

**Intermodal Transfers to Light Rail:  
Using smartcard data to estimate transfer barriers in Seattle, WA**

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## **Abstract**

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Transfers are a necessary inconvenience to public transit riders. They support strong hierarchical networks by connecting various local, regional, and express lines through a variety of modes. This is true in Seattle where many lines were redrawn to feed into the Link Light Rail network. Previous studies using surveys found that perceived safety, distance, and personal health were considerable predictors of transfers. This study aims to use smartcard data and generalized linear modeling to estimate which elements of transfers are commonly overcome – and which are not – among riders boarding the Link Light Rail in Seattle and its suburbs. In this process, this study also seeks to elicit any equity implications about these barriers by comparing transfer counts with the characteristics of ridership of the destination stations and origin lines. The results of this modeling suggest broad agreement with previous studies on transfers, specifically identifying distance and perceived safety as key determinants of transfers.

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## Introduction

High-quality modern public transportation systems should support connectivity, mobility, and access between modes. In other words, trips between an origin and destination should be safe, easy, and dependable regardless of the mode of travel. If a trip involves multiple modes of transit – for example, a bus to light rail connection – the planning of that connection should minimize barriers to making that transfer, where possible. Doing so supports the utility of the network, by offering clear and accessible paths that reduce the disruption of transfers as much as possible.

Transfers, in any case, are a necessary and unavoidable part of any public transit network. The necessity of transfers is especially true in cities with various multimodal options and a clear hierarchy to the network (e.g. regional, rapid, and local transit options). In the case of Sound Transit’s Link Light Rail system – connecting Seattle and its surroundings – 27.6% of riders transfer from other modes of transit. Given the ambitious planned expansions of the network into new cities and neighborhoods, it is imperative that the network understands and maintains a good transfer experience for its riders.

Despite the importance of transfers and the necessity of their existence, they can be an overlooked facet of transit planning’s broader goals. While a group of transit operators surveyed by the U.S. Federal Transit Administration (1996) considered “reducing rider difficulty” the second-highest priority in their transfer system objectives, only three of the 31 respondents offered concrete goals or objectives related to passenger convenience, revenue generation, or other factors. The rest offered transfer rules, but lacked coordinated transfer policy to improve the user experience of the system. The study indicates that transfer policy specifically refers to an agency’s set of guidelines to support transfers, rather than simply the cost or timeline for transfers. Despite naming that transfers are clearly both necessary and disruptive, many operators lack clear approaches to supporting transfer experiences. Optimizing transit users’ experiences requires that planners consider the transfer a crucial part of the trip, and develop policies which support them.

## Transfer Experience and Penalties

The user experience of making connections within systems and between them is crucial in supporting positive public perceptions of transit networks and their success (Cheng and Chen, 2015; Currie, 2005). Previous studies have found the disruption to travel caused by a transfer plays a key role in whether people take transit at all (Cascajo et al., 2019). As a result, transfers can be a ma-

major barrier to the user experience of transit in both perception and relative cost (Garcia-Martinez et al., 2018). While studies have begun to look more closely at transfer penalties in travel demand modeling (Yu et al., 2012; Iseki and Taylor, 2009; Guo and Wilson, 2004), explaining major barriers to transfers based on observed data is a limited field of literature.

Transfer penalties applied in the cost functions frequently used for transit optimization and modeling often appear as a standalone variable. As in Currie (2005), this takes the generalized form as follows.

$$TGC = ((Walk_t * Walk_w) + (Wait_t * Wait_w) + (IVT_t * IVT_w) + (NT * TP) + MSC_m) * VOT + Fare \quad (1)$$

where:

$TGC$  = Transit Generalized Cost

$Walk_t$  = Walk time in minutes to and from Transit service

$Walk_w$  = Passenger valuation of  $Walk_t$

$Wait_t$  = Wait time for transit vehicle to arrive at the stop

$Wait_w$  = Passenger valuation of  $Wait_t$

$IVT_t$  = Transit time in vehicle(s)

$IVT_w$  = Passenger valuation of  $IVT_t$

$NT$  = Number of transfers

$TP$  = Transfer penalty

$MSC_m$  = Mode-specific constant for mode  $m$

$VOT$  = Value of travel time

$Fare$  = Fare per trip

This is meant to capture the generalized cost effect of transferring during a given trip. However, whether this penalty is meant to include both measurable costs (e.g., waiting and walking times), perceptual costs (e.g., feelings of discomfort, safety), or exist as a singular penalty is debated in the literature (Cascajo et al., 2019; Guo and Wilson, 2011). These costs can differ among groups, which also causes potential equity implications not thoroughly covered by existing research (Cheng and Chen, 2015; Guo and Wilson, 2004). Furthermore, the existing research tends to rely on survey and focus group analyses, instead of any observed data on transfers. The effect of these penalties is crucial to understanding how transfer might impact mode choice decisions of travelers. The clear negative impact of transfers is a well-trodden point in the literature (Garcia-Martinez et al., 2018).

The physical and environmental influences of transferring can include concerns about walking distances, elevation changes, or the speed of cars on the adjacent road. The perceptual and mental influences covered by focus groups and surveys include safety, anxiety, and mental disruption (Cheng and Chen, 2015). This study will focus on attempting to measure the former, where observed transfers will be used to determine how far people are willing to stretch the definition of a station area in order to travel to their destination.

### Seattle's Transit Network

The Seattle Link Light Rail system currently stretches across 16 stations in nearly 22 miles, running from Seattle's University District to Angle Lake in Seatac (Sound Transit, 2016). In 2019, Link trains were boarded 79,674 times per week, on average. In 2008 and 2016, voter-approval of further system expansion has led to an ambitious plan for 37 new stations – including stations for Link-less Seattle neighborhoods like Ballard and West Seattle, along with connections to major job centers in major suburban cities such as Bellevue and Redmond. Given the current state of the Link, with 13 of 16 stops in Seattle and running predominantly North-South, transfers are a common and necessary part of the service. This is not necessarily unique to the Link, as the U.S. Federal Transit Administration (1996) point out that the riders in cities across the U.S. predominantly transfer from bus to rail.

The planning and design process of the Link Light Rail (LLR) system and its expansion takes this well into account. In many cases, local transit authorities reroute existing bus lines to serve as more effective “feeder lines” for the LLR. In others, these agencies choose to forgo redundant bus lines altogether (Lindblom, 2019). With further expansion on the horizon, Sound Transit and other local and regional planning agencies continue to follow this process (Sound Transit, 2016). As bus routes – local and express – rearrange to serve the LLR, not all potential transfer stops land on the same block as a Link station entrance. These non-adjacent feeder stations create possible walking transfers, where reaching the LLR system involves interactions with the city beyond the light rail station itself.

### Research Goals

The main goal of this paper is to use observed smartcard transfers to estimate the effects of physical and built environment characteristics of observed transfers to Seattle's Link Light Rail (LLR)



**Figure 1.** Sound Transit Link Light Rail System Map depicting current Link stations and service. (Sound Transit, 2016)

network using One Regional Card for All (ORCA) smartcard data. The purpose of this work is to better understand which barriers are commonly overcome for transfers, and which might not be. Barriers might include physical environment concerns, such as Seattle’s hilly topography, or built environment concerns, such as the connectivity of the walking network in half-mile station areas.

This can support the broader literature about transfer penalties by offering an analysis of what features may create barriers to transferring riders. Further, this can guide station planning efforts to support more convenient high-information transfers where possible. In some cases, this might include adjusting station locations to provide clearer and more accessible routes between

stations. In others, it may involve adjustments of road design and speed limits, offering improved perceptions of safety for transferring riders.

A second goal of this analysis is to infer what overcome barriers might offer in terms of equity. In other words, can certain observed transfer characteristics relate to certain populations? By analyzing transfers through the lens of lines transferred to or from, this study hopes to identify where certain equity-focused transfers may need reexamination and adjustments to ensure that all populations have equitable access to high quality transit. Using the ORCA data's specific user types to parse this information out can offer some exploratory findings on different age and income groups' habits.



## Literature Review

This study requires the understanding of transfer penalties and their characteristics, how equity might interact with station area behavior, and the application of smartcard data towards transit modeling. In this literature review, studies about these topics will be covered with the goal of providing a historical and theoretical framework for this research. This review will begin by discussing transfer penalties and the ways they have been measured. This will be followed by a section on equity and connectivity of the transit network. Finally, the applications of smartcard data along with the strengths and weaknesses inherent to the data will be covered.

### Transfer Penalties and Characteristics

Understanding the behavior of transit users' choices is crucial to improving the connectivity and accessibility of transit networks. Literature on the effects of transfers on individual travelers can be grouped into two broad categories: studies about transfer perception, and studies about transfer modelling and utility. The former tends to identify the effects of transfers through focus groups and surveys (Cheng and Chen, 2015; Cascajo et al., 2019; Chowdhury, Ceder and Sachdeva, 2014; Garcia-Martinez et al., 2018), while the latter deals more directly with transit demand models and their implications for planning (Iseki and Taylor, 2009; Yu et al., 2012; Guo and Wilson, 2004, 2011).

The effect of perception on transfers appears to be significant. Travelers tend to avoid transfers not just due to physical effort, but also to mental effort, while disruptions to their trip also appear as greater barrier than they might be in truth (Cascajo et al., 2019). Regardless of what the true experienced transfer might involve, many find the impact of disruptions to their trip inconvenient, at the very least (Cheng and Chen, 2015). These disruptions can be perceived through physical elements, psychological elements, and transit network elements.

With regard to addressing transfer barriers, Cheng and Chen (2015) found that providing real-time information, reducing busy street crosses, and improving walking condition were some of the least effective on the perception of transit users. However, several other studies posit that real-time information can reduce uncertainty about transfers, and therefore improve the transfer experience for passengers (Cascajo et al., 2019; Ceder et al., 2013; Garcia-Martinez et al., 2018). Many studies find agreement that traffic conditions, transit service, walking convenience, and wait time have considerable impacts on travelers' transfer perceptions and actions (Cheng and Chen, 2015; Cascajo et al., 2019; Ceder et al., 2013; Garcia-Martinez et al., 2018).

In assessing the transfer penalties applied to generalized cost functions, Iseki and Taylor (2009) developed a framework for understanding what could support improved transfers. This involved deconstructing Currie (2005) generalized trip cost function transfer penalty into its possible parts. By further deconstructing the possible parts of a transfer penalty and how they are addressed in the literature, Iseki and Taylor (2009) propose a framework for transfer penalty cost construction which incorporates the fare element, the operational elements, and the physical elements of a transfer. In attempting to optimize a transit network for transfers, Yu et al. (2012) posit that transfers are an often-neglected facet of the optimization process. In an attempt to estimate the true disutility of transfers, Garcia-Martinez et al. (2018) compares the effects of a variety of trip variables between trips with some number of transfers and no transfers using both stated and revealed preference surveys.

### Transit Connectivity and Equity

Some studies have begun to explore how the connectivity of a transit network interacts with equity concerns. Welch and Mishra (2013) cover a broad scope of topics relating to connectivity and equity in attempting to establish a framework for measuring network equity. The importance of this analysis cannot be understated, as addressing equity concerns in transit networks can help address the needs of transit captive populations (Welch and Mishra, 2013; Song et al., 2018). Since then, studies have applied a variety of methods and theories to estimate how transit systems can better address equity in network connectivity.

Connections to transit begin in the first mile/last mile space – where riders either begin or end their journeys. Boarnet et al. (2017) found that the mode of station access among low wage workers in San Diego was more effective at improving job access among these workers than policies like increased frequency. This study hints at something Ingvardson and Nielsen (2019) also suggest: perceptions of transit connectivity vary by populations. In other words, the factors which appeal to low-income users may be different than those which appeal to the broader population. This is supported by other studies which found divergent transit needs in different equity populations. Among users of different ages, abilities, and backgrounds, the needs for certain elements in the transit network can differ (Cheng and Chen, 2015; Garcia-Martinez et al., 2018; Song et al., 2018).

One concern with many equity analyses is the lack of clarity and possible misinterpretation of these studies Carleton and Porter (2018). In order to pursue the equitable outcomes, equity must be clearly defined and the methods for understanding equity must be clear in their assumptions and implications. Many studies use terms such as horizontal or vertical equity (Carleton and Porter, 2018; Dodson, Gleeson and Sipe, 2004; Welch, 2013), with the latter also splitting into even more specific lenses such as socioeconomic and mobility equity. Clear definition of the type of equity of analysis and the limitations of these methods is crucial to supporting the work towards developing more equitable transportation networks.

This study will attempt to explore the vertical equity implications of the link light rail's connectivity based on observed transfers. Using data supplied about low-income, youth, and senior passengers at stations, it is possible to build a better understanding of station and line use by different populations in Seattle. In doing so, this study can begin to address whether the effects of the built environment on transfers are similar or divergent across different groups.

### Smartcard Data

Many studies of transfers and their characteristics focus on survey, focus group, or travel diary methods (Cheng and Chen, 2015; Ceder et al., 2013; Garcia-Martinez et al., 2018). One question surrounding stated preference surveys in particular is the uncertainty of how people act compared to how they say they might act (Garcia-Martinez et al., 2018). As a result, moving toward data collection which describes observed actions is crucial to better understanding transit phenomena. Travel diaries emerged as a response to the accuracy issues, as participants can log each part of their trip, but saturation remains a significant issue, as the participation element was far more involved than a survey (Stopher and Greaves, 2007).

By comparison, the relative size of smart card data offers a more holistic perspective of urban mobility characteristics at the station level. Smart card data offers a greater saturation of data, improves replicability, offers a greater range of temporal comparisons, and is easier to collect once the infrastructure is in place (Pelletier, Trépanier and Morency, 2011). Besides benefits to data gathering, smart cards also improve the general transit experience (Blythe 2004). They can also address uncertainties about cost and intermodal operability which concern some would-be transfer passengers (Cascajo et al., 2019; Garcia-Martinez et al., 2018), and provide some more granular data usable for equity-focused analyses (Carleton and Porter, 2018).

There are still some barriers to both adoption and processing of smart card data, however. First, the adoption of smart card technology comes at a high cost, and usually with some early reliability issues (Pelletier, Trépanier and Morency, 2011). Costs may currently be declining, but the startup price is still quite high, especially for smaller jurisdictions. Next, while studies have estimated the Origin-Destination matrix from smart card data (Alsger et al., 2015), smart cards do not inherently produce linked trip chains (Pelletier, Trépanier and Morency, 2011). It's possible then, that these estimated chains are not necessarily completely accurate, and could be grouping multiple separate shorter trips or separating longer trips.

## Methods

Three major sources of data underpin this research: Open Street Map, King County Metro’s Google Transit Feed Specification, and the Washington State Transportation Center (TRAC) at the University of Washington. These three sources offer the bulk of spatial and analytical data used by this project. This is partially supported by Open Street Map and Google APIs – or Application Programming Interfaces – which offer programmers access to relevant data through the use of their chosen programming language. APIs do not require the user to download massive files in order to work with the data, and many are updated frequently or in real-time. Tools such as R and Python will support the access, analysis, and presentation of this data. Using packages built for these programming languages will offer a highly reproducible working environment with plenty of opportunity for iteration.

## Data

### ORCA

Ridership and transfer observations will be supplied by the Washington State Transportation Center (TRAC) at the University of Washington. The raw data TRAC uses is supplied by Sound Transit, which administers the ORCA card program. TRAC has organized the data into an origin line to destination station matrix of transfer observations, which will be formatted in Python and prepared for the model estimation in R. TRAC has also supplied data on individual station-level use. This station level data includes breakdowns by type of user (e.g., Youth, Senior) and type of card (e.g., E-Purse, Monthly). This study will only use the user type as it is more concerned with how different groups of people might experience transfers differently. A full table of definitions and user composition can be found in Table 1. Data for this breakdown only considers the transit agencies which the transfers engage with: King County Metro, Washington State Ferries, Sound Transit, and Community Transit.

The share of each user group on the four main modes of transit (light rail, bus rapid transit, bus, and ferry) are relatively similar. A comparison across these modes can be found in Figure 3. Based on this plot, it is clear that adult users make up the majority of trips on all modes of transit – although it should be noted that they also are the “default” ORCA card and the largest share of the population as well. Among the other types, LIFT and Youth users tend to use more transit than Senior and Disabled users. This is not usually by much though, as in almost every

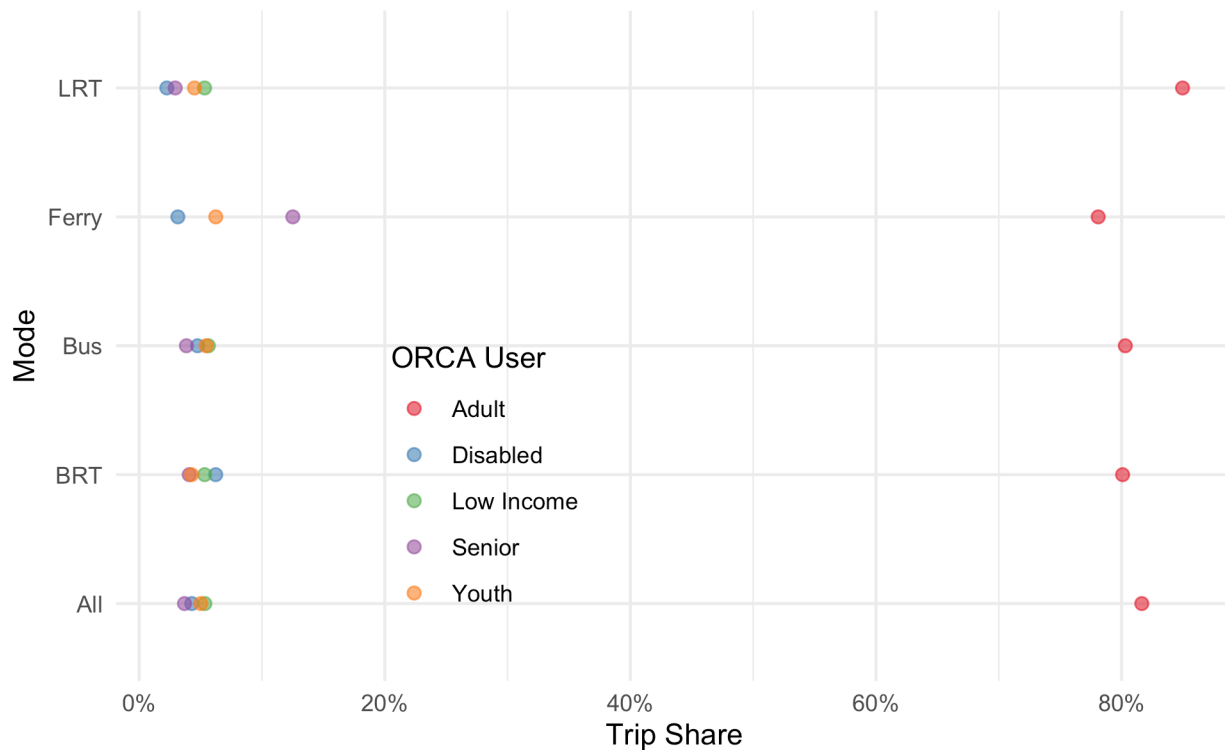
**Table 1. ORCA User Definitions**

User	Qualification	Share (%)
Adult	None	81.6%
Senior	At least 65 years of age	3.7%
Youth	At least 6, but no more than 18 years old	5.0%
LIFT	Household income less than 200% of federal poverty level	5.4%
Disabled	Disability or Medicare recipient	4.3%

Share is ridership as a percentage of all trips recorded in the 2019 TRAC data.  
 Definitions from *ORCA: Get a Card* (N.d.)

case the ridership among these non-Adult user types is within a range of 3%. This trend is only contradicted significantly on ferries, where seniors make up 12.5% of users, more than double the Youth share and four times as much as the Disabled share on that mode. Notably, the data collected shows no LIFT users on the ferry. While Washington State Ferries charge full fares for LIFT users, other ferries such as the King County Metro Water Taxi accept LIFT reduced fares. So, it is possible that LIFT ferry ridership occurs but is registered as Adult fares, or that LIFT users may not use their LIFT card at ferry boardings where they can simply buy a ticket for the ride instead of tapping their card.

