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Fare-Capping Impact Analysis Using Mobile Ticket Data

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Abstract

In the wake of the COVID-19 pandemic, transit agencies experienced ridership and revenue losses alongside operating cost increases. At the same time, transit was further highlighted as an essential public good alongside essential workers who relied on transit to conduct a range of services in critical industries, thus emphasizing the role of transit in promoting accessibility, equity, and economic opportunity. In grappling with the current volatile environment, including the ongoing travel and financial uncertainties from the pandemic, transit agencies have attempted to delicately balance fares and financing. In turn, many have considered progressive fare policies such as fare capping. For transit agencies seeking innovative fare changes, fare impact and equity analyses are necessary to better understand how riders respond to fares and changes in fares, and how changes to fares and ridership affect accessibility, equity, revenue, and funding. With the increased use of mobile ticketing, small to mid-sized transit agencies now have access to detailed rider behavior data that can be used to estimate rider responses to fare structure changes. In this paper, we present a multinomial logit fare product choice model that uses rider insight from a sample of mobile ticketing data to account for switching between fare products. We apply the model to forecast the ridership response to incremental fare changes and fare capping.

Keywords

planning and analysis, data sources, impact analysis, planning data analysis, planning methods, policy and organization, executive management issues, data for decision making, data driven decisions, policy analysis, public transportation, buses, information technologies (cellphone based apps), behavior, fare, payment technologies, ridership

Public transit service is essential to maintaining mobility and sustaining economic activity in many rural and urban communities. According to the 2017 APTA *Who Rides Public Transportation* report, transit riders are disproportionately low income, from communities of color, and without access to a private vehicle. A similar 2020 TransitApp survey showed that the COVID-19 pandemic further compounded the disparities of transit riding demographics. Essential workers became more of the backbone of transit ridership, further highlighting the role of transit in promoting accessibility, equity, and economic opportunity. Higher-income and higher-skilled workers were more likely able to work from home and not need to ride transit, making front-line and low-wage service employees the backbone of transit ridership.

The pandemic impacts were also detrimental to the financial condition at transit agencies. Transit saw up to 70% losses in annual ridership and revenue alongside an increase in operating costs resulting from additional cleaning, social distancing and safety measures, and labor shortages. In an attempt to keep up with the rising cost of operation, transit agencies are compelled to increase fares to increase fare revenues, which partially cover the cost of operating transit. However, increasing fares usually leads to decreased ridership, which negatively affects a major performance metric occasionally tied to apportionment for other funding sources.

Further, when fares are increased, transit-dependent individuals typically experience a higher or disproportionate burden. For some vulnerable transit riders, fare increases become a barrier to access, mobility, and economic opportunity. As a result of these interrelated and

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disparate impacts on ridership and revenue, and downstream impacts on accessibility, equity, and funding, it is important to conduct a fare impact and equity analysis whenever fare changes are considered. Fare models are used to forecast the impact of fare changes on ridership and revenue to aid transit agencies in making decisions that promote accessibility, equity, and funding efficiencies.

In 2021, the Pioneer Valley Transit Authority (PVTA) and its auxiliary staff at the Pioneer Valley Planning Commission (PVPC) conducted a triennial fare analysis to forecast the impact of fare policy and structure changes on ridership and revenue. PVTA was created in 1974 under M.G.L. Chapter 161B and is the second largest transit agency in Massachusetts. PVTA provides public transportation services to 24 communities in Hampden and Hampshire Counties, including Springfield, Holyoke, Northampton, and Amherst. PVTA's service area covers over 600 square miles and a population of 590,000. In FY 2019, with 192 buses, 47 fixed bus routes, and 136 ADA vans, PVTA provided over 10 million fixed-route rides and over 250,000 paratransit trips. As a result of the COVID-19 pandemic, PVTA ridership in FY 2020 dropped to 80% of typical levels. Considering the COVID-19 pandemic, the PVTA Board requested that the fare impact analysis include equitable and innovative fare scenarios that would not overly increase the fare burden for PVTA riders, particularly low-income and people of color, while also not being substantially detrimental to fare revenue.

Building on the work done by other researchers, PVTA conducted a customer behavior-focused fare impact and equity analysis and evaluated innovative fare products such as fare capping. PVTA's recently deployed mobile ticketing application provided a rich source of valuable account-based information about customer behaviors, including how riders choose among available fare products based on their travel frequency. The behaviors from the sample of mobile ticket users were extrapolated and applied to the full fare-paying population. The mobile ticket data were used to estimate a multinomial logit model that predicted switching between fare products in response to a fare change. The model was then applied to predict product choice and ridership changes under a range of fare scenarios, including fare capping.

Fare capping removes the up-front cost of purchasing a multi-use pass by "capping" the single-use fares paid by a customer within a given time period and providing them with an unlimited-ride pass for the remainder of the period after they reach the cap. Fare capping is generally considered to increase equity within transit systems and has been reported to result in more equitable outcomes in case studies in Montreal, Sydney, Indianapolis, Grand Rapids, Oakland, Portland and elsewhere (*1*, *2*).

Fare Impact Forecasting Methods Review

The methods commonly used for fare change analyses generally utilize the application of an elasticity spreadsheet model (*3*). The basic form of this model, previously utilized by PVTA, is a one-stage elasticity spreadsheet model where point elasticities are directly applied to estimate the change in demand following a change in fare product price. A major shortcoming of this method is that it does not account for a user switching to a different fare product or changing their travel frequency in response to the changes in other fare product prices.

Metropolitan Atlanta Rapid Transit Authority (MARTA) (*4*) and Southeastern Pennsylvania Transportation Authority (SEPTA) (*5*) developed a two-stage spreadsheet approach to account for switching between fare categories to estimate the impact of a fare change on ridership and revenue. The two-stage elasticity model first applied direct fare elasticities within each fare group and then applied ridership diversion rates (cross-price elasticities) to estimate switching between different fare groups. New York City Transit Authority (NYCTA) (*6*) and the Massachusetts Bay Transportation Authority (MBTA) (*7*) have adopted modified versions of this two-stage spreadsheet elasticity model. In many cases, the elasticities used in the models are based on widespread transit research or are calculated from observations of ridership changes following historical fare changes within the agency. The bus fare elasticities for NYCTA ranged from −0.26 to −0.40 (*6*).

