Incorporating New Mobility Services into Public Transit in a Post-Pandemic Era: An Integrated Cost-Efficiency and Transportation Equity Perspective

Lamis Abu Ashour

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Reading Committee:

Qing Shen, Chair

Andrew Dannenberg

Don MacKenzie

Rachel Berney

Program Authorized to Offer Degree:

Urban Design and Planning

University of Washington

Abstract

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Lamis Abu Ashour

Chair of the Supervisory Committee:

Qing Shen

Urban Design and Planning

The COVID-19 pandemic has triggered major shifts in work arrangements and activity-travel behavior, significantly reshaping urban mobility. With a focus on advancing post-pandemic public transit, this dissertation delves into the multifaceted impacts of post-pandemic mobility changes, particularly concerning the integration of new mobility services into public transit. For new mobility services to deliver sustainable impacts, they must increase the cost-effectiveness of public transportation and mobility options, especially for marginalized communities, by navigating and addressing emerging equity gaps. Hence, this dissertation aims to understand the changes in post-pandemic mobility needs and travel behavior while identifying opportunities and barriers to integrating new mobility services into public transit and creating a more equitable and sustainable transportation system. The dissertation consists of three studies. The first study

focuses on understanding mobility patterns, needs, and equity gaps in the "new normal" era. Drawing on a comprehensive travel survey conducted with Commute Seattle and the Mobility Innovation Center, this study examines the evolving spatiotemporal patterns of urban mobility and travel behavior and explores the potential shifts in commute mode choice, shedding light on potential challenges for public transit and equity concerns post-pandemic. Using the Multiple Discrete-Continuous Extreme Value (MDCEV) model and accounting for both remote work (telework) and the frequency of mode choice, the study provides critical and timely insights into the factors influencing commute mode choice in the new normal. The findings highlight the significant influence of sociodemographic, job-related, and built environment characteristics on mode choice and the nuanced difference in using each mode. The second study delves into the opportunities and barriers to advancing public transit post-pandemic, focusing on incorporating new mobility services into public transit. Through empirical research and analysis, this study evaluates the cost-effectiveness of incorporating transportation network companies (TNCs) services into transit while underscoring how changes in mobility patterns and policy environments can impact the viability of such partnerships. For this purpose, this study explores three scenarios of future TNC price changes: (1) price trend extension using forecasting models (ARIMA and PROPHET), (2) price increase in response to local policy changes, and (3) TNC/taxi price convergence due to increased competition and investigates the impact of TNC price change on the prospect of transit agency-TNC partnerships, using a case study in the Seattle region. The results highlight the potential of TNCs' average price increase and their consecutive negative impact on the expected cost-effectiveness of transit agency-TNC partnerships. The third study advances the evaluation of new mobility services by incorporating equity into the cost-effectiveness evaluation of transit by incorporating new mobility services

(TIMOD) projects. Using the distributional cost-effectiveness analysis (DCEA) framework, this study models the social distributions of the generalized cost of various mobility alternatives across different income groups and built environments when evaluating TIMOD services. It highlights the importance of integrating equity in the planning decisions. The results show that TIMOD services could increase mobility options and decrease the overall inequality associated with generalized travel costs in suburban areas. However, the trade-off between travel cost reductions and inequality varies based on the built environment characteristics and income level of different suburban areas. Hence, the study discusses how transit agencies would benefit from analyzing equity and efficiency tradeoffs when introducing TIMOD services, as it informs their decision-making process and prioritization of service areas or targeted populations. The three studies collectively contribute to advancing public transit and transportation equity in the 'new normal' era. The dissertation findings have significant implications for ongoing and future projects involving new mobility services, offering valuable insights on effectively and equitably addressing transportation equity challenges in a post-pandemic world.

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Dedication

To my little angel, Adam, although I initially worried your arrival would make finishing my dissertation more complex, your presence ultimately motivated me to take that final push and complete this journey. You are a constant source of joy and excitement – so this one is for you!

Chapter 1. Introduction

1.1 Background

1.1.1 New Mobility and Public Transit Partnerships

Since new mobility services emerged, many public transit agencies have partnered with new mobility service providers, particularly transportation network companies (TNCs) (Curtis et al., 2019). Among questions of integration and substitution effects that TNCs can have on public transit, many researchers have looked into how, when, and where the two can work together. Many transit agencies have tested such a complementary model by partnering with TNCs directly to answer these questions. The main motivations for transit agencies to engage in partnerships with TNCs include filling service gaps, addressing efficiency challenges, and demonstrating innovation (Curtis et al., 2019).

Some agencies start TNC partnerships as a pilot project with a specific type of service in mind. The most common services include first/last mile connections to transit, late-night, early-morning, and on-demand options. A survey reported by TRB shows that first/last mile connection is the most common target market of transit agencies-TNCs partnerships, tackling one of the main barriers to transit ridership (Curtis et al., 2019). For example, the Southeastern Pennsylvania Transportation Authority (SEPTA) initiated a partnership with UberX in 2016 to enhance access to its rail stations and fill first/last mile gaps. The pilot lasted for less than six months and concluded with positive feedback from the general public and increased awareness of using ride-sourcing for first/last mile connections (Curtis et al., 2019).

Similarly, The Metropolitan Transit System (MTS) in San Diego offered a $5 discount on first/last-mile connections to and from its transit stations during certain events (Palm, Farber, Shalaby & Young, 2020). Moreover, pilot projects with specific target populations have also reported positive outcomes. Solano Transportation Authority (STA) partnered with LYFT in 2017 to offer subsidized first/last-mile trips for employees within 5 miles of a rail station. In less than a year, 20 pilot participants have adopted the service and provided positive feedback (Curtis et al., 2019).

Another common target market for these partnerships is ADA paratransit service for people with disabilities. Partnering with TNCs has emerged as a promising alternative for transit agencies operating ADA paratransit services. In addition to the potential cost savings by subcontracting some ADA services to TNCs, transit agencies can raise service quality by enabling same-day scheduling for trips using this new option, which provides higher flexibility than the next-day service offered by the existing paratransit (Kaufman et al. 2016). More generally, TNCs are customer-service oriented, equipping themselves with technological abilities and operational norms for improving customer satisfaction, such as using a well-designed smartphone app to request and pay for a ride and rate the driver (Curtis et al., 2019).

In light of the potential of TNCs to supplement paratransit services, several transit agencies have initiated pilot projects to test this. Boston's Massachusetts Bay Transportation Authority (MBTA) was the first agency to start an on-demand pilot project that provides a ride-sourcing alternative to its conventional ADA paratransit service, the RIDE, in October 2016. The agency has partnered with Uber, Lyft, and Curb as a strategy primarily for cost reduction (Gonzales, Sipetas, and Italiano, 2019). The initial success of MBTA's pilot motivated many transit agencies to start similar pilots. The city of Austin Capital Metropolitan Transit Authority began an ongoing pilot project (Ride|Austin) in June 2018—the project aimed to promote TNCs as an alternative mode of ADA paratransit to improve paratransit services. Ride|Austin focuses on areas lacking fixed-route services but enough paratransit riders, retail, and other short-trip destinations. This service enhances access to specific fixed routes and reduces ADA paratransit's high costs (Koffman, 2016). After a successful pilot in Maryland, Washington Metropolitan Area Transit Authority (WMATA) proposed a new TNC-provided demand response service, "Abilities-Ride," in D.C. and Virginia. The Abilities-Ride program in Maryland started in September 2018 and provided a flexible alternative to MetroAccess using on-demand taxi services at a discounted rate. Manager/CEO Paul J. Wiedefeld said, "Since the program's start, more than 2,700 individual customers have taken over 86,000 trips, most of which would have otherwise been on MetroAccess." (WMATA, 2019).

Although most transit agencies- TNC partnerships generally resulted in positive feedback from participants, especially concerning increased flexibility, time-saving, and cost-saving opportunities, such partnerships should be thoroughly evaluated and re-evaluated given significant changes and evolving mobility services and travel demand changes and challenges.

1.1.2 Problem Statement

In the past few years, the COVID-19 pandemic has caused dramatic changes in work arrangements and activity-travel behavior. The possibility that altered travel patterns persist well into the future could profoundly impact urban mobility, commuting activity, and transport systems. The significant increase in the adoption of telework and the unequivocal decrease in shared mobility, particularly public transit, indicate that these changes alter mobility needs and patterns and impact urban sustainability and transportation equity. Effects on the latter are evident as a growing body of research shows that telecommuting that characterizes the new normal era is adopted by higher-income, higher-educated, technology-savvy, and younger workers in urban contexts (Bonacini et al., 2020; Mohammadi et al., 2022; Rahman Fatmi et al., 2022). Consequently, public transit agencies must grasp the evolving mobility needs and equity implications for the diverse sociodemographic and environmental contexts they serve. In the face of rising efficiency challenges, public transit must also adapt to the fast changes in mobility services and transportation technology to correspond to these dynamic, multifaceted requirements in user travel needs, patterns, and mobility service specifications (e.g., app-based).

The advancements in information and communications technology (ICT) and the growth of new mobility services that leverage mobile apps and digital platforms have been seen as an opportunity by many decision-makers and transit agencies to enhance public transit by integrating new mobility services, as they provide attractive features such as improved flexibility, comfort, and operational efficiency, which can help transit agencies achieve some crucial goals, such as filling service gaps, increasing on-demand options, and lowering the costs of certain services (Ashour & Shen, 2022; Carmella & Alemi, 2018; Feigon & Murphy, 2016; Shen et al., 2021). However, the changes in mobility patterns post-pandemic have also triggered an evolution in the landscape of new mobility services, including ride-hailing, in response to shifting demand and political economy. For instance, the cost of ride-hailing services such as Uber increased by 40% in April 2021 compared to the previous year (Conger, 2021). These changes pose a challenge to the cost-effectiveness and sustainability of integrating new mobility services, making it difficult for transit agencies to design such partnerships or navigate this 'new normal' effectively. Moreover, sociodemographic characteristics and varied travel needs between users have yet to be thoroughly considered in the cost-efficiency assessment of new mobility services, projects, and partnerships with service providers.

Existing studies are limited to spatially aggregated sociodemographic factors or are based on pre-pandemic demand and service prices. Therefore, more research is needed to incorporate equity dimensions into the decision-making process and evaluation of public transit projects, including partnerships with mobility service providers and multi-modal business models, while understanding the changes in both demand and supply sides in the 'new normal' and post-pandemic era where travel needs are more disparate among different users (e.g., essential workers). Additionally, users' sociodemographic characteristics and diverse travel needs must be adequately factored into the cost-efficiency assessments of these services, projects, and partnerships.

1.2 Objectives

This dissertation aims to advance public transportation planning in the post-pandemic era, referred hereafter as the new normal. In recognition of existing research gaps in examining the implications of integrating new mobility services into public transit, considering both cost-efficiency and equity and accounting for the shifts in mobility needs and services post-pandemic, this dissertation aims at 1) investigating the changes in mobility needs, patterns, and equity gaps in the new normal; 2) identifying the opportunities and barriers of integrating new mobility services with public transit; 3) incorporating equity into the cost-effectiveness evaluation of new mobility services and partnerships.

1.3 Structure

To achieve these objectives, this dissertation focuses on three overarching themes: 1) new mobility services, 2) transportation equity, and 3) public transit, with three subthemes as the dissertation chapters: (a) understanding mobility needs and equity implications of the new normal, (b) investigating the opportunities and barriers of incorporating new mobility options into public transit, and (c) incorporating equity in the cost-effectiveness assessment of new-mobility services. Figure (1) illustrates the main themes and subthemes of this dissertation.

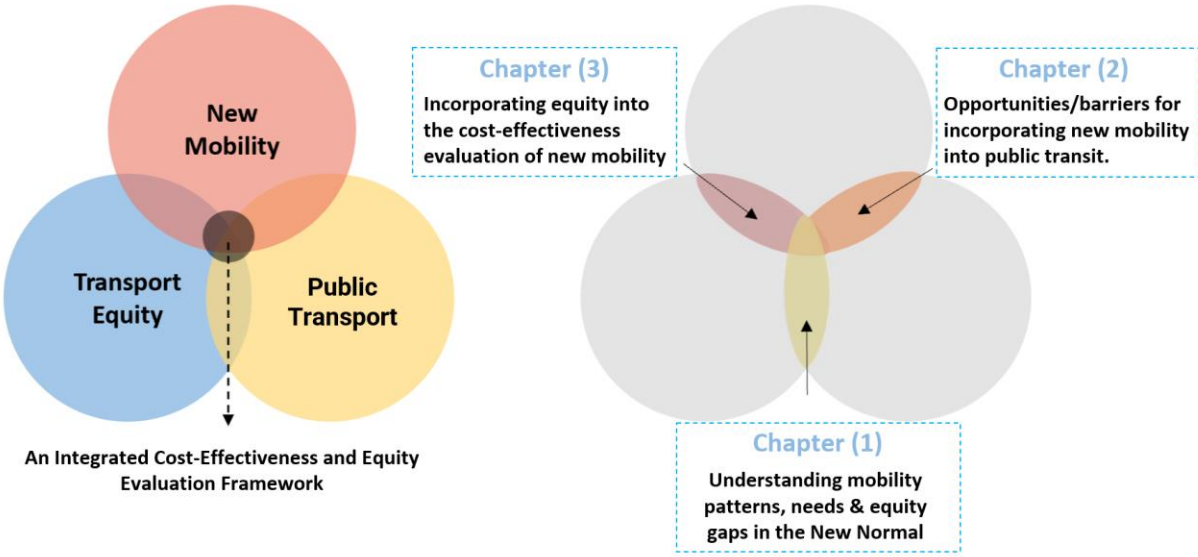

Figure 1.1 Dissertation Themes and Subthemes.

This dissertation includes collaboration with public transportation agencies and research entities in the Seattle region to conduct quantitative analysis with empirical data collected from pilot projects, surveys, and ridership records. Based on the main research themes, I investigate three topics (chapters) that help public transit agencies better understand and navigate changes in user mobility needs and new mobility services and business models to conduct more effective partnerships and service integrations while mitigating equity issues and implications of their existing or prospective partnerships. The dissertation is structured as follows:

- Chapter 1: Introduction that illustrates existing research gaps and objectives of the dissertation.
- Chapter 2: Unveiling Commute Mode Choice Amidst the Rise of Telework in the New Normal. This chapter builds off the 2022 Seattle Commute survey project in partnership with Commute Seattle and the Mobility Innovation Center, for which I conducted a travel survey of over 64,000 responses. The survey was designed to build a thorough

understanding of the changes in spatiotemporal patterns of urban mobility and commute mode choice in the new normal, using Seattle as a case study.

- Chapter 3: Investigating the opportunities and barriers to incorporating new mobility services into public transit. This chapter considers the changes in mobility needs and patterns to explore the effectiveness of incorporating new mobility services in addressing mobility challenges and gaps in the new normal. In particular, this chapter compares and explores the opportunities and barriers to integrating ride-sourcing services into public transit before and after the pandemic. This chapter is based on work reported in two research papers investigating the cost-effectiveness of incorporating ride-sourcing services into ADA paratransit. The first paper, “Incorporating ride-sourcing services into paratransit for people with disabilities: Opportunities and barriers,” explores different conditions under which incorporating ride-sourcing services into public transit is most effective, using Access paratransit, the ADA paratransit services in the Seattle region, as a case study. The manuscript is published in Transport Policy. The second paper investigates the impact of the changes in new mobility services business models, operational norms, and market needs on previously estimated cost-effectiveness of incorporating new mobility services into transit. The two studies show that the changes in the market and policy environment could negatively impact the cost-effectiveness of transit agency-new mobility integration despite the multiple benefits. The findings of this study were presented at the Transportation Research Board (TRB) Annual Meeting, 2023, and the manuscript has been submitted and reviewed by a major journal in transportation research.

- Chapter 4: Incorporating equity into the cost-effectiveness evaluation of new mobility. This chapter takes the evaluation of new mobility services a step further by incorporating equity into the cost-effectiveness analysis of incorporating new mobility services into public transit. In particular, this chapter evaluates transit incorporating mobility-on-demand (TIMOD) compared to fixed-route bus transit, driving alone, and commercial ride-hailing services in suburban areas. Building off a comprehensive analytical framework that evaluates the cost-effectiveness of TIMOD compared to other alternative modes from a societal perspective, the study employs a distributional cost-effectiveness analysis (DCEA) framework to model and evaluate the social distributions of the generalized cost of each mobility alternative across different income groups and residential contexts. This research was presented at the annual TRB meeting in 2024, and a journal manuscript is currently under review.
- Chapter 5: Finally, this chapter discusses how the three core chapters connect and together help advance public transit and transportation equity in the new normal and discusses the implications for changing mobility needs and services for existing and planned projects involving partnerships and integration of new mobility services, and how to timely and proactively address transportation equity challenges. Fig (2) illustrates the connection between the three core chapters.

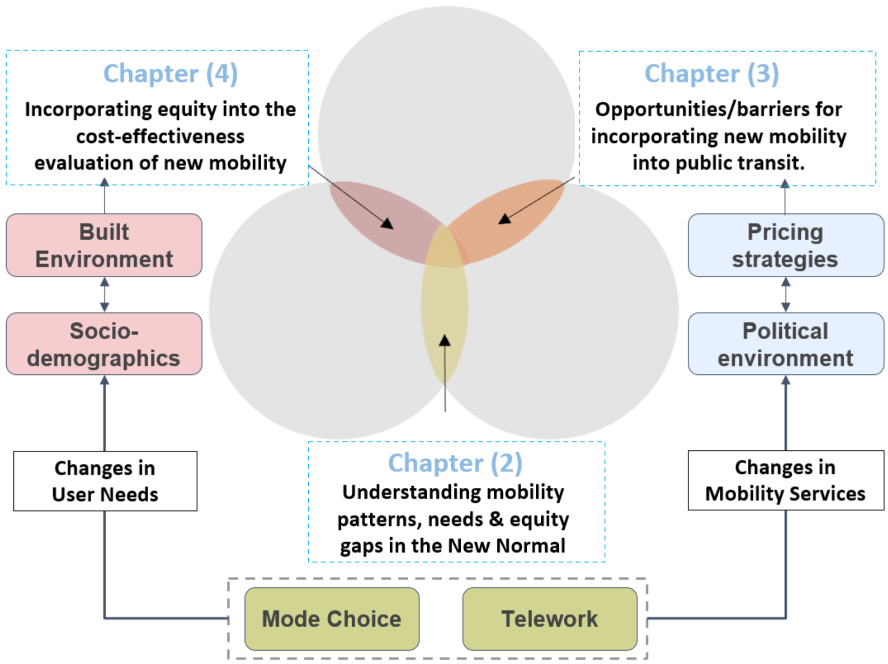

Figure 1.2 Main Chapters Connections

Chapter 2. Unveiling Commute Mode Choice Amidst the Rise of Telework in the New Normal

2.1 Introduction

The COVID-19 pandemic has distinctively altered the urban mobility landscape, work arrangements, daily travel patterns, and transport systems. With the possibility of these changes persisting into the foreseeable future, understanding their impact becomes crucial for adapting to this "new normal" and creating a sustainable transportation system. The rise of telework or work-from-home (WFH) stands as the defining characteristic of this new era, enabled by advancements in communication technology (Ashour et al., 2023; Barrero et al., 2021; Wang & Mokhtarian, 2023). Recent statistics show a significant increase in telework adoption, with 27% of the US workforce teleworking in 2023 compared to a mere 6% in 2018 (Census Bureau, 2023; Barrero et al., 2023). This shift has undoubtedly impacted travel patterns, creating distinct differences between teleworkers (full-remote or hybrid) and non-teleworkers (i.e., essential workers) (Ashour et al., 2023; Barrero et al., 2021; Kim et al., 2023; Wang & Mokhtarian, 2023).

Commute travel, once the backbone of daily life, has been disrupted and replaced by uncertainties and new work realities (Kim et al., 2023). People adapted to the pandemic through various means: embracing telework, acquiring additional cars, relocating to be closer to family, or seeking spacious suburban neighborhoods conducive to telework (Ashour et al., 2023; Cai et al., 2024; Kim et al., 2023; Shen et al., 2022). While telework presents opportunities for improved work-life balance, reduced congestion, and environmental benefits, its long-term effects on sustainable travel patterns, including public transit use and efficiency, drive-alone rates, and active travel, remain to be determined.

Previous studies have suggested that reduced commute frequency resulting from telework has essential implications for travel demand (Handy & Mokhtarian, 1996; Mokhtarian & Salomon, 1994; Mokhtarian et al., 1998); residential location choice (Shen, 2000a) and urban spatial structure (Shen, 2000b), suggesting empirical research to test these arguments. The equity implications of mode choice also require careful consideration, as access to telework options may vary significantly based on income, education, and job type (Bonacini et al., 2020; Mohammadi et al., 2022; Rahman Fatmi et al., 2022; Shen, 1998).

Moreover, this unprecedented increase in telework poses challenges to public transit. The pandemic drastically impacted transit ridership in American cities, causing a significant drop in ridership by over 70% (APTA, 2024). Similar impacts were seen in other cities globally, like Budapest and London, which experienced over 80% drops in ridership during strict lockdown periods (Ferreira et al., 2022). While a gradual transit ridership recovery occurred since the strict lockdowns ended, it has not yet reached pre-pandemic levels. For example, Seattle's daily transit boardings are still significantly below those in February 2020 (APTA, 2024). Similar ridership changes are observed in regional light rail and express bus services, suggesting a persistent shift away from public transit.

Such mobility changes significantly influence travel behavior and mode choice. Recent studies show that household characteristics, including income, vehicle ownership, employment status, and age, significantly influence mode choice, with high-income households leaning towards private vehicles and telework (Abdullah et al., 2020; Bria et al., 2021; Ferreira et al., 2022). Moreover, perceptions of health protocols and pandemic-related safety concerns minimally affect mode choice post-pandemic, with negative perceptions correlating with increased private vehicle usage, while reverting from public transit is no longer strongly associated with safety concerns (Bria et al., 2021; Tu et al., 2021). With increased telework availability through remote and hybrid remote work models, public transit is challenged by increased affordability and reliability of other modes due to reduced travel, especially drive-alone (Ashour et al., 2024).

These work and commute mode changes are particularly pronounced for essential workers, whose commute challenges have been exacerbated by limited access to safe and reliable public transportation during the pandemic (Ashour et al., 2024; Cai et al., 2023; Shen et al., 2022). Studies by Ferreira et al. (2022) and Kim et al. (2023) highlight the profound equity implications of the disparity in telework adoption and its impact on travel behavior. Factors such as income, age, and education play a significant role in telework adoption and accessibility (Bria et al., 2021; Zhang et al., 2022). Although telework has emerged in pre-pandemic literature as a sustainable solution to many transportation issues, the potential downsides of widespread telework are concerning, including reduced public transit ridership, negative impacts on commercial real estate and center cities activity, and increased inequities (Kim et al., 2023; Shen, 1998; Vickerman, 2021).

Existing research provides valuable insights but also reveals critical gaps, especially in understanding the nuanced impacts of telework on travel patterns, considering factors like the frequency and availability of telework through different work models (i.e., hybrid-remote), built environment features, and individual characteristics. Similarly, the effects of working from home (WFH) on transportation equity are understudied (Kazekami, 2020; Nakrošienė et al., 2019; Neufeld & Fang, 2005; Ruth & Chaudhry, 2008; Aboelmaged and El Subbaugh 2012; Pigini & Staffolani, 2019; Sutton-Parker, 2021; Tahlyan et al., 2022). Cross-referencing findings with previous studies and continuous research are crucial to keep pace with the evolving landscape of telework and its impact on urban mobility.

This chapter addresses crucial gaps in current research, particularly regarding understanding mode choice post-pandemic, drawing equity implications, and ensuring that transportation policies and infrastructure investments cater to the diverse needs of communities to enable effective public transportation planning. By modeling the changes in travel mode choice, transit agencies, and planners can better forecast future demands, guide operational decisions and projects to advance public transport post-pandemic, and ensure that transportation systems remain efficient, equitable, and sustainable in the long term. This study leverages the commute trip reduction (CTR) survey required from worksites with 100 or more full-time employees who begin their shift between 6 and 9 a.m. on weekdays in Seattle. I have been a member of the research team leading in designing the 2022 Seattle Commute Survey, from which about 64,000 responses were collected, and a summary report was subsequently published (Ashour et al., 2023). The survey was designed to thoroughly understand the changes in spatiotemporal urban mobility patterns, travel behavior, motives, and needs in the new normal. The main objectives of this chapter are to understand the characteristics of the new normal and the impact and equity implications of the changes in work arrangements and activity-travel behavior in a post-pandemic world by addressing the following questions:

1. What are the key characteristics of individuals' WFH adoption in the new normal?

2. What are the determining factors that influence individuals' commute mode choices in the new normal?

3. What are the resulting equity concerns in this new normal? How can transit agencies advance public transport and ensure that transportation systems remain efficient and equitable?

