Title
A Time and a Place for Every Rider?: Geographic and Temporal Changes in Bay Area Transit Ridership

Author
Wasserman, Jacob L

Publication Date
2019

DOI
10.17610/T6KW22

A Time and a Place for Every Rider?

Geographic and Temporal Changes in Bay Area Transit Ridership

PROJECT LEAD	Jacob L. Wasserman
FACULTY SUPERVISOR	Brian D. Taylor
CLIENT NAME	Metropolitan Transportation Commission

UCLA Institute of Transportation Studies

Technical Report Documentation Page

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.
	N/A	N/A

4. Title and Subtitle A Time and a Place for Every Rider?: Geographic and Temporal Changes in Bay Area Transit Ridership	**5. Report Date** 2019 **6. Performing Organization Code** UCLA-ITS
7. Author(s) Jacob Wasserman	**8. Performing Organization Report No.** LAS1906
9. Performing Organization Name and Address Institute of Transportation Studies, UCLA 3320 Public Affairs Building Los Angeles, CA 90095-1656	**10. Work Unit No.** N/A **11. Contract or Grant No.**
12. Sponsoring Agency Name and Address The University of California Institute of Transportation Studies www.ucits.org	**13. Type of Report and Period Covered** **14. Sponsoring Agency Code** UC ITS

15. Supplementary Notes

DOI: doi:10.17610/T6KW22

16. Abstract

Transit ridership is on the wrong track across America. Yet until 2016, the San Francisco Bay Area appeared immune to the ridership declines plaguing most other cities. However, in 2017, Bay Area ridership began to fall, both regionwide and on almost all major transit operators. But this decline has not occurred uniformly. Thus, to help explain why transit ridership has changed, this report elucidates how, where, and when it has changed across the nine-county Metropolitan Transportation Commission region in the past decade. To answer these questions, I analyze ridership data for the region as a whole and for three of its largest operators in depth. Following this, I conduct a multivariate statistical analysis that simultaneously considers the various factors that have influenced ridership on Bay Area Rapid Transit (BART).

While the landscape of transit use in Northern California is varied and shifting, I find and detail three significant trends. First, while the Bay Area had appeared to have stronger ridership than much of the rest of the country until recently, gains at major Bay Area transit agencies masked longer-term declines in the rest of the region. Second, the region's largest operators are suffering from severe and deepening peaking problems: ridership during off-peak periods and in off-peak directions has cratered, while ridership at peak periods and in peak directions remains steady. Finally, I find that jobs, and particularly concentrated employment, explain far more of variation in ridership than any other determinant analyzed, including factors like service provided. Policymakers must therefore make the difficult decision of whether to channel resources towards the most crowded trip types, to alleviate crowding and double down on their strongest market, or towards slumping trips types, to shore up the weakest parts of the transit network despite their limited control over them.

17. Key Words	18. Distribution Statement
transit transit ridership Bay Area California	No restrictions.

19. Security Classif. (of this report)	20. Security Classif. (of this page)	21. No. of Pages	22. Price
Unclassified	Unclassified	150	N/A

Form DOT F 1700.7 (8-72) Reproduction of completed page authorized

This report was prepared in partial fulfillment of the requirements for the degree of Master of Urban and Regional Planning in the Department of Urban Planning at the University of California, Los Angeles; the requirements for the University of California, Los Angeles Institute of Transportation Studies Fellowship; the requirements for the University of California, Los Angeles Institute of Transportation Studies Capstone Fellowship; and the requirements for the Dwight David Eisenhower Transportation Fellowship Program Graduate Fellowship. It was prepared at the direction of the Department of Urban Planning and of the Metropolitan Transportation Commission as a planning client. The views expressed herein are those of the author and not necessarily those of the Department; the University of California, Los Angeles Luskin School of Public Affairs; the University of California, Los Angeles as a whole; the United States Department of Transportation; or the client.

A special thank you to: Dr. Brian D. Taylor, whose help and guidance throughout this process would fill another whole report; Alix Bockelman and Kenneth Folan, whose support of this project was both thorough and thoughtful; Dr. Evelyn Blumenberg, Maddy Ruvolo, Hannah King, Julene Paul, Andy Schouten, and Mark Garrett, a research team without whom this report would not be where it is today; Katelyn Stangl, for your invaluable review and keen eye; Dr. Michael Manville for your helpful comments; Brendan Monaghan, Aaron Weinstein, Maureen Wetter, Angela Borchardt, Robert Franklin, Craig Bosman, Monique Webster, Tim Quayle, Kevin Keck, Lupita Ibarra, Adam Burger, Jay Tyree, Jason Kim, Mark Shorett, Shimon Israel, Brandon Parker, and Trevor Thomas, for providing and clarifying datasets; Juan Matute, Whitney Willis, Danielle Maris Lacob, Kathy Sekine, Rowena Barlow, Gwen Payne, Ewa Flom, and Brandon Crain, for the logistical and financial support, even on tight deadlines; Maxwell Ulin, for introducing me to transit in Los Angeles; and Sophia Charan, who always keeps me on track.

A Time and a Place for Every Rider?

Geographic and Temporal Changes in Bay Area Transit Ridership

By Jacob L. Wasserman

University of California, Los Angeles
Meyer and Renee Luskin School of Public Affairs
Department of Urban Planning

Applied Planning Research Project
Client: Metropolitan Transportation Commission
Client representative: Alix Bockelman, Deputy Executive Director of Policy
Faculty advisor: Brian D. Taylor
June 4, 2019

A comprehensive project submitted in partial fulfillment of the
requirements for the degree of Master of Urban and Regional Planning

Table of Contents

A Time and a Place for Every Rider? Geographic and Temporal Changes in Bay Area Transit Ridership

Executive Summary

E.1. Context and Background

Transit ridership is on the wrong track across America. Yet until 2016, the San Francisco Bay Area appeared immune to the ridership declines plaguing most other cities. However, in 2017, Bay Area ridership began to fall, both regionwide and on almost all major transit operators in Northern California. Identifying the causes of this downturn, be they unique to the Bay Area or shared with other parts of the country, is a critical first step to reversing it.

The Bay Area's ridership decline has not occurred uniformly. Thus, to help explain *why* transit ridership has changed, this report elucidates *how*, *where*, and *when* it has changed across the nine-county Metropolitan Transportation Commission region in the past decade. To answer these questions, I analyze ridership data for the region as a whole and for three of its largest operators in depth: the San Francisco Municipal Transportation Agency (SFMTA or Muni), Bay Area Rapid Transit (BART), and the Santa Clara Valley Transportation Authority (VTA). Following this, I conduct a multivariate statistical analysis that simultaneously considers the various factors that have influenced ridership on BART.

Across the nuances of research literature and press accounts, external factors beyond the control of transit operators appear to have more influence on ridership than internal factors—increasingly so in the past ten years. This report tests and confirms this. Additionally, this report contributes to the body of research literature on transit ridership by adding distinct focuses on ridership change in the past decade and on spatial and temporal variation within specific agencies.

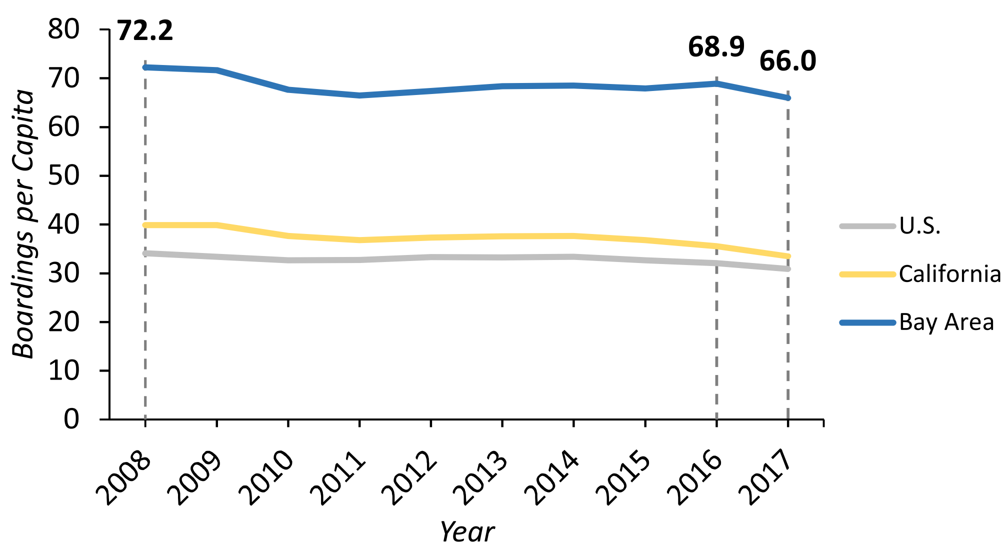
While the landscape of transit use in Northern California is varied and shifting, I find and detail three significant trends in the sections that follow. First, while the Bay Area had appeared to have stronger ridership than much of the rest of the country until recently, gains at major Bay Area transit agencies like BART and Muni masked longer-term declines in the rest of the region. Second, the region's largest operators are suffering from severe and deepening peaking problems: ridership during off-peak periods and in off-peak directions has cratered, while ridership at peak periods and in peak directions remains steady. Finally, I find that jobs, and particularly concentrated employment, explain far more of variation in ridership than any other determinant analyzed, including factors like service provided.

E.2. Where and When: Descriptive Findings

E.2.1. Regional Ridership Trends

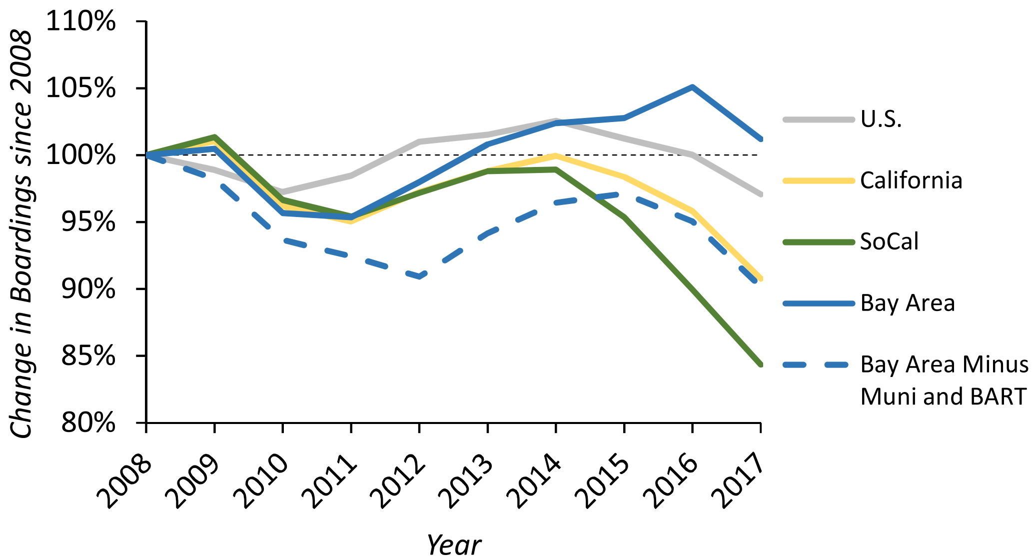
From 2016 to 2017, Bay Area transit patronage fell around four percent, or nearly 20 million annual boardings. But the problem has deeper roots. Annual boardings per capita dropped dramatically in 2017—the steepest one-year drop since the height of the Great Recession—but the region also saw a slower decline of about the same magnitude from 2008 to 2016 (*See Figure E-1*). This last year of freefall should be cause for concern, but so too should the preceding decade of ridership failing to keep pace with rising population.

Figure E-1: The Scale of the Ridership Decline



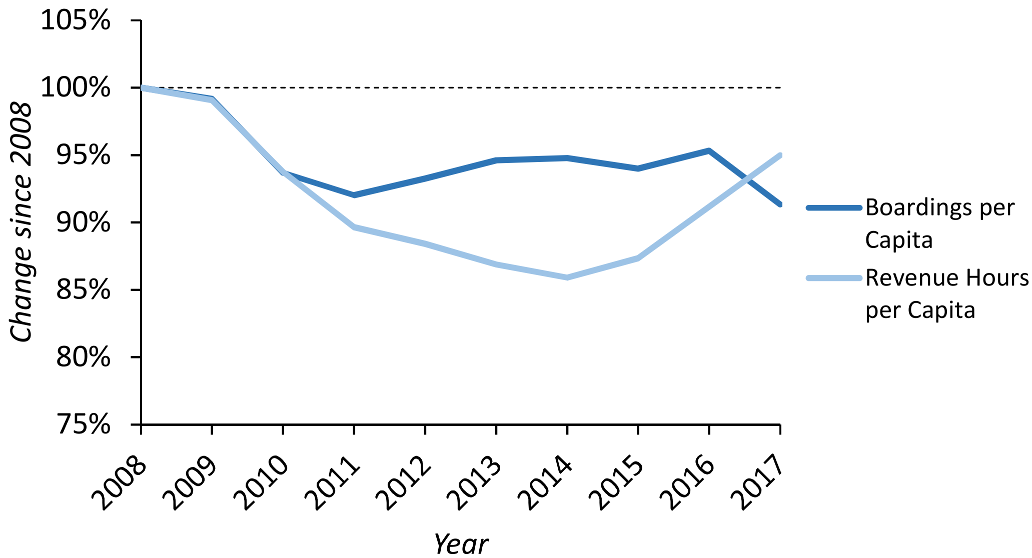
Moreover, gains on BART and Muni until 2017 masked declines on other agencies. When these two agencies, which carried over 70 percent of 2017 regional ridership, are excluded, the region's ridership looks far more similar to the rest of the nation, with an earlier peak and a sharper drop (*See Figure E-2*). Likewise, bus ridership has fared far worse than rail ridership across the region in the past decade, though this does not appear to be because agencies are investing in the latter at the expense of the former.

Figure E-2: A Later Decline in Boardings in the Bay Area



In many agencies across America, service cuts and ridership declines have created a vicious cycle. This is not the case in the Bay Area, where, after recovering from the Great Recession, revenue hours per capita have increased as boardings per capita have decreased (*See Figure E-3*). The Bay Area therefore is not in a transit "death spiral"—but has perhaps landed somewhere even worse. Ridership in Northern California is falling *in spite of more service*.

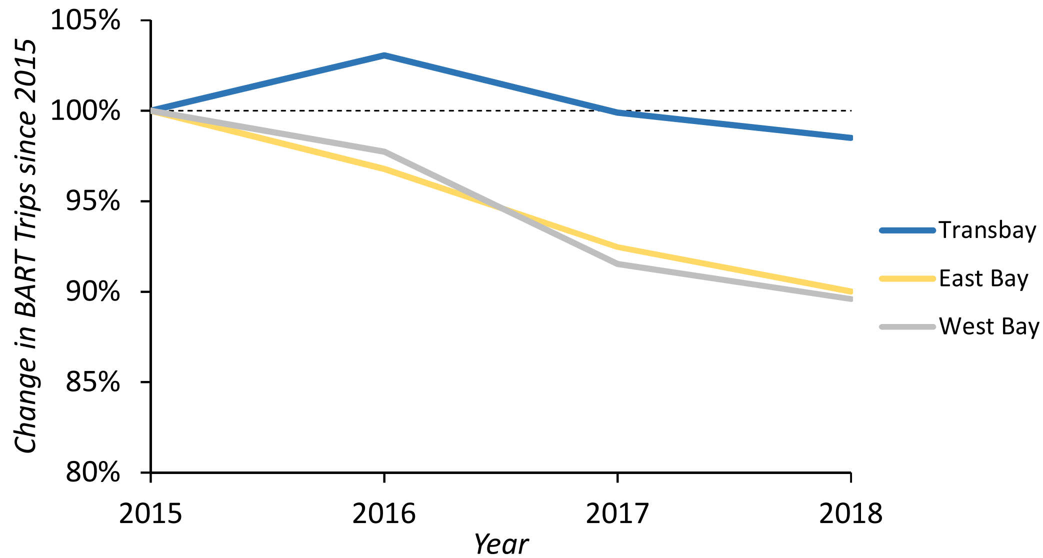
Figure E-3: Service Changes Are Not Causing Recent Ridership Declines



E.2.2. Ridership Trends on Large Operators

BART, Northern California's regional heavy-rail system and its second-most-ridden operator, has experienced the most severe peaking problems of the agencies profiled. On BART, peak and off-peak ridership trends have diverged significantly: patronage in counter-commute directions, outside of rush hours, and on weekends has plummeted, as riders crowd onto packed peak-hour trains. Overall ridership fell over seven million trips between 2015 and 2018, or six percent. But 86 percent of those losses were among trips that did not cross the Bay, despite that trip type making up less than half of 2018 ridership (*See Figure E-4*). Likewise, trips between locations other than downtown San Francisco account for 56 percent of losses, but made up only 34 percent of 2018 ridership. Temporal disparities on BART are just as wide. Weekday ridership only fell four percent between 2015 and 2018, while Saturday patronage dropped 16 percent and Sunday 17 percent. Ridership outside of rush hour fell 11 percent, while peak hour trip counts remained virtually flat. And while these splits have become wider since 2015, BART was experiencing peaking before then. From 2012 to 2015, transbay BART trips accounted for *all* of the growth in BART ridership—and around 43 percent of the *whole region's* growth.

Figure E-4: Geographic Differences in BART Ridership Changes



SFMTA—the region's largest transit agency, located in its most transit-supportive built environment—has also lost patronage and suffered from peaking, but not to the standout degree of BART. Muni lost 6.6 million annual riders in 2017 alone, with even steeper losses on a per capita basis. But unlike BART and VTA, it gained significant ridership in 2016 and has generally had bumpier ridership trends. During this period, SFMTA has seen significant ridership shifts to lines with more frequent service and modes with dedicated rights of way. Between fiscal years 2015 and 2018, weekday local bus boardings fell three percent, while Rapid bus patronage rose 24 percent and light rail six percent. Indeed, many of the lines with the largest losses are the local routes along the same corridors as Rapids, which have seen some of the largest gains (*See Table E-1*). Meanwhile, weekday ridership on lines with peak frequencies of ten minutes or less grew three percent, while less frequent routes carried two percent fewer trips.

Table E-1: SFMTA Ridership Change on Locals versus Rapids

Lines	Local: Absolute Change in Daily Boardings, Fiscal Year 2015-Fiscal Year 2018		Rapid: Absolute Change in Daily Boardings, Fiscal Year 2015-Fiscal Year 2018	
5 / 5R	-1,567	72nd out of 76	+1,053	13th out of 76
9 / 9R	-2,740	75th out of 76	+4,575	2nd out of 76
14 / 14R	-1,242	68th out of 76	+2,692	5th out of 76
28 / 28R	-462	54th out of 76	+2,254	6th out of 76
38 / 38R	-1,429	71st out of 76	+4,649	1st out of 76

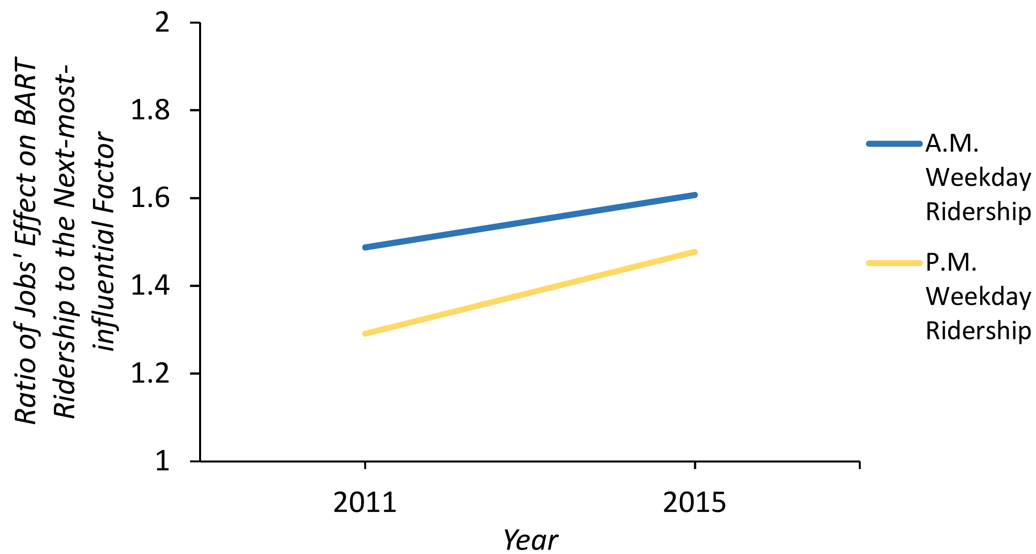
VTA's ridership trajectory looks closer to that of the U.S. than that of the Bay Area overall. VTA has experienced ridership declines across modes and lines, particularly off-peak. While rush-hour ridership jumped ten percent between April 2015 and April 2018, off-peak patronage dipped 18 percent—and dragged the agency's topline ridership number down with it. Light rail routes and outlying bus services have, respectively, suffered some of the agency's largest absolute and relative losses over the same period.

E.3. How and Why: Causal Findings

What explains these changes and divergences? Given BART's rich data and its geographic spread, I looked for answers by employing a robust multivariate statistical model of ridership on BART. To explain ridership between every pair of stations, the model includes the following inputs: residents, jobs, BART-provided parking spaces, and number of lines at the origin and destination; whether the origin/destination is a terminus; the BART travel time between each station pair; the ratio of driving time to BART travel time for each station pair; and whether the trip involves a transfer. I have run the models in the weekday A.M. and P.M. periods for the earliest year of fully available data, 2011; the latest year of fully available data, 2015; and the most recent year, 2018, with some estimated data.

In a word, the most powerful explanatory factor by far is jobs. Jobs concentrated near stations (at the destination in the A.M. and at the origin in the P.M.) explained a greater share of the variation in ridership than any other factor, for all years. BART travel time, the need to make a transfer, and population density also influence ridership significantly, though not to the same degree as employment, while service supply, as measured by the number of lines, has surprisingly little effect. Furthermore, the influence of jobs has grown. Figure E-5 below plots how much more influential jobs are on ridership than the next-most-influential factor, for the years with full data. In both the A.M. and P.M., employment has become more predictive over time.

Figure E-5: The Growing Influence of Jobs on BART Ridership



Outputs for 2018 not shown, as the 2018 models relied on estimates for not-yet-available data. For more details, see Section 5.3.

While the main models explain the continued resilience of peak ridership, variants of the model—one without downtown San Francisco stations and another with off-peak ridership throughout the week—fail to turn up a clear reason for the decline in off-peak ridership, a task left to the forthcoming UCLA Institute of Transportation Studies report.

E.4. Light at the End of the Tunnel?: Conclusion

The story of ridership in the Bay Area has not reached its happy ending, at least just yet. Into 2018, regional ridership is continuing to fall, according to preliminary data. And looking back, key indicators like ridership per capita and productivity have been on the wane for a long time. Thus, if ridership does begin to rise again, but productivity or ridership per capita stay flat or decline, planners should still worry about the longevity of the revival.

Where should the Metropolitan Transportation Commission (MTC) and the Bay Area's transit operators look to reverse the region's troubling transit trends? In light of these findings, I recommend that policymakers focus on new pressures on off-peak transit—the booming expansion of ridehail, the spatial dispersion of non-work destinations, etc. Given the continued strength of peak transit use, these factors merit more scrutiny than peak pressures like employment growth and congestion. In fact, transit operators should devise strategies to handle the problems that come with an over-reliance on peak ridership. When a transit agency carries most of its ridership at weekday rush hours, it must maintain a large fleet and hire many vehicle operators, even if they are only needed at peak. And it must address rider discomfort caused by overcrowding.

It bears specific mention that service supply and headways do not appear to have affected ridership greatly, as demonstrated by the BART regression models. Thus, the addition of new service as a response to the ridership slump may not have the full restorative effect desired. Since 2014, service in revenue hours and revenue miles has increased regionwide and on each of the three profiled agencies. On BART, SFMTA, and VTA, service increases, extensions, and reallocations have improved ridership in some areas, but overall patronage remains stubbornly down.

When it comes to reviving off-peak transit use, my findings present a difficult dilemma for planners. On the one hand, policies targeted at increasing non-commute, reverse direction, evening, and weekend trips are of great importance for addressing the most significant declining trip types. On the other, the most significant factors that influence transit use tend to be beyond agencies' control. Policymakers must therefore make the difficult decision of whether to channel resources towards the most crowded trip types, to alleviate crowding and double down on their strongest market, or towards slumping trips types, to shore up the weakest parts of the transit network despite their limited control over them.

On both horns of this dilemma lie solutions with at least some potential to improve ridership. If MTC and transit operators decide to deepen their investment in—and reliance on—the most well-ridden trip types, they could lengthen trains at rush hour, add more service in commute directions, create more transit-only lanes (and eventually construct a second Transbay Tube), implement congestion pricing, etc. If instead MTC and operators focus on restoring off-peak ridership, they should consider increasing midday, evening, and weekend headways; adding more service in counter-commute directions, restructuring route networks; and regulating or working with ridehail companies to make them better complements to transit. Of course, these latter set of strategies especially are easier said than done, and their individual effects may be small or slow to develop. Still, over-dependence on peak trips is operationally and financially dangerous for transit agencies, so a suite of off-peak investments may be worth pursuing. More research is needed on the effectiveness of off-peak-focused interventions in a region with high use of ridehail, worrying amounts of displacement, and other unique and modern factors.

Long-term, policies that move and/or enable jobs and housing concentrations in the region will significantly affect transit ridership. Plan Bay Area 2040, MTC and the Association of Bay Area Governments' long-range Sustainable Communities Strategy, calls for significant employment and housing growth near transit. While such a strategy serves a number of important policy goals, I urge some caution with respect to its effect on transit ridership. Transit-oriented developments (TOD) in less dense areas, where trips other than commutes may require a car, may reduce ridership if people move there from denser areas. Likewise, TODs without strong affordability policies may displace existing residents who ride transit heavily. Thus, a long-range plan to build transit ridership should not only put housing near transit but also jobs near transit. Better yet, MTC should aim to locate housing near jobs, and transit ridership growth will follow. With such land-use planning strategies and with well-designed affordability and anti-displacement policies, employment and housing may restore off-peak transit use and retain peak transit riders across the region.

A Time and a Place for Every Rider? Geographic and Temporal Changes in Bay Area Transit Ridership

Ridership on the Wrong Track: Introduction

1.1. Study Background and Purpose

Transit ridership is on the wrong track. Instead of recovering after the Great Recession, patronage is plummeting in metropolitan areas across America. After years of general growth, unlinked boardings fell by over 500 million trips nationally from 2014 to 2017; ridership per capita dropped even more steeply. This trend is especially troubling in light of how much money has been invested and service added in recent years. In other words, just as transit is becoming more frequent and better funded, it is hemorrhaging riders.

Until 2016, the San Francisco Bay Area appeared immune to the ridership declines plaguing most other American cities. However, in 2017, Bay Area ridership began to fall, both regionwide and on almost all major transit operators in Northern California. In just that one year, the region lost nearly 20 million annual boardings, representing around four percent of transit patronage—and the trends for 2018 look no better. For Bay Area agencies and leaders trying to reverse this downturn, identifying its causes is a critical first step.

The Bay Area's ridership decline has not occurred uniformly. My analysis finds that transit trips are highly concentrated at certain times, in certain locations, and on certain agencies—so small changes in specific trip types have caused noticeable top-line effects. Thus, to help explain *why* Bay Area transit ridership has changed, this report elucidates *how*, *where*, and *when* it has changed. Any policy response to falling ridership will be aided greatly by focusing on these agencies, lines, times, and places where transit use is changing the most. From these findings, regional policymakers and transit operators can implement targeted strategies to improve service, remedy the causes that they can control, and potentially staunch or reverse the decline.

1.2. Study Context and Contribution

The cause(s) of the transit patronage drop and their relative importance have become among the most critical issues in transportation planning today. Indeed, this report joins an ongoing discussion in the press and research literature, where the recent declines have spurred a vigorous debate. Section 2 describes the latest findings on how service cuts, the growth of ridehail companies like Lyft and Uber, central-city residential displacement, fare increases, macroeconomic changes, gas prices, crime, weather, and more affect transit patronage.

Overall, the literature on the determinants of transit ridership has covered almost every potential factor in depth. While debate continues, external factors beyond the control of transit operators appear to have more influence on ridership—increasingly so in the past ten years. However, two significant gaps remain. First, few works have examined recent ridership trends. New influences like the rise of ridehail, the increase in displacement, the suburbanization of poverty, and the re-urbanization of employment have thus gone relatively unexplored. Second, most previous work studies ridership for the whole country or a whole metropolitan area. Into this lacuna, this report examines ridership change in the past decade and focuses on spatial and temporal variation within specific agencies.

This report follows upon Manville, Taylor, and Blumenberg's 2019 study *Falling Transit Ridership: California and Southern California*, in which they identify increased auto access as the most significant reason for Los Angeles' ridership decline.[1] While their study provides a model and inspired the Metropolitan Transportation Commission to sponsor this report, auto access is *not* the reason for the Bay Area's downturn (or at least not a central one). The factors at play in Northern California's transit ridership changes are different and require examination on their own terms. As anyone from the Bay Area will tell you, the region is unique: A West Coast metropolitan area with an East Coast urban form, it comprises perhaps America's most vibrant economic cluster but also its most visible epicenter of residential displacement. Learning more about transit patronage changes here will therefore illuminate much about the extremes of the transit crisis nationally.

1. Michael Manville, Brian D. Taylor, and Evelyn Blumenberg, *Falling Transit Ridership: California and Southern California*, Jan. 2018.

1.3. Study Outline

This study explores and explains how, where, and when transit ridership has changed across the nine-county Metropolitan Transportation Commission (MTC) region in the past decade. To answer these questions, I analyze ridership data for the region as a whole and for three of its largest operators in depth, followed by a multivariate statistical analysis that simultaneously considers the various factors that have influenced ridership at one major agency, Bay Area Rapid Transit. While the landscape of transit use is varied and shifting, I find and detail three significant trends in the sections that follow. First, while the Bay Area had appeared to have stronger ridership than the rest of the country until recently, gains at a few major agencies had masked longer-term declines in the rest of the region. Second, the region's largest operators are suffering from severe peaking problems: ridership during off-peak periods and in off-peak directions has cratered, while ridership at peak periods and in peak directions remains steady. Finally, I find that jobs explain far more of variation in ridership than any other determinant, including factors like service provided.

In order to ground my work in the latest findings and methods, this report begins with a review of academic literature and press accounts of the determinants of transit ridership, followed by an explanation of my methodology. Next, I offer an overview of ridership trends across the Bay Area, especially in comparison to elsewhere in California and the U.S. Following that, I provide a detailed analysis of spatial and temporal changes at three major transit operators: the San Francisco Municipal Transportation Agency (SFMTA or Muni), Bay Area Rapid Transit (BART), and the Santa Clara Valley Transportation Authority (VTA). The first two carried 70 percent of the region's passengers in 2017. VTA, the area's fourth-largest agency by patronage, offers a helpful control case of sorts, given its operating environment is more similar to the rest of the country. A regression analysis of ridership trends on BART—the agency with the most severe peaking problem and the most complete data—follows, offering a comparison of the relative influences of different factors identified in the literature. Finally, I close with some thoughts on what my findings mean for the future of Bay Area transit ridership and policy implications for how to revive transit ridership in a targeted manner.

What Explains Changes in Transit Use?: Literature Review

2.1. Introduction

With ridership on the decline in California and the nation, the search is on for the prime cause or causes—ideally, in order to then restore ridership by targeting that factor. In the past decade and before, academic researchers and media accounts have explored and weighed the various potential determinants of transit ridership—and have come to many different conclusions. Thus, to provide context for my analysis, the following section reviews these scholarly and descriptive works, organizing them by the primary cause they identify for the ridership slump. Overall, external factors beyond agencies' control, like economic conditions, auto access, and land use, have a greater influence on transit use than internal factors—which, nonetheless, do play a role. The weight of evidence from research literature confirms my findings on the importance of job locations on ridership, detailed in Section 5.

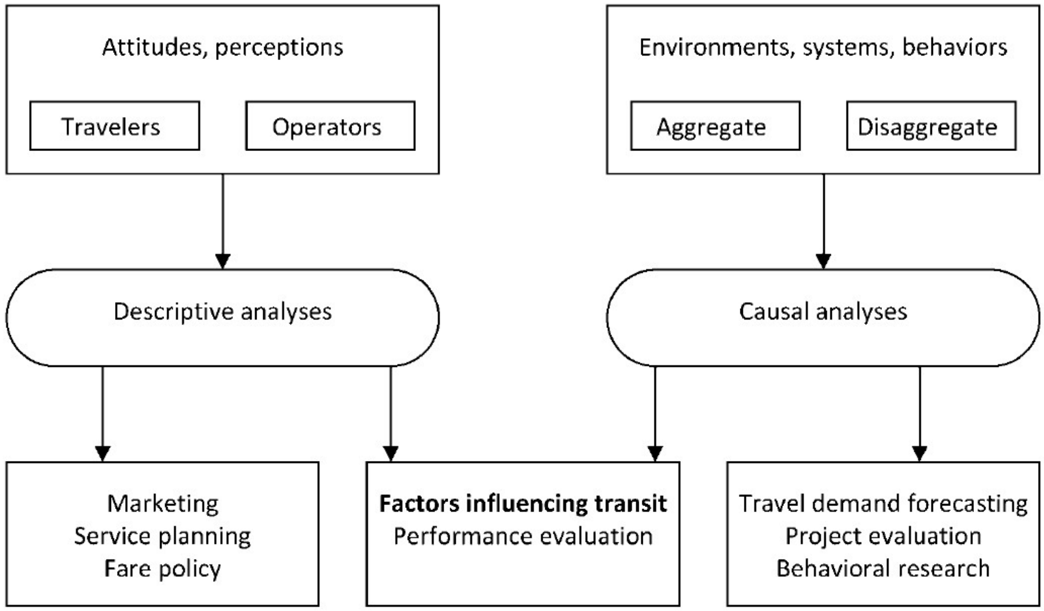
This review focuses heavily—though not exclusively—on literature published in the last decade. While some important pieces from before then continue to presciently describe ridership changes, today's decline in transit use is occurring in a unique landscape different from the operating environment even ten years prior. The adoption of smartphones, the rise of Uber and Lyft, and the intensification of residential displacement,have likely altered the determinants of transit ridership. Of course, these new factors may not actually have had much of an effect, but studies before the last decade did not—and could not—have considered them at all. Likewise, the recent transit ridership drop is steeper and more prolonged than any since the mid-1990s. Today's slump is the first major fall since America began significantly reinvesting in transit; from around 1995 to 2014, ridership generally increased. With that in mind, the explanations for declining ridership may be different than the determinants of steady or rising ridership (For instance, reducing fares—which a few agencies have recently done or considered in response to falling patronage—has an asymmetric effect on ridership compared to raising fares.). These differences all merit a focus on more recent literature. For a synthesis of earlier analyses, Taylor and Fink's reviews (working paper, 2003; updated version, 2013) provide a comprehensive account.[2]

Taylor and Fink provide a helpful framework to understand the different methodological approaches to studying transit ridership. On one hand, many academic and non-academic publications provide descriptive analyses of attitudes and perceptions, treating riders or agencies as the unit of analysis. On the other, a different set of papers has attempted causal analyses of transit systems or rider behavior, including aggregate studies of regions or operators and disaggregate examinations of individual mode choices. The determinants of transit ridership lie in the conversation between and intersection of these two literatures, where the totality of factors can be considered and synthesized (*See Figure 2-1*). Of course, this middle ground needs to exclude some areas of research; Taylor and Fink therefore exclude disaggregate causal analyses of individual and household travel patterns as too broad and far afield.[3] I largely follow their lead but examine a few relevant examples briefly at the end of this review to show how insights from discrete choice analysis might inform aggregate transit ridership. I also include a review of non-academic accounts of ridership changes from newspapers and popular press, to compare their reporting with academic findings and to hone the focus on the Bay Area.

2. Hart Schwartz, "Declining Transit Ridership: Revolutionary or Routine?," *The Fuse*, Apr. 4, 2018; Todd Litman, "Transit Price Elasticities and Cross-Elasticities," *Journal of Public Transportation* 7, no. 2 (2004): 40-1; "Sacramento Regional Transit District Rolls Back Fares," *Sacramento Regional Transit District*, Aug. 28, 2018; Angie Schmitt, "D.C. Metro Seeks Better Service, Fare Cuts to Stop Ridership Death Spiral," *Streetsblog USA*, Oct. 29, 2018; Brian D. Taylor and Camille N. Y. Fink, "The Factors Influencing Transit Ridership: A Review and Analysis of the Ridership Literature," (UCLA Dept. of Urban Planning Working Paper, UCLA, Los Angeles, CA, Sept. 1, 2003); and Brian D. Taylor and Camille N. Y. Fink, "Explaining Transit Ridership: What Has the Evidence Shown?," *Transportation Letters* 5, no. 1 (Winter 2013): 15-26.

3. Taylor and Fink, "Explaining Transit Ridership," 15-8.

Figure 2-1: Taxonomy of Research on Transit Ridership (from Taylor and Fink, 2013)[4]



Within this academic space, researchers have studied two sets of influences, both independently and in combination: internal factors and external factors. The former describe policies that transit agencies control: fares, frequency, routing, marketing, etc. The latter covers everything outside of operator's direct domain, including age-old factors like demographics, economic conditions and employment, land use characteristics, and even weather and newer issues like ridehail and displacement. Generally, Taylor and Fink conclude that external factors have a larger effect on transit ridership but arrive at that conclusion after wading through a muddied and mixed academic landscape. In the years since their review, the evidence in favor of external factors has strengthened, especially given new research on ridehail and displacement.

2.2. Media Accounts

National news media and online transit commentators have written with some anxiety about the collapse of transit ridership for the past few years. While such analyses usually are not conducted with the statistical rigor of academic studies, they do offer 1) an examination of rapidly changing recent trends that may take years to filter into academic journals and 2) a look into what decision-makers, operators, and the public themselves view as the

4. Ibid., 16.

problem. Overall, explanations for ridership declines vary widely—or, as *CityLab's* Laura Bliss put it, "What's behind declining transit ridership nationwide? Pick a culprit."[5] Prominent explanations include service and budget cuts, plummeting reliability, Uber and Lyft, and relatively cheap gas. Many writers worry about a "death spiral" of ridership declines causing fare revenue losses causing service reductions causing ridership declines. But across the country, writers have tended to emphasize factors unique to their metropolitan areas. In New York, the MTA has purportedly spent far too little on rail; in Los Angeles, Metro has spent far too much. In D.C., deadly train crashes and the line-closing repair work that followed forced riders off in dramatic plunges; in other cities, gradual service cuts have supposedly caused a slower ridership erosion. Throughout the media conversation, though, a few metropolitan areas stood out as bulwarks against the tide of ebbing ridership: Seattle, Houston, and San Francisco. In 2017, however, transit patronage began to fall in the Bay Area, knocking Northern California into the roiling sea with the rest of the country.[6] Three main factors emerged in the popular narrative: safety and security, Uber and Lyft, and overcrowding at peak hours.

Local news media have treated Bay Area ridership declines with a fair degree of sensationalism. The relationship between security and ridership on BART has generated particularly significant press coverage. In 2017 and 2018, a number of high-profile crimes led to speculation that safety fears have driven away riders. However, some of these reports, concerning robberies at least, were likely overblown. For instance, when 50 or so teens dramatically robbed a whole train car's worth of passengers in less than five minutes, reporters claimed that the ambush would hurt ridership. According to follow-up reporting, though, many people's posts online that they would stop riding were as much empty racist commentary as actual plans to leave BART. On

5. Laura Bliss, "What's Behind Declining Transit Ridership Nationwide?: Pick a Culprit: The Rise of Ride-hailing Services, Budget Cuts, Cheap Oil, or Bad Service," *CityLab*, Feb. 24, 2017.