In 2006, Zureiqat demonstrated the use of a discrete-continuous modeling approach with automatic fare collection (AFC) panel data for a fare policy analysis at Transport for London (TfL) (*8*). The theory behind the discrete approach is random utility theory. In the case of fare analyses, utility theory postulates that a decision maker would choose the fare product that has the maximum utility among a set of available fare products, where the utilities are based on observed attributes (e.g., price of the products) and unobserved attributes such as the decision maker's inherent preference for one product over another. In practice, logit (logistic probability unit) models are used to express the discrete choice of the decision maker. Linear regression models are the foundation of the continuous approach, which describes the relationship between frequency of travel and the cost of travel. Combined, these discrete-continuous models can be used to predict changes in the demand of fare products and travel frequency in response to changes in fare prices.

Different methods have been employed to estimate the parameters for logit product choice models. For example, Chicago Transit Authority (CTA) estimated logit parameters using stated preference customer surveys. Taking a revealed preference-based approach, Stuntz built on the Zureiqat research to demonstrate the use of AFC data for logit parameter estimation for CTA in 2015 and the MBTA in 2017 (*9*).

These examples demonstrated the application of fare choice logit models for analyzing incremental fare changes, but very few examples have been found in the literature in relation to the impact of fare capping on ridership and revenue. TfL offered a daily fare-capping option at the time of the Zureiqat analysis, but this option was not considered as a fare alternative in the model for simplification. Although not demonstrated, Stuntz also noted that the structure of the application could be adapted for analyzing major fare changes including fare capping. Other models involving a fare-capping scenario such as Chalabianlou et al. (*10*) utilize a simple elasticity model, which does not account for fare product choice or induced ridership. Chu et al. (*11*) estimated and compared ridership and revenue impacts for fare caps of different lengths by making simple accounting adjustments based on rider frequencies from account-linked data but assumed no change in observed trips and did not apply an elasticity.

Our work sought to adapt the discrete-continuous elasticity model demonstrated by Zureiqat and Stuntz to predict changes in demand in the discrete component and changes in travel frequency and induced demand in the continuous elasticity component. We estimated the model from a sample of account-linked mobile ticket data and applied it to the full population to predict the impact of fare changes such as fare capping.

Model Framework

The modeling framework to estimate the expected ridership change in response to fare changes is outlined in Figure 1 and includes the following steps:

- Establish observed baseline ridership from mobile data and AFC data
- Estimate fare product choice model using mobile data
- Generate the synthetic baseline ridership using the baseline fares and the estimated fare product choice model
- Calibrate fare product choice model by comparing the synthetic baseline ridership with the observed baseline ridership
- Apply the fare product choice model under new scenario fares, which includes the application of:
  1. Fare product switching: apply the calibrated fare product choice model using scenario fares, and apply incremental outputs to the observed baseline ridership
  2. Price elasticity: estimate price elasticity from AFC ridership data and apply to fare product switching results
  3. Induced ridership: estimate induced ridership factor from the mobile data and apply to account for the changes in ridership resulting from switching between multi-use passes and single-use fare products

Observed Baseline Ridership

The AFC data are used in combination with the Mobile data to establish the observed baseline ridership.

Automatic Fare Collection (AFC) Data

PVTA riders have historically paid bus fares with cash at the farebox on board the buses or using passes purchased at customer service center and partner retail locations. The data from the AFC system provide unlinked counts

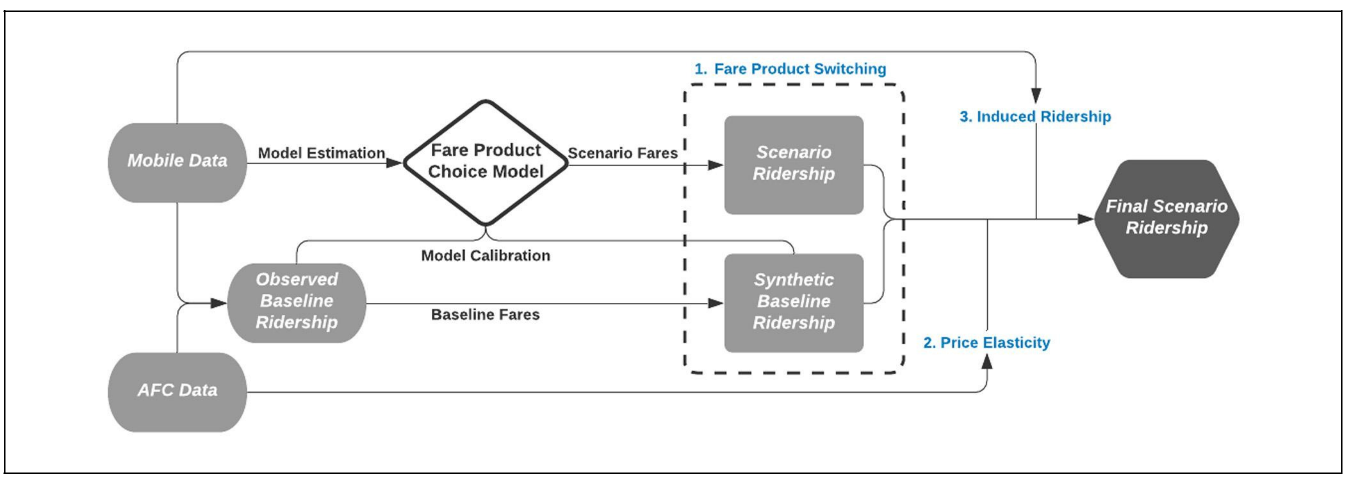

Figure 1. Model structure flowchart.

of ridership and revenue by fare product for the full population of fare-paying riders. The AFC data serve as the primary information for the fare impact model.