The TRAC data covers two time periods in 2019: January 7 to March 23 (winter) and July 1 – August 31 (summer). These time periods are slightly unequal, so transfers and ridership numbers will be converted to weekly averages. A “transfer” defined by the ORCA card system is any boarding which occurs within two hours of a rider’s initial boarding. As a result, there are a considerable number of what might be considered “financial transfers” (Eager and Hallenbeck, 2021), or transfers which occurred within the two-hour time-frame but did not directly connect from the previous mode to LLR. In other words, there was a form of transportation besides transit or walking in between the two rides. There are also transfers from LLR “to”LLR which fall under this same categorization. In these cases, a rider may have taken the light rail, gotten off to run an errand, and returned within the two hours to qualify as a transfer. As a result, only lines with at least one weekly transfer and a station within a 1.5-mile walk will be considered reasonable transfers.



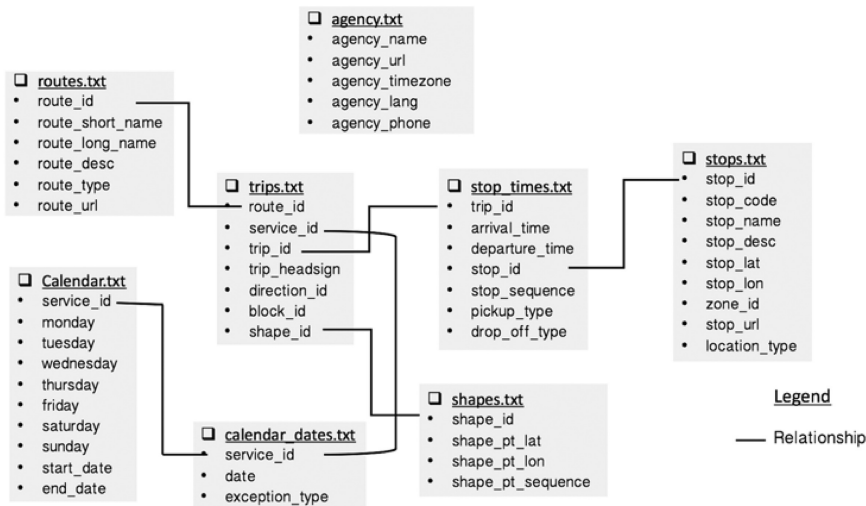
**Figure 3. ORCA User Mode Share** The percentage of all trips on each mode by each ORCA user type. Definitions of user types can be found in Table 1.

### Google Transit Feed Specification

Google Transit Feed Specification (GTFS) offers a common standard for transit agencies to publish spatial and scheduling data of their networks (Google Transit APIs, N.d.). Agencies offer static GTFS feeds made up of timetables, routes, and stops organized in several text files of relational data (Figure 4); and real-time GTFS feeds which are constantly updating with information about arrival and departure times. The static feed is offered as free and public information by King County Metro and offers the stations, timetables, and routes of both KCM and Sound Transit. This data will offer the spatial framework for identifying nearest stops on each line and line characteristics.

### Open Street Map

Open Street Map (OSM) is an open source platform for user-generated maps (Haklay and Weber, 2008). These maps include detailed data on street, transit, and walking networks around the world, supported and updated by an active community of users. For this project, OSM data will be accessed through the OSMnx package in Python, created by Boeing (2017). OSMnx couples the



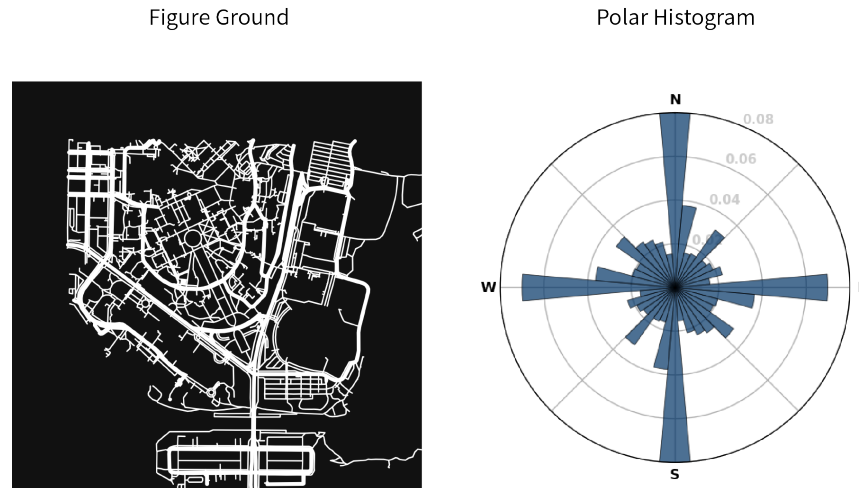
**Figure 4.** *GTFS Static Relationships* The connections between the text files which comprise static GTFS feeds (Prommaharaj et al., 2020)

complex network analysis of the NetworkX package with the data and routing from Open Street Map’s API. As a result, the package offers the ability to easily calculate network and routing metrics along with topological measures using Python. OSM does not provide native topographic data; however, OSMnx can access the Google Elevation API to add elevation data to the underlying transportation networks.

Some of the station area statistics from OSMnx are nontraditional, such as entropy and circuitry of a street network. Per Boeing (2017), the entropy of a street network is a method for evaluating the relative grid adherence of the given network. In other words, the street network entropy statistic aims to answer the question: how grid-like is a street network? Entropy is calculated by classifying the directional bearings of each network segment into bins and calculating the Shannon entropy of the complete group of bearings. This is then normalized on a scale of 0 to 1 for ease of interpretation (Boeing, 2019). An example of the binned directions and the accompanying figure ground of a station area can be found in Figure 5. Circuitry is a measure of how circuitous, or rounded, the network is. In theory, a more ordered and straight network supports a more coherent and successful transfer walking route, as the network is easier to follow.

#### Linking Sources

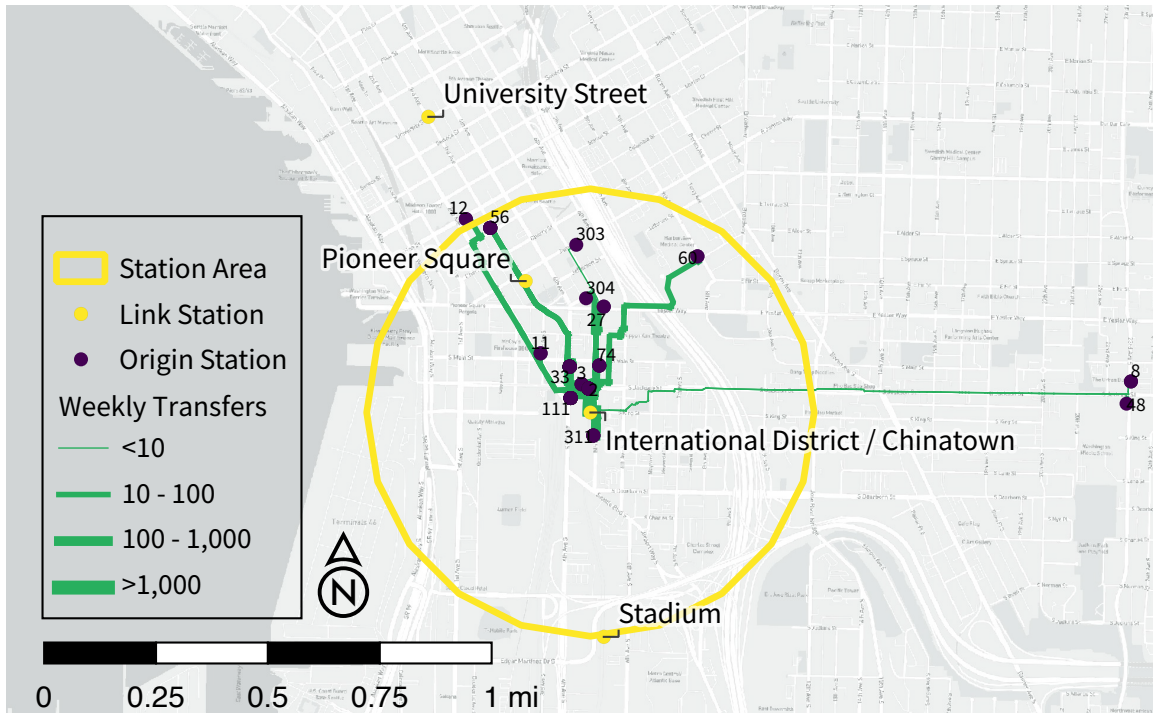
Using Python, the process of connecting these databases involves applying a few different packages for the manipulation and processing of both spatial and relational data such as pandas,



**Figure 5.** *UW Figure Ground and Histogram* Binned values of walking network direction and the accompanying figure ground of the UW station area walking network.

NumPy, and geopandas. Using these packages, the TRAC transfer data is filtered to reasonable transfers and the nearest station for each origin line is identified for the secondary filtering. The remaining stations – within the set distance and frequency standards – are then used for routing analysis. The route with the shortest walking distance is taken and metrics covering the distance, elevation change, and vehicular speed along the route are collected. For each Link station, OSMnx calculates and collects measurements of the order (or gridedness), circuitry, and density of the half-mile station area. Finally, TRAC station-level ridership data is aggregated for each complete origin line and each individual Link station to produce proportions of each ridership type (Adult, Youth, Senior, Disabled, Low-Income) in these contexts. The final versions of these variables and their groups can be found in the data dictionary (Table 2), while the process is detailed by the flowchart in Figure 7. An example of what the final routing looks like is visible in Figure 6; the transfer walking routes for all stations can also be found in the appendix on page v.

Overall, these sources of data provide the outcome, predictor, and control variables to be tested in this study. The main predictors this study is testing are those which make up the transfer walking route. These variables, such as the mean and max grade of the route, offer the clearest parallel to the transfer preference surveys which identified what riders' stated transfer preferences are (Cheng and Chen, 2015; Garcia-Martinez et al., 2018). The station area characteristics will control for how connected, dense, and ordered the street network is in the half-mile surrounding each light rail station. In theory, these characteristics will control for the possibility of other walking



**Figure 6.** *International District/Chinatown Station Transfers*

routes, as density and grid-like street networks offer more coherent walkable paths than those which are less grid-like (Boeing, 2019). Finally, the ridership metrics of both the origin line and the destination Link station will offer a lens for how willing to transfer different groups of riders are.

## Modeling

### Model Selection

To uncover this relationship, a series of negative binomial models are fit predicting the number of transfers from each likely transfer station to each paired Link station. The negative binomial generalized linear model (GLM) should provide an improvement over other common models of count data, such as the Poisson and Gaussian (linear) GLMs. This is a result of the negative binomial not falling to the same assumptions made by these other types of modeling families. The negative binomial model allows for unbounded counts, correlation between events, and assumes an overdispersed outcome.

**Table 2. Data Dictionary**

Code	Description	Source
<i>Transfer Characteristics</i>		
weekly	Weekly transfers from origin line	TRAC
origin	Most recent line ridden before the transfer to Link	TRAC
szn	Season of data collection period (winter or summer)	TRAC
<i>Transfer Walking Route</i>		
wkLen	Shortest possible walking distance	OSM
wkMnSpd	Mean vehicular speed limit along route	OSM
wkMxSpd	Maximum vehicular speed limit along route	OSM
wkGrade	Mean grade of shortest walking path	GEA
wkMxGrd	Max grade of shortest walking path	GEA
wkRise	Total elevation gain of shortest walking path	GEA
<i>Link Station Area</i>		
stEnt	Relative order (entropy) of transfer station area	OSM
stCirc	Total elevation gain of shortest walking path	OSM
stStLen	Sum of length of streets in station area	OSM
stStDen	Sum of street lengths divided by station area	OSM
stIntDen	Number of intersections divided by station area	OSM
<i>Link Station Ridership</i>		
lrLift	Percentage of LIFT (Low-Income) users at Link station	TRAC
lrSenior	Percentage of Senior users at Link station	TRAC
lrYouth	Percentage of Youth users at Link station	TRAC
lrDisable	Percentage of Disabled users at Link station	TRAC
lrAdult	Percentage of Adult users at stations on Link route	TRAC
<i>Origin Line Ridership</i>		
ogLift	Percentage of LIFT users on origin line	TRAC
ogSenior	Percentage of Senior users on origin line	TRAC
ogYouth	Percentage of Youth users on origin line	TRAC
ogDisable	Percentage of Disabled users on origin line	TRAC
ogAdult	Percentage of Adult users on origin line	TRAC

TRAC = Washington State Transportation Center  
 OSM = Open Street Map; GEA = Google Elevation API

First, the outcome of transfers between stations may have an upper bound in a given time period, but this is not clearly defined. One could use the total riders departing that station at each origin as a potential upper bound, but it's possible that by making transfers easier that the number of people using that transit line could increase as a result. Further, the data collection through ORCA does not precisely count alighting at each bus station because there is no requirement to “tap off” at each bus stop. Alternatively, the total boardings at each light rail station could be a potential upper bound, however the application would be the same as with the origin line problem; if the transfer experience improves, the “upper bound” would increase. If there were a clearly defined upper bound, one could apply the beta-binomial model, which also fits the assumptions of the data with regard to overdispersion and correlated events.

Second, the negative binomial does not assume the events captured by the data are completely independent. By contrast, both Poisson and Gaussian models assume events are independent. In the case of people transferring from the bus to LLR, it is possible and likely that the volume of transfers between the two modes continues to pull more people into doing the same. As more people make establish that as their frequent commute, others will see it as a viable option and continue to do the same. Therefore, it is unlikely that these events are uncorrelated.

Finally, the negative binomial assumes an overdispersed count outcome. The Gaussian assumes a normal distribution of the count data. By contrast, the Poisson assumes that  $\mathbb{E}(y) = \text{var}(y) = \lambda$ , where  $y$  is the outcome and  $\lambda$  is a parameter in the Poisson model. Put simply, this implies that the mean of the outcome must equal the variance. As there is only one parameter for both of these in the Poisson model, it cannot account for overdispersed data without reparameterization. The negative binomial takes the systematic component from the Poisson  $\lambda_i = \exp(x_i\beta)$  and adds a random component  $\epsilon_i$  to account for unexplained variance resulting in the component  $\tilde{\lambda}_i = \exp(x_i\beta)\exp(\epsilon_i)$ . This is often simplified further to  $\tilde{\lambda}_i = \lambda_i\delta_i$ , where the  $\delta_i$  is considered the dispersion parameter, essentially (Adolph, 2020).

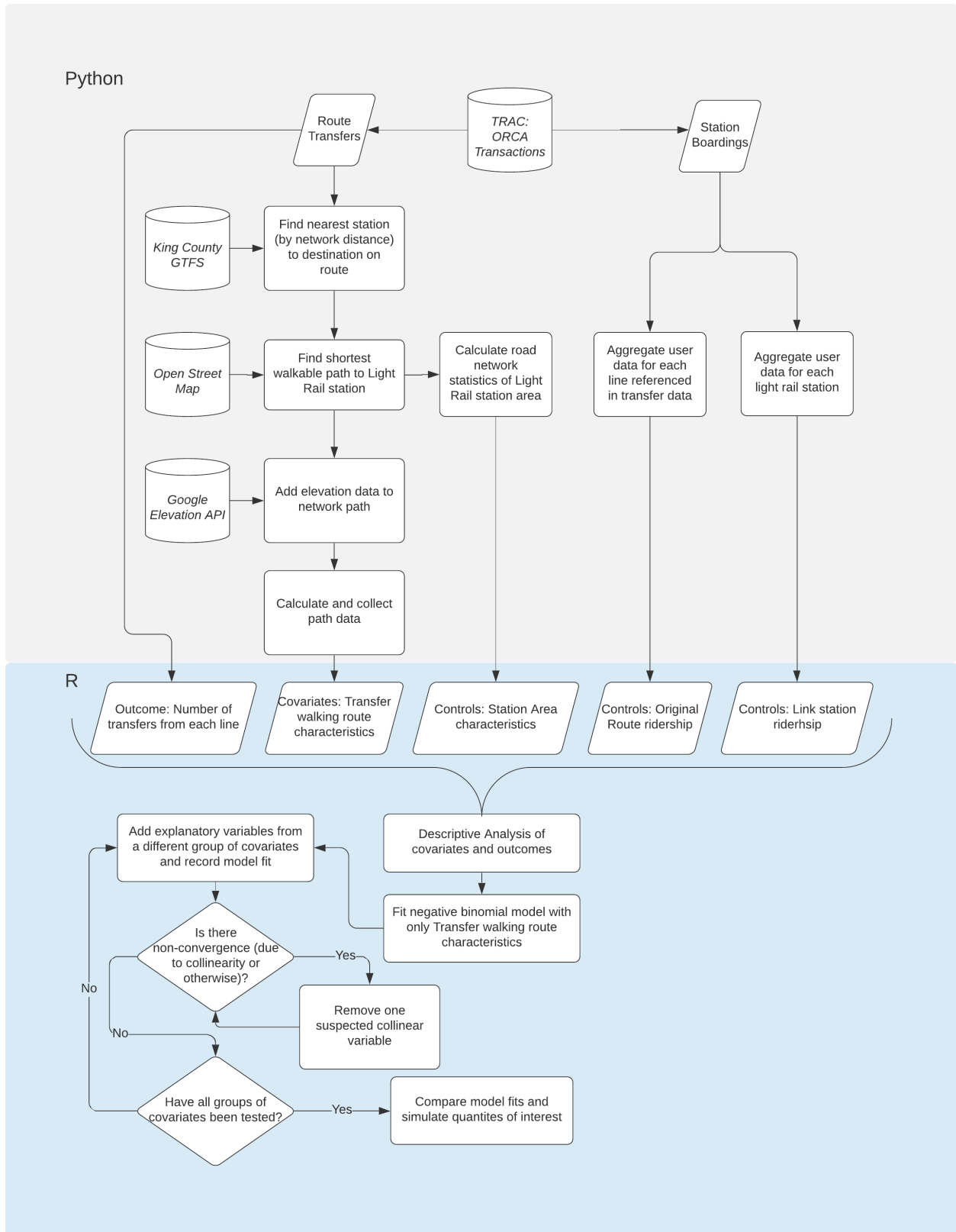
Accounting for these assumptions in the modeling process reduces the bias of the selected model and improves accuracy. For the sake of comparison, the covariates of the final selected negative binomial model can be used to build Poisson and Gaussian models to check the goodness-of-fit and confirm that the negative binomial is the correct choice.