6. Ibid.; Benjamin Kabak, "Where Have All the Transit Riders Gone?," *Second Avenue Sagas*, May 20, 2018; Laura J. Nelson, "The Metro Can Take You Farther than Ever. Here's Why Ridership Dropped—Again," *Los Angeles Times*, Feb. 13, 2017; Laura J. Nelson and Dan Weikel, "Billions Spent, but Fewer People Are Using Public Transportation in Southern California," *Los Angeles Times*, Jan. 27, 2016; Ethan Elkind, "L.A. Times Misleads on Metro Rail Ridership History," Jan. 27, 2016; Thomas A. Rubin, "Is the *Los Angeles Times* Article, 'Billions Spent, But Fewer People Are Using Public Transportation in Southern California,' Misleading?," n.d., *Electronic Drummer*; Lori Arantani, "Metro's Multimillion-dollar Mystery: Where Have Our Riders Gone?," *Washington Post*, Oct. 1, 2016; Henry Grabar, "The Astounding Collapse of American Bus Ridership," *Slate*. Jul. 21, 2016; Jeremy Hobson, "Why Public Transit Ridership Is Down in Most U.S. Cities," *WBUR*, Mar. 21, 2017; Faiz Siddiqui, "Falling Transit Ridership Poses an 'Emergency' for Cities, Experts Fear," *Washington Post*, Mar. 24, 2018; and Skip Descant, "Seattle, Houston Buck Declining Bus Ridership Trend," *Government Technology: FutureStructure*, May 16, 2018.

the other hand, the brutal, unprovoked murder of teenager Nia Wilson at a BART station last July highlighted genuine faults with BART's security systems that have potentially driven away riders of color, especially given the distrust BART Police have engendered since an officer killed Oscar Grant at the Fruitvale Station in 2009. On top of these headline-grabbing crimes, BART and other area transit agencies have faced unprecedented numbers of homeless individuals in stations and on vehicles (the effects of which are discussed in Section 5.5.2), as cities and others literally force people experiencing homelessness underground. Again, news media have focused on homelessness and attendant drops in safety perceptions and system cleanliness as a cause of ridership changes.[7]

The rise of Uber and Lyft and overcrowding on trains have also earned top-billing in popular accounts of Bay Area patronage declines. Regarding the former, reporters and columnists have focused on off-peak use, assuming causation between increased ridehailing and decreased night and weekend transit use. Many officials at transit agencies agree: BART spokesperson Alicia Trost named ridehail and public safety as the two main reasons for the decline. Meanwhile, BART trains have become so overcrowded at peak hours in peak directions that, to paraphrase that master of paradox Yogi Berra, no one rides anymore—it's too crowded. However, a few press accounts have homed in on other issues. A report in the *Marin Independent Journal*, for example, argued that increased congestion slowing down buses and rising rents pushing out low-income transit users have hurt bus ridership across the region. Still, these major causes, identified by academic literature, do not feature prominently in regional press accounts.[8]

7. Rick Hurd, "Audio Dispatch of Oakland BART Mob: 'It's a Group of 50. They Bum-rushed the Entire Train,'" *Mercury News* (San José, CA), Apr. 25, 2017; John Diaz, "BART Attack Brings Out Racist Responses," *SFGATE*, Apr. 29, 2017; KGO-TV, "What We Know about Deadly Stabbing at Oakland's MacArthur BART Station," *ABC7 News*, Jul. 25, 2018; Paul Eichenholtz, "BART Security Strategies Clash with Distrustful Ridership," *Golden Gate Xpress* (SF State), Oct. 23, 2018; Aaron Sankin, "BART Police Department: Is It Necessary?," *Huffington Post*, Aug. 31, 2011; Michael Cabanatuan, "With BART Ridership Down, and Complaints Up, Agency Promises New Cleanup," *San Francisco Chronicle*, Feb. 10, 2018; Michael Cabanatuan, "With Ridership Down, Complaints Up, BART to Look at Homeless Problem," *SFGATE*, May 11, 2017; and Lyanne Melendez, "BART Riders Increasingly Concerned with Safety," *ABC7 News*, Jul. 26, 2018.

8. Phil Matier and Andy Ross, "BART Ridership Drops on Nights, Weekends," *San Francisco Chronicle*, Aug. 20, 2018; Chloe Veltman, "BART Looks for Solutions After Another Steep Drop in Weekend Ridership," *KQED*, Aug. 20, 2018; Jay Barmann "Overcrowded BART Trains Likely Causing Drop in Ridership, Ironically," *SFist*, Feb. 24, 2017; Houston Mitchell, "Yogi Berra Dies at 90: Here Are Some of His Greatest Quotes." *Los Angeles Times*. Sept. 22, 2015; Gary Richards, "Marin Bus Ridership Decline Mirrors Bay Area," *Marin Independent Journal*, Jun. 4, 2018; and Joe Castiglione et al., *TNC's and Congestion*. October 2018.

2.3. Previous Research

Indeed, unlike the popular narratives around ridership declines, the findings of academic literature—with some notable dissenters—point towards factors largely outside of the control of transit agencies (though internal factors do nonetheless have some significant effect). Two types of papers generally indicate this same result. First, a few scholars have tackled a synthetic causal analysis of transit ridership using as many factors as possible as explanatory variables. Most of these papers take data nationwide and use metropolitan areas as the unit of analysis. A second set of works provide more focused examinations of individual factors, determining what effect each alone has on transit ridership through both descriptive and causal lenses. Below, I discuss each in turn.

2.3.1. Synthetic Regressions

In the past decade, two major papers have conducted regressions analyses to explain nationwide ridership tends. In 2009, Taylor et al. modeled patronage for urbanized areas in the U.S. and found a number of significant determinants, including population density, percent of carless households, and median household income. Overall, their regression finds that that internal factors (vehicle revenue miles and fares) account for only 26 percent of transit ridership variation per capita. However, a 2015 Mineta Transportation Institute report by Alam et al. reaches the opposite conclusion for metropolitan statistical areas: of the eight statistically significant variables in the regression, only one (gas prices) is external. In fact, six external variables that are significant in Taylor et al.'s regression end up insignificant in Alam et al.'s. More recently, Boisjoly et al. come to the same conclusion, with revenue vehicle mileage by far contributing the most to ridership in metropolitan areas across the U.S. and Canada.[9]

What explains the difference? Primarily, the divergence arises from ways that each handles transit supply. Taylor et al. assume that service changes both cause and are caused by ridership changes—i.e., agencies supply more service when increased ridership calls for it, which may in turn

9. Brian D. Taylor, Douglas Miller, Hiroyuki Iseki, and Camille Fink, "Nature and/or Nurture?: Analyzing the Determinants of Transit Ridership across U.S. Urbanized Areas," *Transportation Research Part A* 43 (2009): 60-77; Bhuiyan Alam, Hilary Nixon, and Qiong Zhang, *Investigating the Determining Factors for Transit Travel Demand by Bus Mode in U.S. Metropolitan Statistical Areas* (MTI Report 12-30, Mineta Transportation Institute, San José, CA, May 2015); and Geneviève Boisjoly, et al., "Invest in the Ride: A Fourteen-year Longitudinal Analysis of the Determinants of Public Transport Ridership in Twenty-five North American Cities," *Transportation Research Part A:* 116 (2018): 434-45.

further boost ridership. Therefore, the authors estimate a two-stage regression model using a predicted transit service variable independent of ridership. Alam et al., citing a similar finding in 2006 by Thompson and Brown, do not do so, assuming that the reciprocal relationship between transit supply and ridership only occurs in the long term. This objection, though, misunderstands Taylor et al.'s reasoning: even if the reciprocity takes a few years, the circularly causality still holds true, in whatever year the study chooses for its cross-sectional data. Overall, as Taylor et al. write, "when the levels of transit supply and consumption are jointly determined, it is not possible to consider one in isolation from the other."[10] Indeed, since Alam et al. and Boisjoly, et al. find such significance in transit supply, their assumption that transit supply is not in turn caused by ridership surely deserves a statistical analysis in and of itself. In other words, if variation in transit supply determines most of the variation in ridership, far more so than other factors, then this raises the question of what determines variation in transit supply.[11]

Synthetic studies of transit ridership in individual metropolitan areas also give conflicting weights to internal and external factors. In a report for the Southern California Association of Governments, Manville, Taylor, and Blumenberg conducted a number of descriptive and causal analyses of Los Angeles' ridership. They found that increased household auto access accounted for the vast majority of changes in transit trips per capita. Other external factors, like income, immigration status, etc., affected ridership in an indirect, mediated manner: these factors influenced auto access, which in turn influenced transit use. Service hours and miles, meanwhile, increased as ridership fell, and the authors also found fares to have a smaller effect than common elasticities would predict. Nevertheless, other studies have found greater effect from internal factors. Chen et al., for instance, find that the ridership elasticity with respect to fares is higher than the elasticities with respect to gas prices and employment. In Atlanta, Brown and Thompson saw a larger effect in their regression from service and fare levels than from various measures of employment distribution. Still, neither of these studies corrects for the simultaneity of transit supply and demand, though Chen et al. do find that service supply determines service demand far more than the reverse.[12]

10. Taylor et al., "Nature and/or Nurture?," 63.

11. Ibid.; Alam et al., *Investigating the Determining Factors*; Gregory L. Thompson and Jeffrey R. Brown, "Explaining Variation in Transit Ridership in U.S. Metropolitan Areas between 1990 and 2000: Multivariate Analysis," *Transportation Research Record* 1986 (2016): 172-81; and Boisjoly, et al., "Invest in the Ride."

12. Manville, Taylor, and Blumenberg, *Falling Transit Ridership*; Cynthia Chen, Don Varley, and Jason Chen, "What Affects Transit Ridership? A Dynamic Analysis Involving

At a more micro-scale, other papers have examined ridership not by metro area but by individual stations. Here, the regressions involve different methods of geographically weighting variables by distance from stations. At this level of analysis, external factors predominate—though in part because most of the independent variables in the regression models are external factors to begin with. A 2011 paper by Gutiérrez et al. exemplifies the group. Six of the nine statistically significant factors are outside of agencies' control. However, in their model, the numbers of rail and connecting bus lines serve to proxy service supply, but only in some cases are these very well-correlated (e.g., on BART, modeled in Section 5 of this report, whose lines each operate at same headways most of the day). When more detailed variables like number of buses per day are included, as Cervero et al. did in 2010 in studying Los Angeles' Orange Line bus rapid transit, their effect is roughly on par with external attributes like population density.[13] My report largely fits within this literature, but seeks to expand the scope of analysis and bring lessons from macro-scale studies to bear on more granular ridership changes.

One synthetic study of transit ridership is of particular relevance: Gregory Erhardt's 2016 dissertation on modeling BART and Muni ridership. In his thesis, Erhardt uses an advanced time-series model (RegARIMA) to explore why BART patronage grew while Muni ridership fell between 2009 and 2013 (the results of which are presented in Tables 2-1 and 2-2). He concludes that employment was the most important reason BART ridership rose, far more so than service supply. Jobs also boosted Muni ridership, but an unexplained negative factor more than counteracted the effect of employment and pulled down overall patronage. Erhardt leaves this factor unresolved, although he does rule out ridehail and displacement. All told, Erhardt's models demonstrate the greater influence of external factors than of fares and service, though a Muni service cut and BART extensions have had some effect. While his models cover a period before the current decline and

Multiple Factors, Lags, and Asymmetric Behavior," *Urban Studies* 48, no. 9 (Jul. 2011): 1893-1908; and Jeffrey R. Brown and Gregory L. Thompson. "The Relationship between Transit Ridership and Urban Decentralization: Insights from Atlanta." *Urban Studies* 45, no. 5 and 6 (May 2008): 1119-39.

13. Javier Gutiérrez, Osvaldo Daniel Cardozo, and Juan Carlos García-Palomares, "Transit Ridership Forecasting at Station Level: An Approach Based on Distance-decay Weighted Regression," *Journal of Transport Geography* 19, no. 6 (Nov. 2011): 1081-92; Michael Kuby, Anthony Barranda, and Christopher Upchurch, "Factors Influencing Light-rail Station Boardings in the United States," *Transportation Research Part A* 38, no. 3 (Mar. 2004): 223-47; Xuehao Chu, "Ridership Models at the Stop Level" (NCTR-473-04, BC137-31, NCTR, CUTR, USF, Tampa, FL, Dec. 2004); and Robert Cervero, Jin Murakami, and Mark Miller, "Direct Ridership Model of Bus Rapid Transit in Los Angeles County, California," *Transportation Research Record* 2145 (2010): 1-7.

are not geographically disaggregated at the stop level, Erhardt confirms my findings in Section 5 on the predictive power of employment on BART.[14]

Table 2-1: Contributions of Various Factors to Change in Muni Ridership (from Erhardt, 2016)[15]

Factor	*Contribution to Muni Ridership Change, Sept. 2009 to Sept. 2013*
Bus service miles	-4.6%
Rail service miles	+2.2%
Average bus speed	-4.3%
Employment in San Francisco	+11.3%
Unexplained trend	-14.0%
Residual	+2.9%
Total (Net Effect of the Above Factors)	*-6.5%*

Table 2-2: Contributions of Various Factors to Change in BART Ridership (from Erhardt, 2016)[16]

Factor	*Contribution to BART Ridership Change, Sept. 2009 to Sept. 2013*
Service miles	-0.9%
Number of stations	+1.5%
Employment in BART-served counties	+10.4%
Share of employment in San Francisco	+1.9%
Fare	+1.4%
Gas price	+0.5%
Days of BART strike	0.0%
Unexplained trend	+5.3%
Residual	-2.5%
Total (Net Effect of the Above Factors)	*+17.6%*

14. Gregory D. Erhardt, "Fusion of Large Continuously Collected Data Sources: Understanding Travel Demand Trends and Measuring Transport Project Impacts" (PhD diss., Univ. College London, London, 2016), 117-267, 303-5 and Richard A. Mucci and Gregory D. Erhardt. "Evaluating the Ability of Transit Direct Ridership Models to Forecast Medium-Term Ridership Changes: Evidence from San Francisco," *Transportation Research Record* 2672, no. 46 (2018): 21-30.
15. Erhardt, "Fusion of Large," 251.
16. Ibid.

2.3.2. External Factors

As these studies demonstrate, external factors, viewed in total, have a dramatic effect on patronage—though alone, some may only have small influences. Manville, Taylor, and Blumenberg, as discussed above, join a number of authors, like Boisjoly et al., in emphasizing the critical significance of auto access and ownership on transit ridership. Regional economic factors like median income also proved significant in the models of Taylor et al. and others. In academic circles, the most discussed factor influencing travel behavior is likely the built environment. Ewing and Cervero's 2010 meta-analysis and Stevens' updated 2017 meta-regression have both caused a flurry of writing and debate on the effect of land use variables like population and employment density, land use diversity, and intersection density on vehicle miles traveled. These studies indirectly discuss transit use—less driving may mean more transit-riding—but in many cases, they also look at the direct effects of the built environment on transit patronage. To take one study, Guerra and Cervero find significant correlations between population density and ridership and between job density and ridership. Overall, these elasticities are significant but small. Larger are the effects of parking supply and road pricing policy on transit use. For instance, Chatman has found parking in transit-oriented developments better predicts auto ownership (and therefore transit use) than rail access itself.[17]

Other external factors also play roles in transit use. Studies have shown an influence of gas prices on ridership, though a much smaller one than media reports might suggest. On top of the prior examinations detailed in Taylor and Fink's review, a more recent study by Lane finds a significant but small effect. This effect is greater on rail travel than bus and occurs after a variable lag of up to 13 months after a gas price change. Even weather and climate likely have an effect on transit patronage—though a review by Liu et al. finds very mixed results on whether high temperatures and precipitation

17. Manville, Taylor, and Blumenberg, *Falling Transit Ridership*; Boisjoly, et al., "Invest in the Ride"; Taylor and Fink, "Explaining Transit Ridership"; Reid Ewing and Robert Cervero, "Travel and the Built Environment: A Meta-Analysis," *Journal of the American Planning Association* 76, no. 3 (Summer 2010): 265–94; Mark R. Stevens, "Does Compact Development Make People Drive Less?" *Journal of the American Planning Association* 83, no. 1 (Winter 2017): 7–18; Erick Guerra and Robert Cervero, "Cost of a Ride: The Effects of Densities on Fixed-guideway Transit Ridership and Costs," *Journal of the American Planning Association* 77, no. 3 (Summer 2011): 267–90; Michael Manville, "Travel and the Built Environment: Time for Change," *Journal of the American Planning Association* 83, no. 1 (Winter 2017): 29–32; and Daniel G. Chatman, "Does TOD Need the T?: On the Importance of Factors Other than Rail Access," *Journal of the American Planning Association* 79, no. 1 (Winter 2013): 17–31.

increase or decrease ridership.[18]

2.3.2.1. Displacement and Immigration

Displacement of poorer residents from more transit-accessible areas to less has intensified in recent years and likely plays a role in ridership changes in the Bay Area, the poster child for displacement through rising rents. However, while the literature is large on individual and household housing location decisions and their relation to travel behavior, far fewer papers have tied changing residential patterns to aggregate ridership. In a 2017 study, Wang and Woo found that the decentralization of poverty in the Atlanta area has lowered the average income in transit-rich suburban neighborhoods, which in turn has increased transit ridership significantly. On a national scale, Driscoll et al. descriptively note that population is increasing markedly in counties with poor transit service and use. Blumenberg et al. find that millennials—the generation that, according to conventional wisdom, would give up their cars and move back to cities *en masse*—have actually moved to suburbs at much higher rates than to cities, albeit less so than the prior generation. On top of recent changes in intranational residential location, the size and nationalities of immigration flows into the U.S. have also changed. In 2007, Blumenberg found that immigrants accounted for almost all of California's then two-decade transit ridership growth and presciently predicted that decreases in immigration thereafter would pull down patronage. Indeed, the flow of immigrants has decreased, become more Asian and less Hispanic, and overall assimilated into auto use faster than before. Both of these factors merit further study in relation to transit patronage trends.[19]

2.3.2.2. Ridehail

The effect of ridehail on transit has seen hot debate among scholars and policymakers. A number of splashy reports have blamed ridership declines and traffic congestion on Uber and Lyft—but their methods fail to

18. Taylor and Fink, "Explaining Transit Ridership"; Bradley W. Lane, "A Time-series Analysis of Gasoline Prices and Public Transportation in U.S. Metropolitan Areas," *Journal of Transport Geography* 22 (2012): 221-35; and Chengxi Liu, Yusak O. Susilo, and Anders Karlström. "Weather Variability and Travel Behaviour—What We Know and What We Do Not Know," *Transport Reviews* 37, no. 6 (2017): 715-41.

19. Kyungsoon Wang and Myungje Woo, "The Relationship between Transit-rich Neighborhoods and Transit Ridership: Evidence from the Decentralization of Poverty," *Applied Geography* 86 (Sept. 2017): 183-96; Richard A. Driscoll et al., "The Effect of Demographic Changes on Transit Ridership Trends," *Transportation Research Record* 2018: 1-9; Evelyn Blumenberg et al., *Typecasting Neighborhoods and Travelers: Analyzing the Geography of Travel Behavior among Teens and Young Adults in the U.S.*, Sept. 25, 2015, viii, 86; and Taylor and Fink, "Explaining Transit Ridership," 20.

properly consider an alternative scenario without ridehail, and their evidence consists primarily of pointing at a plot of increasing ridehail use and decreasing transit use and inferring causation. They do demonstrate, though, the high stakes of the research on ridehail.[20] Indeed, unlike most other major factors, not only is the magnitude of ridehail's effect on transit disputed, but also the direction. On one hand, Uber and Lyft could be attracting riders away from transit, replacing trips that could have been made—or once were made—on bus or rail. On the other hand, ridehail could complement transit: in the short term, bridging the first-mile/last-mile gap between transit stops and destinations and in the long term, reducing car ownership altogether. Finally, transit service may be deteriorating for reasons unrelated to ridehail, pushing people to Uber and Lyft through no doing of their own.

Some researchers have attempted to investigate the first of these hypotheses by surveying Uber and Lyft customers and asking how they would have traveled if ridehail did not exist. Table 2-3 summarizes their findings:

20. Bruce Schaller, *Unsustainable?: The Growth of App-based Ride Services and Traffic, Travel and the Future of New York City*, Feb. 27, 2017.

Table 2-3: Surveys of Ridehail Customers[21]

Author(s) and Year	Survey Population	Type of Trip Asked About	Percent that Would Take Transit if/when Ridehail Were Not Available	Survey Method
Hampshire et al., 2018	Austin	most recent trip	3%	Internet survey after ridehail left
APTA, 2016	seven cities	most frequent trip	14%	Internet or phone survey
Clewlow and Mishra, 2017	seven metro areas	all trips	15%	Internet or phone survey
Circella et al., 2018	California millennials and Gen Xers	most recent trip	21.1%	Internet or phone survey
Henao, 2017	Denver	most recent trip	22.2%	In-person survey
Rayle et al., 2016	San Francisco	most recent trip	30%	In-person survey
Gehrke et al., 2018	Boston area	most recent trip	42%	In-person survey
NYCDOT, 2018	New York City	most recent trip	50%	Internet or phone survey

As the fourth column shows, the surveys come to very different conclusions.

21. Robert C. Hampshire et al., "Measuring the Impact of an Unanticipated Disruption of Uber/Lyft in Austin, TX" (paper presented at the TRB 97th Annual Meeting, Washington, D.C., Jan. 7-11, 2018); Colin Murphy, *Shared Mobility and the Transformation of Public Transit* (TCRP Project J-11, Task 21, Shared-use Mobility Center, Chicago, IL, Mar. 2016), ed. Tim Frisbie; Regina R. Clewlow and Gouri Shankar Mishra, *Disruptive Transportation: The Adoption, Utilization, and Impacts of Ride-Hailing in the United States* (UC Davis-ITS-Research Report-17-07, ITS, UC Davis, Davis, CA, Oct. 2017); Giovanni Circella et al., *The Adoption of Shared Mobility in California and Its Relationship with Other Components of Travel Behavior*, Mar. 2018; Alejandro Henao, "Impacts of Ridesourcing—Lyft and Uber—on Transportation Including VMT, Mode Replacement, Parking, and Travel Behavior," PhD diss., University of Colorado, 2017; Lisa Rayle et al., "Just a Better Taxi?: A Survey-based Comparison of Taxis, Transit, and Ridesourcing Services in San Francisco," *Transport Policy* 45 (2016): 168-78; Steven R. Gehrke, Alison Felix, and Timothy Reardon, *Fare Choices: A Survey of Ride-hailing Passengers in Metro Boston* (Report #1, MAPC Research Brief, Metropolitan Area Planning Council, Boston, MA, Feb. 2018); NYCDOT, *New York City Mobility Report*, Jun. 2018, 8, 26, 39; and Bruce Schaller, *The New Automobility: Lyft, Uber and the Future of American Cities*, Jul. 25, 2018.

Part of the difference stems from the wording of the question: most surveys ask riders how they would have taken their most recent trip if Uber and Lyft did not exist, while APTA and Clewlow and Mishra asked how riders would have taken their most frequent trip or all their ridehail trips, respectively. These two surveys asked respondents to imagine a counterfactual without ridehail but with their most frequent destinations in the same locations, ignoring the fact that people move, take jobs, choose social venues, etc. based in part on transportation access. Regardless of the question wording, though, seven of the eight surveys rely on stated preferences, yet respondents' actual behaviors could differ greatly than what they tell a surveyor. Only Hampshire et al. rely on revealed preferences, using a natural experiment: looking at behavior of former ridehail customers during a period when Uber and Lyft temporarily left Austin, Texas. Their low three percent transit replacement rate may indicate that ridehail does not substitute for transit to a large degree in an urban area with already relatively low rates of public transit use.[22]

Given the limitations of this type of survey question, researchers have used other methods to investigate ridehail's effects on transit. Some have found that ridehail and transit serve different markets. A number of studies, including many in Table 2-3, have uncovered that the most popular ridehail trip times and purposes are those that transit serves poorly, like late-night and weekend travel. However, per Conway et al., transit users also resemble ridehail users over a number of characteristics. Looking at actual Lyft data, Brown finds that transit stop density is the variable most positively associated with Lyft use among a set of built environment and demographic factors—a discovery that could support ridehail as transit complement or substitute.[23]

Despite the mixed findings above, I see reason for operators to worry about ridehail substituting for transit trips, particularly in the Bay Area. In the Bay Area—a dense, transit-rich region where riderhail has operated longer than anywhere else and where a greater share of people drive for ridehail than anywhere else[24]—these mature services may indeed be substituting for

22. Hampshire et al., "Measuring the Impact"; Murphy, *Shared Mobility*; Clewlow and Mishra, *Disruptive Transportation*; Circella et al., *Adoption of Shared Mobility*; Henao, "Impacts of Ridesourcing"; Rayle et al., "Just a Better Taxi?"; Gehrke et al., *Fare Choices*; and NYCDOT, *Mobility Report*, 8, 26.

23. Rayle et al., "Just a Better Taxi?," 171–2; Murphy, *Shared Mobility*, 11–2; Robert James Evans, "The Value of Data: Analyzing Transportation Network Company Trips for Transit Planning," PhD diss., University of Texas at Austin, 2018; Matthew Wigginton Conway, Deborah Salon, and David A. King, "Trends in Taxi Use and the Advent of Ridehailing, 1995–2017: Evidence from the U.S. National Household Travel Survey," *Urban Science* 2, no. 3 (Sept. 2018): 79 ff.; and Anne Elizabeth Brown, "Ridehail Revolution: Ridehail Travel and Equity in Los Angeles," PhD diss., UCLA, 2018, 65.

24. Diana Farrell, Fiona Greig, and Amar Hamoudi, *The Online Platform Economy in Twenty-seven Metro Areas: The Experience of Drivers and Lessors*. Apr. 2019, 9.

transit. Using differences in when Uber entered various markets, Graehler et al. find that, for every year after the arrival of Uber, heavy rail patronage falls 1.3 percent and bus ridership 1.7 percent, all else equal. "Our research…suggests," they conclude, "that past research findings that [ridehail] and other emerging modes either increase or do not affect transit ridership are likely incorrect."[25] This contradicts an earlier study by Hall et al. that found that Uber increases transit ridership by 5 percent after two years, though Hall et al. uncover significant heterogeneity and do not control for car ownership. But in support of Graehler et al., a piece by Babar and Burtch with comparable methodology finds that ridehail does reduce bus ridership (though it increases subway and commuter rail ridership).[26]

Other papers also point towards substitution of transit trips by ridehail in dense urban settings. Returning to Table 2-3, the more recent surveys and especially those taken in larger metropolitan areas have higher rates of substitution. In a different part of their study, Clewlow and Mishra find that ridehail users who now take transit less often outnumber those who take it more often by six percentage points. Likewise, Henao discovered that only one percent of riders surveyed were taking ridehail to connect to transit. Finally, Lavieri et al. find that higher bus frequencies reduce ridehail use, again supporting substitution over complementarity.[27] Thus, even if ridehail and transit initially served different markets, more mature and ubiquitous ridehail networks do have the potential to substitute for transit's core trips—especially in Uber and Lyft's longest-served market.

2.3.3. Internal Factors

Given the influence on transit use of the many factors discussed above, agencies appear to have little, well, agency. However, even those studies that show external factors predominating also find a significant role for internal policies in determining ridership. As mentioned above, Taylor et al. find that internal factors explain 26 percent of ridership variation per capita. In Alam et

25. Michael Graehler, Jr., Richard Alexander Mucci, and Gregory D. Erhardt, "Understanding the Recent Transit Ridership Decline in Major US Cities: Service Cuts or Emerging Modes?" (paper presented at the TRB 98th Annual Meeting, Washington, D.C., Jan. 13-7, 2019), 15.

26. Ibid.; Angie Schmitt, "Study: Uber and Lyft Caused U.S. Transit Decline," *Streetsblog USA*, Jan. 22, 2019; Jonathan D. Hall, Craig Palsson, and Joseph Price, "Is Uber a Substitute or Complement for Public Transit?" (Working Paper tecipa-585, University of Toronto, Department of Economics, Toronto, ON, Jun. 13, 2018); and Yash Babar and Gordon Burtch, "Examining the Impact of Ridehailing Services on Public Transit Use," Sept. 25, 2017.

27. Clewlow and Mishra, *Disruptive Transportation*; Henao, "Impacts of Ridesourcing"; and Patrícia S. Lavieri et al, "A Model of Ridesourcing Demand Generation and Distribution," *Transportation Research Record* 2672, no. 46 (2018): 39.

al.'s model, such factors together have the largest influence on ridership.[28] Other studies, described below, have looked more specifically at the effects of fares and service levels on ridership.

2.3.3.1. Fares

The literature on ridership elasticity with respect to fares dates back decades and is as much a topic of economics research as of planning. In 2004, Litman conducted a literature review of elasticities with respect to fares and estimated a consensus elasticity of -0.2 to -0.5 in the short term and -0.6 to -0.9 in the long term. Peak-period riders tend to be less elastic in their responses to fare changes than off-peak riders, while suburban commuters have higher elasticities than other riders. Moreover, Litman concluded in his review that riders were more elastic in the responses to service changes than fare changes. These findings confirm research by Cervero in 1990, finding that seniors, people with low incomes, people without a car, commuters, and people taking short trips all have lower elasticities than their counterparts, as they depend on transit more for those trips. More recently, Schimek created a model that confirms Litman's fare elasticities and likewise finds transit to be more elastic with respect to service (measured in terms of vehicle revenue miles) than fares or gas prices.[29]

2.3.3.2. Service

Turning from fares to service, in 2012, Thompson et al. investigated the effects of travel speed and network structure in Broward County, Florida. Their model explains the success of Broward's bus system as a function of its multi-destination, non-radial route structure (as measured by its in-vehicle travel times), more so than the land use or density of the area. Applications of these principles, like Houston's bus network redesign, offer real-world proofs of concept that good management of internal factors can stabilize or increase ridership.[30]

28. Taylor et al., "Nature and/or Nurture?" and Alam et al., *Investigating the Determining Factors*.

29. Litman, "Transit Price Elasticities"; Robert Cervero, "Transit Pricing Research: A Review and Synthesis," *Transportation* 17 (1990): 117–39; and Paul Schimek, "Dynamic Estimates of Fare Elasticity for U.S. Public Transit," *Transportation Research Record* 2538 (2015): 96–101.

30. Gregory Thompson, Jeffrey Brown, and Torsha Bhattacharya, "What Really Matters for Increasing Transit Ridership: Understanding the Determinants of Transit Ridership Demand in Broward County, Florida," *Urban Studies* 49, no. 15 (Nov. 2012): 3327–45.

2.3.4. Discrete Choice Analyses

All these studies of the determinants of transit ridership sit alongside the literature on discrete choice analysis. Discrete choice analysis broadly describes models of how individuals make decisions among defined, mutually exclusive choices. Scholars have applied it to many fields, but it began, fittingly enough, with a model of BART ridership. While the method generally produces disaggregate predictions of behavior outcomes, some applications can also help illuminate aggregate transit ridership trends. For instance, Ben-Akiva and Morikawa find that infrequent service and multiple transfers reduce people's propensity to ride transit, echoing many of the results above. On the external side, Rajamani et al.'s discrete choice model shows that mixed-use environments and higher residential densities increase the likelihood of transit use for non-work travel. Cervero and Duncan complicate this, finding that about 40 percent of the decision to commute by rail is due to residential self-selection, based on data from the Bay Area. Finally, in contrast to Conway et al.'s findings above, Dias et al.'s model determines that ridehail users in the Seattle area differ demographically from core transit riders—the former tend to be younger, more well-educated, and higher-income.[31]

2.3.5. Financial Implications

Affected by all of the influences detailed above, transit ridership in turn influences the financial health of an agency. For instance, Taylor, Garrett, and Iseki found in 2000 that peaking—the concentration of ridership during rush hours—significantly increases the costs of providing service, above what the agency cost-allocation model they examined had estimated. It is expensive to hire workers for full shifts and to maintain a large fleet of vehicles—both of which are mainly needed at peak and sit idle otherwise. On the capital side, Guerra and Cervero calculated in 2011 that many rail projects across the nation did not meet their ridership projections because they were built in an environment not dense enough to support them. This led many to be highly

31. "Discrete Choice Analysis," *Columbia Mailman School of Public Health*, n.d.; Daniel L. McFadden, "The Path to Discrete-choice Models," *ACCESS* 20 (Spring 2002): 2-7; Moshe Ben-Akiva and Takayuki Morikawa, "Comparing Ridership Attraction of Rail and Bus," *Transport Policy* 9 (2002): 107-16; Robert Cervero and Michael Duncan, "Residential Self Selection and Rail Commuting: A Nested Logit Analysis" (working paper, UCTC, Berkeley, CA, Jun. 2008); Jayanthi Rajamani et al., "Assessing Impact of Urban Form Measures on Nonwork Trip Mode Choice after Controlling for Demographic and Level-of-service Effects," *Transportation Research Record* 1831 (2003): 158-65; Conway et al., "Trends in Taxi Use"; and Felipe F. Dias et al., "A Behavioral Choice Model of the Use of Car-sharing and Ride-sourcing Services," *Transportation* 44, no. 6 (Nov. 2017): 1307-23.

cost-ineffective.[32] Whatever the causes of transit ridership changes and ridership peaking, they can cause public agencies profound fiscal harm.

2.4. Conclusion: Gaps and Place in the Literature

With a large dose of nuance and dissent, external factors do appear to have more influence on ridership than internal factors—an influence that has likely grown recently. However, despite the breadth of the literature, two gaps remain. For one, few works have explored recent ridership trends in the last decade. Even fewer examine ridership change, as opposed to absolute levels of ridership. Because of this gap, new influences like the rise of ridehail services like Lyft and Uber, the increase in central-city residential displacement, the suburbanization of poverty, and the re-urbanization of employment have gone relatively unexplored. These factors are especially relevant in the explosive economic climate of the Bay Area, also the nation's epicenter of gentrification and the original home of ridehail. Secondly, most previous work analyzes ridership for the country or for a metropolitan area on aggregate. The pieces that do look at station-level ridership do not consider variation in ridership by time of day or day of the week, and they generally are more focused on methodological debates on how to geographically weigh inputs than broader questions of explaining ridership. By examining recent ridership change and by looking at geographic and temporal variation within agencies, this report offers a novel addition to the existing literature.

32. Brian D. Taylor, Mark Garrett, and Hiroyuki Iseki, "Measuring Cost Variability in Provision of Transit Service," *Transportation Research Record* 1735, no. 1 (2000): 101–12 and Guerra and Cervero, "Cost of a Ride."

A Method to Explore Transit's Madness: Data and Methodology

3.1. Introduction

Like a rowboat that just sprung a leak, transit ridership in the Bay Area is beginning to founder. Patronage regionwide has fallen for the past two years, in both absolute numbers and per capita. But as with the listing boat, pulled down by holes in certain parts of the hull and buoyed by others, transit ridership is dropping unevenly, pulled down by declines in certain trip types and buoyed by other resilient or growing rider markets. In many non-central areas, at off-peak times, and in counter-commute directions, ridership has sunk deeply. These problem areas are the focus of my analysis. Below, I describe the data with which I have identified these patterns—data which can guide policymakers in plugging the Bay Area's patronage leaks and righting their transit ship.

3.2. Methodological Choices

The analysis in this report draws on a variety of data sources, almost all of which function as censuses, not samples. In other words, rather than, say, measuring ridership at a random set of stops, the major datasets I employ are as complete a record of transit ridership and characteristics of transit supply as agencies can provide. These sources—the National Transit Database and ridership reports from three major Northern California operators—provide a full picture of the state of transit today and how it has changed over the past decade, without being so large that sampling becomes necessary. To be sure, rider intercept surveys, like agency customer satisfaction surveys, and travel diary samples, like the National Household Travel Survey, provide a valuable look at how individuals make travel decisions and perceive the quality of their transportation. But an aggregate-level analysis, with agencies, lines, and stops as the units of analysis, best shows operators the regional transit landscape and specific spatial and temporal changes in their service. These sizable datasets also allow the multivariate statistical analysis in Section 5 to return statistically significant results.

This report analyzes the nine-county Metropolitan Transportation Commission region, with specific attention paid to the areas therein where transit use is changing the most.[33] In this report, "Bay Area" will refer to these nine MTC counties. Additionally, when I use the term "ridership," I generally mean *unlinked* passenger trips—i.e., boardings, counting transfers as multiple trips. While this method may appear to inflate patronage, good data on transfers do not exist on most agencies. However, since BART riders do not tag their farecards again when they change trains, BART's ridership reports track *linked* passenger trips, where intra-agency transfers count as a single trip. I use these linked figures only when comparing BART stations and lines to one another (the descriptive analysis in Section 4.2 and the multivariate statistical analysis in Section 5), not across agencies.[34] Finally, I focus far more on change over time than on cross-sectional snapshots in this report. The absolute number of weekend trips on BART in August 2018, say, matters less than the change in weekend trips from 2015 to 2018 in answering the key questions of this report.

3.3. National Transit Database

Before delving into specific geographic and temporal differences within the Bay Area, I analyze ridership at the regional level and provide nationwide context using the National Transit Database (NTD). The NTD includes annual data on ridership and service characteristics on every transit agency that receives federal funds, from 1991 to 2017. These operators submit their data every year to the Federal Transit Administration, which compiles the NTD and hosts it on their website. The NTD includes the following variables, broken down by agency, travel mode, and year: boardings, passenger miles traveled, service miles, service hours, fare revenues, operating expenses, capital expenses, and more. From these, I calculated additional variables, including productivity (boardings per service hour) and boardings per capita.[35] I also grouped agencies by which metropolitan planning organization (MPO) their service area lies within, building from a helpful table created by UCLA transportation researcher Mark Garrett. Finally, I cleaned up a few small errors in the NTD through manual checks.

Using NTD data, I conducted symmetric descriptive analyses of all of the above variables, observed common trends among them, and delved further into indicative geographies and attributes. These analyses use the Bay Area as a whole as the unit of analysis (as compared to the U.S., California,

33. Alameda, Contra Costa, Marin, Napa, San Francisco, San Mateo, Santa Clara, Solano, and Sonoma Counties

34. Save for one instance, which is noted.

35. Using population figures from the Census in decennial years and intercensal population estimates in yeas in between

and Southern California[36]) or use individual agencies as the units of analysis (compared to each other). The findings of these analyses are presented in Section 4.1, outlining national ridership baselines, the timeline of ridership declines regionwide and by agency, and differences in service provision, etc. between agencies and modes.

3.4. Specific Agencies

3.4.1. Choice of Operators

To describe the specifics of transit ridership changes in the Bay Area, I have also conducted a more detailed descriptive analysis of ridership changes at three major agencies: the San Francisco Municipal Transportation Agency, Bay Area Rapid Transit, and the Santa Clara Valley Transportation Authority. The former two carry approximately 70 percent of boardings in the region and represent exceptional agencies different from all others west of the Mississippi. Muni's comparatively small service area—contained almost wholly in the City and County of San Francisco, under 50 square miles—is denser than any other in the state.[37] BART, meanwhile, is the third most extensive heavy rail network in America and the first of the major postwar transit systems.[38] Both operate in an environment where driving and parking are costlier, slower, and more difficult than the rest of the region and where destinations and housing are packed closely together. By studying these two agencies, I not only got a good sense of the majority of Bay Area ridership but also found some peaking issues that differ from transit operators elsewhere.

In contrast, VTA represents a far more typical U.S. transit agency. VTA serves the sprawling, suburbanized South Bay, more characteristic of the state as a whole than San Francisco or Oakland. Its rail system opened much more recently than BART or Muni, at the beginning of the wave of new light-rail systems over the past three decades. Given its similarities with all but the largest transit operators nationwide, VTA therefore represents something of control case for the Bay Area. I chose VTA because it still carries a substantial portion of the region's boardings—the fourth-largest—but unlike third-ranked AC Transit, it operates both rail and bus service and does not overlap with another major agency, as AC does with BART.

36. The five-county Southern California Association of Governments (SCAG) region: Los Angeles, Orange, Riverside, San Bernardino

37. "Population Density for U.S. Cities Statistics," *Governing*, 2019.

38. Yonah Freemark, "Route Miles for U.S. and Canada Rail Systems," *The Transport Politic*, 2019 and Michael C. Healy, *BART: The Dramatic History of the Bay Area Rapid Transit System* (Berkeley, CA: Heyday, 2016).

3.4.2. Data Sources

The datasets for each of the agencies vary in the specific variables collected and the reliability and quality of the numbers. BART has the richest ridership dataset. Unlike most other transit agencies, BART charges a distance-based fare and therefore requires customers to tag their farecards both when entering and exiting. Thus, BART has origin *and destination* data on every paying rider, tabulated from data on the fare gates. Every month, BART staff publishes a matrix of aggregate average daily trips between every pair of stations, divided into weekday, Saturday, and Sunday spreadsheets. I calculated monthly totals by multiplying each matrix cell by the number of weekdays, Saturdays, and Sundays, respectively, in that month and then summing them; I then added up monthly totals to arrive at annual figures. All told, I aggregated matrices from 2001 to 2018 into one dataset. I then calculated the ridership over each segment of BART track by creating a series of functions that assigned the proper segments to every origin-destination pair. BART staff also annually publish an even more comprehensive matrix of ridership between every pair of stations, broken down by date and by hour band; I use these in my causal analysis.

BART's incredibly detailed datasets has allowed me not only to look at which stations have seen the greatest changes in combined entries and exits, but also which lines, segments, and trip types have changed the most, especially just before and since BART's ridership peak in 2016. I analyze most of the agency's metrics by their change between 2015 and 2018—one year of flat ridership followed by two years of decline—adding 2015 to help ensure that changes are not anomalies. As with the NTD data, an initial symmetrical analysis of all of the variables above revealed certain areas and times that merited deeper investigation, the results of which are presented in Section 4.2.

Because Muni and VTA only collect complete rider information upon boarding, their data are somewhat less rich—but nonetheless informative. Muni staff have provided a spreadsheet of average daily boardings from Fiscal Year 1998 to Fiscal Year 2018, broken down by fiscal year, day of the week, and line. These data come from automated passenger counters on vehicles and fareboxes and -gates, with some degree of agency estimation, From information on SFMTA's website, I have matched these data with information on the peak frequency, mode, etc. of each line.[39] I have looked at changes in ridership across these variables and have found the greatest changes are

39. SFMTA, "Muni System Map," *SFMTA*. Aug. 2017.

shifts among different Muni services, as opposed to outright ridership losses. More details follow in Section 4.3. Likewise, VTA staff have provided a spreadsheet of average daily boardings by month, every three months from January 2015 to July 2018, broken down day of the week, time of day, and line and collected in a similar manner as Muni's. I have again matched this dataset to route types and modes from VTA's website.[40] I also eliminated January 2018 from the dataset and replaced that month with averages of the prior and following months. I did this because the reported ridership totals for January 2018 were over 50 percent higher than the months before or after it. This increase was evenly spread across most lines, creating an unexplained spike likely due to a data error. After doing this cleaning, I conducted a comprehensive analysis of the available data and honed in on peaking problems and other significant service changes, outlined in Section 4.4.

