MULTI-MODAL PERFORMANCE MEASURES IN OREGON: DEVELOPING A TRANSPORTATION COST INDEX BASED UPON MULTI-MODAL NETWORK AND LAND USE INFORMATION

Final Report

SPR 760

RESEARCH

Oregon Department of Transportation

MULTI-MODAL PERFORMANCE MEASURES IN OREGON: DEVELOPING A TRANSPORTATION COST INDEX BASED UPON MULTI-MODAL NETWORK AND LAND USE INFORMATION

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16. Abstract

Transportation Cost Index is a performance measure for transportation and land use systems originally proposed and piloted by Reiff and Gregor (2005). It fills important niches of existing similar measures in term of policy areas covered and type of applications. The goal of this research project is to move TCI from prototype towards implementation and application by establishing robust definitions of travel market baskets and robust methods for calculating transportation costs. After reviewing literature, we propose two approaches of defining travel market baskets, namely the cluster-based approach and the survey-based approach, and one method of calculating travel costs. We develop these approaches and implement them in R as an open source project. We then apply TCI to various regions, in particular Portland and Corvallis in Oregon, to showcase its scalability and applicability.

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SI* (MODERN METRIC) CONVERSION FACTORS

APPROXIMATE CONVERSIONS TO SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	millimeters squared	mm^2
ft^2	square feet	0.093	meters squared	m^2
yd^2	square yards	0.836	meters squared	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	kilometers squared	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	ml
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	meters cubed	m^3
yd^3	cubic yards	0.765	meters cubed	m^3
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams	Mg
		TEMPERATURE (exact)		
°F	Fahrenheit	(F-32)/1.8	Celsius	°C

NOTE: Volumes greater than 1000 L shall be shown in m^3.

APPROXIMATE CONVERSIONS FROM SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	millimeters squared	0.0016	square inches	in^2
m^2	meters squared	10.764	square feet	ft^2
m^2	meters squared	1.196	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	kilometers squared	0.386	square miles	mi^2
		VOLUME		
ml	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	meters cubed	35.315	cubic feet	ft^3
m^3	meters cubed	1.308	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.205	pounds	lb
Mg	megagrams	1.102	short tons (2000 lb)	T
		TEMPERATURE (exact)		
°C	Celsius	1.8C+32	Fahrenheit	°F

*SI is the symbol for the International System of Measurement

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DISCLAIMER

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1.0 BACKGROUND

MAP-21 and state laws are placing increasing emphasis on using comprehensive transportation performance measures that include mobility, safety, economy, livability, equity, and environmental to guide transportation decision making. The federal MAP-21 law requires state DOTs and metropolitan planning organizations (MPOs) to set performance targets and report progress with respect to seven comprehensive national goals *(MAP-21 2012)*. The Oregon Jobs and Transportation Act mandates that ODOT develop a least-cost planning (LCP) process that uses performance measures in the comprehensive evaluation of all possible solutions to meet transportation goals.

One of the toughest challenges keeping DOTs and MPOs from adopting comprehensive measures in the decision process is the lack of performance measures allowing consistent comparison of multimodal performance over time and across geographic areas. Fortunately, previous ODOT research offers some direction in meeting this challenge. Proof-of-concept research in SPR 375 *(Reiff and Gregor 2005)* developed a Transportation Cost Index (TCI) for use in comparing transportation performance outcomes for different modes in common terms. The TCI accomplishes this by building on the concept of the widely-used Consumer Price Index (CPI). As a result of the logic appeal of the TCI and the proof-of-concept research, this measure was adopted by the Accessibility Indicator Development Team (IDT) for the Oregon LCP project *(Carr, Hajiamiri, and Gros 2012)*.

The aim of this research project is to advance the TCI from the proof-of-concept stage to implementation in transportation performance measurement and decision-making at the state, MPO, and community levels. In this process there are two key problems to be solved: the definition of "travel market baskets" and the calculation of travel costs to access the travel market baskets. A travel market basket is a set of destinations that provide a good set of choices for meeting daily living needs. Because travel-market-basket definition and travel-cost calculation are based on the travel demand model of the Rogue Valley metropolitan area (Reiff and Gregor, 2005), they may not suit other communities, other travel demand models, or applications that don't rely on a travel demand model.

Our proposed work is unique and addresses two key issues in TCI to advance its implementation and adoption. Reiff and Gregor's *(Reiff and Gregor 2005)* work is the original research that conceives the TCI measure, and there has been no other research effort addressing the issues of travel market basket definition and travel cost calculation for TCI. Since the travel market basket is a new concept in transportation performance measurement, we will look into literature of economics *(e.g., Cage and Greenlees 2003)*, and public health *(e.g., Block and Kouba, 2006)*, etc for guidance and inspiration for alternative definitions. Travel costs have usually been derived from discrete choice models of travel behavior, which is the method Reiff and Gregor use. However, what is the best way to aggregate travel costs for composite measures when multiple transportation modes are available hasn't been addressed in their research or in the literature.

To provide the rigorous theoretical grounding and empirical testing, the project will include refinement and additional development of the TCI and evaluation based upon tests using data representing several communities in Oregon. The project will also identify appropriate data sources needed for computing and forecasting the measure, and provide guidance for the collection and archiving of these data and documentation that enables the application and replication of the TCI by ODOT, MPOs, and other communities in Oregon.

