UC Office of the President
ITS reports

Title
How Dock-less Electric Bike Share Influences Travel Behavior, Attitudes, Health, and Equity: Phase II

Permalink
https://escholarship.org/uc/item/0x373679

Authors
Fukushige, Tatsuya
Fitch, Dillon, PhD
Handy, Susan

Publication Date
2021-07-01

DOI
10.7922/G2FF3QN5

eScholarship.org Powered by the California Digital Library
University of California

RESEARCH REPORT

Institute of Transportation Studies | UNIVERSITY OF CALIFORNIA

How Dock-less Electric Bike Share Influences Travel Behavior, Attitudes, Health, and Equity: Phase II

Tatsuya Fukushige, Graduate Student Researcher, Institute of Transportation Studies, University of California, Davis
Dillon Fitch, Ph.D., Professional Researcher, Institute of Transportation Studies, University of California, Davis
Susan Handy, Ph.D., Professor, Department of Environmental Science and Policy, University of California, Davis

July 2021

ITS UCDAVIS INSTITUTE OF TRANSPORTATION STUDIES

Report No.: UC-ITS-2020-05 | DOI: 10.7922/G2FF3QN5

Technical Report Documentation Page

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.
UC-ITS-2020-05	N/A	N/A

4. Title and Subtitle How Dock-less Electric Bike Share Influences Travel Behavior, Attitudes, Health, and Equity: Phase II	**5. Report Date** July 2021 **6. Performing Organization Code** ITS-Davis
7. Author(s) Tatsuya Fukushige, https://orcid.org/0000-0002-6485-4537 Dillon Fitch, Ph.D. https://orcid.org/0000-0003-3760-322X Susan Handy, Ph.D. https://orcid.org/0000-0002-4141-1290	**8. Performing Organization Report No.** UCD-ITS-RR-21-56
9. Performing Organization Name and Address Institute of Transportation Studies, Davis 1605 Tilia Street Davis, Ca 95616	**10. Work Unit No.** N/A **11. Contract or Grant No.** UC-ITS-2020-05
12. Sponsoring Agency Name and Address The University of California Institute of Transportation Studies www.ucits.org	**13. Type of Report and Period Covered** Final Report October 2019 – September 2020 **14. Sponsoring Agency Code** UC ITS

15. Supplementary Notes
DOI:10.7922/G2FF3QN5

16. Abstract
Dock-less, electric bike-share services offer cities a new transportation option with the potential to improve environmental, social, and health outcomes. But these benefits accrue only if bike-share use replaces car travel. The purpose of this study is to examine factors influencing whether bike-share substitutes for driving and the degree to which and under what circumstances bike-share use reduces car travel. Major findings in this report include (1) bike-share in the Sacramento region most commonly substitutes for car and walking trips, (2) each bike in the Sacramento bike-share fleet reduces users' VMT by an average of approximately 2.8 miles per day, (3) areas with a higher proportion of low-income households tend to use bike-share less, (4) bike-share availability appears to induce new trips to restaurants and shopping and for recreation, (5) bike-share trips from commercial and office areas were more likely to replace walking or transit trips, while bike-share trips from non-commercial areas (and trips to home or restaurants) were more likely to replace car trips, (6) expanding the bike-share service boundary at the same fleet density decreases system efficiency and VMT reductions per bike. Our result suggests the need for an efficient rebalancing strategy specific to areas by time of day to increase the service efficiency and its benefits. Further analysis of the data used in this study to examine questions such as how bike share can improve transit connections and factors inducing bike use at the individual level will contribute to the development of more robust models and provide additional insights for bike share operation strategies and policy implementation.

17. Key Words	18. Distribution Statement
Bicycles, vehicle sharing, electric vehicles, shared mobility, travel demand, travel behavior, travel surveys, demographics, e-scooters, electric bicycles	No restrictions.

19. Security Classification (of this report)	20. Security Classification (of this page)	21. No. of Pages	21. Price
Unclassified	Unclassified	73	N/A

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

About the UC Institute of Transportation Studies

The University of California Institute of Transportation Studies (UC ITS) is a network of faculty, research and administrative staff, and students dedicated to advancing the state of the art in transportation engineering, planning, and policy for the people of California. Established by the Legislature in 1947, ITS has branches at UC Berkeley, UC Davis, UC Irvine, and UCLA.

Acknowledgments

This study was made possible through funding received by the University of California Institute of Transportation Studies from the State of California through the Public Transportation Account and the Road Repair and Accountability Act of 2017 (Senate Bill 1). The authors would like to thank the State of California for its support of university-based research, and especially for the funding received for this project.

Disclaimer

The contents of this report reflect the views of the author(s), who are responsible for the facts and the accuracy of the information presented herein. This document is disseminated under the sponsorship of the State of California in the interest of information exchange. The State of California assumes no liability for the contents or use thereof. Nor does the content necessarily reflect the official views or policies of the State of California. This report does not constitute a standard, specification, or regulation.

How Dock-less Electric Bike Share Influences Travel Behavior, Attitudes, Health, and Equity: Phase II

Tatsuya Fukushige, Graduate Student Researcher, Institute of Transportation Studies, University of California, Davis
Dillon Fitch, Ph.D., Professional Researcher, Institute of Transportation Studies, University of California, Davis
Susan Handy, Ph.D., Professor, Department of Environmental Science and Policy, University of California, Davis

July 2021

ITS UCDAVIS INSTITUTE OF TRANSPORTATION STUDIES

Report No.: UC-ITS-2020-05 | DOI: 10.7922/G2FF3QN5

Table of Contents

Table of Contents

Executive Summary **1**

Introduction **4**

Methodology **6**

Data Collection 6

Analysis 8

Results and Discussion **19**

Factors Influencing Mode Substitution 19

System-level Mode Substitution and VMT Reduction 22

Factors Influencing Dock-less Bike Share Use 26

Scenario Analysis: Mode Substitution and VMT Reduction with Potential Changes in Fleet Size [Before and After Changes in JUMP Operations] 30

Policy Implications and Conclusions **44**

References **46**

Appendix A: Extended Methods **47**

Factors Influencing Mode Substitution 47

System-level Mode Substitution and VMT Reduction 49

Factors Influencing Dock-less Bike Share Usage 50

Scenario Analysis for Service Change: Mode Substitution and VMT Reduction 52

Limitations 53

Appendix B: Model Parameter Summaries **54**

Mode Substitution Model 54

System-level Mode Substitution and its Effect 59

Demand Model 62

List of Tables

Table 1. List of Predictor Variables 10

Table 2. Ratios of Commuting Trips to Non-commuting Trips 13

Table 3. List of Predictor Variables 15

Table 4. Number of Bike Fleet and Bike Density 17

Table 5. Model Specification 48

Table 6. Summary of estimates of mode substitution model for non-commuting trip (full model) including the posterior mean and standard deviation 54

Table 7. Prediction Metrics* 57

Table 8. Summary of estimates of mode substitution model for non-commuting trip (reduced model) including the posterior mean and standard deviation 59

Table 9. Summary of estimates of mode substitution model for commuting trip including the posterior mean and standard deviation 61

Table 10. Summary of estimates of hub weight model including the posterior mean and standard deviation 61

Table 11. Summary of estimates of multivariate model including the posterior mean and standard deviation ..62

Table 12. Summary of estimates of bike share trip flow demand model including mean estimates, standard deviation, and z-value 62

List of Figures

Figure 1. Share of Reported Mode Substitution in the Survey 9
Figure 2. Flowchart for Estimation of VMT Reduction 12
Figure 3. Five Areas for Scenario Analysis 16
Figure 4. Flowchart for Estimation in Scenario Analysis 18
Figure 5. Conditional Combined Effects of Trip Distance and Trip Purpose on Mode Substitution 20
Figure 6. Conditional Combined Effects of Speed and Trip Purpose on Mode Substitution 21
Figure 7. Share of Substituted Modes on Weekdays 23
Figure 8. Share of Substituted Modes on Weekends 24
Figure 9. Estimated VMT Reduction per day 25
Figure 10. Estimates of OD Zone Type (Random Effect) 27
Figure 11. Predicted Bike Demand and Actual Observed Use in Davis 28
Figure 12. Predicted Bike Demand and Actual Observed Use in Davis by time of day 29
Figure 13. Distribution of Estimated Bike-Share Use per day in Woodland by Fleet Size 32
Figure 14. Distribution of Estimated Bike-Share Use per day in Davis by Fleet Size 33
Figure 15. Distribution of Estimated Bike-Share Use per day in Downtown Sacramento by Fleet Size 34
Figure 16. Distribution of Estimated Bike-Share Use per day in Sacramento/West Sacramento by Fleet Size .. 35
Figure 17. Distribution of Estimated Bike-Share Use per day in expanded Sacramento/West Sacramento by Fleet size 36
Figure 18. Estimated VMT Reduction by Fleet Size in Woodland 38
Figure 19. Estimated VMT Reduction by Fleet Size in Davis 39
Figure 20. Estimated VMT Reduction by Fleet Size in Sacramento Downtown 40
Figure 21. Estimated VMT Reduction for Each Policy Scenario in Sacramento/West Sacramento 41
Figure 22. Estimated VMT Reduction by Fleet Size in Expanded Sacramento/West Sacramento Service Area . 43
Figure 23. Map of TAZs classified based on Land Use 51

Executive Summary

Executive Summary

The recent emergence of dock-less electric bike and scooter share services (also known as micromobility services) have allowed a growing number of cities to look toward them to improve the environment, public health and social equity. Expanding bike/scooter share use is likely to increase physical activity for users and reduce their vehicle mile traveled (VMT) and related greenhouse emissions. However, these benefits accrue only if micromobility use replaces car travel. If bike share takes trips from public transit, owned bike, or walking, the benefits will be more limited. However, little is known about what influences car substitution in comparison to other mode substitution. Considering that reducing VMT is a statewide goal (SB 375) for meeting greenhouse gas emissions targets (AB32 and AB 398), understanding how bike/scooter sharing can reduce car travel is important. In addition, understanding how planning and regulation of bike/scooter share systems influences car substitution rates can help cities craft local plans and regulations to maximize VMT reductions from bike/scooter share services.

This study (1) identifies factors influencing mode substitution (2) estimates the number of system-wide vehicle miles reduced by bike share users, (3) develops a model to estimate bike share demand and to examine factors influencing that demand, and (4) estimates potential vehicle miles reduced from changes to bike share services (e.g., a change in service area boundaries or caps on the number of vehicles).

Our findings that long bike share trips and trips that start in non-commercial locations are likely to be a substitute for car modes suggests that rebalancing policies (that dictate the process by which bikes are physically relocated to maintain local availability) should focus on providing bikes in areas where a high portion of trips are longer. But the findings also suggest an interesting trade-off that warrants further exploration, namely, where bike share is most successful at attracting users, such as in congested downtown areas, it may be less likely to reduce car use, since automobile alternatives to driving are already more available in these areas. In addition, mode substitution varies by trip purpose. For example, bike share trips going home or to a restaurant tend to replace ride-hailing. Finally, the fact that some groups, such as women, Hispanics/Latinos and those who have a private car, are more likely to substitute bike share for car-related options points to the possibility of using marketing and incentives targeted to these groups to encourage lower car use.

We find that on weekdays, bikeshare most often substitutes for walking, followed by ride-hailing, private car, owned bike, transit, and carpool trips. In some cases, particularly recreational trips, bike share users indicate they would not have made the trip had the service not been available, which means these trips represent induced travel.

Our analysis of bike share trips in the Sacramento region shows that the bike share service initially reduced vehicle mile traveled (VMT) by an average of 1,795 miles on weekdays and 1,540 miles on weekends in total across the service area. After certain changes in service operations (which included an increase in the bike fleet and expansion of the service boundary, among others) and counting only the VMT of private vehicles and ride-

hailing services when a passenger is in the vehicle, the average decrease in VMT increased to 2,160 miles on weekdays and 1,764 miles on weekends. Adding the potential VMT reduction from the deadheading (traveling to and from picking up passengers) and searching (travel to pick up passengers) associated with ride-hailing services, we estimated VMT reductions of 2,248 miles on weekdays before the changes and 2,702 miles on weekdays after the changes.

The factors that determine bike share use matter for cities and private companies planning to introduce a new bike share system. Our results show that the demand for dock-less e-bike share in the Sacramento region is greatest in commercial areas and areas with a college or university. Lower bike share use in college/university areas on weekends suggests the need for an efficient rebalancing strategy for these areas. As for leveraging bike share to increase transportation equity, a goal in many communities, our results show less bike share use in areas with a higher proportion of low-income households, which suggests that fewer low-income residents are likely to use bike share. This result is consistent with previously reported results from the surveys we conducted in the Sacramento region. However, the relationships between user socio-demographics and population-level socio-demographics in census blocks are weak, suggesting the need for caution in assuming that the findings reported here for trip data reflect the travel patterns for individual users.

It is important for cities and private operators to have a reliable estimate of the number of trips a new bike share system is likely to generate as well as the change in trips they can expect from a change in service boundaries or fleet size. By analyzing a number of different scenarios that assume different increases in the bike-fleet density in our study areas, we find that increasing the number of bikes in existing high demand areas may be economical, but bike share trips there are less likely to substitute for driving. This does not preclude the possibility that non-car substituting trips reduce car use in other ways (e.g., bike share being a factor for not commuting by car in the first place). At the same time, our results show that expanding service boundaries increase the overall number of trips but substantially decreases the efficiency of bike use by reducing the number of trips per individual bike.

By analyzing bike share use in those portions of the Sacramento region that currently have bike share services, we estimate the potential reduction in VMT by bike share users in areas with a minimum of 12.5 bikes per square mile on weekdays would be an average of 84 miles in total in Woodland, 833 miles in Davis, 583 miles in downtown Sacramento, 1,795 miles in the Sacramento/West Sacramento region with the existing service area, and 2,380 miles with an expanded service area.

Contents

Introduction

The recent emergence of dock-less[1] electric bike and scooter share services (also known as micromobility services) have allowed a growing number of cities to look toward them to help improve the environment, social conditions, and public health (1-3). The National Association of City Transportation Officials (NACTO) reported that the number of micromobility trips in the United States increased from 321,000 trips in 2010 to 84 million trips in 2018, about a 260-fold increase just within 8 years (4). Expanding bike/scooter share use is likely to increase physical activity for users and reduce their vehicle miles traveled (VMT) by other modes and related greenhouse gas (GHG) emissions. However, these benefits accrue only if micromobility use replaces car travel. If the major mode shift comes from reduced use of public transit, owned bikes, or walking, the benefits will be more limited. Some studies have shown that 30 to 40 percent of bike and scooter share trips substitute for car trips (5-7). However, little is known about what influences car substitution compared to other mode substitution. Considering that reducing VMT is a statewide goal (SB 375) for meeting GHG emissions targets (AB32 and AB 398), understanding how bike/scooter sharing can reduce car travel is important. In addition, understanding how planning for and regulation of bike/scooter share systems influences car substitution rates can help cities craft local plans and regulations to maximize VMT reductions.

JUMP, one of the largest dock-less e-bike share companies operated in the U.S. opened in 2018 across three California cities: Sacramento, West Sacramento, and Davis. The service covers an area of approximately 50 square miles, though the service areas are not all contiguous (Davis is separated from West Sacramento by about 10 miles). Although the service is dock-less, JUMP has installed bike-hub stations within its service boundaries to provide a place for rebalancing bikes,[2] and users sometimes receive incentives to return bikes to the docks. Since it was launched, JUMP has updated its service in many ways. One major set of changes in operations, implemented in June 2019, was to increase its bike fleet and expand its service area.

This study (1) identifies factors influencing the decision to take bike share trips instead of using other modes (2) estimates system-wide reductions in vehicle miles from bike sharing, (3) develops a model to estimate bike share demand and to examine factors influencing that demand, and (4) estimates potential reductions in vehicle miles from changes to bike share services (e.g., modifying service area boundaries or placing caps on the number of vehicles). The results of this analysis are important to the Sacramento Area Council of Governments (SACOG) region in assessing the value of bike share systems, particularly with respect to their contribution to the region's goals for reducing VMT under California's Senate Bill 375. The results of this study will also help other regions as they consider implementing/permitting their own bike or scooter share systems,

[1] The term "dockless" refers to the fact that the bicycle does not have to be picked up at or returned to a specific location but can be retrieved or dropped off anywhere in the service area.
[2] Since dockless bicycles do not have to be returned to a specific location but may be left anywhere, over the course of the day they may tend to end up in locations where demand is highest, leaving other areas without access to bicycles. Companies periodically pick up bikes and redistribute them throughout the service area, a practice known as rebalancing.

and could potentially be incorporated into analytical tools such as the California Air Resources Board's GHG quantification methods. In addition, the methodologies developed in this study could be applied in other regions to assess the impact of their specific bike share systems.

Methodology

Data Collection

This study uses data from two sources: 1) A two-wave longitudinal survey of JUMP bike share users in the SACOG region, and 2) System-level data on bike share trips webs-craped from the General Bikeshare Feed Specification (GBFS).[3]

Survey Data

We use data from a two-wave longitudinal survey of users of the bike share service. The first-wave survey was conducted in October 2018 and focused on attitudes and perceptions, experience, and travel behavior. This survey captured user behavior after only 4-5 months of service operation. This timing allowed residents to become acquainted with the service, but we suspect that the survey primarily captured early adopters who may have been more excited about trying out the service. The second-wave survey occurred in May 2019 and included a follow-up with the initial sample and a new sample of users. We made only slight changes in the second-wave survey where necessary (e.g., to include e-scooter focused questions, as e-scooters were added to the system in the time between the two surveys).

Recruitment for these surveys included: (1) intercepting users at key locations throughout the study area, (2) taping fliers with the URL and QR code to the survey on bike seats, and (3) for the first-wave recruitment only, Facebook advertisements run by JUMP Inc. on our behalf (targeted by zip code). The goal of our field recruitment strategy was to maximize the number of users intercepted while at the same time recruiting users across all geographies and times of day to ensure that the sample included people using the service in a variety of different ways.

As a part of the survey, respondents were asked to report detailed information for their three most recent e-bike share trips for non-commuting purposes. They were asked to refer to the JUMP app to retrieve the location of the trip start and end by reporting addresses or putting a point on the map, the date and time of the trip, and the trip length in terms of both time and distance. In addition, the survey asked them to indicate the purpose of the trip and the mode they would have taken if a JUMP bike had not been available. The survey also asked about general frequency of use and mode substitution for commute trips but not for the more detailed information requested for non-commute trips. We collected data for a total of 1,172 non-commute trips (up to six per person) and 105 responses about general commuting. After removing unrealistic trips, such as trips with faster than possible speeds, and trips not in the Sacramento/West Sacramento area, we developed a series

[3] The General Bikeshare Feed Specification (GBFS: https://github.com/NABSA/gbfs) is an open-source data format for sharing information about bikeshare availability and locations.

of models to estimate user VMT reduction using this survey data and additional sources (see below) (For more details on the survey content, see the Phase 1 report: Fitch et al. (8).)

GBFS Data

We acquired system-wide bike share trip data by web-scraping the real-time status of JUMP bikes in the Sacramento region provided by the GBFS between April 1, 2019, and February 29, 2020 (prior to the suspension of service).[4] When a bike becomes available for users, the information for the bike appears in the real-time data. We use the disappearance and then reappearance of individual bikes, based on bike ID, to create a database of bike share trips, which we then use to count the number of trips to and from the area around transit stops and stations.

This process required several assumptions. One problem is that bikes also disappear and reappear from the data when they are taken off-line for operational purposes (e.g., battery charging or rebalancing). We removed these false trips from the database based on four simple rules. First, we excluded trips during which the battery level increased because these are almost certainly operational events (e.g., rebalancing or maintenance) rather than actual trips. Second, we removed trips having the exact same longitude and latitude on both origin and destination because the longitude and latitude would be at least slightly different if someone checked out and returned the bike at the same location. We did find some trips with small Euclidean distance and short duration, which are also not likely to be actual trips, given that a round trip would take some time, and most actual trips include the period of time it takes the user to walk to the bike after reserving it. We assume that these cases occurred when users reserved but canceled bikes and removed them from the dataset. This could happen often because those holding memberships in the bike share service could cancel the reservation within 15 minutes at no cost other than using up some of their free usage time. Third, because some obstacles such as tall buildings lower the accuracy of geolocation, we also removed trips with 10 meters or shorter Euclidean distance and less than 15 minutes in duration. Finally, we removed trips of four hours or longer duration, making up about eight percent of total potential trips, because these trips are likely to be operational events rather than actual trips.

Another complication in the bike share data is that the GBFS masked information on bikes located near bike-hub stations before the month of September 2019. This means that trips that started or ended near these stations would show up in the scraped data as only one trip end, and our conversion of scraped data to trips would incorrectly match trip ends, potentially leading to trips of longer than actual duration. No information was available that would enable us to identify these trips, but as noted above we did eliminate excessively long trips.