### Model Building and Interpretation

In order to identify the preferred model – that is, the model which most effectively explains the data – several models must be tested and run. This study will take a stepwise approach to model building, beginning with the transfer route characteristic variables. These are the main predictor variables this study hopes will explain transfer differences, so their inclusion is necessary. Gradually, variables from each following group (Table 2) will be added to explain further variance. Theoretically, at least one variable from each of the link station area, link station ridership, and origin line ridership should be present in the final model, as each of these groups should have some influence on the transfers between stations. Any variables which prove to be collinear or prevent convergence of the model will be removed. A flowchart describing this – along with the data collection process – can be found in Figure 7 on Page 20.

Each model will be tested for Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). These metrics should offer a holistic look at the comparative fit and explanatory power of each model. AIC differs slightly from BIC, but both should offer insight into which model fits best. One reason to use both AIC and BIC is that AIC tends to pick models with more covariates – which BIC penalizes. Further, AIC works on the assumption that these models are working to describe a higher-dimensional reality and there is no “true” model. On the other hand, BIC tries to pick the most true model of the options. It is possible that AIC and BIC will agree on one model. If they do not, it will offer an opportunity to discuss why that might be.

The best-fitting model can then be used to simulate quantities of interest and counterfactual scenarios, which will offer a clearer picture of the model’s implications and uncertainty (Ward and Ahlquist, 2018). While coefficients alone do offer some explanations for how one might interpret the model, creating scenarios and simulating these using the computing power of R can offer a complete look at how the model explains the outcome clearly. Further, the negative binomial uses a logarithmic link function which results in coefficients interpretable as the change in the log of the result given a change of one unit (Venables and Ripley, 2013). The coefficients are also in different units and scales, so their coefficients imply very different interpretations about the influence of each covariate. As such, interpreting coefficients and their interactions directly from a table can be misguided at worst and imperfect at best (Ward and Ahlquist, 2018). As such, simulation offers clearer interpretations and allows for greater detail in discussing the model’s results.



**Figure 7.** Data Collection and Modelling Process Flowchart describing the data collection, processing, and modelling steps outlined in the methods section.

## Limitations

This study's approach to understanding transfers is limited in a couple of ways. First, by focusing on using smartcard data, the collection of transfer information is limited to those who use smartcards and those who transfer to another mode of public transit. Those who tap in or off at LLR stations from other modes were not captured with the same detail. As a result, this study can only truly begin to address the questions of transfers from the LLR to the bus network in Seattle. While the bus network is the most used and most expansive mode in Seattle, there is literature that suggests people are willing to walk different lengths for different modes of transit. It would be interesting to understand if that relationship carries over to transfers.

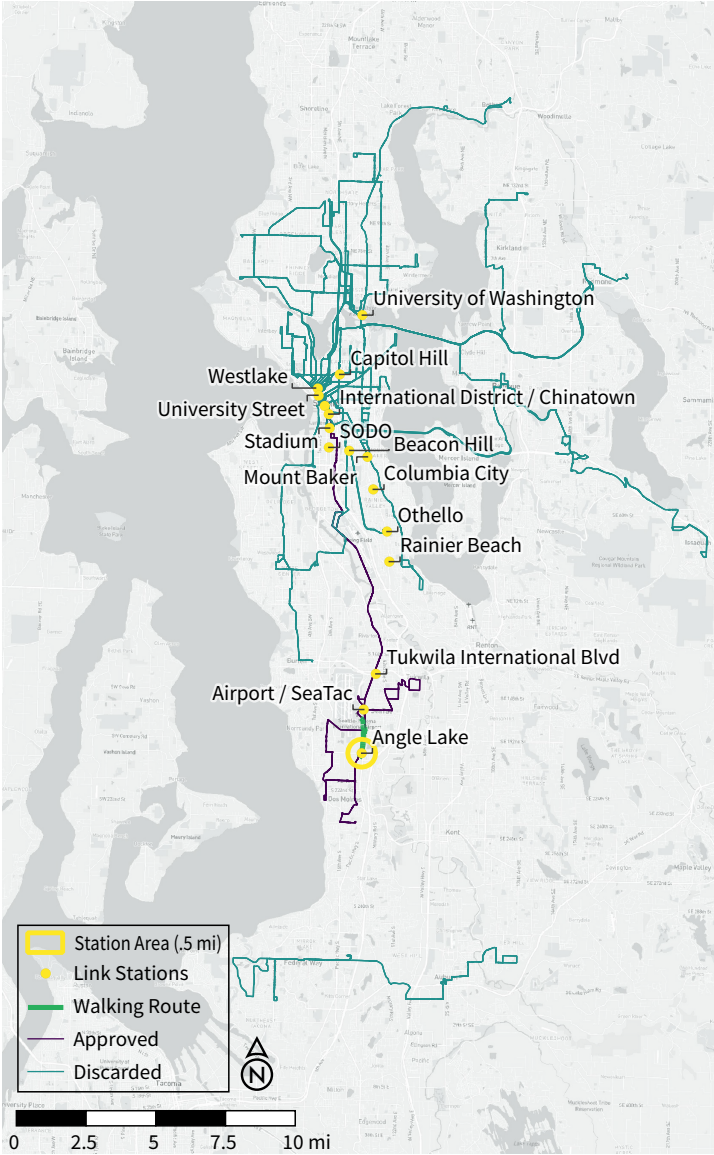
This study will not account for people who simply do not take transit due to transfer limitations. Instead, it can serve as a proxy for which transfer characteristics are most conducive to transfers and support a clearer framework of understanding intermodal transit transfers going forward. Exploring how different barriers interact with the walking distance will still inform the field. Furthermore, some of the more granular analyses using smartcard types or users is limited by the extent of the different cards' ability to get into different populations' hands. For example, it should not be assumed that 100% of those eligible for low-income fares (ORCA LIFT) are using the program, which also applies to the Youth, Senior, and Disabled cards applied in this study.

A couple of current limitations that can be overcome in the near future are those of transfer validation and station connections. First, the data collected on transfers does not always connect the previous line to the following one. In other words, there are a considerable number of "missing" transfer records where a card registered that the user transferred to the LLR system, but did not register which line or mode that transfer was preceded by. This could be due to a difference in the revenue streams from which this data was aggregated ((Eager and Hallenbeck, 2021)), but the exact reason is unclear. There is no evidence that this issue has affected certain station or origin lines more than others, either. Furthermore, the transfer data does not specify a given previous station. As a result, the transfer paths offered here have been based on the assumption that passengers transferring would aim to minimize walking distance – although it is possible that other factors could interfere with this assumption. For example, if someone were to alter their path to stop at a local business between stations the given transfer path would be different.

There is also the possibility – especially in denser more walkable neighborhoods – that people take different paths to transfer with minor differences in distance. This should not alter the results

too much, however. Especially in station-area transfers, it is highly unlikely that the speeds, slopes, and distances of a transfer walking path would differ significantly. Furthermore, the station area covariates are expected to capture some of this potential variance by accounting for the ease by which a rider might take a different walking route.

A difficulty with data collection also relates to the nature of smartcards. It is expected that the majority of riders are diligent about tapping on and off the light rail, and tapping on to other modes which do not require tap-offs. However, based on the TRAC data, it is clear that is not the case. In fact, it seems incredibly common for taps among transferring riders to be inconsistent. Without further research, this study speculates that some riders tap off without tapping on in some cases, resulting in transfers registered for lines which are nowhere near the destination station (Figure 8 and the discussion on page 11). The issues seem somewhat more common for transfer pairs of terminus stations, as evidenced by that Angle Lake figure, where lines far from the light rail station were identified as previous lines.

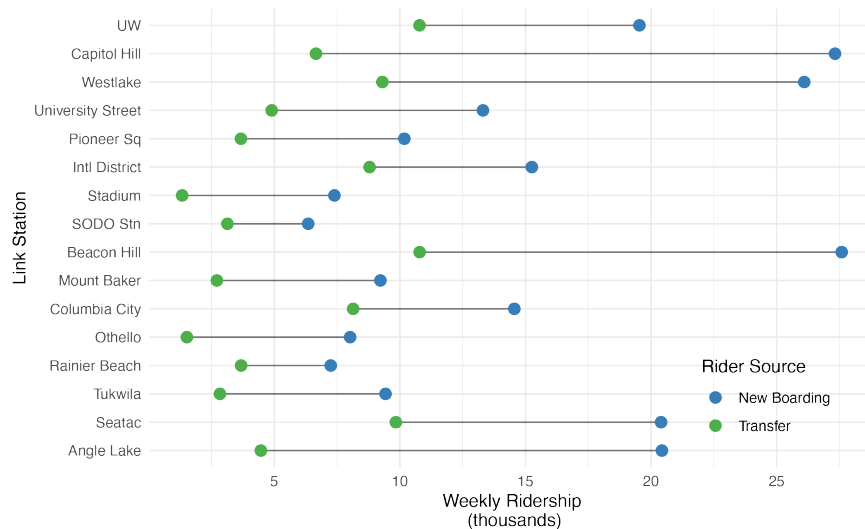


**Figure 8. Angle Lake Transfer Validation** An illustration of the transfer validation process: purple lines met the conditions for inclusion of that transfer pairing in the model. Full-sized map can be found in the Appendix on page 19

## Results

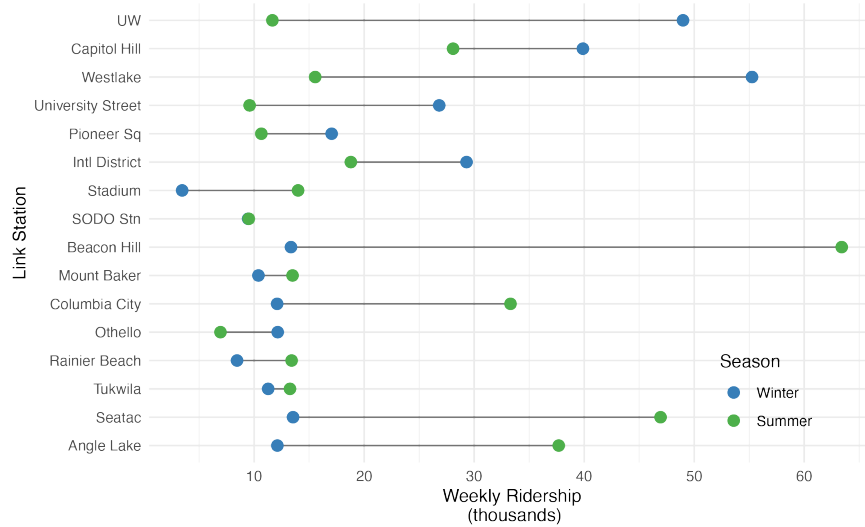
### Descriptive Analysis

While the percentage of transfers from other modes to the Link for the whole system averages around 27.6%, the transfers proportion of each station ranges from about 15% to 37%. Figure 9 shows the mean weekly ridership in new boardings and transfers for each of the Link’s stations, arranged from North to South. It is important to note that these numbers reflect all transfers logged by the ORCA system, including ones which did not connect to a previous line or were not “validated” by the parameters set for the regression in this study.



**Figure 9.** *Mean Station Ridership* Mean composition of each Link Station's weekly ridership in new boardings and transfers in full dataset.

The terminus stations in either direction are uniquely different in their ridership composition. One might expect both to feature a large number of transfer riders due to attracting more feeder lines. However, Sound Transit offers parking at Angle Lake station – located in the Seattle suburb SeaTac. By contrast, the University of Washington station is at the southern end of a dense urban neighborhood in the City of Seattle with much more limited parking, and none offered by Sound Transit. Stations with high proportions of transfer boardings include SODO (33%), where the E-3 Busway offers a wide variety of local and regional bus service. On the contrary, a station like Capitol Hill – located in a dense neighborhood with extensive residential land use – has a low proportion of transfer boardings.



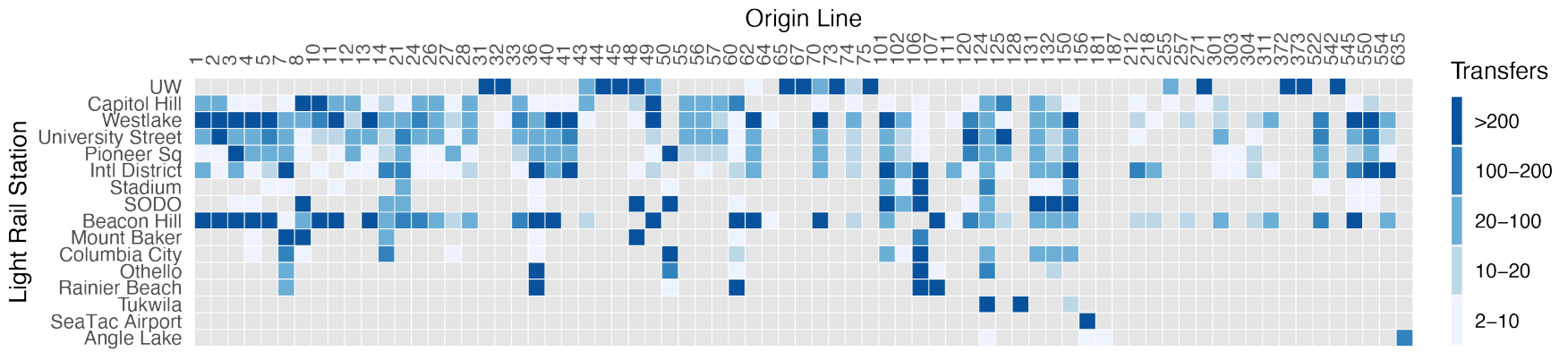
**Figure 10.** *Seasonal Comparison of Weekly Station Ridership in 2019* Mean weekly ridership of each Link Station's compared across both Winter and Summer 2019 periods.

Since the TRAC data offers data on a couple of specific seasons, the seasonal effects on ridership were also explored. Figure 10 examines how ridership changes at each station between the the Summer and Winter of 2019. One important note here which is also discussed in the Limitations on page 21, is an uncharacteristic winter snowstorm in February 2019 which saw ridership drop considerably for at least part of the period studied. As a reminder, the “Winter” period covers January through March while “Summer” covers July and August.

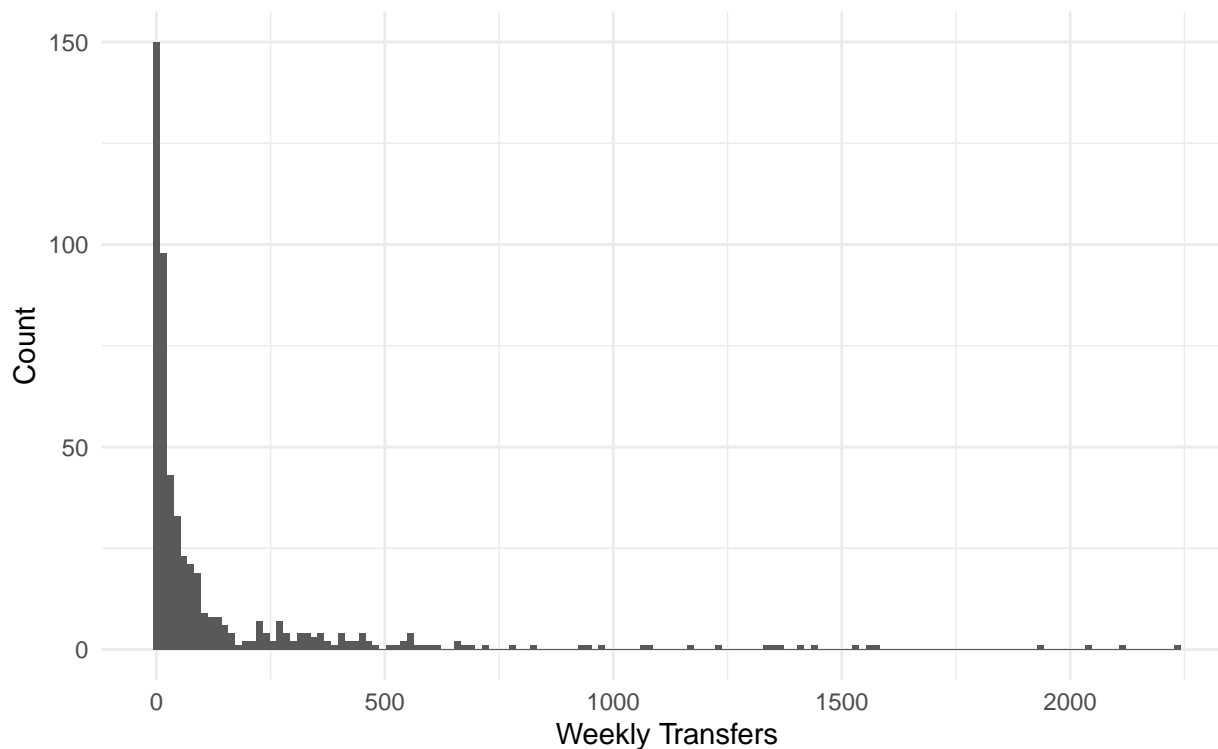
With this in mind, there are some interesting differences among the stations’ seasonal ridership. The UW station is expectedly far busier in the Winter, while school is in session, compared to the summer. Conversely, the SeaTac/Airport station is busier in the summer, during the peak of travel season. It is less clear why stations such as Beacon Hill and Columbia City see such seasonal shifts, especially compared to neighboring stations like Mount Baker. Meanwhile, Tukwila and SODO appear to be the most consistent among the seasons, with little difference between them.

Shifting towards the transfers validated by this study, the heatmap presented in Figure 11 offers a look at which lines tend to feed into the Link stations most often. Some of the most popular feeder lines appear to stop near multiple stations, such as route 7, 36, and 106. Some only appear once, such as route 635 and 181 to Angle Lake. Reading across the plot shows which Link stations received the most validated transfers, and these line up with the full data explored above in Figure 9. For example, it is clear that the University of Washington, Beacon Hill, and Westlake had a high

number of transfers from both the filtered data and the full set. One station which does not match up well, however, is SeaTac. It is unclear why this issue exists, but it can either be explained by a weakness in the data collection process or aggressive filtering for regression – which would suggest many of the transfers to SeaTac in Figure 9 are financial transfers.



**Figure 11.** *Transfer Origin Heatmap* Number of mean weekly transfers between origin transit lines and Link stations.



**Figure 12.** *Weekly Transfers Histogram*

## Modeling Results

### Model Building

The first step in this study's modeling process is checking the distributional characteristics of the data. As a negative binomial was selected, the assumption is that the outcome – transfers between lines – would be overdispersed. The visual way to check for this is by plotting a histogram of the outcome data. Based on Figure 12, it seems that the outcome is overdispersed – or at least strongly skewed.

