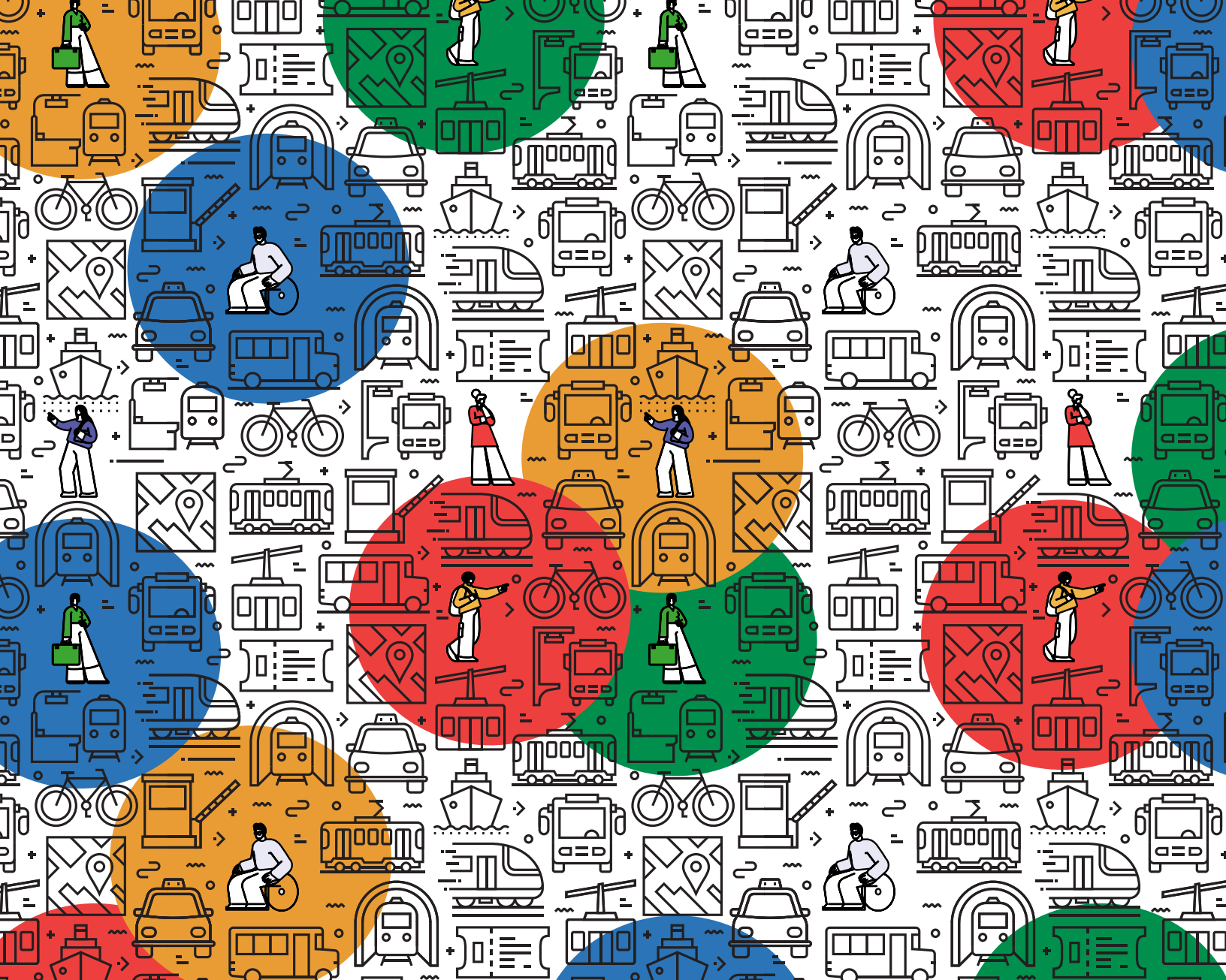
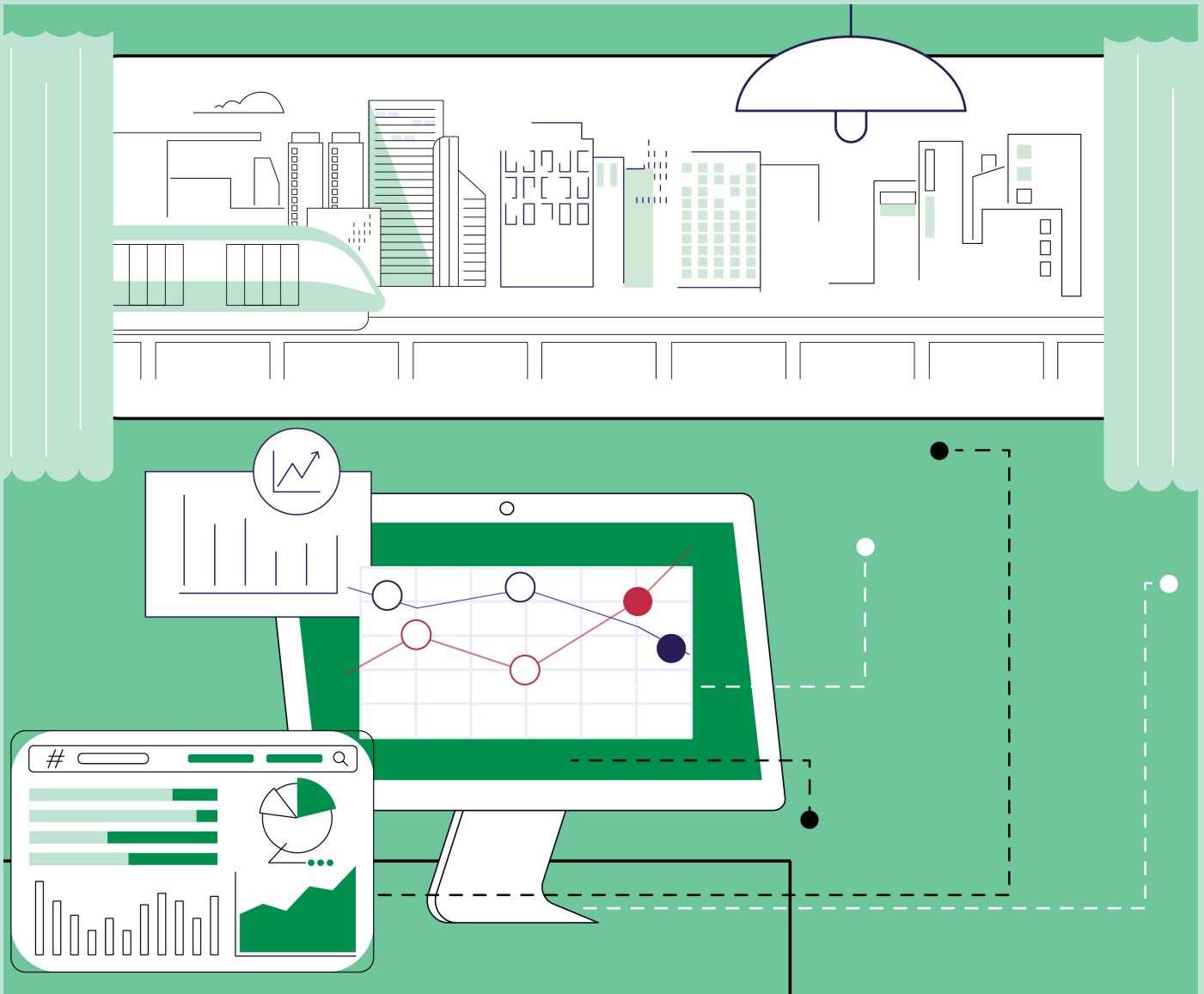




The National Transit Adaptation Strategy





The National Transit Adaptation Strategy

Phase IV - Ridership Model

SAN FRANCISCO MUNICIPAL TRANSPORTATION AGENCY JUNE 2024

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Foreword

COVID-19 was an unprecedented pattern break that disrupted the status quo across America's public and private sectors. The pandemic exacerbated existing challenges faced by the US transit industry, particularly in connection with ridership and revenue, and it posed new challenges. In combination, those challenges require transit agencies to consider the role of public transportation as a public good, and how it can best respond to changes in traveler journey needs and journey patterns, and deliver services that reflect the needs, values and realities of the post-pandemic context.

With public transit ridership changing and fare revenues declining, the transit industry needs to identify ways to restore ridership by, in part, restoring confidence in its service offerings, as it turns its focus from pandemic response to economic recovery.

In 2021, the San Francisco Municipal Transportation Agency (SFMTA) was awarded a Federal Transit Administration competitive grant to develop a National Transit Adaptation Strategy (NTAS). The primary objective for this project is the development of tools and data-supported initiatives that any U.S. transit agency may implement to rebuild confidence in public transit and quickly drive-up ridership.

The National Transit Adaptation Strategy project is comprised of four phases: Phase I—a futures report that identifies possible futures to help transit agencies set a path toward the most probable future scenario, Phase II—a ridership persona report which identifies four public transit user personas that provide the industry with key market segments to understand current and potential riders, Phase III—a marketing campaign and messaging package which transit agencies can use to target specific rider personas given anticipated future scenarios to increase system ridership, and Phase IV—a ridership data model which transit agencies can use to model potential ridership scenarios based on various intervention strategies.

This report on Phase IV of the National Transit Adaptation Strategy is a culmination of subsequent project phases and delivers a data model which transit agencies can use to estimate impacts various service and system interventions will have on transit ridership. The data model was developed by NTAS project partners from the JTL Urban Mobility Lab at the Massachusetts Institute of Technology (MIT), and the qualitative assessments of possible interventions was developed by SFMTA.

Acknowledgments

The San Francisco Municipal Transportation Agency (SFMTA) wishes to acknowledge the support and partnership of several organizations, agencies and individuals, who without this work would not be possible:

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The findings and recommendations of this report are SFMTA's and do not necessarily reflect the views of those listed below. Any errors are the authors' alone.

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Abstract

SFMTA partnered with the Massachusetts Institute of Technology (MIT) to identify and quantify the impacts of interventions—actions taken by transit agencies that introduce new or modified operational approaches and initiatives—that American transit agencies have implemented in the aftermath of the COVID-19 Pandemic. Pairing qualitative assessments of the identified interventions with quantitative measurement and analysis gives transit agencies a strong platform to determine which interventions to implement. SFMTA and MIT collaborated to complete complementing sections of this report. SFMTA first conducted research, identifying the various forms of interventions that transit agencies have taken and making qualitative assessments of the impacts the identified interventions were likely to have on the transit rider personas developed in NTAS Phase II.

Next, SFMTA and MIT compiled and analyzed ridership data from public transit agencies in San Francisco, Washington D.C. and Chicago. MIT created an autoregressive integrated moving average model, trained on ridership data prior to intervention introduction, which predicts expected ridership behavior had there been no intervention and compared that prediction to actual ridership. MIT's data modeling and analysis provides useful examples of outcomes from implementing various types of interventions: service change interventions in Washington, D.C. drove significant ridership increases during both weekdays and weekends; marketing-based interventions in San Francisco drove weekend ridership increases but otherwise didn't have an observable impact on ridership; and fare-based interventions in Chicago drove increased ridership system-wide with the most gains on weekdays. Other transit agencies can use this model methodology to assess outcomes from interventions they have implemented using their own ridership data.

