

The Effects of Commute Trip Reduction Program on Employee Non-SOV Travel Frequency

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Abstract

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Initiated in 1991, Washington State Commute Trip Reduction (CTR) program was one of the earliest employer-based transportation management program in the nation which requires employers to implement strategies to encourage alternative travel modes. This research investigates the effects of the CTR program on employees' non-SOV travel frequency, by controlling employee demographic features and worksite built environment characteristics. The database was assembled from 2015/2016 WA State employer and employee survey data. 84,878 employees in 379 worksites were selected for data analysis and model fit. Poisson model, negative binomial model, zero-inflated model and hurdle model were implemented individually. The hurdle model was eventually selected as the final model due to better goodness-of-fit, the accuracy of model prediction and the practical sense of model interpretation. The model is a combination of a binomial logistic model to predict the odds of being a non-SOV commuter versus an exclusive-SOV commuter and a negative binomial model to predict the number of non-SOV commuting day counts for the non-SOV commuters.

The results of this study corroborate the mainstream view that demographic features, built environment characteristics and CTR policies all have significant effects on employees' non-SOV model choice and travel behavior, yet more dynamic relationships were found among CTR policy components. Controlling for other variables, the parking fee management, transit subsidy,

teleworking option and worksite amenity are expected to increase the odds for an employee of being a non-SOV commuter by 52.52%, 58.32%, 15.44%, 23.77%, respectively, while carpool/ vanpool subsidy and worksite service unexpectedly decrease the odds by 12.88% and 17.73%. Speaking of the non-SOV travel frequency, the parking fee management, transit subsidy, walking/biking subsidy, worksite amenity and service increase the rate of non-SOV commuting days by 4.72%, 2.19%, 1.67%, 3.97% and 3.91%, whereas the carpool/ vanpool, compressed working hour and teleworking option decrease the rate by 5.57%, 4.91%, 5.47%. Overall, the CTR policy package increases the probability for a “typical” employee of being a non-SOV commuter by 22%, though its effect on non-SOV day counts is modest.

Key Words:

Commute Trip Reduction, Policy performance measure, Mode choice, Travel frequency, Count model

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1 INTRODUCTION

1.1 Research Context

Transportation demand management (TDM) has been a popular policy instrument since 1970s to mitigate traffic congestion, reduce energy consumption and address air pollution. Governments and transit agencies have identified a range of policy tools that can be used to improve the efficiency of transportation services. Employer-based trip reduction program is one of the subsets of TDM which specifically targeted on employee commuting trips.

Initiated in 1991, the Washington State Commute Trip Reduction (CTR) is a regional program, affecting 9 most populous counties. Based on CTR law (RCW 70.94.521-551), employers with one hundred or more employees at a single worksite who begin work between 6:00 and 9:00 AM are required to develop strategies to reduce vehicle emission and single-occupied-vehicle (SOV) rate. By 2016, more than 1000 worksites had been counted towards CTR goals. After more than 25-year's implementation, CTR program has been tested to be an effective management tool, helping CTR-affected worksites continually have a higher non-SOV rate -- in 2017, it was 43 percent higher than the state average and 66 percent higher than the national average. One pilot grant program had been expanded to small- and medium-sized businesses (Washington State CTR Board 2017).

While CTR program is a performance-based approach, it is not a typical heavy-handed regulation; it does not mandate which and how many strategies worksites should implement. In other words, the policies are diverse in type, scope and level of the effectiveness in different worksites. While this type of customized approach increases the flexibility of the policy and reflects the guiding principle of public-private collaboration, it also increases the challenges of performance measure. In respond to that, Washington State Department of Transportation (WSDOT) conducts annual employer survey and biannual employee surveys for feedbacks and program updates. Though some case studies on the effectiveness of CTR strategies have been

performed in some worksites, the evidences are still limited in general. More studies are needed to evaluate this policy.

1.2 Research Purpose & Research Question

Given the primary goal of the program is to reduce SOV rate and encourage non-SOV alternative modes, the real challenge is to influence employees' mode choice and travel behavior by offering effective commuter incentives and/or disincentives. Therefore, the purpose of this study is to explore the effectiveness of CTR policies implemented in worksites to encourage non-SOV trips. The uncovered relationship among employee demographic characteristics, worksite built environment factors and CTR policies then become a compass for policy evaluation and updates in the future practices.

While most of the policies under implementation have been analyzed in previous literature either as an individual element or a set of several bundled elements, few researches untangle the complex relationships among a more comprehensive policy package. Therefore, this study will look into the interactions of different policies with the following questions:

- (1) What are the basic characteristics of employees' commuting trips in WA State?**
- (2) How do demographic characteristics, worksite built environment factors and CTR policies affect employees' non-SOV mode choice and travel frequency?**
- (3) What are the overall impacts of the policy package?**

1.3 Thesis Structure

This thesis began with a retrospect of the history of employer-based trip reduction programs and some well-known plans implemented in the nation. Then a conceptual model was built based on critical factors identified in the literatures. Especially, a substantial body of reviews were provided for workplace trip reduction polices. Besides, the concept of "policy package" was introduced as a recommended method of policy evaluation.

Chapter 2 identified variables for employee demographic characteristics, worksite built environment factors and CTR policies in this study. The method for dataset construction was discussed based on CTR employer and employee survey, as well as the results from worksite GIS spatial analysis. Chapter 3 presented a series of preliminary analysis exploring some basic relationships among variables.

Following to that, Chapter 4 introduced four types of count model and the methodology of model selection. The following chapter presented the results from the model and summarized major findings. Finally, the paper concluded by answering 3 research questions and discussing policy recommendations.

2 LITERATURE REVIEW

One of the earliest list of factors known to influence commuters' mode choice were classified by Giuliano et al. (1993) based on their analysis of California Regulation XV data. It includes three categories shown by **Figure 2-1**: workplace organization & transportation incentives, employee characteristics and environmental factors. Later works more or less follow the prototype and the volume of related literature have increased tremendously over the past decades. Researchers continue to add “pillars” to the theory which is referred as “7Ds”: ***Demand Management*** from policy implementation perspective, ***Demographics*** as employee characteristics, and ***Density, Diversity, Design, Destination, Distance*** describing the impacts of built environment factors. While the ***Demand Management*** element is the primary research objective of this study, the “7Ds” theory was treated as an overall guidance for building research framework. This chapter provide reviews on these three groups of factors on commuters' mode choice and travel behavior.

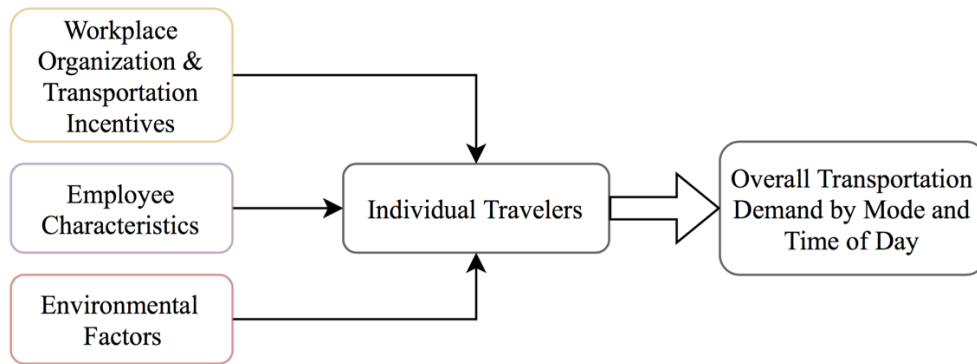


Figure 2-1 Factors influencing work trip mode choice

2.1 TDM Strategies on Employer-based Trip Reduction Program

Since 1970s, many governments and transit agencies have considered TDM as a new way of solving urban issues such as traffic congestion, energy depletion and air pollution (Cervero 1991, Giuliano 1992, TCRP 2002, TCRP 2010). The relatively recognizable and manageable characteristics of commuting trips make workplace an ideal field to test and implement certain

TDM strategies. An important evolution came in the late 1970s after the realization that the best mechanism for implementing work-trip TDM actions was through employers (M. D. Meyer 1999), instead of directly providing information to drivers. Since then, employer-based commute trip reduction program became prevalent in many metropolitan areas. For instance, Washington State initiated its Commute Trip Reduction program in 1991 which was one of the earliest employer-based transportation management program reflecting governmental provision. It requires employers to implement strategies which encourage alternatives to drive-alone. Likewise, CARAVAN was a regional commuter services organization in Boston. RIDES in San Francisco and Southern California RIDESHARE in Los Angeles defined South Coast Air Quality Management Districts as targeted areas for employer-based trip reduction program. As one part of large regional efforts, employee-based trip reduction program has received varying success across the jurisdictions.

2.1.1 Individual Policy

With the growing popularity of employer-based trip reduction program in 1990s, more and more researches contributed to its policy adoption, implementation and evaluation. Some studies looked at overall impacts from the program based on the performance in affected worksites (Giuliano, Hwang and Machs 1993, Orski 1993). The policy can be classified into 3 categories: “pull” policies, “push” policies and “non-vehicle” policies, based on their impacts on people’s motives for or against car usage (Steg and Vlek 1997). Essentially, “pull” policies encourage the alternative travel modes to automobile by providing transit subsidies, encouraging ridesharing and so forth. In contrast, “push” policies attempt to reduce trips by discouraging car usage, through parking pricing, limiting parking spots and the like. With comparison, instead of considering the policy as a dynamic process, some scholars consider it as a market mechanism (incentive/ disincentive) or a system of rewards and penalties (“carrot”/ “stick”). In addition to car-targeted strategies, “non-vehicle” policies refer to flexible work schedules and other program supports. The following section reviews some findings on the effects of employer-based trip reduction policies in different research contexts.

“Pull Policy”

1. Implementing Parking “Cash-out”

Shoup et al. (1992) studied on a parking cash-out program at eight firms, where commuters were offered the option of a cash alternative instead of their parking subsidy. They found that after the implementation, the number of SOV commuters fell by 17%, whereas carpoolers increased by 64%, transit riders increased by 50% and bicyclists/pedestrians increased by 39%. Overall, the vehicle mile travelled from commuting trips in these eight firms decreased by 12%.

2. Offering Transit Pass & Subsidy

Public transit is one of the most important integral component of the transportation systems. Though some studies revealed that fervent car users seldom take public transit (STEG 2003), more and more studies have suggested that with subsidies, public transit can be the primary alternative to personal cars. Especially, several university transit pass programs were successfully tested out. For instance, the U-Pass program launched in University of Washington in 1992, encouraged a tremendous growth in transit use. Until 2012, more than twice as many trips to campus were transit trips than drive-alone vehicle trips (ORC International, Inc 2012). Likewise, after University of California in Los Angeles launching the BruinGo free bus program in 2000, two before-after comparison studies had been done and got a similar result that student transportation incentives increases bus ridership and reduces personal vehicles (Brown, Hess and Shoup 2003, Boyd, et al. 2003).

University transit pass program was often implemented as a pilot program before a regional service expansion. More successful region-wide programs also indicated the universal effectiveness of the program. For instance, by modeling daily transit-trip frequency, a research in great Toronto area got an encouraging result that people with transit pass had four to five times higher rates of transit trips than those who did not (Badoe and Yeneti 2007). A similar result was also found particularly for commuting trips. A study on the impacts of unlimited access of transit pass in Portland, Oregon found that transit passport program increases transit mode share by more than 5% among employers (Dorsey 2005).

3. Improving Worksite Amenity & Service

More recent studies started looking at biking and walking mode share with the increasing prevalence of bike share system and walking promotion plans. With UK National Travel Survey, one study figured out that bicycle-related subsidies significantly influence the propensity of cycling to work (Wardman, Tight and Page 2007). Similarly, another study indicated that facilities and services such as bike parking, showers and shared-use routes can attract cycling and walking (Bachand , Larsen and ElGeneidy 2011).

4. Expanding Carsharing / Carpooling System

A survey of carshare members in San Francisco looks at the effects of the carshare program on vehicle ownership and vehicle mile traveled (VMT) (Cervero and Tsai 2003). The result suggested that two thirds of participants avoided purchasing another car when they had access to carshare program, which reduces 47 percent of VMT on average.

5. Other Promotional Program

More non-SOV promotional programs have been implemented in some cities. For instance, in order to encourage walking trips, City of Portland initiated ten city-sponsored toe expresses, which connects most of the places of interest in the city to encourage walking. More than half of the respondents reported having more than one new trip per week by walking instead of driving.

“Push Policy”

1. Reducing Parking Space

Spack Consulting, a transportation consulting firm, conducted two studies in 15 office sites in Minnesota, analyzing the effectiveness of workplace TDM strategies in reducing peak hour traffic generation and peak parking demand. The findings suggested that the strategies helped to generate 34% to 37% less traffic and occupy 17% to 24% less onsite parking. They also

proposed a 30% trip reduction and 15% parking reduction as expected results in general for workplaces that will be implementing TDM plans.

2. Requiring Parking Fee

Based on 2016 1-Year American Community Survey, 85.3 percent of all commuters drove to work and 76.3 percent of all vehicles had only one occupant. A lot of researches attribute this to underpriced or free parking which distorts people's travel decision, yet parking subsidies continue to be the most prevalent benefit for employees and only about 5 percent of commuters in US pay for parking in their worksites (Pucher 1988, Martin 1990). A survey in San Francisco also suggested that free parking increase the drive-alone rate by as much as 50 percent (San Francisco County Transportation Authority 1996).

Shoup provided convincing evidences that city paid a high price for free car parking policy (D. Shoup 2005). Worse yet, more cars intrigue a vicious circle over time. As one of his researches in Los Angeles indicated, approximately 30 percent of cars were cruising for parking in already congested downtown areas (D. Shoup 2006). Most of the literatures concluded that commuters' mode choices were largely distorted by free parking.

In contrast, required parking fee helps to leverage market forces and thus to reduce car usage. A review of empirical studies of car parking subsidies suggested that eliminating free parking at work would reduce SOV trips between 19 percent and 81 percent (Willson and Shoup 1990). A case study in Los Angeles found out that there were 25 to 34 percent fewer car trips to workplaces when employees were forced to pay for parking (Willson 1992). Another case study in Portland, Oregon estimated that a daily charge of 6 dollars of parking could reduce SOV trips by 16 percent (Hess 2001).

3. Implementing Congestion Pricing

Parking related policies are the most common “push” policy implemented in worksite, yet more policies have been implemented in state and city level in US and other countries to impact a wider range of drivers.

