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Modeling bikeshare user sensitivity and elasticity to pricing using monadic design and ordered logit

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Abstract

Pricing is among the major factors that affect ridership and revenue of bikeshare systems. This paper examines bikeshare users' sensitivity to changes in price by conducting an intercept survey of bikeshare users. Monadic price testing approach was used to design questions on the survey instrument for eliciting responses on sensitivity of Capital Bikeshare (CaBi) users to price changes in fare products. Ordered logit regression method was used to analyze the price sensitivity of the users. The results indicated that income levels and race have statistically significant influence on price sensitivity. High-income group users are less price sensitive than the users of low-income groups. White users are about 20% less price sensitive than other races for both casual users purchasing single-trips and annual members. The monadic design allowed the development of pivot-price elasticities (demand curves) that could be used in evaluating pricing policy changes and project the change in bikeshare ridership and revenue. The price elasticities revealed that females are about 30% and 10% more price sensitive than males for single-trip fare (STF) and annual membership, respectively. Also, sightseeing trips are 30% less price sensitive than work trips for STF purchasers. This study demonstrates that users purchasing STF (casual users) are about 40% more price sensitive than those who purchased annual membership (registered members). The paper also presents an illustrative application of income-based elasticities.

Keywords: Bikeshare; Monadic price test; Monadic design; Price sensitivity; Service sensitivity; Elasticities

1. Introduction

Numerous potential benefits of bikesharing include increased mobility, cost savings from modal shifts, reduction in traffic congestion and fuel use, increased use of public transit, increased health benefits, and greater environmental awareness (Shaheen, Guzman and Zhang 2010). Pricing is one of the major factors that affects ridership and revenue of the bikeshare systems. Various factors such as bikeshare expenses, revenue generated, and socio-demographic

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characteristics are considered in determining the optimal prices of the bikeshare fare products. A few studies revealed reducing bikeshare subscription fees and providing flexible subscriptions to users would increase the bikeshare ridership (Ahillen, Mateo-Babiano & Corcoran 2016; Fishman 2016).

Factors that affect price sensitivity of a transportation mode include user characteristics, trip type, geography, type of price change, time period and mode type (Litman 2005). The simplest way to measure price sensitivity is by developing elasticities, defined as the percent change in price with one percent change in demand. Price elasticities have many applications in transportation policy and planning. Elasticities are used to predict the impact of changes to transit fares on ridership; develop models to predict how changes in transit service will affect vehicle traffic volumes; and they can help evaluate the impacts of new transit services, road tolls, and parking fees (Litman 2005). Several studies focused on analyzing price and service elasticities of transit systems like metro rail and bus services (Dargay & Hanly 2002; Litman 2005; Matas 2004; Cats, Reimal & Susilo 2014; and Schimek 2015). A few studies had evaluated the influence of price changes of vanpool and carsharing services (Consas, Winters & Wambalaba 2005; and Schwieterman & Bieszczat 2017). However, research on assessing price and service sensitivities of the bikeshare users is negligible.

User surveys play a critical role in taking measurements on users' sensitivities to price and service. Several bikeshare user surveys have indicated that bikeshare members are largely influenced by the service elements of the system, such as station density. For example, surveys of registered members of Capital Bikeshare (CaBi), indicated that majority of members reported that they would ride even more if the system had more bikes and docks available (Capital Bikeshare 2016). CaBi is the public bikeshare system in the metro Whashington DC area, which spreads across several jurisdictions in DC and its Northern Virginia and Maryland suburbs. The 2016 CaBi registered member survey also reported that most of the members use bikeshare to get to work and saved an average of $631 on travel costs in a year. However, none of the periodic CaBi member survey reports (2011, 2014 and 2016) and numerous survey reports of users at other bikeshare programs discussed the user sensitivity to bikeshare pricing (Venigalla et al. 2018).

Numerous studies analysed the effect of price change on metro rail, bus, vanpool, and carsharing services. However, to date no studies were conducted on model sensitivities of bikeshare users to price and service. Furthermore, research on price elasticities of bikeshare fare products that could be used in policy calculations to project the change in bikeshare ridership and revenue is also scant. This research fills these gaps through analysis of an intercept survey of bikeshare users conducted at several CaBi locations. The main objective of the research is to examine bikeshare users' sensitivity to changes in price. Additionally, price elasticities of bikeshare fare products were developed. Specifically, this study addresses the following research issues:

1. Identifying variables that influence the price sensitivities of the bikeshare users
2. Deriving price elasticities for different bikeshare fare options available

Definitions

In this study, price elasticity is defined as the percent change in demand with one percent change in price. Pivot-price refers to the prevailing price of the fare product from which changes are proposed in the survey. Registered members (or simply members) are those who have purchased monthly or annual membership whereas casual users are those who have purchased STF, daily or 3-day membership.