The second way to test for overdispersion is by implementing a test outlined by Cameron and Trivedi (1990). This test checks the the Poisson assumptions outlined on page 16, specifically comparing the null hypothesis of  $\text{var}(y) = \lambda$  to an alternative of  $\text{var}(y) = \lambda + c * f(\lambda)$  where the function  $f(\cdot)$  is a linear monoton function. The resulting coefficient  $c$  is a measure of the dispersion of the outcome, where  $c > 0$  implies overdispersion and  $c < 0$  implies underdispersion. The results of this test is in Table 3, and clearly point towards overdispersion, as suspected.

**Table 3. Dispersion Test Results**

	c	z	p
dispersion	647.21	5.13	0.00

As outlined in Figure 7 and on page 19, this study will apply a form of stepwise model building. By adding variables in groups, the study hopes to gauge how well each group of variables adds to the descriptive power of the model. However, during this process some models did not converge. The likely reason is that some covariates are moderately or strongly collinear. As a result, a correlation matrix of the variables collected was created and plotted in Figure 21 (see: Appendix page iv). During model building, non-convergence led to the removal of variables which were collinear and did not contribute significantly to the descriptive power of the model.

The results of the each added group of covariates to the model can be located in Table 4. In the table, model goodness-of-fit, coefficient estimates and their 95% confidence intervals, and frequentist significance is arranged from the least complex model – with only the transfer walking route variables – to the most complex – with all variable groups represented. Given the different scales of the covariates, it is difficult to comment on the comparative strength of each of them, but what is clear is that many of the signs of the coefficients line up with the theory behind this model.

For example, higher street network entropy (*stEnt*) – indicating a more grid-like network – is consistently a positive correlation. Similarly, *wkGrade* – measuring the mean grade of the walking route – is consistently negative through all models. Both of these match the theory underlining this model, where the study expected to find walks along steeper streets would be less conducive to transfers and more grid-like street networks would support or indicate more transfers.

One change that improved the model considerably during the building process was adjusting the length of the transfer walk (*wkLen*) to a logarithmic relationship with the outcome instead of a linear one. Per Figure 13, the data seems to suggest that relationship has a slight curve, with few outliers. This prompted the change to a logarithmic relationship between walking distance and transfers, which will be discussed further in the following sections.

A second change was the decision to include an interaction term in the full model. This interaction was between the mean grade (*wkGrade*) and maximum grade (*wkMxGrd*) variables. The purpose of this interaction term was to better capture the effects of walk grade when accounting for all other variables. Basically what the interaction term asserts, is the effect of having a higher

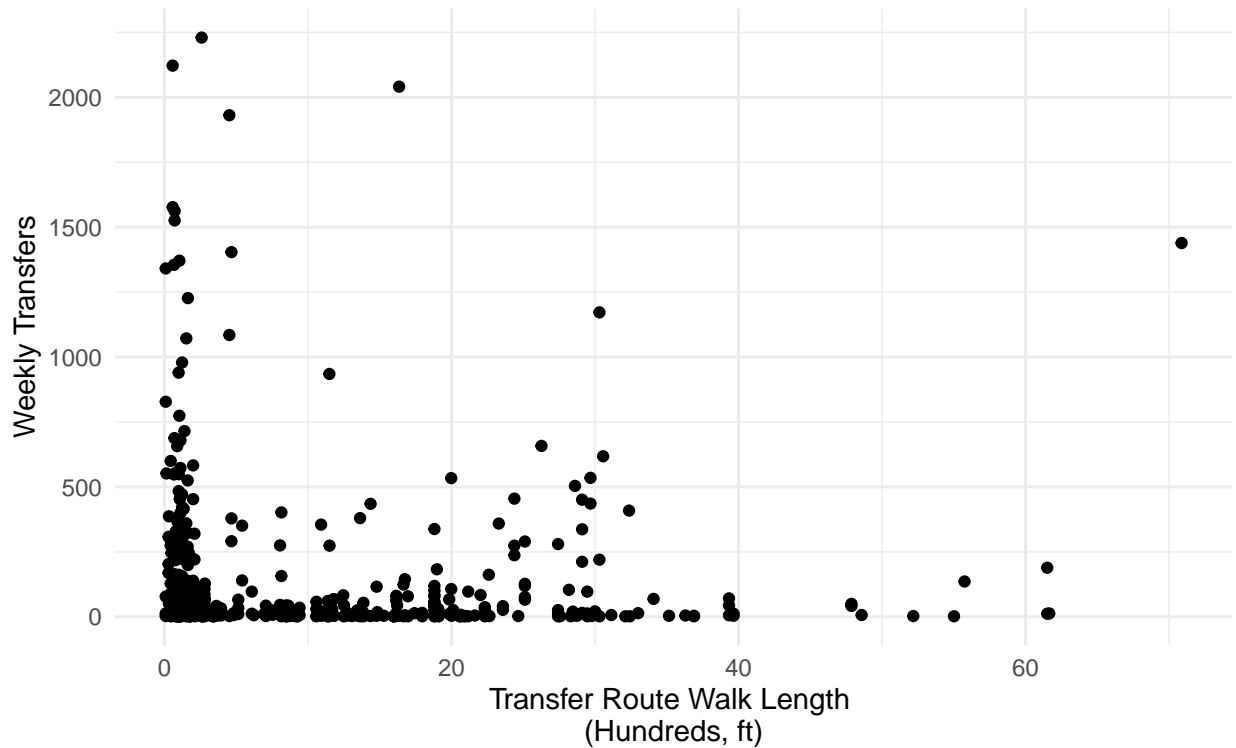
**Table 4. Regression Table**

Covariate estimates, 95% confidence intervals, and significance from model building process

	<i>Dependent variable:</i>			
	weekly			
	Walking Route	+ Station Area	+ Origin Line	+ Link Station
szn	0.455*** (0.159, 0.751)	1.042*** (0.745, 1.339)	0.877*** (0.587, 1.167)	1.075*** (0.787, 1.363)
log(wkLen)	-0.261*** (-0.378, -0.143)	-0.391*** (-0.512, -0.270)	-0.316*** (-0.433, -0.198)	-0.372*** (-0.502, -0.242)
wkMnSpd	0.011 (-0.052, 0.074)	-0.033 (-0.096, 0.029)	-0.051 (-0.112, 0.010)	-0.022 (-0.083, 0.040)
wkMxSpd	-0.014 (-0.043, 0.014)	-0.001 (-0.029, 0.027)	0.006 (-0.022, 0.033)	-0.002 (-0.030, 0.025)
wkGrade	-0.135*** (-0.204, -0.066)	-0.245*** (-0.314, -0.176)	-0.239*** (-0.307, -0.172)	-0.303*** (-0.381, -0.225)
wkMxGrd	0.007** (0.00002, 0.015)	0.022*** (0.015, 0.030)	0.020*** (0.013, 0.027)	-0.007 (-0.032, 0.017)
stEnt		2.497** (0.497, 4.498)	3.560*** (1.608, 5.512)	3.773*** (1.737, 5.808)
stCirc		18.287*** (12.026, 24.548)	13.406*** (7.165, 19.647)	19.158*** (12.882, 25.434)
ogYouth			0.106*** (0.072, 0.139)	0.124*** (0.087, 0.160)
ogSum			0.001*** (0.001, 0.002)	0.001*** (0.001, 0.002)
lrYouth				0.0005** (0.0001, 0.001)
lrSum				0.019*** (0.012, 0.027)
wkGrade:MxGrd				0.005*** (0.002, 0.009)
Constant	5.492*** (4.080, 6.904)	-14.544*** (-20.928, -8.160)	-11.358*** (-17.770, -4.946)	-18.602*** (-25.094, -12.110)
Observations	524	524	524	524
Akaike Inf. Crit.	5,814.004	5,783.977	5,747.850	5,710.561
Bayesian Inf. Crit.	5,848.096	5,826.592	5,798.988	5,774.483

Note:

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01



**Figure 13.** *Walk Length to Weekly Transfers*

mean walking grade is different when the max grade is higher or lower. The significance of this variable, per Table 4, supports this dependent relationship between covariates.

A couple of changes for the sake of easier interpretation were also included in each of these models. These had no impact on results, and only served to support a more coherent discussion about their effects. These involved changing the scales of a few variables. The first was adjusting *wkLen* to hundreds of feet instead of individual feet. Moving a bus stop a single foot does not make sense when considering the effects of distance on transfers, so working in hundreds seemed more interpretable. The other two variables to change in scale were the sums: *ogSum* and *lrSum*. In the case of origin line ridership, it was adjusted to hundreds of weekly riders. Link weekly ridership was adjusted to thousands of weekly riders.

#### Model Interpretation

The main variables this study seeks to understand are those of the transfer walking route. These variables are the main glimpses as to which transfer barriers people are willing to overcome regularly or not. The clearest among these is the length of the walk between stations. The other

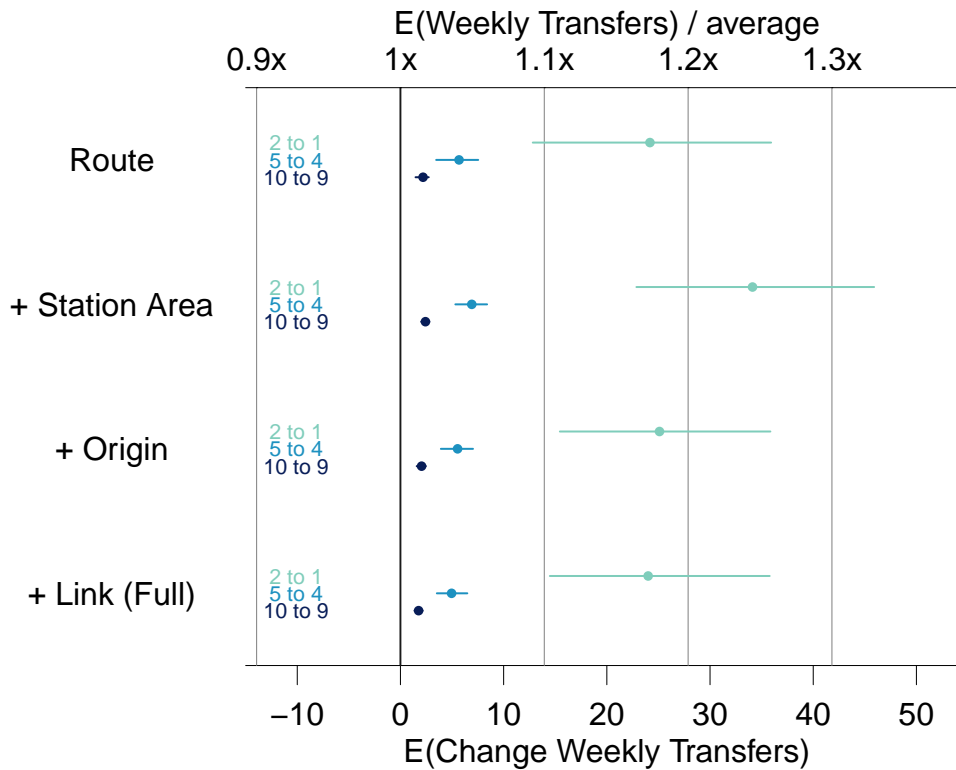
variables tested relating to the walking route were related to the vehicular speed along the route and the grade of the walk (see Tables 2 and 4).

Starting with the effect of walking distance, the logarithmic relationship identified in Figure 13 is further examined by Figure 14. In this graphic, each point and accompanying line represents a difference in ridership (and 95% Confidence Interval) given the stated change in blocks. Both top and bottom x-axes identify the expected (E) change compared to the average weekly transfers (140) as either a multiplicative term or as an integer. A street block is taken as 300 feet, per Open Street Map, and the changes are selected as a minimum distance (2 to 1 blocks), near the mean distance (5 to 4 blocks) and at the edge of the station area distance (10 to 9 blocks). The plot clearly shows that as stations move further out, changes to the walking distance have diminished effects. Changes among nearer stations have stronger effects, but can be considerably more varied, based on the range of the confidence interval. This plot also shows that regardless of controls included, the simulated differences based on distance are not significantly different from one another. In other words, regardless of what gets put in the model, logarithmic distance is a very strong explanatory variable for weekly transfers.

Looking more closely at distance along with grade and vehicular speed, Figure 15 shows the marginal effects for *wkLen*, *WkGrade*, and *wkMaxSpd* on weekly transfers for each of 3 models. One “simple” model contains just the transfer walking route variables and log distance (see column Walking Route in Table 4 on p. 30). The other two models are the final “full” model with log distance and one full model with linear distance. For reference and context, the mean weekly transfer ridership is 140.

First of all, it is clear that the log distance models reflect the data more clearly. As examined by 13, there is clearly not a linear relationship between distance and weekly transfer pairs. The confidence intervals of both log distance models are tighter, and based on the effects they are significantly not 0, while the linear distance effect is effectively 0 – since one could draw a straight flat line within its confidence interval. Furthermore, the full model shows a slightly stronger drop off with walking distance compared to the simple model. This suggests that the other variables included helped explain the increased ridership implied by the simple model more effectively.

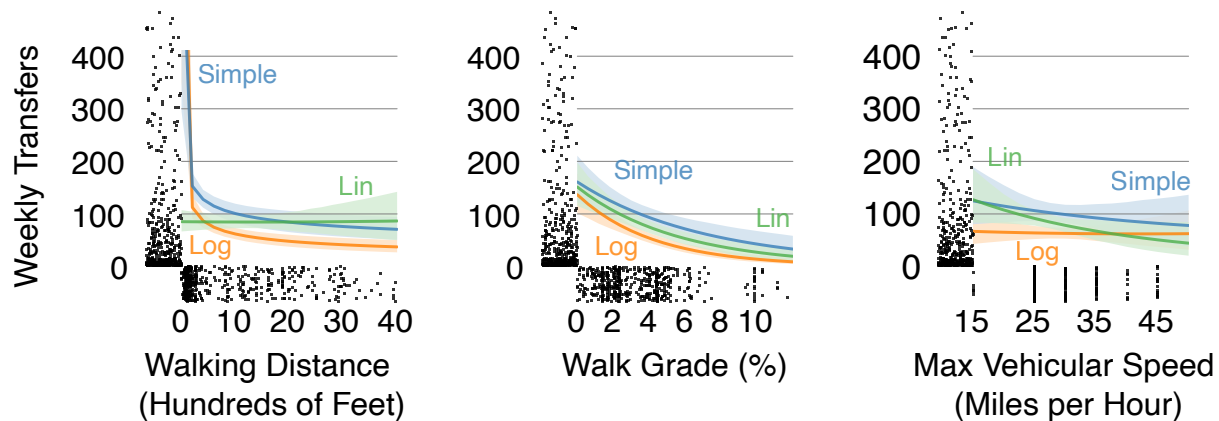
Next, the walking grade plot suggests strong agreement between all models. Effectively, all three models exhibit the same effect of walking grade on transfers. For reference, Seattle’s mean walking network grade is 3.9% and the median is 2.3%. Among the data, walks tend to average



**Figure 14.** *First Differences of Block Adjustments* Given a 300 ft street block, the effect on transfer ridership of moving a station 1 block closer from a given starting position of each model (with 95% CIs). Rugs on the axes show observations for those variables.

around 3.3% with a median of 2.7% – not far off from the rest of the city. From this plot, it is apparent that transfers drop off pretty quickly around a 3 or 4% grade before leveling off. Finally, the max vehicular speed plot also shows the three models to be not significantly different. However, only two of these – the log distance models – are effectively 0. The linear distance model shows a possible slightly negative slope. Regardless, this is clearly the weakest of the three variables, despite the thought that it may have some effect on perceived walking safety.

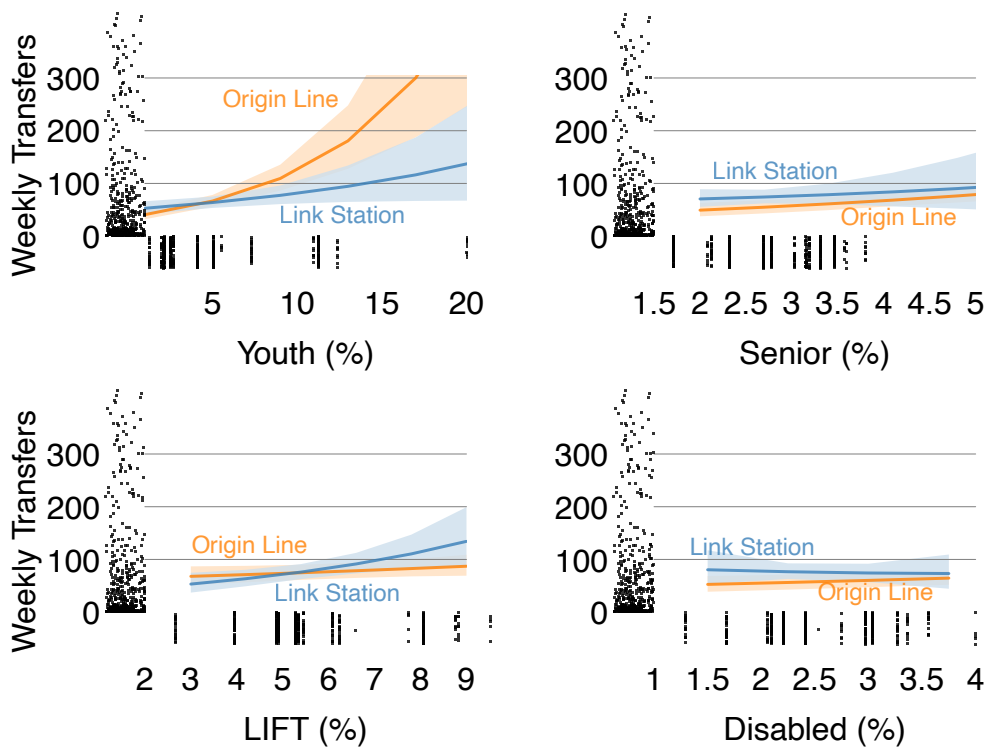
The full and final model fit only included the percentage of ORCA Youth riders at both the Link station and on the originating line. This is not for lack of trying, but because many of the non-Adult ORCA cards were very strongly collinear (see Figure 21 in Appendix p. iv). As a result, only Youth cards were selected as a proxy for healthier and younger riders – which tended to be more willing to transfer per Cheng and Chen (2015). However, to more closely examine the effects each



**Figure 15.** *Marginal Effects Comparison* Simulated transfer volumes and 95% CIs for the Simple model (only walking route variables) and the full models with either a logarithmic walking distance (Log) or a linear walking distance (Lin).

ORCA card type might have on the model, a separate model was fit for each of the other non-Adult types: Disabled, Senior, and LIFT (low-income). The results were used to simulate expected transfers given a change within the ranges of each user type found in the data (in other words, this study is not trying to extrapolate, but simply interpolate). This was done for each card type at both the destination Link station and the originating line, and is presented in Figure 16.