[4] Most data for the month of September 2019 are missing. The missing data include bike ID, latitude, longitude, and battery level (for available bikes only, not for reserved bikes or bikes out of service for maintenance) at each timestamp.

Analysis

We used the collected data in four analyses:

1. Analysis of factors influencing mode substitution based on models that use all available information from the user survey.
2. Estimation of the impacts of bike share on VMT by applying simplified models of mode substitution based on the survey data to system-level trip data.
3. Development of models to estimate bike-share demand and examine factors influencing that demand.
4. Scenario analysis to examine the effect changing service boundaries could have on patronage and reducing VMT.

Factors Influencing Mode Substitution

In analyzing mode substitution, we focused on non-commuting trips from the survey data. The dependent variable in our analysis is mode substitution, a categorical variable derived from the survey response to the question: *If JUMP was not available..., what means would you use to make the trip? Select your one primary method (the one you would use for the longest portion of the trip or the entire trip).* We interpreted the answer to this question to be the mode that was replaced when bike share became available.[5] The potential substituted modes and responses are shown in Figure 1.

[5] We chose this interpretation because this is more directly related to an assessment of the benefits of bike share than the more literal interpretation of the answer, i.e., what mode would be used if bike share went away (though that interpretation is perhaps of more interest now in the wake of COVID-19).

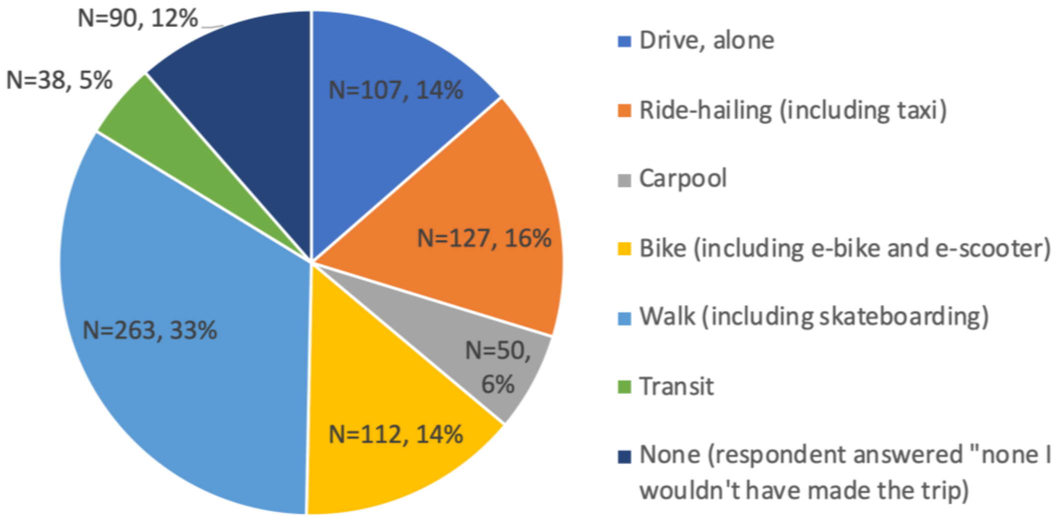

Figure 1. Share of Reported Mode Substitution in the Survey

The models that we developed, as discussed below, can be used to estimate the percentage of bike share trips that substitute for each of these alternative modes. We included a series of variables, including trip attributes, individual characteristics, and land use characteristics, as shown in Table 1, in the models as predictors of mode substitution. The models show how well these variables do in explaining mode substitution. Details of the modelling process are discussed in Appendix A.

Table 1. List of Predictor Variables

Variable	Description
Trip Attributes	
Travel Distance	Log-transform for reported travel distance (mile) for e-bike trip
Speed	Log-transform for reported travel distance / reported travel time
Trip Purpose	1: Home, 2: Shopping, 3: Work related, 4: Recreation/Exercise, 5: Restaurant/Bar/Entertainment, 6: Other
Time of Day	1: Midnight (Midnight-7am), 2: AM peak (7-10am), 3: Off-peak (10am-4pm), 4: PM peak (4-7pm), 5: Night (7pm-midnight)
Weekday/Weekend	1: Weekend/Holiday, 0: Else
Individual Characteristics	
Age	1: Age -24, 2: Age 25-34, 3: Age 35-44, 4: Age 45-54, 5: Age55-
Gender	1: Female, 0: Else
Work Status	1: Commute to at least one workplace, 0: Else
Student Status	1: Full or part-time student, 0: Else
Education	1: Bachelor’s degree or higher, 0: Else
Children (Under 16)	1: One or more children, 0: Else
Vehicle Ownership	1: One or more car per person, 0: Else
Land Use Characteristics	Percent of land use category within 100-meter buffer of trip start or trip end location: 1: Residential use, 2: Commercial/office use, 3: Industrial use, 4: School, and 5: Civic use

System-level Mode Substitution and VMT Reduction

We estimated a series of models to predict the system-wide reduction in vehicle miles produced by substituting bike share for other modes for an average weekday and weekend-day both before and after June 17, 2019, the date of the major change in JUMP operations. This service change included an increase in the bike fleet and expansion of the service boundary, among others. We used GBFS data between April 1 and September 2, 2019, for this post-hoc before-and-after analysis.

We completed five steps to estimate the VMT reduction stemming from the dock-less bike share service (Figure 2). First, we addressed the problem that before September 2019 GBFS masked information on bikes located at bike-hub stations meaning that the number of bike-share trips "observed" in the GBFS data was less than the actual number of bike-share trips. To do so we generated weights for inflating the number of observed trips in each transportation analysis zone (TAZs, as defined by SACOG) containing a hub station to the actual number of trips. This is the "Hub Weight Model" in Figure 2.[6]

[6] While we did acquire web-scraped data for hub stations before the month of September, estimating hub trip variation proved infeasible in the absence of a means of validating the estimates. Instead, we assume that the share of hub trips to non-hub trips in all transportation analysis zones (TAZ) offered in the SACOG data portal with hub stations is identical for any given day. Since trip data starting or ending at any hub station after the month of September is scrapable, we first counted the number of such trips before and after September to estimate the buffer size of the mask. We found that the data points before September within the buffer size of 30 meters (98.4 feet) tend to be extremely few, and so we concluded that this distance is likely to define the extent of the masked area. We examined the relationship between the total number of non-hub trips and hub trips, as well as its uncertainty, based on GBFS data in the month of November to generate the weights.

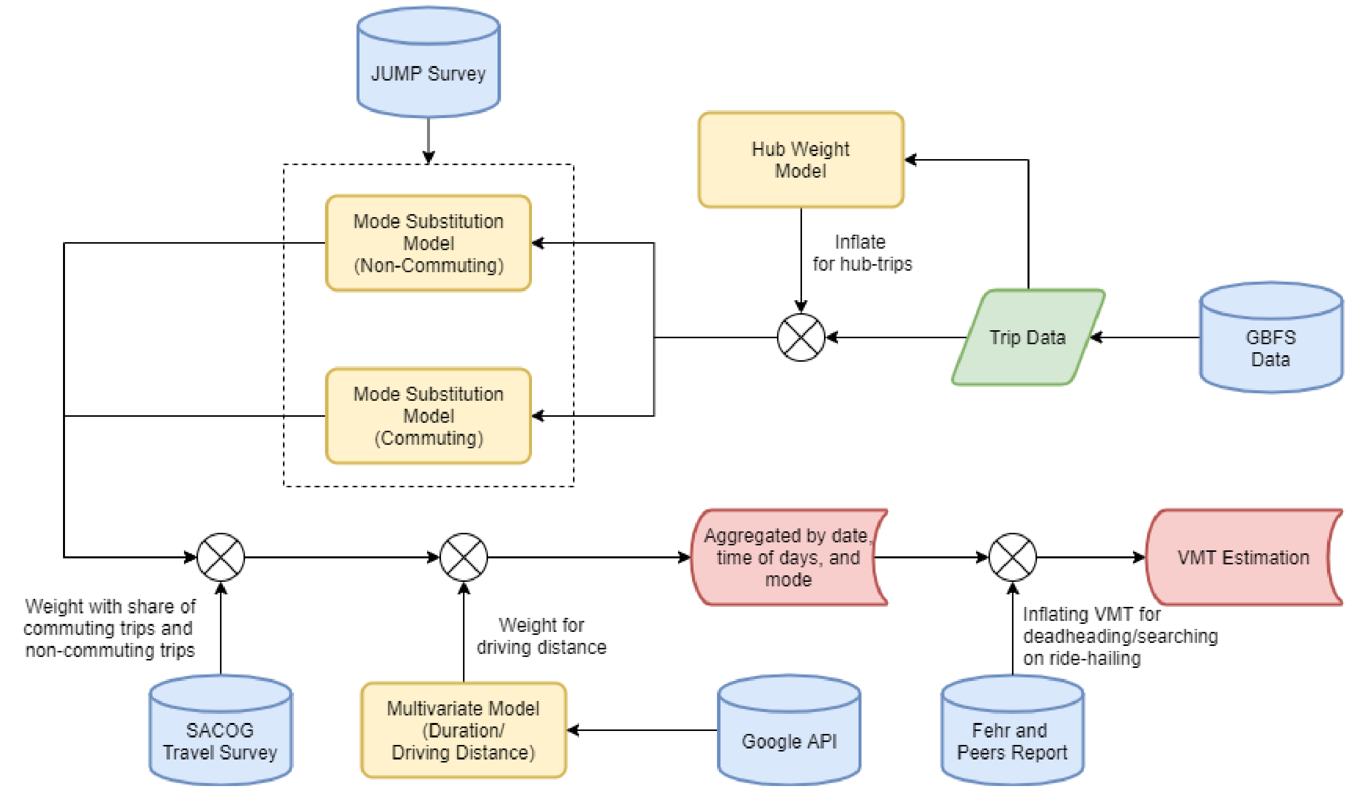

Figure 2. Flowchart for Estimation of VMT Reduction

Second, we developed separate mode-substitution models for commuting trips and non-commuting trips, to predict mode substitution for each type of trip. We developed two separate models because the survey included fewer questions about commute trips, meaning that the potential predictor variables for the models vary by trip purpose. The models developed for this system-level analysis used a limited set of predictor variables compared to the models described in the previous section because the actual trip data in the GBFS was not labeled with individual information, such as the purpose of the trip, gender, and age. In the system-level mode substitution models, predictors are limited to travel time, Euclidean distance, time of day, day of the week, and the proportion of the land use around the trip start/end points.

Third, we estimated the share of non-commuting and commuting trips within the service boundary. One issue with developing two different mode substitution models was that no information about the purpose of the trip for each data point is available in the GBFS dataset that would indicate which mode substitution model to use for each trip. To address this issue, we used travel data from within the JUMP service boundary collected by SACOG as a part of the 2018 SACOG regional household travel survey to estimate weights for commute and non-commute trips by time of the day on weekdays and the weekend (Table 2). Aggregating the weighted output from the mode substitution models by the share of trips by type at different times of day gave us the estimated number of trips for each type of mode substitution.

Table 2. Ratios of Commuting Trips to Non-commuting Trips

		Midnight	AM Peak	Off Peak	PM Peak	Night
Weekday	Non-Commuting	75.1%	71.5%	91.1%	84.7%	93.4%
	Commuting	24.9%	28.5%	8.9%	15.3%	6.6%
Weekend	Non-Commuting	87.0%	87.1%	96.6%	94.3%	97.8%
	Commuting	13.0%	12.9%	3.4%	5.7%	2.2%

Source: SACOG

Fourth, we estimated driving distance for each trip based on Euclidean distance. While Euclidean distance reflects the spatial relationship between the trip start and end points, it underestimates actual travel distances on the road network and thus underestimates the effect of bike-share service on VMT. Querying the estimated driving distance for all trips in the GBFS dataset using routing algorithms such as the Google Maps Application Programming Interface (API) would have been costly. Instead, we sampled 5956 trips from the dataset in November 2019 by drawing 200 data points every 250 meters (about 820 feet) without replacement (in the case that the number of data points in the sample was less than 200, all data points were selected). We then queried the Google-based distance on the road network for each data point using the Google Maps API. We developed a multivariate (two outcome) model, rather than a simple regression model, to predict both travel time and network distance for each trip simultaneously based on Euclidean distance.

The final step in our model was to sum driving distance for the trips classified as "private car" or "ride-hailing." In the aggregation process, we considered several types of potential sources of reductions in VMT from substituting bike-share trips for ride-hailing trips, including mileage due to deadheading (a driver traveling to pick up a passenger) and searching (a driver cruising for next passenger). Thus, we considered three different combinations of VMT reduction from ride-hailing substitution: (1) the trip itself, (2) the trip and deadheading, and (3) the trip, deadheading, and searching. The weights used to adjust savings in VMT were calculated according to Fehr and Peers (9), resulting in upward adjustments of 9-10 percent for deadheading and 38-46 percent for deadheading and searching. Details of the modelling and sampling process described in this section are presented in Appendix A.

Factors Influencing Dockless Bike Share Use (Bike Share Demand)

In this analysis we examined factors influencing dockless bike-share use in the Sacramento/West Sacramento service area. We used GBFS data between October 14 and November 17, 2019, because this allowed us to ignore the hub-trip issue for trips before September 2019 (see above). The average number of trips per day for weekdays and the weekend in this dataset were approximately 2680 and 2440 trips, respectively. We defined a second system of TAZs by using 1km x 1km (3280.8 feet x 3280.8 feet) grids to create 190 TAZs. This means we had a total of 36,100 different TAZ pairs. We counted the number of trips between each TAZ pair and grouped the counts for each TAZ pair by time of day (midnight, AM-peak, off-peak, PM-peak, and night), weekday/weekend and week (n=36,100 x 5 times of day x 2(weekday or weekend) x5 weeks = 1,805,000 observations. We aggregated the counts in this way because five weeks of data for TAZ pairs proved to be an unmanageable amount of data for estimating a single statistical model even on an advanced desktop computer. Also, this aggregation suited the purpose for which we were estimating the number of trips, namely the later scenario analysis (see below).

We used Poisson regression to analyze the factors influencing bike-share use and to predict the number of trip flows for each origin-destination (OD) pair. We considered five different types of predictor variables: trip-related variables, temporal variables, socioeconomic variables, land use / point of interest variables, and built environment variables. Table 3 shows the list of predictor variables used in the model. Details of the modelling process in this section is discussed in Appendix A.

Table 3. List of Predictor Variables

Variable	Description	Data Source
Trip-related Variable		
Distance	Distance between centroids of TAZs (miles)	
Temporal Variables		
Time of Day	1: Midnight (Midnight-7am), 2: AM peak (7-10am), 3: Off-peak (10am-4pm), 4: PM peak (4-7pm), 5: Night (7pm-midnight)	
Weekend	1: Weekend/Holiday, 0: Else	
Density of Bike Fleet Size	Average fleet size (log-transformed; x 10 bikes per square mile)	GBFS
Socioeconomic Variables		
Population (O, D)	Number of Population (x 10^3 persons)	2018ACS
Share of Low-Income Household (O, D)	Share of Household with less than $50,000	2018ACS
Land Use / Point of Interest (POI) Variables		
Cluster Class	5 Land Use Clusters	SACOG
University (O, D)	1: University/College Use, 0: else	SACOG
Airport (O, D)	Area of Airport (x 10^{-1} square mile)	SACOG
Restaurant/Bar (O, D)	Number of POI for Restaurants and Other Eating Places and Specialty Food Stores (Top Category) (x 10^2)	SafeGraph
Built Environment Variables		
No. Bus Stops (O, D)	Number of Bus stops (x 10^3)	SACOG
Length of Bike Lane (O, D)	Length of Bike Lane (miles)	SACOG

*O and D in the parentheses represent two predictors for origin and destination TAZ.

Scenario Analysis: Mode Substitution and VMT Reduction

We used the models described above to estimate potential bike share usage and its effects, such as mode substitution and VMT reduction, under five different scenarios. First, we applied our models to the actual service boundaries in Sacramento/West Sacramento and the City of Davis to understand how accurately the models could estimate bike-share use. Next, we examined how further expansion (or contraction) of the service boundary of the service area might influence bike-share use and VMT effects. We set up an expanded scenario boundary based on major roads and census blocks: Interstate 80 on the north, S. Watt Ave. on the east, Mack Rd. on the south, and the western edge of West Sacramento on the west. We also examined a scenario with a more compact service boundary around only downtown Sacramento. Most of the observed bike share use occurred in this area, but the trip distances are short meaning that car substitution is limited. This boundary is roughly Interstate 80 Business on the south and east, the American River on the north, and Interstate 5 on the west. Finally, we examined demand if bike share were to be launched in the city of Woodland. While the city is similar in size to Davis, land use and socioeconomic characteristics are somewhat different. We set the boundary here as roughly the actual city boundary but excluded the area north of Interstate 5 because most of land there is used for industrial purposes. Figure 3 shows the boundaries for the five different scenarios.

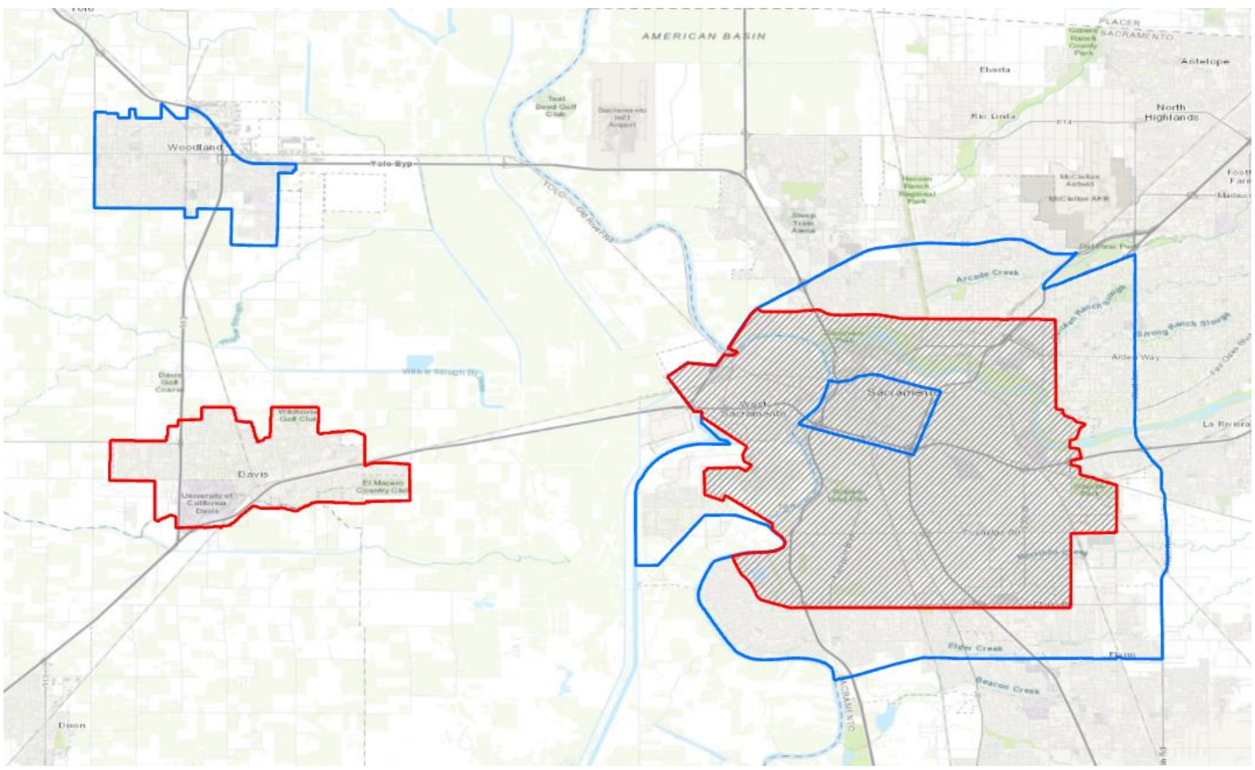

Figure 3. Five Areas for Scenario Analysis (Red: actual service boundary; blue: scenario boundary; shaded: area used to build demand model)

We also explored how a change in bike fleet size might influence bike use and its effect on VMT. Because the daily bike fleet size in Sacramento/West Sacramento ranged from 950 to 1100 (equivalent to from 15.7 to 18.1 bikes per mile square) during the study period for the demand model, we used this range of bike density as a baseline and created scenarios with a larger and smaller bike fleet. Table 4 shows the bike fleet size and bike density for each area we examined in this study (details of the calibration process are discussed in Appendix A).

