ACS2 is 43% higher than that of ACS1. In this experiment, the mere introduction of a decoy in ACS2 has unlocked the value in one of the two other options. Thus, it is conceivable that a carefully designed choice-set of fares will influence the behaviour and choices of bikeshare consumers towards increasing the revenues. We tested two versions of a controlled survey that is similar to Ariely’s experiment. Both versions had the same questions on user demographics (gender and income), prior experience with bikeshare, and willingness to pay for a regular subscription in both versions. However, the choice-set (CS) of fare options is different for both versions.

To assess users’ perception of the relative value of fare op, the following question and the associated information were included in the survey form as the lead to a choice set (CS).

*If bikeshare is/were available in the city where you work OR in the city you are visiting for sightseeing for a weekend, which fare option would you choose? Assume you can pretty much go wherever you want using bikeshare, and the weather is not an issue. Also, there will be a usage fee for usage above 30 min.*

**Table 1** Product lines and prices at the seven largest bikeshare systems in the USA

| Public Bikeshare System                                | For Casual Users       |                           |                            | Subscription Membership    |                            |
|--|------------------------|---------------------------|----------------------------|----------------------------|----------------------------|
|  | Single Trip Fare (STF) | 24-hour pass (Daily Pass) | 3-day pass (Multiday Pass) | 30-day pass (Monthly Pass) | 365-day pass (Annual Pass) |
| CitiBike <sup>1,4</sup> (New York, NY)                 | \$3.00                 | \$12.00                   | \$24.00                    | NA                         | \$169.00                   |
| Divvy <sup>4</sup> (Chicago, IL)                       | \$3.00                 | \$15.00                   | NA                         | NA                         | \$99.00                    |
| Capital Bikeshare <sup>4</sup> , CaBi (Washington, DC) | \$2.00                 | \$8.00                    | \$17.00                    | \$28.00                    | \$85.00                    |
| Metro (Los Angeles, CA)                                | \$1.75                 | \$5.00                    | NA                         | \$17.00                    | \$150.00                   |
| Blue Bikes <sup>2,4</sup> (Boston, MA)                 | \$2.50                 | \$10.00                   | NA                         | \$20.00                    | \$99.00                    |
| Nice Ride <sup>4</sup> (Minneapolis, MN)               | \$2.00                 | \$6.00                    | NA                         | NA                         | \$75.00                    |
| Bay Wheels <sup>3,4</sup> (San Francisco, CA)          | \$2.00                 | NA                        | NA                         | \$15.00                    | \$149.00                   |

<sup>1</sup> Operates in New York City and Jersey City, NJ. The largest Bikeshare provider in the USA

<sup>2</sup> Previously known as Hubway. Rebranded as Blue Bikes in March 2018

<sup>3</sup> Previously known as Go Bike (by Ford) and rebranded in June 2019 as Bay Wheels

<sup>4</sup> Operated by Lyft or its subsidiary company Motivate for the bikeshare provider in the city/region

(Source: Bay Wheels [15]; Blue Bikes [16]; Capital Bikeshare [17]; Citi Bike [18]; Divvy [19]; Metro Bikeshare [20]; and Nice Ride [21])

**Table 2** Ariely’s experiment on decoy pricing for subscription to The Economist magazine

| Subscription Option | Description   | Annual Price                        | Survey responses |          |
|---------------------|---|-------------------------------------|------------------|----------|
|                     |   |                                     | ACS1             | ACS2     |
| 1                   | Web only subscription to economist.com  | \$59                                | 68               | 16       |
| 2*                  | Print only subscription to “The Economist”  | \$125                               | Not given        | 0        |
| 3                   | Subscription to printed copy of “The Economist” + web subscription to economist.com | \$125                               | 32               | 84       |
| *Decoy option       |   | Total revenue Σ (Price x Responses) | \$8,012          | \$11,444 |

(Source: Ariely [28])

The list of fare options presented in the choice sets is described in the survey forms as follows:

1. A bunch of single-trips, each 30-min trip costing \$2
2. 24-hour pass for an unlimited number of 30-min trips, costing \$8
3. 3-day pass for an unlimited number of 30-min trips, costing \$17

Version 1 (CS-1) displays only fare options 1 and 2. In the real world, it replicates the choice sets (not the prices) that are currently available for riders at Divvy, Metro, Blue Bikes, and Nice Ride systems (Table 1). Version 2 (CS-2), which displays all three options, replicates the choice sets available at CaBi and Citi Bike.