The congestion pricing policy was normally implemented within a designated restricted area during daily peak hours. It has been found to be effective in reducing driving and relieving traffic congestion in many cases. In Singapore, the volume of traffic entering the restricted area during peak hour was reduced and led to a 36 percent mode shift from private transportation to public transit, though more traffics had been witnessed outside of the zone and beyond the hours of policy operation (Phang and Toh 2004). In London, the congestion charge, together with a public transportation subsidy program was found to reduce travel delay by 30 percent and eliminate the bus waiting time by one-third. The policy is also implemented in some US cities, cases like HOT lanes on I-15 in San Diego, CA, the SR 91 express lanes in Orange County, CA, the bridge pricing in Lee County, FL and mileage-based pricing test in Oregon, PO (Federal Highway Administration 2017).

“Non-Vehicle Policy”

A host of studies suggested that non-vehicle policies also play an important role on the success of trip reduction program. A study on organizational culture concluded that effective employee transportation coordinators (ETC), employee characteristics and management supports can be important to policy adoption and implementation (Hendricks 2005).

Except for the management efficiency, offering alternative work schedule options, including compressed work weeks, telecommuting, and flexible work hours, is another component of “no-vehicle” policy. Teleworking extends the workplace beyond the tradition office so to reduce business related trips. “Compressed workweek day off” policy normally has 3 types of schedule: 9/80 (common in information-based industries), 4/10 (common in manufacturing) and 3/36 (common in hospitals/ shift work). Flex-time policy offers flexible start/end working time so that employee can avoid the rush hour and reduce delay.

Plenty of literatures indicated that these policies help to shift traffic out of the peak hour period and reduce commuting personal trips as well (Giuliano and Golob 1990, Tanaboriboon 1994,

Bhattacharjee et al. 1997, Nozick et al. 1998, Ory and Mokhtarian 2005). The WorldAtWork study (2015) documented a high adoption rate of these policies among US employers. Fortune Magazine reported that among “100 best companies to work for”, 77 offered compressed work weeks and 85 offer telework in 2013 (King County Metro 2018). Another survey indicated that “flexible work hours” is by far the most desired benefit among workers.

To assess the impacts of those policies in Washington State CTR program, Georggi et al. (2007) did a before-after study comparing the performance of an interstate corridor with and without the program in Seattle area. A microscopic simulation model was built to measure transportation performance parameters, such as vehicle throughout, travel time reliability averaged speed and so forth. The results suggested that the alternative/ flexible working schedule policies provided in worksites that were adjacent to I-5 corridor significantly reduce the traffic.

2.1.2 Policy Package

Most of the aforementioned researches were focused on one single policy at a time. Several reasons may apply for that: 1) In order to study on the effectiveness of a new-proposed strategy, researchers attempted to control other factors and assess the mode choice of targeted population or mode share of the targeted area before and after the policy treatment, such as the researches for UCLA new bus line (Brown, Hess and Shoup 2003, Boyd, et al. 2003) or new park-cash-out program (Shoup and Willson 1992). 2) The lack of enough data for comprehensive analysis is probably another reason. Because of the lag effects of the policies, the performance measure for trip reduction program often requires a longitudinal study which increases the complexity of research.

In reality, however, there is no one-format-fits-all approach for complex issues like traffic congestion. Policies are always intertwined, each influencing the implementation of the other. Thus, many important linkages could be lost if researches only look at one policy at a time. In the meanwhile, considering the reality that policies affect each individual in a different way, it makes much more sense to adopt, implement and evaluate policies as a whole package. This argument is consistent with the concept of “Multi-instrumentality” defined by Viegas (2003) “as

a systematic approach for transport policy integration and implementation” (Vieira, Moura and Viegas 2007).

Multi-instrumentality has a high potential to enhance the success of transport policy implementation. Thorpe et al. (2000) conducted a case study on three “push” policies and one “pull” policy in Cambridge and Newcastle, UK and found out that the acceptance of one policy can be effected by other policies. In addition, by studying on the effects of financing policies on commuter mode choice in Vancouver, Canada, Washbrook et al. (2006) also concluded that effective policies are supposed to combine both incentives and disincentives. Some researches even quantified the level of interaction. Herzog et al. (2006) found out in a comprehensive benefits package with financial incentive and service improvement can reduce trips by 15%, while the absence of financial incentives will cut half off of the effectiveness.

2.2 Demographic features

On policy researches, the demographic features are normally treated as control factors. Some researches focused on one feature, while others treated multiple features as a set. The data used normally came from Personal/Household Travel Survey containing a wide range of socio-economic and demographic features of both individual and households.

1. Gender

Gender is considered to an important variable, usually taking into account the effects on individual and household. Crane (2007) used the American Housing Survey panel data to investigate the revolution in women’s commuting pattern in individual level. The results indicated that though the women’s commuting length increased, the gender gap was still significant. Besides, women employees were found to diminish their reliance on transit quickly and changed their mode to personal car.

2. *Employment Status*

Hanson et al. (1985) drew samples from Baltimore Travel Demand Data to exam the gender difference in work-trip length, arguing that full-time working males commuted less than part-time employed males, though there was no impact found for female workers. Potoglou (2008) did a study examining the influence of family structure, socio-economic characteristics and accessibility in residential area on the number of cars owned. The data was obtained through an Internet-survey in Census Metropolitan Area of Hamilton. The findings indicated that full-time workers tended to own more vehicles than part-time workers who probably have more budget constraints.

3. *Other Factors*

Wardman et al. (2007) built the most comprehensive and largest model within the British context at that time to model cycling work trips. The National Travel Survey data was use to collecting demographic information including age, gender, income, car ownership and employment. They found that higher-income, younger-age males were more likely to cycle, those who drove a company car or used to drive car for commuting were more likely to stick on cars, rather than switching to other modes.

2.3 “5Ds” of Built Environment Characteristics

A voluminous empirical literatures have investigated the impacts of built environment on shaping people’s mode choice. Since commuting trips connect two ends, home and workplace, the built environment characteristics of both locations are considered to be critical.

2.3.1 At Residential Location

Though researchers have investigated the impacts of residential built environment variables on urban travel behavior for decades, studies provide mixed results and evidences due to diverse research contexts and methodologies. For instance, a mode split study was conducted in two distinct neighborhoods in San Francisco to investigate the effects of urban design principles on

transportation efficiency (Cervero and Radisch 1996). The results indicated that residents in the mixed land use neighborhood with gridded route network design made 15 percent fewer auto trips and 22 percent more walking trips than residents living in suburban style neighborhood. In addition, transit oriented development accounts for 20 percent reduction of drive-alone rate. However, another study also done by Cervero (2002) in Montgomery County, Maryland, aiming to weigh the influence of three core dimensions of built environment—density, diversity and design, revealed that the develop intensity and land use mixture had significant impacts on people’s mode choice, whereas the impact of urban design element was modest in this case. The impacts of neighborhood environment characteristics on biking/ walking were also investigated. A study by Saelens et al. (2003) revealed that higher population density, greater connectivity and mixed land use were associated with higher rates of walking/ biking trips.

2.3.2 At Workplace Location

In fact, when Ding et al. (2014) investigated the impacts of built environment in both ends on mode choice behavior, they found that employment density at workplace had an even more significant impact than the density in residential area. Zhao et al. (2002) developed an aggregated model of transit usage at the census tract level and indicated that the most influential factors affecting transit use were density, land use mix, and the transit supply variables of regional accessibility, transit service coverage, and number of daily bus runs.

There are also other variables that are worth noting. The “distance to CBD” model has shaped the assumption of spatial equilibrium for the choice of a firm location, which is a trade-off between positive and negative externalities (Dong and Ross 2015, Tsekeris and Geroliminis 2013). The core function of CBD is to provide agglomerative economic interactions, high-salary employment opportunities and adequate service facilities, while on the other hand, proximity to CBD also usually accompanies with high rent and congestion, which in turn influences the employees’ choice for home location, as well as mode choice and travel behavior. Therefore, home-worksite distance and worksite-CBD distance are both significant factors in our case.

2.4 Summary

This section provides a substantive literature reviews on the impacts of 3 groups of factors (employer-based commute trip reduction policies, employee demographic characteristics, worksite built environment factors) on commuters' mode choice and travel behavior. In general, it is an expansion of Giuliano's framework with additional factors identified by plenty of researchers, shown in **Figure 2-2**. This framework was also treated as a guidance for selecting variables in this study.

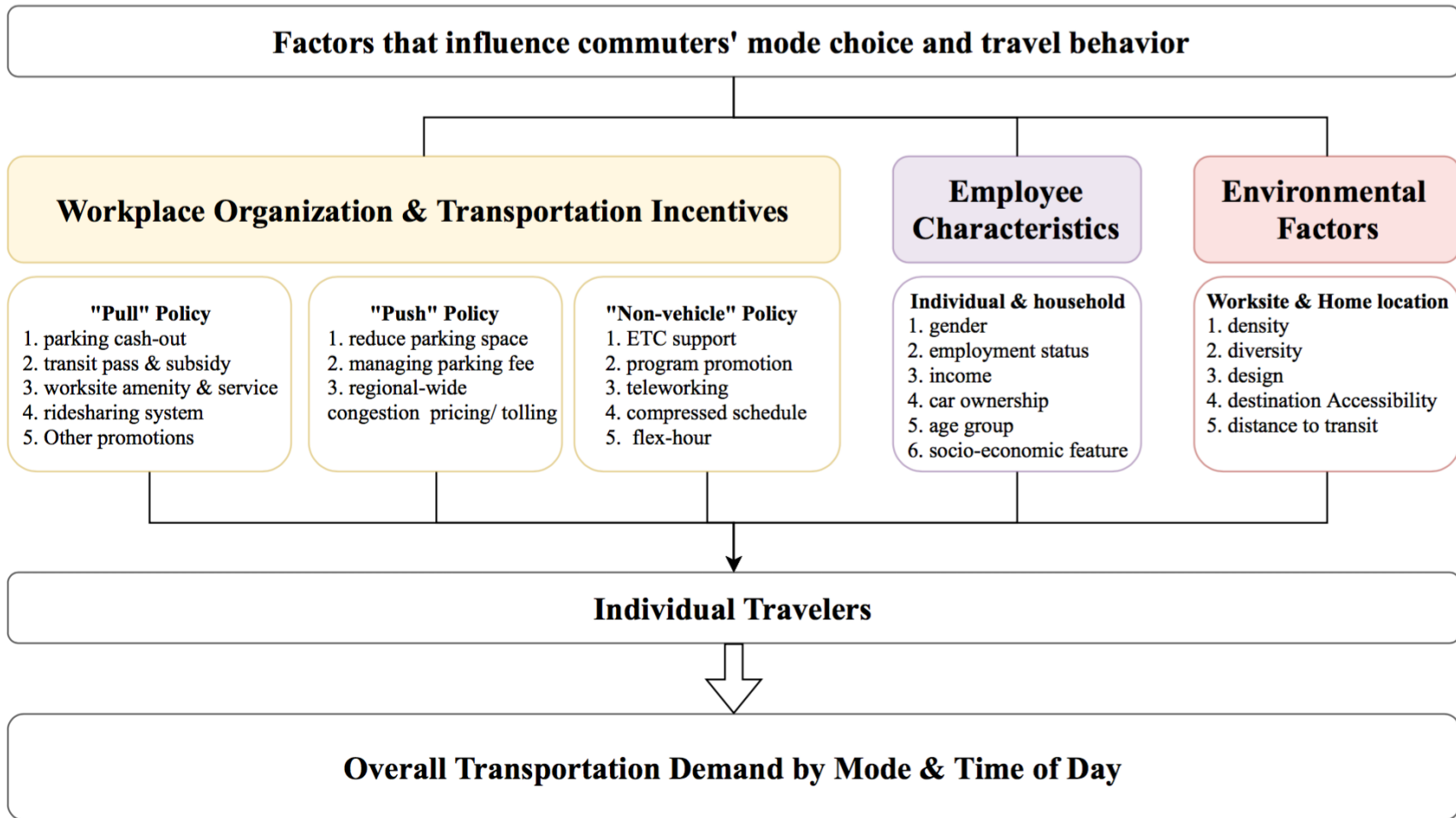


Figure 2-2 Factors influencing commuters' model choice and travel behavior

3 DATA

3.1 Employer Annual Survey

The statewide employer survey is conducted annually by an appointed Employee Transportation Coordinator in each worksite. It is worth noting that one employer may have multiple worksites, while each worksite has a unique ID. For instance, Boeing has 26 different worksites that participate in the CTR program and each of them is evaluated independently. The survey includes more than 160 survey questions to capture enough information about worksites characteristics, as well as the latest status of the CTR policy implementation when the survey is distributed. The questions are summarized in **Table 3-1**.

Except for the statewide survey, there is an important add-on from City of Seattle, the largest city in WA State. Their citywide survey is conducted through online survey tool called “SurveyMonkey”. In comparison to statewide survey, Seattle’s version has less questions, yet still includes the most critical ones, thus those two datasets are compatible. Items that exist in both surveys are starred in **Table 3-1**. One exception is the question about parking management. The statewide survey asks whether any SOV parking fee is required in worksite, while survey by City of Seattle asks whether employer provides SOV parking subsidy with an option from 0 to 100%. One possible way is to assume that only 100% parking subsidy means “free parking”, others were considered as “parking fee required”, even though the amount of subsidy differs in a large range. However, it turned out that in statewide survey, worksites with parking fee versus no parking fee was 1:5, while in Seattle survey, the ratio was 7:1, indicating such assumption is problematic and those two questions are not compatible. In the end, the information of parking fee was collected from one of the questions in employee survey, asking whether they have to pay parking on the most recent day that they drove alone to work.

Among those survey questions co-existed in two surveys, yet, not every corresponding policy is included in the study since some survey questions either have a much lower response rate than other question (eg. pre-tax policy had nearly 20% missing value) or go beyond research scope of this study (eg. the availability of third party ridesharing system probably more relates to other

exterior factors). The ones that are included in the study are highlighted in **Table 3-1**, including parking management, transportation subsidy, working schedules and worksite amenity & service.

