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Impacts of commute trip reduction programs, rail station area built environment changes, and ride-hailing services on traveler behavior

Peng Chen, Xiankui Yang, Philip L. Winters (TDM-CP)
Meiqing Li, Daniel A. Rodriguez, Michael A. N. Montilla, Daniel G. Chatman

For:
National Institute for Congestion Reduction
University of South Florida
Center for Urban Transportation Research | University of South Florida
4202 E. Fowler Avenue, ENG030, Tampa, FL 33620-5375
nicr@usf.edu

NICR
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16. Abstract

Traffic congestion is a recurring problem with temporal and spatial aspects that affect our lives daily. Providing choices such as increasing transit ridership is part of a balanced and diversified approach to addressing the problem. This project is divided into three parts to address how transit can address this multifaceted congestion problem. The first part investigates the successes and failures of transit and transportation network company (TNC) partnerships on ridership. Transit agencies have partnered with TNCs to attract ridership by providing first/last mile access or substituting for low performing fixed route service. TNCs may have induced travel demand by car and reduced public transportation ridership in other areas. The second part examines employer-provided financial incentives on commute behavior. Using an extensive data set from State of Washington's Commute Trip Reduction program and other sources, the role of fare discounts and parking prices will be analyzed. The third part analyzes changes in ridership due to changes in the built environment, evaluating the impact of transit station area built environment changes (e.g., crosswalks, bicycle lanes) on transit ridership and access mode. We will identify changes in walking and biking infrastructure around rail station across time using longitudinal satellite imagery and

compare changes relative to control areas.			
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Executive Summary

This report consists of the background, research design, and findings of three studies investigating strategies to address urban congestion: employer-based travel demand management strategies, transit station area built environments, and ride-hailing. Collectively, the three studies represent complementary strategies to address urban congestion. However, each of them focuses on a particular approach from managing demand side incentives to supply side disruptions.

STUDY A: Employer-based travel demand management in mitigating congestion

Employer-based travel demand management (TDM) strategies, many of which are noted as incentives, are applied to alter employees' travel modes or schedules, targeting to reduce commuting vehicle trips and mitigate congestion. Employer-based TDM programs have been implemented for decades in the US, but rarely longitudinal studies have been implemented to assess the effectiveness of various TDM tools.

In addition, despite drive-alone is the primary travel mode among employees, many commuters occasionally choose alternative modes conditional on their mood, available choices, job requirements, schedule plans, and traffic conditions. Employer-based TDM tools are leveraged to promote multimodal transportation.

This study utilizes the commute trip reduction (CTR) biannual survey implemented by Washington State Department of Transportation (WSDOT) to 1) assess the effectiveness of CTR measures on vehicle trip rates (VTR) over time and on vehicle miles traveled (VMT), 2) quantify the effects of various employer-provided incentives on employees' modal shift towards sustainable alternatives, and identify the most effective incentive tools. The main findings are:

- VTR steadily grows for three decades, and employer-based TDM measures can only decelerate the growth rate but have not reversed the trend;
- CTR's advertising efforts and collective bargaining help reduce VTR;
- Distributing transit passes to employees is negatively associated with VTR;
- Shared mobility incentives, such as carpooling subsidy and ride match, both contribute to increments in VTR;
- Emergency rides are positively associated with VTR;
- Allowing for shared rental cars on worksites is negatively associated with VTR.
- Subsidizing transit passes, flexible work schedules, and parking pricing are the most effective strategies to proportionally alter employees' travel mode choices.
- ETCs play an active role in promoting multimodal transportation.
- Employees living and working in closing areas, corresponding to proximate origins and destinations, were more likely to be a similar way of multimodal transportation.

To inform practice, when rewarding employees, distributing transit passes is a preferred strategy. Carsharing and carpooling-related measures should be applied with caution. Governmental agencies should lead employers to advertise CTR programs and engage employees to identify their favored TDM strategies. To promote multimodal transportation and encourage modal shifts toward sustainability, subsidizing transit, pricing parking, and increasing flexibility in work schedules should be continually supported.

STUDY B: Rail transit ridership and station area characteristics

In this study we documented changes to the built environment around 897 transit stations of eight major transit agencies (Table 1): BART (San Francisco Bay Area), Caltrain (San Francisco Bay Area), CTA (Chicago), MTA (New York City), MTS (San Diego), PATH (New York and New Jersey), SEPTA (Philadelphia), and WMATA (Washington DC). We observed changes between 2010 and 2018 and associated them to changes in transit ridership. Using a before-and-after experimental design with controls at the station-level, we examine associations between ridership and the built environment, including marked crosswalks, while adjusting for other city and station level characteristics.

Consistent with other studies, we find an overall decrease in station boardings, although effects vary significantly by station and transit system. Built environments around rail stations continue to densify and have more mixing of land uses. However, they have a lower percent of low-income households and or zero-vehicle households, consistent with city-specific accounts of changing socio-demographic conditions in transit oriented locations. In addition, we observed a trend towards increased marked crosswalks generally, and specifically high visibility crosswalks.

From the statistical analyses we found that planning strategies to change the built environment to support transit ridership in the station areas examined have been modestly successful in increasing ridership and that changes in the socio-demographic makeup of station areas has contributed to the decline in ridership. Marked crosswalks and high visibility crosswalks did not appear to be related to higher ridership. Moreover, efforts by land use and transit planners to develop strategies to modify station areas to support higher transit ridership are necessary but likely insufficient to achieve environmental sustainability goals. Planning and policy attention to auto ownership and use, either due to changes in regional accessibility (as may be the case for low income workers) or for other reasons, is likely to have beneficial impacts on transit ridership.

STUDY C: Ride-hailing's influence on VMT & auto ownership across levels of transit access in Metro Boston

In STUDY C, we analyzed how the growing availability of the Uber ride-hailing service affected household vehicle use and ownership across levels of transit access in Greater Boston during the initial years of Uber availability. Unlike previous studies examining the impact of transportation network companies on private vehicle use, we used year-specific information on daily VMT and the number of vehicles in each Massachusetts Census tract, sourced from vehicle registrations and inspections; and we looked at data on spatial variability in transit access and Uber availability. We explored the relationships between Uber availability and personal vehicle use and ownership via descriptive data analysis along with panel regression models. We found that while Uber access was associated with decreases in daily VMT and vehicle ownership, predicted reductions were smaller for every transit stop or station per square mile in Uber's service area. In some areas with the strongest transit access, the predicted reductions were wholly offset. The models predict that 31% of the Census tracts in 2014 with Uber availability saw a net increase in VMT, and 33% saw a net increase in passenger vehicles. In short, Uber availability may have enabled less passenger vehicle use and ownership, particularly in areas with poor transit access while encouraging households in transit-rich areas to own and use autos at a constant or higher rate. These results suggest that ride-hailing services are more likely to enable reduced personal vehicle use in areas with poor transit access.

Although we developed these three studies in parallel, they complement each other in addressing congestion with different strategies. Study A and B focus on the economic incentive and land use policy respectively, to evaluate the effectiveness of certain travel demand management strategies. Study C examines the impact of emerging new mobility services on travel behavior, as an addition to traditional travel options.

STUDY A: Employer-based travel demand management in mitigating congestion

1. Introduction

Urban development, growth in population and jobs, and added socioeconomic activities reshapes travel pattern, often comes along with more congested traffic (Bigazzi & Figliozzi, 2012; Davison & Knowles, 2006). Congestion not only undermines the efficiency of socioeconomic activities but also deteriorates the urban environment (Bigazzi & Figliozzi, 2012). The direct cost of congestion added on social life and the local economy is increased travel time, associating with reduced quality of life to residents and system inefficiency (Li, Chen, & Tian, 2021). In addition, congestion leads to more crashes, and crashes in return cause more congested traffic and system inefficiency (Wang, Quddus, & Ison, 2009). Therefore, state and local agencies are dedicated to reduce congestion and optimize system efficiency (B. D. Taylor, 2004; Teodorović & Dell'Orco, 2008).

Travel demand management (TDM) focuses on improving the person-through put efficiency of the traffic system by changing travel behavior (Zaman & Habib, 2011; J. Zhou, Wang, & Schweitzer, 2012). As a demand-side approach to eliminate congestion, TDM strategies have been widely applied to provide incentives or alternatives with financial, social, and informational interventions, essentially to discourage solo driving during peak hours (Bianco, 2000; Castellanos, 2016; Ghimire & Lancelin, 2019; Li et al., 2021). TDM strategies help save energy, promote air quality, and improve system efficiency. TDM emphasizes the importance to keep the balance between trip generation and facility supply, highlights the significance of reducing car dependency and prioritizing transit and active travel modes, promotes transportation equity to better serve the disadvantaged groups, and ensures the mobility services are sustainable, efficient, and safe. TDM is considered a cost-effective approach to manage traffic, and is generally classified in three ways: pull vs. push, generalized vs. personalized, and governmental vs employer-based (Hasnine, Weiss, & Nurul Habib, 2017; Keizer, Sargisson, van Zomeren, & Steg, 2019; Ko & Kim, 2017; Li et al., 2021).

Pull-side policies are mostly favored by the public, such as providing alternatives, informing travelers with real-time traffic conditions, rewarding travelers for choosing sustainable alternatives, subsidizing transits, and improving facilities for biking and walking. Rather than facilitating travelers with more options, push-side policies add costs and difficulties for driving alone. The most representative TDM strategies used to discourage solo driving are parking pricing, tolling, restricted usage roads/areas, and license plate auction (Bianco, 2000; Shin, 2020). The joint use of pull-side and push-side policies help promote changes in travel behavior, essentially assist in managing traffic and mitigating congestion.

Despite the focus of managing traffic shifted from supply-focused to demand-based strategies for decades, the early practice highlighted the use of generalized approaches to design policies. During that period, TDM tools were typically implemented with an increased cost of driving alone, or decreased cost of alternative modes. As examples, some provided monetary incentives, such as congestion pricing and subsidizing transit. Additionally, one prioritized certain groups of travelers by, for example, designating carpool lanes and car-free zones. So far, TDM tools failed to produce travel behavior changes across the community (Gössling & Cohen, 2014; Sammer, 2016). A number of reasons may explain and one may be that cost, in its general term, only constitutes one of the many factors in people's travel choice decisions. Additionally, individuals may have different preferences that are not well recognized by those one-size-fit-all incentives. In contrast to conventional TDM tools, personalized incentives are designed to encourage voluntary travel behavior change for an individual or a group of individuals (Meloni, Sanjust, & Spissu, 2012). The term, voluntary behavior change, is defined as individuals make changes for personal benefits without any top-down mechanism, enforcement, or external compulsion (M. A. Taylor, 2007). Personalized incentives refer to individual or group-based activators that motivate people for behavior change. In the field of pro-environmental behavior, personalized incentives encourage individuals to change towards sustainability, foster responsibility for the environment, and promote a healthy lifestyle (Di Dio, Casto, Micari, Rizzo, & Vinci, 2015); ideally establishing desired habits. Currently, there is a great amount of interest among public agencies in applying such personalized incentives for pro-environmental behavior change (Jariyasunant et al., 2015; L. Ma, Mulley, & Liu, 2015; Teulada & Meloni, 2016; Tulusan, Staake, & Fleisch, 2012), largely due to the prevalence of personal devices such as smartphones, which are now equipped with a wide range of sensors including GPS, accelerometers, gyroscopes, in addition to continuous access to the internet.

As for the implementing entities of TDM interventions, state, regional, and local authorities have developed many TDM strategies to manage traffic and monitor the system performance. In large metropolitan areas, TDM are integrated into the planning processes at all levels with a goal-oriented, performance-based approach that contains a specific setting and measurable objectives. These governmental TDM tools are generalized, which add equal costs or provide same benefits to all travelers. Congestion mostly happens during peak-hours, employer-based TDM programs are employer-sponsored programs designed to mitigate road congestion. Programs generally contain the integration of three approaches to alleviate car trips, parking demand, and road capacity: discourage solo driving and encourage sustainable alternatives, increase vehicle occupancy rates by carpooling, vanpooling, and other ridesharing options, and reduce peak-hour traffic by allowing for alternative works schedules, such as telecommuting, flexible schedules, and compressed workweeks (Ko & Kim, 2017; Shin, 2020). While not an immediate option, employer-based TDM programs often supported by an employee transportation coordinator, who is dedicated to TDM solutions over a locality or region.

Mandated efforts often called commute trip reduction (CTR) programs or trip reduction ordinances (TROs), focus on employer-based TDM strategies, in particular, giving commuters resources and incentives to reduce their solo driving trips during peak hours. Employer-based TDM and CTR are not new. To reduce traffic congestion and improve air quality, starting from the late 1980s, a nationwide CTR program was launched by the US Congress and the Environmental Protection Agency (EPA). The goal was to reduce single-occupant commuting trips during peak hours (Oren, 1998a). Directed by the Employee Commute Options Guidance issued by the EPA, urban areas classified as extreme and severe nonattainment areas for ozone were directed to submit state implementation plans outlining how they intend to achieve their congestion mitigation and emission reduction goals (Dill, 1998; Oren, 1998a) to increase average passenger occupancy by 25 percent. Large employers with more than 100 employees within this nonattainment areas were given two years to develop a compliance plan with two more years to demonstrate the employer's compliance with the goal. Large employers were mandated to leverage CTR measures to encourage their employees to increase their average passenger occupancy (APO). Despite the fact that most early CTR programs had shown progress toward ECO goals success, the ECO mandate was eventually made a voluntary program, effectively ending many employer-led efforts due to various reasons, such as unclear guidance from federal agencies, missteps in implementation, insufficient support from local government, the lack of engagement with stakeholders, and adverse public reaction (Burns, 1987; Dill, 1998; Giuliano et al., 1993; Oren, 1998a, b, c). By the end, Congress made the ECO mandate a voluntary program in the mid-1990s (Oren, 1998a, c), and most CTR programs quickly vanished, except Washington state and other state or local requirements pre-dating ECO such as South Coast Air Quality Management District's Rule 2202. Despite Federal agencies revoked the mandate of CTR programs, many localities kept their CTR programs at least for a period, such as Washington DC, Atlanta, San Francisco, Los Angeles, Houston, and Denver (Ghimire and Lancelin, 2019; Herzog et al., 2006; Zhou et al., 2012; Zuehlke and Guensler, 2007). Looking globally, many cities have comparable employer-based TDM in practice, such as Perth-Australia, Seoul-South Korea, Toronto-Canada, Antwerp/Brussels-Belgium, and Xi'an-China (Hasnine et al., 2017; Ko and Kim, 2017; Vanoutrive, 2019; Wake, 2007; Zhu and Fan, 2018). Employer-based TDM is becoming more localized.

The employer-based TDM approach can be considered a major force of providing pull-side group-level personalized incentives to alter travel choices among employees. To examine the impact and effectiveness of such employer-based TDM strategies, this project carried out a two-level analysis to investigate how CTR programs encourage the use of sustainable alternatives, reduce vehicle trip rates at worksites, and essentially alleviate road congestion for a metropolitan area.

To well address these research objectives, this project asks two questions: 1) at an employer level, what TDM tools have effectively helped reduce vehicle trip rates over time and vehicle miles traveled? 2) at an employee level, what TDM tools have successfully promoted multimodal use by incentivizing individuals to occasionally alter travel choices? To answer these questions, data collected from Washington state's CTR biannual survey are employed with the application of advanced statistical models.

The objective of this report is twofold. From an employer level, the first objective is to present an analysis how various types of employer-based TDM tools generate effects on vehicle trip rates (VTR) over time and on vehicle miles traveled. Besides documenting the successful experience of operating commute trip reduction (CTR) program in Washington state, this analysis provides evidence of how employees alter travel choices contextualizing in a gradually improved multimodal transport system, representing the trend of changing from monomodality to multimodality in large US cities. The primary research questions related to this first objective are:

- What TDM tools are significantly correlated with VTR over time?
- What TDM tools are significantly correlated with VMT?

From an employee level, the second objective of this report is to present an analysis how multimodality is incentivized by employer-based TDM tools. This analysis treats the occasional use of sustainable alternatives as a way of advocating multimodal transportation, using employees' weekly travel choices in King County for empirical analysis. The comparison focuses on employees who always drive alone and employees who drive but occasionally use other alternatives. This research provides a more realistic setting to examining multimodality under the impact of employer-based TDM programs. This research examines a type of underestimated social network effects on travel choices, which is referred as the peer effects among colleagues. By noting the spatial autocorrelations may related to the commuting pattern between employees who work and live in geospatially approximating areas, this research includes site IDs, home zip codes, and the commuting distance as random effects to capture spatial dependencies. Besides this introduction, this report is composed of three additional chapters.

Chapter 2: employer-level analysis, analyzing what are the effects of employer-based TDM tools on VTR over time and VMT? Generalized linear mixed model is the analytical approach, along with geospatial analysis applied to quantify certain features.

Chapter 3: employee-level analysis, analyzing how employer-based TDM tools can incentivize multimodality (drive alone but occasionally use sustainable alternatives)? Multinomial mixed logit model is the analytical approach, along with geospatial analysis applied to quantify certain features.

Chapter 4. policy implications and future research.

2. Revisit Employer-based Travel Demand Management: A Longitudinal Analysis

2.1 Background

Congestion mitigation is the goal of TDM, and various approaches have been used to find solutions to reduce car use (Bigazzi & Figliozzi, 2012; Choo & Mokhtarian, 2008; Fujii & Taniguchi, 2005; Noland & Lem, 2002). The CTR program is a TDM method based on employers that allows both employers and employees to participate in congestion mitigation. With decades of development, employer-based TDM is expanding. It is unclear how the CTR measures affect commuting over time. To answer this question, this study uses a longitudinal dataset to assess the effectiveness of various CTR measures to inform better employer-based TDM practice on worksites and determine the best CTR measures to serve the community.

In Washington state, there are three stages to the development of employer-based TDM programs. In the 1990s, local agencies assisted employers to initiate the programs and utilize various measures by learning from each other. Only a limited number of employers took part in the early programs. In the 2000s, incentivized by tax abatement, more employers have signed up for the program. The CTR program became more established. In the 2010s, with technology advancement and emerging transportation modes, the CTR program now incorporates more TDM strategies.

However, with decades of implementation, the performance measurement of CTR programs was somehow stabilized or even in a reversed trend in recent years. It is time to examine whether or not these CTR measures are still effective at reducing road congestion. There are several noticeable external factors and trends that may have a role in such unintended results. First, the effect of CTR programs in improving traffic conditions may be underestimated because of a booming economy, population growth, and rising property price. Second, to accommodate a variety of mobility needs from employees, CTR tools are dispersed throughout worksites. As a result, CTR programs differ greatly across employers. Local authorities will find it more difficult to track the performance of CTR measures if they are organized in this manner (Dill, 1998). Many measures have not been thoroughly assessed before being integrated into the program and may not be implemented effectively by employers.

The mobility system is changing with the introduction of new options (bikeshare, e-scooters, TNCs), technologies (multimodal fare cards) and new types of incentives (rewards for recording trips). Several new measures incorporated into the CTR program are deserving of our attention. As showing respect, employees are encouraged to engage in a collective bargaining process to choose which CTR measures will be implemented. As principles evolved from parking minimums to district-based parking and performance-based parking, parking schemes and fees are new CTR measures being employed to constrain solo driving. From 2009, ORCA cards have been available in King County. Many employers have begun to distribute subsidies directly to their employees' transit passes since then. This change somehow restricts the use of transit subsidies for other purposes. To be specific, employees can receive transit subsidies despite only occasionally using transit to work. When the subsidies are distributed as terminal-restricted debit cards employees may only use at merchant terminals at points of sale at which only fare media for local transit systems is sold. To be considerate to employees, short-distance mobility services are provided to facilitate access to transit or nearby destinations. Another worksite-level mobility service for employees is the use of an employer-owned vehicle. Emergency ride, a part of guaranteed ride home, is a measure associated with concern for needing to leave work early due to sickness or late due to unexpected overtime on the days they ride to work with others. Such workers have access to taxi, car rental or transportation network companies to help provide a ride home in the event of such emergencies. Most ERH programs require workers to be regular non-SOV mode user. Combining with innovative ideas, new measures, and emerging technologies, these changes lead our interest in timely evaluating the performance of CTR programs over time.

2.2 Literature Review

Employer-based TDM is a well-known approach for discouraging solo driving and mitigating congestion around the world. Several recent studies have compiled findings on this topic (Ko & Kim, 2017; Shin, 2020). To minimize overlapping, this review expands on developing TDM measures, synthesizes research design and associated methods, and focuses on CTR program evaluation.

2.2.1 Employer-based TDM

TDM measures can be classified as 'push' and 'pull' policies. In an employer-based TDM program, pull policies are generally favored among employees, such as improving transit and subsidizing bus fares, while push policies are mostly undesirable, such as increasing parking fees (Bhattacharjee, Haider, Tanaboriboon, & Sinha, 1997). Prior research has looked into the effectiveness of pull policies in reducing solo driving. Monetary incentives can be effective strategies for encouraging the adoption of alternate modes of transportation. Free or subsidized transit pass associated with 156% higher feasibility of commuting by transit conditional on service frequency with data surveyed in Atlanta (Ghimire & Lancelin, 2019). Subsidized/discounted transit worked better to discourage car commuting if combined with parking pricing (Bianco, 2000). Empirical evidence suggested that parking cash-out helped cut solo driving by 17% (Shoup, 1997). For alternative work schedules, flexible work hours suggested encouraging employees to take transit, while a compressed workweek exhibited no significant effect on employees' mode choice (Zaman & Habib, 2011). Longer commute distances made employees more likely to shift from non-telecommuting to telecommuting (L. Zhou, Su, & Winters, 2009). However, whether telecommuting is an option for employees is determined by employers' business and employees' job type. Only large employers can afford to give their employees more options, such as bus/shuttle services and within employer ride-matching (J. Zhou et al., 2012).

The employer-provided bus was considered as an efficient way to replace long-distance solo driving (Vanoutrive, 2019; Zhu & Fan, 2018). With empirical evidence from Belgian gateways, employer-provided bus services were linked to a 12% reduction in solo driving (Vanoutrive, 2019). Ridesharing is thought to aid in the reduction of solo driving. Yet, empirical evidence suggests that the promotion of ridesharing appears to be only associated with a 1.15% reduction in solo driving among employees (Vanoutrive, 2019), and the popularity of ridesharing is influenced by a number of factors, such as parking cost, commuting distance, web/app application, matching preferences, and service flexibility (Erdoğan, Cirillo, & Tremblay, 2015). Employees need strong incentives and facilitate access to ridesharing; otherwise, ridesharing can hardly happen.

Push policies are mostly unpopular but effective, and employers prefer not to use them to avoid negative reactions from employees. Parking schemes, such as no parking for employees and eliminating free parking, appear to be low-cost but efficient ways to discourage solo driving, which contribute to significant shifts in average vehicle ridership (Brockman & Fox, 2011; Ko & Kim, 2017; Willson, 1997).

For the other factors, the built environment plays a role in impacting travel mode choice because density is critical to a successfully operated transit system (Chatman, 2003). The travel options that an employer can provide are intimately tied to the location of a worksite. Larger employers can offer their employees more TDM options (J. Zhou et al., 2012).

2.2.2 Analytical Methods

The general approach utilized in the existing studies to assess the effectiveness of employer-based TDM measures was before and after study, based on expressed preference survey (Bianco, 2000; Hasnine, Weiss, & Nurul Habib, 2016; Higgins, 1996; Vanoutrive, 2019; Zaman & Habib, 2011). The analytical unit was mostly the employee, while one study looked at the perspective of employers (Ko & Kim, 2017). Some early research synthesized findings based on descriptive analysis (Dill, 1998; Giuliano, Hwang, & Wachs, 1993; Lagerberg, 1997). Discrete choice models were implemented to examine the effect of TDM measures on employee's mode choice and employers' policy preference (Ghimire & Lancelin, 2019; Hasnine et al., 2016; Ko & Kim, 2017; C. J. Taylor, Nozick, & Meyburg, 1997; Zaman & Habib, 2011). TDM group measures were subjected to factor analysis (Vanoutrive, 2019). Linear regressions were applied to investigate changed car use related with employer-based TDM strategies (Vanoutrive, 2019). The impact of employer-based TDM on system-level congestion mitigation was also estimated (Hillsman, Reeves, & Blain, 2001). To highlight the importance of causal inference, prior research also recommended the use of experimental design to assess the effectiveness of employer-based TDM strategies (Higgins, 1996). However, many measures are used in a TDM program, and these measures interact each other. Solely focusing on one measure may lead to a biased understanding of the joint effect of multiple measures.

2.2.3 Evaluating CTR program

Regarding performance, it has long been customary for local agencies to consider average vehicle ridership (AVR) (Giuliano et al., 1993; Stewart, 1994; Winters, Perez, Joshi, & Perone, 2005), vehicle trip rates (VTR, the inverse of AVR), and vehicle miles traveled (VMT) per employee as objectives to assess the effectiveness of CTR measures (Lagerberg, 1997; Lopez-Aqueres, 1993). Beyond these frequently used measurements, employees' mode change, emissions, traffic conditions (level of services), and cost to employer are also considered as measurements to evaluate TDM programs' effectiveness (Lopez-Aqueres, 1993).

2.2.4 Summary

There are a few flaws in the existing research that need to be addressed. First, rarely research has jointly examined the effects of multiple TDM measures on car use from an employer's perspective. Second, despite many previous studies used a before and after analytical framework, the period addressed in these studies was constrained, usually ranging one to two years (Giuliano et al., 1993; Hasnine et al., 2016; Higgins, 1996; Lagerberg, 1997; Zuehlke & Guensler, 2007). It is envisaged that future research would cover a longer period and capture more dynamic changes. Third, as new measures are incorporated into the employer-based TDM program, it is necessary to examine the efficiency of these measures. With decades of practice, an established old program coming with many uncertainties, along with the development of more advanced quantitative methods, it is time to examine employer-based TDM and answer our research question: over time, what works and what doesn't work? Therefore, using Washington state as an example, this study assesses the effectiveness of CTR measures, separates out their significance and magnitudes, and prioritizes particular measures for better informed real-world practice.

2.3 Research Design

2.3.1 Institutional Background

Washington state is unique in having the CTR program operated for three decades, with its nine largest counties participating. These nine counties represent the most populous areas in the state and have the higher levels of economic activity. As shown in Figure 1, these areas include the Seattle metropolitan area in the Puget Sound region (King, Kitsap, Pierce, Snohomish) and the outreach (Thurston, and Yakima), the Portland Metropolitan Area (Clark), Metro Vancouver regional district (Whatcom), and the City of Spokane (Spokane). It is worth mentioning that economic activities are not evenly distributed in these areas. About 62.26% of the worksites are located in King County (Seattle Metro), as shown in Figure 2.

CTR programs were first implemented in Washington state in 1991 as a tool to manage peak-hour travel demand (Lagerberg, 1997). By enforcing the CTR law, major employers in the nine largest counties in Washington state were able to produce their CTR programs. For any CTR program, an employee transportation coordinator (ETC) is assigned, who is responsible for monitoring and supervising the CTR program. Each worksite has its own set of strategies. In the 1990s and 2000s, the CTR programs in Washington state have shown to be a huge success based on reported numbers of employer participation, vehicle trip rates, traffic counts and system delays, and vehicle miles traveled per employee (Hillsman et al., 2001; Lagerberg, 1997). With remarkable success, Washington state revised the CTR law in 2006 by increasing support in the local authority, customization, and investment to further promote CTR programs.

2.3.2 Data and Study Area

The Washington State Department of Transportation conducts biennial surveys to get feedback from employers and employees. ETCs usually represent employers to respond to these questions. This study uses the employers' survey data in 2001-2002, 2003-2004, 2005-2006, 2015-2016, and 2017-2018 for analysis VTR, which contains information collected at 265 worksites from 224 employers/ETCs. The dependent variable, vehicle trip rates (VTR) per week is aggregated from the survey of employees (Details in Appendix A). The survey provides VMT estimates in the recent year survey, therefore, this study also examines the effects of various TDM tools on VMT. The VMT data contains information collected at 536 worksites from 440 employers/ETCs.

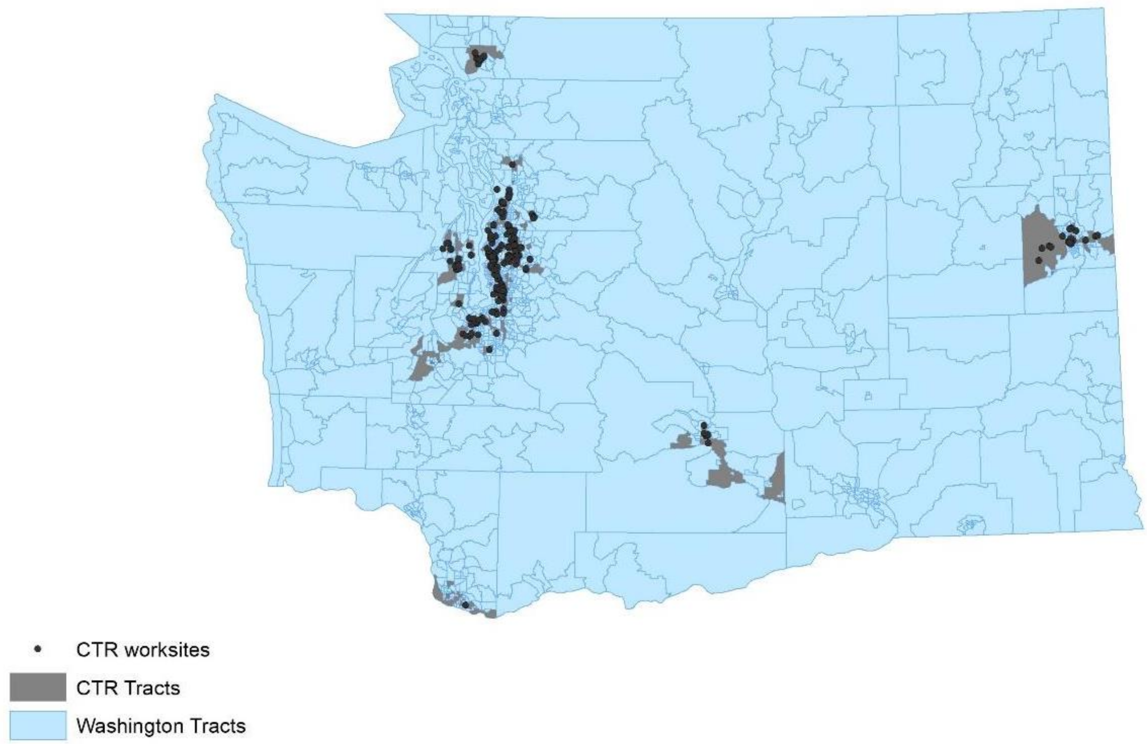


Figure 1 *CTR involved nine counties in Washington state.*

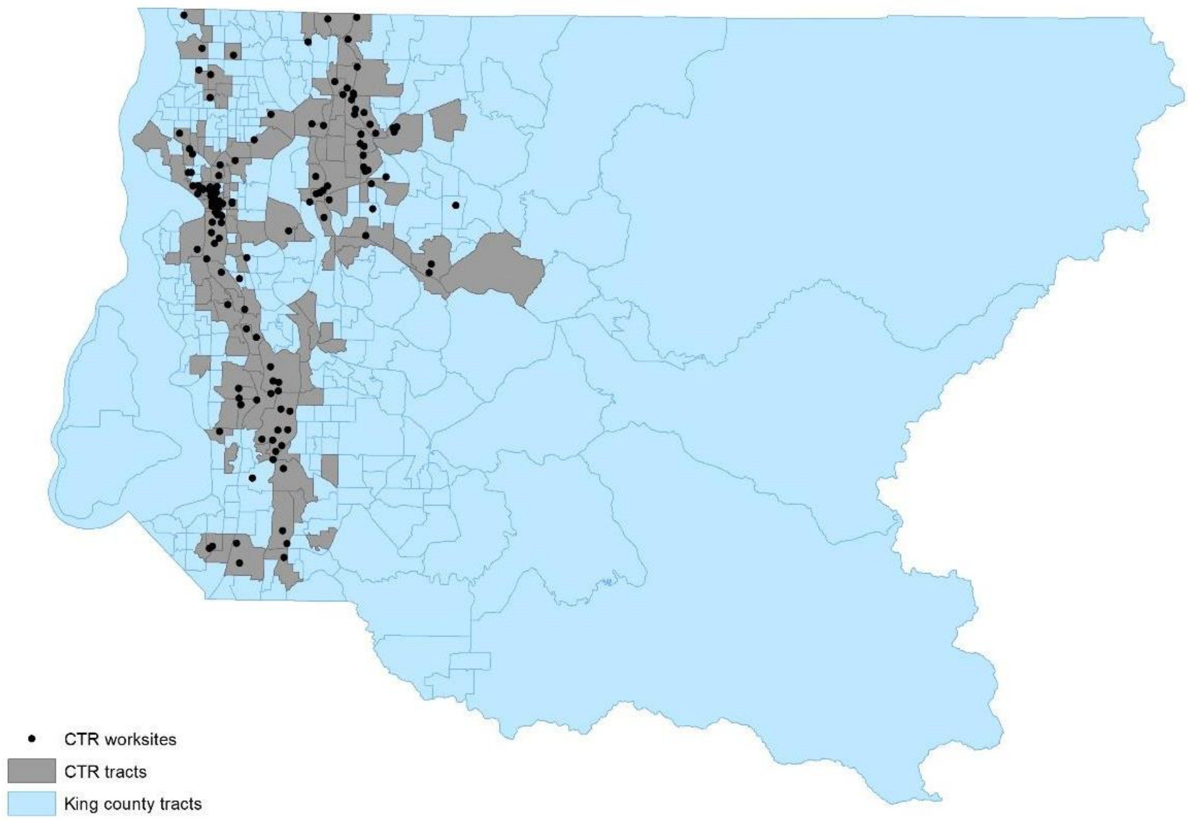


Figure 2 *CTR programs in King County.*

2.3.3 Methodology

The research goal for this study is to see how effective CTR measures are. To describe the link between VTR and CTR measurements, a longitudinal model is estimated. However, in the last decade, several new measures have been introduced to the CTR package, such as transit passes, parking schemes, emergency ride, and short-distance mobility services. The efficiency of such new measures cannot be assessed by the longitudinal model, and therefore a cross-sectional model is further estimated. As only recent year survey contains information of VMT, only a cross-sectional model is estimated to obtain insights into the effect of TDM on commuting distance. To estimate these models, the generalized linear mixed modeling (GLMM) approach is implemented. GLMM is a typical regression model to identity the linear relationship between the dependent variable and independent variables (Jiang, 1998). A spatial clustering effect is observed in King County. Therefore, we presume that employees who work in worksites located in the same zip-code have similar VTR and VMT. To account for such spatial autocorrelations, the site ID would be used as random effects in VTR to account for the heterogeneities, and the zip code is included as random effects in VMT.