2. Prior Research

Several studies derived fare elasticities of metro rail and bus services. Cats et al. (Cats, Reimal & Susilo 2014) evaluated fare-free public transport (FFPT) policy in Estonia based on public transport demand model. The study revealed that passenger demand increases only by 1.2% after the introduction of FFPT. This seemingly small difference could be due to the previous price level, public transport share, and analysis of the short-term impact of this policy. Schimek (2015) estimates fare and service elasticities with panel data for 198 U.S. transit agencies from 1991 to 2012. The dynamic model estimated short-run (less than two years) and long-run (more than five years) elasticities as -0.34 and -0.66 respectively. The results showed that transit demand in large areas was less sensitive to fare and much more sensitive to service compared to small areas. The study also concluded that where fares are initially low, an increase in fare would lead to a greater decline in ridership than in places where fares are high even initially.

A similar study conducted by Dargay and Hanly (2002) indicated that the long-run elasticities are about twice the short-run elasticities. The study examined the fare elasticities for local bus services in England using dynamic econometric model. The analysis revealed that demand was more price-sensitive at higher fare levels and most likely values of the fare elasticity are -0.4 in the short run and -0.9 in the long-run. The per capita bus-kilometers were considered as the measure of service quality. The estimated service elasticities are similar to the fare elasticities in magnitude and opposite in sign. Matas (2004) showed that the introduction of an integrated fare system and improvement in bus and underground networks increased the public transport use. The introduction of a travel card system has increased underground trips and bus trips by 15% and 7% respectively. Pham & Linsalata (1991) conducted a special survey to obtain ridership data 24 months before and 24 months after each fare change for 52 transit systems. The data collected for the study included monthly ridership, vehicle miles and hours, basic adult fare, and total 'farebox' revenues during peak and off-peak periods of the transit systems. The results showed a 10% increase in bus fares would result in a 4% decrease in ridership. The study also ascertained transit riders in small cities are more responsive to fare increases than those in large cities and peak-hour commuters are less responsive to fare changes than off-peak hour commuters. Elasticities for off-peak transit travel are higher than peak period elasticities as the peak period travel consists mainly of commute trips (Litman 2004).

Limited research was performed to assess the influence of price change on vanpool and carsharing services. Concas et al. (2005) studied the effects of fare subsidies on the demand for vanpool services using logistic regression modelling technique. The study used employer and employee data from the survey done in year 1999 as part of the commute trip reduction program in the Puget Sound region (Washington). The results showed 10% increase in vanpool price was associated with a 7.3% decrease in its demand and the probability of choosing a vanpool doubles if subsidies are provided to the employees. The study also presented that individuals become less responsive to price change as the distance increases beyond 60 miles. Schwiterman and Bieszczat (2017) explored the changing prices and taxation level for carsharing between 2011 and 2016 in the United States. The study noted that significant fall in prices made carsharing more affordable to lower-income consumers. The study concluded that tax increases had offset almost a third of the price decline, which negatively affected the operating margins.

Empirical studies based on user surveys indicated that bikeshare users are more likely to be male and young who have higher household income (Fuller et al. 2011; Murphy & User 2015; Bachand-Marleau, Lee & El-Geneidy 2012; and Ogilive & Goodman 2012). Various studies discussed elements affecting bikeshare ridership but did not include pricing as one of the factors. Fishman (2016) reviewed recent bicycle infrastructure and finds out that convenience is the major factor that increases bicycle usage and the introduction of mandatory helmet legislation decreases the bicycle ridership. Judrak (2013) examined the time-specific cost structure of the public bikesharing system of Boston and Washington, DC. The study found that registered (annual or monthly pass) users exhibit higher cost sensitivity around the 30 and 60-minute pricing boundaries compared to the casual (short-term) users. Based on the results, providing ample racks in central location, proper spacing of bikeshare stations to maximize coverage within the cost-free time limit, and dynamic pricing of the public bikeshare system based on the current traffic conditions were recommended in this study.

Ahillen et al. (2016) compared the policies and ridership trends of the Washington, DC's Capital Bikeshare and Brisbane's CityCycle. The findings showed that CaBi had few changes in its pricing policy since its launch in 2010. However, CityCycle reduced the daily subscription fees from $11 to $2, introduced weekly subscriptions and provided free helmets at each of the stations. The results indicated 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. Goodman and Cheshire (2014) examined how the profile of income-deprived and women users changed in the first three years in London bicycle sharing system. The introduction of casual use fare products has encouraged women to use the system and the percentage of income-deprived users doubled as the bikeshare expanded its system to poorer areas. 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 first-time casual users and casual users' monthly ridership by 79% and 41% respectively. In a doctoral dissertation work, Kaviti (2018) presented comprehensive profiles of CaBi users, their price preferences and studied the impact of STF on ridership and revenue. A study report by Venigalla et al. (2018) documented the development of price elasticities for Capital Bikeshare using monadic price testing. The report confined its scope to price elasticity of the single trip fare product.

The research work presented in this paper is based on an expanded scope of price elasticity modelling work performed by Venigalla et al. (2018).

In summary, though several studies and surveys were conducted to analyse the fare and service elasticities of transit system like metro rail and buses, very limited research work was found in literature that evaluated price sensitivity of users towards metro-rail, bus and carsharing services. At the same time, no modelling studies examined the price and services sensitivities of bikeshare users. Only the study by Venigalla et al. (2018) developed price elasticities of bikeshare fare product. Though numerous studies have been conducted to profile bikeshare users and understand their behaviour, very few surveys examined price sensitivity of users. This paper presents the methods used in, and results of the analysis of fare sensitivities of various membership options available for Capital Bikeshare users.