Executive Summary

In October 2020, the Federal Transit Administration issued a NOFO “The Public Transportation COVID-19 Research Demonstration Grant Program,” and in September 2021 awarded the San Francisco Municipal Transportation Agency funding (Grant # CA-2021-183/SFMTA Project C19) for a National Transit Adaptation Strategy. A summary of the Ridership Model phase (Phase IV) of this project is provided in this report.

Current post-pandemic ridership recovery has stagnated nationally around 75%, and with reduced commuting demand due to remote and hybrid work, the NTAS team believes that roughly the same number of people are using transit as before the pandemic, but are now using it less frequently, resulting in the decrease in trips from pre-pandemic levels. This means, critically, that American transit agencies need to generate an increase in transit trips to reach greater financial stability. This will be accomplished either by encouraging existing users to ride more often or by acquiring new users.

This report is divided into three sections: a summary of SFMTA’s research into operational interventions that transit systems in the United States and Canada have taken in response to the uncertainty and precarity that has followed the COVID-19 Pandemic, an explanation of MIT’s analytical framework data modeling and study process, and a description of the expected impacts of possible transit agency interventions on the ridership personas developed in the NTAS Phase II report.

Ridership Analytical Framework

This section, created by SFMTA's research partners at MIT, develops an analytical framework for transit agencies to quantify the effects of service interventions on transit ridership to aid transit agencies in identifying effective measures to enhance ridership. The term "intervention" is used to encompass both internal and external changes that may influence transit ridership, such as changes in transit service delivery (internal), fare adjustments (internal), and implementation of congestion fee to private vehicles (external).

Methodology

Compounding factors such as ridership seasonality and natural post-pandemic ridership growth limit the accuracy and usefulness of a simple comparison of ridership before-and-after an intervention. As a result, MIT utilized the interventional autoregressive integrated moving average (ARIMA) time series model to address these potential influences and accurately quantify the actual change in transit ridership. First, an ARIMA model is calibrated to capture the pre-intervention ridership trend. This model is then applied to predict the post-intervention counterfactual ridership as if the intervention did not occur. A significant difference between the predicted (counterfactual) and observed (factual) post-intervention ridership indicates a non-trivial impact due to the intervention. In such cases, a full ARIMA model is recalibrated using both pre- and post-intervention data, along with an intervention indicator, to rigorously quantify the impact of the intervention.

Case Studies

The following examples in Chicago, San Francisco, and Washington D.C. offer demonstrations of the modeling and analysis procedures. Given the inherent volatility of daily ridership and the insufficient sample sizes available for monthly or annual ridership (a minimum of 50 data points are needed to calibrate the ARIMA model), weekly ridership data was used. The Case Studies show that while marketing campaigns alone are not sufficient to increase weekday ridership, fare policy and service delivery (operations) policies can attract more riders throughout the week.

- **Chicago:** As part of Chicago's "Open Chicago" initiative aimed at revitalizing the city, the Chicago Transit Agency (CTA) reduced fares on three of its popular unlimited ride pass options in an effort to welcome back customers, attract new riders, and incentivize existing customers to utilize public transit more frequently. MIT concluded that the Pass Discount Program stimulates the usage of the CTA transit system, with the most significant increase observed on workdays, suggesting that commuters represent the rider segment with the greatest potential for transit recovery. In this case, calibrating fare policy helped boost ridership, and similar policies could be implemented at other agencies with networks and populations comparable to Chicago would likely produce similar boosts to ridership.
- **San Francisco:** SFMTA launched the "Muni Moves You" campaign in May of 2022 to welcome back riders and highlight the crucial role that public transit plays in fueling the city's economic and cultural life beyond using transit exclusively for commuting. MIT concluded that while the campaign did not measurably increase ridership on weekdays, it attracted more ridership on Sundays, potentially indicating increased leisure usage of Muni.
- **Washington D.C.:** Beginning September 5, 2021, Washington Metropolitan Area Transit Authority (WMATA) increased service on many bus routes across the National Capital Region, featuring increased service frequency of every 20 minutes on 16 lines and every 12 on 20 lines. MIT concluded that the Frequent Service Network increases Metrobus ridership on weekdays and Sundays. The impact is more pronounced on weekdays, indicating that the improved bus services are particularly beneficial for commuters with additional benefits for leisure users of the bus network on Sundays.

A Usable Model

Transit agencies can use MIT's analytical framework to quantify the effectiveness of service interventions on transit ridership. The 8-step analysis guideline includes the following steps:

1. Understand the data
2. Identify the intervention point
3. Estimate the pre-intervention ARIMA model
4. Perform forecasting
5. Compute residuals
6. Identify intervention effects
7. Estimate the full ARIMA model
8. Assess intervention impact

The model is best suited to identify ridership changes immediately following the intervention and may not capture lagged ridership changes or temporary ridership changes, and the model is not recommended for long-term ridership projections unless other relevant interventions are appropriately accounted for.

Overall, the proposed analysis framework provides a useful tool for transit agencies to quantitatively identify effective measures to enhance transit ridership. As more transit agencies adopt this analysis method and share their experiences with ridership interventions, the collective knowledge will help transit communities more effectively increase ridership by choosing, adopting and adapting appropriate intervention measures.

Impacts of Transit Interventions on Rider Personas

The Public Transit Personas developed for Phase II of the National Transit Adaptation Strategy offer useful touchpoints to explore the real-world impacts of potential transit agency interventions on riders. These personas include:

- **Transit System Navigator:** an individual who relies on public transportation for their daily activities and is an expert in navigating public transit systems. They may not have access to a personal vehicle or may be unable to and/or choose not to drive.
- **Versatile Traveler:** a person who values convenience and efficiency and is flexible and adaptable in their transportation preferences, utilizing a variety of transportation modes based on their specific needs and preferences.
- **Event Driven Explorer:** a person who primarily uses public transportation for events and destinations where it is more convenient or efficient than driving, such as a regular commute, sporting events, concerts, festivals, or destinations with limited parking and adequate public transit access. This persona uses public transit for one specific type of destination but does not typically consider transit for other destinations or trip types.
- **Transit Sympathizer:** a user who rarely, if ever, uses public transportation. They may support public transit in principle and even use it for special occasions like business trips or journeys to airports, but they prefer to use a car for their general transportation needs.

Prior to MIT's development of a ridership analytical framework, SFMTA staff researched forms of transit system operational interventions that transit agencies across the United States and Canada took in response to the COVID-19 Pandemic and the associated conditions of declined transit ridership and general uncertainty and precarity. See [Appendix 1](#) for a full list of SFMTA's intervention research findings.

SFMTA identified four common intervention categories that the interventions that transit agencies in the United States and Canada have implemented can be categorized into: Staffing and Security Interventions, Fare and Payment Interventions, Service/Operational Interventions, and Capital Investment Interventions.

Staffing and Security interventions

Staffing and Security interventions would likely have the general effect of making transit feel like a more controlled environment where less deviation from social standards and passenger expectations are tolerated. Higher visibility of staff, both unarmed and armed, reduces feelings of isolation in transit systems and may make passengers feel like they are being watched over or like they are being watched, which can be positive or negative depending on the perspective of the transit rider.

Effectiveness of technology-based solutions depends on quality of implementation and on passenger's ability to utilize those solutions, which may be limited by a digital literacy gap. Transit vehicle operator staffing improvements would have the most consistent impact as higher frequencies universally improve passenger experiences.

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Fare and Payment interventions

Fare and Payment interventions, particularly fare-free transit, are likely to significantly improve ease of access to all existing riders and most potential riders. Event-based fare-free programs can encourage more transit use during those periods and benefit existing riders, and introducing Open Loop payment systems simplifies access to transit for all which particularly benefits new and prospective riders.

Fare and Payment interventions are directly linked with political will, as many transit agencies depend on fare revenue to fund operations, but the positive impacts of fare-free transit are well documented and worth understanding and implementing in practical and effective ways when possible.

Service/Operational interventions

Service/Operational interventions would have the general effect of improving the passenger experience for existing transit riders. These interventions are less likely to encourage the Transit Sympathizer persona to shift modes, but improvements are likely to improve experience for the Versatile Traveler and Event-Driven Explorer personas which may encourage those personas to use transit more.

Service/Operational interventions can work best implemented alongside other measures. Improving and maintaining high levels of system cleanliness can help new riders brought in through other interventions choose to stay and are likely to have a moderate impact on most rider personas.

Capital Investment interventions

Capital Investment interventions that prioritize delivering capacity expansion and higher quality service would likely have strong positive impacts on ridership. Interventions such as implementing bus network redesigns and building transit priority lanes will likely have moderate to significant positive impacts on all types of transit riders, improving the quality of transit journeys with faster travel times and more routing options.

While Capital Investment interventions take the most time and resources to implement, they have the most long-term potential to improve transit ridership. Network redesigns have the potential to provide mobility for a much wider range of trip types than historic American transit network planning has.

The Costs of Interventions

The scope of the data model developed during NTAS research only considered the intervention's impact on ridership and did not include calculation of the cost of implementing these interventions. There may be cases where the costs associated with certain interventions complicate the financial feasibility of implementing those interventions. The NTAS team recommends that any transit agency considering an intervention outlined in this report produce a cost-benefit analysis of considered interventions to assess financial viability.

Conclusion

The range of interventions that transit agencies can implement have a variety of impacts on the persona types identified by SFMTA and MIT for the National Transit Adaptation Strategy. MIT's quantitative ridership data analysis suggested that interventions which increase transit service quality or lower access barriers to public transit will trigger large total gains in system ridership, and that targeted marketing campaigns can reach and encourage transit use at times and places outside of typical commute patterns. SFMTA's qualitative assessment of intervention impacts on transit riders suggests that security-oriented interventions (such as increased staffing of armed and unarmed security and attendant staff) tend to benefit riders who would have alternative choices to using transit, and that infrastructure and operational oriented interventions (such as building transit priority lanes, increased service frequency through increased operator staffing, and community-oriented network redesign) tend to benefit, either mildly or significantly, all personas.

Ridership Analytical Framework

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Reviewed by Joseph Rodriguez and Haris Koutsopoulos, Northeastern University*

Section 1: Introduction

Phase IV of the National Transit Adaptation Strategy (NTAS) project focused on developing an analytical framework for transit agencies to quantify the effectiveness of service interventions on transit ridership. These interventions can include changes in service delivery, fare adjustments, and safety improvements. While the framework primarily addresses agency-driven changes, it can also be applied to analyze the impact of external events or policy changes on transit ridership. Examples of such external factors include the implementation of congestion fees, highway construction, and major events like the Olympic Games.

Throughout the document, the term “intervention” is used to encompass both internal and external changes that may influence transit ridership. The proposed analytical framework aims to aid transit agencies in identifying effective measures to enhance ridership. These measures can potentially be adopted by other agencies seeking to improve ridership on their transit systems.

The report is organized as follows: Section 2 describes the methodology, including a brief introduction to the autoregressive integrated moving average (ARIMA) model and a step-by-step guide for intervention analysis. Section 3 demonstrates the intervention analysis procedures with three case studies in Chicago, San Francisco, and Washington, D.C. Section 4 concludes the report. This structure ensures a comprehensive understanding of the analytical framework and its practical applications, providing a useful tool for transit agencies in their efforts to improve ridership through effective interventions.

Section 2: Methodology

In this section, we introduce the technical details of the autoregressive integrated moving average (ARIMA) model, followed by a comprehensive guideline for conducting intervention analysis.