Both versions of the survey were randomly and evenly distributed to the attendees during a lecture series on bikeshare pricing at six different universities across USA (Table 3). Even distribution of respondents between the two choice sets would ensure equal allocation of total ridership between the sets. The respondents (n=157) included full- and part-time students, faculty, staff, and other seminar attendees at the six universities. When taking the survey, the respondents did not know that two versions of the questionnaire exist. Analysis ( $\chi^2$  test results) presented in Table 3 show that the respondent choices are independent of their gender, income, prior bikeshare experience, or location.

For estimating revenues using the survey data, we assumed that a typical casual user makes an upfront decision to accommodate his/her travel needs with only one of the fare options available, with a limit of three or fewer trips. The reasoning for limiting the number of single trips (ST) purchases to three is that purchasing a 24-hour pass for \$8 for unlimited rides per day would make more economic sense than purchasing four or more single trips at \$2 each. Whichever may be the fare option purchased, some casual users might only use bikeshare once (one single trip, or OST), while others may take dual single trips (DST) or triple single trip rides (TST). Table 4 illustrates normalized revenues for the DST scenario.

Revenue estimates were made for three extreme cases in which every STF buyer would make either only one, two or three trips (i.e., 100% of STF trips would be either OST, DST or TST). Figure 1 illustrates revenue estimates for OST and TST (calculations are shown in Table 4 for DST). For each of the three scenarios and at each location, revenue estimates for the

choice set with the 3-day pass option (CS-2) are significantly higher ( $\alpha = 5\%$ ) than estimates for CS-1. The observed increase in estimated revenues ranges from 25% to 84%. The 95% confidence interval band for normalized revenues narrows and converges towards the estimated mean as the number of single trips increases from one to three (Figure 2).

These observations imply that the value-based pricing strategy for bikeshare pricing has a consistently positive impact on revenues, an impact that is comparable to that of decoy pricing. While decoy pricing may be perceived as ‘deceptive marketing’ or even ‘profiteering,’ value-based pricing has the potential to be well received by bikeshare users.

#### 4 PRESENTATION OF FARE OPTIONS

The casual bikeshare users in the United States typically receive information on the product mix through websites, kiosks, and mobile apps. For the presentation aspect (the fourth P in 4Ps of the marketing mix), we hypothesized that, just as the composition of the product mix affects revenues, presentation of fare options at various points of sale may also impact revenues.

To test this hypothesis, two fictional web designs were developed. The first design mimics actual fare-selection screens on websites of Capital Bikeshare and Citibike. This design requires the user to navigate to a second page to discover a value-priced option. The second design displays all three casual fare options on the same page (Figure 3).

In a short 30-second survey, potential casual users at four different venues were asked to choose a fare from the two designs. To avoid any sample size bias, an attempt was made to distribute the sample evenly between two designs. As the results in Table 5 indicate, user selection of fare option between the two designs is independent of the location of the survey but dependent on the presentation of choices.

The results of this experiment (n = 73) at four different locations indicated estimated revenues with Design 2 are 13% to 149% higher than the estimates for Design 1. On an aggregate basis, the revenue increase with Design 2 is 43% over Design 1. Chi-Square test indicates that the consistent increase in revenues for Design 2 are independent of location of the survey.