3.5. Causal Analysis

3.5.1. Model Overview

While my findings from these agency-specific descriptive analyses contain a multitude of findings of geographic and temporal changes in transit service and use, two major themes run through them: relatively constant peak ridership and precipitously dropping off-peak ridership. What, then, explains the uneven patterns of transit use—and transit use more generally in the Bay Area? To answer this question, I have conducted a multivariate statistical analysis of BART ridership. A statistical model that considers and determines the significance of many possible factors provides an additional degree of certainty to the descriptive breakdowns and shows agencies if factors within their control or outside their control primarily cause ridership changes.

Of the three agencies examined above, BART makes the most sense to study with a multi-variate statistical model. BART has suffered the most pronounced peaking, making it an interesting case study of whether the boom in jobs and population in San Francisco explains the bulk of ridership changes. As mentioned above, the agency also collects of numbers of both entries and exits, by date and by hour, providing a fuller picture than the other operators.

I have estimated a regression model of BART ridership, wherein I used various internal and external factors to explain BART use. Uniquely, I designed the model to explain ridership by origin-destination pair—a strategy I have not seen elsewhere in the research literature. For each pair of entry and exit

40. VTA, "By Type," *Santa Clara Valley Transportation Authority*, 2019.

stations, I have the number on annual trips, from 2011 to 2018. Unlike other models that examine ridership by origin only, this model includes demographic, economic, and built-form factors for both ends of the trip and determines their influence independently. Using ridership by origin-destination pair also increases the number of data points used in the model.

To better delineate origin and destination effects, I ran separate models for A.M. and P.M. weekday ridership. Because much—and likely most—of BART riders on weekday mornings are commuting from home to work, residential patterns are generally reflected at the origin and employment patterns at the destination of each trip. To a lesser extent, the reverse is true of P.M. ridership. To be sure, some A.M. weekday trips may be from work to home (night-shifts commutes), some P.M. weekday trips from home to work (evening shifts), and many trips at both times not commutes at all (errands, etc.). The model therefore includes employment and residential factors for both origins and destinations. Still, by separating the model into periods when riders predominantly travel from home to work and the reverse, effects related to each can be most clearly isolated. The limitations of this decision are discussed further in Section 5.5.3. I also ran a model of all off-peak trips, defined as all weekend trips plus weekday trips at hours beyond morning[41] and evening peak[42] (*See Appendix D*).

3.5.2. Model Inputs

The model includes the following explanatory factors, related to the origin, destination, or trip itself:

41. Defined as the three, hour-wide, weekday, A.M. time bands with the most riders: 7 A.M. to 10 A.M.

42. Defined as the three, hour-wide, weekday, P.M. time bands with the most riders: 4 P.M. to 7 A.M.

Table 3-1: Hypothesized Relationship of Model Inputs to Ridership

	Factor	Data Source	Hypothesized Effect on A.M. Ridership	Hypothesized Effect on P.M. Ridership
Origin	Residents within a half-mile[43]	ACS[44]	+	+
	Jobs within a quarter-mile	LODES[45]	Ø	+
	BART-provided parking spaces	BART internal data, 2019[46]	+	not in model
	Lines serving the station	manual coding	+	+
	Whether the station is a terminus[47]	manual coding	+	Ø
	Median household income within a half-mile[43]	ACS[44]	–	Ø
Destination	Residents within a half-mile[43]	ACS[44]	Ø	+
	Jobs within a quarter-mile	LODES[45]	+	+
	BART-provided parking spaces	BART internal data, 2019[46]	not in model	+
	Lines serving the station	manual coding	+	+
	Whether the station is a terminus[47]	manual coding	Ø	+
	Median household income within a half-mile[43]	ACS[44]	Ø	–
Trip	BART travel time in the A.M./P.M.	MTC travel model[48]	–	-
	Ratio of driving time to BART travel time in the A.M./P.M.	MTC travel model[48]	+	+
	Whether the trip involves a transfer	manual coding	–	-

43. Calculated by proportionally allocating parts of census block groups

44. American Community Survey five-year estimates, centered on the year in question

45. Longitudinal Employer-Household Dynamics Origin-Destination Employment Statistics

46. BART, *Parking Statistics 2019*, 2019.

47. Meaning the end of a branch of track, not necessarily the end of a BART line

48. By transportation analysis zones, 2010 A.M./P.M. peak; BART travel time modeled as average walk-to-transit-to-walk time

The model uses jobs within a quarter-mile and population within a half-mile based on best practices from Guerra and Cervero, 2013.[49]

Tables 3-2 and 3-3 provide summary statistics for each of the inputs, for the earliest year of fully available data, 2011, and the most recent, 2015.

Table 3-2: Summary Statistics, 2011

	Factor		Median	High	Low	Standard Deviation
By station	Residents within a half-mile		8,264	35,510	717	7,817
	Jobs within a quarter-mile		1,005	80,983	13	15,995
	BART-provided parking spaces, 2019[50]		1,006	2,978	0	900
	Lines serving the station		2	4	1	1.13
	Whether the station is a terminus		dummy variable (6 termini; 38 through-stations)			
	Median household income within a half-mile		$69,967	$184,578	$26,921	$31,462
By trip (station pair)	BART travel time	weekday A.M.[51]	1:01	2:52	0:06	0:30
		weekday P.M.[52]	1:01	2:42	0:06	0:30
		off-peak[53]	1:04	2:41	0:08	0:31
	Ratio of driving time to BART travel time	weekday A.M.[51]	0.50	1.94	0.12	0.23
		weekday P.M.[52]	0.53	1.72	0.11	0.20
		off-peak[53]	0.44	1.47	0.10	0.18
	Whether the trip involves a transfer		dummy variable (518 trips with a transfer; 1,418 without)			

49. Erick Guerra and Robert Cervero, "Is a Half-mile Circle the Right Standard for TODs?," *ACCESS* 42 (Spring 2013): 17–22.

50. Historical BART parking data were not available, so the number of spaces in 2019 were used in all models and years.

51. Travel times at morning weekday peak, as defined by MTC's travel model

52. Travel times at afternoon weekday peak, as defined by MTC's travel model

53. Unweighted average of travel times at weekday early morning, midday, and evening, as defined by MTC's travel model

Table 3-3: Summary Statistics, 2015

	Factor		Median	High	Low	Standard Deviation
By station	Residents within a half-mile		8,317	39,491	33	8,564
	Jobs within a quarter-mile		987	95,591	19	20,058
	BART-provided parking spaces, 2019[50]		954	2,978	0	903
	Lines serving the station		2	4	1	1.15
	Whether the station is a terminus		dummy variable (7 termini; 38 through-stations)			
	Median household income within a half-mile		$78,707	$207,385	$29,905	$34,422
By trip (station pair)	BART travel time	weekday A.M.[51]	1:01	2:52	0:06	0:30
		weekday P.M.[52]	1:06	2:42	0:06	0:32
		off-peak[53]	1:04	2:41	0:08	0:30
	Ratio of driving time to BART travel time	weekday A.M.[51]	0.50	1.94	0.12	0.23
		weekday P.M.[52]	0.52	1.72	0.11	0.19
		off-peak[53]	0.44	1.47	0.10	0.18
	Whether the trip involves a transfer		dummy variable (604 trips with a transfer; 1,421 without)			

Of special note in the model is the amount of service supplied, operationalized as the number of lines serving the origin and destination stations. Since BART lines generally operate at the same headways, the number of lines fairly captures service levels as well as a rough measure of destination accessibility. But the amount of service supplied is a complex factor in explaining ridership. While increased service tends to boost ridership, agencies often respond to higher ridership demand by increasing service. The same applies to service cuts. Teasing out this relationship with full rigor requires statistically accounting for the endogeneity between transit service supply and demand. As mentioned in Section 2.3.1, Taylor et al. (2009) estimate two-stage statistical models where predicted (rather than actual) service supply is estimated using variables thought to be otherwise unrelated to transit use. This predicted service supply is then included in a second model, along with a host of other variables, to explain ridership.[54]

While acknowledging the methodological superiority of doing so, I do not attempt to account for endogeneity, for two reasons. First, neither headways nor schedules changed over the model's timeframe. While new extensions have opened, BART has purchased and run new trains to keep headways the same at every station, according to staff. In BART's specific case, at least, staff appear not to be responding to change in ridership with change in headways, reducing potential endogeneity between service supply and patronage within this analysis. Secondly, a one-stage regression model is, in effect, a best-case scenario: if the influence of service supply were to show up anywhere, it would be here. In other words, ignoring endogeneity should heighten the observed effect of service supply. The fact that service has so little influence, as shown in Section 5, is therefore all the more telling.

Returning to the full set of inputs, the factors in Table 3-1 are the outcome of dozens of draft models. In these drafts, I included a number of other inputs that ended up not part of the final model for a number of reasons. Some inputs proved too correlated with other factors, and/or they lacked as strong a theoretical basis for inclusion. The tested but omitted independent variables include: surveyed station cleanliness, surveyed presence of a BART police officer, racial and ethnic percentages of the population within a half-mile of the station, fares between each pair of stations, whether the station lies in downtown San Francisco, whether the station lies in downtown Oakland, and more. The exclusion of these inputs from the final model did not change the primary findings described below; the model proved quite robust.

The model does not include a specific measure of the built environment and urban form around the origin or destination. The job density, population density, and transit service supply variables each partially account for urban form, but only indirectly. Earlier versions of the model included a direct measure—Voulgaris et al.'s (2017) neighborhood typologies, which are a composite of built environment, job access, and transit supply characteristics.[55] However, since this variable was constructed using much of the same data as the other inputs in my model, it explains the same portion of the variation in ridership as they do. I thus excluded the neighborhood typologies from the final model. I also left out MTC's Priority Development Areas, another possible land use input, for lack of a sound theoretical

54. Taylor et al., "Nature and/or Nurture?"

55. Carole Turley Voulgaris et al., "Synergistic Neighborhood Relationships with Travel Behavior: An Analysis of Travel In 30,000 U.S. Neighborhoods," *Journal of Transport and Land Use* 10, no. 1 (2017): 437-61.

relationship to current (as opposed to future) transit use.

3.5.3. Model Outcome Variable

The regression model estimated above is a log-linear model. In other words, the dependent variable of the model—that is, the variable that the model attempts to predict using the inputs—is the natural logarithm of the number of trips between each origin-destination pair. Using a log-linear model instead of a typical linear regression fits the data much better and ensures that the model's residuals are normally distributed. In simpler terms, a log-linear model makes more sense, given that ridership on the most traveled origin-destination pairs is exponentially higher than the least-traveled pairs. Practically, a log-linear model can be interpreted roughly as follows: a unit increase in one of the inputs—say, an additional minute of travel time—results in some percent increase in the number of trips. A linear increase in an input results in an exponential increase in the outcome variable.

Where and When: Descriptive Findings

4.1. Regional Ridership Trends

4.1.1. Boardings

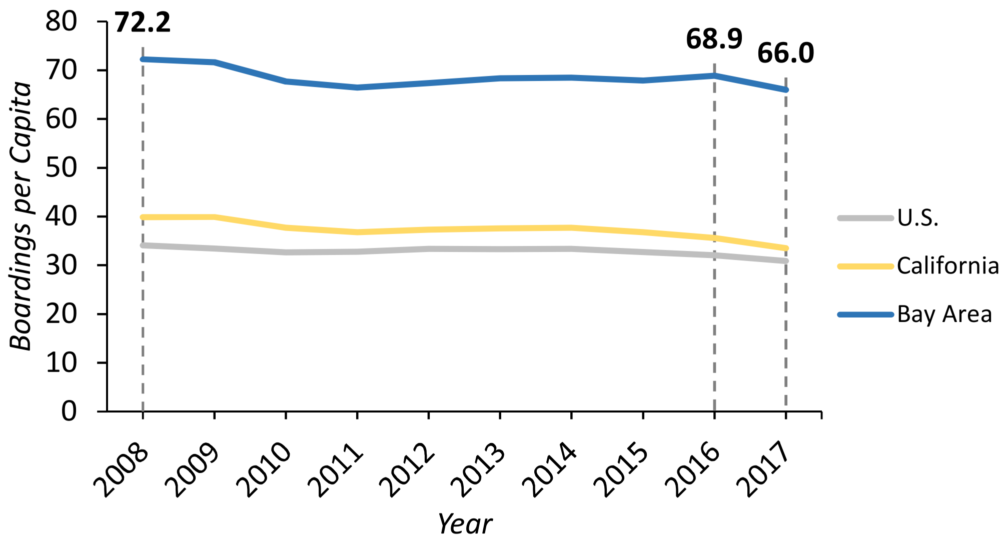
Transit ridership in the Bay Area is declining. This should come as no surprise to anyone who has read this far in this report. However, before delving into reasons for the drop, the decline itself merits examination, given its scale and its timing. Unlike the rest of the country, Bay Area ridership held steady until around the end of 2016. Indeed, ridership had been rising at around two to three percent per year since 2011, a fairly consistent rise that had more than made up for losses during the Great Recession. But in 2017, regionwide patronage fell around four percent, or nearly 20 million annual boardings. Ridership therefore fell to just over 2013 levels, a significant step backwards. In theory, only one year of decline is not necessarily a harbinger of a longer-term trend. However, while 2018 data from the NTD will not be released until October 2019, the 2018 numbers from the three large agencies discussed below indicate continued dips in ridership last year as well. In the Bay Area, ridership continues to veer off the rails.

A look at boardings per capita shows the scale of the region's problem. The Bay Area has experienced substantial population growth in the past decade, growing 11 percent since 2008 (compared to seven percent nationally and seven percent in Southern California).[56] Thus, Bay Area operators' seemingly healthy ridership prior to 2017 may have been caused in large part simply by having more people from which to draw riders. Trends in ridership per capita reveal this to be the case (*See Figure 4-1*). On the positive side, Bay Area agencies have long carried around twice as many trips per person as the United States and California. Still, from 2008 to 2016, the region saw a slow decline in ridership per capita, falling from 72 trips per person to 69. In 2017, ridership per capita plummeted, dropping to 66 trips per person in a single year. This represents the steepest one-year drop since the height of the Great Recession. Thus, as the region gets more and more

56. U.S. Census Bureau, "Annual Estimates of the Resident Population: April 1, 2010 to July 1, 2017," March 2018; U.S. Census Bureau, Population Division, *Intercensal Estimates of the Resident Population for Counties of California: April 1, 2000 to July 1, 2010*, Sept. 2011; and U.S. Census Bureau, Population Division, *Intercensal Estimates of the Resident Population for the United States, Regions, States, and Puerto Rico: April 1, 2000 to July 1, 2010*, Sept. 2011.

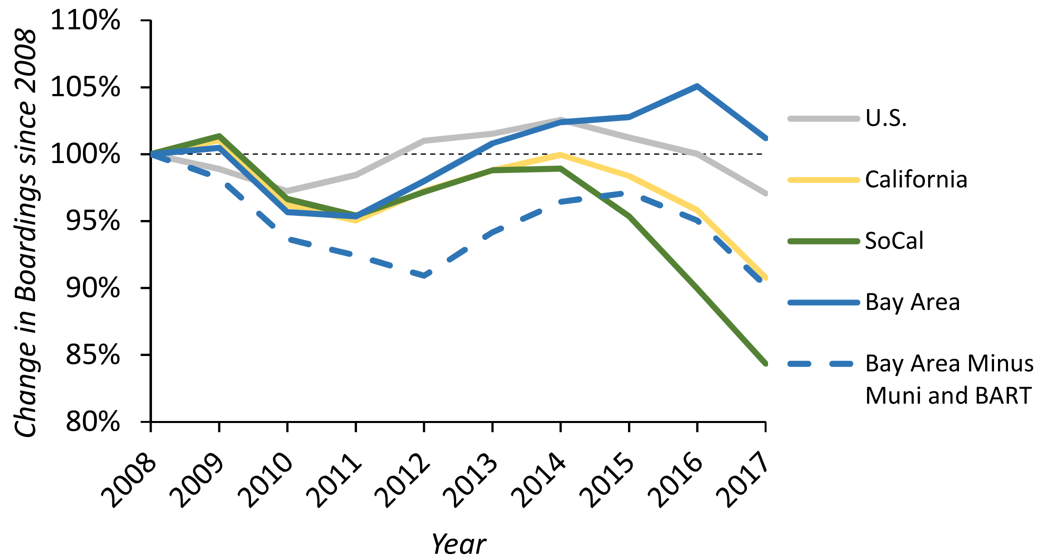
residents, they are riding less and less—dramatically so since the start of 2017. This last year of freefall should be cause for concern, but so too should the preceding decade of ridership failing to keep pace with rising population.

Figure 4-1: The Scale of the Ridership Decline



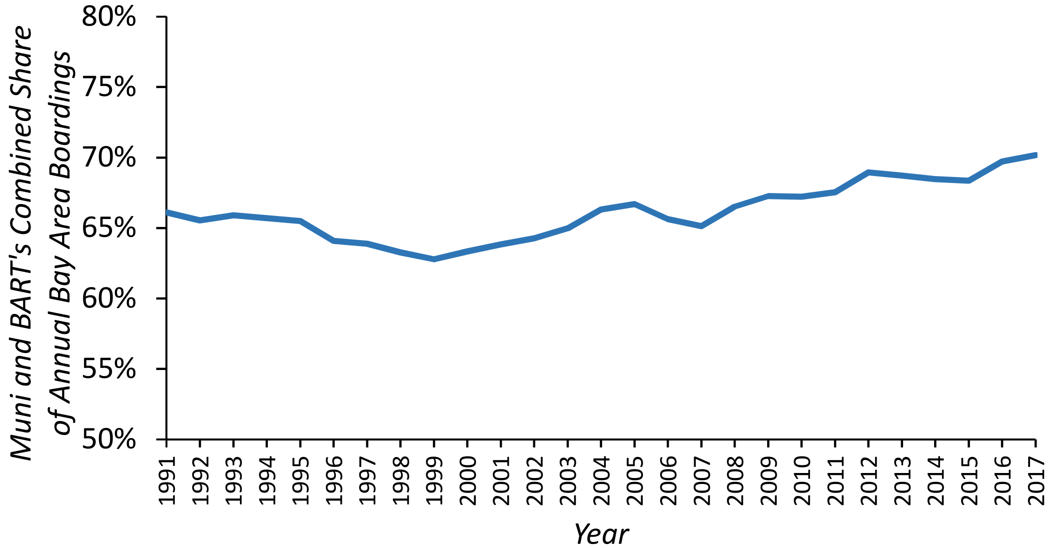
Falling ridership is not unique to the Bay Area. Indeed, across the country and state, transit patronage is down. The difference though, is in timing. Figure 4-2 shows how ridership in the U.S., California, Southern California, and the Bay Area has changed since 2008. The former three peaked in 2014 and have declined ever since, steepening every year. In contrast, the Bay Area continued to climb until 2016, only falling thereafter. At first glance, by this metric, Northern California ridership looks more resilient. The region's decade-long downward trend in ridership per capita, though, shows that these top-line ridership numbers have long masked earlier warning signs. Still, the timing difference between the Bay Area and the rest of the country is notable. This lag may mean that a wholly different set of factors are behind Northern California's drop or merely that the same factors are operating on a delay. The forthcoming UCLA Institute of Transportation Studies report will provide a fuller answer to this question. But based on the fact that Southern California has lost the most riders on its busiest routes, while major Bay Area agencies have lost most of their riders off-peak, the former may well be the case.

Figure 4-2: A Later Decline in Boardings in the Bay Area



The region's ridership trends look quite different when Muni and BART are excluded (*See Figure 4-2*). As in most metropolitan areas, ridership is asymmetric by agency, meaning that a few operators carry most of the trips. In the Bay Area, Muni and BART carried over 70 percent of 2017 regional ridership. In fact, their combined share in 2017 is the highest of any year in the NTD's online data, dating back to 1991 (*See Figure 4-3*). Therefore, not only are riders within in each agency concentrating at peak times and directions, as described below, but riders are also concentrating onto the busiest agencies.

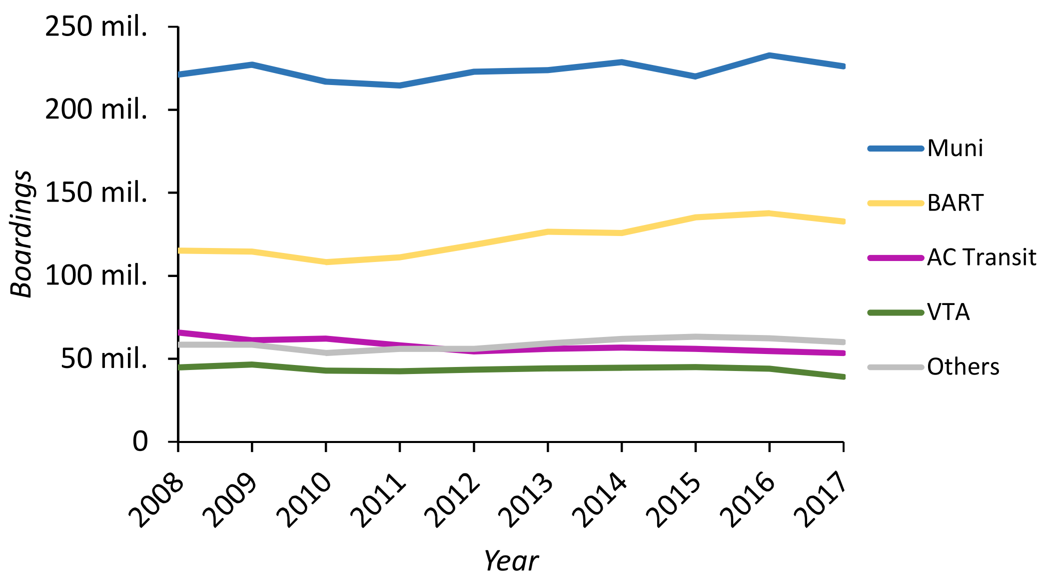
Figure 4-3: Muni and BART's Share of Bay Area Boardings



Taking out these two agencies, Bay Area ridership more resembles the rest of the nation (*See Figure 4-2*). Without Muni and BART, ridership never fully recovered from the Great Recession, during which patronage dropped just over nine percent between 2008 and 2012. Thereafter, non-BART-and-Muni ridership peaked in 2015—one year after the U.S. and one year before the full Bay Area—and has fallen on a similar slope as the country and state ever since. Most of these other agencies do not operate in dense, transit-friendly environments like downtown San Francisco, which may partially explain why their trends look more like the rest of the nation's. Indeed, if different factors than in the rest of the U.S. are causing the Bay Area's ridership decline, these unique influences may actually only affect BART and Muni, while the rest of the region operates under the same forces as elsewhere.

More than that, the differences between the two largest agencies and the rest of the region's operators are not new. The recent patronage decline may have drawn these contrasts to the fore, but ridership trends have differed between agencies for the past decade (*See Figure 4-4*). Since 2008, Muni ridership has remained at roughly the same level—albeit with some noticeable year-to-year jumps and without overall growth despite San Francisco's expanding population. BART, meanwhile, has grown its patronage significantly and steadily, gaining 18 million additional annual boardings between 2008 and 2017. Increases on BART over that period and on Muni between 2011 and 2015 account for essentially all of the region's ridership increase in the past decade. These gains have masked stagnant or slipping ridership on most other operators. VTA, for instance, remained virtually flat for the past decade before falling in 2017. AC Transit, the region's third busiest operator, lost nearly 12.5 million annual trips over the past decade, the most of any agency regionwide. All of the other Bay Area operators together had nearly flat ridership, gaining only a combined 1.5 million annual trips since 2008 and losing ridership per capita. To be sure, some small operators have made gains. But overall, the seeds of the current decline have been germinating for a while, masked by BART's and Muni's relatively robust performance until recently. The top-line ridership figures for the whole region have painted an incomplete and perhaps too rosy picture of regional ridership trends when examined at a more granular level.

Figure 4-4: Ridership Trends among Bay Area Operators:
High Ridership on Muni and BART Has Masked Declines Elsewhere



4.1.2. Service

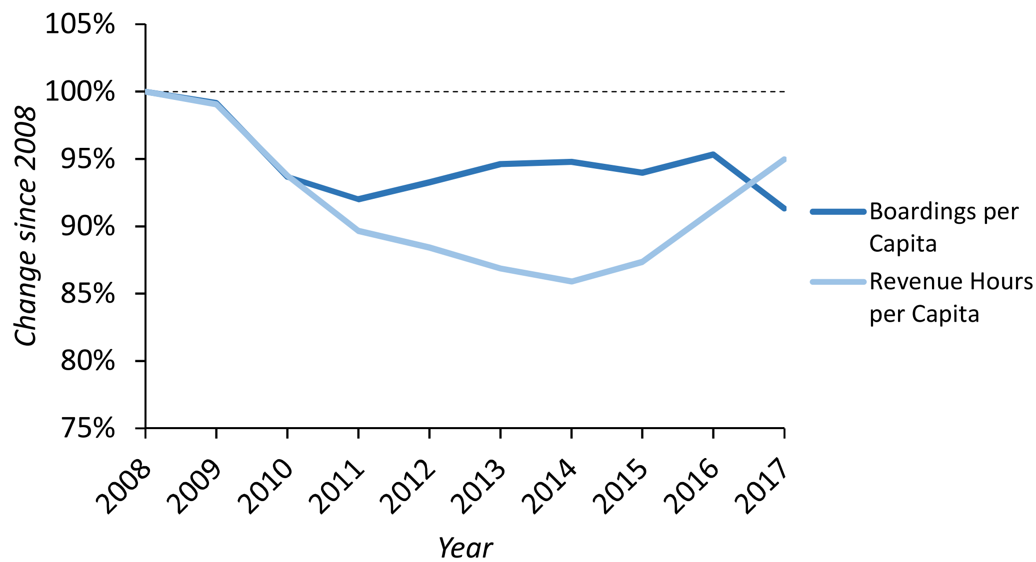
In many agencies across America, service cuts and ridership declines have created a vicious cycle. As headways and reliability fall, riders find other ways to travel, reducing operator farebox revenues and in turn resulting in another round of cutbacks. New York and Washington, D.C., regions with very high levels of transit use, have fallen down this spiral.[57] The Bay Area, though, appears to have escaped it. From this seemingly positive finding, however, follows a perhaps more worrisome conclusion: ridership in

57. Dave Colon, "Who's to Blame for MTA's Declining Ridership?," *Curbed N.Y.*, Jul. 25, 2018 and Arantani, "Metro's Multimillion-dollar Mystery."

Northern California is falling *in spite of* more service.

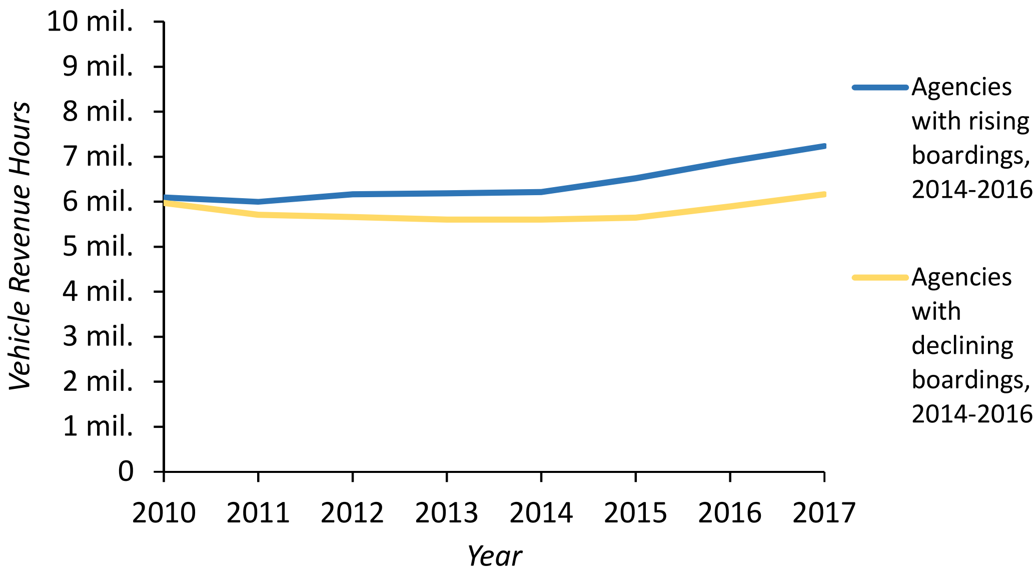
Figure 4-5 shows regionwide trends in revenue hours per capita versus boardings per capita. Overall, the two tracked neatly during the Great Recession. From 2010 to 2014, ridership recovered somewhat, while the lingering effects of recession-induced budget cuts likely kept agencies from restoring service, at least initially. Since then, most Bay Area transit agencies have added significant service, yet in spite of this, ridership has begun to drop. The same trends hold true for revenue miles of service per capita. BART, for instance, has opened two new extensions in as many years, and the Sonoma-Marin Area Rail Transit (SMART) system opened recently as well, but these service-mileage-boosting routes have not increased the region's overall ridership numbers. Overall, service increases as of late appear to be having no effect on bolstering falling ridership.

Figure 4-5: Service Changes Are Not Causing Recent Ridership Declines



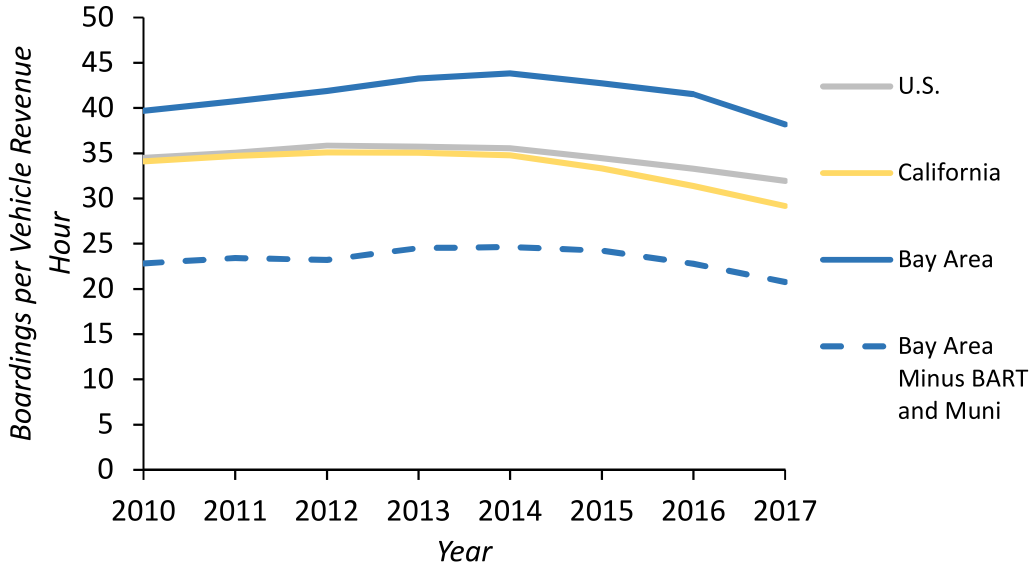
Perhaps, though, service is only increasing on operators with steady ridership, while agencies with falling ridership have cut service. To test this, I separated Bay Area operators into those whose ridership fell between 2014 and 2016 and those whose ridership rose (After 2016, ridership fell at nearly every agency.). Looking at this critical two-year period separates operators with patronage trends similar to most of the rest of the country and operators with the relatively resilient ridership unique to a select few transit-resilient metropolitan areas. Coincidentally, the total number of service hours provided by each of these two categories back in 2010 was nearly equal (*See Figure 4-6*). Since then, the Bay Area agencies whose 2014-2016 ridership rose have added more slightly more service than those whose 2014-2016 ridership fell. Still, both categories of operators have added service since 2014 at roughly the same rate. Given the small difference—and the fact that neither category has actually cut service since 2012—service changes appear to be neither attracting nor repelling riders.

Figure 4-6: Service Hour Differences between Agencies with Different Ridership Trends



These dual trends of falling patronage and rising service have caused transit productivity to drop. Productivity—the number of boardings per hour of service—is a key indicator of how effectively agencies are operating. Like the ocean receding before a tsunami, productivity often ebbs some time before ridership itself crashes down. This has been the case in Southern California, where productivity has fallen every year from 2013 on, two years before overall ridership began its descent. Northern California has followed the same pattern on a slight delay: productivity declines beginning in 2014; ridership declines in 2017 (*See Figure 4-7*). But the Bay Area's recent productivity drop is steeper than America's overall. In fairness, Bay Area transit still operates at a markedly higher rate of service productivity than the state and the nation—a distinction the Bay Area has held all but one year since 1991. But without Muni and BART, the region's productivity lies below America's and California's. Even considering all agencies, with more hours of service supplied for residents who are taking fewer and fewer trips, Northern California operators face a conundrum. As detailed in the following sections, these parallel trends may be explained at least in part by the loss of off-peak riders on many agencies, while ridership remains steady at peak times where capacity constrains prevent more service from being easily added.

Figure 4-7: Productivity



4.1.3. Trends by Mode

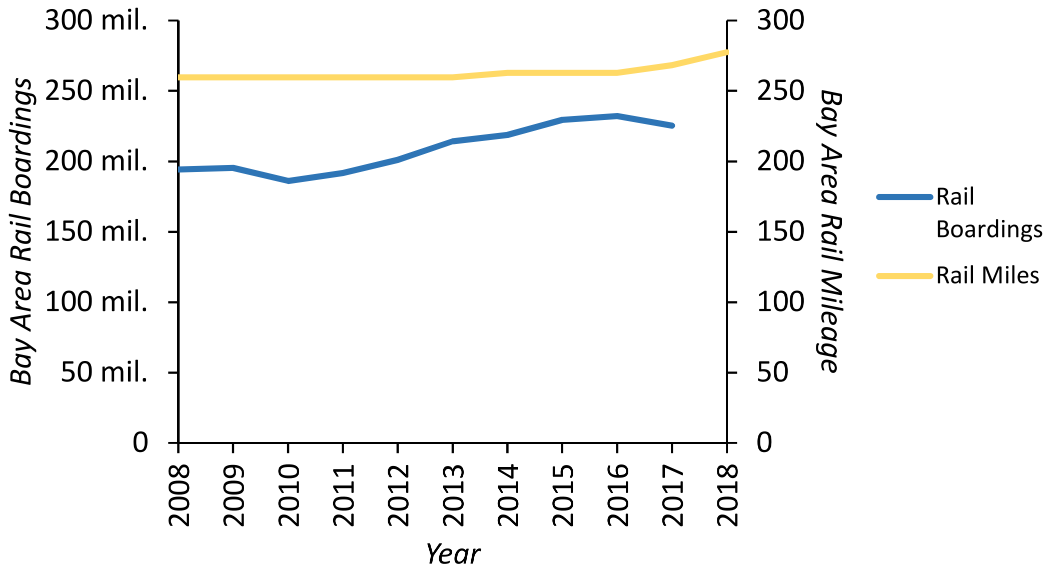
Like in metropolitan Los Angeles, trends in ridership in Northern California vary by mode.[58] However, unlike L.A., the Bay Area has not expanded its rail network much in recent years (*See Figure 4-8*). After a spurt of building by Muni and VTA in the mid-2000s, the region saw no new rail miles opened from 2007 until the opening of BART's Oakland Airport Connector in 2014. Only recently did rail openings pick up again, with BART's Warm Springs/South Fremont extension in 2017 and the East Contra Costa extension in 2018. These two coincide with the recent ridership decline, but given the small scale of these extensions relative to the entire system, the timing appears a coincidence. The overall lack of new rail miles in the past decade suggests that criticisms leveled against Los Angeles' rail expansions—huge new investments that starved buses of funds and riders, per critics—do not apply in the Bay Area.[59] To be sure, the cost-effectiveness and marginal ridership effect of BART and VTA's earlier extensions (from the 1990s and 2000s) are not as high as was hoped or projected. However, within the timeframe of this report, active, new rail expansion is not causing ridership

58. Manville, Taylor, and Blumenberg, *Falling Transit Ridership*.

59. Manville, Taylor, and Blumenberg, *Falling Transit Ridership*; Leroy Demery, *U.S. Urban Rail Transit Lines Opened from 1980*, Mar. 30, 2004, last updated Nov. 2011; VTA, "Light Rail Service Overview," *Santa Clara Valley Transportation Authority*, 2019; BART, "System Facts," *Bay Area Rapid Transit*, 2019; and Matt Tinoco, "Metro's Declining Ridership, Explained," *Curbed L.A.*, Aug. 29, 2017.

declines.

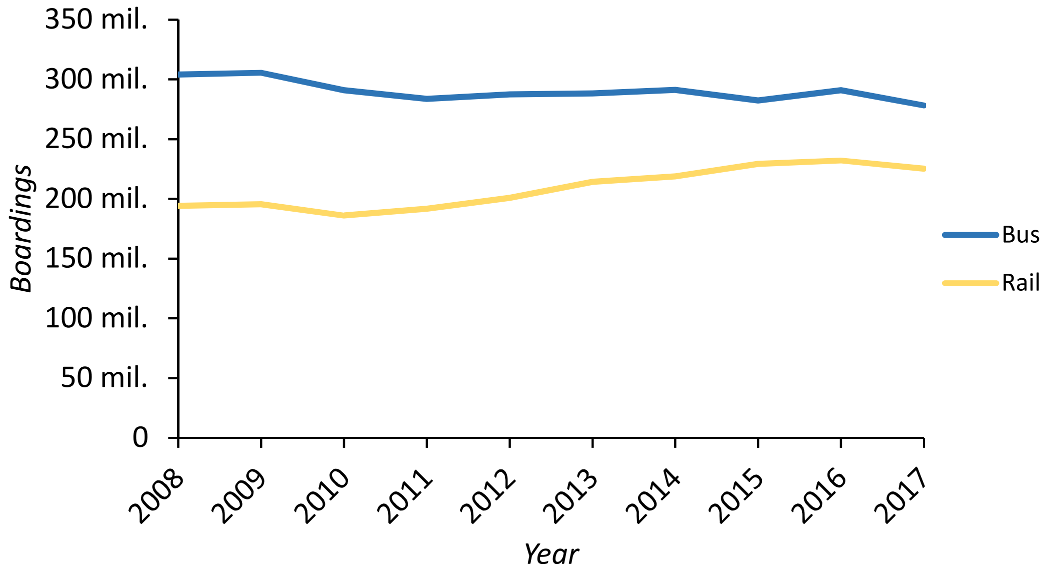
Figure 4-8: Rail Mileage Steady as Rail Boardings Rose and Fell



Track mileage data are available through 2018; regional rail boardings only through 2017.

That said, ridership on rail in the region has increased as ridership on buses has decreased (*See Figure 4-9*). Rail ridership has steadily risen the past decade, save for a brief dip during the Great Recession and a drop in 2017. Trains carried around 31 million more trips in 2017 than 2008. Bus boardings, meanwhile, have slid downward since the Recession, at best flat-lining most years. Buses have lost nearly 26 million trips between 2008 and 2017. To some degree, the difference is due to operating trends specifically on BART, which carried 59 percent of the region's rail riders in 2017 and accounted for 57 percent of rail ridership growth the prior decade. Nonetheless, rail boardings across agencies have grown since the Great Recession to a degree that more than offset losses on buses, until 2017. As the data presented above indicate, this has not occurred because new rail lines have taken ridership from buses, though some riders may be switching from buses to existing rail lines due to increased street congestion, changing job locations, or other factors. Worth noting, though, is the fact that rail and bus ridership finally did start moving in tandem in 2015, both rising the next year and falling the year after. While various pressures may have boosted rail ridership and dampened bus ridership before then, their parallel movements since suggest that a new or newly strengthened set of factors is now affecting both modes similarly.

Figure 4-9: Rail Gains and Bus Losses



All this comes as rail and bus service have increased at relatively similar rates. Bay Area agencies supply far more hours of bus service than rail service, but both have increased markedly since 2014 (*See Figure 4-10)*. Meanwhile, buses and trains have traveled nearly the same number of service miles over the past decade, with a slightly larger uptick for rail since 2014 (*See Figure 4-11*). Again, this evidence does not support a story of investment in rail at the expense of buses, but rather increases in service on both.