3. Methodology

The study procedure includes the following sequential steps:

1. Design, plan and execute a user survey to elicit responses on the demographics and other preferences of the bikeshare users.
2. Model survey data using ordered logistic modelling techniques to draw inferences on the price sensitivities of casual users and members.
3. Estimate the price elasticities of popular fare products of CaBi system using monadic price testing approach.

3.1 Survey Design and Execution

A detailed 5-page, 26-question survey instrument was designed in consultation with CaBi stakeholders. Key elements of the survey that were used in this study include questions on user sensitivity towards bikeshare service and pricing of different fare products. The overall scope of the survey, which was much broader than what was used in this study, included capturing profiles of casual users as well as registered members. In addition to the information on price and service sensitivity, survey questions collected data on user demographics such as age, gender, and household income of the person. Researchers at George Mason University (GMU) conducted the survey in September and October 2017 and a total of 622 users responded. More details about the survey are presented in Venigalla et al. (2018).

3.2 Price Testing Using Monadic Design

Monadic design is one of the most commonly used and the least biased among the techniques used in consumer pricing research (Lyon 2002; & Bakken 2012). In monadic design no respondent ever knows that other prices are being tested or the price is the object of the research. The monadic price test questions included in the survey were intended for studying the sensitivity of CaBi users to potential price changes for various fare products. Each of the respondents was asked about her/her preferences to two new prices of a product he/she is currently using. For a given fare product, one of the two new prices tested is above the current price and the other is below the current price. The question-set for a hypothetical decrease and increase in price by the same amount ($0.50), and the options given to the respondent (ordered in a logical hierarchy or ordinal scale) is shown below:

Q#. Currently the single-trip fare costs $2.00 per trip. If it costs $1.50, how would it affect your bikeshare usage?

1. Likely to use it a lot more
2. Likely to use it somewhat more
3. Does not affect my choice for commuting

Q#. Currently the single-trip fare costs $2.00 per trip. If it costs $2.50, how would it affect your bikeshare usage?

1. Likely to use it a lot less
2. Likely to use it somewhat less
3. Does not affect my choice for commuting

A completely different version of the same survey form polled the same question-set for an altered price pair with a larger difference from the pivot price (current price). Phrasing of the questions was slightly different for monthly and annual membership fares as the membership fares are not on 'per trip' basis. Different versions of the survey form were distributed randomly to the respondents.

3.3 Ordered Logit Regression Model

An ordered logit model (OLM) is typically used when there are more than two ordinal responses are possible for the outcome variable. The model is routinely applied in various fields including sociology, political science, economics, and psychology (Long & Frees 2014). However, literature survey indicated that to date this model was not applied to determine the price sensitivity of transit or bikeshare systems.

Ordered logit modelling technique was employed to analyse the price and service sensitivities of bikeshare users as the response variables and user characteristics as explanatory variables. Both response variables were measured on ordinal scale as they have more than two categories and the values of the answers have a valid sequential order. The generalized form of the ordered logit models developed for this study with *J* alternatives and *(J-1)* intercepts is given as follows:

$$y_i^* = x_i\beta + \varepsilon_i \tag{1}$$

Predicted probability for the ordinal regression model is given as

$$Pr(y = m|x_i) = F(\tau_m - x\beta) - F(\tau_{m-1} - x\beta)\ for\ m = 1\ to\ J \tag{2}$$

$$x\beta = \sum \beta_i x_i \tag{3}$$

$$F\ is\ the\ cumulative\ distribution\ function\ for\ \varepsilon = var(\varepsilon) = \frac{\pi^2}{3}$$

Where:

y = response variable (price and service sensitivity).

x = vector of independent variables varies between the chosen response variables. (Trips (T), Gender (G), Age (A), Income (I), and Race (R) for price sensitivity models

β = vector of regression coefficients.

ε = error term.

4. Ordered Logistic Regression Analysis

The ordered logit models were developed using "*ologit*" (proportional odds model) function in statistical software Stata. Ordered logit regression assumes that the relationship between each pair of outcome groups is the same, which is referred to as the parallel regression assumption (or also as proportional odds assumption). Only one set of coefficients exists, as the relationship between all pairs of groups is same. The Wald test developed by Brant (1990) was used to test the parallel regression assumption by employing 'brant' function in Stata. The advantage of the 'brant' function is that it tests the proportional odds assumption for each variable individually. Several models were developed to determine which variables explain the price and service sensitivity of the bikeshare users. The analysis to test the price sensitivity included one casual user (STF) and one member fare product (annual membership), both of which had adequate representation in the survey sample. Ordered logit regression technique is also employed to test the service sensitivity of all the CaBi users.

Survey questions were designed to test the price sensitivity of the STF, annual and monthly membership fare options. In this study, only STF and annual membership option have been analysed due to the low sample size of monthly membership (n = 12). As mentioned in Table 1, two versions of the survey were designed to perform the monadic price testing. Furthermore, ordered logistic regression was performed only for Version-1 of the survey form due to the limited sample availability for STF (n = 16) and annual membership (n = 45) in Version-2. The following four models were developed to account for price change (increase and decrease from current price) for

STF and annual membership.