**Table 3** Summary statistics of user choices of bikeshare fare options

| Class Variables      |                      | Fare Choice Set 1 |                  |       |          |          | Fare Choice Set 2 |                  |                  |       |          |          |
|----------------------|----------------------|-------------------|------------------|-------|----------|----------|-------------------|------------------|------------------|-------|----------|----------|
|                      |                      | DP <sup>7</sup>   | STF <sup>8</sup> | Total | $\chi^2$ | <i>p</i> | DP <sup>7</sup>   | 3DP <sup>9</sup> | STF <sup>8</sup> | Total | $\chi^2$ | <i>p</i> |
| Gender               | Female               | 12                | 6                | 18    | 1.721    | 0.181    | 8                 | 2                | 7                | 17    | 1.348    | 0.509    |
|                      | Male                 | 28                | 34               | 62    |          |          | 24                | 15               | 21               | 60    |          |          |
| Income               | <\$35k               | 34                | 35               | 69    | 0        | 1        | 21                | 11               | 23               | 55    | 2.479    | 0.289    |
|                      | >\$35k               | 6                 | 5                | 11    |          |          | 11                | 6                | 5                | 22    |          |          |
| Prior user?          | No                   | 30                | 29               | 59    | 0        | 1        | 26                | 12               | 23               | 61    | 0.995    | 0.608    |
|                      | Yes                  | 10                | 11               | 21    |          |          | 6                 | 5                | 5                | 16    |          |          |
| Sample Location      | UA <sup>1</sup>      | 13                | 11               | 24    | 4.224    | 0.518    | 10                | 5                | 10               | 25    | 6.103    | 0.806    |
|                      | UNCC <sup>2</sup>    | 11                | 10               | 21    |          |          | 6                 | 5                | 7                | 18    |          |          |
|                      | Clemson <sup>3</sup> | 2                 | 3                | 5     |          |          | 2                 | 1                | 4                | 7     |          |          |
|                      | GMU <sup>4</sup>     | 5                 | 10               | 15    |          |          | 6                 | 4                | 3                | 13    |          |          |
|                      | Memphis <sup>5</sup> | 6                 | 2                | 8     |          |          | 5                 | 1                | 1                | 7     |          |          |
|                      | TCNJ <sup>6</sup>    | 3                 | 4                | 7     | 3        | 1        | 3                 | 7                |                  |       |          |          |
| Overall Sample Total |                      | 40                | 40               | 80    |          |          | 32                | 17               | 28               | 77    |          |          |

<sup>1</sup>University of Alabama at Tuscaloosa; <sup>2</sup>University of North Carolina at Charlotte; <sup>3</sup>Clemson University; <sup>4</sup>George Mason University; <sup>5</sup>University of Memphis; <sup>6</sup>The College of New Jersey

<sup>7</sup>DP: 24-Hour or Day Pass (\$8); <sup>8</sup>STF: Single Trip (\$2); <sup>9</sup>3DP: 3-Day Pass (\$17)

*Interpretation example:* At a significance level ( $\alpha$ ) = 0.05, the *p*-value of 0.181 indicates that the user choice of fare option is independent of the gender of the respondent

*Conclusion:* Gender, income, prior usage, and location of the sample have no significant influence on the respondent choices

**Table 4** Estimated revenues from 100 casual users with each single-trip buyer making dual single trips (DST)

| Location and Aggregate Statistics | Fare Choice Set 1  |                         |                    | Fare Choice Set 2  |                   |                         | Percent Increase with CS-2 |              |
|-----------------------------------|--------------------|-------------------------|--------------------|--------------------|-------------------|-------------------------|----------------------------|--------------|
|                                   | 24-hour pass (\$8) | Single trips (\$2/trip) | Total              | 24-hour pass (\$8) | 3-day pass (\$17) | Single trips (\$2/trip) |                            | Total        |
| University of Alabama             | \$433              | \$183                   | \$616 <sup>a</sup> | \$320              | \$340             | \$160                   | \$820                      | 33.0%        |
| UNC Charlotte                     | \$419              | \$191                   | \$610              | \$267              | \$472             | \$156                   | \$894                      | 46.7%        |
| Clemson University                | \$320              | \$240                   | \$560              | \$229              | \$243             | \$229                   | \$700                      | 25.0%        |
| George Mason University           | \$267              | \$267                   | \$533              | \$369              | \$523             | \$92                    | \$985                      | 84.6%        |
| University of Memphis             | \$600              | \$100                   | \$700              | \$571              | \$243             | \$57                    | \$871                      | 24.5%        |
| The College of New Jersey         | \$343              | \$229                   | \$571              | \$343              | \$243             | \$171                   | \$757                      | 32.5%        |
| <b>Totals at all locations</b>    | <b>\$400</b>       | <b>\$200</b>            | <b>\$600</b>       | <b>\$332</b>       | <b>\$ 375</b>     | <b>\$145</b>            | <b>\$853</b>               | <b>42.2%</b> |
| Mean                              | \$397              | \$202                   | \$599              | \$350              | \$344             | \$144                   | \$838                      | 40.0%        |
| SE                                | \$117              | \$59                    | \$59               | \$120              | \$126             | \$61                    | \$102                      |              |
| Lower 95% CI                      | \$274              | \$140                   | \$537              | \$224              | \$212             | \$80                    | \$731                      | 36.2%        |
| Upper 95% CI                      | \$520              | \$263                   | \$660              | \$476              | \$476             | \$208                   | \$945                      | 43.1%        |

