Title
Incentive-based Approach to Rebalancing a Dock-less E-Bike-Share System for Sustainability

Author
Fukushige, Tatsuya

Publication Date
2022

Peer reviewed|Thesis/dissertation

Incentive-based Approach to Rebalancing a Dock-less E-Bike-Share System for Sustainability

By

TATSUYA FUKUSHIGE
DISSERTATION

Submitted in partial satisfaction of the requirements for the degree of

DOCTOR OF PHILOSOPHY

in

Transportation Technology and Policy

in the

OFFICE OF GRADUATE STUDIES

of the

UNIVERSITY OF CALIFORNIA

DAVIS

Approved:

____
Susan L. Handy, Chair

____
Dillon T. Fitch, Co-Chair

____
Michael Zhang

Committee in Charge

2022

Abstract

The spatial mismatch between demand and supply over time is a significant concern in a bike-share service. One primary strategy to fill the mismatch is to rebalance a shared bike fleet by vans or trucks. The more vans operators use to meet the demand, the more vehicle miles traveled (VMT) the system produces, offsetting the VMT reduction benefit that was at least a part of the motivation for the city to authorize the service. Another approach to the problem is an incentive-based approach to rebalancing a fleet. This approach incentivizes users to walk farther to get a bike from the oversupplied area (origin-based incentives) or to take a bike to the undersupplied area (destination-based incentives) by offering some reward, such as free bike-share use or a prize of some sort. This approach has proven to be successful in docked bike-share services, but the potential in the context of dock-less bike-share services is unknown. This dissertation examines the potential effect of an incentive-based approach to rebalancing a dock-less e-bike-share fleet on bike-share use and social benefits, focusing mainly on VMT reduction, using a e-bike-share service in the Sacramento area, CA.

This dissertation consists of four studies. The first and the second studies are self-standing. The third study is built on the second study, and the fourth and final study assembles an agent-based model from the models presented in the prior three studies. In the first study, I examine bike-share users' willingness-to-walk to pick up a bike or drop off a bike at some distance from their origins or destinations if rewarded and identify characteristics influencing willingness-to-walk. I find that half of the respondents use bike-share if the available bike is located 8.9 minutes away. Estimates of willingness-to-walk farther than the mean distance for incentives at origins and destinations were 3.8 minutes and 4.2 minutes per dollar, respectively. Based on these results, I find the potential effectiveness of incentives as a strategy for spatially

rebalancing bike-share fleets.

The second study examines the factors influencing mode substitution, defined here as the mode that is replaced when bike-share is used. I find that walking is the dominant mode substitution for trips of less than 1 mile for most trip purposes. Long trips and non-commute trips that start at non-commercial locations are likely to represent car substitution and some groups, such as women, non-membership holders, and those who have a private car, are more likely to report car substitution for any trip purpose.

The third study develops a framework for estimating vehicle miles reduced from the introduction of a dock-less e-bike-share service. I find that the daily car substitution rate, including both “private car” and “ride-haling,” was 28% on weekdays. Furthermore, I find that the dock-less bike-share service with a fleet size ranging between 950 and 1100 was responsible for an estimated VMT reduction of 2,131 vehicle miles per day in total and 0.79 miles per trip on average across the service region on weekdays.

The fourth and final study develops a simulator using an agent-based model to examine how an incentive-based approach helps reduce the spatial mismatch between demand and supply and to estimate impacts on VMT reduction and its social cost in the context of a dock-less e-bike-share service. I find that incentive strategies improve the willingness of bike-share users to go out of their way to pick up or drop off a bike, but the effect varies by fleet size and the size of the incentive budget. The number of trips per bike does not change significantly with rebalancing strategies, suggesting that operators must determine the fleet size carefully before entering the market. I estimate that introducing incentive strategies reduces VMT by 3-6% by increasing the number of bike-share trips and saves US$20-29 in social costs per day. Based on the first three studies, this study demonstrates the potential of the rebalancing strategy's incentive approach to increase the bike-share operation's efficiency and social benefits regarding VMT reduction.

Acknowledgments

First of all, I would like to express my sincere gratitude to my supervisor and chair of my dissertation committee, Susan Handy, for supporting my entire school life at UC Davis. Her support and guidance for my research work, including research design, critical thinking, and even English writing skills, improved my skill sets as a researcher. Not only her direct support of my studies but also her help in connecting me with various sources and opportunities made my school life more fruitful. Without her instruction and support, this achievement would not have been possible.

I am also indebted to another supervisor and co-chair of my dissertation committee, Dillon Fitch, for his consistent support and guidance throughout my graduate student life and this project. He influenced my learning and research more than anyone else during my time at UC Davis. His instruction developed my methodological skills and critical analysis, especially by introducing me to the Bayesian approach in the modeling process which improved my dissertation analysis. I cannot imagine not having his guidance and support.

I thank the following people for helping with this research project. Many thanks to another dissertation committee member, Michael Zhang, without whom I would not have been able to complete this research. His support and guidance from an engineering perspective improved my dissertation. I would like to express my gratitude to Miguel A. Jaller, Giovanni Circella, and Alan Jenn for providing valuable suggestions for my dissertation at the early stages of my research and the qualifying process.

I would like to thank my graduate student colleagues, especially Hossain Mohiuddin, Justin Darr, Gyanendra Chaudhary, and Tzu-Chieh Su, for their friendship and for impacting my research skills and transportation views throughout class projects and out-of-class projects.

I wish to thank my parents, Hideaki and Mariko Fukushige, for their support and belief in me. Their encouragement for me to pursue a Ph.D. degree in the U.S. pushed me forward and made this achievement. I also want to thank my sister, Anna Fukushige, and family, ChingTang Chen and Suchen Cheng, for continuously supporting me, my wife and our son.

Finally, I would like to express my endless gratitude to my wife, PeiWen Chen. She always encourages and supports my decisions. It is wonderful to share this experience and achievement with her. She is my best partner and supporter. I also thank my son Tomoyuki Fukushige for offering me more happiness, excitement, and experiences during my student life.

Table of Contents

1 Introduction

1.1. Overview of Bike-share and its benefits

Many U.S. cities have introduced bike-share services, a type of micromobility service, as a part of the sharing economy since Portland, Oregon, launched the first US bike share service in 1994 (Shaheen et al., 2010). At first, most cities introduced docked bike-share systems. This bike-share service enables users to rent and return bikes at stations usually installed on the sidewalk or sometimes on the street. More recently, cities have adopted dock-less bike-share systems, a technological innovation that private companies brought to cities starting in 2018 (NACTO, 2020). Unlike docked bike-share systems, users can rent and return a bike anywhere within a designated service boundary. The National Association of City Transportation Officials (NACTO) reported that the number of trips by bike-share services, including docked and dock-less bike-share systems, increased in the United States from 321,000 trips in 2010 to 50 million trips in 2019 (NACTO, 2020), though many dock-less bike-share services were closed or suspended due to the emergence of COVID-19 in 2020.

One motivation for cities to introduce bike-share services is that a modal shift from driving to bicycling could produce a sizable reduction in vehicle miles traveled, with broad benefits for transportation, energy consumption, environmental quality, public health, and quality of life (Pedestrian and Bicycle Information Center and FHWA, 2010). The National Association of City Transportation Officials (NACTO) reported that the average trip length of docked and dock-less bike-share range from 1.2 to 2.5 miles in 2018 (NACTO, 2019). The fact that 35% of trips by privately-operated vehicles are less than 2 miles (USDOT, 2018) suggests considerable opportunity to increase the substitution of bike-share for driving, thereby reducing vehicle miles traveled (VMT) and related greenhouse emissions. However, the benefits will be more limited if the major mode shift comes from public transit, owned bike, or walking. Prior studies have found that micromobility services substitute for car travel at a substantial rate. For example, NACTO (2020) and Barnes (2019) reported a high car substitution rate of 45% of micromobility users in multiple US cities. However, Fishman et al. (2014) found that only 19% and 7% of docked bike-share trips in Minneapolis and Washington D.C., respectively, replace private car trips.

Researchers have found that micromobility services generate substantial environmental benefits by producing VMT reductions (Fishman et al., 2014) and greenhouse emissions reductions (Chen et al., 2022; Reck et al., 2022; Saltylpva et al., 2022; Kou et al., 2020; Zhang & Mi, 2018). For example. Fishman et al. (2014) estimated an annual VMT reduction of 444,187 km and 178,62 9km in Washington, D.C., and Minneapolis, respectively. Some researchers have estimated emission reductions rather than VMT reduction. Kou et al. (2020) found that eight U.S. cities, including Seattle, Los Angeles, San Francisco, Philadelphia, Boston, Washington, D.C., Chicago, and New York, had annual GHG emission reductions from 41 tons to 5417 tons of CO2-eq. Chen et al. (2022) also estimated the 30,070 tons reduction in CO2 from a bike-share service in New York. Reck and his colleagues (2022) accounted for emissions from various aspects of operation, including vehicle manufacturing and operational services. They found that the CO_2 generated by a shared e-bike service exceeds the CO_2 reductions attributable to the replacement of bike-share for driving in Zurich, Switzerland.

1.2. Spatial Mismatch and Operational VMT Production in Bike-share Services

Operational tasks, such as maintenance, battery swapping, and fleet rebalancing, play an essential role in maintaining the availability and quality of the service (Pfrommer et al., 2014). Operators usually run such operational activities by van or truck. This means that operational tasks offset the environmental benefit from car substitution in bike-share systems. Fishman and his colleagues (2014) found that docked bike-share service operators produced 150 and 342 miles per day in Minnesota and Washington, D.C, respectively. They also estimated that operational miles exceeded VMT reduction from car substitution for a bike-share service in London. The San Francisco Municipal Transportation Agency (2022) reported that dock-less e-scooter-share operators produced 200 to 600 operational miles per day depending on months and operators. Another study estimated 0.6-2.5 miles per scooter for collection and distribution (Hollingsworth et al., 2019). These miles vary by factors such as bike density, the number of micromobility users, operational budget, and urban structure. Though operational activities maintain and facilitate the service to increase micromobility use, minimizing the operational miles is essential for maximizing benefits.

Rebalancing operations, as a significant component of operational miles and thus operating costs (Pfrommer et al., 2014), is essential for increasing micromobility use and reducing VMT reduction. Bike-share use will be lower – and the system will then produce more limited benefits – if users cannot find bikes where and when they need them. Bike-share operators face a major challenge in avoiding a spatial mismatch between demand and supply. This challenge may be more severe in dock-less bike share systems than docked systems because drop-off locations are not designated. For example, the UC Davis Campus Travel Survey in 2019 found that 70% of respondents who had used the dock-less e-bike-share service in Davis, California, had at least once not been able to find an available bike nearby when they wanted it (Lee, 2020). According to the survey results, fifty percent of the demand in Davis went unsatisfied. The issue stems mainly from an unbalanced distribution of the bike fleet over the day combined with the limited size of the fleet. If users cannot reliably find a bike, they are less likely to consider bike-share for their mode choice, and this will lead to less bike share use overall, less profit for the operator, and less benefit for the community. For these reasons, operators need a well-designed strategy to address the spatial mismatch to increase bike-share use. Policymakers need to know what requirements to impose on operators to maximize the benefits to the community.

One major strategy to fill the mismatch is to rebalance the bike fleet by vans or trucks. This type of strategy has been implemented in many docked and dock-less systems. Some bike-share systems implement a static rebalancing strategy redistributing the bike fleet in the off period. In contrast, other systems rebalance the fleet dynamically throughout the day according to the demand. Rebalancing operations by vans can keep bike usage from falling below acceptable levels but will often be a dominant component of the total operating costs (Pfromme et al., 2014). Furthermore, the more trucks they use to meet the demand, the more VMT they produce. This will offset the VMT reduction's benefit, one common motivation for authorizing the service, by substituting bike share for car travel.

Another rebalancing strategy implemented in some bike-share systems is an incentive approach. This approach incentivizes users to walk farther to get a bike from the oversupplied area (origin-based incentives) or to take a bike to the undersupplied area (destination-based incentives) by offering some reward, such as free-bike-share use or a prize of some sort. The advantage of this approach is that it reduces operational miles. The disadvantage creates uncertainty for operators about rebalancing needs because it depends on users' preferences. In New York City, the Bike Angels program contributes up to 30 % of the total bike rebalancing of the docked bike-share, which is considered successful (Vanderbilt, 2018). JUMP, one dock-less e-bike-share service operator, has also incentivized users to return a bike with a low battery charge to any designated spot (though this purpose is not for rebalancing the bike fleet). However, it is unknown what potential the incentive program has for rebalancing a dock-less e-bike-share system fleet.

1.3. Research Motivation

This dissertation aims to assess the potential effect of incentive-based approaches to rebalancing the fleet on the number of bike-share trips and environmental benefits in the context of a dock-less e-bike-share service. Because of the complex interaction between bike-share users and operators, I develop a framework to estimate a system-level VMT reduction and a series of models for a simulation environment. I also address the following research questions below:

- Who is more likely to walk to pick up a bike? (Chapter 2)
- What additional distance are users willing to walk to pick up or drop off a bike from their origins or destinations if rewarded? (Chapter 2)
- What factors influence the mode substitution of a dock-less e-bike share? (Chapter 3)
- What environmental benefit does a dock-less e-bike-share service produce? (Chapter 4)
- What do the trade-offs among types of incentive programs, budget size, and fleet size look like? (Chapter 5)

1.4. Research Structure and methods

In this dissertation, I develop a framework to estimate a system-level VMT reduction from a dock-less e-bike-share service and a simulation environment for the service. Using the framework and the simulation environment, I evaluate the potential effects of an incentive-based approach to rebalancing the fleet on the acceptance rate of bike-share requests and a system-level

VMT reduction (Figure 1.1.). This dissertation consists of four studies. The first three studies answer sub-research questions and produce outputs to be a part of the simulation environment and the VMT reduction framework. In the fourth study, I use all works from the three studies and conduct a scenario analysis to evaluate the effectiveness of an incentive-based approach in the context of a dock-less e-bike-share service.

Chapter 2 examines bike-share users' willingness-to-walk to pick up or drop off a bike at some distance from their origins or destinations if rewarded and identifies characteristics influencing willingness-to-walk. I conduct a survey with conjoint questions targeting dock-less e-bike-share users in the Sacramento region. I estimate a Bayesian multinomial logit model to understand willingness-to-walk for incentives. Findings from this analysis give operators and policy makers insights into the potential effectiveness of incentives as a strategy for spatially rebalancing the bike fleets. The models developed here will be incorporated into the simulator as a user behavior model in the user behavior component to determine the best choice based on the likelihood of using a bike-share service and what pick-up and drop-off location to choose.

Chapter 3 examines factors influencing mode substitution of a dock-less e-bike share. I use data from a two-wave longitudinal survey of Sacramento-area dock-less e-bike share users in 2018 and 2019 (Fitch et at., 2020). I estimate Bayesian multinomial logit models for commuting and non-commuting trips to identify factors associated with substituted modes. The factors include trip attributes, land use characteristics, mode availability, individual characteristics, and attitudinal variables. Findings provide a basis for developing promotional and operational strategies and policies that enhance the beneficial outcomes of bike-share. The models developed here predict the substituted mode for specific bike-share trips in a part of the VMT reduction framework.

Chapter 4 develops a framework to estimate vehicle miles reduced from the introduction of bike-share service. I use system-level data on dock-less e-bike-share trips for the Sacramento region web-scraped from an open-source data format for sharing information about bike-share availability and locations and bike-share user survey data. The methodologies developed here are themselves a useful product of this work with the potential to be applied in other regions to assess the impact of their specific systems. This framework plays a role in estimating system-level VMT reduction in the simulator.

Chapter 5 evaluates how an incentive-based approach helps reduce the spatial mismatch between demand and supply and increase VMT reduction from the service in the context of a dock-less e-bike-share service. I develop a simulator using an agent-based model as explained above. Running various scenarios with varying fleet sizes and incentive budgets, I provide insights into the potential of an incentive approach to increase the operation's efficiency and the benefits of VMT reduction.

Chapter 6 concludes this dissertation by summarizing previous chapter findings and discussing future research.

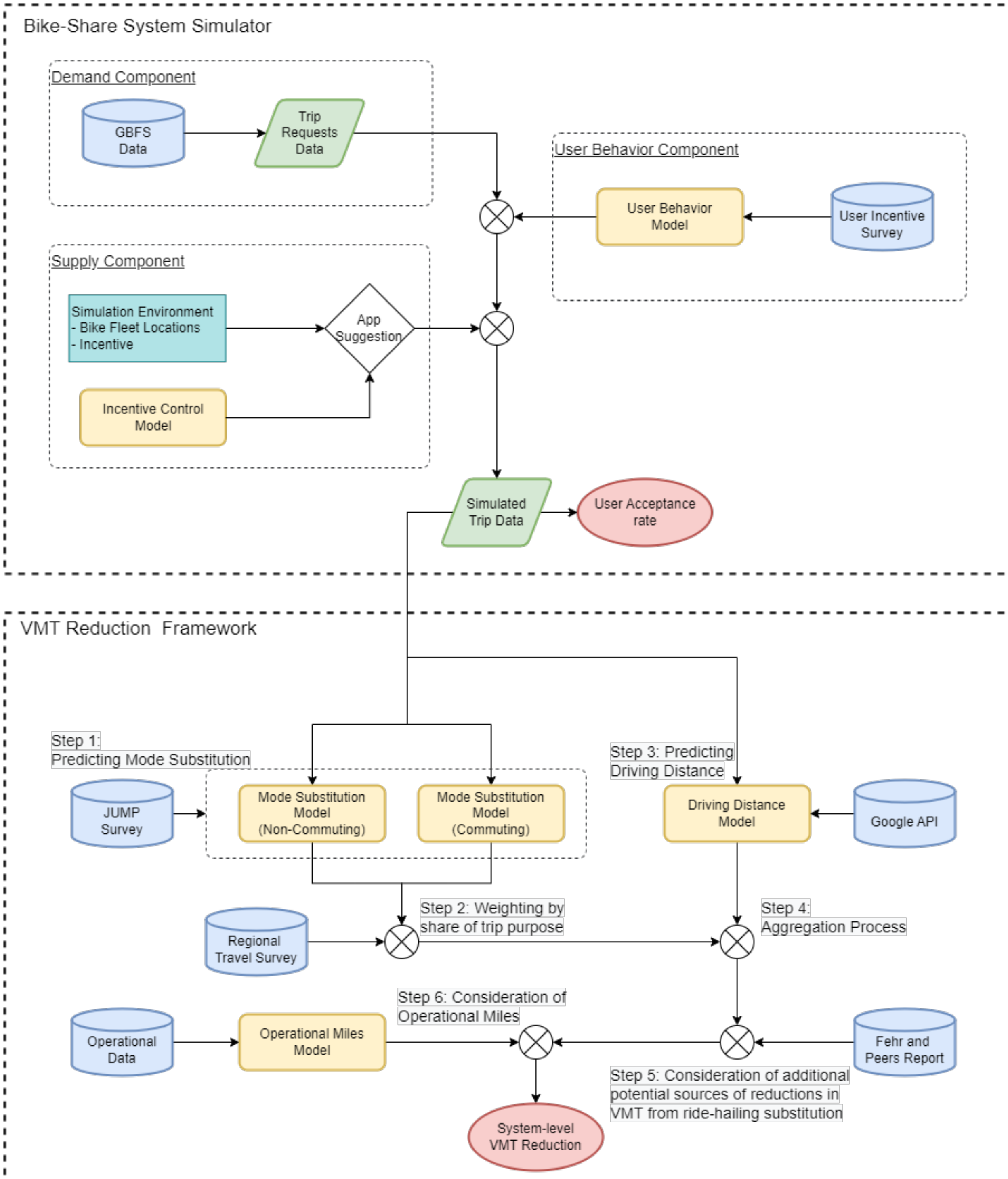


Figure 1. 1 Research and Simulation Structure

References

Barnes, F., 2019. A Scoot, Skip, and a JUMP Away: Learning from Shared Micromobility Systems in San Francisco. https://doi.org/doi:10.17610/T6QP40

Chen, Y., Zhang, Y., Coffman, DM, & Mi, Z. 2022. An environmental benefit analysis of bike sharing in New York City, Cities, 121, 103475, https://doi.org/10.1016/j.cities.2021.103475.

Fishman, E., Washington, S., & Haworth, N., 2014. Bike share's impact on car use: Evidence from the United States, Great Britain, and Australia, Transportation Research Part D: Transport and Environment, 31, 13-20, https://doi.org/10.1016/j.trd.2014.05.013.

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. https://doi.org/10.7922/G2F18X0W

Kou, Z., Wang, X., Fung, S. & Hua Cai, C. 2020, Quantifying greenhouse gas emissions reduction from bike share systems: a model considering real-world trips and transportation mode choice patterns, Resources, Conservation and Recycling, 153, 104534, https://doi.org/10.1016/j.resconrec.2019.104534.

Lee, A. 2020. Results of the 2019-20 Campus Travel Survey. UC Davis: Institute of Transportation Studies. https://escholarship.org/uc/item/9929r4j1

NACTO, 2019. Shared Micromobility in the U.S.: 2018. https://nacto.org/shared-micromobility-2018 (accessed 3.20.21).

NACTO, 2020. Shared Micromobility in the U.S.: 2018. https://nacto.org/shared-micromobility-2019 (accessed 2.5.21).

Pfrommer J., J. Warrington, G. Schildbach and M. Morari. 2014 Dynamic Vehicle Redistribution and Online Price Incentives in Shared Mobility Systems, IEEE Transactions on Intelligent Transportation Systems, 15(4), 1567-1578. https://doi.org/10.1109/TITS.2014.2303986

Pedestrian and Bicycle Information Center and FHWA. 2010. The national walking and bicycling study: 15-year status report. http://www.pedbikeinfo.org/cms/downloads/15-year_report.pdf Accessed June 25, 2019

Reck, D. J., Martin, H, & Axhausen, K. W. 2022. Mode choice, substitution patterns and environmental impacts of shared and personal micro-mobility, Transportation Research Part D: Transport and Environment, 102, 103134, https://doi.org/10.1016/j.trd.2021.103134.

Saltykova, K., Ma, X., Yao, L., & Kong, H. 2022. Environmental impact assessment of bike-sharing considering the modal shift from public transit, Transportation Research Part D: Transport and Environment, 105, 103238, https://doi.org/10.1016/j.trd.2022.103238.

SFMTA, 2022, Monthly E-scooter Operations Reporting

Shaheen, S., Guzman, S., Zhang, H., 2010. Bikesharing in Europe, the Americas, and Asia. Transp. Res. Rec. 159–167. https://doi.org/10.3141/2143-20

U.S. Department of Transportation, 2018. 2017 National Household Travel Survey.

Vanderbilt, T. 2018 The Angel Who Keeps Citi Bike Working for New York., Outside, 8 7 https://www.outsideonline.com/2332671/purest-form-bike-angel, Accessed April, 10, 2021

Zhang, M., & Mi, Z., 2018. Environmental benefits of bike sharing: A big data-based analysis, Applied Energy, 220, 296-301, https://doi.org/10.1016/j.apenergy.2018.03.101.

2 Can an Incentive-Based Approach to Rebalancing a Dock-less Bike-share System Work? Evidence from Sacramento, California[1]

2.1. Introduction

Bike-share services, a type of micromobility service, produce many types of benefits – environmental, physical, and social – by promoting a modal shift from driving to bicycling (Wang & Zhou, 2017; Shaheen et al., 2010). Substituting bike-share trips for car trips reduces vehicle miles traveled (VMT) and related greenhouse emissions (Fukushige et al., 2021; Fishman et al., 2014; Shaheen et al., 2010). This substitution also increases users' physical activity, thereby helping to reduce the risk of chronicle disease and type II diabetes (Otero et al., 2018; Qiu and He, 2018; Ricci, 2015). Bike-share services also help to narrow the gap in the accessibility provided by the transportation system between lower-income and higher-income populations (Gauthier et al., 2014; DeMaio, 2009).

Bike-share use will be lower – and the system will then produce more limited benefits – if users cannot find bikes where and when they need them. Bike-share operators face a major challenge in avoiding a spatial mismatch between demand and supply. This challenge may be more serious in dock-less bike share systems compared to docked systems because drop-off locations are not designated. For example, the UC Davis Campus Travel Survey in 2019/20 found that 70% of respondents who had used the dock-less e-bike-share service in Davis, California, had at least once not been able to find an available bike nearby when they wanted it (Lee, 2020). Fifty percent of the demand in Davis went unsatisfied, according to the survey results. The issue stems mainly from an unbalanced distribution of the bike fleet over the day

[1] This chapter is based on my published work: Fukushige, T., Fitch, D.T. and Handy, S., 2022. Can an Incentive-Based approach to rebalancing a Dock-less Bike-share system Work? Evidence from Sacramento, California. Transportation Research Part A: Policy and Practice, 163, 181-194. https://doi.org/10.1016/j.tra.2022.07.011

combined with the limited size of the fleet. If users cannot reliably find a bike, they are less likely to consider bike-share for their mode choice, and this will lead to less bike share use overall, less profit for the operator, and less benefit for the community. For these reasons, operators need a well-designed strategy to address the spatial mismatch to increase bike-share use, and policy makers need to know what requirements to impose on operators to maximize the benefits to the community.

Rebalancing the bike fleet by van is one common strategy to fix the mismatch. This strategy can keep bike use from falling below acceptable levels but will often be a dominant component of the total operating costs (Pfrommer et al., 2014). Because operational resources are limited, operators often need to prioritize the areas to be rebalanced. The more vans operators use to meet the demand, the more VMT the system produces, offsetting the VMT reduction benefit that was at least a part of the motivation for the city to authorize the service. One study found that vehicle miles associated with the operation of bike-share services could exceed VMT reduction from the system depending on the rate at which bike-share use substitutes for car use driving (Fishman et al, 2014).

Another rebalancing strategy, one that has not garnered much attention so far but has been implemented in some bike-share systems, is user-based incentive rebalancing. In this approach, the operator incentivizes the user to walk farther to get a bike (origin-based incentive) or bring a bike to an undersupplied area (destination-based incentive) by offering a reward of some sort, such as free bike use or a small gift of some sort. This strategy does not produce additional vehicle-related emissions. In New York City, the Bike Angels program contributes up to 30% of total bike rebalancing needs for the docked bike-share system, a level considered successful (Vanderbilt, 2018). JUMP, one of the early dock-less e-bike-share service operators, has also incentivized users to return a bike with a low battery charge to any of the designated spots where it could be recharged, though the purpose of this incentive was more about facilitating recharging than rebalancing the bike fleet. These practices show that some users will walk farther to get a reward. However, it is unclear how much farther users are willing to walk if rewarded.

Few researchers have directly addressed users' walking distance in the context of bike-share service let alone the effect of incentives on their behavior. The findings of Singla and other researchers (2015) show that 50% of docked bike-share users are willing to walk up to 500 meters to access the service, and 80% of users are interested in incentive programs. Another survey conducted in Seoul by Ban and Hyun (2019) shows that about half of docked bike-share users will walk an additional 1000 meters for incentives of 1509.5KRW, approximately US$1.30, in the context of docked-bike share service. These studies assumed that willingness to walk for origin- and destination-incentives are the same. Wang and Wang (2021) examined the difference of users' attitudes toward the two different types of incentives by recruiting through a large crowdsourcing platform in China, but did not look at the relationship between walking distance and an amount of incentive. Kabra et al. (2018) used another approach to estimate the effect of the accessibility of a docked bike-share service on ridership by using a structural demand model with historical trip data in Paris. They found that increasing the walking distance from a station decreases a user's likelihood of using a bike by 0.194% per meter between 0 and 300 meters. This means that users at a location 300 meters (equivalent to approximately 4 minutes) from the station are about 60% less likely to use the service than those close to the station. The effect of distance on the likelihood of using a bike is even more significant for more than 300 meters. The relationship between walking distance and an incentive amount in prior studies has been examined in the context of docked bike-share services with conventional bikes, but whether the findings apply to the context of dock-less bike-share services with e-bikes is unknown.

Rather than looking at individual preferences, a substantial number of prior studies focus on the optimal location of bike stations in docked bike-share systems to maximize bike-share trips (Mix et al., 2022; Chen et al., 2020; Çelebi et al., 2018; Frade & Ribeiro, 2015; O'Mahony & Shmoys, 2015; Garcia-Palomarces et al., 2012). For example, Mix and his colleagues (2022) estimated bike-share demand based on built environment and accessibility variables and determined optimal locations of bike stations to maximize the coverage of the demand. Çelebi et al. (2018) proposed a new method for bike-share service system design considering station capacity and location while Chen et al. (2019) focused on e-bike-share stations. The large number of such studies can be explained by the relatively long history of docked bike-share systems, starting from 1995 in Copenhagen (Shaheen et al., 2010), and to the significant investment required to install docks. The optimal location of dock-less bike-share bikes is a more recent concern. In the absence of docks, some cities are designating parking areas for bikes. Recent work aims to identify and optimize geo-fenced parking space for a dock-less bike-share service (Zhao and Ong, 2021; Sun et al., 2019). These optimal-location studies provide indirect evidence of the willingness of users to walk to access a bike.

Prior studies have also developed bike-share user behavior models to examine whether incentive offers are an effective rebalancing strategy (Duan and Wu, 2019; Pan et al., 2019; Patel et al., 2019; Singla et al., 2015; Pfrommer et al., 2014). Singla and other researchers (2015) considered two factors: maximum distance users are willing to walk to another station and value of time in their user behavior model. They assume that the two parameters are independent; users walk to an alternative bike station only if an alternative station is within the maximum walking distance and the incentive offer is more than the value of time. Patel et al. (2019) incorporated into their model the waiting time at the bike station in the case when the bike was not yet available. Taking another approach, Pfrommer et al. (2014) used the value of time as a parameter in their user model. All these researchers have relied on a rule-based model based on survey data rather than developing a discrete choice model. These prior models have not distinguished between users' preference for origin- and destination-based incentives, while insights into differences in preferences by sociodemographic characteristics, for example, by gender and age, are limited.

This study examines bike-share users’ willingness-to-walk to pick up a bike or drop off a bike at some distance from their origins or destinations if rewarded and identifies characteristics influencing willingness-to-walk. I use data from a survey of dock-less e-bike-share users conducted in the Sacramento region and estimate a Bayesian multinomial logit model to understand willingness-to-walk for incentives. My results give operators and policy makers insights into the potential effectiveness of incentives as a strategy for spatially rebalancing the bike fleets. The models I present here can also be used in simulation models, such as agent-based modeling, to understand the interaction between user behavior and operational strategy (Duan and Wu, 2019; Pan et al., 2019). This integration will produce more realistic, robust, and reliable estimates of the benefits of bike-share service.

2.2. Methodology

2.2.1 Survey Design

2.2.1.1 Overview

I implemented an online survey in June and July 2021 to examine users' behavior in the e-bike share system and their preferences in a system for rewarding users for walking farther to get a bike or dropping off a bike farther from the destination. I targeted dock-less e-bike share users in the Sacramento region for the survey.

JUMP operated a dock-less e-bike share system between May 2018 and March 2020 across three California cities: Sacramento, West Sacramento, and Davis. The service area of approximately 50 square miles was not all contiguous, as Davis was separated from the rest. Although the service was dock-less, JUMP had installed bike-hub stations within its service boundaries to provide a place for locating bikes for operational purposes, including rebalancing and maintenance. JUMP also utilized the stations for returning a bike with a low battery charge by offering users a reward. Users were also incentivized to take a bike parked outside the service boundary and return it inside the boundary. The service was closed due to the emergence of COVID-19, but was relaunched in August 2021 by a new operator, Lime.

In the survey, I asked hypothetical questions about what bike locations, defined by walking time, they would choose if incentives of different types and amounts were offered (as described below). Other questions included general bike-share use behavior, previous bike-share experience in the Sacramento region, bike-share use during and post COVID-19, reward-related questions, socio-demographics, and travel attitudes.

I emailed the subset of 231 people who participated in prior surveys (Fitch et al., 2020; Fitch et al., 2021) and indicated that they were willing to answer follow-up questions. I sent several reminders to those who had not yet responded. This approach yielded 107 complete surveys. I also asked contacts in local organizations, including the Sacramento Area Council of Governments (SACOG), the City of Davis, and the City of West Sacramento, to share the survey link through their channels. Through this method, I received 46 additional responses. After the data cleaning process, I identified 143 valid responses, including 128 respondents who were interested in the incentive program and 15 responses who were not, for a conjoint analysis.

2.2.1.2. Conjoint Analysis

I used a conjoint analysis approach to examine willingness-to-walk for incentives along with the influence of individual characteristics and attitudes on shared-bike location selection. Conjoint analysis is a widely-used survey-based technique, especially in market research (Green and Srinivasan, 1978; Luce and Tukey, 1964), to understand how each attribute of a choice influences decision-making. I provided a context for the conjoint questions, given that the respondent's interest in incentives might depend on the context, in the following way: *Imagine you are taking a 15-minute ride to get to a specific destination (such as work or a store). You open the bike-share app, and the app suggests the nearest bike without a reward as well as bikes farther away with rewards of different amounts. The bikes with rewards usually require additional walking at your origin or/and at your destination location compared to the nearest bike. If you don't like any of the options, please choose "none."* I specified non-recreational trips because participants are more likely to consider the trade-off between incentives and walking time for such trips. Another reason to limit the survey to non-recreational trips is to minimize the workload of participants. Because of the closure of the prior bike-share service (during the time I conducted the survey) and COVID-19 circumstances preventing me from conducting an intercept survey, I expected to have few participants, requiring me to give them many scenarios to consider and take steps to reduce the likelihood of incomplete answers. I set a riding time of

15 minutes as a typical travel time given that the average travel time by dock-less bike-share is about 13 minutes (NACTO, 2019).

Please carefully review the options for this trip.

	Bike A	Bike B	Bike C	Bike D	None
Walking Time (Origin to bike location)	6 min	12 min	6 min	12 min	I wouldn't use bike-share for this trip
Riding a bike	15 min				
Walking Time (Return location to destination)	0 min	0 min	10 min	10 min	
Total Reward	$0	$1.50	$0.75	$2.25	

Figure 2.1 Screenshot of choice question in the survey

I offered five alternatives in each conjoint question (Figure 2.1): (1) a bike without any reward (Bike A), (2) a bike with a reward for an additional walking time at their origin (Bike B), (3) a bike with a reward for an additional walking time at their destination (Bike C), (4) a bike with a reward for an additional walking time at both their origin and destination (Bike D) and (5) a no bike-share(BS) option (None). I included "None, I wouldn't use bike-share for this trip" as a fifth option because adding this alternative enables me to examine the relationship between walking time at their origin coupled with an amount of reward and the decision to use bike-share service for that trip.

I included three types of attributes in the questions: walking time from their origin to a bike location, walking time from the drop-off location to their destination, and the total amount of reward. I did not include other trip attributes, such as use cost and trip distance in order to keep my model simple and focus on the effect of walking time and the reward amount on the bike location selection. I set three levels [2, 6, 10 minutes] for walking time from origin to bike location as a reference for alternatives with no incentive except for "None." I set three levels [4, 8, 12 minutes] for incentivized alternatives. I limited total walking time for incentivized alternatives to 12 minutes as an upper bound because most users are less likely to choose an alternative with more than 12 minutes of walking time from origin to bike location as found in prior studies (Fitch et al., 2020). I set four levels [0, 2, 6, 10 minutes] for walking time from the drop-off point to their destination. I also set three levels [US$0, US$0.75, US$1.5] for an amount of incentive for walking time from origin to bike location and drop-off point to their destination, respectively. I showed walking time at origin and destination separately but summed up both rewards for origin and destination (Figure 2.1).

I used an experimental design technique called fractional factorial design to develop shared-bike location choice alternatives in each scenario presented to the respondents (George et al., 2005). One advantage of this technique is that it enables an efficient analysis of the relationship among attributes, a quality that fits my circumstances well as I expected to have a limited sample size. I applied the fractional factorial designs to all possible combinations but with a fixed walking time for Bike A, a bike without any incentive, and set three scenarios as a block size using D-criterion. I did so to ensure that I could capture the preference for different levels of walking time from each individual, as I explain later. In this process, I obtained 12 different blocks for a 2-minute walking time (Category A), eight blocks for a 6-minute walking time (Category B), and four blocks for a 10-minute walking time (Category C), respectively. I ensured that no dominant alternative existed in the choice sets because such an alternative does not provide me with any additional information.

The problem of including a no-BS alternative is that my collected data may have a substantial number of responses choosing the no-BS alternative, presenting difficulties for my modeling process as a no-BS alternative gives me less information about preferences. I expected to have a limited sample size in this survey, thus I needed to avoid obtaining several responses with a no-BS choice from any one individual. To reduce the risk of having a substantial number of responses with the no-BS alternative, I adapted scenarios for participants based on their preference for walking time to get a bike as indicated in their answer to the following question: *How long would you be willing to walk to pick up a bike-share bike… For a trip to a specific destination such as work or a store?* I asked three blocks of scenarios, totaling nine scenarios, for those interested in incentive programs. In the first group, I preset five blocks of Category B and randomly chose one of them for each participant. I asked about scenarios in this category without any conditions because a prior study found that most users are willing to walk 5 minutes or more (Fitch et al., 2020). Next, I preset nine blocks of Category A and randomly chose one in the same way. In the last group, I preset the rest of the blocks of Category A and B that I did not preset in the previous groups and randomly chose one for those who answered that they are willing to walk up to 2 minutes to get a bike. I did not include any block of Category C here because respondents are highly likely to choose a no-BS alternative in these scenarios. For those who answered "Up to 5 minutes," I drew one of the rest of the blocks of Category B and C. I included blocks of Category C because they might choose an option with incentives. For the rest of the participants willing to walk up to 10 minutes or more, I drew one block of Category C randomly.

2.2.1.3. Sample Size Validation

I validated the minimum sample size based on the Sawtooth Guideline (Johnson and Orme, 2003) as other similar studies have used this metric as a criterion (Olitsky et al., 2017; Van

Cauwenberg et al., 2016; Rose and Bliemer, 2013). The guideline says that the minimum sample size should be as follows:

$$n \geq \frac{500 * c}{q * a}$$

where q is the number of questions shown to each respondent, a is the number of alternatives per question excluding the "No choice" option, and c is the maximum number of levels of any attribute. In my conjoint analysis setting, I asked nine questions for each respondent interested in the incentive system. I gave four different bike options and the "No-BS" option, and the maximum number of levels is four. Following the guideline, my minimum sample size should be 56. I recruited128 participants interested in the incentive program who answered the series of conjoint questions. The number of observations collected from the conjoint survey was 1152.