- Model-1: STF reduced to $1.50
- Model-2: STF increased to $2.50
- Model-3: Annual membership reduced by $8
- Model-4: Annual membership increased by $8

Survey respondents were given three options to choose from based on the increase or decrease from the current price. Ordered logit regression method is used to analyse the price sensitivity of bikeshare users as the response variable has three possible outcomes depending on the price change.

- $Y = 1$ - Likely to use bikeshare a lot more/less (High price sensitive)
- $Y = 2$ - Likely to use bikeshare somewhat more/less (Medium price sensitive)
- $Y = 3$ - Does not affect my usage (Not price sensitive)

All four models were built and tested for a set of five explanatory variables namely Trips (*T*), Gender (*G*), Age (*A*), Income (*I*), and Race (*R*). Descriptive statistics for study sample are summarized in Table 1. The results of the parallel test showed that all variables in Model-1 (STF reduced to $1.50) & Model-2 (STF increased to $2.50) satisfy the proportional odds assumption. However, 'gender' variable was found to violate the parallel regression assumption in Model-3 (Annual membership reduced by $8) and Model-4 (Annual membership increased by $8). Therefore, 'gender' variable was removed from these models to satisfy the proportional odds assumption. Income ranges included in the survey forms were regrouped into low (<$35,000), medium ($35,000 to $100,000), and high (>$100,000) categories according to the U.S. Census Bureau (2017). The weighted average values of the income were used as the income variables in the models.

TABLE 1. Descriptive Statistics for the Study Sample

(a) Response variable

Response Variable, *Y*		Price Sensitivity							
		Model-1: STF reduced to $1.50		Model-2: STF increased to $2.50		Model-3: Annual membership reduced by $8		Model-4: Annual membership increased by $8	
	Values / Levels of *Y*	N	%	N	%	N	%	N	%
Price sensitivity of the bikeshare user (1 to 3 scale)	1=High price Sensitive	26	31.33	14	16.87	35	18.13	39	20.21
	2=Medium price Sensitive	24	28.92	29	34.94	27	13.99	35	18.13
	3=Not price sensitive	33	39.76	40	48.19	131	67.88	119	61.66

(b) Explanatory variables

Variable	Description	Values / Levels	Model-1 & Model-2		Model-3 & Model-4	
			N	%	N	%
Trips, *T*	Number of trips in past month	Number of trips	83	100	193	100
Gender, *G*	Gender of the user	1=Male	43	51.81	143	74.09
		0=Female	40	48.19	50	25.91
Age, *A*	Age range of the user (years)	21-24	19	22.89	11	5.70
		25-34	38	45.78	96	49.74
		35-44	13	15.66	50	25.91
		45-54	8	9.64	22	11.40
		55-64	5	6.02	13	6.74

		>65	-	-	1	0.52
Income, *I*	Group	Income range ($)				
	Low	<$35,000	15	18.06	19	9.84
	Medium	$35,000 to $100,000	38	45.78	72	37.31
	High	≥$100,000	30	36.15	102	52.86
Race, *R*	Race/Ethnicity of the user	1=White	45	54.22	150	77.72
		0=Other race	38	45.78	43	22.28

Ordered logistic regression results for price sensitivity are shown in Table 2. The likelihood ratio for all the models has a p-value less than 0.05 (at 95% confidence level) meaning that all the models are statistically significant, as compared to the null model with no predictors. Model 1 and Model 2 represent regression results when the STF is decreased or increased by half-a-dollar, respectively. The response variable decreases with increase in price sensitivity of the bikeshare users. All the coefficient estimates with positive sign implies decrease in the price sensitivity levels with the increase in value of the explanatory variables. Race is found to be statistically significant at 95% confidence level for Model 1 and Model 2. The positive sign of the coefficient in the race signifies White users are less sensitive to STF price change compared to other races. Model 3 and Model 4 represents regression results when the annual membership is decreased or increased by $8 respectively. Income is the only variable found to be significant in Model-3. Higher income groups were found to be less responsive to the price change. Household income and race were found to be statistically significant in Model-4, which indicates that higher income groups and White users are less sensitive to price compared to other income groups and other ethnicities respectively.