2.2 Research Design

To address these questions, the research method included several components, including designing and distributing a city-wide commute survey, integrating survey data with other resources, and analyzing the data using methods that enable a nuanced and deep understanding of mode choice in the new normal.

2.2.1 Questionnaire Survey

In recognizing the new dynamic of commuting and travel, Commute Seattle, a nonprofit organization, initiated a collaboration with private sector partners, public agencies, and the University of Washington to design and distribute a new commute survey that builds upon the Commute Trip Reduction survey, to collect valuable information on travel frequencies and mode choice, telework adoption, and sociodemographic and geographic influences in the new normal. The CTR survey is legally required from worksites with 100 or more full-time employees who begin their shift between 6 and 9 a.m. on weekdays to conduct a biannual commute survey. Commute Seattle has been leading this survey work and, in partnership with the Downtown Transportation Alliance, employed the survey findings to track the progress of Seattle Center City's mobility goals. The 2022 collaboration aimed to use the redesigned survey to help employers understand the evolving dynamics of commuting in the post-pandemic era, focusing on telework and hybrid work scenarios and addressing transportation challenges.

The University of Washington research team led the 2022 Seattle Commute Survey design with active participation from Commute Seattle and consultation from the City of Seattle. The 2022 survey contains two sections; the first includes the biannual required CTR questions with minor adjustments, and the second comprises an additional module with a gift card incentive. Together, the two sections substantially expanded the antiquated CTR questionnaire and asked the respondents a broader set of questions to understand the characteristics of commute and non-commute travel in the new normal. The survey questions cover critical aspects of mobility, including commute and non-commute travel mode choice, sociodemographic characteristics of commuters, the effects of the pandemic on different modes of transport and commuters' work arrangements, and spatiotemporal patterns of commute trips. The survey was deployed and distributed using Qualtrics software and Google Maps platforms. The university's Institutional Review Board (IRB) reviewed and approved the survey design. A copy of the survey questionnaire is provided in Appendix A.

The responses to the 2022 Seattle Commute Survey, with approximately 10% of Seattle employees participating, provided a much more robust data set to analyze travel patterns than previous surveys. The results provided useful origins and destination data by geolocating the nearest intersections for respondents' home locations and workplace addresses. The home location allowed us to use GIS data to measure key built environment characteristics (e.g., access to transit) of each respondent's residential area.

2.2.2 Data

The primary data source used for this study is the 2022 Seattle Commute Survey, conducted within three months between October 2022 and January 2023. As part of the survey, there were 13 commute mode choices for every day of the week: public transit, ferry, drive alone, motorcycle, vanpool, carpool, employer shuttle, transportation network companies (TNC), taxi, bike/scooter, e-bike/e-scooter, walk, and telework. I subsequently selected and classified modes of interest into five main categories, including transit (ferry and public transit), drive alone (including motorcycle), non-motorized travel (including walking, biking, and e-biking), TNC, and telework. These five modes are set as the alternatives in the mode choice model utilized in this study. Table 2.1 presents the distribution of commute modes and the number of weekdays in which each mode was chosen by survey respondents over the three months, with the frequency showing the number of days a mode is used, with 0 indicating not used at all and five indicating it is used for the whole workweek, as this analysis is limited to respondents who work every weekday (Monday through Friday), regardless of their employment status (part-time or full-time). Hence, the sum of commute modes chosen by every respondent equals five, considered in the model presented in later sections as the total budget.

Table 2.1 Summary of the Number of Weekdays Respondents Choose Each Mode.

Frequency (Days)	Telework	Transit	Drive Alone	NMT	TNC
0	32%	70%	60%	85%	94%
1	5%	7%	10%	3%	2%
2	14%	7%	8%	3%	2%
3	16%	5%	7%	3%	1%
4	14%	2%	2%	1%	0%
5	18%	9%	13%	5%	1%
Grand Total	**26,098 Responses**				

2.2.2.1 Sample Characteristics

The newly developed "Seattle Commute Survey" has focused on worksites in the central part of Seattle, with most respondents living in a four-county metropolitan area. When closed, it received 63,523 complete survey responses from over 500 worksites, 302 of which are large employers with at least 100 peak-hour commuters. For this research, I excluded respondents whose home location was outside King County, where Seattle is located, due to limited point-of-interest data necessary to compute built environment variables articulated in the following sections. Although the questionnaire collected all respondents' home data by zip code, the more precise home location at the nearest intersection was provided as an optional question. Because zip code level home location does not offer precise spatial characteristics, I also excluded respondents who did not provide a home location to the nearest intersection. Finally, the dependent variable of interest in this study is commute mode choice, which is captured through a matrix where respondents can indicate their typical commute mode for every day of the week (Figure 2.1). The sample excludes any respondents who have days off between Monday and Friday. In other words, the sample includes responses with five workdays from Monday through Friday. The resulting sample comprises 26,098 responses, roughly 40% of the total survey sample.

	Mon	Tues	Wed	Thu	Fri	Sat	Sun
Public transit	○	○	○	○	○	○	○
Ferry	○	○	○	○	○	○	○
Vanpool	○	○	○	○	○	○	○
Carpool	○	○	○	○	○	○	○
Employer shuttle	○	○	○	○	○	○	○
Uber/Lyft	○	○	○	○	○	○	○
Taxi	○	○	○	○	○	○	○
Drive alone	○	○	○	○	○	○	○
Motorcycle	○	○	○	○	○	○	○
E-bike/e-scooter	○	○	○	○	○	○	○
Bike/scooter	○	○	○	○	○	○	○
Walk	○	○	○	○	○	○	○
Remote work	○	○	○	○	○	○	○
Day off	○	○	○	○	○	○	○

Figure 2.1 Seattle Commute Survey: Commute Mode Choice Matrix Question

2.2.2.2 Sociodemographic Variables

The survey data includes a wide range of commuters' socioeconomic and demographic variables described in Table 2. These variables are selected specific to the aims of the study. Age, income, and work start time are continuous variables generated using the middle value of interval choices. The number of dependents, work days per week, and home-to-work distance are continuous variables, and the rest of the variables are categorical (binary), which are collected, including gender, highest education degree, race, home ownership, house type, marital status, and commute trip characteristics, including the length of the trip, The survey also collects job-related characteristics that could influence commute mode choice including employment status (work days), work schedule (typical start and end time), telework availability to employees based on their workplace regulations and work location. This study considered dummy variables representing employment status (full-time vs. part-time), work start time (peak vs. off-peak hours), and telework availability.

2.2.2.3 Built Environment Variables

In addition to the myriad variables collected in the survey, the data was further enriched by built environment and spatial characteristics information based on respondents' home locations. Because the data includes the nearest intersection to respondents' home locations, I geolocated the survey respondents approximate home locations and further expanded the data by including spatial characteristics such as the accessibility of each respondent to significant points of interest such as parks, food facilities, schools, and transit/bus locations and job opportunities (Figure 2). The spatial characteristics were measured by mapping the responses using the indicated home location and performing a centrality analysis using the Urban Network Analysis plugin in ArcGIS to measure the reach to services, which is a metric that quantifies the accessibility of various destinations considering the spatial connectivity of the urban environment. I measured the reach to essential points of interest (POI) and job opportunities using different threshold distances, including 0.25 mile, 0.5 mile, and 1 mile, depending on the variable measured. This spatial accessibility-related data, including POI and bus location data, was collected from secondary sources. POI data in King County is published in the King County Open GIS Data, and the job opportunities were collected from the longitudinal employer-household dynamics (LEHD) and origin-destination employment statistics LODES, using the total number of jobs. Using the shortest path, I measured the home-to-work distance in miles using both respondents` reported home and work locations. Table 2.3 summarizes the selected built environment variables.

Table 2.2 Descriptive Summary of the Sociodemographic Variables.

Variable	Subcategory	% Respondents	Mean	Std. Dev.
Income	_	_	$125,861	$43,478
Age	_	_	40.95298	12.28369
Dependents	_	_	0.372303	0.763814
Workdays	_	_	4.790589	0.863568
Work start time	Peak hours	74%	_	_
	Off-peak hours	26%		
Gender	Male	43%	_	_
	Female	57%	_	_
Employment	Part-time	2%	_	_
	Full time	98%	_	_
Race	White	65%	_	_
	Non-white	35%	_	_
Marital status	Married	64%	_	_
	Single	36%	_	_
Housing type	Single-detached	55%	_	_
	Other	45%	_	_
Homeownership	Own	56%	_	_
	Rent	44%	_	_
Telework available	Yes	78%	_	_
	No	22%	_	_
Highest degree	*Graduate degree*	39%	_	_
	Bachelor's degree	48%	_	_
	Training/associate	8%		
	High school	5%		

Table 2.3 Descriptive Summary of the Built Environment Variables.

Variable	% Respondents	Mean	Std. Dev.
Reach to buses/ 0.25 mile.	_	32.1	34.9
Reach to schools/ mile.	_	28.3	30.6
Reach to parks/ mile.	_	15.6	19.8
Reach to jobs/ mile.	_	1969	4537
Home to work distance	_	7.7	36.7

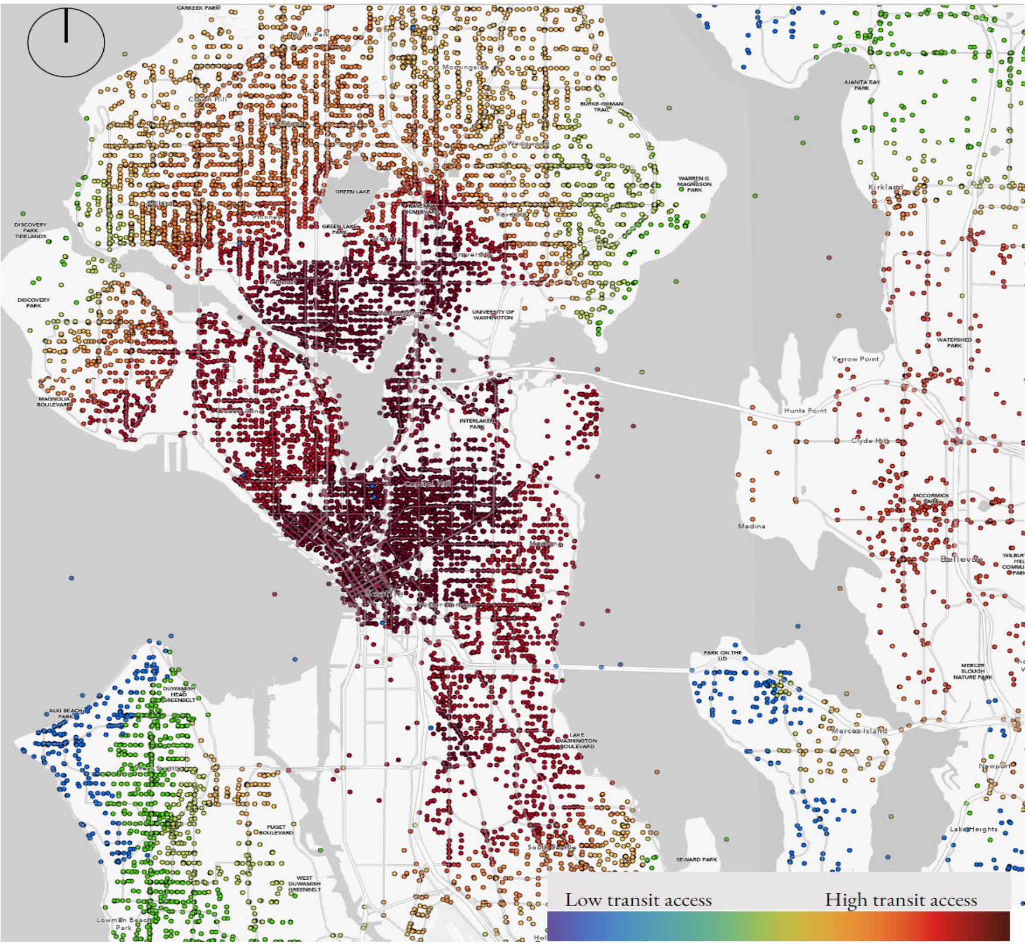

Figure 2.2 Geolocated Respondents` Home Locations and Built Environment Variables (e.g., Reach to Transit)

2.2.3 Model Structure

2.2.3.1 Model Specifications

Previous research has offered valuable insights into the factors influencing the adoption of telework and mode choice during COVID-19 and in the new normal. Most of these studies predominantly utilize conventional choice models such as multinomial or nested logit models or continuous linear regression models to examine mode choice and telework adoption during and post-pandemic. However, these methods fail to capture the intricacies of work arrangements in the new normal, including variations in the frequency of telework, like hybrid telework, which characterizes the post-pandemic world and plays a crucial role in influencing mode choice, resulting in a dynamic mix of commuting modes individuals choose on different workdays. This introduces an intrinsic multiple discreteness in mode choice, which involves a continuous dimension representing the frequency of use that standard discrete choice models are ill-equipped to handle. Hence, this chapter employs the Multiple Discrete-Continuous Extreme Value (MDCEV) model, which was proposed by Bhat, and extended in different directions to estimate discrete and continuous components of consumer choices (Bhat, 2005; Bhat & Sen, 2006; Bhat, 2008; Bhat, 2018; Castro et al., 2012; Enam et al., 2018;).

The MDCEV model simultaneously estimates the discrete and continuous components of mode choices and accounts for diminishing marginal returns and satiation effects of choosing one mode on multiple days. The dependent variable in this model is the weekly frequency of choosing each transportation mode, as captured in the weekly mode matrix shown in Figure 2.1. For simplification, the survey modes were grouped into five main categories: telework or WFH, which was set as the reference mode; public transit (transit, bus, ferries); drive alone, non-motorized transport (NMT) (bike, e-bike, walk) and transportation network companies (TNC)

(Uber/Lyft). Each respondent could choose a different commute mode for each workday (Mon-Fri), making it a multiple discrete-continuous dependent variable with two components: (1) discrete mode choice and (2) continuous mode-specific weekly trip frequencies.

The mode choice is assumed to be influenced by three major categories of factors: (a) sociodemographic characteristics of commuters, (b) job-related characteristics, both shown in Table 2.1 and (c) built environment variables associated with the home location of commuters, shown in Table 2.2. The sociodemographic variables considered in the model specifications included household income, number of dependents, highest degree, age, gender, housing type, home ownership, and marital status. Job-related characteristics include employment status, work start time, and workdays. Built environment variables included home-to-work distance, accessibility to transit, schools, parks, and job opportunities.

In discrete mode choice models, random utility maximization principles are used to quantify the influence of different factors on mode choice. The MDCEV model is also derived from the random utility theory but differs from discrete choice models by relaxing the assumption of mutually exclusive alternatives. MDCEV also adopts an additive but non-linear formulation of the utility function so that the choice of one mode does not affect the utility of other modes (imperfect substitutes). Hence, the utility accrued to a commuter is specified as the sum obtained from the utilities of using each mode from K alternatives (modes), as shown in equation (1).

$$U = \sum_{j=1}^{K} \psi(xj)(mj + \gamma j)^{aj} \tag{1}$$

Where $\psi(xj)$ is the baseline utility for mode j, and mj is the frequency of use (the number of days a mode can be chosen). The utility in MDCEV belongs to the family of translated utility functions, with γj determining the translation factor that allows for corner solutions (allowing one or more alternatives to be not chosen), and aj reflecting the satiation effect, which is the rate of diminishing marginal utility from using a particular mode j (Kim et al., 2002; Bhat, 2005). A high value of $\psi(xj)$ for one mode (relative to all other modes), combined with a value of aj close to 1, implies a high baseline preference and a low satiation for mode j, which represents a strong preference of a primary transportation mode for all days. On the other hand, about equal values of $\psi(xj)$ and small values of aj across the various modes represent the usage of multiple modes to commute to work. More generally, this utility form allows a variety of situations characterizing a commuter's underlying behavioral preferences for different modes and the rate of decrease in utility with frequent usage of the mode. To account for random utility specifications, a statistical model can be developed from the utility structure in Eq. (1) by adopting a multiplicative random element as follows:

$$\psi(xj, \varepsilon j) = \psi(xj). e^{\varepsilon j} \quad (2)$$

Where $e^{\varepsilon j}$captures the unobserved characteristics that impact the baseline utility for mode j. The exponential form for introducing random utility guarantees a positive baseline utility as long as $\psi(xj) > 0$, which involves parameterizing $\psi(xj)$ further as shown in Eq. (3):

$$\psi(xj, \varepsilon j) = exp\ (\beta_{xj} + \varepsilon_j) \quad (3)$$

Where xj includes a constant term to reflect the baseline preference in the population toward mode j, the overall random utility function takes the following form:

$$U = \sum_j \left[exp\left(\beta_{xj} + \varepsilon_j\right)\right].(mj + \gamma j)^{aj} \quad (4)$$

Where the satiation parameter, aj, In the above equation is bounded between 0 and 1.

The MDCEV framework generally assumes a maximum budget that caps consumption to a specific limit. In the current model setup, the frequency of use (*mj*), which represents the total number of days a mode is chosen, is capped to a maximum budget (*M*), set in advance to equal five. From the commuters' standpoint, to maximize random utility (U) as per Equation (4), they need to find the optimal usage of (*K*-1) modes while adhering to the constraint represented by $\sum_{j=1}^{K} mj = M$. Consequently, one of the *K* modes needs to be designated as the base when introducing constant or commuter-specific variables in the utility functions of the K modes, which in this model is set as telework. Hence, the commuter can find the optimal usage of different modes by creating the Lagrangian for Equation (4) by applying Kuhn-Tucker conditions. Assuming that the εj terms are independently and identically distributed across alternatives, following a standard Gumbel distribution, the model simplifies into a concise MDCEV structure (as explained in Bhat, 2005). The probability that a commuter chooses I of the K modes (I ⩾ 1) is given by Equation (5); refer to (Bhat, 2005) for derivation.

$$P\left(m_i^* > 0 \text{ and } m_s^* = 0;\ i = 1,2,\ldots,I \text{ and } s = I+1,\ldots,K\right) \tag{5}$$
$$= \left[\prod_{i=1}^{I} c_i\right]\left[\sum_{i=1}^{I} \frac{1}{c_i}\right]\left[\frac{\prod_{i=1}^{I} e^{V_i}}{\left(\sum_{j=1}^{K} e^{V_j}\right)^{I}}\right](I-1)!,$$

where $c_i = \left(\frac{1-\alpha_i}{m_i^*+\gamma_i}\right)$ and $V_j = \beta' x_j + \ln\alpha_j + (\alpha_j - 1)\ln(m_j^* + \gamma_j)$.

In the scenario where *I* equal 1 for a particular commuter (i.e., only one mode is chosen), the Eq. (5) model reverts to the standard MNL structure. If a commuter exclusively selects one mode, there is no need to estimate a continuous component since the chosen mode covers all workdays (M) provided as input. In cases where every commuter in the sample opts for a single mode, the αj's are constrained to 1, aligning with standard discrete choice models. In this instance, the MDCEV model is equivalent to the linear-in-parameters MNL model. The analysis was conducted using the GAUSS code in R (Bhat, 2005). Specifically, the study utilized the first configuration of the code (config = 1), which estimates separate α values are estimated for all alternatives (modes), and constraints γ values for all alternatives (modes) to be equal to 1, as shown in equation (6):

$$U(\boldsymbol{x}) = \sum_{k=1}^{K} \frac{1}{\alpha_k} \psi_k \left\{ \left(x_k + 1 \right)^{\alpha_k} - 1 \right\} \tag{6}$$

2.3 Results

The resulting model shows the influence of sociodemographic characteristics, job-related characteristics, and residential built environment characteristics on commute mode choice in the new normal. Table 2.4 summarizes the results of each variable.

Table 2.4 Results of the MDCEV Model

Explanatory Variable	Parameter	T-value	P-value	Sig.
		Sociodemographic Characteristics		
Income *($1,000)*				
Transit	-0.0062	13.08	0.000	***
Drive	0.0015	3.136	0.002	***
NMT	0.0014	2.505	0.012	**
TNC	0.0016	1.871	0.061	*
Age *(years)*				
Transit	-0.0395	4.388	0.000	***
Drive	-0.0187	2.123	0.034	**
NMT	-0.0236	2.505	0.035	**
TNC	-0.0893	5.580	0.000	***
Age^2				
Transit	0.0004	4.030	0.000	***
Drive alone	0.0002	2.222	0.026	**
NMT	0.0002	1.551	0.121	
TNC	0.0008	4.608	0.000	***

Dependents *(have dependents = 1/ none = 0)*				
Transit	-0.1962	7.540	0.000	***
Drive	0.1383	6.586	0.000	***
NMT	-0.0272	0.879	0.380	
TNC	-0.0475	1.248	0.212	
Gender *(male=1 /female=0)*				
Transit	0.3847	11.64	0.000	***
Drive	-0.0470	1.516	0.130	
NMT	0.8069	19.99	0.000	***
TNC	-0.1118	1.990	0.047	**
Race *(white=1/ non-white=0)*				
Transit	-0.1111	3.200	0.001	***
Drive	-0.0474	1.452	0.146	
NMT	0.4467	9.865	0.000	***
TNC	-0.3680	6.418	0.000	***
Highest degree				
High school				
Transit	0.1800	1.078	0.281	
Drive	0.1026	0.688	0.491	
NMT	0.5397	1.793	0.073	*
TNC	0.0412	0.166	0.868	
Training/associate degree				
Transit	0.2017	1.275	0.202	
Drive	0.2669	1.898	0.058	*
NMT	0.3991	1.363	0.173	
TNC	0.0726	0.309	0.758	
Bachelor degree				
Transit	0.2286	1.519	0.129	
Drive	0.0180	0.135	0.892	
NMT	0.9302	3.352	0.001	***
TNC	-0.2037	0.918	0.359	
Graduate degree				
Transit	0.3948	2.618	0.009	***
Drive	0.0867	0.650	0.516	
NMT	1.4020	5.056	0.000	***
TNC	-0.0664	0.298	0.766	
Marital status *(married=1 /other=0)*				
Transit	0.1799	4.529	0.000	***
Drive	-0.2086	5.499	0.000	***
NMT	-0.0044	0.092	0.926	
TNC	0.6110	8.488	0.000	***

Housing type *(single-detached=1 /other=0)*				
Transit	-0.2419	5.691	0.000	***
Drive	0.0895	2.223	0.026	**
NMT	-0.3486	6.225	0.000	***
TNC	-0.1283	1.803	0.071	*
Home ownership *(own =1 /other=0)*				
Transit	0.0004	2.996	0.003	***
Drive	-0.0282	0.676	0.499	
NMT	-0.0686	1.226	0.220	
TNC	0.0497	0.665	0.506	
Telework available *(yes=1, no=0)*				
Transit	-3.7640	64.01	0.000	***
Drive	-4.0040	72.81	0.000	***
NMT	-4.0040	61.52	0.000	***
TNC	-3.9880	50.64	0.000	***
Work start time *(peak hours =1 /other=0)*				
Transit	0.1350	3.550	0.000	***
Drive	-0.0638	1.824	0.068	**
NMT	-0.2530	5.867	0.000	***
TNC	-0.0519	0.820	0.412	
Built Environment Variables				
Reach to bus stops per 0.25 mile.				
Transit	0.0033	4.753	0.000	***
Drive alone	-0.0017	2.272	0.023	**
NMT	-0.0026	3.595	0.000	***
TNC	0.0009	0.673	0.501	
Reach to parks per mile.				
Transit	0.0039	3.863	0.000	***
Drive alone	-0.0060	5.608	0.000	***
NMT	0.0118	11.55	0.000	***
TNC	-0.0024	1.245	0.213	
Reach to schools per mile.				
Transit	0.0034	4.123	0.000	***
Drive alone	-0.0027	3.362	0.001	***
NMT	0.0150	16.47	0.000	***
TNC	-0.0027	1.833	0.067	*
Reach to jobs per mile.				
Transit	0.0000	7.671	0.000	***
Drive alone	0.0000	3.109	0.002	***
NMT	0.0001	12.24	0.000	***
TNC	0.0000	1.575	0.115	

Baseline				
Transit	2.8450	9.936	0.000	***
Drive alone	2.7340	10.06	0.000	***
NMT	-0.8172	1.985	0.047	**
TNC	2.4860	5.342	0.000	***

Log-Likelihood: -78093.88
*** 99% significance level, ** 95% significance level, * 90% significance level

2.3.1 *Effect of household sociodemographic characteristics*

The Multiple Discrete-Continuous Extreme Value (MDCEV) model assesses the sociodemographic factors influencing commute mode choice over the five workdays, with telework/WFH as the reference mode. Results show varying impacts on commute mode choice, with different coefficients and significance levels for different categories. The interpretation of the results focuses on the significant variables with a P-value of 0.05 or less. Among the sociodemographic factors considered is household income, which indicates a statistically significant decreased probability of choosing transit with increasing income as denoted by a negative coefficient and a high t-value, in contrast to a less significant but positive increase in choosing to drive alone, NMT, and TNC. A similar effect can be seen among commuters living in single-detached dwellings, who have an increased propensity to use transit compared to others living in apartments, condos, or townhouses. Gender is also found to play a significant role in commute mode choice, with males being more likely to commute using transit and NMT than females. In addition, white commuters show a solid inclination to commute using NMT and a disinclination to commute by transit and TNCs compared to non-white commuters. The results also indicate a disinclination to choose any commute mode other than telework with the increasing age of commuters. However, the positive coefficients of age^2 indicate a U-shaped relationship, which means that the utility of other modes initially decreases with age compared to telework, then increases with higher age values. This aligns with many previous findings conforming to higher availability and adoption of telework among more senior employees. The presence and number of dependents have a significant negative association with commuting by transit, in contrast to the opposite relationship with driving alone, presumably because it is more convenient to drive to work if you are carpooling with other family members or must transport dependents. A similar effect can be seen among commuters living in single-detached dwellings, who are less likely to use transit than others living in apartments, condos, or townhouses. On the other hand, education, represented by the highest degree that commuters have, does not show much significant association with commuting mode choice, except for graduate degree holders showing a strong preference for commuting by NMT and transit, and bachelor's degree holders are also more inclined to use NMT. Commuters who are married or living with a partner are more likely to use transit and less likely to drive alone to work. This result is counterintuitive, possibly due to multicollinearity among some explanatory variables.