In 2015 and 2016 survey circle, there were 233 and 235 respondents, respectively from statewide survey. Some of worksites conducted their surveys in both years, while others only in one year. To make sure the observations are independent, 290 unique worksites from 2015 or 2016 were identified for this study. Combining that with unique 270 worksites from City of Seattle, we got 560 worksites in total. Each policy was coded as dummy variable with “0” (unavailable) and “1” (available), with “0” as the reference group.

Table 3-1 Summary of employer survey conducted by WSDOT and City of Seattle

WSDOT		City of Seattle
Category	Sub-Content	
Sector	Worksite primary business	*
	Government or non-profit organization	
Employee Affected	Total number of employees	*
	Total number of CTR-affected employees	*
	Whether commuter benefits have offered to all employees	
	Whether CTR program subject to collective bargaining	
Accessibility (within 3 blocks)	Accessibility to transit (bus, ferry, train, rail) stop(s)	
	Accessibility to sidewalks or pedestrian trails	
	Accessibility to service (shop, restaurant, child care, ATM/bank)	
Worksite Amenity/ Service		*
	Covered/ Uncovered spaces, cages, racks, or lockers for bicycles	
	Showers/ clothes lockers	*
	Onsite loading/unloading zones or shelters for non-SOVs	
Parking Management	Employer-provided bicycles	*
	Parking fee for SOV commuters	
	Parking fee for carpool/vanpool commuters	
	Counts of on-/off-site owned/leased parking spaces	
Transit Pass/ Subsidy	Counts of on-/off-site owned/leased parking spaces reserved for HOV	
	Transit passes (including ORCA card, FlexPass, UPass, etc.)	*
	Transit (bus, ferry, train, rail) subsidy, allowance, or stipend	*
	Vanpool, Vanshare, and/or carpool subsidy, allowance, or stipend	*

	Biking/walking subsidy, allowance, or stipend	*
Vehicle Support	Vehicle support for carpooling/ business trip/ non-work-related errand	*
	Shuttle /custom bus /van	*
	Internal circulator system	
	Guaranteed/emergency ride home program	*
Carsharing System	Internal ridematch service	*
	Statewide or regional ridematch service(eg.RideshareOnline/ NWCarpool)	
	Third party ridematch service (eg. Zipcar)	*
Program Promotion	Distribute information to all new hires	*
	Post CTR promotional materials	*
	Give CTR presentations to managers, employees	
	Organize transportation events/fairs	
	Send electronic mail messages to employees	
	Publish CTR articles in employee newsletters	
	Distribute CTR information with employee paychecks	
	Publish and update an employee CTR website	*
Work Schedule	Offer multiple shifts	
	Compressed work week schedules (3/36,4/40, 9/80, other)	*
	Flex-time (vary start and end working time)	*
	Telework (at home, a telework center, or satellite office)	*
Cash Benefit	Offer tax credit or grant for ridesharing subsidies	
	Allow Pre-tax income for transit/vanpool pass	*
	Offer cash or prizes, paid leave, other incentives	
Cost Estimate	Yearly in-kind cost estimate for each commuter benefit	
	Yearly monetary cost estimate for each commuter benefit	

* Starred items are the ones co-existed in both statewide survey conducted by WSDOT and survey conducted by City of Seattle.

Highlighted variables are ones included in this study: Highlighted elements are the ones co-existed in both surveys, thus treated as direct information for the study. Highlighted elements are the ones only exist in statewide survey, yet considered to be important for the study, thus the information were either collected from other sources or estimated by the author.

3.2 Employee Biannual Survey

The employee survey (refer to APPENDIX) is conducted biannually in statewide through paper Scantron forms or online version. It includes 13 questions such as employee working schedule, model choice in one continuing week, one-way home-worksite (HW) commuting distance and so forth. Each record from employee survey can be joined with its corresponding worksite using unique worksite ID. In 2015/2016 survey circle, there were 224,590 responses from 598 worksites in total. Two pieces of critical information from employee survey are worth to consider ahead.

1. Had the employee been affected by CTR policies?

In fact, the employee survey was not only distributed to CTR-affected employees, rather, it also got some designated groups involved for other research purposes. Moreover, it was not necessary that every employee in each worksite were affected by the policy as well. For instance, some commuter benefits may only be available to full-time employees in some worksites. Excluding the missing value, a summarized data indicated that employees affected by the CTR program (214,562) had 1.97 non-SOV commuting days per week on average, while employees not affected (9,962) were 0.65 less, which is actually quite different in terms of the average value. To avoid data biases, employees not affected by CTR policies were excluded in the dataset. Otherwise, it would be hard to tell the difference between the absence or ineffectiveness of the CTR policy to impact people's travel behavior.

2. Did the surveyed week a typical week for commuting?

This question also matters a lot since 24,456 employees reported that the surveyed week was not a typical week for their commuting. Those observations were also excluded, in case other exterior factors for employees' temporal travel behavioral changes. For instance, an employee chose to telework two days during the surveyed week because of medical care is definitely different from an employee who telework two days a week on a fixed time schedule.

One limitation of the survey is missing other sociodemographic features and household characteristics of employees, such as gender, age, car ownership and so forth, which may influence their travel behavior. Notwithstanding, employees did provide their employment status, and commuting distance with home zip code. Therefore, these two factors are captured as the demographic variables in this study.

3.3 Worksites Built Environment Variables

Multiple built environment variables were analyzed in software Arc GIS 10.3, including distance to central business district (CBD), development intensity, population density, mixed land use, length of walkable path, number of transit stops, distance to nearest transit stops. The latter 5 variables were measured in the area within quarter mile from each worksite.

1. Worksite-CBD Distance

Though most cities have their designated downtown/ CBD, it is obvious that different cities have different levels of attraction. For instance, the built environment within 2 miles away from downtown Seattle is definitely different from 1 mile away from, say, downtown Everett. In order to make the spatial distances more comparable to each other, it is reasonable to weight them by the number of jobs within CBD, which is one of the most recognizable factors to distinguish CBD from other areas. Based on the spatial concentration of all worksites that were affected by CTR program, 10 core cities were identified in this polycentric region, including Seattle, Bellevue, Everett, Olympia, Tacoma, Spokane, Vancouver, Bellingham, Yakima, Bremerton (cities are sorted by their rank of job counts). The boundary for each downtown area were determined based on the Master Plan of each city. City of Seattle was treated as baseline, meaning the worksite-CBD distances for worksites located within Seattle cluster were the exact spatial distances, while worksites located in other 9 cities were weighted based on the ratio of job counts comparing to Seattle.¹

¹ Here is an example demonstrating how the worksite-CBD distance was calculated. Based on 2010 LEHD Origin-Destination Employment Statistics (LODES) dataset, downtown Seattle and

2. *Development Intensity*

The information of development intensity was collected from 2011 National Land Cover Database, which has 20-class land cover classification scheme with 4 levels (open space/ low intensity/ median intensity/ high intensity) for developed land. Since the intensity was categorized based on the percentage of impervious surfaces of total land cover, areas with higher development intensity are areas “where people reside and work in high numbers” (U.S. Department of the Interior 2018). The development intensity of each worksite was represented by the development intensity of which category it falls into.

3. *Population Density*

Population data was collected from 2015 Census data in block level (United State Census Bureau 2015) and aggregated into areas within quarter mile from each worksite. The population counts were then transferred into density representing the number of population per square mile.

4. *Mixed Land Use (Diversity)*

Diversity is defined as the variety of land use in a given area. The land use mixture was measured with Entropy Index (Shannon Index) which reflects the evenness or dispersion of different land use types within a designated area. The equation is as follows:

$$Entropy = \frac{-\sum(A_{ij} \ln A_{ij})}{\ln N_j}$$

where A_{ij} is the percentage of area j allocated to land use type i , N_j is the number of land use types in area j (including single-family, multi-family, commercial, industry, services and park& recreation), j is the area within ¼ mile radius of each worksite.

downtown Everett had 102,305 and 18,532 jobs, respectively. The former is almost 5.52 times of the latter. For a worksite located in 1 mile away from the centroid of downtown Seattle’s polygon, its worksite-CBD distance is 1 mile. With comparison, a worksite located in 1 mile away from the centroid of downtown Everett’s polygon, its worksite-CBD distance is 5.52 mile.

The dataset used in the study was 2009 Washington Statewide Parcels Database. The Entropy is a value in the range between 0 and 1, where 0 means the land use is extremely homogeneous, while 1 means the land use is maximally mixed.

5. *Length of Walkable Path (Design)*

Design is defined as the spatial layout of streets and blocks. Study found that smaller block size and higher intersection density encourage walking trips. The length of walkable path is also a key determinant of walkability. In this study, the walkable path was calculated by subtracting highways, expressways, freeways, ramps and other non-walkable roads from total length of road network within ¼ mile radius from each worksite.

6. *Transit Accessibility*

Though statewide employer survey did ask several questions about transit accessibility near each worksite, survey in City of Seattle didn't ask for such information. Therefore, measure it consistently across all worksites (inside and outside City of Seattle), the number of transit stops and distance to nearest transit stop from each worksite were calculated uniformly in ArcGIS based on 2017 Washington State Transit Station Dataset.

3.4 Dataset Construction

The final database was developed with the aforementioned 3 datasets, with worksite ID as the key. After data cleaning, 379 worksites with 84,878 employees were included ultimately. Those samples were randomly selected into training group (80%) for building model and testing group (20%) to test the model performance. **Table 3-2** summarizes all variables in this study.

Since the primary goal of CTR program is to reduce SOV commuting trips, this study attempts to take employees' non-SOV travel day counts as the dependent variable. One problem is that a large number of responders (75%) didn't provide information about their travel mode on Saturday and Sunday, and didn't indicate whether they were taking days off either. Therefore, in order to differentiate the schedule shifts from weekday to weekend for the majority of

employees, only weekdays (from Monday to Friday) were taken into consideration. In sum, the dependent variable can be referred to *“the number of days an employee choosing non-SOV as dominant travel mode on weekdays during one week”*. As **Figure 3-1** shows, it is a set of non-negative discrete numerical data with an asymmetric U-shape distribution, bounded by 0 and 5. Namely, a large proportion of data are found in the two tails when non-SOV day count equals to 0 or 5. **Figure 3-2** also depicts the aggregated mode share of samples in the study. The non-SOV mode share is slightly less than 40%, with transit (bus, train, rail, ferry), rideshare, bike/ walk/ motorcycle and flexible schedule (compress working hour, telework) accounting for 17%, 9%, 5%, 5%, respectively.

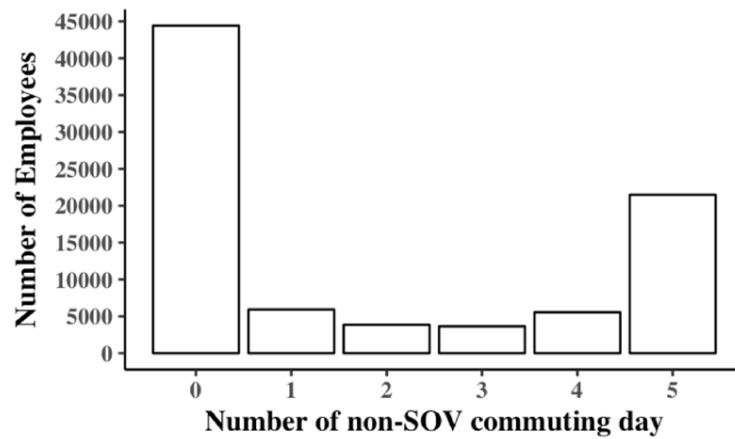


Figure 3-1 Distribution of number of non-SOV commuting day

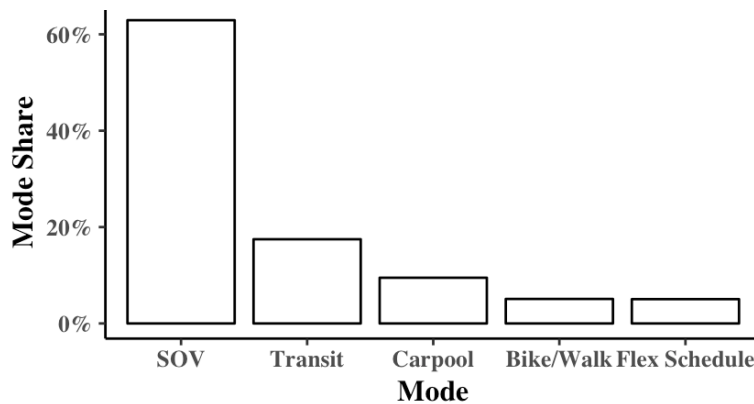


Figure 3-2 Employee mode share

Table 3-2 Description of dependent variables and independent variables

Variables	Mean	S.D.	Description
Non-SOV Travel Frequency on Weekdays			
non-sov	1.82	2.17	Natural count of SOV days on weekdays (0,1,2, ... ,5)
Employee Characteristics			
full-time	0.99	--	Employment status [0: part-time, 1: full-time (≥ 30 h/week)]
disHW	15.32	11.77	One-way home-worksite commuting distance (mile)
Worksite Built Environment Factors			
disWCBD	3.14	4.06	Distance to CBD weighted by number of jobs within boundary (mile)
popDensity	4591	3726	Population Density within ¼ mile of the worksite (population/ sqmi)
entropy	0.60	0.14	Mixed land use index
lenPed	9.05	3.50	Total length of walkable path within ¼ mile of the worksite (mile)
numStop	8.79	7.21	Number of transit stops within ¼ mile of the worksite
disStop	0.21	0.52	Euclidean distance to nearest transit stops (mile)
deveInten	1.40	--	Development intensity (0:low, 1: medium , 2:high)
Employer Factors & CTR Policies			
EmplTotal	639.7	923.32	Total number of employee in each worksite
sovparkfee	0.33	--	Parking fee for SOV (0: no, 1:yes)
tran_subsidy	0.86	--	Transit subsidy & transit pass (0: no, 1:yes)
share_subsidy	0.44	--	Carpool/ vanpool/ vanshare subsidy (0: no, 1:yes)
nonveh_subsidy	0.30	--	Walking/ Biking subsidy (0: no, 1:yes)
compress	0.80	--	Allow for compress working hours (0: no, 1:yes)
telework	0.77	--	Allow for telework (0: no, 1:yes)
flex_hour	0.87	--	Allow for flexible working hour to avoid rush hour (0: no, 1:yes)
amenity	0.91	--	Provide covered spaces or cages or racks for bicycles (0: no, 1:yes)
service	0.92	--	Provide shower or lockers in worksite (0: no, 1:yes)

4 PRELIMINARY ANALYSIS

4.1 Demographic Characteristics

4.1.1 Home-Worksite Commuting Distance

Figure 4-1 depicts the spatial pairs of commuters' home location and worksite location, which were aggregated to county level and city level, respectively. The majority of the commuting destinations were concentrated in 4 counties in central Puget Sound region, while home locations were more sprawl across the state. It is also noticeable that a small portion of employees had an extremely long HW distance, especially for those who almost traveled across the state. It's worth noting that the HW spatial distance is not necessarily equal to the daily commuting distance reported by employees. One assumption is that some people may live in a temporary location close to their worksites during weekdays for commuting purposes, but the location zip code they reported in the survey were for their permanent home location. Therefore, the actual commuting distances reported by themselves were used in this study.