Autoregressive integrated moving average model

Simply comparing transit ridership before and after an intervention may not provide an accurate reflection of the intervention's true impact, as it can be influenced by confounding factors such as ridership seasonality and the natural growth of post-pandemic transit recovery. To address these potential influences and accurately quantify the actual change in transit ridership, we utilize a time series method known as the interventional autoregressive integrated moving average (ARIMA (p, d, q)) model (Box & Jenkins, 1978). In particular, we calibrate a model capturing the pre-intervention ridership trend. We then apply the model to predict the post-intervention counterfactual ridership as if the intervention did not occur. Subsequently, we analyze the difference between the predicted (counterfactual) and observed (factual) post-intervention ridership to assess the intervention's effectiveness in improving transit ridership. If the evidence suggests an increase in transit ridership, we further calibrate a full model using both pre- and post-intervention ridership data to rigorously quantify the impact of the intervention. Similar methodologies have been successfully applied in various transportation contexts (Noland et al., 2008; Wadud, 2020) to comprehensively understand the impacts of policies on transportation system performance. Specifically, Park et al. (2016) adopted the intervention time series approach to analyze the impact of opening of a new railway line on passenger demand changes at transfer stations.

In ARIMA (p, d, q), the variable of interest (i.e., the transit ridership y at time t , y_t) is modelled as a function of its own past trends, using its own lagged values (the autoregressive component, y_{t-1} , y_{t-2} , ..., y_{t-p}) and the lagged errors (the moving average component, ε_t , ε_{t-1} , ε_{t-2} , ..., ε_{t-q}). If the variable is non-stationary, then it is differenced until the series becomes stationary, and then the autoregressive and moving average modelling is done on the differenced variable. The parameters p , d , and q represent the order of autoregression, order of differencing, and the order of moving average, respectively, which are estimated and selected based on the model fit and diagnostic tests. Specifically, AR(p) model forecasts the variable of interest using a linear combination of past values of the variable,

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \dots + \phi_p y_{t-p} + \varepsilon_t,$$

where c is the drift, ϕ_1 , ..., ϕ_p are parameters of the corresponding lagged values of y_t , p is the order of autoregressive, and ε_t is white noise. The estimated value of ϕ_1 , ..., ϕ_p and the selection of p determines different time series patterns.

In addition, MA(q) model forecasts the variable of interest using past forecast errors in a regression-like model,

$$y_t = c + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \dots + \theta_q \varepsilon_{t-q},$$

where ε_t , ..., ε_{t-q} are the error terms (white noises), θ_1 , ..., θ_q are the corresponding parameters, q is the order of moving average. The estimated value of θ_1 , ..., θ_q and the selection of q determines different time series patterns.

Therefore, the combined ARIMA(p,d,q) model follows the equation,

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \dots + \phi_p y_{t-p} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \dots + \theta_q \varepsilon_{t-q} + \varepsilon_t,$$

Intervention analysis guideline

1. Understand the data.

Identify the pattern, seasonality, and trend in the time series transit ridership data.

- Sample size check. Ideally, a minimum of 50 data points are required to ensure statistical power in developing the ARIMA model. Depending on data availability, different granularities (e.g., daily, weekly, monthly, annual) can be selected for analysis.
- Stationarity check. Time series data must be stationary (free from trends, seasonality, or other volatility) for the model to be effective in predicting future periods. The Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test is commonly used to check for stationarity. The null hypothesis of the KPSS test states that the trend is stationary. If the null hypothesis is rejected, the data can be differenced to achieve stationarity.

2. Identify the intervention point.

Determine the point in time when the agency-driven change or external event, i.e. “intervention”, occurred. This could be a policy change, operational change, marketing campaign, economic event, etc.

3. Estimate the pre-intervention ARIMA model.

Fit an ARIMA (p, d, q) model to the data before the intervention point.

- Determine the order of differencing (d). Based on the KPSS test results, choose an appropriate order of differencing to ensure the series is stationary. Typically, differencing once ($d=1$) or twice ($d=2$) will suffice.
- Determine orders p and q for AR and MA terms. Selecting the orders p and q involves several approaches:
 - Model performance measures. Use criteria such as Akaike’s Information Criterion (AIC), Bayesian Information Criterion (BIC), root mean square error (RMSE), and mean absolute percentage error (MAPE) to identify top-performing models.
- ACF and PACF plots. Utilize the Auto Correlation Function (ACF) and Partial Auto Correlation Function (PACF) plots to intuitively select and adjust the orders of p and q based on the observed autocorrelation patterns.
- Fit the model and check performance.
 - Conduct the Ljung-Box test to check if the residuals are autocorrelated.
 - Examine the significance levels of the model coefficients.
 - Verify the presence of unit roots by checking if the sum of the AR coefficients is close to or equal to 1, and/or if the sum of the MA coefficients is close to or equal to 1.
- Adjust the model specification. Modify the orders (p, d, q) as needed and refit the model to improve performance.

4. Perform forecasting.

Use the ARIMA model estimated in step 3 to forecast transit ridership for the period following the intervention.

5. Compute residuals.

Calculate residuals by subtracting the observed values from the predicted values obtained in step 4. These predicted values represent the counterfactual ridership, assuming the intervention had not occurred. The residuals reflect the effectiveness of the intervention on transit ridership.

6. Identify intervention effects.

Examine the residuals around the intervention point and look for sudden changes or outliers that may indicate the impact of the intervention. Conduct statistical tests, such as paired t-tests, between the observed and predicted values to confirm any significant differences.

7. Estimate the full ARIMA model.

If evidence of intervention effects is found in the residuals (through visualization and/or statistical tests), estimate a full ARIMA model. Incorporate the intervention effect by using both pre- and post-intervention data and adding a dummy variable to the model to represent the intervention.

8. Assess intervention impact.

Further assess the impact of the intervention by examining the coefficients of the intervention variable in the full ARIMA model estimated in step 7. This analysis, combined with the visual and statistical tests conducted in step 6, will help quantify the intervention's effect on the time series. Compute residuals. Calculate residuals by subtracting the observed values from the predicted values obtained in step 4. These predicted values represent the counterfactual ridership, assuming the intervention had not occurred. The residuals reflect the effectiveness of the intervention on transit ridership.

Section 3:

Case studies - Applying Our Model to Real-Life Interventions

In this section, we showcase the intervention analysis procedure by presenting three examples using transit ridership data from Chicago, San Francisco, and Washington, DC. The three transit agencies, Chicago Transit Authority (CTA), San Francisco Municipal Transportation Agency (SFMTA), and Washington Metropolitan Area Transit Authority (WMATA) have implemented different strategies to boost transit ridership recovery after the pandemic.

Using these examples, we offer a detailed guidebook demonstrating the modeling and analysis procedures. The coding sample is also publicly accessible, allowing other transit agencies to analyze the impact of diverse interventions on transit ridership.

Aligned with the overarching scope of NTAS, the Phase IV analysis focuses on transit ridership recovery and service interventions during and after the pandemic, specifically from March 2020 onward. Our primary focus is on utilizing weekly transit ridership data during and after the COVID-19 pandemic for analysis. The choice of weekly granularity is intentional, meeting the model's sample size requirement, which mandates a minimum of 50 time-series data points before the intervention to ensure statistical power. Monthly or annual ridership fails to meet the sample size requirement at present, but these may be considered for future analysis when a sufficient number of data points are available. Furthermore, we favor weekly ridership over daily ridership due to its lower volatility, facilitating a more manageable modeling process.

Chicago

Background

As part of Chicago's "Open Chicago" initiative aimed at revitalizing the city, the CTA reduced fares on three of its popular unlimited-ride pass options in an effort to welcome back customers, attract new riders, and incentivize existing customers to utilize public transit more frequently. Specifically, the CTA adjusted the fares for its one-day pass from \$10 to \$5, its three-day pass from \$20 to \$15, and its seven-day pass from \$28 to \$20.

This pilot program kicked off during Memorial Day weekend (Friday, May 28, 2021) and initially ran until Labor Day (Monday, September 6, 2021). Due to its success, the program was extended through November 25, 2021. Eventually, recognizing its positive impact, the CTA made these fare reductions permanent in 2022. For the case study, we will analyze the ridership changes before and after the initial intervention (May 28, 2021), which took place around the Memorial Day weekend of 2021.

Data

We obtained CTA system ridership data from the Chicago Data Portal (<https://data.cityofchicago.org>). Specifically, we used the dataset “CTA – Ridership - Daily Boarding Totals” for our analysis, which provides system-wide boardings for both bus and rail services. Figure 1 presents the total daily (a) and weekly (b) boardings, including both bus and rail, between April 1, 2020, and August 20, 2021. We excluded data prior to April 2020 to avoid the substantial ridership reduction caused by the stay-at-home mandate, which could be considered an intervention itself. The end date of the analysis was chosen to be approximately 12 weeks after the implementation of the pass discount program.

The CTA ridership data reveals distinct patterns across different days of the week and notable changes after an intervention. The data shows that weekday ridership consistently exceeds that of Saturdays, which in turn is higher than ridership on Sundays. This indicates a clear hierarchy in transit usage, with the highest demand occurring on regular weekdays, and may also be a consequence of reduced weekend service. Before the intervention, Monday ridership was similar to that of other weekdays, reflecting a consistent pattern of commuter activity throughout the workweek. Following the intervention, ridership increased promptly on all weekdays except Monday, resulting in lower figures for Monday compared to the rest of the workweek. One potential reason is the stronger tendency for teleworking on Mondays, possibly due to recovering from the weekend or a remedy of the “Monday Blues”, making it more challenging to attract transit ridership back on that day.

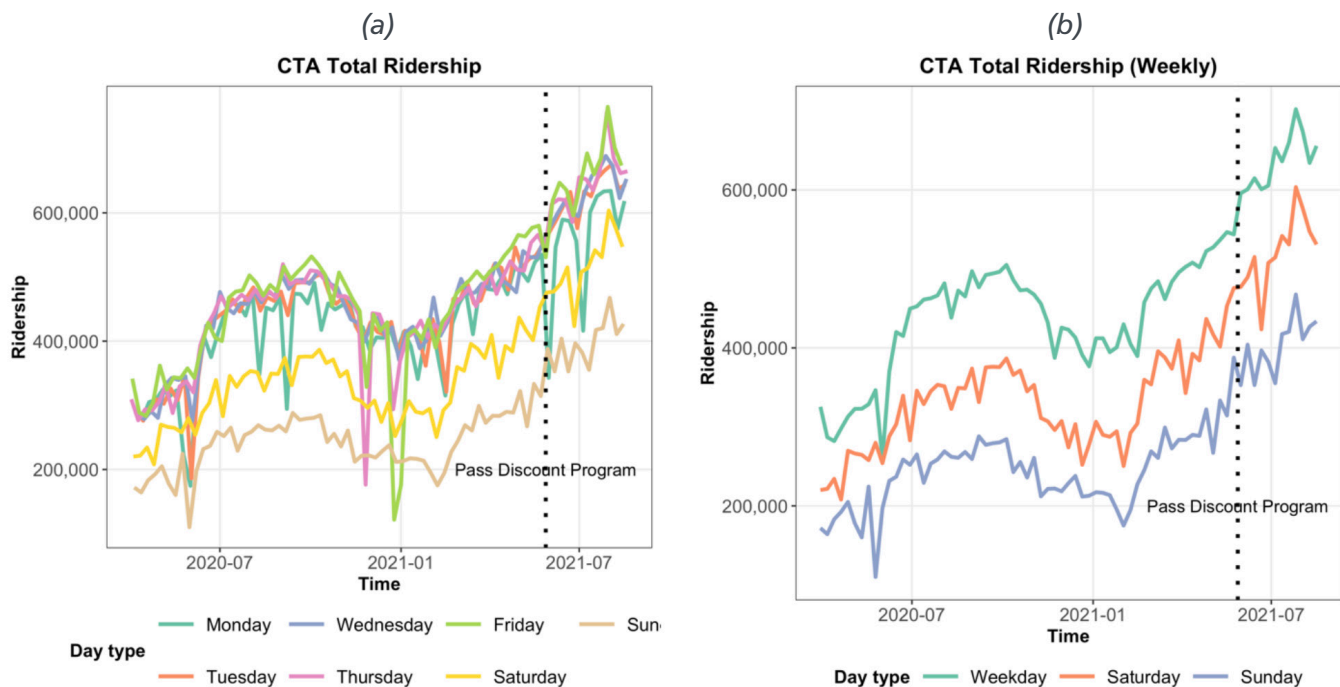


Figure 1.1. CTA total ridership: (a) Daily ridership by day of week, (b) Weekly average ridership of weekday, Saturday, and Sunday (holidays removed)