2.3.2 Effect of Job-related Characteristics

Employment status does not have any significant effect on commute mode choice, but work schedule does. Starting work during morning peak hours increases the likelihood of using transit. It decreases the possibility of driving and using NMT, which traffic levels, safety concerns, and availability of bus and bike lanes could influence. However, the availability of telework to employees, as set by their workplaces, significantly decreases the likelihood of choosing other modes when telework is available to the commuter, explaining the substantial changes in commute and travel patterns that characterize the new normal era.

2.3.3 Effect of Built Environment Variables

Several built environment variables pertaining to commuters' home location were considered in our specifications, focusing on how proximity and accessibility to vital services may impact mode choice, measured using the reach metric. The results indicate that higher reach (accessibility) to public transit and bus stops within a quarter mile (walking distance) is positively and significantly associated with commuting by transit and negatively with commuting by driving alone and NMT. Higher reach to parks and schools within a mile from respondents' home location indicates a positive relationship with using NMT for commute, followed by transit, and a negative relationship with driving alone. Similarly, high accessibility to job opportunities within a mile of the home location shows a strong positive association with using NMT and transit.

2.3.4 Baseline Preference Constants

The baseline preference constants do not have any substantive interpretations because of the presence of continuous exogenous variables in the specification. However, since many of the variables are dummy variables, the constants could be viewed as the generic preference for each commute mode relative to telework. The positive signs on transit, drive-alone, and TNC constants indicate a general baseline preference for these modes over telework. In contrast, the negative sign on NMT indicates a negative baseline utility and a general preference for telework over NMT. These findings loosely suggest that if all variables are constants, commuters generally prefer motorized commute modes to telework.

2.3.5 Satiation Effect

Table 2.5 provides the estimated values of satiation for every mode αj and the P-values. The satiation parameter (α) represents the scale parameter for the continuous utility component.

Higher α values imply a slower diminishing marginal utility over multiple workdays. Several key observations can be drawn from the table. First, the satiation parameters for all modes differ significantly from 1, indicating a clear satiation effect in commute mode choices. This finding challenges the linear utility structure assumed in standard discrete choice models. Second, drive alone has low α values, signifying high satiation effects. This means the marginal utility diminishes rapidly with increased usage of drive alone. Hence, the high baseline utility but high satiation of driving alone suggests that commuters have a strong inherent preference for driving if available due to its convenience and flexibility; however, they tend to diversify their mode choice over more workdays. This could be due to the increased availability of hybrid-remote work arrangements or the higher cost of driving if used on multiple days. In contrast, transit exhibits a higher α value, indicating a slower rate of diminishing utility, which suggests a stronger habitual attachment for transit, with users likely to use it continuously for their commutes. Finally, NMT has the lowest baseline utility but the lowest satiation (highest α value). Of course, NMT is not equally accessible to commuters, especially due to challenges in commute length (trip distance), physical ability, and weather conditions. Hence, it exhibits low baseline utility. The low satiation, however, implies high stickiness to the mode, as those who use NMT for their commute tend to use it on more commute trips (frequently). Telework is a reference mode, so its alpha value is zero, indicating constant marginal utility.

Table 2.5 Satiation Effect of Commute Modes

Mode	**Parameter**	**P-value**	**Sig**
Telework (base)	0.0000	1.000	
Transit	0.7408	0.000	***
Drive alone	0.6586	0.000	***
NMT	0.8138	0.000	***
TNC	0.6774	0.000	***

2.4 Conclusion

The COVID-19 pandemic has acted as a catalyst for fundamental changes in how people work and travel. The widespread adoption of WFH or telework and a shift towards alternative travel modes characterize the "new normal" era. While the pandemic has eventually been controlled through policy measures and vaccines, its residual effects on individual preferences and behavior will likely persist, shaping urban mobility and transport systems for years. Understanding these long-term trends and their implications is crucial for policymakers and planners as they work towards building resilient and sustainable transportation systems for the future.

This study aims to understand the impact of new work arrangements, sociodemographic characteristics and built environment variables on commute mode choice post-pandemic. Using the 2022 Seattle Commute Survey and a Multiple Discrete-Continuous Extreme Value (MDCEV) model, the analysis considers mode choice and the frequency of commuting using each mode on different workdays. The findings provide several key and timely insights into factors impacting commute mode choice in the new normal. Telework and the availability of new work arrangements (i.e., hybrid telework) continue to impact commute mode choice significantly. Telework availability strongly discourages using other commute modes and increases the reluctance to shift away from telework, highlighting its transformative influence on travel patterns. This finding underscores the need for adapting transportation systems and policies to accommodate the increased prevalence of telework and promote sustainable mobility options for non-telework days and for workers who do not have access to telework.

Sociodemographic and built environment factors, including income, housing type, gender, race, age, dependents, and education level, all influence commute mode preferences. Notably, higher-income employees are more likely to drive alone to work than use transit, and

White individuals are less inclined to ride transit. Living arrangements and household characteristics, such as living in single-family dwellings with dependents, are also positively associated with drive-alone commutes. On the other hand, home location and built environment variables such as accessibility to transit, parks, and jobs are positively related to using shared and sustainable travel modes, reinforcing the importance of urban design in promoting sustainable mobility. These findings suggest that increased access to transit, particularly for those with lower income or in areas with less dense housing, could encourage more people to use it. This could involve expanding bus routes, improving service frequency and reliability, and making fares more affordable.

The findings raise multiple equity concerns. For example, income, housing type, and built environment characteristics are significantly related to mode choice, potentially disadvantaging low-income individuals and those without cars. Minorities and vulnerable groups, such as women, low-income individuals, and people of color, face different barriers to sustainable and equitable transportation options. Policies should be designed to address these disparities and ensure that everyone has equitable access to safe and affordable public transportation and alternative commute options.

Similarly, the study shows that people with better access to vital services and pedestrian-friendly environments such as parks are more likely to choose active transportation modes. Communities with poor public transportation and limited access to active transportation options may need additional support. This could include providing more parks, adding protected bike lanes, improving sidewalks, promoting safe walking and cycling initiatives, providing affordable transit passes, or implementing microtransit solutions. As drive-alone rates increase, especially with new work arrangements, policies such as congestion pricing, parking fees, and car-free zones in certain areas could also be enforced to discourage driving and encourage other modes of transport.

The study also highlights the growing popularity of hybrid work arrangements, where employees split their time between working from home and the office. Telework availability plays a significant role in commute mode choice, which could discriminately impact specific jobs and essential workers. Policies could encourage employers to offer these options and make it easier for employees who need them to request them. This could include funding businesses to purchase necessary equipment and software and ensuring reliable internet access for all residents. However, the increased availability of telework could increase drive-alone use, especially for workers who physically commute to their offices only a few days a week, reflected in the high baseline and satiation rate of drive-alone. This suggests that policymakers and employers should work together to provide diverse travel options and manage telework availability to ensure the effectiveness and efficiency of shared mobility options, especially transit.

Finally, decision-makers and employers must prioritize public outreach and educate employees and the public about the benefits of different transportation options and how they can choose the most sustainable and healthy mode for their needs. Future research should examine how new work arrangements and commute mode choice also influence non-commute travel and discretionary trips to understand better the overall impact on travel behavior and urban mobility. Research efforts should continue to track travel behavior changes over time to assess the persistence of pandemic-induced shifts, their effect on urban planning and infrastructure needs, and the effectiveness of existing and planned policies to promote more sustainable and equitable mobility services.

Chapter 3. Investigating the Opportunities and Barriers to Incorporating New Mobility into Public Transit: An Outlook on TNC Price Changes

3.1 Introduction

In the last decade, with the rapid development of mobile information and communication technology (ICT), app-based on-demand mobility services have become the most rapidly growing form of urban transportation (Clewlow et al., 2017; Schaller, 2017; Schaller, 2018). These new mobility services, especially ride-hailing provided by transportation network companies (TNCs), while presenting a severe challenge to the current operations of public transportation, are simultaneously creating many exciting opportunities for building new partnerships between transit agencies and private providers (McCoy et al., 2018; Shen et al., 2020; Wang et al., 2022). Through a complementary operation model, transit agencies partner with TNCs to provide innovative mobility services and fill service gaps. The most common services these partnerships offer include first/last mile connections to transit, late-night and early-morning service, paratransit trips, and on-demand options in low-density areas. To facilitate these partnerships, transit agencies have used a variety of strategies. The most common strategy includes subsidizing TNC trips for certain services (e.g., paratransit), which can help to make TNCs more affordable for riders who rely on them for essential transportation needs. Other strategies include marketing partnerships and service integrations, such as allowing riders to use their transit fare cards to pay for TNC rides or providing TNCs with access to public transit data. This can make it easier for riders to use both TNCs and public transit (Circella & Alemi, 2018; Curtis et al., 2019; Feigon and Murphy, 2016; Wang et al., 2021; Yan, 2019).

However, TNC pricing strategies pose many challenges to transit agencies' expected cost savings. Concerns about TNC prices heightened during the COVID-19 pandemic, as the increased vaccination rate in the United States resulted in more people returning to TNC services, which many see as a safer and more reliable alternative to public transit. Rakuten Intelligence research found that the cost of a TNC ride in the US increased by 37% in March 2021 and 40% in April 2021 compared to the previous year (Conger, 2021). These price increases put the cost-effectiveness and sustainability of transit agency-TNC partnerships at stake, making it difficult for agencies to design or maintain them. As the demand for transportation services in the US is gradually returning to normal, it is essential to investigate the impact of TNC pricing strategies on ride-hailing service fares and understand the implications for transit agencies.

This research aims to assess the impact of TNC price changes and fill major research gaps. First, a dearth of studies analyzes the implications of TNCs' changing pricing strategies. While some studies have explored the potential for TNCs to help public transit agencies achieve cost savings, they usually overlook the long-term impact of TNC pricing strategies in response to the changing market and policy environments, which likely will lead to price increases (Leisy, 2020). Second, a few studies estimate the cost-effectiveness of transit agency-TNC partnerships under different pricing scenarios. Because most transit agencies design their partnership with TNCs based on a subsidy that covers a certain fare, mileage per trip, or a capped number of trips, recent price increases require adjustments and revaluation of partnership design specifics and potentials. Current studies that analyze the cost-effectiveness of transit agency-TNC partnerships often rely on pre-existing and generalized TNC prices (Ashour & Shen, 2022; Curtis et al.,2019;

Gonzales et al., 2019; Cao, 2020; Livingston & Schwieterman, 2020); recent changes in TNC service fares are yet to be seriously examined.

This study employs Chicago ride-hailing trip data (2018 - 2022) and taxi trip data (2013 - 2022) to examine TNC price changes and then uses Access paratransit service trip data operated by King County Metro (KCM), the primary transit service provider in the Seattle region, to explore the impact of TNC price changes on transit agencies-TNC partnerships. I use detailed ride-hailing and paratransit trip data to explore different TNC pricing scenarios and their impact on trip diversion rates between conventional Access paratransit and service operated by TNC in a timely effort to inform transit agencies in planning partnerships with TNCs by answering the following questions:

1. What will likely be the change in TNC service fares in the coming years? How does that compare to changes in traditional taxi prices?
2. What factors pertaining to the TNC market and policy environments contribute to TNC trip price changes?
3. How will TNC price changes affect the prospect of building and sustaining partnerships between transit agencies and TNCs?

3.2 Literature Review

It is evident that Transportation Network Companies (TNCs) such as Uber and Lyft have tremendously shifted urban mobility and impacted travel behavior for many users in the US and worldwide. Partnering with TNCs has emerged as a promising, cost-effective alternative to many transportation agencies in the US, recognizing the ability of TNCs to provide specific types of services with demonstrated flexibility and innovation in improving user experience (Curtis et al.,2019). In 2019, the Transportation Research Board (TRB) published a survey of 38 transit agencies showing that 57% of transit agencies' partnerships with TNCs target people with disabilities, followed by people connecting to transit (first mile/last mile) or traveling in lower-density environments. For providers of paratransit services mandated by the Americans with Disabilities Act (ADA), such partnerships are encouraged by the conceivable cost savings, allowing transit agencies to raise service quality and flexibility compared to their conventional service (Ashour & Shen, 2022; Curtis et al.,2019; Gonzales et al., 2019; Cao, 2020; Livingston & Schwieterman, 2020). However, TNC pricing strategies and business models have reflected instability with price fluctuations, policy changes, and legal challenges. Hence, transit agencies need to consider the dynamics of TNC prices and future changes and carefully analyze their impact on the prospects of their partnerships and the effectiveness of planned pilot projects.

Much of this discussion of the opportunities and barriers for integrating ride-sourcing into ADA paratransit services is based on specific pilot projects that were either limited to a specific number of users without clear representativeness measures or confined by some geographic regions within the transit agency's service area. Relying on findings of existing pilots without empirical assessment of the different barriers to the specific services TNC provides includes a risk that alternative new mobility service providers may not consistently serve the needs of transit and paratransit riders. There are also risks that reliance on private operators to provide paratransit services without carefully structured contracts may undermine agencies' ability to guarantee ADA-compliant service to customers.

Moreover, TNC pricing strategies and tactics pose many challenges to these assumptions. Rakuten Intelligence research found that the cost of a TNC ride increased by 40% in April 2021 compared to the previous year (Conger, 2021). These price increases put the cost-effectiveness and sustainability of transit agency-TNC partnerships at stake, making it difficult for agencies to design or maintain them. While some studies have explored the potential for TNCs to help public transit agencies achieve cost savings, they usually overlook the long-term impact of TNC pricing strategies, which include predatory pricing (below-cost rates), price gouging, and demand pricing, also known as surge pricing that relies on consumer surplus (Leisy, 2019). In addition to exercising control over drivers who act as independent contractors, these pricing strategies assist TNCs in reducing expenses and increasing competitiveness. Such pricing strategies raise concerns about the possibility of market domination by TNCs, causing monopoly pricing (Leisy, 2019). Hence, the below-cost rates of TNC trips are deemed unsustainable and pose long-term threats to the cost-effectiveness of transit agency-TNC partnerships.

Similarly, few studies estimate the cost-effectiveness of transit agency-TNC partnerships under different pricing scenarios. Because most transit agencies design their partnership with TNCs based on a subsidy covering a particular fare, mileage per trip, or the number of trips, recent price increases require adjustments and revaluation of partnership design specifics. Current studies that analyze the cost-effectiveness of transit agency-TNC partnerships rely on pre-existing TNC prices (Curtis et al., 2019; Gonzales et al., 2019; Cao, 2020; Livingston & Schwieterman, 2020; Ashour & Shen, 2021).

Finally, the lack of available TNC data adds another layer of complexity to the prospects of such partnerships. TNCs have always been reluctant to share operational and revenue data that they classify as "trade secrets" due to concerns about privacy, public records requests, and competition. On the other hand, "Sunshine laws" require that specific information obtained by governments be publicly accessible. There has been an ongoing struggle to obtain TNC data from the public or city transportation planners (Bialick, 2022; Curtis et al., 2019). For example, the TNC industry prohibited data distribution by persuading the Seattle City Council to include a privacy provision in the Ordinance (Leisy, 2019). The lack of revenue and operating data makes it challenging to fully understand the potential for transit agencies and TNC partnerships to provide cost-effective mobility alternatives.

3.2.1 TNC Economics

TNCs are digital marketplaces that mediate taxi-like on-demand transportation services by connecting independent drivers to riders through advanced digital platforms (Button, 2019; Kirchner et al., 2022). Since their first entry into the market in 2010, the speed of adoption and expansion of ride-hailing services offered by TNCs has been impressive. Today, Uber operates in more than 80 countries around the world, with many countries cloning Uber's model with minor modifications to meet local regulations and laws. Although they provide services similar to taxis, the key success of TNCs' expansion lies in their business models and operational innovation. Many researchers noted that TNCs (e.g., Uber) established a business model involving venture capital financing with an aggressive strategy to disrupt the established vehicle-for-hire industry (e.g., taxi) by introducing a new digital marketplace (Kirchner et al., 2022). This organizational model allows for a unique work type in which drivers are self-employed and operate services using their own vehicles, which many consider a form of hyper-precariousness (Davis, 2016; Peticca-Harris et al., 2018), exhibiting characteristics of platform-mediated in-person service work known as gig labor. However, TNCs also rely on work types that follow general taxonomies, e.g., "venture labor" performed by high-paid employees who manage and develop the digital infrastructures of TNCs and their activities (Kenney et al., 2019; Vallas et al., 2020).

This business model has been facing legal backlash worldwide and was considered disruptive and illegal in many European countries (Thelen, 2018). However, the shift caused by

TNCs is much less radical than assumed, as digital technology transposes traditionally mediated taxi self-employment to a digital platform (Kirchner et al., 2022). Although platform technology allows for various organizational models, the fierce competition heads toward a few dominant service providers implementing work types that foster the respective working conditions (Fligstein, 2001). In contrast to the disruption induced by tech start-ups with venture capital backing, TNCs generally show a pattern of absorption by incumbents to expand their business and try to superimpose themselves on emerging markets (Streeck et al., 2005).

3.2.2 TNCs vs. Taxis

Although both TNCs and taxis provide similar services, TNCs' business models allow them to control their service pricing and information flow between drivers and riders. In addition, TNCs are based on market deregulation and benefit from many preemptions and laws tailored to their business. On the other hand, heavily regulated taxi companies have to conform to many regulations regarding their prices and driver hiring procedures, which increase their operational costs, resulting in higher trip prices. Although TNCs' business models increase their competitive advantage compared to taxis, they face serious profitability challenges (Leisy, 2020). This is mainly a result of the increased competition due to the ease of market entry, which drives TNCs to lower their trip prices and sometimes charge below-cost rates to price competitors out of the market. However, the TNC model involves fixed costs that are challenging to recover with current pricing strategies. TNCs have sought to overcome these challenges by expanding their market through mergers, acquisitions, and service diversification (e.g., Uber acquired Jump's bike-sharing service for $200 million in 2018). The main goal for TNCs' growth is their strive for market domination (Berger & Bensinger, 2018; Romeo, 2022).

Moreover, the overall decline in demand for taxis and other vehicle-for-hire services following the increased popularity of TNCs, shown by Bagchi (2018), indicates that TNCs are offering more value for their prices (Bagchi, 2018). The increased competition means that in order for traditional taxis to survive, they must adapt to a more technologically advanced model. However, Taxi companies must conform to regulations that increase their costs and prices. TNCs mostly frame their business as a different industry called "rideshare," so they can avoid taxi-like regulations and legal issues. Despite their efforts, TNCs generally have been under regulatory pressure since their entrance into the transportation market. Recently, more policies have been implemented to limit the number of drivers on the road, working hours per driver, and minimum charges and wages for TNC drivers (Berger & Bensinger, 2018). Recent studies show that the policies related to limiting working hours and requiring more regulatory oversight benefit taxi firms, which were previously regulated and did not incur a cost from the new regulations on TNCs (Bagchi, 2018; Curtis et al., 2019; Kirchner et al., 2022). A recent study on the New York for-hire market shows that regulations imposed on TNCs increase taxi rides and revenues (Bagchi, 2018), which further proves that the increasing cost of TNCs increases the ridership of traditional taxis.

3.2.3 TNC Profitability

Although TNCs enjoyed massive revenues in the first seven years, Crunchbase news reported on Uber's 2017 financials and concluded that it lost over one billion US dollars (Dowling et al., 2018). The article attributes the loss to the fact that the majority of Uber's revenue goes to drivers, who are paid over 80% of the collected fares in the form of driver pay and discounts to riders, and the remaining 20% was not sufficient to cover the cost of revenue and other operating expenses. Similar losses were also reported in 2018, as Uber and other TNCs have pursued to charge low rates – also referred to as predatory prices - and offered discounts to achieve remarkable growth to increase their market share or rather dominate the TNC market (Leisy, 2020). Amid this race for market domination, such pricing strategies put the long-term profitability of TNCs at stake, as many riders do not realize that their trips are heavily subsidized, which makes it challenging for TNCs to increase their rates as they would likely lose riders and, therefore, drivers. Although TNCs have obtained a significant market share, reaching more than ten times that of taxis in 2017 (Leisy, 2020), their share is mainly sustained by the fierce price war. For instance, Uber's market share has fallen from 84% to 77% in 2017 alone as its rival Lyft started to accelerate (Muoio, 2020).

In addition to financial challenges, the strive for market dominance by large TNCs is also challenged by their organizational work type, mainly gig workers who can easily switch between different TNC apps. As Lyft and Uber battle for market share, both companies race to the bottom by spending vast amounts of money on promotional discounts for riders (Leisy, 2020; Today, 2022). At first, it seems implausible to question the business plan of that wildly successful TNC. However, a growing number of analysts are questioning whether TNCs can ever become profitable given their pricing strategies that do not generate enough revenue to compensate drivers or profit their shareholders sufficiently. By pricing their services at least 30% below taxi fares and retaining 20% of revenues, TNCs squeeze the revenues available to compensate drivers, who are essential to providing both the labor and resources to serve riders (Sherman, 2022). Currently, there is nothing in TNCs' business models that promise a reduction in costs of ride-hailing services, nor are there inherent economies of scale that would lower unit operating costs with continued growth (Bosa, 2022; Leisy, 2020; Sherman, 2022).

3.2.4 *Recent Changes in TNC Market*

The COVID-19 outbreak had a profound effect on the ride-sharing market, especially on TNCs, as the demand for the service plummeted in large metropolitan areas due to lockdowns and safety concerns (Beck & Hensher, 2020; Hawkins, 2020; Morshed et al., 2021). For instance, during the first three months of the outbreak, Uber announced that trips declined by 60–70% in Seattle and 77% in London and Paris (SERAFIMOVA, 2020). In addition to the decrease in demand, TNC supply saw a similar crash, as the number of active drivers accepting trips declined by 71.6% in the same period (Hedge, 2022). The loss of drivers, albeit a natural result of the reduced demand, can also be attributed to the reluctance of new drivers to join TNC apps during the pandemic and the rising competition of food delivery apps, which are generally safer and in high demand, e.g., Uber Eats (Hegde ., 2022). In 2021, as the pandemic started to recede, the reduction in drivers reportedly forced TNCs to raise their trip fare rates to lure drivers back and safeguard the service supply. Nevertheless, many drivers have complained about not getting a fair share of the increased prices, and some even claimed their pay "has not been raised at all." (Dailymail, 2022). Also, with significantly increased fares, there have not been sufficient raises to compensate for increased costs of living and rising gas prices. Recent reports and surveys show that nearly half of TNC drivers have stopped or reduced their driving hours despite fuel surcharges and increased fares (Hawkins, 2020). Such effects, coupled with a recovering demand in a post-pandemic world, continue to raise TNC fares to unprecedented levels at the time of writing. The soaring TNC prices and inflation create many challenges for passengers and exacerbate the legal backlash that TNCs face in many countries. This continuous struggle to balance supply, demand, and prices in a changing global economy makes it essential to investigate the likely changes in TNC service fares in the coming years and the implications of TNC price changes on partnerships between transit agencies and TNCs.

3.3 Methodology

This study adopts a multi-step methodological framework to examine and forecast TNC prices in the coming years and assess the impact of TNC price changes on transit agency-TNC partnerships. Using publicly available trip data, I employ time-series modeling techniques to forecast future TNC trip prices. I then utilize a transit agency-TNC partnership case to illustrate the implications of predicted price changes for the prospect of such partnerships. Table 3.1 summarizes the different scenarios in which TNC prices will likely change in the coming years.