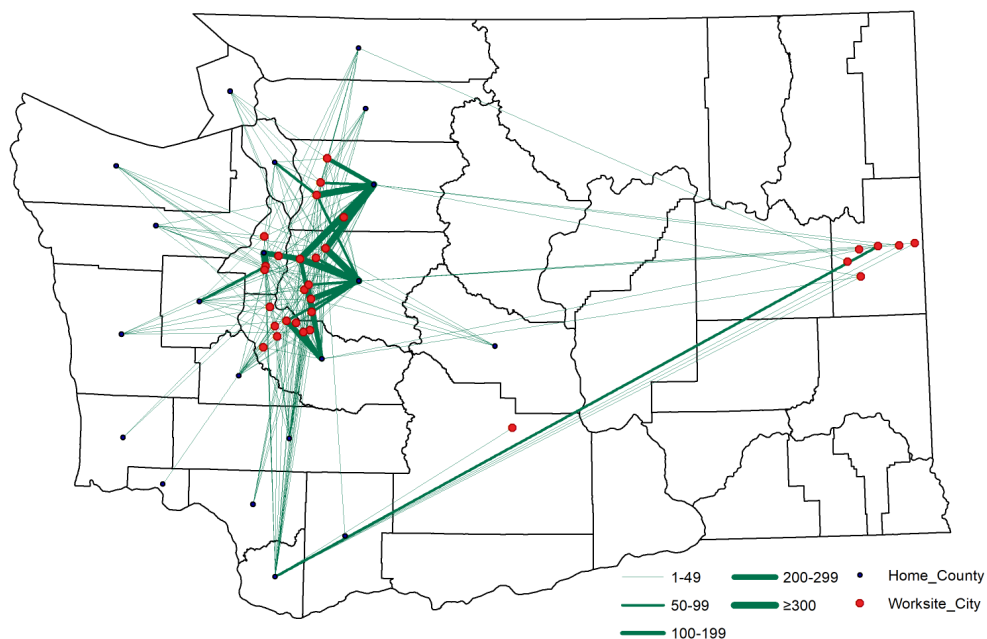


Figure 4-1 Commuter home & worksite location pairs

Considering the common perception of acceptable commuting distance, records with larger than 80 mile commuting distances were considered to be unrealistic for daily commuting and were excluded from the dataset. In the end, the average commuting distance is 15.32 mile, with 75.20% of employees commuting no more than 20 miles. It is also interesting to find that people often tend to round their reported numbers, resulting with excessive counts for some values, shown by **Figure 4-2**.

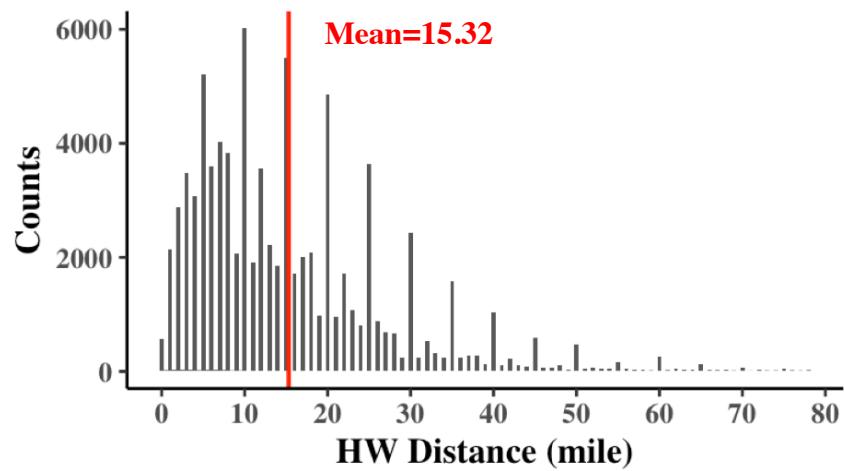


Figure 4-2 Histogram of Home-Worksite Distance

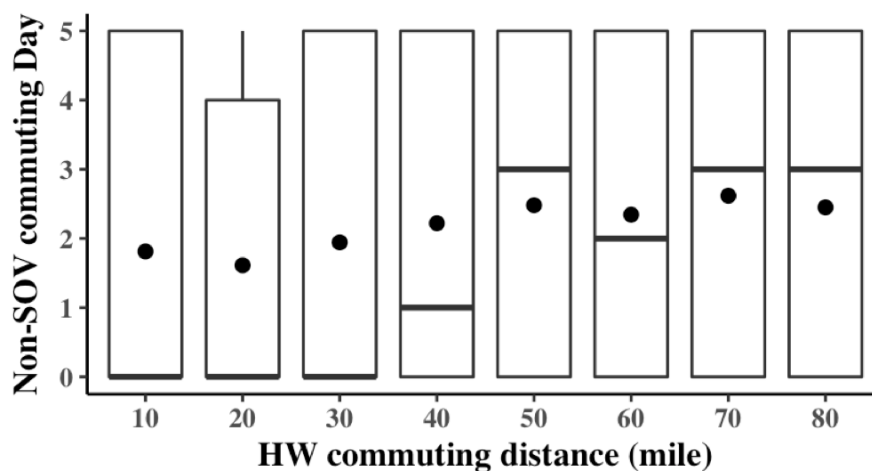


Figure 4-3 Correlation between HW distance and non-SOV travel frequency

Figure 4-3 also depicts the boxplot of HW commuting distance and non-SOV travel frequency, with mean and median value are shown by thick horizontal lines and dots within each bar. It is noticeable that the longer commuting distance positively associates with higher mean and median value of non-SOV travel frequency. This seems to be counterintuitive at the first sight, since it is normally more difficult to travel by transit or active transportation (biking/walking) if having a long commuting distance. However, a comparison of the average travel frequency by different modes grouped by HW distance, shown by **Figure 4-4**, may provide some other explanations.

1) The average biking/walking trips reduce dramatically among people with commuting distance longer than 10 miles, yet we also witness the value bounces back slightly for commuters with extremely long distance. This is probably due to some data errors or due to respondents' misunderstanding of the survey question. For instance, people teleworking that day accidentally reported their other non-commuting biking/walking trips as commuting trips. 2) People with longer commuting distance take more carpool/vanpool trips, yet the frequencies decrease slightly when the commuting distance is larger than 60 miles, indicating the diseconomy of the program for extremely long-distance commutes. 3) In comparison, flexible working schedule, like teleworking, compressed working day off and flex hour increase their prevalence as the commuting distance increase. 4) Public Transit is normally considered as the common alternative to biking and walking, thus people with fewer biking/walking trips tends to have more transit trips. Notwithstanding, the maximum average transit trips is among people with commuting distance ranging from 40 to 50 miles. **Figure 4-5** breaks down the transit modes into bus, ferry, train/ light rail/ streetcar². It is obvious that the average bus trips decrease as the distance increase. Besides, the count of train/light rail/ streetcar reach its peak among people with 40- to 50-mile commuting distance. It's possible that many of these people take commuter trains, such as Amtrak Cascades and Sounder. What's unusual is the ferry trips which increase greatly when distance is larger than 50 miles, both for the walk-on passengers and passengers with vehicles.

² The employee survey takes these three mode as one set of choice, thus there is no way to break them down further.

However, it is worth noting that as **Figure 4-2** shows, the majority of people commute no more than 20 mile, thus one should keep skeptical of the normalization of the observations associating with extremely long commuting distance.

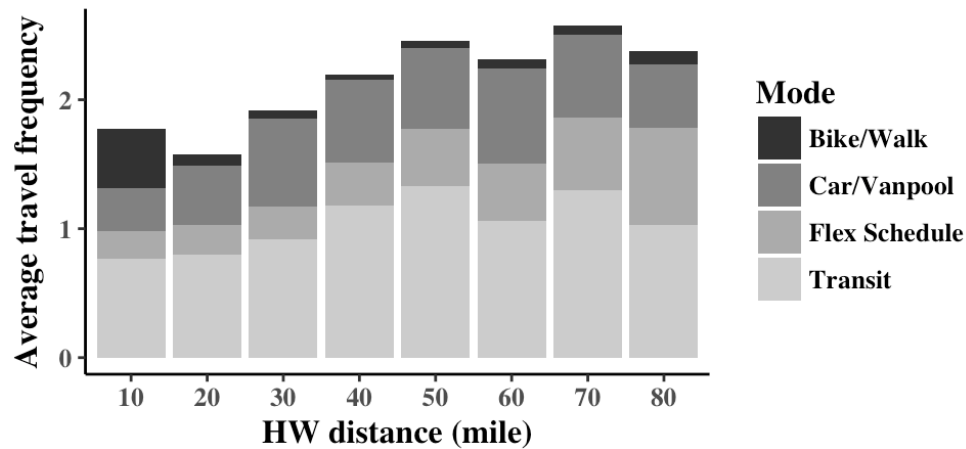


Figure 4-4 Relationship between HW distance and travel frequency by different modes

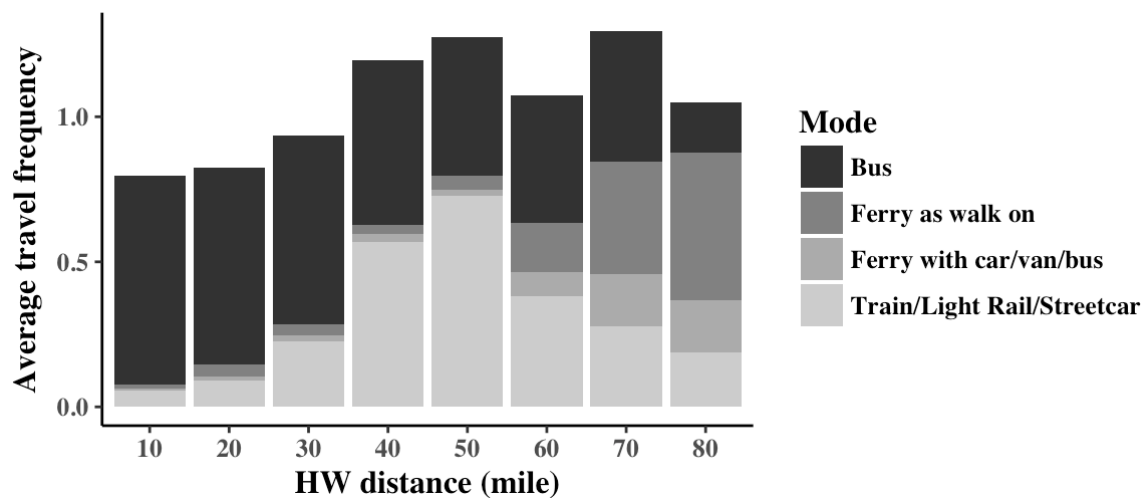


Figure 4-5 Relationship between HW distance and travel frequency by transit modes

4.1.2 Employment Status

Figure 4-6 depicts the boxplot of employment status and non-SOV travel frequency, with mean and median value are shown by thick horizontal lines and dots in each bar. Though the median

value of those scenarios are 0 due to excessive zero values in the dataset, full-time employees do have a higher average value and maximum value of non-SOV frequency, comparing to part-time employees.

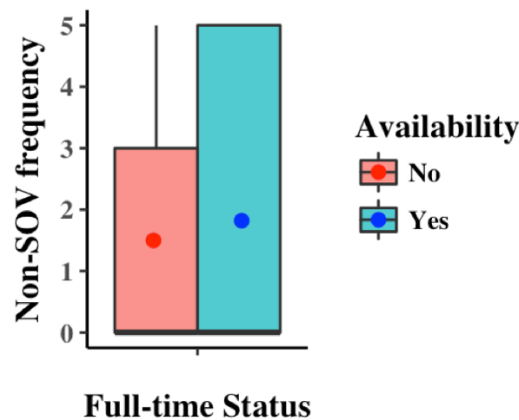


Figure 4-6 Boxplot of employment status and non-SOV travel frequency

4.2 Worksite Built Environment Factors

The built environment factors were estimated in worksite level, thus the employees' non-SOV trip counts were aggregated into average value in each corresponding worksite. One latent issue of built environment variables is the multicollinearity-- when multiple explanatory variables are linearly related, the coefficient of the multiple regression may change erratically. For instance, areas closer to CBD are more likely to have higher density of transit stations. Therefore, a pair-wise correlation matrix was built to determine the pair-wise correlation and overall correlations, as **Table 4-1** shows. It turned out the statistics were modest with pair-wise correlation $|p| < 0.7$. Since there is no evidence of simultaneity, all the variables were kept for model construction.

Here are several findings. 1) The largest negative correlation was observed between worksite-CBD distance and length of walkable path within quarter mile from worksite. In other words, worksites closer to CBD often have a good pedestrian network nearby. 2) The proximity to CBD is also correlated to the concentration of transit services with more transit stops and less walking distance to the nearest transit stop from the worksite. 3) Transit stops tends to be located near

places with higher walkability. 4) Areas with higher population density have higher mixed land use, better transit services and higher walkability. 5) Overall, worksites closer to CBD, with higher population density, mixed land use, higher walkability and better transit services associate with more non-SOV trips.

Table 4-1 Correlation matrix for built environment variables in worksite level

	non-sov	disCBD	popDensity	entropy	lenPed	numStop	disStop
non-sov	1.000						
disCBD	-0.585	1.000					
popDensity	0.218	-0.180	1.000				
entropy	0.102	-0.145	0.041	1.000			
lenPed	0.534	-0.587	0.206	0.093	1.000		
numStop	0.566	-0.469	0.120	0.175	0.560	1.000	
disStop	-0.243	0.309	-0.087	-0.045	-0.292	-0.336	1.000

4.3 CTR Policies

Figure 4-7 depicts the histogram of number of CTR policies that were offered by worksites, thus employee benefited, including 9 elements for parking management, transportation subsidies, flexible working schedule and non-vehicle support. The distribution is skewed to left with a mean of 6.22, indicating a high policy adoption rate.