A generalized linear mixed model (GLMM) was employed in this study. By assumption, there are $\boldsymbol{N}$ observations with $\boldsymbol{p}$ fixed effects and $\boldsymbol{q}$ random effects. A linear mixed model is specified as:

$$Y = X\beta + Z\gamma + \varepsilon, \#(2.1)$$

where $\boldsymbol{Y}$ is a $\boldsymbol{N} \times \boldsymbol{1}$ matrix describing a response variable; $\boldsymbol{X}$ is a $\boldsymbol{N} \times (\boldsymbol{p} + \boldsymbol{1})$ matrix describing the $\boldsymbol{p}$ independent variables with fixed effects; β is a $(\boldsymbol{p} + \boldsymbol{1}) \times \boldsymbol{1}$ matrix describing the parameters for independent variables with fixed effects; $\boldsymbol{Z}$ is a $\boldsymbol{N} \times (\boldsymbol{q}+\mathbf{1})$ matrix describing the $\boldsymbol{q}$ independent variables with random effects; γ is a $(\boldsymbol{q}+\mathbf{1}) \times \mathbf{1}$ matrix describing the parameters for independent variables with random effects; and ε is a $\boldsymbol{N} \times \mathbf{1}$ matrix describing the random errors. If the random errors do not follow the standard normal distribution a transformation is needed, then new random errors can follow the standard normal distribution. Since *Eq. (2.1)* includes random effects, the results would be affected if $\boldsymbol{Y}$ is directly transformed. Based on the linear mixed model, a linear predictor η expressing the combination of fixed effects and random effects.

$$\eta = X\beta + Z\gamma\#(2.2)$$

Then a link function $\boldsymbol{g}(\cdot)$ and a response function $\boldsymbol{h}(\cdot)$ to connect the linear predictor η and the observation $\boldsymbol{Y}$ are specified, where $\boldsymbol{g}(\cdot) = \boldsymbol{h}^{-\mathbf{1}}(\cdot)$, as shown in *Eqs. (2.3 and 2.4)*.

$$g\big(E(Y)\big) = \eta\#(2.3)\ E(Y) = h(\eta)\#(2.4)$$
$$Y = h(\eta) + \varepsilon\#(2.5)$$

Eq. (2.5) is considered as a regular linear model, where fixed effects and random effects become a joint part. For *Eq. (2.5)*, if random errors do not follow the standard normal distribution, $\boldsymbol{Y}$ would be directly transformed so that random errors would follow the standard normal distribution.

For the longitudinal model, the GLMM estimates the joint effect of CTR measures, employer-related features, gas price, and job density on VTR, expressed by *Eq. (2.1)*. Several of them are time-varying variables, which are included as interaction effects to capture changes over time, as shown in *Eq.(2.6).* For the cross-sectional model, the expression is simplified as *Eq. (2.2)*.

$$Y_k = \alpha_0 + \sum_{i=1}^{I_1} \alpha_i X_{ik} + \beta_0 * Time + \sum_{j=1}^{J} \beta_j X_{jk} * Time + \gamma\xi_k + \varepsilon_k\#(2.6)$$
$$Y_k = \alpha_0 + \sum_{i=1}^{I_2} \alpha_i X_{ik} + \gamma\xi_k + \varepsilon_k\#(2.7)$$

where $\boldsymbol{Y_k}$ is the VTR of $\boldsymbol{k}$th surveyed employer, as shown in *Eq. (2.7)*; $\alpha_{\mathbf{0}}$ is the intercept; There are $\boldsymbol{I_1}$ fixed effects of the longitudinal model, and there are $\boldsymbol{I_2}$ fixed effects of the cross-sectional model; $\boldsymbol{X_{ik}}$ is the $\boldsymbol{i}$th fixed effect on the $\boldsymbol{k}$th observation, and the corresponding coefficient is $\alpha_{\boldsymbol{i}}$. $\boldsymbol{Time}$ is the time metric, ranging from 1 to 9, denoting the period of the survey with the corresponding parameter $\beta_{\mathbf{0}}$. $\boldsymbol{X_{jk}} * \boldsymbol{Time}$ is the $\boldsymbol{j}$th interaction effect between the time metric and various time-varying variables on the $\boldsymbol{k}$th observation, and $\beta_{\boldsymbol{j}}$ is the corresponding coefficient; $\xi_{\boldsymbol{k}}$ is the random effect (site ID) on the $\boldsymbol{k}$th observation with the corresponding coefficient γ; $\varepsilon_{\boldsymbol{k}}$ is the random error for the $\boldsymbol{k}$th observation. Random effect and random error are both assumed to follow a normal distribution.

For the VMT model, there are N observations with p fixed effects and q random effects, a linear mixed model expressed as *Eq. (2.8):*

$$Y = \alpha + X\beta + Z\gamma + \varepsilon\#(2.8)$$

where Y is a N×1 matrix denoting VMT; α is the intercept; X is a N×(p+1) matrix describing the p fixed effects; β is a (p+1)×1 matrix denoting parameters of the p fixed effects; Z is a N×(q+1) matrix describing the q random effects; γ is a (q+1)×1 matrix denoting parameters of the random effects; and ε is a N×1 matrix denoting the random errors. The model can be rewritten as *Eq. (2.9):*

$$Y_k = \alpha + \sum_{i=1}^{I} X_{ik}\beta_i + \sum_{j=1}^{J} Z_{jk}\gamma_j + \varepsilon_k \#(2.9)$$

where Y_k is the k^{th} observation in the 546 employers; X_{ik} is the k^{th} observation for i^{th} fixed effect, and the corresponding parameter is β_i; Z_{jk} is the k^{th} observation for j^{th} fixed effect, and the corresponding parameter is γ_j; ε_k is the random error for the k^{th} observation. In this study, the random error follows identity Gaussian distribution, and the random effects also follow the Gaussian distribution.

2.3.4 Model Specification

This study includes a large set of explanatory variables, including employer-related features and various employer-based TDM measures. The dependent variables and independent factors are described in detail in Table 2. Employer-related features include the size, the location, and the business type of the employer. As a set of comprehensive travel demand management strategies, CTR programs have a wide variety of measures. Such measures are divided into five categories in this study, namely marketing and engagement, access to alternative transportation modes and amenities, monetary incentives, alternative work hours, and site services. Marketing and engagement measures are program advertising and collective bargain. To be specific, there are ten different approaches to promote CTR programs, such as distributing information during new employee orientation, publishing information on boards or kiosk, posting promotional materials, giving presentations by ETCs, organizing promotion campaigns, sending emails or flyers, publishing articles on employee newsletters, attaching information along with employee checks, and updating information on employer's website. This study hypothesizes the cumulative effort of incorporating different advertising strategies can create a stronger effect in motivating employees to follow CTR programs' instructions. For collective bargaining, employees at each worksite can bargain with their ETC and employer to claim for the most favorable CTR policies that match their interests.

Congestion can be reduced by switching from solo driving to alternate modes of transportation such as walking, biking, or taking public transportation. Therefore, the physical features near worksites should be taken into account when specifying the models. Monetary reward is an effective incentive to motivate individual travel behavior changes. For employees, monetary incentives include transit passes and subsidies for different transportation modes. Several measures are in place to give employees more flexibility in their work schedules and locations. Employees can take a compressed work schedule by working four days per week but ten hours per day. They can also work on a more flexible schedule. Telecommuting also aids in the reduction of peak-hour traffic. To promote access transit, Employers can give employees with short-distance mobility services to assist them in getting to bus stops. Some employers provide vehicles, in order to reduce the number of personal vehicles among employees. Employees have the option of driving employer-provided vehicles in an urgent situation. Some ETCs assist in the matching of carpoolers in order to facilitate ridesharing. Parking is acknowledged as a very responsive strategy to change travel behavior for its direct impact on the generalized cost of driving. A common strategy is that ridesharing is rewarded for free or prioritized parking whereas driving alone is discouraged through the use of parking fees. While such a priced parking strategy can be effective in encouraging ridesharing, it may receive adverse reactions from car-dependent employees.

Employer-related features are controlled as confounders, and these features can have a significant impact on CTR program efficiency. For example, changes in commuting mode share are associated with worksite features, such as location, size, and business type (Giuliano et al., 1993; J. Zhou et al., 2012; L. Zhou et al., 2009). To identify the difference across different business types, and because Seattle is recognized as a home of high-tech companies, the IT-related industry is used as the reference level in the models. This comparison allows us to obtain insights into the differences between VTR across various business types in comparison with the IT-related industry.

2.4 Results

2.4.1 Descriptive Analysis

Table 1 shows the level of VTR in the nine counties and the number of worksites that engaged in CTR programs from 2001 to2018. King County has the lowest VTR, which is around 56.37 over the years, far lower than that of the other eight counties. In addition, along with the national trend of car growth in the past decades, the level of VTR rises more slowly in King County (Seattle Metro) and Clark County (Portland Metro) but much faster in the other counties.

Table 2 shows the level of VTR and VMT in the nine counties and the number of worksites that engaged in CTR programs during 2017-2018. About 62% of the worksites are located in King County (Seattle Metro). Also, King County has the lowest VTR, far lower than that of the other eight counties, and the highest VMT.

The CTR programs have various TDM measures. The implementation approach for each measure is detailed in Table 2, and the descriptive analysis for the core metrics, employer-related features, and TDM measures is presented in Table 3. The analysis includes a number of time-varying factors. As seen in Figure 3, the most of them remained relatively stable over time with little variation, whereas job density increased greatly in the 2010s.

***Table 1** VTR in Different Periods (Vehicles per 100 employees).*

	Number of Worksites	Mean of VTR					
		2001-2002	2003-2004	2005-2006	2015-2016	2017-2018	Mean over time
King	165	54.69	54.74	54.81	58.50	59.19	56.37
Spokane	21	64.64	70.72	66.81	84.03	82.60	74.67
Whatcom	10	68.99	60.93	67.37	--	--	65.77
Snohomish	26	75.86	72.91	75.00	87.85	82.99	78.82
Yakima	5	74.99	78.83	69.44	83.40	93.51	80.13
Pierce	17	75.45	75.33	74.57	89.53	89.95	80.28
Kitsap	20	65.62	59.56	69.32	83.07	82.93	73.17
Clark	1	--	67.54	--	67.22	70.16	68.30

***Table 2** VTR and VMT in Different Periods during 2017-2018.*

County	# of Worksites	VTR (Vehicle per employee)				VMT (miles)			
		Mean	S.D.	Min	Max	Mean	S.D.	Min	Max
Clark	5	0.87	0.11	0.69	0.95	11.07	2.17	8.38	14.23
King	341	0.59	0.28	0.07	0.98	15.00	3.20	6.43	25.43
Kitsap	28	0.84	0.11	0.46	0.96	13.76	2.41	9.88	21.56
Pierce	39	0.90	0.04	0.80	0.97	14.89	2.62	11.36	21.86
Snohomish	71	0.85	0.08	0.59	0.98	14.68	2.15	10.01	21.16
Spokane	41	0.85	0.09	0.58	0.94	11.62	1.95	7.65	15.90

County	# of Worksites	VTR (Vehicle per employee)				VMT (miles)			
		Mean	S.D.	Min	Max	Mean	S.D.	Min	Max
Whatcom	13	--	--	--	--	--	--	--	--
Yakima	8	0.88	0.09	0.71	0.95	9.57	1.97	7.61	12.80
Total	546	0.69	0.26	0.07	0.98	14.43	3.11	6.43	25.43

Table 3 *Variable Description*

Variable	Description
VTR	The number of vehicle trips per 100 employees on a worksite, in vehicles per 100 persons
Employer-related Features	
Site ID	The site ID of each worksite.
Location (King County)	If a worksite locates in King County, 1; else, 0
Size (# of employees)	The total number of employees at a worksite
IT-related industry	If the business is information services/software/technical, 1; else, 0
Gov. & Edu. related	If the business is military, government, education, 1; else, 0
Manufacturing, transport and utility	If the business is manufacturing, public utilities, construction, or transportation, 1; else, 0
Finance and professional service	If the business is finance, insurance, real estate, professional/personal services, or retail/trade, 1; else, 0
Health care	If the business is health care, 1; else, 0
Agriculture and fishing	If the business is agriculture or fishing, 1; else, 0
Marketing and Engagement	
Promoting efforts	The number of activities in distributing CTR information to affected employees on a worksite
Collective bargaining	Employees can negotiate with employers to collaboratively decide which CTR tools are the best to match their needs. If a program involves employees for a collective bargain for CTR benefits, 1; else 0
Access to Alternative Transportation Modes and Facilities	
Transit access	If a station/bus stop locates within 3 blocks from a worksite, 1; else, 0
Sidewalks	If sidewalks or pedestrian trails are accessible to employees, 1; else, 0
Amenities	If amenities, such as shopping malls, restaurants, and banks, are located within 3 blocks, 1; else, 0
Monetary Incentives	
Transit pass	The average monetary cost of a transit pass that an employee received, in $ per month
Transit subsidy	The average monetary cost assigned as transit subsidy to an employee, in $ per month
Ridesharing subsidy	The average monetary cost assigned as carsharing subsidy to an employee, in $ per month
Bike/walk subsidy	The average monetary cost assigned as walk/bike subsidy to an employee, in $
Alternative Work Hours	
Compressed workweek	If a compressed schedule (typically ten hours per day and four days per week) is offered, 1; else, 0

Variable	Description
Flexible work hours	If employees can decide their starting and ending hours, 1; else, 0
Telecommuting	if employees working from home, a telework center, or a satellite office is allowed, 1; else, 0
Site Services	
Parking fees	Parking schemes, including parking free or prioritized parking spaces for ridesharing and not free for driving alone, 1; else, 0
Employer-provided vehicles	If the employer provides vehicles for employees, 1; else, 0
Short-distance mobility service	If the employer provides mobility services for close destinations (e.g., bus stop), 1; else, 0
Emergency ride	Employees can make agreements with employers to use alternative modes to access work sites. However, for emergency cases, employees can reimburse the cost of transportation, such as taxi and TNC services. Some companies set a cap for annual emergency rides, while some have no restrictions. If the employer provides emergency rides, 1; else, 0
Ride match	If the employer/ETC helps match carpoolers, 1; else, 0
Rental car	If the worksite has rental cars, 1; else, 0
ETC worksites	The number of worksites that an ETC is managing
ETC worktime	The work time of an ETC (hours per week) on a worksite
Temporal and Socioeconomic Factors	
Time	The time-metric labelled for 2001-2002, 2003-2004, 2005-2006, 2015-2016, 2017-2018, from 1, 2, 3, …, 9
Gas price	The average gasoline price in Washington state, \$1.42 in 2001-2002, \$1.79 in 2003-2004, \$2.58 in 2005-2006, \$2.64 in 2015-2016, and \$3.09 in 2017-2018
Job density	The census tract level aggregated job density, in count per square miles

***Table 4** Data Summary for Independent Variables*

Variable	Mean	St. D.	Min.	Max	Percentage of '1/Yes'
VTR	63.08	23.03	2.13	98.4	
Employer-related Features					
Location (King County)	--	--	--	--	86.97%
Size (# of employees)	740.75	1,798.65	10	28,797	--
IT-related industry	--	--	--	--	7.38%
Gov. & Edu. related	--	--	--	--	32.38%
Manufacturing, transport and utility	--	--	--	--	18.54%
Finance and professional service	--	--	--	--	17.89%
Health care	--	--	--	--	10.14%
Agriculture and fishing	--	--	--	--	13.65%
Marketing and Engagement					
Promoting efforts	6.11	1.61	0	10	--
Collective bargaining	--	--	--	--	18.72%

Variable	Mean	St. D.	Min.	Max	Percentage of '1/Yes'
Access to Alternative Transportation Modes and Facilities					
Transit access	--	--	--	--	90.23%
Sidewalks	--	--	--	--	93.03%
Amenities	--	--	--	--	89.41%
Monetary Incentives					
Transit pass	54.31	89.29	0	377	--
Transit subsidy	17.23	26.87	0	244	--
Ridesharing subsidy	16.53	24.46	0	150	--
Bike/walk subsidy	3.98	11.64	0	150	--
Alternative Work Hours					
Compressed workweek	--	--	--	--	62.35%
Flexible work hours	--	--	--	--	81.31%
Telecommuting	--	--	--	--	62.81%
Site Services					
Parking fees	--	--	--	--	1.06%
Employer-provided vehicles	--	--	--	--	68.05%
Short-distance mobility service	--	--	--	--	11.90%
Emergency ride	--	--	--	--	88.23%
Ride match	--	--	--	--	73.79%
Rental car	--	--	--	--	13.12%
ETC worksites	2.1	3.66	0	25	--
ETC worktime	6.35	10.45	0	40	--
Socioeconomic factors					
Gas price	2.29	0.61	1.42	3.09	--
Job density	205.57	325.93	0	1,684	--

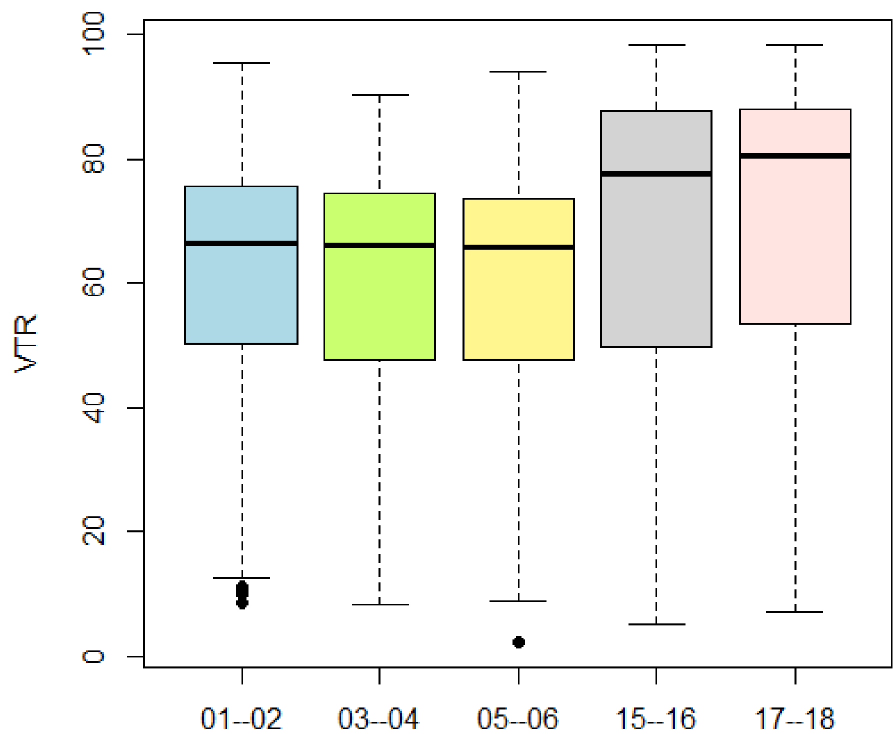
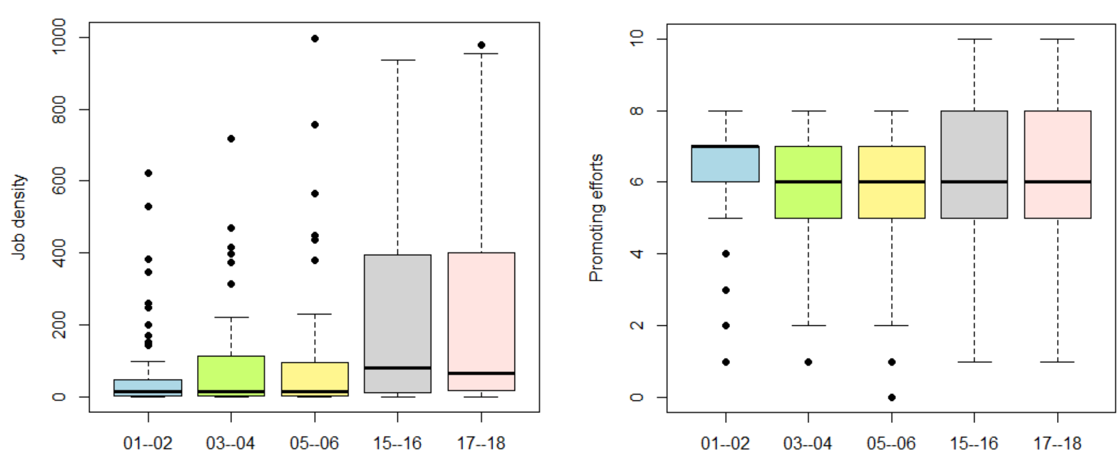


***Figure 3** Boxplots for vehicle trip rates (VTR) at worksites.*



(a) **(b)**

***Figure 4** Boxplots for (a) the number of employees at worksites; (b) the number of ways in promoting CTR.*

***Table 5** GLMM Modeling Outcomes.*

	Longitudinal ($N = 943$)			Cross-sectional ($N = 372$)		
	Estimate	P-value		Estimate	P-value	
(Intercept)	81.120	0.000	***	68.470	0.000	***
Location (King County)	-9.727	0.002	**	-7.398	0.085	.
Size (# of employees)	-0.213	0.631		-0.680	0.329	
Gov. & Edu. Related	-1.893	0.676		9.748	0.230	
Manufacturing, transport and utility	4.365	0.361		8.100	0.325	
Finance and professional service	-9.203	0.056	.	-7.339	0.356	
Health care	-3.187	0.547		9.862	0.249	
Agriculture and fishing	-5.387	0.283		0.777	0.923	
Promoting efforts	-1.278	0.015	*	0.927	0.293	
Transit access	-2.703	0.347		-9.302	0.099	.
Sidewalks	3.046	0.262		-6.209	0.513	
Amenities	1.534	0.495		-2.095	0.740	
Transit subsidy	0.009	0.797		0.040	0.847	
Ridesharing subsidy	0.088	0.019	*	0.112	0.473	
Bike/walk subsidy	-0.086	0.207		-0.365	0.345	
Compressed workweek	-0.868	0.344		2.572	0.515	
Flexible work hours	1.806	0.125		-4.168	0.299	
Telecommuting	0.109	0.918		-2.991	0.373	
Ride match	1.367	0.188		11.190	0.011	*
ETC worktime	-0.108	0.120		-0.332	0.176	
Gas price	-3.427	0.004	**	0.976	0.420	
Job density	-0.014	0.000	***	-0.004	0.000	***
Collective bargaining				-9.629	0.014	*
Parking fees				-2.023	0.706	
Transit pass				-0.083	0.000	***
Employer-provided vehicles				2.019	0.554	
Short-distance mobility service				2.910	0.553	
Emergency ride				14.100	0.003	**
Rental car				-12.390	0.003	**
ETC worksites				0.947	0.342	
Time	2.705	0.000	***			
Time: Promoting efforts	0.147	0.045	*			
Time: Transit access	0.044	0.922				
Time: Sidewalks	-0.012	0.984				
Time: Amenities	-1.632	0.001	***			
Time: Transit subsidy	-0.002	0.895				
Time: Ridesharing subsidy	-0.006	0.541				
Time: Bike/walk subsidy	-0.032	0.123				
Time: Job density	0.001	0.000	***			
Significant codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1						
Random Effects	Variance	Std. Dev.		Variance	Std. Dev.	
Site ID	254.150	15.942		304.100	17.438	
Residual	69.110	8.313		23.780	4.876	
AIC		7,411.702			2,829.942	
BIC		7,571.721			2,955.347	
Log-likelihood		-3,672.851			-1382.971	
Conditional R square		0.870			0.965	

Table 6 *Other Time-varying Variables Changed by Periods.*

Variables	2001-2002	2003-2004	2005-2006	2015-2016	2017-2018
Transit access	90.75%	90.54%	90.50%	89.91%	89.40%
Sidewalks	85.90%	94.14%	94.12%	95.41%	95.85%
Amenities	85.90%	90.09%	89.59%	90.37%	91.24%
Compressed workweek	7.49%	76.13%	70.14%	80.28%	79.72%
Flexible work hours	79.30%	82.43%	79.64%	82.71%	82.63%
Telecommuting	51.10%	63.06%	64.25%	68.69%	67.61%
Ride match	78.54%	60.00%	57.92%	86.24%	86.64%

Table 7 *GLMM Modeling Outcome for VMT*

Variables	**Estimate**		**P-value**
Intercept	14.89	***	<0.001
Location (King County)	2.271	***	<0.001
Size (# of employees)	0.033		0.724
Gov. & Edu. related	0.126		0.868
Manufacturing, transport and utility	1.811	*	0.016
Finance and professional service	0.306		0.659
Health care	-0.718		0.372
Agriculture and fishing	-0.682		0.36
Promoting efforts	-0.052		0.643
Collective bargaining	1.058	*	0.047
Transit access	-1.283	*	0.046
Sidewalks	-0.443		0.692
Amenities	-0.938		0.208
Transit pass	-0.001		0.86
Transit subsidy	0.043		0.154
Ridesharing subsidy	0.040	*	0.033

Bike/walk subsidy	-0.129	*	0.014
Tax credit received	0.691	.	0.08
Compressed workweek	0.464		0.293
Flexible work hours	-0.054		0.915
Telecommuting	0.102		0.815
Parking fee	0.132		0.851
Employer-provided vehicles	0.473		0.245
Short-distance mobility services	0.843		0.163
Emergency rides	0.046		0.937
Ride match	-0.852		0.133
Rental cars	-0.546		0.284
CTR-affected worksites	0.081		0.349

Level of significance: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Random Effects	Variance	S. D.
Zip-code	0.876	0.936
Residual	6.594	2.568
Clustering rate		0.117

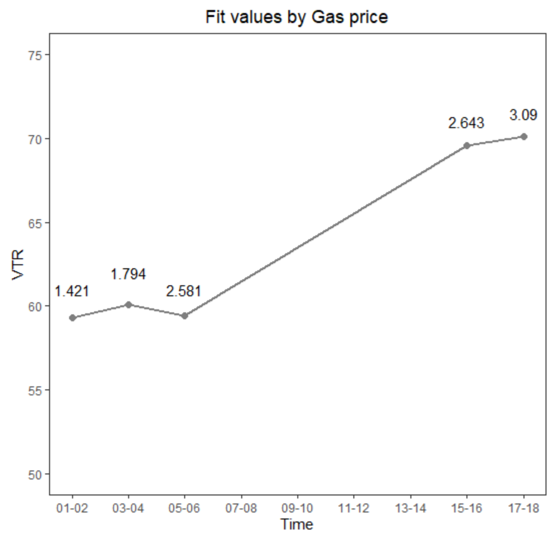
Model fit	Log likelihood	AIC	BIC	Marginal R^2	Conditional R^2
VMT	-650.32	1,360.7	1,469.3	0.256(df = 27)	0.343(df = 28)

2.4.2 Inferential Analysis on VTR

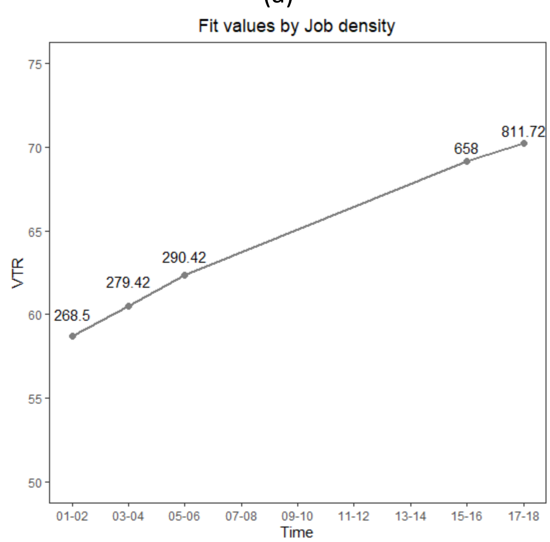
The results of the longitudinal and cross-sectional models are presented in Table 4. Two variables indicate significant effects in both models. First, employees who work in King County have a lower VTR than those who work in other parts of the state. King County is located in the heart of the Seattle metropolitan area and has many high-tech companies clustered, such as Microsoft, Amazon, and Boeing. On one side, owning a car costs more in King County in comparison with the other eight counties. On the other side, access to facilities, such as bus stops, sidewalks, and bike lanes, is significantly better in King County. Second, in areas with a high job density, the VTR is lower. In such areas, people have better access to other modes of transportation, including walking, biking, riding transit and ridesharing. Meanwhile, parking is more constrainedly offered in job dense areas.

According to the result of the longitudinal model, employers who spend more time and money promoting CTR programs have a lower VTR. This is further proof that advertising assists employees in comprehending the situation and encouraging them to engage in multimodal behavior. The result only shows a marginally significant effect on the type of companies. Employees in finance and professional services have a lower VTR than the people working in the IT industry. In general, people working in finance and professional services earn more money than people in the other work types such as education, and their offices usually locate in denser downtown areas. They tend to live closer to their workplaces, and likely to have a lower level of car dependence.

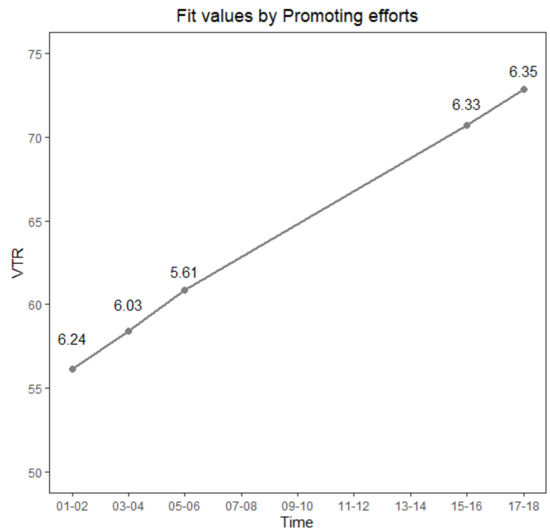
The longitudinal model incorporates numerous interaction terms to account for the effects of time-varying variables. To highlight, VTR grows over time in Washington state, and this trend can also be confirmed from Table 1. Gas price greatly rises over the years. A higher gas price appears to significantly discourage driving and is negatively associated with VTR, as demonstrated in Figure 1(a). Despite VTR is negatively associated with job density, the trend of VTR increase has been noticed in areas with more jobs over the decades, as shown in Figure 4(b). Similarly, despite the advertising effort helps reduce VTR, but such an effect is insufficient to significantly slow the increase of VTR over time, as shown in Figure 4(c). Building more amenities, such as libraries, theaters, and cinemas, is negatively associated with VTR over time, as demonstrated in Figure 4(d). Amenities contribute to the diversification of activities, which may attract more people to live and work in the urban centers, in a way contributing to the reduction of VTR.