2.2.1.4. Pseudo-Choice Questions from General Questions

One problem with my approach is that estimated models are biased to the preference of those interested in incentive programs because I did not present the conjoint questions to those not interested in incentives. To address this issue, I produced pseudo-choice scenarios, including only a bike without any incentive (Bike A) and a no-BS alternative, and pseudo-responses as a binary problem for all participants based on the general question about walking time to get a bike for non-recreational trips (I also collected responses for recreational trips, but did not use them for consistency with the conjoint questions; summary statistics are presented in Section 3.1). I assumed that I asked the participants five simple binary questions: (1) an alternative with 1-minute walking time vs. no-BS alternative, (2) an alternative with 3.5-minute walking time vs. no-BS alternative, (3) an alternative with 7.5-minute walking time vs. no-BS alternative, (4) an alternative with 12.5-minute walking time vs. no-BS alternative, (5) an alternative with 15-minute walking time vs. the no-BS alternative. For example, if participants answered that they are willing to walk up to 5 minutes to get a bike, I assumed that they chose a no-BS alternative in (3), (4), and (5), and a bike in (1) and (2).

I had 15 users not interested in incentive programs (with those interested totaling 143 users) in which I produced 715 samples from the pseudo-choice questions presented above. Adding pseudo-choice questions to the dataset from the conjoint questions, I had a total of 1867 observations for further analysis.

2.2.2. Shared-bike Choice Model

2.2.2.1. Variables

I model the shared-bike choices based on the conjoint experiment and pseudo-choice questions (i.e., the dependent variable is composed of the Bike A-D options described above, the set of which I denote as *J*). I call these *J* choices "shared-bike location selections" since they represent decisions about where to pick up and drop off a bike. *J* also includes the choice to not use a shared bike (no-BS alternative). The number of alternatives varies by type of data source. The number of alternatives is 5 when the data come from the conjoint experiment. The number of alternatives is 2 when the data come from the pseudo-choice questions. In this analysis I examined factors including individual characteristics and attitudinal variables that influence shared-bike location selection. Individual characteristics I explored included age, income, race, gender, student status, college degree, having children, membership, incentive interest, and car ownership (Table 2.1). Based on significance level, the effect on the model performance, and the correlation between variables, I retained membership, incentive interest, gender, and race in the final model.

Table 2. 1 Explored Variables with Summary Statistics for My New Survey and Previous Survey

Variable	n=143
Individual Characteristics	
Age	
- 24	6%
25-34	37%
35-44	27%
45-54	10%
55 -	19%
Woman	
Yes	40%
No	60%
Race	
Asian	15%
Hispanic/Latino	5%
White	66%
Other	14%
Employed (Commute to at least one workplace)	
Yes	87%
No	13%
Student (Full or part-time student)	
Yes	21%
No	79%
College Degree (Bachelor's degree or higher)	
Yes	87%
No	14%
Children (Under 16)	
Yes	13%
No	87%
Car Ownership (One or more car per person)	
Yes	90%
No	10%
Membership	
Yes	22%
No	78%
Incentive Interest	
Yes	90%
No	10%
Income	
Low (Under US$50,000)	20%
Middle (US$50,000 - US$125,000)	49%
High (Over US$125,000)	31%

I considered attitudinal variables and factors related to users' choices about their daily travel in the variable selections given that I used them in a previous study (Fukushige et al., 2021). The variables use an ordinal 5-point response scale (strongly disagree to strongly agree). I sum scores for statements in each of four attitudinal constructs (Table 2.2) – "Like bike," "Bike safe," "Bike pressure," and "Car necessity." I added other types of variables directly into the model to facilitate ease of interpretation. Factors asked in the survey include i) Concern for the environment, ii) Concern for cost, iii) Desire to get exercise, iv) Concern for safety from crime, v) Concern for safety from traffic, vi) Desire for enjoyment, vii) Concern for time, viii) Desire for convenience. In the end, I retained the "Concern for time" factor in the final model.

Table 2. 2 Attitude constructs and question statement

Variable	Question statement
Like bike	- Riding a bike is fun - Riding a bike is enjoyable - Riding a bike is boring* - Riding a bike is pleasant - I like riding a bicycle
Bike Safe	- I feel safe from cars when bicycling in town - I feel comfortable around cars when bicycling in town - I feel anxious around cars when bicycling in town* - I get stressed by cars when bicycling in town*
Bike Pressure	- Many people I know think bicycling is healthy - Many people I know think bicycling is fun - Many people I know think bicycling is safe - Many people I know think I should bicycle
Car necessity	- I need my car to do many of the things I like to do - I need my car to carry shopping or children - I try to limit my driving as much as possible*

* indicates that the ordered scale of the question statement is reversed.

2.2.2.2. Bayesian Multinomial Logit Model for Shared-Bike Location Selection

I used the Bayesian multinomial logistic regression model to understand users' shared-bike location selection and their willingness-to-walk for the incentive at the origin and/or destination. Bayesian techniques can add prior information (prior probabilities) into the model parameters to reduce model overfitting (Attias, 2000). The technique also enables fitting multilevel structures and accounting for individual variability more easily (Lee, 2011; van Ravemzwaaij, 2014).

I used five different trip attributes, including walking time at origin and destination, an amount of incentive at origin and destination, and an indicator for choice-option, as a base to develop a series of choice models. The "no-BS" option is a distinctive alternative as this option can be chosen for various reasons, violating the Independence of Irrelevant Alternative (IIA) property (Haaijer et al., 2001). Model estimates are biased by including the "no-BS" alternative as a reference alternative with the utility of zero as trip attributes of the option are not practically zeros. To reduce the violation of the IIA property, I added an alternative-specific dummy for bike-share options as suggested by Haaijer et al. (2001), which they called the "no-choice alternative."

I fit models using two different approaches: preference space and willingness-to-pay space. Models in the former space specify the distribution of coefficients of cost and time in the utility function first, then estimates of willingness-to-pay are calculated by dividing product parameters of cost by time. The problem with using this approach is that the estimate of willingness-to-pay may have an unreasonably large variance (Train and Weeks, 2005). Because the estimate is the ratio from two randomly generated values, having an extreme large or small value in the denominator (time) produces this issue. To avoid this issue, prior studies suggest estimating willingness-to-pay directly by reparametrizing the model (Train and Weeks, 2005; Sonnier et al., 2007). Because I can specify the distribution of the estimates in the function, I tend to have a more convenient and reasonable distribution (Train and Weeks, 2005). In this paper, I call the variable willingness-to-walk (WTW) rather than willingness-to-pay as a decision-maker views walking time for rebalancing a bike as a cost. The utility functions as a base model for each space are as follows:

Preference Space

$$U_j = \beta_{WTO} * WTO_j + \beta_{WTD} * WTD_j + \beta_{INCO} * INCO_j + \beta_{INCD} * INCD_j + \beta_{BS} * I_j$$

Willingness-to-walk (WTW) Space

$$U_j = \beta_{WTO} * \left(WTO_j + \beta_{WTWO} * INCO_j\right) + \beta_{WTD} * \left(WTD_j + \beta_{WTWD} * INCD_j\right) + \beta_{BS} * I_j$$

where

U_j	Utility for alternatives by j
β	Coefficient
I_j	An indicator for BS-option for alternatives by j: {1: BS-option, 0: no-BS option}
WTO_j	Walking time at origin for alternatives by j
WTD_j	Walking time at destination for alternatives by j
$INCO_j$	Origin-based incentive for alternatives by j
$INCD_j$	Destination-based incentive for alternatives by j
$WTWO_j$	Willingness-to-walk for origin-based incentive for alternatives by j
$WTWD_j$	Willingness-to-walk for destination-based incentive for alternatives by j

I developed four different models in both the preference and willingness-to-walk spaces. The first model, a base model defined above, is a simple multinomial logit model with trip attributes (Model 1). For Model 2, I added uncorrelated varying effects by person and experiment into Model 1 to account for person-level and experiment-level heterogeneity. One problem with applying varying slope to all trip attributes in WTW space is instability in the models (Revelt and Train, 2000; Ruud, 1996). To avoid instability of estimates, I set coefficients of walking time at origin and destination as a fixed effect. To consider the correlation between varying effects, I also fit a multilevel multinomial logit model with correlated varying effects by person and experiment (Model 3). Finally, to understand the effect of different groups (i.e., gender and race), I added person-level predictors with trip attributes to Model 3 to get Model 4. I used leave-one-out cross-validation with expected log pointwise predictive density (elpd-loo) to measure the improvement of each model compared to simpler models. I report estimates of WTW space in the main body and of the preference space in the appendix 2A.

I used the R package RStan using a probabilistic programming language Stan to fit Bayesian models (Stan Development Team, 2018). I used the default Markov chain Monte Carlo (MCMC) simulation method in Stan, drawing random samples from the posterior, to converge the estimator (R-hat < 1.01). Parameters I used include 4 Markov chains, 4000 iterations for each chain (2000 for warmup that I discarded), tuning parameters 0.9 for adapt_delta and 16 for max_tree_depth. I also ensured that the estimation was completed without Stan's diagnostic warnings.

One essential step in Bayesian modeling is to determine an appropriate prior, thereby balancing model under-fitting and over-fitting. Because of a lack of sufficient information on subjective prior beliefs, I ran a series of "prior predictive checks" to find reasonable priors for my models simulating my collected data. The priors derived from this process, called "weakly informative," can constrain parameters softly to reduce potential over-fitting to the data

(McElreath, 2020). I used normal distribution with a mean of 0.0 and standard deviation of 2.0 for all parameters, except for a Cholesky factor with an LKJ correlation matrix density of 3.0.

2.2.3. Limitations

The data in my analysis have several limitations. First, my sampling method may not have produced a representative sample. Without a census or official summary statistics of bike-share users in the Sacramento region, I lack the ability to understand how my sample might be biased as discussed in a prior study comparing characteristics of the respondents of a bike-share user survey to a household-based survey in the examination of the impacts of the bike-share system (Fitch et al., 2020).

My conjoint questions did not consider other trip attributes, such as walking direction toward a destination, bike-share use cost, and trip context. For example, walking direction might also influence decision making. If the bike's direction is opposite to the direction of the destination, users might be less likely to walk to get a bike given that total travel time and cost increase. However, I found only a slight difference in total travel time by walking direction in some cases. If the walking time is 6 minutes (approx. 480 meters with 80 meters/min on foot) and the distance between trip start and end is 3000 meters (equivalent to 12 minutes with 250 meters/min by bike), the difference between walking toward versus away from the destination is three to four minutes. The smaller the waking time is, the smaller the difference is. I decided not to include this factor to avoid confusion for the respondents and add to the response burden. Travel cost also influences mode choice. Membership holders may behave differently from those who are not members because the former group has a different pricing mechanism with an hour of free access per day (if it is the first use in a day). In addition, whether users reserve a bike on the app ahead of time influences bike-share use cost. Adding these factors would increase the minimum sample size and complicate the analysis given that I expected a small sample size. For these reasons, I kept my questions as simple as possible to understand the trade-off between walking time and inventive influence on bike selection.

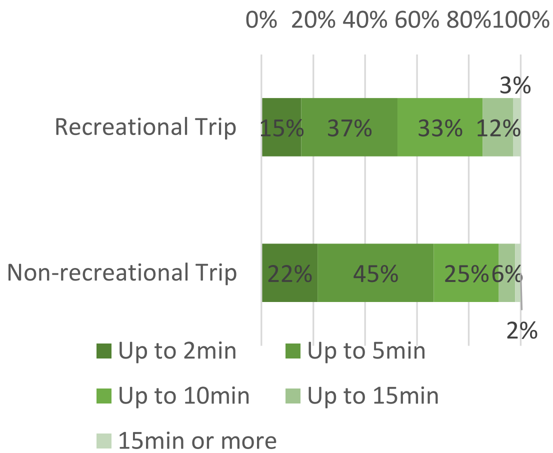
My results may be applicable only to e-bike-share systems. Conventional bike-share systems and e-bike-share systems attract users in different ways as found in a prior study (Campbell et al, 2016). If e-bikes are more attractive and used for longer trips, for example, because of their higher speed and greater comfort, my results might overestimate willingness-to-walk for conventional bike-share systems. Further studies about the difference in willingness-to-walk to get a bike in conventional bike-share system and e-bike share system are needed.

2.3. Results & Discussion

2.3.1. Willingness-to-walk to get a bike and their interest in incentive programs from survey data

My results from general questions about walking time to get a bike show that bike-share users are more willing to walk to get a bike for recreational trips than non-recreational trips (Figure 2.2). This result is intuitive since people are generally less time-constrained when making recreational trips than destination-oriented ones. For recreational trips, 85% of survey participants were willing to walk more than 2 minutes, compared to 78% of participants for non-recreational trips. For recreational trips, half of survey participants were willing to walk more than 5 minutes compared to 33% for non-recreational trips. Bike-share users rarely say they would walk more than 10 minutes to get a bike for either type of trip.

Figure 2.2 also shows that more than 80 % of users would consider both origin- and destination-based incentive offers though they are slightly more favorable toward origin-based incentives, the opposite of findings in a prior study (Wang & Wang, 2021).



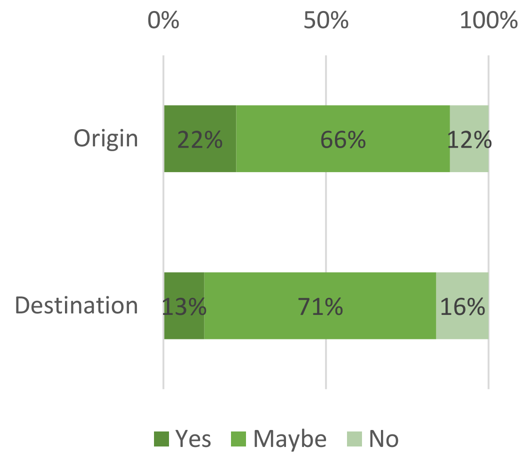


Figure 2. 2 Walking distance at which users are willing to walk to get a bike (left) and interest in incentive offers (right) (n=143)

2.3.2. Willingness-to-walk farther to get a bike for any incentive

2.3.2.1. Model Estimation

Comparisons of all models in the WTW space (Table 2.3) indicate that adding varying effects by person and experiment improves the model performance. This suggests that users' choices vary by personal preference and experimental context. Adding correlated slopes also improved the model performance, but the effect is limited with less than one standard error difference in my objective function (elpd_loo) between Model 2 and 3. I expected that individual characteristics could help explain the decision-making, but adding person-level predictors did not improve model performance, so I discuss the results based on Model 3 in considering the need for further analysis. I used results of Model 4 to explain the effects of individual characteristics and attitudes on the willingness-to-walk.

Table 2. 3 Comparison of Model Estimation in Willingness-to-Walk Space

	Model 1	Model 2	Model 3	Model 4
Walking Time (Origin) (Unit: min)	-0.43 (0.02)	-0.57 (0.04)	-0.56 (0.04)	-0.55 (0.04)
Walking Time (Destination) (Unit: min)	-0.29 (0.02)	-0.42 (0.05)	-0.42 (0.05)	-0.41 (0.05)
WTW (Origin) (Unit: min/US$)	-3.77 (0.14)	-3.89 (0.29)	-3.81 (0.31)	-2.81 (0.75)
WTW (Destination) (Unit: min/US$)	-4.34 (0.20)	-4.33 (0.53)	-4.21 (0.53)	-3.01 (1.07)
Indicator for BS-option	3.24 (0.15)	4.95 (0.53)	4.96 (0.38)	4.69 (0.79)
WTW (Origin)				
Membership				-0.05 (0.62)
Women				-1.30 (0.53)
White				-1.31 (0.54)
Concern for time				0.50 (0.84)
WTW (Destination)				
Membership				-0.72 (0.96)
Women				-1.27 (0.84)
White				-0.73 (0.85)
Concern for time				-0.13 (1.20)
BS-option				
Membership				0.67 (0.46)
Women				0.44 (0.40)
White				0.51 (0.38)
Concern for time				-0.56 (0.69)
Those interested in incentive				0.04 (0.58)
elpd_loo	-1748.5 (35.0)	-1409.4 (37.1)	-1399.2 (37.0)	-1399.6 (37.1)

*The parentheses represent posterior standard deviations.

The ratio of the estimate of the dummy for choice-option to the coefficient for walking time at origin shows that half of the respondents uses bike-share when only a bike without any reward is offered. Model 3 in Table 2.3 shows that half of users would use the service if a bike is located 8.9-minutes away.

Results for the willingness-to-walk models show that users are willing to walk 3.8 more minutes than the mean distance to get a bike at the origin for a one-dollar incentive (Table 2.3). Mean estimates of willingness-to-walk for an incentive at the destination show higher values than at the origin, 4.2 minutes for a dollar. This suggests that people are more willing to walk at their destination than at their origin. This is contrary to the result for the general questions about walking time to get a bike (see Figure 2.2), but partially supports findings in a prior study (Wang

& Wang, 2021). One possible explanation is that because the default walk distance at the destination is zero (since users can generally park the bike right at their destination), they are more willing to add addition time at this end of the trip than at the origin, where they are likely to already have to walk for some minutes.

My results show that the willingness-to-walk for an incentive and acceptable walking time varies by individual characteristics and attitudes. For example, those concerned about travel time are less willing to walk farther at origin if rewarded. On the other hand, women and whites are more willing to walk farther at origin or destination if any rewards are offered. The results suggest that operators are more likely to succeed with such incentive programs in areas where a substantial share of users are in these groups. Membership holders also have a higher willingness-to-walk for incentive at destination, but the variance is considerable. Some types of individuals, including membership holders, women, and whites, are willing to walk about 1 minute longer than the rest of users belonging to none of these groups. Those who are interested in incentive shows estimates of nearly zero.

2.3.2.2. Simulation Analysis

I conducted a simulation analysis to understand the effect of incentive offers on users' behavior in the context of a dock-less bike-share service. I examined three different scenarios: (1) a case with only one bike option either with or without an incentive, (2) a case with one bike without any incentive (Bike A), and another bike with an origin-based incentive (Bike B), and (3) a case with one bike without any incentive (Bike A) and another bike with a destination-based incentive (Bike C). For (2) and (3), I fixed the walking time of Bike A at 3 minutes and an amount of incentive for Bike B and Bike C at US$0.75. I used US$0.75 based on the fact that JUMP bike-share service in the Sacramento region offered US$0.25 Uber cash for returning a bike with a low battery to designated bike stations. The estimate in one study that docked bike-share service in Denver cost about US$1.00 of operating payroll per trip (Andersen, 2016) suggests that the operator might be willing to pay this amount at maximum as an incentive because rebalancing operations are often a dominant component of the total operating costs (Andersen, 2016; Pfrommer et al., 2014). In this simulation, I used Model 3 to find the probability of choosing an alternative because the result can represent the average preference of all participants, rather than specific groups, and because Model 4 did not improve out-of-sample prediction.

What is the probability that users accept any of offers in different contexts? In the one-bike case, Figure 2.3 shows that a user has a 90% probability of being willing to walk up to 5 minutes to get a bike without any reward if no bike with an incentive is offered; half of the users remain willing to walk for a bike if the nearest bike is within 8 minutes. The findings also indicates that an origin-based incentive with US$0.75 increases the likelihood of walking to get a bike about 2.5 times more than no incentive offer when the nearest bike is about 11 minutes away.

In the two-bike case, shown in Figure 2.4, more than half of users would choose a bike with an incentive of US$0.75 if the walking time is less than 6 minutes and the nearest bike without incentive is 3 minutes away. The farther the incentivized bike is, the less likely users will choose the bike, going close to zero probability at 15 minutes. That the probability of choosing the no-BS alternative decreases from 3.7% at 15 minutes to 1.0% at 4 minutes indicates that offering incentive programs would increase the number of bike-share trips. The dominant choice changes at about 3 minutes from Bike C to Bike A, suggesting that 3-minutes additional walking time is acceptable for roughly a half of users if a US$0.75 reward is offered.

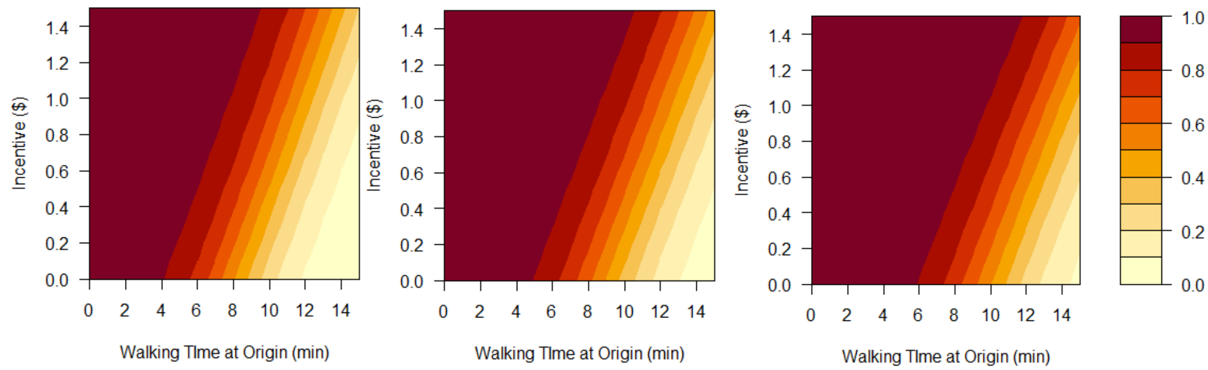


Figure 2. 3 Contour plot showing the probability that users accept an offer when only one bike option is available (left: lower bound of prediction intervals with 5%, middle: mean of prediction intervals, right: upper bound of prediction intervals with 95%).

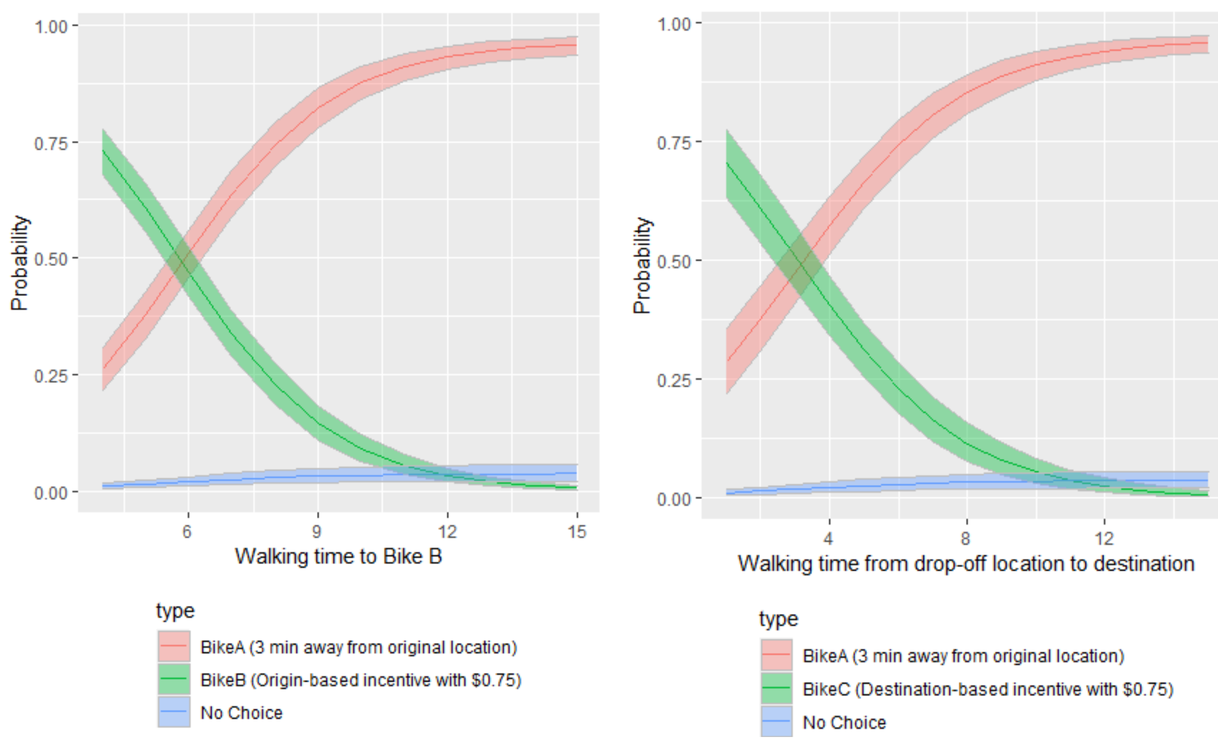


Figure 2. 4 Acceptance rate for a different shared-bike option over walking time (left) and Acceptance rate for a different shared-bike option over walking time from drop-off location to destination (right)

2.3.3. Implication in collaborative incentive program with other entities

My survey shows that bike-share users tend to be interested in free or discounted bike-share rides compared to other types of rewards (Figure 2.5). Fifty-nine percent of participants are moderately, very, or extremely interested in a coupons or gift card for businesses, such as fast food and restaurant while 49% of them are interested in a coupon or gift card for the operator's other transportation service, such as Uber cash. Discount for public transit fare was unpopular as a reward for walking farther to get a bike. I did not examine the reason for the disinterest in a transit incentive in my survey. It might result from a lack of transit service around their living places, or no reasonable connection between their home location and major destinations. Possibly, participants do not use or like to use public transit. Given that the connection between public transit and micromobility service is an important question, further exploration of this finding is needed. My finding that more than 90% of participants are slightly or not interested in points for small goods, such as key chains, also suggests that this is a less effective reward for walking farther to get a bike.

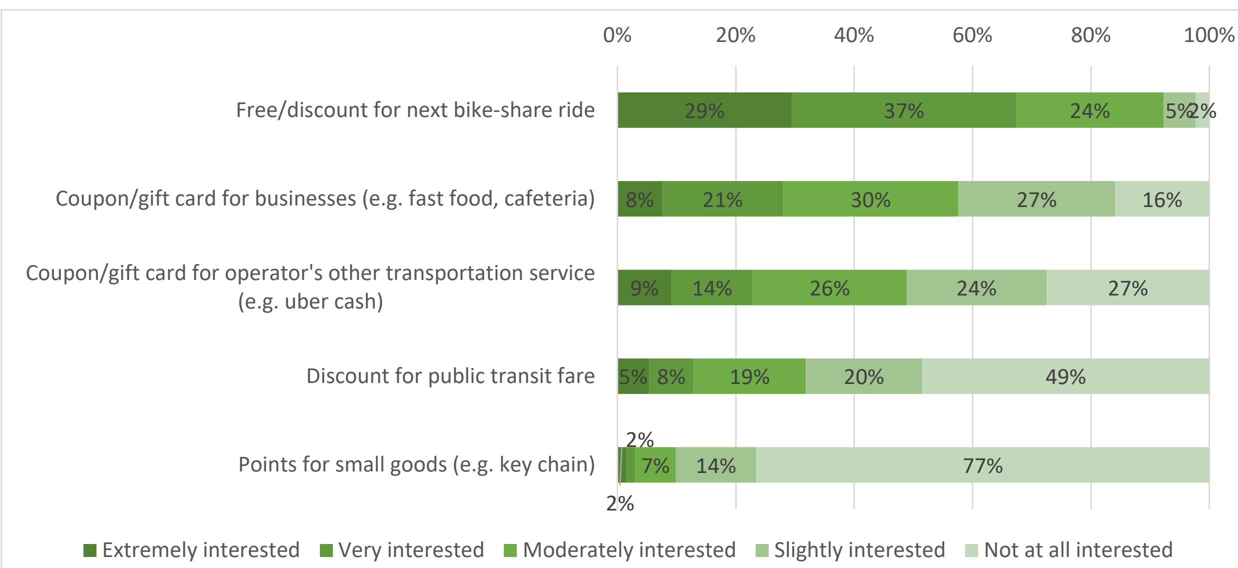


Figure 2. 5 Types of rewards users are interested in

The average preference scores for different types of rewards by individual characteristics show some interesting patterns (Table 2.4). For example, those who are not employed are more favorable to a discount for the operator's other transportation service than are those who are employed. Non-students, women, or those who do not have a college degree or are more than age 45 are more likely to prefer discounts for subsequent bike-share use than cash. Women also tend to like discounts for restaurants. Those who have no college degree favor any type of reward except cash. Hispanic respondents tend to favor rewards of any type over non-Hispanic respondents. Asians also have a higher preference for a discount for restaurant and operator's other transportation service than respondents identifying as white and other races.

Table 2. 4 Average score of Preference in Type of Reward by Group (n=126)

Types of Reward	Cash	Bike-share	Restaurant	Operator	Public Transit	Points
Employed						
Else	3.87	3.60	2.60	3.20	1.87	1.33
Yes	3.87	3.89	2.79	2.42	2.05	1.39
Student						
Else	3.85	3.93	2.78	2.45	2.10	1.42
Yes	3.96	3.61	2.75	2.75	1.79	1.25
Age						
Under age24	4.22	4.11	2.67	2.78	2.44	1.44
Age 25-34	4.04	3.76	2.96	2.65	2.12	1.43
Age 35-44	4.12	4.09	2.55	2.27	1.76	1.36
Age 45-54	3.38	3.54	2.69	1.92	1.62	1.54
Over 55	3.27	3.82	2.77	2.82	2.32	1.18
Women						
Else	3.90	3.81	2.60	2.58	2.12	1.41
Yes	3.83	3.94	3.04	2.42	1.90	1.33
Race						
Asian	4.25	3.55	3.10	3.15	2.05	1.50
Hispanic /Latino	4.50	4.67	3.67	3.83	2.83	3.00
White	3.68	3.83	2.59	2.32	2.04	1.30
else	4.11	4.05	2.89	2.26	1.74	1.11
Having children						
No	3.78	3.81	2.78	2.53	2.04	1.40
Yes	4.44	4.11	2.72	2.44	2.00	1.28
College degree						
No	3.85	4.15	3.15	3.62	2.46	1.85
Yes	3.88	3.82	2.73	2.39	1.98	1.33
Income						
Low	3.93	3.96	2.96	2.81	2.22	1.33
Middle	3.80	3.67	2.83	2.60	2.08	1.48
High	3.95	4.08	2.54	2.18	1.82	1.26
Car ownership						

No	3.27	3.67	2.00	2.67	2.00	1.47
Yes	3.95	3.88	2.87	2.50	2.04	1.37

2.4. Conclusion

This study examined the acceptance rate of walking time and willingness-to-walk for incentives to help rebalance a bike-share service. My findings that half of e-bike-share users would take the service if the nearest bike is 8.9-minutes away from their origin suggests a slightly greater willingness to walk than a finding in a prior study (Singla et al., 2015) that a half of users are willing to walk about 500 meters, equivalent to 6 minutes on foot in the context of a docked bike-share system in a European city. This is less than the average walking time (10 minutes) for walk trips of all purposes (Yong and Diez-Roux, 2012), suggesting that people are not willing to walk as far to get to bike-share as they are to get directly to a destination. These findings suggest the need for further analysis to understand the relationship between walking time to get a bike and bike-share use. My estimates on willingness-to-walk for the incentive at origin and destination are 3.8 minutes and 4.2 minutes per dollar, respectively. This finding that users are more willing to walk at the destination support findings in a prior study (Wang & Wang, 2021). The value of time for each type of incentive offer corresponds to US$15.8 per hour, and US$14.3 per hour is reasonable as the minimum wage in California is about US$13 to 14 per hour (California Department of Industrial Relations, 2021).

This study could help operators and cities plan rebalancing policies to maximize the contribution of bike-share to sustainability. My finding that 90% of users are willing to walk about 5 minutes (approx. 400 meters) to get a bike implies that placing bikes at 800-meter intervals at all times can theoretically satisfy most users. It is difficult to keep such an even distribution of bikes over the service area all day long because of the limited size of the bike fleet and the operational staff, as well as the complex travel patterns of the users. An incentive at the destination would help to mitigate the issue by encouraging users to park bikes in undersupplied areas while an incentive at the origin would lower the bike density in oversupplied areas. Compared to van-based rebalancing policies, user-based rebalancing policies have higher uncertainty in terms of how well the rebalancing works but are more environmentally-friendly. In deciding between the two rebalancing strategies, operators must consider the trade-offs between a number of factors such as variability of demand, ease of rebalancing, operational cost, and different policy objectives.

My findings that incentives nudge users to walk farther to use bike-share suggests that such offers are an option for helping operators to rebalance the bike fleet, especially in areas with substantial use by women, whites, and those who hold memberships. My survey also found that the more popular incentive types are cash and free/discount for the next bike-share ride. However, some groups, such as women, Asians, and those who are not employed, tend to favor other types of incentives, such as coupon/gift cards for business (e.g., fast food, restaurant) and coupon/gift cards for the operator's other transportation services (e.g., Uber cash). The integration of micromobility and transit, potentially improving equity and sustainability, are commonly discussed in the policy domain, but my participants were not interested in a discount for public transit fares. Incentives do not always have to hurt the operator's bottom line or the city's resources. Leveraging incentives from other businesses might help to vitalize the local economy while helping operators reduce operational costs (Krykewycz et al., 2010; Buehler and Hamre, 2015; Fukushige et al., 2021). Because I had a limited sample size, similar studies should be repeated in other cities with large samples to understand the acceptance of such incentive programs and factors associated with the willingness-to-walk.

In this study, I did not measure other factors, such as weather conditions, the context of the trip, total trip length, and the direction of walking toward the bike location, all of which might affect bike location selection. Commuters, for example, might avoid choosing a bike with an incentive if they are in a rush. The context of the conjoint questions I gave may overestimate the estimates because windy and/or rainy days could discourage users from walking farther. The built environment and safety on the street might influence their willingness-to-walk for incentives negatively. I also assumed that all users knew about the incentive programs, though this might not be the case. In fact, my survey found that 23% of participants did not know about the incentive program for returning bikes with low batteries to designated bike stations in the existing JUMP service in the Sacramento region. Users were even more unaware (55% of participants) of an incentive to take bikes from outside the service boundary to inside. A low level of awareness of an incentive program would limit the effectiveness of the program. Well-designed bike share app might mitigate this problem (past designs by JUMP did not seem to communicate the incentives).

This study focuses on the acceptance rate of walking time and willingness-to-walk for an incentive. I used a limited number of trip attributes for simplicity, but other factors, such as the context of trips and weather, may influence users' behavior significantly. I encourage further exploration with revealed data to understand the preference for and uncertainty of the acceptance rate of walking time to get a bike in a real-world setting. In addition, simulation analysis with the models estimated here could help in better understanding the effect of incentive programs on a rebalancing issue as prior studies focus on the efficiency of rebalancing algorithms with simple user behaviors (Duan and Wu, 2019; Pan et al., 2019). Integrating the idea of VMT reduction from car substitution and other social benefits into the simulation analysis would help guide policy recommendations about setting an incentive amount. As a further step, it would be beneficial to partner with a bike-share operator to test these incentives by evaluating their cost-effectiveness in reducing unsatisfied demand and rebalancing the fleet. Pilots would help cities potentially mandate such incentive programs or at least mandate micromobility companies to experiment with their incentives.

References

Andersen, M.. 2016. How much does each bike share ride cost a system? Let's do the math, Better Bike Share Partnership, https://betterbikeshare.org/2016/08/16/much-bike-share-ride-cost-system-lets-math/ (accessed 12.10.21).

Attias, H., 2000. A variational Bayesian framework for graphical models. Advances in neural information processing systems, 12(1-2), pp.209-215.

Ban S. H. and K. H. Hyun. 2019 Designing a User Participation-Based Bike Rebalancing Service, Sustainability, vol. 11(8), 1-14

Buehler, R., & Hamre, A. 2015. Business and bikeshare user perceptions of the economic benefits of capital bikeshare. Transportation Research Record, 2520(1), 100-111. https://doi.org/10.3141%2F2520-12

California Department of Industrial Relations, 2021 Minimum Wage, https://www.dir.ca.gov/dlse/faq_minimumwage.htm (accessed 12.10.21).

Campbell, A. A., Cherry, C. R., Ryerson, M. S., and Yang, X. 2016. Factors influencing the choice of shared bicycles and shared electric bikes in Beijing, Transportation Research PartC: Emerging Technologies, 67, 399-414, https://doi.org/10.1016/j.trc.2016.03.004

Çelebi, D., Yörüsün, A. & Işık, H., 2018. Bicycle sharing system design with capacity allocations. Transportation research part B: methodological, 114, 86-98. https://doi.org/10.1016/j.trb.2018.05.018

Chen, Z., Hu, Y., Li, J. & Wu, X., 2020. Optimal deployment of electric bicycle sharing stations: model formulation and solution technique. Networks and Spatial Economics, 20(1), 99-136. https://doi.org/10.1007/s11067-019-09469-2

DeMaio, P., 2009. Bike-sharing: History, Impacts, Models of Provision, and Future. J. Public Transp. 12, 41–56. https://doi.org/10.5038/2375-0901.12.4.3

Duan Y. and J. Wu. (2019) Optimizing Rebalance Scheme for Dock-Less Bike Sharing Systems with Adaptive User Incentive, 2019 20th IEEE International Conference on Mobile Data Management (MDM), Hong Kong, 176-181 https://doi.org/10.1109/MDM.2019.00-59

Fishman, E., Washington, S., & Haworth, N., 2014. Bike share's impact on car use: Evidence from the United States, Great Britain, and Australia, Transportation Research Part D: Transport and Environment, 31, 13-20, https://doi.org/10.1016/j.trd.2014.05.013.