Figure 4-10: More Revenue Hours for Bay Area Buses than Rail

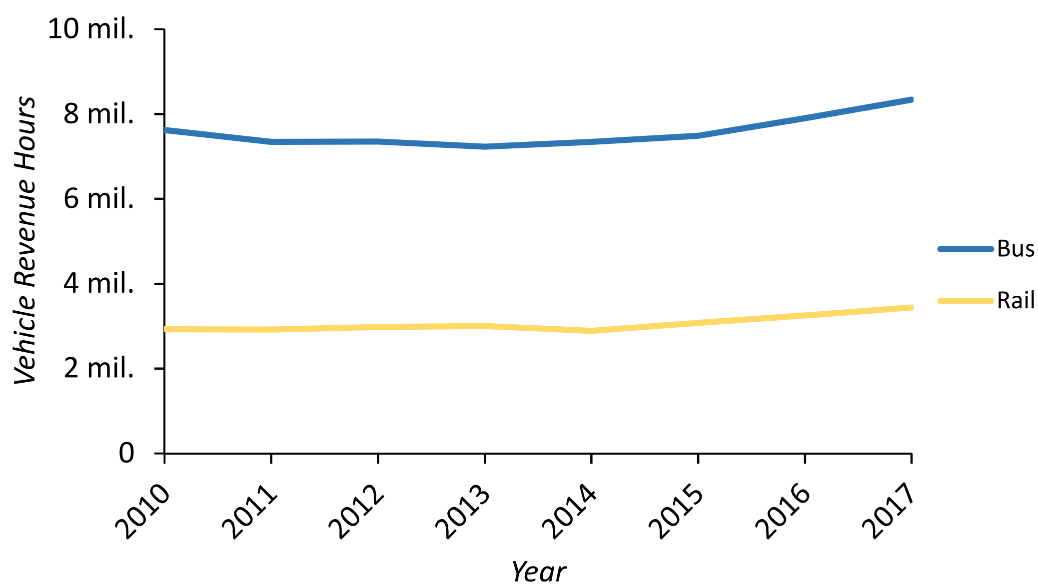
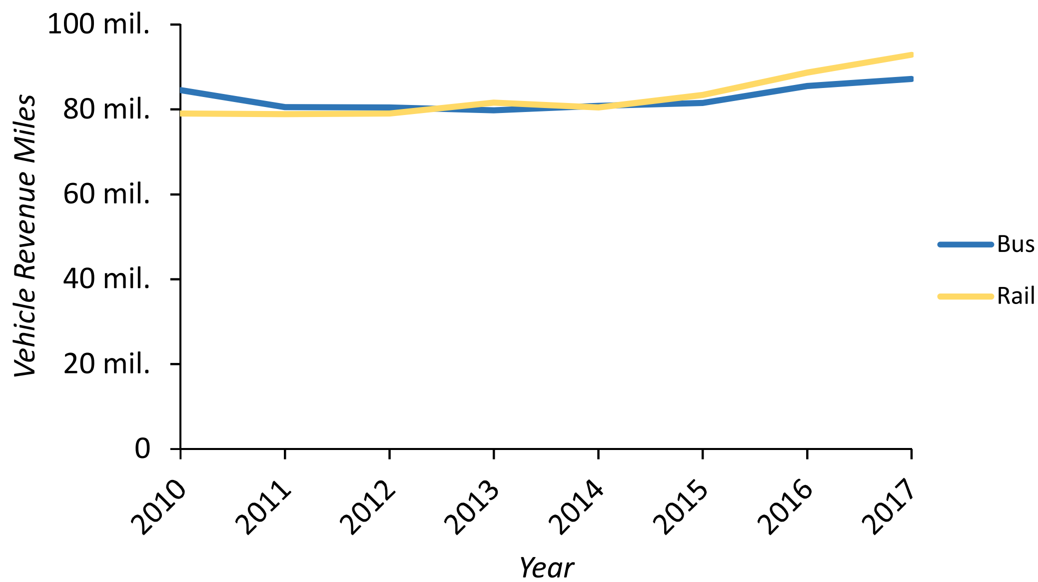
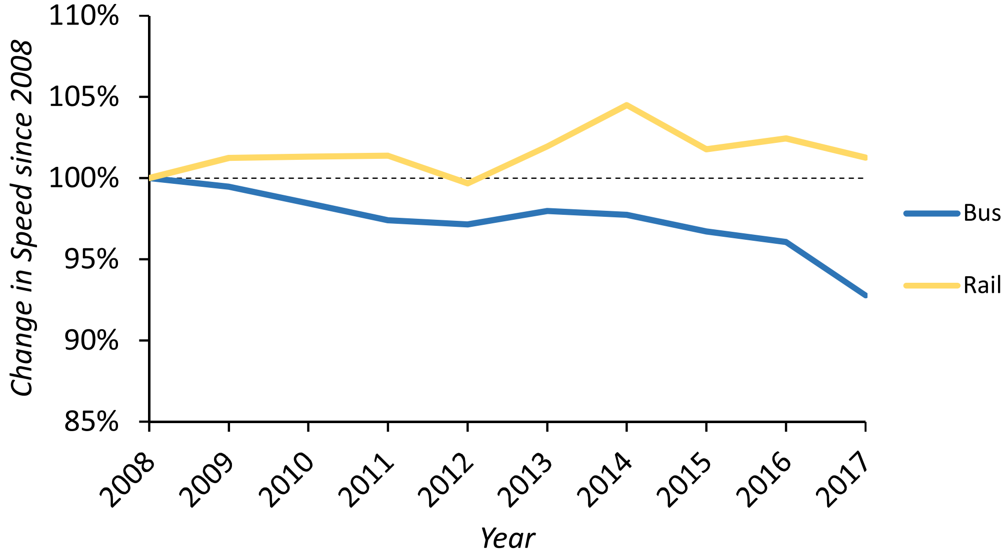


Figure 4-11: Similar Revenue Miles for Bay Area Buses and Rail



Buses in the Bay Area have slowed, but not trains (*See Figure 4-12*). Dividing revenue hours by revenue miles, speeds on buses have dropped 0.8 miles per hour, or seven percent, since 2008 (over half of which occurred in 2017), while rail speeds have increased 0.3 miles per hour, or one percent. Stuck behind traffic with few dedicated lanes, slower buses rather than fewer buses may therefore be a cause of bus ridership declines. In fairness, this speed decrease could also result from shifting service from outlying lines to central routes, where delays are higher. But since the bulk of the speed drop occurred in just one year and since I found no evidence of such a coordinated regional service shift, worsening congestion on existing routes appears the more likely culprit.

Figure 4-12: Slowing Speeds on Buses



4.2. BART Ridership Trends

4.2.1. Overview and Data Validation

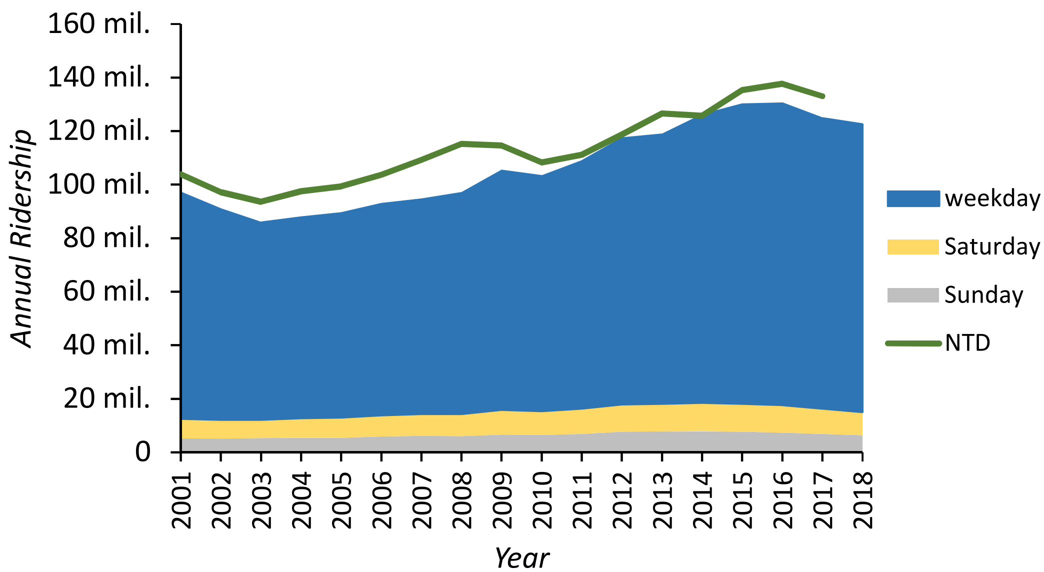
Bay Area Rapid Transit, Northern California's regional heavy-rail system and its second-most-ridden operator, has experienced the most severe demand peaking problems and the largest divergence between peak and off-peak ridership trends of the agencies profiled. BART straddles a sometimes awkward dual role: it functions as commuter rail in the suburbs, at the ends of its branches, and as a high-frequency subway in and between downtown San Francisco, Oakland, and Berkeley at the core of its system. BART serves an (expanding) variety of jurisdictions and land uses, making it the closest to a regionwide operator in the Bay Area. Trends on BART, therefore, carry great import for the whole Bay Area.

As discussed above, BART releases a rich set of origin-destination matrices on its ridership monthly. To test the validity of the matrices, Figure 4-13 below compares the data that BART submit to the National Transit Database with the ridership numbers from the origin-destination matrices.[60] Overall, the numbers are fairly close, with year-over-year changes in each mostly consistent with one another. The NTD numbers are slightly higher,

60. The average weekday, Saturday, and Sunday system ridership from each monthly matrix was multiplied by the number of weekdays, Saturdays, and Sundays, respectively, in that month and then summed for the entire year to arrive at an annual ridership figure.

because they represent BART estimates of unlinked trips, as opposed to the linked trips tracked in the matrices. Neither data source accounts for trips made by fare-evaders, whose numbers fragmentary evidence suggests may be increasing over time and whose travels are not recorded by Clipper-card readers. However, for the purposes of this analysis, the origin-destination matrices are among the highest-quality sources of transit data from any agency nationwide: they track both origins and destinations, unlike most systems, and break down ridership by day and even hour.

Figure 4-13: BART Annual Ridership: NTD versus Origin-Destination Matrices



BART origin-destination trip data are available through 2018; NTD data only through 2017.

4.2.2. BART's Peaking Problem

These data reveal a long period of steady ridership growth for BART, followed by a more recent downswing. As mentioned above, BART experienced steady growth between 2003 and 2015, gaining around 3.7 million riders on average every year and weathering the Great Recession better than most American transit agencies. Since 2016, though, BART ridership has dropped noticeably. Over these two years, BART lost 7.8 million riders, six percent of their 2016 ridership. This decline returned BART to its ridership numbers from around 2013, erasing the three years of growth.

Over this period of decline, one issue appeared again and again: a severe peaking problem. Since 2015, riders have continued packing onto peak trains but abandoning off-peak trips in droves. This trend has created the worrisome levels of crowding to which many news reports discussed earlier have ascribed blame for ridership declines. Meanwhile, both on weekends and in off-commute directions, trains are becoming emptier and emptier. Indeed, peak-hour and -direction crowding cannot explain why off-peak ridership is down. A detailed look at the geography of the system's declines reveals some clues about why these two trends have diverged.

As more jobs are concentrating in downtown San Francisco, ridership into and out of its four BART stations—the system's busiest—has held up far better than other trip types. Trips that begin or end in downtown San Francisco[61] account for a huge share of ridership—66 percent in 2018—compare to 24 percent that begin or end in downtown Oakland[62] and 21 percent that begin and end elsewhere.[63] Figure 4-14 shows just how important downtown San Francisco trips have been for BART and how they have grown since 2003. Since 2015, ridership has declined most heavily in trips outside of downtown San Francisco. All other trip types besides those starting or ending in downtown San Francisco account for over half (56 percent) of system losses. As discussed below, these losses have particularly come from trips starting and ending south of downtown San Francisco and from trips between the north and south halves of the East Bay. While trips to the four Market Street stops have also fallen, all other trip types have dropped off even more (*See Figure 4-15*).

61. Defined by BART as Embarcadero, Montgomery Street, Powell Street, and Civic Center Stations.
62. Defined by BART as MacArthur, 19th Street/Oakland, 12th Street/Oakland City Center, West Oakland, and Lake Merritt Stations.
63. Percentages do not add to 100 percent because trips between downtown San Francisco and downtown Oakland are double-counted.

Figure 4-14: Trips to or from Downtown San Francisco Dominate BART Ridership

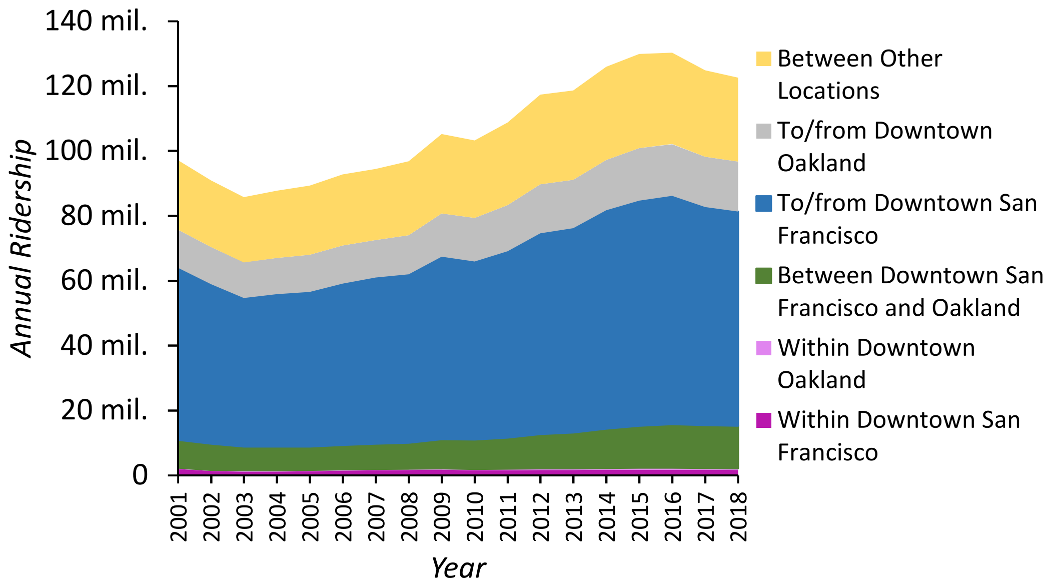
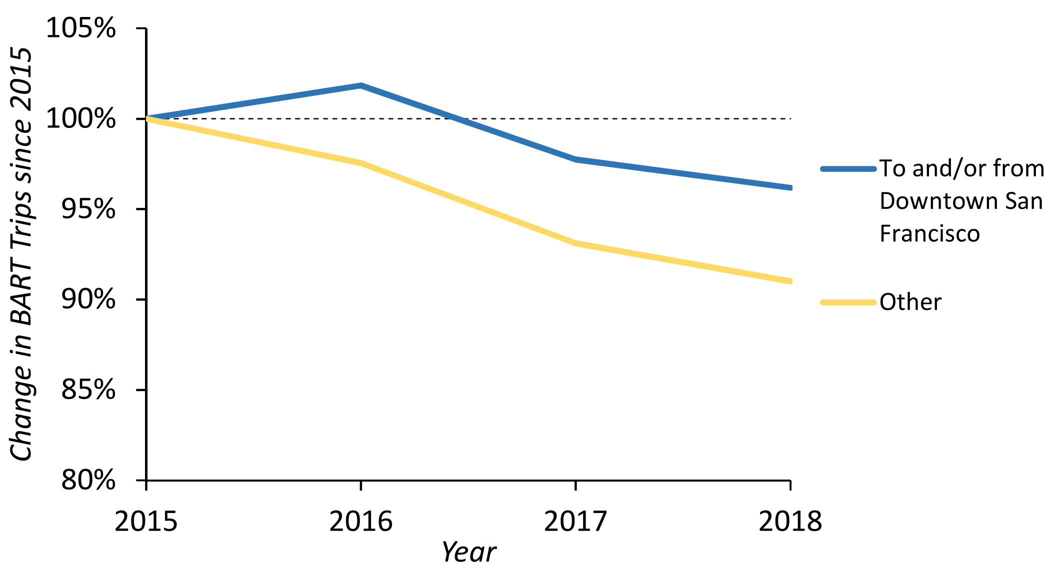


Figure 4-15: Trips to and/or from Downtown San Francisco Have Lost Less Ridership



Ridership changes on either side of the San Francisco Bay are even more skewed. Transbay trips—those that cross San Francisco Bay—made up 55 percent of rides in 2018 but accounted for only 14 percent of 2015-2018 ridership loss. Meanwhile, trips wholly on the east side of the Bay (East Bay) and wholly on the San Francisco Peninsula (West Bay[64]) together represented 45 percent of 2018 trips but an astonishing 86 percent of BART's patronage decline.

This spatial skew in patronage has affected BART long before 2015-2018. Much as BART's overall ridership gains prior to 2015 propped up the whole region's ridership total, BART's transbay ridership propped up the whole system's ridership total. From 2012 to 2015, transbay trips accounted for *all* of the growth in system ridership, while East and West Bay trips remained almost perfectly flat (*See Figure 4-16*). In fact, transbay BART trips accounted for 43 percent of the *whole region's* ridership growth during that period, while making up only 15 percent of 2015 patronage.[65] Since then, all three types saw a drop, but East and West Bay trips have fallen more sharply, largely in tandem (*See Figure 4-17*). In other words, BART has been dependent on transbay trips to prop up its systemwide ridership for most of the past decade. This presents a significant problem for the agency, as the Transbay Tube is operating at capacity and construction of a second tunnel is many years away.[66]

64. Credit to my cousin Lara Ginsberg, proud Oaklander, for introducing me to the term "West Bay" for the San Francisco Peninsula, despite San Franciscans themselves never referring to their side of the Bay in the same manner as the North, South, and East Bay.

65. Admittedly a rough estimate, as the internal BART data on transbay trips count linked trips, while the regional NTD data count unlinked trips.

66. *New Transbay Rail Crossing: Program Overview + Project Contracting Plan*, Nov. 15, 2018, *Bay Area Rapid Transit*.

Figure 4-16: Geographic Differences in BART Ridership Changes since 2012

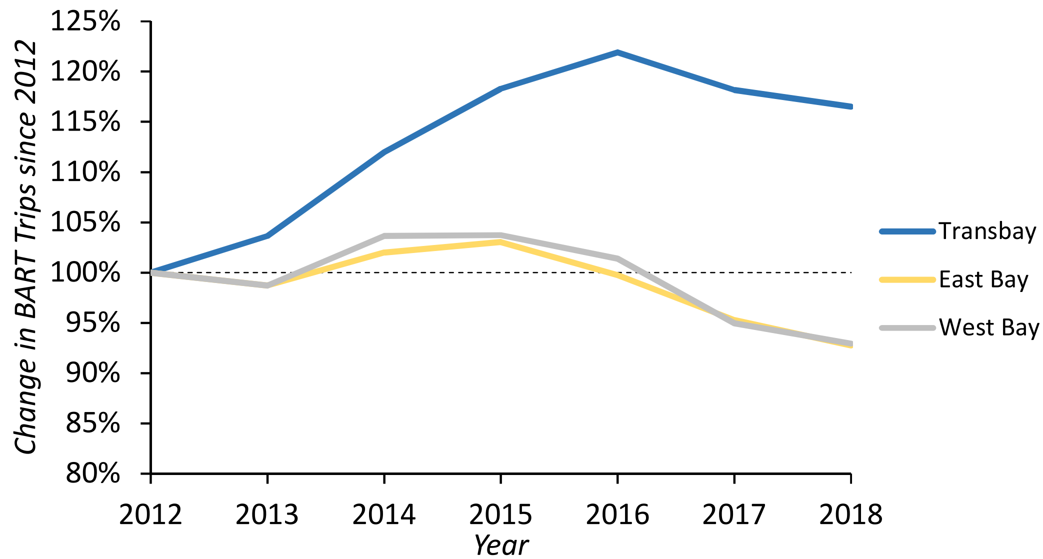
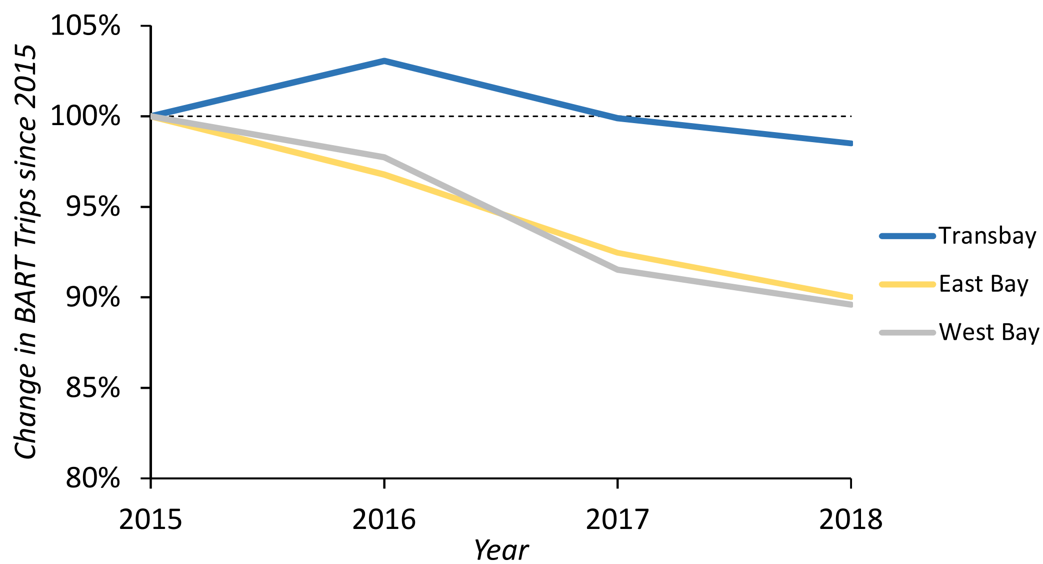
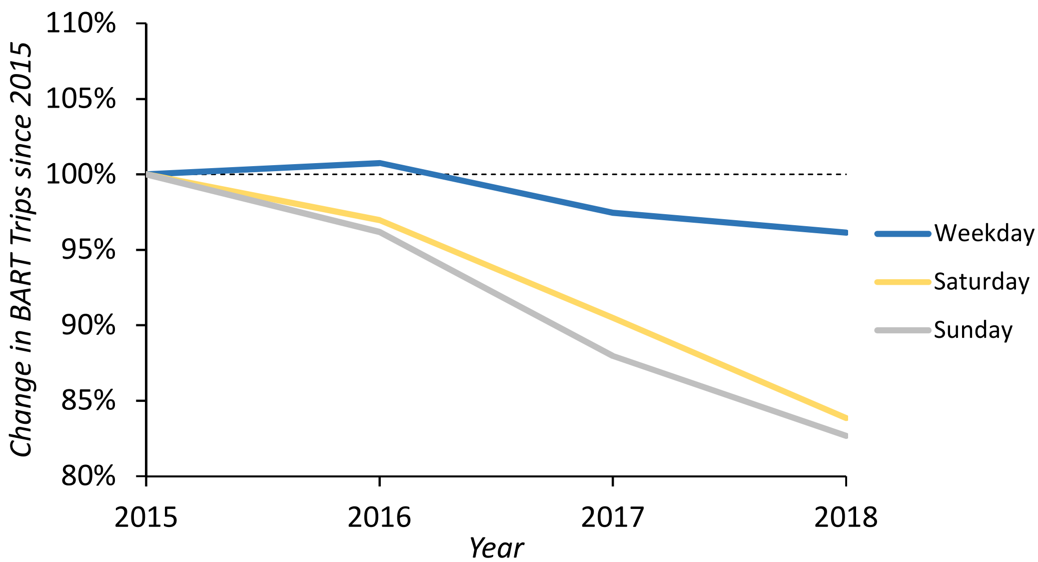


Figure 4-17: Geographic Differences in BART Ridership Changes since 2015



A similar trend is occurring by day of the week. As with transit use nationwide, BART ridership is highest during the traditional work week: around 412,000 riders per weekday in 2018, compared to 172,000 per Saturday and 124,000 per Sunday. Again, though, the off-peak trip type has seen the largest losses. Between 2015 and 2018, weekday ridership only fell four percent, compared to a 16 percent drop on Saturdays and a 17 percent drop on Sundays (*See Figure 4-18*). While jobs are scheduled less and less on a traditional nine-to-five work week, the relative stability of BART's weekday ridership points to its continued usefulness as commuter transportation. This is especially the case given that, unlike on most transit, BART provides a faster travel time than driving for many trips (transbay trips at weekday rush hours, primarily).[67]

Figure 4-18: Temporal Differences in BART Ridership Changes since 2015

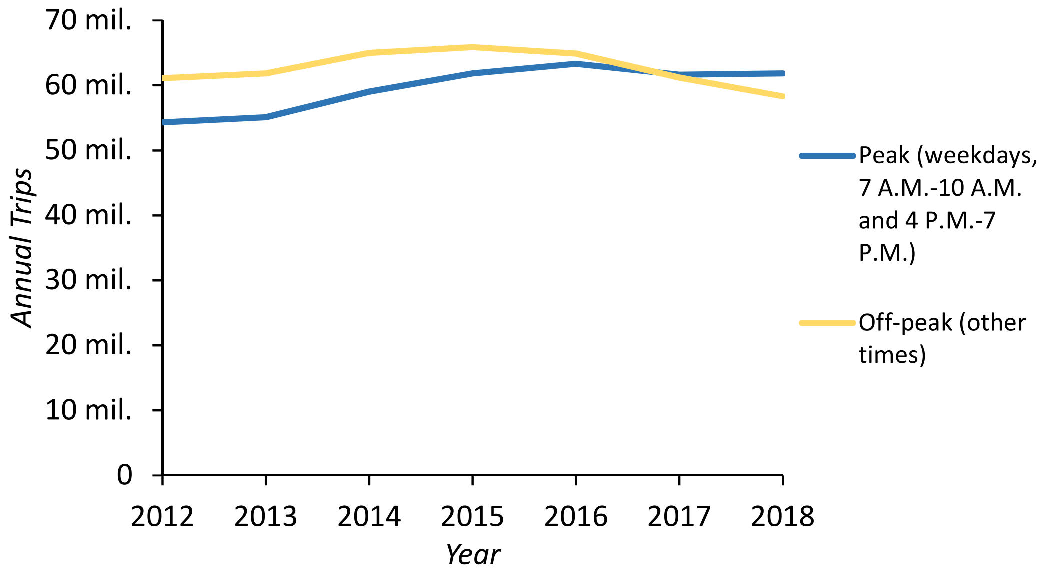


Indeed, at rush hour, ridership remains more resilient than at off-peak times. Figure 4-19 plots the number of annual trips taken on weekdays at the six busiest hours (7 A.M. to 10 A.M. and 4 P.M. to 7 P.M.) versus at all other times (weekends and weekdays outside of rush hour). Since 2012, peak-hour patronage has grown faster than off-peak and has increased its share of the agency's overall ridership, cresting 50 percent in 2017. More than half of all BART trips, in other words, happen within these six weekday hours. Since 2015, rush-hour ridership has dropped only slightly. Meanwhile, off-peak ridership fell over 11 percent, at an increasingly steep rate of descent nearly every year. BART has become a primarily rush-hour service. In so doing, BART is spending more and more on delivering expensive peak service, potentially endangering its financial bottom line. From Fiscal Year 2011 to Fiscal Year 2015, BART consistently spent 33¢ per passenger mile in operating costs, but in Fiscal Year 2017, the agency spent 37¢ per passenger mile, as high as at the

67. Jana Kasperkevic, "Do People Even Work 9-to-5 Anymore?," *Marketplace*, May 28, 2018; Kim Parker et al., "The State of American Jobs," *Pew Research Center*, Oct. 6, 2016; and KGO-TV, "Commute Challenge: This Might Be the Fastest Way around the Bay," *ABC News*, Oct. 24, 2018.

middle of the Great Recession. On top of BART's significant capital expenditures for extensions and system rehabilitation, the cost of rush-hour peaking is worrisome.[68]

Figure 4-19: BART's Peaking Problem, by Time of Day



4.2.3. Detailed Geographic Analysis

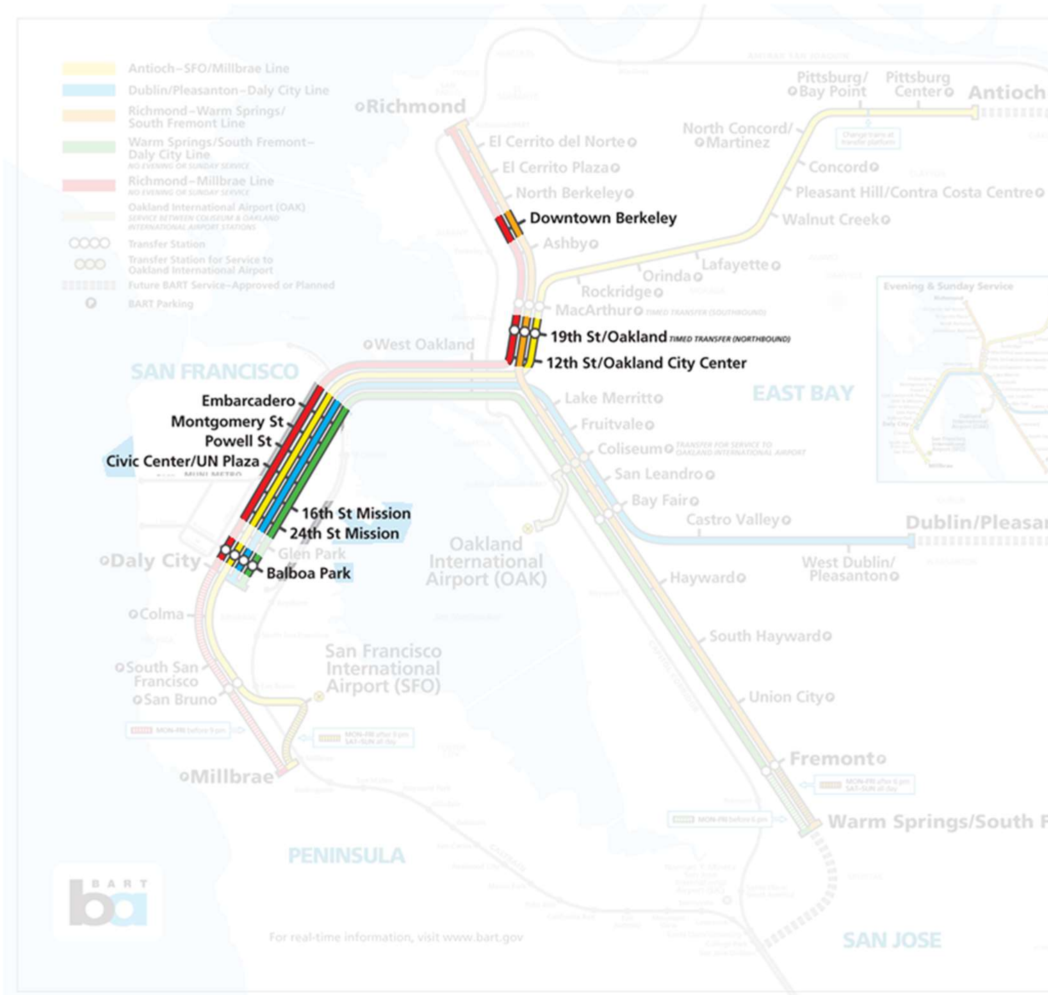
The effects of increased peaking have played out geographically across the BART system by intensifying the passenger load at the busiest stations and on the busiest track segments. For instance, among the 48 stations in the BART network, Table 4-1 lists the top ten stations by number of combined entries and exits in 2018. They are, as one might expect, mostly in job-rich areas like downtown San Francisco, Oakland, and Berkeley (*See Figure 4-20*). More than that, though, these busy stations have tended to weather the recent ridership declines the best. As shown in the last column of Table 4-1, three of these busiest stations are among the ten best-performing stations by percent change in entries and exits between 2015 and 2018; five are among the top 15. The busiest stations have gotten busier, or at least retained their crowds. On the other hand, three of the busiest stations are among the ten worst-performing stations by percent change in entries and exits between 2015 and 2018. Nevertheless, two of the three, Downtown Berkeley and Balboa Park, are outside of BART's core areas (downtown San Francisco and Oakland).

68. BART *Annual Report*, Jan. 2019, 21.

Table 4-1: Stations with the Most Combined Entries and Exits, 2018

Station	*Combined Entries and Exits, 2018*	*Percent Change in Combined Entries and Exits, 2015-2018*	
Embarcadero	25,539,142	+1.7%	5th out of 45
Montgomery Street	24,711,292	-0.4%	7th out of 45
Powell Street	18,154,191	-13.5%	40th out of 45
Civic Center	14,018,068	-4.9%	13th out of 45
12th Street/ Oakland City Center	7,845,980	-4.9%	12th out of 45
16th Street Mission	7,637,341	-9.5%	26th out of 45
19th Street/ Oakland	7,601,917	+1.0%	6th out of 45
24th Street Mission	7,558,706	-9.9%	29th out of 45
Downtown Berkeley	7,083,270	-17.2%	43rd out of 45
Balboa Park	6,468,168	-14.1%	42nd out of 45

Figure 4-20: Stations with the Most Combined Entries and Exits, 2018



From the list of best-performing stations by 2015-2018 change in entries and exits (*See Table 4-2*), perhaps the most striking takeaway is that only six of the 45 stations open during the whole period gained riders. The stations that have gained ridership or dipped only slightly are clustered on either side of the Transbay Tube, in inland Contra Costa County, and in the Tri-Valley. As discussed below, the Contra Costa and Tri-Valley branches have retained riders by percentage, though they carry few riders in absolute terms. On the other hand, many of the stations that have lost the most entries and exits from 2015 to 2018 (*See Table 4-3*) lie south of downtown San Francisco and near Berkeley. The two stations with the largest percentage losses get a pass, though—they used to be their line's terminus, until the Warm Springs/South Fremont and East Contra Costa "eBART" extensions opened in March 2017 and May 2018, respectively.[69] The bottom performers do not necessarily paint a clear picture in which all downtown stations are growing and all suburban stations are declining, but they do show that certain outlying areas have seen significant drops.

Table 4-2: Stations with the Largest Gains in Entries and Exits, 2015-2018, by Percent Change

Station	*Percent Change in Combined Entries and Exits, 2015-2018*
Pleasant Hill	+4.3%
West Oakland	+3.9%
Dublin/Pleasanton	+3.4%
San Leandro	+1.9%
Embarcadero	+1.7%
19th Street/Oakland	+1.0%
Montgomery Street	-0.4%
Orinda	-1.9%
West Dublin/Pleasanton	-3.0%
Walnut Creek	-4.6%

69. Roger Rudick, "Pics from the Warm Springs/South Fremont BART Opening Celebration," *Streetsblog S.F.*, Mar. 24, 2017 and BART, "BART to Antioch: East Contra Costa BART Extension," *Bay Area Rapid Transit*, 2019.

Figure 4-21: Stations with the Largest Gains in Entries and Exits, 2015-2018, by Percent Change

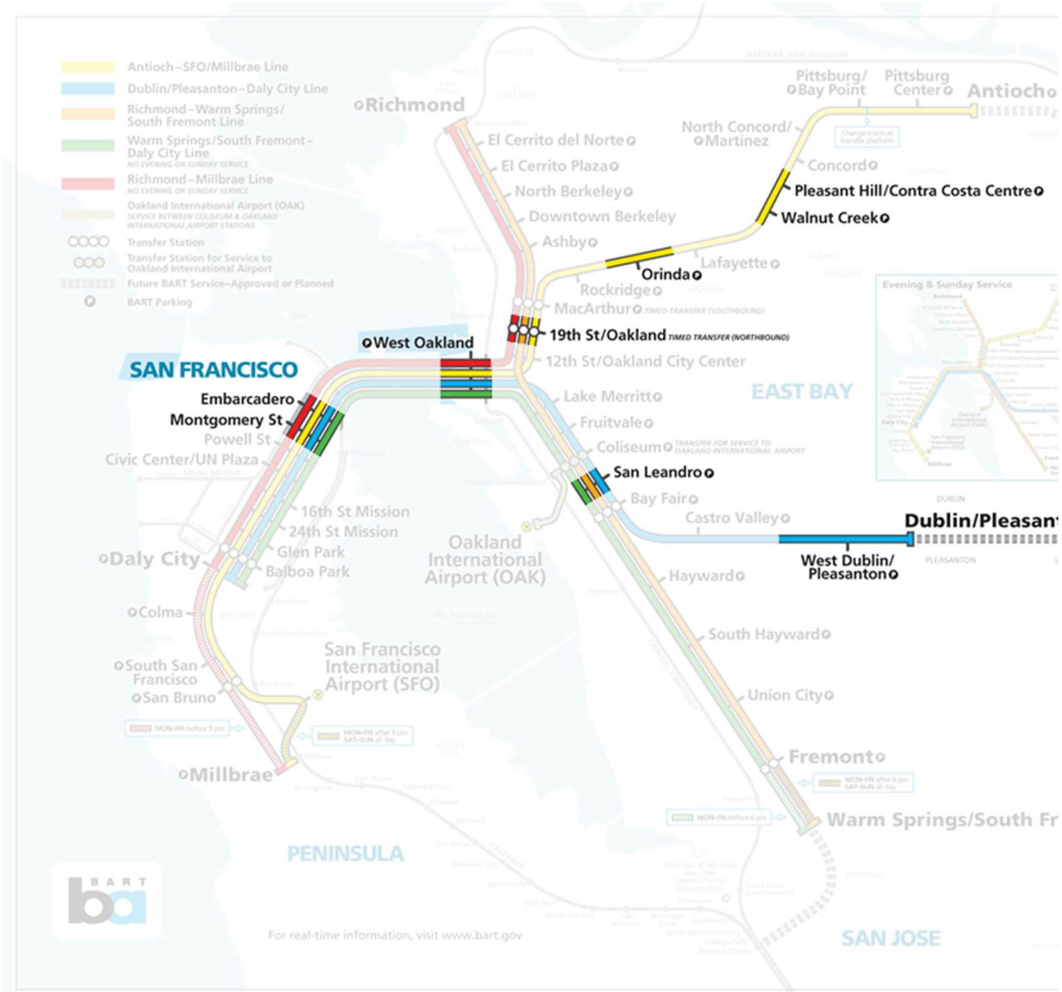


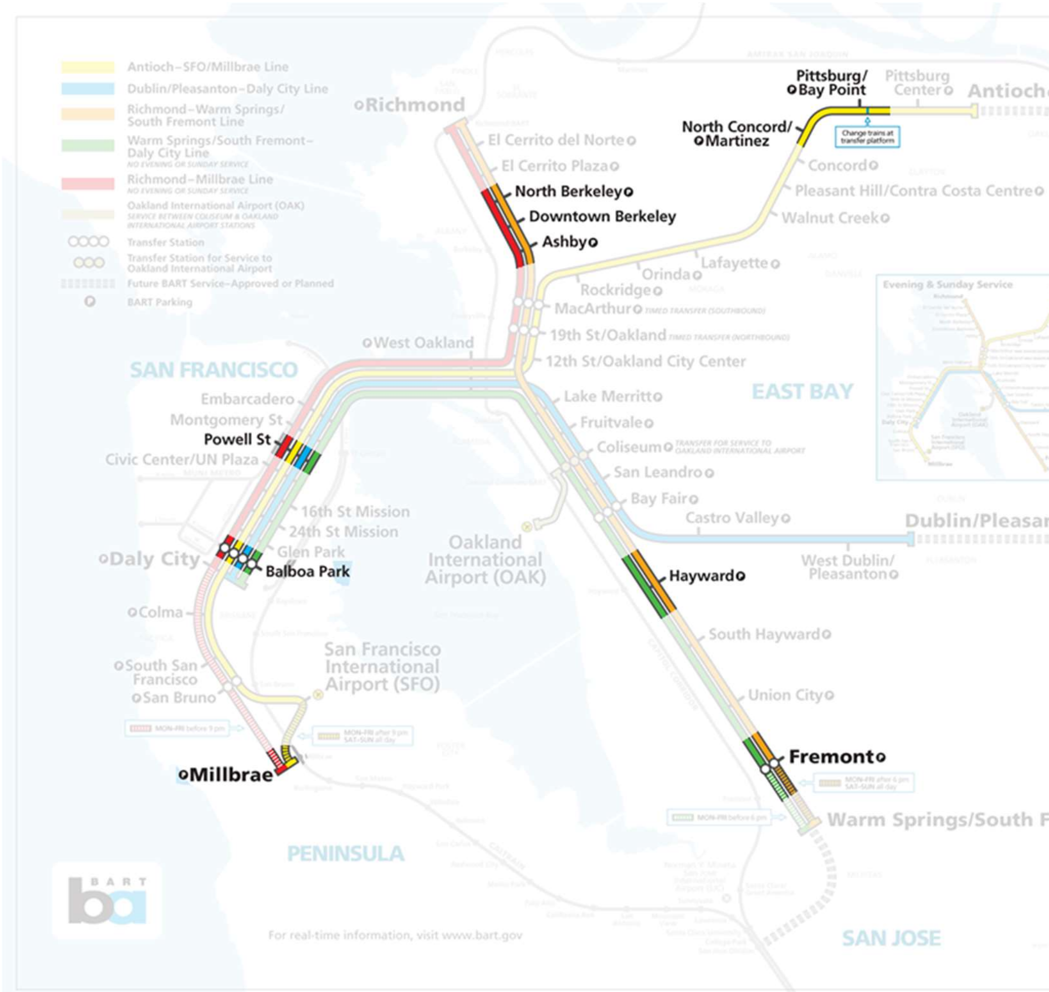
Table 4-3: Stations with the Largest Losses in Entries and Exits, 2015-2018, by Percent Change

Station	*Percent Change in Combined Entries and Exits, 2015-2018*
Millbrae	-11.0%
Hayward	-12.2%
North Berkeley	-12.5%
Ashby	-13.4%
Powell Street	-13.5%
North Concord/Martinez	-13.7%
Balboa Park	-14.1%
Downtown Berkeley	-17.2%
Pittsburg/Bay Point*	-21.7%
Fremont*	-29.3%

*** Ridership losses likely due to the opening of extensions beyond these previously terminal stops during the comparison period**[70]

70. Rudick, "Pics from the Warm Springs," and BART District, "BART to Antioch."

Figure 4-22: Stations with the Largest Losses in Entries and Exits, 2015-2018, by Percent Change



Analyzing BART ridership by track segment instead of by station reveals similar geographic distributions of gains and losses. In this section, I look at ridership over a segment of track instead of the number of entries and exits at a station. In other words, segment ridership measures how many riders traveled over the whole of or part of a given stretch of track, regardless of whether they started or ended their trip along it. Though it does not equate to crowding per se, segments with higher ridership as I measure it here will have more people, on average, on the trains that pass through them. For this analysis, I broke the system down into 15 large segments, each covering a branch or a trunk of the network, and 49 small segments, each covering the track between a pair of adjacent stations.