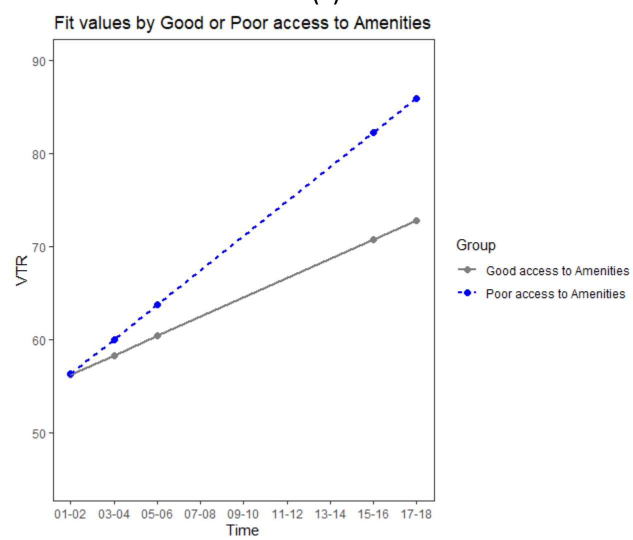
(a)



(b)



(c)



(d)

Figure 5 *Fitted values for significant time-varying variables, (a) gas price; (b) job density; (c) promotion efforts; (d) access to amenities near worksites*

For the cross-sectional model, better access to transit is related with a lower level of VTR. Both ride matching and carsharing subsidies point to a positive relationship with VTR. Local agencies and employers are expecting to increase shared rides among using such measures. On one side, carsharing is still a viable option for encouraging the usage of alternatives to driving alone by making vehicle available for other trips while at work (e.g., errands, doctor appointments, etc.). On the other side, such incentives may entice some employees switching from public transit to carpooling, but may not have the desired effect of reducing the percentage of drive alone commuters.

Three new CTR measures implemented in the recent decade suggest significant effects in reducing VTR. The process of collective bargaining suggests a negative association with VTR. It confirms that engagement has a positive effect. Such a consensus-based CTR measure appears to be popular among employees. As expected, employees are more likely to drive less if they have access to public transportation. Rental cars, such as Zipcar and Car2go, suggest a negative relationship with VTR. Emergency rides appear to have a positive relationship with VTR.

2.4.3 Inferential Analysis on VMT

Employees working in King County tend to have a higher VMT. Housing prices in King County's cities are more expensive, such as Seattle and Bellevue. Affordability effectively forces employees of lower income to live further from their workplaces, and resulting in a higher VMT. Among different business types, employees working in manufacturing, transportation, and utility industries commute for longer distances than employees in the IT industry. In general, people working in manufacturing, transportation, and utility have a lower income, especially compared to the high-income IT engineers. Income can be translated into affordability, which again explains the variations in VMT among employees that work in different industries.

VMT shows a positive association with collective bargaining. This finding indicates that employees who have longer commute distances are more likely to negotiate with their employers. In the bargaining process, employees can ensure that the adopted CTR tools will satisfy their needs and maximize their benefits.

VMT suggests a negative association with distributing transit passes to employees. Despite King County having one of the best transit systems in the US, the access to transit, the level of service, the service hours, and the coverage greatly varies between the downtown and suburban areas. Employees that have longer commuting distances live in more suburban areas, and transit cannot be their preferred choice. It is also convincing that employee having longer commuting distances can accept ridesharing subsidies but cannot take walk/bike subsidies. Employers that have employees commuting for longer distances, such as companies located in King County, tend to receive more tax abatement or grants as a way to reward their efforts in developing and operating CTR programs. To explain, the economic base of such companies is generally larger; on the other hand, they hire more employees.

Effective CTR tools that can help reduce VMT are improving transit access, organizing collective bargaining, and offering ridesharing and walk/bike subsidies. Yet, there are many external factors impacting employees' home location choice that this study fails to capture, such as school quality and amenities. The relationship between CTR tools and VMT cannot be casually interpreted. Individuals rarely change home location because of small incentives.

2.5 Discussion

This discussion section focuses on findings from the VTR models. Car growth appeared to be an unavoidable trend in the past decades in the US, and more people developed a high level of car dependence. Both municipal agencies and employers face challenges in discouraging car use and maintaining a low level of VTR on work sites. It's encouraging to see how many CTR measures are assisting in slowing car growth and reducing road congestion. With the abovementioned findings, the highly recommended CTR measures are: advertising CTR programs to employees, distributing transit passes to bus riders, engaging employees using collective bargaining, adding amenities near workplaces, and incentivizing carpooling options with caution.

CTR programs are evolving, and the long-term changes that come with them demand our attention. Figure 4 shows the fitted values of significant time-varying variables. Gas price continually increases and generates a negative impact on VTR. However, increases in petrol costs are insufficient to halt the growth of automobiles. It is worth noting that from 2003 to 2006, a decrease in VTR is linked to a steeper shift in gas price. Therefore, a higher gas tax could be an effective way to discourage solo driving. Job density has been tripled among the participated employers over the years. Despite the job density has a decelerating effect on VTR, again such an effect is insufficient to strongly reverse the trend of VTR growth. Similar findings apply to the effort in advertising CTR over time. It can only slow down but cannot stop the growth. VTR can be reduced over time by promoting access to amenities such as shopping malls, cinemas, and gyms.

Several measures are newly added to the CTR program, and several of them are incentives to encourage carsharing, such as carsharing subsidy, ride match, emergency ride, and shared (rental) cars. Whatever measure is taken, as long as it involves the use of cars, the measure may not help lower VTR. Promoting carsharing result in two scenarios. On one side, these measures may encourage employees to switch from solo driving to carpooling, which is the expected outcome. On the other side, employees may forego walking, biking and riding transit, in favor of carpooling which is not the intended outcome. Therefore, for worksites having good access to sustainable transportation modes, carsharing-related CTR measures should be implemented with caution. Despite rental cars appear to outperform ride match and carsharing subsidies to lower VTR, however, it deserves our attention that shared rental cars are owned by companies. Therefore, this finding can only explain shared rental cars are negatively associated with VTR but cannot guarantee this measure helps reduce road congestion. It continues to contribute to a growth in the number of vehicles on the road. Emergency rides appear to have a positive relationship with VTR. As Uber and Lyft are booming, employees have increased access to and are able to finance emergency transportation. In practice, some agencies have imposed a limit on the number of emergency rides that can be used each year, while some companies place no restrictions, which may result in the abused use of emergency rides. Therefore, this measure should be properly constructed to prevent it from being overused, or it should be permitted with additional limits, despite it is favored by most employees.

Despite lacking statistical significance, several CTR measures perform in the right way. They are contributing transit access, improving walking and biking environments near worksites, allowing employees with flexible work schedules, encouraging teleworking, designing different parking schemes for carpoolers, and promoting employees with short-distance mobility services and employer-provided vehicles. These CTR measures should be kept in the program if they do not have any counter effects on VTR.

2.6 Conclusions and Limitations

The rise of car use in past few decades is obvious. With three decades of practice, CTR programs continue to assist the state of Washington in managing traffic and reducing congestion. The difference in VTR between high-density and low-density areas is significant. In King County, the VTR overtime is 56.37, while VTR ranges from 68.30 to 80.28 in the other eight Washington counties. Employees who work in more densely populated regions are more susceptible to CTR implementation. Therefore, CTR measures need to be more carefully designed and selected by considering the various local environments and mobility needs.

Among various CTR measures, several of them stand out for their effectiveness in restraining car growth and reducing road congestion. Employers should continually subsidize transit for employees, enable shared rental cars on worksites, continually publicize CTR programs, and organize collective bargaining on a regular basis. Three CTR measures may be considered for use with extra restrictions, including emergency rides, carsharing subsidy, and ride match.

Due to the pandemic, the percentage of telecommuting has increased from 4% to 40% in some metropolitan cities. In addition, aided by smartphone technology, social carpooling and micro-mobility options demand the attention of both government agencies and employers. After the pandemic, telecommuting may become the new normal. Future CTR programs should investigate how such trends and emerging mobility options would affect the traffic and design new measures to smartly capture such requests.

This study has potential limitations. First, CTR survey data before 2000 are not included in the analysis. On one side, during that time, the sample size was very small. A limited number of employers took part in the program. On the other side, several time-varying variables during that period, such as job density and gas price, were missing. Therefore, the whole three decades of CTR development in Washington state are not included in this study. Second, the present analysis is based on the dataset of the employers who have implemented various CTR tools. Due to the self-selection and bias of the CTR employers, the findings of the analysis may be uninformative and cannot be applied to other situations. Such a bias is expected to be corrected by surveys of employers who refuse to implement CTR programs. As positive effects of CTR programs in reducing car use are confirmed, this study still give evidence to back up the practice of employer-based TDM strategies worldwide. Lastly, in the United States, the Seattle metropolitan region offers both the best transit service and the friendliest walking and biking environments, which contributes to the success of CTR programs. The result of CTR programs in other cities and counties may significantly differ if alternative transportation modes are poorly provided, which also limits the generalizability of this study.

3.Multimodality Incentivized by Employer-based Travel Demand Management

3.1 Background

Individuals that use different modes of transportation to reach their destinations are referred to as multimodality (An, Heinen, & Watling, 2021; Eva Heinen & Mattioli, 2019). Travel demand management (TDM) tools are widely leveraged to encourage multimodality by local agencies and employers aiming at travel behavior change towards sustainability. Distributing incentives, advertising, building infrastructures, and restricting car access and use are just a few examples of such efforts (Shin, 2020; Zaman & Habib, 2011). Employer-based TDM is a typical strategy for promoting multimodality and encouraging modal shift among employees, with the goal of reducing car dependencies and reducing congestion during peak hours. Promoting multimodality provides our civil society socio-economical, environmental, and health benefits. The shift from monomodaility to multimodality helps reduce solo driving and in consequence enhancing the efficiency of traffic systems (Klinger, 2017). Employers who support sustainable transportation might either obtain a tax abatement or avoid paying an additional tax (Ko & Kim, 2017; Shaheen, Cohen, & Bayen, 2018). Employees can be eligible for subsidies in exchange for their willingness to choose sustainable alternatives (Shin, 2020). Employees can avoid congestion by utilizing carpool/bus lanes. Employees can improve their physical health conditions if continually walk or bike. With a focus on the intersection of multimodality and employer-based TDM, this study contributes to the current literature from the following aspects.

First, despite multimodality and incentivizing individuals to utilize alternative modes are both emerging fields, multimodality and employer-based TDM are rarely combined in research. The impact of socioeconomic factors on multimodality was the focus of previous research, while the joint impact of various employer-based TDM tools was largely missing. Examining the effects of employer-based TDM tools on proportional travel mode shift is unique when contextualized under multimodality.

As aforementioned, incentives can be classified as information (including travel feedback), rewards, infrastructure developments, and social network (Li et al., 2021). The effect of social networks is widely neglected because of difficulty in observing and collecting such data. To be specific, peer effect, specifically the impact from colleagues, is a social network factor that can influence travel mode choices among employees. Ride match and collective bargaining on worksites are conditional on the mutual agreements among employees. Therefore, the peer effect on multimodality deserves more attention.

Lastly, existing studies are mostly based on expressed preference surveys, and people only report their most frequently utilized mode. A hidden assumption is that individuals are monomodal. Yet, despite people mostly drive alone, in large cities, the travel mode is highly substitutional because of the availability of alternatives. Individuals can occasionally utilize alternatives at their convenience, and such a behavioral shift is still rewarding. A partial shift, not a full shift, is still better than no shift (Eva Heinen & Mattioli, 2019). Yet, how to build the compatibility between solo driving and sustainable alternatives has not been analyzed in the literature.

This study aims to address the above-mentioned gaps adopting King County's commute trip reduction (CTR) biannual weekly survey data to explore the pattern of multimodality, in a way demonstrating the potential of modal substitution among employees. The analytical unit is an employee, and the analytical method is discrete choice modeling. The results aid in the identification of effective employer-based TDM tools that promote multimodality and, in the long run, encourage modal shifts towards sustainability.

3.2 Literature Review

This section of the literature review focuses on two fields: factors influencing multimodality and modal shift, and using employer-based TDM tools to incentivize multimodality and modal shift. To be specific, the employer-based TDM strategies are classified as information, incentives, social network, and infrastructure developments.

3.2.1 Factors Impacting Multimodality/Modal shift

Multimodality, utilizing multiple modes over the course of a week to access destinations, becomes an attended field in the literature, demonstrating a trend of multimodal travelers adopting non-automobile modes (An et al., 2021). Individuals alter their primary travel mode from one to another, which is referred to as modal shift. Modal shift frequently takes place at different stages of life because of changes in socioeconomic status and life course events, such as job change, marriage, the birth of children, retirement, and residential relocation (Scheiner, Chatterjee, & Heinen, 2016; Scheiner & Holz-Rau, 2013). Recent research indicated that multimodality has no significant correlation with modal shift (Eva Heinen, 2018). People in the United States have high degrees of car dependence. Travel mode change implicates a complicated decision process and is difficult to sustain. Many interventions made by TDM tools fail to encourage such voluntary changes and received negative feedback from the public, such as raising the generalized cost of parking and adding difficulty to drive-alone (Evangelinos, Tscharaktschiew, Marcucci, & Gatta, 2018).

Shifting from monomodality to multimodality mostly takes place in metropolitan areas (Klinger, 2017). In large cities, alternative modes are preferred when traffic is heavy during peak hours, when access to alternative modes becomes easy, when the services are good, and when the generalized cost of driving remains high. A dense urban setting is the presupposition to promote multimodality. In terms of sociodemographic features, there is a trend of multimodality in the US since Gen Y and Gen Z are more multimodal and favor urban life (Lee, Circella, Mokhtarian, & Guhathakurta, 2019; Olsson, Friman, Lättman, & Fujii, 2020; Kelcie M Ralph, 2017). In Germany, a similar trend has been detected (Kuhnimhof, Buehler, Wirtz, & Kalinowska, 2012;

Kuhnimhof, Wirtz, & Manz, 2012). In England, which is largely stratified by socioeconomic status, the result is more mixed (Eva Heinen & Mattioli, 2019).

It's crucial to recognize the various aspects of multimodality. Multimodality has been studied for years, and a recent achievement in the field is the identification of the multimodality trend utilizing longitudinal data (Eva Heinen & Mattioli, 2019). The number of modes is used as a measurement of multimodality to determine the level of multimodality (Eva Heinen & Mattioli, 2019). Overall, multimodality is getting more attention by both transportation planning researchers and professionals.

Modal shift, or voluntary travel mode change, is influenced by many external factors, such as built environment features at origins and destinations, availability of different travel modes, the quality of facilities and the level of services, socioeconomic factors, travel time budget, travel cost, and self-selection effects (Lee et al., 2019; Satiennam, Jaensirisak, Satiennam, & Detdamrong, 2016; Urbanek, 2021). Some individuals are highly loyal to a single mode, whilst other people's mode choices are widely interchangeable. The travel mode choice is determined by temporal moods, travel distances, access to various travel modes, schedule constraints, budget and monetary incentives. The number of viable alternatives and their relative market shares determines the modal shift (Flügel, Fearnley, & Toner, 2018). TDM tools therefore can be used to incentivize individuals to switch from solo driving to sustainable alternatives. Employees' home location choices and car ownership are influenced by employer-based TDM tools, as are household members' travel behaviors (Shin, 2020). To investigate modal shifts, a pilot research design (before and after) is commonly used (Sebastian Bamberg, 2006; Ruiz & García-Garcés, 2015; Taniguchi, Hara, Takano, Kagaya, & Fujii, 2003). Yet, unless a travel journal covering numerous trips or days is used, this method cannot accurately capture cross-sectional level multimodality.

3.2.2 Employer-based TDM to encourage multimodality and modal shift

TDM tools have been widely used to encourage modal shifts towards sustainability. As incentivized to motivate travel behavior change, TDM tools can be largely categorized as pull and push policies. Chapter one has more detailed discussion on pull and push policies. Pull policies offer travelers with incentives, and can be further categorized as information (including travel feedback), rewards, social network, and infrastructure developments (Sebastian Bamberg & Rees, 2017; Li et al., 2021; Skarin, Olsson, Friman, & Wästlund, 2019). Push policies raise the cost of driving or make parking more difficult. Rather than forcing people to change, attracting people to change is more preferred by the public. Therefore, there are far more pull tools than push tools. This section looks back at how employer-based TDM tools help encourage multimodality and trigger modal shifts.

Information has been given to individuals in a way to inform the availability of alternatives, such as advertising bus schedule posters and matching carpoolers. Essentially information promotes people to utilize alternatives. An empirical study in Australia indicated that providing local information helps reduce solo driving and increase walking, biking, riding transit and carpooling (Kelcie M Ralph & Brown, 2019; M. A. Taylor, 2007). However, results also indicated that information-based campaigns are largely insufficient for motivating long-term behavioral change (Skarin et al., 2019; M. A. Taylor, 2007). The use of smartphone apps to assist travelers in making plans is an extended way of providing information, and the related results on how travel plans help alter travel behavior are encouraging (Li et al., 2021; Sunio & Schmöcker, 2017).

Monetary incentive, or economic reward, is widely utilized to result in an employee's voluntary shift in travel behavior. Various types of incentives and subsidies, such as transit passes, are commonly used as reward and ridership retention tools. Using smartphone apps to give monetary incentives to encourage people to walk, bike, ride transit and carpool, has been implemented in many countries (Li et al., 2021; M. A. Taylor, 2007; Tsirimpa, Polydoropoulou, Pagoni, & Tsouros, 2019). Empirical research in Europe suggested that transit is mostly instigated by rewards. The transition from driving to taking public transportation accounts for a major share of modal shift. While driving and walking can rarely be encouraged to change toward biking (Hu, Chen, & Chen, 2021; Li et al., 2021; Tsirimpa et al., 2019). Empirical research from Colombia indicated that monetary incentive does motivate more people to walk and bike, but such a change is not statistically significant (Castellanos, 2016).

In addition to monetary incentives, other employer-provided services at work sites, such as employer-provided vehicles and short-distance mobility services, can help promote multimodality and encourage modal shift. Yet, being considered as a type of public good, employer-provided vehicles cannot assist employees reduce solo driving but increase commuting distance and the frequency of non-commuting trips (Shin, 2020). Employers can also provide employees with more flexibility, such as enabling for telecommute, compressed workweeks, and flexible work schedules. Empirical research indicated that schedule flexibility expands the choice set of employees (Vanoutrive et al., 2010).

Regarding social networks, existing studies have discussed spillover influences of travel mode choice among household members (Arroyo, Ruiz, Casquero, & Mars, 2018; Shin, 2020). Afternoon trips are mostly influenced and the effects vary depending on the level of persuasion (Arroyo et al., 2018). Similar effects in other types of social networks, such as the peer effect among colleagues, have only been studied rarely.

Changes in travel behavior can occur along with planning efforts made by infrastructure developments, such as the construction of bike lanes and the launch of bikeshare programs, and the expansion of transit coverage and the improvement of transit services. To encourage voluntary travel mode change and minimize car dependency, local agencies have built better sidewalks and bike lanes to motivate the adoption of sustainable alternatives. Yet, empirical research indicated that infrastructure alone is insufficient to stimulate changes in mode shift from driving to walking and biking (Song, Preston, & Ogilvie, 2017). Bikeshare has greatly altered mobility patterns in large metropolitan areas. The bikeshare programs in Washington DC, Minneapolis, the United States, and Delft, the Netherlands, all indicated a decrease in driving and increase in bicycling (X. Ma, Yuan, Van Oort, & Hoogendoorn, 2020; Martin & Shaheen, 2014; Sun, Feng, Kemperman, & Spahn, 2020), while the modal shift towards or away from transit was mixed and it is heavily influenced by location and locality (X. Ma et al., 2020; Martin & Shaheen, 2014).

For the impact of transit improvement on modal shift, empirical results from Thailand indicated that the establishment of a bus rapid transit system can stimulate many motorcyclists to change their travel modes, while the effect is quite limited on private car users (Satiennam et al., 2016). The result from China suggested that building a strong metro network sustains the modal change from private cars to transit (Yang, Wu, Rasouli, Cirillo, & Li, 2017). Empirical findings from Poland and England indicated that expanding transit infrastructure or promoting service alone is not enough to cause a modal shift toward transit (Ahanchian, Gregg, Tattini, & Karlsson, 2019; Davison & Knowles, 2006; Urbanek, 2021). It is just as important to raise the overall cost of driving (Batty, Palacin, & González-Gil, 2015; Urbanek, 2021). Therefore, the result of modal shifts toward transit is mixed, and is dependent on a variety of external factors in the local environment.

On the push side, increasing the generalized cost of driving, such as pricing and tolling, is a common strategy for discouraging solo driving (Urbanek, 2021). A parking fee is commonly used to encourage employees to use alternatives. Other push approaches are designed to make driving more difficult. These policies are more implemented in East Asia densely populated cities, where transit is more readily available, such as Seoul and

Beijing. The examples include but are not limited to ‘no parking for employees’, ‘weekly no driving day for employees’, and ‘metro level license plate rationing program’ (Ko & Kim, 2017). Push policies are rarely voluntarily adopted by employers in the US because of the adverse reactions from employees.

3.2.3 Summary
Multimodality, modal shift, employer-based TDM triggered voluntary travel mode change are all emerging fields in the literature in the recent decade. Yet, rarely do research cross these fields, and as such the combined influence of multiple employer-based TDM technologies on multimodality remains unclear. Multimodality is tough to track since data collection is complicated. A pilot study's design (before and after) may be able to capture modal shifts over time, but it may not be able to adequately depict multimodality if just the principal mode of transportation is reported. The existing research has done extensive research to assess the effects of different types of TDM tools, such as information, incentive and subsidy, infrastructure developments and new alternatives, while the related research on social networks is rather limited.

3.3 Research Design
Contextualized in the implementation of a CTR in Washington state, this study focuses on examining what employer-based TDM tools can encourage employees to use multimodality. The importance of this study lies in the following aspects. First, to better understand multimodality, the proportional substitution among employees is investigated in this study. Second, this study identifies the effective employer-based TDM tools that can be leveraged to encourage modal substitution. Third, by controlling worksite ID, home zip codes, and commuting distance as random effects, the purpose of this study is to see if there are any spatial autocorrelations in employee travel mode choices. Lastly, to account for the fixed effects of ride match and collective bargaining, this research can look at an underappreciated peer influence on voluntary travel modal switching, especially towards carpooling. The data source and study area, as well as the model specification and method, are described in the following sections.

3.3.1 Study Area and Data Source
Washington state Department of Transportation (WSDOT) has conducted the commute trip reduction (CTR) program for three decades, which aims to reduce carbon emissions and eliminating congestion on the busiest commute routes. A biannual survey is utilized to monitor the performance of the CTR program regularly. The survey captures travel mode information on a weekly basis, which provides rich data to analyze the effect of employer-based TDM tools on multimodality. This study utilized this CTR data collected from 2017 to 2018 in King County, Washington state. Multimodality happens in large metropolitan areas with sustainable alternatives available, such as King County, where the Seattle Metropolitan is located, qualifies for this selection criterion.

In total, 65,909 employees supplied worksite information and completed the survey in King County. The sample was divided into two groups, nine to five Monday to Friday standard work schedules, and non-standard work schedules. The sub-sample of non-standard work schedules was removed because employees in this group are less likely to increase congestion to peak-hour traffic. The number of employees having standard work schedules was 41,440. There were some outliers in the data. Employees who commute with unreasonable distance were excluded from the final sample, such as driving for more than 100 miles, or biking for more than 25 miles. The final sample consisted of 41,287 employees from 182 worksites of 157 companies. After removing cases with missing values, a sample of 31,174 employees was obtained. As the goal of this study is to discover effective TDM tools to motivate employees to change travel modes from driving alone to one sustainable alternative, therefore, employees commuting by one sustainable alternative, shifting between two sustainable alternatives, and using more than three sustainable alternatives were excluded from this study, resulting in a final sample of 18,591 from 182 work sites of 157 companies, as shown in Figure 5.

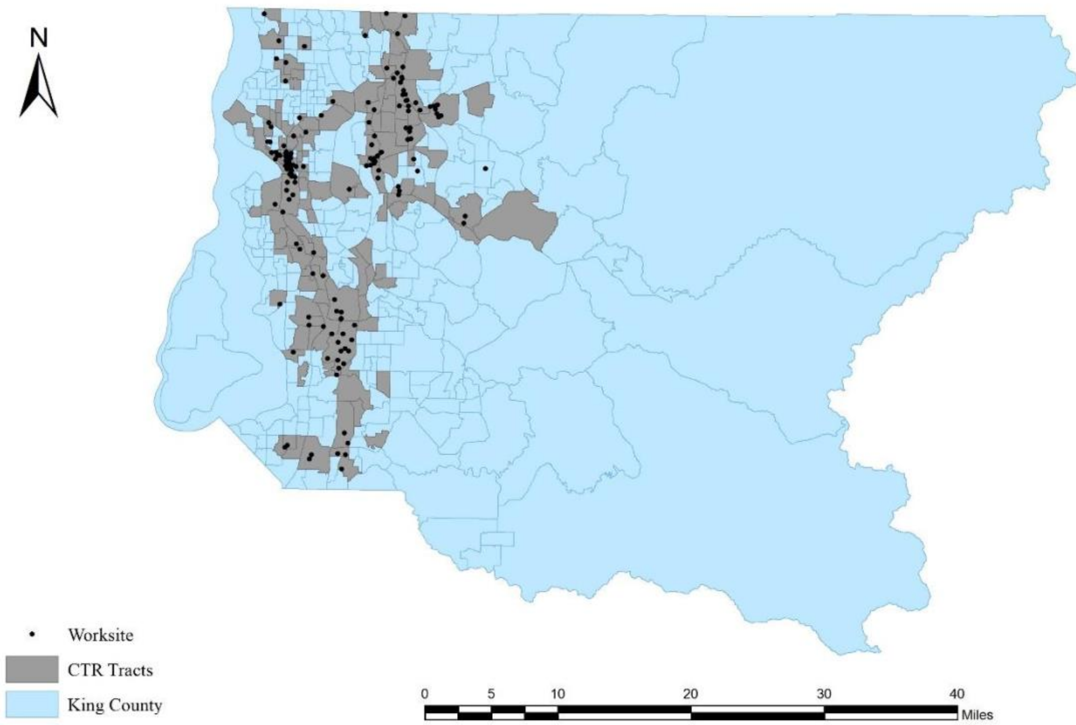


Figure 5 *Worksites Involved in Commute Trip Reduction, King County, Washington state, 2017-2018*

3.3.2 Model Specification

Travelers who use multiple modes in a given period are said to be multimodal (Kuhnimhof, Chlond, & Von Der Ruhren, 2006). Although utilizing sustainable alternatives for a single trip, such as "walk and ride," is strongly encouraged, using different modes on different days of the week is still rewarding because sustainable alternatives always help mitigate congestion. Therefore, in this study, multimodality is defined as using multiple ways of travel on different workdays. Multimodality is defined as a weekly partial shift that nonetheless shows realistic substitutional effects between different travel modes. To examine multimodality, this study utilizes a discrete choice modeling framework and centers on drive-alone. The alternatives are defined as 'drive-alone (DA)', 'DA & carpool', 'DA & transit', 'DA & telework', and 'DA & walk or bike', as shown in Table 8.

Table 8 *Commute Distance and Multimodality*

Commute distance	Percent	DA	DA & Carpool	DA & Transit	DA & telework	DA & Walk or Bike
≤ 1 mile	1.28%	1.14%	0.30%	0.31%	1.37%	14.53%
1 - 5 miles	15.15%	15.55%	11.16%	16.93%	10.12%	29.07%
5 - 15 miles	45.25%	45.69%	38.03%	47.75%	44.45%	43.25%
15 - 25 miles	25.46%	25.31%	33.47%	21.73%	26.44%	13.15%

25 - 50 miles	11.79%	11.40%	15.21%	12.23%	15.27%	0.00%
> 50 miles	1.07%	0.91%	1.83%	1.04%	2.35%	0.00%

Employer-based TDM tools, as well as worksite-related features and employees' attitudinal factors adjusted as control variables, are at the core of the fixed effects. Employer-based TDM tools are generally divided into two types of policies: pull and push. Pull policies were further classified as information, social networks, monetary incentives, mobility services, infrastructure developments, and alternative work schedules in this study. As push policies may result in negative reactions from employees, only a parking fee was implemented by some CTR programs. Among various TDM tools, employers allowing for telecommuting was removed because of multicollinearity. To be specific, according to the results of a correlation test, employers who allowed for compressed workweeks and flexible workhours were also likely to enable work from home.

Self-selection effects hand over a great portion in explaining travel mode choices. WSDOT surveyed respondents what are the most important three factors related to choose sustainable alternatives or driving alone at the end. Therefore, confounding effects were controlled by adjusting attitudinal factors. To be specific, employees select sustainable alternatives or drive alone for various reasons. Employees may select sustainable alternatives because of monetary incentives, health, parking, efficiency, convenience, and physical constraints. Employees can drive alone because of convenience, the lack of transit information, job requirement, family obligations, and safety concerns. However, this study decided to drop questions related to employees' responses on why they select sustainable alternatives for the following two reasons. First, in the final sample, all employees were capable of driving due to the alternatives were centered on drive-alone, and nearly 80% of them did not select sustainable alternatives to access workplaces. Alternatively saying, these drivers owned no or limited experience of commuting by sustainable alternatives. Their responses on why they selected sustainable alternatives could be ideological based on their assumptions or imaginations. Somehow their responses on this part were subjective. Second, a significant portion of drive-alone employees omitted the questions on why selected sustainable alternatives. If these questions are included in the final model, a significant number of cases will be lost due to missing values and involve in the bias of sample selection.

To capture spatial autocorrelations, worksite ID, employees' home zip codes, and commute distance are considered as random effects to improve the modeling accuracy. Variable descriptions are detailed in Table 9.

Table 9 *Variable Descriptions*

Incentives	Description
Worksite features	
site ID	The site ID of a worksite
zip code	The zip code of an employee's home
ETC worktime	Weekly hours that an employee transportation coordinator (ETC) works, in hours
IT-related industry	If a worksite is for information services/software/technical, 1; else, 0
Gov. & Edu. Related	If a worksite is for military, government, and education, 1; else, 0
manufact, transport and utility	If a worksite is for manufacturing, public utilities, construction, and transportation, 1; else, 0
finance and professional service	If a worksite is for finance, insurance, real estate, professional/personal services, and retail/trade, 1; else, 0

healthcare	If a worksite is for medical services or healthcare, 1; else, 0
agriculture and fishing	If a worksite is for agriculture and fishing, 1; else, 0
Employee features	
commute distance	Commuting distance, coded into six levels, < 1 mile, 1- 5 miles, 5 – 15 miles, 15 – 25 miles, 25 – 50 miles, >50 miles
Employer-based TDM tools	
Pull Tools	
Information: promoting efforts	The types of activities used to advertise CTR program to employees on a worksite
Social networks:	
ride match	If an employer/ETC helps employees match rides, 1; else, 0
collective bargaining	Collective bargaining is a process that employees jointly select TDM tools with their employer or ETC by negotiation. If a CTR program involves employees for collective bargaining, 1; else, 0
Monetary incentives:	
transit pass	If an employer provides transit pass to employees, 1; else, 0
transit subsidy	If an employer provides transit subsidies to employees, 1; else, 0
carsharing subsidy	If an employer provides carsharing subsidies to employees, 1; else, 0
bike/walk subsidy	If an employer provides walk/bike subsidies to employees, 1; else, 0
Mobility services	
vehicle providing	If an employer provides vehicles to employees, 1; else, 0
short-distance mobility service	If an employer provides short-distance mobility services to employees, 1; else, 0
emergency ride	If an employer reimburses the cost of emergency rides, 1; else, 0
Infrastructure developments:	
transit access	If a bus stop/transit station is located within 3 blocks from a worksite, 1; else, 0
amenities	If amenities, such as shopping malls, are located within 3 blocks from a worksite, 1; else, 0
rental car	If rental cars, such as Zipcar or Car2go, are available on a worksite, 1; else, 0
Alternative Work Hours:	
compressed workweek	If an employer allows for compressed work week, 1; else, 0
flexible work hours	If an employer allows for flexible work schedule, 1; else, 0
telecommute	If an employer allows for working from home, 1; else, 0
Push Tools:	
parking fee	If employees pay parking fees for driving alone, 1; else, 0

Attitudinal factors	
Drive alone reasons:	
convenience	An employee commutes by driving alone for the convenience of driving or the inconvenience in accessing transit, 1; else, 0
information	An employee commutes by driving alone due to the lack of information about sustainable alternatives, 1; else, 0
job requirement	An employee commutes by driving alone for the requirement of the job, 1; else, 0
family obligation	An employee commutes by driving alone for childcare or other family obligations, 1; else, 0
safety	An employee commutes by driving alone because of the danger of bicycling or walking, 1; else, 0

The commuting pattern may be influenced by the location of work sites and the characteristics of the business. Worksites are divided into six types of industries in this study, including IT, governmental and educational, manufacturing, transportation and utility, finance and professional services, healthcare, and agricultural and fishing. As Seattle is famous as the home of high-tech companies, the IT industry is chosen as the reference level in making comparisons with other industries.