Table 1.1. CTA ARIMA model results

	Weekday				Saturday				Sunday			
	Pre-intervention model (5, 1, 3)		Full model (5, 1, 3)		Pre-intervention model (4, 1, 3)		Full model (1, 1, 0) + drift		Pre-intervention model (2, 1, 1)		Full model (1, 1, 0) + drift	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
ar1	-0.64	0.23**	-0.65	0.23**	-0.51	0.25*	-0.50	0.10	0.34	0.27	-0.58	0.10***
ar2	-0.37	0.28	-0.43	0.29	-0.25	0.28	-	-	0.50	0.16**	-	-
ar3	0.64	0.24*	0.62	0.26*	0.66	0.30*	-	-	-	-	-	-
ar4	0.32	0.15*	0.34	0.14*	0.54	0.14***	-	-	-	-	-	-
ar5	0.30	0.13*	0.35	0.12**	-	-	-	-	-	-	-	-
ma1	0.43	0.22	0.44	0.23	0.08	0.28	-	-	-0.86	0.26**	-	-
ma2	0.22	0.24	0.22	0.27	0.40	0.25	-	-	-	-	-	-
ma3	-0.70	0.22**	-0.69	0.23**	-0.74	0.28*	-	-	-	-	-	-
Drift	-	-	-	-	-	-	4321.78	2294.48	-	-	3499.31	1995.56
Intervention indicator	-	-	43033.28	23917.80	-	-	7551.46	26005.47	-	-	12743.58	23413.96
MAPE ¹	4.46%		4.15%		6.07%		6.41%		8.53%		8.03%	
N	60		72		60		72		60		72	
Ljung-Box statistics on residuals (p-value)	1.21 (0.750)		1.54 (0.673)		3.25 (0.354)		9.95 (0.354)		2.73 (0.909)		2.66 (0.976)	
KPSS Unit Root Test ²												
d=0	0.74		1.26		0.70		1.26		0.61		1.21	
d=1	0.11		0.12		0.16		0.11		0.17		0.14	
d=2	0.16		0.14		0.19		0.15		0.16		0.18	

Notes:

*** Coefficient is statistically significant at the 0.001 level.

** Coefficient is statistically significant at the 0.01 level.

* Coefficient is statistically significant at the 0.05 level.

. Coefficient is statistically significant at the 0.1 level.

¹ Mean absolute percentage error: $\frac{1}{N} \sum_{t=1}^N \frac{|\text{Observed ridership} - \text{predicted ridership}|}{\text{Observed ridership}}$

MAPE is commonly used as a forecast error measure. We did not use information criteria such as AIC since they are not comparable across different orders of differencing.

² KPSS significance level (critical values): 0.05 (0.463); 0.025 (0.574); 0.001 (0.739)

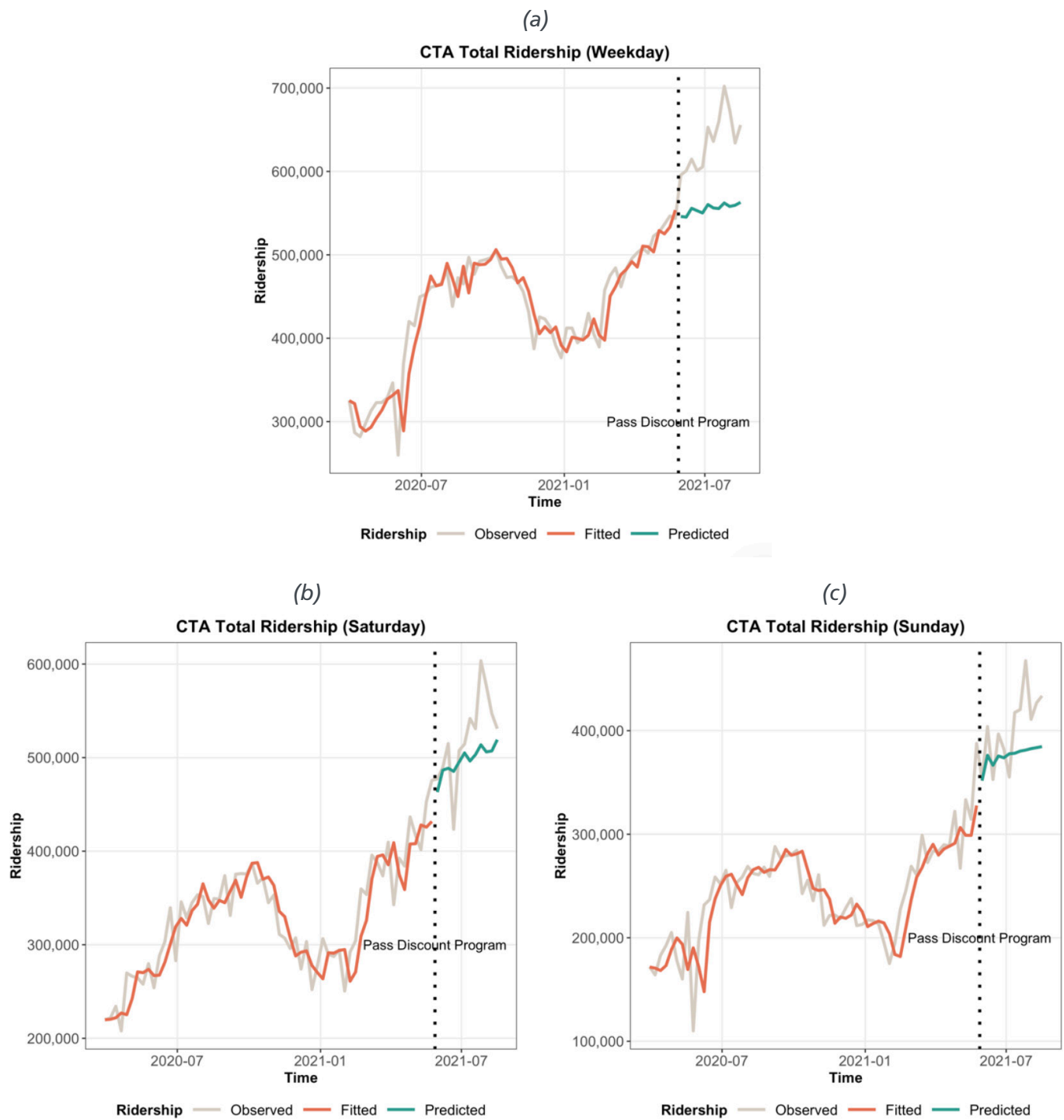


Figure 1.2. CTA observed and predicted ridership

Note: Since the time series data is aggregated on a weekly basis, there will be a one-week gap between the end of the fitted line and the start of the predicted line on the time axis.

Intervention analysis

Table 1.1 presents ARIMA model results and corresponding statistical tests for weekdays, Saturdays, and Sundays, separately. The Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test shows that no differencing ($d=0$) rejects the null hypothesis of stationarity for all models, indicating that the time series ridership is non-stationary. Consequently, the best model for each group is selected from those with at least first-order differencing ($d > 0$).

A grid search was conducted on selected hyperparameter spaces ($p = [0, 5]$, $d = [1, 5]$, $q = [0, 5]$) for each model. The final models were chosen based on a comprehensive evaluation of various criteria listed in Section 2.2, such as model performance, significance of the coefficients, unit root checks, residual autocorrelation checks, and more.

Figure 1.2 visualizes the observed ridership, the pre-intervention model fit, and the predicted ridership of the pre-intervention models. Figure 1.2(a) shows that the weekday model predicts a slow increase in ridership without a fare pass intervention (i.e., the green line). However, the actual post-intervention ridership (i.e., the gray line) significantly exceeds these predictions, suggesting that the Pass Discount Program effectively boosts weekday ridership. For weekends, both Saturday and Sunday show strong recovery trends in ridership even before the intervention, and the models therefore predict increased ridership without the intervention (i.e., the gap between the fitted and predicted lines, as well as the increasing trend in the green lines). Despite this, the actual post-intervention ridership is still higher than the predicted levels, indicating that the Pass Discount Program likely enhances weekend ridership as well. To confirm our observations, we conducted paired t-tests for the observed and predicted values after the intervention. The test results also suggest that the observed ridership is significantly higher than the predicted ridership (weekday: t-statistic = 9.53 [p-value = 0.000]; Saturday: t-statistic = 2.21 [p-value = 0.025]; Sunday: t-statistic = 3.00 [p-value = 0.006]).

Therefore, for each day type, we estimated a full ARIMA model incorporating data points from both before and after the intervention, including an intervention dummy variable to represent the effect of the program. Consistent with the paired t-test results, all three intervention indicators have positive coefficients, indicating that the Pass Discount Program induces more ridership. However, only the intervention indicator in the weekday full model is marginally significant ($p = 0.079$).

Overall, we conclude that the Pass Discount Program stimulates the usage of the CTA transit system, with the most significant increase observed on weekdays. This suggests that commuters represent the segment with the greatest potential for transit recovery. The reduced fare may not only attract commuters from other modes of transportation but also encourage more people to opt for on-site work. For future steps, the agency could enhance the analysis by utilizing their internal ridership data instead of relying on the aggregated public dataset. This would allow for more targeted analyses, such as examining the intervention's effects on specific rider groups (e.g., monthly pass holders, short-term pass users) and different times of day (e.g., AM/PM peak, mid-day).

San Francisco

Background

The San Francisco Municipal Transportation Agency (SFMTA) launched the “Muni Moves You” campaign during the week of May 10, 2022, to welcome back Muni riders as the city continued its pandemic recovery. The campaign aimed to attract customers through a widely distributed campaign on buses, social media, digital platforms, and outdoor media throughout the city. It also served as a reminder of how the transportation system had evolved during the pandemic, with improvements to routes and the expansion of transit lanes across San Francisco. Through the campaign, SFMTA sought to highlight the crucial role that public transit plays in fueling the city’s economic and cultural life and specifically highlight the types of destinations that riders can reach on Muni beyond commutes to and from job centers.