The AFC base year ridership and revenue totals by fare product are the main model inputs. The base year for the study was FY 2021 (July 2020 to June 2021). The baseline data are typically calculated by projecting ridership and revenue by fare product from the most recent full year of data to account for existing trends without the fare change impacts. However, as this fare study was conducted in the months following the coronavirus pandemic, the most recent half year of data (July 1st 2020–December 31st 2020) was used because it ensured that the coronavirus impacts (causing an initial 67% ridership loss), ongoing covid recovery trends, and typical seasonality effects on ridership were accounted for.

Mobile Ticket Data

PVTA launched a mobile ticketing application in July 2020, which allowed riders to purchase and pay bus fares using their smart devices. The mobile app offers the same fare products available outside the app. The data from the mobile application provide linked records of ridership and revenue by fare product for the sample of riders that use the app. The linked ridership information yields customer behavior insights such as how often riders travel on transit and what fare products they choose for their anticipated travel, which can be used to estimate revealed preference parameters for a logit model to predict how riders might respond under different fare scenarios.

The mobile ticket data serve as the secondary input for the fare impact model. The mobile data provide a record of a ticket activation when a user opens a pre-purchased pass in the mobile ticket app. Each activation is recorded in the pass activity data set, which includes the activation timestamp, fare product, latitude and longitude based on the cell phone location when available, and a unique user ID (UUID). The final sample size of 107,131 activations was collected during the half year period, and accounted for 12% of all fare-paying rides.

Fare Products

The fare products are the choice set of fares available to customers and considered in the model. For PVTA, these were Single-Use Fares (SUFs), which include 1-Ride and Transfer tickets, 1-Day Passes, 7-Day Passes, and 31-Day Passes. SUFs and 31-Day Passes are provided at a 50% discount to registered Elderly & Disabled (E&D) riders, who made up 30% of total ridership during the study period. The same fare products were available for mobile app and non-mobile app customers. In a given time period, a customer may select one or more fare products to use based on their travel frequency and cost.

Customer Weeks, User Frequency, Active Days

The group of activations recorded within a given week for each customer is referred to as the Customer Week, whereas the total number of activations of each fare product in each customer week is the User Frequency. The user frequency and the number of active days (days with at least one activation) are calculated for each customer week.

Customer Segments

Customer segments are groups of customers that exhibit distinct travel behaviors and attributes. In the fare impact model, segmentation allows riders in different segments to be modeled under different assumptions about their travel behavior and ultimately product choice. PVTA customers are segmented based on customer types and travel behaviors.

Examples of customer types can include seniors, students, and adults. The PVTA model considered two customer types: Regular riders and E&D riders. E&D riders have access to fare products that provide 50% price discount on regular fares.

The frequency of travel within a customer week was used as a proxy for travel behavior segmentation under the assumption that riders that travel more frequently portray different characteristics when selecting fare products that differentiate them from riders that travel less frequently. Riders with different user frequencies are assumed to have different weekly costs, and are therefore predicted to make different product choice decisions. Figure 2 shows the density of weekly user frequency for each fare product, suggesting that the distribution of trip frequencies varies by fare product. Customers who purchase SUF fares (1-Ride or Transfer tickets) make on average 3.7 trips in a week, compared with an average of 5.3 trips for 1-Day Pass users, 10 trips for 7-Day Pass users, and 8.9 trips for 31-Day Pass users.

The user frequency distributions informed the selection of frequency bins used for customer segmentation. The bin sizes were selected to capture the similarities and differences in trip frequency within and across the fare products. PVTA used six bins with the following intervals: [0,2), [2,4), [4,6), [6,8), [8,12), [12, ∞). These bins were selected at intervals where the changes in fare product market shares stepped up or down at relatively constant rates. Figure 3 shows the share of rides taken on each fare product for the 6 user frequency bin selected. As the number of trips per week increases from left to

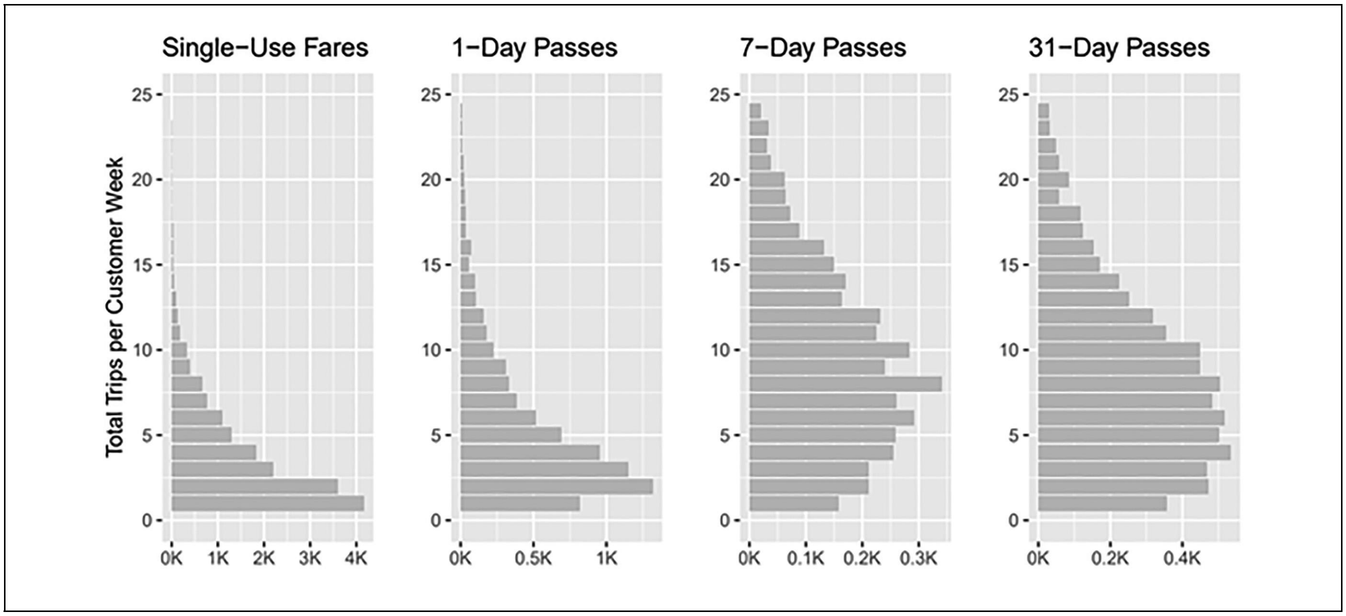

Figure 2. Distribution of customer weeks by user trip frequency for each fare product from the mobile ticket data sample in the half year period (July 2020 to December 2020). The distribution of trip frequencies varies by fare product.