3.3.3 Methodology

A mixed multinomial logit model (MMNL) was employed in this study. An MMNL is a multinomial logit model, which explains the heterogeneities by estimating coefficients of parameters for the individual choice. For the MMNL, mixed refers to the combination of a multinomial logit model and a random-effects model. Therefore, an MMNL assumes that there are $\boldsymbol{N}$ choices with $\boldsymbol{p}$ fixed effects and $\boldsymbol{q}$ random effects. The utility function, $\boldsymbol{U_i}$, is expressed as *Eq. (3.1).*

$$U_i = \beta_{0i} + \beta_{ji}X_j + \gamma_k Z_k + \varepsilon_i \#(3.1)$$

where $\boldsymbol{i = 1, 2, \dots, N-1}$, $\boldsymbol{j = 1, \dots, p}$ and $\boldsymbol{k = 1, \dots, q}$. For this study, N equals five, and the five choices are DA, DA & carpool, DA & transit, DA& telework, DA & walk or bike. The $\boldsymbol{p}$ fixed effects contain factors of employer-based TDM tools, worksite features, and attitudinal factors. The $\boldsymbol{q}$ random effects are worksite ID, employees' home zip codes, and commute distance. For each choice, the probability function is expressed as *Eqs. (3.2), (3.3) and (3.4).*

$$P(Y = i) = \frac{e^{U_i}}{1 + \sum_{i=1}^{N-1} \quad e^{U_i}}, where\ i = 1,2, \dots, N-1 \#(3.2)$$

$$P(Y = N) = \frac{1}{1 + \sum_{i=1}^{N-1} \quad e^{U_i}} \#(3.3)$$

$$ln\left(\frac{P(Y = i)}{P(Y = N)}\right) = U_i = \beta_{0i} + \beta_{ji}X_j + \gamma_k Z_k + \varepsilon_i \#(3.4)$$

where the N^{th} choice would be considered as the reference choice. In this study, the reference choice is DA. β_{0i} is the intercept for the ith choice comparing with the Nth choice; X_j is the jth independent variable in this model, and β_{ji} is the coefficient for the jth independent variable with the ith choice; Z_k is the kth random effect in this model, and γ_k is the coefficient for the kth random effect where $\gamma_k Z_k$ both follow a normal distribution; ε_i describes the random error for the ith choice following identity Gaussian distribution. In the mixed multinomial logit model, if $ln\left(\frac{P(Y=i)}{P(Y=N)}\right) > 0$ or $P(Y = i) > P(Y = N)$, then a conclusion is that the ith choice is preferred to be chosen rather than the Nth choice; on the other hand, the N^{th} choice is preferred to be chosen. If the ith choice and the mth choice need to be compared, then the following *Eq. (3.5)* would be applied.

$$ln\left(\frac{P(Y=i)}{P(Y=m)}\right) = ln\left(\frac{P(Y=i)}{P(Y=N)}\right) - ln\left(\frac{P(Y=m)}{P(Y=N)}\right) \#(3.5)$$

Since the sample size was large, Markov Chain Monte Carlo was used to estimate the MMNL (Bansal, Krueger, Bierlaire, Daziano, & Rashidi, 2020). This MMNL was estimated by the MCMCglmm package in R program.

3.4 Results

3.4.1 Descriptive Analysis

Excluding individuals working for non-standard schedules resulted in a final sample of 18,591 employees from 182 worksites in King County, Washington. The majority of those who responded worked in the industry of finance and professional services (34.20%). According to the sample, employees generally had easy access to transit (91.21%) and amenities (96.09%) near worksites, and 31.19% of worksites had carsharing programs initiated, such as Car2go and Zipcar.

Most employers allowed for a compressed workweek (70.00%), flexible work hours (80.00%), and telecommute (69.16%) to give employees more flexibility. To foster the consensus between employers and employees, a process of collective bargaining was launched by employers to help employees negotiate for CTR benefits that best match their needs, while the proportion of companies that implemented collective bargaining was small (13.36%). Employers and employee transportation coordinators (ETCs) promoted sustainable alternatives to employees on various occasions and by various means, such as new employee orientation, flyers, emails, and newsletters. The mean of approaches that employers utilized to promote sustainable alternatives was 6.45, ranging from 1 to 9.

For the monetary incentives, 80.21% of employers offered transit passes to their employees, while only 28.40% of employers provided subsidies for walking and biking. For the worksite mobility services, 26.09% of employers supplied short-distance shuttles to assist employees' access nearby bus stops, and 50.08% offered vehicles to employees for occasional use, guaranteed to ride back home, and work-related trips. Most employers reimbursed emergency rides for their employees. However, based on the survey, it was uncertain whether these employers had a quota for emerging rides, such as once a month.

Regarding attitudinal factors, the survey investigated two components, including why employees prefer driving alone and why employees prefer sustainable alternatives. However, a sample selection bias is related in the way of structuring questions since employees who drive alone may have no or limited experience with sustainable alternatives. Among the 18,591 respondents, 6,258 employees did not explain why they did not select sustainable alternatives. To understand why employees favored drive-alone, all other factors were outperformed by convenience, which was 86.05%; followed by family obligations, which was 45.09%. Other reasons were less weighted to explain why employees favored drive-alone.

Despite the attitude factors are excluded in final data because of the subjective answer from the employees who only drive alone, the proportion of various attitude factors chosen by employees among different trip modes was shown in Table 3.4. Employees who only drive alone have 17.04% of them agreeing that the physical constraints are a reason to choose the alternative mode, which is far away from the proportion of other employees who had alternative mode experiences. There is no prominent reason for those employees who chose occasionally car sharing. In contrast, the incentive is the main reason for those employees who chose occasionally riding transit as 83.82%, convenience was agreed by 85.97% of employees who selected occasionally working from home as a reason, and 87.64% of employees who chose occasionally walking or biking consider health as a reason.

Table 10 *Data Summary*

Variable	Without sample selection bias (18,591)				
	Mean	St. D.	Min.	Max	Pct of '1/Yes'
Worksite features					
ETC worktime	14	14.69	0	40	-
IT-related industry	-	-	-	-	14.14%
gov. & edu. related	-	-	-	-	10.84%
manufacturing, transport and utility	-	-	-	-	16.80%
finance and professional service	-	-	-	-	34.20%
health care	-	-	-	-	10.44%
agriculture and fishing	-	-	-	-	13.58%
Employer-based TDM tools					
Information:					
promoting efforts	6.59	1.6	1	9	-
Social network:					
ride match	-	-	-	-	93.70%
collective bargaining	-	-	-	-	13.36%
Monetary incentive:					
transit pass	-	-	-	-	80.21%
transit subsidy	-	-	-	-	43.54%
carpooling subsidy	-	-	-	-	51.70%
bike/walk subsidy	-	-	-	-	28.40%
Non-monetary incentive (mobility service on worksite):					
vehicle providing	-	-	-	-	50.08%
short-distance mobility service	-	-	-	-	26.09%
emergency ride	-	-	-	-	93.78%
Infrastructure developments:					
transit access	-	-	-	-	91.21%
amenities	-	-	-	-	96.09%
rental car	-	-	-	-	31.19%
Alternative work hours:					
compressed workweek	-	-	-	-	70.00%
flexible work hours	-	-	-	-	80.00%
telecommute	-	-	-	-	69.16%
Push tool:					
parking fee	-	-	-	-	41.00%
Attitudinal factors (why drive-alone)					
convenience	-	-	-	-	86.05%

information	-	-	-	-	4.57%
job requirement	-	-	-	-	9.72%
family obligation	-	-	-	-	45.09%
safety	-	-	-	-	11.13%

Table 11 *Attitudinal factors explaining why employees favor sustainable alternatives*

	# of employees	Incentive	Health	Parking	Time	Convenience	Physical Constraints
Drive alone	8959	47.49%	41.28%	21.27%	27.77%	35.91%	17.04%
DA - Car sharing	876	48.97%	43.84%	32.08%	49.89%	4.68%	5.14%
DA - Public transport	927	83.82%	43.47%	54.48%	12.94%	5.83%	3.78%
DA - Telework	1304	25.61%	36.20%	15.11%	19.17%	85.97%	4.68%
DA - Walk & Bike	267	41.57%	87.64%	17.23%	3.75%	9.36%	2.25%

3.4.2 Inferential Analysis

An MMNL model was estimated in this study, and Table 12 shows the modeling outcome. The MMNL model estimated why employees select multimodal rather than drive-alone in the surveyed week. The reference level was drive-alone, and the alternatives were the combination between drive-alone and carpool, transit, telework, and walk or bike. In the sample, 79.75% of employees preferred to drive alone, 5.3% of employees occasionally carpooled, 5.15% of employees by chance utilized transit, 8.24% of employees often worked from home, and 1.55% of employees sometimes walked or biked in addition to driving alone during the week. Markov Chain Monte Carlo was the estimation method in this study, and coefficients with no likelihood of zero were significant.

As aforementioned, three random effects were included in the model, including employees' home zip codes, worksite IDs, and commute distance. All three random effects showed significance, demonstrating the existence of spatial autocorrelations among employees' travel choices, no matter at home, at workplaces, or the distance between home and workplace. Worksite ID had the highest estimated variance of the three random effects, at 0.819, followed by commute distance and then home zip codes. Therefore, the heterogeneities of worksites had the largest effect on the random error of multimodality.

The impact of worksite features on multimodality was limited for employees who drove alone but occasionally carpooled. Among various TDM tools, charging parking fees on employees and providing short-distance mobility services both indicated positive associations with occasional carpooling, while allowing for compressed workweeks suggested a negative association with occasional carpooling. Employees preferred drive-alone due to the convenience, also because employees had limited information on sustainable alternatives. In addition, employees were discouraged from occasional carpooling because of safety concerns on alternative modes.

An ETC's work time was positively associated with the occasional utilization of transit as the manager of a commute trip reduction program. This adds to the evidence that ETC's efforts aid in the promotion of multimodality. Between always drive-alone and drive-alone but occasionally ride transit, people in the industries of manufacturing, transportation, utility, and healthcare were more loyal to drive-alone in comparison with employees in the IT industry. Several TDM tools showed positive effects in encouraging the occasional utilization of transit, including offering transit passes and employer-owned vehicles, being close to bus stops and amenities, permitting for flexible workhours, and charging parking fees on worksites. Employees rejected to utilize transit due to a lower level of convenience, the lack of information on transit, and safety concerns.

Regarding the occasional telecommuting, employees in the IT industry have the most flexibility in terms of working from home. Several TDM tools supplied aids to access worksites had negative relationship with occasional telecommuting, including offering carsharing subsidies, employer-owned vehicles, short-distance shuttles, and transit access to employees. The modeling result indicated both compressed workweeks and flexible workhours had positive relationship with the occasional telecommuting. Permitting employees to have a collective bargaining process, assisting employees match shared rides, and charging parking fees on worksites were also positively association with occasional telecommuting. Among the many attitudinal factors, employees may occasionally telecommute due to convenience and family obligations. However, there are still a variety of reasons explaining why employees prefer driving alone, including the lack of information on alternative modes and job requirements.

In comparison with people in the IT industry, employees in the financial and professional services industries were less likely to occasionally walk or bike to work. Several employer-based TDM showed significant effects in encouraging the multimodality between driving alone and walking or biking. Allowing flexible workhours, offering transit pass, implementing carshare programs on worksites, and charging parking fees all ways to encourage employees to the occasional commute by walking or biking. However, compressed workweeks suggested a negative correlation with the occasional commute by walking or biking. Regarding attitudinal factors, considering convenience, the lack of information of alternative modes, and job requirements, driving alone was the preferred mode.

3.5 Discussion

The relationship between multimodality and employer-based TDM tools was set as a research objective in this study, where multimodality was classified as the partial switch from drive-alone to the occasional use of sustainable alternatives. Such a partial modal shift among employees still contributes to reducing congestion and is a stage achievement towards the full modal shift among employees. Results supplied evidence to support the implementation of CTR programs in Washington state, as well as a better use of relevant TDM tools to greatly influence employees' travel mode choices.

Despite ETC's work time only showed a significance for drive-alone and occasionally riding transit, the mean coefficients on other alternatives were all positive, suggesting ETCs play an active role in encouraging multimodality (Lopez-Aqueres, 1993; Orski, 1993). Their dedication assisted employers administer and monitor the performance of CTR programs and motivated employees to try and utilize sustainable alternatives. Only small differences in the preference of multimodal choices among the employees working in different industries were determined. There is the most noticeable difference that employees in the IT industry were more likely to work from home than those in other industries.

To summarize the findings, the most effective employer-based TDM tools to promote multimodality are offering transit passes, allowing for flexible work schedules, and charging parking fees on worksite. These results are all consistent with what has already been discovered in the literature (Tsirimpa et al., 2019; Urbanek, 2021; Vanoutrive et al., 2010). They jointly encourage multimodality from the pull side and push side by conducting employees to occasionally utilize sustainable alternatives. It is worth noting that allowing for a compressed workweek is aimed at reducing peak hour traffic congestion rather than modal change (Vanoutrive et al., 2010). Due to a variety of concerns, such as reduced transit services, increased difficulty in matching rides, hazardous walking surroundings, and less visible biking environments, access to the use of sustainable alternatives after peak hours can be less convenient or comfortable. It is critical to have easy access to bus stations in order to encourage people to use transit (Sivakumaran, Li, Cassidy, & Madanat, 2014). Locating near amenities, such as shopping malls, entertainment centers, and cinemas, encourage the occasional usage of transit. This finding is also consistent with previous research (Miramontes, Pfertner, Rayaprolu, Schreiner, & Wulfhorst, 2017). Despite no direct evidence on these amenities was identified in this study, this can be regarded as a result of chained activities and livability. After completing their duties, employees are free to shop, socialize, and have dinner. During peak hours, parking in such areas might be more difficult or expensive, whereas 'walk and ride' perfectly matches their mobility demands.

This study aimed to learn new knowledge about the peer influence of employer-based TDM tools among colleagues, such as ride match and collective bargaining. However, these two variables were only significant for the alternative of drive-alone but occasionally telework. When negotiating for TDM tools that employees are in favor of, colleagues can be united, such as asking employers to enable telecommuting. And by chance, these telecommuters appear to be more amenable to sharing rides. Because there is no direct evidence, the following discussion may involve speculation. Employees are generally weaker affected by social networks. On one side, as a human, Employees prefer to own privacy, regardless of personal matters or activity schedules. On the other side, sharing rides consume their convenience and efficiency, such as waiting for a colleague at a worksite or detouring for picking up or dropping a colleague. In comparison to family ties and friendships, such a relationship is not as close. In general, it is difficult to use social network to encourage employees to change their travel modes.

The results from attitudinal factors indicated a high level of consistency between behavior and attitudes. Their preferences greatly explained why they drove alone to workplaces in most cases. However, the option of telecommuting appeared to provide better convenience for employees and more flexibility for them to fulfill their family obligations at home.

3.6 Conclusions and Limitations

Multimodality and employer-based TDM tools were combined in this study. The findings indicated that offering employees transit passes, enabling flexible work schedules, and charging parking fees at worksites were the most effective strategies to proportionally shift employees' travel mode choices toward sustainability. Multimodality and modal shift were actively promoted by ETCs. Their contribution to the successful operation of CTR programs cannot be overlooked. The spatial autocorrelations in multimodality were also confirmed in this study across different worksite, home, and commuting distances. People who live and work in closing areas were more likely to use multimodal in a similar way.

There are a few limitations to this study as well. First, socioeconomic factors and built environment factors play an important role in explaining travel mode choice. Individual socioeconomic profiles and residential information were not adequately captured in the CTR survey, especially the effects of home-based built environment factors and socioeconomic factors were not well captured. Second, employees who consistently chose sustainable alternatives or used more than three modes were excluded from the final sample since the selected alternatives centered on drive-alone. Their reasons for choosing multimodal were complementary to findings determined from this study. Thirdly, attitudinal factors that explain why employees selected sustainable alternatives were not taken into account in this study. The responses from people who always drive alone were not trustworthy given their limited experience in utilizing sustainable alternatives, while they showed a great proportion of cases in the final sample.

Table 12 Modeling Results (18,591 Employees, Percentage of DA: 79.75%).

Variable	DA & Car sharing			DA & Transit			DA & Telework			DA & Walk or Bike		
	Estimate	l-95% CI	u-95% CI	Estimate	l-95% CI	u-95% CI	Estimate	l-95% CI	u-95% CI	Estimate	l-95% CI	u-95% CI
intercept	-2.765	-4.200	-1.311	-8.396	-10.390	-6.494	-3.306	-4.610	-2.043	-4.042	-5.778	-2.422
Worksite features												
ETC worktime	0.010	-0.008	0.030	0.020	0.000	0.040	0.008	-0.011	0.028	0.010	-0.010	0.031
IT-related industry												
Gov. & Edu. related	0.518	-0.223	1.255	0.121	-0.647	0.851	-1.462	-2.135	-0.658	0.548	-0.263	1.378
manufact, transport and utility	-0.108	-0.875	0.516	-0.742	-1.499	-0.025	-2.737	-3.367	-1.960	-0.324	-1.110	0.541
finance and professional service	-0.123	-0.754	0.431	-0.098	-0.681	0.501	-0.774	-1.308	-0.243	-1.003	-1.761	-0.319
health care	-0.142	-0.917	0.640	-0.656	-1.465	0.195	-1.266	-1.968	-0.560	-0.205	-1.058	0.684
agriculture and fishing	0.040	-0.699	0.708	-0.458	-1.134	0.258	-1.436	-2.116	-0.778	-0.206	-0.972	0.545
Employer-based TDM tools												
Information:												
promoting efforts	-0.009	-0.123	0.116	-0.077	-0.203	0.044	0.059	-0.056	0.175	-0.062	-0.216	0.060
Social network:												
ride match	0.088	-0.476	0.693	0.356	-0.196	1.063	0.785	0.254	1.409	-0.511	-1.202	0.150
collective bargaining	-0.087	-0.701	0.474	0.264	-0.329	0.865	1.211	0.599	1.771	-0.084	-0.724	0.640
Monetary incentive:												
transit pass	0.184	-0.237	0.662	0.829	0.295	1.369	-0.036	-0.520	0.398	0.459	0.000	1.026
public transport subsidy	0.152	-0.222	0.576	-0.366	-0.750	0.037	0.081	-0.346	0.447	-0.032	-0.506	0.411
car-sharing subsidy	0.044	-0.433	0.452	-0.171	-0.577	0.282	-0.540	-0.964	-0.108	0.084	-0.426	0.600
bike/walk subsidy	0.216	-0.251	0.669	-0.322	-0.802	0.117	-0.002	-0.444	0.447	0.498	-0.047	1.007
Non-monetary incentive (mobility service on worksite):												
vehicle providing	-0.074	-0.448	0.360	0.583	0.145	0.995	-0.775	-1.171	-0.399	-0.230	-0.746	0.249
short-distance mobility service	0.674	0.178	1.288	-0.141	-0.690	0.459	-1.286	-1.779	-0.689	0.524	-0.153	1.268
emergency ride	-0.312	-0.939	0.271	-0.047	-0.714	0.654	-0.292	-0.859	0.295	0.100	-0.718	0.935
Infrastructure developments:												

transit access	-0.145	-0.940	0.603	1.673	0.441	3.482	-1.165	-1.967	-0.488	-0.121	-1.144	1.008
amenities	0.072	-0.704	0.906	1.810	0.333	3.056	0.351	-0.424	1.254	0.689	-0.301	1.675
rental car	0.182	-0.266	0.670	0.395	-0.071	0.799	-0.292	-0.730	0.132	0.948	0.401	1.470
Alternative Work Hours:												
compressed workweek	-0.445	-0.847	-0.033	0.401	-0.040	0.867	0.607	0.218	1.040	-0.612	-1.113	-0.148
flexible work hours	0.078	-0.430	0.660	0.622	0.028	1.332	1.728	1.103	2.287	0.932	0.347	1.567
Push tool:												
parking fee	0.807	0.369	1.192	2.516	1.996	2.884	0.862	0.498	1.293	0.614	0.163	1.155
Attitudinal factors												
Drive alone reason:												
convenience	-0.400	-0.640	-0.201	-0.429	-0.657	-0.211	0.229	0.020	0.428	-1.152	-1.455	-0.888
information	-0.579	-0.955	-0.259	-0.560	-0.947	-0.167	-0.314	-0.581	-0.014	-0.824	-1.395	-0.270
job requirement	0.108	-0.096	0.356	-0.012	-0.254	0.229	-0.314	-0.581	-0.072	-0.386	-0.861	0.022
family obligation	0.196	-0.047	0.352	0.210	-0.052	0.382	0.311	0.181	0.433	0.100	-0.170	0.374
safety	-0.249	-0.455	-0.033	-1.002	-1.403	-0.659	-0.093	-0.276	0.077	-0.133	-0.594	0.255
Random effects	**Mean**		**l-95% CI**		**u-95% CI**							
zip code	0.128		0.082		0.187							
site ID	0.834		0.589		1.111							
vehicle trip distance	0.472		0.084		1.073							
DIC: 23,451.66												

STUDY B: Rail transit ridership and station area characteristics

1. Background and Review

1.1 The changing nature of transit ridership in the United States

Transit ridership across the US has experienced a decline over the past decade. By 2017 transit ridership had decreased from the previous year in 31 of 35 major US metropolitan areas (Siddiqui, 2018). For example, according to a recent study, San Francisco Bay Area transit ridership saw a decrease between 2008 and 2018 from 72 to 65 annual trips per resident (Blumenberg et al., 2020a). Many other transit agencies mirror this trend. Despite major attempts to improve service quality, maintaining or increasing transit ridership continues to be a significant challenge even though transit remains critical in providing access to those without automobiles and more generally can play an important role in decreasing the ecological footprint of cities.

Changes in the mobility ecosystem such as the availability of shared mobility and ride hailing are common explanations for the decrease in transit use. For example, the emergence of ride hailing may substitute for transit. Some studies find that transportation network companies (TNCs), such as Uber and Lyft, are responsible for a net ridership decline in San Francisco (Erhardt et al., 2019), while another study in Philadelphia finds TNCs' impact not so significant for heavy and light rail (Dong, 2020). Meanwhile, evidence suggests several other factors including changes in transit service, passenger satisfaction, fares, changes in gas prices and employer shuttles do not appear to be major causes of the transit ridership decline (Blumenberg et al., 2020b).

Part of the declining trend in transit ridership can be attributed to changes in location patterns and vehicle ownership. Exogenous factors outside transit operators' control such as rising household vehicle access has been shown to play a role in decreasing the attractiveness of transit (Manville, Taylor, & Blumenberg, 2018; Taylor et al., 2020). When auto use is heavily subsidized, transit's relative advantage rapidly dwindles. For example, Taylor et al. (2020) find that a substantial decline in zero-vehicle households since 2000 across transit-friendly neighborhoods in California. In addition, changes in vehicle ownership go hand-in-hand with changes in location patterns. Taylor et al (2020) find significant decreases in job accessibility by transit over time, indicating that changes in the locations of jobs and residences also contribute to weaken transit viability.

1.2 Can ridership be retained with more transit friendly built environments?

Researchers, policy-makers and advocates have suggested that transportation and land use policies be modified to encourage transit-friendly environments. Together with changes in service and fare policies, changes to the built environment may be effective in maintaining or increasing transit ridership (Manville, Taylor, Blumenberg, et al., 2018) and achieving the sustainability, accessibility and mobility goals of transit. Significant research has examined empirically associations between the built environment and transit use. Ewing and Cervero (2010) conducted a meta-analysis based on 18 studies published prior to 2010. They estimated weighted average elasticities of transit use with respect to built environment variables, demonstrating that high street connectivity (measured as intersection density) and appropriate transit coverage (measured as distance to transit stops) appear to be the characteristics more strongly correlated with transit demand.

More recently, Aston et al. (2020) performed an updated meta-analysis by reviewing current studies with improved access to data, stronger research designs, larger samples, and more diverse geographic representation. The updated analysis found similar factors associated with transit use, but underscore the importance of finer-grained measures of the built environment as relevant to transit use. Specifically, design factors such as safety, local access, and amenities all show strong correlations with transit use, but are included in few studies due to data limitations.

Among these fine-grained design measures are attempts to quantify the walking environment around transit-served areas. The walking environment is composed of the physical and social characteristics of walking areas such as the infrastructure for pedestrians, the street enclosure, building setbacks, traffic noise, and lighting. Ewing et al. (2013) examined Lynchean dimensions of desirable built environments such as legibility, imageability, and transparency and found them difficult to measure reliably. Despite measurement challenges, these frequently emerge in empirical studies of walkability (Moran et al., 2018) and in subjective descriptions of built environments that support walking (Sallis et al., 2009) Since walking is a critical access mode for transit (Azimi et al., 2021), considering these more fine-grained attributes of the built environments may be critical to enhance the appeal of transit.

Crosswalks are a specific attribute of the built environment that can enhance the sense of safety for pedestrians. Safety from traffic, especially at intersections, has been associated with pedestrian decisions about what routes to use (Rodríguez et al., 2015). Crosswalks can be categorized into unmarked and marked types. There are several types of marked crosswalks including parallel lines, zebra or ladders, raised crosswalks, and crosswalks with enhanced visibility treatments like flashing lights and reflectors (Federal Highway Administration, 2009). Although they may increase the sense of safety, some studies have questioned the actual safety impacts of crosswalks, especially those at midblocks (Zegeer et al., 2001), speculating that a false sense of safety or risk compensation by pedestrians may be responsible for the lower safety performance detected in midblock marked crosswalks. Other studies (Mitman et al., 2008; Mooney et al., 2016) have examine the safety benefits of marked crosswalks suggesting their role in enhancing transit accessibility.

Despite the apparent importance of the built environment for transit ridership, there are several limitations in previous research. First, availability of built environment and ridership data has restricted the scope and context of empirical research. Studies often focus on single metropolitan areas and mostly consider land use variables. Moreover, due to the many challenges pertaining to obtaining and understanding transit ridership data (Wasserman et al., 2021), not many studies include direct observations of transit ridership, and few account for variations between stations. Second, most studies are cross-sectional, and hence subject to concerns about reverse causality and omitted variables. And third, the measurement of fine-scaled pedestrian environments has been hampered by limitations in data availability and quality. For example, there is no single database of sidewalks, crosswalks, or urban design features nationally. Systematic studies of neighborhood and street-level characteristics at a national scale are rare.

1.3 Application of artificial intelligence and computer vision

An emerging approach to address the paucity of fine-grained built environment data in transit areas is to use artificial intelligence and computer vision. Recent advances in these technologies have enabled the measurement of urban environmental in a systematic and reliable fashion. A growing body of researches apply these techniques to extract built environment features at larger spatial-temporal scales (Li & Sheng, 2021). For example, some researchers have applied machine learning on Google Street View imagery to assess built environment of TOD station areas (World Bank, 2020). A few others have leveraged the spatial-temporal availability of Street View and satellite imagery to extract certain built environment features such as marked crosswalks, sidewalks and other active transportation infrastructure (Ahmetovic et al., 2017; Berriel et al., 2017; Coughlan et al., 2006; Huang et al., 2018; Ivanchenko et al., 2008; Weld et al., 2019). In this study we rely on these emerging technologies to measure aspects of the built environment not included in prior work due their limited availability on a national scale.

1.4 Objectives

Given the findings or limitations of prior research, the objectives of this project are three-fold. First, we examine station-level trends in transit ridership for transit oriented development (TOD) stations across eight major US transit agencies between 2010 and 2018. Second, we use a novel longitudinal database and apply artificial intelligence algorithms to measure standard and novel built environment attributes in these TOD station areas during the same period. Third, we investigate how changes in marked crosswalks and other built environment characteristics in these areas are associated with changes in station-level transit ridership. The rest of this report will introduce the methodology of the study, including the data and sampling, as well as model specifications. Then, we will discuss the findings and conclude with recommendations.

2. Research Design and Methods

We follow a before-and-after experimental design with controls by observing changes in station-level ridership and the built environment, including marked crosswalks, over time while adjusting for other city and station level characteristics. We rely on three main data sources: for ridership outcomes, we collected station-level ridership data over time from transit agencies; for neighborhood built environment data, we use EPA's Smart Location Database (SLD) for 2010 and 2018 (Chapman et al., 2021) and for marked crosswalks, we use artificial intelligence to and computer vision extract them from Google Street View images over time.

2.1 Outcome variable: station-level transit ridership

We collected average weekday ridership data over time for transit agencies with heavy rail and light rail service across the US. After assessing data quality, we focused on 897 TOD stations of eight major transit agencies (Table 1): BART (San Francisco Bay Area), Caltrain (San Francisco Bay Area), CTA (Chicago), MTA (New York City), MTS (San Diego), PATH (New York and New Jersey), SEPTA (Philadelphia), and WMATA (Washington DC). The location and designation of TOD stations come from National TOD Database (Center for Transit-Oriented Development, 2021) as of January 2021. We eliminated stations whose average weekday ridership was less than 10 passengers in either 2010 or 2018. Although not all data was collected in the same way and time period, we attempted to use data for February. This was not possible for SEPTA and MTS, where the months of data collection varied by stop (Table 2).

Table 1 Number of TOD stations by transit agency

	BART	Caltrain	CTA	MTA	MTS	PATH	SEPTA	WMATA	Total
# of stations	43	28	137	332	49	9	218	81	897
% of total	4.8%	3.1%	15.3%	37.0%	5.5%	1.0%	24.3%	9.0%	

Table 2 Description of ridership data by agency

Agency	Base year	Recent year	Description
BART	2010	2018	February average weekday station entry
Caltrain	2010	2018	February average weekday on boarding
CTA	2010	2018	February average weekday rides
MTS	FY2010	Spring 2018	Average weekday ridership
PATH	2012	2018	February average weekday ridership
SEPTA*	2010	2018	Average weekday APC
WMATA	2010	2018	August average weekday boarding
MTA	2013	2018	Average weekday ridership

** Available years vary by station.*

2.2 Built environment data

We rely on two years (2010 and 2020[1]) of EPA's SLD to compile a comprehensive dataset of built environment variables for each TOD station area including neighborhood demographics and density, diversity, design, and destination accessibility. Although the SLD contains a large number of variables, we selected a subset on prior theory and empirical evidence that balance between different aspects of the built environment. Of those, we only retained variables that had variance inflation factors (VIF) less than 5 in the saturated models. Since the geographic unit of analysis of the SLD is census block group, for each station we calculate the weighted average of the demographic, density, diversity, and design variables of all block groups that intersect with a half-mile airline buffer of the station (Table 3). For index variables (regional diversity and regional centrality index), we assign the respective value of the block group where the station is located. For all built environment variables we then calculate the change between the two years.

Table 3 Selected built environment variables from SLD

Category	Selected variables	Aggregating method by station
Demographics	Percent of zero-vehicle households	Number of zero-vehicle households/total households
	Percent of low-income workers	Number of low-income workers/total workers
Density	Population density (persons/acre)	Total population/area
	Job density (jobs/acre)	Total employment/area
Design	Street intersection density (intersection/sq. mile)	Total number of intersections/area
Diversity	Regional diversity index*	Block groups overlapping with station area buffer
Destination accessibility	Regional centrality index**	Block groups overlapping with station area buffer

** Regional diversity of employment to population. Calculated based on total population and total employment by block group. It quantifies the deviation of the block group ratio of jobs/population from the regional average ratio of jobs/population.*

*** Average block group auto accessibility score relative to max CBSA accessibility score.*

2.3 Measuring marked crosswalks over time[2]

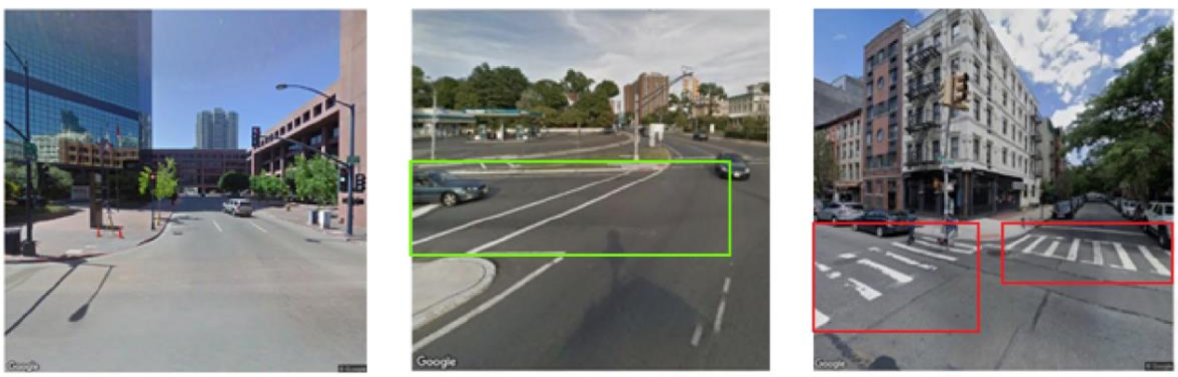
To measure the prevalence of marked crosswalks over time within a 250-m distance of the transit station, we developed a deep learning-based object detection model trained on 4,925 hand-labeled Google Street View

[1] Since most of the 2020 measures are based on census data from 2018, we consider 2018 as the *recent year* for comparison with *base year*.