More specifically, **Figure 4-8** shows the distribution of CTR policies availability to employee, indicating some policies were more prevalent and highly adopted than others. For instance, the worksite amenity and service were available to 91.03% and 92.47% of the employees among the samples. The flexible working hour, transit subsidy, compressed working schedule and teleworking were at comparable level of 87.49%, 86.49%, 80.34% and 77.20%, respectively. With comparison, rideshare subsidy, required parking fee and non-vehicle subsidy were at lower adaption rate of 44.12%, 33.35% and 29.54%, respectively.

So, is every policy positively associated with non-SOV commuting? **Figure 4-9** depicts a boxplot of non-SOV frequency grouped by different CTR policies with median value and average value. Considering each policy independently, if the average non-SOV frequency is different when the policy is available versus unavailable, then we may consider that such policy may be positively associated with non-SOV commuting. In our case, SOV parking fee, transit and teleworking seem to have salient positive associations, non-vehicle subsidy, worksite amenity & service, flex working hour have marginal positive associations, while rideshare subsidy and compress working schedule are negatively associated with non-SOV commuting. More in-depth analyses on the policies are discussed as follows.

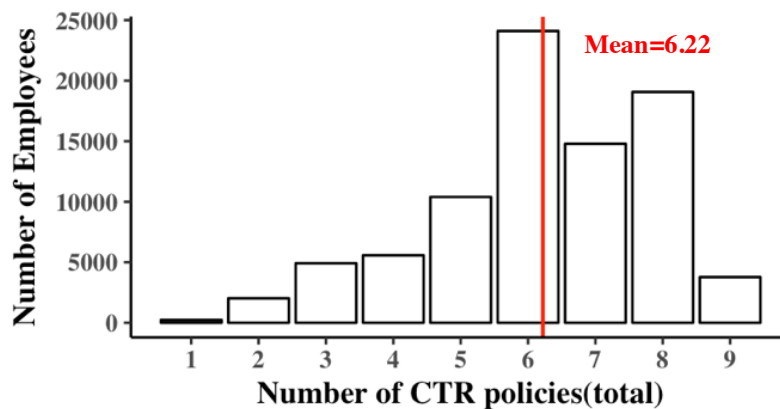


Figure 4-7 Histogram of number of CTR policies available to employees

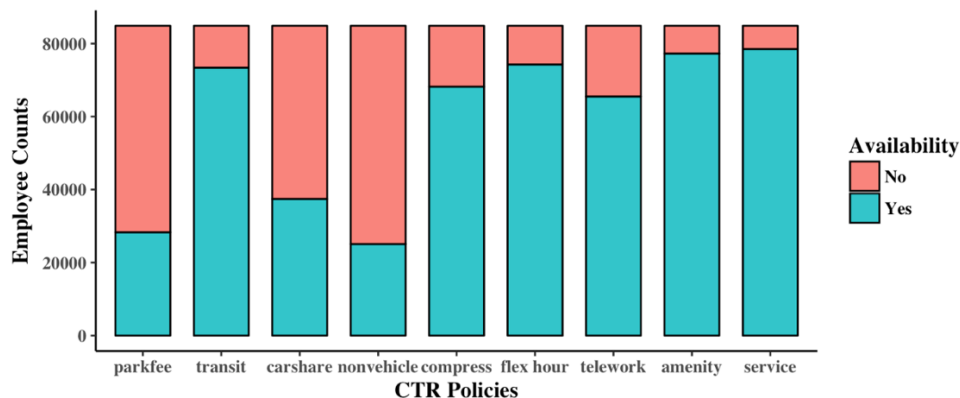


Figure 4-8 Histogram of CTR policies available to employee

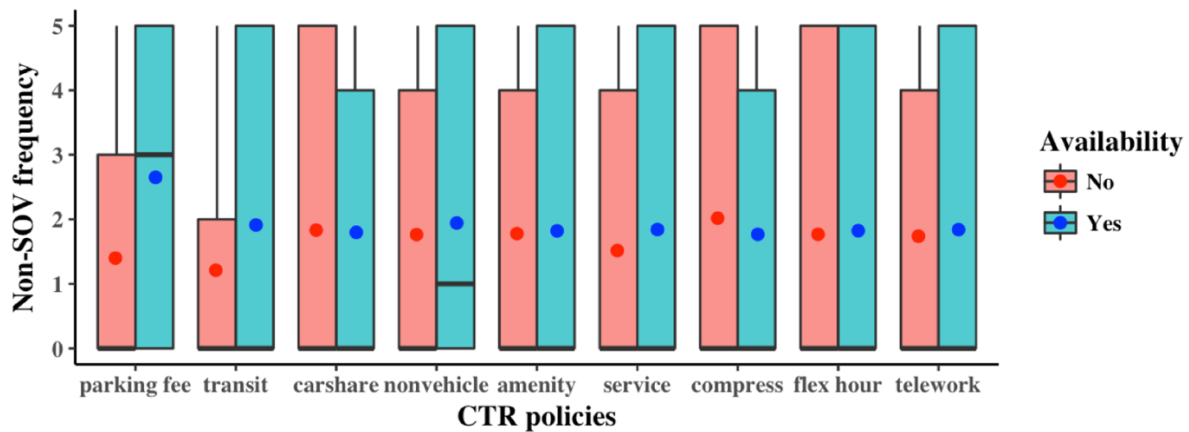


Figure 4-9 Boxplot of Non-SOV frequency grouped by different CTR policies

1. SOV Parking Fee

Given a great number of researchers argue that free parking policy and minimum parking requirement are the ones to blame for high SOV rate, only 15.88% of worksites and 6.56% of employees in our study manage parking fee and pay parking fee in practice. **Figure 4-10**³ shows the boxplot of worksite parking rate (number of parking spots owned or leased by employer / total number of employee) with three scenarios of parking management (no fee required in any situation / fees required under certain situation / always require fees). The median value of parking rates of worksites with no and some SOV parking fee is around 0.7 and 0.5, respectively. With comparison, the median value for worksites always require SOV parking fee is around 0.05, one tenth of 0.5. In other words, less than every two employees equip with one parking spot in former condition, while every twenty employees equip with one parking spot in latter condition. Besides of that, the upper bound of those boxplots decrease when scenario turning from “no” to “some” to “yes”. Therefore, we can safely draw the conclusion that the higher parking availability, the less likely that employers will require parking fee. The truth is the boxplot has already remove some outliers. In fact, still more than 50 worksites with a parking

³ Data for parking analysis is only a portion of the statewide survey dataset due to low response rate of survey questions related to parking management policy.

rate large than 1, meaning there are always plenty of parking spots available, which in turn offer more motives for employees to drive alone.

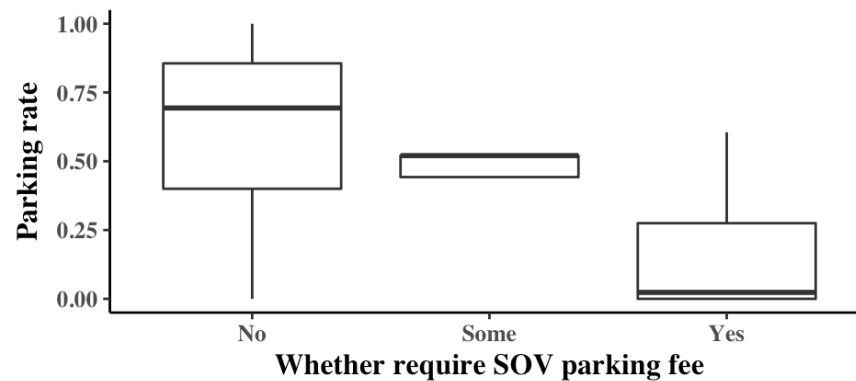


Figure 4-10 Boxplot of parking rate and SOV parking fee

2. Transportation Subsidy

Figure 4-11 depicts one part of previous summary plot, comparing among 3 types of subsidies and averaged employee non-SOV frequencies. Unlike the impacts of transit subsidy and non-vehicle subsidy which lead to higher mean value or median value of non-SOV frequency (shown by color dots and thicker line in boxplot), rideshare availability slightly correlates to lower non-SOV frequency. This observation is counterintuitive and inconsistent with current policy practices.

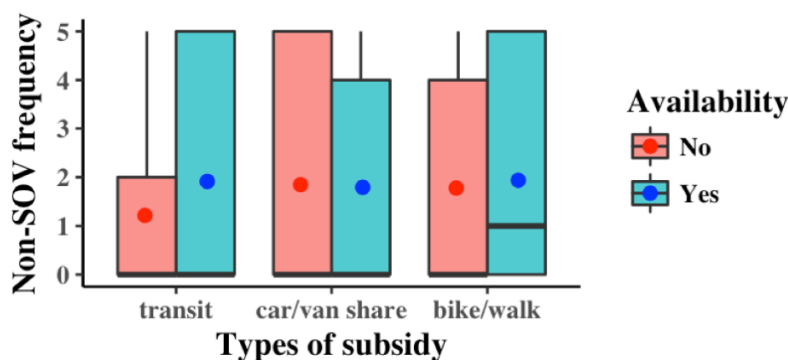


Figure 4-11 Boxplot of subsidies and non-SOV frequency

One assumption is that since carpool/ vanpool policy normally have larger impacts on employees with longer commuting distance, so it is possible that the subsidy accidentally available to people with shorter commuting distance. The assumption, yet, was rejected after the diagnosis. As **Figure 4-12** shows, the distribution is actually well-balanced, though people with the subsidy do have a slightly shorter HW distance. While the finding is contradictory with some findings in literature and in practice, this may come from the particular feature of this dataset. More researches are needed to uncover the underlying relationship.

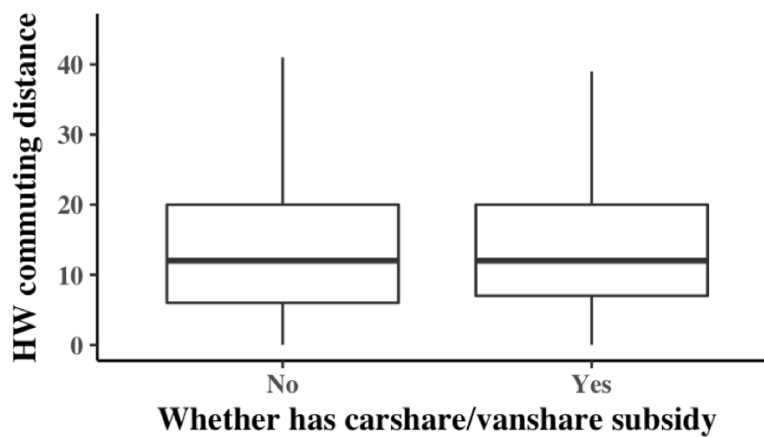


Figure 4-12 Boxplot of carpool/vanpool subsidy and home-worksite distance

Other possible reasons could be the relatively low availability of rideshare benefit among employees, as shown in **Figure 4-8**. Besides, employees who have the access to this option doesn't necessarily implement it simply because it is not economical for people with shorter commuting distance, comparing to SOV or other alternative modes. As shown in **Figure 4-4**, commuters travelling less than 10 miles have a low counts of rideshare days.

3. Flexible Work Schedule

Figure 4-13 compares the relations between 3 types of working schedule related CTR policies and averaged non-SOV frequencies. Overall, the teleworking and flex hour positively associated with high non-SOV travel frequency, but in a marginal scale. In contrast, compresses working hour slightly correlates to lower non-SOV frequency.

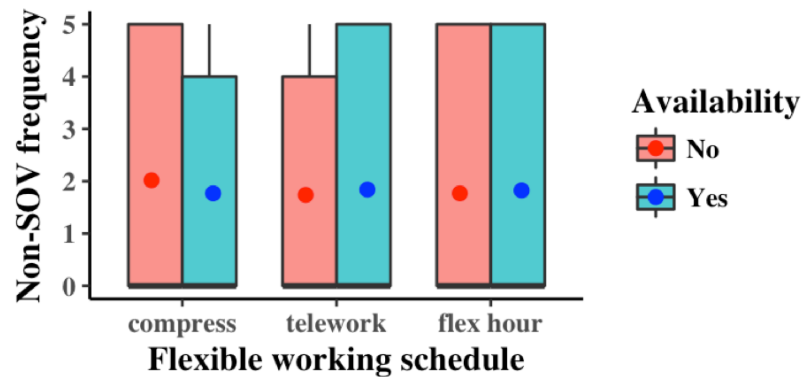


Figure 4-13 Boxplot of working schedule and non-SOV travel frequency

Compressed working schedule and teleworking are two policies that were both surveyed in employer and employee survey. It is a great opportunity to compare the situation of policy availability in worksite level reported by employer (er) and policy implementation in individual level reported by employee (ee). The results are depicted in **Figure 4-14**, which indicates several findings. 1) As 1st and 3rd bars show, those two policies were available to 68,193 (80.34%) and 65,523 (77.20%) employees, respectively, while 13,923 (15.62%) and 30,810 (34.90%) of them reported they did implement those policies during the surveyed week. In sum, the implementation rate (implementation / availability) for these two policies are 19.45% and 45.20%, meaning given those two policies available, employees are more in favor of teleworking, rather than compressed working hour. Those findings may helpful for decision making in terms of policy adaption rate and effectiveness. For instance, if both policies are found to be effective and employers do offer such benefits, while employees still have a low implementation rate due to lack of knowledge and guidance, then more efforts should be made in policy promotion.