Table 3.1 TNC Price Change Scenarios

TNC Price Change Scenario	Analytical Method	Price Change Measure
(1) Price Trend Extension	• Time series forecasting to predict TNC fares. • Model parameters tuning to find the best fit	• Forecast average USD/Mile in 2022-2023 based on the price trend. • Measure % change in forecasted price compared to 2019.
(2) Price Increase in Response to Local Policy Changes	• Track the impact of local regulations and policy changes on prices (e.g., minimum wage ordinance)	• Use publicly available estimates of % change in TNC price. • Combine with forecasted % change in scenario (1)
(3) TNC/Taxi Price Convergence Due to Increased Competition	• Time series forecasting to predict taxi fares. • Price convergence in the for-hire market (taxis)	• Use forecasted taxi and TNC data to measure the % difference between their future prices

3.3.1 Price Trend Extension

3.3.1.1 Trips Data

The City of Chicago has been publishing trip-level data for every TNC trip since November 1, 2018. TNCs in Chicago, called Transportation Network Providers, include Uber, Lyft, and Via. Although many other cities in the US have made TNC data publicly available or accessible, to our best knowledge, the Chicago dataset is the only one that includes trip fare variables. As I wrote this chapter in Oct 2022, the dataset includes approximately 263 million trip records (rows) and 21 features (columns) for trips dated from November 1, 2018, through October 1, 2022. I used selected features from this data, including Trip Start Timestamp (rounded to the nearest 15 minutes), Trip Miles, Trip Fare, Additional Charges, and Total Trip Fare. As the dataset is too large to be processed without a supercomputer, I generated a random sample of 2 million trips from Nov 2018 to June 2022 with valid pickup and drop-down area information. To explore the data, I processed the features to extract date information from the timestamp and created a new variable that includes each trip's average fare per mile (excluding tips and additional charges, mainly taxes).

The City of Chicago also publishes trip level data for taxi trips from 2013 to the present. Due to the data reporting process, not all trips are reported, but most trips are. Taxicabs in Chicago, Illinois, are operated by private companies and licensed by the city. About seven thousand licensed cabs are operating within the city limits. The data has been sampled and processed similarly to TNC data, using a sample of 2 million trips for the same period (November 1, 2018, through October 1, 2022). Please refer to Appendix B, Table B-1, for more details on the Chicago TNC trip data.

Forecasting models ascertain the trend and the seasonality in TNC price time-series data, which can generate valuable insights and predictions of future TNC price changes. The trend represents the general direction in which the time series of TNC prices is headed. Seasonality is a recurring pattern in the data (e.g., daily, weekly, or yearly). What cannot be explained by the seasonality and trend is the random fluctuation in price.

In order to find out approximate future TNC price changes based on previous trends, I aim to forecast the time series of daily average fare per mile in Chicago based on existing data recorded from November 01, 2018, until October 1, 2022, and exhibit the patterns of the time series of daily average fare per mile for one year ahead. I apply two different approaches that can produce future results. They are the Auto-Regressive Integrated Moving Average (ARIMA) model and PROPHET forecasting procedure. ARIMA models are popular and have been applied in many fields for decades. At the same time, PROPHET can be considered a new approach, as it was released in 2017 and is renowned for its usability and modeling capacity.

3.3.1.2 Accounting for Geographical Differences

To make the Chicago TNC price trend generalizable to Seattle, I first normalized the price data in the form of daily average fare per mile, which is a function of many variables, including different trip origin, destination, surge pricing, lengths, and durations. I then used the average daily fare per mile as the unit for our time series price forecast. In this way, the time series data for Chicago is not overly sensitive to context-specific factors (e.g., surge price for certain subareas) but rather captures the general price changes that can be applicable to other cities such as Seattle.

Second, I also considered multiple variables to control for the effects of city-specific factors on price changes. External regressors were included to explain the remaining price variations. I identified climate, gas prices, and COVID-19 lockdown as important regressors in the case of TNC prices. Hence, I combined the trip data with Chicago weather data, including average temperature in degrees, snow depth (inches), and precipitation (inches) obtained from the National Center for Environmental Information and average monthly gas prices (USD/gallon) in Chicago obtained from the Energy Information Administration. I also added a dummy variable for the COVID-19 lockdown, severely impacting TNC and other transportation services from March 20, 2020, to July 25, 2020. In addition, seasonal events were also included to isolate their effects on the overall price trends by adding dummy variables for selected holidays in the US: Christmas, New Year, Thanksgiving, Easter, and Independence Day (ID). Please refer to Appendix B, Table B-2, for an illustrative example of the processed data.

Lastly, to account for policy changes peculiar to Chicago and directly impacting TNC prices, I tested a dummy variable that captures the day the Chicago congestion fee became effective (January 6, 2020). The fee increased the tax on TNC trips to or from the airports, Navy Pier, or McCormick Place and imposed a Downtown Zone Surcharge on trips that start or end within the designated Downtown Zone Area during peak times, weekdays (M-F) between 6 AM and 10 PM. The Downtown Zone Surcharge does not apply to trips on Wheelchair Accessible Vehicles (WAVs).

3.3.1.3 Forecasting with ARIMA

The AR in ARIMA stands for autoregressive, represented by p in equation (2). It refers to the number of y(t) lags used as the predictor. A pure AR model will be where y(t) depends only on its past values (y(t-1), y(t-2) …). A typical representation of an autoregressive model of order p can be written as

$$y(t) = c + a1y(t-1) + a2y(t-2) + a3y(t-3) \ldots\ldots + et \qquad (1)$$

where it represents white noise, i.e., random fluctuation. Unlike the AR model, which uses past values, the moving average (MA) model depends only on past forecast errors, represented by q in equation (2). Finally, the I in ARIMA stands for Integrated, which reflects the number of differencing needed to make the data stationary before estimating the AR and MA parts of the model. In this context, differencing is the reverse of integration. The formula for ARIMA could be represented as

$$y(t) = \mu + \phi 1 y(t-1) + \cdots + \phi p\, y(t-p) \; - \; \theta 1\, e(t-1) \; - \cdots - \; \theta q\, e(t-q) \qquad (2)$$

y(t) represents the series of differences as it may have been differenced multiple times, while the right side of the formula includes both lagged values of the AR model and lagged errors from the MA model. Here (θ) represents the moving average parameters with a negative sign[1]. In the case of seasonal ARIMA, known as SARIMA, the data is split into two parts, seasonal and non-seasonal, with the seasonal part optimized similarly to that in ARIMA. SARIMAX is a SARIMA model that adds external regressors to explain variations caused by non-seasonal factors such as weather, lockdown, marketing campaigns, and discounts.

To identify the appropriate ARIMA model for daily average fare per mile, I used the Auto ARIMA function in R, which returns the best ARIMA model parameters according to AIC or BIC values. First, I used November 28, 2018, to April 1, 2022, TNC trip data for training the model and April 1, 2022, to October 1, 2022, TNC tip data as a test set for validation to evaluate the model performance. Second, I used the whole data set (November 28, 2018, to October 1, 2022) for training, and based on the trained model, I predicted average daily prices in the next three years. All the holidays and exogenous variables mentioned in the Data Preparation section were included in the model.

[1] In the R programming language, ARIMA parameters have plus signs, and are denoted by AR(1), AR(2), …, and MA(1), MA(2), … etc.

3.3.1.4 Forecasting with PROPHET

PROPHET is a procedure for forecasting time series data created by Facebook's Core Data Science team. It aims to provide an easy-to-use tool for modeling time series data. PROPHET works best with time series data with strong seasonality and extensive historical data and is robust to outliers and shifts in the trend. It also has built-in cross-validation for parameter tuning. PROPHET has additional functionality to help explore the impact of dynamic holidays such as Christmas, separately from regressors, with the ability to explore a window of their impact in near dates, and it is capable of dealing with non-linear regressors.

$$y(t) = c(t) + s(t) + h(t) + x(t) + e \tag{3}$$

c(t): trend

s(t): seasonality

h(t): holidays: PROPHET enables the exploration of the neighboring days of holidays.

x(t): external regressor: non-recurrent variables (events that are not on the same dates every year) or disruptive events like the COVID-19 pandemic.

e: error

Again, I followed the same procedure as described above to train and test the model. PROPHET enables the inclusion of holidays separately and allows for exploring the effects of neighboring days. I included two neighboring days for every holiday. I applied PROPHET built-in cross-validation, which conducts several test sets to tune the model parameters, increase the model's accuracy for different seasonality, and reinforce the validation of the model by testing it in different scenarios. I ran 185 forecasts, which involved different parameter values, and used the resulting parameters of the most accurate model to forecast future price changes.

3.3.2 Price Increase in Response to Local Policy Changes

The first scenario forecasts prices in the three years (Oct 2022 - Oct 2025) based on TNC trip data from Chicago. However, many legal and political influences impact TNC prices differently. In January 2020, the city of Chicago introduced a congestion fee that impacts the prices of TNC services (Uber, Lyft, or Via), especially for trips starting or ending in the downtown zone. The fee varies depending on the start and end zones, the number of passengers sharing the trip, and accessibility requirements. Policies vary from one city to another, and it is important to understand their effect on predicted TNC prices when applied to other cities. In this paper, I use TNC price changes observed in Chicago to help understand the implications for a pilot project involving a transit agency-TNC partnership in Seattle. Thus, in addition to considering a similar percent change in TNC prices in Seattle, I must consider local policies that only impact Seattle's TNC prices.

The most relevant local policy is the legislation passed by the Seattle City Council (effective in 2021) that sets the minimum wage for TNC drivers to $17 per hour. In response, TNCs such as Uber and Lyft had to raise trip prices. Initial estimates indicate that TNC prices increased by as much as 25% and could reach as much as 50% (Hawkins, 2022). In addition, a new ordinance relating to app-based worker labor standards – (effective starting 2024) - establishes a similar compensation scheme for app-based workers (gig workers), amending Sections 3.02.125, 3.15.000, and 6.208.020 of the Seattle Municipal Code and adding a new Title 8 and Chapter 8.37 to the Seattle Municipal Code. In this scenario, I track reports and publications that estimate the percent increase in TNC prices to comply with regulations and policy changes.

3.3.3 TNC/Taxi Price Convergence Due to Increased Competition

With the ongoing regulatory process and legal pressure on TNCs, their trip prices may keep fluctuating and mainly increasing to correspond to new laws and ordinances (e.g., minimum wage requirements and drivers' work hours limitations). In return, the higher trip prices will decrease the competitive advantage of TNCs and increase the competition between TNCs and taxis. As long as the taxis are regulated as they are today, they will continue to bear the total weight of the regulatory burden, whether TNCs are regulated or not. Regulating TNCs could only increase their operating cost and thus raise their prices, making taxi fares less undesirable to riders. A continuation of these policies, accompanied by the adaptation of technologically advanced capabilities by taxis, will burden TNC consumers who might shift away from TNCs or become indifferent to which mode they choose. Under the assumption of increased competition between taxis and TNCs, and given the lack of profitability of TNCs, it is conceivable that TNCs' average fare per mile will become equivalent to that of taxis.

The City of Chicago has published trip-level data for every taxi trip since 2013. I used the taxi fare data to estimate the average daily fare per mile for taxis and to compare the difference between their trip prices and TNCs at different times. I also used taxi trip data to forecast future changes. Based on our observation, taxi fares have been declining, alluding to a potential convergence with TNC prices, which will be explained in more detail in the next section. In this scenario, I use forecasted future taxi prices to estimate changes in TNC pricing in increased competition.

3.3.4 Assessing Likely Impacts on Transit Agency-TNC Partnership

To assess the likely effects on the cost-effectiveness of transit agencies-TNC partnerships, I use a case study of a planned transit agency-TNC partnership to assess the impact of TNC price changes. The case involves subcontracting some paratransit services currently operated by King County Metro through its Access paratransit program to TNCs, often referred to as same-day-service (SDS). For this purpose, I use the trip diversion rate as the primary metric to assess the effectiveness of SDS by adopting criteria developed by Ashour and Shen (2022), which consider significant trip diversion barriers and measurable conditions to estimate potential trip diversion rates. Although the previous study investigates the effects of three main barriers/conditions for the operation of SDS trips, I only use one main barrier here to reevaluate the effects of TNC price changes and estimate potential trip diversion from conventional ADA paratransit to SDS. This condition considers the fixed subsidy amount as set by transit agencies for the SDS trips. The conventional Access paratransit trips have a fixed fare (cost for riders), which does not change with trip distance. However, transit agencies provide a specified subsidy amount for the alternative services operated by TNCs. Because longer trips impose higher costs on passengers than regular Access services, this condition uses trip distance as a pivotal point for diverting trips from Access to TNCs. At the onset of this partnership pilot, King County Metro considered a maximum of $40 subsidy amount per trip for SDS trips, which can be used to estimate the trip distance that the subsidy amount can cover. KCM estimated this $40 subsidy, and it is potential for TNC partners to cover a 10-mile SDS trip during regular hours. This figure might not reflect the average TNC trip prices in King County, as SDS entails additional operational challenges and specifications. Finally, I use the change in cost-effectiveness of the transit agencies-TNC partnership, measured here by the change in trip diversion rate to TNC, as an empirical basis to discuss possible changes to transit agency-TNC partnerships resulting from future TNC price changes.

3.4 Results

3.4.1 Scenario (1): Price Trend Extension

The yearly seasonality graphs for average daily TNC prices, shown in Figure 1, and taxi prices, shown in Figure 2, reflect some important differences between the two services. Although both services have witnessed fluctuations in their prices during the pandemic, TNC prices continue to fluctuate highly and rise above pre-pandemic prices in 2019, while taxi prices started to settle less than pre-pandemic prices, starting in 2021.

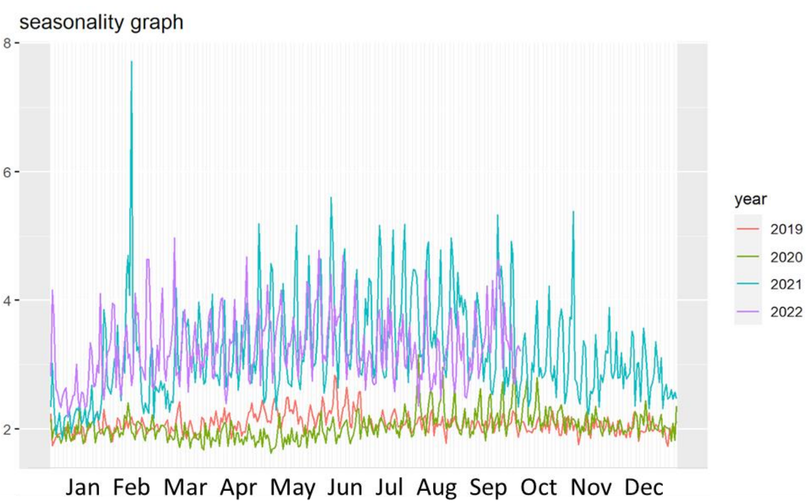

Figure 3.1 Yearly Seasonality Graph of TNC Fares (USD/Mile)

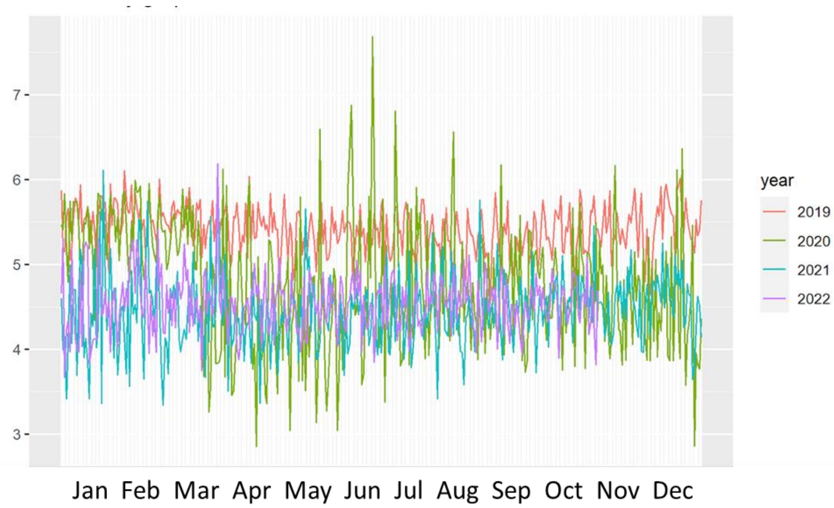

Figure 3.2 Yearly Seasonality Graph of Taxi Fares (USD/Mile)

3.4.1.1 Forecasting TNC Prices with ARIMA

Using both ARIMA and PROPHET models, I forecasted the average TNC fare per mile within the next three years (October 1, 2022 - October 1, 2025). I used a SARIMAX model, which splits the data into two parts, seasonal and non-seasonal, the latter with the ability to understand the effect of exogenous regressors that seasonality does not explain. I used the auto ARIMA function in R to optimize the model parameters using AIC and BIC. I trained the model using the last five months of TNC prices (May 2022 - Oct 2022) and included seasonal holidays (Christmas, Easter, Thanksgiving "T-DAY," New Year's Eve "NYE," and Independence Day "ID") and external factors (Average Temperature "TAVG" Precipitation "PRCP," snow levels "Snow," average daily gas prices "Gas," and Chicago congestion fee effective date "CHI Fee") as exogenous regressors, and obtained the following results:

Table 3.2 ARIMA Parameters

	ar1	**ar2**	**ma1**	**sma1**
coeff	1.1687	-0.2114	-0.8285	-0.8372
s.e	0.1064	0.0701	0.0924	0.0239

Table 3.3 ARIMA Results - Exogenous Variables

	Christmas	**Easter**	**T-DAY**	**NYE**	**ID**	**Lockdown**	**PRCP**	**Snow**	**TAVG**	**Gas**	**CHI Fee**
Unit	**binary**	**binary**	**binary**	**binary**	**binary**	**binary**	**inches**	**inches**	**degree**	**USD/gal**	**binary**
coeff	-0.2023	0.1441	0.2355	0.5425	-0.085	-0.0867	0.0583	0.0283	-0.0008	0.1871	-0.0021
s.e	0.1697	0.1474	0.1685	0.1513	0.1687	0.1273	0.0297	0.0158	0.0014	0.1922	0.1762

For exogenous regressors shown in Table 3.3, the model indicates that NYE, PRCP and Snow have a statistically significant positive correlation with average TNC fare. The SARIMAX model results in an RMSE of 0.446 and MAPE of 10.195. I used this model to predict future TNC prices for the next three years, as illustrated in figure 3.3.

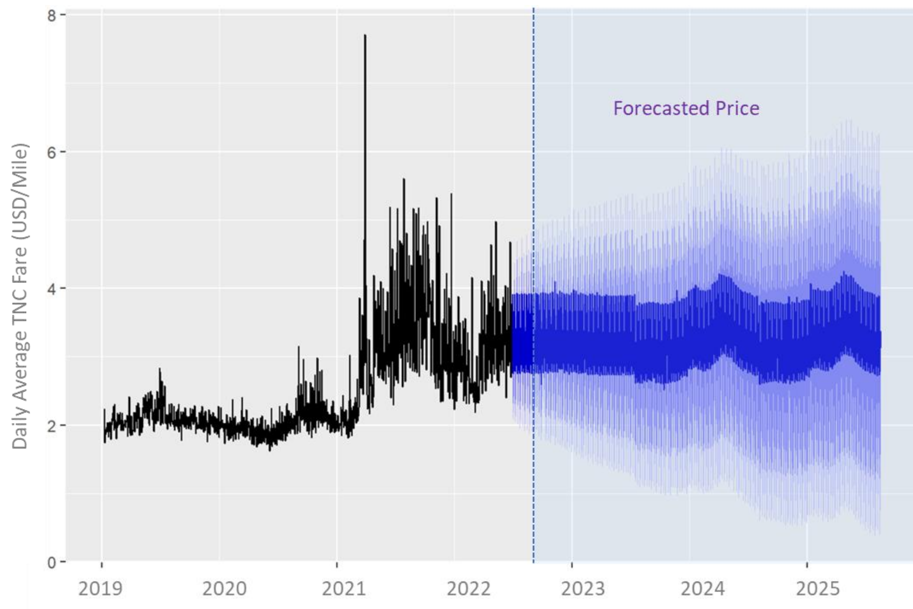

Figure 3.3 ARIMA TNC Price Forecast

3.4.1.2 Forecasting TNC Prices with PROPHET

The forecast with PROPHET results in an RMSE of 0.48 and MAPE of 10.593. Figure 4 shows the price predictions using PROPHET.

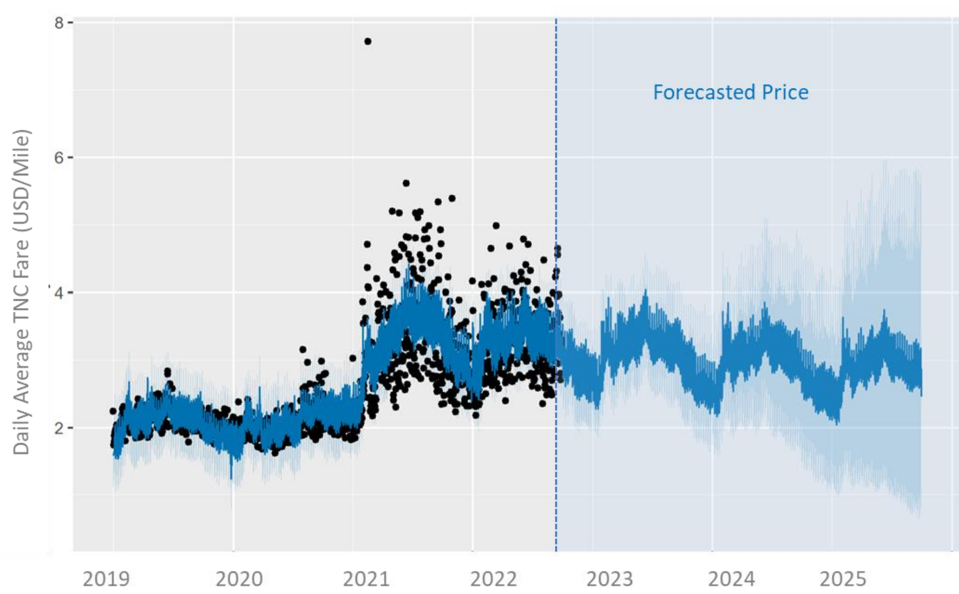

Figure 3.4 PROPHET TNC Price Forecast

Figure 3.5 shows the decomposition of the PROPHET model, reflecting the impact of dynamic holidays, including Christmas, NYE, Independence Day (ID), Thanksgiving (T-DAY), and

Easter, as well as the exogenous regressors combined, including gas prices (Gas), average temperatures (TAVG), precipitation (PRCP), Snow, Chicago Congestion Fee (CHI Fee) and Lockdown.

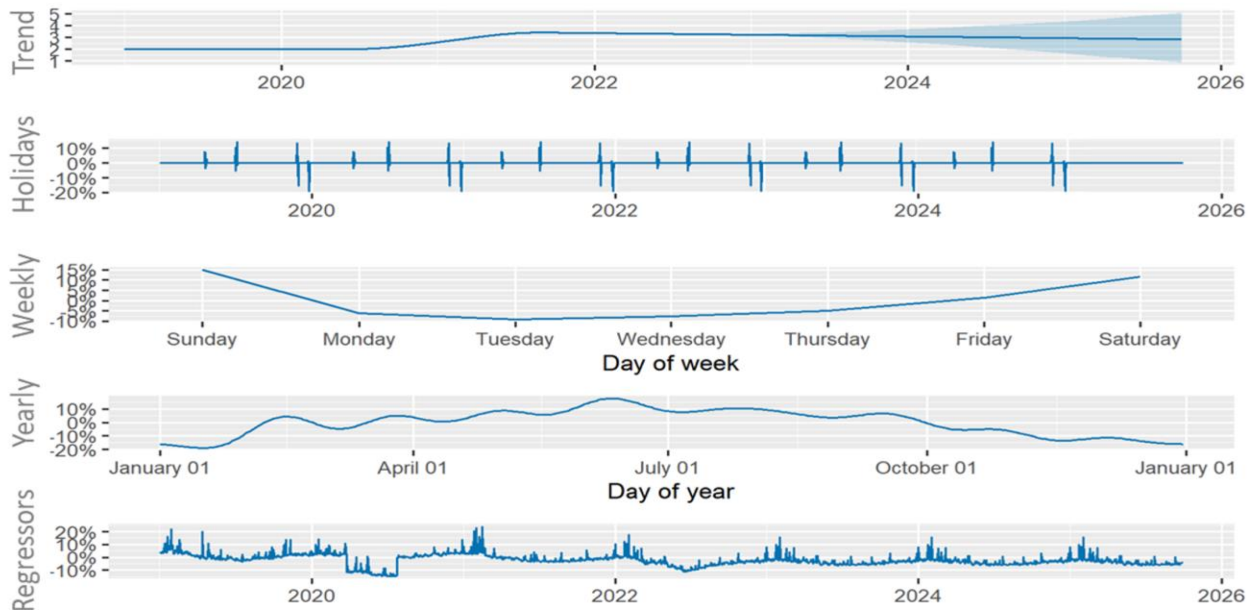

Figure 3.5 PROPHET Model Components

3.4.1.3 ARIMA and PROPHET Comparison

To compare the forecasts from the two models further, I plotted the average monthly forecast prices, as shown in Figure 3.6. Both ARIMA and PROPHET show that although TNC prices have decreased since their peak in 2021, there has been an overall increasing trend in TNC prices since the outbreak of the pandemic in 2020. As forecasted in ARIMA, the average fare/mile of TNC trips could be around \$3.23/mile throughout the upcoming three years, while the average fare/mile in 2019 was around \$2.1/mile, which is 40% less than the forecasted change. As shown in Table 3.5, by applying the forecasted 40% increase to the \$4/mile base fare in Seattle, the resulting TNC price will be \$5.6/mile in Scenario (1).