Fitch, D. T., Mohiuddin, H., Handy, S.L., 2021. Examining the Effects of the Sacramento Dockless E-Bike Share on Bicycling and Driving. Sustainability. 2021; 13(1): 368. https://doi.org/10.3390/su13010368

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. https://doi.org/10.7922/G2F18X0W
Frade, I, & Ribeiro, A., 2015. Bike-sharing stations: A maximal covering location approach, Transportation Research Part A: Policy and Practice, 82, 216-227, https://doi.org/10.1016/j.tra.2015.09.014.
Fukushige, T., D. T. Fitch, Handy, S. 2021 Factors influencing dock-less E-bike-share mode substitution: Evidence from Sacramento, California, Transportation Research Part D: Transport and Environment, 99, https://doi.org/10.1016/j.trd.2021.102990.
García-Palomares, J. C., Gutiérrez, J., & Latorre, M., 2012. Optimizing the location of stations in bike-sharing programs. A GIS approach. Applied Geography, 35, 235-246, https://doi.org/10.1016/j.apgeog.2012.07.002
Gauthier, A., Hughes, C., Kost, C., Li, S., Linke, C., Lotshaw, S., Mason, J., Pardo, C., Rasore, C., Schroeder, B., Treviño, X., 2014. The Bike-Share Planning Guide. New York, NY, USA.
George, E. P., Hunter, J. S., Hunter, W. G., Bins, R., Kirlin IV, K., and Carroll, D. 2005. Statistics for experimenters: Design, innovation, and discovery (Vol. 2). New York, NY, USA:: Wiley.
Green, P. E., and Srinivasan, V. 1978 Conjoint analysis in consumer research: issues and outlook. Journal of consumer research, 5(2), 103-123., https://doi.org/10.1086/208721
Haaijer, R., Kamakura, W. A., and M. Wedel. 2001. The'no-choice'alternative in conjoint choice experiments, International Journal of Market Research, 43
Johnson, R., Orme, B. 2003 Getting the most from CBC, Sawtooth Software Research Paper Series, Sawtooth Software, Sequim
Kabra, A., E. Belavina, and K. Girotra. 2018 Bike-Share Systems: Accessibility and Availability. Chicago Booth Research Paper No. 15-04
Krykewycz, G. R., Puchalsky, C. M., Rocks, J., Bonnette, B., and Jaskiewicz, F. 2010. Defining a primary market and estimating demand for major bicycle-sharing program in Philadelphia, Pennsylvania. Transportation research record, 2143(1), 117-124. https://doi.org/10.3141%2F2143-15
Lee M. D., 2011. How cognitive modeling can benefit from hierarchical Bayesian models, Journal of Mathematical Psychology, 55:1, 1-7, https://doi.org/10.1016/j.jmp.2010.08.013
Lee, A. 2020. Results of the 2019-20 Campus Travel Survey. UC Davis: Institute of Transportation Studies. https://escholarship.org/uc/item/9929r4j1
Luce, R. D. and J. W. Tukey, 1964 Simultaneous conjoint measurement: A new type of fundamental measurement, Journal of Mathematical Psychology, 1(1), 1-27, https://doi.org/10.1016/0022-2496(64)90015-X
McElreath, R., 2020. Statistical rethinking. A bayesian course with examples in R and stan. CRC Press, Boca Raton
Mix, R., Hurtubia, R. & Raveau, S., 2022. Optimal location of bike-sharing stations: A built environment and accessibility approach, Transportation Research Part A: Policy and Practice, 160, 126-142, https://doi.org/10.1016/j.tra.2022.03.022.
NACTO, 2019. Shared Micromobility in the U.S.: 2018. https://nacto.org/shared-micromobility-2018 (accessed 3.20.21).
Olitsky, M., Lerman, Y., and Avineri, E.. 2017 Analysis of Stated Preferences for Accessible Services and Commerce in a Walkable Distance from Home, Transportation Research Procedia, 27, 1001-1008, https://doi.org/10.1016/j.trpro.2017.12.064.

O'Mahony, E. & Shmoys, D., 2015. Data analysis and optimization for (citi) bike sharing. In Proceedings of the AAAI Conference on Artificial Intelligence, 29(1), https://doi.org/10.1609/aaai.v29i1.9245
Otero, I., Nieuwenhuijsen, M.J., Rojas-Rueda, D., 2018. Health impacts of bike sharing systems in Europe. Environ. Int. 115, 387–394. https://doi.org/10.1016/j.envint.2018.04.014
Pan, L., Cai, Q., Fang, Z., Tang, P., & Huang, L. 2019. A deep reinforcement learning framework for rebalancing dockless bike sharing systems. In Proceedings of the AAAI conference on artificial intelligence, 33(1), 1393-1400 https://doi.org/10.1609/aaai.v33i01.33011393
Patel S.J., R. Qiu, and A. Negahban. 2019 Incentive-Based Rebalancing of Bike-Sharing Systems, Advances in Service Science, 21-30
Pfrommer J., J. Warrington, G. Schildbach and M. Morari. 2014 Dynamic Vehicle Redistribution and Online Price Incentives in Shared Mobility Systems, IEEE Transactions on Intelligent Transportation Systems, 15(4), 1567-1578. https://doi.org/10.1109/TITS.2014.2303986
Qiu, L.Y., He, L.Y., 2018. Bike sharing and the economy, the environment, and health-related externalities. Sustain. 10, 1–10. https://doi.org/10.3390/su10041145
Revelt, D., and Train, K.. 2000 Customer-specific taste parameters and mixed logit, http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.321.4964&rep=rep1&type=pdf (accessed 12.1.21)
Ricci, M., 2015. Bike sharing: A review of evidence on impacts and processes of implementation and operation. Res. Transp. Bus. Manag. 15, 28–38. https://doi.org/10.1016/j.rtbm.2015.03.003
Rose, J.M., Bliemer, M.C.J. 2013 Sample size requirements for stated choice experiments. Transportation 40, 1021–1041. https://doi.org/10.1007/s11116-013-9451-z
Ruud, P. 1996. Approximation and simulation of the multinomial probit model: an analysis of covariance matrix estimation, Department of Economics, Berkeley, 1-17
Shaheen, S., Guzman, S., Zhang, H., 2010. Bikesharing in Europe, the Americas, and Asia. Transp. Res. Rec. 159–167. https://doi.org/10.3141/2143-20
Singla A., M. Santoni, G. Bartók, P. Mukerji, M. Meenen, and A. Krause. 2015 Incentivizing users for balancing bike sharing systems. In Proceedings of the Twenty-Ninth AAAI Conference on Artificial Intelligence (AAAI'15). AAAI Press, 723–729.
Sonnier, G., Ainslie, A., and Otter, T. 2007. Heterogeneity distributions of willingness-to-pay in choice models. Quantitative Marketing and Economics, 5(3), 313-331.
Stan Development Team, 2021. Stan Modeling Language. Stan User's Guide 2.28. Ref. Man. 1–488., http://mc-stan.org/manual.html%5Cnpapers2://publication/uuid/C0937B19-1CC1-423C-B569-3FDB66090102 (accessed 12.1.21).
Sun, Z., Li, Y. & Zuo, Y., 2019. Optimizing the location of virtual stations in free-floating bike-sharing systems with the user demand during morning and evening rush hours. Journal of Advanced Transportation, https://doi.org/10.1155/2019/4308509
Train K., Weeks M. 2005 Discrete Choice Models in Preference Space and Willingness-to-Pay Space., Applications of Simulation Methods in Environmental and Resource Economics. The Economics of Non-Market Goods and Resources, 6, https://doi.org/10.1007/1-4020-3684-1_1
van Buuren, S., & Groothuis-Oudshoorn, K., 2011. mice: Multivariate Imputation by Chained Equations in R. Journal of Statistical Software, 45(3), 1 - 67. http://dx.doi.org/10.18637/jss.v045.i03

Van Cauwenberg, J., De Bourdeaudhuij, I., Clarys, P. et al. 2016 Street characteristics preferred for transportation walking among older adults: a choice-based conjoint analysis with manipulated photographs. International Journal of Behavioral Nutrition and Physical Activity, 13, 6, https://doi.org/10.1186/s12966-016-0331-8

Vanderbilt, T. 2018 The Angel Who Keeps Citi Bike Working for New York., Outside, 8 7 https://www.outsideonline.com/2332671/purest-form-bike-angel, Accessed April, 10, 2021

Wang, J., and Wang, Y. 2021. A two-stage incentive mechanism for rebalancing free-floating bike sharing systems: considering user preference. Transportation research part F: traffic psychology and behaviour, 82, 54-69. https://doi.org/10.1016/j.trf.2021.08.003

Wang, M., Zhou, X., 2017. Bike-sharing Systems and Congestion: Evidence from US cities, Journal of Transport Geography, 65: 147-154. https://doi.org/10.1016/j.jtrangeo.2017.10.022

Yang, Y. and Diez-Roux, A.V., 2012. Walking distance by trip purpose and population subgroups. American journal of preventive medicine, 43(1), 11-19. https://doi.org/10.1016/j.amepre.2012.03.015

Zhao, D. and Ong, G. P.. 2021. Geo-fenced parking spaces identification for free-floating bicycle sharing system, Transportation Research Part A: Policy and Practice, 148, 49-63, https://doi.org/10.1016/j.tra.2021.03.007

Appendix 2A Comparison of Model Estimation in Preference Space

	Model 1	Model 2	Model 3	Model 4
Walking Time (Origin) (Unit: min)	-0.43 (0.02)	-0.58 (0.04)	-0.57 (0.04)	-0.57 (0.04)
Walking Time (Destination) (Unit: min)	-0.29 (0.02)	-0.43 (0.05)	-0.42 (0.05)	-0.43 (0.05)
Incentive (Origin) (Unit: US$)	1.65 (0.09)	2.27 (0.23)	2.22 (0.24)	1.90 (0.48)
Incentive (Destination) (Unit: US$)	1.26 (0.11)	1.98 (0.33)	1.84 (0.34)	1.72 (0.62)
Indicator for BS-option	3.24 (0.15)	4.97 (0.37)	5.03 (0.38)	4.80 (0.79)
Incentive (Origin)				
Membership				0.03 (0.35)
Women				0.76 (0.32)
White				0.71 (0.32)
Concern for time				-0.61 (0.53)
Incentive (Destination)				
Membership				0.33 (0.45)
Women				0.60 (0.40)
White				0.24 (0.39)
Concern for time				-0.45 (0.66)
BS-option				
Membership				0.68 (0.45)
Women				0.46 (0.40)
White				0.52 (0.40)
Concern for time				-0.56 (0.69)
Those interested in incentive				0.05 (0.57)
elpd_loo	-1748.4 (35.1)	-1409.3 (37.3)	-1397.4 (37.1)	-1398.0 (37.5)

Appendix 2B Survey Instrument

Bike Share Incentive Survey

Welcome to the bike share survey!
Our research team at the University of California, Davis is conducting a study about your use of the JUMP bike-share system.

This study focuses on the willingness of bike-share users to walk a bit farther to get to a bike in exchange for a reward of some sort. One problem that the operators of bike-share systems have is that the bikes often get dropped off in areas where they are not needed. Some operators have been offering rewards to bike-share users to pick-up or drop-off bikes in specific areas, which may mean more walking, to make sure that the bikes are more evenly distributed.

In this survey, we would like to know your thoughts about such a reward system, whether or not you are currently using the bike-share system. The information we collect in this survey will be used for academic purposes only.

Participation in this study is completely voluntary. You are free to decline to take part in the survey. You can decline to answer any questions, and you can stop taking part in the survey at any time. You will incur no penalty to you and you will not lose any benefits to which you are otherwise entitled if you choose not to participate, skip questions, or stop participating.

How long...
The survey should only take **10 - 15 minutes**. We recommend that you take the survey on a normal web browser, not your smartphone.

What you get...
After completing the survey, you will be entered into a drawing for 10 $10 Amazon gift cards. You can also enter the drawing without completing the survey. To be included in the drawing, please complete the survey (or contact us) by July 19, 2021. Even if you can't complete the survey by then, we would still like you to complete the survey, as every response is important to our study.
Questions
If you have any questions about this research, please feel free to contact us.

Contact
Tatsuya Fukushige
tfukushige@ucdavis.edu

- ○ I agree to participate in this survey (1)
- ○ I do not wish to participate (2)

Have you ever used bike share in Sacramento, West Sacramento, or Davis before March, 2020 or after September, 2020?

- ○ Yes, I have used JUMP bike both before March, 2020 and after September, 2020 (2)
- ○ Yes, I used JUMP bike only before March, 2020 (5)
- ○ Yes, I have used JUMP bike only after September, 2020. (6)
- ○ No (4)

Which of the following options best describes how you typically find a bike when you use JUMP?

- ○ I typically reserve a bike on the app first and then walk to the bike. (9)
- ○ I typically search for a bike on the app first but do not reserve a bike, and then walk to get a bike. (10)
- ○ I typically do not use the app to find a bike. When I find a bike by chance, I use it. (11)
- ○ Other (17) ____

How long would you be willing to walk to pick up a bike-share bike for a trip for recreation or exercise? For a trip to a specific destination such as work or a store?

	Up to 2 minutes (1)	Up to 5 minutes (2)	Up to 10 minutes (3)	Up to 15 minutes (4)	More than 15 minutes (5)
Trip for recreation or exercise (1)	○	○	○	○	○
Trip to a specific destination (e.g. work or a store) (2)	○	○	○	○	○

We would like to ask about your previous bike-share experience before the COVID-19 stay-at-home orders.
Which of the following options best describe how you paid for JUMP bike.

- ◯ Pay for each trip individually (Pay as I go) (2)
- ◯ General monthly membership (3)
- ◯ Student monthly membership (4)
- ◯ Other discounted monthly membership (5)

Did you know that JUMP offered a reward for returning bikes with a low battery charge to designated bike stations?

- ◯ I did not know about this reward. (1)
- ◯ I did know, but I did not ever take advantage of this reward. (2)
- ◯ I did know, and I earned this reward at least once. (31)

Why did you not take advantage of the reward? (Select all that apply)

- ▢ The reward was not offered for any of the bikes I used. (4)
- ▢ I did not want to walk farther to my destination. (5)
- ▢ The amount of reward was not worth it. (6)
- ▢ Other (7) ____

Did you know that JUMP offered a reward for picking-up bikes from outside of the service boundary and dropping them off inside the service boundary?

○ I did not know about this reward. (1)

○ I did know, but I did not take advantage of this reward. (2)

○ I did know, and I earned this reward at least once. (3)

Why did you not take advantage of the reward? (Select all that apply)

▢ The reward was not offered for any of the bikes I used. (1)

▢ I didn't want to walk farther to my destination. (2)

▢ The amount of reward was not worth it. (4)

▢ Other (5) ____

How often did you use the following transportation modes before the COVID-19 stay-at-home orders.?

	Every day or almost every day (1)	A few times per week (2)	A few times per month (3)	A few times per year (4)	Less than one trip a year (5)	Never (6)
Bike-share service (JUMP, Lime, etc) (6)	○	○	○	○	○	○
Scooter-share service (Lime, etc) (4)	○	○	○	○	○	○
Drive a private car (7)	○	○	○	○	○	○
Ride-hailing service (Lyft, Uber, etc.) (1)	○	○	○	○	○	○
Car-sharing service (Zipcar, GIG, etc.) (5)	○	○	○	○	○	○
Public transit (3)	○	○	○	○	○	○
Personally owned bicycle (8)	○	○	○	○	○	○

Think about a situation where the bike-share operator offers the same services as before COVID-19 and life goes back to pre-COVID-19 conditions. Compared to what you did before COVID-19, how often do you think you would use the bike-share system?

- ○ Not at all - I would never use bike-share (1)
- ○ I would use bike-share less than I did before (3)
- ○ I would use bike-share about as often as I did before (4)
- ○ I would use bike-share more than I did before (5)

Please tell us why you would use bike-share service less than before or not at all. Select all that apply.

- ☐ I will need to go out less often even after our lives are back to normal. (3)
- ☐ I prefer using a shared e-scooter. (6)
- ☐ I do not want to use a bike someone else has used. (2)
- ☐ Other (5) ____

We would like to know about your current bike-share experience.
How do you pay for current bike-share use?

- ○ Pay for each trip individually (Pay as I go) (2)
- ○ Monthly membership (3)
- ○ Other (5) ____

For what purposes do you use the bike-share service? Select all that apply.

- ▢ Commute to/from school (1)
- ▢ Commute to/from primary workplace (2)
- ▢ Get to work-related activities (meetings) (3)
- ▢ Get to a grocery store (4)
- ▢ Get to other shopping (5)
- ▢ Run errands (6)
- ▢ Get to/from a restaurant, bar, or other entertainment (7)
- ▢ Visit friends/family (8)
- ▢ For recreation/exercise (9)
- ▢ Other (10) ____

Currently, how often do you uses the following services?

	5 + trips a week (1)	3-4 trips a week (2)	1-2 trips a week (3)	1-3 trips a month (4)	Less than one trip a month (5)	Never (6)
Lime operated shared Jump bikes (1)	○	○	○	○	○	○
Shared e-scooters (Lime, Spin, Razor, Bird) (2)	○	○	○	○	○	○

Next, we would like to know your thoughts about new types of reward programs.

Would you consider (1) walking farther to get a bike or (2) parking the bike farther from your destination if you could earn some sort of reward?

	Yes, I would always pursue this reward (1)	Maybe, it would depend on the reward (2)	No, I would not (3)
(1) Walking farther to pick up a bike (1)	○	○	○
(2) Parking the bike farther from your destination (2)	○	○	○

In the previous question, you answered that it would depend on the reward. How important are the following factors to your decision?

	Not important at all (1)	Slightly important (2)	Moderately important (3)	Very important (4)	Extremely important (5)
The amount of reward (1)	○	○	○	○	○
The type of reward (2)	○	○	○	○	○
The amount of extra walking (3)	○	○	○	○	○
Other (4)	○	○	○	○	○

In the previous questions, you answered that you would be willing to walk farther if you could earn some sort of reward. How interested are you in the following types of rewards?

	Not at all interested (1)	Slightly interested (2)	Moderately interested (3)	Very interested (4)	Extremely interested (5)
Cash (1)	○	○	○	○	○
Free/discount for next bike-share ride (5)	○	○	○	○	○
Coupon/gift card for operator's other transportation service (e.g. uber cash) (2)	○	○	○	○	○
Discount for public transit fare (3)	○	○	○	○	○
Coupon/gift card for businesses (e.g. fast food, cafeteria) (4)	○	○	○	○	○
Points for small goods (e.g. key chain) (7)	○	○	○	○	○

In the **next 9 questions**, we would like you to select the option that best describes what you would choose to do if new reward programs were offered.

Imagine you are taking a 15-minute ride to get to a specific destination (such as work or a store). You open the bike-share app, and the app suggests the nearest bike without a reward as well as bikes farther away with rewards of different amounts. The bikes with rewards usually require additional walking at your origin or/and at your destination location compared to the nearest bike. If you don't like any of the options, please choose "none."

(Sample)

Please carefully review the options for this trip.

	Bike A	Bike B	Bike C	Bike D	None
Walking Time (Origin to bike location)	6 min	12 min	6 min	12 min	I wouldn't use bike-share for this trip
Riding a bike	15 min				
Walking Time (Return location to destination)	0 min	0 min	10 min	10 min	
Total Reward	$0	$1.50	$0.75	$2.25	

Which of these options would you choose?

- Bike A (20)
- Bike B (21)
- Bike C (22)
- Bike D (23)
- None (24)

A Few things about you

Thank you so much for your input! In this section, we would like to learn a little more about you. Remember, this information will remain anonymous and is for research only.
What city do you live in?

- ○ Sacramento (2)
- ○ West Sacramento (5)
- ○ Davis (6)
- ○ Other city in the greater Sacramento region (specify city) (3) ____
- ○ Other city outside the greater Sacramento region (specify city and state) (4) ____

What is your age?

____

To which gender do you most identify?

- ○ Woman (1)
- ○ Man (2)
- ○ Not listed: (3) ____
- ○ Prefer not to say (5)

Please tell us which race and ethnicity categories best describe you (select all that apply):

- ☐ Black/African American (1)
- ☐ Hispanic/Latino (2)
- ☐ White (3)
- ☐ Asian (4)
- ☐ Pacific Islander/Native Hawaiian (5)
- ☐ American Indian/Alaskan Native (6)
- ☐ Other (please specify) (7) ____

What is your work status?

- ○ Working, and I commute to at least one workplace (1)
- ○ Working, and I don't commute (e.g. from home or without fixed workplace locations) (2)
- ○ Retired but I still commute to at least one workplace (4)
- ○ Retired and I don't commute to a workplace (5)
- ○ Not currently working (6)
- ○ Permanently unable to work (7)

Are you currently a student?

- Full-time student (1)
- Part-time student (2)
- Not a student (3)

What is your highest completed level of education?

- No formal education (1)
- Grade school or Jr. High (2)
- High school diploma or GED (3)
- Associate or technical certificate (4)
- Bachelor's degree(s) (5)
- Graduate degree(s) (6)

Do you live with family members or others with whom you share an income?

- Yes (1)
- No (2)

How many people live in your household, including you?

	(1)
Number of people under 16 (1)	
Number of people 16 years and older (2)	

Last year, what was your approximate **personal** income before taxes?

- Less than $10,000 (1)
- $10,000-$25,000 (2)
- $25,001 - $50,000 (3)
- $50,001 - $75,000 (4)
- $75,001 - $100,000 (5)
- $100,001 - $125,000 (6)
- $125,001 - $150,000 (7)
- $150,001 - $175,000 (8)
- $175,001 - $200,000 (9)
- More than $200,000 (10)

Last year, what was your approximate **household** income before taxes?

- Less than $10,000 (1)
- $10,000-$25,000 (2)
- $25,001 - $50,000 (3)
- $50,001 - $75,000 (4)
- $75,001 - $100,000 (5)
- $100,001 - $125,000 (6)
- $125,001 - $150,000 (7)
- $150,001 - $175,000 (8)
- $175,001 - $200,000 (9)
- More than $200,000 (10)

Do you have a driver's license issued by a U.S. state?

- Yes (1)
- In the past but not currently (2)
- Have never had one (3)

How many motor vehicles does your household have? (For example, cars, trucks, or motorcycles.)

▼ 0 (1) ... 5+ (6)

For the following statements about bicycling, please indicate how accurately each describes how you feel.

	Strongly disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)
Riding a bike is fun (1)	○	○	○	○	○
Riding a bike is enjoyable (10)	○	○	○	○	○
Riding a bike is boring (11)	○	○	○	○	○
Riding a bike is pleasant (26)	○	○	○	○	○
I like riding a bicycle (17)	○	○	○	○	○
I feel safe from cars when bicycling in town (5)	○	○	○	○	○
I feel comfortable around cars when bicycling in town (6)	○	○	○	○	○
I feel anxious around cars when bicycling in town (7)	○	○	○	○	○
I get stressed by cars when bicycling in town (8)	○	○	○	○	○
Many people I know think bicycling is healthy (12)	○	○	○	○	○

Many people I know think bicycling is fun (13)	○	○	○	○	○
Many people I know think bicycling is safe (14)	○	○	○	○	○
Many people I know think I should bicycle (15)	○	○	○	○	○
I need my car to do many of the things I like to do (18)	○	○	○	○	○
I need my car to carry shopping or children (19)	○	○	○	○	○
I try to limit my driving as much as possible (20)	○	○	○	○	○

How important are the following factors to the choices you make about your daily travel?

	Not at all important (5)	Slightly important (4)	Moderately important (3)	Very important (2)	Extremely important (1)
Concern for the environment (1)	○	○	○	○	○
Concern for cost (2)	○	○	○	○	○
Desire to get exercise (3)	○	○	○	○	○
Concern for safety from crime (4)	○	○	○	○	○
Concern for safety from traffic (5)	○	○	○	○	○
Desire for enjoyment (6)	○	○	○	○	○
Concern for time (7)	○	○	○	○	○
Desire for convenience (8)	○	○	○	○	○

Last thing...
Imagine that an app became available that let you pay for both public transit (bus, light rail transit) and micromobility (both bike-share and scooter-share) from the same app. How likely would you be to use such an app?

○ Very likely (1)

○ Somewhat likely (2)

○ Neither unlikely or likely (3)

○ Somewhat unlikely (4)

○ Very unlikely (5)

Now imagine that monthly subscription plans became available on that app so that you could take a specified number of minutes of micromobility rides and a certain amount of public transit trips for a fixed **monthly fee**. How likely would you be to subscribe to each of the following versions of such a plan?

	Very unlikely (1)	Somewhat unlikely (2)	Neither unlikely nor likely (3)	Somewhat likely (4)	Very likely (5)
Up to 100 minutes of micromobility rides and 50 public transit tickets for $50 (6)	○	○	○	○	○
Up to 300 minutes of micromobility rides and unlimited public transit for $100 (1)	○	○	○	○	○
Up to 450 minutes of micromobility rides and unlimited public transit rides for $125 (4)	○	○	○	○	○
Up to 600 minutes of micromobility rides and unlimited public transit rides for $150 (3)	○	○	○	○	○

How would the use of this monthly subscription affect your likelihood of using public transit for your regular commute?

- I would not use transit at all (1)
- I would use transit less than before (2)
- I would use transit the same amount as before (3)
- I would use transit more than before (4)

OPTIONAL:
After completing the survey, you will be entering into a drawing for 10 $10 Amazon gift cards. To be included in the drawing, please complete the survey by July 15, 2021. We will randomly select 10 people from those who complete the survey to receive this prize.

If you wish to be included in the drawing or you are willing to be contacted further, please provide the following information. We will only use it for the purposes you authorize.

Can we contact you ...

	Yes (1)	No (2)
if you win a $10 gift card prize? (3)	○	○
if we have any questions about your survey? (1)	○	○
for future bike-share related surveys by UC Davis? (8)	○	○

Please provide your email so we can contact you for the purposes you just indicated.

- e-mail: (1) ____

Please distribute the link of this survey to your family member and friends who may have used bike share in Sacramento, West Sacramento, or Davis. More responses will help our study!

https://bit.ly/ucdavis-bikeshare-incentive-survey

THANK YOU! We would value any additional comments you may have on this survey. Please write them in the space below:

____

____

3 Factors Influencing Dock-less E-Bike-Share Mode Substitution: Evidence from Sacramento, California[2]

3.1. Introduction

The recent emergence of dock-less e-bike-share, one type of shared micromobility service, has allowed a growing number of cities to look toward these services as a way to improve environmental, social, and health outcomes from the transportation system (Otero et al., 2018; Shaheen et al., 2010; Wang & Zhou, 2017). The National Association of City Transportation Officials (NACTO) reported that dock-less e-bike-share in the United State reached 10 million trips in 2019 (NACTO, 2020), with an average trip length of 1.6 miles in 2018 (NACTO, 2019). The fact that 35% of trips by privately-operated vehicles are less than 2 miles (USDOT, 2018) suggests considerable opportunity to increase the substitution of bike-share for driving, thereby reducing vehicle miles traveled (VMT) and related greenhouse emissions. However, if the major mode shift comes from public transit, owned bike, or walking, the benefits will be more limited. NACTO (2020) reported that 45% of users in Santa Monica, CA, Alexandria, VA, Bloomington, IN, Brookline, MA, Hoboken, NJ, Oakland, CA, and San Francisco, CA, substitute micromobility, including bike share and scooter, for car travel. Barnes (2019) found similar results for San Francisco, with 45% of dock-less e-bike-share trips substituting for car travel including private car, ride-hailing, and carpool. Fishman et al. (2014), however, found that only 19% and 7% of docked bike-share trips in Minneapolis and Washington D.C., respectively, replace private car trips (2014). These results suggest that variation in car substitution between US cities is considerable.

[2] This chapter is based on my published work: Fukushige, T, Fitch, D. T., and Handy, S., 2021. Factors Influencing Dock-less E-Bike-Share Mode Substitution: Evidence from Sacramento, California, Transportation Research Part D., 99, https://doi.org/10.1016/j.trd.2021.102990

Policy makers and operators would benefit from an understanding of how the characteristics of bike-share users and their trips influence mode substitution. Prior studies have examined factors influencing car substitution for bike-share systems. Individual characteristics, including gender, age, income, household size, commute type, trip distance, and vehicle ownership were important in one study (Barbour et al., 2019). Another study found that bike share is likely to replace ride-hailing for short trips or trips ending around transit facilities and shopping malls (Qin et al.,2018). Prior research has also focused on transit substitution rather than car substitution. One study of U.S. cities showed that bike-share trips are more likely to substitute for public transit in denser areas of the city (Martin and Shaheen, 2014), but a second study did not find an association between density and public transit substitution (Kong et al., 2020). The latter study did find that public transit substitution was greater on weekends and for users who are not members of the bike-share service (Kong et al., 2020). Two studies showed that the introduction of bike-share service was spatially associated with declines in transit ridership (Campbell and Brakewood, 2017; Jin et al., 2019), suggesting a net substitution effect of bike-share for transit.

Other researchers have explored the influence of micromobility, including docked and dock-less bike-share, on the outcomes associated with car substitution. Fishman et al. (2014) estimated reductions in vehicle kilometers of travel resulting from docked bike-share use based on substitution rates and average trips distances; in another study they estimated the effect of the service on physical activity (Fishman et al., 2015). Zhang and Mi (2018) estimated reductions in energy use from car substitution, relying on the simple and potentially problematic assumption that all bike-share trips of more than 1 km replaced car trips. Another study inferred mode substitution based on several trip attributes, such as trip distance, time of day, and trip purpose, assigning the substituted mode for each bike share trip based on the mode share for trips of those characteristics for that city as indicated by NHTS data (Kou et al., 2020). These studies give approximations of the benefits of bike-share systems as they reduce car use, but they all rest on strong assumptions or a single average rate of car substitution. To improve these estimates and to better understand micromobility travel behavior, a better understanding of the factors that influence micromobility mode substitution is needed.

In this study, I examine factors influencing mode substitution of a dock-less e-bike share. I use data from a two-wave longitudinal survey of Sacramento-area dock-less e-bike share users in 2018 and 2019. This system, one of the largest dock-less e-bike-shares in the US at the time, was operated by Jump in the cities of Sacramento, West Sacramento, and Davis between 2018 and 2020 (when it closed with the emergence of COVID-19). The service covered an area of approximately 50 square miles, though the service areas were not contiguous, Davis being separated from West Sacramento by about 10 miles. Although the service was dock-less, Jump installed bike-hub stations in the service boundary to provide a place for rebalancing bikes, and users were during some periods incentivized to return bikes to the docks. I use data from a two-wave longitudinal survey of users and estimate Bayesian multinomial logit models for commuting and non-commuting trips to identify factors associated with substituted modes. The factors I examine include trip attributes, land use characteristics, mode availability, individual characteristics, and attitudinal variables. My findings provide a basis for developing promotional and operational strategies and policies that enhance the beneficial outcomes of bike-share. My models can be used to predict the substituted mode for specific bike-share trips and produce more robust and reliable estimates of the benefits of bike-share service.

3.2. Methodology

3.2.1. Data

3.2.1.1. Survey Data

I use data from a two-wave longitudinal survey of dock-less e-bike share users. The first-wave survey was implemented 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 I suspect that it 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. I 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 the following techniques: (1) intercepting users at key locations throughout the study area, (2) taping fliers with the URL and QR code to the survey to bike seats, and (3) for the first-wave recruitment only, Facebook advertisements run by Jump Inc. on the behalf (targeted by zip code). The goal of the 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 information for their three most recent e-bike share trips for non-commute purposes. They were asked to refer to the Jump or Uber app to retrieve the location of the trip start and end by reporting addresses or putting a point on a Google map embedded in the survey, the date and time of the trip, and the trip length in terms of both time and distance. In addition, I asked respondents 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 and substitution for commute trips but not for the more detailed information requested for non-commute trips. Because of the difference in the survey design for measuring commute vs. non-commute trips, I analyze the mode substitution separately for these trip purposes. I collected data for a total of 1,172 non-commute trips. After removing unreasonable trips, such as trips with faster than possible speeds, and trips not in the Sacramento / West Sacramento boundary, I identified 823 valid trips to use in developing a mode substitution model for non-commute purposes.

Data on bike-share use for work and school commutes were collected in a different format. Respondents were asked to report general information about bike-share commute mode substitution if they had used the service for commuting purposes, rather than reporting the details of actual trip information. Some respondents used Jump bikes as a primary mode while others used it as a secondary mode. For the former, I used reported home and workplace/school address as the trip origin and destination because they were likely to have checked-in and checked-out the bike around these locations. I excluded the trip data of respondents who answered for those using bike share as a secondary mode because I did not collect information about where they checked-out the shared e-bike. I used 105 valid individual responses to develop a mode substitution model for commute trips. (For more details on the survey content, see Fitch et al. (2020).)

3.2.1.2. GBFS Data

I used system-wide bike-share status and hub station status data to create a bike availability index by web-scraping the real-time status of Jump bikes in the Sacramento region provided by the General Bikeshare Feed Specification (GBFS) between April 9th and May 6th, 2019 (prior to the suspension of service). The bike status data include the list of free status bikes at each timestamp, and the information of each bike includes bike ID, longitude, latitude, and state of charge. When a bike becomes unavailable due to a reservation or goes out of service for maintenance, the information for the bike disappears from the real-time data. The station status data includes the number of free bikes for each bike-hub station at each timestamp. I used the station status data because GBFS masked information on individual bikes located near bike-hubs.

3.2.2. Variables

3.2.2.1. Mode Substitution

The dependent variable for the mode substitution model for non-commute trips is a categorical variable derived from the response to the survey 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).* I interpret the answer to this question to be the mode for which the use of bike share substitutes, that is, the mode that was replaced when bike share became available. I choose 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). The substitution modes include drive alone (N=113, 13.7% of trips), carpool (N=53, 6.4%), ride-hailing (including taxi) (N=133, 16.2%), bike (including e-bike and e-scooter) (N=118, 14.3%), walk (including skateboarding) (N=273, 33.2%), transit (N=41, 5.0%) and “none, I wouldn’t have made the trip” (N=92, 11.2%).

The dependent variable for the mode substitution model for commute trips was derived from a similar question: *If JUMP was not available to you, how would you commute to your primary workplace (or school)? Select your one primary method (the one you would use for the longest portion of the trip or the entire trip).* The substitution modes are car (including private car, ride-hailing and carpooling) (N=21, 24.7% of trips), bike (including e-bike and e-scooter) (N=41, 48.2%), walk (including skateboarding) (N=27, 31.8%), and transit (N=16, 18.8%). I aggregated three different car modes, including drive alone, ride-hailing and carpooling, into one because ride-hailing and carpooling had only 4 and 1 observations, respectively.

Table 3. 1 Predictor Variables with Summary Statistics for Non-Commute and Commute Trip Samples

Variable	Non-Commute Sample (n=823)	Commute Sample (n=105)
Trip Attributes		
Travel Distance (Miles) - Median	1.49	1.86
Speed (Miles per minute) - Median	0.13	
Trip Purpose		
Home	17%	
Shopping (Grocery shopping, Other shopping)	6%	
Work related	14%	
Recreation/Exercise	11%	
Restaurant/Bar/Entertainment	31%	
Other (Errands, Visit friends/family etc)	20%	
Period		
Midnight (Midnight - 7am)	7%	
AM peak (7 - 10am)	12%	
Off-peak (10am - 4pm)	45%	
PM peak (4 - 7pm)	22%	
Night (7pm – midnight)	14%	
Weekend		
Yes	30%	
No	70%	
Land Use Characteristics		
Start (a quarter-mile buffer) - Median		
Residential use	36.2%	60.0%
Commercial/Office use	41.5%	15.8%

Variable	Non-Commute Sample (n=823)	Commute Sample (n=105)
Industrial use	0.2%	0.4%
School use	0.0%	0.0%
Civic use	4.8%	1.8%
*End (a quarter-mile **buffer**) - Median*		
Residential use	38.3%	16.1%
Commercial/Office use	40.9%	70.8%
Industrial use	0.2%	0.0%
School use	0.0%	0.0%
Civic use	4.6%	6.1%
Mode Availability		
Start (a quarter-mile buffer) - Median		
Number of Bus Stops	14	7
Number of LRT Stations	0	0
Total length of bike lanes (miles)	1.9	1.3
Shared bike availability	0.88	0.84
End (a quarter-mile buffer) - Median		
Number of Bus Stops	15	33
Number of LRT Stations	0	2
Total length of bike lanes	2.0	2.2
Shared bike availability - Median	0.88	0.88
Individual Characteristics		
*Age (n=799/76)**		
- 24	9%	13%
25-34	43%	39%
35-44	30%	32%
45-54	10%	7%
55 -	8%	9%
Woman		
Yes	40%	26%
No	60%	74%
*Race (n=787/75)**		
Asian	14%	11%
Hispanic/Latino	10%	9%
White	64%	69%
Other	12%	11%
Employed (Commute to at least one workplace)		
Yes	87%	
No	13%	
Student (Full or part-time student)		
Yes	12%	13%
No	88%	87%
College Degree (Bachelor's degree or higher)		
Yes	82%	58%
No	18%	42%
Children (Under 16)		

Variable	Non-Commute Sample (n=823)	Commute Sample (n=105)
Yes	28%	47%
No	72%	53%
Car Ownership		
*(One or more car per person) (n=793|76)**		
Yes	64%	49%
No	36%	51%
*Membership(n=665|78)**		
Yes	17%	22%
No	83%	78%
*Income(n=671|73)**		
Less than 50,000	7%	18%
50,001 to 100,000	24%	43%
100,000 to 200,000	56%	31%
More than 200,000	13%	8%

* indicates that the predictor has missing value. Summary statistics of the variables are calculated without missing value, so the sample size is different. Values in the parenthesis show the number of observations for non-commute (left) and commute (right).

3.2.2.2. Trip Attributes

The first set of predictor variables for the non-commute model are trip attributes, including trip distance, primary trip purpose, period (i.e. time of day), and weekday/weekend (Table 3.1). I used reported travel distance for e-bike trip as trip distance. Based on the assumption that slow speed is an indicator of non-destination-oriented trip making, I created the predictor "speed" by dividing reported travel distance by reported travel time; I applied log-transformation to travel distance and speed. This is because the distribution of the data is highly skewed, those log-transformed variables led to better model prediction, and it makes conceptual sense that distance and speed are order of magnitude effects on mode substitution (e.g. no one substitutes walking for a 10-mile bike-share trip).

In the commute model, trip distance is the only trip-specific attribute (given the limited data on commute trips collected in the survey). I used the Google API to estimate trip distance between reported home and workplace/school locations. This estimate is relatively accurate if commuters take the shortest route or a similar route but would underestimate distance for commuters who take a longer route, e.g. to get more exercise on their commute.

3.2.2.3. Land Use Characteristics

I defined land use characteristics as the mix of land uses in the areas around the trip start and end locations. I used the parcel-level land use data for 2016 from the Sacramento Area Council of Governments (SACOG) to characterize land use. The SACOG dataset classifies land use into 45 categories which I aggregated into six general categories: (1) Residential use, (2) Commercial/office use, (3) Industrial use, (4) School, (5) Civic use, and (6) Other use (i.e. agriculture, forest, airport). I 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 lengths: radii of 1/32 mile (50m), 1/16 mile (100m), 1/8 mile (200m), 1/4 mile (400m), 1/2 mile (800m) and 3/4 mile (1200m) for the start and end point. To determine appropriate buffer lengths for the start and end points for non-commute trips and commute trips, I fit Bayesian multinomial logistic regression models using different buffer lengths for the start and end points for the models for both types of trips. I 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, and weighted F1 Score (Details of the modeling process and the metrics are discussed in Section 3.2.3).