Table 4. Number of Bike Fleet and Bike Density

Area		Fleet Size (Number of Bike per Mile Square)			
	Scenario 1 (12.5)	Scenario 2 (15.0)	Scenario 3 (17.5)	Scenario 4 (20.0)	Scenario 5 (22.5)
Sacramento/West Sacramento	763	916	1068	1221	1374
Davis	174	209	243	278	313
Expanded Sac./W. Sac.	1351	1622	1892	2162	2432
Downtown Sac.	53	64	75	85	96
Woodland	126	151	176	201	226

The process of estimating VMT reduction in the various scenarios is similar to that described in the previous section. One difference is that we used the number of trips aggregated by TAZ pair based on the demand model, so that we do not have trip attributes for estimating the VMT reduction in this analysis (Figure 4). We created synthesized trip data for all possible TAZs by generating the point data for each TAZ randomly and pairing two data points as a synthesized trip. Since two-point data gives us a spatial relationship, we estimated travel time and driving distance based on the multivariate model developed in the previous section. We predicted mode substitution for each trip and averaged driving distance for the trips predicted as "private car" or "ride-hailing." We used this output as a representation of estimated VMT reduction per trip for each TAZ pair. Details of the modelling and sampling process in this section are discussed in Appendix A.

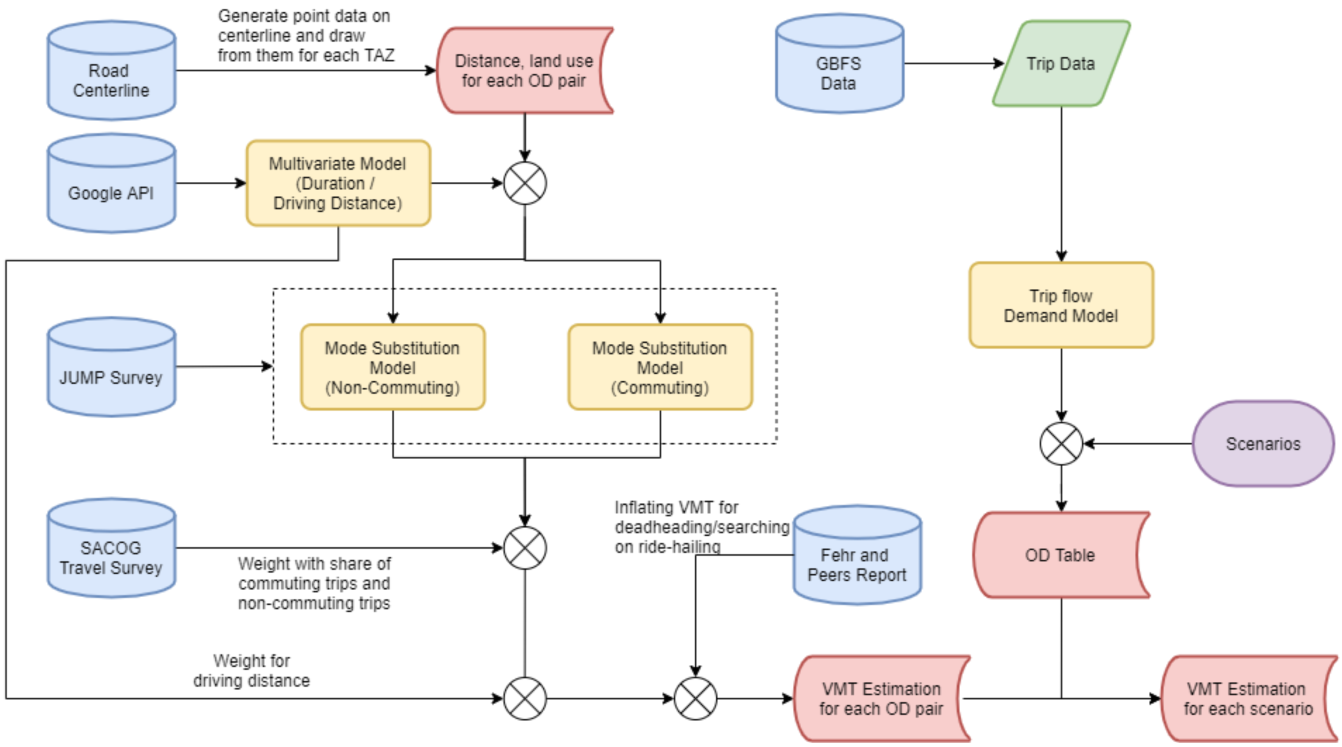

Figure 4. Flowchart for Estimation in Scenario Analysis

Results and Discussion

Factors Influencing Mode Substitution

Our analysis suggests that mode substitution varies by personal preference and trip context to some extent. We found that accounting for individual characteristics and local land use characteristics resulted in only a modest improvement in the ability of the model to predict which modes bike sharing was likely to replace, and only a select few characteristics proved to have measurable effects on mode substitution.

Trip Attributes

Trip Distance

Trip distance has a notable effect on which mode bike-share substitutes for. The shorter the trip distance, the more likely people are to use bikeshare in place of walking (Figure 5). For longer trips people are more likely to substitute bike-share for motor vehicles, particularly ride-hailing.

Trip Purpose

The purpose for taking a trip also has an effect on how likely people are to substitute bike share for some other mode (Table 5). Walking is the mode mostly likely to be replaced by bike-share for trips under 1 mile, regardless of trip purpose. Recreational trips are an exception: as trips approach 1 mile in length, bike-share becomes mostly likely to induce trips rather than replace walking or other modes. In other words, recreational trips of 1 mile or more would not have been made had bike-share not been available. The availability of bike share seems to prompt shopping and restaurant trips that might not otherwise have been taken, which could increase local economic activity as well as providing physical activity for the user. For trips to restaurant and trips returning home, bike-share has a relatively high likelihood of substituting for ride-hailing; for shopping trips, ride-hailing is less likely to be replaced by bike-share.

Trip Speed

Mode substitution varies more by purpose than by speed (Table 6). Trip speed does not change the fact that people are more likely to give up recreation trips when bike-share is unavailable. For restaurant trips and trips home, as trip speeds increase, people are more likely to use bikeshare in place of walking or ride-hailing. For shopping trips, bike-share is likely to replace walking and biking for trip speeds over 5 mph. For work-related and other trips, bike-share replaces walking except for trips of very low speed. The likelihood that bike-share replaces walking increases with trip speed for every trip purpose.

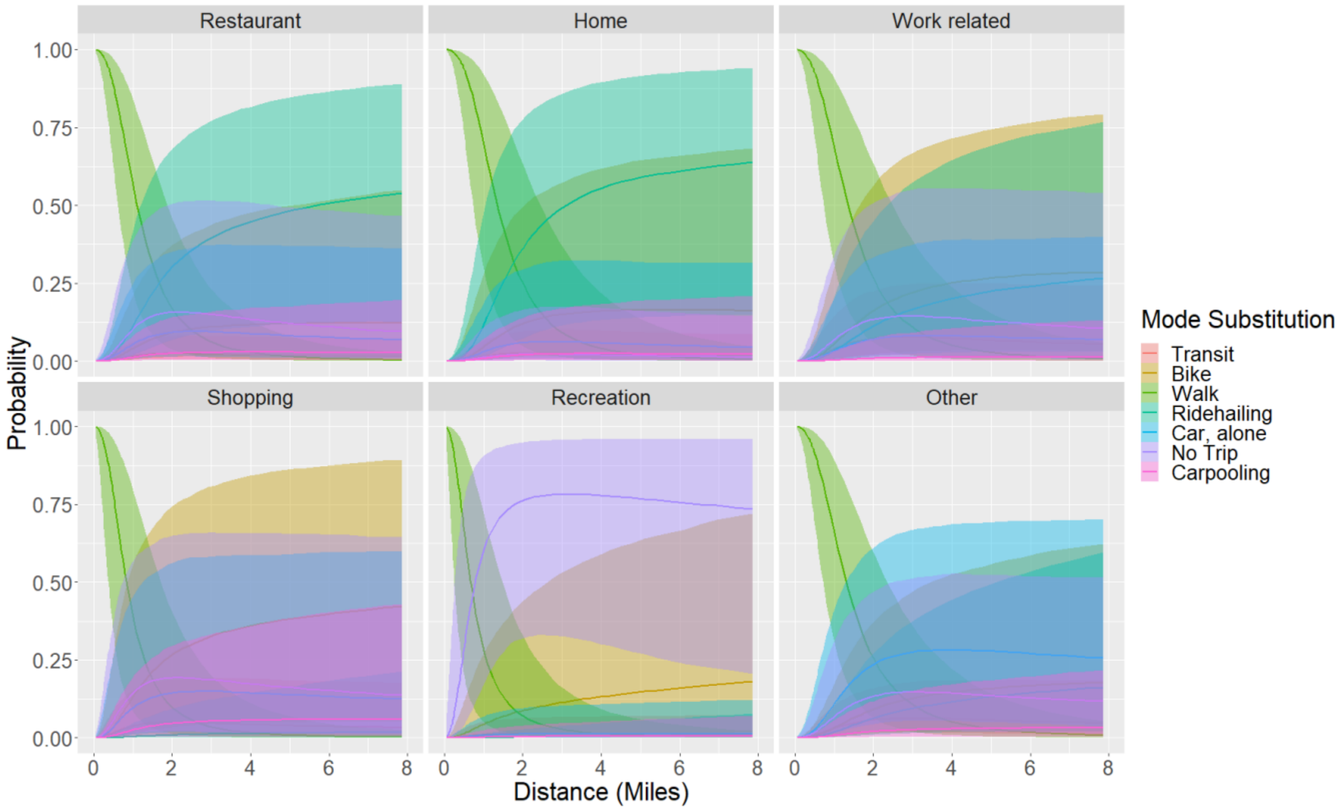

Figure 5. Conditional Combined Effects of Trip Distance and Trip Purpose on Mode Substitution (Conditions: Off Peak; Age 25-34; Weekday; Non-student; No child; Employed; Male; Car owner; mean values of continuous predictors)

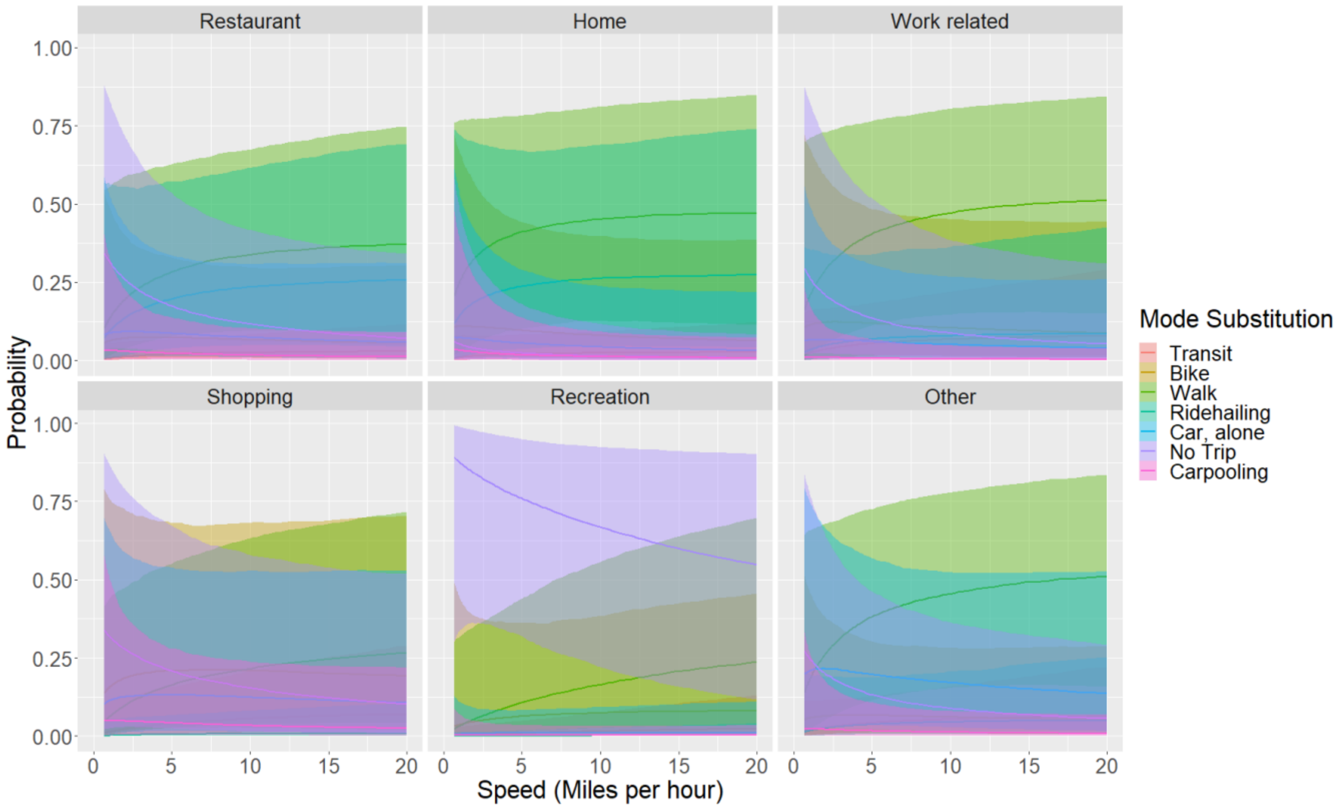

Figure 6. Conditional Combined Effects of Speed and Trip Purpose on Mode Substitution (Conditions: Off Peak; Age 25-34; Weekday; Non-student; No child; Employed; Male; Car owner; mean values of continuous predictors)

Individual Characteristics

Age

Age is also a factor in mode substitution, Bike-share users who are less than 44 years old are more likely to replace a ride-hailing with bike share. Younger (25-34 years old) and older (55 years old or more) users are more likely to substitute bike share for personal bicycling compared to those between 35 and 54 years old. Those aged 55 years or older are highly likely to say they would not have made the trip if the bike share service were not available, suggesting that bike share induces physical activity for this age cohort.

Student Status

The model results suggest that students are more likely to substitute a bikeshare trip for a ride-hailing trip but much less likely to substitute a bike-share trip for a trip in a private car compared to other travelers. This is consistent with findings in several studies that younger adults are in general more likely to choose ride-hailing and less likely to own private vehicles (10, 11). Interestingly, being a student had a relatively small effect on using bike share instead of a personal bike. This may be because students are more likely to own a bicycle and those who have their own bikes have less reason to use bike share.

Gender

Individuals who Identify as a woman are more likely to substitute bike share for car travel, particularly private car use and carpooling than other individuals but are less likely to use bike-share as a substitute for personal bicycling. The latter result is consistent with the fact that women are far less likely to bicycle in general but suggests that bike-share has some potential to increase the rate at which women substitute bicycling for car travel.

Car Ownership

Those who have one or more private cars per person in the household are more likely to substitute bike share for driving alone, not surprising given their higher likelihood of driving compared to individuals without access to a car.

Land Use

Land use characteristics also influence mode substitution. Those who use bike share starting from commercial/office areas are unlikely to use a private car or ride-hailing if a bike-share were not available. This finding is consistent with the fact that most of the commercial/office land in the Sacramento bike-share service area is in the dense downtown area which is relatively walkable and has good access to public transit. A higher share of commercial/office use at the end point of the trip also makes it less likely that bike-share users would have instead taken a private car for the trip. One explanation for this could be the relatively high parking fees in these areas. Those who start their trip in a location with a high share of residential land use tend to substitute bike share for car-related options as well as private bikes. Very few other land use variables had strong relationships with mode substitution.

System-level Mode Substitution and VMT Reduction

Share of Mode Substitution

Both before and after JUMP expanded is boundaries and increased its fleet size, the most common mode of travel that bikeshare replaced was walking, followed by ride-hailing, private car, personal bicycle, transit, no trip, and carpooling. This pattern was the same on weekdays (Figure 7) and on weekends (Figure 8), though the shares across modes are more equal on weekends. The policy changes appear to have had little impact on the mode for which bike-share substitutes for either weekdays or weekends.

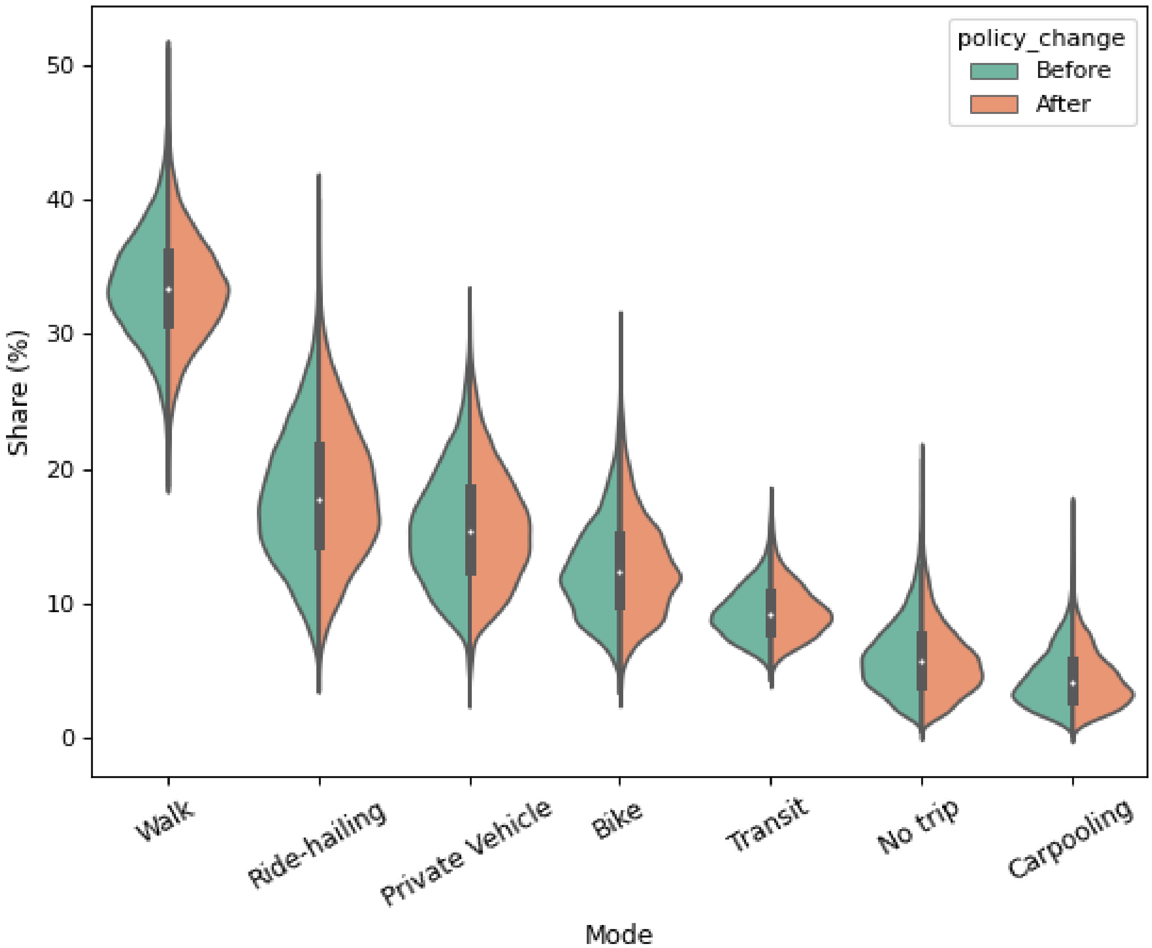

Figure 7. Share of Substituted Modes on Weekdays

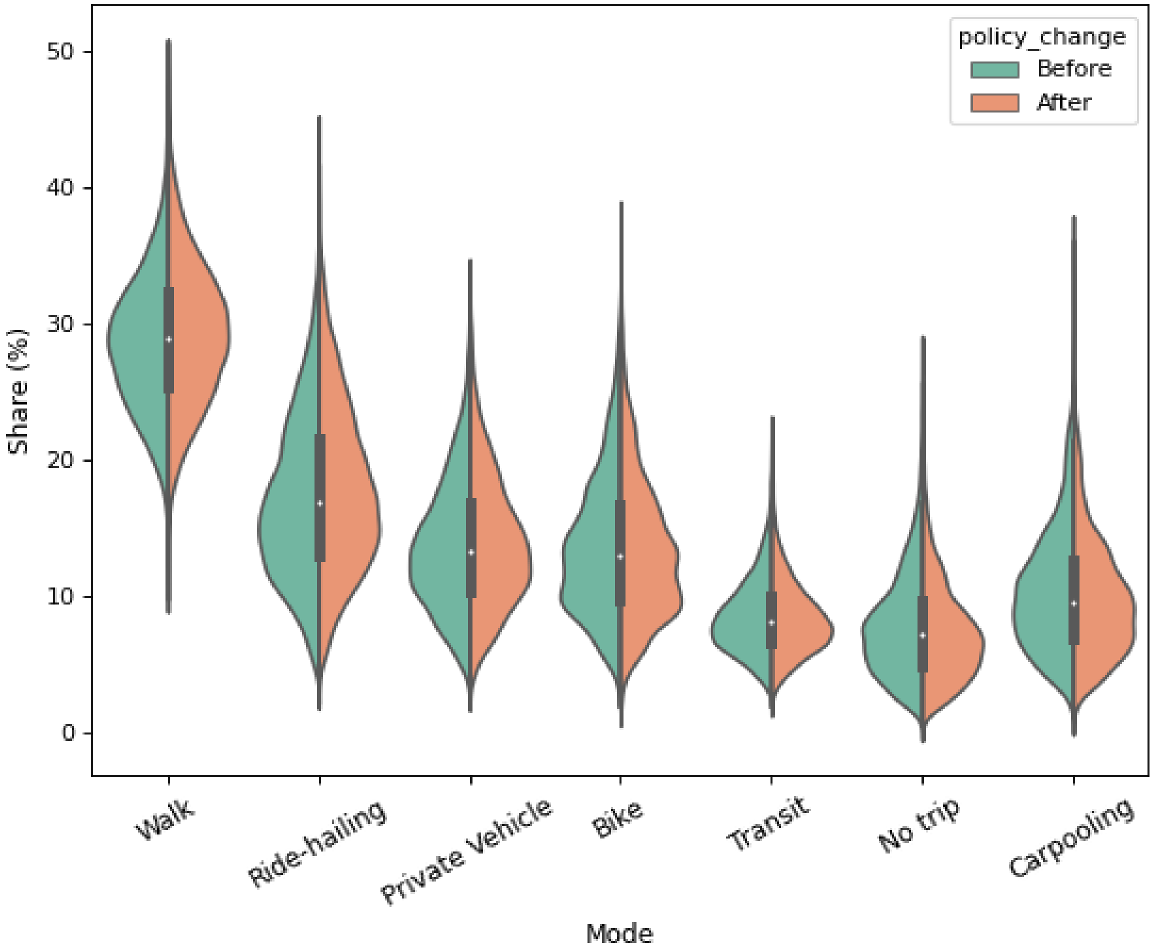

Figure 8. Share of Substituted Modes on Weekends

Vehicle Mile Traveled Reduction

Based on our model we estimate that JUMP bike-share services were initially responsible for 1795 fewer daily vehicle miles on average across the region on weekdays and 1540 miles on weekend days (counting only the VMT of private vehicle and ride-hailing when a passenger is in the vehicle). After the change in its operation those numbers increased to 2160 miles on weekdays and 1764 miles on weekends. Adding the potential VMT reduction from deadheading and searching associated with ride-hailing services, we estimate VMT reductions of 2248 miles on weekdays before the expansion in operations and 2702 miles afterward.