Appendix A provides maps of each of the larger segments and graphs of their ridership trends. Figure 4-23 below excerpts the segments with the largest relative ridership gains between 2012 and 2018; Figure 4-24 the largest losses. In nearly every case, ridership rose between 2012 and 2015 and has fallen since. The most variation occurred in 2018, where about half of the segments stabilized or slightly grew their ridership, while the other half continued on the roughly same downward trajectory as the year or two prior. Across the spread of different segments, though, ridership appears again to be healthiest into and out of downtown San Francisco, while patronage is falling from the airports, among intra-East-Bay trips, and on the Richmond-Berkeley and southern San Francisco routes.

Among the best performing segments between 2012 and 2018 by percent change (*See Figure 4-23*) are the two branches immediately east of West Oakland in the Oakland Wye (#1 and #4).[71] While these segments appear small, recall that the measure of ridership in use here includes all trips that pass through a stretch of track, and these two segments carry all riders between San Francisco and the southern East Bay and between San Francisco and the northern East Bay, respectively. The second-highest-ranked segment is the Dublin/Pleasanton branch, a surprisingly strong performer, and the third-highest is the Transbay Tube and Market Street in downtown San Francisco. Three of these four are further evidence of BART's peaking problem and show why crowding and train capacity constraints in the Transbay Tube have become such problems for the agency.

71. The three-way intersection of BART lines between West Oakland, 12th Street/Oakland City Center, and Lake Merritt

Figure 4-23: BART Track Segments with the Largest Relative Ridership Gains, 2012-2018

At the other end of the rankings (*See Figure 4-24*) lie the south of the City of San Francisco (#10), the Berkeley-Richmond branch (#11), and the two airport connections (#12 and #13). The poor performance of the first may indicate some mode shift of people with jobs in San Mateo County and Silicon Valley switching from BART (or a BART-Caltrain combination) to company shuttles or other means of transportation. The plummeting ridership on the two airport connections, meanwhile, indicate further problems for these routes that compete with ridehail, taxis, and airport shuttles. In the case of the Oakland Airport Connector, falling patronage represents the latest bad news for an extension plagued by cost overruns and civil-rights concerns since its inception.[72] Most tellingly, the segment between 12th Street/Oakland City Center and Lake Merritt, the north-south track in the Oakland Wye (#14), had the greatest drop in riders between 2012 and 2018. Carrying all riders between

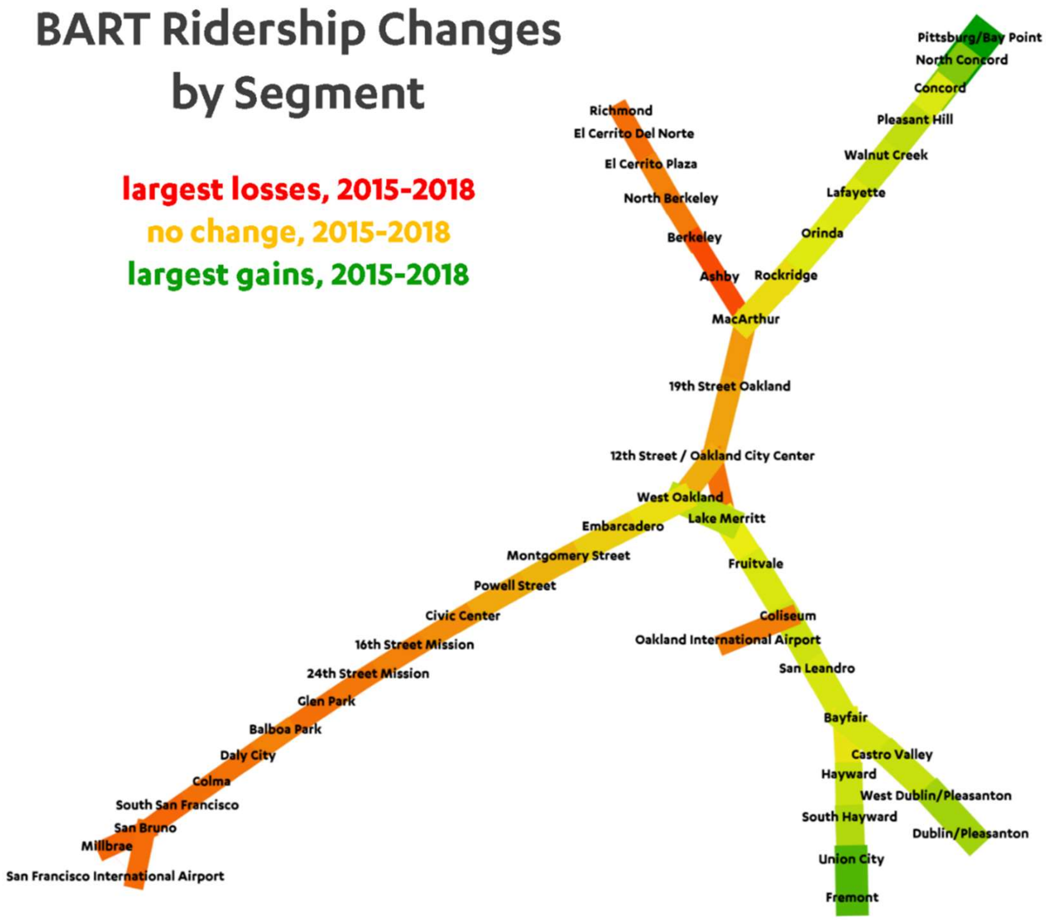
72. Jay Barmann, "BART Says Their Oakland Airport Connector Is Losing Money Because Of Uber, Lyft," *SFist*, Mar. 8, 2017; Phil Matier, "BART's Oakland Airport Connector Turning into Big Money Loser," *San Francisco Chronicle*, Mar. 8, 2017, last updated Mar. 9, 2017; Phil Matier, "BART's Oakland Airport Connector Isn't a Big Money Maker Yet," *KPIX 5: CBS S.F. Bay Area*, Mar. 8, 2017; Phil Matier and Andy Ross, "BART's Oakland Airport Connector Too Costly to Stop," *SFGate*, May 11, 2011; Michael Cabanatuan, "Oakland Airport Connector Back to BART Board," *SFGate*, Jul. 22, 2010; and Michael Rhodes, "Civil Rights Complaint Filed Against BART Over OAK Airport Connector," *Streetsblog S.F.*, Sept. 4, 2009.

the north and south East Bay, this segment not only experienced a precipitous decline since 2015 but also did not grow, like the other segments, during the boom years between 2012 and 2015. The epicenter of BART's ridership problems, then, is intra-East-Bay trips.

Figure 4-24: BART Track Segments with the Largest Relative Ridership Losses, 2012-2018

A look at segment ridership between each station reveals more nuance. Figure 4-25 maps changes between 2015 and 2018 for each station segment. Again, the segments south of downtown San Francisco, north from Oakland to Richmond, and to the airports have lost a large share of riders over the past three years. The ends of the Pittsburg/Bay Point, Dublin/Pleasanton, and Fremont branches have experienced significant growth in relative terms, though their absolute growth is small compared to the downtown parts of the system. While the Pittsburg/Bay Point and Dublin/Pleasanton stations themselves may have lost riders due to extensions opening beyond them (not pictured in Figure 4-25), the number of riders passing through them has increased for the same reason. Moreover, while many segments in the East Bay have experienced growth, the short segment between 12th Street/Oakland City Center and Lake Merritt again shows up in the negatives. Therefore, while some of the East Bay branches have grown their ridership, these travelers are going to San Francisco instead of other East Bay destinations. This somewhat contradictory finding—large parts of the East Bay have experienced ridership growth but overall travel within the East Bay is falling—shows yet again the difficulties of BART's peaking problem.

Figure 4-25



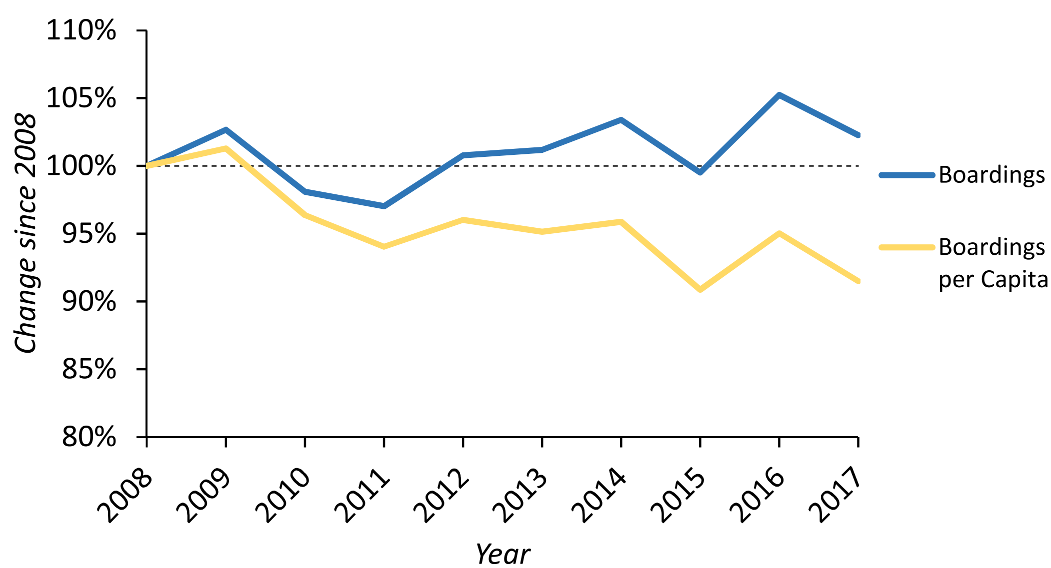
4.3. SFMTA Ridership Trends

4.3.1. Overview

If BART represents a clear case of peaking problems across a regional network, Muni shows the more uneven decline of an operator in one of the most transit-favorable areas in America. For context, the SFMTA, whose transit service is called Muni, carries the most riders of any transit agency in the Bay Area, bearing 44 percent of trips in 2017 (*See Figure 4-4*). Confined almost exclusively to the compact, 47-square-mile City and County of San Francisco, Muni enjoys the benefit of operating in the densest service area of any Bay Area agency—or, in fact, of any agency in the state. San Francisco is the second-densest city in America of 100,000 people or more, meaning that if transit can succeed anywhere beyond New York, it would be San Francisco.[73] And indeed, with 256 boardings per capita in 2017, Muni does boast impressive ridership and mode share.

However, Muni has lost riders in recent years all the same. Figure 4-26 shows change in absolute boardings and boardings per capita on SFMTA, from the NTD. Muni's overall ridership trend is far bumpier than BART's, with relatively substantial changes year to year. Patronage fell in 2015, only to recover in 2016 roughly back to where it would have been if its growth had proceeded evenly since 2012. Ridership again dropped in 2017, this time by 6.6 million annual riders, but in light of Muni's 2016 recovery, the agency may be better positioned to recover than other transit agencies. As for ridership per capita, the trends are more worrisome. Boardings per capita have never recovered from the effects of the Great Recession, staying flat until 2014 and then jaggedly falling again. San Francisco's population has grown quite a bit, but Muni ridership has failed to keep pace.

Figure 4-26: SFMTA Ridership Bumpy and Not Keeping Pace with Population Growth



4.3.2. Breakdown by Mode and Frequency

How do these trends vary temporally and spatially? To answer this, I reviewed data provided by Muni staff, breaking down ridership by fiscal year

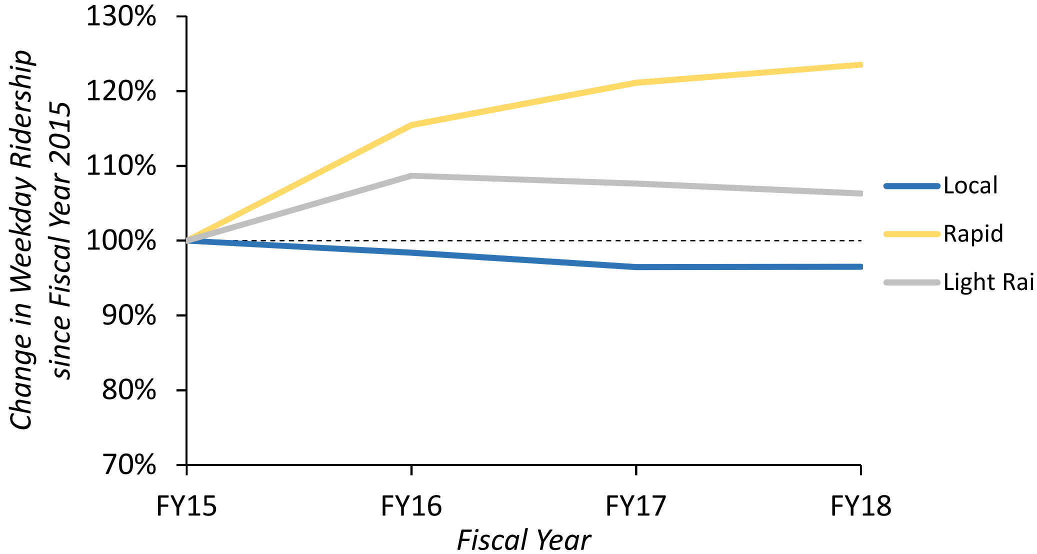
73. "Population Density for U.S. Cities Statistics."

(July 1–June 30), mode, and route. Unfortunately, SFMTA's data are not as complete as BART's. Muni riders only need to pay a fare upon entry, so their exits are not tracked. Nonetheless, important differences in the data reveal a waxing peaking problem on Muni as well, albeit not as stark as on BART.

One facet of Muni's peaking issues is that ridership has concentrated on certain modes. Beyond bus versus rail, SFMTA operates many different modes. Per the NTD, only four agencies nationwide operate more transit modes than SFMTA. Muni runs motorbuses, trolleybuses, light rail, historic streetcars, (contracted) paratransit, and the only cable car fleet in the country. Furthermore, Muni also categorizes bus lines as Rapid, Express, Owl, etc. based on their service pattern. To sort through this, Figure 4-27 breaks down three core categories of Muni service: light rail (excluding the more tourist-oriented cable cars and streetcars), local bus (excluding peak-only expresses), and Rapid bus (a network of limited-stop lines, some of which have features of bus rapid transit, that saw a rebranding and service increase in April 2015).[74] Since Fiscal Year 2015, weekday ridership on light rail is up six percent, and weekday patronage on Rapids has jumped 24 percent. Over the same period, local bus trips—over half of the agency's total boardings—have fallen three percent on weekdays. Whether the same passengers are changing mode or whether different passengers are riding locals less and rail and Rapids more is unclear, though evidence from specific lines below points toward the former. Either way, these trends show a slightly different peaking problem than BART—a modal peaking problem—that could bring to Muni the type of crowding and capacity issues experienced on BART.

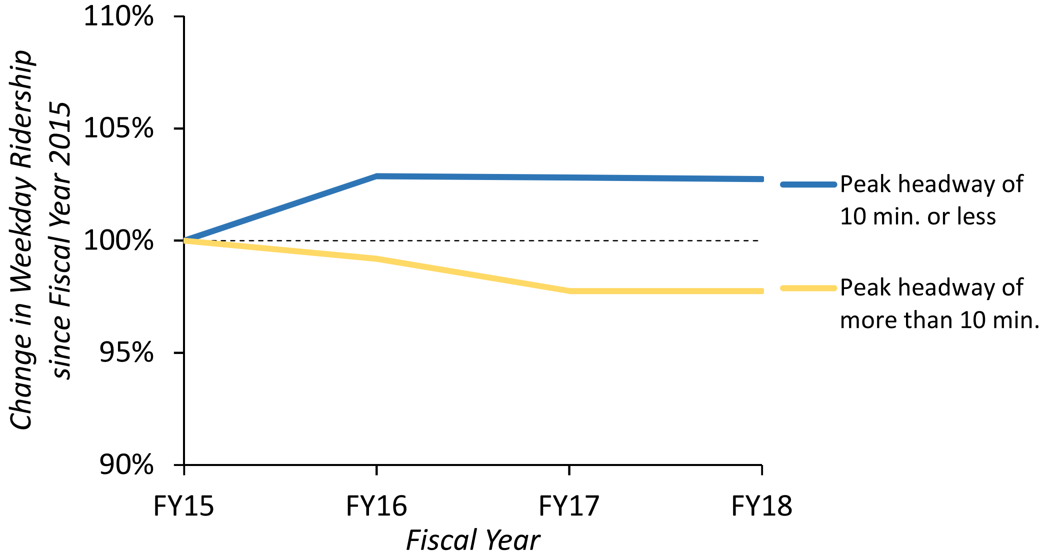
74. SFMTA, "Muni Forward Brings You More Service, Muni Rapid, New Map," *SFMTA*, Apr. 3, 2015.

Figure 4-27: Local Buses Losing Ridership as Rapid Buses and Light Rail Grow



Divergent patterns likewise emerge when ridership is broken down by route frequency. On routes with peak weekday headways of 10 minutes or less, weekday ridership is up three percent from Fiscal Year 2015, while on routes with longer peak weekday headways, ridership is down two percent (*See Figure 4-28*). These changes are relatively small, but their different directions nevertheless indicate that busier routes are getting busier and the converse.

Figure 4-28: Ridership Growth on High-frequency Lines and Losses on Low-frequency Lines



4.3.3. Breakdown by Line

Unlike on VTA, discussed below, Muni's most patronized routes have seen the greatest absolute ridership gains (*See Table 4-4*). Four of the agency's light rail lines top the list by ridership last fiscal year, and the Geary Rapid rounds out the top five—a route that, along with its local counterpart, are among "the busiest bus lines west of the Mississippi and carry almost as many riders as Caltrain's entire daily service," as the *San Francisco Examiner* put it.[75] These lines all also rank in the top ten in terms of gains since Fiscal Year 2015, roughly when the Bay Area's regionwide ridership slump began. These busy lines are carrying more and more trips, causing crowding and necessitating high amounts of service and a number of planned improvements to give them priority lanes.[76]

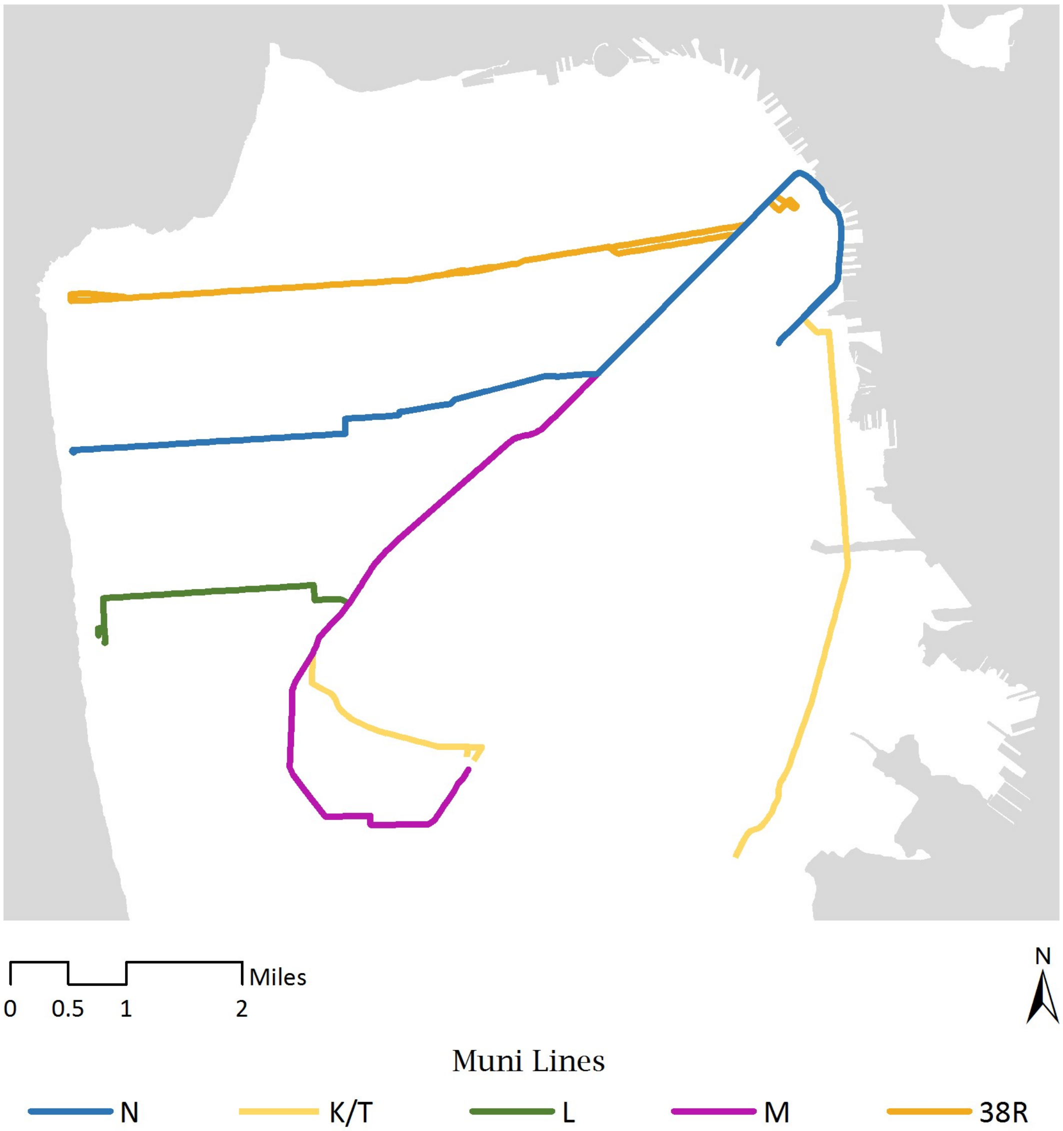
75. Joe Fitzgerald Rodriguez, "Geary Bus Rapid Transit Gets Environmental 'Green Light to Advance' From Feds," *San Francisco Examiner*, Jun. 21, 2018.

76. Ibid.

Table 4-4: Lines with the Most Boardings, Fiscal Year 2018

Line	*Daily Boardings, Fiscal Year 2018*	*Absolute Change in Daily Boardings, Fiscal Year 2015-Fiscal Year 2018*	
N (light rail)	48,152	+2,027	8th out of 76
K/T (light rail)	41,609	+4,493	3rd out of 76
L (light rail)	32,302	+1,746	9th out of 76
M (light rail)	29,907	+2,059	7th out of 76
38R (Rapid bus)	29,484	+4,649	1st out of 76

Figure 4-29: Lines with the Most Boardings, Fiscal Year 2018



Notably, some of Muni's most ridership-gaining lines are Rapid buses, while some of its most ridership-losing lines are the local buses along the same corridors. Table 4-5 lists the five corridors with Rapid bus routes[77] and compares the change in boardings since Fiscal Year 2015 on each. The local buses have all lost significant ridership, with three of the five placing in the bottom five by absolute change. Meanwhile, the Rapids have all markedly grown in patronage, with three placing in the top five by absolute change. The 38 and 38R on Geary Boulevard exemplify the group, with the former losing

77. The five corridors with Rapid bus routes today, to be specific. The 7R, discontinued in August 2017, is not included (SFMTA, "7R Service to Become 7 Local Service," *SFMTA*, Aug. 14, 2017.).

six percent of its riders and ranking 71st and the latter gaining 19 percent and ranking first. Among lines that lost riders since Fiscal Year 2015, the five local routes in Table 4-5 account for just over a quarter of their total losses, while the five Rapid routes account for 39 percent of total gains among lines that increased in patronage. While these data do not directly indicate that the same individual passengers have switched from locals to Rapids, the weight of these statistics makes this scenario very likely. To be sure, Muni has suffered outright losses on other lines that are pulling the system's numbers down. But it also is shifting riders onto faster service options, which, despite the risk of crowding and expense, represents a positive outcome for the agency.

Table 4-5: Ridership Change on Locals versus Rapids

Lines	*Local: Absolute Change in Daily Boardings, Fiscal Year 2015-Fiscal Year 2018*		*Rapid: Absolute Change in Daily Boardings, Fiscal Year 2015-Fiscal Year 2018*	
5 / 5R	-1,567	72nd out of 76	+1,053	13th out of 76
9 / 9R	-2,740	75th out of 76	+4,575	2nd out of 76
14 / 14R	-1,242	68th out of 76	+2,692	5th out of 76
28 / 28R	-462	54th out of 76	+2,254	6th out of 76
38 / 38R	-1,429	71st out of 76	+4,649	1st out of 76

Looking at the agency overall, the lines that have gained the most riders lie along major transit corridors: three Rapid lines, the longest light rail line, and a major local, trunk-line bus (*See Table 4-6 and Figure 4-30*). By percent change, the biggest gainers include a few significant north-south routes and few local buses in rapidly developing areas like Park Merced (*See Table 4-7 and Figure 4-31*). Overall, the lines that already had high ridership have grown.

Table 4-6: Lines with the Largest Absolute Gains, Fiscal Year 2015-Fiscal Year 2018

Line	Absolute Change in Daily Boardings, Fiscal Year 2015-Fiscal Year 2018
38R (Rapid bus)	+4,649
9R (Rapid bus)	+4,575
K/T (light rail)	+4,493
49 (local bus)	+2,703
14R (Rapid bus)	+2,692

Table 4-7: Lines with the Largest Percentage Gains, Fiscal Year 2015-Fiscal Year 2018

Line	Percent Change in Daily Boardings, Fiscal Year 2015-Fiscal Year 2018
28R (Rapid bus)	+103%
57 (local bus)	+89%
9R (Rapid bus)	+65%
14X (express bus)	+59%
35 (local bus)	+39%

Figure 4-30: Lines with the Largest Absolute Gains, Fiscal Year 2015-Fiscal Year 2018

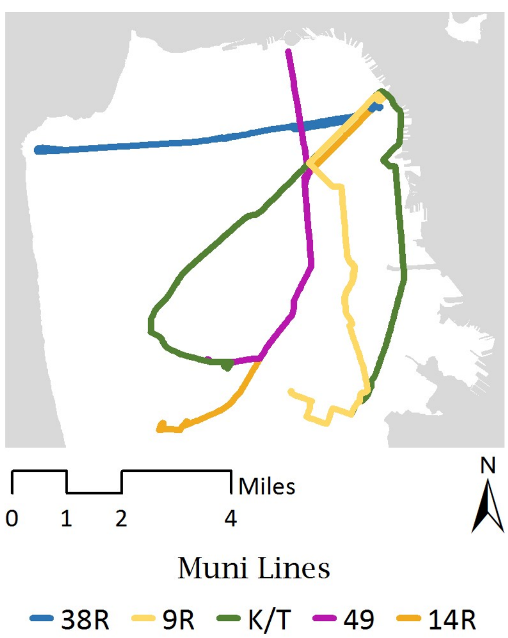
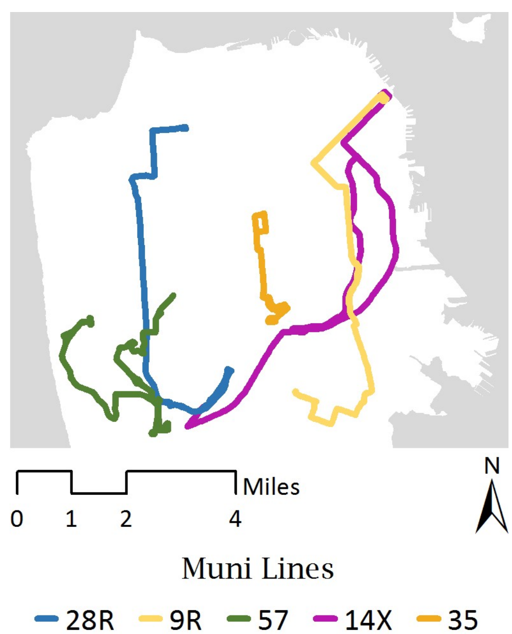


Figure 4-31: Lines with the Largest Percentage Gains, Fiscal Year 2015-Fiscal Year 2018



Meanwhile, the lines that have shed the most riders include a number of long local routes (again, some of whose riders may be switching to Rapids) and the F historic streetcar (*See Table 4-8 and Figure 4-32*). The F's ridership decline is more bad news for an already troubled line facing an operator shortage due to safety concerns.[78] The five lines that have seen the largest percentage losses include another set of local buses and two commuter-focused express services (*See Table 4-9 and Figure 4-33*).

78. Joe Fitzgerald Rodriguez, "Historic Muni Streetcar Shortage Highlights Driver Training Woes," *San Francisco Examiner*, Sept. 8, 2016.

Table 4-8: Lines with the Largest Absolute Losses, Fiscal Year 2015-Fiscal Year 2018

Line	*Absolute Change in Daily Boardings, Fiscal Year 2015-Fiscal Year 2018*
5 (local bus)	-1,567
F (streetcar)	-1,653
29 (local bus)	-1,695
9 (local bus)	-2,740
30 (local bus)	-3,498

Table 4-9: Lines with the Largest Percentage Losses, Fiscal Year 2015-Fiscal Year 2018

Line	*Percent Change in Daily Boardings, Fiscal Year 2015-Fiscal Year 2018*
18 (local bus)	-21%
30X (express bus)	-21%
9 (local bus)	-22%
3 (local bus)	-34%
83X (express bus)	-37%

Figure 4-32: Lines with the Largest Absolute Losses, Fiscal Year 2015-Fiscal Year 2018

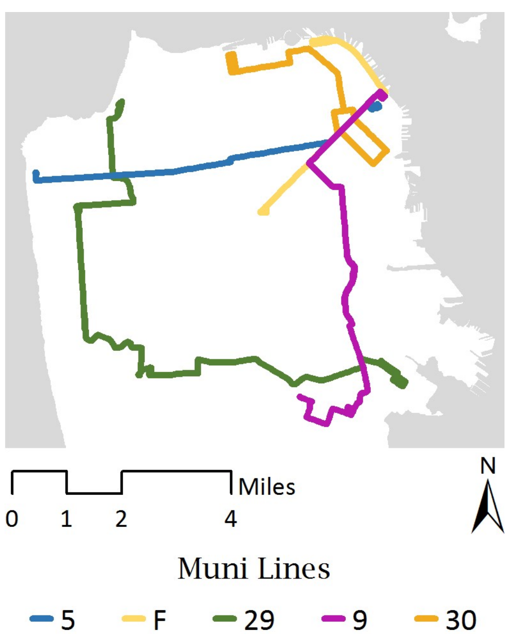
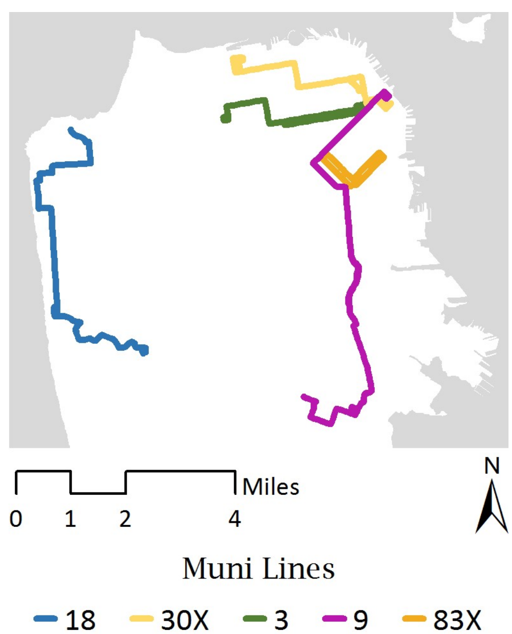


Figure 4-33: Lines with the Largest Percentage Losses, Fiscal Year 2015-Fiscal Year 2018



4.4. VTA Ridership Trends

4.4.1. Overview and Data Validation

Compared to BART and Muni, the Santa Clara Valley Transportation Authority operates in a more typical American metropolitan environment. Home to the office parks, corporate campuses, and single-family suburbs of Silicon Valley, Santa Clara County contains just over 1,500 people per square mile, as compared to 2,250 people per square mile in Alameda County and around 18,900 people per square mile in San Francisco. To be sure, Santa Clara is still quite urban—San José is America's tenth-most-populous city, after all—but the more spread-out urban form in which VTA operates is still markedly different from Muni's San Francisco or AC Transit's inner East Bay cities. Indeed, using the neighborhood typology created by Voulgaris et al., one percent of Santa Clara County residents live in the most transit-supportive neighborhood type, "old urban," compared to seven percent in Alameda County and 36 percent in San Francisco.[79]

Likewise, VTA itself is more typical of transit agencies nationwide. In 1991, VTA opened the first segment of its light rail system, near the start of America's current light-rail building boom, while BART began rail service in 1972 and Muni in 1912. Buses carried over three quarters of VTA's unlinked trips in 2017, while Guerra and Cervero calculated that VTA's rail extensions were among the least cost-effective, per passenger mile traveled, of the 59 projects they analyzed across America.[80] Thus, a detailed look at VTA can reveal whether unique influences have affected ridership across the whole Bay Area or whether the rest of the region's otherwise nationally typical ridership trends are largely hidden by Muni and BART.

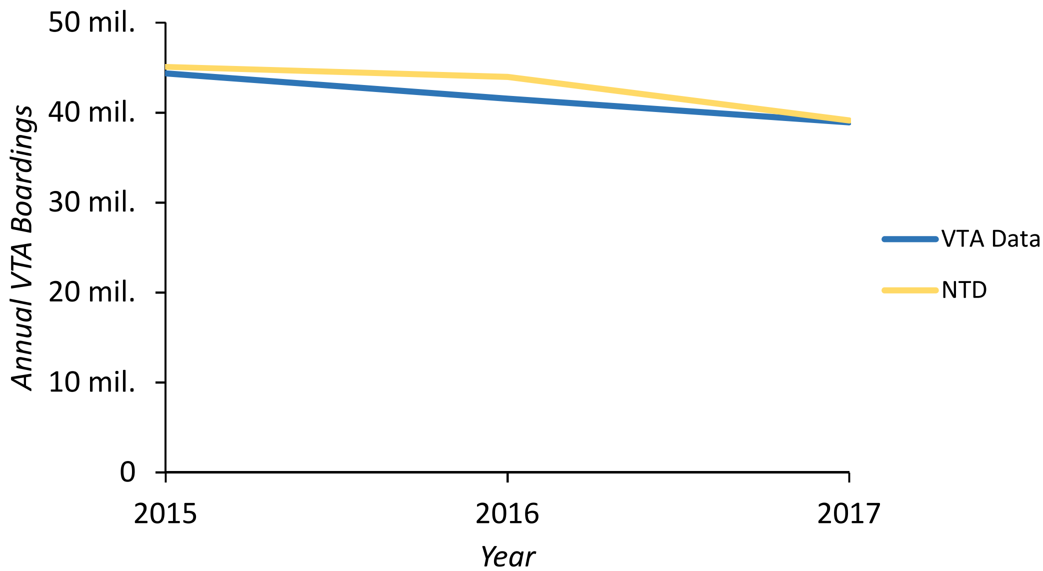
VTA staff have provided data on the agency's monthly ridership every three months, from January 2015 to July 2018, broken down by line, time of day, and day of the week. Aside from one month of likely erroneous data—addressed in Section 3.4.2—I summed up the four months of ridership each year, multiplied by three to estimate annual ridership, and compared the results to numbers from the National Transit Database to validate them (*See Figure 4-34*). The two datasets appear to track fairly closely, in both absolute

79. Census Bureau, "Annual Estimates"; and "CA Geographic Boundaries," *California Open Data Portal*, Feb. 2, 2017, last updated Feb. 27, 2019; and Voulgaris et al., "Synergistic Neighborhood Relationships."

80. *Santa Clara Valley Transportation Authority History*, Nov. 7, 2005, *Santa Clara Valley Transportation Authority*, 1; *BART Historical Timeline: Achievements Over the Years*, n.d., *Bay Area Rapid Transit*; SFMTA, "Muni History," *SFMTA*, 2019; and Guerra and Cervero, "Cost of a Ride," 268, 283.

values and direction of trends over time. Therefore, VTA's own data appear valid for comparison internally and with other agencies.

Figure 4-34: VTA Annual Ridership: NTD versus Internal VTA Data



4.4.2. Temporal Breakdown of VTA Ridership

VTA's ridership trajectory looks closer to that of the U.S. than that of the Bay Area overall. VTA ridership, for instance, flattened in 2015 and fell thereafter. This pattern looks similar to American transit's overall 2014 plateau and subsequent drop but different from MTC's later, sharper 2016 peak and ensuing decline (*See Figure 4-2*). While, like BART and Muni, VTA trips have increasingly concentrated in the peak, VTA has generally seen declines across the board. Unlike BART in particular, VTA ridership does not exhibit as stark a divide between peak and off-peak service, nor are most of its ridership trends moving as cleanly up or down.

Take changes in ridership by day of the week and time of day. Between the first month (January 2015) and last month (July 2018), weekday ridership has slowly and steadily declined (*See Figure 4-35*). Meanwhile, Saturday ridership has fallen by a larger percentage, and Sunday ridership has—excluding a spike in the last two months of data—dropped similarly but with more variability. Looking past the monthly bumps and troughs, ridership is generally falling throughout the week. Ridership also fell somewhat uniformly by time of day, until mid-2017 (*See Figure 4-36*). A significant service reallocation that year ended up increasing morning and afternoon ridership and decreasing ridership at other times of day.[81] Again, ridership has concentrated at peak times, but only after the service change.

Figure 4-35: Change in Monthly Ridership by Weekday

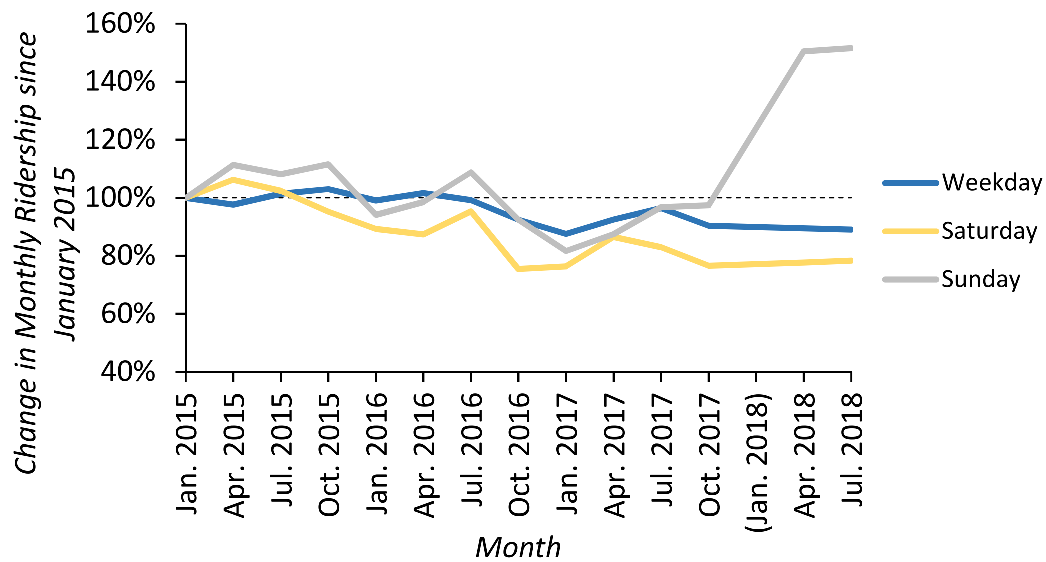
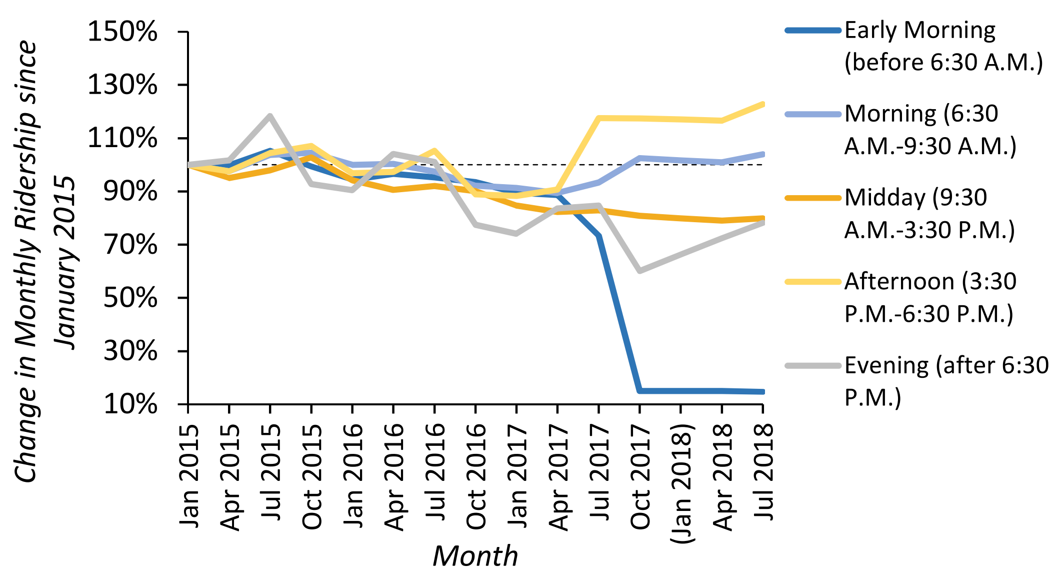


Figure 4-36: Change in Monthly Ridership by Time of Day

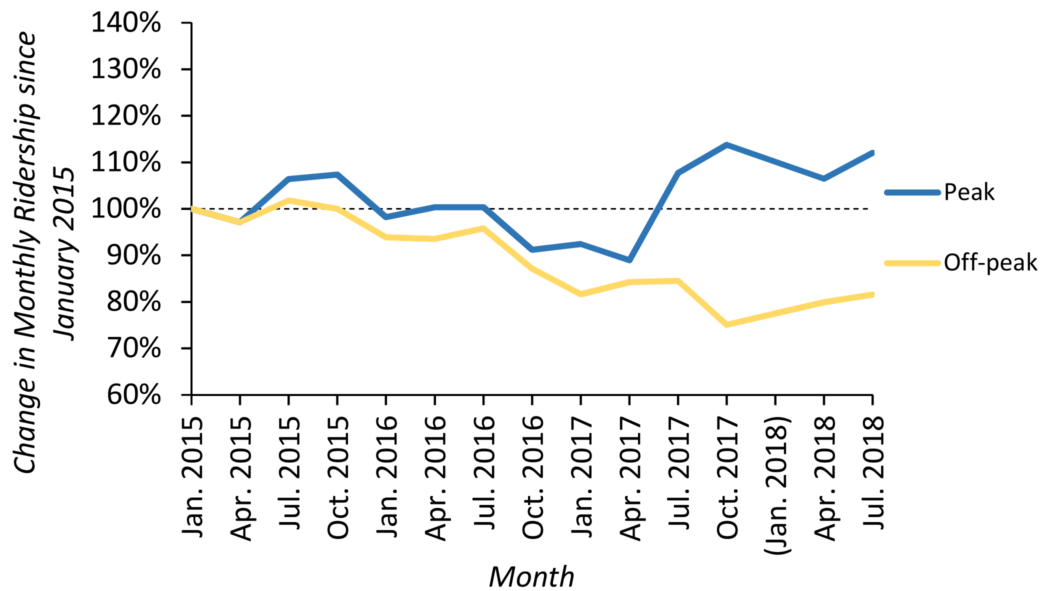


VTA's peaking problem shows up most clearly when dividing ridership into weekday peak versus all other times (*See Figure 4-37*). Since the service

81. Ling Hoang, "VTA's Transit Service Redesign Plan Is Approved," *Santa Clara Valley Transportation Authority*, May 5, 2017 and Gary Richards, "VTA Proposes Biggest Transit Overhaul since 2008," *Mercury News* (San José, CA), Jan. 6, 2017.

changes, peak patronage has recovered to around ten percent above January 2015 ridership—an increase that any transit agency would be thrilled to have. But at the same time, off-peak patronage has continued to drop, down around 20 percent since January 2015. This decline has dragged VTA's top-line ridership down with it.