Table 3. 2 Prediction metrics of models by different buffer lengths to determine the effect of buffer lengths of land use on model performance

Trip Type	**Non-commute trips (n=823)**					
Start/End	**Start**			**End**		
Metric	**elpd**	**Accuracy**	**Weighted F1 score**	**elpd**	**Accuracy**	**Weighted F1 score**
Intercept model	-1467.4 (15.9)	19.4% (1.3%)	14.2% (8.7%)	-1467.4 (15.9)	19.4% (1.3%)	14.2% (8.7%)
1/32 mile (50 m)	-1475.1 (16.6)	19.4% (1.3%)	14.3% (8.7%)	-1475.2 (16.2)	19.3% (1.3%)	14.2% (8.7%)

1/16 mile (100 m)	-1454.3 (17.8)	20.6% (1.3%)	14.9% (9.0)	-1460.1 (17.1)	20% (1.3%)	14.7% (8.9%)
1/8 mile (200 m)	-1450.1 (18.1)	20.8% (1.3%)	15.1% (9.2%)	-1450.1 (18.1)	20.8% (1.3%)	**15.1% (9.2%)**
1/4 mile (400 m)	*-1446.4 (18.2)*	*21.0% (1.3%)*	*15.1% (9.2%)*	*-1457.7 (17.5)*	*20.4% (1.4%)*	*14.8% (9.0%)*
1/2 mile (800 m)	**-1438.7 (18.2)**	**21.2% (1.3%)**	15.2% (9.3%)	-1453.8 (17.5)	**20.4% (1.3%)**	14.8% (9.1%)
3/4 mile (1200 m)	-1439.4 (18.1)	21.2% (1.3%)	**15.3% (9.3%)**	**-1451.2 (17.2)**	20.4% (1.4%)	14.9% (9.1%)
Trip Type	**Commute trips (n=105)**					
Start/End	**Start**			**End**		
Metric	**elpd**	**Accuracy**	**Weighted F1 score**	**elpd**	**Accuracy**	**Weighted F1 score**
Intercept model	-139.4 (3.5)	27.9% (4.4%)	24.6% (9.9%)	-139.4 (3.5)	27.9% (4.4%)	24.6% (9.9%)
1/32 mile (50 m)	-143.6 (3.9)	27.2% (4.2%)	23.9% (9.7%)	**-137.4 (3.7)**	**28.5% (4.3%)**	**25.5% (10.1%)**
1/16 mile (100 m)	-138 (3.5)	28.4% (4.3%)	25.6% (10.1%)	-137.8 (3.4)	28.4% (4.3%)	25.5% (10.1%)
1/8 mile (200 m)	-140.6 (4.4)	28.5% (4.3%)	25.1% (10.2%)	-138.7 (3.5)	28.2% (4.3%)	25.1% (10.0%)
1/4 mile (400 m)	*-135.7 (4.6)*	*30% (4.2%)*	*26.5% (10.5%)*	*-142.3 (3.6)*	*27.5% (4.2%)*	*24.3% (9.9%)*
1/2 mile (800 m)	**-129.0 (4.6)**	**32.3% (4.4%)**	**28.5% (11.0%)**	-140.9 (3.5)	27.8% (4.2%)	24.7% (9.9%)
3/4 mile (1200 m)	-130.0 (4.3)	31.5% (4.3%)	28.0% (10.9%)	-140.3 (3.5)	27.8% (4.2%)	24.5% (10.0%)

* The values in the parentheses represent the standard error.
**Bold represents the best performance for each metric and italic represents the result of 1/4 mile (400m) used for further analysis.

Table 3.2 shows that the buffer length that performs the best for trip start and for trip end in the non-commute model varies by performance metric, but the differences are not substantial (the 1/2 mile (800m) model for trip start had the best performance on elpd and accuracy while the 3/4 mile (1200m) model had the best performance on weighted F1 score). The best scores on the elpd, accuracy, and weighted F1 metrics for end trip were for the 3/4 mile (1200m), 1/2 mile (800m), and 1/8 mile (200m) models, respectively. In commute trip models, the best performance for each metric was consistent: the best buffer length for trip start was 1/2 mile (800m) and for trip end was 50m; none of models shows clear predictive improvement over the others.

The lack of a difference in the results led me to select a buffer length for trip start and end based on the distance at which users are willing to walk to get a bike. Figure 3.1 based on the survey result shows that about 74 percent of the respondents are willing to walk up to 5 minutes to get a bike. Average walking speeds for old and young pedestrians have been measured as 4.25 ft/s (1.3 m/s) and 4.74 ft/s (1.45 m/s), respectively (Fitzpatrick et al., 2006). These speeds correspond to approximately a quarter-mile (400m) per 5 minutes. Another survey in Europe about the maximum walking distance to docked bike-share station found that more than half of respondents are willing to walk 0.31 mile (500 m) to bike stations (Singla et al., 2015), suggesting my selection of a quarter-mile (400m) to be a reasonable buffer distance.

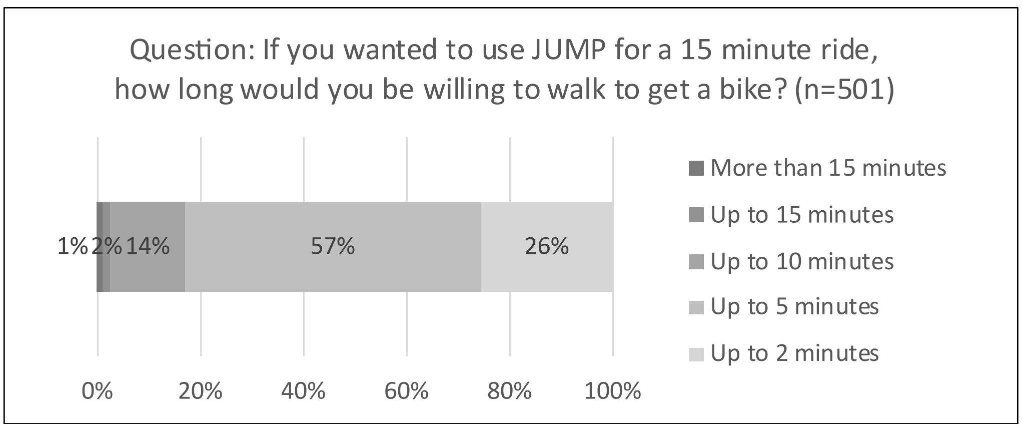


Figure 3. 1 Walking distance at which users are willing to walk to get a bike

3.2.2.4. Mode Availability

I used the number of bus stops and light-rail transit (LRT) stations and the total length of bike lanes within a buffer length of trip start and end locations as measures of the availability of other transportation modes. Bike-share availability is a determinant factor for individual level adoption and bike-share use (Kabra et al, 2019). The availability can also capture other spatial information about popular trip destinations of bike-share users which land use predictors cannot reflect. To consider availability, I created a bike-share availability index for trip starts and ends based on the 4-week free bike-share status data. I calibrated the index for each trip start and end location by checking the presence of any bike within the buffer length of the location, summing the total duration of the presence of any bike and dividing the sum by four-weeks. I examined the effect of buffer lengths for mode availability on mode substitution in the same way as for land use characteristics. The results shown in Table 3.3 suggest only slight differences in performance for different buffer lengths, so I used a quarter-mile (400m) for trip start and end buffers in both non-commute and commute models to be consistent with the buffers for land-use characteristics.

Table 3. 3 Prediction metrics of models by different buffer lengths to determine the effect of buffer lengths of mode availability on model performance

Trip Type	**Non-commute trips (n=823)**					
Start/End	**Start**			**End**		
Metric	**elpd**	**Accuracy**	**Weighted F2 score**	**elpd**	**Accuracy**	**Weighted F2 score**
Intercept model	-1467.4 (15.9)	19.4% (1.3%)	14.2% (8.7%)	-1467.4 (15.9)	19.4% (1.3%)	14.2% (8.7%)
1/32 mile (50 m)	-1467.3 (16.6)	19.7% (1.3%)	14.5% (8.8%)	-1474.4 (16.4)	19.4% (1.3%)	14.3% (8.7%)
1/16 mile (100 m)	-1459.2 (16.8)	19.9% (1.3%)	14.7% (9.0%)	-1457.8 (17.1)	20.1% (1.3%)	14.8% (9.1%)
1/8 mile (200 m)	-1456.9 (17.5)	20.3% (1.3%)	14.8% (9.0%)	-1455.7 (17.5)	20.4% (1.4%)	14.9% (9.1%)
1/4 mile (400 m)	*-1450.6 (18)*	*20.7% (1.3%)*	*15.0% (9.2%)*	*-1456.3 (17.6)*	*20.4% (1.3%)*	*14.9% (9.0%)*
1/2 mile (800 m)	-1443.0 (18.7)	21.3% (1.4%)	**15.3% (9.2%)**	**-1450.6 (17.8)**	**20.6% (1.3%)**	**15.0% (9.1%)**
3/4 mile (1200 m)	**-1440.3 (18.6)**	**21.4% (1.3%)**	15.3% (9.4%)	-1451.2 (17.8)	20.6% (1.3%)	15.0% (9.2%)
Trip Type	**Commute trips (n=105)**					
Start/End	**Start**			**End**		
Metric	**elpd**	**Accuracy**	**Weighted F2 score**	**elpd**	**Accuracy**	**Weighted F2 score**
Intercept model	-139.4 (3.5)	27.9% (4.4%)	24.6% (9.9%)	**-139.4 (3.5)**	27.9% (4.4%)	24.6% (9.9%)
1/32 mile (50 m)	-139.8 (4.2)	28.5% (4.3%)	25.1% (9.9%)	-140.6 (3.9)	28.2% (4.2%)	24.9% (9.8%)
1/16 mile (100 m)	-137.5 (4.3)	29.5% (4.4%)	26% (10.1%)	-143.8 (3.9)	27.1% (4.2%)	23.9% (9.5%)
1/8 mile (200 m)	-137.1 (5.2)	30.3% (4.4%)	26.6% (10.4%)	-140.8 (4.0)	**28.2% (4.2%)**	**25.0% (10.0%)**
1/4 mile (400 m)	*-132.7 (5.4)*	*31.9% (4.3%)*	*28.7% (11.1%)*	*-143.5 (3.9)*	*27.2% (4.3%)*	*23.9% (9.5%)*
1/2 mile (800 m)	-126.8 (5.2)	33.5% (4.4%)	30.1% (11.9%)	143.2 (3.9)	27.3% (4.2%)	24.1% (9.8%)

3/4 mile (1200 m)	**-126.2** **(5.6)**	**34.2%** **(4.3%)**	**30.9%** **(11.9%)**	-142.5 (3.5)	27.1% (4.1%)	24.1% (9.6%)

* The values in the parentheses represent the standard error.
**Bold represents the best performance for each metric and italic represents the result of 1/4 mile (400m) used for further analysis.

3.2.2.5. Individual Characteristics

I included individual characteristics in both models, including age, income, race, gender, student status, college degree, having children, membership and car ownership (Table 3.1). I included employment status in the non-commute model but not in the commute model (since everyone in this sample was employed).

3.2.2.6. Attitudinal variables

I added attitudinal variables as another group of predictors in my models. Previous studies point to the important role of attitudes in explaining mode choice behavior (e.g. Kuppam et al, 1999; Domarchi et al., 2008). Respondents in the survey were asked several questions using an ordinal 5-point response scale (strongly disagree to strongly agree) about their perceptions of and attitudes toward bicycling: *For the following statements about bicycling, please indicate how accurately each describes how you feel*. I created four attitudinal constructs – "Like bike", "Bike safe", "Bike pressure" and "Car necessity" – by summing scores for statements within each of my defined constructs (Table 3.4). I used this approach to make it easier to interpret the sense of the constructs and also because I wanted the attitudinal constructs to include the common and unique item variation (as opposed to just the common item variation which is the result of factor-analytic type approaches).

Table 3. 4 Attitude constructs and question statement

Variable	Question statement
Like bike	- Riding a bike is fun - Riding a bike is enjoyable

Variable	Question statement
	- Riding a bike is boring* - Riding a bike is pleasant - I like riding a bicycle
Bike Safe	- I feel safe from cars when bicycling in town - I feel comfortable around cars when bicycling in town - I feel anxious around cars when bicycling in town* - I get stressed by cars when bicycling in town*
Bike Pressure	- Many people I know think bicycling is healthy - Many people I know think bicycling is fun - Many people I know think bicycling is safe - Many people I know think I should bicycle
Car necessity	- I need my car to do many of the things I like to do - I need my car to carry shopping or children - I try to limit my driving as much as possible*

* indicates that ordered scale of the question statement is reversed.

I also used responses to eight other question statements about the importance of factors in their daily mode choice on ordinal 5-point response scales (not at all important to extremely important): *How important are the following factors to the choices you make about your daily travel?* The questions statements include i) Concern for the environment, ii) Concern for cost, iii) Desire to get exercise, iv) Concern for safety from crime, v) Concern for safety from traffic, vi) Desire for enjoyment, vii) Concern for time, viii) Desire for convenience. I added these factors as independent variables directly because of the ease of interpretation and because each statement is not mode specific. Because these factors are measured from a single item they may be less reliable.

3.2.2.7. Multiple imputation for missing values

Missing values in specific individual characteristics (i.e. race, income, and car ownership) and attitudinal variables potentially reduces the sample by 29% for commute models and 4% for non-commute models. Because case-wise deletion of records with missing data reduces a substantial proportion of the data for the commute model, a problem known to cause bias (Rubin, 1976), I used a technique called Multiple Imputation by Chained Equations to fill in missing data. This method imputes missing data for each variable through an iterative series of predictive models based on other variables. Imputed data always has predictive error. This method reflects this uncertainty by generating multiple datasets.

I used the R package MICE to impute missing values (Van Buuren and Groothuis-Oudshoorn, 2011). I applied the default method in the package with the exception of the number of imputations to define the number of datasets to be produced and the number of iterations. Rubin (1987) found that fewer than 10 imputations are usually enough while Schafer (1997) suggests using more than 10 imputations when the portion of missing values in the original dataset is large. Because I use Bayesian analysis and 10-fold cross validation in my modeling process (see Section 2.3 below), a high number of imputations was not possible because of long computation time, thus I set 10 as the number of imputations. I set the number of Markov chain iterations to 150 for commute trip data and 500 for non-commute trip data and confirmed that the number of iterations were enough for imputation convergence by plotting the mean and standard deviation of the imputed values, and evaluated R-hat for all variables (R-hat < 1.01). I used the portion of the data that included individual characteristics and attitudinal variables to generate 10 different datasets in the imputation process and removed data with no mode substitution or trip attributes.

3.2.3. Bayesian multinomial logistic regression

I used Bayesian multinomial logistic regression for both models to analyze the effects of the predictor variables on mode substitution. One advantage of Bayesian techniques is they attempt to reduce model overfitting by encoding prior information to the model parameters (prior probabilities), while frequentist approaches ignore overfitting (Attias, 2000). Also, Bayesian estimation techniques can more easily fit multilevel structures and allow for accounting for individual variability (Lee, 2011; van Ravemzwaaij, 2014). Another advantage of Bayesian techniques is that they do not rely on asymptotics (unlike frequentist techniques) to make inferences from the parameters, and so are more robust for handling problems with small sample sizes (McNeish, 2016). Because I would like to guard against overfitting, fit multilevel model structures, and I have a small sample size for one model group (commute model), Bayesian estimation is perfectly suited to the data in my study.

I estimated a series of models with increasing complexity to examine the effects of groups of variables (Table 3.5). I added groups of variables in the following order: trip attributes, land use characteristics, mode availability, individual characteristics, and attitudinal variables.

In the non-commute model (NCM), I allow the average probability of mode substitution to vary by person because respondents provide data for several trips. This approach accounts for person-level heterogeneity in mode substitution. The first model (NCM-I) was the baseline version of the non-commute model without any predictors but with alternative specific constants (intercepts). NCM-II extended NCM-I by including varying intercepts by person. In NCM-III I added trip attributes, such as trip distance and trip purpose to NCM-II to evaluate the effects of trip information on decision making. I added land use, mode availability, individual characteristics, and attitudinal variables in that order, but the models show small predictive improvement for each group of variables. I report NCM-IV (spatial factors including land use and mode availability added to NCM-III) and NCM-V (individual characteristics and attitudinal variables added to NCM-IV).

In the commute model (CM), CM-I was the baseline model without any predictors but with alternative specific constants (intercepts). CM-II extended CM-I by including trip attributes and CM-III extended CM-II by including mode availability. I did not include land use variables in the commute model because they did not improve model performance metrics making inferences potentially unreliable. I added individual characteristics and attitudinal variables to CM-III. I do not report a series of other models I tested (e.g. a model including trip attributes, mode availability and individual characteristics but no individual characteristics or attitudinal variables) because model predictions were nearly equivalent, and NCM-V and CM-IV allowed me to report conditional effects for all variables.

Table 3. 5 Predictors Included in Mode Substitution Models

	Intercept	Varying Intercept (Person)	Trip Attributes	Land Use	Mode Avail.	Individual Characteristics	Attitudinal Vars
Non-Commute Model							
NCM-I	x						
NCM-II	x	x					
NCM-III	x	x	x				
NCM-IV	x	x	x	x	x		
NCM-V*	x	x	x	x	x	x	x
Commute Model							
CM-I	x						
CM-II	x		x				
CM-III	x		x		x		
CM-IV*	x		x		x	x	x

* indicates that details of estimates are discussed in the result section.

I used the R package brms, an interface to fit Bayesian models using a probabilistic programming language Stan, to develop my mode substitution models (Bürkner, 2017; Stan Development Team, 2018). I used the default Markov chain Monte Carlo (MCMC) simulation method in Stan, drawing random samples from the posterior, to converge the estimator (R-hat < 1.01), with setting parameters: 4 Markov chains, 4000 iterations for each chain (2000 for warmup that I discarded), tuning parameters 0.9 for adapt_delta and 16 for max_tree_depth, and ensured the estimation completed without Stan diagnostic warnings for each imputed dataset. I pooled the estimated parameters for 10 different datasets and summarized them as a final output.

The model formula and priors are as follows:

$$y_i \sim Categorical\ Logit(U_{ij})$$

$$U_{ij} \sim a_j + a_{j,person[i]} + \sum_{m=1}^{M} \beta_{mj} X_{mi}$$

Prior probability distributions for non-commute models

$a_{j,person[i]} \sim Normal(0, \sigma_{person})$

$\beta_{mj} \sim Normal(0, 1.5)$

$a_j \sim Normal(0,3)$

$\sigma_{person} \sim HalfStudentT(3,0,2)$

Prior probability distributions for commute models

$\beta_{mj} \sim Normal(0, 1.5)$

$a_j \sim Normal(0, 1.5)$

where y_i is a substituted mode for individual i, U_{ij} is the utility equation of substituted mode j for individual i, a_j is the constant intercept of substituted mode j, $a_{j,person[i]}$ is the varying intercept of substituted mode j for individual i, β_{mj} is a parameter of variable m for substituted mode j and X_{mi} is a predictor of variable m for individual i. Because commute models did not include varying intercept by person, the term, $a_{j,person[i]}$, is not in the equation.

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 (learning 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, I chose priors based on a series of "prior predictive checks" that suggested that my priors simulated reasonable data (i.e. allowing the occasional extreme simulation outcomes, such as 90% substitution of one mode, but ensuring that more frequent simulations provided more balanced and uniform mode substitutions). Following visualizations of a variety of priors ("prior predictive checks"), I decided to use priors for each model as shown above. 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 (McElreath, 2020).

In addition to setting weakly informative priors to reduce potential over-fitting, I compare 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. I used stratified 10-fold cross-validation by class for each dataset 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 except it is pointwise per MCMC iteration (not simply a point estimate) and it is based on the held-out data thus making a natural assessment of model predictive accuracy. Overall accuracy is the proportion of correctly classified samples in the held-out data. This metric demonstrates a more intuitive performance of the model. However, the metric has a flaw when the classes of sample data are very imbalanced. For instance, in my non-commute trip data, walking is 33.2% of the total while transit is only 5.0%. To understand how well the model predicts each class, I also used true positive rate, the proportion of correctly classified responses of one specific class out of the number of predictions of that class, and false positive rate, the proportion of correctly classified responses of one specific class out of all the samples of that class. Furthermore, there is a tradeoff between the true positive rate and false positive rate; one metric may increase as the other decreases. Therefore, I also report the F1 score by class, the harmonic mean of both metrics. In addition, I used a weighted average F1 score, combining 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. Except elpd (I reported the range of the means), I pooled each prediction metric for each model by dataset and reported the mean and standard error of the metric because each model includes 2,000 different posterior distribution samples and I have 10 different imputed datasets (the number of iterations post warm-up I ran for each model).

3.2.4. Limitations

The data and methods have several limitations worthy of note. First, my sample is not likely to be fully representative of the entire bike-share user population. Because there is no census of bike-share users, it is impossible to know how my sample might be biased other than how I hypothesize in the paper and as Fitch et al. (2020) also discuss in comparing characteristics of the respondents of this survey of users to respondents from a household-based survey as a part of a larger study of the impacts of the bike-share system. However, this issue is not expected to cast doubt on my result in examining factors associated with the mode substitution as Babbie (2015) points out that the sample bias is less concerned in explanatory research than in descriptive research.

The reported trip data, 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 was 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 adds unknown error. In addition, inaccuracy of the speed measure may have reduced model reliability. In the Jump app, the user could hold their reservation for up to 15 minutes. Some people may have reserved the bike first and walked to the bike location while others reserved the bike at the bike location. Because the use duration includes the reservation time, the reported travel time might have overestimated the actual travel time, skewing my calculated measure of speed. Another limitation is that some users might have had several trip purposes at the destination though the survey asked them to report only the "primary" purpose of their trip.

Mode substitution might not be accurately captured for several reasons. The question about mode substitution for their actual trip is hypothetical. I asked them 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. To complicate matters, the mode substitution decision might change with circumstances. For example, other scheduled activities before or after the reported trip may change a person's reported mode substitution. In addition, the grouping of similar transportation modes in the survey may hide important variation in mode substitution. For example, I created a group called "ride-hailing" including taxi and ride-hailing services, but an existing study has pointed out that the modes have different user characteristics (Rayle, et al., 2016).

Finally, the small sample for the commute model means that my estimates are uncertain, although not untrustworthy. In particular, few observations for commutes to school in the Sacramento/West Sacramento service boundary and the lack of data for commute trips using Jump as a secondary mode prevented me from modeling factors influencing mode substitution for all types of trips.

3.3. Results and Discussion

3.3.1. Non-commute trips

3.3.1.1. Model Comparison

Comparisons of all models (Table 3.6) indicate that the varying effects by person and trip attributes help explain mode substitution (i.e. all predictive metrics improve with more than 1 standard error). This suggests that mode substitution varies by personal preference and trip context, to some extent. I found only modest improvement in out-of-sample prediction by adding land use, mode availability, individual characteristics, and attitudinal variables, and only a select few characteristics proved to have measurable effects on mode substitution. Using 10-fold stratified cross-validation to predict out-of-sample mode substitution, NCM-III showed lower elpd than other models while NCM-V the best accuracy and weighted F1 score.

Table 3. 6 Prediction Metrics for Non-commute Model*

	NCM-I	**NCM-II**	**NCM-III**	**NCM-IV**	**NCM-V**
Elpd	-1467.3 ~ -1467.3	-1193.7 ~ -1164.4	-1119.6 ~ -1081.0	-1121.3 ~ -1089.6	-1157.3~ -1116.3
Accuracy	19.4% (1.3%)	34.5% (1.5%)	40.6% (1.4%)	41.4% (1.4%)	43.1% (1.4%)
True Positive rate					
Transit	5.1% (3.4%)	8.7% (4.4%)	13.8% (5.2%)	14.8% (5.3%)	16.9% (5.5%)
Bike	14.3% (3.2%)	35.6% (4.0%)	38.5% (3.9%)	38.6% (3.9%)	41.7% (3.8%)
Walk	33.1% (2.9%)	48.2% (2.8%)	57.0% (2.6%)	57.7% (2.6%)	59.0% (2.4%)
Ride-hailing	16.1% (3.2%)	30.3% (3.8%)	38.9% (3.7%)	39.7% (3.7%)	41.3% (3.5%)
Car, Alone	13.7% (3.2%)	28.6% (3.9%)	30.8% (3.8%)	32.8% (3.9%)	33.9% (3.7%)
No Trip	11.1% (3.3%)	28.4% (4.3%)	32.9% (4.4%)	33.2% (4.4%)	35.4% (4.3%)
Car-pooling	6.5% (3.4%)	15.5% (4.6%)	19.9% (4.9%)	20.9% (4.9%)	22.7% (5.0%)
False Positive rate					
Transit	4.9% (3.3%)	8.7% (4.3%)	14.3% (5.1%)	15.5% (5.2%)	18.2% (5.6%)
Bike	14.3%	35.8%	38.5%	38.4%	41.8%

	NCM-I	NCM-II	NCM-III	NCM-IV	NCM-V
	(3.0%)	(3.5%)	(3.4%)	(3.3%)	(3.3%)
Walk	33.2%	47.9%	56.8%	57.9%	59.0%
	(2.3%)	(2.2%)	(2.1%)	(2.1%)	(2.0%)
Ride-hailing	16.1%	30.3%	39.1%	39.8%	41.8%
	(2.9%)	(3.4%)	(3.7%)	(3.2%)	(3.1%)
Car, Alone	13.7%	29.2%	31.7%	33.4%	34.5%
	(3.0%)	(3.5%)	(3.6%)	(3.4%)	(3.4%)
No Trip	11.1%	28.6%	32.7%	33.3%	34.9%
	(3.1%)	(3.9%)	(3.8%)	(3.9%)	(3.8%)
Car-pooling	6.5%	15.3%	19.2%	19.5%	21.0%
	(3.1%)	(4.3%)	(4.4%)	(4.3%)	(4.3%)
F1 Score					
Transit	5.6%	8.9%	14.0%	15.1%	17.4%
	(2.9%)	(4.0%)	(5.0%)	(5.1%)	(5.3%)
Bike	14.3%	35.6%	38.4%	38.5%	41.7%
	(3.0%)	(3.4%)	(3.4%)	(3.3%)	(3.2%)
Walk	33.1%	48.0%	56.9%	57.8%	59.0%
	(2.5%)	(2.3%)	(2.0%)	(2.0%)	(1.9%)
Ride-hailing	16.1%	30.3%	39.0%	39.7%	41.5%
	(3.0%)	(3.4%)	(3.2%)	(3.2%)	(3.0%)
Car, Alone	13.7%	28.8%	31.2%	33.1%	34.1%
	(3.0%)	(3.5%)	(3.5%)	(3.4%)	(3.3%)
No Trip	11.1%	28.5%	32.8%	33.2%	35.1%
	(3.2%)	(3.9%)	(3.9%)	(3.9%)	(3.7%)
Car-pooling	6.6%	15.4%	19.5%	20.1%	21.8%
	(3.1%)	(4.3%)	(4.5%)	(4.4%)	(4.4%)
Weighted F1 Score	14.2%	27.9%	33.1%	33.9%	35.8%
	(2.5%)	(3.5%)	(3.7%)	(3.7%)	(3.6%)

* The values in the parentheses represent the standard error.

Another metric for the classification problem, F1 score by class, also gives insight into what groups of predictors help in predicting specific classes. For example, adding varying effects by person has a strong effect on improving the scores for bike, walking, ride-hailing, private car, and no trip. In addition, adding trip attributes to the model helps explain mode substitution especially for walking and ride-hailing. Adding land use, mode availability, individual characteristics, and attitudinal variables showed small predictive improvement for each mode. All models show low scores for transit and carpooling. This might be due to the small number of observations for these modes with 41 and 53, respectively; or it could be due to unobserved factors, such as trip context and driver's schedule in the case of carpooling.

3.3.1.2. Model Estimates

Trip Attributes

While trip attributes improved the model prediction (Table 3.6), several trip attributes showed distinctive associations with the dependent variable (Table 3.7). Trip distance is a commonly reported factor that influences mode choice (Buehler, 2011). The estimate of the effect of trip distance on walking was the most negative, with a coefficient of -2.71 (se=0.47). It is intuitive that people are less likely to walk if trip distance is longer. While trip distance had positive coefficients for all car-related options, the estimate for ride-hailing was the most sensitive to trip distance with a coefficient of 0.79 (se=0.47).

Trip purpose also has some interesting effects on mode substitution. A positive coefficient for the no-trip option for restaurant and shopping purposes suggests that the bike-share service induced trips for these purposes, which could contribute to increased economic vitality for the community as well physical activity for the user (Fishman, 2016; Ricci, 2015; Shaheen, et al., 2010). Those who use the bike-share for recreational purposes tend to say they would give up making a trip if the bike were unavailable, another indicator that the service induces some physical activity. Also, Table 3.7 shows that the estimates of the effects of recreational purpose for active modes are positive while for car-related modes they are negative. The estimated effects of the trip purposes *going to home* and *restaurant* are positive and relatively strong for ride-hailing at 2.44 (se= 0.74) and 2.75 (se=0.69), respectively, while the estimated effect of *shopping* on ride-hailing is negative.

Time of day also helps explain mode substitution. For those who used the bike-share for non-commute trips in the AM peak, my models predict they would have used private bicycles and not walked or driven a private car had bike-share been unavailable. Off-peak was most positively associated with carpooling from among all modes. Those who cannot find an accessible bike at night are likely to take ride-hailing. Also, that weekend trips are likely to substitute for carpooling is intuitive because people's schedule are more flexible than on weekdays.

Graphs of the conditional effect of trip distance by trip purpose **(**Figure 3.2**)** suggest that the dominant substitution-mode shifts from walking to other modes for trip distances of more than 1 mile for any trip purpose. Recreational trips are an exception: for these trips, the dominant substitution-mode shifts from walking to giving up the trip when the distance is less than one mile. This result suggests that most long trips for recreational purposes are induced by the bike sharing service.

Speed also has differential effects by mode. The estimated effect is lowest for giving up the trip. In addition, mode substitution varies depending on speed and trip purpose **(**Figure 3.3**)**. For any level of speed, the most likely mode substitution is “no trip” for a recreational trip. This is consistent with my expectation and existing research that non-destination-oriented trips are associated with slower speeds (Almannaa et al., 2020) and suggests that shared e-bikes induce recreational trips. Figure 3.3 also shows that the likelihood of substituting walking increases for every purpose as speed increases.

Land Use

The model shows that the percentage of land that is commercial/office use at the starting point of the trip is another important factor explaining car substitution. The negative effect indicates that those who use dock-less e-bike-share starting from commercial/office areas are unlikely to use private car and ride-hailing if a bike is not available. On the other hand, the portion of commercial/office use at the starting point has large positive effect on walking. This is intuitive since 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. Also, the model shows that the share of use with commercial/office at the end point of the trip has a negative effect on the choice of private car, but a positive effect on of ride-hailing. One explanation for this could be the relatively high parking fees in these areas. The model also shows that those who start their trip in a location with a high share of non-commercial use tend to substitute e-bike-share for car-related options. Trips starting in locations with a high proportion of civic land use are less likely to substitute for walking while traveling *to* civic land uses had an opposite tendency.

Mode Availability

Although prior studies have found that more bike paths can promote bicycling (e.g. Moudon et al., 2005), my study shows just a small effect of bike lanes at the trip start on the choice of private bicycle in the absence of bike-share, suggesting strong predictors of travel mode may not be strong predictors of travel mode substitution. Bike-share substitutes for ride-hailing less often when bikes are more frequently available at the start of trips, but more often when bikes are often available at the end of trips. Also, on average, greater bike availability at the end of trips makes people likely to substitute a private bicycle or vehicle (the latter effect is weak). These results make sense for trips that are the first leg of a round-trip: users know they have a high probability of finding bike-share bike for their return trip. They also make sense if the trip is the second leg of a round-trip, for which private vehicle or private bicycle is not likely to be an option if it was not used for the first leg (and if it was used, bike-share would almost certainly not be used for the second leg). Bike availability at either end of the trip is a general indicator of the reliability of finding a bike when needed, which is especially important when substituting bike-share for personally-owned modes for round trips. Trips starting or ending in areas with easy access to public transit, including LRT and bus, are less likely to substitute for private car or ride-hailing.

Individual Characteristics

The estimates of the effects of individual characteristics suggest that some types of people are more likely to choose a specific substitution mode than others. For example, students are more likely to substitute ride-hailing but much less likely to substitute private car. This is intuitive because younger adults are in general more likely to choose ride-hailing and less likely to own private vehicles (Alemi et al., 2018; Young and Farber, 2019). The relationship between age and use of ride-hailing can also be observed in my model, which shows that those who are less than 44 years old are more likely to substitute ride-hailing. Interestingly, being a student had a relatively small effect on substituting bike share for personal bikes. This may be because those who have their own bikes have less reason to use bike share. Substituting bike share for personal bike does, however, vary by age. Younger (25-34 years old) users are more likely to substitute for personal bicycling compared to those 35 years old or older. Also, those who are 55 years old or older have a high probability of saying they would give up a trip if the bike share service were not available, suggesting that bike share is inducing physical activity for this age cohort.

Other characteristics also influence the substitution mode. College degree has a large effect on substituting personal bicycling. Identifying as a woman is strongly associated with substituting bike share for car travel, particularly private car and carpooling, and only rarely with substituting for personal bicycling. My results also show differences by racial identity.

Identifying as Asian is strongly associated with substituting carpooling while identifying as Hispanic and/or white show negative associations with substituting carpooling. 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 since they can make this substitution) but also for carpooling and ride-hailing, although the latter effect is weaker. Those who have a bike-share membership are less likely to use ride-hailing or private car. The predictor of household income between $100,000 and $200,000 has a large positive effect on the choice of carpooling as the substitution mode, but those who have household income more than $200,000 are less likely to choose carpooling. Those who have household income between $50,000 and $100,000 are less likely to substitute bike-share for ride-hailing and private vehicle.