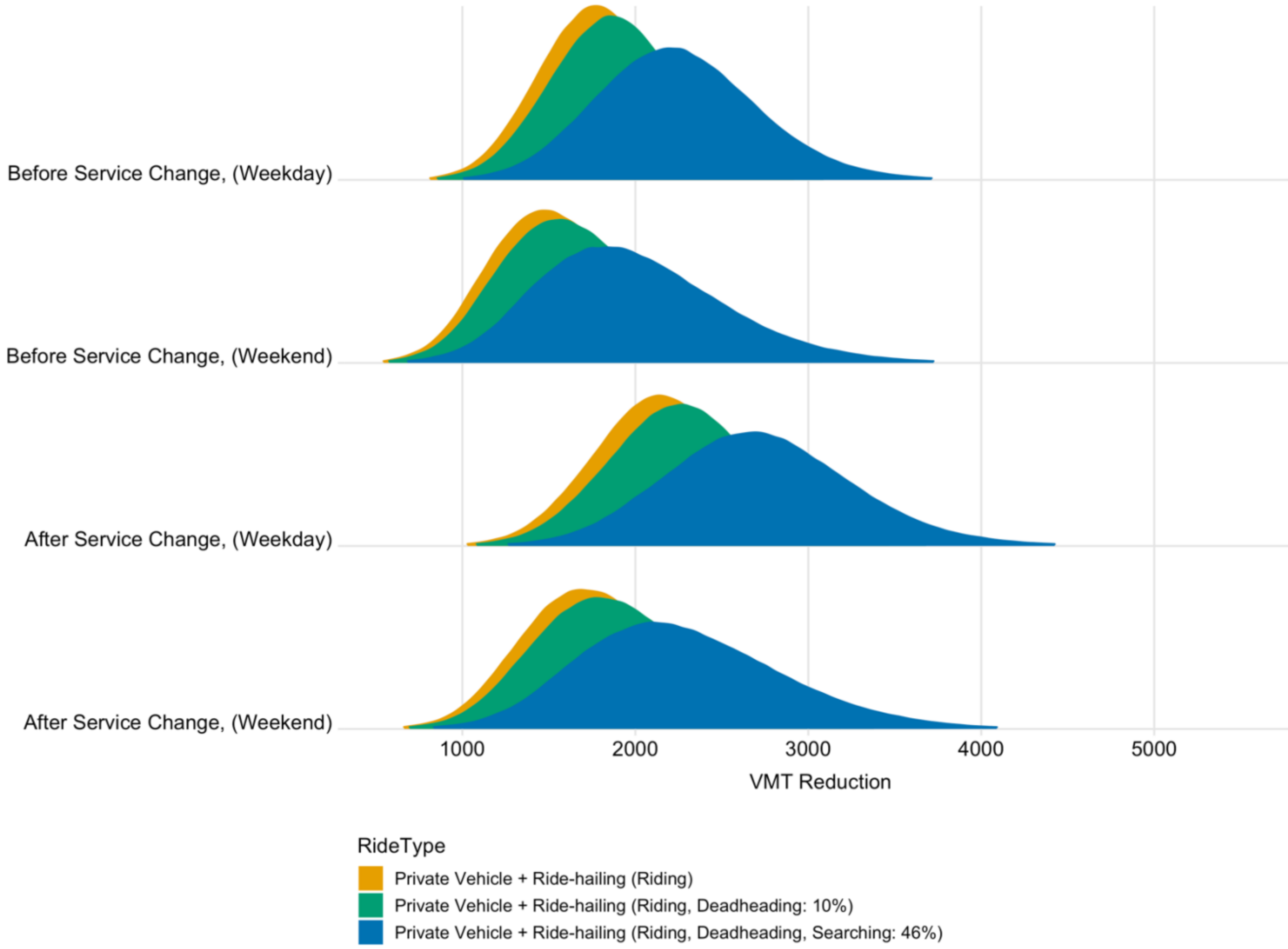

Figure 9. Estimated VMT Reduction per day

Factors Influencing Dock-less Bike Share Use

Our analysis found that bike-share use is associated with factors, including trip attributes. socioeconomic factors, transportation facilities, land use and point of interest.

Bike Density

According to the demand model, a higher bike-fleet density in a TAZ appears to be associated with higher bike-share use. A higher density of bikes means a higher probability of finding bikes within walkable distance; however, this effect per bike will decline as fleet size increases.

Trip attributes

The model shows greater flows of bike-share trips to destinations within the same TAZ ("internal" trips) or to destinations in nearby TAZs than to more distant TAZs for which trip distances would be longer. Weekend travel have little effect on bikeshare flows compared to weekdays. However, in university/college areas, bikeshare trips are less likely on weekends, consistent with the fact that most classes at the university are offered on weekdays. Bike share demand is higher during PM peak and off-peak periods.

Socioeconomic Factors

More bikeshare trips begin and end in TAZs where more people live. They are also more likely in areas with higher incomes. The city of Sacramento has, since May 2019, required bike share operators to routinely locate some portion of the bike fleet in "opportunity zones" (designated low-income communities) in the morning to improve service equity.

Transportation Facilities

The model results show that TAZs with a higher number of bus stops have higher bike share use. This might be attributable to the use of shared bikes to connect to and from public transit. Another possibility is that the number of bus stops may reflect how attractive a TAZ is as a destination due to the density of commercial activity. Origin and destination zones with more bike lanes also tend to have more bike-share use. Bike lanes are usually installed on major roads with many points of interest and roads with high bicycle counts. Since this analysis aggregated trip data based on zones, we cannot determine what facilities, if any, induced bike-share trips. Further analysis is needed to determine whether such transportation facilities have a causal effect on bike share use.

Land Use / Points of Interest

Origin and destination TAZs near a university/college tend to have higher bike share use, as do areas with a large the number of restaurants and bars, especially in the Sacramento region. Figure 10 shows that the highest number of bike share trips took place between "commercial/office" areas and that the second most frequent bike share trips were between "industrial" areas. Trips from industrial areas to commercial/office areas were next, followed by trips from commercial/office to industrial areas, respectively. This result suggests that people working in industrial areas use bike share for errands or other non-commuting trip purposes.

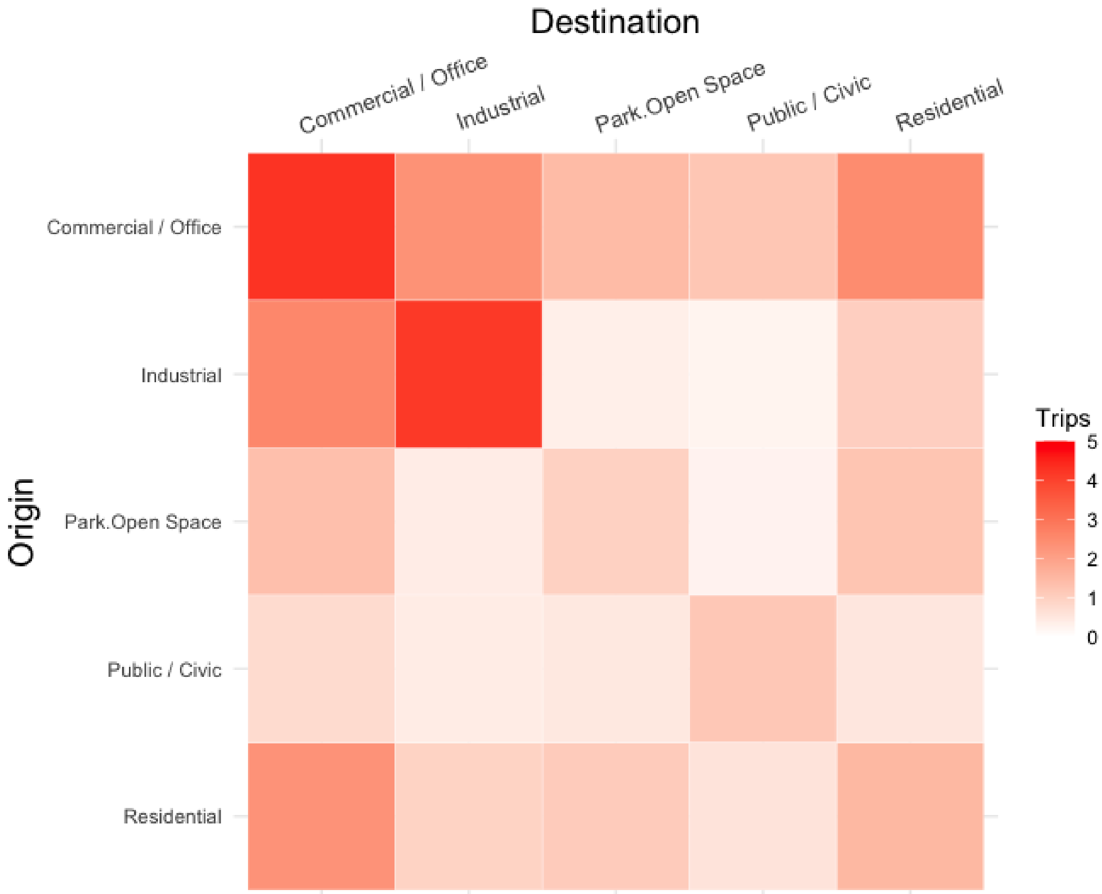

Figure 10. Estimates of OD Zone Type (Random Effect) (Unit: trips per OD zone pair per time of day)

Model Validation

As a part of the validation process, we applied the model to the data from Davis to examine the difference between observed and predicted bike-share use. One concern with applying the demand model to another city is that different land use characteristics, demographics, and trip patterns may cause large errors. With actual observed trip data from Davis, we are able to assess the ability of the model to produce accurate estimates in a city other than the one in which it was calibrated.

The comparison between the predicted number of bike share trips and actual bike share trips on a typical weekday and weekend in Davis shows that our model overestimates demand, as shown in Figure 11. While the number of actual bike share trips on weekdays range mostly between 1100 and 1300, our model predicted use mostly in the range between 1300 and 1500. The model also overestimates demand on weekends. One explanation for this overestimation is the relatively low use of bike share in Davis, as reported in the Phase 1 report (*8*). Davis has a higher rate of bike ownership and use than Sacramento and thus residents may have less reason to use bike share. Even so, the predictions overlap with observed counts, suggesting that the model is not far off the mark. Applying the model in cities more comparable to Sacramento would provide a more robust validation of the model.

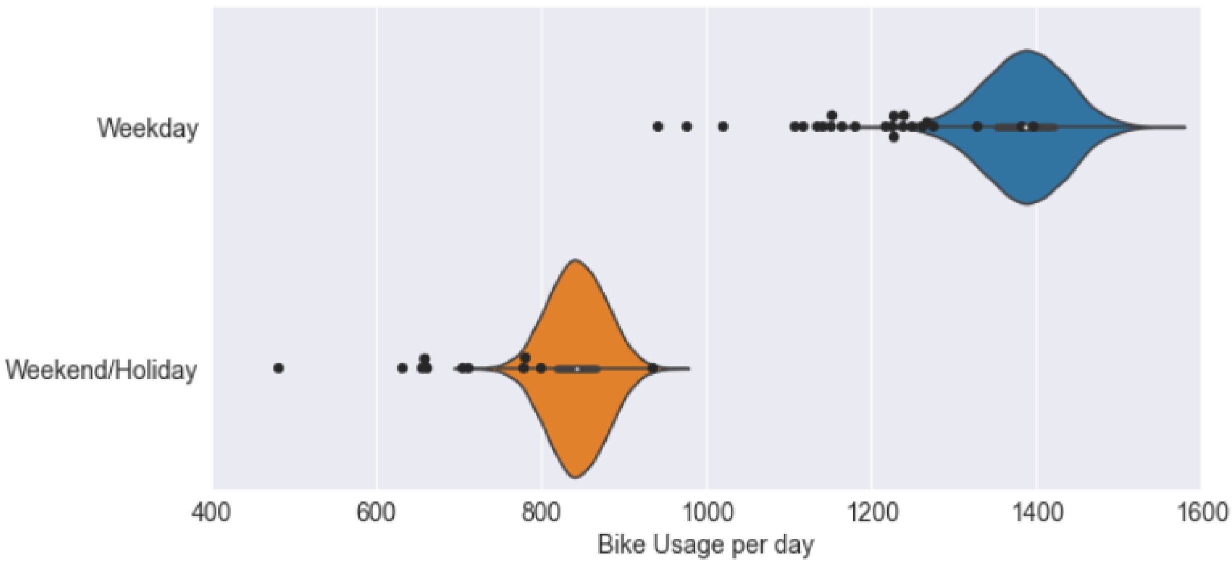

Figure 11. Predicted Bike Demand and Actual Observed Use in Davis (violin plot: predicted demand, dot: observed usage)

We also compared the actual number of trips in Davis with the predicted number by time of the day (Figure 12). The model predicted bike use well for AM peak and off-peak periods for weekdays while overestimating trips for midnight, PM peak, and night periods. Many users in the city of Davis are affiliated with the University of California, Davis, where most course schedules finish before 6 PM. Also, students may be less likely to engage in some activities, such as going to restaurants and bars, during night and midnight periods on weekdays, compared to residents of Sacramento. For weekend trips, the model predicts bike use well for midnight, off-peak and night periods but not AM peak and PM peak periods.

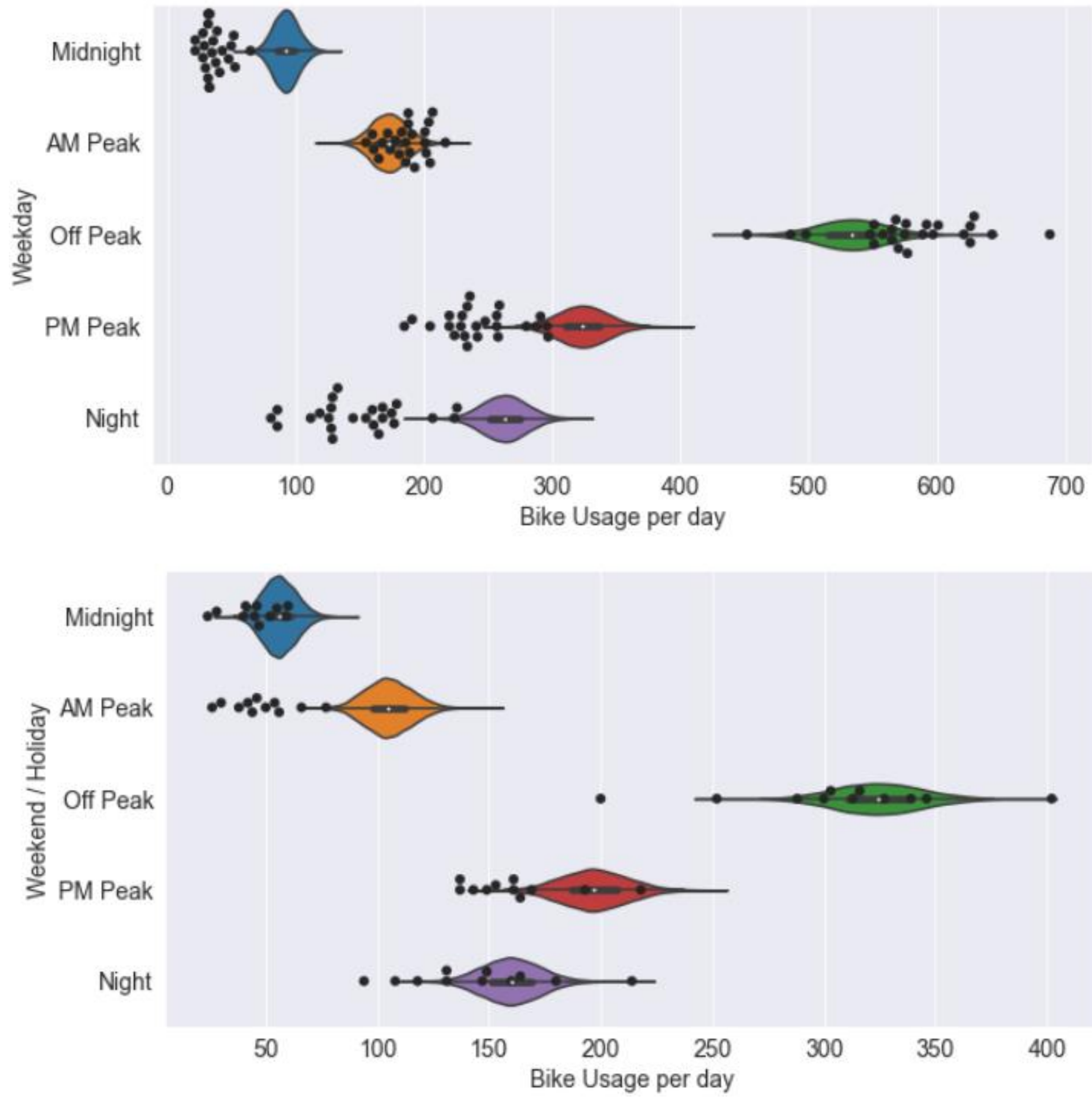

Figure 12. Predicted Bike Demand and Actual Observed Use in Davis by time of day (violin plot: predicted demand, dot: observed usage)

Scenario Analysis: Mode Substitution and VMT Reduction with Potential Changes in Fleet Size [Before and After Changes in JUMP Operations]

Demand Estimation

Our scenario analysis shows that increasing fleet density (number of bikes per square mile) increases the number of bike trips but generally lowers the number of trips per bike. We estimated the number of bike share trips per day for each of the five different service boundaries (described earlier) for five different levels of bike fleet density (12.5, 15.0, 17.5, 20.0 and 22.5 bikes per square mile). The estimated mean number of daily bike trips in Woodland is 126 assuming 12.5 bikes per square mile and 158 per day on weekdays. It is 118 on weekends with a fleet density of 12.5 bikes per mile, and 148 with a fleet density of 22.5 (Figure 13). Increasing the weekday fleet size from 126 bikes to 226 bikes decreases the efficiency of the bikes from 1.0 users per bike per day to 0.7.

In Davis, the estimated mean numbers of predicted bike-share trips are 1291 and 1663 on weekdays and 772 and 999 on weekends for the lowest and highest bike fleet densities (12.5 and 22.5, respectively) (Figure 14). Unlike in Woodland, bike share demand is sufficient to achieve a high efficiency of bike use in Davis: the number of trips per bike on weekdays are 7.4 trips assuming 12.5 bikes per square mile and 5.3 trips with 22.5 bikes per square mile.