*This illustration assumes all users opting for single trips would purchase two single trips at \$2 each. Confidence intervals as based on the *t*-distribution assumption for the sample.*

<sup>a</sup> Example calculation: Of the 24 respondents of choice set 1 at University of Alabama, 13 and 11 opted for 24-hr pass and single-trip, respectively. Thus, for this case revenue for 100 users when choosing from CS-1 would be:  $100 \times [(13 \div 24) \times \$8 \text{ per pass} + (11 \div 24) \times \$2 \text{ per trip} \times 2 \text{ trips by each user}] = \$433 + \$183 = \$616$

## 5 CONCLUSIONS AND DISCUSSION

The research shows that, for a given ridership level, changes to fare options could result in significant variations in revenues. The changes are attributable to bikeshare users' perception of value among available fare options. Statistically significant revenue increases are feasible with a fare-choice set containing an additional value-priced option when compared to a binary choice set.

Though the range of projected revenue increases attributable to value-pricing is rather wide (25%-84%), the experiment underscores the point that the mere introduction of a value-based pricing option may have a consistently positive and statistically significant impact on revenue. Similarly, the second experiment on presentation of fare options to users demonstrates that the user's choice is influenced by the presentation of product menu at points of sale, such as websites, kiosks, and mobile apps.

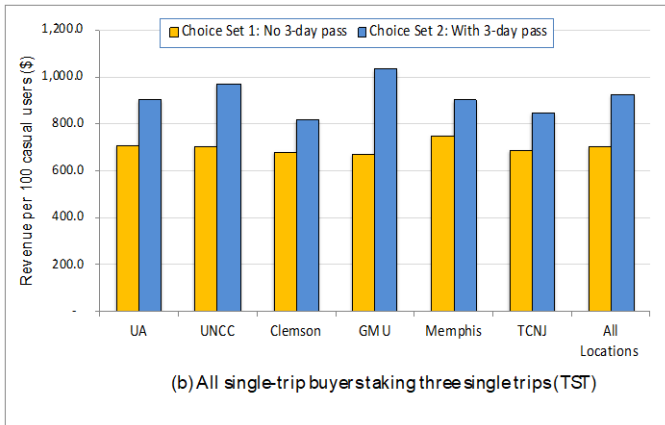
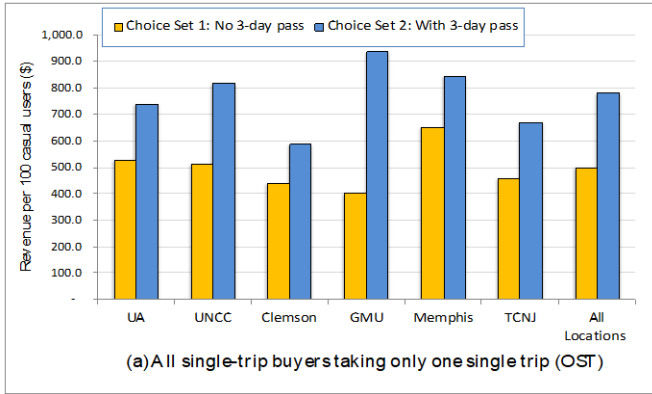