Table 3. 7 NCM-V parameter means and standard errors

Base = Transit	Bike	Walk	Ride-hailing	Car, Alone	No Trip	Carpooling
Intercept	-6.36 (3.84)	2.65 (3.48)	-2.29 (3.86)	1.4 (3.88)	-0.12 (3.83)	-8.41 (3.98)
Person-level Std. Dev.	4.01 (0.74)	3.84 (0.59)	4.04 (0.71)	4.33 (0.79)	3.82 (0.76)	3.05 (0.81)
Trip Attribute						
Travel Distance (log)	0.55 (0.46)	-2.71 (0.47)	0.79 (0.47)	0.35 (0.45)	-0.01 (0.43)	0.78 (0.48)
Speed (log)	-0.73 (0.61)	-0.16 (0.53)	-0.15 (0.62)	-0.72 (0.61)	-0.86 (0.58)	-0.66 (0.63)
Trip Purpose (Base: other)						
Restaurant	1.07 (0.71)	0.59 (0.61)	2.75 (0.69)	0.00 (0.66)	1.02 (0.67)	0.78 (0.75)
Home	1.06 (0.73)	0.97 (0.68)	2.44 (0.74)	-0.88 (0.76)	-0.98 (0.87)	0.86 (0.82)
Work related	0.31 (0.76)	-0.47 (0.64)	0.50 (0.78)	-1.66 (0.81)	-0.55 (0.83)	-1.22 (0.88)
Shopping	1.29 (0.84)	-0.87 (0.77)	-2.10 (1.03)	-0.28 (0.87)	0.36 (0.83)	1.37 (0.94)
Recreation	1.66 (0.82)	0.38 (0.74)	-1.67 (0.96)	-1.87 (0.85)	3.54 (0.82)	-0.26 (0.90)
Time of Day (Base: Midnight)						
AM Peak	1.09 (0.84)	-1.26 (0.77)	0.37 (0.80)	-0.74 (0.83)	-0.94 (0.91)	-0.25 (0.89)
Off Peak	0.53 (0.75)	-0.32 (0.64)	-0.04 (0.69)	0.50 (0.72)	0.57 (0.75)	0.93 (0.80)
PM Peak	0.31 (0.79)	-1.06 (0.69)	-0.35 (0.74)	-0.50 (0.76)	-0.56 (0.80)	-0.27 (0.86)
Night	0.37 (0.85)	-0.63 (0.76)	0.96 (0.79)	-0.20 (0.84)	-0.15 (0.94)	-0.03 (0.94)
Weekend	0.02 (0.62)	0.04 (0.56)	-0.53 (0.61)	-0.45 (0.63)	-0.52 (0.67)	0.69 (0.67)
Land Use						
Start (a quarter-mile buffer)						
Residential use	0.62 (1.09)	0.16 (1.03)	1.19 (1.07)	0.12 (1.08)	-0.41 (1.11)	0.52 (1.13)
Commercial/Office use	-0.32 (1.15)	0.78 (1.08)	-0.69 (1.14)	-1.14 (1.15)	0.30 (1.17)	-1.00 (1.20)
Industrial use	-0.07 (1.44)	-0.43 (1.43)	0.28 (1.45)	-0.11 (1.44)	0.25 (1.44)	0.43 (1.45)
School use	-0.26 (1.45)	-0.43 (1.39)	0.22 (1.45)	0.21 (1.43)	-0.04 (1.41)	0.71 (1.44)
Civic use	0.55 (1.32)	-1.11 (1.29)	0.22 (1.32)	0.51 (1.31)	-0.43 (1.36)	-0.34 (1.37)
End (a quarter-mile buffer)						
Residential use	-0.10 (1.05)	0.09 (1.03)	0.34 (1.09)	1.26 (1.09)	-0.14 (1.07)	-0.94 (1.11)
Commercial/Office use	0.09 (1.13)	1.76 (1.09)	1.04 (1.14)	-0.65 (1.15)	-0.31 (1.13)	-0.06 (1.18)
Industrial use	-0.33 (1.34)	-0.20 (1.45)	-0.34 (1.43)	0.90 (1.35)	0.24 (1.42)	0.35 (1.42)
School use	-0.49 (1.31)	-0.84 (1.34)	-0.45 (1.34)	-0.66 (1.38)	-0.26 (1.29)	0.60 (1.31)
Civic use	-0.24 (1.32)	1.23 (1.23)	0.09 (1.34)	-0.84 (1.30)	-1.03 (1.34)	-0.16 (1.35)
Mode Availability						
Start (a quarter-mile buffer)						
# Bus stops	-0.61 (1.18)	0.18 (1.10)	-0.24 (1.15)	-1.37 (1.20)	0.53 (1.18)	0.13 (1.23)
# LRT stations	-0.57 (1.16)	1.32 (1.04)	-0.12 (1.12)	-1.65 (1.17)	-1.49 (1.16)	0.28 (1.18)

Base = Transit	Bike	Walk	Ride-hailing	Car, Alone	No Trip	Carpooling
Length of Bike Lanes	0.39 (1.00)	0.00 (0.92)	-0.08 (1.02)	-1.89 (1.05)	-0.22 (1.04)	0.07 (1.09)
Bike availability	0.06 (1.31)	-0.39 (1.27)	-1.02 (1.33)	-0.19 (1.30)	-0.15 (1.34)	0.19 (1.34)
End (a quarter-mile buffer)						
# Bus stops	-0.98 (1.13)	0.63 (1.08)	-0.14 (1.15)	0.28 (1.17)	0.06 (1.14)	0.06 (1.21)
# LRT stations	0.82 (1.09)	-0.53 (1.01)	0.88 (1.09)	-0.58 (1.15)	-0.23 (1.11)	-1.47 (1.18)
Length of Bike Lanes	-1.01 (0.96)	0.15 (0.89)	-0.89 (0.99)	-1.32 (0.95)	0.03 (1.00)	0.35 (1.03)
Bike availability	-0.46 (1.26)	-0.21 (1.22)	1.32 (1.30)	-0.20 (1.30)	-1.12 (1.28)	-0.36 (1.32)
Individual Characteristics						
Age (Base: less than 25)						
25 – 34	1.10 (0.91)	-0.08 (0.81)	0.85 (0.88)	-0.05 (0.91)	0.69 (0.88)	0.60 (0.89)
35 – 44	-0.24 (0.96)	-0.28 (0.86)	0.42 (0.92)	-0.23 (0.95)	-0.51 (0.96)	-0.39 (0.95)
45 – 55	0.00 (1.10)	-0.20 (0.99)	-0.39 (1.08)	-0.97 (1.10)	-1.05 (1.10)	0.72 (1.04)
55 –	0.16 (1.14)	-0.06 (1.07)	-1.57 (1.20)	-0.10 (1.14)	1.28 (1.11)	0.71 (1.13)
Woman	-0.84 (0.80)	0.16 (0.69)	0.01 (0.77)	0.85 (0.80)	-0.57 (0.79)	1.89 (0.78)
Race (Base: Else)						
Asian	-0.60 (1.15)	0.00 (0.99)	0.23 (1.06)	-0.83 (1.12)	0.45 (1.07)	1.38 (1.05)
Hispanic/Latino	0.47 (1.07)	-0.53 (0.96)	-0.35 (1.07)	0.46 (1.11)	-0.07 (1.06)	-1.20 (1.12)
White	1.06 (0.91)	0.34 (0.80)	0.24 (0.85)	0.00 (0.89)	-0.14 (0.87)	-0.58 (0.87)
Employed	1.02 (1.00)	-0.85 (0.81)	1.26 (0.97)	0.33 (0.99)	-0.16 (0.94)	0.06 (0.96)
Student	-1.06 (1.04)	0.52 (0.88)	0.49 (0.97)	-0.99 (1.05)	0.05 (0.99)	-0.33 (1.00)
College Degree	1.76 (0.90)	0.04 (0.79)	0.07 (0.86)	0.38 (0.89)	0.24 (0.90)	0.32 (0.89)
Having Children	0.31 (0.84)	-0.61 (0.75)	-1.37 (0.82)	0.05 (0.86)	-0.47 (0.86)	0.53 (0.85)
Car Ownership	0.16 (0.75)	-0.14 (0.65)	0.41 (0.76)	0.97 (0.82)	0.66 (0.74)	0.55 (0.73)
Bike-share Membership	-0.09 (0.90)	0.31 (0.91)	-1.11 (1.04)	-0.51 (0.93)	-0.49 (0.93)	-0.20 (1.00)
Income (US dollars)						
50,001 to 100,000	-0.44 (0.87)	-0.59 (0.77)	-1.06 (0.85)	-0.74 (0.88)	-0.42 (0.94)	0.51 (0.88)
100,000 to 200,000	-0.76 (0.98)	-0.32 (0.85)	0.68 (0.91)	0.36 (0.90)	0.67 (0.91)	1.53 (0.90)
More than 200,000	0.67 (1.09)	-0.47 (1.03)	-0.10 (1.10)	0.46 (1.05)	0.17 (1.16)	-1.26 (1.24)
Attitude						
Like Bike	0.19 (1.37)	1.16 (1.29)	-0.10 (1.37)	0.04 (1.38)	-1.78 (1.37)	0.45 (1.40)
Bike Safety	-0.08 (1.33)	0.34 (1.26)	-1.15 (1.34)	0.46 (1.31)	0.18 (1.35)	0.50 (1.36)
Bike pressure	0.23 (1.29)	0.45 (1.20)	0.72 (1.28)	-0.88 (1.30)	-0.13 (1.28)	0.39 (1.31)
Car necessity	-1.70 (1.23)	0.70 (1.12)	-0.77 (1.18)	0.64 (1.26)	-0.30 (1.24)	1.77 (1.26)
Concern for the environment	1.05 (1.11)	0.14 (1.03)	-0.17 (1.10)	-0.77 (1.14)	-1.12 (1.10)	-1.00 (1.11)
Concern for cost	-0.61 (1.13)	-0.87 (1.06)	0.79 (1.12)	-1.03 (1.16)	-0.24 (1.16)	0.31 (1.14)

Base = Transit	Bike	Walk	Ride-hailing	Car, Alone	No Trip	Carpooling
Desire to get exercise	0.76 (1.16)	-0.74 (1.07)	-0.72 (1.12)	-0.18 (1.15)	-0.01 (1.12)	-1.05 (1.10)
Concern for safety from crime	1.44 (1.09)	-0.17 (0.99)	-1.81 (1.07)	-1.15 (1.11)	-0.13 (1.08)	-0.15 (1.07)
Concern for safety from traffic	1.31 (1.11)	0.02 (1.04)	0.04 (1.14)	-0.28 (1.14)	1.01 (1.13)	-0.60 (1.12)
Desire for enjoyment	0.63 (1.17)	-0.10 (1.08)	0.90 (1.14)	-1.20 (1.18)	-0.45 (1.16)	-0.03 (1.15)
Concern for time	-0.77 (1.19)	-0.51 (1.11)	-0.64 (1.20)	1.33 (1.21)	0.35 (1.18)	0.87 (1.19)
Desire for convenience	-0.30 (1.27)	-0.15 (1.21)	0.51 (1.27)	0.72 (1.31)	0.44 (1.27)	1.51 (1.29)

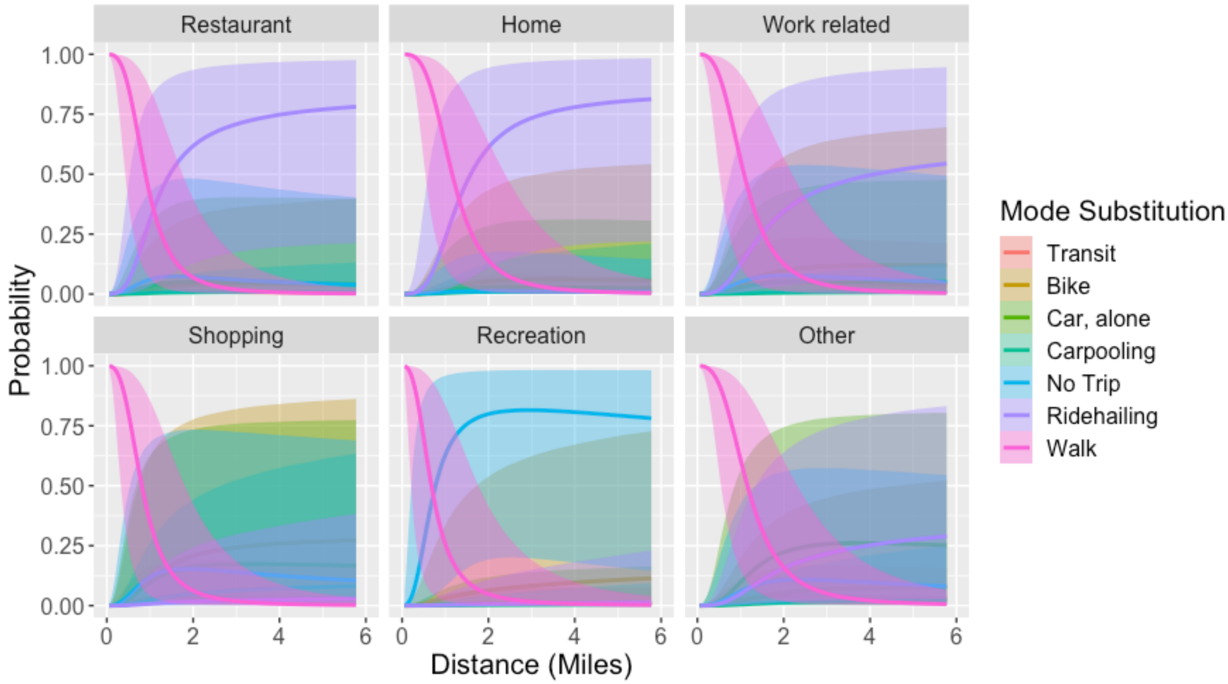


Figure 3. 2 Conditional Combined Effects of Trip Distance and Trip Purpose on Mode Substitution (Conditions: Off Peak; Age25-34; Weekday; College degree; Non-student; No child; Employed; Male; White; Car owner; Household income ($100,000-200,000); non-membership; mean values of continuous predictors)

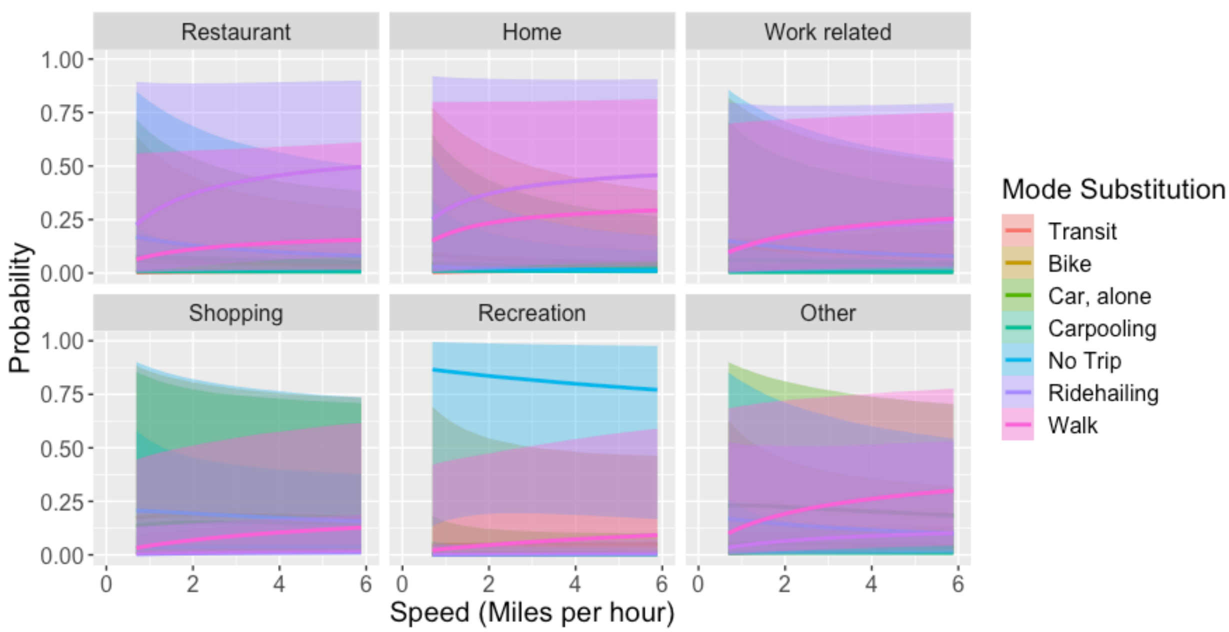


Figure 3. 3 Conditional Combined Effects of Speed and Trip Purpose on Mode Substitution (Conditions: Off Peak; Age25-34; Weekday; College degree; Non-student; No child; Employed; Male; White: Car owner; Household income ($100,000-200,000); non-membership; mean values of continuous predictors)

Attitudinal Variables

Our results show some interesting influences of attitudes on mode substitution. For example, the finding that those who think that they need their own car for some activities tend to choose private car and carpooling as substitution modes is intuitive. Such individuals are less likely to use their own bicycles when bike-share was unavailable. Those with a high score for "bike pressure" are less likely to substitute private car, but more likely to substitute other car options. My findings show that "like bike" and "bike safe" have positive but small effects on the choice of bicycling as the substitution mode.

Some factors considered important in daily mode choice are also associated with mode substitution. One clear result is that environmental concern increases the likelihood of substituting for active travel modes and decreases the likelihood of substituting for car-related options. That those who consider convenience an important factor in their daily mode choice tend to choose car-related options suggests the need for bike-share operators to have a good rebalancing strategy to ensure convenient access to bike-share bikes in order to reduce the use of cars. Those who desire exercise tend to substitute bike share for private bicycle but not walking. The findings that those who are more concerned about safety from crime and traffic are less likely to choose car-related options are not intuitive and merit further exploration. Another interesting finding is that those who are more concerned about cost are more likely to substitute bike-share for ride-hailing and carpooling. Those who put importance on enjoyment tend not to substitute private car but do substitute ride-hailing. Those who are concerned about time are more likely to substitute private car and carpooling, but less likely to substitute ride-hailing. Explanations for many of these findings are not readily apparent.

3.3.2. Commute trip

3.3.2.1. Model Comparison

Among the commute models, CM-IV showed the best accuracy and weighted F1 score (Table 3.8). Comparisons of all models indicate that trip distance and individual characteristics/attitudinal variables help to explain mode substitution compared to mode availability. However, the standard error of each metric shows the large uncertainty in the models probably owing to the fact that the number of observations was small. Also, the range of elpd for CM-IV is larger than others because of multiple imputations. The results of F1 score by class showed high predictive improvement for walk as the substitution mode by adding trip attributes. Individual characteristics/attitudinal variables also help explain mode substitutions from walk, car, and bike. Interestingly, no variables I explored in this analysis improved prediction of transit substitution leaving estimates transit substitution much more uncertain than other modes.

Table 3. 8 Prediction Metrics for Commute Model*

	CM-I	CM-II	CM-III	CM-IV
Elpd	-139.4 ~ -139.4	-128.8 ~ -126.6	-132.3 ~ -126.6	-144.6 ~ -126.5
Accuracy	28.0% (4.3%)	33.6% (4.4%)	34.4% (4.4%)	38.7% (4.1%)
True Positive rate				
Transit	15.9% (9.5%)	16.7% (9.3%)	17.8% (9.5%)	15.5% (9.0%)
Bike	38.7% (8.0%)	39.0% (7.6%)	40.5% (7.6%)	46.6% (7.0%)
Car	19.8% (8.9%)	24.8% (9.4%)	25.3% (9.3%)	29.7% (9.0%)
Walk	25.4% (8.7%)	42.3% (8.8%)	42.3% (8.7%)	47.5% (8.3%)
False Positive rate				
Transit	15.1% (8.5%)	16.0% (8.5%)	17.2% (8.7%)	15.5% (8.6%)
Bike	39.0% (6.1%)	39.6% (6.0%)	40.9% (5.9%)	47.2% (5.4%)
Car	20.1% (8.2%)	24.8% (8.3%)	25.3% (8.3%)	28.5% (7.6%)
Walk	25.6% (7.5%)	42.6% (7.3%)	42.7% (7.2%)	48.6% (7.3%)
F1 Score				
Transit	16.4% (7.7%)	17.0% (7.8%)	18.0% (8.1%)	16.4% (7.6%)
Bike	38.6% (6.6%)	39.2% (6.4%)	40.5% (6.3%)	46.7% (5.7%)
Car	19.9% (7.9%)	24.6% (8.3%)	25.1% (8.3%)	28.9% (7.8%)
Walk	25.3% (7.6%)	42.2.% (7.4%)	42.2% (73.0%)	47.8% (7.0%)

	CM-I	CM-II	CM-III	CM-IV
Weighted F1 Score	24.7% (9.9%)	30.5% (11.8%)	31.2% (12.1%)	34.7% (13.1%)

* The values in the parentheses represent the standard error.

3.3.2.2. Model Estimation

Trip Attributes

The estimate of the effect of trip distance on mode substitution in the commute model is similar to the estimate in non-commute mode (Table 3.9). The effect on walking is the most negative, with a coefficient of -3.24 (se=0.86) while the effect on car was the most positive, with a coefficient of 0.93 (se=0.89). Interestingly, the effect on personal bike substitution was near zero, indicating that trip distance may not help distinguish between bike and transit as a substituted mode.

Table 3. 9 CM-IV parameter means and standard errors

Base = Transit	Bike	Walk	Car
Intercept	1.45 (2.99)	1.49 (3.53)	-1.10 (3.38)
Trip Attribute			
Travel Distance (log)	0.00 (0.75)	-3.24 (0.86)	0.93 (0.89)
Mode Availability			
*Start (*a quarter-mile *buffer)*			
# Bus stops	-0.68 (1.35)	1.14 (1.35)	-0.45 (1.41)
# LRT stations	1.16 (0.83)	0.39 (0.90)	-0.82 (1.05)
# Length of Bike Lanes	-1.86 (1.11)	1.06 (1.19)	-1.44 (1.18)
Bike availability	-0.02 (1.28)	-0.18 (1.38)	-0.50 (1.31)
*End (*a quarter-mile *buffer)*			
# Bus stops	-0.91 (1.16)	0.30 (1.22)	0.04 (1.26)
# LRT stations	-0.18 (1.15)	0.30 (1.22)	-0.96 (1.22)
# Length of Bike Lanes	0.66 (1.07)	-0.24 (1.19)	-0.18 (1.16)
Bike availability	-0.74 (1.44)	0.25 (1.47)	0.30 (1.45)
Individual Characteristics			
Age (Base: less than 25)			
25 – 34	-0.38 (0.90)	-0.12 (1.00)	-0.72 (1.03)
35 – 44	-0.74 (1.00)	0.92 (1.06)	-0.77 (1.01)
45 – 55	0.80 (1.14)	-0.47 (1.24)	-0.15 (1.25)
55 –	0.30 (1.07)	-0.51 (1.33)	0.81 (1.20)
Woman	-0.47 (0.81)	-0.90 (0.93)	0.65 (0.90)
Race (Base: Else)			
Asian	-0.7 (1.09)	-1.00 (1.17)	-0.47 (1.07)
Hispanic/Latino	0.50 (1.06)	0.60 (1.13)	-0.79 (1.20)
White	0.28 (0.90)	0.95 (1.02)	0.24 (0.98)

Base = Transit	Bike	Walk	Car
Student	0.58 (0.99)	-1.34 (1.12)	-0.32 (1.06)
College Degree	0.90 (0.86)	-1.14 (0.94)	0.87 (0.90)
Having Children	-0.91 (0.83)	0.33 (0.96)	1.09 (0.89)
Car Ownership	-0.35 (0.79)	0.90 (0.93)	0.90 (0.89)
Bike-share membership	-0.68 (0.88)	0.46 (0.91)	-0.65 (0.98)
Income (US dollars)			
50,001 to 100,000	-0.47 (0.84)	-0.35 (0.93)	1.06 (0.96)
100,000 to 200,000	0.18 (0.96)	-0.01 (1.04)	1.80 (1.05)
More than 200,000	0.01 (1.14)	0.91 (1.15)	0.02 (1.27)
Attitude			
Like Bike	1.64 (1.24)	0.03 (1.24)	-1.21 (1.28)
Bike Safety	0.18 (1.22)	1.01 (1.31)	0.06 (1.29)
Bike pressure	0.46 (1.19)	0.05 (1.29)	-0.07 (1.26)
Car necessity	-1.63 (1.17)	0.77 (1.28)	-0.26 (1.37)
Concern for the environment	0.98 (1.07)	0.50 (1.15)	-0.24 (1.22)
Concern for cost	0.71 (1.11)	-0.96 (1.23)	-0.10 (1.22)
Desire to get exercise	0.07 (1.30)	-0.32 (1.30)	0.25 (1.46)
Concern for safety from crime	0.72 (1.07)	-1.17 (1.23)	-0.35 (1.13)
Concern for safety from traffic	0.57 (1.10)	-0.23 (1.27)	0.97 (1.20)
Desire for enjoyment	0.33 (1.19)	-0.46 (1.25)	-1.11 (1.22)
Concern for time	-0.44 (1.15)	-0.12 (1.25)	0.82 (1.26)
Desire for convenience	-0.82 (1.22)	-0.49 (1.41)	1.13 (1.28)

Mode Availability

The total length of bike lanes near home and workplace/school are negatively associated with the choice of car as the substitution mode. Interestingly, those who commute from home location with more bike lanes in the vicinity are less likely to use private bicycles. High bike-share availability near the home location has a negative effect on the substitution of car. Transit facilities, including the number of bus stops and LRT stations near home and the number of LRT stations near workplace/school, reduce the likelihood of car substitution for commuting trips.

Individual Characteristics

The estimates of the effects of individual characteristics on mode substitution for commute trips are similar to the ones for non-commute trips (Table 3.7 and Table 3.9). For example, identifying as a woman increases the likelihood of substituting bike-share for car travel while decreasing the likelihood of bicycling. Those who have a college degree are more likely to substitute for personal bicycling and car travel while less likely to substitute for walking. But some results differ. For example, students tend to substitute bike share for personal bicycling for commute trips more so than they did for non-commute trips. This substitution may happen because the e-bike-share offers faster travel to scheduled classes than their own bikes. All age groups except for those who are 55 or older are less likely to substitute car. Racial identity also has an effect as identifying as Asian is negatively associated with all substituted modes, suggesting that they are more likely to use bike share for transit. Hispanic and Latino respondents are less likely to substitute car modes, the opposite of the non-commute results. Identifying as white is the only group having a positive association with substituting for car but the effect is weak. Bike-share members are likely to substitute bike-share for walking. Those who have household incomes with less than $200,000 are more likely to choose cars while those with higher household incomes are less likely to do so and tend to walk for their commute when dock-less e-bike-share was not available.

Graphs of the conditional effect of trip distance by gender (Figure 3.3), suggest that the dominant substitution mode shifts from walking to biking for trip distances of more than 1 mile for any gender. One difference is that women who commuted by bike share for more than 1.5 miles shifted mostly from car options, but other combinations of gender and commute distance did not.

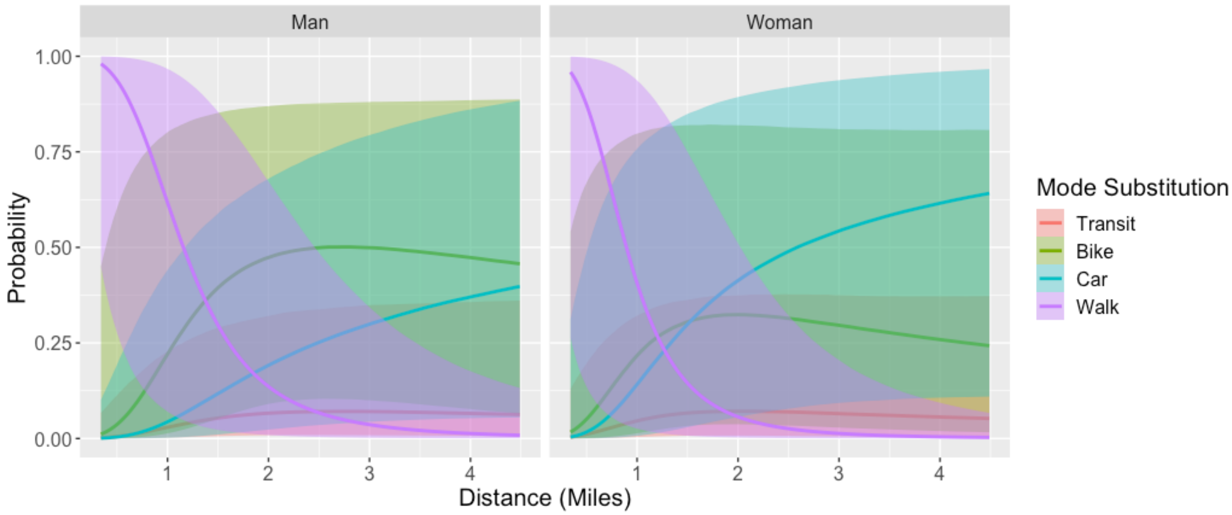


Figure 3. 4 Conditional Combined Effects of Trip Distance and Gender on Mode Substitution (Conditions: Age25-34; Non-student; College degree; No child; White; Car owner; Household income ($100,000-200,000); mean values of continuous predictors)

Attitudinal Variables

The influence of attitudinal variables for commute trips was similar to the influences for non-commute models, particularly for environmental concern, crime concern, desire for enjoyment desire for convenience, and time concern. The influence of "like bike" is also similar to its influence in non-commute models, but the effect in the commute model is stronger. Higher scores for "bike safe" and “bike pressure" have positive effects on personal bike substitution, but the former effect is weaker. Unlike non-commute models, the score for "car necessity" is not positively associated with car substitution. Also, those who are concerned about traffic safety tend to substitute for car use for commuting trips. The "desire to get exercise" had a small effect for all modes suggests. The finding that cost is negatively associated with walking as the substitution mode is not intuitive.

3.4. Conclusion

In this paper, I examined the influence of a wide range of factors, including trip attributes, land use, mode availability, individual characteristics, and attitudinal variables, on mode substitution for dock-less e-bike-share for both non-commute trips and commute trips. Some of my findings for the Sacramento region are consistent with results from prior studies for the variables they have in common. For example, prior findings that woman are less likely to bike (e.g. Emond et al., 2010) is consistent with my findings on mode substitution that woman using the bike-share were less likely than men to say they would use a private bicycle if the e-bike-share were not available. Those who are concerned about the environment in their daily mode choice were more likely to substitute bike-share for active travel modes, consistent with prior studies showing a link between environmental concern and the use of these modes (Bouscasse et al., 2018; Handy et al, 2010; Wang et al., 2015). On the other hand, my findings on substitution mode by age group do not entirely align with results reported by Barbour et al. (2019), nor did my findings by income group, suggesting the need for further exploration of the role of these characteristics.

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. The results are potentially useful in providing guidance for designing bike-share operations to enhance car substitution as well as physical activity. For example, my result showing that greater "time concern" and "desire for convenience" increase the likelihood of substitution for car-related options in both types of trips (with the exception of the effect of "time concern" on ride-hailing in non-commute trips) points to the importance of the efficient operations that enhance bike availability and address both time concerns and convenience. The finding that long trips and non-commute trips that start in non-commercial locations are likely to substitute for car modes suggests that rebalancing policies 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: where bike share is most successful at attracting users, such as in downtown areas, it may be less likely to be successful at reducing car use.

The results also hint at other strategies to enhance the substitution of bike share for driving. Cities and/or bike-share operators might work closely with businesses, such as restaurants, bars and entertainment establishments, to incentivize the use of bike share, as trips to these destinations tend to substitute for driving and especially ride-hailing. Specific demographic groups, such as women and those who have a private car or household income between $100,000 and $200,000, and no bike-share membership are more likely to substitute bike share for car-related options for both commute and non-commute trips. Cities and/or bike-share operators might consider marketing and incentives targeted to these groups to encourage a reduction in car use.

The substitution of bike-share for other modes might be affected by other factors not measured here, such as urban from, lifestyle, cultural norms, and the quality of transportation service. For example, one study shows that the substitution of bike share for car and taxi in cities like Lyon and Dublin is only 7 to 8% while in Minneapolis the rate is nearly 22% (Fishman et al, 2013). But this is still much less than my finding that about 36% of bike share trips substitute for car-related modes. My finding is more comparable to evidence that e-scooter sharing substitutes for car-related options by about 34% of the trips in Portland, 32% of those in Denver and 64% of those in San Francisco (Chang et al., 2019). Whether my findings can be generalized to other forms of micromobility (i.e. docked bike-share and dock-less e-scooter-share) is an interesting question, as prior studies have found some similarities and differences (McKenzie, 2019; Younes et al., 2020). An understanding the factors influencing mode substitution for each form of micromobility would help cities in implementing new services as a strategy for reducing driving dependence.

This study focuses on mode substitution of dock-less e-bike-share for both non-commute and commute trips. Because I had a limited sample size for commute trips, my results are less certain than those for non-commuting. Also, I used only one trip attribute in examining factors influencing mode substitution in commute trips. Because the influence of other trip attributes, such as time of day and day of the week, may be different for commute trips and non-commute trips, and because as much as 35 to 55% of bike-share trips are for commuting (City of Austin, 2019; Lime, 2018), I encourage further exploration of mode substitution for commute trips. If combined with system-level data, such as the data available from the General Bikeshare Feed Specifications (GBFS), the models estimated here could also be useful in estimating the effect of the introduction of shared e-bikes on vehicle-miles-traveled and physical activity at the system level. Understanding the benefits of a bike-share system, which depend on the modes that bike-share replaces, is important in assessing its value as a part of the transportation system.

References

Alemi F., Circella, G., Handy, S., Mokhtarian, P., 2018. What influences travelers to use Uber? Exploring the factors affecting the adoption of on-demand ride services in California, Travel Behaviour and Society, 13: 88-104. https://doi.org/10.1016/j.tbs.2018.06.002

Almannaa, M. H., Ashqar, H. I., Elhenawy, M., Masoud, M., Rakotonirainy, A. and Rakha, H., 2020. A Comparative Analysis of E-Scooter and E-Bike Usage Patterns: Findings from the City of Austin, TX, International Journal of Sustainable Transportation, https://doi.org/10.1080/15568318.2020.1833117

Attias, H., 2000. A variational Bayesian framework for graphical models. Advances in neural information processing systems, 12(1-2), pp.209-215.

Babbie, Earl R., 2015, The Practice of Social Research. Cengage Learning, Boston

Barbour, N., Zhang, Y., & Mannering, F., 2019. A statistical analysis of bike sharing usage and its potential as an auto-trip substitute, Journal of Transport & Health, 12, 253-262, https://doi.org/10.1016/j.jth.2019.02.004.

Barnes, F., 2019. A Scoot, Skip, and a JUMP Away: Learning from Shared Micromobility Systems in San Francisco. https://doi.org/doi:10.17610/T6QP40

Bouscasse, H., Joly, I. & Bonnel, P., 2018. How does environmental concern influence mode choice habits? A mediation analysis, Transportation Research Part D: Transport and

Environment, 59, 205-222, https://doi.org/10.1016/j.trd.2018.01.007.
Buehler, R., 2011. Determinants of transport mode choice: a comparison of Germany and the USA, Journal of Transport Geography, 19(4), 644-657, https://doi.org/10.1016/j.jtrangeo.2010.07.005
Bürkner, P.C., 2017. brms: An R package for Bayesian multilevel models using Stan. J. Stat. Softw., 80.
Campbell, K. B., & Brakewood, C., 2017. Sharing riders: How bikesharing impacts bus ridership in New York City, Transportation Research Part A: Policy and Practice, 100, 264-282, https://doi.org/10.1016/j.tra.2017.04.017.
Chang, A.Y. J., Miranda-Moreno, L., Clewlow, R., Sun, L., 2019. Trend or Fad? Deciphering the Enablers of Micromobility in the US. A Report of SAE International, 2019. https://www.sae.org/binaries/content/assets/cm/content/topics/micromobility/sae-micromobility-trend-or-fad-report.pdf (accessed 6.5.20).
City of Austin, 2019. Dockless mobility community survey report. http://austintexas.gov/sites/default/files/files/Transportation/Dockless_Mobility_Community_Survey_Report_2-28-19.pdf (accessed 6.5.20).
Domarchi, C., Tudela, A. & González, A., 2008. Effect of attitudes, habit and affective appraisal on mode choice: an application to university workers. Transportation 35, 585–599. https://doi.org/10.1007/s11116-008-9168-6
Emond, C. R., Tang, W., & Handy, S. L., 2009. Explaining Gender Difference in Bicycling Behavior. *Transportation Research Record*, 2125(1), 16–25. https://doi.org/10.3141/2125-03
Fishman, E., Washington, S., Haworth, N., 2013. Bike Share: A Synthesis of the Literature, Transport Reviews. 33.2: 148-165. https://doi.org/10.1080/01441647.2013.775612
Fishman, E., Washington, S., & Haworth, N., 2014. Bike share's impact on car use: Evidence from the United States, Great Britain, and Australia, Transportation Research Part D: Transport and Environment, 31, 13-20, https://doi.org/10.1016/j.trd.2014.05.013.
Fishman, E., Washington, S., & Haworth, N., 2015. Bikeshare's impact on active travel: Evidence from the United States, Great Britain, and Australia, Journal of Transport & Health, 2(2), 135-142, https://doi.org/10.1016/j.jth.2015.03.004.
Fishman, E., 2016. Bikeshare: A Review of Recent Literature, Transport Reviews, 36:1, 92-113. https://doi.org/10.1080/01441647.2015.1033036
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. https://doi.org/10.7922/G2F18X0W
Fitch, D. T., Mohiuddin, H., Handy, S.L., 2021. Examining the Effects of the Sacramento Dockless E-Bike Share on Bicycling and Driving. Sustainability. 2021; 13(1): 368. https://doi.org/10.3390/su13010368
Fitzpatrick, K., Turner, S.M., Brewer, M., Carlson, P.J., Ullman, B., Trout, N.D., Park, E.S., Whitacre, J., Lalani, N., and D. Lord., 2006. Improving Pedestrian Safety at Unsignalized Crossings. Transit Cooperative Research Program (TCRP) Report 112 or NCHRP Report 562, published by Transportation Research Board, Washington https://nacto.org/wp-content/uploads/2010/08/NCHRP-562-Improving-Pedestrian-Safety-at-Unsignalized-Crossings.pdf, (accessed 3.21.21).
Handy, S.L., Xing, Y., & Buehler, T. J., 2010. Factors associated with bicycle ownership and use:

a study of six small U.S. cities. Transportation, 37(6), 967-985. https://doi.org/10.1007/s11116-010-9269-x
Jin, H., Jin, F., Wang, J., Sun, W., & Dong, L., 2019. Competition and Cooperation between Shared Bicycles and Public Transit: A Case Study of Beijing, Sustainability, 11(5), 1323, https://doi.org/10.3390/su11051323
Kabra, A., Belavina, E. & Girotra, K., 2020. Bike-Share Systems: Accessibility and Availability, Management Science 2020 66:9, 3803-3824, https://doi.org/10.1287/mnsc.2019.3407
Kou, Z., Wang, X., Fung, S. & Hua Cai, C. 2020, Quantifying greenhouse gas emissions reduction from bike share systems: a model considering real-world trips and transportation mode choice patterns, Resources, Conservation and Recycling, 153, 104534, https://doi.org/10.1016/j.resconrec.2019.104534.
Kuppam, A. R., Pendyala, R. M. and Rahman, S., 1999. Analysis of the Role of Traveler Attitudes and Perceptions in Explaining Mode-Choice Behavior, Transportation Research Record, 1676(1), pp. 68–76. https://doi.org/10.3141/1676-09
Lee M. D., 2011. How cognitive modeling can benefit from hierarchical Bayesian models, Journal of Mathematical Psychology, 55:1, 1-7, https://doi.org/10.1016/j.jmp.2010.08.013
Lime, 2018. Year-End Report 2018, https://www.li.me/hubfs/Lime_Year-End%20Report_2018.pdf (accessed 6.5.20).
Martin, W. Q. & Shaheen, S. A., 2014. Evaluating public transit modal shift dynamics in response to bikesharing: a tale of two U.S. cities, Journal of Transport Geography, 41, 315-324, https://doi.org/10.1016/j.jtrangeo.2014.06.026.
McKenzie, G., 2019. Spatiotemporal comparative analysis of scooter-share and bike-share usage patterns in Washington, D.C., Journal of Transport Geography, 78, 19-28, https://doi.org/10.1016/j.jtrangeo.2019.05.007.
McElreath, R., 2020. Statistical rethinking. A bayesian course with examples in R and stan. CRC Press, Boca Raton
McNeish, D. 2016. On Using Bayesian Methods to Address Small Sample Problems, Structural Equation Modeling: A Multidisciplinary Journal, 23:5, 750-773, https://doi.org/10.1080/10705511.2016.1186549
Moudon, A.V., Lee, C., Cheadle, A.D., Collier, C.W., Johnson, D., Schmid, T.L., & Weather, R. D., 2005. Cycling and the built environment, a US perspective. *Transportation Research Part D: Transport and Environment*, 10(3), 245-261. https://doi.org/10.1016/j.trd.2005.04.001
NACTO, 2019. Shared Micromobility in the U.S.: 2018. https://nacto.org/shared-micromobility-2018 (accessed 3.20.21).
NACTO, 2020. Shared Micromobility in the U.S.: 2019. https://nacto.org/shared-micromobility-2019 (accessed 3.20.21).
Otero, I., Nieuwenhuijsen, M.J., Rojas-Rueda, D., 2018. Health impacts of bike sharing systems in Europe, Environment International, 115: 387-394. https://doi.org/10.1016/j.envint.2018.04.014
Qin, J., Lee, S., Yan, X. & Tan, Y., 2018. Beyond solving the last mile problem: the substitution effects of bike-sharing on a ride-sharing platform, Journal of Business Analytics, 1:1, 13-28, https://doi.org/10.1080/2573234X.2018.1506686
Rayle, L., Dai, D., Chan, N., Cervero, R., & Shaheen, S., 2016. Just a better taxi? A survey-based comparison of taxis, transit, and ridesourcing services in San Francisco. Transport Policy,

45, 168-178. https://doi.org/10.1016/j.tranpol.2015.10.004
Ricci, M., 2015. Bike sharing: A review of evidence on impacts and processes of implementation and operation, Research in Transportation Business & Management, 15, 28-38. https://doi.org/10.1016/j.rtbm.2015.03.003
Rubin, D. B., 1976. Inference and missing data, Biometrika, 63(3), 581-592. https://doi.org/10.1093/biomet/63.3.581
Rubin, D., 1987. Multiple imputation for nonresponse in surveys. New York: Wiley.
Schafer, J., 1997. Analysis of incomplete multivariate data. New York: Chapman & Hall.
Singla A., M. Santoni, G. Bartók, P. Mukerji, M. Meenen, and A. Krause., 2015. Incentivizing users for balancing bike sharing systems. In Proceedings of the Twenty-Ninth AAAI Conference on Artificial Intelligence (AAAI'15). AAAI Press, 723–729.
Shaheen, S. A., Guzman, S. and Zhang, H., 2010. Bikesharing in Europe, the Americas, and Asia: Past, Present, and Future, Transportation Research Record, 2143(1), 159–167. https://doi.org/10.3141/2143-20
Stan Development Team, 2018. Stan Modeling Language. User's Guid. Ref. Man. 1–488., http://mc-stan.org/manual.html%5Cnpapers2://publication/uuid/C0937B19-1CC1-423C-B569-3FDB66090102 (accessed 6.5.20).
U.S. Department of Transportation, 2018. 2017 National Household Travel Survey.
van Buuren, S., & Groothuis-Oudshoorn, K., 2011. mice: Multivariate Imputation by Chained Equations in R. Journal of Statistical Software, 45(3), 1 - 67. http://dx.doi.org/10.18637/jss.v045.i03
van Ravenzwaaij, D., Moore, C.P., Lee, M.D. & Newell, B.R., 2014. A hierarchical Bayesian modeling approach to searching and stopping in multi-attribute judgment. Cognitive Science, 38(7), 1384-1405. https://doi.org/10.1111/cogs.12119
Wang, C.H., Akar, G., & Guldmann, J.M., 2015. Do your neighbors affect your bicycling choice? A spatial probit model for bicycling to The Ohio State University. Journal of Transport Geography, 42, 122-130. https://doi.org/10.1016/j.jtrangeo.2014.12.003
Wang, M., Zhou, X., 2017. Bike-sharing Systems and Congestion: Evidence from US cities, Journal of Transport Geography, 65: 147-154. https://doi.org/10.1016/j.jtrangeo.2017.10.022
Younes, H., Zou, Z., Wu, J. & Baiocchi, G., 2020. Comparing the Temporal Determinants of Dockless Scooter-share and Station-based Bike-share in Washington, D.C., Transportation Research Part A: Policy and Practice, 134, 308-320, https://doi.org/10.1016/j.tra.2020.02.021.
Young, M., Farber, S., 2019. 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, 119: 383-392 https://doi.org/10.1016/j.tra.2018.11.018
Zhang, M., & Mi, Z., 2018. Environmental benefits of bike sharing: A big data-based analysis, Applied Energy, 220, 296-301, https://doi.org/10.1016/j.apenergy.2018.03.101.