Intervention analysis

Table 1.2 presents the ARIMA model results and corresponding statistical tests for weekdays, Saturdays, and Sundays separately. Similar to the CTA models, the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test indicates that no differencing ($d=0$) rejects the null hypothesis of stationarity for all models. Therefore, first-order or higher differencing ($d > 0$) is required to achieve stationarity in the ARIMA model. A grid search was conducted on selected hyperparameter spaces ($p = [0, 5]$, $d = [1, 5]$, $q = [0, 5]$) for each model. The final models were chosen based on a comprehensive evaluation of various criteria listed in Section 2.2, including model performance, significance of the coefficients, unit root checks, residual autocorrelation checks, and more.

Data

Figure 1.3 presents the weekly automated passenger counter (APC) data received from SFMTA, segmented by weekdays, Saturdays, and Sundays. To avoid the substantial ridership reductions caused by the stay-at-home mandate at the beginning of the pandemic, our analysis focuses on data from April 2020 onward. The end date of the analysis is set approximately 12 weeks after the “Muni Moves You” campaign.

As shown in Figure 1.3, average weekday ridership is substantially higher than that on Saturdays, followed by Sundays. Ridership on Saturdays and Sundays increased around the time of the campaign. However, weekday ridership remains relatively stable post-campaign. A notable ridership drop occurred at the beginning of 2022 due to the Omicron outbreak, with Saturday ridership experiencing the most significant reduction.

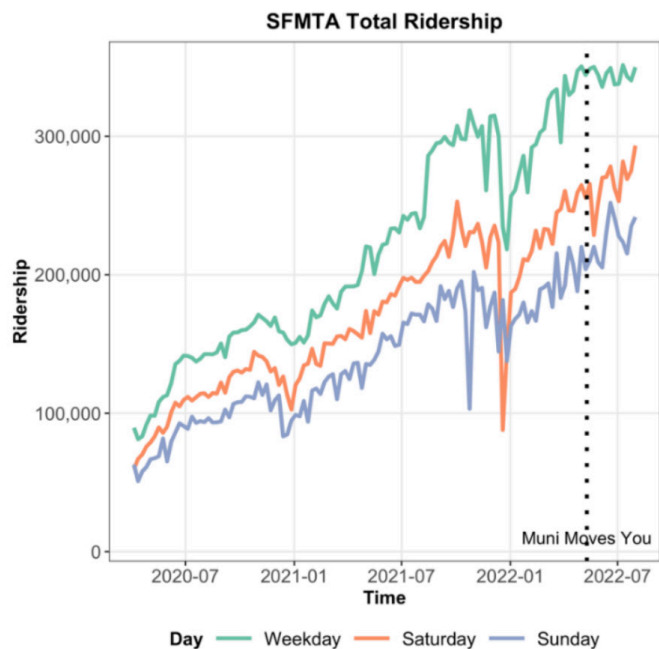


Figure 1.3. SFMTA Weekly Ridership

Table 1.2. SFMTA ARIMA model results

	Weekday		Saturday		Sunday			
	Pre-intervention model (2, 1, 2) + drift		Pre-intervention model (0, 1, 2) + drift		Pre-intervention model (0, 1, 1) + drift		Full model (1, 1, 0) + drift	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
ar1	1.18	0.08***	-	-	-	-	-	-
ar2	-0.79	0.08***	-	-	-	-	-	-
ma1	-1.43	0.06***	-0.28	0.09**	-0.72	0.06***	-0.72	0.06***
ma2	0.93	0.06***	-0.26	0.09**	-	-	-	-
Drift	2371.6	1080.66*	1766.88	712.45*	1363.16	391.63***	1406.60	370.79***
Intervention indicator	-	-	-	-	-	-	6063.93	10086.14
MAPE ¹	3.76%		5.48%		7.11%		6.90%	
N	109		109		109		121	
Ljung-Box statistics on residuals (p-value)	9.59 (0.143)		5.11 (0.746)		6.35 (0.705)		4.81 (0.851)	
KPSS Unit Root Test ²								
d=0	2.19		2.11		2.18		2.41	
d=1	0.04		0.04		0.03		0.04	
d=2	0.05		0.04		0.05		0.05	

Notes:

*** Coefficient is statistically significant at the 0.001 level.

** Coefficient is statistically significant at the 0.01 level.

* Coefficient is statistically significant at the 0.05 level.

. Coefficient is statistically significant at the 0.1 level.

¹ Mean absolute percentage error: $\frac{1}{N} \sum_{t=1}^N \frac{|\text{Observed ridership} - \text{predicted ridership}|}{\text{Observed ridership}}$

MAPE is commonly used as a forecast error measure. We did not use information criteria such as AIC since they are not comparable across different orders of differencing.

² KPSS significance level (critical values): 0.05 (0.463); 0.025 (0.574); 0.001 (0.739)

Figure 1.4 visualizes the observed ridership, the pre-intervention model fit, and the predicted ridership of the pre-intervention SFMTA ridership models. As mentioned earlier, the post-intervention weekday ridership trend is relatively flat, making it much lower than the predicted ridership. The observed Saturday ridership has similar trend line to the predicted ridership, but more fluctuated. The Sunday observed ridership is also quite variable. However, most Sunday points are close to or above the predicted trend line. The paired t-test suggests that the observed Sunday ridership is significantly higher than the predicted counterparts (t-statistic = 2.64, p-value = 0.011). Therefore, we estimated a full ARIMA model for Sunday ridership (see Table 1.2). Although the coefficient of the intervention indicator is positive, it is not statistically significant.

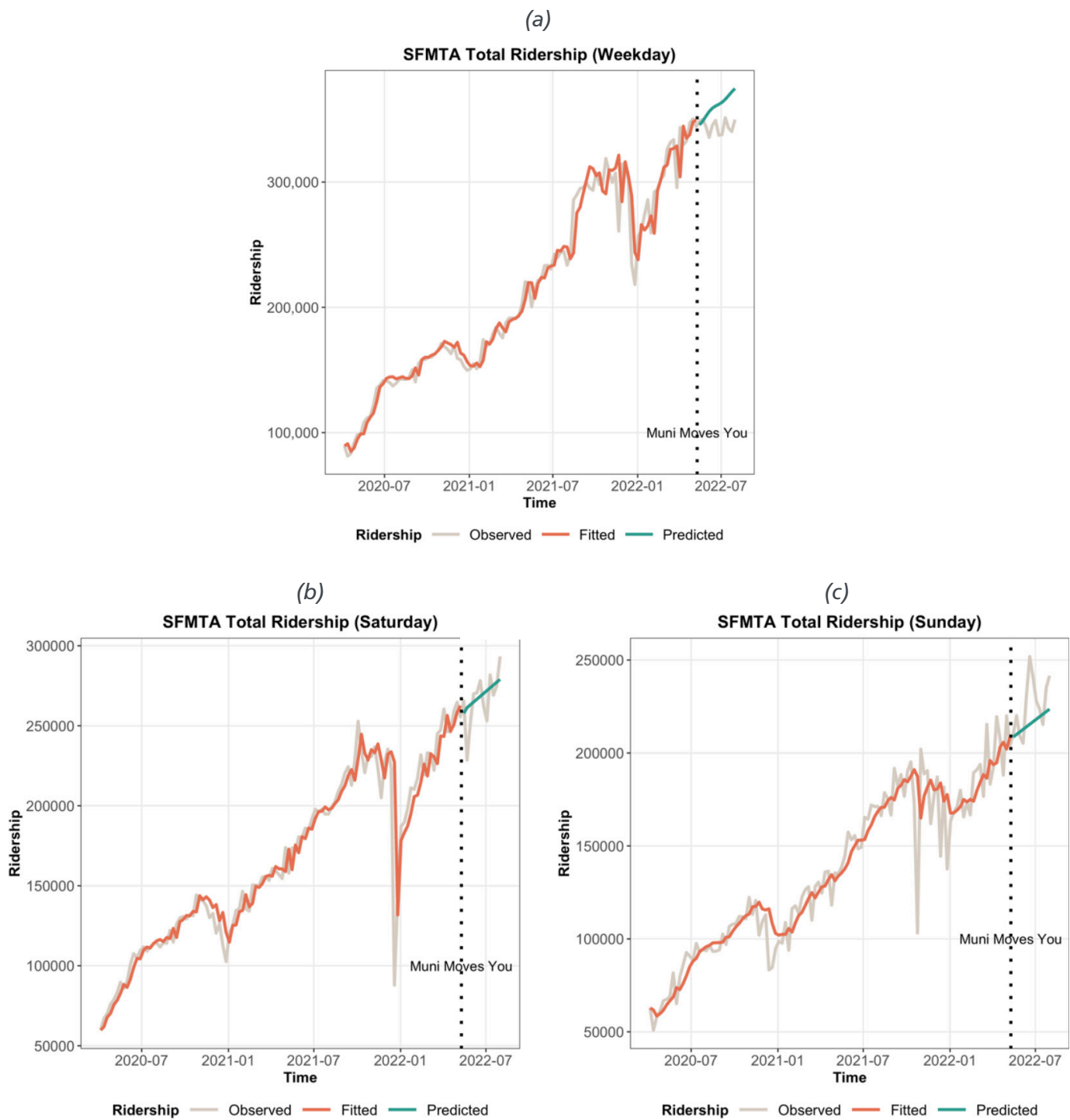


Figure 1.4. SFMTA observed and predicted ridership

Overall, we observe that the “Muni Moves You” campaign did not measurably increase ridership on weekdays, it attracted more ridership on Sundays, potentially indicating increased leisure usage of Muni. This is significant as these results align with the campaign’s theme, which focuses on promoting various reasons to use transit for exploring the city, including dining, shopping, nightlife, and museums.

Lastly, in addition to the APC data used in this study, we also have access to Clipper data, which tracks smart card usage within the SFMTA system. While Clipper data typically shows lower ridership counts than APC data due to not all Muni customers using smart cards, it offers the significant advantage of distinguishing between different fare products. This capability enables targeted analyses on specific fare products or customer groups. For instance, we tested models on rolling pass usage, a fare product often associated with recreational travel, which aligns with the “Muni Moves You” campaign. However, the smaller user base of this fare product led to greater fluctuations in the time series trends, resulting in less reliable models. Despite this, we recommend agencies consider conducting granular analyses on segmented data to gain more detailed insights into the impact of interventions.

Washington, D.C.

Background

Beginning September 5, 2021, WMATA adjusted service on many bus routes across the National Capital Region,⁵ featuring increased service frequency and expanded routes within the Metrobus system. Specifically, buses will be scheduled to arrive every 12 minutes on 20 lines, and every 20 minutes on 16 lines throughout the region. This frequent service network will benefit 60% of Metrobus customers.

Data

We obtained hourly automatic fare collection (AFC) bus ridership data by route from WMATA's internal database. We aggregated the total ridership by day, and Figure 1.5 presents the total daily (a) and weekly (b) boardings from the beginning of 2021 to the end of November 2021, approximately 12 weeks after the implementation of the Frequent Service Network. We excluded the 2020 data because the implementation of the Metrobus fare waiver⁶ affected AFC data collection and introduced a different intervention on ridership. The fare waiver mandated rear-door only boarding to protect frontline workers, necessitating the suspension of fare collection, as the equipment is only located near the operator. Consequently, the analysis contains a shorter time series, resulting in larger standard errors in model estimation and therefore lower statistical power of the models.

As shown in Figure 1.5, average weekday ridership is substantially higher than Saturday ridership, followed by Sunday ridership. Weekday ridership increases substantially after the implementation of the Frequent Service Network. However, there are noticeable drops in ridership across all three categories (weekday, Saturday, and Sunday) at the end of November, coinciding with the Thanksgiving holiday.