TABLE 2. Ordered Logistic Regression Results for Price Sensitivity

<table>
<tr><td colspan="6">Model 1: STF reduced to $1.50</td></tr>
<tr><td></td><td>Coef.</td><td>Std. Err.</td><td>z</td><td>P>|z|</td><td>Inference</td></tr>
<tr><td>Trips, T</td><td>-0.055</td><td>0.037</td><td>-1.50</td><td>0.135</td><td rowspan="2">Number of weekly trips and gender of the bikeshare user have no significant impact for reduction in price for STF product.</td></tr>
<tr><td>Gender, G</td><td>0.235</td><td>0.439</td><td>0.54</td><td>0.592</td></tr>
<tr><td>Age, A</td><td>0.018</td><td>0.232</td><td>0.79</td><td>0.428</td><td rowspan="2">Age and income of the bikeshare user do not influence the bikeshare usage by lowering the price by $0.50</td></tr>
<tr><td>Income, I</td><td>-0.003</td><td>0.004</td><td>-0.60</td><td>0.547</td></tr>
<tr><td>Race, R</td><td>1.086</td><td>0.442</td><td>2.45</td><td>0.014</td><td>White users are less reactive to change in price than users of ‘other’ races.</td></tr>
<tr><td>Y=1|Y=2</td><td>0.014</td><td>0.748</td><td colspan="3" rowspan="2"></td></tr>
<tr><td>Y=2|Y=3</td><td>1.321</td><td>0.763</td></tr>
<tr><td colspan="6">Model 2: STF increased to $2.50</td></tr>
<tr><td>Trips, T</td><td>-0.014</td><td>0.038</td><td>-0.37</td><td>0.712</td><td rowspan="5">• Influence of number of trips, gender and age of the bikeshare on usage is not statistically significant if the STF price is increased by $0.50 to $2.50
• At α=10%, lower income groups are more susceptible to price change to $2.50.
• White users are 1.7 log-odd times less sensitive to price than other race groups.</td></tr>
<tr><td>Gender, G</td><td>-0.224</td><td>0.468</td><td>-0.48</td><td>0.632</td></tr>
<tr><td>Age, A</td><td>-0.009</td><td>0.026</td><td>-0.34</td><td>0.736</td></tr>
<tr><td>Income, I</td><td>0.008</td><td>0.005</td><td>1.71</td><td>0.087</td></tr>
<tr><td>Race, R</td><td>1.688</td><td>0.484</td><td>3.49</td><td>0.00</td></tr>
<tr><td>Y=1|Y=2</td><td>-0.706</td><td>0.833</td><td colspan="3" rowspan="2"></td></tr>
<tr><td>Y=2|Y=3</td><td>1.345</td><td>0.838</td></tr>
<tr><td colspan="6">Model 3: Annual membership reduced by $8.00</td></tr>
<tr><td>Trips, T</td><td>0.028</td><td>0.007</td><td>0.37</td><td>0.709</td><td rowspan="4">• Trips made and age of the bikeshare user have no significant impact for increase in annual membership price.
• Higher income groups were found to be in higher levels (medium or not sensitive) of price sensitivity.
• Race appears to have no influence on price sensitivity if the price were lowered by $8.</td></tr>
<tr><td>Age, A</td><td>0.006</td><td>0.020</td><td>0.27</td><td>0.784</td></tr>
<tr><td>Income, I</td><td>0.011</td><td>0.004</td><td>3.19</td><td>0.001</td></tr>
<tr><td>Race, R</td><td>0.156</td><td>0.378</td><td>0.41</td><td>0.680</td></tr>
<tr><td>Y=1|Y=2</td><td>0.046</td><td>0.725</td><td colspan="3" rowspan="2"></td></tr>
<tr><td>Y=2|Y=3</td><td>0.868</td><td>0.728</td></tr>
<tr><td colspan="6">Model 4: Annual membership increased by $8.00</td></tr>
<tr><td>Trips, T</td><td>0.007</td><td>0.007</td><td>1.01</td><td>0.313</td><td rowspan="4">• Trips made and age of the bikeshare user is insignificant to $8 increase in price for annual membership.
• Lower income groups are more responsive to price increase by $8.
• White users are less sensitive to $8 increase in annual membership price.</td></tr>
<tr><td>Age, A</td><td>-0.002</td><td>0.019</td><td>-0.12</td><td>0.908</td></tr>
<tr><td>Income, I</td><td>0.015</td><td>0.003</td><td>4.29</td><td>0.00</td></tr>
<tr><td>Race, R</td><td>0.984</td><td>0.356</td><td>2.77</td><td>0.006</td></tr>
<tr><td>Y=1|Y=2</td><td>0.901</td><td>0.710</td><td colspan="3"></td></tr>
</table>

Y=2|*Y*=3	1.986	0.723	

Notes:
- *Negative sign for coefficient of any explanatory variable indicates that higher value of that variable, lower the price sensitivity*
- *Bold emphasis indicates statistical significance at α=5%.*
- *Y = 1, 2, and 3 are the cut points (intercepts) of the model. Y = 1 - Likely to use bikeshare a lot more/less; Y = 2 - Likely to use bikeshare somewhat more/less; and Y = 3 - Does not affect my usage*

5. Price Elasticity Analysis

A frequently used rule-of-thumb, known as the Simpson-Curtin rule, suggests that an average fare elasticity has a value of -0.3 meaning that each 3% price increase reduces ridership by 1%. This method can be used for rough estimates and cannot be used for detailed modelling techniques. Development of price elasticities using monadic price testing approach would be more scientific and obviate the need for the use of rules of thumb. The monadic experiment included in the survey data was used to create a demand curve for different pricing options pivoted to current price of the fare product. Price elasticity of demand for calculating price sensitivity is given as follows.

$$Price\ elasticity\ of\ demand\ (PED) = \frac{\%\ change\ in\ price}{\%\ change\ in\ demand} = \frac{\Delta P/P_1}{\Delta D/D_1} \tag{4}$$

Where, P_1 is the current price, P_2 is the new price, D_1 is the current demand, and D_2 is the new demand