4 Estimating Vehicle-miles Traveled reduced from Dock-less E-bike-share: Evidence from Sacramento, California

4.1. Introduction

Bike-share services have the potential to bring environmental, social, and health benefits to the communities where they are implemented (Otero et al., 2018; Qiu & He, 2018; Wang & Zhou, 2017; Shaheen et al., 2010; DeMaio, 2009). With the hope of achieving such benefits, many US cities have introduced bike-share services since the first system was implemented in Portland, OR in 1994 (Shaheen et al., 2010). The use of such systems has grown substantially: the number of trips by bike-share services, including docked and dock-less systems increased in the United State from 321,000 trips in 2010 to 50 million trips in 2019 (NACTO, 2020), though many dock-less bike-share services were closed or suspended due to the emergence of COVID-19 in 2020. The environmental benefits of these trips, in the form of reductions in vehicle miles traveled (VMT) and related greenhouse emissions, depends on the degree to which these bike share trips replace driving rather than other sustainable travel modes, such as public transit, a personal bike, or walking. Prior studies have produced varying estimates of the driving substitution rate: 45% of users across seven cities in one study (NACTO 2020), versus only 19% and 7% of docked bike-share trips in Minneapolis and Washington DC, respectively, in another study (Fishman et al., 2013).

But the substitution rate is not the only important factor determining the environmental benefits of bike-share services. One drawback of these services is that the operation of the service itself generates VMT and thus emissions when vans and trucks are used for operational tasks such as maintenance, battery swapping, and fleet repositioning. Although VMT generated by operational tasks offset the benefits from car substitution, the operational tasks are essential to maintaining the availability and quality of the service (Pfrommer et al., 2014). Without an effective repositioning operation, for example, the service is unlikely to produce much reduction in driving by the users of the service. Only a few studies have reported actual operational VMT associated with micromobility services. Fishman and his colleagues (2014) reported that docked bike-share operators produced average daily operational VMT of 47 to 2,381 miles in London, Minnesota, Washington, DC, and Melbourne, while the San Francisco Municipal Transportation Agency (SFMTA, 2022) reported average daily operational miles of 58 to 636 miles in San Francisco.

Estimating the net effect of bike-share services on VMT reduction is important but challenging for cities. Prior studies have produced a range of estimates the environmental benefits of introducing bike-share systems. For example, Fishman et al. (2014) estimated annual VMT reductions of 444,187 km and 178,629 km in Washington, D.C. and Minneapolis, respectively. Some researchers have estimated emission reductions rather than VMT reduction. Kou et al. (2020) found that eight U.S. cities, including Seattle, Los Angeles, San Francisco, Philadelphia, Boston, Washington, D.C., Chicago, and New York, had annual GHG emission reductions in the range from 41 tons to 5417 tons of CO2-eq. Chen et al. (2022) estimated a reduction in CO2 emissions of 30,070 tons from bike-share service in New York. Other studies have estimated environmental benefits in Chinese cities (Saltylkova et al., 2022; Zhang & Mi, 2018). Reck and his colleagues (2022) accounted for emissions from various aspects of operation, including vehicle manufacturing and operational services, and found that the CO2 generated by a shared e-bike service exceed the CO2 reductions attributable to the replacement of bike-share for driving in Zurich, Switzerland.

Such estimates are valuable to cities in assessing the potential benefits of a new bike-share system, but the estimates rely on some strong assumptions. For example, Fishman et al. (2014) estimated vehicle-kilometer travel reduced from car substitution as the product of the total number of bike-share trips, the car substitution rate based on survey responses, and the average bike-share trip distance, an approach that assumes that all bike-share trips have the same likelihood of car substitution regardless of distance. Zhang and Mi (2018) assessed reductions in energy use and car emissions using trip-level bike-share data assuming that trips of more than 1km all substitute for car travel. Another similar study focusing on eight U.S. cities considered several trip attributes, such as trip distance, time of day and trip purpose, to assign mode substitution to each trip based on mode share data for each city from the National Household Travel Survey (Kou et al., 2020). Other studies have used a similar methodology to estimate the reduction in emissions (Chen et al., 2022; Saltylkova et al. 2022). Saltylkova and colleagues (2022) considered whether bike-share use substitutes for transit, has a complementary relationship (as in areas not well served by public transit), or is integrated with transit use (as when it is used to get to/from public transit stops). Li et al. (2020) conducted a sensitivity analysis using a simulation model to examine changes in environmental benefits produced by changes in operation strategies, including the number of bike stations and the change of operational truck route, to determine the required mode substitution rate needed to offset operational emissions. Reck and colleagues (2022) took a different approach by developing a mode choice model that included micromobility services as an option and using this model to understand the effect of the mode substitution rate on emissions by then removing micromobility services as an option in the model and re-predicting mode choice. None of the prior studies, to the best of my knowledge, has developed a framework for estimating the environmental benefits of the introduction of a new bike-share service to a city based on a predictive model of the substituted mode at the person-trip level.

This study develops a framework for estimating vehicle miles reduced from the introduction of bike-share service. I use system-level data on dock-less e-bike-share trips for the Sacramento region web-scraped from an open-source data format used for sharing information about bikeshare availability and locations in conjunction with data from a survey of bike-share users. This system, operated by Jump in the cities of Sacramento, West Sacramento, and Davis, CA between 2018 and 2020, was one of the largest dock-less e-bike-shares in the US at the time, but it closed due to the emergence of COVID-19. I estimate a series of models, including multinomial logit models on mode substitution and a linear regression model for driving distance and operational miles, to understand the environmental benefits of a dock-less bike-share system. The mode substitution models I develop in this study are derived from my prior study examining associations between mode substitution and various predictive factors (Fukushige et al., 2021). The results of this analysis are important in assessing the value of the system to the Sacramento region. My findings provide a basis for developing promotional and operational strategies that enhance the beneficial outcomes of bike-share. The methodologies developed in this study can be applied in other regions to assess the impact of their specific systems.

4.2. Methodology

4.2.1. Data

4.2.1.1. Bike-share Trip Data

I assembled system-wide bike-share trip data by web-scraping the real-time status of Jump bikes in the Sacramento region provided by the General Bikeshare Feed Specification (GBFS) between

October 2nd and November 23rd, 2019 (prior to the suspension of service). GBFS is an open-source data format for sharing information about shared-micromobility availability and locations. This data has been used by several prior studies to analyze micromobility-share data (Xu et al., 2022; Qian et al., 2020; Zou et al., 2020). The data include the list of bikes with "free" (i.e. available) status at each timestamp. Attributes of a bike in the dataset include bike ID, longitude and latitude of a bike location, and state of charge. When a bike becomes unavailable, for example, due to a reservation or being out of service for maintenance, the information for the bike disappears from the real-time data. I used the disappearance and then reappearance of individual bikes, based on bike ID, to create an initial dataset of bike-share trips.

One problem with this process is that the initial dataset contains false trips. I eliminated trips in five situations, as these are likely to be false trips, as follows:

i. *Trips during which the battery level increased*: these are almost certainly operational events rather than actual trips.
ii. *Trips having the exact same latitude and longitude on both origin and destination:* given the degree of precision in the geolocation data, the probability that the longitude and latitude are exactly the same for the check-out location and the return location is essentially zero, even if someone returns the bike to the same spot.
iii. *Trips with small Euclidean distance and short duration*: I found some trips of short Euclidean distances and short duration that are also not likely to be actual trips. I assume that these cases occurred when users reserved but canceled vehicles. Because obstacles such as tall buildings lower the accuracy of geolocation, the recorded bike location could change

slightly if users canceled bikes at such locations. I removed trips of 10 meters or shorter Euclidean distance and those less than 15 minutes in duration.

iv. *Trips of four hours or longer duration:* I found that such trips make up a small percentage (0-3% by date) of total potential trips. It is possible, for example, that tourists take bikes for such long durations, but I assumed these were operational events (i.e., maintenance or rebalancing).

v. *Trips with Euclidean trip speed of more than 15 mph:* It is rare that Euclidean speed (i.e., Euclidean distance / trip duration) is more than 15 mph in the Sacramento region because the top e-bike speed is 20 mph, and Euclidean trip speed is slower than actual trip speed (because Euclidean – straight-line – distance is always less than actual trip distance). I found a few trips with Euclidean trip speed of more than 15 mph in both the GBFS data and a previous survey (Fitch et al., 2020).

The final dataset contains 142,936 trips.

4.2.1.2. User Survey Data

I use data from a two-wave longitudinal survey of dock-less e-bike share users in October 2018 (the first-wave survey) and in May 2019 (the second-wave survey). The surveys focused on attitudes and perceptions, experience, and travel behavior of the users. Users were recruited for the survey mainly by intercepting them at key locations throughout the study area. As a part of the survey, respondents were asked to report information such as origin, destination, and mode they would have taken if a shared bike had not been available for their e-bike share trips for non-commute purposes and commuting purposes. I used these data to develop mode substitution models to predict mode substitution for each trip. For more details on the survey content, see Fitch et al. (2020).

4.2.1.3. Micromobility Operational Mile Data

For the analysis of operational vehicle miles, I used data on monthly operational miles by month and dock-less e-scooter-share operator (n=27) provided by the San Francisco Municipal Transportation Agency (SFMTA, 2022) between October, 2021 and June, 2022. The data include monthly operational miles, fleet size in the beginning of the month, and the number of trips by the operator.

4.2.2. Framework to estimate VMT reduction of e-dock-less bike-share service

I developed a framework, comprising six steps, to estimate VMT reduction from a dock-less e-bike-share service using trip-level data and user survey data (Figure 4.1). The six steps are: 1. prediction of mode substitution of a bike-share trip, 2. estimation of the share of non-commuting and commuting trips within the service boundary, 3. estimation of the driving distance of bike-share trips that substituted for car trips, 4. an aggregation of all estimations to estimate total VMT reduction, 5. consideration of several types of additional potential sources of reductions in VMT from the substitution of bike-share trips for ride-hailing trips, and 6. consideration of VMT produced from operational tasks.

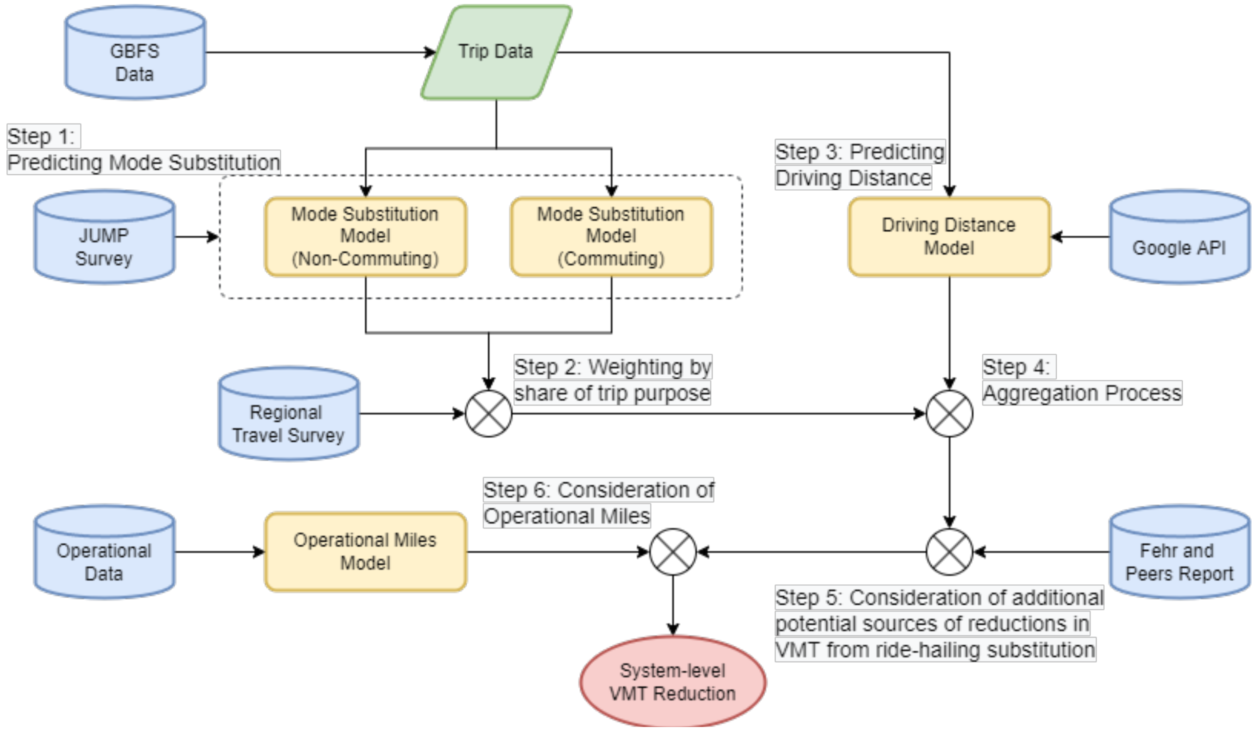


Figure 4.1 Flow chart of Framework to estimate VMT reduction of e-dock-less bike-share service

Step1: Predicting Mode Substitution

I developed separate mode-substitution models for commuting trips and non-commuting trips based on the user survey. This analysis included two different models because of different format data on bike-share use for commuting trip and non-commuting trips. Bayesian methods were used to estimate multinomial logit models to predict probabilities of each possible mode substitution for a bike-share trip in the case of commuting trips and non-commuting trips, respectively. The models developed here are similar to models developed in my prior study (Fukushige et al., 2021) but use a more limited set of predictor variables because the actual trip data in the GBFS was not labeled with individual-level information, such as trip purpose, gender, or age.

Step2: Weighting by share of trip purpose

I 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, I used travel data from within the Jump service boundary collected by Sacramento Area Council of Governments (SACOG) as a part of the 2018 SACOG regional household travel survey to estimate weights for commute and non-commute trips by time of day on weekdays and weekends separately (Figure 4.2). Aggregating the weighted output from the mode substitution models by the share of trips by type for a sample gives me the estimated number of trips for each type of mode substitution.

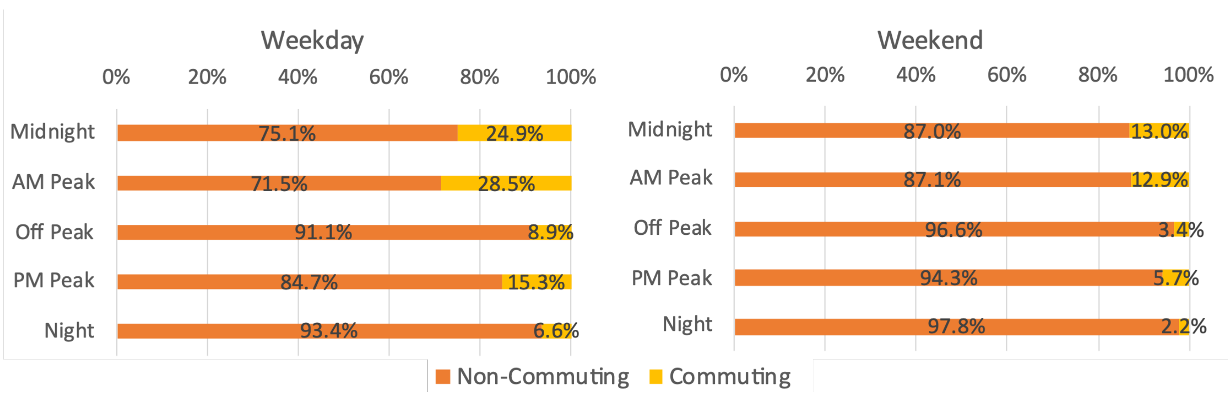


Figure 4.2 Ratio of Commuting Trip to Non-commuting Trip (Source: SACOG)

Step 3: Predicting Driving Distance

I developed a Bayesian linear regression model to predict driving distance for each trip based on Euclidean distance. Euclidean distance underestimates actual travel distances on the road network and thus underestimates the effect of bike-share service on VMT. But querying the estimated actual 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, I sampled 5956 trips from one month of the bike-share trip dataset by grouping trip data by every 5/32 mile (250 meters) of Euclidean distance between trip start and end location. I then sampled 200 data points from each group without replacement (in the case that the number of data points in the sample was less than 200, I selected all data points). I then queried the Google-based distance on the road network for each data point using the Google Maps API and ran the linear regression on Euclidean distance on driving distance.

Step 4: Aggregation Process

I sum driving distance for the trips predicted to substitute for "private car" or "ride-hailing" weighted by the share of non-commuting and commuting trips by time of day. I considered the uncertainty of the estimation by sampling from the posterior distribution of my Bayesian models. This approach allows me to present the distribution of estimated VMT reduction taking account of the uncertainty of the models. In the sampling process, I drew 1,000 samples from the posterior distribution of the mode substitution models, which allowed me to have 1,000 different predicted outputs for each data point. I used the same approach for converting from Euclidean distance to driving distance. Finally, I aggregated the driving distances of trips predicted to substitute for driving and ride-hailing to estimate a system-wide VMT reduction for each date, such that each date had 1,000 different outcomes. In each process I generated the posterior within a 95% confidence interval for each draw to avoid extreme values in my simulations.

Step 5: Consideration of additional potential sources of reductions in VMT from ride-hailing substitution

I considered two 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 their next passenger). I thus considered two different combinations of VMT reduction from ride-hailing substitution: (1) the trip itself, and (2) the trip, deadheading, and searching. The factors used to adjust savings in VMT were calculated according to Fehr and Peers (2019), resulting in upward adjustments of 46 percent for deadheading and searching.

Step 6: Consideration in Operational Miles

I developed a Bayesian linear regression model to predict daily operational miles based on the actual operational miles of dock-less e-scooter-share services in San Francisco (SFMTA, 2022). I reduced the estimated VMT reduction from car substitution in Step 4 and 5 by the estimated daily operational miles from this model to estimate the final VMT reduction from the service.

4.2.3. Models

4.2.3.1. Mode Substitution Models

In Step 1, I developed separate multinomial logit models for non-commuting and commuting trips to predict mode substitution for each trip using the same data and the same general modeling process from my prior study (Fukushige et al., 2021). The models were estimated using individual-level data from a survey of Jump users.

I interpreted the answer to the following question for non-commuting trips to be the mode for which the use of bike share substitutes: *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).* For commuting trips, I derived a substituted mode from the question: *If JUMP was not available to you, how would you commute to your primary workplace (or school)? Select your one primary method (the one you would use for the longest portion of the trip or the entire trip)*. The number of observations for non-commuting trips and commuting-trips are 823 and 105, respectively. The substitution modes for non-commuting trips include drive alone (n=113, 13.7% of trips), carpool (n=53, 6.4%), ride-hailing (including taxi) (n=133, 16.2%), bike (including e-bike and e-scooter) (n=118, 14.3%), walk (including skateboarding) (n=273,[19] 33.2%), transit (n=41, 5.0%) and "none, I wouldn't have made the trip" (n=92, 11.2%). The substitution modes for commuting trips include car (including private car, ride-hailing and carpooling) (n=21, 24.7% of trips), bike (including e-bike and e-scooter) (n=41, 48.2%), walk (including skateboarding) (n=27, 31.8%), and transit (n=16, 18.8%).

Because the models are applied to actual trip data in GBFS that does not include any personal identifiers, I examined a limited set of predictor variables: travel time, Euclidean speed (dividing Euclidean distance between trip start and end by travel time), time period (midnight: midnight-7am, AM peak: 7am-10am, off peak: 10am-4pm, PM peak: 4-7pm, and night: 7pm-midnight), weekend, land use characteristics within a quarter-mile buffer of trip start and end (residential use, commercial use, industrial use, school use, and civic use), and mode availability within a quarter-mile buffer of trip start and end (number of bus stops, number of LRT stations, and total length of bike lane).

I estimated a series of models with increasing complexity to examine the predictability of the models as I did in my prior study (Fukushige et al., 2021). I added groups of variables in the following order: trip attributes, land use characteristics, and mode availability. For non-commuting trips, I also included varying intercepts by person because respondents repeatedly provided substituted modes for several trips in the survey. I used stratified 10-fold cross-validation by travel mode and determined the best model based on overall accuracy. Table 4.1 shows variables and overall accuracy of each model. I decided to use CM-IV as a commuting mode substitution model and NCM-V as a non-commuting mode substitution model for further analysis. CM-IV and CM-V had the same overall accuracy, but I chose CM-IV to keep my predictive model simpler.

Table 4.1 Predictors Included in Mode Substitution Models

	Intercept	Varying Intercept (Person)	Trip Attributes	Land Use	Mode Avail.	Overall Accuracy
Commute Model						
CM-I	x					28.0% (4.3%)
CM-II	x		x			33.2% (4.2%)
CM-III	x		x	x		33.7% (4.2%)
CM-IV*	x		x		x	34.3% (4.2%)
CM-V	x		x	x	x	34.3% (4.1%)
Non-Commute Model						
NCM-I	x					19.4% (1.3%)
NCM-II	x	x	x			34.3% (1.4%)
NCM-III	x	x	x			39.8% (1.4%)
NCM-IV	x	x	x	x		40.5% (1.4%)
NCM-V*	x	x	x	x	x	41.9% (1.4%)

* indicates models used in the further analysis.

I used the brms package developed in R, an interface to fit Bayesian linear and non-linear models using a probabilistic programming language “Stan”, to develop my mode substitution models (Bürkner, 2017; Stan Development Team, 2018). I used Markov chain Monte Carlo (MCMC) simulation method to converge the estimator (R-hat < 1.01). This method draws random samples from the posterior. I set 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. I determined reasonable and appropriate priors by running a series of “prior predictive checks” for my models simulating my collected data.

The model formula and priors are as follows:

$$y_i \sim Categorical\ Logit(U_{ij})$$
$$U_{ij} \sim a_j + a_{j,person[i]} + \sum_{m=1}^{M} \beta_{mj} X_{mi}$$

Prior probability distributions for non-commute models

$$a_{j,person[i]} \sim Normal(0, \sigma_{person})$$
$$\beta_{mj} \sim Normal(0, 1.5)$$
$$a_j \sim Normal(0, 3)$$
$$\sigma_{person} \sim HalfStudentT(3, 0, 2)$$

Prior probability distributions for commute models

$$\beta_{mj} \sim Normal(0, 1.5)$$
$$a_j \sim Normal(0, 1.5)$$

where y_i is a substituted mode for individual i, U_{ij} is the utility equation of substituted mode j for individual i, a_j is the constant intercept of substituted mode j, $a_{j,person[i]}$ is the varying intercept of substituted mode j for individual i, β_{mj} is a parameter of variable m for substituted mode j and X_{mi} is a predictor of variable m for individual i. Because commute models did not include varying intercept by person, the term, $a_{j,person[i]}$, is not in the equation. Estimates of models are shown in Table 4A and 4B of the Appendix. Details of data processing, the model development and interpretation of the results are provided in my prior study (Fukushige et al., 2021)

4.2.3.2. Driving Distance Model

For Step 3, I used a Bayesian linear regression model to estimate Google Map-based distance with Euclidean distance as the sole predictor. I queried driving distance from Google API for origin-destination pairs because I am interested in VMT reduction. I applied log-transformation for a dependent variable to avoid having negative output. I used the same R package and process as the mode substitution models.

The model formula and priors are as follows:

$$y_i \sim Normal(\mu_i, \sigma)$$
$$\mu_i \sim a + \beta X_i$$

Prior probability distributions

$$a \sim Normal(0,2)$$
$$\beta \sim Normal(0,2)$$
$$\sigma \sim HalfStudentT(3, 0, 2.5)$$

where y_i is a log-transformed driving distance for trip i, a is the constant intercept of driving distance, β is a parameter of variable and X_i is a predictor of variable for trip i. Estimates of the model are shown in Table 4C of the Appendix.

4.2.3.3. Operational Miles Model

For Step 5, I used a Bayesian linear regression model to estimate daily operational VMT. I used the data (n=27) provided by the San Francisco Municipal Transportation Agency (SFMTA, 2022). Bayesian techniques are more appropriate to fit a model with a small sample size than frequentist techniques because the former techniques do not rely on asymptotics to make inferences from the parameters (McNeish, 2016). I applied log-transformation for a dependent variable to avoid having negative output. I included varying intercepts by operator because the dataset contains several monthly information for each operator. I also added trip efficiency, the number of bike-share trips per bike per day, as an independent variable. I used the same R package and process as the mode substitution models. The only difference in this case is that I chose an informative prior for the parameter for trip efficiency. With the prior I assumed that the impact of an additional bike-share trip per bike per day on average. It is intuitive that trip efficiency would have a positive effect on operational VMT because more charging is needed when each bike is used more frequently. With a small sample size my analysis results in large uncertainty and my selected priors have more weight than in analyses with larger sample sizes. Using this process, I gain an understanding of the effects of the explanatory variables despite the small sample size.

The model formula and priors are as follows:

$$y_i \sim Normal(\mu_i, \sigma)$$
$$\mu_i \sim a + a_{operator[i]} + \beta X_i$$

Prior probability distributions

$$a \sim Normal(0,1)$$
$$a_{operator[i]} \sim Normal(0, \sigma_{operator})$$
$$\beta \sim Normal(0.05,0.1)$$
$$\sigma \sim HalfStudentT(3,0,2.5)$$
$$\sigma_{operator} \sim HalfStudentT(7,0,1)$$

where y_i is a log-transformed daily operational VMT for service i, a is the constant intercept of operational miles, and β is a parameter of a variables, $\sigma_{operator[i]}$ is the varying intercept for operator of service i and X_i is a predictor of a variable for service i.

4.2.4. Limitations

My methods have several limitations worthy of note. First, the GBFS data did not differentiate between commute and non-commute trips, so I assumed that the shares of non-commuting trips and commuting trips across all modes are equal to the shares for bike-share services and used these shares to weight the predicted mode substitution for each type of trip. It is possible that the split between commute and non-commute trips for bike-share differs from the split across all modes. Second, my 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 might not have considered alternatives to driving. My estimates thus provide a low-end estimate of the impact that bike-share can have on VMT.

A third limitation is that my estimates of operational miles might have biases. I used operational miles of dock-less e-scooter-share services, but operational miles per vehicle in a dock-less e-bike-share service may be different because one van can accommodate more e-scooters than e-bikes in the same time. My estimates are based on e-scooter operators in San Francisco, which has vastly different geographic area, urban structure, and terrain than Sacramento, although the number of daily trips and the fleet size are similar. Despite the potential biases, I believe that this is the best possible approach to estimating operational miles, given that actual operational miles for micromobility services are not usually available publicly. Including an estimate of operational miles, even if its accuracy is uncertain, in an analysis of the impacts of bike share on VMT is better than leaving it out, given that prior studies show that micromobility operators produce considerable operational miles in their daily operations (SFMTA, 2022; Fishman et al, 2014).

4.3. Descriptive analysis of Bike-share Trip Data

I first explored bike-share trip data to understand basic trip characteristics including daily trip frequency, fleet size, bike use duration, Euclidean distance between trip start and end, and weather. Figure 4.3 shows that the number of bike-share trips per day ranged from 2500 to 3500 trips in October 2019, but gradually decreased in November 2019. Fleet size ranged between 950 and 1100 in October 2019 but increased at 10% in November though that dropped in mid-November. Average daily temperature gradually decreased over the study period. That average daily temperature makes the trend in a similar way as trip frequency suggests the association between temperature and bike-share use (Shen et al., 2018; Gebhart & Noland, 2014). It appears that days with high wind speed had fewer bike-share trips, something also noted in other studies (Wang & Chen, 2020; Kim, 2018). I did not include precipitation in this analysis because no precipitation was observed in the study period.

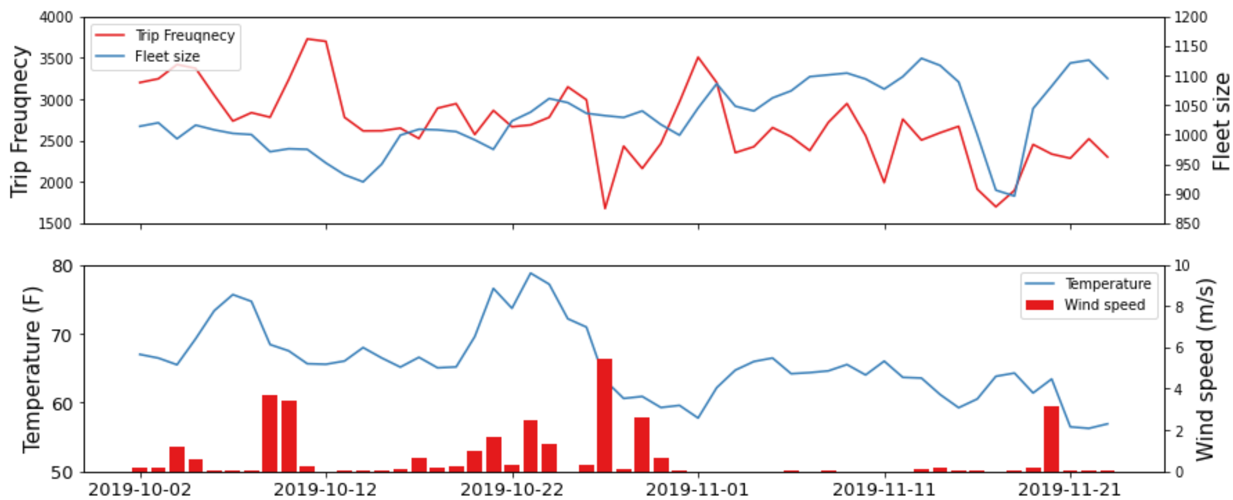


Figure 4.3 Trend of Trip Frequency, Fleet size, Average Temperature and Precipitation

The median and mean of travel time was 13 minutes and 19 minutes, respectively (Figure 4.4). These values are a little higher than the average of 12 minutes reported in the NACTO's report (NACTO, 2019). The distribution of travel time with a long right tail shows that 82% of trips ended within 25 minutes. The figure shows a small peak at 60 minutes. One possible explanation for this peak is that a substantial number of membership holders used all of the free access time, 60 minutes, at once and retuning a bike to avoid an additional usage fee.

Another possible explanation could be that these long trips are noise. The median and mean of Euclidean distance between trip start and end was 0.7 miles and 0.9 miles, respectively. Though not directly comparable, NACTO reported 1.6 miles of the average trip distance of dock-less bike-share service (NACTO, 2019).

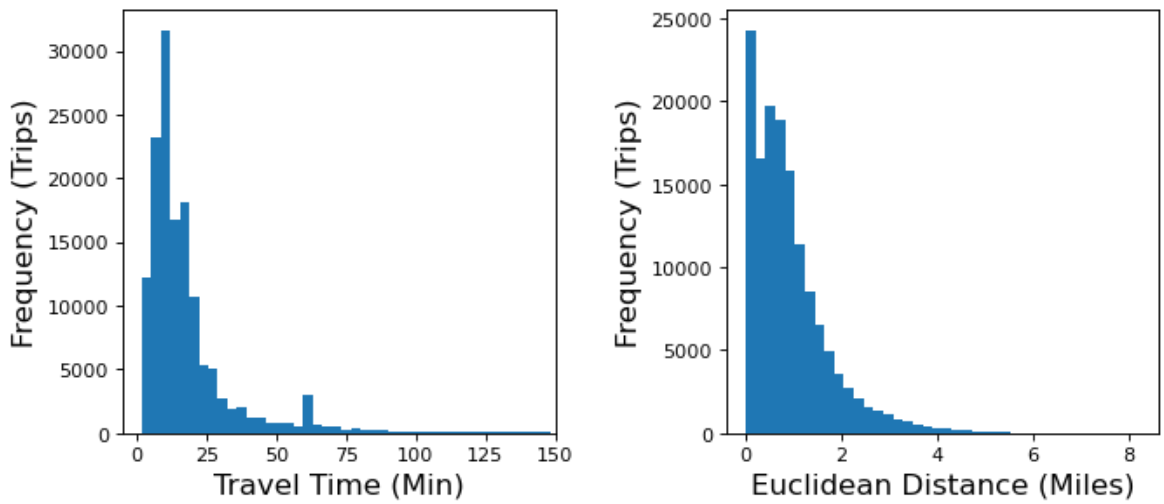


Figure 4.4 Distribution of Trip Travel Time and Euclidean Distance

I mapped the trip data by quarter-mile (400 meters) grid cells to examine the spatial distribution of bike-share use. Figure 4.5 shows trip frequency in grid zones covering the downtown Sacramento on weekdays and weekends. Trip frequency is high on weekdays in the downtown area which has a high density of office space, while slightly higher near retail and restaurants on weekends. A right side of the map shows a higher frequency only on weekdays, corresponding to the class schedule at Sacramento State University. On both weekdays and weekends, the farther from downtown, the lower the bike-share use per day.

Figure 4.6 shows the average Euclidean distance between trip start and end by zone. A long-distance bike-share trip is strongly associated with car substitution (Fukushige et al., 2021). The average Euclidean distance of trips starting in high-volume areas, such as downtown

Sacramento, is less than 1 mile. On the other hand, fringe areas or areas farther from the downtown tend to have higher average distances.

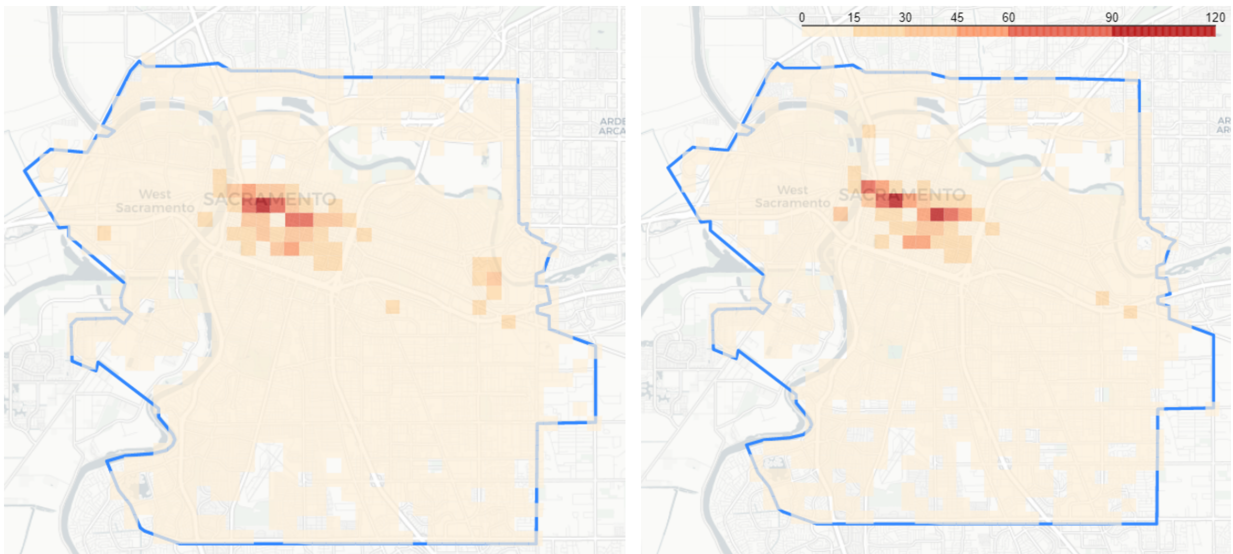


Figure 4.5 Average number of trips by zone on weekday (Left) and weekend (right); Blue line shows a service boundary (Unit: trips per day)

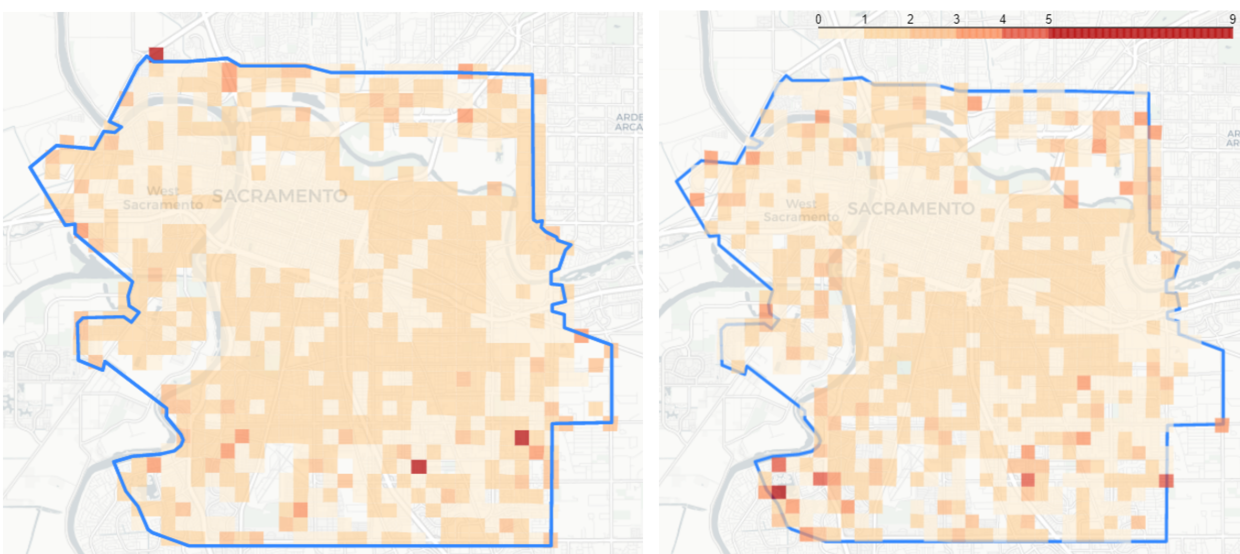


Figure 4.6 Average Euclidean Distance between trip start and end by zone on weekday (Left) and weekend (right); Blue line shows a service boundary. (Unit: miles)

4.4. Results and Discussion

4.4.1. Mode Substitution Share

The most common mode of travel that bike-share replaced on weekday was walking (mean: 43.8%/sd: 4.8%) (Figure 4.7). That is followed by "Ride-hailing" (14.2%/4.1%), "Private Car" (14.0%/4.5%), "Bike" (10.6%/3.2%), "Transit" (8.0%/1.8%), "No Trip" (6.8%/3.0%), and "Carpooling" (2.5%/1.5%). It is reasonable that the primary substituted mode was walking because 35 % of bike-share trips in my dataset had less than a half mile of Euclidean distance between trip start and end, equivalent to the average walking time (10 minutes) for walk trips of all purposes (Yong & Diez-Roux, 2012). The car substitution rate, including "Private Car" and "Ride-haling," was 28%. That 6.8% of trips are predicted as "No Trip" suggests that bike-share service induces new trips and may contribute to increase of physical activity and vitalization of local economy.