[2] This section was also reported in Li, Meiqing, Hao Sheng, Jeremy Irvin, Heejung Chung, Andrew Ying, Tiger Sun, Andrew Y. Ng, Daniel A. Rodriguez, "Using Computer Vision on Street View Imagery to Map Crosswalks of Transit-Oriented Development Station Areas in the United States from 2007 to 2020", *101th Annual Meeting of the Transportation Research Board, January 2022*, Washington D.C.

images to automatically detect the number of marked (parallel-line and high-visibility) crosswalks in each image. High-visibility crosswalks include a variety of marked crosswalks such as ladder, continental, or diagonal markings (Federal Highway Administration, 2009). The training sample was selected from the inventory of all available Google Street View historical images and balanced across urban and suburban areas.
We deployed the model to all 922,144 historical images obtained from Google Street View, which produced the number of parallel-line and high-visibility crosswalks detected at each intersection. Only 402 (~ 1%) of the 38,350 unique intersections do not have any Street View images within 15 meters throughout the years. We dropped these intersections from the final dataset.

We used a combination of deep learning model prediction and imputation to infer the number of parallel-line and high-visibility crosswalks at each intersection in each year between 2007 and 2020. We deployed the best model to detect parallel-line and high-visibility crosswalks at each intersection in a particular year whenever the Street View image is available. For each Street View image, the model outputs bounding boxes indicating either parallel-line or high-visibility crosswalks (Figure 1). We combined the four 90-degree images from each panorama by summing up the number of bounding boxes locating parallel-line and high-visibility crosswalks. Since one crosswalk could be present in more than one image, the total number of parallel-line or high-visibility crosswalks per panorama ranges from 0 to 18.



(a) Unmarked crosswalk (b) Parallel-line crosswalk (c) High-visibility crosswalk

For years with no Street View image, we imputed the presence and number of crosswalk infrastructure through nearest interpolation. Table 4 demonstrates the imputation process at a sample intersection. The model detected no parallel-line crosswalk at this intersection for 2009 and three parallel-line crosswalks for 2013. Missing years at the very beginning and end of the timespan (2007-2020) were imputed from the next and previously available model detections, respectively. Missing years between two available years were interpolated from the nearest available year. When the distance to the previous and next available data point is the same, the former was used for imputation.

Table 4 Example of the imputation process at one intersection

	2007	2008	2009	2010	2011	2012	2013	2014

# of parallel-line crosswalks from deep learning model	n/a	n/a	0	n/a	n/a	n/a	3	n/a
# of parallel-line crosswalks after imputation	**0**	**0**	0	**0**	**0**	**3**	3	**3**

Note: n/a shows years with missing data. Data for imputed years in bold.

We scaled this crosswalk analysis to all the TOD stops included in the CTOD database, and therefore produce a national dataset of crosswalks prevalence around TODs over time. The final dataset includes crosswalk counts per category at 51,746 intersections[3] corresponding to 4,417 transit stations and 77 transit agencies for 14 consecutive years between 2007 and 2020.

For this report, we selected the subsample of intersections within 250-m buffers of the 897 TOD stations and merged it with the other built environment data for further analysis. We use 250-m on the expectation that marked crosswalks closer to the stop are likely to be more important for station access than crosswalks further way.

2.4 Statistical analysis

We pool all stops and use least squares linear regression to estimate the relationship between crosswalk enhancements and changes in average weekday ridership at TOD station areas between 2010 and 2018. Our final specification includes the change in average weekday ridership as dependent variable. Two models were estimated, one for using percent of marked crosswalks as independent variable (model 1) and another using percent high-visibility crosswalks within the 250-m buffer of each TOD station (model 2). Other independent variables of interest include variables measuring change to other built environment attributes, as well as the value of both crosswalks and the built environment at baseline.

In addition, we examined whether the association between changes in crosswalks and ridership changes is moderated by baseline ridership and by population density. In other words, we explored whether crosswalks changes were more relevant were ridership was already high (or low), or when population density was high (or low). As a result, we included two interaction terms: *crosswalk change * base year ridership* and *crosswalk change * base year population density*. Other SLD variables of interest included percent of low-income workers, population density, job density, street intersection density, regional diversity index, and regional centrality index. (1) shows a generalized form of model specifications in equation,

$$\Delta ridership = f(\ crosswalk_{base}\ , BE_{base}\ , \Delta crosswalk, \Delta BE, interaction, c\ ) \tag{1}$$

Where,

$\Delta ridership\ is$ the change of average weekday ridership at each station between the recent (2018) and base (2010) years;

$crosswalk_{base}$ is the 2010 percent coverage of marked crosswalks (including high-visibility) within a 250-m buffer of each station;

BE_{base} is the selected 2010 built environment variables from SLD;

[3] This includes 38,350 unique intersections since one intersection may be associated with multiple transit stations.

$\Delta crosswalk$ is the difference between 2018 and 2010 in the percent coverage of marked crosswalks (including high-visibility) within a 250-m buffer of each station;

ΔBE is the difference in the selected built environment variables between SLD 2020 and SLD 2010; $interaction$ includes the two interaction terms, *crosswalk change * base year ridership* and *crosswalk change * base year population density*; and

c is the model intercept.

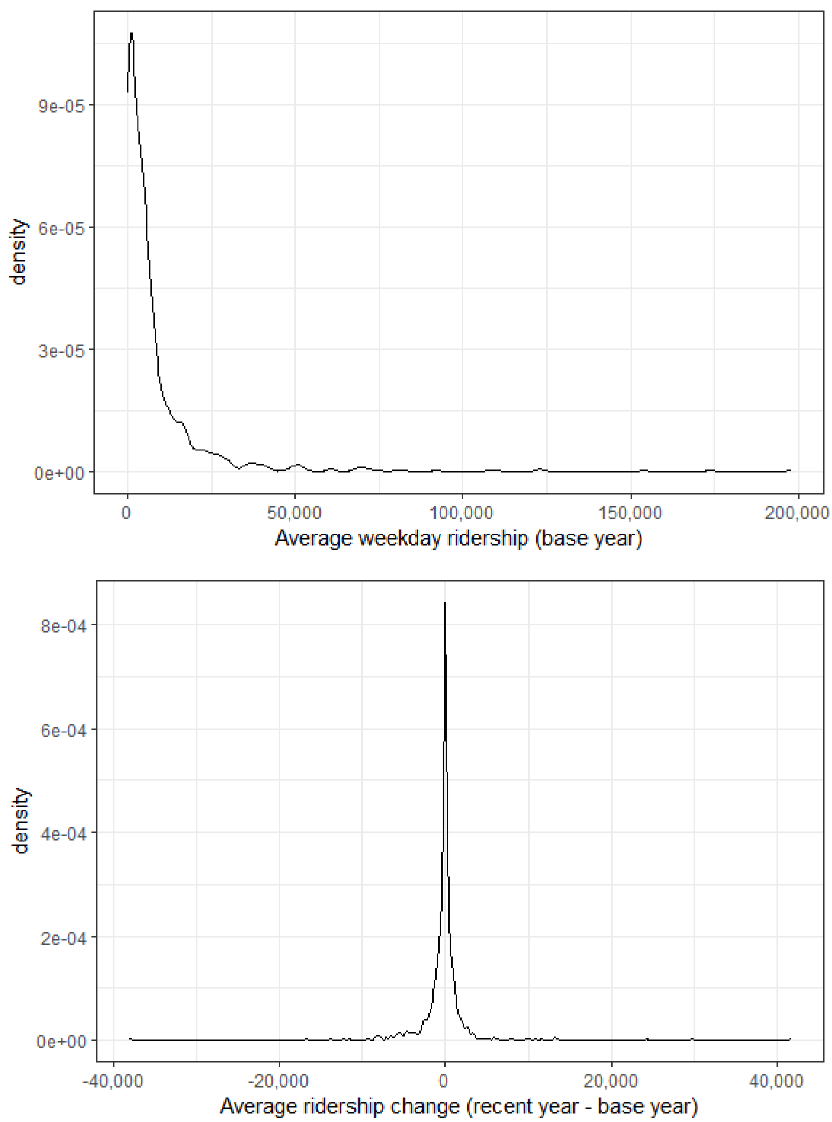
We estimate both models with robust errors clustered by agency to account for the agency-specific effects. We also examined other model specifications and estimation approaches including a "change-on-change" model (with no baseline value variables), quantile regression (at quartiles), agency fixed effects, and matching. All models produced similar results in terms of strength, significance and sign of explanatory variables, so we report the more parsimonious least squares models.

3. Results

We first present descriptive statistics of ridership and the built environment, followed by statistical models of association of changes in both over the period between 2010 and 2018.

3.1 Station-level transit ridership, 2010 and 2018

Figure 2 shows the kernel density of base year average weekday ridership for each TOD station and the change between base and recent years. While there is a significant variation in base year ridership, ranging from 0 to 200,000, more than half of the stations have daily ridership lower than 4,000.



Overall, ridership in the stations considered decreased by 2.3% between 2010 and 2018. This is similar to the national trend and significantly smaller than the ridership change for California in the same period reported in (Taylor et al., 2020). Across the eight agencies, there were stations that gained ridership and others that lost ridership in the eight-year period. Notably, a majority of BART and PATH stations gained ridership whereas stations of other agencies saw a mix of gains and losses (Figure 8 in Appendix). Among the ten stations that had the largest ridership gain, eight are in New York City (Table 5) even though MTA and PATH represent less than 40% of all stations in the sample. At the same time, seven out of the ten stations that experienced biggest ridership loss are MTA stations (Table 6).

Table 5 Top stations with ridership gain

#	Station name	Agency	Base year ridership	Recent year ridership	Difference
1	Atlantic Av - Pacific St	MTA	1,580	43,211	41,631
2	Fulton St	MTA	68,727	98,452	29,725
3	72 St	MTA	49,920	74,202	24,282
4	South Ferry	MTA	20,405	33,797	13,392
5	Montgomery St.	BART	30,605	43,823	13,218
6	Chambers St	MTA	82,070	93,699	11,629
7	World Trade Center	PATH	50,733	61,601	10,868
8	Embarcadero	BART	30,265	40,500	10,235
9	57 St - 7 Av	MTA	28,159	37,870	9,711
10	96 St	MTA	74,758	82,715	7,957

Table 6 Top stations with ridership loss

#	Station name	Agency	Base year ridership	Recent year ridership	Difference
1	Atlantic Av	MTA	39,871	1,842	-38,029
2	15th St Station	SEPTA	22,275	5,535	-16,740
3	68 St - Hunter College	MTA	36,562	22,757	-13,805
4	Lexington Av/59 St	MTA	67,841	55,608	-12,233
5	77 St	MTA	42,535	30,981	-11,554
6	28 St	MTA	50,452	41,118	-9,334
7	Metro Center	WMAT A	28,682	20,206	-8,476
8	34 St - Penn Station	MTA	173,759	165,526	-8,233
9	Wall St	MTA	51,784	43,713	-8,071
10	8th St & Market St	SEPTA	12,922	4,881	-8,041

3.2 Built environment in TOD station areas, 2010 and 2018

Beginning with the base year (2010), on average 78.37 percent of intersections contain parallel crosswalks, 58.87 percent contain high-visibility crosswalks, with a total of 90.98 percent contains marked crosswalks. Unsurprisingly, stations areas have high population and job density (Table 7, Table 8), relative to the overall density of urbanized area in the US[4]. About 47.60 percent of households in stations areas did not have a vehicle available and 22.58 percent of workers in the area were classified as low income. Table 9 and Table 10 show summary statistics of changes for variables that characterize station-area built environment including marked crosswalk coverage[5]. Notably, a few outliers around MTS and MTA stations lead to extreme values of change in street intersection density, possibly due to irregular network topology. Similarly, one outlier station (Kostner in Chicago) results in a significant percent change in regional diversity index. We also test the statistical significance of the difference of each variable using paired t-tests (Table 11).

Table 7 Summary statistics of station-level variables – base year (N = 897)

Variable	Mean	St. Dev.	Min	Max
Weekday ridership	8,488	16,599	14	197,696
Percent of intersections with parallel crosswalks	78.37	19.54	0.00	100
Percent of intersections with high-visibility crosswalks	58.87	24.74	0.00	100
Percent of intersections with marked crosswalks	90.98	15.50	0.00	100
Percent of zero-vehicle households	47.60	25.14	0.46	108.37
Percent of low-income workers	22.58	5.33	9.57	37.12
Population density (persons/acre)	32.23	30.74	0.07	158.27
Job density (jobs/acre)	39.67	100.80	0.02	878.52
Street intersection density (intersections/sq. mile)	112.89	72.16	0.16	506.09
Regional diversity index	26.00	0.26	0.00	1.00
Regional centrality index	0.57	0.19	0.11	1.00

Table 8 Summary statistics of station-level variables - recent year (N = 897)

Variable	Mean	St. Dev.	Min	Max
Weekday ridership	8,294	16,750	11	204,017
Percent of intersections with parallel crosswalks	64.27	19.17	0.00	100
Percent of intersections with high-visibility crosswalks	74.58	23.48	0.00	100
Percent of intersections with marked crosswalks	91.98	14.32	0.00	100
Percent of zero-vehicle households	36.84	19.81	0.96	76.65
Percent of low-income workers	21.00	5.70	8.40	34.36

[4] According to U.S. Census Bureau, the population density of urbanized area is 2,534.4 persons per square mile (3.96 persons per acre).

[5] See Appendix for summary statistics by agency.

Population density (persons/acre)	33.61	31.09	0.07	147.82
Job density (jobs/acre)	45.51	118.69	0.02	1090.91
Street intersection density (intersections/sq. mile)	160.74	116.01	0.45	991.05
Regional diversity index	0.36	0.27	0.00	1.00
Regional centrality index	0.63	0.15	0.11	1.00

Table 9 Difference in station-level variables between 2018 and 2010 (N = 897)

Variable	Mean	St. Dev.	Min	Max
Weekday ridership	-194.11	3,120	-38,029	41,631
Percent of intersections with parallel crosswalks	-14.09	22.96	-100	100
Percent of intersections with marked crosswalks	1.00	11.38	-100	100
Percent of intersections with high-visibility crosswalks	15.71	21.12	-100	100
Percent of zero-vehicle households	-10.76	8.46	-55.98	7.29
Percent of low-income workers	-1.58	1.94	-8.99	8.11
Population density (persons/acre)	1.38	3.27	-16.71	21.39
Job density (jobs/acre)	5.84	25.16	-133.17	244.43
Street intersection density (intersections/sq. mile)	47.85	84.32	-171.16	828.26
Regional diversity index	0.09	0.24	-0.77	0.85
Regional centrality index	0.06	0.12	-0.35	0.35

Table 10 Percent change of station-level variables between 2018 and 2010 (N = 897)

Variable	Mean	St. Dev.	Min	Max
Average weekday ridership	6.41	167.68	-95	4,161
Percent of intersections with parallel crosswalks	-13.84	35.88	-100	400
Percent of intersections with high-visibility crosswalks	45.14	93.62	-100	1300
Percent of intersections with marked crosswalks	2.17	18.84	-100	250
Percent of zero-vehicle households	-19.16	23.07	-69.19	288.39
Percent of low-income workers	-7.38	9.33	-33.08	37.59
Population density (persons/acre)	7.11	15.64	-24.10	224.82
Job density (jobs/acre)	22.88	38.96	-77.50	303.84
Street intersection density (intersections/sq. mile)	50.88	65.12	-51.24	575.11
Regional diversity index	193.42	752.92	-100	19,738.33
Regional centrality index	15.75	24.71	-47.94	114.84

Table 11 Paired t-test results comparing base year and recent year variables (N = 897)

Variable	t-statistic	p-value
Average weekday ridership	-0.305	0.761

Percent of intersections with parallel crosswalks	-15.301	0
Percent of intersections with high-visibility crosswalks	16.407	0
Percent of intersections with marked crosswalks	1.651	0.099
Percent of zero-vehicle households	-15.931	0
Percent of low-income workers	-6.631	0
Population density (persons/acre)	1.185	0.236
Job density (jobs/acre)	1.565	0.118
Street intersection density (intersections/sq. mile)	10.323	0
Regional diversity index	7.776	0
Regional centrality index	6.848	0

We first summarize key findings characterizing the broad built environment in station areas using SLD. We highlight three important finding from these descriptive summaries of change. This is followed by findings of the multivariable statistical analyses.

First, the percentage of zero-vehicle households in the station areas decreased markedly by more than 10 percentage points (Table 9). This is almost a 20% decrease in zero-vehicle households in these areas in less than a decade (Table 10). For comparison, the Census Bureau reports that the overall change in the percent of zero-vehicle households in the US also dropped, but only 0.6 percentage points from 9.1% (2010) to 8.5% (2018). It is possible that these decreases reflect broader changes concentrated in urban areas, and more specifically, in highly urban areas, but may partly explain the broad decrease in transit ridership documented here and elsewhere.

Second, population and job density in station areas increased. However, there is significant variation at the station-level within each system. For example, among all 897 TOD stations, the most drastic increase or decrease of population density all happened around MTA stations (Table 12, Table 13). Figure 3 shows the spatial distribution of the top and bottom decile in population density change for the block groups intersecting the station areas in each city. That is, the 10% station areas that gained the most population density and the 10% stations areas that lost the most density. In most cases gains in density happened in first-ring suburbs surrounding established areas with high employment centers. New York City has a more variegated pattern, with many areas with significant increase or decrease of population density. Similarly, job density in station areas increased significantly, especially for MTA. On average the density of MTA station areas increased by 2.35 persons and 10.89 jobs per acre, with a maximum increase of 21.39 persons and 244.43 jobs per acre (Table 25 in Appendix).

Table 12 Stations with most increase in population density

#	Station name	Agency	Base year population density	Recent year population density	Difference
1	Nevins St	MTA	61.03	82.42	21.39
2	Hoyt - Schermerborn Sts	MTA	58.12	77.33	19.21
3	Hoyt St	MTA	58.30	75.48	17.18
4	Jay St - MetroTech	MTA	64.44	81.56	17.12

5	Bergen St	MTA	64.71	77.95	13.24
6	Lafayette Av	MTA	62.00	75.06	13.06
7	Jackson Av	MTA	88.31	100.89	12.57
8	Court St	MTA	19.64	32.09	12.45
9	135 St	MTA	98.35	110.78	12.43
10	Atlantic Av - Pacific St	MTA	61.43	73.53	12.10

Table 13 Stations with most decrease in population density

#	Station name	Agency	Base year population density	Recent year population density	Difference
1	74 St - Broadway	MTA	118.76	102.04	-16.71
2	90 St - Elmhurst Av	MTA	158.27	146.19	-12.08
3	Saratoga Av	MTA	90.37	78.95	-11.42
4	82 St - Jackson Hts	MTA	147.90	138.10	-9.80
5	Delancey St	MTA	146.98	138.92	-8.06
6	2 Av	MTA	137.42	130.12	-7.30
7	Bowery	MTA	117.89	111.28	-6.61
8	Junction Blvd	MTA	144.84	138.28	-6.56
9	Sutter Av - Rutland Rd	MTA	94.84	88.28	-6.56
10	30 Av	MTA	87.07	80.55	-6.52

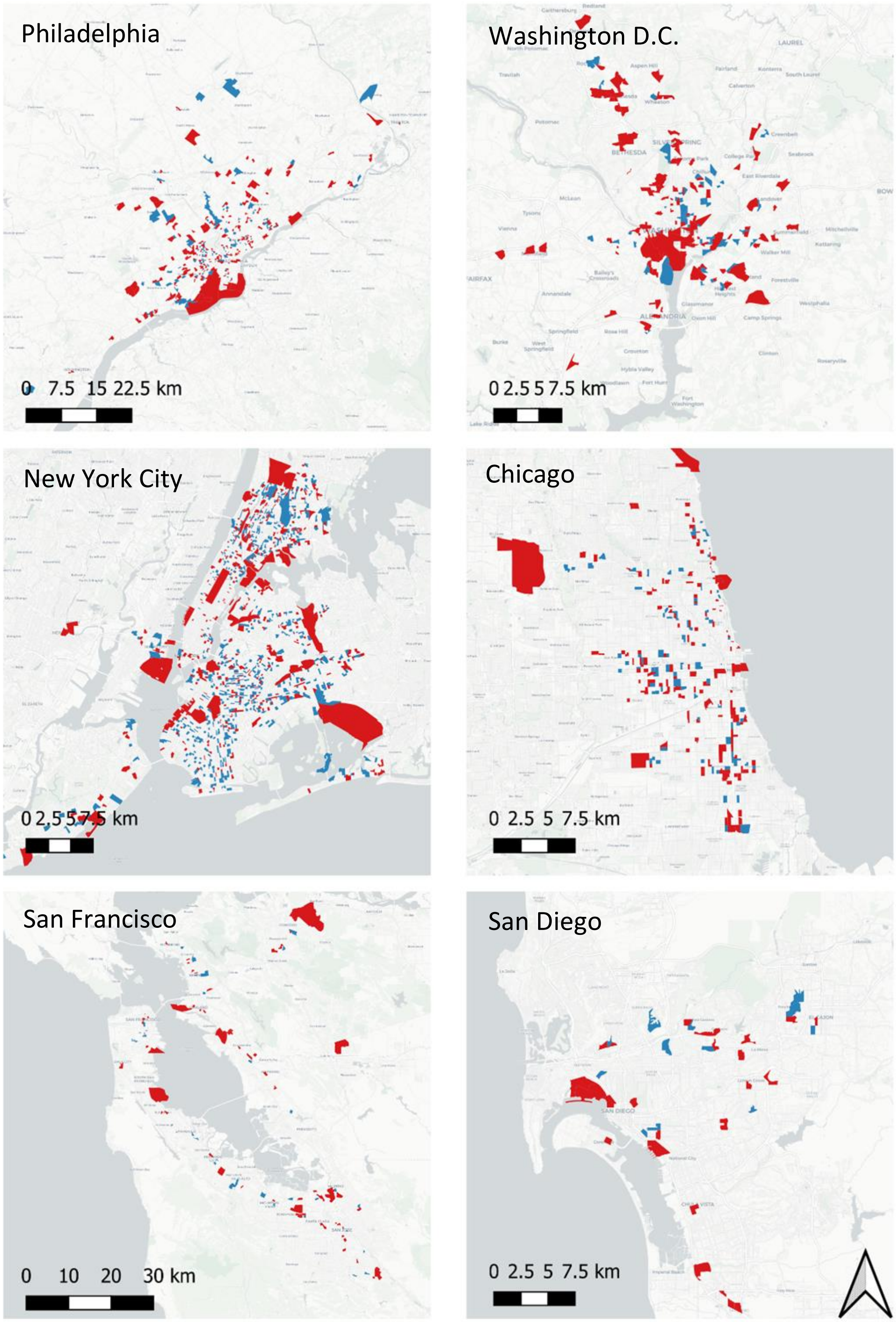
Third, the percent of low income workers around TOD stations decreased by 1.58 on average, with the largest decreases in BART and MTA station areas (Table 14). Similarly, the percent of zero-vehicle households largely decreased, likely due to the density increase and demographic shift.

Table 14 Top stations with decrease in percent of low income workers

#	Station name	Agency	Base year percent	Recent year percent	Difference
1	Marcy Av	MTA	33.26	24.27	-8.99
2	Hewes St	MTA	34.60	26.33	-8.27
3	12th St Oakland City Center	BART	27.38	19.30	-8.07
4	19th St Oakland	BART	27.30	19.69	-7.61
5	MacArthur	BART	24.92	17.79	-7.14
6	Lake Merritt	BART	26.71	19.89	-6.82
7	32nd St/Commercial Station	MTS	31.42	24.63	-6.79
8	West Oakland	BART	30.12	23.33	-6.79
9	Bedford Av	MTA	21.82	15.11	-6.71

10	Montgomery St	BART	22.47	15.79	-6.68

The t-tests suggest that changes were statistically significant for household vehicle access, percent of low-income workers, street intersection density, regional diversity index and regional centrality index across transit-oriented station areas over the eight-year period. The changes in overall population and job density were not significant between before and the after period, although as noted there are significant differences by transit system.


Philadelphia
0 7.5 15 22.5 km
Washington D.C.
0 2.5 5 7.5 km
New York City
0 2.5 5 7.5 km
Chicago
0 2.5 5 7.5 km
San Francisco
0 10 20 30 km
San Diego
0 2.5 5 7.5 km

3.3 Marked crosswalks in TOD station areas, 2010 and 2018[6]

There is a notable increase in marked crosswalks in the study areas and a shift from parallel-line to high visibility sidewalks. Figure 4 shows the distribution of the number of marked crosswalks as well as changes in estimated number of parallel-line and high-visibility crosswalks for the 51,746 transit-adjacent intersections from 2007 to 2020, which includes our baseline and current study periods. There has been an overall increase in the number of marked crosswalks including both parallel-line and high-visibility crosswalks as shown by the decrease of intersections with no marked crosswalk, and a shift of distribution to higher numbers of crosswalk occurrence. The medians of each year are shown by dashed lines.

Table 15 presents results from Kolmogorov-Smirnoff test of each pair of distributions in Figure 4, which demonstrates statistically significant changes in the presence of different types of crosswalks over the years. Comparing the plots, we find a shift from parallel-line to high-visibility crosswalks. On the contrary, the number of intersections with unmarked crosswalks substantially decreased during this period. This shows the growth in crosswalk visibility enhancements at transit station areas across the United States in the past decade.

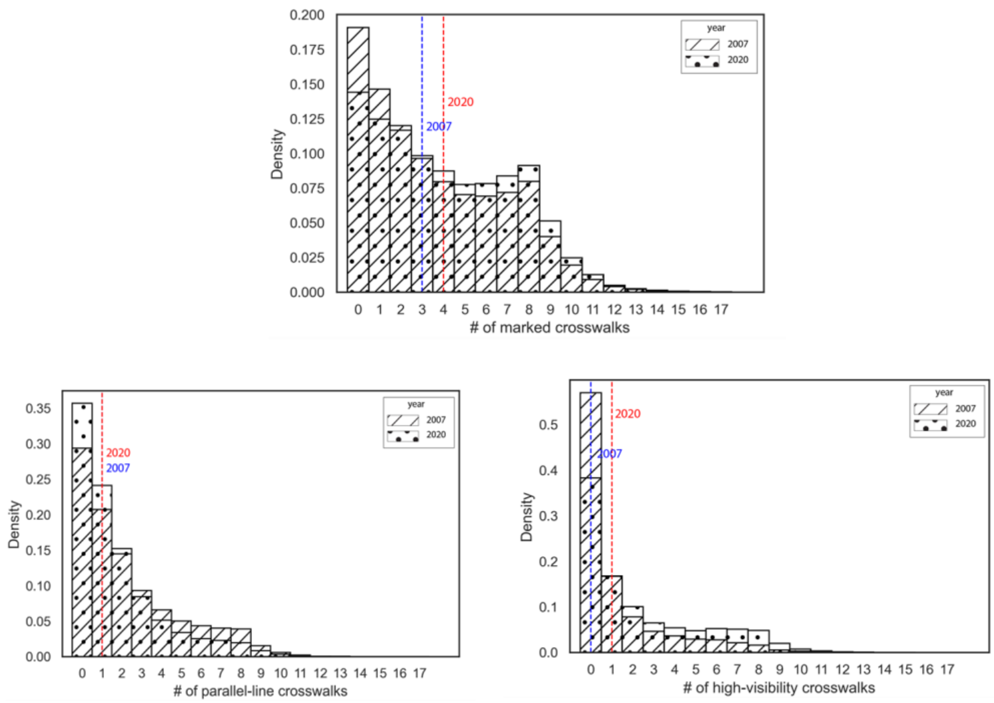


Table 15 Kolmogorov-Smirnoff test results of the three distributions between 2007 and 2020

Crosswalk type	KS-statistic	p-value
Marked crosswalk	0.0718	0.000

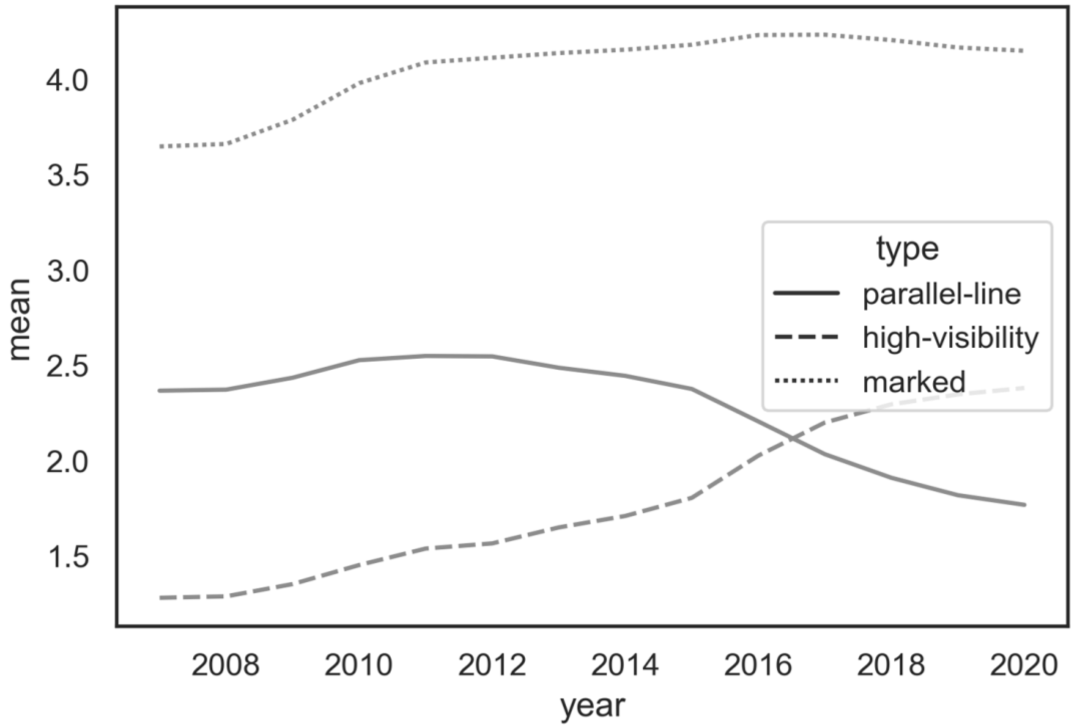
[6] This section is part of Li, Meiqing, Hao Sheng, Jeremy Irvin, Heejung Chung, Andrew Ying, Tiger Sun, Andrew Y. Ng, Daniel A. Rodriguez, "Using Computer Vision on Street View Imagery to Map Crosswalks of Transit-Oriented Development Station Areas in the United States from 2007 to 2020", *101th Annual Meeting of the Transportation Research Board, January 2022*, Washington D.C.

Parallel-line crosswalk	0.1045	0.000
High-visibility crosswalk	0.1870	0.000

The percentage of intersections with no marked crosswalk in the sample decreased from 14.4% in 2010 to 12.9% in 2018. Similarly, the percentage of intersections with parallel-line crosswalks decreased from 74.1% to 67.4%, while the percentage of intersections with high-visibility crosswalks significantly increased from 50.4% to 62.0%. Such a pattern and shift to high-visibility crosswalks is evident by the increase in the average number of marked and high-visibility crosswalks per intersection. Taken together, this shows noteworthy increases in crosswalk visibility enhancements by installing marked crosswalks and upgrading parallel-line crosswalks to high-visibility crosswalks.

The pattern of upgrading to marked crosswalks is consistent across all transit systems in the study. Figure 5 shows the growing trend of marked crosswalks and high-visibility crosswalks in station areas of 10 transit agencies with the highest service areas intersection density. However, regional variation exists among these dense transit service areas. In 2010, the percentage of intersections with marked crosswalks ranged from more than 95% in New York City (service area of MTA) to a little more than 80% in Boston and Long Island (service areas of MBTA and LIRR). The areas starting with the lowest crosswalk coverage appear to have the fastest rate of growth, catching up with the other agencies by the end of the period. By 2018, all agencies have more than 80% coverage of marked crosswalks at service area intersections.

The growth of high-visibility crosswalks presents a similar pattern. The high-visibility crosswalk coverage in most agencies' services areas was less than 50% and kept increasing over the years. Notably, transit service areas in New York City and San Francisco have seen the fastest increases in the coverage of high-visibility crosswalks since 2014, from 67.3% to 92.0% and from 50.2% to 78.4%, respectively. The only drop is observed in Philadelphia (service area of SEPTA), possibly due to less frequent maintenance and repaving.