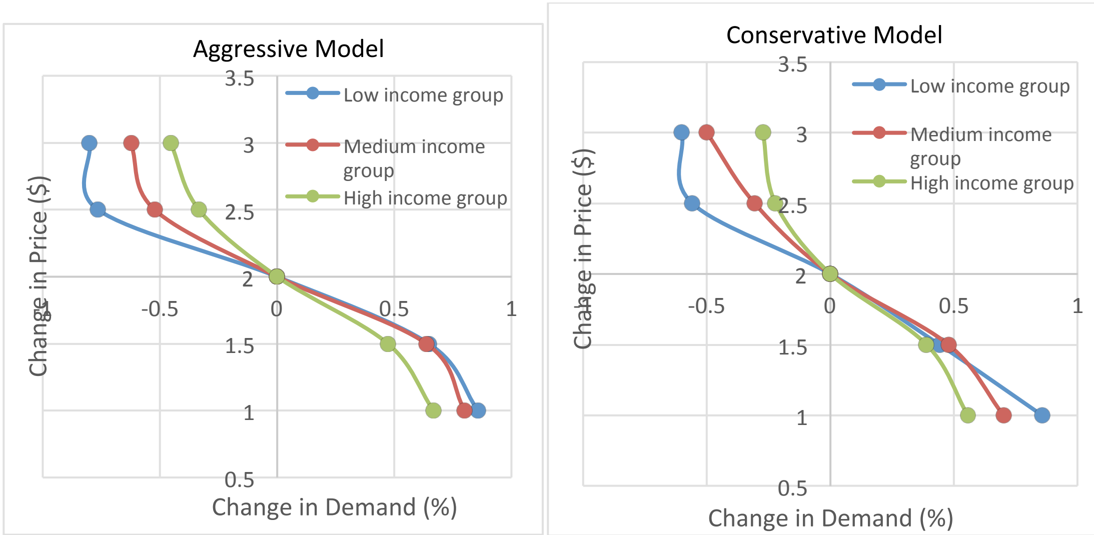
Two sets of assumptions were made to derive two different sets of price elasticities: ‘aggressive’ and ‘conservative’. In the aggressive case, 100% of the users choosing $Y = 1$ (high price sensitive) or $Y = 2$ (medium price sensitive) would be considered as likely to use the product more based on price decrease (alternatively, use less in case of price increase). In the conservative case 100% of the users choosing $Y = 1$ and 50% of the users choosing $Y = 2$ would likely use the product more more/less based on price decrease increase, respectively, than they are currently using. Aggressive and conservative price elasticity models were developed only for STF and annual membership options. Due to very low sample sizes, price elasticities for other fare products were not developed. Ordered logit modelling discussed earlier revealed that race and income are influential on price sensitivity. Therefore, price elasticities developed were categorized by income and race. However, elasticities were also developed for other categories including gender, trip purpose and membership type.

5.1 Income-Based Elasticities

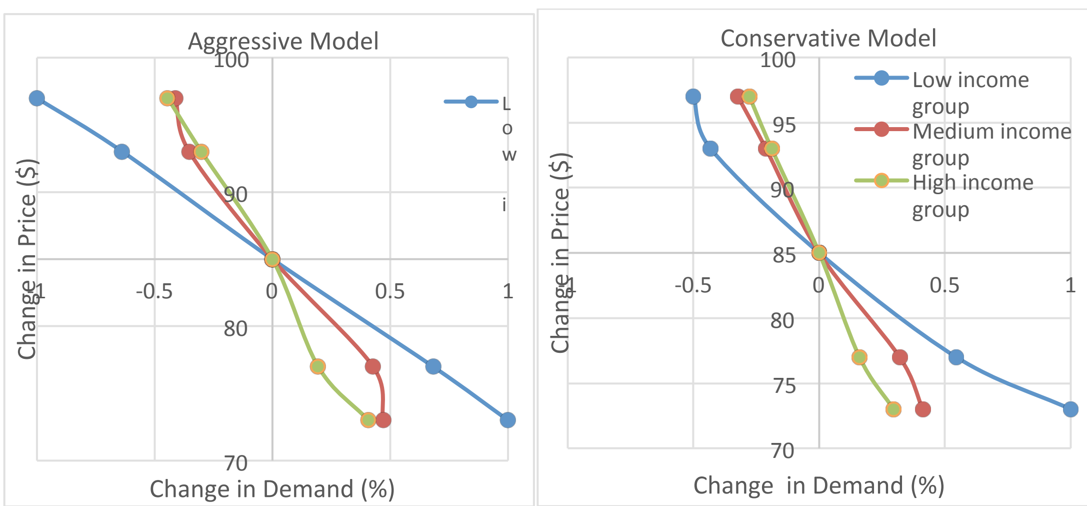
Data are grouped into the following income groups, as defined by the US Census Bureau for developing price elasticities (US Census 2017).

- Low-income group (income less than $35,000)
- Medium income group (income $35,000 to $99,999)
- High-income group (income greater than $100,000)

Figure 1 illustrates income-based price elasticity curves for single-trip fare. Both models show that for all income groups the demand is sensitive to price. As would be expected, low-income groups are more sensitive to price than the middle and high-income groups, which confirms intuition. Low-income group’s price sensitivity ranges from +85.7% to -80.0% for a $1 decrease or $1 increase in STF, respectively (aggressive model). The same range for high-income group is +66.7% to -45.5%. In aggressive model, high-income group price sensitivity ranges from +40.7% to -44.4% for a $12 decrease or $12 increase respectively from current price for annual membership. The same range for low-income group is +/- 100%.