In downtown Sacramento, the estimated mean numbers of bike-share trips are 1191 and 1536 on weekdays and 1208 and 1553 on weekends for the two bike fleet densities (Figure 15). The number of trips per bike on weekdays is 22.5 trips with a density of 12.5 bikes per square mile and 16.0 trips with 22.5 bikes per square mile. This result indicates that offering bike share service in a highly populated area results in highly efficient bike use.

In Sacramento/West Sacramento, the estimated mean numbers of bike-share trips are 2347 and 3020 on weekdays and 2142 and 2750 on weekends for the two bike fleet densities (Figure 16). The number of trips per bike on weekdays are 3.1 trips with a density of 12.5 bikes per square mile and 2.2 trips for 22.5 bikes per square mile. This result indicates that expanding the boundary to include mostly residential areas decreases service efficiency.

In the expanded Sacramento/West Sacramento scenario, the estimated mean numbers of bike-share trips are 2902 and 3748 on weekdays and 2694 and 3493 on weekends for the two bike fleet densities (Figure 17). The number of trips per bike on weekdays are 2.1 trips with at density of 12.5 bikes per square mile and 1.5 trips with 22.5 bikes per square mile. This result also supports the finding that expanding the boundary of the service area reduces efficiency.

It should be noted that our model assumes that increasing bike-fleet density inflates bike-share use for each origin-destination (OD) TAZ pair in the same way. However, the effect of the change on use may vary by each OD pair because some TAZs with plenty of bikes have satisfied demand even before the hypothetical increase in fleet density. Also, if the level of demand for some TAZ pairs is skewed by the time of day, some users might not be able to find any bike within a walkable distance. A rebalancing strategy that relocates the bike fleet for efficient use will influence what effect expanding service boundaries will have. Of course, increasing the bike fleet within the existing service boundary makes it easier for users to pick up a bike when needed. The increase in reliability may also induce more people to try bike share. Because these behavioral effects are outside of the scope of this research, further analysis is needed to understand how bike density influences the number of users, not just the number of trips.

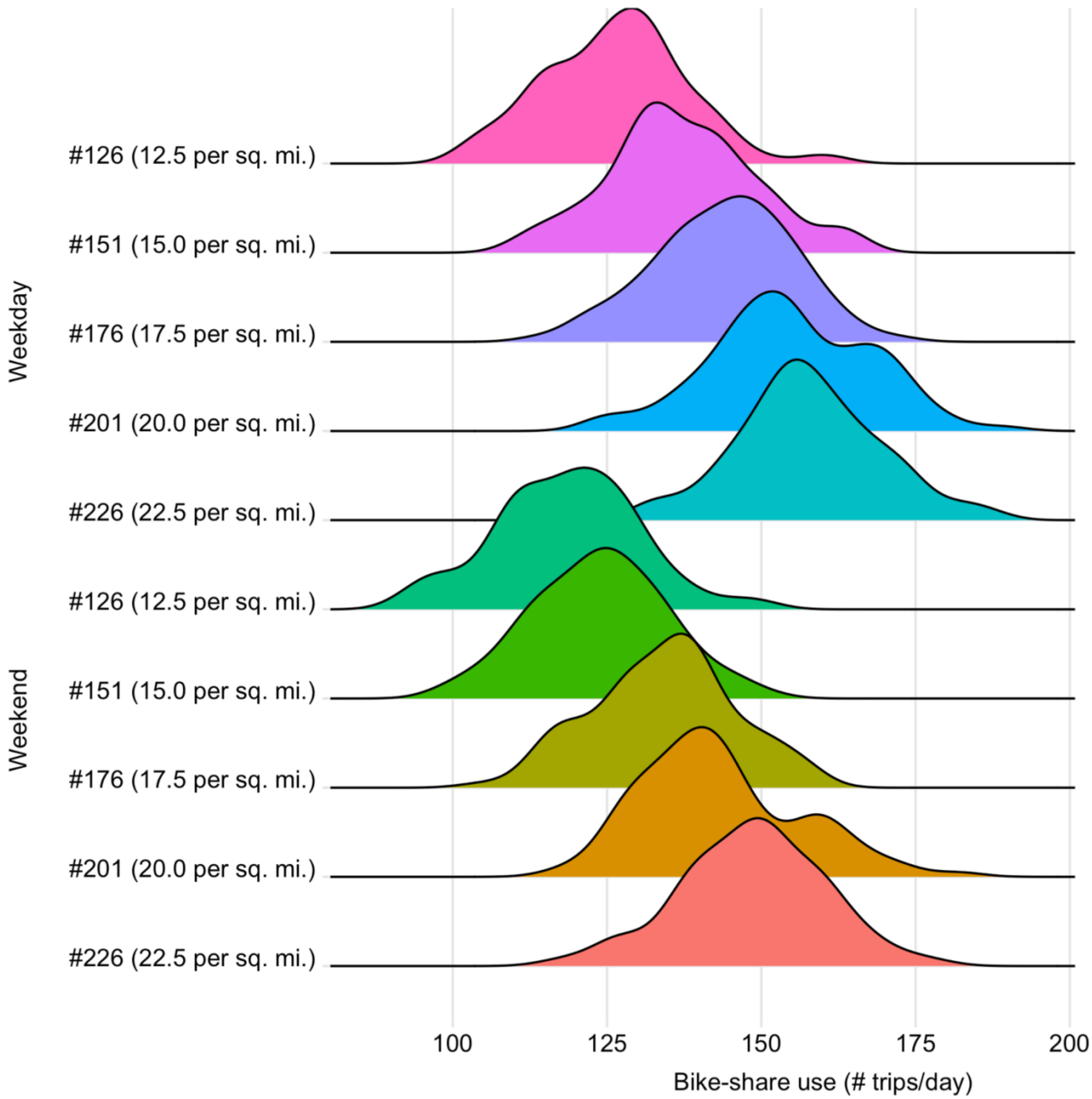

Figure 13. Distribution of Estimated Bike-Share Use per day in Woodland by Fleet Size (# (Number of bikes per square mile))

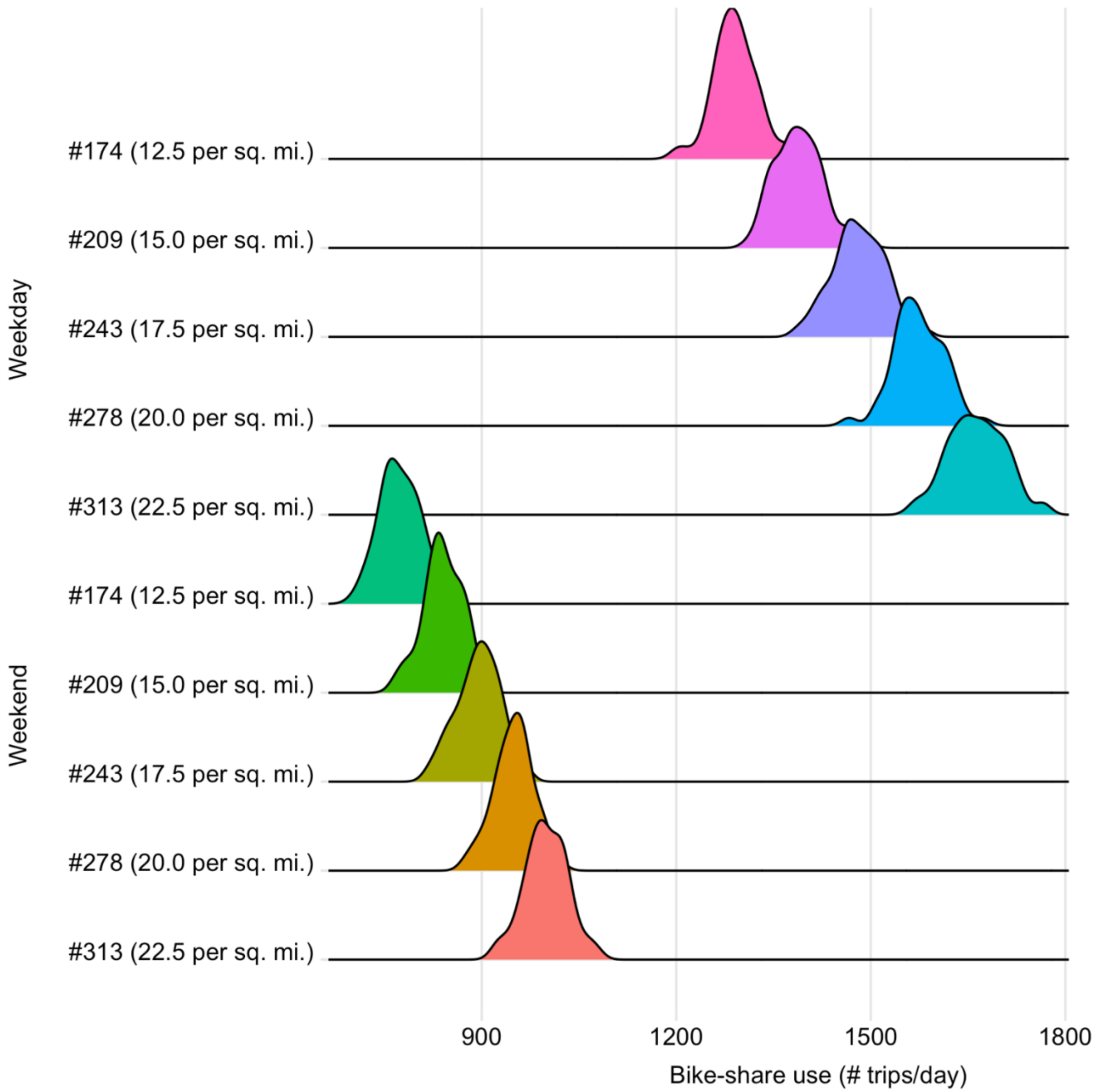

Figure 14. Distribution of Estimated Bike-Share Use per day in Davis by Fleet Size (# (Number of bikes per square mile))

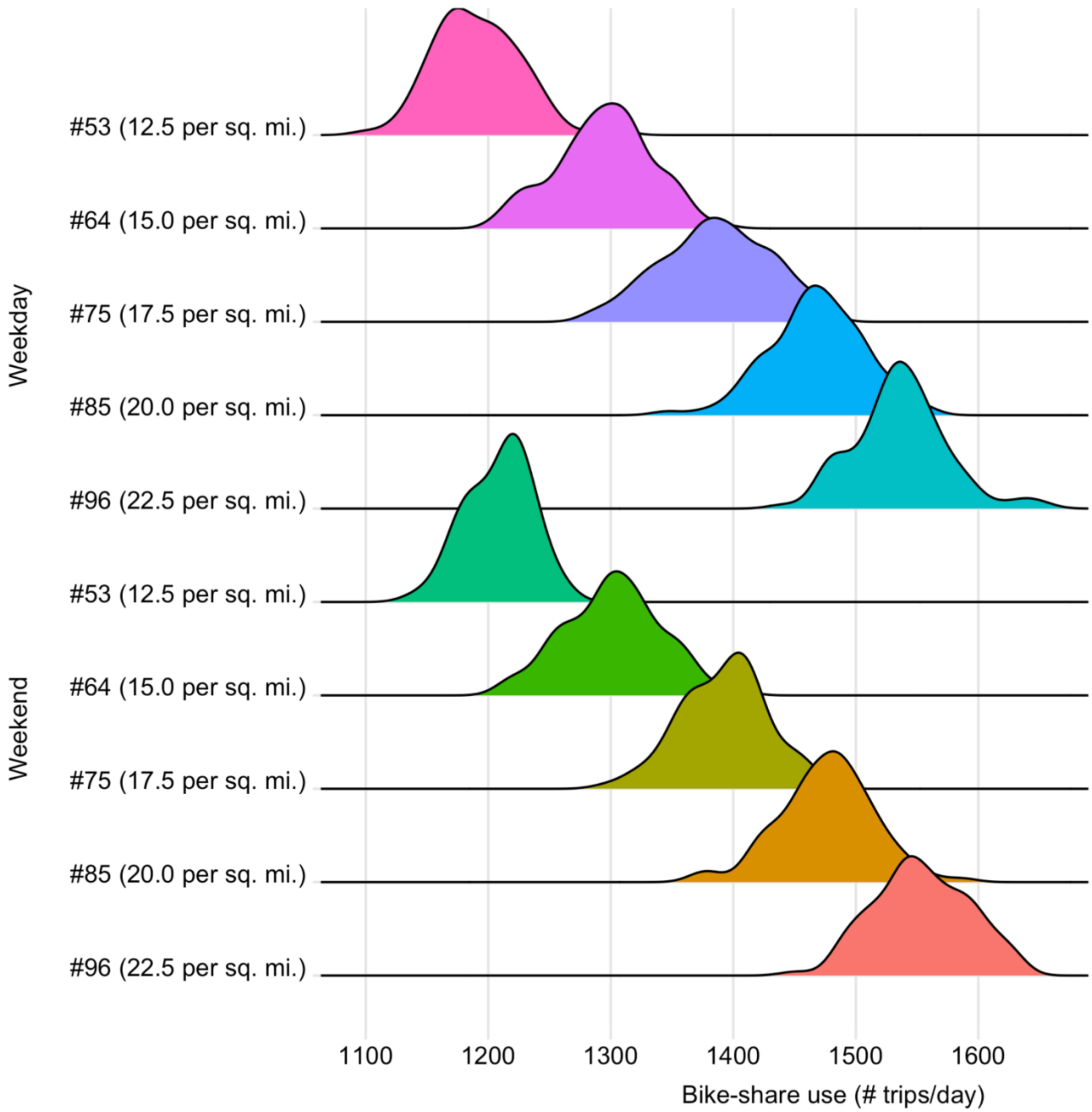

Figure 15. Distribution of Estimated Bike-Share Use per day in Downtown Sacramento by Fleet Size (# (Number of bikes per square mile))

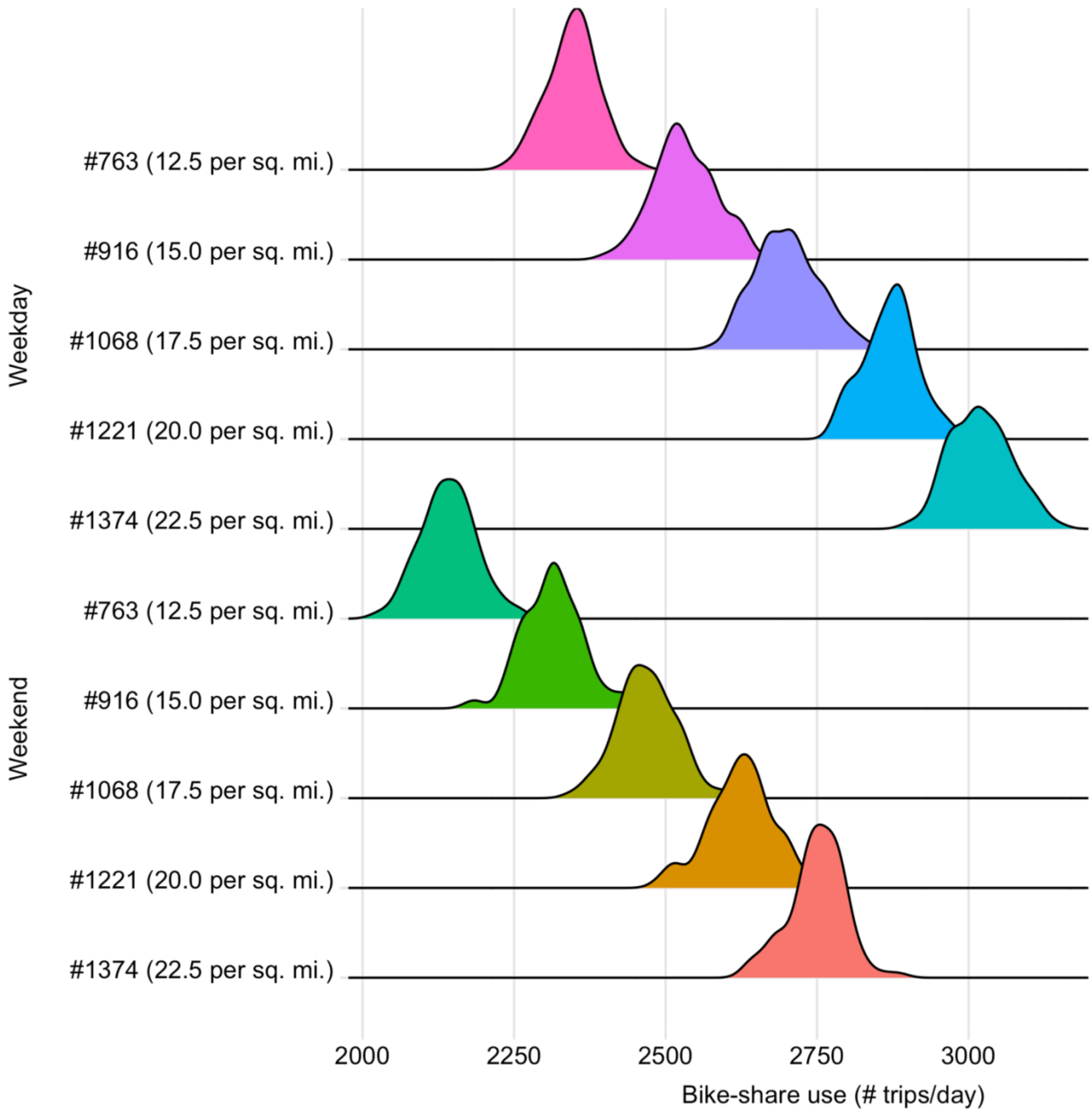

Figure 16. Distribution of Estimated Bike-Share Use per day in Sacramento/West Sacramento by Fleet Size (# (Number of bikes per square mile))

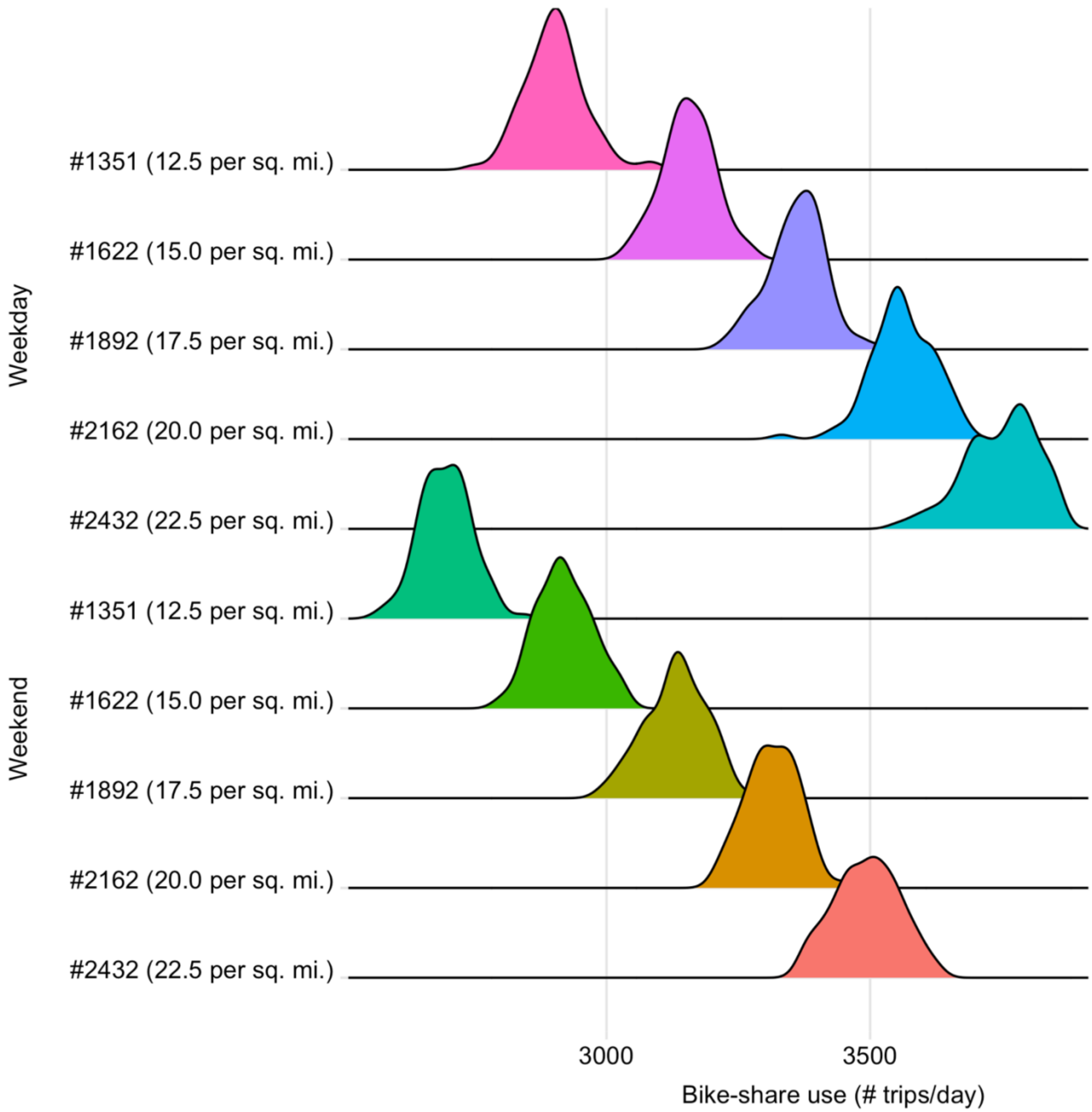

Figure 17. Distribution of Estimated Bike-Share Use per day in expanded Sacramento/West Sacramento by Fleet size (# (Number of bikes per mile square mile))

VMT Estimation

We estimated the reduction in VMT per day from displaced private vehicle and ride hailing trips for the five different potential bike fleet densities. The results for each of the five different service boundaries are presented in Figure 18 through 22. In Woodland (Figure 18), the mean expected VMT reduction with 12.5 bikes per square mile on weekdays is 84 miles. This means that the system produces a reduction of 0.7 VMT per day per bike. Adding deadheading and searching (+46%), the expected reduction increases to 105 miles. With 22.5 bikes per square mile, the mean expected VMT reduction is 105 miles with only ride-hailing and 131 miles (se=18) including ride-hail riding, deadheading and searching. The expected reduction on weekends is slightly lower than on weekdays.