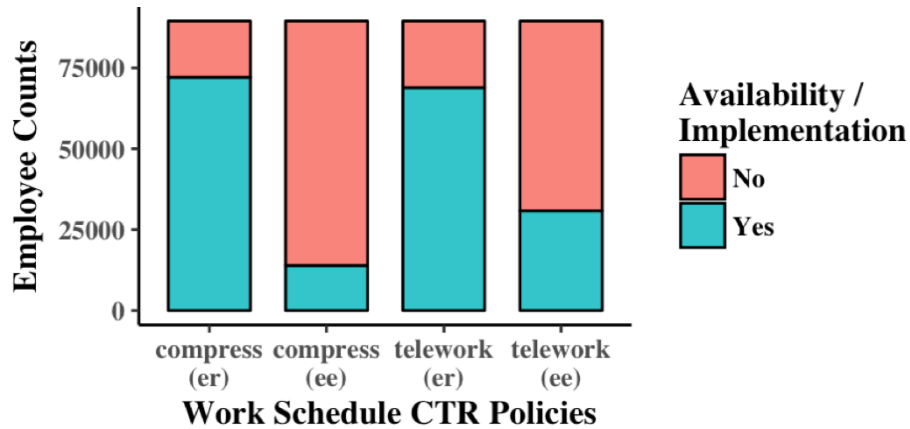


Figure 4-14 Comparison of policy availability and policy implementation

4. Worksite Amenity & Service

Likewise, **Figure 4-15** depicts the relation between policies related to worksite amenity and service and non-SOV travel frequency. Both of them are positively correlated, while the worksite service appears to have a larger effect than worksite amenity.

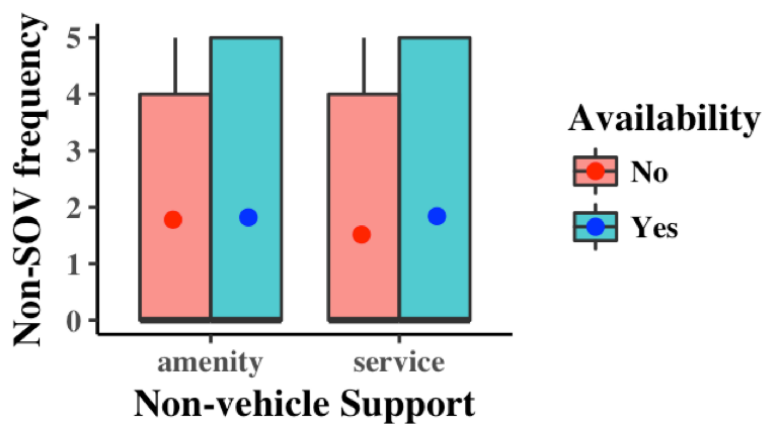


Figure 4-15 Boxplot of non-vehicle support and non-SOV travel frequency

4.4 Summary

A series of preliminary analysis was performed to investigate the relationship among multiple variables. For a start, HW commuting distance and employment status are two variables captured for demographic features. While employees' home locations widely spread out across the state, the affected worksites in this study are mainly located in 5 counties (King, Kitsap, Snohomish, Pierce and Spokane). The average commuting distance of all employees was 15.32 miles, with nearly 70% of them were less than 20 miles. Surprisingly, people with longer commuting distance was found to be associated with higher non-SOV travel frequency. Though the biking and walking travel frequency decreases dramatically as the commuting distance increases, the average day counts for transit, car/vanpool and flexible working schedule are in fact increase. In terms of employment status, full-time employees were found to have a higher non-SOV travel frequency.

Secondly, 7 variables were measured for built environment characteristics. The most significant finding is shown by the pair-wise correlation matrix that worksites adjacent to CBD also have easier access to mixed use land, higher density of walkable path, higher density of transit services.

Finally, 9 elements in CTR policy package were evaluated. It was found that the policy had a high adoption rate, with 6 elements adopted each worksite on average. Notwithstanding, not every policy was equally prevalent and on the same level of effectiveness. Some policies were unexpected to show negative association with non-SOV day counts., such as carpool subsidy and compress working schedule.

5 COUNT MODELS

5.1 Overview of Count Model

As explained, the distribution of SOV day count doesn't follow a normal distribution (bell-shape), therefore linear regression model is not applicable. This section will introduce 4 types of models for modeling count data with their function form. Then a series of evaluation methods are provided for model comparison and selection.

5.1.1 Poisson Regression Model

The Poisson regression model (PRM) is the most common way to model count data. The probability density function (PDF) of Poisson[E1] only has one parameter λ_i , donating to the mean number of event or the rate of occurrence over a designated time period. It is a multiplicative model with a log-linear relationship between the mean count and predictor [E2]. The exponentiated coefficients refer to the incident rate ratio (IRR) indicating the change in risk with one-unit change of covariate, given other factors to be consistent.

The Poisson distribution has some critical assumptions and properties. 1) It assumes a equidispersion; its mean equals to the variance [$E(y|x) = var(y|x) = \mu$]. 2) The counts should be non-negative integers. 3) It is more suitable for rare event counts with small means. 4) It is usually unbounded and trail off the upper end.

$$Pr(Y_i = y_i / X_i) = \frac{e^{-\mu_i} \lambda^{y_i}}{y_i!}, y_i = 1, 2, \dots, n \quad [E1]$$

$$\ln(\mu_i) = \beta_1 X_{i1} + \beta_2 X_{i2} + \dots + \beta_k X_{ik} \quad [E2]$$

where y_i is the number of event occurrences, μ_i =mean number of event occurrences, and X_i is an explanatory variable.

5.1.2 Negative Binomial Model

The equidispersion assumption of classical Poisson Model tends to be a restrictive property that it is very likely to be violated. In practice, the variance of the response variable is larger than the mean in most instances, which is referred to “overdispersion”. In that case, the negative binomial model (NBM) is an alternative with an additional dispersion parameter θ comparing to PRM, which allows for a wider range of variability [$var(y|x) = \mu + \theta \mu^2$]. Graphically, NBM is more skewed with more zero values with a fatter tail toward positive infinity. Therefore, θ is also called shape parameter. The PDF of NBM is a mixture of Poisson distribution and gamma function (Tao 2007) [E3].

$$Pr = (Y_i = y_i | X_i, \theta) = \frac{\Gamma(y_i + \theta)}{\Gamma(\theta) y_i!} \frac{\mu^{y_i} \theta^\theta}{(\theta + \mu)^{y_i + \theta}} \quad [E3]$$

where y_i is the number of event occurrences, μ_i is mean number of event occurrences, and X_i is an explanatory variable, θ is the dispersion parameter, $\Gamma(\cdot)$ is the gamma function.

5.1.3 Zero-Inflated Poisson/Negative Binomial Model

When count data exhibits an excess number of zeros, then both PRM and NBM are prone to underestimate zero counts. Instead, the zero-inflated Poisson model (ZIPM) or zero-inflated negative binomial model (ZINB) address this issue by combining a count component and a point mass at zero (Lambert 1992, Mullahy 1986), which increases the likelihood of predicting a zero value. The model assumes that zero observations come from two different sources: the “sampling zeros” are from unobserved events due to sampling limitations, while the “structural zeros” are from the “always zero” members (Mohri and Roark 2007). For instance, when reporting the number of non-SOV commuting days, some participants used to have non-SOV trips, but just not in the week during the survey, therefore they had eliminated their counts. This is referred to “sampling zeros”. With comparison, “structural zeros” are from the rest of participants who reported zero simply because they never had a non-SOV commuting trip.

The probability density function of ZIPM and ZINB is defined as [E4] and [E5], respectively, with a logistic regression to predict the probability of excessive zeros, then a Poisson/ NB regression to predict count, regarding positive number and probably the rest of the zeros that are not predicted by the aforementioned logistic regression.

$$pr(Y_i = y_i | X_i) \begin{cases} p_i + (1 - p_i)e^{-\mu_i}, & y_i = 0 & (1) \\ (1 - p_i) \frac{e^{-\mu_i} \mu_i^{y_i}}{y_i!}, & y_i > 0 & (2) \end{cases} \quad [E4]$$

$$pr(Y_i = y_i | X_i) \begin{cases} p_i + (1 - p_i) \frac{1}{(1 + k\mu_i)^{k-1}}, & y_i = 0 & (1) \\ (1 - p_i) \frac{\Gamma(y_i + \theta)}{\Gamma(\theta) y_i!} \frac{\mu^y \theta^\theta}{(\theta + \mu)^{y+\theta}}, & y_i > 0 & (2) \end{cases} \quad [E5]$$

where P_i is the probability of extra zero counts, y_i is the number of event occurrences, μ_i =mean number of event occurrences, and X_i is an explanatory variable, θ is the dispersion parameter, $\Gamma(\cdot)$ is the gamma function.

5.1.4 Hurdle Model

In comparison to ZIM, though the hurdle model also helps to handle zero-inflation and over-dispersion, it has a different interpretation of zero counts and different model components. For a start, it assumes that all zeros are from “structural” source. Thus, the salient difference between 0 and positive value should be modeled separately. Second, it combines with a left-truncated count component and a right-censored hurdle component (Mullahy, Specification and testing of some modified data models 1986). The former is typically a binary logit model with specified distribution to predict zeros versus non-zeros, following with a Poisson or NB model to predict positive counts only, as [E6] demonstrates. Since the latter part of the model only consider non-zero values, it is also called “zero-truncated” model. Different independent variables may count for these two models. For modeling non-SOV commuting trips, the idea is that there are a group of factors causing something qualitatively different about people who never have non-SOV trips versus those who do. Likewise, there can be something qualitatively different about people who always have non-SOV trips versus who only do sometimes.

$$pr(Y_i = y_i | X_i) = \begin{cases} p_i, & y_i = 0 \\ \frac{(1-p_i)e^{-\mu_i} \mu_i^{y_i}}{(1-e^{-\mu_i}) y_i!}, & y_i > 0 \end{cases} \quad [E6]$$

where P_i is the probability of extra zero counts, y_i is the number of event occurrences, μ_i is the mean number of event occurrences.

5.2 Measures of Model Goodness-of-Fit

5.2.1 Likelihood Ratio Chi-square Statistic

The maximum likelihood estimation (MLE) with the log likelihood (LL) ratio test [E7] is most common approach to measure count data models. It is an iterative procedure to adjust the coefficients of each predictor variable based on Chi-square(χ^2). Until there is no additional improvement in the ability to predict the value of the outcome variables, the model will be called converged model. The null hypothesis that the converged model is not statistically better than the base model with no coefficients can be rejected if the likelihood ratio is larger than χ^2 value with a degrees of freedom equals to the difference in the number of parameters between those two models (Kim and Susilo 2013).

$$2(LL_{converged} - LL_{base}) \sim \chi^2 \text{ (number of new parameters in converged model)} \quad [E7]$$

5.2.2 Pseudo R^2 & Adjusted Pseudo R^2

The Pseudo R^2 and adjusted Pseudo R^2 [E8, E9] are used to measure the capability of a model to explain the variability of the dependent variable. The log likelihood of the base model is a total sum of squares indicating the variability of the dependent variable, and the log likelihood of the converged model is the total sum of squared errors indicating the variability of the dependent variable that is not predicted by the model. Thus, by subtracting the log likelihood ratio from 1, Pseudo R^2 explains how much variability have been explained by the model. It ranges from 0 to 1 with higher values indicating better model fit. With comparison, the adjusted Pseudo R^2 takes

an extra consideration of the effectiveness of each predictor to the model. Therefore, the adjusted R^2 may decrease with an addition of a predictor, even if the R^2 increases.

$$Pseudo R^2 = 1 - \frac{LL_{converged}}{LL_{base}} \quad [E 8]$$

$$Adjusted Pseudo R^2 = 1 - \frac{LL_{converged} - K}{LL_{base}}, \quad K = \text{number of parameters} \quad [E 9]$$

5.2.3 Akaike & Bayesian Information Criteria

Both Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC) are estimates of the relative information lost when a model is used to represent the “true model”. As [E10] and [E11] shows, they have a constant plus the relative distance between the true likelihood function of the data and the fitted likelihood function of the model. The difference between AIC and BIC are the heaviness of the penalty for the model complexity. Though they do not estimate the absolute quality of a model, it indicates the quality relative to other models. Therefore, given a set of models for one dataset, the smaller the AIC/ BIC value, the better the model fits, given that they have the same number of parameters.

$$AIC = -2LL_{converged} + 2K, \quad K = \text{number of parameters} \quad [E10]$$

$$BIC = -2LL_{converged} + \log(n)K, \quad K = \text{number of parameters} \quad [E11]$$

6 RESULTS

6.1 Model Comparison

6.1.1 Model Fit

The results of 4 models are summarized in **Table 6-1**.

1. “One-component” Model

Poisson and NB are “one-component” model with one function. The observed mean and variance of the response variable (the number of non-SOV commuting days during one weekday) across all participants were 1.82 and 4.71, respectively. Thus the observed variance to mean ratio is 2.59, indicating an over-dispersion. Same as we expected, the overdispersion test for the Poisson model indicates the data is indeed overdispersed. In contrast, the dispersion parameter of NB is $0.606 < 1$, meaning NB model successfully handles the problem. When comparing the estimates of Poisson and NB model, there is a pattern that Poisson model underestimates the effects of the majority of independent variables, yet more variables are insignificant in NB model. The much higher value of AIC and BIC for Poisson model also reflect the issue of under-fitting. In sum, all the information reveals the potential risk of erratically applying a model when the underlying assumptions are violated.

Though the statistics suggests that NB model is better than Poisson model, there is no way to confirm the goodness of NB per se, because as Figure 3-3 shows, the response variable also has a great number of zero count (52.33%). This feature may not be adequately handled by neither Poisson model nor NB model, therefore more robust models have also been tested.

2. “Two-component” Model

The ZINB and hurdle model are “two-component” models with two functions. It is surprising that the results of these two models are quite similar, which means the logistic regression model almost predicts all the zero counts as “structural zeros” -- people report zero simply because they

never have a non-SOV at all. This turns out very few zeros are counted into step 2 NB model in ZINB model, and thus two models almost become the same. We do have good reasons for this phenomenon. As discussed previously, to make sure the dataset more representative and relevant, only those survey responses from people who indicated that all the reported information was for a typical commuting week, thereby large portion of “sampling zeros” were excluded at the first place. We may argue that this is actually a very good sign, which not only demonstrates the high accuracy of participants’ responses, but also makes sure the representativeness of travel behaviors our model will capture.

It is worth noting that as **Table 6-1** listed, though both negative binomial models in ZINB model and hurdle model are quite similar, the coefficients of zero-inflated model always have opposite signs compared to zero-hurdle model. This is due to their different interpretation of logistic model, the former is interpreted as the probability of being zero counts of dependent variable (zero non-SOV commuting day), while the latter is the probability of having at least one count of dependent variable (at least one non-SOV commuting days). Essentially, they are the counterpart of each other.

Since hurdle model has a lower AIC value, lower Chi-square(χ^2) value, higher pseudo R^2 , we may get the conclusion that hurdle model is slightly better than ZINB model. Besides, to determine if hurdle model is an improvement over standard NB model, a Vuong test was performed. It turned out to be statistically significant.