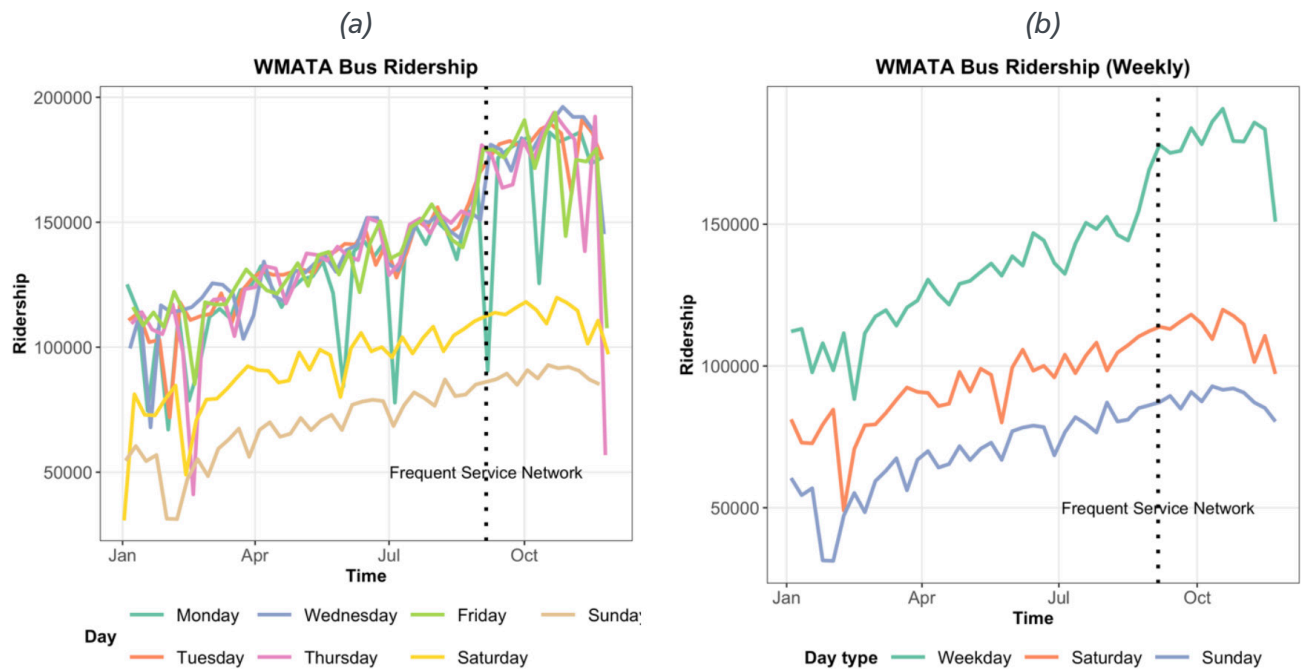


Figure 1.5. WMATA total ridership: (a) Daily ridership by day of week, (b) Weekly average ridership of weekday, Saturday, and Sunday (holidays excluded)

Intervention analysis

Table 1.3 presents the ARIMA model results and corresponding statistical tests for weekdays, Saturdays, and Sundays separately. The Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test indicates that no differencing ($d=0$) rejects the null hypothesis of stationarity for all models. Therefore, first-order or higher differencing ($d > 0$) is required to achieve stationarity in the ARIMA model.

A grid search was conducted on selected hyperparameter spaces ($p = [0, 5]$, $d = [1, 5]$, $q = [0, 5]$) for each model. The final models were chosen based on a comprehensive evaluation of various criteria listed in Section 2.2, including model performance, significance of the coefficients, unit root checks, residual autocorrelation checks, and more. However, due to the limited sample size, the models did not fit the data as well as the CTA and SFMTA models.

Figure 1.6 visualizes the observed ridership, the pre-intervention model fit, and the predicted ridership of the pre-intervention WMATA bus ridership models. Post-intervention, weekday ridership increases substantially, surpassing the predicted ridership. Observed Sunday ridership is also visibly higher than the predicted values. Paired t-tests indicate that both observed weekday and Sunday ridership are significantly higher than their predicted counterparts (weekday: t-statistic = 6.74, p-value = 0.000; Sunday: t-statistic = 4.53, p-value = 0.000). In contrast, observed Saturday ridership does not show a significant increase compared to the predicted ridership.

Therefore, we estimated full ARIMA models for weekday and Sunday ridership (see Table 1.3). The positively significant intervention indicator in the weekday model suggests that the Frequent Service Network significantly increases weekday Metrobus ridership. Although the intervention indicator in the Sunday model is positive, it is not statistically significant.

Overall, the Frequent Service Network increases Metrobus ridership on weekdays and Sundays. The impact is more pronounced on weekdays, indicating that the improved bus services are particularly beneficial for commuters. Additionally, the service attracts more leisure usage of the bus network on Sundays. For future steps, we recommend conducting granular analyses, such as segmenting routes by levels of service increases and examining relevant rail ridership at transfer locations. Additionally, the service attracts more leisure usage of the bus network on Sundays. For future steps, we recommend conducting granular analyses, such as segmenting routes by levels of service increases and examining relevant rail ridership at transfer locations.

Table 1.3. WMATA ARIMA model results

	Weekday				Saturday		Sunday			
	Pre-intervention model (3, 1, 0)		Full model (3, 1, 0) + drift		Pre-intervention model (2, 1, 0)		Pre-intervention model (0, 1, 5)		Full model (0, 1, 1)	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
ar1	-0.40	0.17*	-0.56	0.17**	-0.53	0.16**	-	-	-	-
ar2	-0.17	0.20	-0.45	0.19*	-0.41	0.15*	-	-	-	-
ar3	-0.38	0.18*	-0.44	0.16*	-	-	-	-	-	-
ma1	-	-	-	-	-	-	0.04	0.24	-0.34	0.17*
ma2	-	-	-	-	-	-	-0.31	0.16*	-	-
ma3	-	-	-	-	-	-	0.08	0.20	-	-
ma4	-	-	-	-	-	-	0.38	0.24	-	-
ma5	-	-	-	-	-	-	-0.60	0.18**	-	-
Drift	-	-	969.89	537.27*	-	-	-	-	-	-
Intervention indicator	-	-	18404.66	6819.72*	-	-	-	-	2309.92	6366.35
MAPE	4.98%		4.43%		7.65%		7.60%		8.45%	
N	34		46		34		34		46	
Ljung-Box statistics on residuals (p-value)	0.83 (0.935)		3.24 (0.779)		2.64 (0.755)		2.43 (0.488)		6.95 (0.542)	
KPSS Unit Root Test [†]										
d=0	0.94		1.17		0.89		0.84		1.01	
d=1	0.20		0.16		0.09		0.10		0.07	
d=2	0.19		0.12		0.07		0.09		0.07	

Notes:

*** Coefficient is statistically significant at the 0.001 level.

** Coefficient is statistically significant at the 0.01 level.

* Coefficient is statistically significant at the 0.05 level.

. Coefficient is statistically significant at the 0.1 level.

¹ Mean absolute percentage error: $\frac{1}{N} \sum_{t=1}^N \frac{|\text{Observed ridership} - \text{predicted ridership}|}{\text{Observed ridership}}$

MAPE is commonly used as a forecast error measure. We did not use information criteria such as AIC since they are not comparable across different orders of differencing.

² KPSS significance level (critical values): 0.05 (0.463); 0.025 (0.574); 0.001 (0.739)

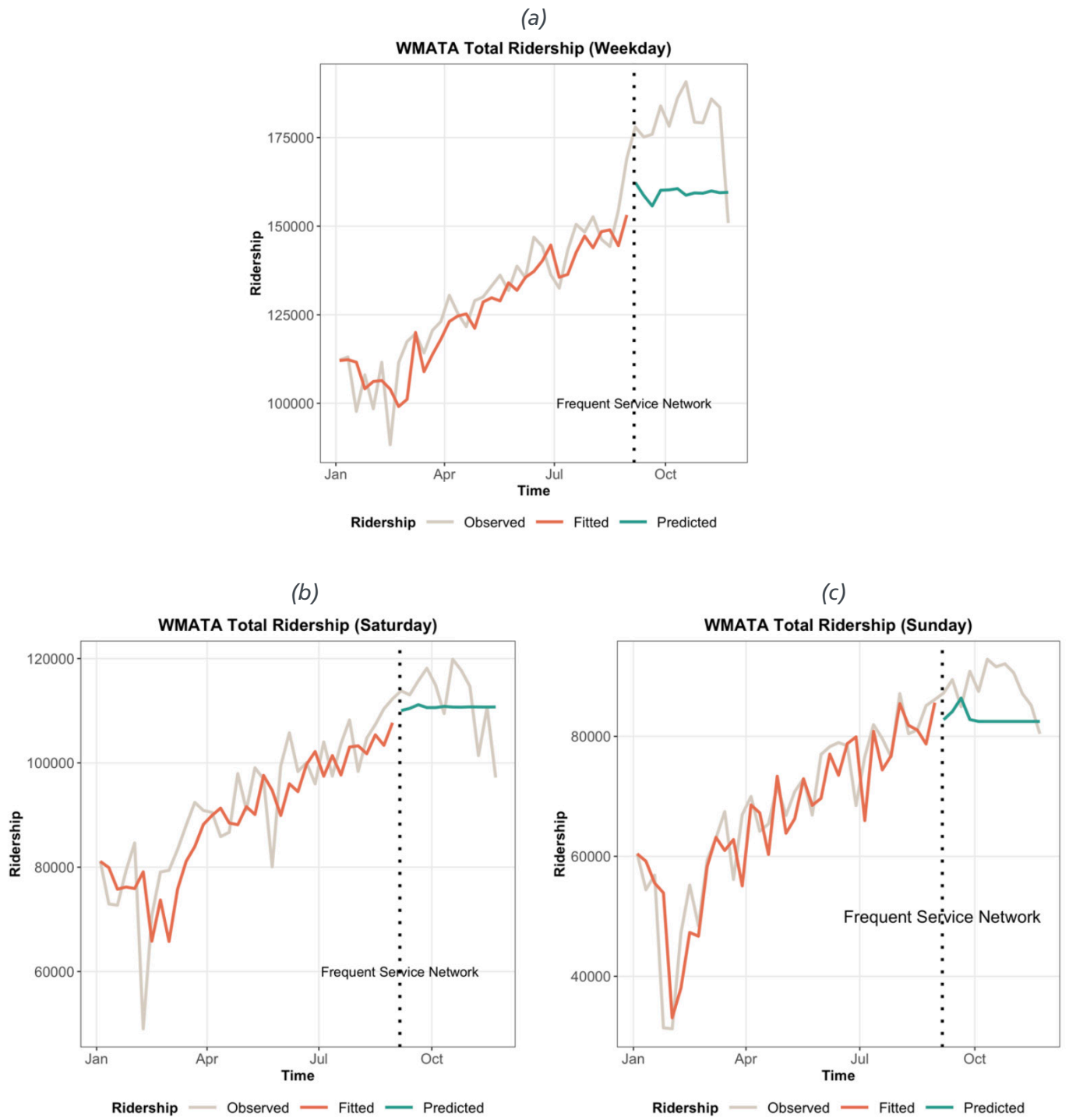


Figure 1.6. WMATA observed and predicted ridership

Section 4:

A Useable Model to Assess Effectiveness of Interventions to Increase Transit Ridership

In this report, we developed an analytical framework for transit agencies to quantify the effectiveness of service interventions on transit ridership. We propose an 8-step analysis guideline, which includes:

- | | |
|--|----------------------------------|
| 1. Understand the data | 5. Compute residuals |
| 2. Identify the intervention point | 6. Identify intervention effects |
| 3. Estimate the pre-intervention ARIMA model | 7. Estimate the full ARIMA model |
| 4. Perform forecasting | 8. Assess intervention impact |

We demonstrated the 8-step analysis procedure with three case studies in Chicago, San Francisco, and Washington, D.C. Specifically, the Chicago Transit Authority (CTA) implemented a Pass Discount Program in May 2021. This program stimulated overall CTA transit system usage on weekdays, Saturdays, and Sundays, with the most significant increase observed on weekdays. The San Francisco Municipal Transportation Agency (SFMTA) launched the “Muni Moves You” campaign in May 2022, which primarily attracted ridership on Sundays, potentially indicating increased leisure usage of Muni. These results align with the campaign’s theme, which focuses on promoting various reasons to use transit for exploring the city, including dining, shopping, nightlife, and museums. The Washington Metropolitan Area Transit Authority (WMATA) implemented the Frequent Service Network in September 2021, which increased Metrobus ridership on weekdays and Sundays. The impact was more pronounced on weekdays, indicating that the improved bus services are particularly beneficial for commuters.