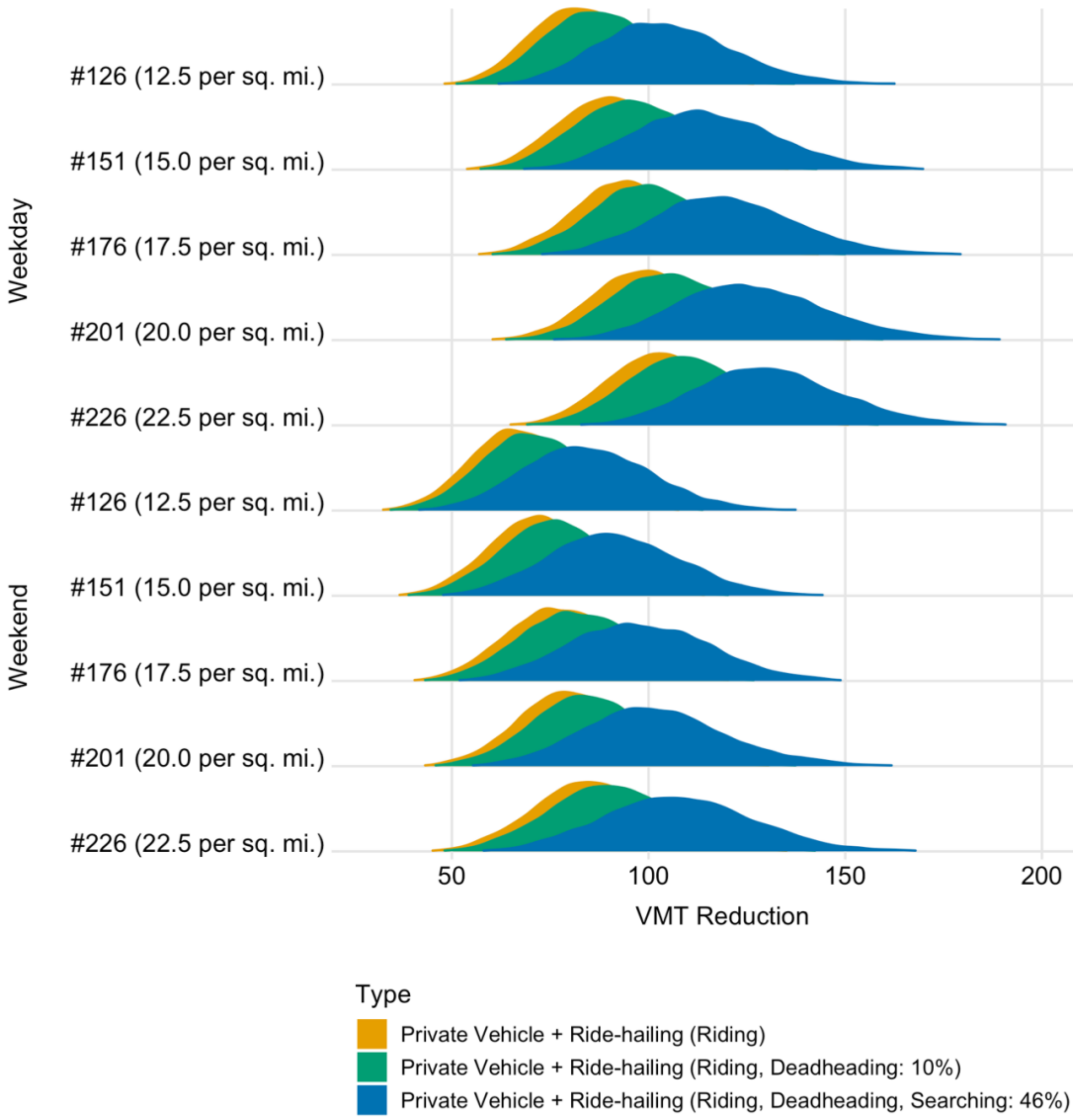

Figure 18. Estimated VMT Reduction by Fleet Size in Woodland

In Davis (Figure 19) the mean expected VMT reduction in the case of 12.5 bikes per square mile on weekdays is 833 miles. This indicates that the system produces a reduction of 4.8 VMT per day per bike. Adding deadheading and searching (+46%), the expected reduction increases to 1033 miles. With 22.5 bikes per square miles, the mean expected VMT reduction is 1073 miles with only ride-hailing riding and 1331 miles with ride-hail riding, deadheading and searching (+46%). Unlike Woodland, the VMT reduction on weekends is 45 percent less than on weekdays.

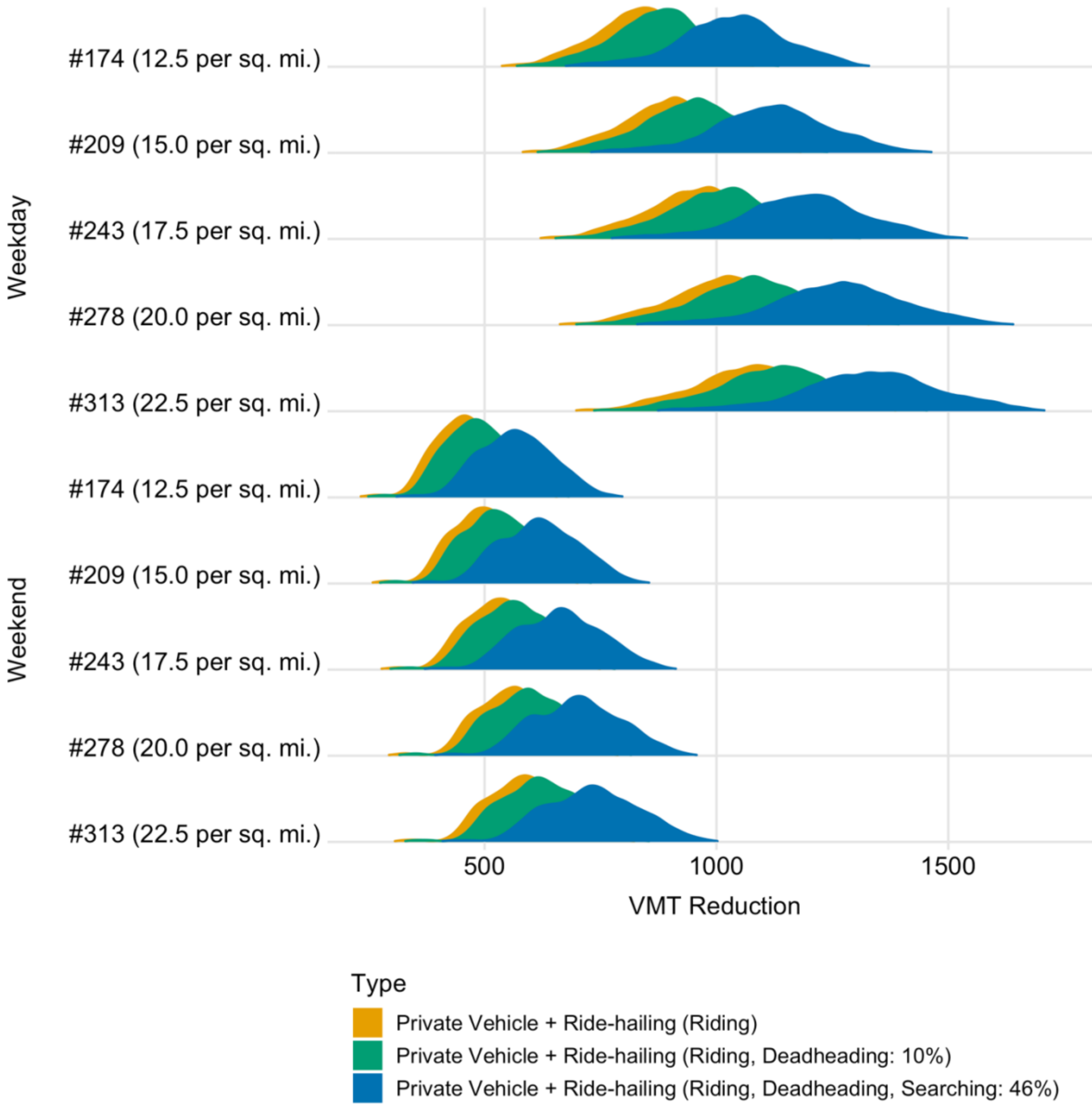

Figure 19. Estimated VMT Reduction by Fleet Size in Davis

In downtown Sacramento (Figure 20), the mean of expected weekday VMT reduction assuming 12.5 bikes per square mile is 583 miles. This indicates that the system produces a reduction of 11 VMT per day per bike. Adding deadheading and searching (+46%), the expected reduction would be 781 miles. With 22.5 bikes per square miles, the mean of expected VMT reduction is 751 miles with only ride-hailing riding and 1006 miles with ride-hail riding, deadheading and searching (+46%). These are equivalent to reductions of 7.8 VMT and 10.5 VMT, respectively.

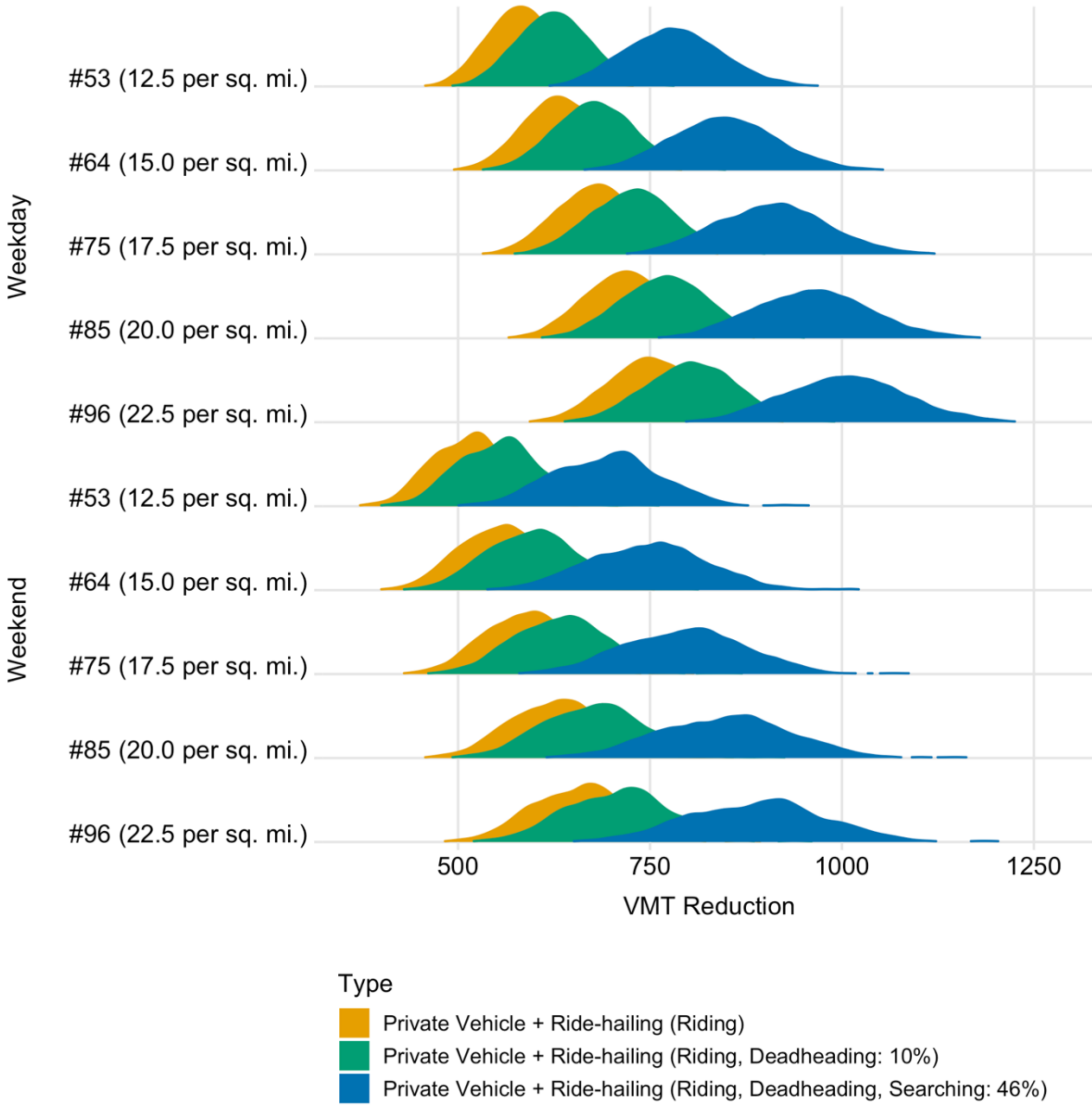

Figure 20. Estimated VMT Reduction by Fleet Size in Sacramento Downtown

In Sacramento/West Sacramento (Figure 21), the mean expected weekday VMT reduction assuming 12.5 bikes per square mile is 1795 miles. This indicates that the system produces a reduction of 2.4 VMT per day per bike. Adding deadheading and searching (+46%), the expected reduction increases to 2322 miles. With 22.5 bikes per square miles, the mean expected VMT reduction is 2329 miles with only ride hail riding and 3011 miles including riding, deadheading and searching (+46%). These are equivalent to 1.7 VMT and 2.2 VMT, respectively.

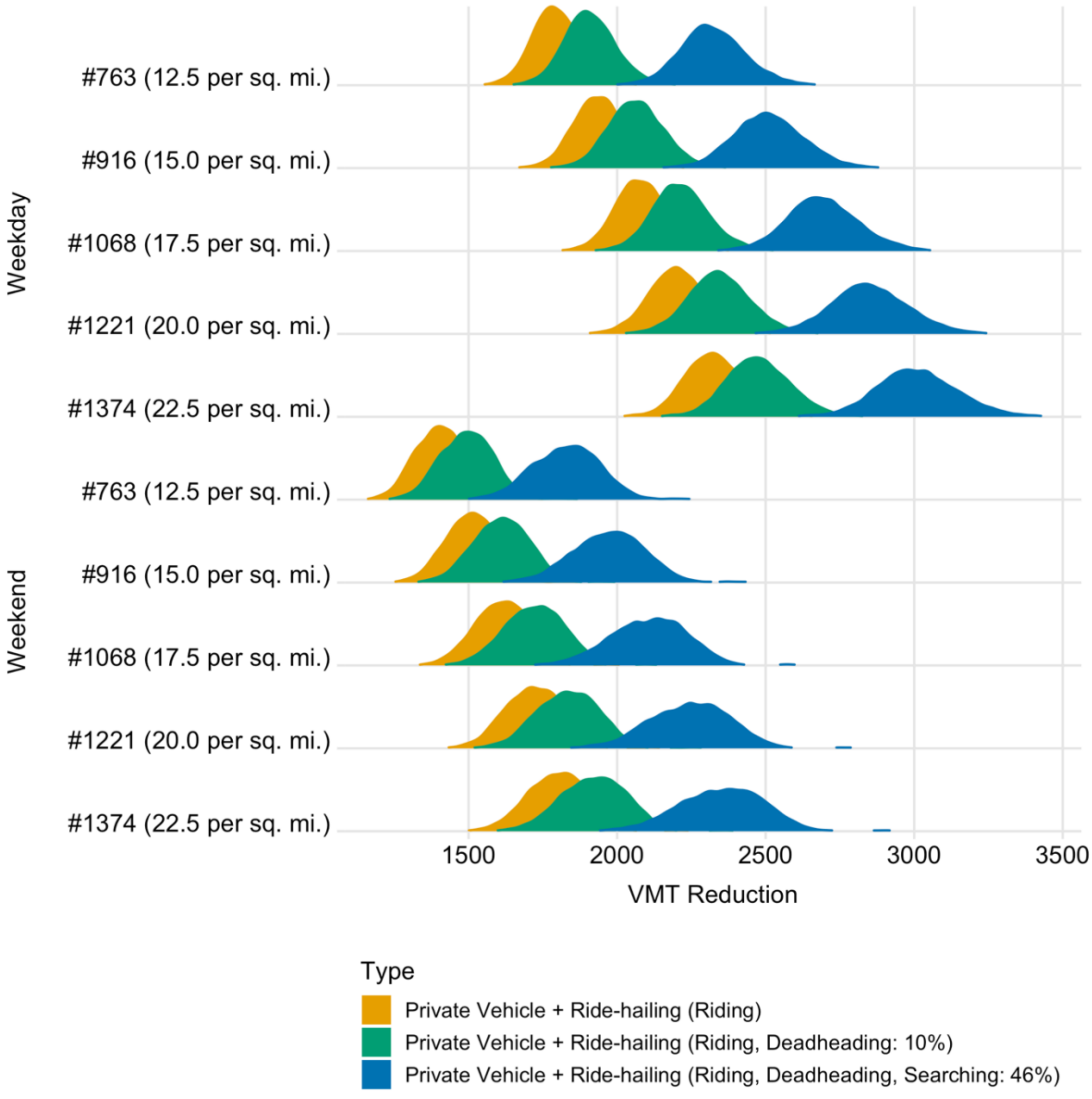

Figure 21. Estimated VMT Reduction for Each Policy Scenario in Sacramento/West Sacramento (Upper: Weekday, Lower: Weekend)

In the expanded Sacramento/West Sacramento service area (Figure 22), the mean of expected VMT reduction in the case of 12.5 bikes per square mile on weekdays is 2380 miles. This means that the system produces a reduction of 1.8 VMT per day per bike. Based on the previous estimates, this indicates that expanding the service boundary may increase bike use but reduce the efficiency of VMT reduction per bike. Adding deadheading and searching (46%), the expected reduction inflates to 3056 miles. In the case of 22.5 bikes per square miles, the mean of expected VMT reduction is 3082 miles with only ride-hailing riding and 3955 miles with ride-hail riding, deadheading and searching (46%). These are equivalent to 1.3 VMT and 1.6 VMT, respectively.