This figure clearly shows the interpolated marginal effects of each card type on the regression. Some appear to have limited impact, such as Disabled. While Youth clearly had the strongest impact in both the origin line and Link station. In all cases, the impact was effectively the same between the origin line and Link station. LIFT users at the Link station also seem to explain higher transfer ridership, though not to the extent of Youth users. Theoretically, it is possible that LIFT users are transit-captive at higher rates than other user types. The results of this study would suggest that Link stations with a greater proportion of LIFT users are more likely to have higher transfer volumes, potentially connecting to transit-captivity as low-income users are forced into making transfer regardless of convenience.



**Figure 16.** *Marginal Effects ORCA Card Type* Simulated transfer volumes and 95% CIs for models applying each non-Adult ORCA card type. Rugs show observed data at the Link station on the x-axis and of transfers on the y.

#### Model Robustness

While the dispersion test and visual checks in Figure 12 and Table 3 strongly suggest the negative binomial to be an improvement over other models, it is still worth checking the goodness-of-fit of the full negative binomial compared to the other two common models of unbounded count data. Table 5 compares the same goodness-of-fit measures as the model building process. The same covariates used in the final negative binomial model are applied to a Poisson and a Gaussian (or linear) model. Based on both AIC and BIC, the negative binomial model appears to fit the data more successfully. It is important to note that coefficients between the negative binomial and Poisson are somewhat comparable, while the Gaussian coefficients are not – due to Poisson and negative binomial models using a logarithmic link function, compared to the Gaussian’s linear link function.

Table 5. Model Robustness Table Comparison

	<i>Dependent variable:</i>		
		weekly	
	<i>Negative Binomial</i>	<i>Gaussian</i>	<i>Poisson</i>
	(1)	(2)	(3)
szn	1.075*** (0.787, 1.363)	-6.368 (-64.090, 51.354)	-0.019** (-0.037, -0.001)
log(wkLen)	-0.372*** (-0.502, -0.242)	-17.250 (-43.383, 8.882)	-0.121*** (-0.129, -0.113)
wkMnSpd	-0.022 (-0.083, 0.040)	-0.047 (-12.355, 12.262)	0.016*** (0.012, 0.020)
wkMaxSpd	-0.002 (-0.030, 0.025)	-1.570 (-7.015, 3.874)	-0.023*** (-0.025, -0.020)
wkGrd	-0.303*** (-0.381, -0.225)	-21.798*** (-37.402, -6.194)	-0.134*** (-0.139, -0.129)
wkMxGrd	-0.007 (-0.032, 0.017)	-1.832 (-6.719, 3.056)	-0.003*** (-0.004, -0.001)
stEnt	3.773*** (1.737, 5.808)	709.045*** (300.407, 1,117.683)	4.409*** (4.299, 4.519)
stCirc	19.158*** (12.882, 25.434)	1,217.441* (-43.570, 2,478.451)	8.382*** (8.075, 8.690)
ogYouth	0.124*** (0.087, 0.160)	13.380*** (6.149, 20.611)	0.081*** (0.079, 0.083)
ogSum	0.001*** (0.001, 0.002)	0.087 (-0.037, 0.211)	0.001*** (0.001, 0.001)
lrYouth	0.047** (0.007, 0.087)	12.221*** (4.205, 20.236)	0.067*** (0.066, 0.069)
lrSum	0.019*** (0.012, 0.027)	1.767** (0.228, 3.306)	0.015*** (0.015, 0.015)
wkGrade:MxGrd	0.005*** (0.002, 0.009)	0.328 (-0.382, 1.038)	0.001*** (0.001, 0.001)
Constant	-18.602*** (-25.094, -12.110)	-1,734.802*** (-3,039.074, -430.530)	-8.067*** (-8.385, -7.750)
Observations	524	524	524
Akaike Inf. Crit.	5,710.6	7,426.1	140,667.5
Bayesian Inf. Crit.	5,774.5	7,490.0	140,727.1

Note:

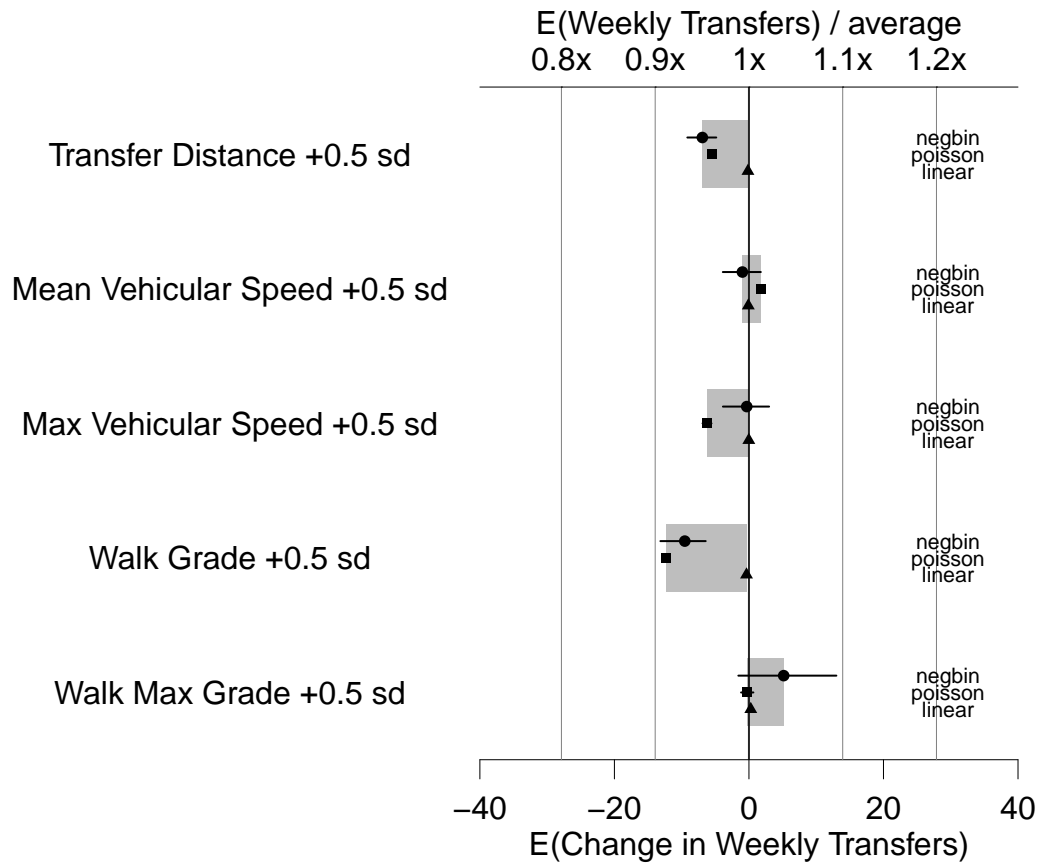
\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

An examination of how the walking route coefficients compare between the models is displayed by Figure 17. Each row of the plot shows how an increase in one standard deviation to each covariate impacts the expected transfer volume. The grey boxes highlight the range of point estimates (not confidence intervals) for each covariate. Based on this plot, there are basically only two walking route coefficients which are statistically the same: mean vehicular speed (*wkMnSpd*) and max walk grade (*wkMxGrd*). Despite these similarities, a couple of things stand out from this plot. First, the negative binomial incorporates considerably more uncertainty in its estimates. The confidence interval ranges for the negative binomial model extend far longer than either of the others. Second, the Poisson finds significant influence from each of these variables on the outcome. This is a flawed finding, as the data do not fit the assumptions of the Poisson, and serves as an example as to why careful model selection is so crucial to defensible results.

A point raised by TRAC in this study's communication with the organization, was to be wary of certain stations' influence on broader results (Eager and Hallenbeck, 2021). UW station was brought up frequently as one which could have adverse effects due to its sheer volume of ridership and relative weight as the most northerly point on the current system. To take a closer look at this, the same full model was run in different extents of the study's geography. Starting with the full extent of the line, each proceeding model was filtered to either include all stations besides UW, downtown transit tunnel stations, stations in downtown Seattle, and stations within the City of Seattle. The results of this filtering is in Table 6.

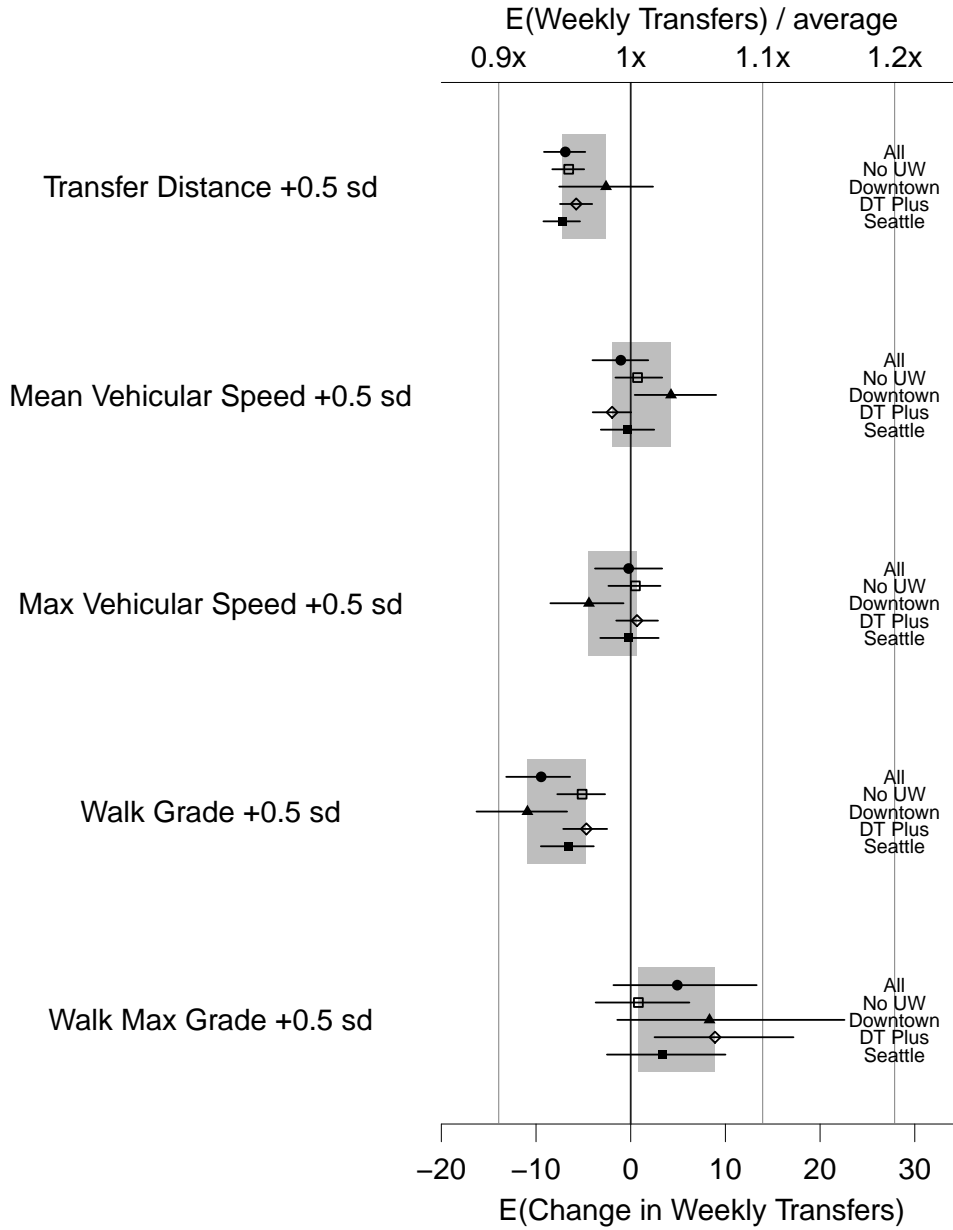
Before discussing the implications of this check further, it is important to note that the bottom row reveals whether the model in question converged within 100 iterations. If the answer is no – as it was for the most limited filters – the estimates and fit metrics might not be defensible. This is a complex model, and the observations required to converge the model is beyond what was offered by downtown and the transit tunnel's data. In the table, we can see that there are minimal differences among the first 3 models: Full, No UW, and Seattle. No UW appears to flip the sign and remove the significant of *stEnt*, but the confidence intervals of the three models still overlap slightly. The only value which changes significantly is the constant among those three models.

With regard to each geography's explanation of transfer walking routes, Figure 18 shows the expected change in weekly transfer volumes given an increase in 0.5 standard deviations from the mean of each covariate. In the plot, almost all of the confidence intervals in each covariate overlap, suggesting no significant difference between the effects in these models. Despite some



**Figure 17.** *Walking Route Coefficients across Model Types* Simulated transfer volumes and 95% CIs given a 0.5 SD change among the negative binomial (negbin), Poisson, and Gaussian (linear) models.

significant differences in other covariates given the station filters, it is clear from this plot that the walking route effects are very similar, still.



**Figure 18.** *Station-Filtered Regression Comparison* Simulated transfer volumes and 95% CIs given a 0.5 SD change among each geographic filter.

Table 6. Modeling Area Geography Regression Comparison

	<i>Geography:</i>				
	Full	No UW	Seattle	Downtown	Transit Tunnel
szn	1.075*** (0.787, 1.363)	1.114*** (0.831, 1.396)	1.167*** (0.880, 1.454)	1.776*** (1.395, 2.156)	2.288*** (1.421, 3.156)
log(wkLen)	-0.372*** (-0.502, -0.242)	-0.467*** (-0.599, -0.335)	-0.440*** (-0.574, -0.307)	-0.527*** (-0.693, -0.362)	-0.133 (-0.386, 0.120)
wkMnSpd	-0.022 (-0.083, 0.040)	0.018 (-0.043, 0.078)	-0.010 (-0.071, 0.051)	-0.076* (-0.152, 0.001)	0.391** (0.023, 0.759)
wkMxSpd	-0.002 (-0.030, 0.025)	0.005 (-0.021, 0.032)	-0.002 (-0.029, 0.025)	0.010 (-0.024, 0.043)	-0.111** (-0.197, -0.025)
wkGrade	-0.303*** (-0.381, -0.225)	-0.219*** (-0.296, -0.141)	-0.252*** (-0.338, -0.167)	-0.191*** (-0.298, -0.085)	-0.318*** (-0.454, -0.183)
wkMxGrd	-0.007 (-0.032, 0.017)	-0.013 (-0.039, 0.012)	-0.009 (-0.033, 0.016)	0.023 (-0.006, 0.052)	0.007 (-0.029, 0.042)
stEnt	3.773*** (1.737, 5.808)	-0.453 (-2.770, 1.864)	3.006*** (0.948, 5.064)	-8.569*** (-13.292, -3.845)	-182.635*** (-271.290, -93.980)
stCirc	19.158*** (12.882, 25.434)	7.860** (1.507, 14.214)	35.678*** (20.831, 50.525)	-9.375 (-32.278, 13.528)	-383.577** (-691.305, -75.849)
ogYouth	0.124*** (0.087, 0.160)	0.135*** (0.099, 0.170)	0.120*** (0.084, 0.156)	0.107*** (0.058, 0.156)	0.151*** (0.086, 0.216)
ogSum	0.001*** (0.001, 0.002)	0.001*** (0.001, 0.002)	0.001*** (0.0004, 0.002)	0.0004 (-0.0002, 0.001)	0.0004 (-0.001, 0.001)
lrYouth	0.047** (0.007, 0.087)	0.051*** (0.012, 0.090)	0.047** (0.007, 0.086)	-0.398*** (-0.567, -0.229)	1.047 (-1.018, 3.112)
lrSum	0.019*** (0.012, 0.027)	0.014*** (0.006, 0.022)	0.022*** (0.014, 0.030)	0.037*** (0.018, 0.056)	0.141*** (0.075, 0.208)
wkGrade:MxGrd	0.005*** (0.002, 0.009)	0.005** (0.001, 0.008)	0.005*** (0.001, 0.008)	0.001 (-0.004, 0.005)	0.002 (-0.003, 0.007)
Constant	-18.602*** (-25.094, -12.110)	-5.012 (-11.829, 1.804)	-35.357*** (-50.537, -20.177)	21.941* (-2.147, 46.030)	529.807*** (159.011, 900.603)
Observations	524	502	513	384	255
Akaike Inf. Crit.	5,710.561	5,358.147	5,580.869	3,971.172	2,691.663
Bayesian Inf. Crit.	5,774.483	5,421.426	5,644.473	4,030.431	2,744.782
Converged?	Yes	Yes	Yes	No	No

Note:

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

## Conclusions

### Findings

Based on this study and referenced work, distance is one of the main barriers to effective and convenient transfers. Along with distance, the slope of a walk and possibly the speed of nearby vehicles can influence would-be transfers negatively. While smartcards are designed to at least make the transferring experience more clear and efficient, these physical barriers continue to affect perceptions and actions related to transferring. The most considerable physical barriers to transferring to the Link Light Rail system are distance and grade of the walking path.

With regard to equity, it is clear that users with limited mobility or disability are not transferring at the same rates as other users. This could partially be due to a general aversion to transfers or high physical barriers due to Seattle's innate topography; but is directly tied to these users' limited mobility. Conversely, at stations with higher proportions of low-income and Youth users, transfers are more common. This suggests some level of potential transit-captivity for LIFT users. The considerable increase of transfers among stations with high Youth ridership is an expected confirmation of survey-based research which considered youthfulness and health as explanatory variables for transfers.

### Policy Implications

In response to these findings, there are a few potential policy implications for planners in the region to consider. Clearly, station proximity plays a large role, but can not always be adjusted to the extent necessary due to other factors. However, given the effect of vehicular speed in some models, it is worth considering identifying transfer routes where vehicular speed may pose a perceived barrier. For example, walking along Rainier Ave to get to the Mount Baker station poses a perceived safety issue for pedestrians. Reducing speed limits or implementing street calming measures can support an improved transfer experience there. Finally, in planning future stations, planners should consider the street networks in the surrounding areas. Placing stations as close to grid-like, dense, and non-circuitous networks helps support increased transfers as routes between stations are likely easier to follow in these networks due to their order. In less dense regions, mobility hubs could provide support, and these hubs could offer amenities such as real-time updates on arrivals and departures.

Furthermore, in response to the limitations of this research, agencies should strive to maintain clear and valid smartcard data, along with clear and coherent use guidelines, as much as possible. These results are limited by the extent to which the available data was collected and compiled. Invalid transfers and unlikely transfers alike contributed to the limitations. Some of these will likely persist, as riders may frequently forget to tap on or off at different stations. Other limitations could be addressed through more coherent and clear data collection for transfers.

Finally, with regard to different user groups, supporting low-mobility users may simply be a case of finding crucial transfers and reducing the proximity between stations. Other solutions might include more demand-responsive measures to eliminate the need for inconvenient and difficult transfers where possible. In the case of low-income users, ensuring that transit-captive populations have access to frequent and affordable transit which mirrors their schedule is important. Seattle's current network is focused considerably on first-shift professional commutes. Making sure that lines reaching lower income neighborhoods are responsive to their potentially different needs in span, frequency, and location are crucial.