Figure 1 Revenues per 100 casual users with and without value-based price option

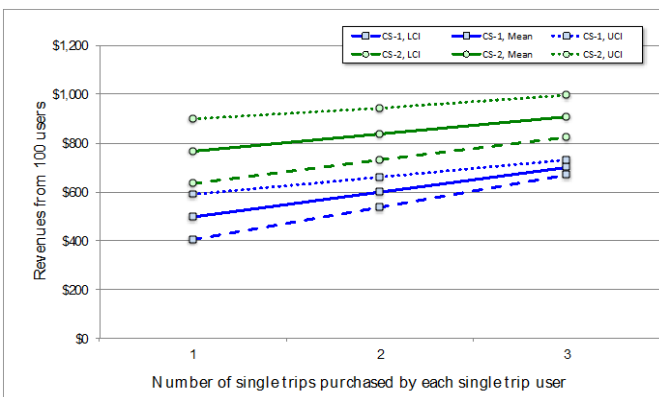


Figure 2 Revenues per 100 users based on the number of single trip fares purchased by users

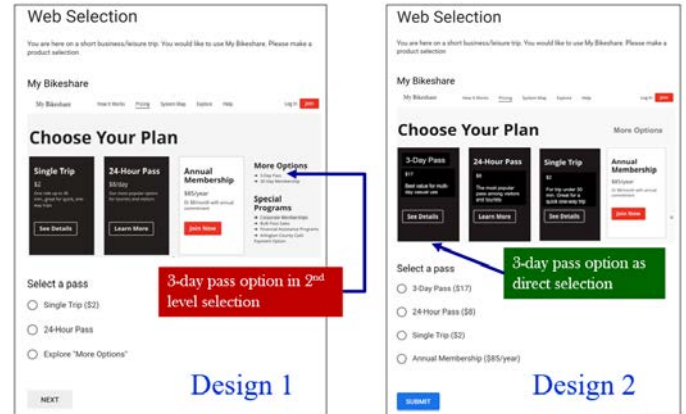


Figure 3 Alternative designs for the web-based presentation of value-based options to users

Table 5 User selection of fare options for two alternate designs

| Location | Fare  | Design 1 |       | Design 2 |         | Change in Rev. with Design 2 |
|----------|-------|----------|-------|----------|---------|------------------------------|
|          |       | n        | %     | n        | %       |                              |
| 1.       | Total | 7        | 100%  | 6        | 100%    |                              |
|          | NS    | 0        | 0%    | 0        | 0%      |                              |
|          | STF   | 3        | 43%   | 2        | 33%     |                              |
|          | DP    | 1        | 14%   | 1        | 17%     |                              |
|          | 3DP   | 3        | 43%   | 3        | 50%     |                              |
|          | Rev.  |          | \$928 |          | \$1,050 | 13%                          |
| 2.       | Total | 14       | 100%  | 11       | 100%    |                              |
|          | NS    | 1        | 7%    | 4        | 36%     |                              |
|          | STF   | 8        | 57%   | 3        | 27%     |                              |
|          | DP    | 4        | 29%   | 1        | 9%      |                              |
|          | 3DP   | 1        | 7%    | 3        | 27%     |                              |
|          | Rev.  |          | \$464 |          | \$591   | 27%                          |
| 3.       | Total | 9        | 100%  | 11       | 100%    |                              |
|          | NS    | 0        | 0%    | 0        | 0%      |                              |
|          | STF   | 5        | 71%   | 4        | 67%     |                              |
|          | DP    | 3        | 43%   | 2        | 33%     |                              |
|          | 3DP   | 1        | 14%   | 5        | 83%     |                              |
|          | Rev.  |          | \$729 |          | \$1,817 | 149%                         |
| 4.       | n     | 6        |       | 9        |         |                              |
|          | NS    | 0        | 0%    | 2        | 22%     |                              |
|          | STF   | 3        | 50%   | 3        | 33%     |                              |
|          | DP    | 3        | 50%   | 0        | 0%      |                              |
|          | 3DP   | 0        | 0%    | 4        | 44%     |                              |
|          | Rev.  |          | \$500 |          | \$822   | 64%                          |
| All      | n     | 36       |       | 37       |         |                              |
|          | NS    | 1        | 3%    | 6        | 16%     |                              |
|          | STF   | 19       | 53%   | 12       | 32%     |                              |
|          | DP    | 11       | 31%   | 4        | 11%     |                              |
|          | 3DP   | 5        | 14%   | 15       | 41%     |                              |
|          | Rev.  |          | \$586 |          | \$841   | 43%                          |