Table 6-1 Results of Poisson, NB, ZINB & Hurdle Models

Poisson				Negative Binomial			Zero-inflated NB				Hurdle		
Variable	Estimate	S.E.	p-value	Estimate	S.E.	p-value	Variable	Estimate	S.E.	p-value	Estimate	S.E.	p-value
							Zero-inflation Model				Zero-hurdle Model		
(Intercept)							(Intercept)	1.5110	0.1025	***	-1.5380	0.0989	***
fulltime							fulltime	-0.1629	0.0806	*	0.1729	0.0778	*
disWCB							disWCB	0.0809	0.0032	***	-0.0865	0.0030	***
disHW							disHW	-0.0119	0.0007	***	0.0119	0.0007	***
lenPed							lenPed	-0.0293	0.0033	***	0.0282	0.0032	***
numStop							numStop	-0.0416	0.0016	***	0.0410	0.0015	***
entropy							entropy	-0.3787	0.0630	***	0.3733	0.0611	***
EmplTotal							EmplTotal	0.0001	0.0000	***	-0.0001	0.0000	***
sovParkfee							sovParkfee	-0.4264	0.0210	***	0.4221	0.0202	***
tran_subsidy							tran_subsidy	-0.4656	0.0287	***	0.4594	0.0277	***
share_subsidy							share_subsidy	0.1269	0.0185	***	-0.1378	0.0178	***
telework							telework	-0.1621	0.0213	***	0.1436	0.0207	***
amenity							amenity	-0.2096	0.0314	***	0.2133	0.0303	***
service							service	0.2061	0.0358	***	-0.1952	0.0344	***
							NB Model				NB Model		
(Intercept)							(Intercept)	1.2014	0.0363	***	1.1950	0.0363	***
fulltime							fulltime	0.0781	0.0310	*	0.0799	0.0311	*
disWCB							disWCB	-0.0324	0.0014	***	-0.0324	0.0014	***
disHW							disHW	0.0019	0.0002	***	0.0018	0.0002	***
numStop							numStop	0.0053	0.0005	***	0.0054	0.0005	***
disStop							disStop	0.0555	0.0077	***	0.0572	0.0077	***
sovParkfee							sovParkfee	0.0454	0.0070	***	0.0461	0.0069	***
tran_subsidy							tran_subsidy	0.0203	0.0111	.	0.0217	0.0111	.
share_subsidy							share_subsidy	-0.0582	0.0068	***	-0.0574	0.0067	***
nonveh_subsidy							nonveh_subsidy	0.0174	0.0071	*	0.0166	0.0071	*
compress							compress	-0.0496	0.0079	***	-0.0503	0.0080	***
telework							telework	-0.0576	0.0078	***	-0.0562	0.0078	***
amenity							amenity	0.0405	0.0113	***	0.0389	0.0113	***
service							service	0.0358	0.0136	**	0.0383	0.0136	**
Observations	68063			68063				68063			68063		
Dispersion Parameter	--			Θ 0.606				Log(Θ) 11			Log(Θ) 16		
LL Ratio Test	27784			6670				10382			10386		
—2* LL	279759			236869				206552			206547		
Pseudo R2	0.0903			0.0274				0.0479			0.0488		
Adjust Pseudo R2	0.0902			0.0272				0.0476			0.0476		
AIC	279793			236903				206609			206605		
BIC	279948			237058				--			--		

Significance Code: Pr(>|z|) 0.000 ‘***’, 0.001 ‘**’, 0.01 ‘*’, 0.05 ‘. ’, 0.1 ‘ ’, 1

6.1.2 Model Prediction

The prediction power is also a critical criterion for model comparison. As explained, a cross-validation process had been implemented: 80% of data points (N=68,063) were used to train the model, then the converged model we got was fitted to rest of 20% of data points (N=16,815). The predicted values indicate what outcome would be expected given the patterns observed between independent variables and dependent variable, which is reflected in our predictive model. In order to compare the outcome from model prediction with observation, the probability of each outcome (non-SOV day count can be 0, 1, ..., 5) was estimated for each case in the data, then those expected probabilities of each sample was summed up to obtain the expect counts for each outcome. **Figure 6-1** and **Table 6-2** show the frequency of non-SOV day counts from observation (bar chart) and predictions from 4 models separately (line charts).

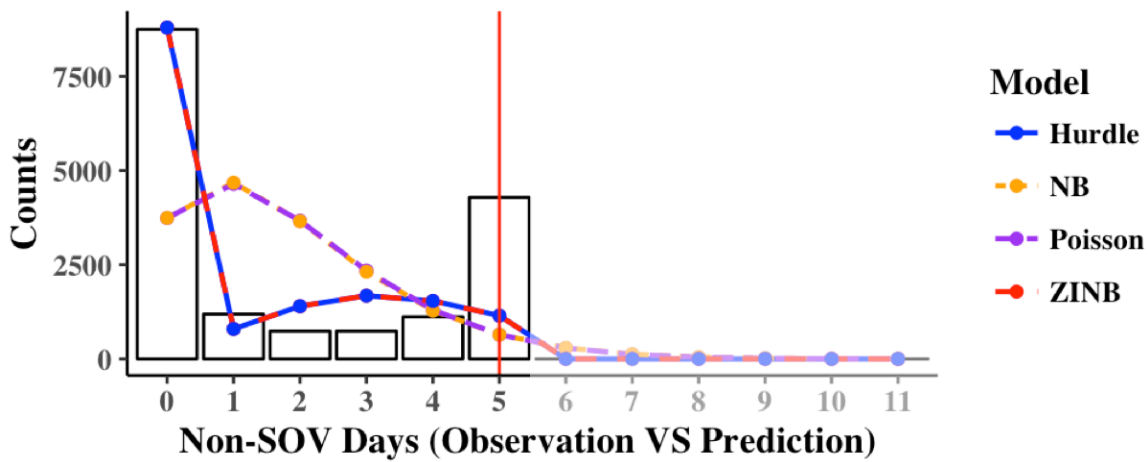


Figure 6-1 Comparison between observation and predication

Table 6-2 Counts of prediction from Poisson, NB, ZINB & Hurdle Models

0	1	2	3	4	5	6	7	8	9	10	11	Model
8748	1190	737	737	1117	4286	0	0	0	0	0	0	Observation
3739	4644	3669	2345	1301	644	288	118	44	16	5	2	Poisson
3742	4679	3655	2311	1283	644	296	126	50	19	7	2	NB
8797	796	1399	1677	1538	1149	0	0	0	0	0	0	ZINB
8796	795	1399	1677	1539	1150	0	0	0	0	0	0	Hurdle

Here are several findings. 1) Both of Poisson and NB predict values that more than 5. This is not uncommon for an unbounded count model, but it is hard to interpret the reason and the result. 2) Poisson and NB actually have a bad prediction at zero value which is less than 50%. Besides, both of them overestimate 1 to 4 value but underestimate the counts of 5. However, based on the counts, NB has a wider range of variability due to dispersion parameter. 3) As expected, ZINB and hurdle models have very similar prediction distribution with slight differences. These two models have perfect prediction for zero value, meaning they successfully handle excessive zeros. It has in an acceptable error range for predicting values from 1 to 4, but obviously underestimate counts of 5. Essentially, the value from 1 to 5 follows a “U” shape distribution based on observation, while the prediction model is a kind of smooth bell shape. Overall, it has a good classification rate (= accurate predication / total observation) of 81.35%.

6.2 Hurdle Model Interpretation

Based on all the foregoing comparison, we may now get the conclusion that hurdle model is the best model.

As explained, hurdle model is a “two-component” model. First, the zero-hurdle (ZH) model (binomial logistic model) is generated for “structural zero”, predicting whether or not an employee would have at least one non-SOV commuting day (to make it easier to understand, the following interpretation will also refer it to “non-SOV” group versus “zero non-SOV” group). Then, the zero-truncated model (negative binomial model) predicts the frequency of the non-SOV days with positive counts ranging from 1 to 5. Since both models apply log link, it is easier for interpretation by using exponentiated estimate of each independent variable listed in **Table 6-3**, which referred to odds ratio (OR⁴) in ZH model and incident rate ratio (IRR⁵) in NB model.

⁴ In logit regression model, the odds are defined as the ratio of the probability of success (p) and the probability of failure (q) of an event, $\log(\text{odds}) = \log(p/q) = a + bx$. Take our case as an example, the OR of “fulltime” variable can be interpreted as, the odds of being a non-SOV commuter for a full-time employee is 1.1877 times that of that for a part-time employee, while controlling all other variables in the model.

⁵ In negative binomial model, the model coefficients are interpreted as the difference between the log of expected counts by one unit change in the predictor variable, which is equal to the log of their quotient,

The former represents for the odds of being in a non-SOV commuter versus zero non-SOV commuter, while the latter indicates the rate of non-SOV day count. The “% change” was calculated as OR/ IRR minus 1, indicating the percentage of increase or decrease.

Noticing that different predictive variables in ZI model and NB model, suggesting that some variables are significant in predicting whether someone is in “non- SOV” group or not, but not necessarily in predicting the counts of non-SOV days, and vice versa. Following sections are the interpretations of each variable. All situations are discussed under the condition with one-unit change of an independent variable when holding other variables constant.

Table 6-3 OR & IRR of hurdle models

Variable	Zero-hurdle Model				NB Model			
	OR	% Change	Confidence Interval		IRR	% Change	Confidence Interval	
			2.5%	97.5%			2.5%	97.5%
(Intercept)	0.2148	-78.52%	0.1770	0.2608	3.3035	230.35%	3.0766	3.5471
fulltime	1.1887	18.87%	1.0206	1.3844	1.0831	8.31%	1.0192	1.1511
disHW	1.0120	1.20%	1.0106	1.0134	1.0018	0.18%	1.0014	1.0023
disWCBD	0.9171	-8.29%	0.9117	0.9226	0.9682	-3.18%	0.9655	0.9708
lenthPed	1.0286	2.86%	1.0221	1.0352	--	--	--	--
numStop	1.0418	4.18%	1.0387	1.0449	1.0055	0.55%	1.0044	1.0065
disStop	--	--	--	--	1.0589	5.89%	1.0430	1.0751
entropy	1.4525	45.25%	1.2887	1.6372	--	--	--	--
EmplTotal	0.9999	-0.01%	0.9999	1.0000	--	--	--	--
sovParkfee	1.5252	52.52%	1.4659	1.5869	1.0472	4.72%	1.0330	1.0615
tran_subsidy	1.5832	58.32%	1.4994	1.6716	1.0219	2.19%	0.9999	1.0444
share_subsidy	0.8712	-12.88%	0.8414	0.9022	0.9443	-5.57%	0.9319	0.9568
nonveh_subsidy	--	--	--	--	1.0167	1.67%	1.0027	1.0309
compress	--	--	--	--	0.9509	-4.91%	0.9362	0.9659
telework	1.1544	15.44%	1.1086	1.2022	0.9453	-5.47%	0.9310	0.9599
amenity	1.2377	23.77%	1.1664	1.3134	1.0397	3.97%	1.0169	1.0630
service	0.8227	-17.73%	0.7690	0.8801	1.0391	3.91%	1.0118	1.0671

$\log(\mu_{X0+1}) - \log(\mu_{X0}) = \log(\mu_{X0+1}/\mu_{X0})$. This explains the “ratio” of the IRR. Besides, even though the response variable is count data, in essence, it is the number of events occurring per unit of time, thus it is also referred to “rate”. In addition, the rate at which events take place is called the “incident rate”. Take our case as an example, the IRR of “fulltime” variable can be interpreted as, if a people were to change his employment status from part-time to full-time, his rate for non-SOV commuting days would be expected to increase by a factor of 1.0831, or increase 8.31%, while controlling all other variables in the model.

6.2.1 Demographic Features

The HW commuting distance and employment status are the two demographic features we can capture, and they are significant in both ZH model and NB model. There is an expected 1.20% increase of the odds of being a non-SOV commuter for every mile increase in the home-worksite distance. Likewise, every additional mile in commuting distance leads to an increase the rate of non-SOV day by 0.18%. This is consistent with the observation shown by **Figure 4-4** that the average carpool/vanpool/commuter rail trips and flexible work days increase as the HW commuting distance increase.

For the employment status, the OR in ZH model suggests that the odds of being a “non-SOV” commuter increase 18.87% for a full-time employee, and the rate for non-SOV commuting day increase 8.31%, comparing to a part-time employee. This reflect the finding from the literature discussed before as well as the observation shown by **Figure 4-6**. Part-time employees may have more trip chains due to frequent work schedule shifts, which makes them more vehicle dependent.

6.2.2 Built Environment Characteristics

5 and 3 built environment variables were observed to be significant in ZH model and NB model, respectively. The small magnitude of the coefficients indicates that the effects of the built environment variables on commuters’ mode choice are marginal, yet most of them are consistent with findings in the literature.

1. Longer worksite-CBD discourage non-SOV commuters and decrease non-SOV travel frequency.

The ZH model suggests that the odds of a person being in “non-SOV” group decreases 8.29% for every additional mile of worksite-CBD distance. Likewise, the NB model indicates that the impacts of spatial distances are also positive for decreasing non-SOV day counts. The expected decrease in non-SOV counts of additional mile of worksite-CBD distance is 3.18%. This makes a lot of practical sense areas near downtown are normally equipped with excellent transit services

and other facilities, therefore employees can rely on alternative modes for travel and thus less dependent on their cars.

2. Higher walkability and mixed land use in areas within quarter mile from worksites increase the odds of employees to be non-SOV commuters, while these variables are found not significant in impacting non-SOV travel frequency.

In the ZH model, the ORs suggest that the odds of an employee to be non-SOV commuters increase 2.86% and 45.25% with an additional mile of walkable path and an additional unit of mixed land use index (entropy) within quarter mile from worksites, respectively. The unexpected high effect of land use index is because the index is weighted from 0 to 1. Therefore, a 45.25% increase of the odds only expected to happen hypothetically when a place is transferred from a monotonous land into an extremely diverse area. As NB model shows, however, both variables are not significant. This implies that those factors can be considered as one part of the reasons why commuters only drive alone or make mode shifts from time to time, yet they are not directly correlated to the travel frequency.