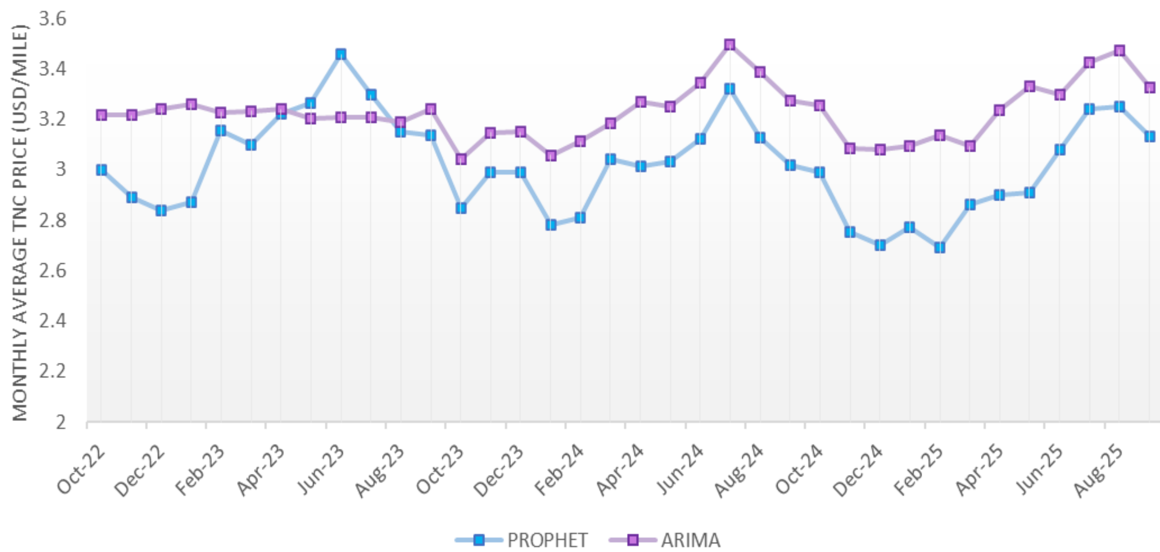

Figure 3.6 PROPHET and ARIMA Forecasted Average Monthly Price Comparison

Although ARIMA and PROPHET both resulted in comparable accuracy when used to predict the last five months of available TNC data (May 2022 - Oct 2022), ARIMA performs better when I compare the root-mean-square error (RMSE), a measure of the differences between forecasted and actual values, and MAPE, the mean absolute percentage error. Table 3.4 shows the accuracy of the comparison of the two models.

Table 3.4 Accuracy Comparison of ARIMA and PROPHET

	RMSE	**MAPE**
ARIMA	0.446	10.195
PROPHET	0.48	10.593

3.4.2 Scenario (2): Price Increase in Response to Policy Changes

In this scenario, I have tracked policy changes and regulations peculiar to the city of Seattle that have impacted TNC prices since 2019 but are not captured in the price trend extension in scenario (1). Due to the lack of available TNC trip fare data for Seattle, I have tracked online journal papers and newsletters that report on significant policy changes and the expected or estimated percentage change in TNC prices accordingly. I have found that the minimum wage ordinance and the new Seattle wage law have significantly impacted TNC prices, and they are predicted to continue to influence TNC prices in the upcoming years. Specifically, the prices for TNC trips in Seattle have jumped by 25% in response to a new law requiring drivers to be paid the city's $16.69 per hour minimum wage in 2021 (Bialick, 2022; Foroohar, 2021; Kiro7, 2022). This minimum wage is also expected to increase in the following years, which is reported by the city of Seattle to equal $18.69/hour in 2023 (Harmsworth, 2022). The same resources also show that TNC prices will continue to increase in response to these changing policies and could become 50% higher in the upcoming years. In this scenario, given that Chicago did not enact similar policies, I use the reported percent increase in Seattle's TNC prices due to local policy changes, at 25%, and combine it with the forecasted change in scenario (1). Hence, the TNC price in scenario (2) would be 25% higher than the resulting fare in scenario (1), which is $7/mile (see Table 3.5).

3.4.3 Scenario (3): TNC/Taxi Price Convergence Due to Increased Competition

For this scenario, I used available Chicago taxi trip data to compare the historical and forecasted trip prices between TNC and taxis. I used price forecast models similar to those presented in scenario (1) to forecast future taxi prices. I chose the results from the ARIMA forecast because they reflect higher accuracy when comparing price trends for taxi and TNC services in the upcoming three years.

In 2019, the average TNC trip fare per mile was $2.1 in Chicago, which at that time was only 37% of the average taxi fare/mile of $5.6. The gap was around $3.5 per mile. With a 57% increase in TNC prices and a 25% decrease in taxi prices, as forecasted for 2023, this gap will significantly decrease to only $1.17, as illustrated in Figure 3.7. These converging trends in price will continue with increased competition between TNCs and taxis, which could result in TNCs pricing their trips in a comparable way to taxis. The average forecasted fare per mile for taxis in the upcoming three years is 50% higher than that for TNCs. Hence, in this scenario, I assume that TNC prices could be subject to an additional 50% increase to the forecasted price in scenario (1) for 2023-2025, under increased competition from taxis.

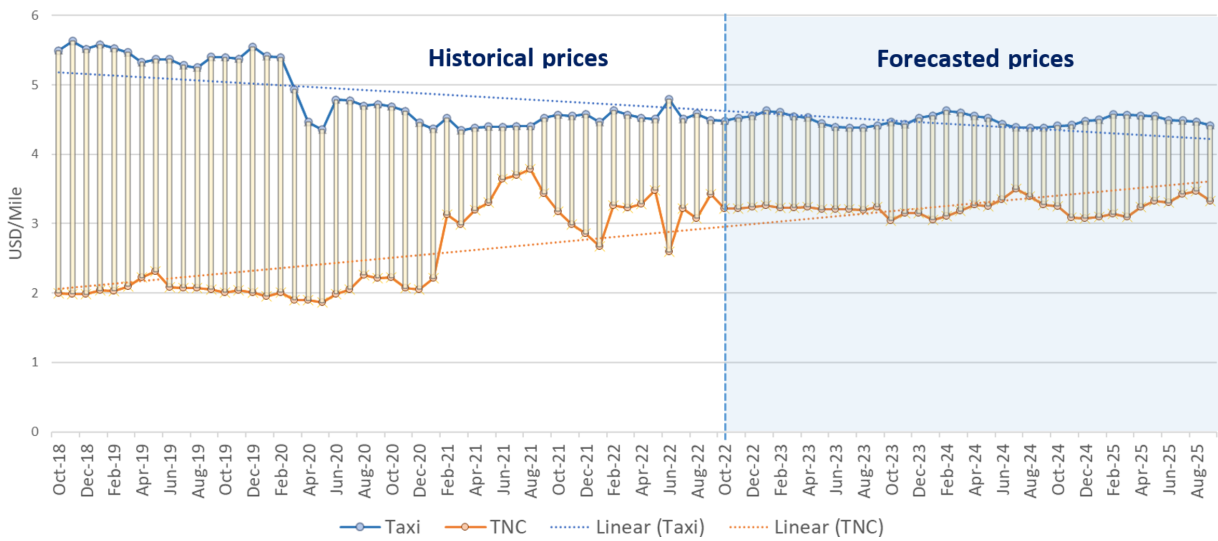

Figure 3.7 Taxi and TNC Price Comparison: Existing and Forecasted for Chicago

3.4.4 Assessing Likely Impacts on Transit Agency-TNC Partnership

This analysis measures the extent to which TNCs can supplement paratransit trips under each of the three TNC price change scenarios and compares the results to initial estimates of trip diversion based on 2019 TNC prices (Ashour & Shen, 2022). I assumed that the total annual ADA trips (i.e., the total demand for ADA service) in the coming years 2023-2025 would stay the same as in 2019, and I applied a fixed subsidy amount of $40 per TNC trip (determined by the transit agency, KCM, to cover a 10-mile SDS trip through TNCs) to estimate the number of trips that this subsidy can cover under each of the following scenarios:

Scenario (1). Price trend extension: 40% increase in TNC prices compared to 2019.

Scenario (2). Price increase in response to policy changes: additional 25% increase in TNC prices on top of the price trend extension forecasted for the first scenario.

Scenario (3). TNC/Taxi price convergence due to the increased competition: an additional 50% increase in TNC prices on top of the price trend extension forecasted for the first scenario.

As noted in the methods section, the $40 subsidy was estimated to cover a 10-mile SDS trip using TNCs in 2019. This figure indicates an average trip cost of $4/mile. The price difference reflects the arrangement between transit agencies and TNCs and the operational specifications of operating paratransit services, which does not necessarily represent the average TNC price in Seattle. In 2019, KCM's Access paratransit delivered 645,668 paratransit trips, 70% of which were 10 miles or less and hence can be considered divertible at the specified subsidy of $40 per TNC trip. At the same level of subsidy, and assuming the total annual demand for paratransit trips remains constant for 2023-2025, I measured the change in divertible trips for every price change scenario, assuming that the % change in price would also reflect on the average $4/mile base cost in 2019 in Seattle. Table 3.5 summarizes the main results and the percentage of divertible trips for each scenario. The first column shows the estimated price per mile for TNC trips in 2019, the corresponding number of miles the $40 subsidy per trip covers, and the number and percentage of divertible trips. The second column, Scenario (1), shows the price per mile by applying the forecasted 40% increase in TNC prices. This results in a reduction of the divertible trip rate from 70% in 2019 to 55%. The third column, Scenario (2), shows an additional price increase resulting from policy changes, which is compounded with the % increase in the first scenario, assuming that the two price changes are independent of each other, which drops the divertible trip rate to 51%. Finally, the fourth column, Scenario (3), shows the expected price per mile if forecasted TNC prices become similar to those of taxis, which is also compounded with the % increase from the trend extension, assuming that the two price change effects are independent of each other, dropping the divertible trip rate further to 45%.

Table 3.5 Summary of Price Change Scenarios and Resulting Divertible Trips Per Year

	2019	**Scenario (1)**	**Scenario (2)**	**Scenario (3)**
	No Change (Baseline)	**Price Trend** (Time-series)	**Policy Change** (Seattle region)	**Increased Competition**
% Price Change Compared to 2019	**0%**	**+ 40%**	**+ 40%** **+ 25%**	**+ 40%** **+ 50%**
Price (USD/Mile)	$4.0	$5.6	$7.0	$8.4
Trip length covered by $40	10 Miles	7.15 Miles	5.7 Miles	4.7 Miles
Divertible trips (count)	450,212	353,060	330,981	270,287
Divertible trips (percentage)	**70%**	**55%**	**51%**	**42%**

3.4.5 Validation of Price Trend Estimates

Due to a lack of trip price data in Seattle, I have only applied the forecasted percentage increase in trip prices to the pre-pandemic average price per mile in Seattle. Our results show that the daily average price per mile could increase up to 40% of its pre-pandemic levels within the upcoming three years. To validate our results, I have investigated reported changes in TNC prices in Seattle, and indeed, this estimated percentage is on the lower end of the observed changes. For example, a major local news channel reported that average prices in Seattle increased by 50-60% in 2021 (Johnson, 2021). Other research also showed that prices, after the pandemic measures were lifted, were higher, and waits were longer nationwide: Rakuten Intelligence conducted a study that found the cost of a ride was up as much as 40% compared to pre-pandemic (2019), and at least 90% higher than 2018 nationwide (Szymkowski, 2021).

3.5 Conclusion

Since their entrance to the market in 2010, TNCs have been widely recognized as disruptive innovators that have significantly impacted the taxi market. Even though TNCs and taxis provide comparable services, TNCs' business models allow them to control their service pricing and information flow between drivers and riders. In addition, TNCs are based on market deregulation and benefit from many preemption laws. Although TNCs' business models and market deregulation have given them a competitive advantage over taxis, this advantage has been eroded by profitability challenges and government regulations. Initially, TNC prices were low due to the ease of market entry and the desire to increase market share by offering lower cost rates. However, TNCs have been under regulatory pressure, facing many legal struggles that increase their operating costs and exacerbate their profitability challenges. For example, many cities implemented regulations to limit work hours by drivers (e.g., New York City) and influence prices to meet the minimum living wage (e.g., Seattle) (Berger & Bensinger, 2018). As many cities add new regulations that not only increase operating costs but also constrain the supply of drivers for TNCs, their prices will continue to increase and may eventually be as high as taxi prices. As many cities continue to regulate TNCs with taxes and driver limits, TNC prices will continue to increase and may eventually reach as high as taxi prices.

This chapter explores three scenarios of TNC price changes based on (1) price trend extension, (2) price increase in response to local policy changes, and (3) price convergence with taxis under increased competition. I use two different time series models, namely ARIMA and PROPHET, to forecast price changes within the next three years (2022-2025) using Chicago TNC and taxi trip data. I assess the impact of scenarios on potential price changes on transit agency-TNC partnerships, using Access paratransit operated by the primary transit agency in the Seattle region as an example.

In Scenario (1), forecasting TNC price changes in the upcoming three years (Oct 2022 - Oct 2025) shows that the daily average fare per mile could be 40% higher than pre-pandemic rates. The forecasted percent increase in average TNC fare per mile could be higher in some cities due to local policy changes. Therefore, in Scenario (2), TNC prices would increase by a minimum of 25% in response to recent changes in the minimum wage law in Seattle. As a result, TNC prices might average $7 per mile. In Scenario (3), based on our forecast for TNC and taxi prices in the upcoming three years, TNC prices could additionally increase by 50% and converge with taxi prices, reaching up to $8.4 per mile in Seattle.

Our findings about future TNC price increases put the effectiveness of transit agency-TNC partnerships at stake. Although partnerships with TNCs could still provide many benefits, transportation planners and policymakers should carefully examine significant barriers likely resulting from TNC market and policy environments and design their partnerships with TNCs accordingly. Since most transit agencies- TNC partnerships involve subsidies of TNC services, price changes will pose critical challenges for transit agencies, as their budget may not be sufficient to provide the level of subsidy necessary for achieving the objectives of such projects. To mitigate the negative effects of TNC price changes on these partnerships, transit agencies can enter contractual agreements to regulate TNC prices, such as setting maximum fares. However, this may be difficult to achieve, as TNCs are likely to resist strict regulations of their prices, which would deter drivers from serving such trips. Alternatively, transit agencies can negotiate with TNCs to keep prices stable for a certain period, but if prices continue to increase, transit agencies would need to consider such changes after the agreed period expires. With many changes and uncertainties concerning TNCs, transit agencies should develop alternative transportation options, reduce reliance on TNCs, and ensure that public transportation will continue to be accessible for all riders. In addition, transit agencies should explore longer-term service innovations such as electric vehicles and autonomous vehicles, which can have significant implications for mobility services and TNC business models and prices.

This research has some limitations. An obvious shortcoming is that the price changes were estimated based on daily average trends in Chicago and then applied to Seattle, but the two cities may not follow identical trends. Another limitation is the unavailability of data pertaining to TNCs' promotional discounts, traffic, and the number of available drivers, which impact trip prices but are not included in the model. As the city of Chicago started to regulate surge pricing and fees in the downtown area and for single-rider trips, our spatially aggregated data may not adequately capture the effect of these policies. Finally, it should be noted that the fares in the Chicago data are rounded to the nearest multiple of $2.50, reducing the precision of the estimated average fare per mile and forecasted price change.

Chapter 4. Incorporating Equity into the Cost-Effectiveness Evaluation of New Mobility: A Comparative Evaluation

4.1 Introduction

Public transportation in low-density suburban areas faces unique challenges due to the dispersed population distribution and low service demand (Bronsvoort et al., 2021; Tirachini & Cats, 2020). In such areas, it is difficult for residents to reach essential destinations such as healthcare facilities, schools, and shopping centers by public transportation (Pucher, 2005). Traditional fixed-route transit services are often unsuitable for these areas as they are costly to operate and do not effectively meet the needs of the residents, leading to a heavy reliance on private cars for travel (Bronsvoort et al., 2021; Pucher, 2005). As a result, transportation planners continuously seek solutions to provide adequate mobility services in areas where fixed-route services are ineffective.

The advent of app-based mobility-on-demand (MOD) services has created many exciting opportunities for transit agencies to build partnerships with new mobility providers to supplement existing public transit services with flexible and efficient travel options (Clewlow et al., 2017; McCoy et al., 2018; Schaller, 2018; Shen et al., 2021; Yan et al., 2019). MOD services, whether commercial ride-hailing operated by Transportation Network Companies (TNCs) such as Uber, or demand-responsive services offered through transit agencies, have the potential to provide first-mile/last-mile (FM/LM) solutions, guaranteed ride-home options, or even a replacement for low-efficiency transit services in low-density areas (Maretić, 2020; Wang & Shen, 2023). These services can be designed to optimize routing and scheduling, offering on-demand trips based on sociodemographic and built environment factors and helping transit agencies provide accessible and efficient mobility services (Dytckov et al., 2022). In this paper, I use Transit Incorporating Mobility on Demand (TIMOD) to denote projects and partnerships in which transit agencies incorporate MOD services to supplement or replace parts of traditional transit (Wang & Shen, 2023), especially in suburban areas.

Many transit agencies have realized the potential and begun experimenting with TIMOD programs, which have been most commonly applied to supplement FM/LM connections, tackling one of the main barriers to transit ridership, such as Via to Transit (Curtis et al., 2019). In particular, TIMOD projects have been widely tested and adopted in low-density areas that suffer from poor public transport service quality, where the costs of sustaining a good service frequency and service area coverage are high due to the low demand density (Wang & Shen, 2023). While TIMOD services theoretically show a high potential mobility solution in low-density areas, their suitability for suburban contexts depends on various sociodemographic and built-environment factors. For this purpose, transit agencies and researchers have been implementing different approaches to evaluate TIMOD services. At the forefront of these efforts, cost-effectiveness analysis is a valuable tool that aids decision-making processes by quantifying alternative interventions' relative costs and benefits and provides critical insights for integrating these innovative approaches into public transit networks.

The literature evaluating the cost-effectiveness of TIMOD is still emerging, and there are several gaps in current research. First, there is a lack of consideration of the variations among different suburban areas, including different sociodemographic profiles of residents, such as income levels, reflecting the type and frequency of trips, as well as access to certain travel modes such as car ownership, all of which could profoundly vary and impact the effects of TIMOD. Second, considerations of different built environment characteristics between suburban areas, including density and accessibility, are limited. Lastly, most cost-effectiveness evaluation approaches overlook the equity implications of TIMOD projects. Therefore, it is difficult to compare and thoroughly understand the cost-effectiveness of TIMOD in different suburban areas, making it harder for transit agencies to make informed decisions and effectively allocate their resources for such projects. The primary purpose of this chapter is to incorporate equity into a comprehensive framework that evaluates the cost-effectiveness of TIMOD services in suburban areas. The study explores two distinct suburbs in the Seattle metropolitan area, where a TIMOD service, MetroFlex, is provided. While both areas comprise suburban neighborhoods, they vary in population density, sociodemographic characteristics, and transit supply and demand levels. Using Metro Flex data, I evaluate the cost-effectiveness of TIMOD services considering different service provision scenarios compared to baseline mobility alternatives, including fixed-route public transit services and driving alone. To enable a fair comparison, I assume there is a given amount of travel demand to be met by traditional transit, TIMOD service, or other modes. The study aims to address the following questions:

1. How does the cost-effectiveness of TIMOD compare to other alternative modes in low-density suburban areas and in different built environments?
2. What are the equity implications of the comparative cost and benefit distributions of TIMOD among different income groups?
3. Which TIMOD service intervention scenario is the most equitable? Which built environment variables and income groups should be prioritized for TIMOD services?

4.2 Literature Review

4.2.1 Transit Incorporating Mobility-on-Demand Services (TIMOD)

Information and communication technology (ICT) advancements changed mobility services, resulting in a new class of private mobility providers that leverage mobile apps and digital platforms to connect riders. These mobility-on-demand services, including ride-hailing, car-sharing, and microtransit, provide attractive features such as enhanced flexibility, comfort, and operational efficiency. By incorporating these new mobility services, transit agencies can achieve some crucial goals, such as filling service gaps, increasing on-demand options, and lowering the costs of certain services (Clewlow et al., 2017; McCoy et al., 2018; Shaheen, 2018; Schaller, 2018; Shen et al., 2021; Yan et al., 2019). Many public transit agencies have realized such potential and begun testing and implementing partnerships with on-demand mobility service providers and TNCs. Numerous studies have examined how, when, and where the two can work together. Scholars studying MOD public-private partnerships in the United States have identified four key types of partnerships: FM/LM, low density, off-peak, and paratransit (Lucken et al., 2019; Patel et al., 2022). For example, the Southeastern Pennsylvania Transportation Authority (SEPTA) initiated a partnership with UberX in 2016 to enhance access to its rail stations and fill FM/LM gaps. Similarly, The Metropolitan Transit System (MTS) in San Diego offered a $5 discount on FM/LM connections to and from its transit stations during certain events (Lucken et al., 2019). Moreover, many pilot projects target low-density and rural areas. Dallas Area Rapid Transit (DART) aimed to integrate TNCs (Uber and Lyft) and other MOD providers like carpool services and bike-share programs to replace inefficient fixed-route services in low-density areas (Cordahi, 2018).

4.2.2 Evaluation of TIMOD

Several studies have evaluated different aspects of TIMOD through public-private partnerships. Patel et al. (2022) identified the most common challenges of MOD sandbox pilots as ensuring equitable access to services and estimating the cost for transit agencies (Patel et al., 2022). While reducing costs is often not the main objective of these partnerships, providing cost-effective alternatives is essential. Zhou (2019) developed a method to identify low-demand routes in fixed-route transit using smart card data and proposed replacing them with shared mobility options if the on-demand modes had an occupancy rate greater than two (Zhou, 2019). Agent-based modeling studies by Shen et al. (2018) and Gurumurthy et al. (2020) investigated scenarios where MOD services can yield potential performance gains in replacing buses as FM/LM connections to urban rails (Gurumurthy, 2020; Shen et al., 2018).

Yan et al. (2019) examined commuters' responses to TIMOD services and predicted mode choices. They found that the proposed TIMOD service could lower costs primarily by reducing riders' waiting time. Other studies revealed that residents already using ride-hailing favored on-demand services over traditional fixed-route transit (Wang et al.,2022). A lack of reliable access to necessary technological resources could be a significant barrier to adopting such services for low-income travelers (Yan et al., 2021).

While these studies provide initial insights into TIMOD services, they were exploratory and had limitations restricting their applicability in guiding transportation decision-making. Many studies used simulations based on hypothetical scenarios, which may only partially reflect the complexities of designing and implementing TIMOD. Other studies relied on respondents' stated preferences, which may not always align with their actual behavior for various reasons such as habit, convenience, or external factors. Future research should carefully evaluate real-world TIMOD projects to provide more transferable lessons. By analyzing real behavior and outcomes, transportation researchers can better understand the impacts of TIMOD services and better inform relevant decision-making.

4.2.3 Cost-Effectiveness of TIMOD Services

The comparative cost-effectiveness of providing mobility options in low-density areas has been a topic of interest in transportation research. One study highlights the cost-effectiveness challenges of fixed-route transit in low-demand and sparsely populated areas (Bauchinger, 2021). The authors argue that on-demand services can be a more cost-effective alternative in such areas. Another study argues that fixed-route services are expensive and do not provide good service at nighttime in low-density areas. In contrast, on-demand services with flexible and dynamic routing systems are more cost-effective in these areas (Sanaullah et al., 2021).

Some studies focused on transit agency costs and aimed to solve a supply optimization problem of TIMOD services. They assumed that agencies were responsible for all service costs and made vehicle assignments in response to incoming requests. Typically, the costs considered in the optimization include the agency's operating costs (distance traveled, fleet size, labor) and the user's time cost (waiting time and in-vehicle time) (Quadrifoglio & Li, 2009; Nourbakhsh & Ouyang, 2012; Grahn et al., 2022). Other studies focused on users' costs. Fixed-route transit would add to users' access and egress times because they have fixed pick-up and drop-off locations (Kumar & Khani, 2021). The agency's cost is often not included in these studies, for example, when assessing the incorporation of shared autonomous vehicles into public transportation systems (Nourbakhsh & Ouyang, 2012; Shen et al., 2018).