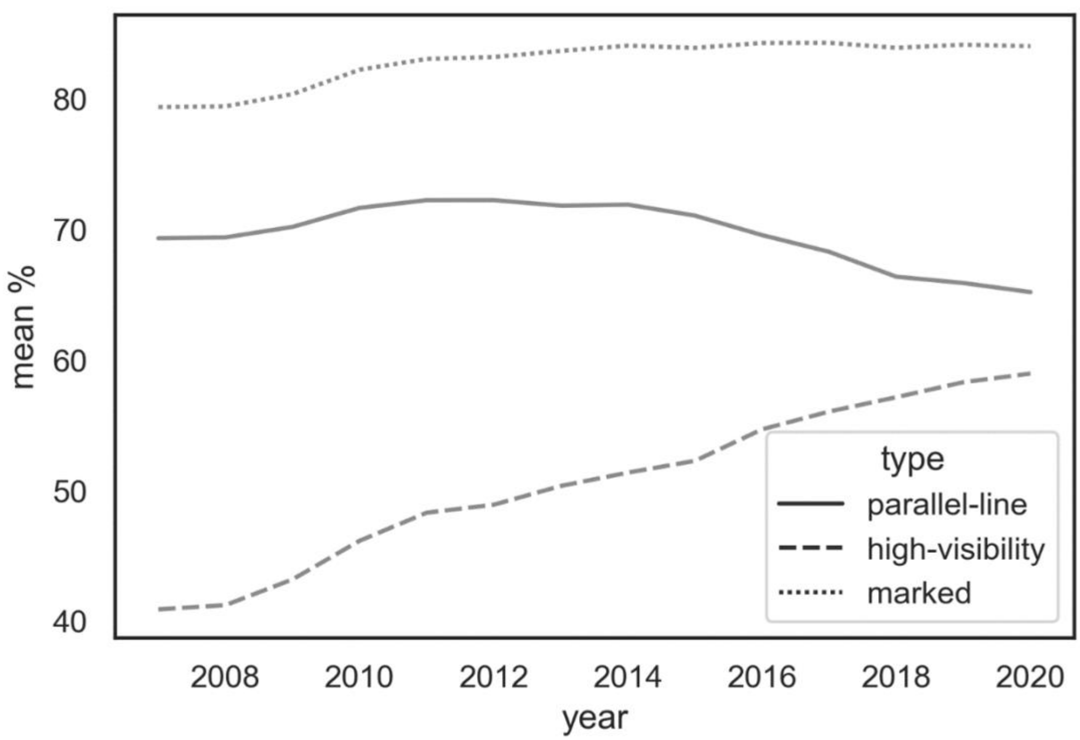
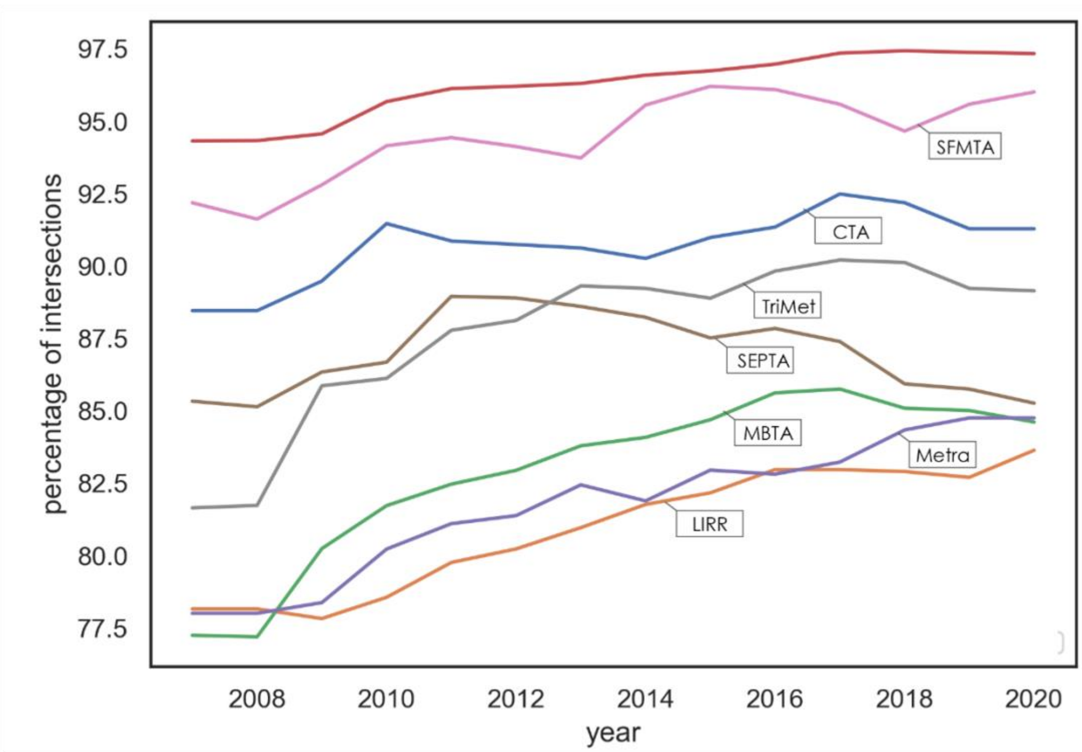
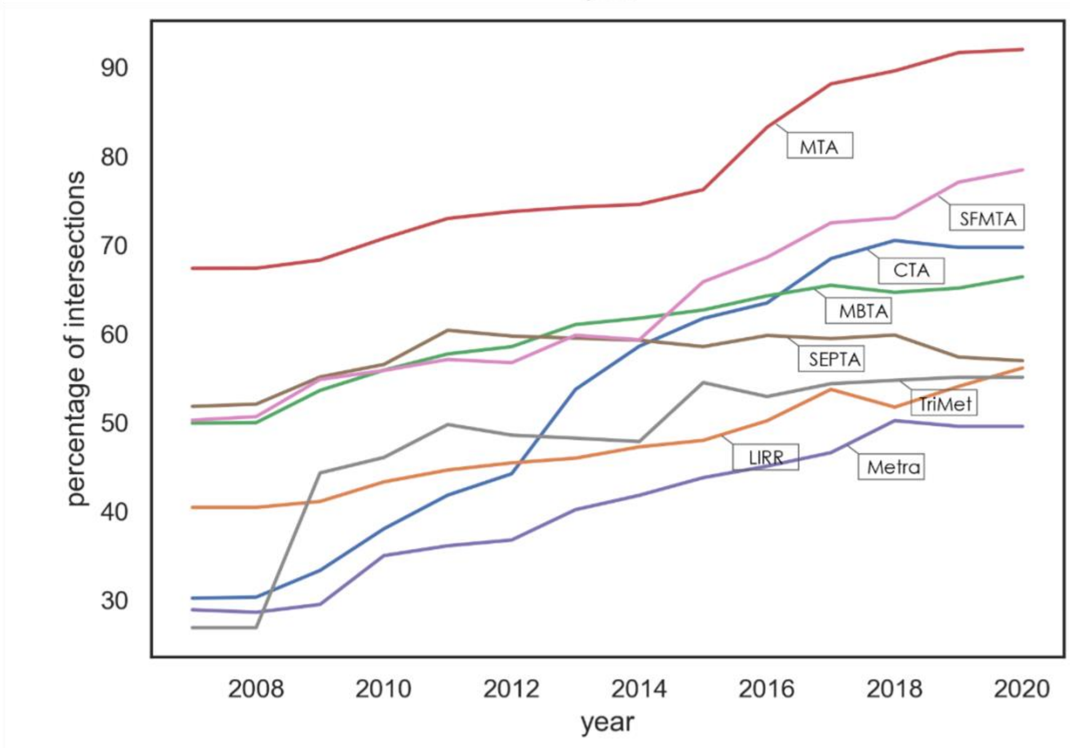


Figure SEQ Figure * ARABIC 5 Top: average number of marked crosswalks per intersection (N=38,350), 2007-2020; Bottom: Average percentage of intersections with marked crosswalks at each TOD station area (N=4,417), 2007-2020.


97.5
95.0
92.5
90.0
87.5
85.0
82.5
80.0
77.5
percentage of intersections
SFMTA
CTA
TriMet
SEPTA
MBTA
Metra
LIRR
2008
2010
2012
2014
2016
2018
2020
year


90
80
70
60
50
40
30
percentage of intersections
MTA
SFMTA
CTA
MBTA
SEPTA
TriMet
LIRR
Metra
2008
2010
2012
2014
2016
2018
2020
year

3.3.1 Intersection-level crosswalk improvements in the MTA and SFMTA

We further examine the placement of intersectional-level crosswalk enhancements at stations of two transit agencies, MTA of New York City and SFMTA of San Francisco, which exhibit significant crosswalk visibility improvement over time. Figure 7 maps the changes of intersections with high-visibility crosswalks along transit lines of MTA and SFMTA. For both cities, there has been a clear expansion of high-visibility crosswalks. In New York City, the number of intersections with high-visibility crosswalks grew from 4,950 to 6,762, a 36% increase over the past decade. In San Francisco, the number increased by 56%, from 1,786 to 2,788.

In both cities, crosswalk enhancements were implemented around stations in both urban and suburban areas with a balanced improvement across geographic areas. The enhancements tend to fill crosswalk gaps along major corridors (red dots), for example, Broadway and Lexington Avenue in New York City, and Market Street in San Francisco. By 2020, most intersections in New York City have been covered by high-visibility crosswalks, whereas there are still some gaps in San Francisco, as shown by green dots in Figure 7. These gaps are more prevalent outside the downtown area and major corridors.

To demonstrate other uses of these data that can be combined with other available data, here we use the SLD to further investigate the association between crosswalk enhancement and neighborhood characteristics around each transit station in both cities. We aggregate the SLD measures to all census block groups that intersect with the half-mile buffer of each TOD station. Table 16 shows the association between the percent coverage of intersections with two types of marked crosswalks (parallel-line and high-visibility) at each TOD station and the station-area built environment characteristics. As of 2018 when the latest SLD variables were measured, both the percent coverage of all types of marked crosswalks and high-visibility crosswalks were positively associated with built environment characteristics typical of higher density urban station areas, whereas the percent coverage of conventional parallel-line crosswalks is negatively associated with density attributes. Likewise, stations with higher average weekday ridership, areas with higher percentage of zero-vehicle households or low-income workers tend to have higher percent coverage of marked or high-visibility crosswalks, but lower percent coverage of parallel-line crosswalks. As expected, this implies that transit stations with higher ridership and those in areas with denser population, jobs and road network tend to exhibit better walkability with higher coverage of pedestrian infrastructure.

Table 16 Pearson's correlation between station area crosswalk coverage and built environment characteristics (2018)

	Marked crosswalk	**Parallel-line crosswalk**	**High-visibility crosswalk**
Average weekday ridership	0.152	-0.125	0.257
Percent of zero-vehicle households	0.455	-0.284	0.683
Percent of low-income workers	0.145		0.141
Population density (persons/acre)	0.324	-0.268	0.504
Job density (jobs/acre)	0.128	-0.154	0.251
Road network density (miles/square mile)	0.242	-0.139	0.341

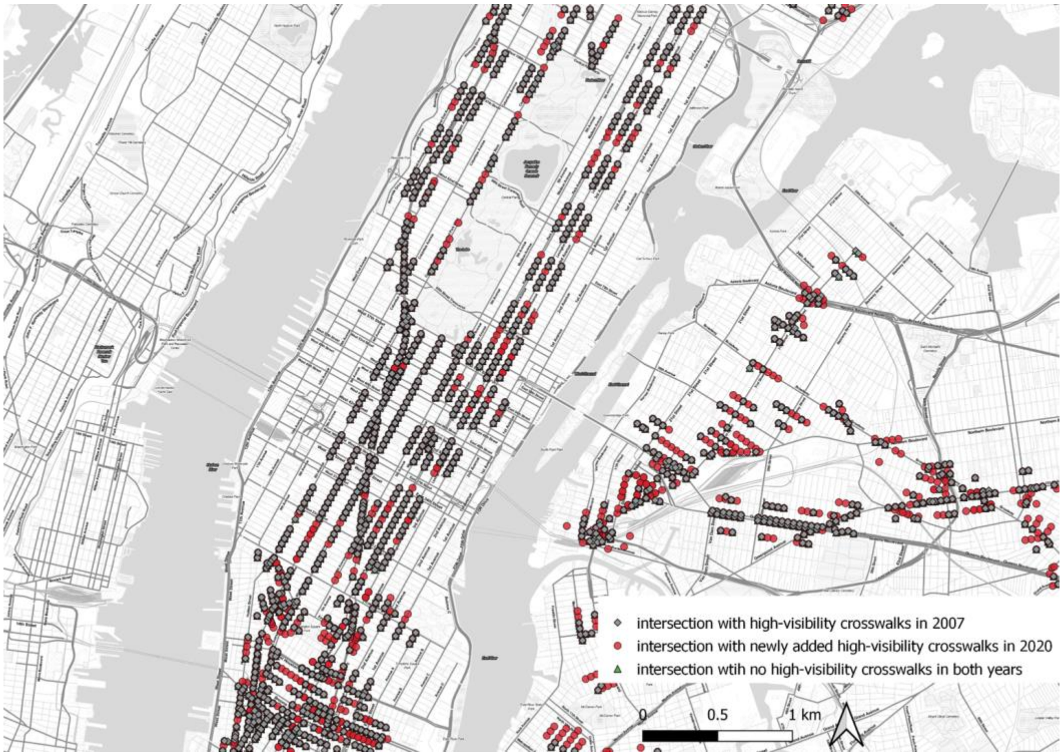
Note: Only coefficients with p < 0.05 are shown.

In terms of crosswalk enhancement between 2010 and 2018, higher density residential neighborhoods and neighborhoods with a higher percentage of zero-vehicle households tend to have received crosswalk upgrades between 2010 and 2018. As Table 17 shows, *Percent of zero-vehicle households* and *Population density* are positively associated with the increase of percent coverage of intersections with high-visibility crosswalk. On the other hand, areas with higher job density and jobs-housing mix are less likely to have improved pedestrian access to transit stations, reflected by the negative association between increase in high-visibility crosswalk coverage and *Job density*, as well as *Jobs per household*. This suggests an increased use of high visibility crosswalks in residential areas. However, the increase in employment centers was not as high, likely because high job-density areas already tend to have more high-visibility crosswalks (Table 16).

Table 17 Pearson's correlation between station area crosswalk coverage change (2010-2018) and built environment characteristics (2018)

	Marked crosswalk	**Parallel-line crosswalk**	**High-visibility crosswalk**
Percent of zero-vehicle households		-0.374	0.169
Percent of low-income workers		-0.18	
Population density (persons/acre)		-0.358	0.185
Job density (jobs/acre)			-0.107
Road network density (miles/square mile)		-0.213	
Auto network density (miles/square mile)			-0.164
Jobs per household (miles/square mile)	-0.104		-0.163

Note: 1) Only coefficients with $p < 0.05$ are shown; 2) change in terms of the difference in the percentage of intersections with marked, parallel-line, or high-visibility crosswalk.


intersection with high-visibility crosswalks in 2007
intersection with newly added high-visibility crosswalks in 2020
intersection wtih no high-visibility crosswalks in both years
0
0.5
1 km


intersection with high-visibility crosswalks in 2007
intersection with newly added high-visibility crosswalks in 2020
intersection with no high-visibility crosswalks in both years
0
2
4 km

3.4 Associations between changes in station-level marked crosswalk, built environment, and transit ridership

We estimated the impact of station area crosswalk enhancement for both marked (model 1) and high-visibility crosswalks (model 2) on ridership changes of 897 TOD stations over the period between 2010 and 2018, while controlling for other built environment variables, with robust standard error clustered by transit agency (Table 18). We first discuss our results for changes in crosswalks, followed by results for changes in other built environment characteristics, and ending with our findings for baseline variable values.

Table SEQ Table * ARABIC 18 Associations between built and social environment changes and station area weekday ridership changes

	Dependent variable:			
	Change in average weekday ridership			
	(1)		(2)	
Intercept	-1,180.83		-1093.85	
	(1,035.27)		(772.92)	
Crosswalk coverage:				
Percent of intersections with marked crosswalks (base year)	2.02			
	(6.78)			
Percent of intersections with marked crosswalks (change)	-24.58	***		
	(6.06)			
Percent of intersections with high-visibility crosswalks (base year)			-1.40	
			(4.13)	
Percent of intersections with high-visibility crosswalks (change)			2.37	
			(3.86)	
Built environment variables:				
Percent of low-income workers (base year)	63.83	**	60.85	
	(31.37)		(36.96)	
Population density (base year)	-12.32	***	-12.99	***
	(2.35)		(2.58)	
Job density (base year)	6.39	***	6.70	***
	(2.05)		(1.93)	
Street intersection density (base year)	1.82	**	2.16	***
	(0.90)		(0.69)	
Regional diversity index (base year)	404.83		525.18	
	(376.62)		(456.35)	
Regional centrality index (base year)	-2,457.86	***	-2,130.71	**
	(887.13)		(829.78)	

Percent of low-income workers (change)	-289.92	***	-285.85	***
	(73.61)		(81.87)	
Population density (change)	87.73	***	87.10	***
	(12.41)		(15.00)	
Job density (change)	-6.13		-8.76	
	(9.63)		(10.85)	
Street intersection density (change)	1.24		0.80	
	(0.78)		(0.89)	
Regional diversity index (change)	494.93		529.29	
	(383.10)		(371.69)	
Regional centrality index (change)	-1,323.27		-1,288.08	
	(938.70)		(815.37)	
Interaction terms:				
Percent of intersections with marked crosswalks (change) * Average weekday ridership (base year)	0.003			
	(0.003)			
Percent of intersections with marked crosswalks (change) * Population density (base year)	0.94	**		
	(0.44)			
Percent of intersections with high-visibility crosswalks (change) * Average weekday ridership (base year)			-0.001	
			(0.001)	
Percent of intersections with high-visibility crosswalks (change) * Population density (base year)			0.27	***
			(0.090)	
Observations	897		897	
R^2	0.07		0.07	
Adjusted R^2	0.05		0.05	
F Statistic	3.99*** (df = 16; 880)		4.05*** (df = 16; 880)	
Note:			*p<0.1; **p<0.05;***p<0.01	
			Significance reported based on robust errors clustered around each transit agency	

First, the addition of high-visibility crosswalks had a positive association with transit ridership though the effect was not statistically significant in either model. Model 2 suggests that a 1 percent increase in intersections with high-visibility crosswalks in a station area was associated with a modest increase of 2.4 riders per weekday in that station. Contrary to expectations, the addition of marked crosswalks (from unmarked crosswalks) at station areas was associated with a decrease in average weekday ridership.

Second, changes in local and regional built environment and socio-economic variables were associated differently with changes in ridership. Local built environment variables such as population density and intersection density were positively associated with ridership, although only population density was significant at conventional levels of confidence. Models 1 and 2 suggest that an increase of 1 person per acre was associated with an increase in 87.7 and 87.1 riders per day, respectively. For population density, using the model estimate from change we estimate an elasticity of 0.331. Aston et al. (2020) estimate an elasticity of 0.1, while Ewing and Cervero (2010) of 0.07.

We also estimate that an increase in the percent of low income workers in the station area is associated with lower ridership. Specifically, an increase of 1 percent in low income workers was associated with a decrease of between 290 or 286 riders per weekday, respectively. Unexpectedly, this result means that stations areas that gained low income workers relative to other residents, lost more ridership. Changes in overall accessibility as captured by regional centrality, and station area job specialization relative to the metropolitan area, were not associated with changes in ridership.

Observing associations between baseline values and ridership, we found that station areas with higher levels of job density, intersection density and percentage of the working population that is low income in 2010 had higher ridership changes. Specifically, an additional job per acre in 2010 was associated with 6.4 (model 1) and 6.7 (model 2) additional riders per weekday; and an additional intersection per square mile was associated with between 1.24 and 0.80 additional riders. Having one percent higher low income workers in 2010 was associated with 63.8 and 60.85 more riders between 2018 and 2010. Similarly, higher population density and higher regional centrality in 2010 were negatively associated with station-level ridership change, suggesting that station areas with higher density at baseline, after controlling for density changes, were more likely to lose riders over time than stations with lower density. Specifically, station areas with one person per acre more in 2010 had between 12 and 13 fewer riders in 2018 than in 2010, whereas station areas with higher regional accessibility had a larger decrease in riders between the two years.

The effect of the interaction terms suggests that changes in marked crosswalks were associated with ridership when population density in the station area was higher at baseline. Thus, density modifies the association between marked crosswalks and ridership, though the magnitude of the association is very small (0.94 riders per day). Interactions with base year ridership appear to have neither a statistically significant nor a practically significant association with ridership changes.

Our results for high visibility crosswalks, population density, intersection density, and job density and percent of low-income paint a complex picture of ridership change. On the one hand, the built environment changed in ways that are supportive of transit ridership. Indeed, our evidence suggests that when some of those changes occurred, ridership was changed positively. On the other hand, despite those environmental changes, overall ridership decreased. Furthermore, estimates for the percent of low income workers suggest that transit ridership decreased in areas that increased the proportion of low income workers. Low income workers have been shown to sacrifice accessibility –including transit accessibility- to afford housing expenses.

Although we didn't associate changes in zero-vehicle households with changes in ridership, the decrease in station areas is notorious and possibly related to changes in vehicle ownership. Indeed, the percentage of zero-vehicle households in the station areas decreased markedly by 20% and the percent of low income workers decreased by 5%. By contrast, nationwide the change in zero-vehicle households was 6% percent during the same time period. Thus, vehicle ownership rose significantly in station areas. This suggests that planning strategies to change the built environment to support transit ridership have been modestly successful. However, they have been insufficient in stemming the decrease in transit ridership. Socio-economic factors such as the auto ownership and changes in accessibility for low income workers appear to be contributing factors explaining the decrease in transit ridership.

Even though the addition of high-visibility crosswalks does appear to have positive associations with ridership, we do not find strong associations between changes in the presence of marked crosswalks and ridership changes. This is not entirely surprising given that marked crosswalks *on their own* are unlikely to remove barriers to transit use. Furthermore, we confirmed that marked crosswalks were associated with ridership when population density in station areas was higher.

The unexpected results from marked crosswalks raise broader questions about possible bias due to omitted variables and selectivity. For example, if station areas that do not have marked crosswalks and therefore are eligible for an upgrade are systematically more or less likely to gain or lose ridership over time in ways that are unobserved, then the coefficient for crosswalks will be biased. This may be the case if such stations are in less urban locations, with fewer mixture of land uses or an environment that is less friendly to pedestrians which may make them more susceptible to ridership losses over time.

A similar concern applies to high visibility crosswalks: high visibility upgrades are not randomly assigned to intersections. Au contraire, they are deliberately assigned to areas with significant pedestrian activity. If over time those stations are likely to retain transit ridership better than other stations, this would be reflected in the coefficient of high visibility crosswalks. We attempted to mitigate this limitation through the use of a broad set of control variables such as a walkability index, road network density, auto network density, pedestrian network density, percent of zero-vehicle households, although some of those variables were not included in the final models because of their high p-values and multicollinearity (variables with high variance inflation factors). Other possible variables of interest that were not examined include station access modal share at baseline, land use mix (especially retail, office, institutional and residential uses), the presence of traffic signals, and road safety information (e.g., traffic speed, and prior crash history).

Despite the relatively high accuracy (around 0.7) of our crosswalk detection model, potential errors remain in our crosswalk variables. We also found several inconsistent built environment measures between two versions of SLD, which we excluded from the final models. We also used propensity score matching to compare station areas with high and low marked crosswalk coverage (and high and low high visibility crosswalk coverage) as well as a simple "change on change" model, but results were similar to the models presented. In addition, we tested quantile regression to examine the coefficient estimates at different levels of ridership, which does not imply major differences of the model estimation.

STUDY C: Ride-hailing's influence on VMT & auto ownership across levels of transit access in Metro Boston

1. Background and Review

Transportation network companies (TNCs) have grown remarkably fast on local, national, and international scales. Uber, the most dominant of the TNCs in the U.S., began offering TNC services in San Francisco in 2009; within a decade, had expanded into every major American city; and now claims to operate in over 10,000 cities worldwide ("Use Uber in Cities…", 2021). As it grew, Uber began offering diversified services, and saw the formation of competitors such as Lyft and Via. The rapid expansion of the TNC industry has been in direct response to the popularity and explosive demand for TNC services. TNCs provide a convenient service for users leading many to envision a transition away from widespread personal vehicle ownership to a future in which urban transportation demands are satisfied through a combination of TNCs, other new forms of mobility, and public transit. On one hand, surveys of TNC riders indicate that TNC availability may encourage some groups including urban commuters and single millennials to forego private vehicle ownership (Coogan et al., 2018). But despite the potential for these services to discourage car ownership, current data suggest that driving has increased since the advent of TNCs. Several studies conclude that TNC operations increase congestion and vehicle miles traveled (VMT) within urban service areas (Erhardt, et al., 2019; Henao & Marshall, 2019). Furthermore, there are doubts whether TNCs complement public transit in urban contexts with high-level transit services (Young, Allen & Farber, 2020; Hall, Palsson & Price, 2018). Thus, the potential of TNCs to encourage less personal vehicle use while synergizing with other forms of shared mobility and transit in an efficient and desirable way remains uncertain.

1.1 TNCs, VMT and vehicle ownership

A curious pattern has emerged in the results of previous studies on TNCs relationship with VMT and vehicle ownership. One line of studies indicates that TNC services are related to decreasing personal vehicle use and ownership, while another set of studies indicate that TNCs are associated with higher VMT. These two findings may seem in conflict, but there are potential phenomena that help to explain how TNCs can simultaneously relate to lower reliance on personal vehicles, and higher VMT. One way is rather direct; TNC services attracting users from transit, active mobility, and other shared modes. Another is *deadheading*. For TNCs to provide as convenient a service as possible requires widespread availability of unused vehicles or vehicles engaged in similar trips to potential customers' trips. Unused TNC vehicles traveling without passengers are said to be deadheading, and research has indicated that TNC vehicles deadhead for considerable VMT while available for pick-ups (Henao & Marshall, 2019; Schaller, 2021).

Evidence for an association between TNC services and reduced personal vehicle use and ownership comes mainly from research using survey data. A study using data from a 2017 survey targeting residents living in American TNC markets indicates that TNCs draw their rider base mainly from personal vehicle users, and that some TNC users delayed purchasing a new vehicle. Asking participants how they would complete their most frequent trip in the absence of their most frequent mode, the researchers report that about 66% of frequent TNC users in the survey responded that they would drive a personal vehicle, while 14% would switch to transit.

Furthermore, approximately 10% of surveyed TNCs users reported postponing the acquisition of a new vehicle because of TNC services (Bansal et al., 2020).

Similar results concerning vehicle ownership can be found in the 2016 Transit Cooperative Research Program (TCRP) survey. As reported by Coogan et al. (2018), 26% of total respondents indicated less need for a car because of new services including TNCs, but urban commuters and single millennials were particularly likely to respond in this manner. 62% of urban commuters, and 56% of single millennials agreed that they felt less need for a car because of TNCs and other new transportation services.

Furthermore, a 2021 study by Wu and MacKenzie based primarily on trip data from the 2017 US National Household Travel Survey (NHTS) found that vehicle ownership among TNC users decreased the more often they used TNC services. They also found that among drivers who could access a vehicle at home, frequent TNC users recorded the lowest VMT.

Conversely, other studies have shown that TNC services are associated with higher VMT and congestion. In a 2019 study by Erhardt et al., the authors analyzed traffic time data in conjunction with TNC pick-up and drop-off data sourced from Uber and Lyft's Application Programming Interfaces (APIs). Utilizing the San Francisco Chained Activity Modelling Process (SF-CHAMP), they modeled expected changes in congestion under multiple scenarios including a 2010 scenario without TNCs, a 2016 condition without TNCs, and the observed conditions in 2016 with TNCs active. They found that VMT increased by 13% from 2010 to 2016, but estimated that VMT would have increased by only 7% over the same time period without TNCs. These findings led them to conclude that TNCs were the primary contributor to increased congestion in the city over the study period, and that even though TNC services were replacing some car trips, most TNC trips were leading to, "…[N]ew cars on the road (Erhardt et al., 2019, 10)."

Henao and Marshall (2019) also found a connection between TNCs and higher vehicle use in a study utilizing data sourced from rider surveys and by the researchers driving 416 trips for either Uber or Lyft in the Denver area. They estimate that TNC services contributed to 83.5% more VMT in the Denver region compared to estimates supposing TNCs were not available. Interestingly, even the previously mentioned study by Wu & MacKenzie (2021) found that TNC services were associated with 7.8 million additional daily miles of VMT nationwide at the time of the 2017 NHTS survey, leading them to mention how TNC services seem to have distinctive influences on different populations.

As a whole, the existing research on TNCs relationship with vehicle use and ownership seems to suggest that TNCs are associated with both lower vehicle use and increased VMT depending on various conditions including age and other population factors. Likely one of the most important of these conditions is public transit accessibility. Predictions of TNCs operating alongside public transit while reducing VMT rely on TNCs encouraging less motor vehicle use in the context of transit availability, and existing studies indicate that as of right now, TNCs typically substitute for transit services in areas with high transit access, and complement transit only where transit options are limited.

1.2 TNCs and transit

Are TNCs complements or substitutes for transit? The answer is likely dependent on the level of transit availability. Research indicating a substitutional relationship between TNCs and transit includes Graehler, Mucci and Erhardt's 2019 longitudinal study (2002-2018) utilizing panel data sourced from the National Transit Database. Utilizing a random-effects model, they estimate that heavy rail ridership declined 1.29% for every year after Uber began operating in a metropolitan area. Likewise, they predict drops of 1.70% in bus ridership for each year after Uber enters a large urban market. The relationship between TNCs and transit may vary depending on metropolitan population, so the results of this study may be irrelevant outside major U.S. cities. Still, the results indicate a substitutional effect in large cities, and this finding is echoed in additional research.

Surveys of TNC riders in the San Francisco area indicate that many TNC trips begin and end near transit options (Rayle et al., 2016). Other studies have also shown that TNC users rarely transfer to other modes of travel to complete trips. Henao and Marshall (2019) surveyed Uber and Lyft passengers in Denver, and only 5.5% of riders included another mode of transportation as part of their trip – a finding supported by surveys from Santiago, Chile where just 3.8% of TNC users reported using other modes as part of their TNC journeys (Tirachini & del Rio, 2019)

While there is notable evidence that TNC and transit services are often substitutes, there are also studies suggesting that they are complements in most American contexts. Using data from the National Transit Database, alongside city-specific data on Uber's market penetration, Hall, Palsson and Price (2018) examined if Uber operations and transit were complementary or substitutional in every metropolitan area with public transit. They estimated that Uber entering a metropolitan area increased transit ridership by 6% for agencies with below-median ridership nationwide. For agencies with ridership above the national median, Uber's introduction led to a 2.1% decrease in transit ridership. When comparing metropolitan populations, the authors found that the strongest complementary effect was for small transit agencies in large cities. They contend that this result, "…[I]s likely because a small transit agency in a large city provides the least flexible service in terms of when and where they travel, and so Uber's ability to add flexibility for such agencies is valuable to riders (Hall, Palsson & Price, 2018, 42)." They conclude that Uber complements services operated by average U.S. transit agencies, and that transit ridership increases by 5% two years after Uber begins local operations.

Additional research has found complementary and substitutional effects *within* metropolitan areas depending on the transit context. Using General Transit Feed Specification (GTFS) data and TNC rider surveys from the Toronto area, Young, Allen and Farber (2020) concluded that the quality and availability of transit services are associated with TNCs relationship to transit. By assessing if TNC trips had a corresponding transit trip available, the authors found evidence of TNCs complementing transit in areas with few transit options, and substituting for transit in areas with many transit options. 26.9% of the TNC trips included in their study had a transit alternative that would have added 30 minutes or more to the rider's journey, suggesting a complementary effect in rarely served areas. On the other hand, 30.6% of TNC trips had a transit alternative adding 15 minutes or less to total journey time, a result suggesting a substitutional relationship in areas with high-level transit service.

In short, some studies suggest that TNCs might complement transit in contexts with low levels of transit service and access, and substitute for transit in areas with established and frequent transit offerings. However, previous studies have not directly investigated data on vehicle use or ownership, nor have they had access to actual travel data at the neighborhood level within cities to help better understand the behavioral phenomena at work.