We note unavoidable limitations in the analysis. For example, due to the limited time span between the beginning of the pandemic and the intervention, we did not have enough data points to capture the seasonality in transit ridership. Despite this, the model performance is excellent for CTA and SFMTA, and acceptable for WMATA, future analyses could benefit from adopting seasonal ARIMA to better capture seasonal transit ridership trends. The model is more suitable for identifying ridership changes immediately following the intervention and may not capture lagged ridership changes or temporary ridership changes. Also, the proposed intervention analysis approach cannot separate the impact of the targeted intervention on transit ridership from other interventions that occurred simultaneously or closely to the targeted intervention. Finally, similar to other forecasting approaches, we do not suggest using the proposed method to predict long-term ridership, as the model can only capture the impact of a targeted intervention, not other unknown future interventions.

Overall, the proposed analysis framework provides a useful tool for transit agencies to quantitatively identify effective measures to enhance transit ridership. As more transit agencies adopt this analysis method and share their experiences with ridership interventions, the collective knowledge will help transit communities more effectively increase ridership by choosing, adopting and adapting appropriate intervention measures.

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Impacts of Transit Interventions on Rider Personas

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Reviewed by Darton Ito and Jonathan Rewers, SFMTA

Introduction

The Public Transit Personas developed for Phase II of the National Transit Adaptation Strategy offer useful touchpoints to explore the real-world impacts of potential transit agency interventions on riders. This chapter qualitatively explores the impacts that each potential intervention might have on each NTAS Public Transit Persona.

Prior to MIT's development of a ridership analytical framework, SFMTA staff researched forms of transit system operational interventions that transit agencies across the United States and Canada took in response to the COVID-19 Pandemic and the associated conditions of declined transit ridership and general uncertainty and precarity. SFMTA identified four common intervention categories: Fare and Payment Interventions, Service/Operational Interventions, Capital Investment Interventions, and Staffing and Security Interventions. See Appendix 1 for a full list of SFMTA's intervention research findings.

Some of the findings in this section qualitatively validate existing conclusions and notions within the transit industry. NTAS research provides value by giving a way of segmenting the market of riders in a way that enables agencies to direct resources in a more targeted manner to see stronger return per dollar spent in the form of increased ridership and associated increases in revenue. MIT's model, in conjunction with SFMTA's analysis on the rider persons, allows transit agencies to get more targeted and precise insights into how certain efforts impact and grow ridership.

This chapter is organized into three sections: first, an explanation of the general intervention impacts at a transit system-wide level, second, reintroducing the ridership personas and explaining how the aforementioned interventions impact those personas, and third, a series of summary tables at the end of the chapter to provide an at-a-glance view of the information from the previous sections.

General Interventions Impacts

In this section, we showcase the intervention analysis procedure by presenting three examples using transit ridership data from Chicago, San Francisco, and Washington, DC. The three transit agencies, Chicago Transit Authority (CTA), San Francisco Municipal Transportation Agency (SFMTA), and Washington Metropolitan Area Transit Authority (WMATA) have implemented different strategies to boost transit ridership recovery after the pandemic.

Impacts of Staffing and Security interventions

1. Expedited hiring process for vehicle operators to overcome staffing shortages
2. Hiring 'ambassador' (non-police, unarmed) staff to assist riders
3. Increasing visibility of armed security in systems
4. Partnering with existing social work organizations to help unhoused and struggling people on or near transit systems
5. Deploying CCTV cameras on transit fleets monitored by a 24/7 staff
6. Implementing a mobile app for customers to report safety concerns

Staffing and Security interventions which increase personnel visibility on systems would likely make transit feel like a more controlled environment where less deviation from social standards is tolerated. Higher visibility of staff, both unarmed and armed, reduces feelings of isolation in transit systems and may make passengers feel like they are being watched over or like they are being watched, which can be both a positive and a negative depending on the perspective of the transit rider.

Effectiveness of technology-based solutions depends on quality of implementation and on passenger's ability to utilize those solutions, which may be limited by a digital literacy gap.

Transit vehicle operator staffing improvements would have the most consistent impact as higher frequencies universally improve passenger experiences.

See the "Intervention Impact Tables" section for a more detailed explanation of Staffing and Security interventions on each NTAS Ridership Persona.

Impacts of Fare and Payment interventions

1. Developing semi-permanent fare-free policies in smaller cities
2. Introducing Fare-free policies for youth, either ongoing or for the first day of school year
3. Creating Public-Private Partnerships (P3s) to offer free transit rides after sports games/events
4. Implementing Open Loop payment options
5. Implementing weekend transit passes to encourage off-peak ridership
6. Expanding and publicizing free and reduced fare programs

Fare and Payment interventions, particularly fare-free transit, are likely to significantly improve ease of access to all existing riders and most potential riders as this type of change will induce demand for the service by reducing a key barrier of entry. Event-based free fare programs can encourage more transit use during those periods and introduce infrequent riders to transit. Introducing Open Loop payment systems simplifies access to transit by not requiring exact change or a specific payment mechanism (proprietary transit payment card, payment app, paper ticket) which particularly benefits new and prospective riders.

Fare and Payment interventions are directly linked with political will, as many transit agencies depend on fare revenue to fund operations, but the positive impacts of fare-free transit are clear and worth understanding and implementing in practical and effective ways when possible.

See the "Intervention Impact Tables" section for a more detailed explanation of Fare and Payment interventions on each NTAS Ridership Persona.

Impacts of Service/Operational interventions

1. Fully restoring pre-pandemic service, or increasing service on high priority routes/corridors
2. Improving system cleanliness

Service/Operational interventions would have the general effect of improving the passenger experience for existing transit riders. These interventions are less likely to encourage new riders to shift modes, but improvements are likely to improve experience for the occasional transit rider which may encourage those people to use transit more in the future.

Service/Operational interventions can work best when implemented alongside other measures. For example, improving and maintaining high levels of system cleanliness can encourage new riders brought in through other interventions to choose to continue using transit while also having a moderate impact on existing riders.

See the “Intervention Impact Tables” section for a more detailed explanation of Service/Operational interventions on each NTAS Ridership Persona.

Impacts of Capital Investment interventions

1. Implementing bus network redesigns based on community input
2. Building Transit Priority lanes on critical corridors
3. Introducing demand-response transit services

Capital Investment interventions that prioritize delivering higher quality service would likely have strong positive impacts on ridership. Interventions such as implementing bus network redesigns and building transit priority lanes will likely have moderate to significant positive impacts on all transit riders, improving the quality of transit journeys with faster travel times and more routing options.

While Capital Investment interventions take the most time and resources to implement, they have the most long-term potential to improve transit ridership. Network redesigns have the potential to provide mobility for a much wider range of trip types than has historic American transit network planning with a focus on commute trips.

See the “Intervention Impact Tables” section for a more detailed explanation of Capital Investment interventions on each NTAS Ridership Persona.

Intervention Costs and Future Scope of Work

MIT’s ARIMA model focuses on the direct impact of interventions on ridership and does not factor in the costs of the identified interventions. Financial feasibility may be complicated by the scope and scale of some of the identified interventions, and NTAS staff recommend thorough analysis of financial feasibility of these strategies prior to implementation. Future phases of this work should include more thorough analysis of perceived benefits of interventions, financial benefits and costs, and the cost of customer acquisition by each identified market segment (NTAS rider persona).

Impacts of Interventions by Persona

Each of the Transit Agency Interventions outlined above will have varying degrees of impact on distinct types of transit riders. Traditionally, transit agencies have not performed market segmentation to understand variances among transit rider needs. The NTAS personas provide greater granularity in responding to the needs and wants of all people who ride public transit in the USA. This will enable agencies to make more informed decisions about which personas to target spending toward to increase use, to improve customer experience, and to acquire new users. The information in this section builds upon the personas described in the Phase II Report and provides a foundation for analysis that can pinpoint the type of intervention each persona needs and would benefit from enhancement or investment in.

NTAS Personas

The SFMTA and MIT have developed four primary Transit Rider Personas that provide a useful and representative touchpoint of the types of riders on North American transit systems. These personas are elaborated on in the NTAS Phase II Report. The four personas are:

- **Persona A - The Transit System Navigator:** Riders who rely on public transportation, are experts at using transit systems, and use transit for a variety of purposes. They need reliable, affordable service, and accurate real-time transit information.
- **Persona B - The Versatile Traveler:** Riders who use a variety of transportation modes based on their unique needs and preferences, valuing and prioritizing convenience and efficiency that come from real-time information, fast and reliable transit, and modal priority (bike and bus lanes, grade-separated transit).
- **Persona C - Event-Driven Explorer:** Riders who primarily use public transportation for events and specific destinations when it is more convenient than driving and they are familiar with using the public transit system to reach these particular places, and therefore value event-based services and real-time information and trip-planning tools.
- **Persona D - Transit Sympathizer:** Riders who rarely or never use public transportation and support transit in principle but choose not to use transit in their daily lives, often because they don't see it as a viable option for daily use.

Impacts on Transit System Navigators

As the Transit System Navigator relies upon public transit for most of their travel needs, they would likely benefit the most from increased vehicle operator hiring, universal fare-free transit, fare-free youth programs, expanded free and reduced fare programs, improved system cleanliness, increased span of priority transit lanes, bus network redesign, and return of full pre-pandemic service.

This persona has few travel options and thus would likely benefit moderately from increased presence of security staff, partnerships with social service organizations, deployment of 24/7 security camera systems, deployment of mobile app to report security threats, fare increases excluding sensitive groups, Open Loop fare payment options, and introduction of demand-response services.

This persona uses transit for most trips, and deployment of transit ambassador staff, implementation of P3s for event-based fare-free transit, and introduction of special weekend transit passes are unlikely to increase transit use.

Impacts on Versatile Travelers

The Versatile Traveler chooses from a range of travel options based on considerations affecting each trip and thus would likely benefit the most from partnerships with social services organizations, deployment of mobile app to report security threats, universal fare-free transit, implementation of P3s for event-based fare-free transit, increased span of priority transit lanes, and introduction of demand-response services.