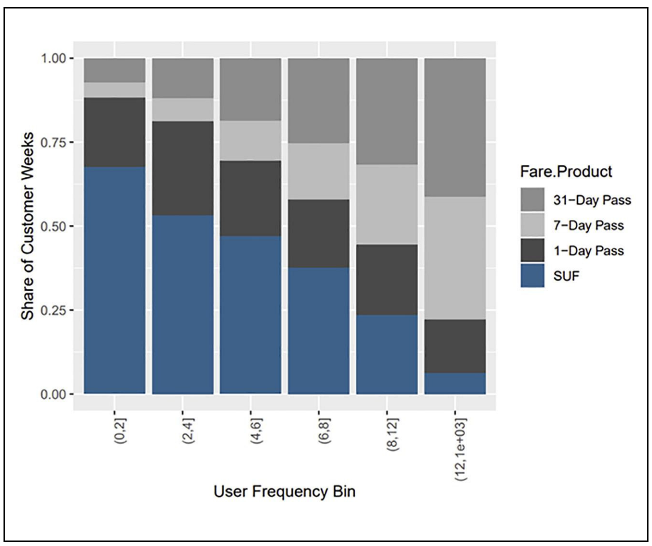

Figure 3. Share of customer weeks by fare product for each of the selected user frequency bins developed from the mobile ticket data sample in the half year period (July 2020 to December 2020).
Note: SUF = single-use fare.

right, the share of trips using SUF decreases, while the share of trips on 31-Day and 7-Day passes increases.

Weekly Cost

The baseline Weekly Cost C is calculated from the mobile data for each customer segment s and fare product. The Weekly Cost is the prorated cost of transit to the user had they used the given fare product exclusively for that week. This is calculated using the baseline fare prices P and ridership R as follows:

$$C_{s,SUF} = P_{SUF} \times R_{s,SUF} \tag{1}$$

$$C_{s,Day} = P_{Day} \times D_{s,Day} \tag{2}$$

$$C_{s,7D} = P_{7D} \times W_{s,7D} \tag{3}$$

$$C_{s,31D} = P_{31D} \times \frac{7}{31} \times W_{s,31D} \tag{4}$$

As SUF includes the 1-Ride and 1-Ride and Transfer trips, the baseline price for SUF is calculated using a transfer rate applied to the One Ride and Transfer fares as $P_{SUF} = (1 - r) \times \left(P_{OneRide,Base} + r \times P_{Transfer,Base}\right)$. The weekly cost for the 1-Day pass is calculated using the number of active days D, and for 7-Day and 31-Day passes using the number of customer weeks W attributed to those fare products. The baseline weekly costs are shown in Table 1. In the model application stage, these values are recalculated using scenario fares rather than baseline fares.

Observed Baseline

The distribution of ridership by fare products was determined directly from the AFC data because fare product preferences for mobile ticket users differ from those for the non-mobile ticket users. Because of the greater convenience of accessing passes via the mobile ticket app, passes are used more often among mobile ticket users

Table 1. Customer Segmentation and Observed Baseline

	Cust.	Weekly frequency	Baseline ridership				Baseline average weekly cost			
	Type	Frequency	SUF	1-Day	7-Day	31-Day	SUF	1-Day	7-Day	31-Day
Customer segment	Regular	(0,2)	75,766	15,407	695	2,047	$1.54	$3.50	$15.00	$12.19
		[2,4)	267,785	121,370	4,092	14,017	$3.72	$5.70	$15.00	$12.19
		[4,6)	271,343	145,344	7,760	28,312	$6.82	$9.51	$15.00	$12.19
		[6,8)	238,310	111,342	12,123	35,751	$9.92	$12.38	$15.00	$12.19
		[8,12)	290,220	215,269	31,887	88,680	$14.19	$15.05	$15.00	$12.19
		[12, ∞)	103,069	231,905	76,015	179,116	$25.34	$18.43	$15.00	$12.19
	E&D	(0,2)	20,910	346	12	1,820	$ 0.77	$3.50	$15.00	$5.87
		[2,4)	97,448	3,919	41	10,403	$1.82	4.84	$15.00	$5.87
		[4,6)	87,782	4,111	124	44,991	$3.38	$7.99	$15.00	$5.87
		[6,8)	78,511	5,033	353	52,533	$4.92	$10.61	$15.00	$5.87
		[8,12)	86,993	8,875	1,077	129,772	$7.05	$14.81	$15.00	$5.87
		[12, ∞)	45,568	11,027	3,415	380,474	$14.41	$19.48	$15.00	$5.87
AFC totals	Regular		1,246,494	840,635	132,571	347,923	na	na	na	na
	E&D		417,210	33,310	5,022	619,993	na	na	na	na

Note: AFC = automatic fare collection; E&D = elderly and disabled; SUF = single-use fare; Cust. = customer; na = not applicable.

compared with non-mobile ticket users. During the study period, 28% of non-mobile ticket rides were taken on a 31-Day pass compared with 48% on mobile tickets.