1.3 Uber's early history in the study area

Uber's early history in the Boston region provides an interesting opportunity to study the immediate influence of TNC services on personal vehicle use and ownership across various levels of transit access. TNCs were a novel concept at the time of Uber's launch in the area, and Uber spent years constrained to the urban core before expanding to the rest of the metropolitan area. Uber introduced its services to Boston early in its history compared to most cities, but for its first few years in the region, it operated mainly within a small service area at the hub of region delimited by the borders of Boston and Cambridge. Instead of growing to neighboring municipalities, Uber developed a variety of service offerings before expanding their availability outwards. On October 27th, 2011, Uber began operating in Boston by offering *Secret Uber* services ("5 Years of Memories…", 2016). Over the course of the following year, it began offering its *Uber Black* luxury car service, and then launched its flagship ride hailing service (now branded *UberX*) on September 19th, 2012 (Moore, 2012). While a handful of Uber trips extended beyond the Boston and Cambridge service area in the early years of operations, Uber did not formally expand its service area until July 2013 by offering availability to the South Shore inner suburbs of Quincy and Braintree ("South Shore…", 2013). Six months later, in January of 2014, Uber expanded once again to include the North Shore suburbs in its service area ("North Shore…", 2013). By October 2014, Uber operated in Worcester to the west of Boston extending their services to central Massachusetts ("Worcester…", 2014). It may have taken Uber some time to begin expanding in the Boston area, but once it started, it did so quite rapidly.

The Boston metropolitan region is a convenient one in which to investigate the early effects of TNC services because of how Uber launched and expanded in the area. It spent years operating almost exclusively within Boston and Cambridge, providing researchers with a delineation of areas with and without formal Uber availability for a few years. By holding off on expansion within the area for a few years, Uber's association with personal vehicle use and ownership can be analyzed both across areas inside and outside of its service area, and across time as Uber expanded its reach. The variability in Boston's transit network also allows for researchers to explore Uber's relationship with vehicle use and ownership across various levels of transit access.

1.4 Objectives

STUDY C explores the interplay between vehicle use and the availability of ride-hailing across levels of transit access by asking the following research question: How did the growing availability of Uber affect personal vehicle VMT and ownership in the Boston region during the early years of Uber operations in the area? In contrast to previous research, this current study uses data that can more directly measure whether access to TNCs, or access to both TNCs and public transit, affect the use of individual personal vehicles by analyzing changes in auto ownership and use using data from the Massachusetts Vehicle Census (MAVC) for the years 2010 to 2014. The MAVC was compiled using mileage and storage data from all inspected and registered vehicles in Massachusetts, and as such, is built upon actual changes in the usage patterns of individual vehicles. By comparing variations in VMT and the number of registered vehicles in each census tract across levels of transit access and Uber availability as Uber rolled out in the Boston area, this study explores the nascent effects of the introduction of TNC services to a large American metropolis with an established transit network.

2. Research Design and Methods

To estimate the influence of Uber availability on private vehicle use and ownership as the service began and subsequently expanded in the Boston area, we created a pair of fixed-effects panel regression models. The first utilized population normalized MAVC data on daily passenger vehicle VMT at the Census tract level as the dependent (outcome) variable, while the other utilized population normalized MAVC data on the number of passenger vehicles stored in each census tract as the dependent variable. Overall, we relied on three main data sources; the MAVC itself, the Massachusetts Bay Transit Authority's (MBTA) GTFS archive to locate transit access points, and the U.S. Census Bureau including the American Community Survey (ACS).

2.1 Outcome Variables: *VMT/Population* and *Vehicles/Population*

Both of STUDY C's analytical models used Census tract level data on auto ownership and mileage taken from the second quarter (Q2) of each year of the MAVC from 2010 to 2014. We estimated per capita auto ownership and mileage in each Census tract by dividing the MAVC figures by the U.S. Census Bureau's ACS estimates of population across Census tracts and years (U.S. Census Bureau American Community Survey 2020b). One model used mileage per capita as the dependent variable (*VMT/Population*) and the other used vehicles per capita (*Vehicles/Population*). The MAVC data include estimates for every quarter of the study period. We used data from Q2 of each year because the Census uses April 1st, the first day of Q2, as the reference day for decennial population estimates ("Independent Census Bureau…", n.d.).

2.2 Transit and Uber availability data

Another step in estimating the models was to obtain data on the location of transit stops and the availability of Uber for use as the independent variables of interest. We obtained date-specific spatial data on the location of transit stops and stations from the MBTA's GTFS archive (2021) and created accessibility scores for each Massachusetts Census tract for each year from 2010 to 2014, using the archive record closest to April 1st of each year. We reviewed and cleaned the data excluding duplicate stops and special transit nodes such as ferry docks, and airport shuttle bus stops. As such, stops and stations served by multiple transit routes were counted only once in the accessibility scores. We also reviewed an extensive history of MBTA service changes to ensure the stops and stations included in our data were operational during Q2 of each year (Belcher, 2021).

We then performed a series of spatial joins in ESRI's ArcGIS joining the station and stop points to 2010-2019 census tract polygons sourced from the U.S. Census' TIGER/Line shapefile (2010) for Massachusetts. The result of these joins was a set of five data layers, each representing every census tract in Massachusetts for the years between 2010 and 2014, and each recording the number of MBTA bus stops, commuter rail stations, and rapid transit stations in each tract both separately and combined. These totals were then divided by the land area of each census tract (in square miles), to create four spatially normalized transit access scores for each census tract.

Another series of spatial joins was performed alongside the aforementioned joins to create a dummy variable indicating the Census tracts with Uber availability during Q2 of each year. For 2010 and 2011, no Census tracts had Uber availability. For 2012 and 2013, we designated only Boston and Cambridge Census tracts as having Uber availability since Uber had yet to expand to other parts of the region. We utilized official boundary shapefiles from the cities of Boston and Cambridge to flag these Census tracts (“City of Boston…”, 2020; “City Boundary Shapefile”, 2020). Then, for 2014, we designated all Census tracts in the Boston Region Metropolitan Planning Organization’s (MPO) extents as having Uber availability using a boundary shapefile showing all MPOs in Massachusetts (“MPO Boundary Shapefile”, 2019). While we are not certain that every census tract in the MPO had Uber availability in Q2 2014, we are confident that most if not all did seeing that Uber had expanded to both the northern and southern ranges of the MPO by January 2014, and had begun operating in Worcester, which is outside the MPO, by October 2014. A map of these three boundaries is provided in Figure 2 below.

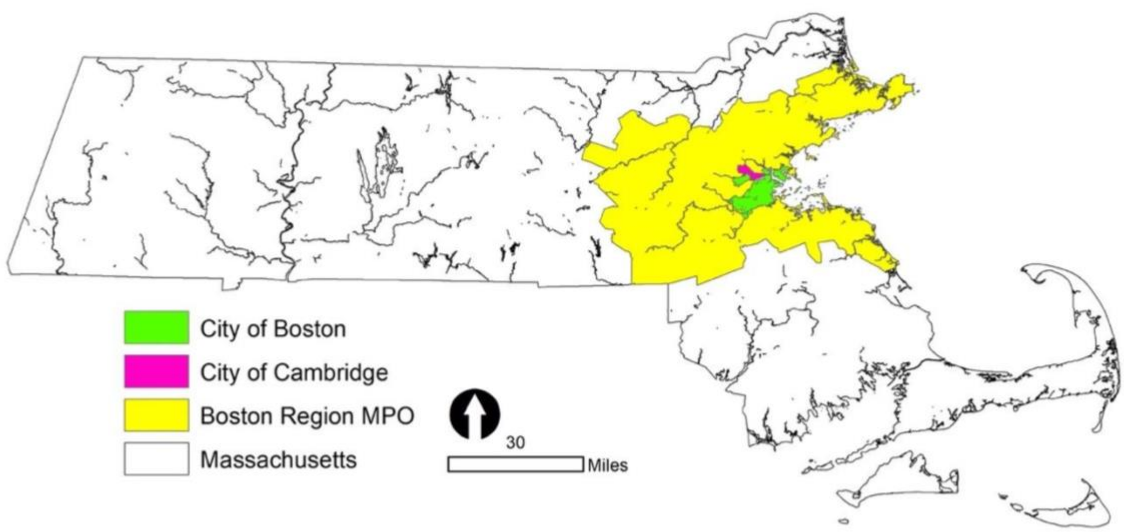


Figure 1 Study areas for STUDY C

We also generated interaction terms between Uber availability and each of the four transit access scores in order to analyze the influence of transit access on Uber’s associations with vehicle use and ownership.

2.3 Population data and control variables

We then merged the MAVC and MBTA data at the Census tract level to ACS Census tract level 5-year estimates of household income, age, and race/ethnicity for each year (U.S. Census Bureau American Community Survey, 2020a, 2020b, 2020c). The resulting database had 7,390 observations, each representing one of the 1,478 Massachusetts Census tracts (including tracts with no population) for each year of analysis, 2010-2014, and each including the population normalized MAVC data, the transit access scores, the dummy variable indicating Uber availability, the four interaction terms between Uber and the transit access scores, and the ACS data.

2.4 Statistical Analysis

In preparation for regression analysis, we reviewed a correlation matrix of all potential variables. Due to the high correlation between the number of bus stops per square mile and the number of all transit stops or stations per square mile (.989), we decided to solely use the all transit stops or stations by square mile scores and their interaction terms with Uber as potential independent variables representing transit access. Utilizing the Stata statistical software package, we then performed a series of panel regressions with fixed-effects using the Census tract as the panel variable, and the year as the time variable. A recurring result of these trial regressions was that the transit accessibility scores were statistically insignificant predictors of auto ownership or use by themselves, but were significant in interaction with Uber availability. In the end, we developed two models, one using daily per capita VMT as a dependent variable (*VMT/Population*), and the other using vehicles per capita (*Vehicles/Population*). Both models use the same set of nine independent variables: 1. The dummy variable indicating Uber availability (1 = available), 2. The interaction between Uber availability and the number of all transit stops or stations per square mile, 3. The number of all transit stops or stations per square mile, 4. The population density (the ACS population estimate divided by the land area in square miles), 5. The ACS estimate for the percent of the census tract population 25 years old or younger, 6. The ACS estimate for the percent of the census tract population 65 years old or older, 7. The ACS estimate for average time to work, 8. The ACS estimate for median income, and 9. The ACS estimate for median age. Summary outputs for both of the panel regressions used to generate these models are shown in the Results section as Tables 19 & 20.

After running these regressions, we performed a series of diagnostic tests to assess the statistical fit of the analytical models and the normality of the residuals. First, we ran Hausman specification tests on the fixed-effect panel regressions, and both resulted in rejected null hypotheses indicating that the analytical models based on these regressions did not exhibit misspecification, and that the regressions were better fits for the variables compared to panel regressions with random-effects. We then checked the normality of the residuals by generating kernel density estimates of the residuals and compared it to a normal curve which both regressions approximated. We must note that the normality of the residuals for both regressions could not be confirmed using the Shapiro-Wilk test, but subsequent review of their kernel density estimates indicated that the residuals closely followed a normal distribution.

3. Results

The panel regressions performed as part of STUDY C indicate that Uber availability was related to decreases in both daily VMT and passenger vehicle ownership over the period data were available in the Boston area. However, these changes were modest. Moreover, daily VMT and vehicle ownership were shown to be positively associated with the number of MBTA transit stops or stations in Census tracts with Uber availability.

3.1 VMT/Population, 2010 – 2014

First, the model using *VMT/Population* as the dependent variable (Table 1) shows a slight but noticeable association with Uber availability that is statistically significant at the 95% confidence level. In simple terms, passenger vehicles registered or stored in Census tracts with Uber availability produced 0.26 fewer daily miles traveled per person living in these tracts. The association between *VMT/Population* and the interaction between Uber availability and the number of MBTA transit stops or stations per square mile is similarly significant. In Census tracts with Uber availability, every additional MBTA transit stop or station per square mile was related to the vehicles registered or stored in these tracts travelling 0.006 additional miles per day per person living in the tract, which estimates to about an extra 1.2 VMT a day per person in the tract with the strongest transit availability. The net result of these associations indicates that of the 685 Census tracts in 2014 with Uber availability, 31% (213 tracts) saw the decreases in VMT per capita associated with Uber availability wholly offset by increases in VMT per capita associated with the number of transit stops or stations per square mile. However, both of these associations were less significant than that of any of the controls including the age and income independent variables.

3.2 Vehicles/Population, 2010 – 2014

Moving on, the other model using *Vehicles/Population* as the dependent variable (Table 2) parallels the results of the first. Most importantly, it indicates an inverse association between Uber availability and *Vehicles/Population* that is significant at the 95% confidence level. Census tracts with Uber availability housed about .013 fewer passenger vehicles per person living in these tracts compared to before the introduction of Uber. In other words, Uber expansion led to 1.3 fewer cars per 100 residents in Census tracts gaining Uber availability. Moreover, this model estimates that the relationship between *Vehicles/Population* and the interaction term for Uber availability and the number of MBTA transit stops or stations per square mile is also significant. In Census tracts with Uber availability, every additional MBTA transit stop or station per square mile was associated with 0.00031 additional passenger vehicles per capita. Once again, the net result of these associations indicates that of the 685 Census tracts in 2014 with Uber availability, 32% (219 tracts) saw the decreases in total passenger vehicles per capita associated with Uber availability wholly offset by increases in total passenger vehicles per capita associated with the number of transit stops or stations per square mile.

Table 1 Regression Output Using *VMT/Population* as the Dependent Variable

Dependent Variable = *VMT/Population*		
R-Squared (R^2) Values	Number of Observations 7,772	
Within = 0.1111 Between = 0.5752 Overall = 0.5652	Number of Groups 1,456	
Independent Variables	Coefficient	P>|t|
Uber Availability*	-0.262727	0.001
Uber(Transit Stops & Stations per SqMile)#	0.0062407	0.000
Transit Stops & Stations per SqMile†	-0.0006047	0.940†
Population Density	-0.0002178	0.000
% of Population <=25 Years Old	-0.046492	0.000
% of Population >=65 Years Old	0.0816751	0.000
Average Time to Work in Minutes	0.0645546	0.000
Median Household Income	0.0000164	0.000
Median Age	0.1388497	0.000
* Indicates a Dummy Variable # Indicates an Interaction	† Indicates NOT Significant at the 95% Confidence Level	

Table 2 Regression Output Using *Vehicles/Population* as the Dependent Variable

Dependent Variable = *Vehicles/Population*		
R-Squared (R^2) Values	Number of Observations 7,772	
Within = 0.1097 Between = 0.6189 Overall = 0.6010	Number of Groups 1,456	
Independent Variables	Coefficient	P>|t|
Uber Availability*	-0.0127945	0.000
Uber(Transit Stops & Stations per SqMile)#	0.0003134	0.000
Transit Stops & Stations per SqMile†	-0.0001171	0.699†
Population Density	-0.0000092	0.000
% of Population <=25 Years Old	-0.001538	0.000
% of Population >=65 Years Old	0.0030861	0.000
Average Time to Work in Minutes	0.0024269	0.000
Median Household Income	0.00000069	0.000
Median Age	0.0048692	0.000
* Indicates a Dummy Variable # Indicates an Interaction	† Indicates NOT Significant at the 95% Confidence Level	

Conclusions

STUDY A: Employer-based travel demand management in mitigating congestion

This project explored the effects of employer-based travel demand management (TDM) strategies on congestion mitigation from two levels, employers and employees. The first analysis contextualized in the nine counties in Washington state that have the most important economic activities, aggregated vehicle trip rates at worksites, and analyzed how different TDM tools may help discourage solo driving, essentially help mitigate road congestion. The second analysis placed a focus on multimodality and examined how to utilize employer-based TDM tools can incentivize employees' travel modal shift towards sustainability. The main findings are:

- VTR steadily grows for three decades, and employer-based TDM measures can only decelerate the growth rate but cannot reverse the trend;
- CTR's advertising efforts and collective bargaining help reduce VTR;
- Distributing transit passes is negatively associated with VTR;
- Shared mobility incentives, such as carsharing subsidy and ride match, both contribute to decreases in VTR;
- Emergency rides are positively associated with VTR;
- Allowing for shared rental cars on worksites is negatively associated with VTR.
- Subsidizing transit passes, flexible work schedules, and parking pricing are the most effective strategies to proportionally alter employees' travel mode choices.
- ETCs play an active role in promoting multimodality.
- Employees living and working in closing areas were more likely to be a similar way of multimodal transportation.

To inform practice, when rewarding employees, distributing transit passes is a preferred strategy. Carsharing-related measures should be applied with caution. Governmental agencies should lead employers to advertise CTR programs and engage employees to identify their favored TDM strategies. To promote multimodality and encourage modal shifts toward sustainability, subsidizing transit, pricing parking, and increasing flexibility in work schedules should be continually supported.

There are several future research opportunities connected to the work presented in this report. First, there are many emerging transportation modes in recent years, such as bikesharing, e-scooter sharing, and socio-carpooling. These emerging travel options may greatly alter individuals' travel choices. Vehicle trip rates can be further reduced, and multimodality can be operated at a larger scale. The existing employer-based TDM programs should incorporate such trends to ensure alternatives are attractive to employees. Second, also aided with technical advancements and smartphone use, the parking system is smarter. Various parking strategies, such as shared-parking initiatives, performance-based parking, parking cash-out, can be integrated into the framework of existing employer-based TDM programs. As parking has been identified as one of the most effective tools to discourage driving, the use of various parking policies may make parking a strong but acceptable component in managing road traffic. Third, the coronavirus pandemic has greatly changed the way of working, and nearly 40% of employees telecommute in early 2020. Historically, the importance of alternative schedules is underestimated among various employer-based TDM tools, while the significance of these tools deserves better attention. Fourthly, cities are promoting multimodality and mobility as a service. Direct evidence would be the reduced cost for using multiple travel options. A deeper and broader impact of multimodal transportation incentivized by employer-based TDM can better help plan the transportation system. Lastly, autonomous vehicles are emerging. The early research suggests shared autonomous vehicles can greatly save parking space in downtowns but may also incur further urban sprawl in suburban areas. How to ensure the development of autonomous vehicles can help mitigate congestion rather than incur congestion deserves more careful simulation and investigation.

STUDY B: Rail transit ridership and station area characteristics

In this study we examined changes to the built environment around 897 transit stations belonging to eight agencies and associated them to changes in transit ridership between 2010 and 2018. During this period ridership decreased an average of 2.4%, although there were some stations that gained ridership. Average ridership declined even when the built environment around stations became more pedestrian and transit user friendly. Population density, job density, intersection density, and marked crosswalks all increased during this time, and there was a shift from parallel-line crosswalks to high-visibility crosswalks. Yet, the percent of low income households and zero-vehicle households, traditional mainstay of transit riders, also decreased overall. This suggests that planning strategies to change the built environment to support transit ridership in the station areas examined have been modestly successful and that changes in the socio-demographic makeup of station areas have contributed to the decline in ridership.

We found that addition of high-visibility crosswalks was positively associated with transit ridership changes, though its impact was statistically significant only when population density was high. By contrast, the addition of marked crosswalks was associated with decreases in ridership during the same period, likely the result of excluded variables. Similar methods can be used to identify other station area infrastructure changes such as sidewalks and bike lanes, which may add to a more comprehensive analysis of the built environment changes and their impact on transit use. Furthermore, population density changes were positively associated with ridership, but increases in the percentage of workers that are low income were negatively associated with ridership changes.

Despite changes to the built environment that are supportive of transit, ridership decreased during the study period. Socio-economic factors such as changes in accessibility for low-income workers appear to be contributing factors explaining the decrease in transit ridership. We found that transit ridership decreased in areas with increased proportion of low-income workers. Furthermore, increased auto ownership around transit station areas was shown to be changing more rapidly than elsewhere in the country. These changes can be the result of an influx of new auto-reliant low-income residents, the outflow of low-income transit dependent residents, or changes in auto ownership of remaining residents contributing to hamper transit demand.

The evidence presented here suggests that efforts by land use and transit planners to develop strategies to modify station areas to support higher transit ridership are necessary but likely insufficient to achieve environmental sustainability goals. Planning and policy attention to auto ownership and use, either due to changes in regional accessibility (as may be the case for low-income workers) or for other reasons, is likely to have beneficial impacts on transit ridership.

STUDY C: Ride-Hailing's influence on VMT & auto ownership across levels of transit access in Metro Boston

In STUDY C, we used data sourced from vehicle odometer readings and storage information to estimate the relationship between Uber availability and vehicle use and ownership across levels of transit access in the Boston area. As Uber began operations in the Boston area, Uber availability was statistically related to small decreases in both daily VMT and vehicle ownership in Uber's service area, partially or completely offset by increases in daily VMT and vehicle ownership in Census tracts with the highest transit accessibility. In summary, Census tracts with Uber availability produced .26 less daily passenger vehicle VMT per person, and stored .013 fewer passenger vehicles per person, but these reductions were smaller for every transit stop or station per square mile. These findings suggest that transit access may constrain reductions in VMT and vehicle ownership associated with Uber availability. Uber availability may have encouraged modestly less passenger vehicle use and ownership in areas with access to Uber, except in areas with strong transit services, where auto use and ownership would be predicted to remain constant or increase.

These findings parallel the results of previous research showing that TNCs may have heterogeneous effects on VMT or transit use depending on context, specifically depending on the level of transit service. One possible explanation for these results is that TNCs draw their users from all other modes; thus, where viable mode choice is limited to mainly personal vehicles, TNCs would draw most of their customers from personal vehicle users. In such a scenario, TNCs could help curb reliance on automobiles, and ultimately lower VMT. However, in areas with a variety of modes including transit, TNCs may draw customers away not only from personal vehicles, but from transit and potentially active mobility and other shared modes as well. By drawing from these non-automotive modes, TNCs would actually increase reliance on automobiles and could potentially inflate VMT. Note that although greater TNC use would not tend to increase auto ownership and use on its own, it could affect Census tract level auto ownership and use if TNC drivers live near their customers in some cases; and also, because TNC use could encourage greater auto ownership and use if it stimulated a preference for driving.

We must note that in the early years of Uber operations in Boston, other variables besides TNC availability had similarly strong associations with personal vehicle use and ownership. While it is noteworthy that Uber availability had observable relationships with VMT and vehicle ownership so early on in the existence of TNCs in the area, the control variables (including population density, age, income, and commuting time variables) all had significant associations as well. TNCs influence may have grown over time, but this current study was restricted to the early years of Uber operations in the Boston area given available data.

The results of STUDY C suggest that if a region's transportation planning goals include intentions to reduce personal vehicle use and ownership, then TNC services should be encouraged in areas without, or with low-level transit access, and perhaps better managed in areas with stronger transit services where TNCs might contribute more to road congestion, particularly slowing down bus service. If the potential of TNCs to reduce personal vehicle use and ownership lies primarily with residents with low to medium levels of transit access, this presents additional justification and opportunity to manage Uber and other TNCs in those particularly high-density, high-transit-access areas such as central business districts.

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Appendix A Algorithm for VTR Aggregation

A.1. Introduction

The vehicle trip rate is calculated based on the number of personal vehicle trips per 100 employees. Employers must appoint an employee to act as an Employee Transportation Coordinator (ETC) to manage the CTR program at the worksite. The ETC would reach to employees to complete the CTR biannual survey. The VTR computation is based on data collected from an approved CTR-supported company's employee who starts to work between 6:00 a.m. and 10:00 a.m. The VTR is computed by dividing the total number of cars arriving at a worksite by the total number of employees reporting to that worksite.

According to CTR, the VTR must be calculated between the hours of 6:00 a.m. and 10:00 a.m., Monday through Friday, unless the business is open for seven days a week. For businesses operating seven days a week, the VTR window is 6:00 a.m. to 10:00 a.m., and the VTR reporting period is the five consecutive days of the seven working days when the majority of the employees are scheduled to start work. Businesses that operate seven days a week may conduct surveys over seven days in order to account for individual employees throughout the portion of their five-day workweek that falls inside the five consecutive days for VTR reporting purposes.

A.2. VTR Adjustment

In this study, there were multiple surveys reported in the CTR program. The vehicle trip credit would be determined for all employees who drove over the course of a week during peak hours (6:00 a.m. -10:00 a.m.). there are multiple steps involved in calculating the VTR, specified as follows:

Step 1. Calculate the daily vehicle trip credit for each employee

The drive mode credit is determined based on CTR as Table A1.

1. Driving alone is counted as a single-occupant vehicle. The assigned credit is 1.

2. Carpooling is counted as 2-15 people traveling together. The credit is using 1 divided by the total number of occupants in this vehicle.

3. Employees walking, bicycling, telecommuting, using public transit, or other options as approved by the Executive Officer or designee, or on their day off under a compressed workweek, should be counted as employees arriving at the worksite with no vehicle. The credit is given as 0.

4. Compressed workweek days off and overnight business trips are also counted as employees arriving at the worksite with no vehicle because these two modes would not be a conflict with the vehicle trip during peak hours. The credit is also given as 0.

Table A1. The drive mode credit calculation

Drive alone = 1	Telework = 0
Carpooled = 1/ (number of occupants on the vehicle)	Compressed workweek day off = 0
Vanpooled = 1/ (number of occupants on the vehicle)	Overnight business trip = 0
Ride a bus = 0	Did not work = 0
Ride a train/light rail/streetcar = 0	Boarded Ferry with car/van/bus = 0
Ride a bicycle = 0	Boarded Ferry as walk-on passenger = 0
Walk = 0	Other = 0

Step 2. aggregate the weekly vehicle trip credit for each employee

According to the above rules, an employee trip credit for a week would be calculated by the average daily vehicle trip credit of the workdays in that week. For example, if an employee chooses to drive alone on Monday, Wednesday, and Thursday, and carpool with one friend on Tuesday and Friday, the credits from Monday to Friday are 1, 0.5, 1, 1, and 0.5; therefore, the trip credit of the employee in this week is 0.8 vehicle.

Step 3. Calculate the vehicle trip rate for each worksite

Employees are assigned to different groups based on their worksite ID of employees' information. Then the VTR of the worksite would be aggregated as the average of the vehicle trip credits of its employees, denoted as the number of vehicles per 100 employees.

Appendix B. Details for Employer Data and Employee Data

In this study, employer data and employee data were collected by the Washington State Department of Transportation (WSDOT). Employer data were required to submit by employers who implemented CTR programs on their worksites; and employee data were collected by the ETC who distributed the questionnaires on their worksites. Despite employer data and employee data had enough information about the CTR effects and employees' own experience, some unreasonable answers or information were presented in the final results for unknown reasons. In this section, the details about how to deal with these data are described.

B.1. Employee Worksite Data

In employee original data, there are ten questions about ways of distributing information for employees, such as CTR presentations, electronic mail messages, and CTR articles. It is difficult to estimate the effect of each method. Therefore, the number of methods was counted as the efforts in advertising CTR to employees, as shown in Figure B1. The types of worksites were set as 14 types. Since there were only 265 worksites of 224 employers used in the analysis, the type of worksite was aggregated to 6 types, including IT-related industry, Gov. & Edu. - related, manufacturing, transportation and utility, finance and professional service, health care, and agriculture and fishing, as shown in Figure B2.

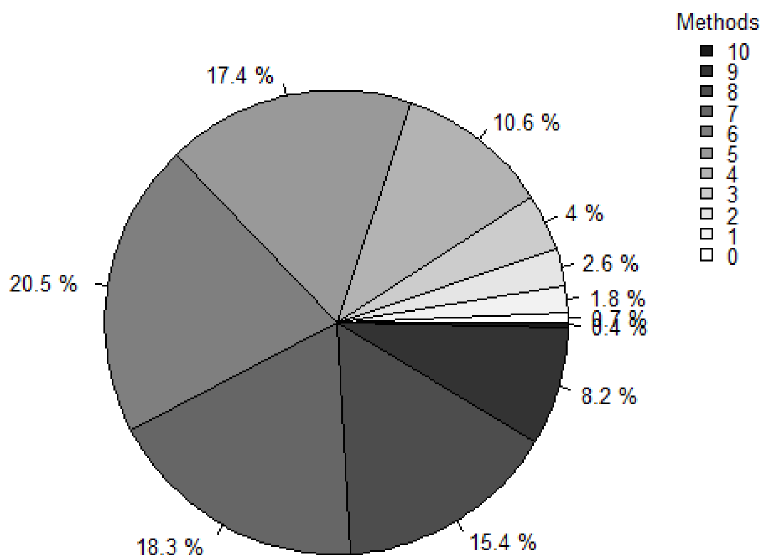

Figure B1. The pie chart for the number of methods used to advertise CTR program on worksites

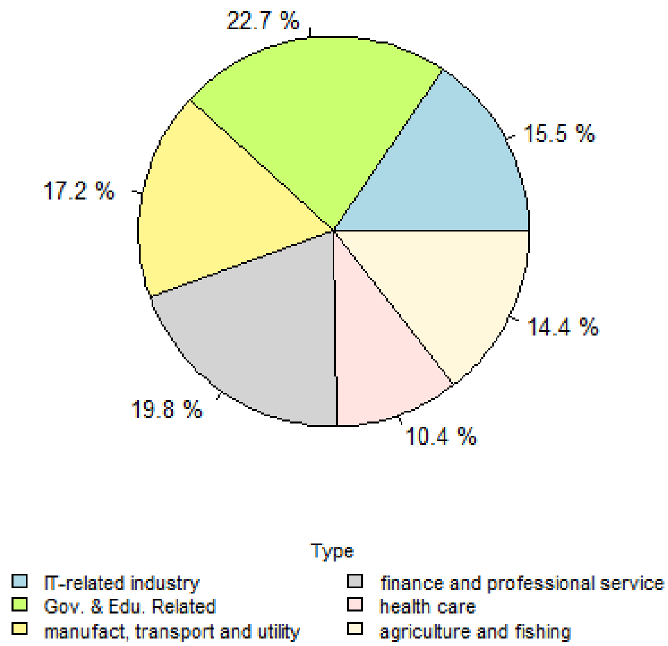

Figure B2. The pie chart of aggregating industries (business types) on worksites

B.2. Employee Data

A major research objective in the second analysis is multimodality, and the availability of sustainable alternatives is important for analysis. As King County is core of Washington State, where Seattle Metropolitan is located in, economic activities are centered, and a multimodal transportation system is well-built, this study narrowed the geospatial analysis scope to King County. By sorting out cases with non-standard work schedule, 41,440 cases were remained in the sample. The questionnaire asked employees their commuting mode on a daily basis, and the alternatives are drive alone, carpool/vanpool, public transit, telework, walk, bike, and 'others'. Since 'other' is an ambiguous answer, cases answered 'others' were excluded in final data. The exclusion process is detailed in Table B1.

Table B1. Pseudocode of algorithm for commuting modes

Procedure
Begin
Input T = Employee's travel modes in one week
If type(T) = 1

```
        Generate Y with the choice of six travel modes
      End If
      If type(T) = 2
        If Drive-alone in type (T)
          Generate Y with the choice of six travel modes excluding drive alone
        End If
        If Drive-alone not in type(T)
          Generate Y with the main choice of six travel modes
        End If
      End If
      If type(T) >= 3
        Generate Y with multimodality
      End If
    End
```

Appendix C. Commute Trip Reduction Survey Questions

Commute Trip Reduction

State of Washington

Employee Questionnaire

Directions

- All questions refer to work for this employer only.
- Use a No. 2 pencil.
- Fill in the circles completely.
- Erase cleanly any marks you wish to change.
- Do not make any stray marks on the form.

1. Which of the following best describes your employment status?

- ○ Full-time (35 hours or more each week)
- ○ Part-time (20 to 34 hours each week)
- ○ Part-time (less than 20 hours each week)

2. What days do you typically begin work between 6 and 9 a.m.? (Mark all that apply)

- ○ Monday
- ○ Tuesday
- ○ Wednesday
- ○ Thursday
- ○ Friday
- ○ Saturday
- ○ Sunday
- ○ Never

3. ONE WAY, how many miles do you commute from home TO your usual work location?

- DO NOT use roundtrip or weekly distance.
- Include miles for errands or stops made daily on the way to work.
- If you telework, report the miles from your residence to your work location.
- Round off the distance traveled to the nearest miles.
- Write numbers in the boxes and fill in the corresponding circles.

0	0	0
1	1	1
2	2	2
3	3	3
4	4	4
5	5	5
6	6	6
7	7	7
8	8	8
9	9	9

4. Last week, what type of transportation did you use each day to commute TO your usual work location?

- If you used more than one type, fill in the type used for the LONGEST DISTANCE.
- 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.
- Fill in "Teleworked" if you eliminated a commute trip by working at a location less than half the distance from your usual work location.
  If you teleworked part of the day then went to your usual work location, fill in how you got to your usual work location.

M	T	W	Th	F	Sa	Su	
○	○	○	○	○	○	○	Drove Alone
○	○	○	○	○	○	○	Carpooled (2 or more people)
○	○	○	○	○	○	○	Vanpooled
○	○	○	○	○	○	○	Rode a motorcycle
○	○	○	○	○	○	○	Rode a bus
○	○	○	○	○	○	○	Rode a train/light rail/streetcar
○	○	○	○	○	○	○	Rode a bicycle
○	○	○	○	○	○	○	Walked
○	○	○	○	○	○	○	Teleworked
○	○	○	○	○	○	○	Compressed workweek day off
○	○	○	○	○	○	○	Overnight buisness trip
○	○	○	○	○	○	○	Did not work (day off, sick, etc.)
○	○	○	○	○	○	○	Boarded Ferry with car/van/bus
○	○	○	○	○	○	○	Boarded ferry as walk-on passenger
○	○	○	○	○	○	○	Other: ____________

5. If you carpooled or vanpooled as part of your commute, or if you rode a motorcycle, how many people (age 16 or older) were usually in the vehicle including yourself?