3. Increasing the number of transit stops increase employees' non-SOV dependency and encourage higher non-SOV travel frequency. One the other hand, the distance to the nearest transit stop from worksite was unexpectedly found to increase non-SOV day counts as well.

The OR in ZH model indicates that an additional transit stop associated with a 4.18 % increase in the odds of being non-SOV dependent. The IRR in NB model also suggests a 0.55% increase of non-SOV day counts for every additional transit stop within quarter mile from the worksite. Nevertheless, what beyond expectation is that the distance to the nearest transit stop has the similar impacts, in NB model, but not significant in ZH model. It shows that the longer the walking distance to a transit stop, the rate of having more non-SOV trips increase 5.89%. One possible reason is as **Table 4-1** built environment variable correlation matrix indicates, the number of transit stops does have a negative 0.347 correlation to the distance to the nearest transit stop. Even though the correlation is still relatively small, these two variables could

collectively represent the transit accessibility and spatial concentration, therefore, one coefficient probably be a trade-off of the other.

6.2.3 CTR Policies

Since the availability of CTR policies were coded by dummy variables (0/1), the OR in ZH model and IRR in NB model are in a much larger magnitude. Unlike demographic features and built environment characteristics that normally have same trend of impact on non-SOV mode dependency and non-SOV travel frequency, CTR policies have more dynamic impacts on employees' commuting pattern.

1. Requiring SOV parking fee on worksite is validated to be an effective “push” policy to encourage non-SOV commuter and also increase non-SOV travel frequency.

As OR in ZH model suggested, the odds of being non-SOV dependent increase 52.52% if SOV parking fee is required in worksites. The IRR in NB model also indicates the implementation of parking fee associates with 2.19% of increasing in the non-SOV commuting days. This result is consistent with previous literature as well as observation in our case, shown by **Figure 4-10**.

2. As “pull” policies, transit subsidy significantly increases non-SOV dependency and encourage more non-SOV commuting days. The non-vehicle subsidy was also found to have significant positive impact on non-SOV travel frequency. However, carpool/ vanpool subsidy has an unexpectedly opposite effects on both.

The policy of providing subsidy shows a dynamic effect. On the one hand, the ZH model suggests that the availability of transit subsidy increase the odds of being in non-SOV dependent by 58.32%. The corresponding result is also observed in NB model that it relates to 2.19% increase of non-SOV days. On the other hand, the carpool/vanpool subsidy seems to deviate from the goal of encouraging non-SOV trips, which is indicated by the opposite sign of “share_subsidy” variable in both ZH model and NB model. The effects from carpool/vanpool subsidy also defy the empirical observations for increasing non-SOV trips.

3. *Compressed working schedule and teleworking option effectively increase non-SOV dependency, yet they were also found to decrease non-SOV travel frequency.*

It is worth noting that any alternative ways to SOV are considered as non-SOV. Therefore, even though employees who telework probably didn't generate trips at all, this working day is also counted as non-SOV day. As indicated by ZH model, teleworking has an outstanding positive effect to increase the odds of being non-SOV dependent by 15.44%. However, compressed work schedule and option of teleworking actually decrease the rate of non-SOV commuting days. As the IRR suggests, employees with those two policies have 4.91% and 5.47% lower rate of non-SOV commuting days. This dynamic impacts may also reflect by the actual observations, depicted by Figure 4-13, that people with the option of compressed working schedule have unexpectedly lower non-SOV travel frequency comparing to people who are not.

4. *Worksite amenities encourage non-SOV commuters and both amenities and services help to increase non-SOV commuting days.*

As the ZH model shows, worksite amenities like covered/uncovered spaces, cages, racks, or lockers for bicycles, and on-site loading/unloading zones or shelters for non-SOVs increase the odds of being non-SOV commuter by 23.77%. In contrast, worksite services such as cloth lockers and showers were surprisingly found to discourage non-SOV commuters. Notwithstanding, in NB model, both two policies are expected to increase the counts of non-SOV commuting days by 3.97% and 3.91%, respectively.

6.3 Overall Impacts of Policy Package

Figure 6-2 summarizes the results from the hurdle model and the impact of each individual variable. The demographic characteristics and the built environment factors show more consistent impacts on encouraging non-SOV commuters and increasing non-SOV travel frequency, yet CTR policies show more dynamic impacts.

Except for the impact from each individual variable, we are also interested in the overall impact of the policy package. In this case, the demographic characteristics and built environment factors were estimated with the mean value of all the samples in “test” group, while the CTR policies dummy variables were set to be all unavailable (“0”) and all available (“1”), respectively. The results indicate that the probability for this “typical” employee of being non-SOV commuter increase 22%, from 32.86% to 54.87%, while the mean count of its non-SOV commuting days actually decrease 0.008, partially due to the under fitted of NB model for zero-truncated data counts.

In conclusion, we are more confident about the predict power of zero-hurdle model, which predicts that the overall CTR policy package increase the probability for this “typical” employee of being non-SOV commuter increase 22%. However, the overall impacts on non-SOV day counts need further study.

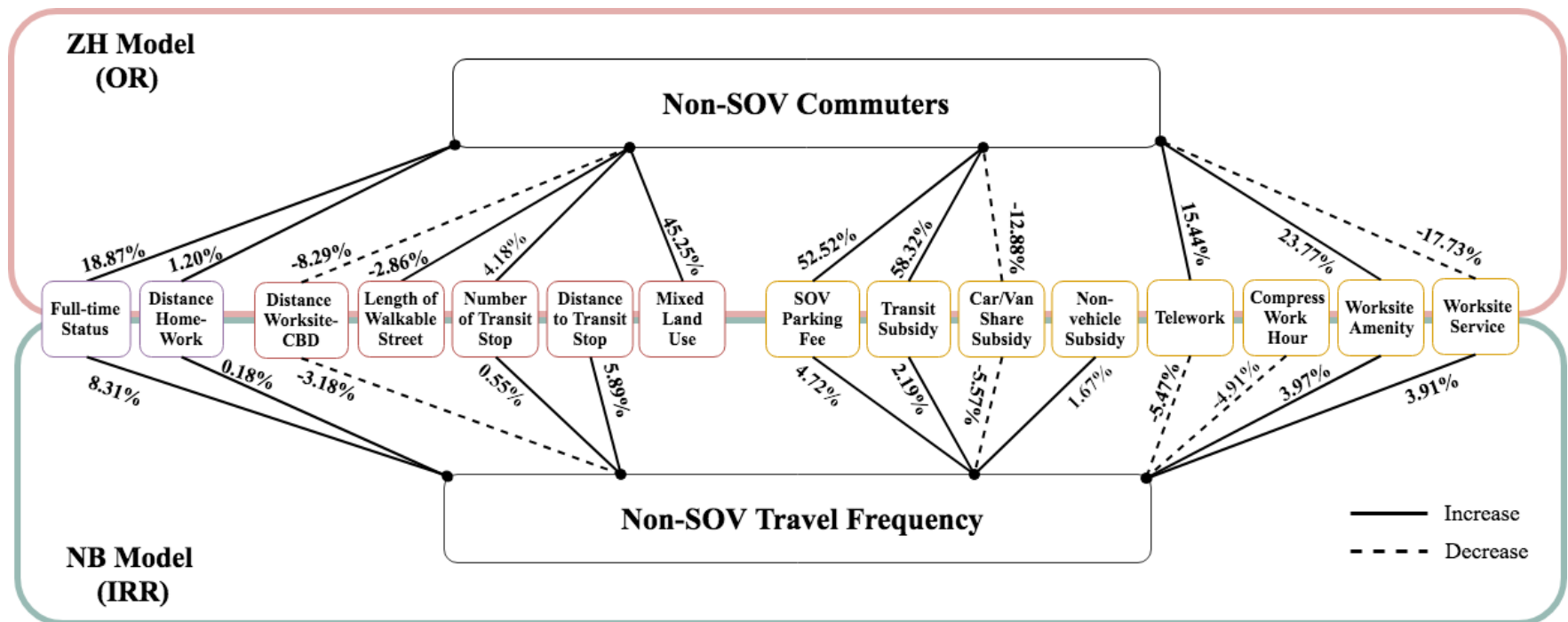


Figure 6-2 Relations among all variables

7 CONCLUSIONS & POLICY RECOMMENDATIONS

7.1 Conclusions

The aim of this study is to measure the effects of CTR program on commuters' choice of non-SOV modes, by exploring the interrelationships among employee demographic characteristics, worksite built environment factors and CTR policies. 84,878 employees from 379 worksites, mainly located in 5 counties in WA State (King, Kitsap, Pierce, Snohomish and Spokane), were examined in the study.

Taking non-SOV commuting day counts during one surveyed weekdays as the dependent variable, 4 types of count model (Poisson model, NB model, ZINB model and hurdle model) were implemented individually. The hurdle model was selected as the final model due to better goodness-of-fit, the accuracy of model prediction and the practical sense of model interpretation. The results of this research are consistent with previous literature that employee demographic characteristics, worksite built environment factors and CTR policies all have impacts on commuters' mode choice and travel behavior. This chapter attempts to highlight some critical findings from this study by answering the 3 research questions.

1. What are the basic characteristics of employees' commuting trips in WA state?

Though driving alone was still the dominate mode among employees, nearly 40% of all commuting days were by non-SOV modes, which was much higher than national average (23.6%) and statewide average (27.4%) (Washington State CTR Board 2017)⁶. More specifically, throughout the surveyed weekdays, 55.33% of employees commuted exclusively by SOV, 25.31% commuted exclusively by non-SOV modes, with the rest of 22.36% switched between those two modes from time to time. Overall, the distribution of the non-SOV day counts reflects an apparent pattern that people are more likely to stick on one mode all the time, rather than switch modes frequently.

⁶ The national and statewide average non-SOV mode share were measured in 2015.

2. How do demographic features, worksite built environment characteristics and CTR policies affect employees' non-SOV mode choice and travel frequency?

The hurdle model is a “two-component” model which generates two sets of results. The zero-hurdle model is a binomial logistic regression model predicting the odds of an employee being a non-SOV commuters, meaning having at least one commuting day by non-SOV mode during weekdays. The zero-truncated model is a negative binomial model predicting the rate of non-SOV travel frequency. Those three groups of factors were all found significant in two models, though individual elements inside have more dynamic impacts. More specifically, SOV parking fee management, transit subsidy and worksite amenity were found to be positively significant on increasing the odds of being a non-SOV commuter as well as increasing the non-SOV travel days. However, teleworking, compressed working schedule and worksite services tended to make opposite effects on both models. Most surprisingly, carpool/ vanpool subsidy was found to be negatively associated with the odds of being non-SOV commuter as well as non-SOV commuting day counts.

3. What is the overall impact of CTR policy package?

The overall impact of all policy element within the CTR policy package was estimated to increase the probability for a “typical” employee of being non-SOV commuter by 22%. The overall impact of the policy package was actually decrease by several elements, such as carpool/vanpool subsidy which was consistently found to have opposite impacts compared to other commuter benefits. More analyses are needed to untangle the interaction among the policy package.

7.2 Policy Recommendations

After exploring the interactions among all the factors, the more essential question is how to design the policies by fully incorporating commuters' interests, demographic characteristics and worksite built environment factors, and thus achieving the maximum impacts on people's mode choice and travel behavior. Obviously, there is no one-size-fit-all approach to addressing complex transportation issues, yet finding underlying patterns may help to explore the directions

for future efforts. Here are some recommendations for policy implementation based on findings from this study.

1. It is more effective to provide commuter benefits based on employee's unique demographic feature.

As indicated, the average non-SOV travel frequency by modes differ significantly among people with different commuting distance --biking and walking obviously only work for short distance, while the carpool/vanpool service is more prevalent among commuters with longer commuting distance. Therefore, with finite resources and subsidies, the most effective approach is to customize policies based on employees' demographic features and transportation profiles.

2. It is important to coordinate public infrastructure and services with CTR policies.

The study revealed that transit accessibility, mixed land use and walkability encourage non-SOV modes, thus it is essential to take public infrastructure and services into policy consideration as well. For instance, there are more than 6% of worksites in this study where provided transit subsidy to employees yet located more than a quarter mile away from their nearest transit station. To make transit subsidy fully play the role, transit services should be promoted simultaneously, or other alternatives should be considered, such as bike share to deal with the last mile commute, or establish an internal shuttle services. Besides, to reduce the needs of driving, areas around employment center should be with easier access to services, such as restaurants, banks and coffee shops, without driving. Likewise, a safe, walkable pedestrian network itself is a big attraction for walking trips.

3. The better way of estimating program performance is by policy implementation rate in individual level, rather than policy adoption rate in worksite level.

Currently, the way to estimate the policy performance is by aggregating each individual's mode choice into worksites' mode share, which is then related back to policies implemented in worksite level. However, the study revealed that there is a gap between worksite policy availability and employee policy implementation. In other words, a worksite may have multiple commuter benefits available, yet few employees actually implement it. Therefore, it is more accurate to measure the policy performance from employees' end.

The following discusses two possible reasons for the gap and what can be done to improve the performance. First of all, employees don't implement certain policies simply because they don't know they exist. If this is the case, more promotion activities and education may be needed, although 98% of ETCs reported that they had implemented at least one type of program promotion in the employer survey. The second scenario relates to the easiness of getting actions started. The carpool/vanpool program normally requires vehicle registration and rider-matching. People probably don't have the strong motivation to take action and go through the pre-process. If this is the case, employers may consider having ETCs as mediators or online ride-matching services to make things easier. In sum, the criteria for measuring the policy implementation should not be limited to how many options exist in the worksite, but the percentage of employees are implementing it.

4. Parking management policy is one of the most effective way to encourage non-SOV commuters and increase non-SOV trips.

Parking management policy was referred to both parking space management and parking fee management. This study revealed that the more available parking spaces, the less likely for the employers to require parking fees. However, the study clearly indicated that the SOV parking required had significant impacts on shaping commuters' mode choice and travel frequency. Notwithstanding, only 15.88% of worksites and 6.56% of employees in the study managed parking fee and paid parking fee in practice. Therefore, more efforts are required to advocate this policy.

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9 APPENDIX

CTR employee survey questionnaire



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 business 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 ☐ Nine people
☐ Two people ☐ Ten people
☐ Three people ☐ Eleven people
☐ Four people ☐ Twelve people
☐ Five people ☐ Thirteen people
☐ Six people ☐ Fourteen people
☐ Seven people ☐ Fifteen or more people
☐ Eight 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

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!