The user's time costs should be transformed into dollar values to compare the alternative modes better and contribute to the rider's utility function (Masoud et al., 2017). Service performance under different levels of demand density was also discussed (Kumar & Khani, 2021). Other factors could also contribute to the rider's cost but were often not considered in the literature, such as the cost of parking if choosing to drive and the perceived discomfort in the rider's experience.

4.2.4 Equity Implications of TIMOD services

New mobility services and transportation technologies such as MOD have been shown to bring substantial economic, environmental, and health benefits to society (Ashour et al., 2022; Li et al., 2016). However, the benefits may not be distributed among population groups in an equitable manner. Although equity is conceptually well-defined, there is no standard approach for assessing the equity performance of transportation systems. Existing studies often adopt a framework that considers population measurements, cost-benefit measurements, and inequality measurements. Population measurements define the human population for which the cost/benefit measure will be determined and compared, basically answering the question "equity for whom?" (Guo et al., 2020) Outcomes can be measured for individuals and for population groups that are defined based on either spatial location if horizontal equity is to be evaluated or based on sociodemographic characteristics if vertical equity is evaluated (Delbosc, 2011; Ricciardi, 2015). Cost/benefit measurement, on the other hand, quantifies the costs or benefits of interest (e.g., accessibility) for each population group. Inequality measurements are generally used to compare the outcomes among the spatially distributed population (horizontal equity) or among population subgroups (vertical equity) (Guo et al., 2020). This approach is often adopted to evaluate equity separately from the cost-effectiveness analysis, which has been most commonly used to inform decisions related to TIMOD projects.

Conventional cost-effectiveness analysis focuses on evaluating the economic costs and gains of transportation services. However, it does not address the question of who benefits and who loses from the new transportation services, which should be of important consideration for decision-makers. In recent years, there has been a growing interest among government institutions in incorporating equity concerns in many fields, including transportation, which has been amplified during the COVID-19 pandemic (Love-Koh et al., 2019). One of the most promising methods for incorporating equity into the cost-effectiveness analysis is the distributional cost-effectiveness analysis (DCEA), widely used in health-related research. DCEA facilitates a quantitative assessment of how the effects and costs are distributed between groups in a population (Asaria et al., 2015; Love-Koh et al., 2019).

4.3 Data and Methodology

4.3.1 Case Background and Data

This study evaluates the comparative cost-effectiveness of Metro Flex, which is a TIMOD service in the Seattle region. Metro Flex offers convenient, fast, and affordable rides in various areas: Juanita, Kent, Othello, Rainier Beach, Renton Highlands, Sammamish, Skyway, and Tukwila. The service costs the same as a regular Metro bus ride, with fares ranging from $2.75 for adults to free rides for youth aged 6-18. The service also provides ADA-accessible vehicles for passengers with mobility devices. For this study, I selected Sammamish and Rainier Beach (Figure 3.1), two service areas with distinct differences in transit accessibility, population density, and sociodemographic characteristics. Service hours vary depending on the location, ranging from 5:00 a.m. to 1:00 a.m. in Rainier Beach and 7:00 a.m. to 6:00 p.m. in Sammamish. Metro Flex can be booked through a user-friendly app or by calling 206-258-7739, offering a convenient and efficient way to travel within the designated service areas. The service replaces two previous transit options: Community Ride, a point-to-point on-demand service in Sammamish, and Via to Transit in Rainier Beach. Metro Flex offers on-demand services within the service area limits, regardless of the purpose of the trip.

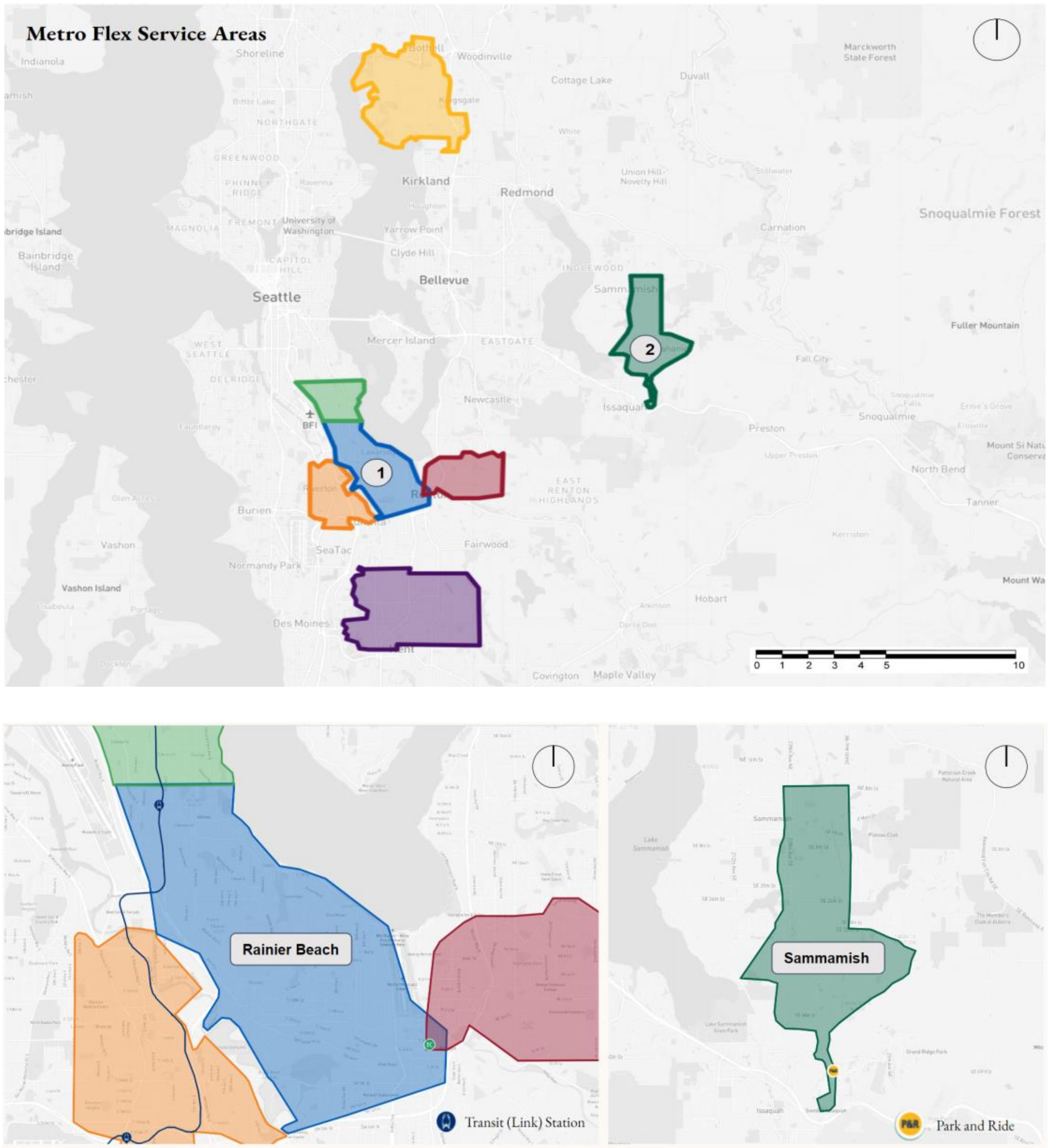

Figure 4.1 Metro Flex Service Areas and Case Studies

For Metro Flex trips, I used existing service trip data on May 4, 2023, which reflects the average ridership on a typical weekday based on daily ridership for May 2023[2]. The data consists of the request, pick-up, and drop-off times (in minutes) for every trip, origin and destination geo-coordinates, trip distance, and the number of seats requested. For TNCs, I used publicly available service apps to estimate the service costs and trip duration for the same trips in the counterfactual

[2] Metro Flex started operating in March 2023, and its ridership started to stabilize in May 2023.

scenario where Metro Flex was unavailable. For transit services, I worked with King County Metro (KCM) to obtain the costs for providing performance-equivalent fixed-route services. In the case of driving alone, I used historical traffic data from ArcGIS to estimate speed limits during different hours. I also estimated the cost of parking provided, which can be estimated using KCM data.

4.3.2 Methodological Framework

This study builds upon an analytical framework proposed by Wang and Shen (2023) for quantifying the economic costs of expanding mobility services in new or underserved areas. The framework emphasizes using marginal cost instead of system-wide average cost when considering service expansion or new mobility options, as it provides more pertinent information for decision-making. This chapter substantiates the conceptual framework to incorporate equity into the cost-effectiveness evaluation of TIMOD services from a societal perspective by considering the differences in sociodemographic and built-environment variables of different service areas. To do so, the study compares the cost-effectiveness of TIMOD services to two alternative baseline modes (drive-alone and fixed-route services) by estimating the users' (i.e., travelers') cost for each option. Travel cost estimates are based on Metro Flex trip data, which is used to simulate travel times for the alternative modes under the counterfactual scenario where Metro Flex is unavailable. For each alternative mode, the generalized costs are estimated, including monetary and time costs of travel (access, waiting, and egress times). Refer to Appendix C for more details on how the total generalized cost for each alternative mode (bus/drive alone) were estimated based on this framework.

4.3.3 Incorporating Equity into the Cost-Effectiveness Analysis

When transit agencies assess new service interventions, they often prioritize projects that enhance overall mobility services, reduce costs, and address existing inequality. However, traditional cost-effectiveness analyses do not fully consider the equity impacts or the tradeoffs between improving mobility services and reducing inequality. Distributional cost-effectiveness analysis (DCEA) is a well-established framework in health-related studies that can also be used to incorporate inequality impacts into transportation services evaluation. In this study, I use DCEA to model the social distribution of travel costs associated with different TIMOD service provision scenarios across different suburban areas and income groups and to evaluate the social distribution of travel costs.

The modeling stage involves estimating the baseline travel cost, which is represented by the generalized cost associated with existing alternative modes (fixed-route services and drive alone), modeling changes to this distribution due to the introduction of TIMOD services (Metro Flex), and comparing different service provision scenarios using the generalized travel cost for alternative (Asaria et al., 2015; Love-Koh et al., 2019). In this study, I have followed the Love-Koh et al. (2019) approach, conducting the following analysis steps:

- Define the relevant groups of interest: The first step includes defining the groups, which could be by geography, age, socioeconomic status, etc. Defining the group is analytically simple but challenging as no "right" group subdivision exists, especially when considering equity. In this chapter, I focus on income and built environment context as the main variables of interest. Due to the lack of rider-level income data, I have used the American Community Survey (ACS) median household income data by census block group to estimate the income of each traveler by spatially joining the census block group with Metro Flex trip data in ArcGIS, assuming that trip origins represent users' home location. Figure 4.2 illustrates the distributions of trip origins and census block group median household incomes.

- Defining the strategies/scenarios to evaluate: In this study, TIMOD is considered as an intervention that the transit agency (KCM) is looking to provide to enhance mobility options for travelers who live in suburban areas. To do so, the agency should better understand the different ways the service could be provided and the optimum scenarios, considering the effects of the service. Using travel cost as the main measure to denote the quality of the service and its effects on users, I explore and test different scenarios by which the service can be provided, as follows:

1. **Scenario (1):** Providing TIMOD Metro Flex service for all travelers in the two selected service areas. This scenario is similar to the default service KCM provides and uses the actual Metro Flex trip data to measure the generalized cost.
2. **Scenario (2):** Providing Metro Flex service for travelers living in high-density suburban areas (Rainier Beach) only. It is important to note that Rainier Beach also consists of lower-income groups than Sammamish. In this case, Sammamish travelers are assumed to use an alternative mode (bus or drive alone).
3. **Scenario (3):** Provide Metro Flex service for travelers living in low-density suburban areas (Sammamish) only.
4. **Scenario (4):** Provide Metro Flex service for travelers living in low-income areas (block groups) only, regardless of the neighborhood. According to the Seattle Housing Authority, low household income is estimated to be less than 77,000 in the Seattle Area. Hence, block groups with income below this threshold are selected from both areas and offered Metro Flex services. Others are assumed to use alternative modes (bus or drive alone).

While recognizing that there are more alternative modes and various inter-modal scenarios of using existing fixed routes, I simplify the comparison by considering three mutually exclusive options in the analysis:

- Bus: existing fixed-route service consists of buses in both service areas.
- Metro Flex: using the TIMOD service as an alternative to fixed-route transit.
- Drive alone: Driving alone is another alternative to fixed-route services.

To evaluate these alternative scenarios/modes, I measured the generalized cost for each trip by multiplying the different components of travel time (in-vehicle time, wait time, access, and egress times) and their estimated coefficients with the hourly income rate for every user. The resulting cost is the average cost for every income group by mode. Different income groups have different trip numbers that vary by service area, affecting the total generalized cost for each.

- Measure the baseline situation: The baseline situation is when Metro Flex (TIMOD) services are not available. In this case, travelers would use other available modes, including fixed-route buses or drive alone. In this study, I test two sets of scenarios, one in which users are assumed to use a fixed-route bus in the absence of TIMOD services in both service areas. This assumption has many limitations, especially since the Sammamish constitute a higher-income population with a high rate of car ownership and exhibit very poor fixed route service that is inefficient for local trips. Hence, the second set of scenarios assumes that the baseline mode for Sammamish travelers would be driving alone, in contrast to Rainier Beach, which would be fixed route buses. Both sets of assumptions evaluate the scenarios outlined in the section above.

- Measuring inequality in the resulting cost distribution: The impact of the technology here is seen as the difference in the cost of travel between fixed-route buses and Metro Flex. I have also looked at the impact of driving alone, as it resulted in the minimum generalized cost in the cost-effectiveness analysis. Inequality in cost distributions can be quantified in multiple ways, but I use two main indices to inform different inequality concerns from transit agencies. The first is Atkinson, a relative inequality index that measures the proportional change in cost across the distribution. The Atkinson index considers the number of population groups and inequality aversion to quantify how social welfare is reduced by relative inequality, as shown in equation (4):

$$A\varepsilon = 1 - \left[\frac{1}{N}\sum_{i=1}^{N} \left(\frac{Qi}{Q}\right)^{1-\varepsilon}\right]^{\frac{1}{1-\varepsilon}} \qquad (4)$$

Where $A\varepsilon$ is the Atkinson index, Q_i is the travel cost for income group *i* by introducing a new service (Metro Flex), measured by the generalized cost for group i, Q is the baseline cost for using existing fixed-route services, N is the number of individuals or subpopulation groups, and ε the inequality aversion parameter that quantifies the concern for relative inequality (ratios), which ranges from 0 to positive infinity, where 0 implies no aversion to income inequality, and values greater than 1 indicate a stronger aversion to income inequality. The specific value of ε is often arbitrary and determined based on the researcher or decision-maker's context objectives and preferences. It can also be chosen based on the desired level of sensitivity to income inequality in a particular economic or social study. The Atkinson index formula typically includes the aversion coefficient ε in its calculation, allowing for flexibility in measuring income inequality based on the degree of aversion chosen. Atkinson 1970 discusses that estimating and selecting the epsilon (ε) parameter should reflect societal preferences and equity objectives informed by empirical evidence and theoretical considerations. Researchers often use various methods to estimate ε, including experimental studies, survey data analysis, and theoretical models that incorporate preferences for equity. Existing literature employs inequality aversion values to inform optimal policies and decisions depending on the context. Climate policy-related studies have applied a narrow range of 0 to 3 (Azar and Sterner,1996; Anthoff, Hepburn, and

Tol, 2009; Dennig et al., 2015), while health-related policies have explored a wider range of epsilon values reaching up to 10. Comparatively, intertemporal inequality aversion values for benefit-cost analyses vary widely. In transportation-related research, however, the Atkinson inequality indicator is not commonly used or inadequately represented in measuring transport inequality. In this chapter, I explore three values to denote different levels of inequality aversion, including 2 (denoting low aversion), 5 (moderate aversion) and 10 (high aversion).
I also looked at the Kolm index, which measures the absolute change in cost across the distribution, as shown in equation (5):

$$K\alpha = \left(\frac{1}{\alpha}\right) \log \left(\frac{1}{N} \sum_{i=1}^{N} \; e^{\alpha[Q-Qi]}\right) \tag{5}$$

Where Kα is the Kolm index, Qi is the travel cost for income group i by introducing a new service (Metro Flex), measured by using generalized cost for group i, Q is the baseline cost for using existing fixed-route services, N is the number of individuals or subpopulation groups, and α represents the level of constant absolute inequality aversion. Comparing Atkinson and Kolm indices before and after introducing a TIMOD service (e.g., Metro Flex) provides insights into the inequality of the generalized cost distribution between different income groups. If the Atkinson index decreases with TIMOD service, it indicates a decrease in the cost distribution inequality, especially if it decreases for higher ε values, which suggests a focus on reducing inequality. Similarly, a decrease in the Kolm index signifies a reduction in cost distribution inequality to achieve equity. Hence, a lower Atkinson index value (with the same ε) indicates reduced inequality and a lower Kolm index value means less cost needs to be distributed among different income groups for perfect equality.

- Social welfare analysis: Having separately quantified the average cost for every income group and inequality resulting from each alternative mode (Metro Flex and drive alone), I combined concerns for minimizing travel cost and concerns for minimizing inequality across different income groups using social welfare analysis. I compared the different modes using social welfare indices that explicitly trade off increases in the mean cost against greater equality in the cost distribution by calculating an "equally distributed equivalent" (EDE) cost level each income group would receive in a hypothetically perfectly equal distribution. I focus on two social welfare indices constructed by combining the mean cost with the Atkinson and Kolm indices.

$$EDEx_{A\varepsilon} = (1 - A\varepsilon)Q \tag{6}$$

$$EDEx_{K\alpha} = (Q - K\alpha) \tag{7}$$

In the case of no concern for inequality (α = ε = 0), the social welfare indices collapse to the average cost. The difference between the average cost by mode and EDE for different inequality aversion values indicates the average increase in cost for travelers to achieve a perfectly equal cost distribution, which allows for ranking alternative travel modes over a range of possible inequality aversion levels.

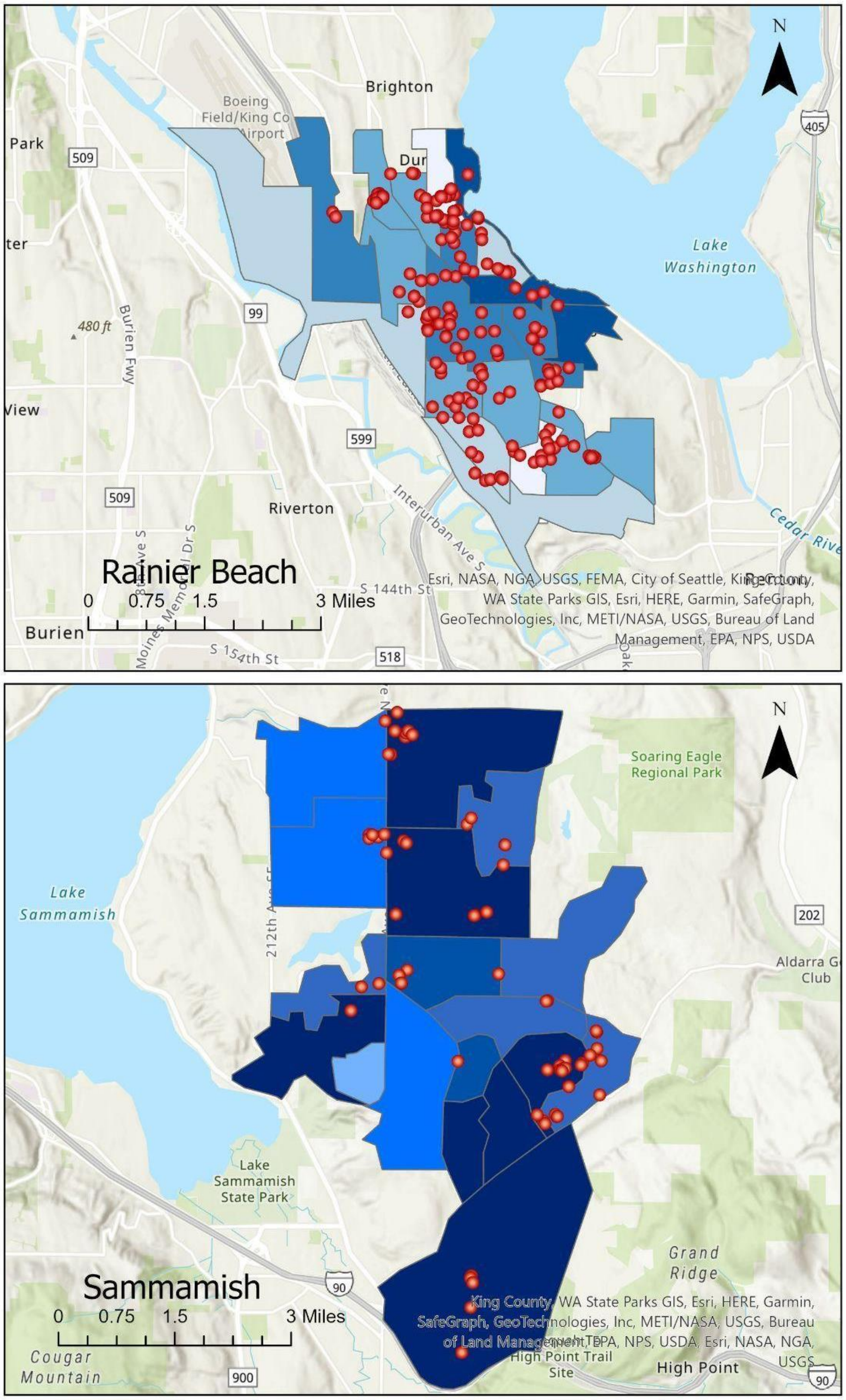

Figure 4.2 Median Income and Metro Flex Trips

4.4 Results

4.4.1 Comparing Travel Time by Mode of Transportation

Figure 4.1 and Table 4.1 show the distributions of travelers' total travel time by each transportation mode. Table 4.1 provides a detailed breakdown of the time components for each mode. The travel time by Metro Flex was obtained from observed trip data. The time interval between request creation time and pickup time equals the sum of walk access time and waiting time. The maximum walk access time was assumed to be 5 minutes. If the time interval between request creation time and pickup time was less than 5 minutes, the passengers were assumed to spend all the time walking. The travel times by driving alone and transit were estimated by SUMO simulation.

Table 4.1 Descriptive Statistics of Travel Time by Mode

Mode	**Mean**	**Std.**	**Min.**	**Max.**
Metro Flex	22.16	10.35	3.09	58.72
Access Time	4.85	0.53	1.05	5.00
Waiting Time	7.49	7.36	0.00	38.46
Shared Trips	8.03	7.37	0.00	38.46
Non-shared Trips	6.42	7.23	0.00	36.99
In-vehicle Time	9.82	5.99	1.32	34.50
Shared Trips	11.30	6.32	1.80	34.50
Non-shared Trips	6.88	3.85	1.32	27.63
Transit (bus)	31.72	16.67	4.78	96.95
Access Time	15.73	11.45	0.28	56.62
Waiting Time	8.12	10.72	0.00	68.58
In-vehicle Time	7.72[3]	6.97	0.00[4]	38.27
Drive Alone	9.44	3.17	4.00	21.13
In-vehicle Time	7.44	3.17	2.00	19.13
Parking Time	2	0	2	2

[3] The average in-vehicle time for fixed-route transit is shorter than that of Metro Flex because the low density of transit service in the study areas results in many transit riders only taking bus for a small segment of their trip.
[4] The minimum in-vehicle time by fixed-route transit is zero because for some of the trips, transit is not even an option due to the limited service coverage. In these cases, people are assumed to walk to their destinations, resulting in a long access time.

From the overall distribution of trip durations, Metro Flex takes more time than driving alone and less time than transit. Compared to driving alone, Metro Flex trips have a much longer average in-vehicle time and a much longer average waiting time, similar to transit. Although non-shared Metro Flex trips have a shorter average waiting time than shared trips, it is still over 6 minutes. In addition, the long transit trips with long access and waiting times result from the low transit service coverage in the study areas, especially Sammamish. The average in-vehicle time for transit excludes trips that could not be made through transit.

4.4.2 Equity Implications and Tradeoffs of Alternative Services

4.4.2.1 Descriptive Analysis

Before analyzing the distribution of travel cost and inequality analysis of different TIMOD scenarios, I initially explore the travel cost of each mode separately and as mutually exclusive options (bus, drive alone, and Metro Flex). Figure 4.3 shows the baseline distribution of generalized travel costs for fixed-route buses. The travel cost of existing fixed routes is disproportionately higher for high-income groups, especially if the generalized travel cost is adjusted and calculated based on their hourly income rate.