Survey Locations

1. TRB Annual Meeting, Washington DC
2. University of California, Irvine, CA
3. George Mason University (GMU-1)
4. George Mason University (GMU-2)

- n: Sample size
- NS: No Selection
- STF: Single Trip (\$2)
- DP: 24-Hour Pass (\$8)
- MDP: 3-Day Pass (\$17)
- Rev.: Revenue/100 Riders

## 5.1 Key Takeaway

The key takeaway from this research is that a scientific method that leverages the concepts of consumer pricing research and behavioural economics to set bikeshare pricing could significantly increase revenues from casual users of bikeshare.

Changes to fare products can be tested with a simple survey of carefully sampled potential users using the methods described in this paper. That is, bikeshare systems across the world could use the methodology and/or results of this study in strategizing and redesigning product-mix; product-testing and then presenting various price options for bikeshare users. For example, five of the seven largest bikeshare systems in the USA (Table 1) could potentially increase revenues from their casual users by simply introducing a multi-day pass.

It should be noted that the conclusions of this research are subject to a few limitations. The respondents in the sample are not from diverse population groups. The research found that income has no impact on users' choice, which is akin to stated preference. However, income influence may have been absent in the responses as they were based on a hypothetical situation which does not actually involve spending money (i.e., a stated preference instead of a revealed choice). Though the research only shows promise of improving economic sustainability through increased revenues, more work is needed in this regard for establishing the suitable set of pricing options for a given bikesharing service.