This persona has a range of travel options and would likely benefit moderately from increased vehicle operator hiring, deployment of transit ambassador staff, increased presence of armed guards, deployment of 24/7 security camera systems, fare-free youth programs, fare increases excluding sensitive groups, Open Loop fare payment option, introduction of special weekend transit passes, return of full pre-pandemic service, improved system cleanliness, and bus network redesign.

This persona would likely benefit the least from expanded free and reduced fare programs.

Impacts on Event-Driven Explorers

The Event-Driven Explorer is familiar with using transit to reach specific destinations and would likely benefit the most from deployment of transit ambassador staff, universal fare-free transit, implementation of P3s for event-based fare-free transit, Open Loop fare payment options, improved system cleanliness, and increased span of priority transit lanes.

This persona likely travels during peak periods and they would likely benefit moderately from increased vehicle operator hiring, increased presence of armed guards, partnerships with social services organizations, deployment of 24/7 security camera systems, deployment of mobile app to report security threats, fare-free youth programs, introduction of special weekend transit passes, return of full pre-pandemic service, bus network redesign, and introduction of demand-response services.

Largely using transit for a single purpose, this persona is generally less impacted by the cost of the transit trip and would likely benefit the least from fare increases excluding sensitive groups and expanded free & reduced fare programs.

Impacts on Transit Sympathizers

The Transit Sympathizer has limited knowledge of how to use a transit system and would likely benefit the most from partnerships with social services organizations, deployment of transit ambassador staff, increased presence of armed guards, Open Loop fare payment option, and improved system cleanliness.

This persona would likely benefit moderately from universal fare-free transit, implementation of P3s for event-based fare-free transit, increased vehicle operator hiring, deployment of 24/7 security camera systems, introduction of special weekend transit passes, and bus network redesign.

This persona would likely benefit the least from deployment of mobile apps to report security threats, increased span of priority transit lanes, introduction of demand-response services, fare-free youth programs, fare increases excluding sensitive groups, return of full pre-pandemic service, and expanded free and reduced fare programs.

Intervention Impact Summary Tables

The tables below provide summaries of each identified intervention and the impacts of each intervention on each ridership persona, grouped by intervention category.

Table 2.1: Fare and Payment Interventions

Intervention	Anticipated System Impact	Impact on Transit System Navigator	Impact on Versatile Traveler	Impact on Event-Driven Explorer	Impact on Transit Sympathizer
Universal fare-free transit	Increased ridership & public access	Significant: would reduce financial burden that may limit use of transit and increase access to opportunities	Significant: would improve value proposition of transit and can encourage more transit use	Significant: would improve value proposition of transit and can encourage more transit use	Moderate: the ability to try transit at no cost might encourage more exploration into transit for some trips
Fare-free transit for youth	Eliminates cost as a factor that could limit use of transit resulting in increased transit access for youth	Significant: would reduce financial burden and improve access for youth to school, after school activities and jobs	Moderate: is less likely to be youth, but those who do qualify would benefit considerably	Moderate: would reduce cost for existing trips and would allow youth to use transit for additional trip purposes	Minimal: the ability to try transit at no cost might encourage more exploration into transit systems by youth
P3s for event-based fare-free transit	Increased ridership on event days and may lead to increased transit use after the event	Minimal: many qualify for reduced or free fares, minimizing impact	Moderate: can encourage increased use for specific events	Moderate: could increase quality/value proposition of transit use	Significant: could encourage more transit use by raising awareness of transit access to specific events
Open Loop fare payments	Ease of fare payment	Moderate: likely already has a transit pass, but additional fare payment options are a universal benefit	Moderate: may have a fare card but may also benefit from additional methods of payment	Significant: do not need to obtain transit specific payment media	Significant: reduces barrier of entry for infrequent transit users, simplifying attempts to use transit
Special weekend transit passes	Encourage increased weekend ridership when excess capacity is more likely to exist	Minimal: regular transit riders likely have existing routines that are less likely to benefit from this type of promotion	Moderate: may encourage the use of transit for new trips or to shift existing trips to transit	Moderate: if passes align with events the rider will be attending, this could decrease passenger costs	Moderate: promotion of weekend passes might encourage more exploration into transit systems
Expanding free & reduced fare programs	Improve access for lower-income transit riders and increase frequency of transit use by all	Significant: likely to be eligible and could reduce financial burden on existing trips	Moderate: less likely to qualify, those who do will experience notable benefits	Minimal: less likely to qualify, and may not benefit those that use transit on a limited basis	Minimal: unlikely to qualify and free transit options may provide limited incentive to try transit

Table 2.2: Service/Operational interventions

Intervention	Anticipated System Impact	Impact on Transit System Navigator	Impact on Versatile Traveler	Impact on Event-Driven Explorer	Impact on Transit Sympathizer
Restore pre-pandemic service	Encourage full ridership recovery	Significant: decreased wait times and crowding and increased travel opportunity within network	Moderate: would benefit riders who had service reduced or eliminated on routes routinely used	Moderate: would benefit riders who had service reduced or eliminated on routes routinely used	Minimal: unlikely to have used routes that were cut and therefore would not be substantially impacted
Improving system cleanliness	Improve rider comfort and perception of safety	Minimal: improved quality of existing trips but unlikely to increase transit use	Moderate: could minimize a factor pushing person away from transit use, leading to more transit use	Moderate: improved quality of existing trips, positive impression of transit could encourage more transit use	Moderate: when persona uses transit, would leave a more positive impression and could encourage more transit use
Redesign bus network based on community input	Better serve transit rider's travel needs	Significant: opens up new possible trips and improves existing passenger experience	Moderate: could introduce services convenient for persona, motivating more transit use	Moderate: could introduce services convenient for persona, motivating more transit use	Moderate: new routes could better serve this persona, encouraging exploration into transit systems

Table 2.3: Capital Investment Interventions

Intervention	Anticipated System Impact	Impact on Transit System Navigator	Impact on Versatile Traveler	Impact on Event-Driven Explorer	Impact on Transit Sympathizer
Build Transit Priority lanes	Reduce transit travel times and improve on-time service performance	Significant: improved travel time and comfort of existing trips	Significant: Improved service quality improves value proposition and could encourage increased use	Moderate: improved service quality improves value proposition and could encourage increased use	Minimal: improved service could encourage increased transit system use
Introduce demand-response transit service	Serve new potential riders	Moderate: may open up trips previously not possible in existing transit network	Moderate: may offer higher value proposition than ride-hail services and therefore encourage transit use	Moderate: may open up trips previously impractical to this persona, encouraging transit use	Minimal: persona is likely to already own a private vehicle and may have limited need for a demand-response service

Table 2.4: Staffing and Security interventions

Intervention	Anticipated System Impact	Impact on Transit System Navigator	Impact on Versatile Traveler	Impact on Event-Driven Explorer	Impact on Transit Sympathizer
Increase vehicle operator hiring	Increased service frequency	Significant: improved passenger experience	Moderate: may encourage shift to more transit use as transit becomes more optimal	Moderate: more frequent service may improve perception of transit	Minimal: impact unlikely to be noticed by occasional transit riders
Hire + deploy passenger ambassadors	Increased staff presence on system	Moderate: potential improvements in personal safety/ passenger comfort	Moderate: may encourage shift to more transit use as transit becomes safer	Moderate: ambassador staff may provide navigation/ security help during events	Moderate: can help new users navigate the system, creating a more positive impression of using transit
Increase visibility of armed guards	Increased compliance with system social norms	Significant: may discourage transit use over harassment concerns, may deter fare evasion	Moderate: may discourage fare evasion, or improve security and perceived safety	Moderate: may contribute to a feeling of tighter security on crowded trains	Moderate: promise of enhanced security may inspire giving transit use more of a chance
Partner with social services organizations	Reduce vagrancy & disruptions on system	Significant: reducing instances of anti-social behavior will increase passenger comfort and perception of safety	Moderate: reducing instances of anti-social behavior may encourage more transit use	Moderate: reducing instances of anti-social behavior improves quality of existing rides & opinion of transit	Moderate: reducing instances of anti-social behavior improves quality of existing rides & opinion of transit
Deploy 24/7 monitored security camera system	Better real-time information & responses + Increased compliance	Moderate: decreased antisocial behavior would improve existing passenger experience	Moderate: decreased antisocial behavior would improve comfort & encourage more use	Minimal: usually rides during peak periods and therefore sees less anti-social behavior	Moderate: decreased antisocial behavior, if publicized, could encourage more trips on transit
Mobile app to report security concerns	Better real-time information & passenger security	Minimal: persona unlikely to use, but the system may enhance security & improve passenger experience	Moderate: persona likely to be tech-savvy, and enhanced security options may encourage increased transit use	Minimal: persona usually rides during peak periods and likely experiences fewer safety concerns	Minimal: unlikely to use during limited transit use

Conclusion

Transit agencies, faced with steep competition from private vehicle ownership and from the emerging private transportation market, need to take steps previously not taken in order to continue existing. With uncertainty of funding for public transit, agencies need to ensure that they operate with optimal efficiency and are taking steps to grow their ridership base and increase system utilization. Marketing should be a tool utilized by transit agencies to achieve these goals.

The “Together We Go” campaign created in NTAS Phase III is a versatile and evergreen marketing campaign that transit agencies can modify and deploy as they see fit. The campaign, when deployed in Chicago and San Francisco, appeared to have a positive impact on weekend ridership.

Marketing Campaigns represent a cost-effective form of intervention that transit agencies can take when facing decreased public trust and ridership. Leveraging a campaign to improve public sentiment about public transit can help in the short term by motivating people to choose transit, and can also help in the longer term by giving people a more positive view of public transit which can influence decisions about politically supporting public transit, such as voting for ballot measures to fund transit and voting for pro-transit political figures for public office.

Appendices and Resources

Appendix 1 – Transit System Interventions Research

<https://www.sfmta.com/reports/appendix-1-transit-system-interventions-research>

NTAS Data Model (GitHub)

<https://github.com/wxy470/NTAS>

Acronyms and Glossary

ARIMA: AutoRegressive Integrated Moving Average

NTAS: National Transit Adaptation Strategy

FTA: Federal Transit Administration

MIT: Massachusetts Institute of Technology

NOFO: Notice of Funding Opportunity

SFMTA: The San Francisco Municipal Transportation Agency

WMATA: Washington Metropolitan Area Transit Authority

Transit App: A mobile app which provides real-time public transit information.

Intervention: Actions taken by transit agencies that introduce new or modified operational approaches intended to improve transit system performance.

Legacy Transit Systems: Systems in major U.S. metropolitan areas since before 1955 and historically based upon a streetcar system or pre-existing rail network designed to serve a downtown business core.

Transformative transit systems: Systems which exist in mid-size and major U.S. metropolitan areas, began operating after 1955, and have seen significant growth and system expansion in the last 20 years.

Rural and connector transit systems: Systems found outside of mid or major metropolitan areas, and which operate as a connector service, began operating after 1955, and serve less than 500,000 riders annually.

Transit System Navigator: Public transit riders who rely on public transportation for their daily activities due to a lack of access to a personal vehicle or the inability to drive, for some or all trips.

Versatile Traveler: Individuals with an adaptable and versatile approach to transportation who utilize various mobility options based on specific purposes and situations, making decisions that prioritize convenience, cost-effectiveness, and practicality.

Event-Driven Explorer: A transit user person who primarily uses public transportation for pre-determined events and destinations where it is more convenient, efficient, or cost-effective than driving.

Transit Sympathizer: Individuals who seldom, if ever, utilize public transit for their daily needs, though they may express support for transit in surveys or other contexts.

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