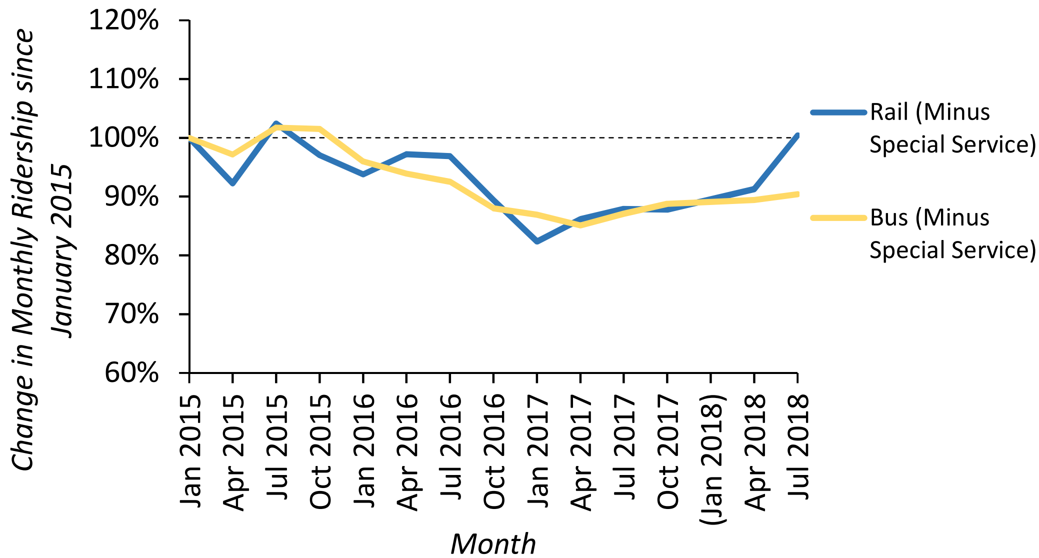
Figure 4-37: VTA's Peaking Problem



4.4.3. Modal and Geographic Breakdown of VTA Ridership

As described at the beginning of this section, ridership trends in the Bay Area as a whole vary considerably by mode, with bus ridership consistently falling and rail ridership growing until recently. However, VTA has not seen the same split. As with differences by day of the week, VTA's patronage is down on both of its primary modes. Since January 2015, rail and bus ridership have each fallen around ten percent, with significant month-to-month variability in the former. Removing special service, like extra game-day shuttles, somewhat smooths out these trends and produces the values in Figure 4-38. Ridership on the two modes track nearly perfectly throughout the timeframe of the data. Without BART to prop up the region's rail numbers, rail and bus use have declined similarly on an agency like VTA.

Figure 4-38: Modal Similarities in VTA Ridership Change



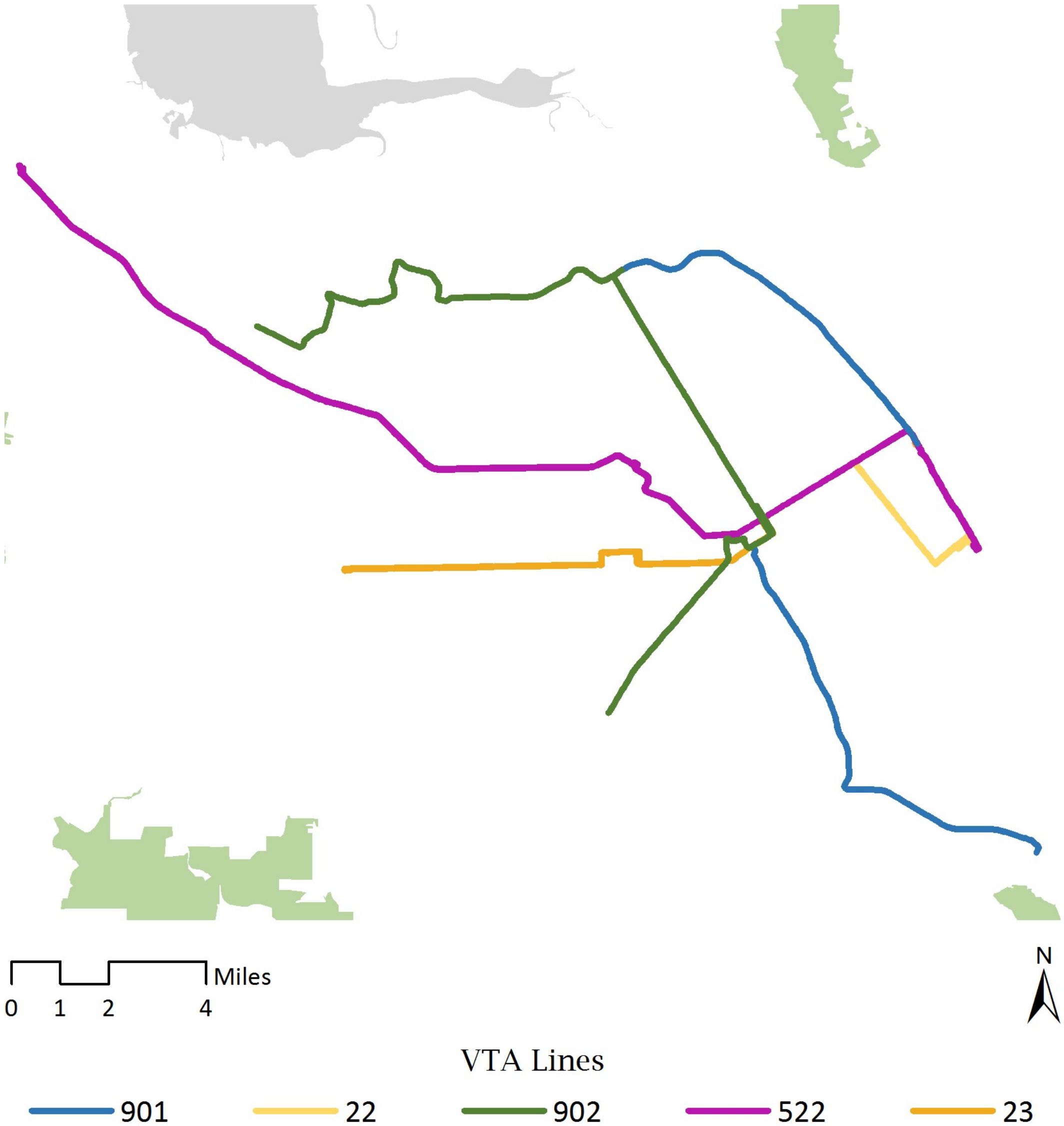
Across bus and rail, VTA ridership is concentrated in a few lines. The top five of VTA's 79 lines in April 2018, listed in Table 4-10, carried 42 percent of the agency's total ridership. Among them are the two main light-rail lines and three buses along major east-west corridors (*See Figure 4-39)*. These lines, however, suffered some of the largest absolute declines between April 2015 and April 2018. Indeed, four of the five lines in Table 4-10 rank in the bottom five by absolute change over that three-year period. As in Los Angeles[82] but unlike on BART and SFMTA, VTA's losses come from its most-patronized lines.

82. Manville, Taylor, and Blumenberg, *Falling Transit Ridership*.

Table 4-10: Lines with the Most Boardings, April 2018

Line	Monthly Boardings, April 2018	Absolute Change in Monthly Boardings, April 2015-April 2018	
901: Alum Rock-Santa Teresa (light rail)	408,178	-42,568	71st out of 72
22 (regular bus)	300,053	-88,336	72nd out of 72
902: Mountain View-Winchester (light rail)	285,021	-17,628	68th out of 72
522 (limited-stop bus)	200,446	+17,766	3rd out of 72
23 (regular bus)	188,990	-31,810	70th out of 72

Figure 4-39: Lines with the Most Boardings, April 2018



Meanwhile, 38 percent of VTA lines are gaining riders. The top five of these lines, both by absolute numbers and by percentage, lie west of San José, for the most part either long corridors ending at or shorter local routes within Silicon Valley (*See Tables 4-11 and 4-12 and Figures 4-40 and 4-41*). Despite the reputation of tech workers as taking private shuttles over public transportation, the high, growing number of jobs of all types in Silicon Valley, coupled with the lack of new housing nearby, may be fueling a rise in transit trips there.[83]

83. Louis Hansen, "Bay Area Tops U.S. in New Office Space, but Lags in Housing Starts," *Mercury News* (San José, CA), Oct. 22, 2018.

Table 4-11: Lines with the Largest Absolute Gains, April 2015-April 2018

LINE	ABSOLUTE CHANGE IN MONTHLY BOARDINGS, APRIL 2015-APRIL 2018
81 (regular bus)	+27,135
68 (regular bus)	+17,781
522 (ltd.-stop bus)	+17,766
88 (regular bus)	+8,927
53 (regular bus)	+7,218

Table 4-12: Lines with the Largest Percentage Gains, April 2015-April 2018

LINE	PERCENT CHANGE IN MONTHLY BOARDINGS, APRIL 2015-APRIL 2018
304 (ltd.-stop bus)	+234%
88 (regular bus)	+231%
328 (ltd.-stop bus)	+136%
81 (regular bus)	+124%
89 (regular bus)	+92%

Figure 4-40: Lines with the Largest Absolute Gains, April 2015-April 2018

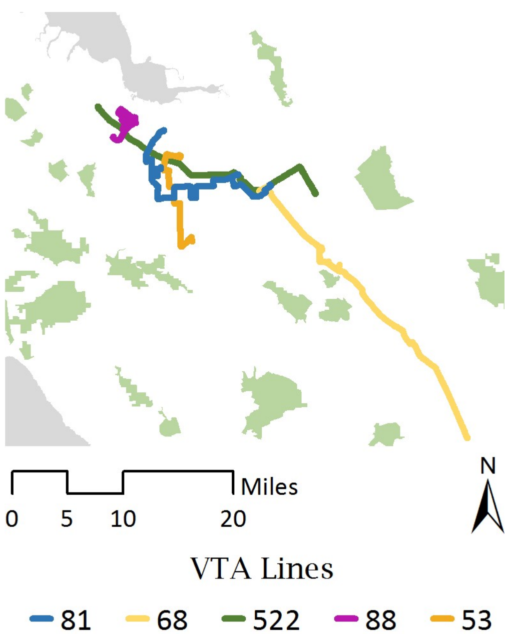
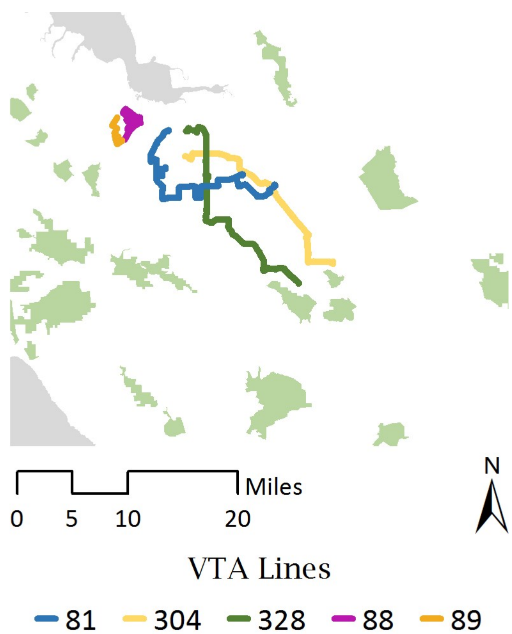


Figure 4-41: Lines with the Largest Percentage Gains, April 2015-April 2018



The lines with the greatest absolute losses, on the other hand, are radial light-rail and bus routes extending out from downtown San José (*See Table 4-13 and Figure 4-42*). As economic and job growth shift, perhaps central San José is no longer as much of an attractor of transit riders it once was. But these routes still carry the bulk of VTA ridership; as mentioned above, these lines mostly overlap with the list of highest-patronage lines (*See Table 4-10*). The lines with the largest percent change, on the other hand, are a collection of outlying local lines in smaller cities like Campbell and Gilroy (*See Table 4-14 and Figure 4-43*). These decreases indicate that, despite the losses in high-ridership lines, trips are also down on relatively low-ridership, low-service lines in built environments that are not especially transit-supportive.

Table 4-13: Lines with the Largest Absolute Losses, April 2015-April 2018

LINE	ABSOLUTE CHANGE IN MONTHLY BOARDINGS, APRIL 2015-APRIL 2018
902 (light rail)	-17,628
26 (regular bus)	-23,093
23 (regular bus)	-31,810
901 (light rail)	-42,568
22 (regular bus)	-88,336

Table 4-14: Lines with the Largest Percentage Losses, April 2015-April 2018

LINE	PERCENT CHANGE IN MONTHLY BOARDINGS, APRIL 2015-APRIL 2018
14 (cmty. bus)	-31%
120 (express bus)	-33%
49 (regular bus)	-36%
48 (regular bus)	-39%
180 (express bus)	-62%

Figure 4-42: Lines with the Largest Absolute Losses, April 2015-April 2018

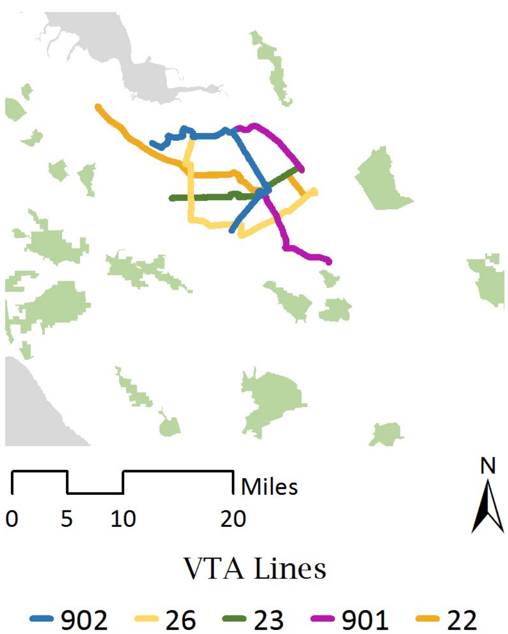
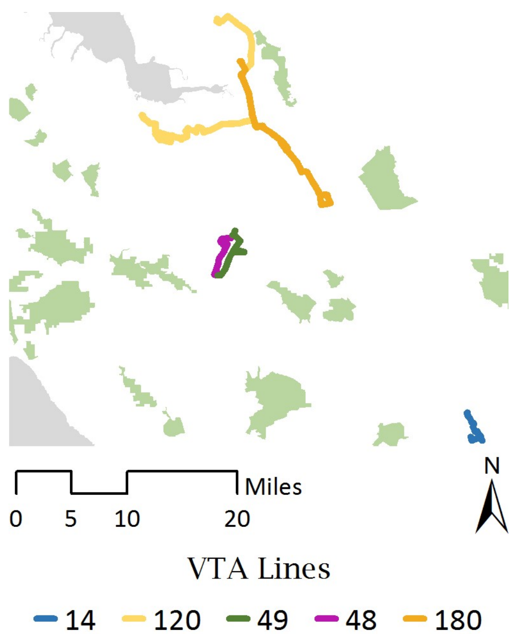


Figure 4-43: Lines with the Largest Percentage Losses, April 2015-April 2018



How and Why: Causal Findings

5.1. The Determinants of BART Ridership

Over the whole Bay Area and on three of its largest agencies, troubling peaking problems and precipitous off-peak drops have proven harmful to top-line ridership. The causes of these trends are thus of great importance if the region hopes to recover from its recent transit-use decline. Using the multivariate statistical model detailed in Section 3.5, this section estimates the effects of a number of possible influences on ridership on BART, Northern California's second-largest operator. In a word, the most powerful explanatory factor by far is jobs.

5.2. Ridership Influences on Weekday Mornings

Table 5-1 gives a summary of the A.M. weekday regression model for 2011, the earliest year with full data available for each variable, and Table 5-2 gives a summary of the same model for 2015, the most recent year with full data availability. Each model explains more than 70 percent of the variation in ridership. Even with fourteen explanatory factors, the adjusted R^2 only drops slightly in each case. Among the determinants, twelve have a statistically significant effect on ridership with 95 percent confidence or better in both models and ten with 99.9 percent confidence or better in both models.

Table 5-1: Model Output, 2011, Weekday A.M.

Factor	Standardized Coefficient	Significance
Jobs at destination	0.445	0.000***
BART travel time	-0.299	0.000***
Population at destination	0.225	0.000***
Transfer	-0.223	0.000***
Destination at a terminus	0.161	0.000***
BART parking at origin	0.155	0.000***
Population at origin	0.124	0.000***
Origin at a terminus	0.099	0.000***
Household income at origin	-0.095	0.000***
Jobs at origin	0.085	0.000***
Lines at destination	0.053	0.011*
Household income at destination	-0.035	0.012*
Drive-time-to-BART-time ratio	-0.026	0.127
Lines at origin	0.022	0.300
(Constant)	N/A	0.000***

*** significant at a 95 percent confidence level**
**** significant at a 99 percent confidence level**
***** significant at a 99.9 percent confidence level**

Coefficient of Determination	Adjusted Coefficient of Determination	Number of Origin-Destination Pairs
$R^2 = 0.709$	adjusted $R^2 = 0.707$	n = 1,877

Table 5-2: Model Output, 2015, Weekday A.M.

Factor	Standardized Coefficient	Significance
Jobs at destination	0.445	0.000***
Transfer	-0.227	0.000***
Population at destination	0.232	0.000***
BART travel time	-0.232	0.000***
Destination at a terminus	0.177	0.000***
BART parking at origin	0.155	0.000***
Population at origin	0.114	0.000***
Jobs at origin	0.112	0.000***
Household income at origin	-0.106	0.000***
Origin at a terminus	0.071	0.000***
Lines at destination	0.051	0.009**
Household income at destination	-0.035	0.008**
Drive-time-to-BART-time ratio	-0.003	0.867
Lines at origin	0.003	0.898
(Constant)	N/A	0.000***

*** significant at a 95 percent confidence level**
**** significant at a 99 percent confidence level**
***** significant at a 99.9 percent confidence level**

Coefficient of Determination	Adjusted Coefficient of Determination	Number of Origin-Destination Pairs
$R^2 = 0.719$	adjusted $R^2 = 0.717$	n = 1,965

As these tables show, the number of jobs near the destination station far outweigh any of the other explanatory variables. Tables 5-1 and 5-2 are ordered by the standardized coefficient, a relative measure of the strength of the effect of each input. With only a few possible BART lines, an additional single line obviously adds more ridership than an additional single job, but the standardized coefficient corrects for that. By this measure, in each year, jobs at the destination had around a 1.5 times greater effect or more on ridership than the next-most important factor. Employment at the A.M. destination dominates the model. With only job numbers by station and no other factors, an analyst could predict morning BART ridership at a relatively high accuracy.

Moreover, the influence of jobs on BART patronage has grown during the years studied. While standardized coefficients for a given input cannot be directly compared across models, the ratio between two standardized coefficients in 2011 can be compared with the same ratio in 2015. In 2011, jobs at the destination had a 1.49 times greater effect on ridership than the next-most predictive factor, travel time. By 2015, this ratio had grown: that year, jobs at the destination had a 1.61 times greater effect on ridership than the next-most important factor, whether the trip involves a transfer. This suggests that, increasingly, BART is a commuter-dominated system. This dependence on trips to work explains the sharp peaking trends detailed in Section 4.2.

A few other factors stand out, though none so tall. In 2011, BART travel time placed second in its influence on ridership and whether the trip required a transfer ranked fourth; these inputs swapped spots in 2015. In either case, a long trip or a trip that involves changing trains depresses ridership, as research literature would suggest. Interestingly, though, the ratio of driving travel time to BART travel time was not a statistically significant influence on ridership (BART travel time, whether the trip involved a transfer, and the drive-time-to-BART-time ratio were not highly colinear, so I felt comfortable including them all in the model; including only BART travel time without the latter two did not substantively change the results.).

Placing third both years was population density at the destination station. I did not expect it to be so influential on ridership, especially given that it placed much higher than population at the origin. However, on a commuter system like BART, population within a half-mile of the origin does not capture the wide catchment area for park-and-ride commuters. Population at the destination, meanwhile, likely less reflects the influence of people returning home in the A.M. and more serves as a proxy for a built environment that facilitates last-mile connections to destinations. For instance, if the area around a destination station has a dense population, it is also likely to be walkable, to have connecting local bus services (difficult to capture otherwise due to the need to obtain data from each connecting agency), etc.

Notably, the number of lines at the destination—effectively a measure of headways/service frequency—is low on the list of influential factors, and the number of lines at the origin is not statistically significant at all. While Jarrett Walker is generally right that “frequency is freedom,” on a commuter system like BART, many workers may be willing to make trips regardless of how long they have to wait for train.[84] After all, as detailed in Section 2.3.3.1, peak-period ridership is generally less elastic than off-peak, and increasingly more of BART's ridership is at peak times.[85] And unlike some other trip types, the fixity of many work start times and BART's relatively strict schedule allows riders to plan their arrival times at the origin station to minimize wait. Important to keep in mind, though, is that this statistical model does not correct for the endogeneity between service supply and ridership, as described in Section 3.5.2. In other words, the relatively low influence of service supply on BART ridership demonstrated by the models above actually represents a best-case scenario for the factor's effect. In fairness, the number of lines serving each station varies only from one to four each; this small variance does dampen its effect in the model. Nevertheless, this reflects the realities of BART's system, on which headways are consistent and relatively similar on the corridors with the large majority of riders.

All other inputs have roughly the expected effects on ridership, in the expected directions.

5.2. Ridership Influences on Weekday Afternoons and Evenings

The same factors influence weekday BART ridership after noon as well. Tables 5-3 and 5-4 summarize the results of the model for P.M. weekday ridership in 2011 and 2015, respectively. Again, the models overall are quite predictive, explaining an even greater part of the variation in ridership than the A.M. models.

84. Jarrett Walker, *Human Transit: How Clearer Thinking about Public Transit Can Enrich Our Communities and Our Lives* (Washington: Island, 2012), 85.
85. Litman, "Transit Price Elasticities."

Table 5-3: Model Output, 2011, Weekday P.M.

FACTOR	STANDARDIZED COEFFICIENT	SIGNIFICANCE
Jobs at origin	0.407	0.000***
BART travel time	-0.315	0.000***
Population at origin	0.252	0.000***
Transfer	-0.226	0.000***
Jobs at destination	0.224	0.000***
Population at destination	0.215	0.000***
Origin at a terminus	0.151	0.000***
Drive-time-to-BART-time ratio	-0.137	0.000***
BART parking at destination	0.136	0.000***
Destination at a terminus	0.120	0.000***
Household income at destination	-0.080	0.000***
Household income at origin	-0.065	0.000***
Lines at origin	0.033	0.090
Lines at destination	0.013	0.535
(Constant)	N/A	0.000***

*** significant at a 95 percent confidence level**
**** significant at a 99 percent confidence level**
***** significant at a 99.9 percent confidence level**

COEFFICIENT OF DETERMINATION	ADJUSTED COEFFICIENT OF DETERMINATION	NUMBER OF ORIGIN-DESTINATION PAIRS
$R^2 = 0.734$	adjusted $R^2 = 0.732$	n = 1,862

Table 5-4: Model Output, 2015, Weekday P.M.

FACTOR	STANDARDIZED COEFFICIENT	SIGNIFICANCE
Jobs at origin	0.399	0.000***
Transfer	-0.270	0.000***
BART travel time	-0.260	0.000***
Jobs at destination	0.244	0.000***
Population at origin	0.236	0.000***
Population at destination	0.201	0.000***
Origin at a terminus	0.160	0.000***
Drive-time-to-BART-time ratio	-0.158	0.000***
BART parking at destination	0.120	0.000***
Destination at a terminus	0.105	0.000***
Household income at destination	-0.077	0.000***
Household income at origin	-0.069	0.000***
Lines at origin	0.040	0.029*
Lines at destination	0.030	0.122
(Constant)	N/A	0.000***

*** significant at a 95 percent confidence level**
**** significant at a 99 percent confidence level**
***** significant at a 99.9 percent confidence level**

COEFFICIENT OF DETERMINATION	ADJUSTED COEFFICIENT OF DETERMINATION	NUMBER OF ORIGIN-DESTINATION PAIRS
$R^2 = 0.746$	adjusted $R^2 = 0.744$	n = 1,965

Again, station-area jobs predominate. The location and number of jobs at the origin (as opposed to at the destination in the A.M. models) is the most influential factor on BART ridership both years. After noon, BART riders appear to primarily use the system to return from work. Since the P.M. includes afternoon pre-peak and evening post-peak periods, in which many non-work trips occur, the effect of jobs is less than in the A.M. Still, in both years, jobs at the origin are more than 1.25 times more predictive than the next-most influential factor.

Like in the morning, the influence of jobs at the origin is growing over time. In 2011, jobs at the origin were 1.29 times more influential than the next-most predictive factor, travel time, while in 2015, jobs at the origin were 1.48 times more influential than the next factor, whether the trip requires a transfer. In both the morning and evening, jobs increasingly drive BART usage.

Unlike the A.M. model, jobs at both ends of the trip are highly predictive. In the P.M., jobs at the destination ranked fifth-most influential in 2011 and fourth in 2015. This factor may represent evening-shift commutes, but also the effects of running errands, social trips, etc. In the latter case, the traveler may not be taking BART to their own job, but they are traveling to job centers nonetheless.

Otherwise, the P.M. models look fairly similar to the A.M. models. The few differences include: in the P.M., the drive-time-to-BART-time ratio is significant, but less influential than most of the other factors. The number of lines at each end of the trip is even less influential in the P.M. model than the A.M.; in 2011, neither lines at the origin nor lines at the destination reached a 95 percent threshold of significance. All told, though, the top-line story is the same: jobs, jobs, jobs.

5.3. 2018 Weekday Ridership Influences

How have the determinants of BART ridership changed since 2015, as patronage has dropped? To explore this, I ran the same model for 2018 weekday A.M. and P.M. BART ridership. This model, though, is a decidedly rougher estimation than the previous ones, due to data availability issues. LODES jobs numbers—the most influential determinant of BART ridership in the prior models—have only been released up to 2015, and ACS population estimates have only been published up to the five-year span centered on 2015. To account for growth since then, for each factor with unavailable 2018 data, I constructed a linear best-fit line for each station based on data points from 2011 through 2015. I thereby projected three further years of data, to 2018. This method is admittedly imperfect. For instance, jobs in parts of San Francisco appear to be increasing faster than linearly. Nonetheless, the output remains essentially the same if 2015 jobs and population data are used to explain 2018 ridership instead of the 2018 jobs and population estimates created via the method above.

Tables 5-5 and 5-6 show the A.M. and P.M. results, with inputs again ordered from most to least predictive of ridership. The models explain a similar share of the variation in ridership as the 2011 and 2015 models, over 70 percent. Indeed, the 2018 outputs generally look similar to the 2011 and 2015 results and provide the same key takeaway: jobs still predict BART ridership the most. In the morning, jobs at the destination top the list of influential factors. In the evening, jobs at the origin do so, with jobs at the destination ranked fifth as well. In the A.M., jobs at the destination were 1.50 times more influential than the next most predictive factor, while in the P.M., jobs at the origin were 1.44 times more influential. These ratios are less than in 2015, but since the input job numbers are somewhat rough estimates, I am not ready to say for sure that jobs have decreased in their effect on ridership. Regardless, the model does show that jobs continue to drive ridership, even as transit use falls and employment continues to grow and concentrate.

Table 5-5: Model Output, 2018, Weekday A.M.

Factor	Standardized Coefficient	Significance
Jobs at destination	0.429	0.000***
Transfer	-0.284	0.000***
BART travel time	-0.219	0.000***
Population at destination	0.209	0.000***
Destination at a terminus	0.169	0.000***
BART parking at origin	0.146	0.000***
Jobs at origin	0.117	0.000***
Household income at origin	-0.096	0.000***
Population at origin	0.088	0.000***
Origin at a terminus	0.069	0.000***
Lines at destination	0.055	0.005**
Drive-time-to-BART-time ratio	0.043	0.008**
Household income at destination	-0.040	0.002**
Lines at origin	0.006	0.757
(Constant)	N/A	0.000***

*** significant at a 95 percent confidence level**
**** significant at a 99 percent confidence level**
***** significant at a 99.9 percent confidence level**

Coefficient of Determination	Adjusted Coefficient of Determination	Number of Origin-Destination Pairs
$R^2 = 0.713$	adjusted $R^2 = 0.711$	n = 2,053

Table 5-6: Model Output, 2018, Weekday P.M.

Factor	Standardized Coefficient	Significance
Jobs at origin	0.404	0.000***
Transfer	-0.281	0.000***
BART travel time	-0.237	0.000***
Population at origin	0.230	0.000***
Jobs at destination	0.223	0.000***
Origin at a terminus	0.166	0.000***
Population at destination	0.148	0.000***
BART parking at destination	0.108	0.000***
Household income at destination	-0.093	0.000***
Destination at a terminus	0.085	0.000***
Lines at origin	0.080	0.000***
Drive-time-to-BART-time ratio	-0.078	0.000***
Household income at origin	-0.050	0.000***
Lines at destination	0.004	0.851
(Constant)	N/A	0.000***

*** significant at a 95 percent confidence level**
**** significant at a 99 percent confidence level**
***** significant at a 99.9 percent confidence level**

Coefficient of Determination	Adjusted Coefficient of Determination	Number of Origin-Destination Pairs
$R^2 = 0.733$	adjusted $R^2 = 0.731$	n = 2,038

5.4. Model Variants

5.4.1. Elasticities

The models above do not easily convey a key measure of the influences on BART ridership: elasticity. The elasticity of ridership with respect to a given input answers the question: what percentage does ridership change when the input increases one percent, all else equal? To calculate the elasticity of ridership with respect to the various inputs above, I ran a "log-log model," in which I took a natural logarithm of *both* BART ridership and all the input factors[86] and then ran the regression. The results are presented in Appendix B.

Overall, the log-log models explain less of the variation in ridership than the log-linear models above, albeit slightly, nor do they have a stronger theoretical basis for their use in this situation. That said, the model outputs are generally similar: jobs again rank most influential on ridership, as measured by the standardized coefficient. Other factors do have higher elasticities, but that is because each input is measured in different units. For instance, a 50% increase in the number of jobs near a station is hard to compare directly against a 50% increase in the number of lines serving a station, given the widely different ranges of these two inputs (*See Tables 3-2 and 3-3)* The most significant difference from the models above is that the number of lines ranks higher, placing third or fourth. All in all, the tables in Appendix B both confirm the prior findings and provide rule-of-thumb elasticities to communicate how changes in different inputs change BART ridership.

5.4.2. Excluding Downtown San Francisco

As described above, much of BART's ridership comes from transbay trips to and from the four downtown San Francisco stations on Market Street. The outsized influence of these four outliers may obscure trends in the rest of the system, where most of the ridership loss is occurring. To help examine this, I re-ran all the above regressions, excluding all trips that end at the four downtown San Francisco stations in the A.M. and all trips that begin there in the P.M. The results of these models are presented in Appendix C. As expected, the influence of jobs falls, no longer taking the top spot in most of the models. However, even without downtown San Francisco's huge job cluster, employment still is the second- or third-most predictive factor on ridership in most of the models. Travel time and whether the trip requires a transfer have more influence than in the full model, with the former's effect decreasing slightly over time and the latter's rising. Surveying this set of outputs, I see no clear "culprit" emerge to explain the decrease in ridership outside of downtown San Francisco. BART travel times have not changed much over the period analyzed, and almost every trip pair that required a

86. Except the dummy variables, which were put into the model as normal. For BART-provided parking at the origin and destination, I took the natural logarithm of (the number of spaces plus one), since many stations have no BART parking spaces; the logarithm of zero is undefined.

transfer in 2011 also did in 2015 and 2018. Thus, the ultimate cause of the BART ridership drop outside of downtown San Francisco is due to some other factor or factors, like ridehail use or residential displacement, that, for lack of clear data, the models in this section do not capture.

5.4.3. Off-peak

As BART has seen the most severe ridership declines at off-peak hours, my final set of models consider only off-peak ridership. That is, I used annual BART ridership on weekends and weekdays outside of rush hours (as defined in Section 4.2.2) as the dependent variable for these models. The results, as well as further methodology, are presented in Appendix D. Each model explains a comparable share of the variation in ridership as the prior ones.

Again, I find no smoking gun. In fact, jobs concentrations continue to top the lists of most influential factors. In all three years considered, jobs at the destination ranked most influential. Since both A.M. and P.M. ridership are included in these off-peak models, jobs at the origin also placed highly. It ranked third-most influential in 2011, rising to second-most in 2015 and 2018. Thus, even excluding the most commute-heavy times of day, jobs explain the largest share—and a growing share—of variation in BART ridership. Again, the reason for the off-peak slump lies beyond what these regressions can reveal.

5.5. Caveats and Robustness

5.5.1. Robustness Testing

The models described above were robust to the inclusion and exclusion of a number of different variables, listed in Section 3.5.2. I also ran models using a half-mile radius for both jobs and population and using a quarter-mile radius for both. Like Guerra and Cervero, I found that these radius changes made little difference, but that a quarter-mile for jobs and a half-mile for population was slightly more predictive than the alternatives.[87]

5.5.2. Homelessness, Police, and Cleanliness

As described in Section 2.2, issues of safety and cleanliness on BART have dominated media coverage of the ridership decline. The lack of good time-series data on these factors, however, impeded me from including them in a model like the one above. Likewise, perceptions of cleanliness and safety can vary widely depending on how surveys are structured; people's stated

87. Guerra and Cervero, "Is a Half-mile?"

preferences and feelings on these issues may well differ from their actual preferences and feelings.

Acknowledging those caveats, what modeling I was able to do shows no substantiable effects on ridership from these types of factors. Specifically, the effect on ridership from the number of homeless people in a station, the presence of police in a station, and the perception of cleanliness at a station are either not significant or inseparable from other factors' effects. First, the 2018 homeless counts in the four downtown San Francisco stations[88] were too colinear with population density to establish an independent effect; the number of origin-destination pairs with full data dropped dramatically as well. Moreover, perceived station cleanliness—as measured on a four-point scale by a BART rider survey[89]—was too correlated with population and with number of lines to include in a model. Put differently, people experiencing homeless tend to be in dense areas, and stations with more people nearby and more lines going through tend to be more unclean. These conclusions are intuitive, but they prevent the independent effects of each factor from being analyzed in a model like the ones above. In general, though, it appears far more likely that population density and number of lines are responsible for this portion of the variation in ridership than presence of people experiencing homelessness or the perception of dirty stations.

BART also surveyed riders in 2017 and 2018 asking if they had seen a police officer in the station.[90] Unlike the factors above, the results of this survey were not substantially colinear with other inputs and therefore could be added into the model. When included, police presence did not have a statistically significant effect on ridership. I cannot, though, firmly draw conclusions here. In all likelihood, the presence of police both affects and is affected by the crime rate in the station, the crime rate in the area, and, unfortunately, the demographics of each station's ridership. Without controlling for these other factors—and accounting their endogeneity—the ridership effects of police cannot be rigorously established (and hence why I left it out of the models above). Still, as a basis for potential future research, my analysis at least suggests that police presence does not significantly influence ridership.

5.5.3. Methodological Limitations

Despite their robustness to adding or swapping inputs, the statistical

88. BART, *Station Count Data*, 2019.
89. BART, *Station Data Summary*, n.d.
90. Ibid.

models above do have some shortcomings. For one, the main models focus on weekday ridership, when jobs likely have a greater effect. Weekend ridership patterns divide less evenly into A.M. and P.M. directional flows, meaning that the effects of people traveling from home versus to home would not be as readily separable. The selection of BART itself to model—a system that effectively functions as commuter rail on its branches—also slants the results towards jobs being important, as compared to a model of, say, Muni. Even so, the scale of jobs' effect is impressive. In the hot Bay Area economy, employment affects not just housing, tax revenue, and neighborhood change, but also transit use.

Light at the End of the Tunnel?: Conclusion

6.1. Analysis

The story of ridership in the Bay Area has not reached its happy ending, at least just yet. Into 2018, regional ridership is continuing to fall, according to preliminary data. And while, from the top-line numbers, 2018 would only be the second straight year of declines, key indicators like ridership per capita and productivity have been on the wane for a longer time. Gains on BART and generally high ridership on Muni have long obscured worrying drops among other operators across the region. Bus ridership has seen a slow but deepening decline for the past decade. Thus, policymakers should remain wary if ridership does begin to rise again. If ridership rebounds but productivity or ridership per capita stay flat or decline, planners should still worry about the longevity of the revival.

On the Bay Area's largest agencies, the same warning applies. While the details of each operator's patronage changes vary, they share a common trend: peak ridership is either rising or falling only slightly, while off-peak ridership is dropping precipitously. On BART, more and more riders have packed into weekday, transbay trips into downtown San Francisco, while other trip types have shed riders significantly. On SFMTA, the busiest lines with the most frequent headways have picked up riders—some from local routes along the same corridor—as lower-service lines carry fewer and fewer trips. And on VTA, while the most well-traveled lines have lost trips, ridership during peak periods and into the heart of Silicon Valley is up as ridership at off-hours and in outlying areas is down. Undeniably, each of these conclusions comes with nuance and exceptions—especially concerning VTA, where losses have been more broad-based and more similar to declines observed elsewhere in America. But a common thread runs through each agency—a thread not woven into the ridership tapestry of other regions. For instance, in Southern California, the largest agencies and the most well-used lines through some of the densest parts of the metropolitan area have seen the greatest declines. In the Bay Area, the reverse tends to be true.[91]

The number and location of jobs help explain why this is the case. As my statistical models demonstrate, concentrated station-area employment has the most influence, and a growing influence, on ridership on the region's

91. Manville, Taylor, and Blumenberg, *Falling Transit Ridership*.

largest multi-jurisdiction operator, BART. This confirms not only the descriptive trends on BART but those across the region. Jobs have increasingly concentrated in employment clusters like downtown San Francisco, to, from, and in which transit use has remained strong.[92] Ridership depends upon commuting now more than ever, as BART and likely other agencies increasingly become home-to-work transportation primarily.