(a) STF



(b) Annual membership

FIGURE 1. Income-based pivot-price elasticity curves

5.2 Elasticities by Different Categories

Table 3 summarizes price elasticities for different fare options tested in this survey categorized by income; race; trip purpose and gender. The negative sign indicates drop in the bikeshare demand due to the increase in price of the chosen fare product. It can be concluded that high-income, White and males are less sensitive to change in fares for STF and annual membership. White users were found to be less price sensitive compared to other ethnicities for both STF and annual membership options. Price sensitivity of White users ranges from +61.5% to a negative 61.5% for a $1 decrease or $1 increase in STF, respectively, for aggressive model. Other races were found to be about 10-20% more price sensitive than White users for both the models of the STF option. “Other race” price sensitivity ranges from +66.67% to -75% for a $12 decrease or $12 increase in annual membership respectively for aggressive model. White users were found to be 20% less price sensitive than ‘other race’ for the annual membership option. Sightseeing or touring trips are less sensitive to price than commuting (work) trips.

Table 3. Summary of Price Elasticities

(a) STF

STF (Pivot: $2.0)		Aggressive Model				Conservative Model			
		$1.0	$1.5	$2.5	$3.0	$1.0	$1.5	$2.5	$3.0
Income	Low	85.7%	64.7%	-76.5%	-80.0%	85.7%	44.1%	-55.9%	-60.0%
	Medium	80.0%	63.6%	-52.3%	-62.5%	70.0%	47.7%	-30.7%	-50.0%
	High	66.7%	47.2%	-33.3%	-45.5%	55.6%	38.9%	-22.2%	-27.3%
Race	White	61.5%	49.3%	-37.3%	-61.5%	50.0%	39.6%	-23.9%	-42.3%
	Other	81.8%	73.2%	-75.6%	-76.5%	59.1%	56.1%	-52.4%	-61.8%
Trip purpose	Work	88.9%	62.9%	-60.0%	-80.0%	61.1%	48.6%	-44.3%	-70.0%
	Touring	58.3%	55.4%	-44.6%	-50.0%	45.8%	44.6%	-28.5%	-37.5%
Gender	Male	68.8%	50.8%	-44.4%	-50.0%	53.1%	41.3%	-31.7%	-37.5%
	Female	83.3%	64.3%	-53.6%	-100%	83.3%	50.9%	-34.8%	-66.7%
STF Aggregate		69.6%	55.7%	-48.4%	-60.9%	58.7%	44.7%	-32.8%	-43.5%
Illustrative interpretation: Low income group price elasticity for $1.0 as new single trip fare +85.7% using an aggressive assumption. It indicates that at $1.0, there would be an 85.7% increase of single trip rides purchased by low-income users. Similarly, if the single trip fare were to be raised to $3.0 (from the current price of $2.0), there would be an 80%, 62.5% and 45.5% drop in trips made by low, medium and high-income groups, respectively.									

(b) Annual membership

Annual membership (Pivot: $85)		Aggressive Model				Conservative Model			
		$73	$77	$93	$97	$73	$77	$93	$97
Income	Low	100%	68.2%	-63.6%	-100%	100%	54.5%	-43.2%	-50.0%
	Medium	47.1%	42.7%	-35.3%	-41.2%	41.2%	32.0%	-21.2%	-32.4%
	High	40.7%	19.4%	-30.1%	-44.4%	29.6%	16.0%	-18.9%	-27.8%
Race	White	45.2%	32.9%	-36.0%	-45.2%	35.7%	24.7%	-22.6%	-29.8%
	Other	66.7%	42.1%	-47.4%	-75.0%	66.7%	34.2%	-30.3%	-50.0%
Trip purpose	Work	41.7%	36.3%	-38.7%	-39.0%	31.9%	28.0%	-23.2%	-25.0%
Gender	Male	41.7%	32.5%	-33.8%	-41.7%	37.5%	24.2%	-20.7%	-27.1%
	Female	50.0%	44.4%	-50.8%	-52.0%	37.5%	36.5%	-31.7%	-40.0%
Aggregate for annual membership		44.7%	36.5%	-39.2%	-44.7%	35.1%	28.4%	-24.3%	-29.8%
Note: Only work trips exist in annual membership. Low-income group price elasticity for annual membership reduced to $73 is +100% using an aggressive assumption. It indicates that at $73, there would be a 100% increase of using bikeshare by low-income users.									

5.3 Example Application of Elasticities

A potential use for the elasticities is presented in this section by developing revenue and ridership projections of single-trip fare and annual memberships for the monadic prices tested in the survey. The illustration assumes the ridership changes are only due to change in price for both products.

For the 12-month period after the introduction of single-trip fare in June 2016, 368,634 single trips ($2 each) were purchased at CaBi kiosks booking $737,268 as revenue (data obtained from DDOT). These numbers were considered as the based case for projections. It was assumed that the income distribution of the users of these single trips is the same as the income groups represented by the CaBi user survey (low-income: 18.64%, medium-income: 41.53% and high-income: 31.83%). Additionally, it was also assumed that there would be no organic growth (or decline) in demand from the levels recorded in the 12-month period after the implementation of STF. Income-based elasticities were applied to estimate annual ridership and revenues resulting from each monadic price tested in the survey.