However, the AFC data did not contain information to segment the ridership into user frequency bins. As a result, the distribution from the mobile ticket sample was used to allocate the AFC data into the appropriate user frequency bins. Customer weeks from the mobile data were categorized by fare product based on the most frequently used fare product in a given week (some customers use more than one fare product in a week). The breakdown of user frequency bins by fare product from the mobile data sample was then applied to the full population AFC data. The observed baseline ridership and weekly costs for each customer segment and fare product are shown in Table 1.

The baseline ridership for each customer segment s and fare product f, $R_{s,f,Base}$ is calculated by distributing the AFC ridership totals by customer type and fare product ($R_{s,f,AFC}$) into customer segments based on the observed ridership in the mobile data.

$$R_{s,f,Base} = \Sigma_{i=1}^{S} R_{i,f,AFC} * \frac{R_{s,f,Mobile}}{\Sigma_{i=1}^{S} R_{i,f,Mobile}} \quad (5)$$

The baseline market share M of trips on each fare product within each customer segment is calculated from the baseline ridership values.

$$M_{s,f,Base} = \frac{R_{s,f,Base}}{\Sigma_{i=1}^{F} R_{s,i,Base}} \quad (6)$$

Product Choice Model Overview

The model was structured to forecast the likelihood that an average customer with a given frequency of weekly trips would select each fare product based on weekly cost. The model is used to predict changes in ridership between fare products under various scenario fares. Model parameters are estimated from individual user activity in the mobile data and applied to the full population in the observed baseline. The results are then compared with the observed baseline ridership to calibrate the model parameters as shown in Figure 1.

For each customer segment s and fare product , the baseline weekly cost is used to calculate the general specification of the utility for the product choice model and a stochastic error term. The systematic utility perceived by a customer V is calculated as follows:

$$V_{s,f} = \alpha_f + C_{s,f} * \beta_{WeeklyCost} \quad (7)$$

where
α_f is the Alternative-Specific Constant of fare product f
C is the weekly cost, and
$\beta_{weeklyCost}$ is the coefficients for weekly cost. The coefficient β represents the response of the rider to the weekly cost, and the alternative-specific constant α represents the inherent attractiveness of a product over other products, assuming other factors such as cost were the same.

A logit model assumes that the stochastic error terms of the different products are independent and identically distributed with a Weibull distribution. This allows a particularly simple form for expressing the probability of customer segment s choosing fare product f for estimating the market share M shown in the following equation:

$$M_{s,f} = \frac{e^{V_{s,f}}}{\Sigma_{i=1}^{F} e^{V_{s,i}}} \quad (8)$$

Table 2. Product Choice Parameters

	SUF	1-Day	7-Day	31-Day	
Alternative-specific constants (α)					
	0.000	−0.186	−1.570	−0.112	
Adjusted alternative-specific constants (α)					
Regular	0.000	−0.340	−2.118	−1.647	
E&D	0.000	−1.650	−3.278	−0.068	
Generic coefficient (β)					
All riders	na	na	na	na	−0.176

Note: E&D = elderly and disabled; SUF = single-use fare; na = not applicable.

This market share is multiplied by the total baseline ridership in each customer segment to yield the synthetic baseline. The synthetic baseline results are then compared with the observed baseline to calibrate the model parameters.

Model Parameter Estimation

The model parameters were estimated using the mobile ticket data. The alternative-specific constants α and weekly cost coefficient β were calculated from a multinomial logit regression predicting fare alternative choice for each customer-day where a fare choice was made. A user's fare choice on a single choice-day was expressed as a function of their expected rider frequency for the following week. As their future ridership was not actually known at the time of the choice, the previous week's ridership was used as a proxy for their expected ridership.

A choice-day was defined as a customer-day where a fare product decision was made. It did not include pass-holding days as no choice was made on those days. Additionally, the user must have at least one record of travel in the week before their choice-day for use in the product choice prediction.For each choice-day, the fare choice was calculated as the fare product with the most number of activations in that day. The fare choice of each customer-day was predicted from the weekly cost of each fare product based on the number of trips taken in the 7 days before the customer-day in question. The rider's frequency from the prior week was considered a proxy for their expected trips for the following week, which influences their product choice. The alternatives included in the multinomial logit regression were the four fare products categories: SUF, Day Pass, 7-Day Pass, and 31-Day Pass, with SUF as the comparison group.

The product choice parameters estimated with PVTA's mobile data are listed in Table 2. It is important to note that the parameters estimated represent user behavior under each fare product and were not used to determine how often each fare product was chosen. For example, we do not have reason to believe that the behavior of a mobile ticket user who purchased a 7-day pass is different from the behavior of a non-mobile ticket user who also purchased a 7-day pass. However, as the mobile ticket sample was not representative in relation to the fare product market shares, the AFC ridership totals by fare product were used as weights in the logit regression. Additionally, because of limitations in the E&D sample size, separate parameters for each customer type were not estimated. Instead, both Regular and E&D riders were included in the parameter estimation, and were calibrated separately to account for differences in customer type behavior.

Model Calibration

For the calibration of the model, we applied the model using the estimated parameters and the weekly costs calculated from the baseline fares, which yielded the synthetic baseline results. Additive adjustment factors were then incorporated to minimize the difference in ridership for each fare product between the synthetic and observed baseline ridership. A Generalized Reduced Gradient algorithm was used to determine the additive adjustments that minimized the differences between the synthetic and observed baseline market shares for each fare product. This was done separately for each customer type L to account for differences in fare product preferences between customer types.

The calibration process yielded the adjusted alternative-specific constants (α) shown in Table 2. The alternative-specific constants represent the attractiveness of the Pass products relative to the SUF product. The negative alternative-specific constants indicate that assuming the cost of all the fare products were equal, PVTA customers would preferentially select the SUF product more than the pass products. For Regular riders, the preferences of PVTA customers are for 1-Day passes followed by 31-Day pass, and lastly 7-Day pass. The E&D customer preferences differ from the Regular customers. The results show E&D customers prefer the SUF followed by 31-Day pass, then 1-Day pass, and 7-Day passes. This is likely because PVTA offers a 50% price discount on the SUF and 31-Day Pass products for E&D customers but no discounts on the 1-Day and 7-Day passes.