### Future Research

Future studies on this topic could incorporate ridership surveys in the region to validate or expand on the topics covered by this study. Potentially, using more precise data on user groups transfer habits could expand on the briefly-discussed equity questions brought up in this study. Other possibilities include looking at the stations themselves and their amenities to describe whether these have any effect on transfers. Looking beyond transfers to the Link and looking at transfers from the Link to other modes to see if the same barriers exist is also a possibility.

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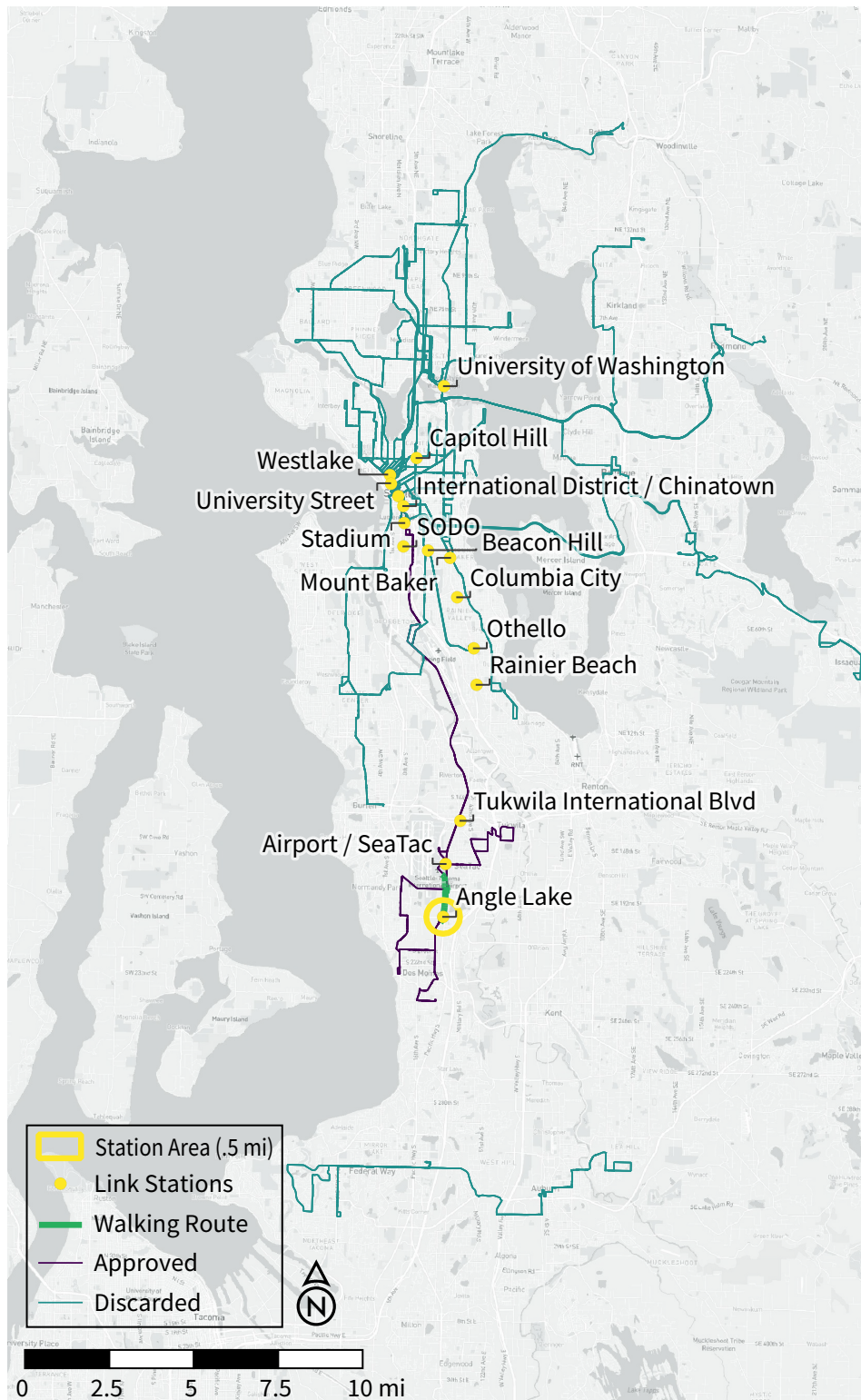
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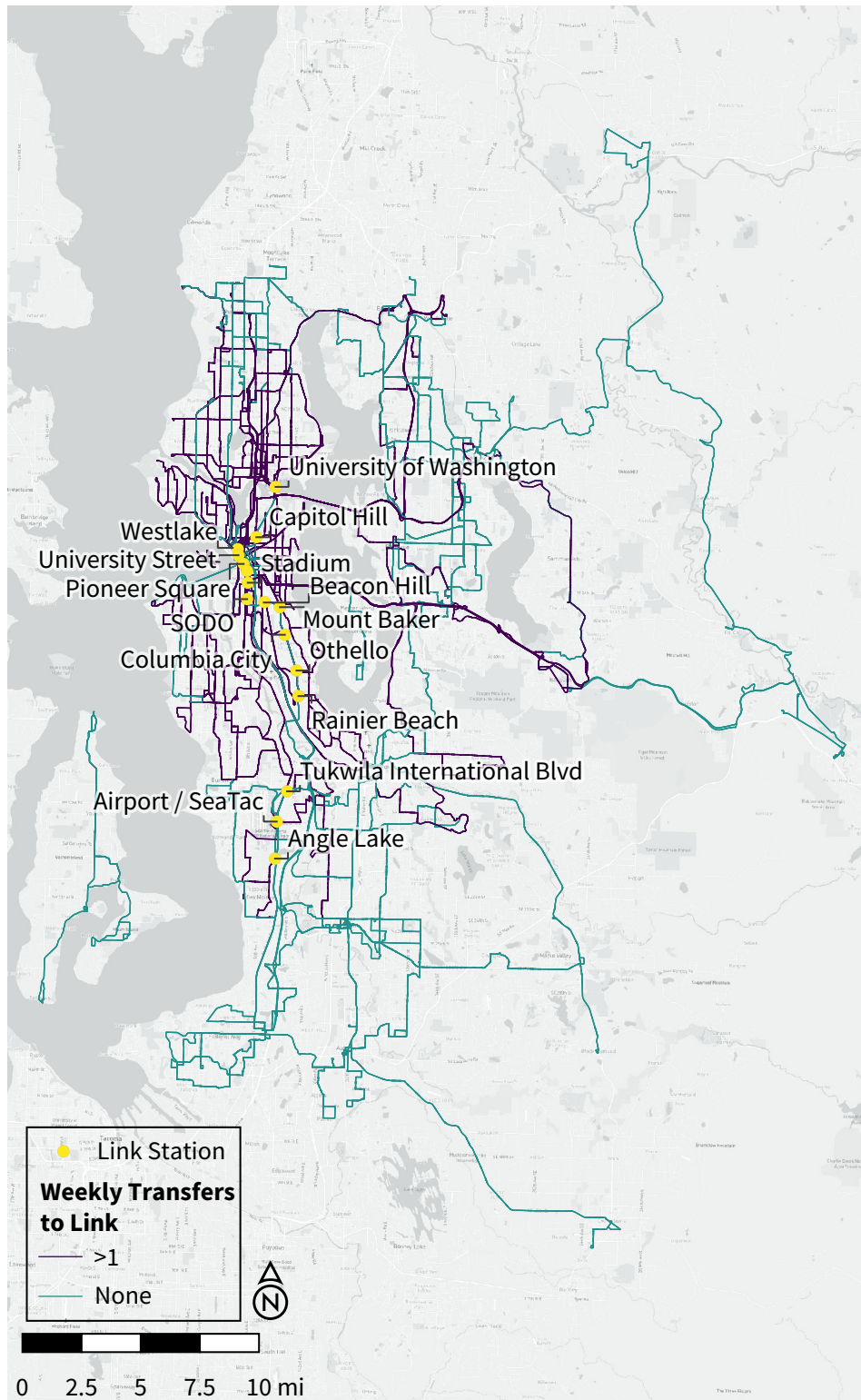
**URL:** <https://www.sciencedirect.com/science/article/pii/S0968090X11001689> 2, 7, and 8

## Appendix

### Figures



**Figure 19.** *Angle Lake Transfer Validation* Full size version of Figure 8 on Page 23.



**Figure 20.** *Transfer Origin Lines* Each line with at least one weekly transfer observed to the Link and with a station within 1.5 miles of a Link station is shown in purple.

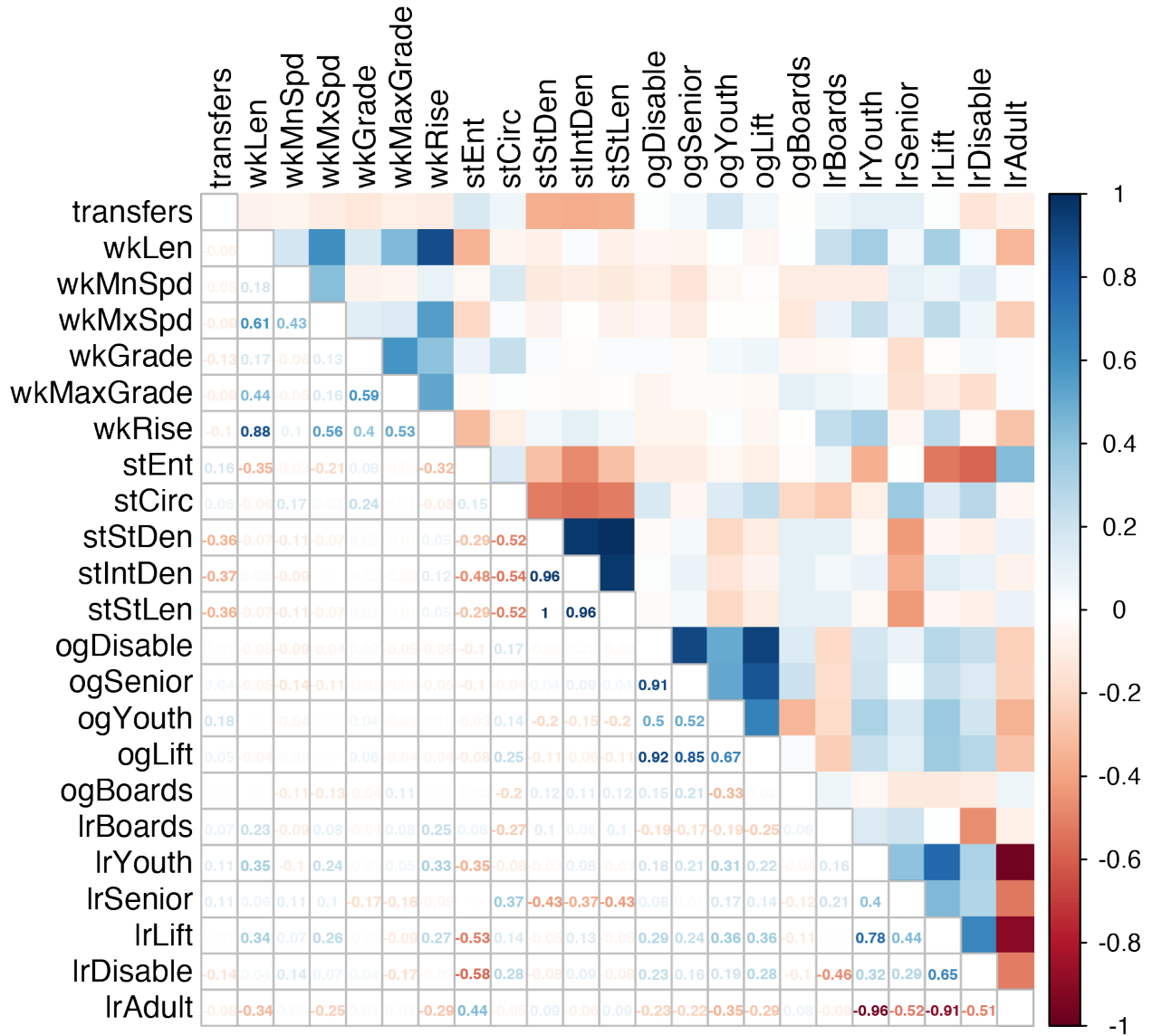
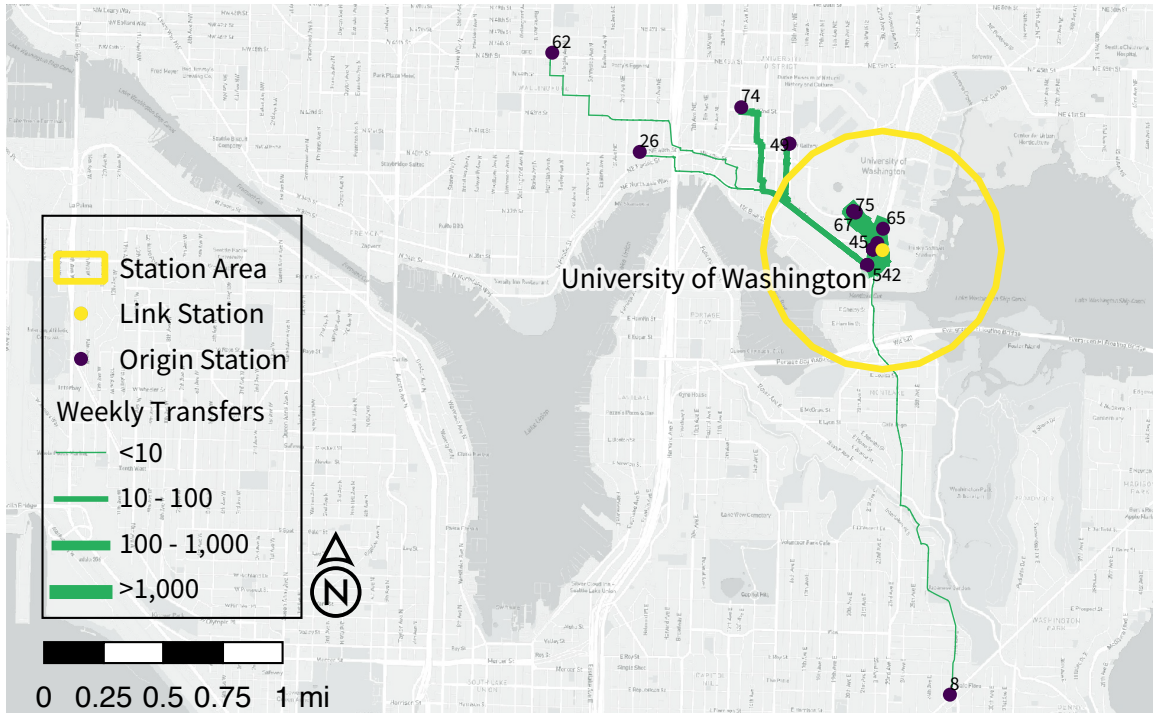


Figure 21. Covariate Correlation Matrix R-squared values between each pair of covariates considered for the model.

All Transfer Paths

Each of the following display the likely walking paths from Open Street Map and weekly transfer volumes from TRAC between origin lines and the destination Link Station.