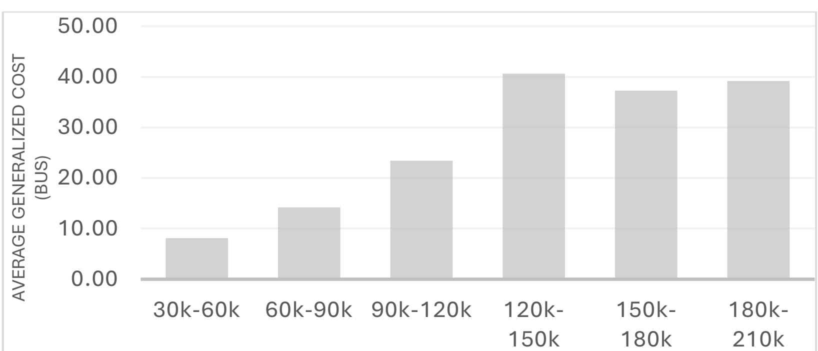

Figure 4.3 Bus (Baseline) Generalized Cost by Income Group

However, it is important to note that the two service areas have distinctly different income compositions. Sammamish has predominantly higher-income groups compared to Rainier Beach (as shown in Figure 4.4). Despite this, Rainier Beach has a much higher trip volume (demand) than Sammamish. This could be explained by the different population densities of the two areas, as well as the income disparity, which may indicate a higher reliance on driving in Sammamish.

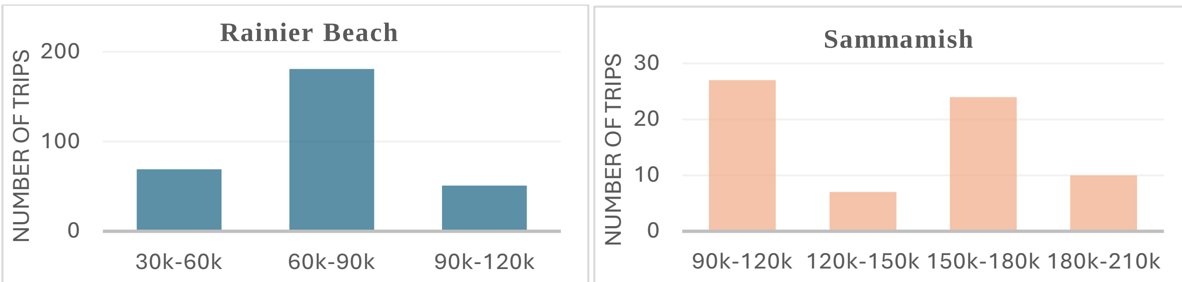

Figure 4.4 Number of TIMOD Trips per Income Group

I next look at the impact of TIMOD (Metro Flex) on the baseline cost distribution and compare it to other baseline modes (bus and drive alone). Figure 4.5 shows the average generalized cost for every income group by mode. Figure 4.6 shows the total generalized travel cost for every income group by mode, which reflects the difference in demand levels and volume of trips. The latter shows that lower-income groups have a higher demand for TIMOD services, indicating a higher need to prioritize equity among the poorest.

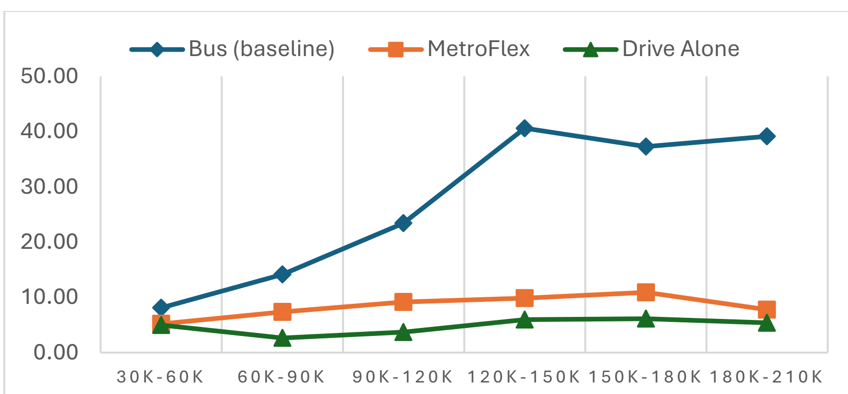

Figure 4.5 Average Generalized Travel Cost by Income Group

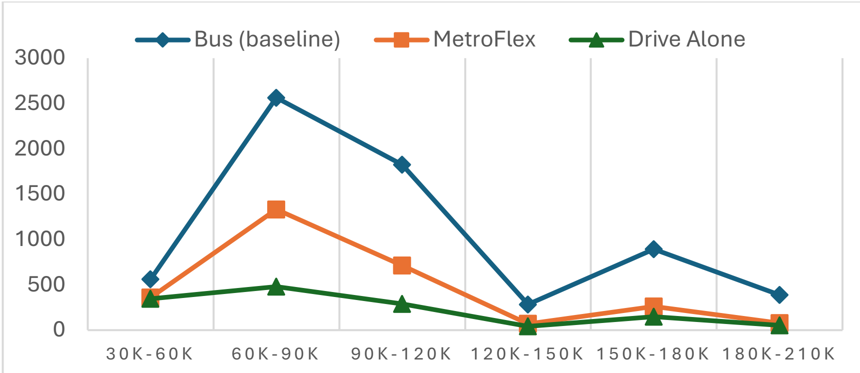

Figure 4.6 Total Generalized Travel Cost by Income Group

Compared with the fixed route (bus), the average generalized travel cost and total generalized travel cost drop for all six income groups using Metro Flex or driving alone. Table 4.2 shows the average generalized cost for different income groups by mode per service area, reflecting different hourly wage rates for each group. By comparing travel costs across the different modes, the table shows that the cost reduction compared to the fixed route (bus) is disproportionately higher for high-income groups ($120k and above) for both driving alone and Metro Flex. Using the distribution of trips and median income, Metro Flex and Drive alone reduce the overall travel costs compared to that of fixed routes (bus) in both Sammamish and Rainier Beach.

Table 4.2 Traveler's Generalized Cost for Different Income Groups by Mode

Sammamish			
Group	Bus (baseline)	Metro Flex	Drive Alone
90k-120k	34.00	10.20	6.34
120k-150k	36.02	8.17	5.92
150k-180k	37.26	10.91	6.14
180k-210k	39.16	7.79	5.41
Average cost	36.61	9.27	5.95
Difference vs. Baseline		27.34	30.66
Rainier Beach			
Group	Bus (baseline)	Metro Flex	Drive Alone
30k-60k	8.11	5.20	5.01
60k-90k	14.17	7.36	2.65
90k-120k	17.81	8.59	2.33
Average cost	13.36	6.90	4.67
Difference vs. Baseline		6.46	8.69

Rainier Beach + Sammamish (combined)			
Group	Bus (baseline)	Metro Flex	Drive Alone
30k-60k	8.11	5.20	5.01
60k-90k	14.17	7.36	2.65
90k-120k	23.41	9.15	3.72
120k-150k	40.61	9.89	5.98
150k-180k	37.26	10.91	6.14
180k-210k	39.16	7.79	5.41
Average cost	28.86	9.32	4.62
Difference vs. Baseline	-	19.54	24.24

4.4.2.2 Scenario-Based Analysis – Cost and Benefit Distribution

This previous descriptive analysis compares the three modes, assuming that they are mutually exclusive. The graphs adjust the overall cost to account for varying hourly rates among the different groups. Transit trips in high-income areas, such as Sammamish, are considerably longer due to the limited fixed-route options available. Additionally, the average hourly income is much higher in Sammamish. Because of this, the following scenario analysis is based on the average hourly income rate in Seattle for all travelers. The scenarios involve different levels of provision of TIMOD services and different geographical area (service area) limitations. It is assumed that the average income of travelers is similar to their location. Two different scales of location are considered to formulate these scenarios. First, the neighborhood scale (e.g., Sammamish vs. Rainier Beach), and second, the census block group scale (to denote the median income of travelers).

Table 4.3 reports a range of absolute and relative inequality measures calculated for each Metro Flex service provision scenario compared to alternative travel modes. The table shows the scenarios under two assumptions: travelers lacking access to Metro Flex would use the fixed-route bus instead as the baseline mode, or the baseline mode varies between Rainier Beach (bus) and Sammamish (drive alone) as well as low-income census block groups (bus) and high income census block groups (drive alone).

Table 4.3 Relative and Absolute Inequality Indices by Mode/Intervention

			Baseline mode: bus				**Baseline mode: drive**	
			Scenario (1)	**Scenario (2)**	**Scenario (3)**	**Scenario (4)**	**Scenario (2)**	**Scenario (4)**
Mode	**Bus**	**Drive Alone**	**For all**	**Metro Flex (Rainier Beach)**	**Metro Flex (Sammamish)**	**Metro Flex (low-income)**	**Metro Flex (Rainier Beach)**	**Metro Flex (low-income)**
Mean Travel Cost ($)	19.40	4.04	**8.51**	13.44	14.47	9.95	**7.79**	9.24
Relative Inequality Indices								
Atkinson Index (ε=2)	0.334	0.238	0.229	0.450	0.269	0.352	**0.199**	0.369
Atkinson Index (ε=5)	0.617	0.500	0.552	0.714	0.529	0.631	**0.512**	0.657
Atkinson Index (ε=10)	0.754	0.656	0.756	0.846	0.765	0.773	**0.734**	0.789
Absolute Inequality Indices								
Kolm Index (α=0.1)	9.519	0.743	1.691	11.480	3.575	4.068	**1.421**	4.067
Kolm Index (α=0.15)	13.806	0.747	1.864	16.322	4.331	6.283	**1.528**	6.104
Kolm Index (α=0.5)	23.245	0.827	5.286	25.831	9.330	13.971	**2.943**	13.661

Bold font indicates the most equal mode.

ε=2 represents low relative inequality aversion while ε=10 represents high relative inequality aversion

α=0.1 represents low absolute inequality aversion while α=0.5 represents high absolute inequality aversion

The Atkinson index, which measures proportional differences and is sensitive to changes across the entire distribution, was adjusted by three inequality aversion parameters ϵ, to capture different levels of equality consideration. The analysis shows that relative inequality is lower for Scenario (2), which involves providing service exclusively in Rainier Beach, under the assumption that Sammamish travelers would drive alone if Metro Flex were not available. Conversely, if Sammamish travelers are assumed to use the bus as their baseline mode, Scenario (1), which provides Metro Flex service to all areas/travelers, becomes the most equitable option. Additionally, Scenario (2) results in the lowest average travel cost when Metro Flex is available only in Rainier Beach, assuming Sammamish travelers drive alone. This suggests that providing TIMOD services in high-density suburban areas, often including lower-income populations, is the most equitable intervention based on the Atkinson index. On the other hand, the Kolm index focuses on absolute differences in the distribution and measures the actual disparities in costs, adjusted by the inequality aversion parameter α. The absolute inequality measures (Kolm) also show that Scenario (2), under the assumption of drive alone, exhibits the most equitable distribution of travel costs in absolute terms.

If transit agencies would like to rank these scenarios (interventions), it is possible to use alternative economic dominance rules provided by Atkinson (Atkinson, 1970). In this case, the dominance rule would apply to the intervention with the lowest travel cost and inequality. On this criteria, scenario (2) would dominate if transit agencies find the assumption that Sammamish travelers would drive alone for their trips if Metro Flex were not available. Otherwise, scenario (1) would be a more equitable intervention, but it would increase the average travel cost.

Having used distributional dominance to eliminate scenario (3) and scenario (4), to compare the remaining two scenarios, it is important to conduct a social welfare analysis to understand the tradeoff between reducing total travel cost and the level of cost inequality (i.e., the amount of travel cost that a decision maker would be willing to increase/impose on travelers to achieve an equal distribution). Because the inequality aversion parameters are difficult to interpret on a raw scale, I derived the equally distributed equivalent (EDE) travel cost calibrated on the same scale, which presents the additional cost each person in the population would receive in a hypothetically perfectly equal distribution. The values of these indices are shown in Table 4.4.

Table 4.4 Relative and Absolute EDE Indices by Mode/Intervention

			Baseline mode: bus				Baseline mode: drive	
			Scenario (1)	Scenario (2)	Scenario (3)	Scenario (4)	Scenario (2)	Scenario (4)
Mode	**Bus**	**Drive Alone**	**For all**	**Metro Flex (Rainier Beach)**	**Metro Flex (Sammamish)**	**Metro Flex for low-income**	**Metro Flex (Rainier Beach)**	**Metro Flex for low-income**
Relative Inequality Indices								
Atkinson EDE (ε=2)	12.914	3.083	6.558	7.384	10.576	6.451	6.242	**5.827**
Atkinson EDE (ε=5)	7.424	2.021	3.813	3.840	6.812	3.668	3.804	**3.165**
Atkinson EDE (ε=10)	4.775	1.392	2.074	2.074	4.704	2.262	2.074	**1.949**
Absolute Inequality Indices								
Kolm EDE (α=0.1)	9.878	3.300	6.817	**1.955**	10.896	5.884	6.309	5.171
Kolm EDE (α=0.15)	5.592	3.297	6.644	**2.886**	10.140	3.670	6.221	3.134
Kolm EDE (α=0.5)	-3.847	3.216	3.222	**1.396**	5.141	1.519	3.075	1.423

The social welfare indices show that, considering relative inequality, providing Metro Flex services for low-income areas alone maximizes social welfare even as inequality aversion increases. However, this intervention scenario has been excluded in the step above. Under the assumption that the baseline mode for Sammamish is driving alone, the results show that travelers would bear the least additional costs to achieve equality if Metro Flex services were provided in Rainier Beach only. Overall, the results show that providing Metro Flex in high-density, low-income suburbs decreases relative inequality, regardless of the assumed baseline mode. In the case of Sammamish, most residents are high-income, and they are highly unlikely to rely on fixed routes as their baseline mode. Hence, under the assumption that people in Sammamish would drive alone in the absence of TIMOD services, providing TIMOD becomes more equitable in high-density suburban areas such as Rainier Beach. Under the same assumption, providing TIMOD exclusively in Rainier Beach or similar suburban areas (considering density and income levels) would maximize social welfare by minimizing the additional costs travelers must bear to achieve equitable social distribution of the costs and benefits of new mobility interventions. Transit agencies should carefully consider the built environment variables and income levels of suburban areas in which they provide new interventions to allocate resources where they are most needed and increase overall equality and efficiency of mobility services.

4.5 Conclusion

This study develops a framework incorporating equity into a comparative cost-effectiveness evaluation framework of Transit Incorporating Mobility on Demand (TIMOD) in low-density suburban areas. The findings underscore the potential of TIMOD services, particularly in addressing first-mile/last-mile connections and supplementing fixed-route transit in low-density areas.

The results revealed various insights into the cost-effectiveness of different modes of transportation. Assuming unified rider sociodemographic characteristics, Metro Flex has the advantage of saving travelers time over fixed-route transit. However, driving alone is the most cost-effective mode of transportation in the study areas. The situation may differ in densely populated areas, where heavy traffic and induced congestion can significantly and negatively affect driving speed. In Sammamish, where the density of transit service is relatively low, the total generalized cost per transit rider is relatively high for using transit, making TIMOD services an effective alternative. However, Sammamish is also a high-income area, where residents will likely own a car and drive for most of their local trips. This suggests that whether TIMOD can be cost-effective as an alternative to fixed-route transit is context-dependent.

By incorporating distributional cost-effectiveness analysis (DCEA), the study quantifies how the effects and costs of TIMOD services are distributed among travelers based on their income and geographic location. The analysis reveals that while TIMOD services can lead to cost reductions for all income groups, they are particularly beneficial for lower-income groups, thus helping to mitigate inequality in transportation costs. Considering three mutually exclusive alternative modes, which are TIMOD service (MetroFlex), fixed-route (bus), and drive alone, the distributional cost-effectiveness analysis shows that for different levels of relative inequality aversion (ε=2, ε=5, and ε=10), the Atkinson index is lowest for Metro Flex, followed by drive alone, and then fixed-route transit. This suggests that Metro Flex is the most equitable transportation mode in relative inequality. On the other hand, driving alone appears more attractive in terms of its absolute inequality and maximizing social welfare, mainly due to its lower travel costs. While both alternative modes improve social welfare compared to fixed-route buses, providing TIMOD services such as Metro Flex reduces relative inequality of travel cost, especially among lower income groups, which offers affordable travel options in suburban areas, especially for those who don`t have access to cars.

TIMOD services are costly for transit agencies. Hence, a more nuanced understanding of the costs and benefits associated with providing the service in different geographic contexts and for other groups could help agencies strategize their service provision and prioritize certain areas/groups while improving mobility and equality in suburban areas. Sammamish and Rainier Beach have different built environments and sociodemographic characteristics, resulting in different time values for users of fix-route transit and microtransit in the two regions. Using a scenario-based approach, this chapter finds that providing TIMOD services in all suburban areas, especially when replacing inefficient fixed-route transit, can reduce relative inequality. However, in comparison to affluent areas like Sammamish, where residents predominantly rely on private vehicles rather than fixed routes, TIMOD would enhance equity more effectively in denser, low-income suburbs such as Rainier Beach. Focusing TIMOD efforts in low-income and high-density suburban areas would optimize social welfare by minimizing additional travel costs and ensuring a more equitable distribution of benefits across varying income and density levels. Transit agencies would also benefit from reducing the overall cost of providing TIMOD in low-density, high-income suburbs to better allocate resources for areas that would maximize the overall social welfare and minimize inequality. Therefore, it is rather essential for planners and transit agencies to consider local built environments and income demographics when planning TIMOD interventions to maximize equity outcomes.

Overall, this study contributes to the growing body of research on integrating innovative mobility solutions into public transit networks. By providing insights into the cost-effectiveness and equity implications of TIMOD services, our findings can inform decision-making processes for transportation planners and policymakers aiming to improve mobility in low-density suburban areas. However, further research is needed to explore the long-term impacts and scalability of TIMOD services and their potential to address broader transportation equity concerns. Moreover, additional research and policy considerations are needed to address the challenges and potential benefits of implementing TIMOD services for different contexts and urban environments.

Chapter 5: Discussion

The COVID-19 pandemic has catalyzed significant shifts in work arrangements and travel behavior, reshaping urban mobility and transportation systems. As telework becomes more prevalent and shared mobility, particularly public transit, witnesses a decline, understanding the implications of these changes is paramount for ensuring equitable and efficient transportation systems. This dissertation addresses these evolving dynamics and their impact on transportation equity, cost-effectiveness, and integrating new mobility services into public transit.

5.1 Summary of the three studies:

The dissertation's objectives revolve around investigating post-pandemic mobility needs, identifying opportunities and barriers to integrating new mobility services into public transit, and incorporating equity into cost-effectiveness evaluations. Chapter 2 delves into understanding mobility patterns, needs, and equity gaps in the "new normal." Using data from the 2022 Seattle Commute Survey, the analysis reveals the transformative influence of telework on travel patterns, with higher-income individuals more likely to drive alone and disparities existing in access to sustainable transportation options. Using the Multiple Discrete-Continuous Extreme Value (MDCEV) model, the study provides critical and timely insights into the factors influencing commute mode choice. The findings highlight the significant influence of sociodemographic characteristics, job-related factors, and built environment variables on mode choice. The findings underscore the need for policies promoting equitable access to public transit and alternative commute options, especially for vulnerable groups. This chapter lays the groundwork by examining how the COVID-19 pandemic has reshaped travel behavior and mobility patterns. It investigates the impact of telework on commute mode choice and highlights disparities in access to sustainable transportation options, particularly affecting vulnerable groups. By identifying these equity gaps and understanding the evolving needs of commuters, Chapter 2 sets the stage for subsequent discussions on integrating new mobility services into public transit while ensuring equitable access for all individuals.

Chapter 3 investigates the opportunities and barriers to incorporating new mobility services into public transit, particularly ride-sourcing services. The study forecasts potential TNC price increases and their implications for transit agency-TNC partnerships, highlighting challenges posed by regulatory pressures and profitability concerns. Despite the benefits of such partnerships, escalating TNC prices jeopardize their effectiveness, necessitating careful examination and potential regulatory measures to mitigate adverse impacts on transit agencies and riders. Building on the insights gained from Chapter 2, this chapter delves into the opportunities and challenges of integrating new mobility services, such as ride-sourcing, into public transit. It forecasts potential TNC price increases and assesses their implications for transit agency-TNC partnerships by employing two time-series models, namely ARIMA and PROPHET. The results show that TNC's daily average price could increase by 40% from pre-pandemic rates average rates. Moreover, by examining the evolving market and policy environments surrounding new mobility services, Chapter 3 provides valuable insights into the feasibility and sustainability of such partnerships, thereby addressing the objectives of understanding the barriers and opportunities in integrating new mobility services into public transit.

In Chapter 4, the dissertation takes a deeper dive into the equity implications of Transit Incorporating Mobility on Demand (TIMOD) services in low-density suburban areas. By developing a framework that incorporates equity into the cost-effectiveness evaluation of

TIMOD, using distributional cost-effectiveness analysis (DCEA), this chapter addresses the objective of integrating equity considerations into transportation planning. It highlights the potential of TIMOD services to mitigate transportation cost disparities among different income groups and geographic contexts, especially considering the nuances between different suburban areas (density, transit accessibility, and income), and emphasizes the importance of analyzing equity and efficiency trade-offs when introducing new services like TIMOD, using scenario planning to inform decision-making processes for transportation planners and policymakers.

5.2 Contributions

This dissertation makes several significant contributions to the field of transportation planning and equity, with direct and practical implications. Firstly, it provides insights into the impact of telework on travel behavior, a topic of increasing relevance in the post-pandemic era, and the need for equitable access to sustainable transportation options. The study on telework (Chapter 2) sheds light on how remote work arrangements influence commute mode choice. This information can help city planners understand the potential changes in traffic patterns and demand for public transit on different workdays. This timely knowledge can be used to optimize infrastructure investments and service schedules for buses, trains, and other public transportation options. Secondly, it highlights the challenges and opportunities of integrating new mobility services into public transit, a pressing issue in the face of TNC price increases. The study on TNC price increases (Chapter 3) explores the challenges of integrating new mobility services like ride-hailing with public transit. City planners can use this information to develop strategies for fostering partnerships with TNCs while ensuring affordability and effectiveness for riders. Thirdly, it offers a framework for incorporating equity into evaluating innovative mobility solutions like TIMOD, shedding light on their potential to address transportation equity concerns in suburban areas. The research on TIMOD services (Chapter 4) explores their potential to address transportation mobility efficiency and equity concerns, particularly in low-density suburban areas. City planners can leverage these findings and methods to assess the cost-effectiveness of implementing TIMOD services in specific neighborhoods and identify targeted groups and areas where they can offer the most significant benefits for residents with limited mobility options while maximizing equity and efficiency of their mobility services.

Throughout the dissertation chapters, I highlight the pressing need to recognize evolving disparities in access to sustainable transportation options faced by low-income individuals, minorities, people with disabilities and individuals who depend on public transit to meet their mobility needs. The knowledge presented here could serve as a call to action, informing policy decisions aimed at promoting affordable and accessible public transit, as well as alternative commute options to create a more just and inclusive transportation system for all in Seattle and nationwide, and support evidence-based decision-making when allocating resources for transportation infrastructure and services.

The dissertation offers valuable insights into the evolving landscape of transportation in the post-pandemic era, but some limitations affect the generalizability and applicability of its findings:

- Chapter 2: (Telework Impact on Commute Mode Choice):

The study relies on data from the 2022 Seattle Commute Survey, limiting generalizability to other cities with potentially different demographics, urban planning, and transportation infrastructure. The data collection period (2022-2023) captures a specific timeframe post-pandemic. Travel behavior might change over time, requiring further research to assess the persistence of observed trends.

- Chapter 3: (TNC Price Increases and Transit Agency Partnerships):

The study forecasts and applies TNC price changes in Chicago to Seattle, assuming similar trends, which might only be partially accurate. The model does not account for factors like TNC discounts, traffic patterns, and driver availability, which can impact trip prices. The analysis uses spatially averaged data, potentially missing the impact of localized regulations on surge pricing.

- Chapter 4: (Equity in TIMOD Cost-Effectiveness):

The cost-effectiveness of TIMOD services compared to fixed-route transit and driving alone depends on factors like population density and existing transit infrastructure. The study focuses on low-density suburbs, specifically two different suburbs in the Seattle Area, and the findings might be confined to this context. The cost-effectiveness analysis assumes similar rider characteristics (e.g., income level) per neighborhood or geographic area (e.g., census block group). Real-world scenarios might involve variations in travel needs and preferences. Finally, the study explores equity in TIMOD services within specific geographic areas. Further research is needed to understand their broader applicability in addressing transportation equity concerns across different contexts.