On weekends and holidays, the most common mode of travel that bike-share replaced was the same as on weekdays, walking (mean: 43.5%/sd: 6.2%). That is followed by "Ride-hailing" (13.1%/4.8%), "Private Car" (11.4%/4.5%), "Bike" (10.6%/4.2%), "No Trip" (8.4/3.8%), "Transit" (7.2%/2.2%), and "Carpooling" (5.8%/3.0%). The order between "No Trip" and Transit" on weekend/holiday was opposite from on weekdays. It is intuitive that "Transit" is lower on weekends because public transit services are usually less frequent, thus people may be less likely to consider public transit an option to use on weekends. Though "Carpooling" was the least substituted mode on any days, the share on weekends was 3.3 percentage points higher than on weekdays.

Figure 4.7 shows that the average car substitution rate (including "Private vehicle" and "Ride-hailing") by zone is higher at zones farther from the Sacramento downtown according to

Euclidean distances. On the other hand, zones with low car substitution rates are also found in more distant areas, suggesting other reasons for car substitution besides distance from downtown. Because zones in the outer areas have less than 15 trips per zone per day, some of the spatial patterns are likely due to noise and not meaningful differences in behavior.

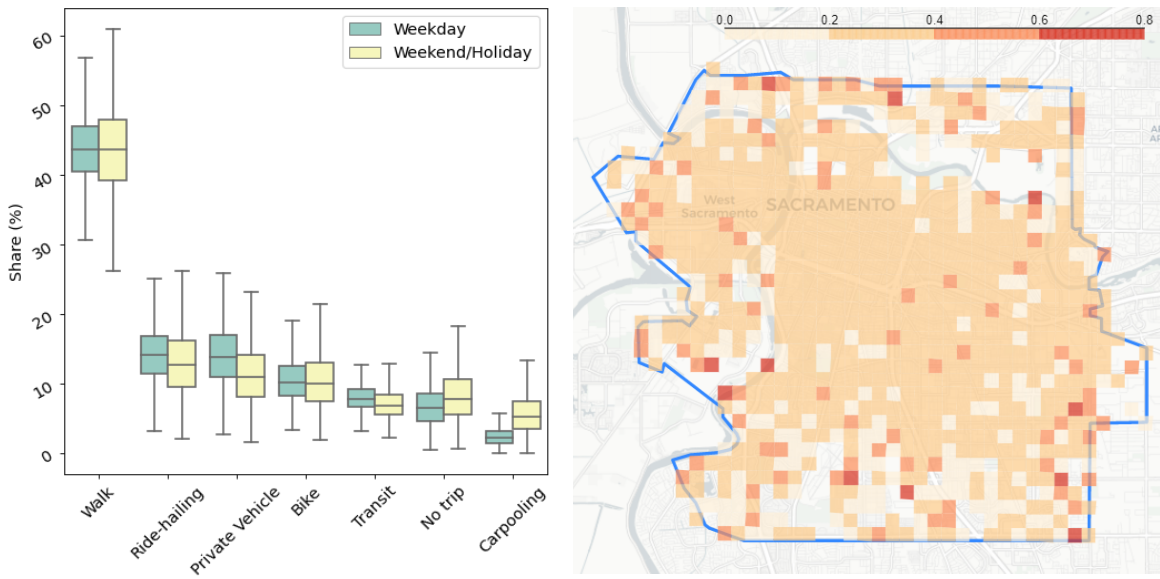


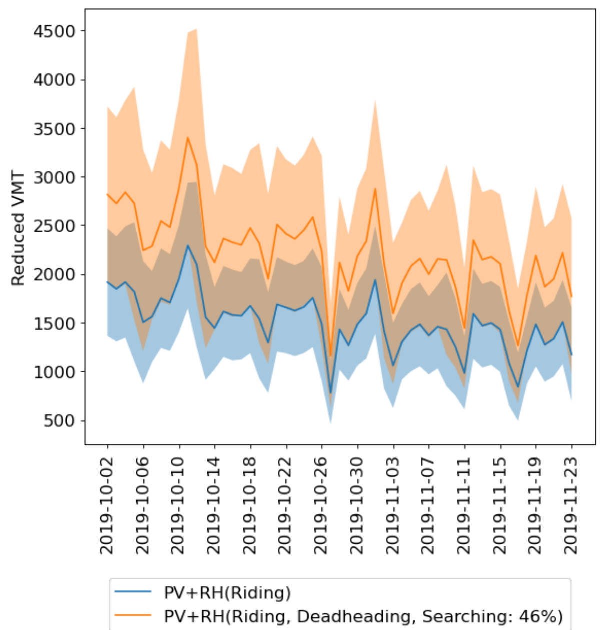
Figure 4.7 Share of Substituted Modes on Weekdays and weekends per day (95% confidence interval) (Left) and Average car substitution rate by zone on weekdays (Right)

4.4.2. VMT Reductions from Mode Substitution

Based on my model I estimate that the dock-less e-bike-share service with a fleet size ranging between 950 and 1100 was responsible for 1572 daily vehicle miles (sd: 333 miles) on average across the service region on weekdays and 1355 miles (438 miles) on weekend days (counting only the VMT of private vehicle and ride-hailing when a passenger is in the vehicle) (Figure 4.8). Adding the potential VMT reduction from deadheading and searching associated with ride-hailing services, I estimate VMT reductions of 2307 miles (522 miles) on weekdays and 2026 miles (684 miles) on weekend days. Standard deviations both on weekdays and weekends are large because the estimates vary by trip frequency and estimates of mode substitution and driving distance for bike-share trips.

I estimate VMT reduction per trip (Figure 4.8) of 0.58 miles per trip (sd: 0.09 miles) on weekdays and 0.51 miles per trip (0.11 miles) on weekend days (counting only the VMT of private vehicle and ride-hailing when a passenger is in the vehicle). Adding the potential VMT reduction from deadheading and searching associated with ride-hailing services, I estimate VMT reductions of 0.85 miles per trip (0.15 miles) on weekdays and 0.76 miles per trip (0.18 miles) on weekend days. The estimate of VMT reduction per trip tends to be stable over the days in this study.

The pattern of total VMT reduction from car substitution by zone (Figure 4.9) depends more on trip frequency by zone (Figure 4.5) than on estimated car substitution rate by zone (Figure 7). Though zones with longer distance trips and higher car substitution rates producing more VMT reduction per trip are located farther from the downtown, most of the environmental benefits from a dock-less bike-share service occur in the high-density area with high trip frequency. The results suggest that, to maximize environmental benefits, operators must focus on satisfying as many trip requests as possible in the high-density area. This will increase the number of trips per bike and VMT reductions simultaneously.



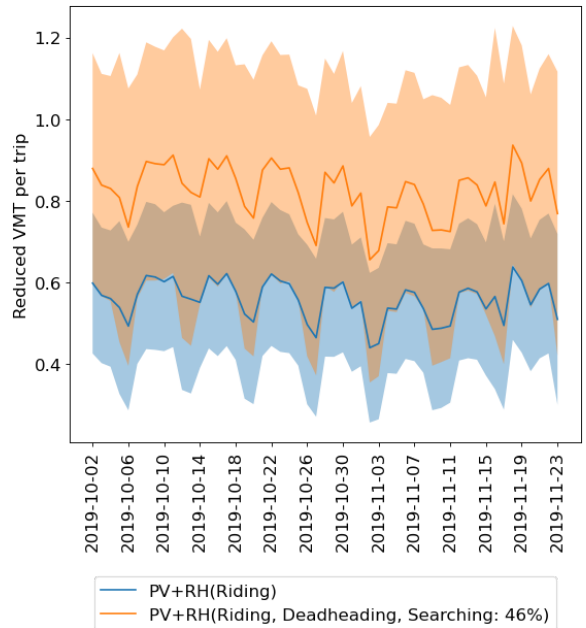


Figure 4.8 Estimated VMT Reduction for each day (Left) and VMT Reduction per trip for each day (95% confidence interval)

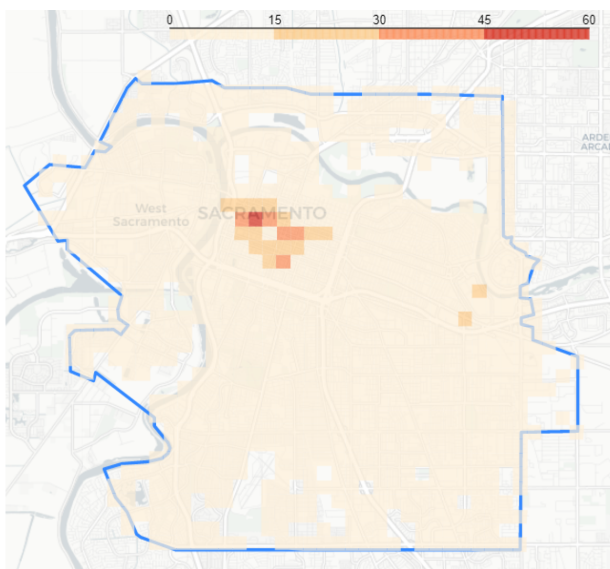


Figure 4.9 VMT reduction from car substitution by zone on weekday (Unit: miles per day)

4.4.3. Considering Operational VMT

The model for operational miles (Table 4.2) shows that the intercept has a large effect on operational miles. I interpret the intercept as the minimum operational miles an operator produces by launching a service in a high-populated city. It is not intuitive that a service with no fleet size and no trips still produces operational miles. Generally speaking, however, operators do deploy a number of micromobility vehicles within the service boundary with the expectation that they will be used. For this reason, having the intercept in the model will not harm interpretability of parameter estimates and the applicability of the model for estimating operational miles.

My findings show that trip efficiency, the number of bike-share trips per bike per day, is positively associated with operational miles. This makes sense because the more micromobility trips the service has, the sooner each micromobility vehicle needs battery swapping or charging and maintenance given the constant fleet size, thereby increasing operational miles. However, such operational activities are less required if the fleet size is larger. Another notable finding is that the varying effect of the intercept by operators have large estimates, suggesting that operational strategies vary by operator. The small sample size for this model contributes to a large uncertainty in parameter estimates.

Table 4.2 Summary of estimates of operational miles model including the posterior mean and standard deviation

(n=27)	Estimate
Random effect (Operator-level Std. Dev.)	
Intercept	0.98 (0.44)
Operational Miles (log hundred mile)	
Intercept	0.33 (0.49)
Trip Efficiency (log, 100 vehicles)	0.05 (0.09)
Sigma	0.31 (0.05)

My estimation of operational miles with the model developed here shows that a typical operator in a large city produced 177 operational miles per day on average. This value is reasonable as docked bike-share services in Minneapolis and Washington, DC reportedly produced 145 and 342 daily operational miles, respectively (Fishman et al., 2014). I used operational miles estimated with the model as operational miles per day in the Sacramento region. Adding operational miles, I estimate that the dock-less e-bike-share service was responsible for a reduction of 1395 daily vehicle miles (0.51 miles per bike-share trip) on average across the service region on weekdays (counting only the VMT of private vehicle and ride-hailing when a passenger is in the vehicle). Adding the potential VMT reduction from deadheading and searching associated with ride-hailing services, I estimate VMT reductions of 2131 miles (0.79 miles per bike-share trip) on weekdays. My estimates suggest that a dock-less e-bike-share service reduced VMT by replacing car trips though associated operational tasks offset a part of the reductions in the range of 8 % to 11%.

4.5. Conclusion

The purpose of this study was to propose a new framework to estimate vehicle miles reduced from the introduction of bike-share service based on trip-level data and retrospective counter-factual survey responses about mode substitution.

My estimates show that on weekdays, bike-share 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. That car substitution rate of 28%, including “Private Car” and “Ride-haling”, is less than NACTO’s report showing 45 % of users in various cities but higher than findings from Fishman et al. showing substitution rates of 19% and 7% in Minneapolis and Washington D.C. (NACTO, 2020; Fishman et al., 2013). The lower rates in the latter two cities may reflect the pronounced drop in bike share demand in winter months and the fact that my study is of shared e-bikes, which when privately owned have been shown to reduce driving to a greater extent compared to conventional bikes (Fitch, 2019), amongst other factors. Fishman et al. (2014) estimated annual VMT reductions of 444,187 km and 182,390 km (equivalent to 0.14 mile and 0.42 mile per trip) from car substitution in Washington, D.C. and Minneapolis, respectively, lower than my estimated reductions only from car substitution for Sacramento of 0.58 to 0.85 miles per trip on weekdays and 0.51-0.76 miles per trip on weekend days.

My findings that high-volume areas with shorter trips, which are less likely to be associated with car substitution, still produce a larger VMT reduction than other areas suggest that operational tasks important for increasing the number of trips are important for maximizing VMT reduction. On the other hand, operational tasks are usually made by vans or trucks, thereby at least partially offsetting the VMT reduction. Data from SFMTA (2022) shows that operational miles vary across operator, who need to carefully consider the trade-off between operational tasks by van or truck and VMT production. One potential way to reduce van-based operational tasks in a dock-less e-bike-share service is, for example, to introduce an incentive-based rebalancing program. Such programs incentivize the user to walk farther to get a bike in oversupplied areas or bring a bike to an undersupplied area to reduce the spatial mismatch between supply and demand over time. One study found a positive effect of an incentive program on the rebalancing task in a docked bike-share system in New York city (Vanderbilt, 2018). My recent study on the willingness to walk farther to get a shared bike in a dock-less e-bike-share system also suggests the potential effectiveness of incentives as a strategy to address the spatial mismatch (Fukushige et al., 2022).

My framework for estimating VMT reduction from a dock-less bike-share service can be helpful to cities and regions in estimating the environmental benefits of bike-share services in the current transport landscape. While I did not explore societal benefits beyond the VMT reduction that bike share brings to the community, my methodology can be extended to the assessment of benefits for public health, social equity, among others. However, calibrating my framework to another region would require a user survey to collect data on mode substitution using a counterfactual question that is subject to validity concerns. Nonetheless, without this information, estimating the impact of bike-share services on the sustainability of transportation, even in the use-phase, is challenging.

As future work, I encourage the collection of data in multiple cities to enable the development of a generalizable tool for estimating mode substitution for trip-level data. Applying my estimation framework to a longer study period (e.g., year) would be helpful in understanding VMT reduction more fully given bike-share is a strongly seasonal service in many cities. My estimation of bike-share benefits considers only the outcome from car substitution. In future work, I may consider VMT associated with transit miles that substitute for driving. 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 also contribute to the development of more robust models and provide additional insights for bike share operation strategies and policy implementation.

References

Bürkner, P.C., 2017. brms: An R package for Bayesian multilevel models using Stan. J. Stat. Softw., 80.

Chen, Y., Zhang, Y., Coffman, DM, & Mi, Z. 2022. An environmental benefit analysis of bike sharing in New York City, Cities, 121, 103475, https://doi.org/10.1016/j.cities.2021.103475.

DeMaio, Paul. 2009. Bike-sharing: History, Impacts, Models of Provision, and Future, Journal of Public Transportation, 12(4), 41-56. http://doi.org/10.5038/2375-0901.12.4.3

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/

Fishman, E., Washington, S., & Haworth, N., 2014. Bike share's impact on car use: Evidence from the United States, Great Britain, and Australia, Transportation Research Part D: Transport and Environment, 31, 13-20, https://doi.org/10.1016/j.trd.2014.05.013.

Fishman, E., Washington, S., Haworth, N., 2013. Bike Share: A Synthesis of the Literature, Transport Reviews. 33.2: 148-165. https://doi.org/10.1080/01441647.2013.775612

Fitch, D. 2019. Electric Assisted Bikes (E-bikes) Show Promise in Getting People out of Cars. UC Office of the President: University of California Institute of Transportation Studies. Retrieved from https://escholarship.org/uc/item/3mm040km

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. https://doi.org/10.7922/G2F18X0W

Fukushige, T, Fitch, D. T., and Handy, S., 2021. Factors Influencing Dock-less E-Bike-Share Mode Substitution: Evidence from Sacramento, California, Transportation Research Part D., 99, https://doi.org/10.1016/j.trd.2021.102990

Fukushige, T., Fitch, D.T. and Handy, S., 2022. Can an Incentive-Based approach to rebalancing a Dock-less Bike-share system Work? Evidence from Sacramento, California. Transportation Research Part A: Policy and Practice, 163, 181-194. https://doi.org/10.1016/j.tra.2022.07.011

Gebhart K. and R. Noland. 2014. The impact of weather conditions on bikeshare trips in Washington, DC. Transportation. 41. 1205-1225

Kim K. 2018. Investigation on the effects of weather and calendar events on bike-sharing according to the trip patterns of bike rentals of stations, Journal of Transport Geography, vol. 66, 309-320.

Kou, Z., Wang, X., Fung, S. & Hua Cai, C. 2020, Quantifying greenhouse gas emissions reduction from bike share systems: a model considering real-world trips and transportation mode choice patterns, Resources, Conservation and Recycling, 153, 104534, https://doi.org/10.1016/j.resconrec.2019.104534.

Li, X. Cottam, A., Wu, Y.J., & Khani, A.. 2020. Can a bikesharing system reduce fuel consumption? Case study in Tucson, Arizona, Transportation Research Part D: Transport and Environment, 89,102604, https://doi.org/10.1016/j.trd.2020.102604.

McNeish, D. 2016. On Using Bayesian Methods to Address Small Sample Problems, Structural Equation Modeling: A Multidisciplinary Journal, 23:5, 750-773, https://doi.org/10.1080/10705511.2016.1186549

NACTO, 2019. Shared Micromobility in the U.S.: 2018. https://nacto.org/shared-micromobility-2018 (accessed 2.5.21).

NACTO, 2020. Shared Micromobility in the U.S.: 2018. https://nacto.org/shared-micromobility-2019 (accessed 2.5.21).

Otero, I., Nieuwenhuijsen, M.J., Rojas-Rueda, D., 2018. Health impacts of bike sharing systems in Europe, Environment International, 115: 387-394. https://doi.org/10.1016/j.envint.2018.04.014

Pfrommer J., J. Warrington, G. Schildbach and M. Morari. 2014 Dynamic Vehicle Redistribution and Online Price Incentives in Shared Mobility Systems, IEEE Transactions on Intelligent Transportation Systems, 15(4), 1567-1578. https://doi.org/10.1109/TITS.2014.2303986

Qian, X., Jaller, M., Niemeier, D., 2020. Enhancing Equitable Service Level: Which Can Address Better, Dockless or Dock-Based Bikeshare Systems?, Journal of Transport Geography. 86, 102784 https://doi.org/10.1016/j.jtrangeo.2020.102784.
Qiu, Lu-Yi, & Ling-Yun He. 2018. Bike Sharing and the Economy, the Environment, and Health-Related Externalities, Sustainability. 10(4), 1145. https://doi.org/10.3390/su10041145
Reck, D. J., Martin, H, & Axhausen, K. W. 2022. Mode choice, substitution patterns and environmental impacts of shared and personal micro-mobility, Transportation Research Part D: Transport and Environment, 102, 103134, https://doi.org/10.1016/j.trd.2021.103134.
Saltykova, K., Ma, X., Yao, L., & Kong, H. 2022. Environmental impact assessment of bike-sharing considering the modal shift from public transit, Transportation Research Part D: Transport and Environment, 105, 103238, https://doi.org/10.1016/j.trd.2022.103238.
SFMTA, 2022, Monthly E-scooter Operations Reporting
Shaheen, S. A., Guzman, S. and Zhang, H., 2010. Bikesharing in Europe, the Americas, and Asia: Past, Present, and Future, Transportation Research Record, 2143(1), 159–167. https://doi.org/10.3141/2143-20
Shen Y., X. Zhang, J. Zhao. 2018. Understanding the usage of dockless bike sharing in Singapore. International Journal of Sustainable Transportation. 12. 1-15
Stan Development Team, 2018. Stan Modeling Language. User's Guid. Ref. Man. 1–488., http://mc-stan.org/manual.html%5Cnpapers2://publication/uuid/C0937B19-1CC1-423C-B569-3FDB66090102 (accessed 6.5.20).
Wang K. and Y. J. Chen. 2020. Joint analysis of the impacts of built environment on bikeshare station capacity and trip attractions, Journal of Transport Geography, Volume 82
Wang, M., and Zhou, X., 2017. Bike-sharing Systems and Congestion: Evidence from US cities, Journal of Transport Geography, 65: 147-154. https://doi.org/10.1016/j.jtrangeo.2017.10.022
Vanderbilt, T. 2018 The Angel Who Keeps Citi Bike Working for New York., Outside, 8 7 https://www.outsideonline.com/2332671/purest-form-bike-angel, Accessed April, 10, 2021
Xu, Y., Yan, X., Sisiopiku, V.P., Merlin, L.A., Xing, F. and Zhao, X., 2022. Micromobility Trip Origin and Destination Inference Using General Bikeshare Feed Specification Data. Transportation Research Record, 1-16, https://doi.org/10.1177%2F03611981221092005
Yong, Y. and Diez-Roux, A.V., 2012. Walking distance by trip purpose and population subgroups. American journal of preventive medicine, 43(1), 11-19. https://doi.org/10.1016/j.amepre.2012.03.015
Zhang, M., & Mi, Z., 2018. Environmental benefits of bike sharing: A big data-based analysis, Applied Energy, 220, 296-301, https://doi.org/10.1016/j.apenergy.2018.03.101.
Zou, Z., Younes, H., Erdoğan, S. and Wu, J., 2020. Exploratory analysis of real-time e-scooter trip data in Washington, DC. Transportation research record, 2674(8), 285-299., https://doi.org/10.1177%2F0361198120919760

Appendix 4A Summary of estimates of mode substitution model for commuting trip including the posterior mean and standard deviation (n=105)

Base = Transit	Bike	Walk	Car
Intercept	1.70 (1.28)	0.29 (1.39)	1.34 (1.48)
Trip Attribute			
Travel Distance (log)	-0.44 (0.63)	-2.16 (0.72)	0.53 (0.73)
Mode Availability			
*Start (*a quarter-mile *buffer)*			
# Bus stops	-0.24 (0.62)	0.71 (0.60)	-0.64 (0.81)
# LRT stations	1.01 (0.71)	0.11 (0.77)	-0.62 (0.96)
# Length of Bike Lanes	-0.77 (0.39)	-0.20 (0.42)	-0.91 (0.47)
*End (*a quarter-mile *buffer)*			
# Bus stops	0.07 (0.34)	-0.02 (0.36)	0.61 (0.37)
# LRT stations	-0.19 (0.38)	0.08 (0.40)	-0.81 (0.44)
# Length of Bike Lanes	0.29 (0.41)	0.05 (0.47)	-0.10 (0.47)

Appendix 4B Summary of estimates of mode substitution model for non-commuting trip (reduced model) including the posterior mean and standard deviation

Base = Transit	Bike	Walk	Ride-hailing	Car, Alone	No Trip	Carpooling
Intercept	1.67 (1.67)	-1.18 (1.56)	1.40 (1.64)	3.73 (1.62)	1.56 (1.70)	-0.21 (1.73)
Person-level Std. Dev.	3.83 (0.69)	2.84 (0.49)	3.52 (0.59)	3.84 (0.75)	3.25 (0.64)	2.63 (0.65)
Trip Attribute						
Travel Time (log)	0.31 (0.44)	-2.47 (0.43)	0.82 (0.44)	0.19 (0.46)	-0.60 (0.42)	0.88 (0.49)
Speed (log)	-0.62 (0.30)	-1.19 (0.28)	0.18 (0.32)	-0.50 (0.29)	-1.25 (0.29)	-0.02 (0.34)
Time of Day (Base: Midnight)						
AM Peak	0.79 (0.80)	-1.53 (0.69)	0.02 (0.74)	-0.86 (0.77)	-1.29 (0.86)	-0.06 (0.82)
Off Peak	0.58 (0.73)	-0.42 (0.58)	-0.11 (0.65)	0.45 (0.68)	0.40 (0.70)	0.98 (0.74)
PM Peak	0.07 (0.75)	-0.80 (0.63)	-0.47 (0.68)	-0.44 (0.71)	-0.69 (0.76)	-0.05 (0.79)
Night	0.27 (0.82)	-0.40 (0.70)	1.44 (0.72)	-0.25 (0.79)	-0.45 (0.87)	0.11 (0.87)
Weekend	0.19 (0.57)	0.20 (0.49)	-0.27 (0.54)	-0.25 (0.57)	0.17 (0.60)	0.86 (0.60)
Land Use						
Start (a quarter-mile buffer)						
Residential use	0.57 (1.05)	0.09 (0.97)	0.95 (1.05)	-0.20 (1.04)	-0.07 (1.08)	0.43 (1.09)
Commercial/Office use	-0.28 (1.15)	0.81 (1.07)	-0.75 (1.13)	-0.13 (1.17)	-0.15 (1.18)	-0.66 (1.24)
Industrial use	0.14 (1.45)	-0.35 (1.38)	0.19 (1.45)	-0.23 (1.44)	0.27 (1.40)	0.24 (1.44)
School use	-0.28 (1.43)	-0.34 (1.39)	0.26 (1.40)	0.03 (1.39)	-0.04 (1.40)	0.64 (1.41)
Civic use	0.31 (1.29)	-1.03 (1.23)	0.59 (1.25)	0.62 (1.28)	-0.41 (1.31)	-0.42 (1.32)
End (a quarter-mile buffer)						
Residential use	0.05 (1.02)	0.26 (0.96)	0.70 (1.02)	1.12 (1.02)	-0.76 (1.01)	-0.56 (1.04)
Commercial/Office use	0.44 (1.15)	1.37 (1.06)	1.52 (1.13)	-0.28 (1.16)	-0.74 (1.13)	0.08 (1.19)
Industrial use	-0.26 (1.34)	-0.41 (1.42)	-0.16 (1.39)	0.84 (1.35)	0.19 (1.39)	0.33 (1.42)
School use	-0.66 (1.28)	-0.82 (1.31)	-1.07 (1.26)	-0.74 (1.33)	0.98 (1.27)	0.04 (1.26)
Civic use	-0.44 (1.30)	1.47 (1.17)	-0.49 (1.30)	-0.61 (1.24)	-1.34 (1.29)	-0.01 (1.30)
Mode Availability						
Start (a quarter-mile buffer)	0.01 (0.37)	0.04 (0.3)	0.09 (0.33)	-0.23 (0.38)	0.42 (0.35)	0.21 (0.40)
# Bus stops	-0.37 (0.42)	0.03 (0.33)	-0.26 (0.37)	-0.43 (0.42)	-0.78 (0.41)	-0.35 (0.44)
# LRT stations	0.06 (0.36)	-0.06 (0.31)	-0.11 (0.36)	-0.78 (0.39)	-0.32 (0.37)	0.02 (0.39)
# Length of Bike Lanes	0.01 (0.37)	0.04 (0.30)	0.09 (0.33)	-0.23 (0.38)	0.42 (0.35)	0.21 (0.40)
End (a quarter-mile buffer)						
# Bus stops	-0.34 (0.33)	0.19 (0.29)	-0.23 (0.33)	0.23 (0.34)	0.14 (0.33)	0.51 (0.38)
# LRT stations	0.31 (0.36)	-0.32 (0.31)	0.13 (0.36)	-0.39 (0.39)	-0.32 (0.37)	-1.06 (0.45)
# Length of Bike Lanes	-0.57 (0.33)	-0.05 (0.29)	-0.30 (0.33)	-0.57 (0.33)	-0.16 (0.33)	-0.23 (0.35)

Appendix 4C Summary of estimates of driving distance model including the posterior mean and standard deviation

(n=5956)	Estimate
Driving Distance (log mile)	
Intercept	0.40 (0.00)
Euclidean distance (log mile)	0.98 (0.00)
Sigma	0.29 (0.00)

5 Incentive-based Approach to Rebalancing a Dock-less E-Bike-Share System: Efficiency and Environmental Benefits

5.1. Introduction

As climate change concerns grow, policy makers are promoting micromobility services (e.g., docked bike-share, dock-less e-bike-share, dock-less e-scooter-share) as substitutes for car travel and thus as a way to reduce vehicle miles traveled (VMT) and related greenhouse emissions in cities (Fishman et al., 2014; Shaheen et al., 2010). The average trip length of micromobility services is between 1.0 and 2.5 miles, depending on the type of micromobility services and user (NACTO, 2019). The fact that 35% of trips by private vehicles are less than 2 miles, according to data from the National Household Travel Survey (USDOT, 2018), suggests a vital opportunity to increase the substitution of micromobility for driving. Prior studies have found that micromobility services substitute for car travel at a substantial rate, though the rate varies between 7% and 45% by city by city (NACTO, 2020; Barnes, 2019; Fishman et al., 2014). Micromobility services generate substantial environmental benefits by producing VMT reductions (Fishman et al., 2014) and greenhouse emissions reductions (Chen et al., 2022; Saltykova et al., 2022; Cazzola & Crist, 2020; Kou et al., 2020; Zhang & Mi, 2018).

Such benefits will be offset if operators run various operational activities by van or truck, including maintenance, charging, and rebalancing. A few studies report operational miles associated with micromobility services (SFMTA, 2022; Hollingsworth et al., 2019; Fishman et al., 2014). Fishman and his colleagues (2014) found that docked bike-share service operators produced 150 miles and 342 miles per day in Minnesota and Washington, D.C. They also estimated that operational miles exceeded VMT reduction from car substitution for a docked bike-share service in London. The San Francisco Municipal Transportation Agency (2022) reported that dock-less e-scooter-share operators produced 200 to 600 operational miles per day depending on months and operators. Another study estimated 0.6-2.5 miles per scooter for collection and distribution (Hollingsworth et al., 2019). These miles vary by factors such as bike density, the number of micromobility users, operational budget, and urban structure. Though operational activities maintain and facilitate the service to increase micromobility use, minimizing the operational miles is essential for maximizing benefits.

Rebalancing operations, as a major component of operational miles and thus operating costs (Pfrommer et al., 2014), are important for both increasing micromobility use and reducing VMT reduction. A spatial mismatch between demand and supply means that potential users may not have access to a micromobility vehicle where and when they want it. Most operators fix the mismatch by relocating the vehicles from oversupplied to undersupplied areas by van or truck, thereby offsetting at least some of the environmental benefits. To address this problem, some docked bike-share services have adopted an incentive approach. This approach incentivizes users to walk farther to get a micromobility vehicle from the oversupplied area (origin-based incentives) or to take a micromobility vehicle to the undersupplied area (destination-based incentives) by offering some reward, such as free-micromobility use or a prize of some sort. The advantage of this approach is that the approach does not produce additional operational miles. The disadvantage is that the approach remains uncertainties for operators because acceptance of incentive offers depends on users' preference. A prior study found that the Bike Angels program in New York City contributed up to 30% of total bike rebalancing needs for the city's docked bike-share (Vanderbilt 2018), but the effectiveness of the incentive approach for a dock-less micromobility system has not yet been tested in an actual operating setting.

Prior studies on rebalancing incentive programs have used computer simulations, focusing on the model architecture for setting the incentive (Duan & Wu, 2019; Pan et al., 2019; Singla et al., 2015; Pfrommer et al., 2014). Singla et al. (2015) developed a dynamic incentive control model called Dynamic Budgeted Procurement using Upper Confidence Bounds (DBP-UCB), considering both origin- and destination-based incentives. Pfrommer et al. (2014) controlled both the incentive and truck operations with dynamic programming in the context of a docked bike-share service. They found that truck operations and incentive approaches are a trade-off between incentive cost and staff salary, but the incentive program does not work well in rush-hour. Pan et al. (2019) developed Hierarchical Reinforcement Pricing using the Deep Deterministic Policy Gradient algorithm considering spatial and temporal dependency to set an origin-based incentive in the context of dock-less bike-share. Duan and Wu (2019) added a destination-based incentive into their reinforcement learning algorithm.

Although prior studies have analyzed the effectiveness of incentive programs on service performance, they have used rule-based models about user behavior in their simulators. Some studies used the product of the maximum distance users are willing to walk to another station and an assumed cost to determine whether the user accepts a given incentive offer (Duan & Wu, 2019; Pan et al., 2019; Singla et al., 2015). Patel et al. (2019) considered the waiting time when the bike was unavailable at the station in the user behavior model. These researchers have relied on a rule-based model without uncertainty rather than developing any model that accounts for uncertainty. One of the issues with an incentive approach is uncertainty for the operators that users may not accept an incentive offer. To better understand the effectiveness of an incentive program, it is important to consider the uncertainty in users' decision-making.

This study examines how an incentive-based approach helps reduce the spatial mismatch between demand and supply in the context of a dock-less e-bike-share service. Using prior studies on the estimation of VMT reduction from a bike-share service and social cost per VMT, I evaluate the environmental and monetary benefits of the service. Because this study does not focus on the incentive control model architecture, I adapted the DBP-UCB developed by Singla et al. (2015) for my dock-less e-bike-share simulator. Because the size of the incentive budget and the size of the fleet influence the performance of an incentive program, I examined the trade-offs among types of incentive programs, budget size, and fleet size. This study provides insights into the potential for an incentive approach to increase operation efficiency and VMT reduction. The findings about the effect of fleet size will be helpful to policy makers in defining service requirements for operators. The methodologies developed in this study can be applied in other areas to assess the impact of policy changes and operational improvements.

5.2. Methodology

5.2.1. Studies Areas & Analysis Scenarios

I used the Sacramento, California region as my study area to examine the effect of incentive programs on service efficiency and VMT reduction. JUMP operated a dock-less e-bike-share system between May 2018 and March 2020 (closed due to the emergence of COVID-19) across three California cities: Sacramento, West Sacramento, and Davis. The service area was not all contiguous, as Davis was separated from the rest, thus I used a subset of the bike-share service area that included Sacramento and West Sacramento as a focus area to develop the simulator. My goal is to understand the effect of incentive programs on service efficiency and VMT reduction. I define four different rebalancing strategies to evaluate incentive programs: (1) no rebalancing incentive strategy, (2) only origin-based incentive strategy, (3) only destination-based incentive strategies, and (4) origin- and destination-based incentive strategies. The effectiveness of the hypothetical incentive strategies varies by budget and fleet size. I examined the incentive budget range from US$100 to US$500 per day by US$100. The actual fleet size during the actual service ranged from 950 to 1100, so I examined the fleet size range from 200 to 2000 bikes by 200 bikes to understand the variation in effects by size of the market.

5.2.2. Simulation Environment

I developed a simulator for the Sacramento JUMP service using an agent-based model, a type of simulation method helpful in evaluating the outcome of the complex interactions of individual decision-makers. Because experimenting with incentive programs for the actual bike-share system would be costly, this model can be an important tool for understanding the potential effect of incentive programs on bike-share use and VMT reduction. This simulator consists of three main components interacting with one another in the simulation environment: (1) demand component, (2) supply component, and (3) user behavior component.

5.2.2.1. Demand Component

The Demand Component defines trip request patterns and trip attributes of a trip in the simulation environment. I used system-wide bike-share trip data by web-scraping the real-time status of Jump bikes in the Sacramento region provided by the General Bikeshare Feed Specification (GBFS) between October 2nd and October 29th, 2019 (4 weeks), to reflect a realistic pattern of trip requests. I directly used the location of destination, trip request time, duration, and the Euclidean Bike speed (based on Euclidean distance between origin and destination/duration) from this data source. In the simulator, I considered these four trip attributes, as well as the origin of a bike trip, walking speed, whether to reserve a bike first, and whether to make a trip to the destination directly. The latter attributes were estimated in the following ways. For simplicity, I assumed that all trips are independent and requested by different users.

One problem with using the location of the origin from the GBFS data is that one trip's destination is identical to another trip's origin. The GBFS data does not detect bike-share access between the actual “origin” and a bike location. This issue complicates the examination of the effect of incentive programs on service performance in the simulation. I addressed this issue by assigning a grid zone by a quarter-mile (400 meters) of the origin to the trip request and randomly drawing from the points in the zone.

Walking speed represents a characteristic of trip requests. The speed largely varies by user and determines the travel time to access the bike. TCRP/NCHRP report (Fitzpatrick et al., 2006) showed that the 50^{th} percentile and 15^{th} percentile walking speeds for young people between the ages of 13 and 60are 1.45 m/s and 1.15 m/s, respectively. Fitch et al. (2020) reported that the median age of bike-share users in the Sacramento region in two surveys were 37 and 33 years, respectively. I draw the walking speed for each trip request from the normal distribution (mean: 1.45m/s; std: 0.3m/s). I truncated the interval within two standard deviations to avoid an extreme value.