Employment patterns explain the resilience of peak ridership, but the causes of the region's decline—i.e., the causes of the sharp fall in off-peak patronage—remain to be determined. Research underway by the UCLA Institute of Transportation Studies aims to explore these factors, including residential displacement, ridehail growth, etc. Still, knowing that peak ridership is not the cause for concern—or, perhaps, a cause for concern due to overcrowding—helps to narrow the scope of further research.

6.2. Policy Implications

Where should MTC and the Bay Area's transit operators look to reverse the region's troubling transit trends? In light of these findings, I recommend that policymakers focus on new pressures on off-peak transit—the booming expansion of ridehail, the spatial dispersion of non-work destinations, etc. Given the continued strength of peak transit use, these factors merit more scrutiny than peak pressures like employment growth and congestion.

In fact, transit operators should devise strategies to handle the problems that come with an over-reliance on peak ridership. When a transit agency carries most of its ridership at weekday rush hours, it must purchase and maintain a large fleet that sits mostly empty the rest of the day. It must hire, pay, and schedule many vehicle operators for full shifts, even if they are only needed at peak. And it must address rider discomfort caused by overcrowding. Until ridership evens out temporally and geographically, these problems and others like them will plague Bay Area transit agencies.

It bears specific mention that service supply and headways do not appear to have affected ridership greatly. Thus, the addition of new service as a response to the ridership slump may not have the full restorative effect desired. Since 2014, service in revenue hours and revenue miles has increased regionwide and on each of the three profiled agencies. BART has opened extensions and kept headways the same, SFMTA has rolled out its Rapid Network, and VTA has reallocated service to peak times of day. The latter two of these have improved ridership on peak lines and times, but overall, despite

92. Hannah King, "Employment Clusters Update," Mar. 7, 2019.

the service increases, ridership remains stubbornly down. Likewise, the BART regression models show that service supply explains ridership weakly at best and not nearly as much as jobs, even under a favorable model design (To be sure, the number of BART lines at each station only varies from one to four, which may dampen its influence.). This finding does not necessarily mean that service boosts have been or will be in vain but rather that other forces are overwhelming their effects. This suggests that another round of service reallocation will not be enough to fix the problem.

When it comes to reviving off-peak transit use, my findings present a difficult dilemma for planners. On the one hand, policies targeted at increasing non-commute, reverse direction, evening, and weekend trips are of great importance for addressing the most significant declining trip types. On the other, the most significant factors that influence transit use tend to be beyond agencies' control. Transit operators cannot make short-term change to the location of jobs. None of the policy levers at agencies' disposal, at least today, will have much effect on off-peak factors either. MTC and Bay Area cities could potentially have some influence on ridehail use, for instance, but trends like the replacement of errands with online shopping are too broad to be affected much by local policy. Policymakers must therefore make the difficult decision of whether to channel resources towards the most crowded trip types, to alleviate crowding and double down on their strongest market, or towards slumping trips types, to shore up the weakest parts of the transit network despite their limited control over them.

On both horns of this dilemma lie solutions with at least some potential to improve ridership. If MTC and transit operators decide to deepen their investment in—and reliance on—the most well-ridden trip types, they could pursue a number of peak-focused strategies. In the short term, agencies could lengthen trains at rush hour, add more service in commute directions, create more transit-only lanes (and eventually construct a second Transbay Tube), implement congestion pricing, etc. Such strategies may help retain or grow peak-hour and peak-direction ridership, although they may do as much or more to improve trip satisfaction and speed for existing riders. If instead MTC and operators focus on restoring off-peak ridership, they should consider increasing midday, evening, and weekend headways; adding more service in counter-commute directions, restructuring route networks; and regulating or working with ridehail companies to make them better complements to transit. Of course, these latter set of strategies especially are easier said than done, and their individual effects may be small or slow to develop. Still, over-dependence on peak trips is operationally and financially dangerous for transit agencies, so a suite of off-peak investments may be worth pursuing. More research is needed on the effectiveness of off-peak-focused interventions in a region with high use of ridehail, worrying amounts of displacement, and other unique and modern factors; perhaps different agencies could test different strategies and compare results.

While peak-focused and off-peak focused strategies are not mutually exclusive, policymakers should recognize that they may still be at odds, in a world of limited resources. Moreover, agencies should shape every strategy, as best they can, around the most influential factors on ridership, like job and population density. Service increases, for instance, will do little good if they do not serve major job or activity centers. Finally, MTC should consider supporting or incentivizing the above strategies with the capital and operating funds it disperses.

Long-term, policies that move and/or enable jobs and housing concentrations in the region will significantly affect transit ridership. Plan Bay Area 2040, MTC and the Association of Bay Area Governments' long-range Sustainable Communities Strategy, calls for significant employment and housing growth near transit. The plan anticipates that over two-thirds of new housing and jobs will occur in Priority Development Areas around high-quality transit stops. While such a strategy serves a number of important policy goals, I urge some caution with respect to its effect on transit ridership. For one, adding housing around outlying BART stations or other far-flung transit nodes may actually reduce ridership. For example, someone living and working in Oakland will make many trips by foot or transit, since so many destinations are close, even if they drive to work. If that person moves to a transit-oriented development (TOD) on an outlying BART branch, they may start taking transit to work, but most of their other trips will have to be by car to reach stores, schools, etc. Even in a dense area, a TOD may also reduce ridership if it does not have strong affordability protections or requirements. As modeled by William Dominie, people who move into new TODs may use transit more than they used to, but at the same time, low-income, transit-dependent residents are often displaced from the area—resulting in a net ridership loss.[93]

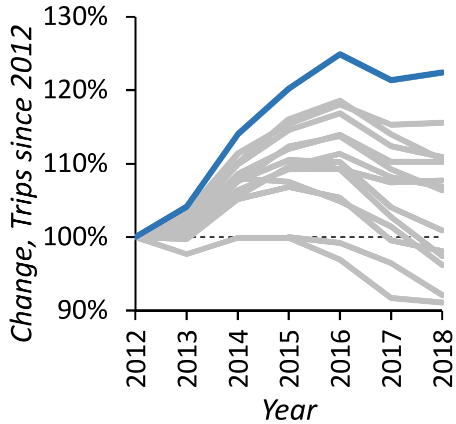
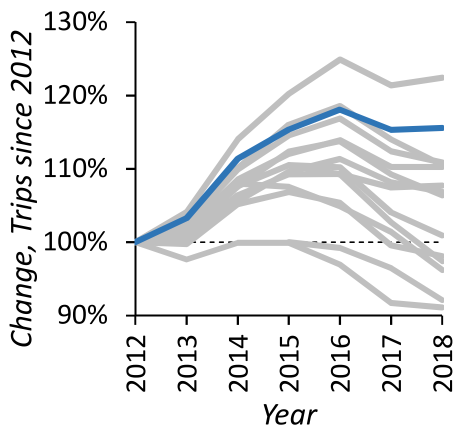
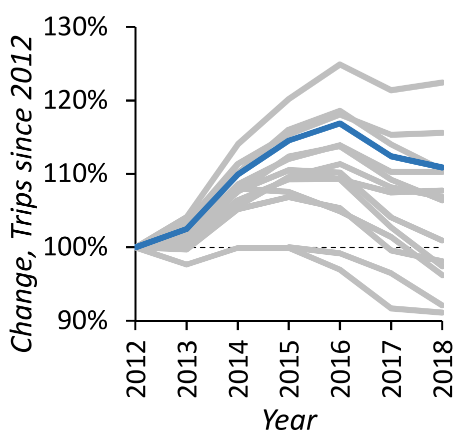
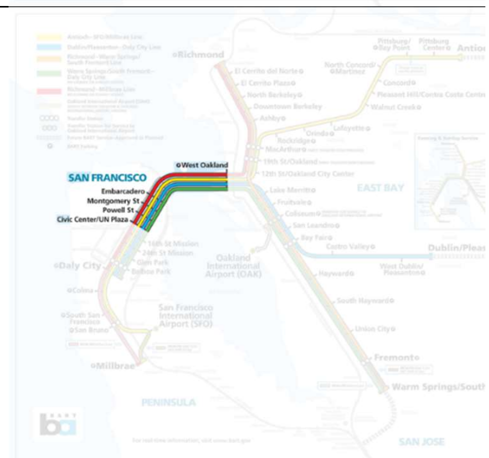
93. MTC and ABAG, *Plan Bay Area 2040: Regional Transportation Plan and Sustainable Communities Strategy for the San Francisco Bay Area, 2017–2040*, Jul. 26, 2017; MTC, "Priority Development Areas." *Metropolitan Transportation Commission*, 2019; William Dominie, "Is Just Growth Smarter Growth? The Effects of Gentrification on Transit Ridership and Driving in Los Angeles' Transit Station Area Neighborhoods," APRP, UCLA, Los Angeles, 2012; and Miriam Zuk et al., "Gentrification, Displacement and the Role of Public Investment: A Literature Review" Working Paper 2015-05, Community Development

A long-range plan to build transit ridership should not only put housing near transit but also jobs near transit. Better yet, MTC should aim to locate housing near jobs, and transit ridership growth will follow. With such land-use planning strategies and with well-designed affordability and anti-displacement policies, employment and housing may restore off-peak transit use and retain peak transit riders across the region.

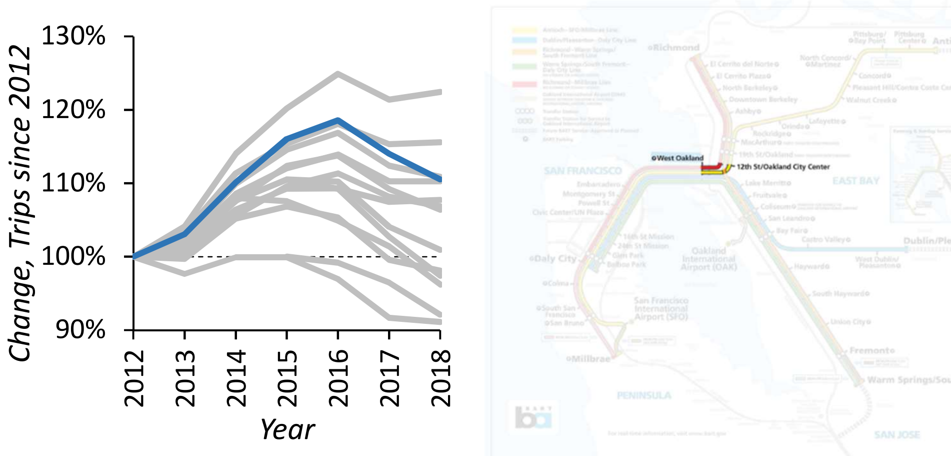
Investment Center, Federal Reserve Bank of San Francisco, San Francisco, CA, Aug. 2015), 68.

Appendix A: BART Segment Ridership

Table A-1: BART Track Segments (Ordered by Change in the Number of Trips that Begin in, End in, and/or Pass through the Segment, 2012-2018)

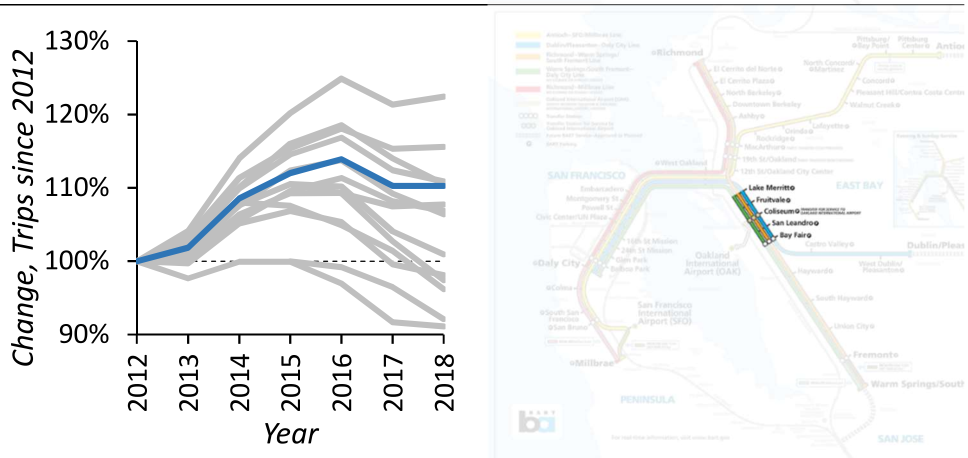
1		
2		
3		

4



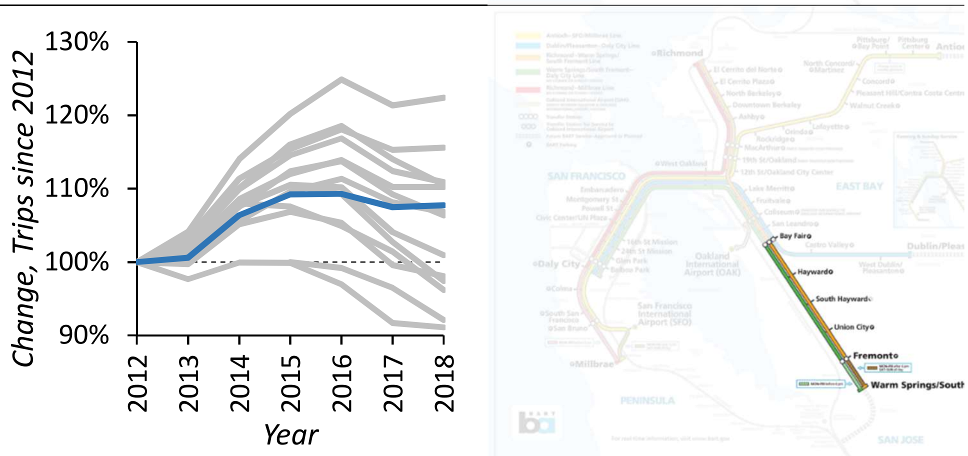
130%
120%
110%
100%
90%
Change, Trips since 2012
2012
2013
2014
2015
2016
2017
2018
Year
West Oakland
12th St/Oakland City Center
SAN FRANCISCO
EAST BAY
PENINSULA
SAN JOSE

5



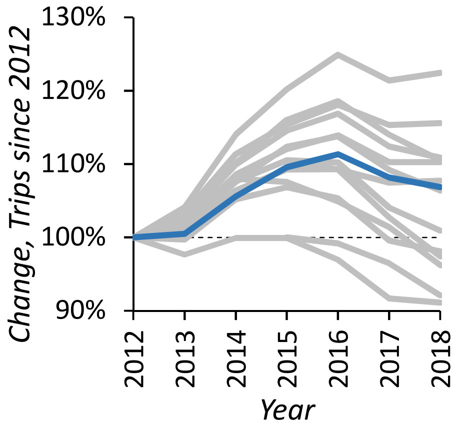
130%
120%
110%
100%
90%
Change, Trips since 2012
2012
2013
2014
2015
2016
2017
2018
Year
Lake Merritt
Fruitvale
Coliseum
San Leandro
Bay Fair
SAN FRANCISCO
EAST BAY
PENINSULA
SAN JOSE

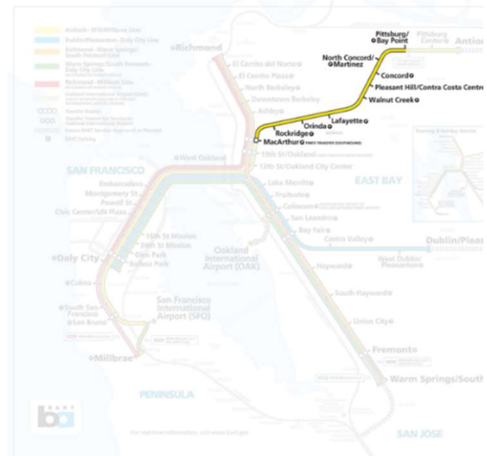
6



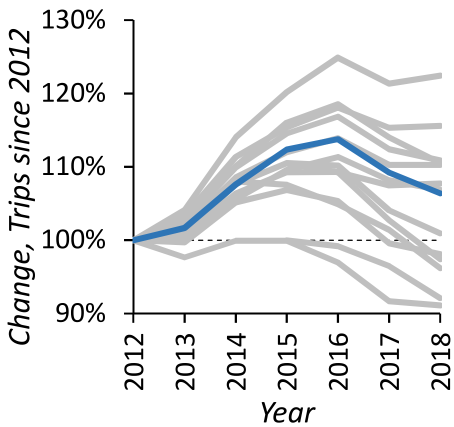
130%
120%
110%
100%
90%
Change, Trips since 2012
2012
2013
2014
2015
2016
2017
2018
Year
Bay Fair
Hayward
South Hayward
Union City
Fremont
Warm Springs/South
SAN FRANCISCO
EAST BAY
PENINSULA
SAN JOSE

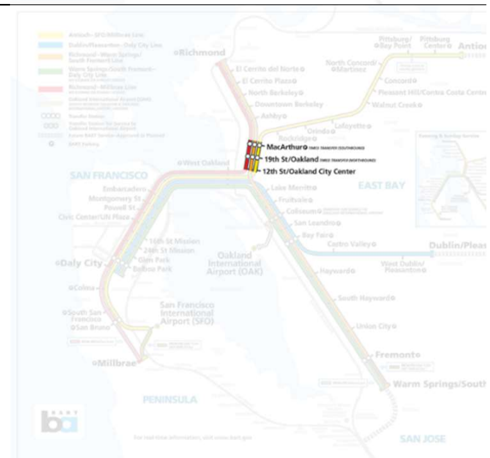
7


130%
120%
110%
100%
90%
2012
2013
2014
2015
2016
2017
2018
Year
Change, Trips since 2012

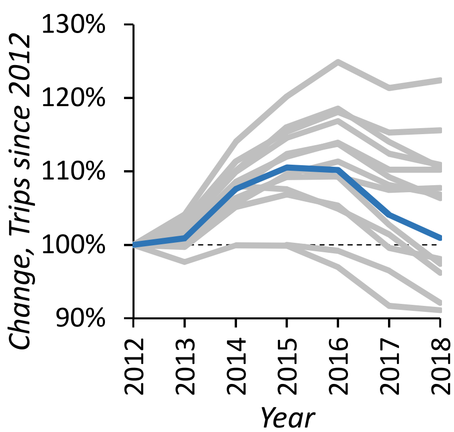

Pittsburg/Bay Point
North Concord/Martinez
Concord
Walnut Creek
Lafayette
Orinda
Rockridge
MacArthur

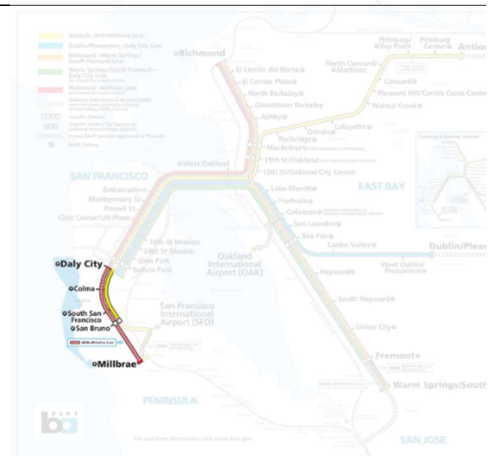
8


130%
120%
110%
100%
90%
2012
2013
2014
2015
2016
2017
2018
Year
Change, Trips since 2012

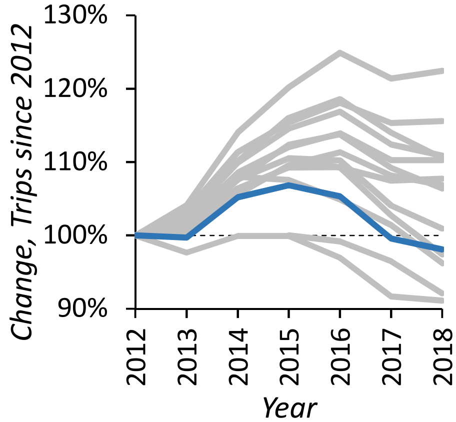

MacArthur
19th St/Oakland
12th St/Oakland City Center

9


130%
120%
110%
100%
90%
2012
2013
2014
2015
2016
2017
2018
Year
Change, Trips since 2012

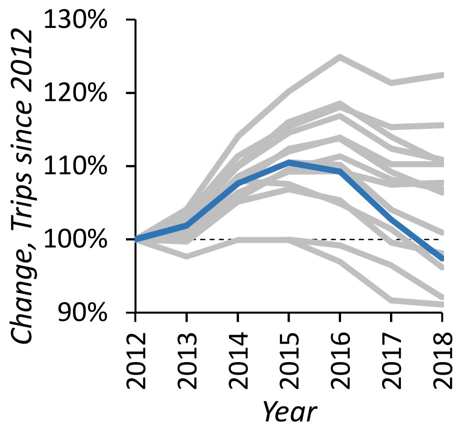

Daly City
Colma
South San Francisco
San Bruno
Millbrae

10


130%
120%
110%
100%
90%
Change, Trips since 2012
2012
2013
2014
2015
2016
2017
2018
Year

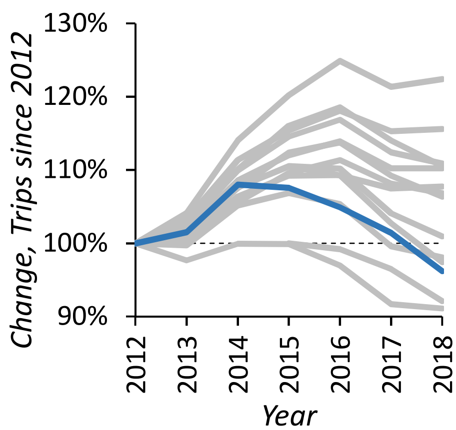

Civic Center/UN Plaza
16th St Mission
24th St Mission
Glen Park
Balboa Park
Daly City

11


130%
120%
110%
100%
90%
Change, Trips since 2012
2012
2013
2014
2015
2016
2017
2018
Year

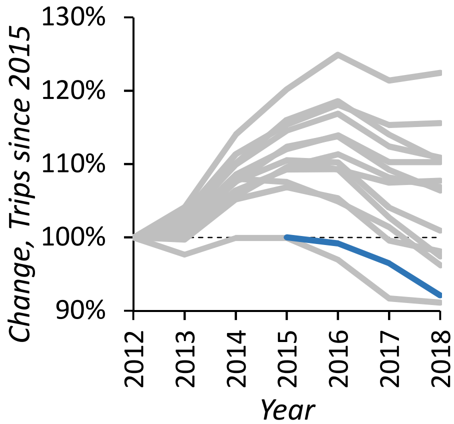

Richmond
El Cerrito del Norte
El Cerrito Plaza
North Berkeley
Downtown Berkeley
Ashby

12


130%
120%
110%
100%
90%
Change, Trips since 2012
2012
2013
2014
2015
2016
2017
2018
Year


San Francisco International Airport (SFO)
San Bruno
Millbrae

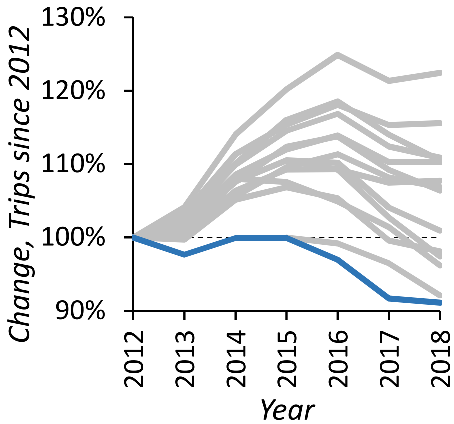
13



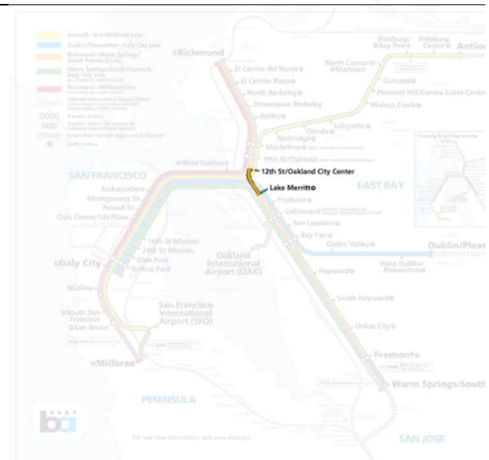
130%
120%
110%
100%
90%
Change, Trips since 2015
2012
2013
2014
2015
2016
2017
2018
Year

Coliseum
Oakland International Airport (OAK)

14



130%
120%
110%
100%
90%
Change, Trips since 2012
2012
2013
2014
2015
2016
2017
2018
Year



12th St/Oakland City Center
Lake Merritt

Appendix B: Elasticities of BART Ridership

Log-Log Model Outputs of BART Ridership

Table B-1: Model Output, 2011, Weekday A.M.

Factor	Standardized Coefficient	Elasticity	Significance
Jobs at destination	0.437	0.380	0.000***
Transfer	-0.269	N/A[94]	0.000***
BART travel time	-0.247	-0.735	0.000***
Lines at destination	0.214	0.633	0.000***
Destination at a terminus	0.134	N/A[94]	0.000***
Origin at a terminus	0.122	N/A[94]	0.000***
Drive-time-to-BART-time ratio	0.086	0.345	0.000***
Jobs at origin	0.084	0.073	0.000***
Population at origin	0.078	0.150	0.000***
Population at destination	-0.064	-0.122	0.000***
BART parking at origin	0.050	0.025	0.000***
Household income at origin	-0.047	-0.169	0.000***
Household income at destination	-0.003	-0.011	0.846

(continued on next page)

94. Dummy variables were not transformed into logarithms, so elasticity cannot be established through this method, but these variables were still included in the model.

(continued from previous page)

Factor	*Standardized Coefficient*	*Elasticity*	*Significance*
Lines at origin	0.001	0.002	0.975
(Constant)	N/A	N/A	0.000***

*** significant at a 95 percent confidence level**
**** significant at a 99 percent confidence level**
***** significant at a 99.9 percent confidence level**

Coefficient of Determination	*Adjusted Coefficient of Determination*	*Number of Origin-Destination Pairs*
$R^2 = 0.676$	adjusted $R^2 = 0.673$	n = 1,877

Table B-2: Model Output, 2011, Weekday P.M.

FACTOR	STANDARDIZED COEFFICIENT	ELASTICITY	SIGNIFICANCE
Jobs at origin	0.410	0.343	0.000***
BART travel time	-0.276	-0.791	0.000***
Transfer	-0.270	N/A[95]	0.000***
Lines at origin	0.199	0.568	0.000***
Jobs at destination	0.157	0.131	0.000***
Origin at a terminus	0.143	N/A[95]	0.000***
Destination at a terminus	0.128	N/A[95]	0.000***
Population at destination	0.069	0.129	0.000***
Household income at destination	-0.043	-0.150	0.000***
Drive-time-to-BART-time ratio	-0.040	-0.165	0.000***
BART parking at destination	-0.019	-0.009	0.311
Household income at origin	-0.012	-0.040	0.455
Lines at destination	0.006	0.016	0.800
Population at origin	-0.005	-0.009	0.817
(Constant)	N/A	N/A	0.000***

*** significant at a 95 percent confidence level**
**** significant at a 99 percent confidence level**
***** significant at a 99.9 percent confidence level**

COEFFICIENT OF DETERMINATION	ADJUSTED COEFFICIENT OF DETERMINATION	NUMBER OF ORIGIN-DESTINATION PAIRS
$R^2 = 0.684$	adjusted $R^2 = 0.681$	n = 1,862

95. Dummy variables were not transformed into logarithms, so elasticity cannot be established through this method, but these variables were still included in the model.

Table B-3: Model Output, 2015, Weekday A.M.

Factor	Standardized Coefficient	Elasticity	Significance
Jobs at destination	0.495	0.428	0.000***
Transfer	-0.303	N/A[96]	0.000***
Lines at destination	0.231	0.678	0.000***
BART travel time	-0.200	-0.611	0.000***
Destination at a terminus	0.184	N/A[96]	0.000***
Jobs at origin	0.130	0.113	0.000***
Origin at a terminus	0.118	N/A[96]	0.000***
Population at destination	-0.108	-0.150	0.000***
Drive-time-to-BART-time ratio	0.098	0.397	0.000***
Population at origin	0.092	0.128	0.000***
Household income at origin	-0.074	-0.284	0.000***
BART parking at origin	0.067	0.033	0.000***
Lines at origin	-0.023	-0.067	0.254
Household income at destination	0.022	0.082	0.106
(Constant)	N/A	N/A	0.000***

*** significant at a 95 percent confidence level**
**** significant at a 99 percent confidence level**
***** significant at a 99.9 percent confidence level**

Coefficient of Determination	Adjusted Coefficient of Determination	Number of Origin-Destination Pairs
$R^2 = 0.718$	adjusted $R^2 = 0.716$	n = 1,965

96. Dummy variables were not transformed into logarithms, so elasticity cannot be established through this method, but these variables were still included in the model.

Table B-4: Model Output, 2015, Weekday P.M.

FACTOR	STANDARDIZED COEFFICIENT	ELASTICITY	SIGNIFICANCE
Jobs at origin	0.475	0.398	0.000***
Transfer	-0.301	N/A[97]	0.000***
Lines at origin	0.233	0.664	0.000***
BART travel time	-0.227	-0.673	0.000***
Jobs at destination	0.210	0.176	0.000***
Origin at a terminus	0.186	N/A[97]	0.000***
Destination at a terminus	0.132	N/A[97]	0.000***
Population at destination	0.096	0.129	0.000***
Drive-time-to-BART-time ratio	-0.076	-0.299	0.000***
Population at origin	-0.066	-0.089	0.000***
Household income at destination	-0.061	-0.225	0.000***
BART parking at destination	-0.017	-0.008	0.293
Lines at destination	0.005	0.015	0.792
Household income at origin	-0.004	-0.013	0.782
(Constant)	N/A	N/A	0.000***

*** significant at a 95 percent confidence level**
**** significant at a 99 percent confidence level**
***** significant at a 99.9 percent confidence level**

COEFFICIENT OF DETERMINATION	ADJUSTED COEFFICIENT OF DETERMINATION	NUMBER OF ORIGIN-DESTINATION PAIRS
$R^2 = 0.737$	adjusted $R^2 = 0.735$	n = 1,965

97. Dummy variables were not transformed into logarithms, so elasticity cannot be established through this method, but these variables were still included in the model.

Table B-5: Model Output, 2018, Weekday A.M.

Factor	Standardized Coefficient	Elasticity	Significance
Jobs at destination	0.472	0.364	0.000***
Transfer	-0.308	N/A[98]	0.000***
Destination at a terminus	0.270	N/A[98]	0.000***
Lines at destination	0.218	0.659	0.000***
BART travel time	-0.194	-0.610	0.000***
Jobs at origin	0.156	0.121	0.000***
Origin at a terminus	0.145	N/A[98]	0.000***
Drive-time-to-BART-time ratio	0.134	0.567	0.000***
Population at origin	0.093	0.126	0.000***
BART parking at origin	0.089	0.046	0.000***
Household income at origin	-0.074	-0.271	0.000***
Lines at origin	-0.014	-0.043	0.472
Household income at destination	-0.013	-0.048	0.321
Population at destination	-0.002	-0.003	0.903
(Constant)	N/A	N/A	0.000***

*** significant at a 95 percent confidence level**
**** significant at a 99 percent confidence level**
***** significant at a 99.9 percent confidence level**

Coefficient of Determination	Adjusted Coefficient of Determination	Number of Origin-Destination Pairs
$R^2 = 0.721$	adjusted $R^2 = 0.719$	n = 2,053

98. Dummy variables were not transformed into logarithms, so elasticity cannot be established through this method, but these variables were still included in the model.

Table B-6: Model Output, 2018, Weekday P.M.

Factor	Standardized Coefficient	Elasticity	Significance
Jobs at origin	0.472	0.347	0.000***
Transfer	-0.310	N/A[99]	0.000***
Origin at a terminus	0.282	N/A[99]	0.000***
Lines at origin	0.249	0.719	0.000***
Jobs at destination	0.234	0.173	0.000***
BART travel time	-0.221	-0.663	0.000***
Destination at a terminus	0.153	N/A[99]	0.000***
Household income at destination	-0.085	-0.298	0.000***
Population at destination	0.081	0.105	0.000***
BART parking at destination	0.030	0.015	0.066
Household income at origin	-0.017	-0.060	0.174
Drive-time-to-BART-time ratio	0.015	0.066	0.256
Population at origin	0.013	0.017	0.423
Lines at destination	-0.009	-0.026	0.637
(Constant)	N/A	N/A	0.000***

*** significant at a 95 percent confidence level**
**** significant at a 99 percent confidence level**
***** significant at a 99.9 percent confidence level**

Coefficient of Determination	Adjusted Coefficient of Determination	Number of Origin-Destination Pairs
$R^2 = 0.741$	adjusted $R^2 = 0.739$	n = 2,038

99. Dummy variables were not transformed into logarithms, so elasticity cannot be established through this method, but these variables were still included in the model.

Appendix C: BART Model Excluding Downtown San Francisco

Table C-1: Model Output, 2011, Weekday A.M., Excluding Destinations in Downtown San Francisco

Factor	Standardized Coefficient	Significance
BART travel time	-0.363	0.000***
Jobs at destination	0.337	0.000***
Transfer	-0.249	0.000***
Destination at a terminus	0.221	0.000***
BART parking at origin	0.179	0.000***
Population at origin	0.168	0.000***
Lines at destination	0.136	0.000***
Jobs at origin	0.135	0.000***
Household income at origin	-0.130	0.000***
Origin at a terminus	0.126	0.000***
Population at destination	0.099	0.000***
Household income at destination	0.032	0.058
Drive-time-to-BART-time ratio	-0.025	0.148
Lines at origin	0.017	0.501
(Constant)	N/A	0.000***

*** significant at a 95 percent confidence level**
**** significant at a 99 percent confidence level**
***** significant at a 99.9 percent confidence level**

Coefficient of Determination	Adjusted Coefficient of Determination	Number of Origin-Destination Pairs
$R^2 = 0.642$	adjusted $R^2 = 0.639$	n = 1,705

Table C-2: Model Output, 2011, Weekday P.M., Excluding Origins in Downtown San Francisco

Factor	*Standardized Coefficient*	*Significance*
BART travel time	-0.380	0.000***
Jobs at destination	0.301	0.000***
Jobs at origin	0.277	0.000***
Population at destination	0.276	0.000***
Transfer	-0.245	0.000***
Origin at a terminus	0.198	0.000***
Drive-time-to-BART-time ratio	-0.183	0.000***
BART parking at destination	0.158	0.000***
Destination at a terminus	0.152	0.000***
Population at origin	0.130	0.000***
Household income at destination	-0.103	0.000***
Lines at origin	0.101	0.000***
Household income at origin	-0.020	0.222
Lines at destination	0.015	0.519
(Constant)	N/A	0.000***

*** significant at a 95 percent confidence level**
**** significant at a 99 percent confidence level**
***** significant at a 99.9 percent confidence level**

Coefficient of Determination	*Adjusted Coefficient of Determination*	*Number of Origin-Destination Pairs*
$R^2 = 0.680$	adjusted $R^2 = 0.677$	n = 1,690

Table C-3: Model Output, 2015, Weekday A.M., Excluding Destinations in Downtown San Francisco

Factor	*Standardized Coefficient*	*Significance*
Jobs at destination	0.314	0.000***
Transfer	-0.311	0.000***
BART travel time	-0.289	0.000***
Destination at a terminus	0.248	0.000***
BART parking at origin	0.181	0.000***
Jobs at origin	0.173	0.000***
Population at origin	0.153	0.000***
Population at destination	0.142	0.000***
Household income at origin	-0.142	0.000***
Lines at destination	0.111	0.000***
Origin at a terminus	0.094	0.000***
Household income at destination	0.014	0.409
Drive-time-to-BART-time ratio	0.009	0.595
Lines at origin	-0.004	0.854
(Constant)	N/A	0.000***

*** significant at a 95 percent confidence level**
**** significant at a 99 percent confidence level**
***** significant at a 99.9 percent confidence level**

Coefficient of Determination	*Adjusted Coefficient of Determination*	*Number of Origin-Destination Pairs*
$R^2 = 0.636$	adjusted $R^2 = 0.633$	n = 1,789

Table C-4: Model Output, 2015, Weekday P.M., Excluding Origins in Downtown San Francisco

Factor	Standardized Coefficient	Significance
Jobs at destination	0.330	0.000***
BART travel time	-0.317	0.000***
Transfer	-0.293	0.000***
Jobs at origin	0.268	0.000***
Population at destination	0.259	0.000***
Drive-time-to-BART-time ratio	-0.217	0.000***
Origin at a terminus	0.215	0.000***
Population at origin	0.147	0.000***
BART parking at destination	0.137	0.000***
Destination at a terminus	0.134	0.000***
Household income at destination	-0.097	0.000***
Lines at origin	0.090	0.000***
Lines at destination	0.040	0.072
Household income at origin	-0.036	0.023*
(Constant)	N/A	0.000***

*** significant at a 95 percent confidence level**
**** significant at a 99 percent confidence level**
***** significant at a 99.9 percent confidence level**

Coefficient of Determination	Adjusted Coefficient of Determination	Number of Origin-Destination Pairs
$R^2 = 0.690$	adjusted $R^2 = 0.687$	n = 1,789

Table C-5: Model Output, 2018, Weekday A.M., Excluding Destinations in Downtown San Francisco

FACTOR	STANDARDIZED COEFFICIENT	SIGNIFICANCE
Transfer	-0.322	0.000***
Jobs at destination	0.302	0.000***
BART travel time	-0.274	0.000***
Destination at a terminus	0.237	0.000***
Jobs at origin	0.178	0.000***
BART parking at origin	0.168	0.000***
Population at destination	0.156	0.000***
Household income at origin	-0.129	0.000***
Population at origin	0.116	0.000***
Origin at a terminus	0.092	0.000***
Lines at destination	0.089	0.000***
Drive-time-to-BART-time ratio	0.060	0.000***
Household income at destination	-0.012	0.474
Lines at origin	0.000	0.986
(Constant)	N/A	0.000***

*** significant at a 95 percent confidence level**
**** significant at a 99 percent confidence level**
***** significant at a 99.9 percent confidence level**

COEFFICIENT OF DETERMINATION	ADJUSTED COEFFICIENT OF DETERMINATION	NUMBER OF ORIGIN-DESTINATION PAIRS
$R^2 = 0.624$	adjusted $R^2 = 0.622$	n = 1,873

Table C-6: Model Output, 2018, Weekday P.M., Excluding Origins in Downtown San Francisco

FACTOR	STANDARDIZED COEFFICIENT	SIGNIFICANCE
Transfer	-0.310	0.000***
Jobs at destination	0.305	0.000***
BART travel time	-0.292	0.000***
Jobs at origin	0.254	0.000***
Origin at a terminus	0.223	0.000***
Population at destination	0.194	0.000***
Population at origin	0.179	0.000***
BART parking at destination	0.125	0.000***
Household income at destination	-0.117	0.000***
Drive-time-to-BART-time ratio	-0.117	0.000***
Lines at origin	0.113	0.000***
Destination at a terminus	0.113	0.000***
Household income at origin	-0.029	0.063
Lines at destination	0.005	0.813
(Constant)	N/A	0.000***

*** significant at a 95 percent confidence level**
**** significant at a 99 percent confidence level**
***** significant at a 99.9 percent confidence level**

COEFFICIENT OF DETERMINATION	ADJUSTED COEFFICIENT OF DETERMINATION	NUMBER OF ORIGIN-DESTINATION PAIRS
$R^2 = 0.664$	adjusted $R^2 = 0.662$	n = 1,858

Appendix D: Model of Off-peak BART Ridership

D.1. Methodology

Unlike the others, these off-peak models lump together weekday A.M., weekday P.M., and weekend trips. Doing so provides a greater model size and allows me to draw conclusions across all off-peak times. However, some input variables differ between weekends and weekdays, so I had to make a few approximations. Since a significant majority of off-peak ridership occurs on weekdays—even without rush-hours, five weekdays of ridership outweigh two weekend days of ridership—I used weekday service patterns for the "transfer" and "number of lines" inputs. For the "BART travel time" and "drive-time-to-BART-time ratio" inputs, I lacked weekend data altogether. I therefore used an average of early morning, midday, and evening weekday travel times, all of which are quite similar and all of which likely nearly match weekend travel times.