The preference for SUF products over passes could be because PVTA customers perceive the flexibility of "pay-as-you-go" as more attractive than committing to a pass. It could also be an influence of the specific demographic makeup of PVTA customers. PVTA serves a mixed socioeconomic area, with a large proportion of low-income population in the region. According to the 2013–2017 5-year American Community Survey data, of the 129 census tracts in PVTA's service area, 47 or 36% of them have a population with poverty rate greater than 20%. The average poverty rate for these communities is 37%. The southern hubs of PVTA service in Springfield and Holyoke have an average poverty rate of 32% and 29%, respectively. The preference for SUF products might also be a function of the large proportion of PVTA customers who are unable to afford the up-front cost of the passes.

Application of Model for New Fare Scenario

The model application for evaluating new fare scenarios included three major stages. First, the logit model was applied to predict fare product switching in response to the fare change. Second, elasticity factors were estimated and applied to account for the price sensitivity of the riders under each product that had a fare change. The price sensitivity of riders was estimated from the observed effective elasticity from the FY 2019 fare change. When riders switch from SUFs to multi-use passes, they are expected to increase their ridership as the marginal cost of each ride is zero. The opposite effect is expected when riders switch from multi-use passes to SUFs. Third, induced (and negative induced) demand factors were estimated and applied to reflect ridership changes for customers who switched between SUF and Pass products. The induced factors were estimated from the mobile ticket data. The three model application stages are discussed in more detail below.

Stage 1. Scenario Fare Product Switching

The logit model was applied to predict fare product switching in response to the fare change. Weekly costs are recalculated using the scenario fares. For fare-capping scenarios, the weekly costs are capped at the appropriate prorated weekly fare cap amount. The scenario logit utilities and market shares were calculated using the scenario weekly costs and the calibrated model parameters α and $\beta_{WeeklyCost}$ as in Equations 7 and 8. The Stage 1 ridership and customer weeks were then calculated from the market shares incorporating the change between the scenario ridership and the synthetic baseline ridership. These results are used in Stages 2 and 3 to account for price sensitivity and induced demand.

Stage 2. Price Elasticity

Elasticity factors were estimated and applied to account for the price sensitivity of the riders under each product that had a fare change.

Estimation of Price Elasticity. The price sensitivity of riders was estimated from the effective elasticity observed for the FY 2019 fare change using PVTA's AFC ridership data. An average year-over-year (YOY) rate of change in ridership by fare product was first calculated using data for FY 2014 to FY 2018 to account for the non-fare-related trend in ridership. As the fare increase was effected between FY 2018 and FY 2019, the YOY percentage change for that period compared with the earlier calculated FY 2014 to FY 2018 YOY changes was used to extract the change in ridership attributed to the fare increase. The elasticity was calculated separately for each fare product using the exact percentage change in the product prices effected for the fare increase. The percent changes in ridership R and the percent change in fare P for each fare product f were used to calculate specific fare product point elasticities ε_f, which were averaged with ridership weights to estimate the elasticity $\bar{\varepsilon}$ as follows:

$$\varepsilon_f = \frac{\%\Delta R_{f,Actual}}{\%\Delta P_f} \tag{9}$$

$$\bar{\varepsilon} = \frac{\sum_{i=1}^{F} \varepsilon_i * R_i}{\sum_{i=1}^{F} R_i} \tag{10}$$

PVTA's estimated elasticity of −0.163 is within the expected benchmark values compared with other industry estimates for bus transit elasticity, which range from −0.08 at TfL (*6*), to −0.21 at MBTA (*7*), and −0.37 at NYCT (*4*).

Application of Price Elasticity. The elasticity was applied to the percent difference in weekly cost between the baseline and the scenario. This differs for those who do and do not switch to a different fare product. First, the scenario ridership results were categorized into ridership that switched between fare products, and ridership that remained on the same fare product after the product switching model was applied in Stage 1. The ridership volumes under "switchers" and "non-switchers" was obtained by simply comparing the scenario ridership in each customer segment s and fare product f with the baseline ridership. Any growth in ridership was categorized as ridership that switched from another fare product.

For the non-switchers, the estimated average elasticity was applied to the percent change in the fare price P, as in this case the percent change in the fare product price was the same as the percent change in weekly cost for non-switchers.

$$R_{s,fNon-Switch,Scn,Stage2} = R_{s,f,Scn,Stage1} * (1 + \bar{\varepsilon}) * \frac{P_{f,Scn} - P_{f,Base}}{P_{f,Base}} \tag{11}$$

For switchers to fare product , the difference in weekly cost C was used rather than the difference in fare price. As the difference depended on which product was switched *from*, a weighted average baseline weekly cost was calculated for the ridership switching to a fare product $\rightarrow j$ from all the other fare products $\leftarrow j$. The weighted average baseline weekly cost $\bar{C}$ was calculated from the market shares M as follows:

$$\bar{C}_{s,Switch \rightarrow j,Base} = \frac{\sum_{i=1}^{F \in \leftarrow j}(-min(M_{s,i,Scn} - M_{s,i,Base}) * C_{s,i,Base})}{\sum_{i=1}^{F \in \leftarrow j} - min(M_{s,i,Scn} - M_{s,i,Base})} \tag{12}$$

Stage 3. Induced Ridership Factors

When riders switch from SUFs to multi-use passes, they are expected to increase their ridership, and vice versa. Induced and negative induced demand factors were estimated and applied to reflect ridership changes for customers who switched between SUF and multi-use pass products.

Estimation of Induced Ridership Factor. Using the mobile data, an induced ridership of 0.53 was estimated. The induced ridership factor can be calculated for each combination of fare products using the mobile ticket data sample. However, in PVTA's case, only two fare product categories, short-term and long-term passes, were considered because of the size of the sample data. 7-Day and 31-Day passes were considered long-term passes, whereas SUF (1-Rides and Transfer tickets) and 1-Day passes were considered short-term passes. 1-Day passes were considered short-term passes because the ridership patterns of 1-Day Pass users were very similar to those of SUF users. PVTA estimated only one induced ridership factor for switching between short-term and long-term fare products.