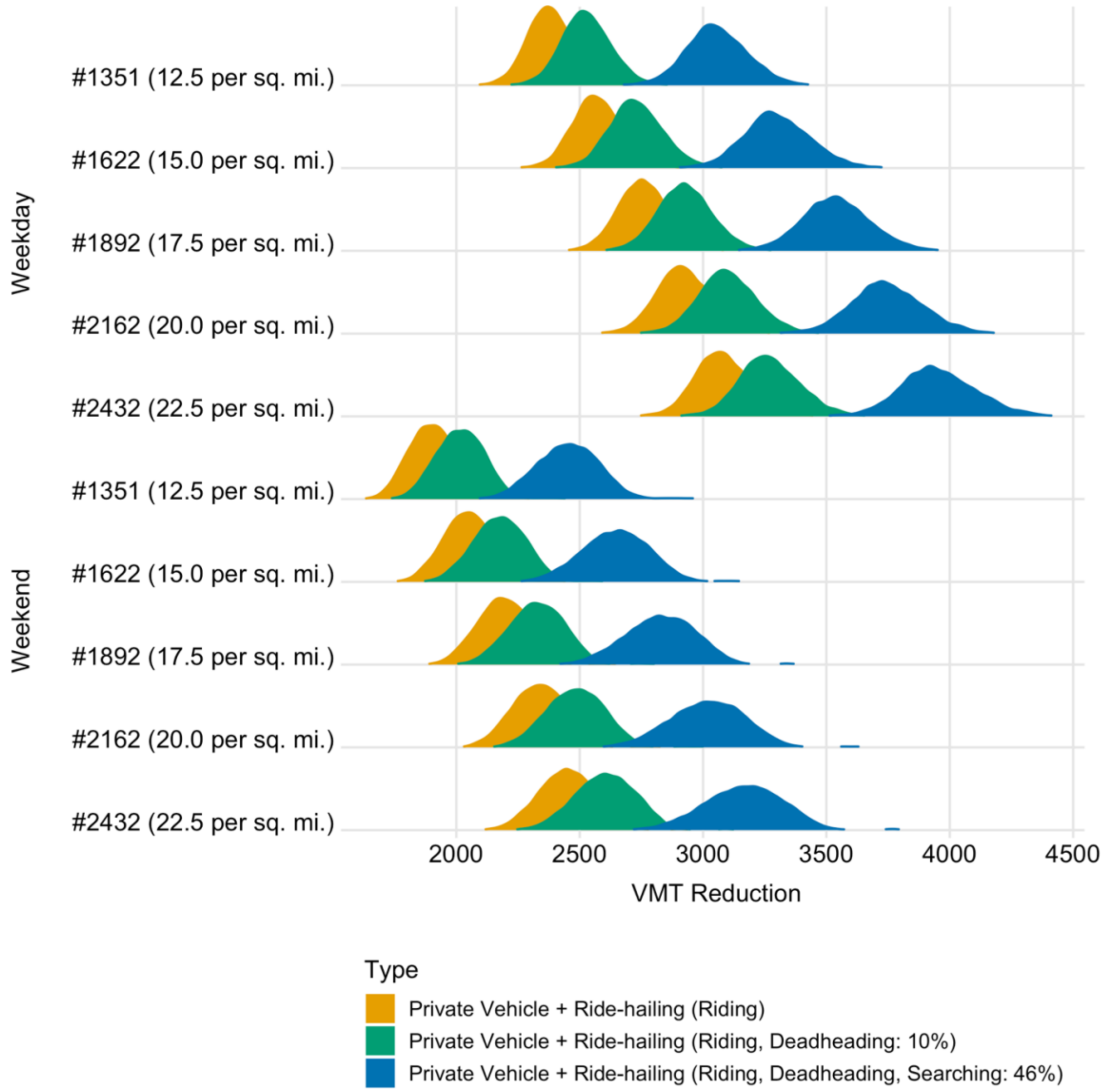

Figure 22. Estimated VMT Reduction by Fleet Size in Expanded Sacramento/West Sacramento Service Area

Policy Implications and Conclusions

The rich set of variables analyzed in this study adds to the list of factors known to explain how bike share influences the use of other modes. Our analysis shows that mode substitution varies by trip purpose. For example, bike-share is likely to replace ride-hailing for trips to and from restaurants, while recreational bike-share trips would probably not have been taken by other modes in the absence of bike-share. The fact that some groups, such as women and those who have a private car, are more likely to substitute bike share for car-related options point to the possibility of using marketing and incentives targeted to these groups to encourage reductions in car use. One expected benefit of introducing bike share service in a city is to reduce VMT. But how much reduction in VMT can a city expect? In the case of the Sacramento region, we estimated average VMT reductions ranging from 1760 miles per day to 2160 miles per day in total depending on the day of the week and the weather conditions. Our scenario analysis suggests that strategically changing the density of bikes in the system and adjusting the boundaries of the service area can increase the reduction in VMT. It is important to note that our trip-level analysis does not capture the more complex ways that bike share may reduce car use. For example, someone may choose to use transit or carpool to work rather than driving knowing that they can use bike-share to reach other destinations during their workday. Had bike share not been available, that same person may not have considered alternatives to driving. We also did not explore societal benefits beyond VMT reduction that bike share brings to the community, including benefits for public health and social equity.

The results presented here are potentially useful in providing guidance for bike share operations and planning toward the goal of enhancing car substitution as well as physical activity. For example, the finding that bikeshare is more likely to substitute for car use for long trips and trips that start in non-commercial locations suggests that rebalancing policies should focus on providing bikes in areas where a high portion of trips are longer, assuming the goal is to reduce VMT. The substantial differences in bike-share use on weekdays and weekends in areas with a college or university suggest the need for an efficient rebalancing strategy specific to these areas on weekends by time of day.

It is important for both cities and private operators to have a reliable estimate of the number of trips a new bike-share system is likely to generate as well as any change in use they can expect from expanding service boundaries or fleet size. Our results show that increasing the bike density in areas where high bike share demand is expected results in a far greater increase in bike-share trips than results from the same increase in bike density in lower demand areas. Our results also show that expanding the service boundary can increase trips but also substantially decrease the efficiency of bike use per bike. On the other hand, as noted above, demand is high, such as in a downtown area, trips may be less likely to substitute for driving, suggesting a potential trade-off between strategies that increase the efficiency of the system versus strategies that maximize VMT reduction. Further exploration of this potential trade-off is warranted.

This study examined the factors influencing mode substitution by bike-share users and estimated VMT reduction, both before and after the 2019 service changes in JUMP that, among other things, expanded the bike share fleet. We developed a trip-flow demand model and estimated the expected demand and VMT reduction for future potential service modifications. Further analysis of the data used in this study to examine questions such as how bike share can improve transit connections and factors inducing bike use at the individual level will contribute to the development of more robust models and provide additional insights for bike share operation strategies and policy implementation.

References

1. Shaheen, S. A.; S. Guzman, and Z. Hua, Bikesharing in Europe, the Americas, and Asia: past, present, and future. *Transportation Research Record*, 2010, 2143.1: 159-167.
2. Otero, I., M.J. Nieuwenhuijsen, and D. Rojas-Rueda, Health impacts of bike sharing systems in Europe, *Environment International*, 2018, 115: 387-394.
3. Wang, M. and X. Zhou, Bike-sharing Systems and Congestion: Evidence from US cities, *Journal of Transport Geography*, 2017, 65: 147-154,
4. NACTO, *Shared Micromobility in the U.S.: 2018.* https://nacto.org/shared-micromobility-2018.
5. Lime, *Year-End Report 2018*, 2018. https://www.li.me/hubfs/Lime_Year-End%20Report_2018.pdf
6. Portland Bureau of Transportation, *2018 E-Scooter Findings Report*, 2018. https://www.portlandoregon.gov/transportation/article/709719
7. Barnes, F. *A Scoot, Skip, and a JUMP Away: Learning from Shared Micromobility Systems in San Francisco*, 2019. https://escholarship.org/uc/item/0515r58q
8. Fitch, D., Mohiuddin, H., & Handy, S. (2020). Investigating the Influence of Dockless Electric Bike-share on Travel Behavior, Attitudes, Health, and Equity. UC Office of the President: University of California Institute of Transportation Studies. http://dx.doi.org/10.7922/G2F18X0W Retrieved from https://escholarship.org/uc/item/2x53m37z
9. Fehr & Peers, Estimated TNC Share of VMT in Six US Metropolitan Regions (Revision 1), 2019, Retrieved from https://www.fehrandpeers.com/what-are-tncs-share-of-vmt/
10. Alemi F., G. Circella, S. Handy, and P. Mokhtarian, What influences travelers to use Uber? Exploring the factors affecting the adoption of on-demand ride services in California, Travel Behaviour and Society, 2018. 13: 88-104
11. Young, M. and S. Farber. The who, why, and when of Uber and other ride-hailing trips: An examination of a large sample household travel survey, Transportation Research Part A: Policy and Practice, 2019. 119: 383-392
12. Bürkner, P.C., brms: An R package for Bayesian multilevel models using Stan. *J. Stat. Softw*. 2017, 80.
13. Stan Development Team, Stan Modeling Language. *User's Guid. Ref. Man*. 1–488., 2018. http://mc-stan.org/manual.html%5Cnpapers2://publication/uuid/C0937B19-1CC1-423C-B569-3FDB66090102
14. R. McElreath, Statistical rethinking. *A bayesian course with examples in R and stan*. CRC Press, Boca Raton, 2020

Appendix A: Extended Methods

Factors Influencing Mode Substitution

In this analysis, we used three different types of predictor variables. The first set of predictor variables are trip attributes, including trip distance, trip purpose, time of day, and weekday/weekend (see Table 1). We also created a predictor variable called "speed" by dividing reported travel distance by reported travel time because we hypothesized that slow speed was an indicator of non-destination-oriented trip making (such as more pleasure) and thus likely to have been induced travel that would not have occurred if bikeshare was not available (i.e., respondent replied "none, I wouldn't have made the trip"). We applied a log-transformation to the data on travel distance and speed because of their highly skewed distributions. Income was excluded from the analyses due to our missing values for nearly one third of the responses. We also included individual characteristics of the respondent as a second set of predictor variables.

The final set of predictor variables reflect the land-use mix of the areas around the trip start and end locations. We used the parcel-level land use data for 2016 from SACOG to characterize land use. The SACOG dataset classifies land use into 45 categories which we aggregated into five general categories: (1) Residential use, (2) Commercial/office use, (3) Industrial use, (4) School, and (5) Civic use. We extracted the percentage of each category of land use for the area surrounding the start and end points of each trip using a variety of buffer radii: 100 meters, 200 meters and 400 meters for the start point; and 25 meters, 50 meters and 100 meters for the end point. We specified shorter radii for the destinations compared to the origins because we assumed users attempt to park as close to their destination as possible, while their starting point may require a longer walk to reach an available shared e-bike. However, based on our preliminary analysis, the size of the buffer had little effect on the relationship between land use and mode substitution, so we chose to use a 100-meter buffer for both the trip origins and destinations.

We used multi-level multinomial logistic regression to analyze the effects of the three types of predictor variables on mode substitution. We allowed the average probability of mode substitution to vary by person. In repeated questions, their decision might vary because of other factors we did not measure. By adding the varying effect by person, we can account for person-level variation beyond that explained in mode substitution.

We used the R package brms, an interface to fit Bayesian models using a probabilistic programming language "Stan," to develop our mode substitution models (12, 13). We used Markov chain Monte Carlo (MCMC) simulation method, drawing random samples from the posterior, to converge the estimator (R-hat $<$ 1.1), with setting parameters, including 4 chains for the number of Markov chains, 4000 for the number of iterations, 2000 for the number of warmups, 0.9 for adapt_delta, and 16 for max_tree_depth.

Determining an appropriate prior in Bayesian modelling is an important step in balancing model under-fitting (inability to learn from the data) and over-fitting (learn too much from the sample with the risk of not generalizing beyond the sample). In the absence of sufficient information or subjective prior beliefs about bike share mode substitution in the greater Sacramento region, we chose priors based on a series of "prior predictive checks" that suggested our priors simulated reasonable data (i.e., allowing occasional extreme outcome simulation such as 90% of mode substitution by one mode but ensure that more frequent simulations provided more balanced and uniform mode substitutions). Following visualizations of a variety of priors ("prior predictive checks"), we decided to use Gaussian distribution priors (mean = 0, std. dev. = 1.5) for intercepts and predictor variables, and Student's t priors (deg. of freedom = 6, mean = 0, std. dev = 1.5) for the varying intercepts by person. These priors can be thought of as "weakly informative" because they provide soft constraints on parameters to reduce potential over-fitting to the data yet still allow the parameters to be largely driven by the data (14).

We compared a series of models with increasing complexity to examine the effects of groups of variables (see Table 5). Model I is the baseline model without any predictors but with alternative specific constants (intercepts). Model II extends Model I by including varying intercepts by person. In Model III we incorporated trip attributes, such as trip distance and trip purpose to Model II to evaluate the effects of such information on trip decision making. Finally, in Model IV we added individual characteristics and land use variables. We do not report several other models we tested (e.g., a model including trip attributes and land use but no individual characteristics) because those model predictions were nearly equivalent and Model IV allowed us to report conditional effects for all variables.

Table 5. Model Specification

	Intercept	Varying Intercept (Person)	Trip Attribute	Individual Characteristics	Land Use
Model I	x				
Model II	x	x			
Model III	x	x	x		
Model IV	x	x	x	x	x

We compared the models through a series of metrics designed to measure out-of-sample predictions. Unlike in-sample prediction metrics, out-of-sample prediction metrics explicitly balance under- and over-fitting. We used stratified 10-fold cross-validation by class to compare the results of models and calculated the following prediction metrics: expected log pointwise predictive density (elpd), overall accuracy, true positive rate, false positive rate, F1 score, and weighted F1 Score. Elpd can be thought of as a traditional log-likelihood metric except that it is pointwise per MCMC (Markov Chain Monte Carlo) iteration (not simply a point estimate) and it is based on the held-out data thus providing a natural assessment of model accuracy. Overall accuracy is the proportion of correctly classified samples in the held-out data. This metric provides a more intuitive assessment of the performance of the model. However, the metric has a flaw when the classes of sample data are very imbalanced.

To understand how well the model predicts each class of trips, we also used the true positive rate, the proportion of correctly classified responses of one specific class out of the number of predictions of that class, and the false positive rate, the proportion of correctly classified responses of one specific class out of all the samples of that class. There is a tradeoff between the true positive rate and false positive rate: one metric may increase as the other decreases. Therefore, we also report the F1 score by class, the harmonic mean of both metrics. In addition, we used a weighted average F1 score, combining the F1 score by class into one metric with the weight of the number of samples by each class to reflect model performance that balances true positives with true negatives by response class sample size. We reported the mean and standard error of each prediction metric for each model because each model includes 2,000 different posterior distribution samples (the number of iterations post warm-up we ran for each model).

System-level Mode Substitution and VMT Reduction

Hub Weight Model

We used a Bayesian linear regression model to estimate hub weights. Using GBFS data in November, we defined the share of all hub-trips to non-hub trips in the TAZs as the dependent variable for each time of day (midnight, AM-peak, off-peak, PM-peak, and night) (n=150). The independent variables we used were the number of non-hub trips in the TAZs and time of day. We applied log-transformations for continuous variables to avoid having negative output. We used the Markov chain Monte Carlo (MCMC) simulation method, drawing random samples from the posterior, to converge the estimator (R-hat < 1.1), with setting parameters, including 4 chains for the number of Markov chains, 4000 for the number of iterations, 2000 for the number of warmups. In a similar way to that described in the previous section to determine appropriate priors, we decided to use Gaussian distribution priors (mean = 0, std. dev. = 0.25) for predictor variables, and Student's t priors (deg. of freedom = 6, mean = 0, std. dev = 0.5) for intercepts and the varying intercepts.

Mode Substitution Models

In the mode substitution model for commuting trips, we used the Euclidean distance between reported home location and reported school/workplace as only a predictor to predict mode substitution because of the lack of detailed information. We used responses that started and ended a commute trip within the Sacramento/West Sacramento service boundary and answered "JUMP was my primary vehicle - I used it for the longest part of the trip or the entire trip" to the survey question, *Think of your last JUMP trip as a part of your commute to or from your primary workplace and tell us how you used JUMP?* We obtained 105 observations as a final dataset. The final dataset had six different mode substitutions excluding *no trip*. However, two substituted modes, *Carpooling* and *Ride-hailing*, had only five observations. Because the model cannot estimate the covariate appropriately, we categorized all car related modes as "Car" and considered this as "Private Car" in the VMT estimation. The substitution modes include Car (N=21, 15.2% of trips), Bike (including e-bike and e-scooter) (N=41, 39.0%), Walk (including skateboarding) (N=27, 25.7%), and Transit (N=16, 15.2%).

We used Bayesian Multinomial Logistic Models for both commuting trips and non-commuting trip. The modelling process and R packages we used are the same as in the previous section. We used the same approach for setting parameters and priors as in the previous sections.

Multivariate Model for Driving Distance and Travel Time

We queried driving distance from Google API for origin-destination pairs to investigate VMT reduction. We used the Bayesian Multivariate Linear Regression Model to estimate GoogleMap-based distance and travel time simultaneously with Euclidean distance the sole predictor for each. The advantage of a multivariate model is that we can consider the correlation between two outcome variables in the model. Because travel time and distance should have high correlation, this model improved the prediction of both travel time and GoogleMap-based drive distance when conducted independently. We applied log-transformation for continuous variables to avoid having negative output. We used the same R package and processing as the first mode substitution model. We decided to use Gaussian distribution priors (mean = 0, std. dev. = 1.25) for a predictor variable and sigma for both equations, Student's t priors (deg. of freedom = 8, mean = 0, std. dev = 1.25) for intercepts of both equations and lkj(1) for residual correlation.

Sampling Process

We used GBFS data between April 1 and September 2, 2019. We removed data points of dates with precipitation or missing values to show the estimation and its uncertainty of VMT reduction on a non-rainy day on weekday and weekend before and after the company's operational changes. In the sampling process, we drew 1,000 samples from the posterior distribution of the mode substitution models, which allowed us to have 1000 different predicted outputs for each data point. Also, we drew 1,000 samples of weights to convert from Euclidean distance to driving distance and to inflate for the number of hub-trips, and applied them in the sequential order into the results from the mode substitution models. Finally, we aggregated them to estimate VMT reduction for each date, such that each date has 1000 different samples. We generated the posterior within a 95% confidence interval for each to avoid extreme values in our simulations.

Factors Influencing Dock-less Bike Share Usage

Cluster Analysis

Because we could not estimate a demand model with all possible combinations of TAZs (computationally intractable for our available resources), we used k-mean clustering to classify TAZs based on land use characteristics. We used land use data in 2016 offered from SACOG. The land use data defines 49 different land use types and we aggregated the area for each land use type by TAZ. We did not consider some land use types, including Road, Water, Blank Place Type, Airport, Forest, and Agriculture, in this analysis because it is unlikely that such land uses generate or attract bike share usage. We used the average Silhouette score to determine the number of clusters. The Silhouette coefficient is one measure to interpret and validate the consistency within each cluster and the average score is the mean of the coefficients for all clusters. A larger value indicates the data point is far from other clusters. We found that five clusters had the highest score, but four and six clusters also had similar scores. Then, we compared the output with our local and priori knowledge and decided on five clusters. We designated the five clusters "Park/Open Space Use," "Residential Use," "Commercial/Office Use," "Industrial Use," and "Public/Civic Use," and classified each TAZ into one of five land use categories using land use data from SACOG.[7] We assumed that TAZs with similar land uses generate similar trip patterns. In all, there are 25 possible combinations for trips between different categories of TAZ pairs to account for possible land use effects.[8] We used these clusters in the following demand model.

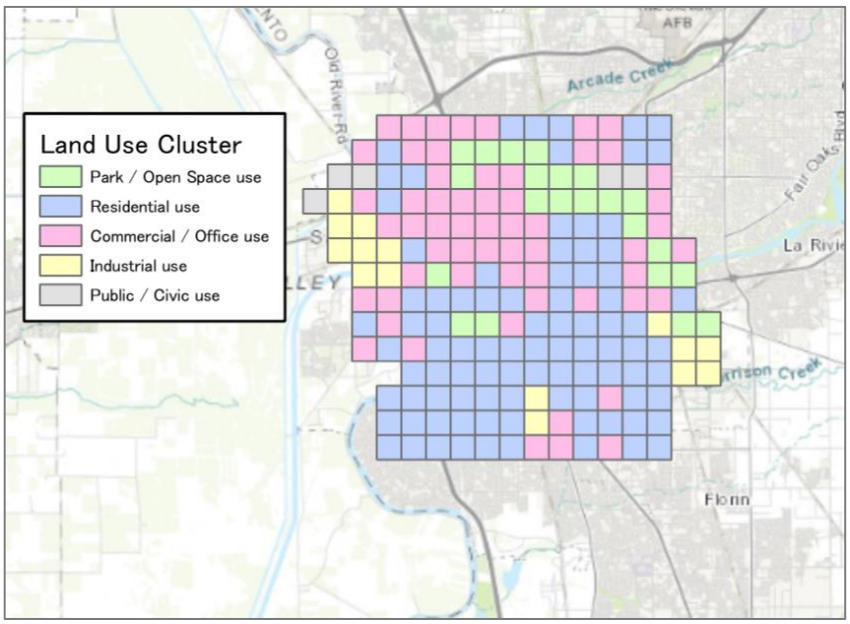

Figure 23. Map of TAZs classified based on Land Use

[7] The demand varies by TAZ pairs, such that we might capture unobserved factors by including random effects in the model. However, the large number of TAZ pairs (36,100 pairs) requires a long computation time. Also, a large variance in the varying (random) effects might lead to large uncertainty in the scenario simulation. We created the land use categories to retain the varying (random) effects in our model.

[8] We finalized the model based on the prediction performance and clear theoretical interpretability based on existing studies. We used three different metrics, including mean root square for a whole test dataset, data points with zero trip and data points with non-zero trip. While k-fold cross validation is preferred to examine model performance, we split our dataset into training (70 percent) and test (30 percent) subsets because our dataset was large.

Bike share Trip Flow Demand Model

We used the R package glmer to fit a Poisson mixed effects model as a count model and to develop a bike share trip flow demand model (n=1,805,000 obs.). We used the logarithm as the link function and set the offset of the number of hours for each data point because we aggregated the counts by the time of day, weekend/weekday and week. In the model section, we checked whether our model over- or -underfit zeros in the output with 0.01 tolerance (1,756,896 – 1,792,388 obs.) by comparing the number of observed zeros (n= 1,774,642 obs.) with the number of predicted zeros. We used more strict tolerance than the default of 0.05 (1,685,910 – 1,863,374 obs.) in the package because the default accepts all-zero prediction. The result of this check showed that the number of predicted zeros were 1,764,351 observations, which was within the tolerance. Thus, we decided to use the Poisson model rather than other count models, such as a negative binomial model and zero-inflated model.