D.2. Model Outputs

Table D-1: Model Output, 2011, Off-peak

Factor	Standardized Coefficient	Significance
Jobs at destination	0.352	0.000***
BART travel time	-0.329	0.000***
Jobs at origin	0.303	0.000***
Population at destination	0.282	0.000***
Population at origin	0.234	0.000***
Transfer	-0.219	0.000***
Drive-time-to-BART-time ratio	-0.185	0.000***
Destination at a terminus	0.148	0.000***
Origin at a terminus	0.145	0.000***
BART parking at destination	0.078	0.000***
Household income at origin	-0.067	0.000***
Lines at destination	0.049	0.000***
BART parking at origin	0.039	0.000***
Household income at destination	-0.024	0.107
Lines at origin	0.012	0.568
(Constant)	N/A	0.000***

*** significant at a 95 percent confidence level**
**** significant at a 99 percent confidence level**
***** significant at a 99.9 percent confidence level**

Coefficient of Determination	Adjusted Coefficient of Determination	Number of Origin-Destination Pairs
$R^2 = 0.713$	adjusted $R^2 = 0.711$	n = 1,713

Table D-2: Model Output, 2015, Off-peak

FACTOR	STANDARDIZED COEFFICIENT	SIGNIFICANCE
Jobs at destination	0.354	0.000***
Jobs at origin	0.316	0.000***
BART travel time	-0.277	0.000***
Transfer	-0.273	0.000***
Population at destination	0.253	0.000***
Population at origin	0.211	0.000***
Drive-time-to-BART-time ratio	-0.162	0.000***
Origin at a terminus	0.153	0.000***
Destination at a terminus	0.145	0.000***
Household income at origin	-0.079	0.000***
BART parking at destination	0.063	0.000***
Lines at destination	0.053	0.000***
Household income at destination	-0.032	0.000***
BART parking at origin	0.020	0.218
Lines at origin	0.017	0.394
(Constant)	N/A	0.000***

*** significant at a 95 percent confidence level**
**** significant at a 99 percent confidence level**
***** significant at a 99.9 percent confidence level**

COEFFICIENT OF DETERMINATION	ADJUSTED COEFFICIENT OF DETERMINATION	NUMBER OF ORIGIN-DESTINATION PAIRS
$R^2 = 0.733$	adjusted $R^2 = 0.730$	n = 1,795

Table D-3: Model Output, 2018, Off-peak

Factor	Standardized Coefficient	Significance
Jobs at destination	0.349	0.000***
Jobs at origin	0.322	0.000***
Transfer	-0.292	0.000***
BART travel time	-0.241	0.000***
Population at destination	0.209	0.000***
Population at origin	0.185	0.000***
Origin at a terminus	0.152	0.000***
Destination at a terminus	0.136	0.000***
Drive-time-to-BART-time ratio	-0.117	0.000***
Household income at origin	-0.085	0.000***
Lines at destination	0.058	0.000***
BART parking at destination	0.049	0.000***
Household income at destination	-0.049	0.000***
Lines at origin	0.034	0.080
BART parking at origin	0.012	0.449
(Constant)	N/A	0.000***

*** significant at a 95 percent confidence level**
**** significant at a 99 percent confidence level**
***** significant at a 99.9 percent confidence level**

Coefficient of Determination	Adjusted Coefficient of Determination	Number of Origin-Destination Pairs
$R^2 = 0.732$	adjusted $R^2 = 0.729$	n = 1,877

Bibliography

Data Sources

Bay Area Rapid Transit District, San Francisco. "Find Closest Station." *Bay Area Rapid Transit*. 2018. *Internet Archive*. https://web.archive.org/web/20181203181333/https://www.bart.gov/stations/closest.

———. "Geospatial Data." *Bay Area Rapid Transit*. 2019. https://www.bart.gov/schedules/developers/geo.

———. *Parking Statistics 2019*. 2019.

———. *Station Count Data*. 2019.

———. *Station Data Summary*. N.d.

———. "Ridership Reports." *Bay Area Rapid Transit*. 2019. https://www.bart.gov/about/reports/ridership.

———. "System Facts." *Bay Area Rapid Transit*. 2019. https://www.bart.gov/about/history/facts.

"CA Geographic Boundaries." *California Open Data Portal*. February 2, 2017, Last updated February 27, 2019. https://data.ca.gov/dataset/ca-geographic-boundaries.

"CaliDetail." University of California, Los Angeles Common Collaboration and Learning Environment Shared System.

Demery, Leroy. *U.S. Urban Rail Transit Lines Opened from 1980*. March 30, 2004. Last updated November 2011. *Internet Archive*. https://web.archive.org/web/20131104023212/http:/www.publictransit.us/ptlibrary/NorthAmericaRailTransitOpenings/Railopenings_US_Updated2011.pdf.

"The National Transit Database (NTD)," *Federal Transit Administration*, 2017, https://www.transit.dot.gov/ntd.

San Francisco Municipal Transportation Agency. *Annual Ridership FY98-Present*.

———. "GTFS Transit Data." *S[an] F[rancisco] M[unicipal] T[ransportation] A[gency]*. June 11, 2013. https://www.sfmta.com/reports/gtfs-transit-data.

———. "Muni Simple Routes." *DataSF*. April 28, 2019. https://data.sfgov.org/Transportation/Muni-Simple-Routes/9exe-acju.

———. "Muni System Map." *S[an] F[rancisco] M[unicipal] T[ransportation] A[gency]*.

[August 2017]. https://www.sfmta.com/maps/muni-system-map.

———. "7R Service to Become 7 Local Service." *S[an] F[rancisco] M[unicipal] T[ransportation] A[gency]*. August 14, 2017. https://www.sfmta.com/travel-updates/7r-service-become-7-local-service.

SF Bay Transit. N.d. https://sfbaytransit.org/.

Thomas, Trevor. *MTA Drive/Transit Time Skims*. December 1, 2015.

Valley Transportation Authority, Santa Clara (VTA). *APR15* to *JUL18*.

———. "By Type." *Santa Clara Valley Transportation Authority*. 2019. http://www.vta.org/getting-around/schedules/by-type.

———. "GTFS Information." *Santa Clara Valley Transportation Authority*. 2019. http://www.vta.org/getting-around/GTFS-Info/GTFS-Information.

———. "Light Rail Service Overview." *Santa Clara Valley Transportation Authority*. 2019. http://www.vta.org/getting-around/light-rail-service-overview.

Voulgaris, Carole Turley, Brian D. Taylor, Evelyn Blumenberg, Anne Brown, and Kelcie Ralph. "Synergistic Neighborhood Relationships with Travel Behavior: An Analysis of Travel in 30,000 U.S. Neighborhoods," *Journal of Transport and Land Use* 10, no 1. (2017): 437-61. *University of California, Los Angeles] Institute of Transportation Studies*. https://www.its.ucla.edu/publication/synergistic-neighborhood-relationships-with-travel-behavior-an-analysis-of-travel-in-30000-u-s-neighborhoods/.

United States Census Bureau. *American Community Survey*. 2009-17. *American FactFinder*. https://factfinder.census.gov.

———. "Annual Estimates of the Resident Population: April 1, 2010 to July 1, 2017." March 2018. *American FactFinder*. https://factfinder.census.gov/bkmk/table/1.0/en/PEP/2017/PEPANNRES/0100000US.

———. "Cartographic Boundary Shapefiles—Block Groups." *United States Census Bureau*. April 9, 2018. https://www.census.gov/geo/maps-data/data/cbf/cbf_blkgrp.html.

———. "Cartographic Boundary Shapefiles—Census Tracts." *United States Census Bureau*. April 9, 2018. https://www.census.gov/geo/maps-data/data/cbf/cbf_tracts.html.

U[nited] S[tates] Census Bureau, Center for Economic Studies. "L[ongitudinal] E[mployer]-H[ousehold] D[ynamics Origin-Destination Employment Statistics]." *OnTheMap*. N.d. https://onthemap.ces.census.gov/.

U[nited] S[tates] Census Bureau, Population Division. *Table 1. Intercensal Estimates of the Resident Population for Counties of California: April 1, 2000 to July 1, 2010*.

September 2011. https://www2.census.gov/programs-surveys/popest/tables/2000-2010/intercensal/county/co-est00int-01-06.xls.

———. *Table 1. Intercensal Estimates of the Resident Population for the United States, Regions, States, and Puerto Rico: April 1, 2000 to July 1, 2010*. September 2011. *United States Census Bureau*. https://www2.census.gov/programs-surveys/popest/tables/2000-2010/intercensal/state/st-est00int-01.xls.

Secondary Sources

Alam, Bhuiyan, Hilary Nixon, and Qiong Zhang. *Investigating the Determining Factors for Transit Travel Demand by Bus Mode in U.S. Metropolitan Statistical Areas*. M[ineta] T[ransportation] I[nstitute] Report 12-30, Mineta Transportation Institute, San José, California, May 2015. *Mineta Transportation Institute*. http://transweb.sjsu.edu/sites/default/files/1101-transit-bus-demand-factors-in-US-metro-areas.pdf.

Arantani, Lori. "Metro's Multimillion-dollar Mystery: Where Have Our Riders Gone?" *Washington Post*. October 1, 2016. https://www.washingtonpost.com/local/trafficandcommuting/metros-multimillion-dollar-mystery-where-have-our-riders-gone/2016/10/01/2949d226-85b8-11e6-92c2-14b64f3d453f_story.html.

Babar, Yash and Gordon Burtch. "Examining the Impact of Ridehailing Services on Public Transit Use." September 25, 2017. S[ocial] S[cience] R[esearch] N[etwork]. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3042805.

Barmann, Jay. "BART Says Their Oakland Airport Connector Is Losing Money Because Of Uber, Lyft." *SFist*. March 8, 2017. https://sfist.com/2017/03/08/bart_says_their_oakland_airport_con/.

———. "Overcrowded BART Trains Likely Causing Drop in Ridership, Ironically." *SFist*. February 24, 2017. http://sfist.com/2017/02/24/overcrowded_bart_trains_likely_caus.php.

BART Historical Timeline: Achievements Over the Years. N.d. *Bay Area Rapid Transit*. https://www.bart.gov/sites/default/files/docs/bart-historical-timeline.pdf.

Bay Area Rapid Transit District, San Francisco. *Annual Report*. January 2019. *Bay Area Rapid Transit*. https://www.bart.gov/sites/default/files/docs/BART_Annual_%20Report%202018_web.pdf.

———. "BART to Antioch: East Contra Costa BART Extension." *Bay Area Rapid Transit*. 2019. https://www.bart.gov/about/projects/ecc.

Ben-Akiva, Moshe and Takayuki Morikawa. "Comparing Ridership Attraction of Rail and Bus." *Transport Policy* 9 (2002): 107-16. ScienceDirect. https://www.sciencedirect.com/science/article/pii/S0967070X02000094.

Bliss, Laura. "What's Behind Declining Transit Ridership Nationwide?: Pick a Culprit: The Rise of Ride-hailing Services, Budget Cuts, Cheap Oil, or Bad Service." *CityLab*. February 24, 2017. https://www.citylab.com/transportation/2017/02/whats-behind-declining-transit-ridership-nationwide/517701/.

Blumenberg, Evelyn, Anne Brown, Kelcie Ralph, Brian D. Taylor, and Carole Turley Voulgaris. *Typecasting Neighborhoods and Travelers: Analyzing the Geography of Travel Behavior among Teens and Young Adults in the U.S.* September 25, 2015. *U[niversity of] C[alifornia] L[os] A[ngeles] Lewis Center for Regional Policy Studies*. http://www.lewis.ucla.edu/wp-content/uploads/sites/2/2015/10/Geography-of-Youth-Travel_Final-Report.pdf.

Boisjoly, Geneviève, Emily Grisé, Meadhbh Maguire, Marie-Pier Veillette, Robbin Deboosere, Emma Berrebi, and Ahmed El-Geneidy. "Invest in the Ride: A Fourteen-year Longitudinal Analysis of the Determinants of Public Transport Ridership in Twenty-five North American Cities." *Transportation Research Part A: Policy and Practice* 116 (2018): 434-45. ScienceDirect. https://www.sciencedirect.com/science/article/pii/S0965856418300296.

Brown, Anne Elizabeth. "Ridehail Revolution: Ridehail Travel and Equity in Los Angeles." PhD dissertation, University of California, Los Angeles, 2018. *ITS: [University of California, Los Angeles] Institute of Transportation Studies*. https://www.its.ucla.edu/2018/06/27/ridehail-revolution-groundbreaking-its-dissertation-examines-discrimination-and-travel-patterns-for-lyft-uber-and-taxis/.

Brown, Jeffrey R. and Gregory L. Thompson. "The Relationship between Transit Ridership and Urban [Decentralization]: Insights from Atlanta." *Urban Studies* 45, no. 5 and 6 (May 2008): 1119-39. SAGE Journals. https://journals.sagepub.com/doi/pdf/10.1177/0042098008089856.

Cabanatuan, Michael. "Oakland Airport Connector Back to BART Board." *SFGate*. July 22, 2010. https://www.sfgate.com/bayarea/article/Oakland-Airport-Connector-back-to-BART-board-3257972.php.

———. "With BART Ridership Down, and Complaints Up, Agency Promises New Cleanup." *San Francisco Chronicle*. February 10, 2018. https://www.sfchronicle.com/bayarea/article/With-BART-ridership-down-and-complaints-up-12585051.php.

———. "With Ridership Down, Complaints Up, BART to Look at Homeless Problem." *SFGATE*. May 11, 2017. https://www.sfgate.com/bayarea/article/With-ridership-down-complaints-up-BART-to-look-11140277.php.

Castiglione, Joe, Drew Cooper, Bhargava Sana, Dan Tischler, Tilly Chang, Greg[ory] Erhardt, Sneha Roy, Mei Chen, and {Richard] Alex[ander] Mucci. *TNC's and Congestion*. October 2018. *San Francisco County Transportation Authority: Plan. Fund. Deliver.* https://www.sfcta.org/sites/default/files/content/Planning/TNCs/TNCs_Congestion_Report_181015_Final.pdf.

Cervero, Robert. “Transit Pricing Research: A Review and Synthesis.” *Transportation* 17 (1990): 117-39. SpringerLink. https://link.springer.com/content/pdf/10.1007%2FBF02125332.pdf.

Cervero, Robert, Jin Murakami, and Mark Miller. “Direct Ridership Model of Bus Rapid Transit in Los Angeles County, California.” *Transportation Research Record* 2145 (2010): 1-7. *The National Academies of Sciences, Engineering, [and] Medicine: TRB: Transportation Research Board*. https://trrjournalonline.trb.org/doi/pdf/10.3141/2145-01.

Cervero, Robert and Michael Duncan. “Residential Self Selection and Rail Commuting: A Nested Logit Analysis.” Working paper, University of California Transportation Center, Berkeley, California, June 2008. eScholarship: UC Open Access Publications. https://escholarship.org/uc/item/1wg020cd.

Chatman, Daniel G. “Does TOD Need the T?: On the Importance of Factors Other than Rail Access.” *Journal of the American Planning Association* 79, no. 1 (Winter 2013): 17-31. Taylor and Francis Online. https://www.tandfonline.com/doi/pdf/10.1080/01944363.2013.791008.

Chen, Cynthia, Don Varley, and Jason Chen. “What Affects Transit Ridership? A Dynamic Analysis Involving Multiple Factors, Lags[,] and Asymmetric [Behavior].” *Urban Studies* 48, no. 9 (July 2011): 1893-1908. SAGE Journals. http://journals.sagepub.com/doi/pdf/10.1177/0042098010379280.

Chu, Xuehao. “Ridership Models at the Stop Level.” N[ational] C[enter for] T[ransit] R[esearch]-473-04, BC137-31, National Center for Transit Research, Center for Urban Transportation Research, University of South Florida, Tampa, Florida, December 2004. *National Center for Transit Research: A Program of the Center for Urban Transportation Research at the University of South Florida*. https://www.nctr.usf.edu/pdf/473-04.pdf.

Circella, Giovanni, Farzad Alemi, Kate Tiedeman, Susan Handy, and Patricia Mokhtarian. *The Adoption of Shared Mobility in California and Its Relationship with Other Components of Travel Behavior.* March 2018. *National Center for Sustainable Transportation*. https://ncst.ucdavis.edu/wp-content/uploads/2016/10/NCST-TO-033.1-Circella_Shared-Mobility_Final-Report_MAR-2018.pdf.

Clewlow, Regina R. and Gouri Shankar Mishra. *Disruptive Transportation: The Adoption, Utilization, and Impacts of Ride-Hailing in the United States*. University of California, Davis-Institute of Transportation Studies-Research Report-17-07, Institute of Transportation Studies, University of California, Davis, Davis, California, October 2017. *ITS: UC Davis Institute of Transportation Studies*. https://itspubs.ucdavis.edu/wp-content/themes/ucdavis/pubs/download_pdf.php?id=2752.

Colon, Dave. “Who’s to Blame for MTA’s Declining Ridership?” *Curbed New York*. July 25, 2018. https://ny.curbed.com/2018/7/25/17613544/nyc-subway-mta-ridership-decline.

Conway, Matthew Wigginton, Deborah Salon, and David A. King. “Trends in Taxi Use and the Advent of Ridehailing, 1995-2017: Evidence from the U.S. National Household Travel Survey.” *Urban Science* 2, no. 3 (September 2018): 79 ff. MDPI. https://www.mdpi.com/2413-8851/2/3/79.

Descant, Skip. “Seattle, Houston Buck Declining Bus Ridership Trend: The Two Cities Have Improved Bus Service at a Time when Transit Ridership in the United States Dropped 2.9 Percent in 2017.” *Government Technology: FutureStructure*. May 16, 2018. http://www.govtech.com/fs/transportation/Seattle-Houston-Buck-Declining-Bus-Ridership-Trend.html.

Dias, Felipe F., Patrícia S. Lavieri, Venu M. Garikapati, Sebastian Astroza, Ram M. Pendyala, and Chandra R. Bhat. “A Behavioral Choice Model of the Use of Car-sharing and Ride-sourcing Services.” *Transportation* 44, no. 6 (November 2017): 1307-23. SpringerLink. https://link.springer.com/content/pdf/10.1007%2Fs11116-017-9797-8.pdf.

Diaz, John. “BART Attack Brings Out Racist Responses.” *SFGATE*. April 29, 2017. https://www.sfgate.com/opinion/diaz/article/BART-attack-brings-out-racist-responses-11108000.php.

“Discrete Choice Analysis.” *Columbia [University] Mailman School of Public Health*. N.d. https://www.mailman.columbia.edu/research/population-health-methods/discrete-choice-analysis.

Dominie, William. “Is Just Growth Smarter Growth? The Effects of Gentrification on Transit Ridership and Driving in Los Angeles’ Transit Station Area Neighborhoods.” Applied planning research project, University of California, Los Angeles, Los Angeles, 2012.

Driscoll, Richard A., Kurt R. Lehmann, Steven Polzin, and Jodi Godfrey. “The Effect of Demographic Changes on Transit Ridership Trends.” *Transportation Research Record* 2018: 1-9. SAGE Journals. https://journals.sagepub.com/doi/pdf/10.1177/0361198118777605.

Eichenholtz, Paul. “BART Security Strategies Clash with Distrustful Ridership.” *Golden Gate Xpress* (San Francisco State University). October 23, 2018. https://goldengatexpress.org/2018/10/23/bart-security-strategies-clash-with-distrustful-ridership/.

Elkind, Ethan. “L.A. Times Misleads on Metro Rail Ridership History.” *Ethan Elkind: Writings on the Environment and Politics, and Music*. January 27, 2016. http://www.ethanelkind.com/l-a-times-misleads-on-metro-rail-ridership-history/.

Erhardt, Gregory D. “Fusion of Large Continuously Collected Data Sources: Understanding Travel Demand Trends and Measuring Transport Project Impacts.” PhD dissertation, University College London, London, 2016. *Dropbox*. https://www.dropbox.com/sh/z16unyvcxy4ug78/AADxjVHsqdetibWXtaNmE9TAa?dl=0&preview=Erhardt+Thesis-Final.pdf.

Evans, Robert James. "The Value of Data: Analyzing Transportation Network Company Trips for Transit Planning." PhD dissertation, University of Texas at Austin, Austin, 2018. *The University of Texas at Austin: Texas ScholarWorks: University of Texas Libraries*. https://repositories.lib.utexas.edu/bitstream/handle/2152/68999/EVANS-THESIS-2018.pdf.

Ewing, Reid and Robert Cervero. "Travel and the Built Environment: A Meta-Analysis." *Journal of the American Planning Association* 76, no. 3 (Summer 2010): 265-94. Taylor and Francis Online. https://www.tandfonline.com/doi/pdf/10.1080/01944361003766766.

Farrell, Diana, Fiona Greig, and Amar Hamoudi. *The Online Platform Economy in Twenty-seven Metro Areas: The Experience of Drivers and Lessors*. April 2019. *JPMorgan Chase and Co[mpany]*. https://www.jpmorganchase.com/corporate/institute/document/institute-ope-cities.pdf.

Fitzgerald Rodriguez, Joe. "Geary Bus Rapid Transit Gets Environmental 'Green Light to Advance' From Feds." *San Francisco Examiner*. June 21, 2018. http://www.sfexaminer.com/geary-bus-rapid-transit-gets-environmental-green-light-advance-feds/.

———. "Historic Muni Streetcar Shortage Highlights Driver Training Woes." *San Francisco Examiner*. September 8, 2016. https://www.sfexaminer.com/news/historic-muni-streetcar-shortage-highlights-driver-training-woes/.

Freemark, Yonah. "Route Miles for U.S. and Canada Rail Systems." *The Transport Politic*. 2019. https://www.thetransportpolitic.com/databook/route-miles-for-us-and-canada-rail-systems/.

Gehrke, Steven R., Alison Felix, and Timothy Reardon. *Fare Choices: A Survey of Ride-hailing Passengers in Metro Boston*. Report #1, MAPC Research Brief, Metropolitan Area Planning Council, [Boston, Massachusetts], February 2018. *MAPC: Metropolitan Area Planning Council*. http://www.mapc.org/wp-content/uploads/2018/02/Fare-Choices-MAPC.pdf.

Graehler, Michael, Junior, Richard Alexander Mucci, and Gregory D. Erhardt. "Understanding the Recent Transit Ridership Decline in Major US Cities: Service Cuts or Emerging Modes?" Paper presented at the Transportation Research Board 98th Annual Meeting, Washington, District of Columbia, January 13-7, 2019. *Streetsblog USA*. http://usa.streetsblog.org/wp-content/uploads/sites/5/2019/01/19-04931-Transit-Trends.pdf.

Guerra, Erick and Robert Cervero. "Cost of a Ride: The Effects of Densities on Fixed-guideway Transit Ridership and Costs." *Journal of the American Planning Association* 77, no. 3 (Summer 2011): 267-90. Taylor and Francis Online. https://www.tandfonline.com/doi/pdf/10.1080/01944363.2011.589767.

———. “Is a Half-mile Circle the Right Standard for TODs?,” *ACCESS* 42 (Spring 2013): 17-22. http://www.accessmagazine.org/spring-2013/half-mile-circle-right-standard-tods/.

Gutiérrez, Javier, Osvaldo Daniel Cardozo, and Juan Carlos García-Palomares. “Transit Ridership Forecasting at Station Level: An Approach Based on Distance-decay Weighted Regression.” *Journal of Transport Geography* 19, no. 6 (November 2011): 1081-92. ScienceDirect. https://www.sciencedirect.com/science/article/pii/S0966692311000512.

Grabar, Henry. “The Astounding Collapse of American Bus Ridership.” *Slate*. July 21, 2016. http://www.slate.com/blogs/moneybox/2016/07/21/buses_in_new_york_and_other_u_s_cities_are_in_crisis.html.

Hall, Jonathan D., Craig Palsson, and Joseph Price. “Is Uber a Substitute or Complement for Public Transit?” Working Paper tecipa-585, University of Toronto, Department of Economics, Toronto, Ontario, June 13, 2018. *UTORweb: Individual Web Pages at the University of Toronto*. http://individual.utoronto.ca/jhall/documents/Uber_and_Public_Transit.pdf.

Hampshire, Robert C., Chris Simek, Tayo Fabusuyi, Xuan Di, and Xi Chen. “Measuring the Impact of an Unanticipated Disruption of Uber/Lyft in Austin, TX.” Paper presented at the Transportation Research Board 97th Annual Meeting, Washington, District of Columbia, January 7-11, 2018. S[ocial] S[cience] R[esearch] N[etwork] https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2977969.

Hansen, Louis. “Bay Area Tops U.S. in New Office Space, but Lags in Housing Starts.” *Mercury News* (San José, CA). October 22, 2018. https://www.mercurynews.com/2018/10/22/bay-area-tops-u-s-in-new-office-space-but-lags-in-housing-starts/.

Healy, Michael C. *BART: The Dramatic History of the Bay Area Rapid Transit System*. Berkeley, California: Heyday, 2016.

Henao, Alejandro. “Impacts of Ridesourcing—Lyft and Uber—on Transportation Including VMT, Mode Replacement, Parking, and Travel Behavior.” PhD dissertation, University of Colorado, 2017. ProQuest. https://search.proquest.com/docview/1899208739.

Hoang, Ling. “VTA’s Transit Service Redesign Plan Is Approved.” *Santa Clara Valley Transportation Authority*. May 5, 2017. http://www.vta.org/News-and-Media/Connect-with-VTA/VTAs-Transit-Service-Redesign-Plan-is-Approved.

Hobson, Jeremy. “Why Public Transit Ridership Is Down in Most U.S. Cities.” *WBUR*. March 21, 2017. http://www.wbur.org/hereandnow/2017/03/21/public-transit-ridership-down.

Hurd, Rick. “Audio Dispatch of Oakland BART Mob: ‘It’s a Group of 50. They Bum-rushed the Entire Train.’” *Mercury News* (San José, California). April 25, 2017. https://www.mercurynews.com/2017/04/25/audio-dispatch-of-oakland-bart-mob-its-a-group-of-50-they-bum-rushed-the-entire-train/.

Kabak, Benjamin. "Where Have All the Transit Riders Gone?" *Second Avenue Sagas*. May 20, 2018. http://secondavenuesagas.com/2018/05/20/transit-riders-gone/.

Kasperkevic, Jana. "Do People Even Work 9-to-5 Anymore?" *Marketplace*. May 28, 2018. https://www.marketplace.org/2018/05/28/business/ive-always-wondered/why-do-keep-using-9-5.

King, Hannah. "Employment Clusters Update." *Google Slides*. March 7, 2019.

Kuby, Michael, Anthony Barranda, and Christopher Upchurch. "Factors Influencing Light-rail Station Boardings in the United States." *Transportation Research Part A: Policy and Practice* 38, no. 3 (March 2004): 223-47. ScienceDirect. https://www.sciencedirect.com/science/article/pii/S0965856403001046.

KGO-TV. "Commute Challenge: This Might Be the Fastest Way around the Bay." *ABC7 News*. October 24, 2018. https://abc7news.com/traffic/commute-challenge-this-might-be-the-fastest-way-around-the-bay/4549557/.

———. "What We Know about Deadly Stabbing at Oakland's MacArthur BART Station." *ABC7 News*. July 25, 2018. https://abc7news.com/what-we-know-about-deadly-oakland-bart-stabbing/3812465/.

Lane, Bradley W. "A Time-series Analysis of Gasoline Prices and Public Transportation in U.S. Metropolitan Areas." *Journal of Transport Geography* 22 (2012): 221-35. ScienceDirect. https://www.sciencedirect.com/science/article/pii/S0966692311001578.

Lavieri, Patrícia S., Felipe F. Dias, Natalia Ruiz Juri, James Kuhr, and Chandra R. Bhat. "A Model of Ridesourcing Demand Generation and Distribution." *Transportation Research Record* 2672, no. 46 (2018): 31-40. SAGE Journals. https://journals.sagepub.com/doi/pdf/10.1177/0361198118756628.

Litman, Todd. "Transit Price Elasticities and Cross-Elasticities." *Journal of Public Transportation* 7, no. 2 (2004): 37-58. Scholar Commons: University of South Florida. http://scholarcommons.usf.edu/cgi/viewcontent.cgi?article=1339&context=jpt.

Liu, Chengxi, Yusak O. Susilo, and Anders Karlström. "Weather Variability and Travel Behaviour—What We Know and What We Do Not Know," *Transport Reviews* 37, no. 6 (2017): 715-41. Taylor and Francis Online. https://www.tandfonline.com/doi/pdf/10.1080/01441647.2017.1293188.

Matier, Phil. "BART's Oakland Airport Connector Isn't a Big Money Maker Yet." *KPIX 5: CBS S[an]F[rancisco] Bay Area*. March 8, 2017. https://sanfrancisco.cbslocal.com/2017/03/08/barts-oakland-airport-connector-isnt-a-big-money-maker-yet/.

———. "BART's Oakland Airport Connector Turning into Big Money Loser." *San Francisco*

Chronicle. March 8, 2017. Last updated March 9, 2017. https://www.sfchronicle.com/bayarea/article/BART-s-Oakland-airport-connector-turning-into-10984679.php.

Matier, [Phil] and [Andy] Ross. "BART Ridership Drops on Nights, Weekends." *San Francisco Chronicle*. August 20, 2018. https://www.sfchronicle.com/bayarea/matier-ross/article/BART-ridership-drops-on-nights-weekends-13166386.php.

———. "BART's Oakland Airport Connector Too Costly to Stop." *SFGate*. May 11, 2011. https://www.sfgate.com/bayarea/matier-ross/article/BART-s-Oakland-Airport-Connector-too-costly-to-2372367.php.

Manville, Michael [Keith]. "Travel and the Built Environment: Time for Change." *Journal of the American Planning Association* 83, no. 1 (Winter 2017): 29-32. Taylor and Francis Online. https://www.tandfonline.com/doi/pdf/10.1080/01944363.2016.1249508.

Manville, Michael [Keith], Brian D. Taylor, and Evelyn Blumenberg. *Falling Transit Ridership: California and Southern California*. January 2018. *SCAG: Innovating for a Better Tomorrow*. https://www.scag.ca.gov/Documents/ITS_SCAG_Transit_Ridership.pdf.

McFadden, Daniel L. "The Path to Discrete-choice Models." *ACCESS* 20 (Spring 2002): 2-7. https://www.accessmagazine.org/wp-content/uploads/sites/7/2016/07/access20-01-the-path-to-discrete-choice-models.pdf.

Melendez, Lyanne. "BART Riders Increasingly Concerned with Safety." *ABC7 News*. July 26, 2018. https://abc7news.com/bart-riders-increasingly-concerned-with-safety-/3829762/.

Metropolitan Transportation Commission. "Priority Development Areas." *Metropolitan Transportation Commission.* 2019. https://mtc.ca.gov/our-work/plans-projects/focused-growth-livable-communities/priority-development-areas.

Metropolitan Transportation Commission and Association of Bay Area Governments. *Plan Bay Area 2040: Regional Transportation Plan and Sustainable Communities Strategy for the San Francisco Bay Area, 2017–2040*. July 26, 2017. *Plan Bay Area 2040: Plan Bay Area*. http://2040.planbayarea.org/cdn/ff/buje2Q801oUV3Vpib-FoJ6mkOfWC9S9sgrSgJrwFBgo/1510696833/public/2017-11/Final_Plan_Bay_Area_2040.pdf.

Mitchell, Houston. "Yogi Berra Dies at 90: Here Are Some of His Greatest Quotes." *Los Angeles Times*. September 22, 2015. https://www.latimes.com/sports/sportsnow/la-sp-sn-yogi-berra-turns-90-quotes-20150512-story.html.

Mucci, Richard A[lexander] and Gregory D. Erhardt. "Evaluating the Ability of Transit Direct Ridership Models to Forecast Medium-Term Ridership Changes: Evidence from San Francisco." *Transportation Research Record* 2672, no. 46 (2018): 21-30. SAGE

Journals. https://journals.sagepub.com/doi/pdf/10.1177/0361198118758632.

Murphy, Colin. *Shared Mobility and the Transformation of Public Transit*. Transit Cooperative Research Program Project J-11, Task 21, Shared-use Mobility Center, Chicago, Illinois, March 2016. Edited by Tim Frisbie. *APTA: American Public Transportation Association*. http://www.apta.com/resources/reportsandpublications/Documents/APTA-Shared-Mobility.pdf.

Nelson, Laura J. "The Metro Can Take You Farther than Ever. Here's Why Ridership Dropped—Again." *Los Angeles Times*. February 13, 2017. http://www.latimes.com/local/lanow/la-me-ln-2016-metro-ridership-decline-20170209-story.html.

Nelson, Laura J. and Dan Weikel. "Billions Spent, but Fewer People Are Using Public Transportation in Southern California." *Los Angeles Times*. January 27, 2016. http://www.latimes.com/local/california/la-me-ridership-slump-20160127-story.html.

New Transbay Rail Crossing: Program Overview + Project Contracting Plan. November 15, 2018. *Bay Area Rapid Transit*. https://www.bart.gov/sites/default/files/docs/6-A%20%20New%20Transbay%20Rail%20Crossing%20Update%20Presentation.pdf.

N[ew] Y[ork] C[ity] Department of Transportation. *New York City Mobility Report*. June 2018. *The Official Website of the City of New York*. http://www.nyc.gov/html/dot/downloads/pdf/mobility-report-2018-print.pdf.

[Parker, Kim et al.] "The State of American Jobs." *Pew Research Center: Social and Demographic Trends*. October 6, 2016. http://www.pewsocialtrends.org/2016/10/06/1-changes-in-the-american-workplace/.

"Population Density for U.S. Cities Statistics." *Governing*. 2019. http://www.governing.com/gov-data/population-density-land-area-cities-map.html.

Rajamani, Jayanthi, Chandra R. Bhat, Susan Handy, Gerritt Knaap, and Yan Song. "Assessing Impact of Urban Form Measures on Nonwork Trip Mode Choice after Controlling for Demographic and Level-of-service Effects." *Transportation Research Record* 1831 (2003): 158-65. *TRB: Transportation Research Board*. https://trrjournalonline.trb.org/doi/pdf/10.3141/1831-18.

Rayle, Lisa, Danielle Dai, Nelson Chan, Robert Cervero, and Susan Shaheen. "Just a Better Taxi?: A Survey-based Comparison of Taxis, Transit, and Ridesourcing Services in San Francisco." *Transport Policy* 45 (2016): 168-78. ScienceDirect. https://www.sciencedirect.com/science/article/pii/S0967070X15300627.

Rhodes, Michael. "Civil Rights Complaint Filed Against BART Over OAK Airport Connector." *Streetsblog San Francisco*. September 4, 2009.

https://sf.streetsblog.org/2009/09/04/civil-rights-complaint-filed-against-bart-over-oak-airport-connector/.

Richards, Gary. "Marin Bus Ridership Decline Mirrors Bay Area." *Marin Independent Journal*. June 4, 2018. http://www.marinij.com/general-news/20180604/marin-bus-ridership-decline-mirrors-bay-area.

———. "VTA Proposes Biggest Transit Overhaul since 2008." *Mercury News* (San José, CA). January 6, 2017. https://www.mercurynews.com/2017/01/06/vta-proposes-biggest-transit-overhaul-since-2008/.

Rubin, Thomas A. "Is the *Los Angeles Time[s]* Article, 'Billions Spent, But Fewer People Are Using Public Transportation in Southern California,' Misleading?" N.d. *Electronic Drummer: The Website of the Thoreau Institute*. http://ti.org/docs/RubinonLATimesStory.doc.

Rudick, Roger. "Pics from the Warm Springs/South Fremont BART Opening Celebration." *Streetsblog San Francisco*. Mar. 24, 2017. https://sf.streetsblog.org/2017/03/24/pics-from-the-warm-springssouth-fremont-bart-opening-celebration/.

"Sacramento Regional Transit District Rolls Back Fares: Board Approves Sweeping Ridership Building Initiatives, Including Fare Reductions, 25-cent Transfers, and 15-minute Frequency for Light Rail Service on Weekends." *Sacramento Regional Transit District*. August 28, 2018. http://www.sacrt.com/apps/sacramento-regional-transit-district-rolls-back-fares/.

S[an] F[rancisco] M[unicipal] T[ransportation] A[gency]. "Muni Forward Brings You More Service, Muni Rapid, New Map." *S[an] F[rancisco] M[unicipal] T[ransportation] A[gency]*. April 3, 2015. https://www.sfmta.com/blog/muni-forward-brings-you-more-service-muni-rapid-new-map.

———. "Muni History." *S[an] F[rancisco] M[unicipal] T[ransportation] A[gency]*. 2019. https://www.sfmta.com/getting-around/muni/muni-history.

Sankin, Aaron. "BART Police Department: Is It Necessary?" *Huffington Post*. August 31, 2011. https://www.huffingtonpost.com/2011/08/31/bart-police-department-necessary_n_944103.html.

Schaller, Bruce. *The New Automobility: Lyft, Uber and the Future of American Cities*. July 25, 2018. *Schaller Consulting*. http://www.schallerconsult.com/rideservices/automobility.pdf.

———. *Unsustainable?: The Growth of App-based Ride Services and Traffic, Travel and the Future of New York City*. February 27, 2017. *Schaller Consulting*. http://www.schallerconsult.com/rideservices/unsustainable.pdf.

Schimek, Paul. "Dynamic Estimates of Fare Elasticity for U.S. Public Transit." *Transportation Research Record* 2538 (2015): 96-101. *TRB: Transportation Research Board*.

https://trrjournalonline.trb.org/doi/abs/10.3141/2538-11.

Schmitt, Angie. "D.C. Metro Seeks Better Service, Fare Cuts to Stop Ridership Death Spiral." *Streetsblog USA*. October 29, 2018. https://usa.streetsblog.org/2018/10/29/d-c-metro-seeks-better-service-fare-cuts-to-stop-ridership-death-spiral/.

———. "Study: Uber and Lyft Caused U.S. Transit Decline." *Streetsblog USA*. January 22, 2019. https://usa.streetsblog.org/2019/01/22/study-uber-and-lyft-are-responsible-for-u-s-transit-decline/.

Schwartz, Hart. "Declining Transit Ridership: Revolutionary or Routine?" *The Fuse: Igniting Conversations and Commentary about Energy*. April 4, 2018. http://energyfuse.org/declining-transit-ridership-revolutionary-routine/.

Siddiqui, Faiz. "Falling Transit Ridership Poses an 'Emergency' for Cities, Experts Fear." *Washington Post*. March 24, 2018. https://www.washingtonpost.com/local/trafficandcommuting/falling-transit-ridership-poses-an-emergency-for-cities-experts-fear/2018/03/20/ffb67c28-2865-11e8-874b-d517e912f125_story.html.

Stevens, Mark R. "Does Compact Development Make People Drive Less?" *Journal of the American Planning Association* 83, no. 1 (Winter 2017): 7-18. Taylor and Francis Online. https://www.tandfonline.com/doi/pdf/10.1080/01944363.2016.1240044.

Taylor, B[rian] D. and C[amille] N. Y. Fink. "Explaining Transit Ridership: What Has the Evidence Shown?" *Transportation Letters* 5, no. 1 ([Winter] 2013): 15-26. Taylor and Francis Online. https://www.tandfonline.com/doi/pdf/10.1179/1942786712Z.0000000003.

———. "The Factors Influencing Transit Ridership: A Review and Analysis of the Ridership Literature." U[niversity of] C[alifornia] L[os] A[ngeles] Department of Urban Planning Working Paper, University of California, Los Angeles, Los Angeles, California, September 1, 2003. eScholarship: UC Open Access Publications. https://cloudfront.escholarship.org/dist/prd/content/qt3xk9j8m2/qt3xk9j8m2.pdf.

Taylor, Brian D., Mark Garrett, and Hiroyuki Iseki. "Measuring Cost Variability in Provision of Transit Service." *Transportation Research Record* 1735, no. 1 (2000): 101-12. SAGE Journals. https://journals.sagepub.com/doi/pdf/10.3141/1735-13.

Taylor, Brian D., Douglas Miller, Hiroyuki Iseki, and Camille Fink. "Nature and/or Nurture?: Analyzing the Determinants of Transit Ridership across U.S. Urbanized Areas." *Transportation Research Part A: Policy and Practice* 43 (2009): 60-77. ScienceDirect. https://www.sciencedirect.com/science/article/pii/S0965856408001274.

Thompson, Gregory L. and Jeffrey R. Brown. "Explaining Variation in Transit Ridership in U.S. Metropolitan Areas between 1990 and 2000: Multivariate Analysis." *Transportation Research Record* 1986 (2016): 172-81. SAGE Journals. https://journals.sagepub.com/doi/pdf/10.1177/0361198106198600121.

Thompson, Gregory [L.], Jeffrey [R.] Brown, and Torsha Bhattacharya. "What Really Matters for Increasing Transit Ridership: Understanding the Determinants of Transit Ridership Demand in Broward County, Florida." *Urban Studies* 49, no. 15 (November 2012): 3327-45. SAGE Journals. http://journals.sagepub.com/doi/pdf/10.1177/0042098012443864.

Tinoco, Matt. "Metro's Declining Ridership, Explained." *Curbed Los Angeles*. August 29, 2017. https://la.curbed.com/2017/8/29/16219230/transit-metro-ridership-down-why.

V[alley] T[ransportation] A[uthority, Santa Clara]. *Santa Clara Valley Transportation Authority History*. November 7, 2005. *Santa Clara Valley Transportation Authority*. http://www.vta.org/sfc/servlet.shepherd/version/download/068A0000001FaML

Veltman, Chloe. "BART Looks for Solutions After Another Steep Drop in Weekend Ridership." *KQED*. August 20, 2018. https://www.kqed.org/news/11687848/bart-looks-for-solutions-after-another-steep-drop-in-weekend-ridership.

Walker, Jarrett. *Human Transit: How Clearer Thinking about Public Transit Can Enrich Our Communities and Our Lives*. Washington: Island, 2012.

Wang, Kyungsoon and Myungje Woo. "The Relationship between Transit-rich Neighborhoods and Transit Ridership: Evidence from the Decentralization of Poverty." *Applied Geography* 86 (September 2017): 183-96. ScienceDirect. https://www.sciencedirect.com/science/article/pii/S0143622817307166.

Zuk, Miriam, Ariel H. Bierbaum, Karen Chapple, Karolina Gorska, Anastasia Loukaitou-Sideris, Paul Ong, and Trevor Thomas. "Gentrification, Displacement and the Role of Public Investment: A Literature Review." Working Paper 2015-05, Community Development Investment Center, Federal Reserve Bank of San Francisco, San Francisco, California, August 2015. *Federal Reserve Bank of San Francisco*. https://www.frbsf.org/community-development/files/wp2015-05.pdf.