Customer weeks that could be categorized as either short-term or long-term pass weeks were aggregated to the user account level. The pass type used most during a given customer week was used to categorize the customer weeks. Although all customers weeks were used in the application of the induced factor, only 24% of users who switched between pass categories were considered in the estimation to reduce the noise from customers with few observations. They represented those with more than one switch between pass categories, more than three average trips per week, and at least two active customer weeks on both short-term and long-term passes. These users had enough observations to ensure a reliable estimation. The percent difference in ridership between long-term and short-term pass weeks was calculated for each user, and averaged to estimate the induced ridership factor.

Application of Induced Ridership Factor. For the application, the induced ridership factor was only applied when riders switched between short-term and long-term passes in response to the fare change. The induced factor was applied directly for riders who switched from a short-term pass to a long-term pass, whereas the negative induced factor was applied for riders who switched from a long-term pass to a short-term pass. This reflects the ridership incentive that a multi-use pass provides, as well as the relative disincentive of making another trip when the additional cost of each SUF product needs to be considered. The induced ridership factor λ was applied to the ridership R in each customer segment s that switched to fare product j as follows:

$$R_{s,Switch \rightarrow j,Scn} = R_{s,Switch \rightarrow j,Scn,Stage2} * (1 + \lambda) \tag{13}$$

Ridership Forecast Results

PVTA considered over 20 fare change scenarios for its 2021 fare review but only certain scenarios are profiled in this paper. The fare scenarios highlighted here include a 10% incremental fare increase on 1-Ride and Transfer (SUF) tickets, a \$15 weekly and \$57 monthly fare cap, and a combination of fare capping with an incremental fare increase. Table 3 shows the estimated percent changes in ridership, revenue, and market share for the incremental fare change scenario and the fare-capping

Table 3. Ridership, Revenue, and Market Share Results

Scenario	% Δ Ridership					% Δ	Cust.	Market shares (%)			
	SUF	1-Day	7-Day	31-Day	Total	Rev.	Type	SUF	1-Day	7-Day	31-Day
Baseline	na	na	na	na	na	na	Reg.	48.5	32.7	5.2	13.6
							E&D	38.8	3.1	0.5	57.6
10% SUF inc.	−11.9	−0.5	29.5	17.0	−0.1	6.5	Reg.	42.7	32.7	6.7	17.9
							E&D	34.4	2.8	0.5	62.3
$15 Week cap	11.5	−4.0	−31.3	−12.3	−0.2	−2.5	Reg.	56.1	31.2	3.5	9.2
							E&D	38.7	3.6	0.5	57.2
$54 Month cap	14.7	2.1	−45.3	−21.4	−0.2	−4.8	Reg.	57.2	32.9	2.7	7.2
							E&D	41.2	4.3	0.4	54.0
$54 Month cap + % SUF inc.	8.1	3.6	−42.0	−17.9	−1.8	−0.2	Reg.	55.0	34.1	3.0	7.9
							E&D	38.9	4.3	0.5	56.3

Note: Reg. = regular; Rev. = revenue; inc. = increase; E&D = elderly and disabled; SUF = single-use fare; Cust. = customer; na = not applicable.

scenarios. A detailed discussion of each scenario is included in the following section.

Incremental Fare Change

We modeled an incremental fare change of a 10% price increase on SUF fares.The fare change makes it more cost-effective for riders to use long-term passes rather than SUFs. The forecast results reflect the expected effects, with the regular SUF market share decreasing to 42.7% compared with the baseline of 48.5%, and the 31-Day market share increasing from 13.6% to 17.9%. The overall result shows a minimal decrease in ridership of −0.1% and an increase in revenue of 6.4%. The results are in line with the expected impacts of a deep discounting fare strategy: maintaining low pass multiples to encourages multi-use pass usage, which bolsters both revenue and ridership in spite of fare increases by placing more of the fare burden on riders who purchase SUF products. Despite the favorable ridership and revenue impacts of this strategy, some research warns that this can "create regressive outcomes in which higher-income riders pay less for transit" because the SUF rider group typically includes those who cannot afford the up-front price of a multi-use pass (*1*, *2*). For this reason, PVTA considered additional fare structures such as fare capping.

Fare Capping

PVTA evaluated a weekly cap at $15 and a monthly cap at $54. In effect, an unlimited-ride pass would be issued to riders who have purchased more than $15 worth of bus fare tickets within a 7-day period and $54 worth of bus fare tickets within a 31-day period, respectively. The results for both scenarios reflect a shift in ridership from multi-use pass products to SUFs. Regular 31-Day ridership decreases by 12.3% for the $15 weekly cap, and by 21.4% for the $54 monthly cap. This is partly because riders who previously purchased multi-use passes would now have access to the same discount with the single-use fare caps. Additionally, a negative induced ridership factor was applied to riders who switched from multi-use passes to SUFs, as these riders would now experience a non-zero marginal cost with each additional ride until they reach the cap. The total ridership impacts for these scenarios were a decrease of 0.2% for both the weekly and monthly fare caps. Frequent SUF riders receive a discount and some riders who switch to SUF fares because of preference will not ride enough to reach the cap, contributing to projected revenue losses of 2.5% and 4.8% for the weekly and monthly fare caps, respectively.

Fare Capping and Incremental Combined

Finally, we explored the combination of the $54 monthly fare cap and the 10% SUF increase. Similar market forces as discussed in the individual scenarios mitigate the negative effects on revenue, resulting in a −0.2% change in revenue. Despite the increase in the price of SUF and 1-Day passes, ridership for these products increases slightly as a result of switching from the passes as a result of the available fare cap. The results in Table 3 show a 1.8% decrease in ridership overall. In particular, ridership on multi-use passes, especially the 7-Day pass, is projected to decrease, as the decreased pass multiple causes more riders to switch to the preferred SUF.