## REFERENCES

- [1] Venigalla, M.M., T. Brennan, S. Rayaprolu, & S. Kaviti. (2020a). Increasing Bikeshare Revenue through Value-Based Pricing: Lessons from Behavioral Economics. 99th Annual Meeting of the Transportation Research Board. National Research Council. Washington DC. (Jan 12-15, 2020).
- [2] Venigalla, M.M., Kaviti, S., & Brennan, T. (2020b). Impact of bikesharing pricing policies on usage and revenue: An evaluation through curation of large datasets from revenue transactions and trips. *Journal of Big Data Analytics in Transportation* (in print).
- [3] Pucher, J., Dill, J., & Handy, S. (2010). Infrastructure, programs, and policies to increase bicycling: An international review. *Preventive Medicine*, 50, S106–S125. <https://doi.org/10.1016/J.YPMED.2009.07.028>
- [4] de Nazelle, A., Nieuwenhuijsen, M. J., Antó, J. M., Brauer, M., Briggs, D., Braun-Fahrlander, C., ... Lebre, E. (2011). Improving health through policies that promote active travel: A review of evidence to support integrated health impact assessment. *Environment International*, 37(4), 766–777. <https://doi.org/10.1016/J.ENVINT.2011.02.003>
- [5] Kaviti, S., Venigalla, M. M., Zhu, S., Lucas, K., & Brodie, S. (2018). Impact of pricing and transit disruptions on bikeshare ridership and revenue. *Transportation*, 1–22. <https://doi.org/10.1007/s11116-018-9904-5>
- [6] Kaviti, S., & Venigalla, M. M. (2019). Assessing service and price sensitivities, and pivot elasticities of public bikeshare system users through monadic design and ordered logit regression. *Transportation Research Interdisciplinary Perspectives*, 1(1), 100015. <https://doi.org/10.1016/J.TRIP.2019.100015>
- [7] Kaviti, S., Venigalla, M. M., & Lucas, K. (2019). Travel behavior and price preferences of bikesharing members and casual users: A Capital Bikeshare perspective. *Travel Behaviour and Society*, 15, 133–145. <https://doi.org/10.1016/J.TBS.2019.02.004>
- [8] Venigalla, M.M., Kaviti, S., Pierce, W. and Zhu, S. (2018). Analysis of Single-trip fare data for Capital Bikeshare. *District Department of Transportation (DDOT), Final Report*.
- [9] McCarthy, E.J., Shapiro, S.J., & Perrealt, W.D. (1979). Basic marketing. (pp. 29-33). Irwin-Dorsey.
- [10] Citi Bike (2019b). December 2018 Monthly Report. Retrieved August 8, 2019 from <http://citibikenyc.com/system-data/operating-reports>
- [11] McFadden, D. (1974), Conditional logit analysis of qualitative choice behavior. In P. Zarembka, ed., *Frontiers in Econometrics*, Academic Press, New York, pp. 105– 142.
- [12] Lovelock, C.H. (1975). "Researching and Modeling Consumer Choice Behavior in Urban Transportation", in NA - *Advances in Consumer Research* Volume 02, eds. M.J Schlinger and A. Abor, MI: *Association for Consumer Research*, Pages: 851-862.
- [13] Hinterhuber, A. (2008). Customer value-based pricing strategies: why companies resist. *Journal of business strategy*, 29(4), 41-50.
- [14] Venigalla, M., Kaviti, S., & Brennan, T. (2020). Impact of Bikesharing Pricing Policies on Usage and Revenue: An Evaluation Through Curation of Large Datasets from Revenue Transactions and Trips. *Journal of Big Data Analytics in Transportation*, 1-16.
- [15] Bay Wheels (2020). Bay Wheels Pricing. Retrieved January 30, 2020 from <http://lyft.com/bikes/bay-wheels/pricing>
- [16] Blue Bikes (2020). Choose Your Plan. Retrieved January 30, 2020 from <http://bluebikes.com/pricing>
- [17] Capital Bikeshare (2020). Choose Your Plan. January 30, 2020 from <http://capitalbikeshare.com/pricing>
- [18] Citi Bike (2020). Choose Your Plan. Retrieved January 30, 2020 from <http://citibikenyc.com/pricing>
- [19] Divvy (2019). Choose Your Plan. Retrieved August 8, 2019 from <http://divvybikes.com/pricing>
- [20] Metro Bikeshare (2020). Pricing. Retrieved January 30, 2020 from <http://bikeshare.metro.net/pricing/>
- [21] Nice Ride (2020) Choose Your Plan. Retrieved January 30, 2020 from <http://niceridemn.com/pricing>
- [22] Boz, H., Arslan, A., & Koc, E. (2017). Neuromarketing aspect of tourism pricing psychology. *Tourism Management Perspectives*, 23, 119–128. <https://doi.org/10.1016/J.TMP.2017.06.002>
- [23] Gonzalez-Prieto, D., Sallan, J. M., Simo, P., & Carrion, R. (2013). Effects of the addition of simple and double decoys on the purchasing process of airline tickets. *Journal of Air Transport Management*, 29, 39–45. <https://doi.org/10.1016/J.JAIRTRAMAN.2013.02.002>
- [24] Huber, J., Payne, J. W., & Puto, C. (1982). Adding Asymmetrically Dominated Alternatives: Violations of Regularity and the Similarity Hypothesis. *Journal of Consumer Research*, 9(1), 90. <https://doi.org/10.1086/208899>
- [25] Heide, M., White, C., Grønhaug, K., & Østrem, T. M. (2008). Pricing Strategies in the Restaurant Industry. *Scandinavian Journal of Hospitality and Tourism*, 8(3), 251–269. <https://doi.org/10.1080/15022250802451065>
- [26] Kasavana, M. L., Smith, D. I., & Schmidgall, R. S. (1990). *Menu engineering : a practical guide to menu analysis*. Retrieved from <http://agris.fao.org/agris-search/search.do?recordID=US19920039139>

- 
- [27] McFadden, D., Machina, M. J., & Baron, J. (1999). Rationality for Economists? In *Elicitation of Preferences* (pp. 73–110). [https://doi.org/10.1007/978-94-017-1406-8\\_4](https://doi.org/10.1007/978-94-017-1406-8_4)
- [28] Ariely, D. (2008). *Predictably irrational: the hidden forces that shape our decisions*. Retrieved from <https://search.proquest.com/docview/235821459?pq-origsite=gscholar>
- [29] Rayaprolu, R., & Venigalla, M.M. (2020). Motivations and Mode-choice Behavior of Micromobility Users in Washington, DC. *Journal of Modern Mobility Systems, 1*, (pp. 110-118).