The projections shown in Table 4 indicate that using the aggressive assumptions, STF ridership could increase by as much as 75% (for STF $1.00) or decrease by as much as 59% (for STF $3.00). The corresponding projected revenue, however, could decrease by 12% and 38.5%, respectively. Using the conservative model, ridership may increase by 67% with a corresponding decrease of 16% in revenue when STF is set at $1.00. Both aggressive and conservative models suggest that when STF is set at $1.50, ridership could increase by 57% and 43% with a corresponding increase in revenue of 18% and 7%, respectively. Thus, $1.50 may be regarded as an optimal price for STF from the current pricing at $2 for the same fare option.

TABLE 4. Ridership and Revenue Projections from Changes to Single-Trip Fare Based on Income

STF		Low Income	Medium Income	High Income	Trips	Percent change	Revenue	Percent change
	Estimated split[1]	18.64%	41.53%	39.83%				
$2.00 Current	Number of trips June 16-May 17	68,728	153,077	146,829	368,634[2]	Base case	$737,268	Base case
New fare	Aggressive Model							
$1.00	Change in demand	85.7%	80.0%	66.7%				
$1.50		64.7%	63.6%	47.2%				
$2.50		-76.5%	-52.3%	-33.3%				
$3.00		-80.0%	-62.5%	-45.5%				
$1.00	Estimated trips	127,638	275,538	244,715	647,891	75.8%	$647,891	-12.1%
$1.50		113,200	250,489	216,165	579,854	57.3%	$869,780	18.0%
$2.50		16,171	73,059	97,886	187,117	-49.2%	$467,792	-36.6%
$3.00		13,746	57,404	80,088	151,238	-59.0%	$453,714	-38.5%
New fare	Conservative Model							
$1.00	Change in demand	85.7%	70.0%	55.6%				
$1.50		44.1%	47.7%	38.9%				
$2.50		-55.9%	-30.7%	-22.2%				
$3.00		-60.0%	-50.0%	-27.3%				
$1.00	Estimated trips	127,638	260,231	228,400	616,269	67.2%	$616,269	-16.4%
$1.50		99,050	226,136	203,929	529,115	43.5%	$793,672	7.7%
$2.50		30,321	106,110	114,200	250,632	-32.0%	$626,579	-15.0%
$3.00		27,491	76,538	106,785	210,814	-42.8%	$632,443	-14.2%

Sources: [1] Intercept Survey; [2] DDOT

6. Conclusions, Recommendations And Discussion

This research examined bikeshare users' sensitivity to changes in price and their preferences on service by conducting an intercept survey of Capital Bikeshare (CaBi) users. Monadic design was used in the wording of survey questions relevant to pricing. The survey data was used to obtain demand curves or price elasticities that could be used in policy calculations to project the change in bikeshare ridership and revenue. Ordered logit regression method was used to analyse the price sensitivity of bikeshare users. For all four prices tested, the bikeshare user's race was found to have a statistically significant influence on price sensitivity. For three of the four models, household income was found to be statistically significant determinant of the user's price sensitivity. The results showed that higher household income groups and White users are less sensitive to price compared to other income groups and other races/ethnicities respectively. Predicted probabilities showed that approximately 39% and 47% of STF users are not sensitive to price decrease or increase, respectively, by half-a-dollar. Nearly 2/3 (or 64% and above) of the annual members were found not to be impacted by an $8-change in membership price.

The most significant among many contributions made by this study is the methodological innovation in the application of monadic price testing, which is a widely used technique in consumer pricing research, in bikeshare research. Furthermore, innovative application of ordered logistic regression method facilitated better understanding of bikeshare user sensitivities to price. Thus, this paper fills a significant gap in literature on research related to bikeshare pricing.

Judrak (2013) found that registered members exhibit higher cost sensitivity compared to the casual users. However, this study proves that persons purchasing STF (casual users) are about 40% more price sensitive than those who purchased annual membership (registered members). An illustrative application of income-based elasticities indicated that reducing the STF to $1.50 (from $2.00 per trip) and annual membership to $73.00 (from $85 per year) were found to improve both ridership and revenue of the CaBi system. Further studies are needed to investigate the optimal pricing of the other fare products available at various the bikeshare systems.

It is expected that the contributions from this study would provide insights and guidance on evaluating future pricing policy changes at various bikeshare systems. For example, effective July 2018 Metro Bike (bikeshare system in Los Angeles) reduced it single trip fare from $3.50 per trip to $1.75 (Sotero 2018). It is not known if this price reduction was based on the results of any structured study such as this one. However, the Metro board would have benefitted from the results and methods used in this study in evaluating their policy decision to reduce STF by half. Additionally, a structured study of the impact the STF product price reduction at Metro, similar to the price impact studies by Venigalla et al. (2018), Kaviti et al. (2018), and Kaviti (2018) and this study would be not only of academic interest, but is also of immense value for policy makers at various bikeshare systems.

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