Conclusion

In this paper, we provided a methodology for utilizing mobile ticket data for fare impact analyses. We demonstrated the use of a sample of account-linked mobile ticket data for estimating a multinomial logit product choice model, which was then applied to the full unlinked AFC transaction data to forecast ridership and revenue impacts of fare capping and other fare changes. The impact analysis included fare product switching, rider price sensitivity, and induced demand.

The results demonstrated the importance of considering not only price sensitivity in fare change analyses but also fare product switching and induced ridership. The data showed that riders switch between fare products based on their travel frequency and expected costs in response to fare changes. Additionally, when riders switch from SUFs to multi-use passes, as the marginal cost of each additional trip on the pass is zero, other trips are typically induced, which increases their ridership. The inverse effect is also expected when riders switch from multi-use pass products to SUFs.

The results revealed that fare product switching can be expected to occur even in the case of fare capping, where actual fare prices are not changed and SUFs paid by a customer within a given time period are capped to the equivalence of a weekly or monthly pass. A major finding from the analysis was that fare capping affected not just SUF riders but made all riders across all fare products reevaluate their fare product choices based on their travel frequency and expected costs in response to the fare cap. Under the fare-capping scenarios, riders were observed to switch from multi-use passes to SUFs as they could now access the same discounts from the passes on SUFs. The reduction in multi-use pass purchase together with the SUF fare cap discounts resulted in an overall revenue reduction. Further, riders who switched from multi-use passes to SUFs were expected to consider the marginal cost of each ride, reverse inducing some trip making, and resulting in an overall reduction in ridership.

These findings highlight some of the behavioral and financial implications to consider when instituting a policy like fare capping that provides significant social benefits. At PVTA, a fare equity analysis was conducted together with the fare impact analysis. The equity analysis utilized the fare changes and ridership results from the product choice model together with survey data to assess the changes in average cost per ride for various rider groups, including low-income and minority riders. The results were used to quantify the ridership and revenue decreased against the positive equity benefits from fare capping. This analysis allowed the PVTA Board to make a more informed and confident fare change decision, and ultimately implement fare capping.

Industry Application and Future Work

The forecasting approach discussed in this paper can be adapted to evaluate a wide range of fare changes by incorporating the appropriate customer segmentation and if necessary additional customer behavior parameters. For example, in a multimodal system, customer segments can include various mode combinations, and for a change from a flat fare to a distance-based fare, distance-based segmentation and distance coefficients can be incorporated. Low-income pricing or other discounted groups can also be modeled by adding a low-income customer type.

Because of operational delays in deploying the fare capping module on the mobile ticket application, the data needed to compare the model estimates with actual impacts were not available within the timeline of this paper. Notwithstanding, we believed the absence of actual impacts did not diminish the relevance of the paper, especially for transit practitioners seeking to employ mobile ticket data in their planning process or to estimate the ridership impacts of fare capping.

Some next steps for this paper include validating the model once fare capping data are available, and further improvements to the parameter estimations to eliminate the need for adjustments to the alternative-specific constants as the mobile sample increases. Other areas for future work include incorporating additional COVID-19 impacts on the baseline ridership as pandemic conditions reach a steady state, forecasting the long-term effects of fare capping, and modeling if different lengths of fare caps are perceived differently by customers.

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Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: A. Morrissey, T. Oke; data collection: A. Morrissey, T. Oke; analysis and interpretation of results: A. Morrissey, T. Oke; draft manuscript preparation: A. Morrissey, T. Oke. All authors reviewed the results and approved the final version of the manuscript.

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References

1. Hickey, R. L., A. Lu, and A. Reddy. Using Quantitative Methods in Equity and Demographic Analysis to Inform Transit Fare Restructuring Decisions. *Transportation Research Record: Journal of Transportation Research Board*, 2010. 2144: 80–92.
2. Verbich, D., and A. El-Geneidy. Public Transit Fare Structure and Social Vulnerability in Montreal. Canada. *Transportation Research Part A: Policy and Practice*, Vol. 96, 2017, pp. 43–53.
3. Boyle, D. *Fixed-Route Transit Ridership Forecasting and Service Planning Methods*. Transit Cooperative Research Program (TCRP) Synthesis 66. Transportation Research Board, Washington, D.C., 2006.
4. Harris, A. E., R. Thomas, and D. Boyle. Metropolitan Atlanta Rapid Transit Authority Fare Elasticity Model. *Transportation Research Record: Journal of Transportation Research Board*, 1999. 1669: 123–128.
5. Yuan, F., and B. Lane. *SEPTA Fare Sensitivity Analysis Using DVRPC's Regional Travel Forecasting Model*. Southeastern Pennsylvania Transportation Authority, 2010.
6. Hickey, R. Impact of Transit Fare Increase on Ridership and Revenue: Metropolitan Transportation Authority, New York City. *Transportation Research Record: Journal of the Transportation Research Board*, 2005. 1927: 239–248.
7. Andrews, S., A. Demchur, K. Dumas, and K. DeLauri. *Potential MBTA Fare Changes in SFY 2017 - Option 1 Impact Analysis*. Massachusetts Bay Transportation Authority, 2017.
8. Zureiqat, H. M. *Fare Policy Analysis for Public Transport : A Discrete-Continuous Modeling Approach Using Panel Data*. Thesis. Massachusetts Institute of Technology, 2008.
9. Stuntz, A. W. *Transit Fare Policy: Use of Automated Data to Improve Incremental Decision Making*. Thesis. Massachusetts Institute of Technology, 2018.
10. Chalabianlou, R., A. Lawrence, and B. Baxter. A Review and Assessment of Fare Capping as a Passenger Incentive Mechanism for Australia and New Zealand. *Australasian Transport Research Forum*, Vol. 2015, 2015, p. 15.
11. Chu, A., L. Andre, and C. Robert. *Evaluating the Impact of Fare Capping and Guaranteed Best Fare Policies*. Autorité Régionale de Transport Métropolitain, Polytechnique Montreal, 2019.