How a user checks out a bike may influence the acceptance rate, the ratio of bike-share trips to the number of trip requests. Some users walk first and check out a bike to save usage fees, while others want to reserve a bike first before walking toward the location to secure their travel mode. A few users may see a bike on the street and check out the bike. My prior survey found that 58 percent of participants usually reserve a bike before walking. The survey also showed that a small portion of users check out a bike when they see it on the street. For simplicity, I assume only two types of users in this simulator: walk first before checking out a bike and reserve a bike first before walking. I draw reservation types randomly following the Bernoulli distribution with probability 0.58 and assign the draw into each type request as reservation behavior in the simulator.

The assumption that all trips in the simulator move at the Euclidean bike speed are problematic in the case that the Euclidean bike speed is very slow. Suppose the Euclidean distance of a slow trip in the simulator is much longer than the original Euclidean distance in the GBFS data. In that case, the duration derived from the Euclidean bike speed becomes much longer. It is more realistic to use the duration of the trip request from the GBFS data as travel time rather than the Euclidean bike speed because such a slow Euclidean bike speed is more likely to be associated with a trip via intermediate stops or round trips. I classified trip requests into two types of trip requests: destination-oriented trips and non-destination-oriented trips. A destination-oriented trip represents a trip going from the origin to the destination without any intermediate stops using nearly the shortest route. All other trips were classified as non-destination-oriented trips. I classified trips based on the Euclidean bike speed. The speed distribution showed two peaks at nearly zero km/h and 7.2 km/h. The bottom between the two peaks was around 1.8 km/h; thus, I set that value as the threshold between the two types.

5.2.2.2. Supply Component

The Supply Component defines how an operator offers dock-less bike-share service, including the deployment of the bike fleet and incentive offers for rebalancing.

A bike fleet is a collection of bikes deployed in the simulation environment. Each bike contains identifier and location information, including bike ID, x-coordinate, y-coordinate, and current grid zone. I used actual bike location data to initialize the bike location realistically in the simulator. I used a collection of bike locations at midnight of each date between 2019/10/2 and 10/29 (28 days). I calibrated the distribution of bikes by grid zone and randomly drew bikes from the collection without replacement by following the distribution until the defined number of bikes was satisfied.

I added a user-based incentive rebalancing strategy to the simulator. The operator incentivizes users to walk farther to get a bike (origin-based incentive) or bring a bike to the undersupplied area (destination-based incentive) by offering a cash reward. The incentive model determines an optimal number of origin- or destination-based incentives for each trip request. The detail of the incentive model is discussed in the next section.

In this simulator, users are offered options for up to four different routes, including pick-up location, drop-off location, and the number of incentives based on predicted bike availability and input trip information. Potential choices include (1) a bike without any reward (Bike A), (2) a bike with a reward at their origin (Bike B), (3) a bike with a reward at their destination (Bike C), and (4) a bike with a reward at both their origin and destination (Bike D). How to determine whether rewards are offered is discussed in the later section.

5.2.2.3. User Behavior Component

The user behavior component defines how users behave in the simulation environment. This simulator assumes that users follow the process sequence to check out and check in a bike-share bike. Firstly. the simulated users input where to go and whether to go to the destination directly. Given the input information and the simulation environment, the App suggests up to four options, as explained in the previous section. Users would choose the best option from the suggested options. If none of the alternatives satisfies the user, the user gives up taking the bike-share service at the trip request. This decision is made following a user behavior model developed in Chapter 2. In this decision-making, I assume that users know their ability with respect to walking speed and biking speed. If travel time on foot from origin to destination is shorter than travel time by choosing an option, the user ignores the option. This function helps avoid unreasonable behavior in this simulator, and supplement lack of consideration of a total travel time in the user behavior model. Users would then reserve a bike first and walk to a bike location of the selected option, or walk to the bike location without any reservation and check out the bike. If the person cannot check out a bike due to check-out by another user, the user gives up using the bike-share service. Although people may change their minds even after making any decision, my simulation assumes that users have only one chance to use bike-share.

Decision making of users follows an output from a discrete choice model developed in Chapter 2. This model estimates the likelihood of using a bike-share service and what pick-up and drop-off location to choose given the options. Parameters in the utility function of this model include walking time from the origin to bike location and drop-off location to the destination and a number of incentives. Alternative specific attributes derive from the information, including possible bike locations and drop-off locations in the simulation environment, bike availability and user specific attributes. Details of the modeling process and the estimates are discussed in Chapter 2.

5.2.3. Incentive Mechanism

I developed a two-step incentive allocation mechanism in the context of a dock-less bike-share service inspired by a prior study on a docked bike-share service (Singla et al., 2015). The first step of the mechanism identifies potentially problematic zones with undersupply or oversupply around the origin and destination of trip requests. Compared to the docked bike-share service allowing users to pick up or drop off bikes at stations with limited capacities, it is not easy to define the undersupply or oversupply in the context of dock-less bike-share service. One reason is that the walkable distance varies by user (Fukushige et al., 2022; Wang & Wang, 2021; Singla et. al., 2015). Prior studies (Duan & Wu, 2019; Pan et al., 2019) suggest predicting the number of bikes available based on the current bike availability and the number of future arrivals and departures. If the expected number of bikes available is negative, the operator needs to move bikes to the area. If, instead, the predicted number of bikes available is positive, that means an oversupply in the area. Once the mechanism identifies potentially problematic zones, the agent, in the second step, determines the number of incentives to be offered given the remaining budget and the expected acceptance rate. The steps of the mechanism are as follows.

First step: Identifying Problematic Zones

The first step is to identify a problematic zone where more bikes should be placed or moved to another zone to avoid prolonged idleness. The location or zone in the context of dock-less bike-share is not well-defined because users can drop off a bike anywhere in the service boundary. To make it easier to understand the state of the simulation environment, I set grid zones by a quarter-mile (400 meters) in the service boundary. The predicted number of available bikes for each zone would be a metric of the future spatial mismatch between supply and demand (Duan & Wu, 2019; Pan et al., 2019). Predicting the number of available bikes in a zone at the beginning of time interval t (e.g., 15 min, 30 min, 1hr) can be calculated with the number of available bikes in a zone at the beginning of time interval t-1, the number of bike arrivals in a zone in time interval t-1 and the number of bike departures in a zone in time interval t-1.

It is problematic to use the predicted number of available bikes calibrated at the beginning of the time interval for all incentive offers during the time interval. The simulation environment close to the end of the time interval has already reflected most predictions. Determining such incentive offers relying on the prediction determined at the beginning of the time interval may not be appropriate for the rebalancing purpose. One reason is that the prediction is more likely to be reflected in the status of bike availability when the time is closer to the end of a time interval. To address the issue, I divided the sum of the predicted number of arrivals and departures by the ratio of the remaining time in the time interval. This operation assumes that the bike arrivals or departures occur following the uniform distribution in the interval. In this simulation I assume that an operator can make the demand prediction accurately.

$$\hat{S}_i(t) = S_i + \frac{(p-d) * \ (\hat{A}_i(t-1) - \widehat{D}_i(t-1))}{p}$$

where

$\hat{S}_i(t)$: the predicted number of available bikes at the beginning of time interval t in zone i

S_i: the number of available bikes at the current time in zone i

p: the length of the time interval

d: the length of the time interval passed

$\hat{A}_i(t)$: the predicted number of bikes arriving in zone i during time interval t

$\widehat{D}_i(t)$: the predicted number of bikes departing from zone i during time interval t

I used a model predicting the potential number of trip starts and end by zone accurately, but the uncertainty remains in the simulation. One reason is that a user in a zone with bike availability does not always use a bike in the zone. If a nearest bike is in the neighbor zone, the user may choose the nearest bike. This still results in the gap between the predicted number of departures and the actual number of departures. A prolonged idle state of bikes may harm the service performance in the long term without resulting in any loss in demand because of no direct effect on any trip request. On the other hand, no available bikes near a trip request are more likely to cause the loss of a ride. For these reasons, I made a conservative rule, and considered zero as an undersupplied zone.

I looked at the metric of 7 x 7 zones (candidate region), accessible within 15 minutes on foot, in the neighbor zones of the origin and destination to identify problematic zones. I excluded 3 x 3 zones (walkable region) in the neighbor zones of the origin from the candidate problematic zones to avoid wasting the daily incentive budget. My prior study (Fukushige et al., 2022) shows that 70% of people can potentially walk up to 7 min to get a bike without any reward. I predicted the number of available bikes at each trip request and identified problematic zones in the candidate region of the origin and destination of trip requests. Among bikes and drop-off locations in the problematic zones, I chose one nearest bike or drop-off location to be incentivized, if available. For simplicity, I assumed that a drop-off location in the zone is in the middle of the zone.

I made several rules not to offer rewards in some instances. One case of not offering any origin-based incentive is when the origin zone is classified as oversupplied. In the same way, if the destination zone is classified as undersupplied, I did not offer any destination-based incentive.

Second-step: Incentive Allocation Model

I set an incentive price for picking up an incentivized bike or dropping off a bike if available. I assume that the price is discrete and ranges between p_0 and p_k by 0.25.

$$price = \{p_0, \dots, p_i, \dots p_k\}$$

I developed an incentive allocation model based on the Dynamic Budgeted Procurement using Upper Confidence Bounds (DBP-UCB) suggested by Singla et al. (2015). This algorithm uses a multi-armed bandit framework with UCB as a sampling method. Under the budget constraint and given that the optimal incentive price to be offered is unknown, the model approximates to an optimal incentive price giving a better system performance as the simulation proceeds. The greater incentive would motivate the user to walk more, and the operator can expect a higher acceptance rate, but the number of offers would be smaller. Therefore, the algorithm considers this trade-off. The core of the algorithm is below:

$$\tilde{F}_i^n = F_i^n + \sqrt{\frac{2 * \ln(n)}{N_i^n}}$$

$$i^n = argmax_i \min\left\{\tilde{F}_i^n, \frac{B}{N * p_i}\right\} = argmax_i \min\{N\tilde{F}_i^n, \frac{B}{p_i}\}$$

where

n: The number of users who were offered any incentive price

F_i^n: The acceptance rate at an incentive price i at iteration n

N_i^n: The number of times the incentive price p_i has been offered

N: The predicted number of incentive offers in the budget period

B: Total budget

In the process of the simulation, the acceptance rate at the incentive price p_i, which is calibrated by dividing the number of successes by the number of attempts, is updated. The exploration term is added to explore all choices in some adjusted ways by considering the upper confidence bounds. The second term of $\tilde{F}_i^n$ function indicates that increasing the number of times the incentive price p_i has been offered (N_i^n) makes the term smaller, so the algorithm can consider the tradeoff between exploitation and exploration. Budget constraint is also considered by comparing the acceptance rate with the potential budget per incentive offer based on the predicted number of incentive offers. The expected utility at the incentive price p_i will be the smallest one so that the minimum value is chosen from two different utilities at the price p_i.

One problem with this algorithm is that the number of incentive offers in the budget period is unknown. Prior studies (Wang & Wang, 2021; Singla et al., 2015) assume that they provide an incentive to all users, so they used a demand forecasting model to predict the total number of users and multiplied the prediction by two because each user may offer up to two different incentive offers, including origin- and destination-based incentives. However, this depends on the first step of the mechanism. If I overestimate the number of incentive offers, the budget will remain and not improve the service performance. If I underestimate it, I use up the budget in the early stage and cannot make some incentive offers due to no budget remaining. Predicting the number of incentive offers is challenging. Because this study focusses on the effect of incentive programs on bike-share use, I simulated scenarios with no incentive and counted the number of potential offers if the operator adopted the incentive program to the scenarios. I weighted the predicted number of bike-share trips by the average number of offers per trip.

5.2.4. VMT Estimation

VMT Reduction from a dock-less e-bike-share service

I developed a framework to estimate a system-level VMT reduction from a dock-less e-bike-share service in Chapter 4. This framework uses trip-level data and user survey data and comprises six steps. In the first step, I predict probability of each possible mode substitution for a bike-share trip in the case of commuting and non-commuting trips. One issue with predicting probabilities by trip purpose is a lack of information about the purpose of the trip for each trip data. As the second step, to address this issue, I estimate the share of non-commuting and commuting trips within the service boundary by time of day on weekdays and weekends. In the third step, I estimate the driving distance of bike-share trips that are substituted for car trips based on the Euclidean distance between trip start and end. I query a shortest distance made by a car between trip start and end using the Google Maps Application Programming Interface (API) and use this output as a driving distance for a bike-share trip. This process makes the driving distance in a more realistic way. In the fourth step, I aggregate driving distance for the trips predicted to substitute for "private car" or "ride-hailing" weighted by the share of trip purposes by time of day. In the fifth step, I consider additional potential sources of reduction in VMT from ride-hailing substitution, such as deadheading (a driver traveling to pick up a passenger) and searching (a driver cruising for their next passenger). This adjustment calculated according to Fehr and Peers (2019) inflates VMT reduction from ride-hailing by 46%. Finally, I reduce estimated operational miles per day from the total VMT reduction from car substitution to estimate the net VMT reduction. Details of the framework and the model development are provided in Chapter 2 and Chapter 4.

5.2.5. Evaluation Metric

I used four metrics to evaluate service performance and social benefits in the simulation environment. My data covers trip requests for four weeks, but I used the first week as warmup that I discarded because the incentive mechanism needs time to approximate to the optimum incentive price. The first metric is the acceptance rate, the ratio of the number of bike-share trips to the number of trip requests (Pfrommer et al., 2014). This metric represents the service performance from user's perspective as the availability of bikes matters to them.

The second metric is the net profit considering a total of incentive use and additional income from the increase in bike-share trips by introducing incentive-based programs. This metric represents the program performance from an operator's perspective as Chapter 4 and survey data collected by Fitch and his colleagues (2020) shows that mean of travel time was 19-20 min, thus I used 20 min as a typical travel time in this simulation. Based on actual pricing mechanism ($1.5 for a 10-minute bike access and $0.2 per additional min), I assumed that the average usage fee per trip is US$2.5 and all trips are independent users with non-membership.

The third metric is the net VMT reduction from the service. VMT reduction from the service comes from car substitution that users replace bike-share for car trips. On the other hand, daily van-based operations, such as maintenance and rebalancing, make VMT and offset the VMT reduction from car substitutions. I define VMT reductions from car substitutions reduced by operational VMT as the net VMT reduction in this simulation. I estimated the net VMT reduction based on the framework and models developed in Chapter 2 and Chapter 4. This metric represents social benefits as VMT reduction is one major policy target in U.S. cities.

I expanded the benefit of VMT reduction to social cost reduction to understand the contribution of the service at the monetary scale. I used a prior study on estimating social costs of VMT, including emissions of greenhouse gases, crash cost, roadway congestion, and space consumption (Lemp & Kockelman, 2008). They found that the external cost per VMT was

US$0.236 in 2006. Considering the inflation rate, I inflated this value to US$0.32 in 2021.

5.2.6. Limitation

My simulation has several limitations. First, the assumption that each grid zone has a parking spot for destination-based incentives may overestimate the effect of the incentive program. One issue is to determine appropriate locations of bike stations. This would be due to lack of available sites and cost of parking facilities. I made this simple assumption because the optimum location of bike stations is out of the scope from this study. Further analysis will be required to assess the effect of station locations on the service quality and the program performance in a more realistic setting.

I did not consider unrealized trips, trips of users failing to use the bike-share service due to unavailability nearby, in this simulation analysis. GBFS data contains only realized trip data but not unrealized trip requests. Ignoring unrealized trips may not assess the number of trips and VMT reductions accurately at the system level. However, the purpose of this study is to understand the effect of incentive programs on service quality and VMT reduction, not to assess the overall performance in a dock-less e-bike-share system. Some prior studies (Gammelli et al., 2020; Meellou & Jaillet, 2019) have developed a model to estimate the number of unrealized trips based on the number of realized trips and other external information in the context of docked bike-share services. Further studies to develop a similar model in dock-less micromobility services will be encouraged.

5.3. Results & Discussion

5.3.1. User Satisfaction

I examine the effect of incentive programs on service efficiency and VMT reduction using the Sacramento, California region as my study area. My results show that the average acceptance rate without any rebalancing strategy was 59% when the fleet size was 200 (Figure 5.1). Adding fleet size improves the service level, but the effect of an increase in the acceptance rate especially when the fleet size is more than 800 is weaker. When the fleet size is 2000, the service level achieved 84%. Adding origin-based incentive strategies with a budget of US$200 per day improved bike-share use by 40 – 90 trips per day, depending on fleet size. When the fleet size is larger than 600, the effect on the acceptance rate was smaller.

Destination-based incentive strategies with a budget of US$200 improved bike-share use by 50 – 80 trips per day depending on fleet size, more stable effect than origin-based incentive. When the fleet size was 1800 or more, the increase achieved at around 80 trips per day. Unlike origin-based incentives, scenarios with destination-based incentives involve similar costs for the incentives at any fleet size. In a small fleet size scenario, the number of available bikes in many areas is negative or close to zero; thus, dropping off a bike in the oversupplied area does not cause a prolonged idle state of bikes. On the other hand, in a large fleet size scenario, a few undersupplied areas emerge over the time. Destination-based incentives might help improve the service availability better at markets with high density of fleet size.

The origin- and destination-based incentive strategy with a budget of US$200 generally produces better results than only origin- or destination-based incentive strategies when the fleet size is more than 600. Increasing the budget by US$100 roughly improves user satisfaction but with the uncertainty as some results show that scenarios with a small budget increased the number of bike-share trips more than scenarios with a large budget did (Figure 5.1). This unintuitive result may come from the uncertainty of users' decision. The simulation also shows the tendency of a greater improvement at all budgets (except $400) as fleet size increases.

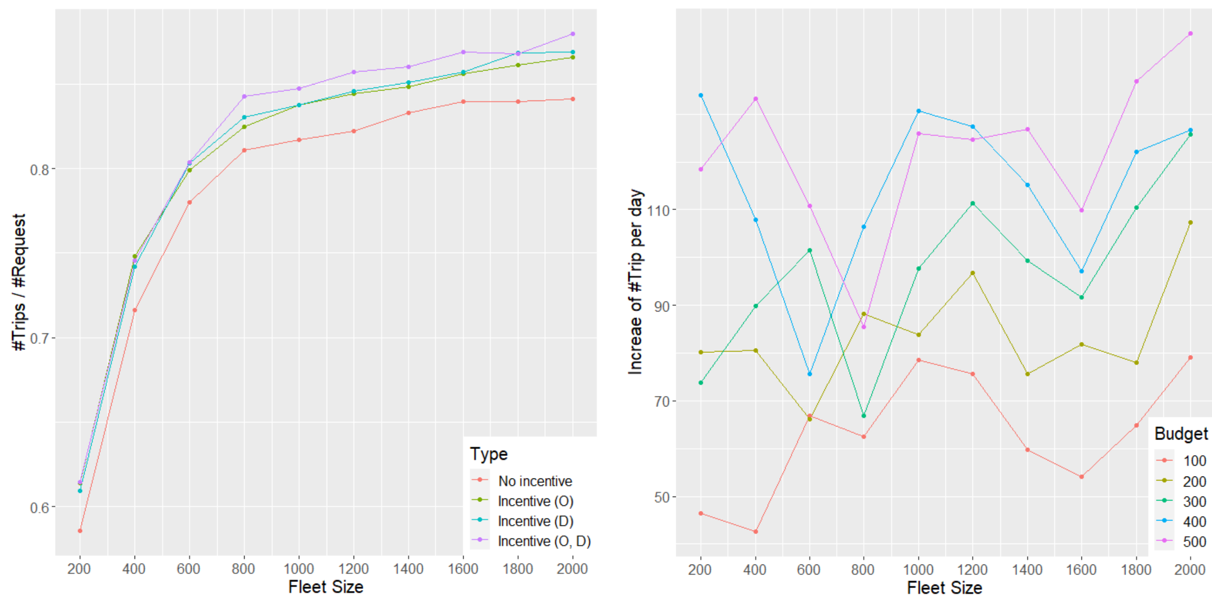


Figure 5.1 Effects of fleet size on acceptance rate by rebalancing strategies (Left)[3] and increase of acceptance rate by budget (Right)[4]

5.3.2. Service Efficiency

Increasing the fleet size gradually reduces fleet efficiency from 8.5 trips/day/bike at 200 bikes to 1.2 trips/day/bike at 2000 bikes (Figure 5.2). Any rebalancing strategy shows a minor efficiency improvement, suggesting that operators must determine the fleet size mainly by predicting the number of potential trips before entering the market.

Operators may be concerned about profitability by introducing the incentive strategy. Figure 5.2 shows the increase of the number of trips per an incentive dollar by fleet size and budget size. The results show that scenarios with lower budget tend to have a higher profitability.

---

[3] The budget of each incentive strategy is US$200.

[4] Incentive strategy, including origin- and destination-based incentives, is used in this plot

When the fleet size is 200 vehicles and the budget is US$100, one dollar produces 0.5 trips per day. This performance increases to 1.1 trips per day as the fleet size is up to 2000 vehicles. Assuming that an average usage fee per trip is US$2.5 as mentioned above.US$1 incentive budget should produce 0.4 trips at least to make incentive programs profitable. The results show that all scenarios with a budget of US$100 were profitable. On the other hand, most scenarios with a daily budget of US$200 or more show unprofitability. The results suggest that operators may profit with incentive programs but must be careful in balancing the fleet size and the incentive budget.

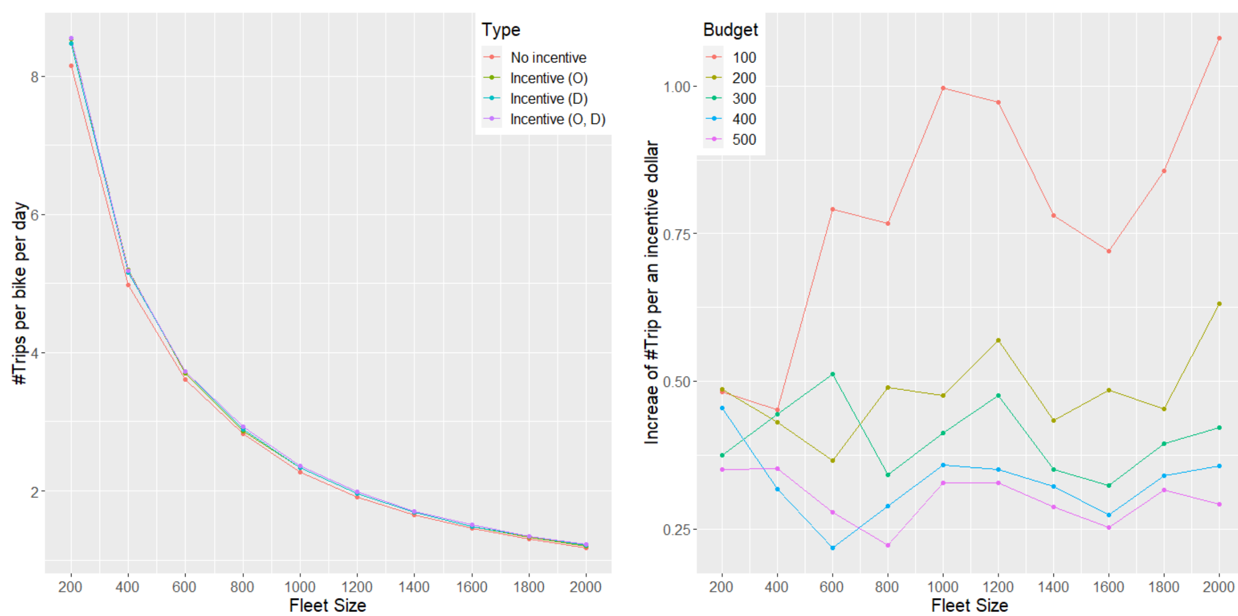


Figure 5.2 Fleet Efficiency by fleet size (Left) and increase of the number of trips per an incentive dollar (No incentive vs. Incentive (O, D)) (Right)

5.3.3. Environmental benefit

Introducing an incentive strategy will make a city more environmentally sustainable. In the scenario with a budget of US$200, an incentive strategy, including both origin- and destination-based incentives, increases by 40 to 60 miles of VMT reduction per day (private vehicle and a riding portion of ride-hailing use) by fleet size (Figure 5.3). Adding the potential VMT reduction from deadheading and searching associated with ride-hailing services, the total amounts of reduction increased to 60 to 90 miles per day by fleet size, equivalent to 3-6% increase.

Incentive strategies create social benefits by increasing car substitution. Additional VMT reduction from the increase in bike-share trips accounts for US$20-29 per day as social monetary benefits (Figure 5.3). The results show that consideration of social monetary benefits into the net profit of an operator results in positive net benefits in all scenarios. This suggests that cities may mandate operators to introduce the incentive program but at the same time offer them some subsidies for the number of benefits they city may receive from the strategy.

Figure 5.3 Contribution of incentive strategy on VMT reduction (Left) and Net monetary benefit for an operator and the city (Right)

5.4. Conclusion

This study evaluated the effectiveness of the incentive-based approach in reducing the spatial mismatch between demand and supply in the context of a dock-less e-bike-share service by using various metrics, including user acceptance rate, the net profit, VMT reduction, and its social benefits. I found that incentive strategies improve the acceptance rate, but the effect varies by fleet size and budget size. The finding that the bike efficiency does not change significantly by rebalancing strategies suggest that operators must determine the fleet size carefully before entering the market. I estimated that introducing incentive strategies reduce VMT by 3-6% and save US$20-29 per day.

Introducing an incentive will likely improve the acceptance rate of all trip requests. Still, operators need to be careful in determining the budget for incentive-based strategies because the cost-effectiveness varies by fleet size and budget. Some scenarios in this study show a profit reduction by introducing the incentive strategy. One potential idea to leverage incentives would be partnered with other businesses. Such monetary scheme in the operation will reduce the risk of introducing the incentive program and improve the profitability. Such partnership might also help to vitalize the local economy (Buehler & Hamre, 2015; Krykewycz et al., 2010).

The finding that introducing incentives contributes to positive social benefits from VMT reduction by increasing the number of realized bike-share trips suggests that cities might want to mandate such incentive programs. This study focused only on VMT reduction from the introduction of bike-share service, making my estimates of benefits conservative. Cities and operators can expect other benefits, such as an increase in physical activity and accessibility and local vitalization by inducing trips by increasing the number of trips. An increase in service reliability is more likely to retain users in the service or even increase users. Mandating the incentive programs but subsidizing operators for additional social benefits will make a more sustainable service and, if the operator is private, less risk of the service leaving the city.

This study examined the effect of incentive programs on bike-share performance and social benefits but did not consider several instances observed in the real services, such as failure of bikes, van-based operational works (maintenance, rebalancing, and battery charging), and traffic conditions. It would be encouraged to improve the simulator for more reliable and realistic outcomes. I focused on VMT reduction and associated social benefits in this study, but other benefits from bike-share services, such as economic benefits by inducing trips and health benefits, could also be evaluated. As a further step, these incentives could be tested by assessing their cost-effectiveness in reducing the spatial mismatch by making a partnership with a micromobility operator.

References

Barnes, F., 2019. A Scoot, Skip, and a JUMP Away: Learning from Shared Micromobility Systems in San Francisco. https://doi.org/doi:10.17610/T6QP40

Buehler, R., & Hamre, A. 2015. Business and bikeshare user perceptions of the economic benefits of capital bikeshare. Transportation Research Record, 2520(1), 100-111. https://doi.org/10.3141%2F2520-12

Cazzola, P., and Crist, P., 2020. Good to go? Assessing the environmental performance of new mobility. Available at: https://www.itf-oecd.org/sites/default/files/docs/environmental-performance-new-mobility.pdf [Accessed by: 7/18/22]

Chen, Y., Zhang, Y., Coffman, DM, & Mi, Z. 2022. An environmental benefit analysis of bike sharing in New York City, Cities, 121, 103475, https://doi.org/10.1016/j.cities.2021.103475.

Duan Y. and J. Wu. (2019) Optimizing Rebalance Scheme for Dock-Less Bike Sharing Systems with Adaptive User Incentive, 2019 20th IEEE International Conference on Mobile Data Management (MDM), Hong Kong, 176-181 https://doi.org/10.1109/MDM.2019.00-59

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/ Fishman, E., Washington, S., & Haworth, N., 2014. Bike share's impact on car use: Evidence from the United States, Great Britain, and Australia, Transportation Research Part D: Transport and Environment, 31, 13-20, https://doi.org/10.1016/j.trd.2014.05.013.

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. https://doi.org/10.7922/G2F18X0W

Fitzpatrick, K., Turner, S.M., Brewer, M., Carlson, P.J., Ullman, B., Trout, N.D., Park, E.S., Whitacre, J., Lalani, N., and D. Lord., 2006. Improving Pedestrian Safety at Unsignalized Crossings. Transit Cooperative Research Program (TCRP) Report 112 or NCHRP Report 562, published by Transportation Research Board, Washington https://nacto.org/wp-content/uploads/2010/08/NCHRP-562-Improving-Pedestrian-Safety-at-Unsignalized-Crossings.pdf, (accessed 3.21.21).

Fukushige, T., D. T. Fitch, Handy, S. 2021 Factors influencing dock-less E-bike-share mode substitution: Evidence from Sacramento, California, Transportation Research Part D: Transport and Environment, 99, https://doi.org/10.1016/j.trd.2021.102990.

Fukushige, T., Fitch, D.T. and Handy, S., 2022. Can an Incentive-Based approach to rebalancing a Dock-less Bike-share system Work? Evidence from Sacramento, California. Transportation Research Part A: Policy and Practice, 163, 181-194. https://doi.org/10.1016/j.tra.2022.07.011

Gammelli, D., Peled, I., Rodrigues, F., Pacino, D., Kurtaran, H.A., Pereira, F.C..2020. Estimating latent demand of shared mobility through censored Gaussian Processes, Transportation

Research Part C: Emerging Technologies, 120, 102775, https://doi.org/10.1016/j.trc.2020.102775.
Hollingsworth, J., Copeland, B. and Johnson, J.X., 2019. Are e-scooters polluters? The environmental impacts of shared dockless electric scooters. Environmental Research Letters, 14(8), 084031. https://doi.org/10.1088/1748-9326/ab2da8
Kou, Z., Wang, X., Fung, S. & Hua Cai, C. 2020, Quantifying greenhouse gas emissions reduction from bike share systems: a model considering real-world trips and transportation mode choice patterns, Resources, Conservation and Recycling, 153, 104534, https://doi.org/10.1016/j.resconrec.2019.104534.
Krykewycz, G. R., Puchalsky, C. M., Rocks, J., Bonnette, B., and Jaskiewicz, F. 2010. Defining a primary market and estimating demand for major bicycle-sharing program in Philadelphia, Pennsylvania. Transportation research record, 2143(1), 117-124. https://doi.org/10.3141%2F2143-15
Lemp, J.D., Kockelman, K.M., 2008. Quantifying the external costs of vehicle use: Evidence from America's top-selling light-duty models. Transportation Research Part D: Transport and Environment. 13, 491–504. https://doi.org/10.1016/j.trd.2008.09.005.
Mellou, K. & P. Jaillet. 2019. Dynamic Resource Redistribution and Demand Estimation: An Application to Bike Sharing Systems. SSRN. http://dx.doi.org/10.2139/ssrn.3336416
NACTO, 2019. Shared Micromobility in the U.S.: 2018. https://nacto.org/shared-micromobility-2018 (accessed 3.20.21).
NACTO, 2020. Shared Micromobility in the U.S.: 2019. https://nacto.org/shared-micromobility-2019 (accessed 3.20.21).
Pan, L., Cai, Q., Fang, Z., Tang, P., & Huang, L. 2019. A deep reinforcement learning framework for rebalancing dockless bike sharing systems. In Proceedings of the AAAI conference on artificial intelligence, 33(1), 1393-1400 https://doi.org/10.1609/aaai.v33i01.33011393
Patel S.J., R. Qiu, and A. Negahban. 2019 Incentive-Based Rebalancing of Bike-Sharing Systems, Advances in Service Science, 21-30
Pfrommer J., J. Warrington, G. Schildbach and M. Morari. 2014 Dynamic Vehicle Redistribution and Online Price Incentives in Shared Mobility Systems, IEEE Transactions on Intelligent Transportation Systems, 15(4), 1567-1578.
Saltykova, K., Ma, X., Yao, L. and Kong, H., 2022. Environmental impact assessment of bike-sharing considering the modal shift from public transit. Transportation Research Part D: Transport and Environment, 105, 103238. https://doi.org/10.1016/j.trd.2022.103238
SFMTA, 2022, Monthly E-scooter Operations Reporting
Shaheen, S., Guzman, S., Zhang, H., 2010. Bikesharing in Europe, the Americas, and Asia. Transp. Res. Rec. 159–167. https://doi.org/10.3141/2143-20
Singla A., M. Santoni, G. Bartók, P. Mukerji, M. Meenen, and A. Krause. 2015 Incentivizing users for balancing bike sharing systems. In Proceedings of the Twenty-Ninth AAAI Conference on Artificial Intelligence (AAAI'15). AAAI Press, 723–729.
U.S. Department of Transportation, 2018. 2017 National Household Travel Survey.
Vanderbilt, T. 2018 The Angel Who Keeps Citi Bike Working for New York., Outside, 8 7 https://www.outsideonline.com/2332671/purest-form-bike-angel, Accessed April, 10, 2021
Wang, J., and Wang, Y. 2021. A two-stage incentive mechanism for rebalancing free-floating bike sharing systems: considering user preference. Transportation research part F: traffic psychology and behaviour, 82, 54-69. https://doi.org/10.1016/j.trf.2021.08.003

Zhang, M., & Mi, Z., 2018. Environmental benefits of bike sharing: A big data-based analysis, Applied Energy, 220, 296-301, https://doi.org/10.1016/j.apenergy.2018.03.101.

6 Conclusion

This dissertation examines the potential effect of an incentive-based approach to rebalancing a dock-less e-bike-share fleet on bike-share use and social benefits, focusing mainly on VMT reduction. I develop a framework to estimate system-level VMT reduction from the service and develop a simulation environment for a dock-less e-bike-share service using an agent-based model.

Results from Chapter 2 that incentives nudge users to walk farther to use bike-share suggest that such offers are an option for helping operators rebalance the bike fleet, especially in areas with substantial use by women, white residents, and those who hold memberships. The finding that some groups of users tend to favor coupon/gift cards for businesses (e.g., fast food, restaurants) as incentive rewards suggests that leveraging incentives from other businesses might help to vitalize the local economy while helping operators reduce operational costs (Krykewycz et al., 2010; Buehler and Hamre, 2015; Fukushige et al., 2021). That my estimates on willingness-to-walk for the incentive at origin and destination are 3.8 minutes and 4.2 minutes per dollar also gives operators and policy makers insights into the potential effectiveness of incentives as a strategy for spatially rebalancing the bike fleets.

Findings on factors influencing car substitutions presented in Chapter 3 are essential for cities and operators developing strategies for enhancing the substitution of bike share for driving. My finding that bike-share trips to destinations, such as restaurants, bars, and entertainment establishments, tend to substitute for driving, especially ride-hailing, suggests the need to involve local businesses in the incentive approach. My modeling estimates that specific demographic groups, such as women and those who have a private car, are more likely to replace car trips, suggest that cities and operators target such groups for marketing and incentives.

My estimates on VMT reductions from a dock-less e-bike-share service built on the models developed in Chapter 2 showed that the car substitution rate, including “Private Car” and “Ride-haling,” was 28% and that VMT reduction per trip on weekdays was 0.58-0.85 miles per trip. These findings were higher some, lower than other prior findings (NACTO, 2020; Fishman et al., 2013) but still offer some evidence that a dock-less e-bike-share system helps reduce environmental loads by shifting from car use. Another contribution from this chapter is that my framework for estimating VMT reduction from a dock-less bike-share service can be helpful to cities and regions in evaluating the environmental benefits of bike-share services in the current transport landscape.

The findings from my simulation in Chapter 5 that introducing incentives contributes to positive social benefits from VMT reduction by increasing the number of realized bike-share trips suggest that cities might want to mandate such incentive programs. On the other hand, my results showing a risk for operators introducing the incentive program in less profit suggests that operators need to be careful in determining the budget for incentive-based strategies or leveraging incentives by partnering with other businesses. The findings also indicated that the city should subsidize operators to reduce the risk of introducing the incentive program. Such subsidy for additional social benefits from the program makes the service more sustainable and, if the operator is private, less risk of the service leaving the city.

Overall, with a series of models, this study showed the positive effect of incentive programs on bike-share performance and social benefits. Integration of a framework to estimate VMT reduction from a micromobility service and a simulation environment offered a novel approach to evaluating service quality and social benefits to cities and operators. This simulation would be helpful in the planning of incentive programs. For future work, the simulation environment should be made more realistic by adding various operational activities and types of user behavior. While I focused on VMT reduction as one social benefit from the service, this can be expanded to other benefits, such as increased physical activity and economic vitalization from inducing trips. As a further step, cities could test these incentives to empirically evaluate their cost-effectiveness in reducing the spatial mismatch by partnering with a micromobility operator. Mandating operators to introduce the incentive program is likely to result in the increase of micromobility use and bring more social benefits to cities. On the other hand, such requirement will make operators risk in reducing the profit. To make cities more sustainable, risk sharing of cities and operators should also be discussed.

References

Buehler, R., & Hamre, A. 2015. Business and bikeshare user perceptions of the economic benefits of capital bikeshare. Transportation Research Record, 2520(1), 100-111. https://doi.org/10.3141%2F2520-12

Fishman, E., Washington, S., Haworth, N., 2013. Bike Share: A Synthesis of the Literature, Transport Reviews. 33.2: 148-165. https://doi.org/10.1080/01441647.2013.775612

Fukushige, T., D. T. Fitch, Handy, S. 2021 Factors influencing dock-less E-bike-share mode substitution: Evidence from Sacramento, California, Transportation Research Part D: Transport and Environment, 99, https://doi.org/10.1016/j.trd.2021.102990.

Krykewycz, G. R., Puchalsky, C. M., Rocks, J., Bonnette, B., and Jaskiewicz, F. 2010. Defining a primary market and estimating demand for major bicycle-sharing program in Philadelphia, Pennsylvania. Transportation research record, 2143(1), 117-124. https://doi.org/10.3141%2F2143-15

NACTO, 2020. Shared Micromobility in the U.S.: 2018. https://nacto.org/shared-micromobility-2019 (accessed 2.5.21).