Scenario Analysis for Service Change: Mode Substitution and VMT Reduction

Simulation Process

We estimated the number of bike share trip for each TAZ pair by scenario based on the trip flow demand model developed in the previous section. To reflect the uncertainty, we generated three samples at the mean and 95% confidence interval level. We did not draw many samples for each OD pair, unlike what was done in the other sampling steps, in order to reduce the computation time. Because the output for each TAZ pair is continuous, this method still shows the valid range of each effect from introducing bike share and changing operational characteristics.

We estimated the share of trip substitutions for each mode and VMT reduction per trip for each OD pair. To begin, we generated synthesized trip data for each OD pair because the mode substitution models predict substituted mode only with trip level data. We generated data points on the road centerline data every 0.05 miles to ensure all TAZs have at least one data point. We drew 10 data points of origin and destination TAZs without replacement and made them pairs in the order for each TAZ pair, such that we have 10 synthesized trips for each TAZ pair. We set this number of samples to maintain the practical computation time though the small sample size might reduce the ability to communicate the model's full uncertainty (e.g., the number of trips for the expansion scenario in Sacramento/West Sacramento are 1,162,810 obs). Also, we drew 10 samples of driving distance and travel time from posterior distribution within a 95% confidence interval for each trip for predicting mode substitution and estimating VMT reduction (e.g., the number of trips for the expansion scenario in Sacramento/West Sacramento are 11,628,100 obs). Merging all required predictors in the models with the trip data, we predicted mode substitution and drew 10 samples for each trip. We applied the weight of commute/non-commute trip and calibrated the shares of mode substitution and mean of VMT reduction for each TAZ pair by draw of mode substitution. This process generated 10 samples of average estimates per trip for each OD pair. Finally, by multiplying this output with the three samples of OD demand, we estimated the range of the effects for each scenario.

Limitations

The mode substitution models have several limitations worthy of note. First, the reported trip data in the survey, especially the location of trip starting and ending points, may not be accurate. Some people selected a location on the map in the middle of a building, which is probably not where they picked-up or dropped-off the bike. Since the bike parking location is not always directly next to the actual origin and destination of the trip, the difference between reported pick-up/drop-off location and actual pick-up/drop-off location may compromise the model estimation. Second, potential errors in calculating the travel speed measure may reduce the reliability of the model. In the JUMP app, the user can hold their reservation for up to 15 minutes. Some people may reserve the bike first and walk to the bike location while others reserve the bike at the bike location. Because the reported travel time includes the reservation time it might overestimate the actual travel time, skewing our calculated measure of travel speed. Third, the survey question about mode substitution for their actual trip is hypothetical. We asked the respondents to retrospectively report on what mode they would have chosen in the absence of bike share, but whether this mode is what they would have actually chosen is uncertain. In addition, the decision might change under different circumstances. For example, the user might choose to drive in place of using bike share when it is a very hot day or likely to rain, when they would normally choose active transportation modes instead. Also, other scheduled activities before or after the reported trip may change a person's reported mode substitution.

The trip flow demand model is applicable to a limited range of scenarios. During the time period covered by the dataset, the number of bikes in the fleet grew from 950 to 1100 while the service boundary remained constant, leading to low variability in bike density in the dataset, which can lead to implausible predictions outside of this range. While we considered the effect that the presence of a university might have on weekend bike share use, we did not consider the density of buildings or student population which are both likely to affect bike share demand. Also, we selected predictors based on theoretical interpretation and model performance, but all we have established is that such predictors are correlated with bike use in Sacramento. The effects of each predictor may differ in other cities which may cause some bias when applying the model elsewhere. Further analysis to understand the relationship between factors and bike usage at the micro level will be required to develop more robust models. Furthermore, we did not consider how operational behavior (e.g., rebalancing the bike fleet) influenced bike share demand. The strategy and the ease of operations may vary by the size of the boundary. We also ignored VMT produced by operational vehicles in this analysis. While VMT reduction is not the only goal in providing bike share service, this trade-off between operational efforts and VMT reduction (including the operational VMT) should be examined in the future analysis.

Appendix B: Model Parameter Summaries

Mode Substitution Model

Table 6. Summary of estimates of mode substitution model for non-commuting trip (full model) including the posterior mean and standard deviation

Base = Transit (n=787)	Bike	Walk	Ride-hailing	Car, Alone	No Trip	Carpooling
Intercept	-6.19 (2.28)	3.42 (1.89)	-4.07 (2.17)	-1.22 (2.23)	-3.21 (2.15)	-5.68 (2.32)
Person-level Std. Dev.	3.69 (0.61)	3.11 (0.5)	3.36 (0.57)	3.31 (0.6)	3 (0.59)	2.52 (0.61)
Trip Attribute						
Travel Distance (log)	0.6 (0.42)	-2.29 (0.42)	0.81 (0.44)	0.19 (0.42)	0.04 (0.4)	0.47 (0.43)
Speed (log)	-0.48 (0.58)	-0.09 (0.49)	-0.09 (0.58)	-0.57 (0.57)	-0.91 (0.55)	-0.77 (0.59)
Trip Purpose (base = other)						
Restaurant	0.85 (0.68)	0.47 (0.58)	2.38 (0.65)	-0.05 (0.63)	1.01 (0.64)	1.05 (0.69)
Home	1.07 (0.72)	0.78 (0.66)	2.52 (0.72)	-0.52 (0.76)	-0.98 (0.84)	0.8 (0.81)
Work related	0.31 (0.74)	-0.19 (0.6)	0.33 (0.74)	-1.41 (0.76)	-0.26 (0.79)	-1.06 (0.84)
Shopping	1.16 (0.8)	-0.78 (0.72)	-1.74 (0.98)	-0.34 (0.81)	0.46 (0.79)	0.95 (0.88)
Recreation	1.41 (0.78)	0.21 (0.7)	-1.68 (0.93)	-1.43 (0.78)	3.2 (0.78)	-0.1 (0.85)
Time of Day (base = Midnight)						
AM Peak	1.01 (0.82)	-1.3 (0.72)	0.43 (0.77)	-0.77 (0.79)	-0.82 (0.86)	-0.21 (0.88)

Base = Transit (n=787)	Bike	Walk	Ride-hailing	Car, Alone	No Trip	Carpooling
Off Peak	0.64 (0.73)	-0.24 (0.61)	-0.19 (0.67)	0.22 (0.68)	0.52 (0.71)	0.91 (0.76)
PM Peak	0.22 (0.76)	-1.15 (0.64)	-0.43 (0.7)	-0.78 (0.71)	-0.7 (0.77)	-0.15 (0.8)
Night	0.22 (0.83)	-0.78 (0.72)	0.84 (0.76)	-0.19 (0.79)	-0.25 (0.9)	-0.04 (0.88)
Weekend	0.21 (0.58)	0 (0.53)	-0.38 (0.58)	-0.42 (0.58)	-0.35 (0.63)	0.59 (0.63)
Land Use						
Start (100m buffer)						
Residential use	0.89 (0.88)	0.37 (0.84)	0.78 (0.87)	0.67 (0.86)	0.01 (0.89)	0.57 (0.91)
Commercial/Office use	-0.3 (0.94)	0.4 (0.85)	-0.68 (0.94)	-2.43 (0.92)	0.18 (0.94)	-0.57 (0.96)
Industrial use	0.01 (1.48)	-0.64 (1.42)	-0.25 (1.48)	0.95 (1.39)	-0.06 (1.47)	0.12 (1.48)
School use	-0.09 (1.37)	-1.07 (1.33)	0.27 (1.38)	0.84 (1.32)	0.36 (1.31)	0.23 (1.4)
Civic use	1.1 (1.02)	-0.43 (1.01)	1.26 (1.01)	-0.59 (1)	-0.46 (1.1)	-0.15 (1.09)
End (100m buffer)						
Residential use	0.5 (0.92)	-0.18 (0.84)	0.32 (0.92)	0.5 (0.88)	0.32 (0.88)	0 (0.92)
Commercial/Office use	0.28 (0.89)	0.83 (0.79)	1.78 (0.91)	-0.88 (0.89)	-0.24 (0.87)	-0.38 (0.95)
Industrial use	-0.51 (1.31)	-0.89 (1.36)	0.22 (1.34)	1.63 (1.28)	-0.62 (1.41)	0.38 (1.33)
School use	-0.58 (1.22)	-1.16 (1.21)	-0.43 (1.25)	-0.23 (1.2)	-0.34 (1.13)	0.13 (1.19)
Civic use	-0.01 (1.02)	-0.36 (0.91)	0.5 (1.05)	0.02 (0.97)	-1.13 (1.04)	-0.8 (1.04)
Individual Characteristics						

Base = Transit (n=787)	Bike	Walk	Ride-hailing	Car, Alone	No Trip	Carpooling
Student	-0.67 (0.98)	0.47 (0.78)	0.52 (0.86)	-0.91 (0.91)	0.17 (0.88)	-0.05 (0.9)
Having Children	-0.07 (0.79)	-0.29 (0.68)	-1.14 (0.74)	0.11 (0.75)	-0.18 (0.75)	0.44 (0.73)
College Degree	1.94 (0.9)	-0.25 (0.71)	0.12 (0.8)	0.41 (0.82)	0.1 (0.8)	0.59 (0.83)
Employed	1.08 (0.94)	-0.73 (0.73)	1.21 (0.91)	0.4 (0.87)	-0.11 (0.84)	0.15 (0.85)
Age (Base = less than 25)						
25 – 34	1.13 (0.84)	0.01 (0.73)	0.53 (0.8)	-0.1 (0.79)	0.8 (0.8)	0.61 (0.81)
35 – 44	-0.1 (0.9)	-0.4 (0.77)	0.17 (0.84)	-0.37 (0.84)	-0.53 (0.85)	-0.44 (0.87)
45 – 55	0.06 (1.03)	-0.31 (0.88)	-0.19 (0.98)	-0.93 (1)	-0.83 (1.01)	1 (0.97)
55 –	0.65 (1.06)	0.03 (0.96)	-1.72 (1.14)	-0.09 (1.04)	1.13 (1.01)	0.04 (1.06)
Woman	-0.84 (0.72)	-0.11 (0.59)	0.34 (0.66)	0.97 (0.66)	-0.76 (0.67)	1.46 (0.67)
Car Ownership	-0.2 (0.67)	0.06 (0.55)	0.63 (0.63)	1.38 (0.66)	0.78 (0.62)	0.67 (0.64)
Expected log predictive density from approximated leave-one-out cross validation (elpd_loo)	-1006.0 (33.3)					

Table 7. Prediction Metrics*

	Model I	Model II	Model III	Model IV
Elpd	-1400.1 (15.7)	-1114.5 (27.0)	-1048.8 (31.3)	-1054.8 (34.6)
Accuracy	19.5% (1.4%)	34.9% (1.5%)	40.7% (1.5%)	42.3% (1.4%)
True Positive rate				
Transit	5.2% (3.5%)	8.1% (4.4%)	13.3% (5.4%)	16.3% (5.4%)
Bike	14.1% (3.3%)	36.4% (4%)	38.9% (3.9%)	40.3% (4%)
Walk	33.2% (3%)	48.9% (2.8%)	56.8% (2.7%)	57.9% (2.6%)
Ridehailing	16.2% (3.2%)	29.5% (3.8%)	40.6% (3.7%)	41% (3.8%)
Car, Alone	13.6% (3.3%)	29.8% (4%)	29.2% (4%)	33.9% (3.9%)
No Trip	11.3% (3.4%)	29% (4.3%)	33.3% (4.4%)	35% (4.3%)
Car-pooling	6.3% (3.4%)	14% (4.6%)	18.9% (5.2%)	19% (4.7%)
False Positive rate				
Transit	4.8% (3.2%)	8.1% (4.3%)	13.8% (5.3%)	17.6% (5.6%)
Bike	14.2% (3.1%)	36.5% (3.7%)	38.7% (3.6%)	41.7% (3.7%)
Walk	33.4% (2.4%)	48.7% (2.4%)	57% (2.1%)	58.7% (2.2%)
Ridehailing	16.2% (3%)	29.8% (3.2%)	40.1% (3.3%)	40.5% (3.2%)
Car, Alone	13.6% (3%)	29.7% (3.6%)	30.5% (3.6%)	34% (3.6%)
No Trip	11.3% (3.2%)	29.6% (4%)	33.3% (3.9%)	34.2% (3.9%)
Car-pooling	6.3% (3.3%)	13.9% (4.4%)	17.8% (4.5%)	17.2% (4.1%)
F1 Score				
Transit	5.7% (2.8%)	8.4% (4%)	13.5% (5.1%)	16.8% (5.3%)
Bike	14.1% (3.2%)	36.4% (3.5%)	38.7% (3.3%)	40.9% (3.4%)
Walk	33.3% (2.5%)	48.7% (2.3%)	56.9% (2%)	58.2% (2%)
Ridehailing	16.2% (3%)	29.6% (3.3%)	40.3% (3.1%)	40.7% (3.1%)
Car, Alone	13.6% (3.1%)	29.7% (3.5%)	29.8% (3.5%)	33.9% (3.4%)
No Trip	11.2% (3.2%)	29.2% (3.8%)	33.2% (3.8%)	34.5% (3.7%)

	Model I	Model II	Model III	Model IV
Car-pooling	6.5% (3.1%)	13.9% (4.4%)	18.3% (4.6%)	18% (4.2%)
Weighted F1 Score	14.2% (2.9%)	27.9% (4.2%)	32.9% (4.6%)	34.7% (4.5%)

* The values in the parentheses represent the standard error.

System-level Mode Substitution and its Effect

Table 8. Summary of estimates of mode substitution model for non-commuting trip (reduced model) including the posterior mean and standard deviation

Base = Transit (n=823)	Bike	Walk	Ride-hailing	Car, Alone	No Trip	Carpooling
Intercept	-3.56 (1.5)	4.94 (1.27)	-2.34 (1.43)	-0.14 (1.43)	-1.3 (1.49)	-2.85 (1.62)
Person-level Std. Dev.	3.05 (0.52)	2.46 (0.4)	2.86 (0.48)	2.81 (0.52)	2.79 (0.54)	2.05 (0.5)
Trip Attribute						
Euclidean Speed (log)	-0.04 (0.14)	-0.31 (0.12)	0.14 (0.15)	-0.17 (0.13)	-0.39 (0.13)	0.01 (0.15)
Travel Time (log)	0.59 (0.36)	-1.7 (0.35)	0.69 (0.35)	0.23 (0.36)	0 (0.35)	0.64 (0.38)
Time of Day (base = Midnight)						
AM Peak	0.81 (0.77)	-1.5 (0.64)	-0.01 (0.68)	-1.15 (0.73)	-1.26 (0.82)	-0.15 (0.78)
Off Peak	0.7 (0.7)	-0.18 (0.54)	-0.1 (0.61)	0.13 (0.63)	0.36 (0.66)	0.93 (0.71)
PM Peak	0.28 (0.71)	-0.84 (0.58)	-0.34 (0.62)	-0.55 (0.66)	-0.73 (0.72)	-0.04 (0.75)
Night	0.49 (0.77)	-0.46 (0.65)	1.44 (0.7)	-0.27 (0.73)	-0.48 (0.82)	0.16 (0.82)
Weekend	0.19 (0.52)	0.14 (0.46)	-0.22 (0.51)	-0.16 (0.51)	0.12 (0.55)	0.74 (0.54)
Land Use						
Start (100m buffer)						
Residential use	1.1 (0.85)	0.29 (0.77)	0.68 (0.82)	0.58 (0.79)	0.29 (0.86)	0.62 (0.83)
Commercial/Office use	0.02 (0.86)	0.08 (0.79)	-0.62 (0.86)	-2.19 (0.83)	-0.58 (0.9)	-0.72 (0.89)

Base = Transit (n=823)	**Bike**	**Walk**	**Ride-hailing**	**Car, Alone**	**No Trip**	**Carpooling**
Industrial use	-0.04 (1.44)	-0.61 (1.4)	-0.16 (1.45)	1.07 (1.38)	-0.18 (1.46)	0.05 (1.47)
School use	0 (1.37)	-0.71 (1.23)	0.24 (1.33)	0.52 (1.25)	0.63 (1.34)	0.13 (1.39)
Civic use	1.03 (0.99)	-0.52 (0.95)	1.36 (0.98)	-0.55 (0.98)	-0.16 (1.06)	-0.19 (1.04)
End (100m buffer)						
Residential use	0.99 (0.81)	0.06 (0.73)	1.07 (0.82)	0.56 (0.8)	-0.15 (0.82)	0.11 (0.83)
Commercial/Office use	0.34 (0.82)	0.79 (0.74)	1.52 (0.8)	-0.44 (0.84)	-0.22 (0.83)	-0.44 (0.86)
Industrial use	-0.1 (1.24)	-1.27 (1.35)	0.47 (1.32)	1.72 (1.2)	-0.68 (1.41)	0.19 (1.27)
School use	-0.9 (1.17)	-1.08 (1.12)	-0.65 (1.16)	-0.29 (1.15)	0.31 (1.11)	-0.32 (1.09)
Civic use	0.32 (0.94)	-0.07 (0.85)	0.16 (0.96)	0.19 (0.91)	-1.57 (0.99)	-0.77 (0.98)
Expected log predictive density from approximated leave-one-out cross validation (elpd_loo)	-1105.1 (32.6)					

Table 9. Summary of estimates of mode substitution model for commuting trip including the posterior mean and standard deviation

Base = Transit (n=105)	Bike	Walk	Car Options
Intercept	1.04 (0.38)	0.83 (0.38)	-0.08 (0.47)
Trip Attribute			
Euclidean Distance (log)	-0.27 (0.63)	-2.52 (0.75)	0.67 (0.72)
Expected log predictive density from approximated leave-one-out cross validation (elpd_loo)	-132.0 (7.0)		

Table 10. Summary of estimates of hub weight model including the posterior mean and standard deviation

(n=150)	Estimate	Est.Error
Intercept	0.06	0.3
Sd (Intercept)	0.36	0.26
Non-Hub Trips (Log Transform)	-0.17	0.07
Sd (Non-Hub Trips (Log Transform))	0.1	0.08
sigma	0.21	0.01
Expected log predictive density from approximated leave-one-out cross validation (elpd_loo)	15.2 (10.8)	

Table 11. Summary of estimates of multivariate model including the posterior mean and standard deviation

(n=5956)	Estimate	Est.Error
Driving Distance (log)		
Intercept	0.39	0.00
Euclidean distance (log)	1.00	0.00
Sigma	0.34	0.00
Travel Time (log)		
Intercept	2.96	0.01
Euclidean distance (log)	0.31	0.01
Sigma	0.65	0.01
Residual Correlation	-0.05	0.01
Expected log predictive density from approximated leave-one-out cross validation (elpd_loo)	-7806.7 (346.5)	

Demand Model

Table 12. Summary of estimates of bike share trip flow demand model including mean estimates, standard deviation, and z-value

(n= 1,805,000 obs)	Estimate	Std. Error	z value
Fixed Effects			
Intercept	-5.992	0.340	-17.6
Density of Fleet Size (log, x 10 bikes per square mile)	0.433	0.080	5.4
Distance (mile)	-1.459	0.004	-327.1
Weekend	0.011	0.008	1.4
Length of Bike Lane (O) (mile)	0.248	0.004	58.9

(n= 1,805,000 obs)	Estimate	Std. Error	z value
Length of Bike Lane (D) (mile)	0.246	0.004	58.5
University (O)	0.967	0.014	68.5
University (D)	0.955	0.014	67.2
Airport (O) (x 10^{-1} square mile)	-1.122	0.099	-11.4
Airport (D) (x 10^{-1} square mile)	-0.857	0.081	-10.6
Restaurant/Bar (O) (x 10^{2})	0.459	0.023	19.9
Restaurant/Bar (D) (x 10^{2})	0.511	0.023	22.2
Population (O) (x 10^{3}persons)	0.174	0.005	34.5
Population (D) (x 10^{3}persons)	0.176	0.005	35.0
% Low Income (O)	-0.368	0.028	-13.1
% Low Income (D)	-0.242	0.028	-8.6
# Bus Stop (O) (x 10^{3})	1.231	0.024	51.3
# Bus Stop (D) (x 10^{3})	1.189	0.024	49.7
Weekend:University (O)	-0.461	0.028	-16.8
Weekend:University (D)	-0.443	0.028	-16.0
Random Effects			
Land Use Types of OD pairs	0.733	0.856	
Time of Day	0.567	0.753	
AIC	284,111.8		
BIC	284,384.7		
Log-liklihood	-142,033.9		