**Figure 22.** *University of Washington Station Transfers*

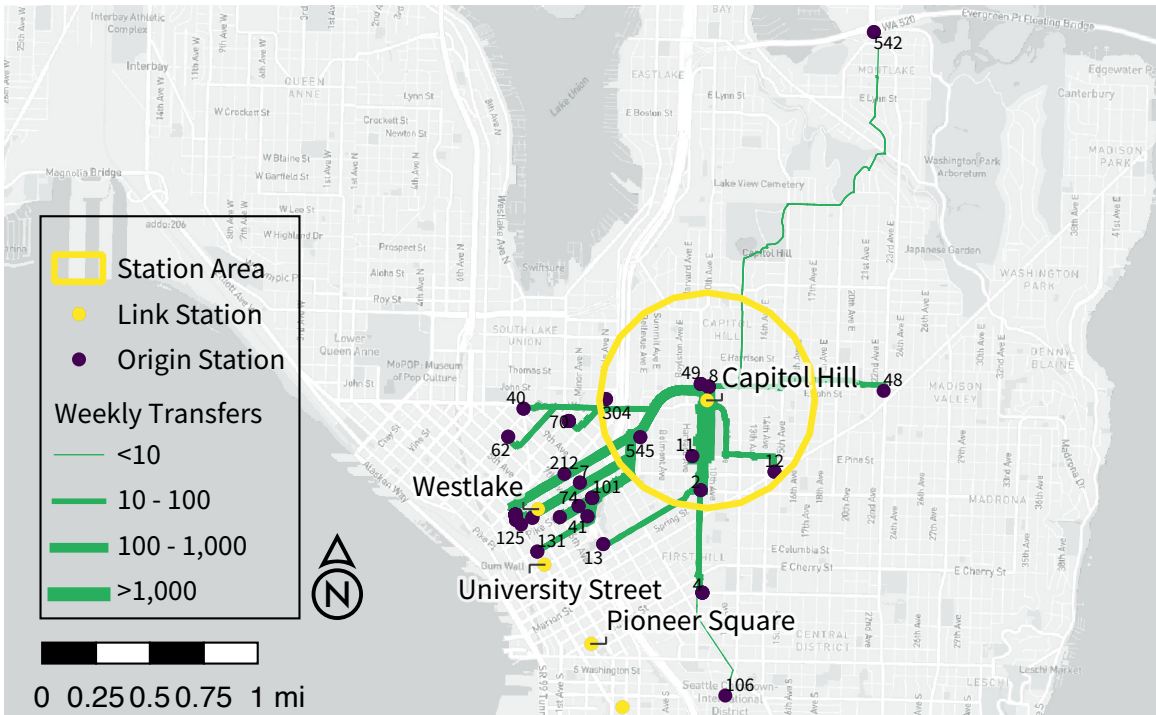


Figure 23. Capitol Hill Station Transfers

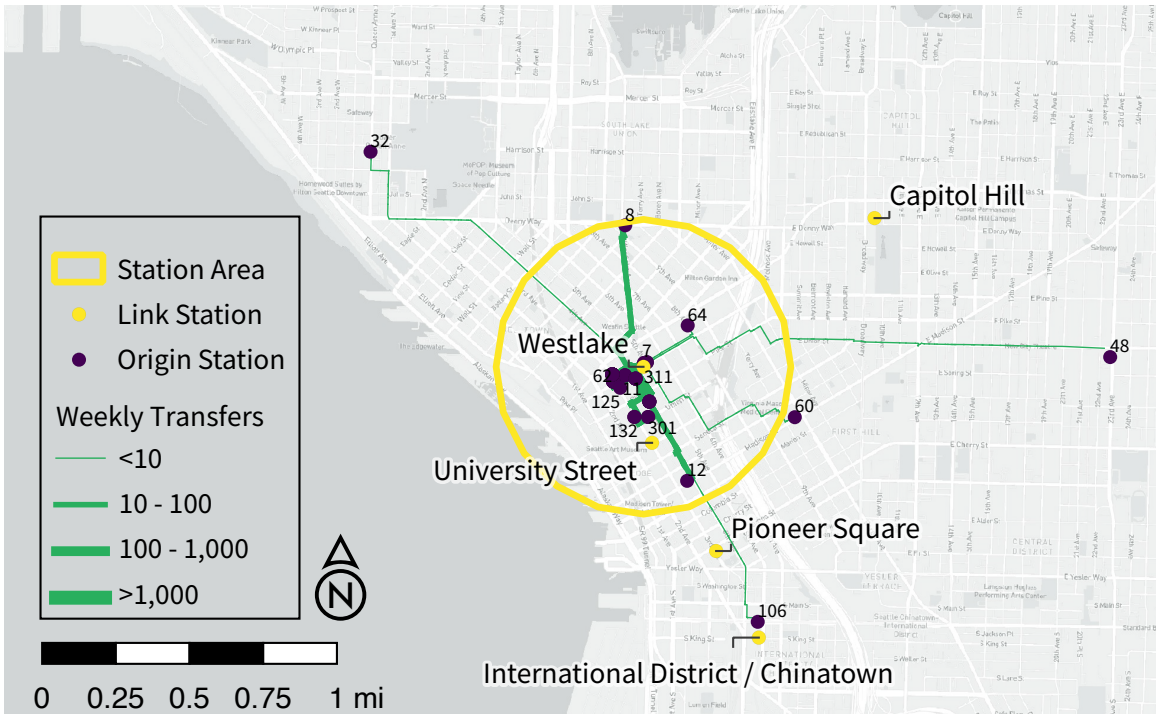
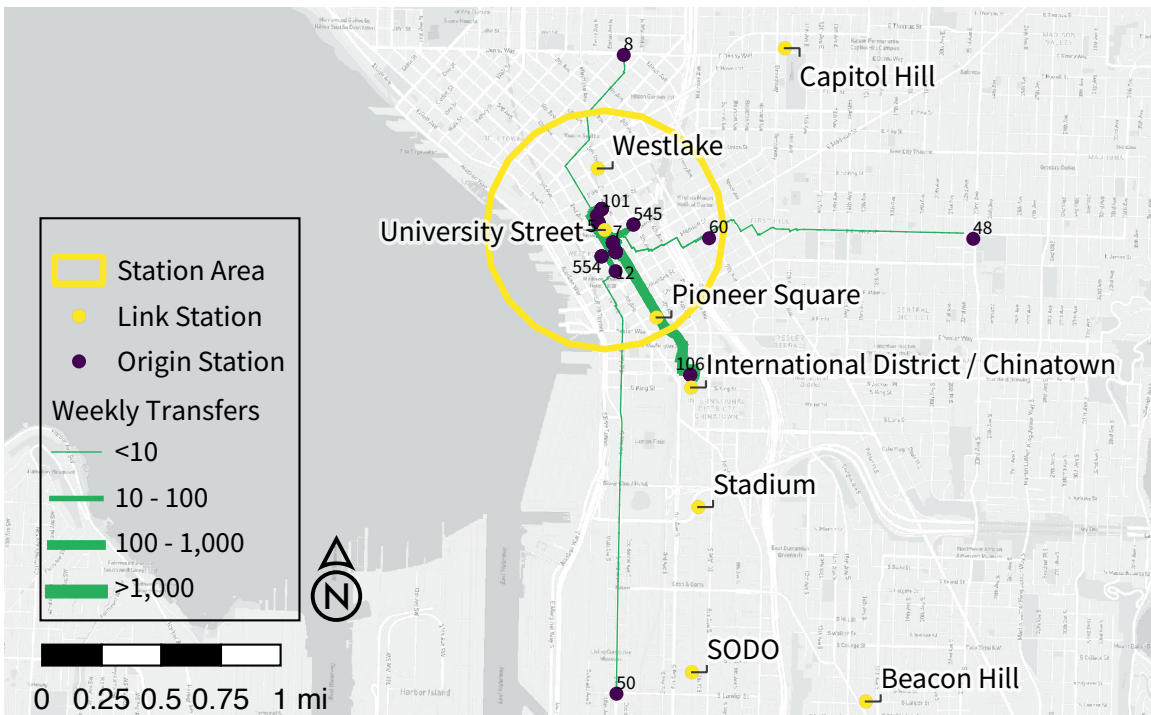
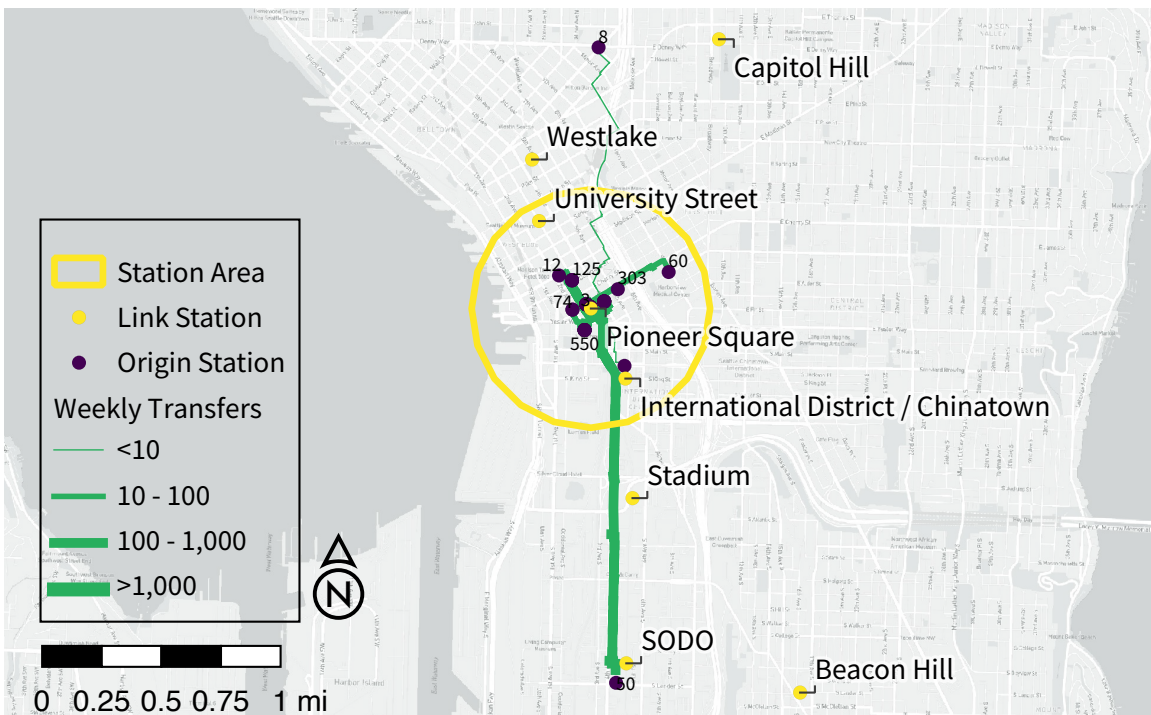


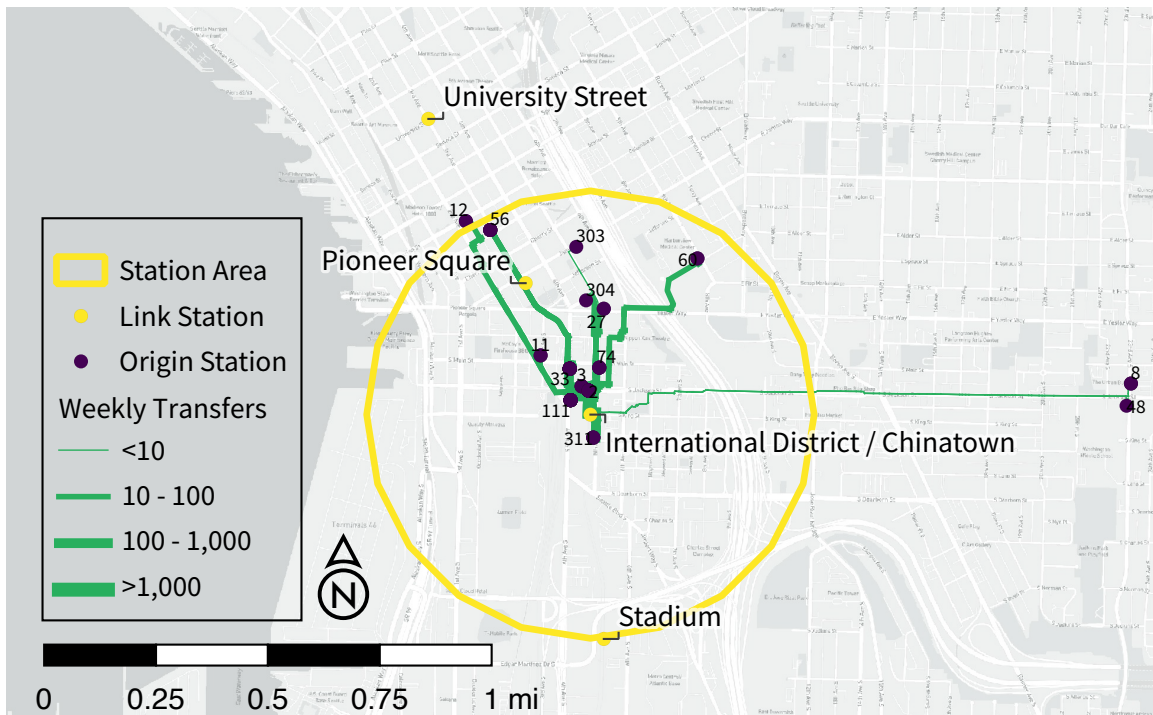
Figure 24. Westlake Station Transfers



**Figure 25.** *University Street Station Transfers*



**Figure 26.** *Pioneer Square Station Transfers*



**Figure 27.** *International District/Chinatown Station Transfers*



**Figure 28.** *Stadium Station Transfers*

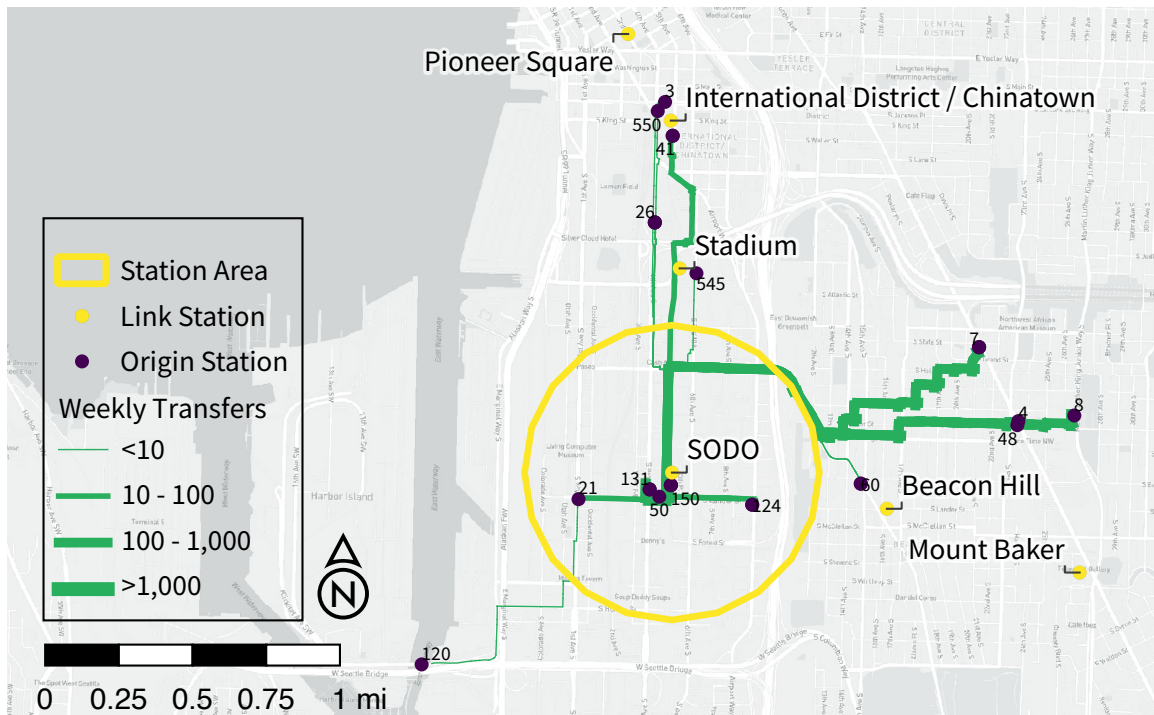


Figure 29. SODO Station Transfers

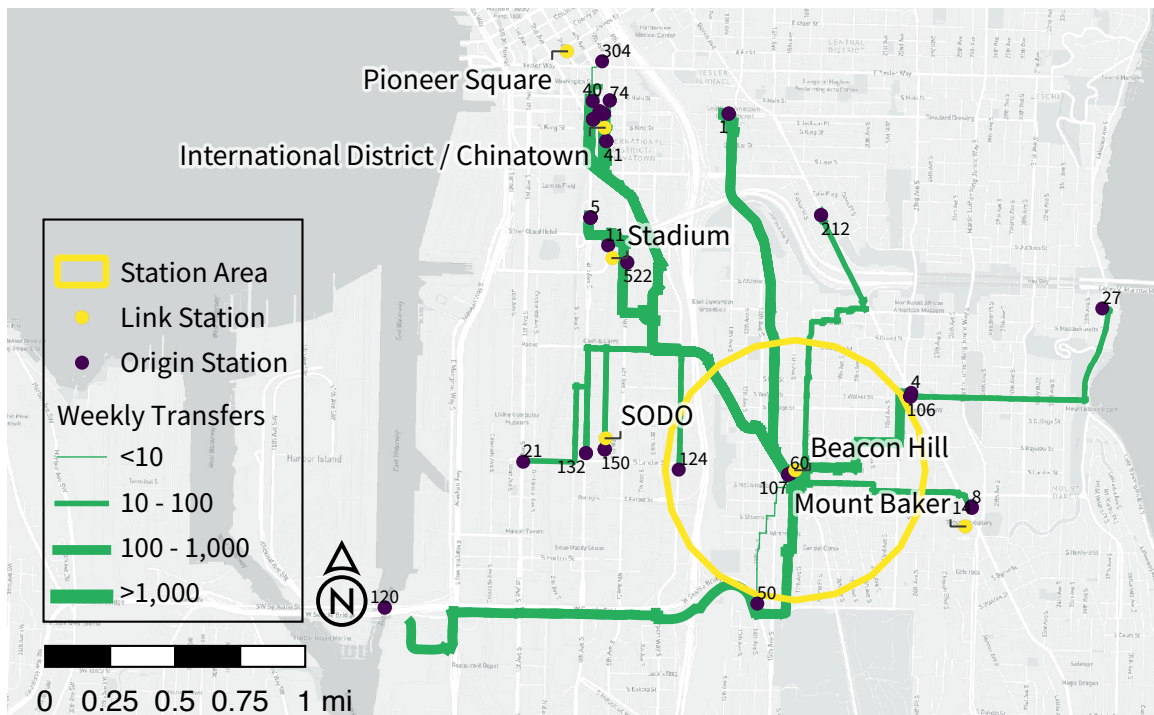
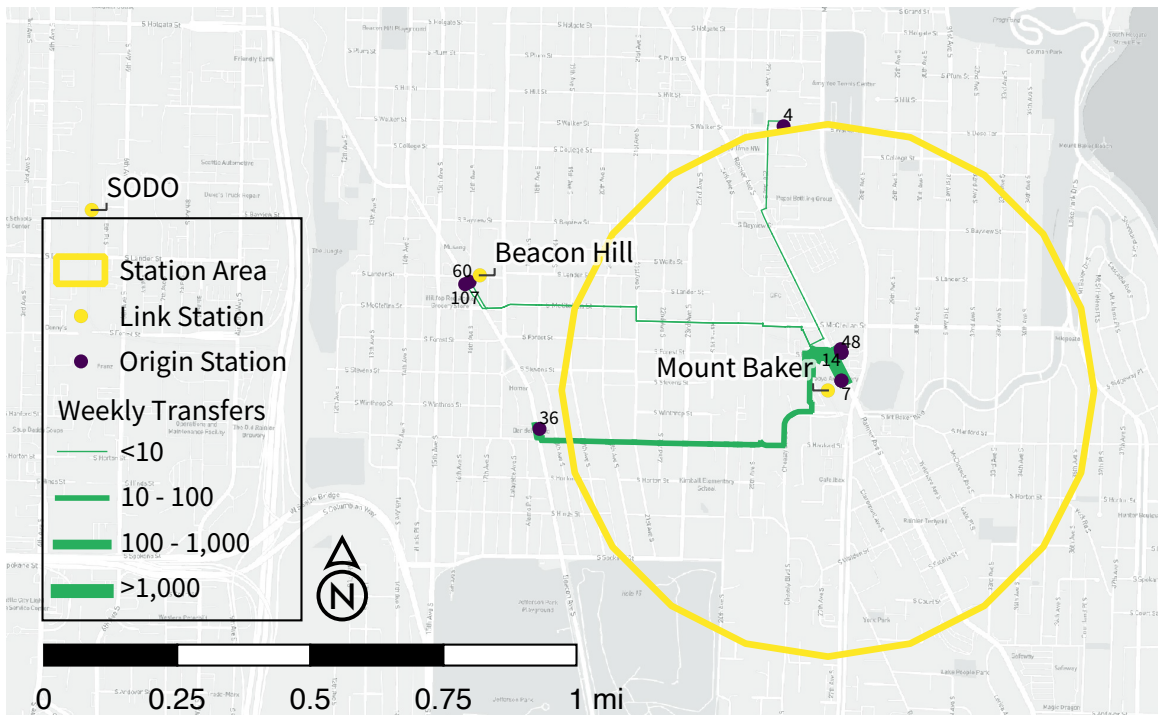
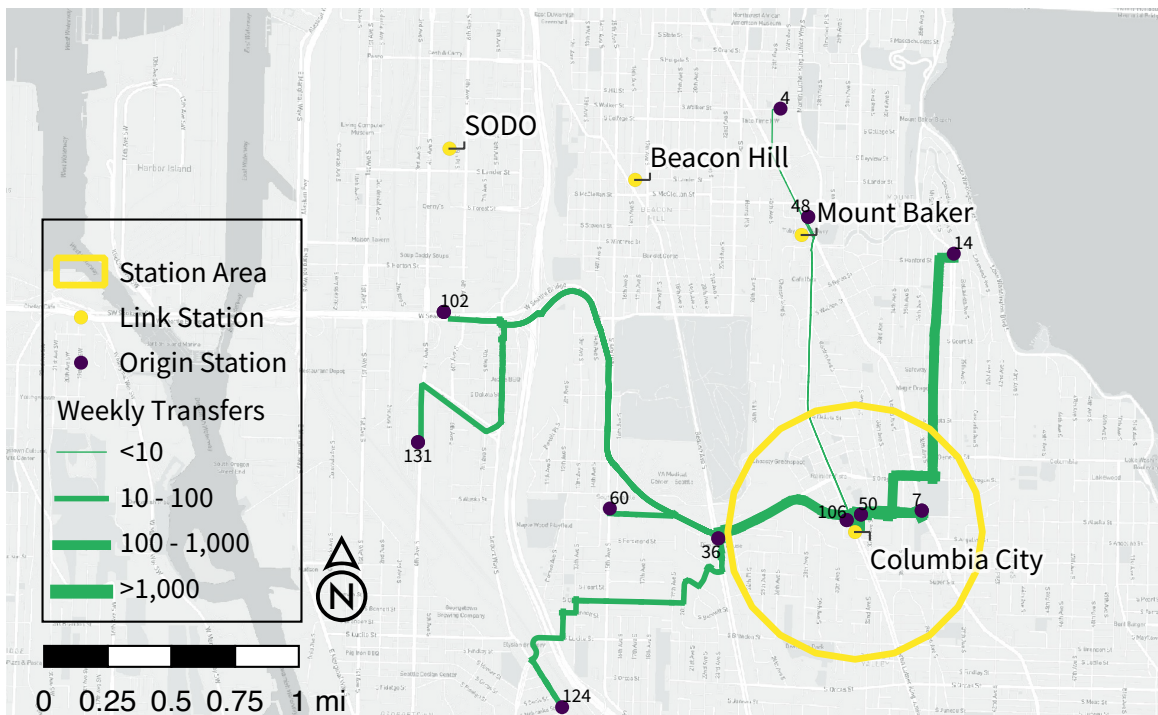