- ○ One person
- ○ Two people
- ○ Three people
- ○ Four people
- ○ Five people
- ○ Six people
- ○ Seven people
- ○ Eight people
- ○ Nine people
- ○ Ten people
- ○ Eleven people
- ○ Twelve people
- ○ Thirteen people
- ○ Fourteen people
- ○ Fifteen or more people

6. What is your home zip code? (Write numbers in the boxes and fill in the corresponding circles.)

0	0	0	0	0
1	1	1	1	1
2	2	2	2	2
3	3	3	3	3
4	4	4	4	4
5	5	5	5	5
6	6	6	6	6
7	7	7	7	7
8	8	8	8	8
9	9	9	9	9

7. **Was last week a typical week for commuting?**
   - ○ Yes ○ No

8. **Which of the following best describes your work schedule?**
   - ○ 5 days a week
   - ○ 4 days a week (4/10s)
   - ○ 3 days a week
   - ○ 9 days in 2 weeks (9/80)
   - ○ 7 days in 2 weeks
   - ○ Other: ______________________________

9. **On the most recent day that you drove alone to work, did you pay to park?** (Mark "yes" if you paid that day, if you prepaid, if you are billed later, or if the cost of parking is deducted from your paycheck.)
   - ○ Yes ○ No ○ I don't drive alone

10. **How many days to you typically telework?**
    - ○ I don't telework
    - ○ Occasionally, on an as-needed basis
    - ○ 1-2 days/month
    - ○ 1 day/week
    - ○ 2 days/week
    - ○ 3 days/week

11. **When you do not drive alone to work, what are the three most important reasons?**
    - ○ Financial incentives for carpooling, bicycling or walking
    - ○ Free or subsidized bus, train, vanpool pass or fare benefit
    - ○ Personal health or well-being
    - ○ Cost of parking or lack of parking
    - ○ To save money
    - ○ To save time using the HOV lane
    - ○ I have the option of teleworking
    - ○ Driving myself is not an option
    - ○ Emergency ride home is provided
    - ○ I receive a financial incentive for giving up my parking space
    - ○ Preferred/reserved carpool/vanpool parking is provided
    - ○ Environmental and community benefits
    - ○ Other: ______________________________

12. **When you drive alone to work, what are the three most important reasons?**
    - ○ Riding the bus or train is inconvenient or takes too long
    - ○ I need more information on alternative modes
    - ○ My job requires me to use my car for work
    - ○ My commute distance is too short
    - ○ Family care or similar obligations
    - ○ I like the convenience of having my car
    - ○ Bicycling or walking isn't safe
    - ○ There isn't any secure or covered bicycle parking
    - ○ Other: ______________________________

Thank you for completing the survey!

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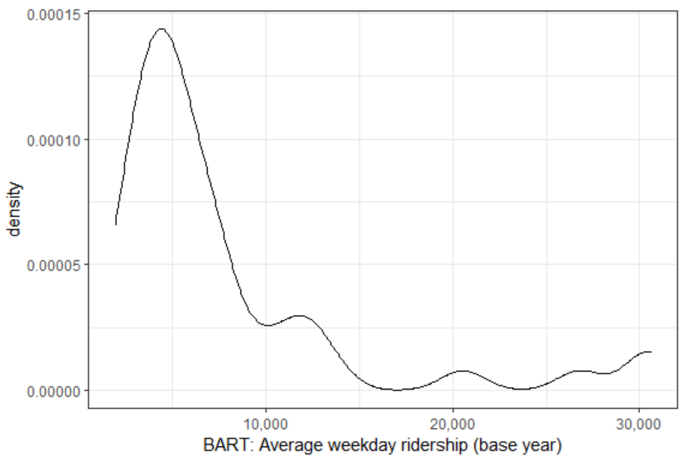
Appendix D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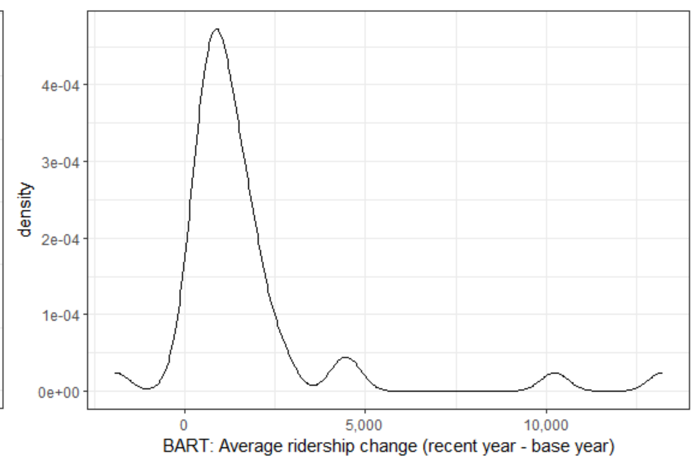
BART: Average weekday ridership (base year)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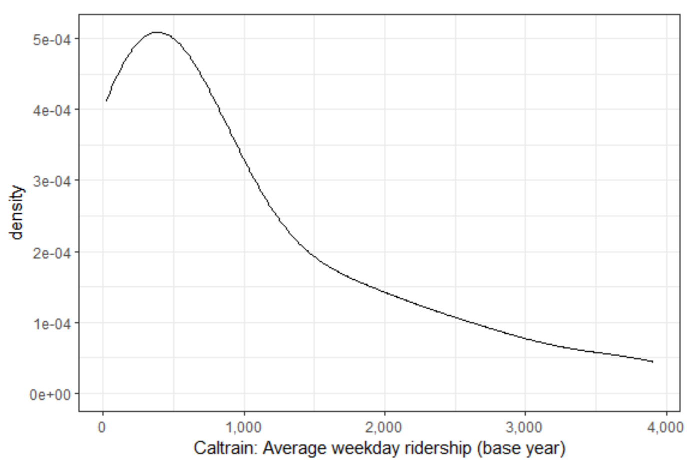
BART: Average ridership change (recent year - base year)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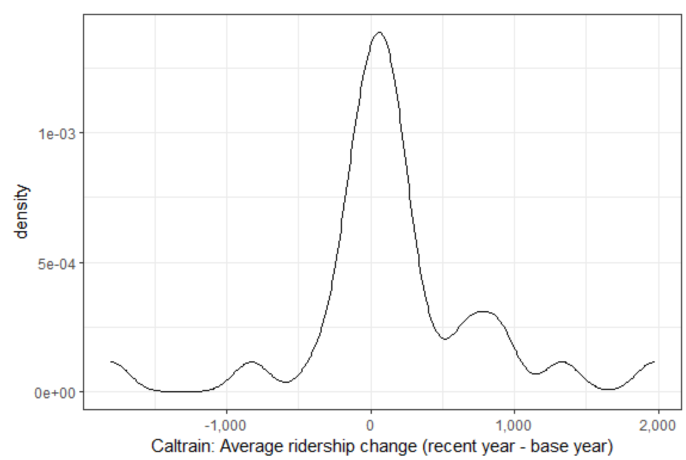
Caltrain: Average weekday ridership (base year)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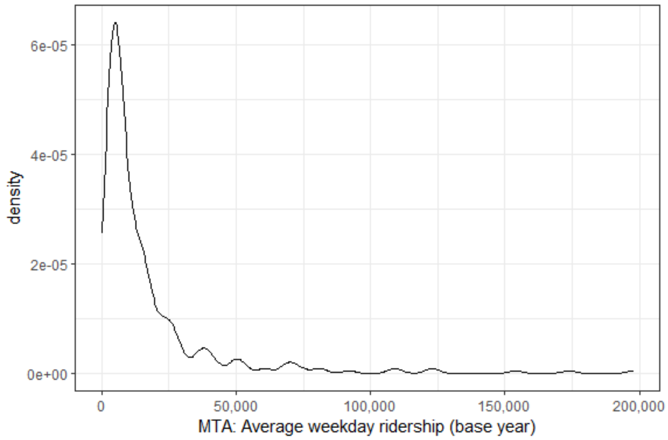
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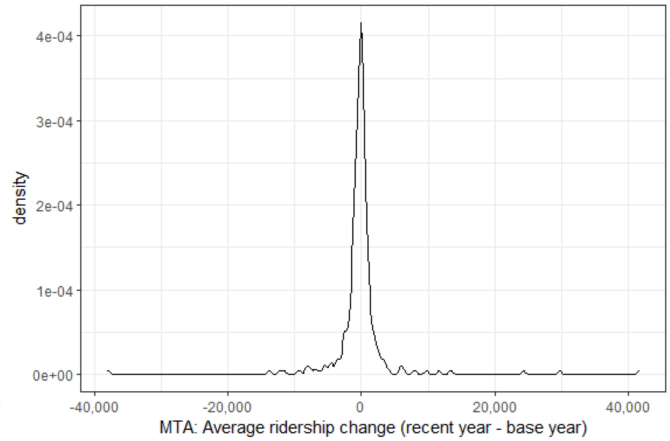
MTA: Average weekday ridership (base year)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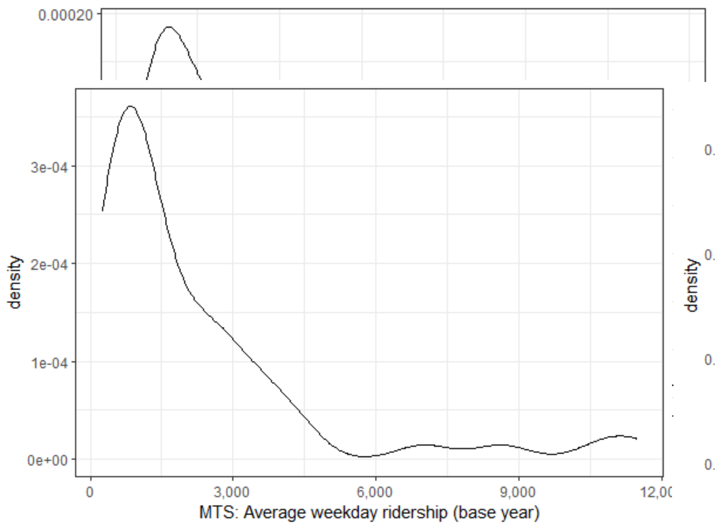
MTA: Average ridership change (recent year - base year)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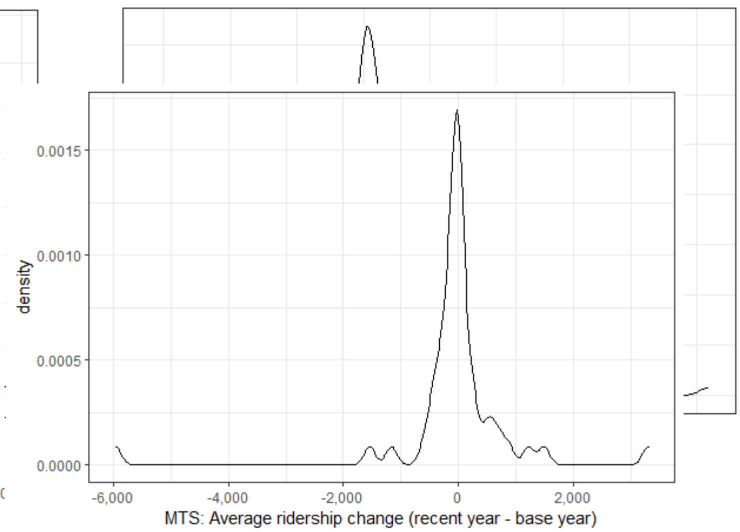
MTS: Average weekday ridership (base year)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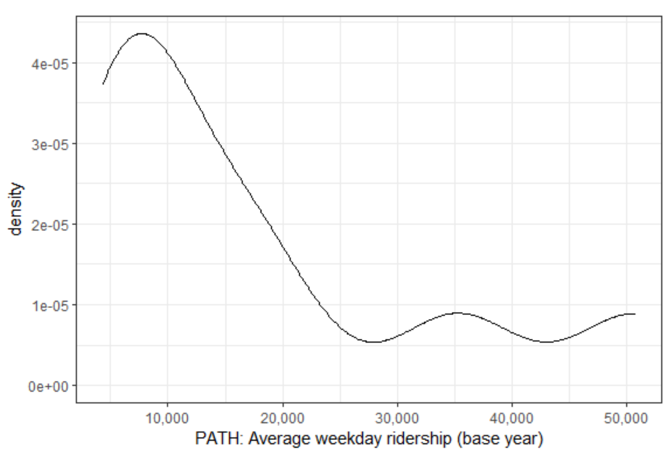
MTS: Average ridership change (recent year - base year)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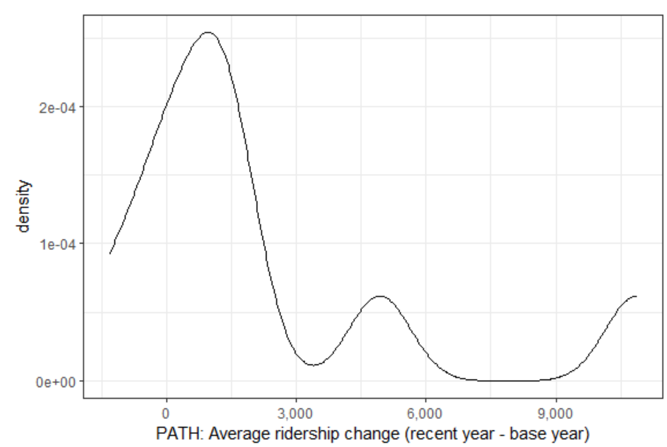
PATH: Average weekday ridership (base year)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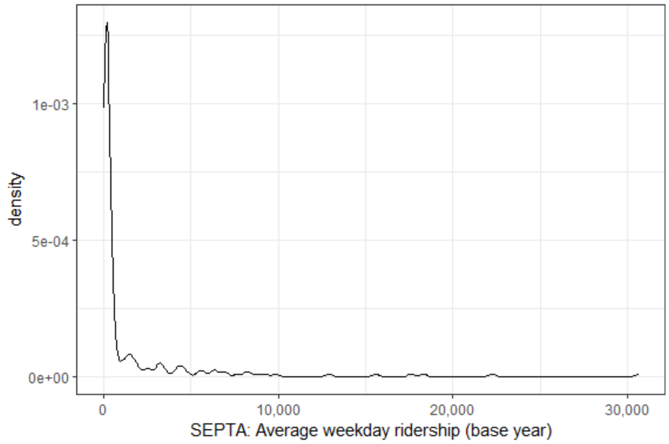
PATH: Average ridership change (recent year - base year)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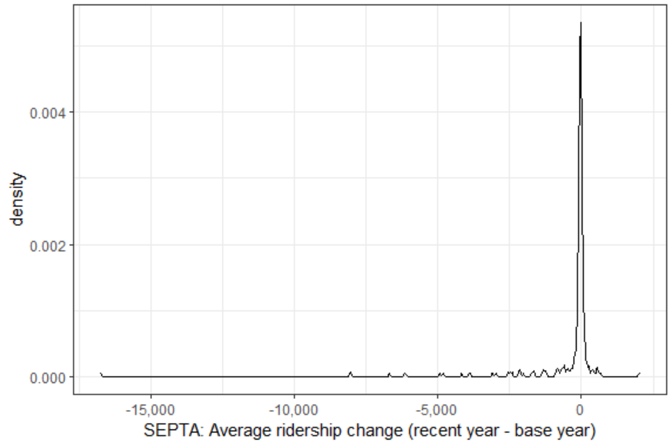
SEPTA: Average weekday ridership (base year)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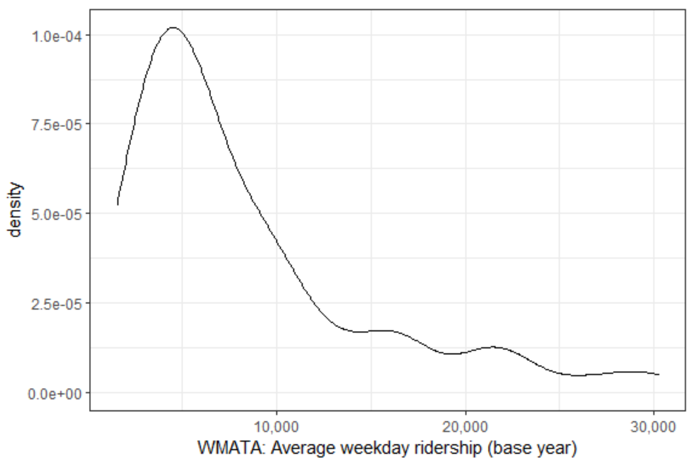
SEPTA: Average ridership change (recent year - base year)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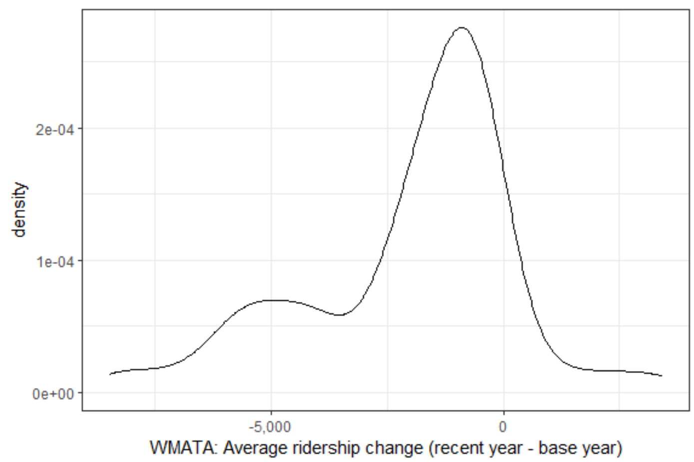
WMATA: Average weekday ridership (base year)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WMATA: Average ridership change (recent year - base year)

Table 19 Difference of station-level variables between recent year and base year - BART (N=43)

Variable	Mean	St. Dev.	Min	Max
Average weekday ridership	1,679.74	2,507.51	-1,934	13,218
Percent of intersections with parallel crosswalks	-2.51	18.00	-50.00	33.33
Percent of intersections with high-visibility crosswalks	10.55	21.90	-33.33	50.00
Percent of intersections with marked crosswalks	2.68	11.39	-33.33	33.33
Percent of zero-vehicle households	-4.35	6.66	-22.68	7.29
Percent of low-income workers	-4.38	1.61	-8.07	-1.64
Population density (persons/acre)	1.28	1.27	-0.01	5.34
Job density (jobs/acre)	7.47	20.02	-1.75	98.06
Street intersection density (intersections/sq. mile)	38.83	42.49	1.19	183.19
Regional diversity index	0.08	0.25	-0.53	0.60
Regional centrality index	-0.02	0.10	-0.24	0.16

Table 20 Percent of change of station-level variables between recent year and base year - BART (N=43)

Variable	Mean	St. Dev.	Min	Max
Average weekday ridership	22.34	14.38	-14.34	53.55
Percent of intersections with parallel crosswalks	3.29	40.89	-60.00	200.00
Percent of intersections with high-visibility crosswalks	34.18	62.20	-66.67	200.00
Percent of intersections with marked crosswalks	9.01	34.37	-33.33	200.00
Percent of zero-vehicle households	-11.85	25.62	-60.45	79.86
Percent of low-income workers	-19.98	6.16	-32.56	-8.00
Population density (persons/acre)	11.02	7.35	-0.04	29.20
Job density (jobs/acre)	24.24	25.56	-30.22	124.07
Street intersection density (intersections/sq. mile)	42.57	37.57	0.63	130.06
Regional diversity index	134.77	241.07	-72.81	1,107.55
Regional centrality index	-3.16	15.43	-40.14	30.05

Table 21 Difference of station-level variables between recent year and base year - Caltrain (N=28)

Variable	Mean	St. Dev.	Min	Max
Average weekday ridership	166.50	664.42	-1,804	1,973
Percent of intersections with parallel crosswalks	-7.26	20.82	-50	25
Percent of intersections with high-visibility crosswalks	7.78	18.11	-50	40
Percent of intersections with marked crosswalks	-4.72	18.58	-50	25
Percent of zero-vehicle households	-1.38	2.77	-7.58	2.78
Percent of low-income workers	-3.68	1.14	-5.61	-1.58
Population density (persons/acre)	0.93	0.77	-0.19	2.60
Job density (jobs/acre)	1.61	1.97	-1.84	6.57
Street intersection density (intersections/sq. mile)	53.60	44.90	0.68	198.48
Regional diversity index	0.07	0.26	-0.40	0.38
Regional centrality index	-0.06	0.09	-0.29	0.07

Table 22 Percent of change of station-level variables between recent year and base year - Caltrain (N=28)

Variable	Mean	St. Dev.	Min	Max
Average weekday ridership	37.13	74.99	-90.29	230.43
Percent of intersections with parallel crosswalks	-6.99	29.87	-100	50
Percent of intersections with high-visibility crosswalks	24.75	44.60	-85.71	100
Percent of intersections with marked crosswalks	-4.40	27.90	-100	50
Percent of zero-vehicle households	0.34	65.09	-60.40	288.39
Percent of low-income workers	-20.23	7.18	-33.08	-7.69
Population density (persons/acre)	11.68	9.13	-4.67	37.94
Job density (jobs/acre)	21.64	16.88	-12.85	62.35
Street intersection density (intersections/sq. mile)	65.06	38.77	4.32	147.84
Regional diversity index	38.36	82.96	-56.89	332.13
Regional centrality index	-10.16	14.47	-47.94	15.58

Table 23 Difference of station-level variables between recent year and base year - CTA (N=137)

Variable	Mean	St. Dev.	Min	Max
Average weekday ridership	262.52	933.93	-3,186	5,176
Percent of intersections with parallel crosswalks	-17.76	20.12	-87.50	50.00
Percent of intersections with high-visibility crosswalks	32.67	25.73	-50.00	100.00
Percent of intersections with marked crosswalks	0.71	6.08	-17	25
Percent of zero-vehicle households	-8.58	7.86	-35.08	5.35
Percent of low-income workers	-1.10	2.15	-5.41	8.11
Population density (persons/acre)	1.28	2.63	-4.63	9.48
Job density (jobs/acre)	6.79	14.68	-19.36	64.04
Street intersection density (intersections/sq. mile)	70.12	33.64	0.09	143.71
Regional diversity index	0.10	0.22	-0.52	0.66
Regional centrality index	0.10	0.11	-0.31	0.25

Table 24 Percent change of station-level variables between recent year and base year - CTA (N=137)

Variable	Mean	St. Dev.	Min	Max
Average weekday ridership	6.01	17.72	-33.59	71.52
Percent of intersections with parallel crosswalks	-19.47	24.13	-87.50	100.00
Percent of intersections with high-visibility crosswalks	141.86	176.26	-50.00	1300.00
Percent of intersections with marked crosswalks	1.04	7.92	-20	37
Percent of zero-vehicle households	-19.84	15.18	-47.56	37.85
Percent of low-income workers	-7.13	11.45	-28.51	37.59
Population density (persons/acre)	5.49	13.06	-24.10	42.28
Job density (jobs/acre)	16.13	28.24	-71.69	93.62
Street intersection density (intersections/sq. mile)	67.45	44.57	3.62	232.34
Regional diversity index	246.22	1699.36	-100.00	19,738.33
Regional centrality index	23.08	19.66	-30.93	73.45

Table 25 Difference of station-level variables between recent year and base year - MTA (N=332)

Variable	Mean	St. Dev.	Min	Max
Average weekday ridership	-145.17	4,495.44	-38,029	41,631
Percent of intersections with parallel crosswalks	-25.86	20.01	-100.00	46.15
Percent of intersections with high-visibility crosswalks	18.64	14.27	-27.27	66.67
Percent of intersections with marked crosswalks	1.56	5.32	-16.67	33.33
Percent of zero-vehicle households	-13.14	8.47	-55.98	0.88
Percent of low-income workers	-2.02	1.43	-8.99	4.25
Population density (persons/acre)	2.35	4.66	-16.71	21.39
Job density (jobs/acre)	10.89	35.02	-133.71	244.43
Street intersection density (intersections/sq. mile)	21.00	27.55	-171.16	118.99
Regional diversity index	0.14	0.26	-0.66	0.85
Regional centrality index	0.08	0.14	-0.35	0.35

Table 26 Percent change of station-level variables between recent year and base year - MTA (N=332)

Variable	Mean	St. Dev.	Min	Max
Average weekday ridership	9.34	146.54	-95.38	2,634.87
Percent of intersections with parallel crosswalks	-28.50	22.56	-100.00	100.00
Percent of intersections with high-visibility crosswalks	32.73	35.29	-33.33	250.00
Percent of intersections with marked crosswalks	2.13	8.26	-16.67	100.00
Percent of zero-vehicle households	-18.56	8.74	-55.02	1.83
Percent of low-income workers	-9.00	5.98	-31.11	14.29
Population density (persons/acre)	9.20	21.60	-14.07	224.82
Job density (jobs/acre)	43.26	38.61	-51.97	303.84
Street intersection density (intersections/sq. mile)	28.70	37.80	-51.24	307.80
Regional diversity index	235.99	397.66	-100.00	3,742.61
Regional centrality index	25.35	30.40	-40.14	114.84

Table 27 Difference of station-level variables between recent year and base year - MTS (N=49)

Variable	Mean	St. Dev.	Min	Max
Average weekday ridership	-52.53	1,095.89	-5,959	3,301
Percent of intersections with parallel crosswalks	-6.02	26.20	-100.00	50.00
Percent of intersections with high-visibility crosswalks	13.65	32.25	-100.00	100.00
Percent of intersections with marked crosswalks	-1.12	22.37	-100.00	50.00
Percent of zero-vehicle households	-5.42	6.99	-23.49	4.39
Percent of low-income workers	-2.99	1.39	-6.79	-0.26
Population density (persons/acre)	0.53	0.65	-0.76	2.39
Job density (jobs/acre)	0.40	1.31	-2.86	4.61
Street intersection density (intersections/sq. mile)	184.43	300.03	2.77	828.26
Regional diversity index	-0.02	0.29	-0.47	0.53
Regional centrality index	-0.04	0.07	-0.28	0.09

Table 28 Percent change of station-level variables between recent year and base year - MTS (N=49)

Variable	Mean	St. Dev.	Min	Max
Average weekday ridership	6.95	44.52	-60.98	205.52
Percent of intersections with parallel crosswalks	-5.19	33.64	-100.00	100.00
Percent of intersections with high-visibility crosswalks	47.53	103.11	-100.00	500.00
Percent of intersections with marked crosswalks	0.20	28.86	-100.00	100.00
Percent of zero-vehicle households	-14.45	42.11	-63.22	152.31
Percent of low-income workers	-12.11	4.26	-21.61	-1.49
Population density (persons/acre)	7.53	8.71	-7.26	26.52
Job density (jobs/acre)	9.57	16.73	-37.81	45.63
Street intersection density (intersections/sq. mile)	153.19	190.59	3.05	575.11
Regional diversity index	82.83	331.87	-65.08	2,239.62
Regional centrality index	-4.72	8.19	-29.56	14.36

Table 29 Difference of station-level variables between recent year and base year - PATH (N=9)

Variable	Mean	St. Dev.	Min	Max
Average weekday ridership	2138.67	3,700.29	-1,305	10,868
Percent of intersections with parallel crosswalks	-5.79	33.83	-36.84	66.67
Percent of intersections with high-visibility crosswalks	11.31	13.74	0.00	36.84
Percent of intersections with marked crosswalks	2.47	4.04	0	11
Percent of zero-vehicle households	-17.88	7.13	-23.76	-4.56
Percent of low-income workers	-2.44	1.55	-6.06	-0.67
Population density (persons/acre)	1.55	2.77	-1.03	7.36
Job density (jobs/acre)	54.63	84.54	-35.45	238.18
Street intersection density (intersections/sq. mile)	2.91	33.91	-72.83	42.61
Regional diversity index	-0.03	0.31	-0.34	0.49
Regional centrality index	-0.14	0.15	-0.30	0.17

Table 30 Percent change of station-level variables between recent year and base year - PATH (N=9)

Variable	Mean	St. Dev.	Min	Max
Average weekday ridership	12.16	12.28	-3.70	30.82
Percent of intersections with parallel crosswalks	9.30	76.32	-38.89	200.00
Percent of intersections with high-visibility crosswalks	16.90	23.98	0.00	70.00
Percent of intersections with marked crosswalks	2.70	4.48	0	12
Percent of zero-vehicle households	-23.13	4.31	-25.97	-12.70
Percent of low-income workers	-15.28	7.31	-25.82	-5.60
Population density (persons/acre)	5.32	7.02	-1.80	14.52
Job density (jobs/acre)	22.60	23.54	-24.23	49.69
Street intersection density (intersections/sq. mile)	9.40	24.36	-26.41	43.68
Regional diversity index	14.74	100.20	-67.20	250.80
Regional centrality index	-14.59	24.31	-34.81	43.47

Table 31 Difference of station-level variables between recent year and base year - SEPTA (N=218)

Variable	Mean	St. Dev.	Min	Max
Average weekday ridership	-428.73	1,584.77	-16,740	2,039
Percent of intersections with parallel crosswalks	-3.99	17.95	-100.00	40.00
Percent of intersections with high-visibility crosswalks	3.95	14.25	-36.36	60.00
Percent of intersections with marked crosswalks	-0.68	10.44	-37.50	40.00
Percent of zero-vehicle households	-13.50	7.40	-34.82	4.58
Percent of low-income workers	-0.72	1.45	-6.45	3.72
Population density (persons/acre)	0.21	1.35	-3.65	5.06
Job density (jobs/acre)	1.02	4.27	-32.75	12.06
Street intersection density (intersections/sq. mile)	46.21	25.95	2.99	98.46
Regional diversity index	0.07	0.20	-0.77	0.58
Regional centrality index	0.07	0.08	-0.17	0.24

Table 32 Percent change of station-level variables between recent year and base year - SEPTA (N=218)

Variable	Mean	St. Dev.	Min	Max
Average weekday ridership	5.25	285.20	-93	4,161
Percent of intersections with parallel crosswalks	1.79	47.63	-100.00	400.00
Percent of intersections with high-visibility crosswalks	12.21	52.11	-50.00	600.00
Percent of intersections with marked crosswalks	1.16	18.24	-37.50	133.33
Percent of zero-vehicle households	-26.72	18.04	-69.19	103.86
Percent of low-income workers	-3.15	6.35	-23.60	17.64
Population density (persons/acre)	1.36	6.73	-11.86	19.02
Job density (jobs/acre)	10.87	35.17	-73.00	174.95
Street intersection density (intersections/sq. mile)	55.85	43.42	5.91	216.72
Regional diversity index	210.22	486.33	-100.00	4,235.48
Regional centrality index	12.93	11.75	-19.00	40.36

Table 33 Difference of station-level variables between recent year and base year - WMATA (N=81)

Variable	Mean	St. Dev.	Min	Max
Average weekday ridership	-1,999.80	2,283.06	-8,476	3,417
Percent of intersections with parallel crosswalks	-1.19	25.69	-47	100
Percent of intersections with high-visibility crosswalks	13.85	22.78	-67	75
Percent of intersections with marked crosswalks	5.88	20.92	-67	100
Percent of zero-vehicle households	-6.43	6.65	-30.66	4.04
Percent of low-income workers	0.27	1.79	-5.08	4.05
Population density (persons/acre)	1.43	1.79	-2.37	8.23
Job density (jobs/acre)	-4.97	9.00	-32.54	9.82
Street intersection density (intersections/sq. mile)	49.82	37.64	2.35	123.96
Regional diversity index	0.08	0.21	-0.47	0.67
Regional centrality index	0.02	0.11	-0.26	0.19

Table 34 Percent change of station-level variables between recent year and base year - WMATA (N=81)

Variable	Mean	St. Dev.	Min	Max
Average weekday ridership	-21.90	19.36	-79.22	56.93
Percent of intersections with parallel crosswalks	-4.70	27.66	-100.00	100.00
Percent of intersections with high-visibility crosswalks	32.81	59.66	-100.00	300.00
Percent of intersections with marked crosswalks	6.84	35.58	-100.00	250.00
Percent of zero-vehicle households	-13.17	33.99	-57.78	179.29
Percent of low-income workers	2.40	10.94	-24.45	32.28
Population density (persons/acre)	13.06	11.24	-22.92	46.81
Job density (jobs/acre)	-9.08	46.00	-77.50	183.45
Street intersection density (intersections/sq. mile)	42.65	25.23	5.22	143.56
Regional diversity index	57.46	102.82	-96.81	469.43
Regional centrality index	6.36	17.74	-25.76	46.68

The National Institute for Congestion Reduction (NICR) will emerge as a national leader in providing multimodal congestion reduction strategies through real-world deployments that leverage advances in technology, big data science and innovative transportation options to optimize the efficiency and reliability of the transportation system for all users. Our efficient and effective delivery of an integrated research, education, workforce development and technology transfer program will be a model for the nation.

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