5.3 Future Research

Future research endeavors should explore the long-term impacts and scalability of TIMOD services and their potential to address broader transportation equity concerns beyond suburban areas. Additionally, further investigation is needed into the persistence of pandemic-induced shifts in travel behavior and their implications for urban planning and infrastructure needs. Studies should also assess the effectiveness of existing and planned policies to promote sustainable and equitable mobility services, considering evolving societal trends and unforeseen events. The dissertation lays the groundwork for future research that can refine and expand upon its findings. Here are some critical areas for exploration:

- Investigate how telework arrangements influence travel behavior over time and how this affects urban planning and infrastructure needs.
- Explore the equity implications of integrating TNCs with public transit, considering factors like accessibility, affordability, and service availability in underserved communities.
- Assess the long-term sustainability and scalability of TIMOD services in various urban environments, including denser areas.
- Analyze the policy landscape surrounding TIMOD implementation, considering its effectiveness under different regulatory frameworks and funding mechanisms.
- Conduct broader cost-effectiveness analyses that compare TIMOD services with other emerging mobility options alongside traditional fixed-route transit and driving.

By addressing these limitations and pursuing further research, policymakers and transportation planners can better understand the evolving transportation landscape and make informed decisions to ensure equitable and sustainable mobility for all.

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Appendix A: Seattle Commute Survey (2022) Questionnaire

Start of Block: Default Question Block

Q1 **Thank you for participating in the Seattle Commute Survey!** Help Seattle plan for more transportation choices! The core survey will take around 5 minutes to complete with the option to take additional questions.
Commute Seattle, the Mobility Innovation Center at the University of Washington (UW), and the Seattle Department of Transportation (SDOT) are committed to maintaining the anonymity of every individual who takes the Seattle Commute Survey. While, as a public agency, SDOT is required by RCW 42.56 to provide certain information in response to Public Disclosure Requests, the information provided under such a request will not include the identities of individual survey respondents. The electronic survey system does not allow users to view or export data in a way that connects personally identifying information with a respondent's survey answers.

Q2 **Please enter the name of your company or employer**

○ Company/employer Name (e.g., Amazon) (1)
____

Q3 **Please enter the full address of your worksite (e.g. 1800 9th Ave, Seattle, WA 98101)**
If you work from home full-time, please enter your employer`s address Use the search box below the map to find your worksite

____

Q4 Suite/floor # (if not applicable, enter NA or leave empty)

____

Q5 **Which of the following best describes your employment status?**

○ Full-time (35+ hours per week) (1)

○ Part-time (less than 35 hours per week) (2)

Q6 **Which of the following best describes your work schedule?**

○ 5 days a week (1)

○ 4 days a week (7)

○ 3 days a week (8)

○ 9 days in 2 weeks (9)

○ 7 days in 2 weeks (10)

○ Other (please specify) (11) ________________

Q7 **Do you expect this schedule to be consistent for the next six months?**

○ Yes (2)

○ No (6)

○ Unsure (3)

Q8 **When do you typically begin work?**

- 6 am - 8:59 am (3)
- 9 am - 11:59 am (4)
- 12 pm - 2:59 pm (5)
- 3 pm - 5:59 pm (6)
- 6 pm - 8:59 pm (7)
- 9 pm - 11:59 pm (8)
- 12 am - 2:59 am (1)
- 3 am - 5:59 am (2)

Q9 **When do you typically end work?**

- 6 am - 8:59 am (3)
- 9 am - 11:59 am (4)
- 12 pm - 2:59 pm (5)
- 3 pm - 5:59 pm (6)
- 6 pm - 8:59 pm (7)
- 9 pm - 11:59 pm (8)
- 12 am - 2:59 am (1)
- 3 am - 5:59 am (2)

Q10 **Currently, during a typical week, how do you get to work each day?**
If you do not have a typical week, please report on last week.
Please select the option you use for the LONGEST DISTANCE to get to work.
Fill in ONLY ONE type of transportation per day.
Fill in "Carpooled" only if at least one other person age 16 or older was in the vehicle

	Public transit (1)	**Ferry** (2)	**Vanpool** (3)	**Carpool** (4)	**Employer shuttle** (5)	**Uber/Lyft** (6)	**Taxi** (7)	**Drive alone** (9)	**Motorcycle** (10)	**E-bike/e-scooter** (11)	**Bike/scooter** (12)	**Walk** (13)	**Remote work** (14)	**Day off** (15)
Mon (1)	○	○	○	○	○	○	○	○	○	○	○	○	○	○
Tues (2)	○	○	○	○	○	○	○	○	○	○	○	○	○	○
Wed (14)	○	○	○	○	○	○	○	○	○	○	○	○	○	○
Thu (3)	○	○	○	○	○	○	○	○	○	○	○	○	○	○
Fri (4)	○	○	○	○	○	○	○	○	○	○	○	○	○	○
Sat (5)	○	○	○	○	○	○	○	○	○	○	○	○	○	○
Sun (6)	○	○	○	○	○	○	○	○	○	○	○	○	○	○

Page Break

Q11 **How many people are usually in your vehicle (age 16 or older), including yourself?**

	Number of people						Unsure				
	1	2	3	4	5	6	6	7	8	9	10
Carpool ()											
Uber/Lyft ()											
Motorcycle ()											
Vanpool ()											
Taxi ()											

Q12 **How do you typically get to the ferry?**

- ○ Drive alone (1)
- ○ Bike/scooter (2)
- ○ E-bike/e-scooter (3)
- ○ Walk (4)
- ○ Taxi (5)
- ○ Uber/Lyft (6)
- ○ Public transit (bus, light rail..) (7)
- ○ Other (8)

Q13 **Which type of vehicle do you typically use when driving to work?**

- ○ Gasoline engine (1)
- ○ Diesel (2)
- ○ Electric (3)
- ○ Hybrid electric (4)
- ○ Other (8)

Q14
On days you commute physically, approximately how many miles is your <u>typical</u> commute length? (the one-way distance from home to work) *If you do not know, enter 999* *Enter numerical values only*

○ Miles (2) ____

Q15 **Please enter your home location zip code (e.g. 98101)**

○ Home zip code (1) ____

Q16 **Could you please help us answer some additional questions? Your input will enable transit agencies and employers to better serve your commuting needs.**

After you complete the survey, you can be redirected to the survey raffle for a <u>chance to win one of ten $100 gift cards</u>

○ Yes (1)

○ No (2)

Q17
Thanks for taking participating in the Seattle Commute Survey.

End of Block: Thank you message

Start of Block: Optional Questions

Q18 **What is your age?**

- ○ 15 - 24 (8)
- ○ 25 - 34 (11)
- ○ 35 - 44 (12)
- ○ 45 - 54 (13)
- ○ 55 - 64 (14)
- ○ 65 - 74 (15)
- ○ 75 - 84 (16)
- ○ 85 or older (17)

Q19 **Do you identify as…**

- ○ Male (1)
- ○ Female (4)
- ○ Non-binary or non-conforming (5)
- ○ Transgender (6)
- ○ Prefer not to answer (7)
- ○ Prefer to self describe (8) ____

Q20 **Which of the following best describes your household income last year?**

- ○ Less than 30,000 (1)
- ○ 30,000 - 59,999 (4)
- ○ 60,000 - 89,999 (5)
- ○ 90,000 - 119,999 (6)
- ○ 120,000 - 149,999 (7)
- ○ 150,000 or more (8)
- ○ Prefer not to answer (9)

Q21 **What is the highest degree or level of education you have completed?**

- ○ Less than high school (9)
- ○ High school (10)
- ○ Vocational/technical training (11)
- ○ Associate degree (12)
- ○ Bachelor's degree (13)
- ○ Graduate degree or postgraduate studies (14)
- ○ Other (15)
- ○ Prefer not to answer (16)

Q22 **Please specify your race/ethnicity.**
(Choose multiple boxes if you are multiracial)

- ☐ White (1)
- ☐ Black or African American (4)
- ☐ Hispanic or Latino (5)
- ☐ Asian (6)
- ☐ American Indian or Alaska Native (7)
- ☐ Native Hawaiian or Other Pacific Islander (8)
- ☐ Other/Unknown (9)
- ☐ ⊗Prefer not to answer (10)

Q23 **Do you have regular access to any of the following vehicles?**
(Select all that apply)

- ☐ Car or truck (1)
- ☐ Electric/electric hybrid vehicle or truck (4)
- ☐ Motorcycle or moped (5)
- ☐ Non-electric personal mobility device such as bicycle or scooter (6)
- ☐ Electric personal mobility device such as e-bike, e-scooter, hoverboard or one-wheel (7)
- ☐ ⊗None of the above (8)

Q24 **How many vehicles of the following types do you have regularly available?**

	Unsure 0 1 2 3 4 5 6 7 8 9 10
Car or truck ()	
Electric/electric hybrid vehicle or truck ()	

Q25 **Do you have access to a smartphone or similar handheld internet-capable device while commuting?**

- Yes (1)
- No (2)

Q26 **How do you use your smartphone or similar handheld internet-capable device for commuting?** (select all that applies)

- ▢ Mobile payment/booking for transportation (1)
- ▢ Routing/navigation/wayfinding (4)
- ▢ Transportation service information/schedule (6)
- ▢ Work-related activities (e.g., writing e-mails) (7)
- ▢ Entertainment/sports/news (e.g., listening to music, read sports/news) (9)
- ▢ Socializing (e.g., chatting with friends) (10)
- ▢ Other (specify) (8) ____

Q27 **What is your marital status?**

- ○ Single (1)
- ○ Married (4)
- ○ Living with a partner (5)
- ○ Widowed/divorced/separated (6)

Q28 **Do you have children under 18 or adults living in your household who need assistance for transportation?**

- Yes (1)
- No (2)

Q29 **How many children under 18 and/or adults living in your household who need assistance for transportation?**

	0	1	2	3	4	5	6	7	8	9	10
Children under 18 ()											
Adults ()											

Q30 **What type of housing do you currently live in?**

- Single-detached house (1)
- Townhouse (4)
- Apartment/condo (5)
- No permanent housing (6)
- Other (7)

Q31 **Do you own or rent your current residence?**

- ○ Own (1)
- ○ Rent (2)
- ○ Other (3)

Q32 **Compared to before the pandemic (pre-March 2020), how long is your typical commute trip now?**

- ○ No regular commute now (e.g., telework) (1)
- ○ Longer than pre-pandemic (more minutes) (6)
- ○ Shorter than pre-pandemic (fewer minutes) (7)
- ○ No change (8)

Q33 **Compared to before the pandemic (pre-March 2020), how frequent are your commute trips now?**

- ○ No regular commute now (e.g., telework) (1)
- ○ I am commuting more frequently (4)
- ○ I am commuting less frequently (5)
- ○ No change (6)

Q34 **Which transportation mode did you <u>most frequently</u> use to commute to work before the pandemic (pre-March 2020)?**

- ○ Public transit (e.g., bus, light rail) (1)
- ○ Ferry (2)
- ○ Vanpool (3)
- ○ Carpool (4)
- ○ Employer shuttle (5)
- ○ Uber/Lyft (16)
- ○ Taxi (6)
- ○ Motorcycle (7)
- ○ Bike/Scooter (8)
- ○ E-bike/E-scooter (9)
- ○ Walk (12)
- ○ Remote work (13)
- ○ No commute (14)
- ○ Other (please specify) (15) ____

Q35 **Compared to before the pandemic (pre-March 2020), in what ways has your typical commute mode changed?**

- ○ I still use the same commute mode (no change) (1)
- ○ I changed my commute mode during the pandemic (2020-2021), but already have switched back to pre-pandemic mode (7)
- ○ I have been using a different commute mode since the outbreak of the pandemic (8)
- ○ I have been using a different commute mode, but I am planning to switch back to pre-pandemic mode (9)

Q36 **Are any of the changes in your commute mode or commute duration mainly caused by a change in <u>employer or worksite</u>?**

- ○ Yes, change in job type (9)
- ○ Yes, change in employer or worksite (10)
- ○ Yes, change in work location (e.g., work from home or remotely) (12)
- ○ No (11)

Q37 **Are any of the changes in your commute mode or commute duration mainly caused by a change in <u>home location</u>?**

- ○ Yes, I moved closer to my worksite (1)
- ○ Yes, I moved farther from my worksite (4)
- ○ No (5)

Q38 **Please select one option that best describes the availability of remote work for you.**

- ○ I continue to primarily work remotely (e.g., from home) (8)
- ○ I worked remotely during 2020-2021 but have since returned to the worksite full time (12)
- ○ I work remotely for a few days of the week (13)
- ○ I have the option to work remotely, but I do not use it (14)
- ○ My workplace does not allow me to work remotely (15)
- ○ The nature of my work cannot be done remotely (16)

Q39 **What are the main reasons you drive alone to work?**
(Select up to three boxes)

- ☐ I like the convenience of having my car (1)
- ☐ It is less expensive to drive (4)
- ☐ Family care or other obligations (e.g., ability to run other errands, school dropoff) (5)
- ☐ Short commute time/It makes my commute significantly faster (6)
- ☐ I have access to free/subsidized parking (7)
- ☐ I am concerned about exposure to crime or safety-related issues when choosing another travel option (8)
- ☐ I am concerned about COVID-19 or lack of hygiene when choosing another travel option (9)
- ☐ My job requires me to use a car (10)
- ☐ Other (specify) (11) ____

Q40 **What are the main reasons you do not drive alone to work?**
(Select up to three boxes)

- ☐ I do not own a car (4)
- ☐ It is expensive to drive and park (20)
- ☐ It is stressful to drive (12)
- ☐ I use other options to avoid traffic (13)
- ☐ I want to reduce my contribution to air pollution and carbon emission (14)
- ☐ I make use of my commute time when using other transport options (15)
- ☐ I have free or subsidized transit pass/incentives for using other options (16)
- ☐ I am concerned about car crashes (17)
- ☐ I use other modes to increase my physical activity (18)
- ☐ There is no parking at my workplace (19)
- ☐ Other (specify) (11) ____

Q41 **Generally, what are the main considerations that affect your travel decisions?**
(Select up to three boxes)

- ▢ Time/duration (1)
- ▢ Cost/affordability (4)
- ▢ Flexibility/convenience (5)
- ▢ Comfort (13)
- ▢ Environmental impact (e.g., reduce my contribution to CO2 emissions) (6)
- ▢ Value of travel time (e.g., I make use of my travel time for other activities) (7)
- ▢ Subsidies (e.g., my commute mode/option is subsidized) (8)
- ▢ Safety (e.g., I feel safe from crimes using this mode) (9)
- ▢ Protection from viral infections (e.g., the COVID-19 pandemic) (14)
- ▢ Health/fitness (e.g., higher physical activity) (10)
- ▢ Facilities (e.g., my worksite has sufficient facilities needed by this mode, e.g., parking) (11)
- ▢ Habit (e.g., I developed a habit of using certain modes) (15)
- ▢ Weather (e.g., climate plays a major role in my mode choice) (16)
- ▢ Other (specify) (12) ____

Q42 **How long in minutes does it usually take you to**

	More than 30						
	0	5	10	15	20	25	30
Walk to/from the nearest transit stop/station station from your <u>home location</u>? ()							
Walk to/from your <u>work location</u> from the nearest transit stop/station? ()							
Wait at the transit stop/station? ()							

Q43 **How many <u>transfers</u> do you have to make when using transit to travel to/from work?**

	0	1	2	3	4	5	6	7	8	9	10
Number of transfers ()											

Page Break

Q44 **What is the main mode you most frequently use for the following trips?**

	Not applicable (NA) (1)	**Public transit** (11)	**Ferry** (12)	**Carpool** (13)	**Uber/Lyft** (9)	**Taxi** (10)	**Drive alone** (4)	**Motorcycle** (5)	**Bike/Scooter** (6)	**E-bike/e-scooter** (7)	**Walk** (8)
Grocery shopping (1)	o	o	o	o	o	o	o	o	o	o	o
School pickup/dropoff (4)	o	o	o	o	o	o	o	o	o	o	o
Health/medical treatment (5)	o	o	o	o	o	o	o	o	o	o	o
Leisure/ social (6)	o	o	o	o	o	o	o	o	o	o	o
Fitness/ exercise (7)	o	o	o	o	o	o	o	o	o	o	o
Other trips (8)	o	o	o	o	o	o	o	o	o	o	o

Q45 **Compared to before the pandemic (pre-March 2020), how frequent are your non-commute trips (e.g., grocery shopping)?**

○ More frequent (more trips) (1)

○ Less frequent (fewer trips) (4)

○ No change (5)

Q46 **If you could, please point out the <u>nearest</u> intersection to your home. This information helps us understand how local services (e.g., parks, stores) influence travel decisions.**
(Either point/click on the map using the red marker, or use the search box below the map)

____

Q49 **Would you like to be entered for a raffle to win a $100 gift card?**
If yes, you will be redirected to an anonymous survey to enter your name and email address

○ Yes (1)

○ No (2)

End of Block: Optional Questions

Start of Block: Default Question Block

Q1 Please enter your name and e-mail address
(This information will ONLY be used for drawing prizes)

○ Name (1) ____

○ E-mail address (2) ____

End of Block: Default Question Block

Appendix B: Chicago TNC Trips Data

Table B-1 Chicago TNC Trips Data – Unprocessed

Trip Start Timestamp	Trip End Timestamp	Trip Seconds	Trip Miles	Pickup Census ...	Dropoff Census...	Pickup Community...	Dropoff Community ...	Fare	Tip	Additional Charges	Trip Total
11/28/2019 08:30:00 PM	11/28/2019 09:00:00 PM	1,780	14.1		17031839000		32	$22.5	$0	$5.84	$28.34
11/19/2019 06:00:00 PM	11/19/2019 06:30:00 PM	1,861	5.2	17031839100	17031240500	32	24	$17.5	$0	$2.55	$20.05
11/06/2019 04:00:00 PM	11/06/2019 04:15:00 PM	861	2.8			39	42	$7.5	$0	$2.55	$10.05
11/22/2019 08:15:00 AM	11/22/2019 08:30:00 AM	697	1.9	17031310600	17031838200	31	28	$7.5	$0	$2.55	$10.05
11/29/2019 06:30:00 AM	11/29/2019 06:45:00 AM	416	2.0	17031620400	17031980100	62	56	$5	$1	$7.55	$13.55
11/18/2019 04:15:00 PM	11/18/2019 04:30:00 PM	1,255	2.2	17031839100	17031081401	32	8	$2.5	$1	$2.55	$6.05
11/04/2019 11:45:00 AM	11/04/2019 11:45:00 AM	527	1.7	17031080100	17031081800	8	8	$5	$0	$2.55	$7.55
11/03/2019 06:30:00 AM	11/03/2019 07:00:00 AM	1,637	7.7	17031841300	17031081201	31	8	$10	$2	$0	$12
11/08/2019 09:30:00 AM	11/08/2019 09:45:00 AM	1,463	4.1	17031242700	17031081500	24	8	$12.5	$0	$2.55	$15.05
11/29/2019 08:30:00 PM	11/29/2019 09:00:00 PM	1,085	8.6	17031320400	17031160601	32	16	$15	$0	$2.55	$17.55
02/25/2020 07:15:00 AM	02/25/2020 07:15:00 AM	679	2.2	17031330100	17031839100	33	32	$7.5	$0	$4.83	$12.33
11/15/2019 01:30:00 PM	11/15/2019 01:45:00 PM	573	2.4			19	25	$7.5	$0	$2.55	$10.05
11/16/2019 06:15:00 PM	11/16/2019 06:30:00 PM	476	0.8	17031081403	17031081700	8	8	$5	$0	$2.55	$7.55
11/19/2019 04:00:00 PM	11/19/2019 04:15:00 PM	851	1.8	17031280100	17031081401	28	8	$7.5	$2	$2.55	$12.05
11/27/2019 10:45:00 AM	11/27/2019 11:00:00 AM	552	1.5	17031081800	17031081201	8	8	$5	$1	$2.55	$8.55
11/01/2019 08:00:00 AM	11/01/2019 09:00:00 AM	2,737	12.9			21	76	$47.5	$0	$7.85	$55.35

This snapshot shows the basic columns used to process the data. Using this data, I measured the average fare per mile (excluding tips) per trip. I then summarized the data by day and measured the daily average fare per mile. Using the date records, the data was also joined with holiday data and exogenous variables as Table B-2 shows an example of a few selected days:

Table B-2 Chicago TNC Trips Data – Processed

TNC data (Chicago)		Holidays					Exogenous Variables						
ds (date)	y ($ avg daily price)	Christmas	Easter	Thanksgiving	New_year	Independence_day	Lockdown	PRCP	SNOW	TAVG	gas	Congestion_fee	Unemployment_rate
1/1/2019	2.2332	0	0	0	1	0	0	0.01	0.1	31	2.118	0	4.9
12/25/2019	1.8067	1	0	0	0	0	0	0	0	47	2.605	0	3.1
1/1/2020	2.1523	0	0	0	1	0	0	0	0	28	2.644	0	3.9
3/26/2020	1.8483	0	0	0	0	0	1	0	0	48	2.156	1	6.1
2/21/2021	2.9966	0	0	0	0	0	0	0.32	1.2	26	2.754	1	7.6

Appendix C: Generalized Travel Cost Calculation of Alternative Travel Modes

Simulating Travel Time and Travel Costs

To estimate travel costs associated with every mode, Metro Flex trip dataset was used for Metro Flex trips, and was applied to a transportation simulation approach to model the counterfactual scenarios where Metro Flex was not an option, and all Metro Flex riders needed to choose alternative modes. The study used Eclipse SUMO, a free and open-source software, for the simulation. SUMO is highly customizable and can directly model real-world road networks and individual-traveler-level traffic flows. The road network map and related information on the number of lanes, speed limit, permitted vehicle types, sidewalks, pedestrian crossings, and traffic lights were obtained from OpenStreetMap (OSM) and the bus stop and route information from KCM General Transit Feed Specification General Transit Feed Specification (GTFS) data tables. In the simulation, travelers were assumed to depart at the same time as when they requested MetroFlex for the counterfactual modes. Speed factors were applied to reflect traffic levels, using historical traffic data from Esri online.

Estimating the Generalized Costs for Travelers

Travel time for each mode was monetized using percentages of the average hourly wage rate as the values of travelers' time during trips, under the simplified assumption that the trips were either commuting trips or non-commuting trips made by average working adults during a typical weekday. The average hourly wage for the Seattle Metropolitan Statistical Area was $38.47 in 2022. Travelers’ values of time for various trip components are listed in Table C-1. These values were determined for the following reasons:

1) The U.S. Department of Transportation recommended plausible ranges for personal trip values of travel time savings for surface modes other than high-speed rail. These were 35% to 60% of hourly earnings for time spent in a vehicle and 80% to 120% of hourly earnings for time spent on walking.
2) For the value of in-vehicle time as a percentage of hourly earnings, Metro Flex and TNCs were assigned the lowest value rounded to the nearest 10 (i.e., 40%), while driving alone was assigned the highest value (60%). Metro Flex and TNC vehicles were expected to have a higher level of comfort than buses, given their available seats for all passengers, which contributes to their lower opportunity cost of in-vehicle time than transit. Compared to other modes, drivers of private vehicles cannot use their in-vehicle time freely, so they were expected to have the highest opportunity cost of in-vehicle time.
3) Metro Flex and TNC were also set to have a lower wait time value than transit. Metro Flex and TNC riders have more control over the distribution and use of their time waiting and walking to pickup locations. Even if they were a few minutes later than the estimated pickup time, drivers would stay for a short time (about 2 minutes) to allow riders to arrive at pickup locations.

Table C-1 Travelers' Values of Time for Trip Components as Percentages of Hourly Wage

Time components	Metro Flex	Transit (bus)	TNC	Drive alone
Access time	100%	100%	100%	100%
Waiting time	50%	75%	50%	/
In-vehicle time	40%	50%	40%	60%
Egress time (i.e., parking time)	/	/	/	100%

The other monetary costs for travelers by mode are shown in Table C-2. First, an adult using Metro Flex or transit pays only a standard fare of $2.75. The cost of a TNC trip consists of the base fare, the cost of the miles traveled, and the cost of the time traveled. If the sum of costs is less than the minimum fare, the minimum fare will be paid. The ranges of TNC fares shown in Table C-2 was obtained for the study areas of this study.

Moreover, trips made by driving alone do not have to pay a ride fare. Instead, these trips pay for the cost of fuel consumption and the cost of maintaining and owning a vehicle for the miles traveled. The average price of gasoline (including all taxes) in Washington State is currently $4.821 per gallon. Fuel consumption for driving alone was estimated using the SUMO simulation, which accounts for the influence of a vehicle's speed and acceleration during a trip on fuel consumption.

Table C-2 **Travelers' Monetary Costs by Mode**

Monetary Cost	Metro Flex	Transit (bus)	Drive alone
Base Fare	$2.75	$2.75	/
Minimum Fare	/	/	/
Cost Per Mile	/	/	/
Cost Per Minute	/	/	/
Cost of Fuel Consumption	/	/	$4.821 per gallon (including all taxes)
Car Maintenance Cost	/	/	$0.0982 per mile
Car Ownership Cost (including insurance, license, and depreciation	/	/	$0.564 per mile (AAA, 2021)