Figure 30. Beacon Hill Station Transfers



**Figure 31.** *Mount Baker Station Transfers*



**Figure 32.** *Columbia City Station Transfers*

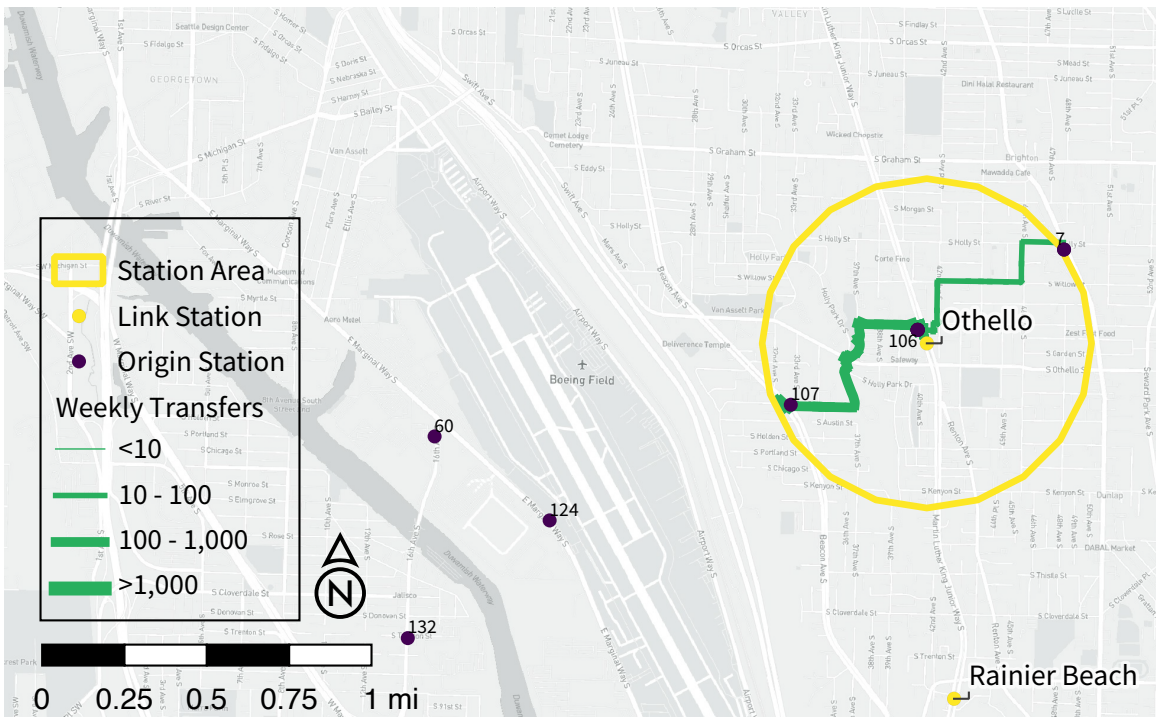


Figure 33. *Othello Station Transfers*

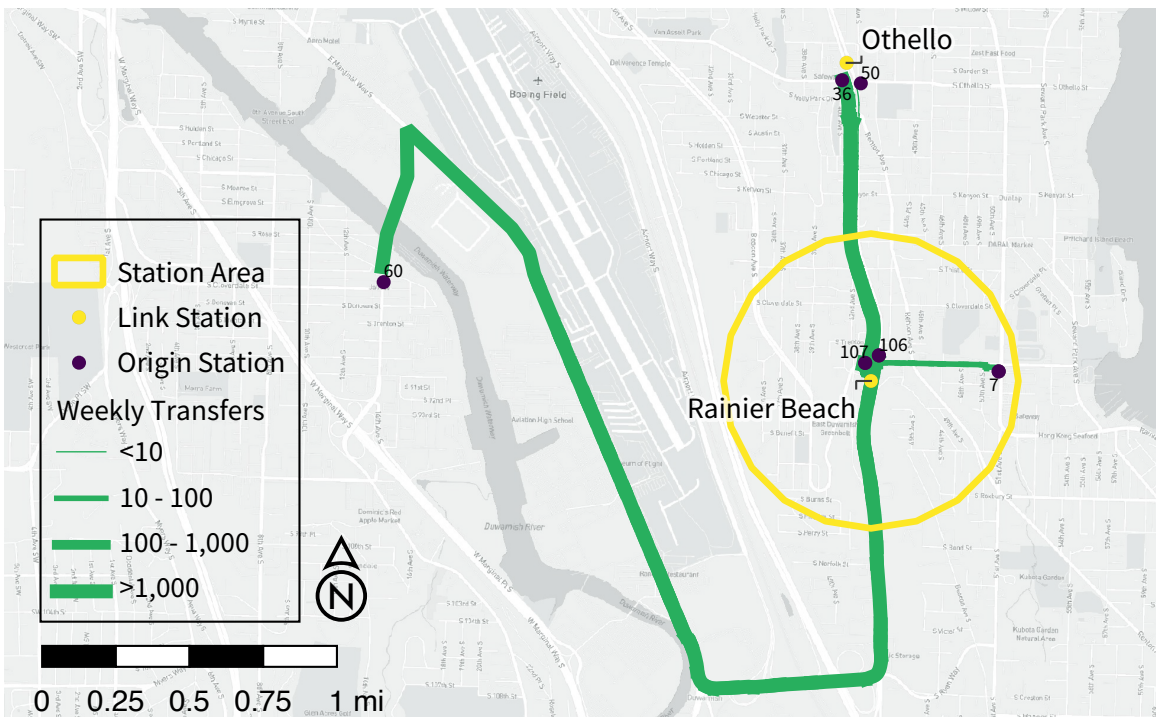
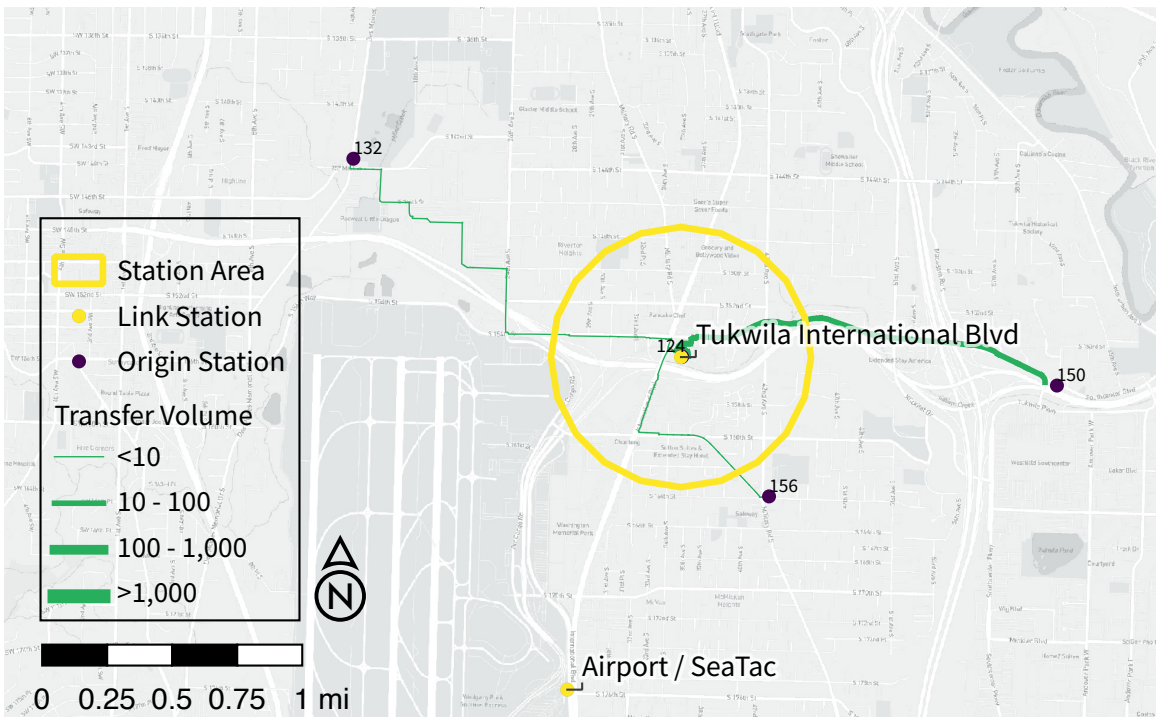
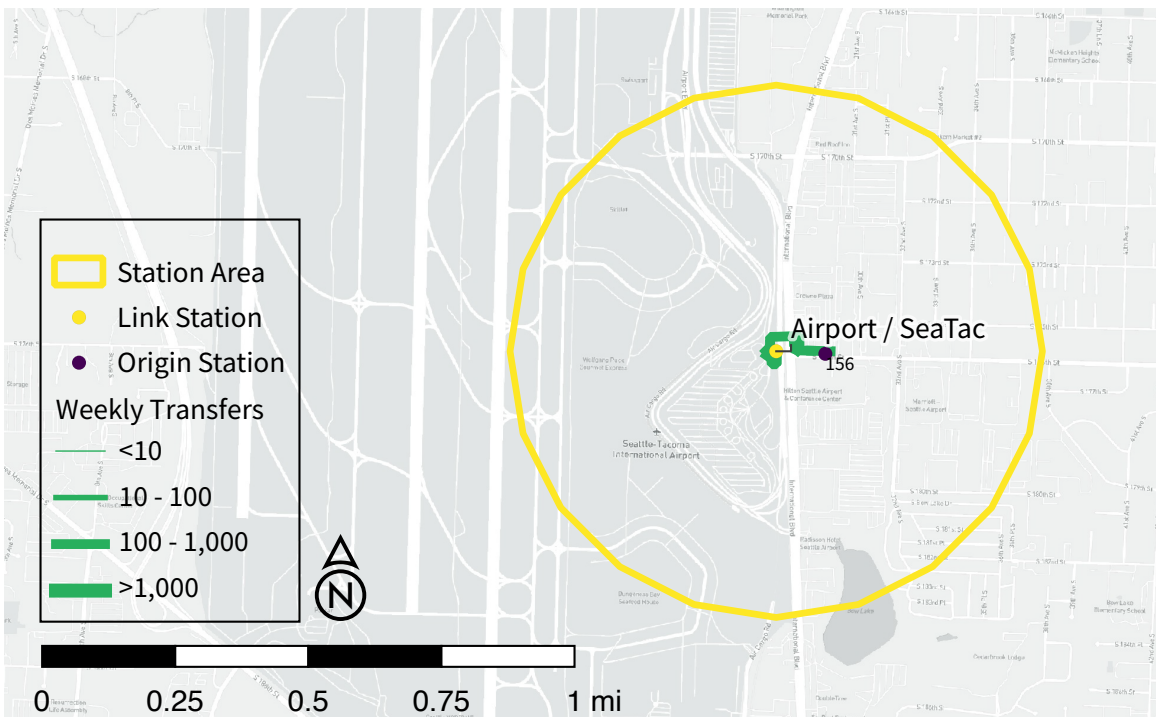


Figure 34. *Rainier Beach Station Transfers*



**Figure 35.** *Tukwila Station Transfers*



**Figure 36.** *SeaTac/Airport Station Transfers*

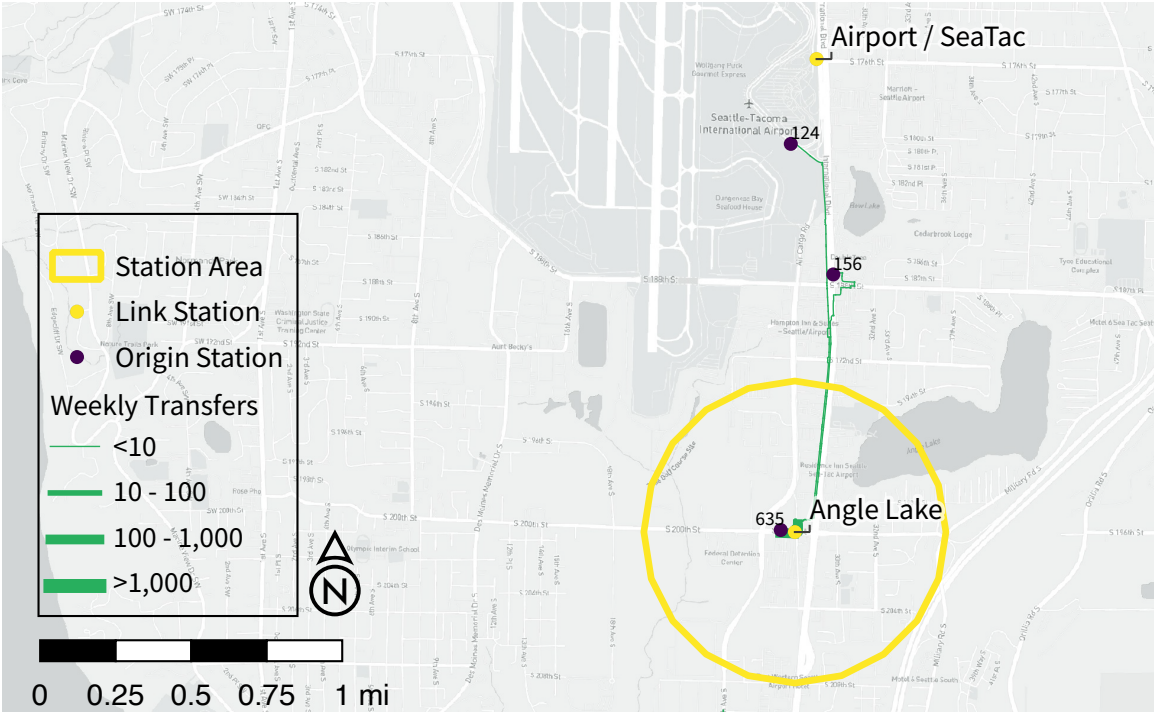


Figure 37. Angle Lake Station Transfers

Tables

Table 7. Descriptive Statistics of Covariates

	N	Mean	SD	Min	Q1	Median	Q3	Max
weekly	524	139.38	300.63	2.00	6.00	26.00	107.50	2230.00
wkLen	524	935.91	1181.78	8.26	106.15	264.99	1597.54	7087.57
wkMnSpd	524	24.24	2.35	15.66	23.94	24.23	24.52	40.02
wkMxSpd	524	27.30	6.37	15.91	24.23	24.98	26.84	60.02
wkGrade	524	3.30	2.23	0.00	1.66	2.73	4.47	11.70
wkMxGrd	524	14.36	21.56	0.00	3.90	9.80	19.00	390.20
wkRise	524	33.53	45.58	0.00	2.17	6.53	69.18	210.81
stEnt	524	0.77	0.07	0.64	0.74	0.79	0.80	0.95
stCirc	524	1.03	0.02	1.02	1.02	1.03	1.04	1.19
stStDen	524	40246.01	6426.35	19063.51	37814.70	41854.07	44498.99	47203.83
stIntDen	524	346.18	50.00	161.28	330.87	358.24	373.88	392.46
stStLen	524	82347.00	13148.90	39005.68	77372.32	85637.23	91048.98	96583.34
lrDisable	524	5.49	2.33	1.23	4.01	5.31	7.56	12.92
lrSenior	524	4.64	1.78	1.41	3.12	4.19	5.88	8.78
lrYouth	524	4.60	3.96	0.85	2.38	3.01	4.71	22.73
lrLift	524	6.57	2.72	1.34	4.94	6.32	7.68	16.67
lrSum	524	51131	21520	240	33040	52864	68212	92714
ogYouth	524	0.05	0.04	0.01	0.02	0.04	0.05	0.22
ogSenior	524	0.03	0.01	0.02	0.02	0.03	0.03	0.06
ogLift	524	0.06	0.02	0.03	0.05	0.05	0.06	0.10
ogDisable	524	0.02	0.01	0.01	0.02	0.02	0.03	0.04
ogAdult	524	0.84	0.06	0.62	0.86	0.86	0.87	0.91
ogSum	524	29994	17699	3457	17048	28084	39884	63408

**Table 8. Seasonal Station Transfer Summary**

	Station	szn	NonTransfer	Transfer	Total
1	Angle Lake	S	30536	7151	37687
2	Angle Lake	W	10330	1783	12113
3	Beacon Hill	S	46868	16540	63408
4	Beacon Hill	W	8314	5034	13348
5	Capitol Hill	S	22010	6074	28084
6	Capitol Hill	W	32640	7244	39884
7	Columbia City	S	18580	14725	33304
8	Columbia City	W	10537	1554	12091
9	Intl District	S	15358	3433	18791
10	Intl District	W	15154	14154	29308
11	Mount Baker	S	11371	2121	13492
12	Mount Baker	W	7081	3311	10392
13	Othello	S	5949	993	6942
14	Othello	W	10093	2050	12144
15	Pioneer Sq	S	6810	3846	10656
16	Pioneer Sq	W	13550	3498	17048
17	Rainier Beach	S	8634	4775	13409
18	Rainier Beach	W	5861	2586	8447
19	Seatac	S	29422	17523	46944
20	Seatac	W	11379	2157	13537
21	SODO Stn	S	6237	3274	9511
22	SODO Stn	W	6465	2992	9457
23	Stadium	S	12098	1898	13996
24	Stadium	W	2690	768	3458
25	Tukwila	S	10885	2375	13260
26	Tukwila	W	7976	3299	11274
27	University Street	S	6569	3019	9588
28	University Street	W	20048	6776	26825
29	UW	S	8355	3304	11660
30	UW	W	30724	18261	48984
31	Westlake	S	13165	2387	15552
32	Westlake	W	39037	16222	55259