The overall purpose of the research is to help to move the TCI substantially towards statewide implementation by establishing robust definitions of travel market baskets and robust methods for calculating travel costs to access the travel market baskets. In this context, robust definitions and methods are ones that:

1. Are well justified by theory and testing;

2. Are scalable across communities of all sizes;

3. Are understandable by an informed audience;

4. Can be used with different levels of data specificity that are likely to be available for different application contexts such as:

    - Monitoring transportation performance using transportation network and land use data that is collected on a periodic basis;

    - Estimating the effects of potential transportation network and/or land use changes in a screening or rapid response approach that does not entail running a travel demand model; and

    - Estimating the effects of potential transportation network and/or land use changes in a more comprehensive analysis approach involving the use of a travel demand model.

Specifically, this proposed project has two objectives:

1. Develop **robust definitions** of the transportation market baskets to use in calculation of the TCI. The Transportation Plan Performance Measures study *(Reiff and Gregor, 2005)* developed definitions of market baskets of travel destinations based on the structure and data encoded in the travel demand model of the Rogue Valley metropolitan area. These definitions may not suit application of the TCI in different communities or in different types of applications that don't rely on a travel demand model or that use travel demand models of different types. Definitions need to be developed that do not depend on a particular model specification or data structure. The definitions need to be understandable by an informed audience, well supported by theory, and shown to be applicable in different size communities. The definitions need to be implementable using data that is currently available (e.g. Census Longitudinal Employer-Household Dynamics data) or data that could become available in the future.

2. Develop **robust methods** for calculating the average travel cost to access each defined market basket by each travel mode (auto, public transit, walk, bike) and by different household market segments; and develop robust methods for aggregating costs at different geographic levels (e.g. neighborhood, city, metropolitan region). The Transportation Plan Performance Measures study developed methods for using utilities from the travel demand model to calculate composite travel costs (time and money). This approach is too dependent on one particular model structure to be generally applied in communities across Oregon. More general methods are needed that are not dependent on a travel demand model but may use information generated by a travel demand model (e.g. travel time skims). The methods need to be well justified with respect to how they calculate composite costs and how they aggregate costs by geographic area. The methods need to address issues of cross modal aggregation and income equity identified in the Transportation Plan Performance Measures study report.

2.0 LITERATURE REVIEW

We firstly review existing similar performance measures of transportation and land use systems, largely labeled as accessibility measures in the literature. We pay special attention to a set of accessibility measures developed by the Accessibility Observatory at University of Minnesota. We then review relevant literature for travel market baskets definition and travel cost calculation. This review serves to provide theoretic background and information for the two objectives of this project: developing robust definitions of the transportation market baskets to be used in the calculation of the Transportation Cost Index (TCI); and to develop robust methods for calculating and aggregating multi-modal travel cost to access market baskets by different modes including auto, public transit, walk, bike and by different household segments.

2.1 EXISTING SIMILAR PERFORMANCE MEASURES

There has been a growing body of literature documenting accessibility metrics and its application as performance measures. Handy and Niemeier *(Handy and Niemeier 1997)* discuss common used accessibility measures and their limitations. NCHRP 446 *(Cambridge Systematics 2000)* categorizes a set of performance measures including accessibility by the policy areas they represent, and recommends practice for selecting performance measures.

The three common accessibility measures *(Handy and Niemeier 1997)* – cumulative opportunities measures, gravity-based measures and utility-based measures – face a dilemma in application. Comprehensive accessibility measures, such as utility and gravity-based metrics, are good at presenting an overall picture of a community's accessibility level, but they are very technical and hard to communicate to the public what they actual measure. On the other hand, specific accessibility measures are intuitive but can hardly convey a comprehensive picture of accessibility. For example, cumulative opportunities measures such as number of employment accessible with 30 minutes during am peak by transit is appealing in that it is very straightforward to communicate what it measures, but they can hardly be used to present an overall picture of a community, as they reflect only a certain aspect of a much more complex picture.

Another topology of accessibility measures is proposed by Geurs and van Wee *(Geurs and van Wee 2004)* after reviewing accessibility measures that are suitable for evaluation of land-use and/or transportation strategies. They classify accessibility measures by its perspective: infrastructure-based measures, location-based measures, person-based measures, and utility-based measures. While infrastructure-, location-, and person-based measures are relatively easier to interpret, it is more difficult for these measures to present a comprehensive picture of the systems to be measured; vice-versa for utility-based measures. For example, most travel time-based and opportunity-based accessibility indicators are location- or person-based measures. Within this topology, the TCI is a location-based measure and aims to be an intuitive measure of overall system performance.

The idea of Transportation Cost Index is in line with the approach Koopmans et al. *(Koopmans et al. 2013)* propose – measuring generalized travel cost as an indicator of monitoring accessibility change. They calculate the average costs per kilometer of trips by transportation mode, trip purpose, trip distance, region and time-of-day, and monitor the cost change over time. The measure has the advantage of easy interpretability, but since it only account for per distance costs for motorized trips and thus ignores potential land use changes, it is infeasible as a measure for land use and transportation systems. By tracking the generalized travel cost to access a pre-defined travel market basket, the TCI will be sensitive to changes in both land use and transportation systems.

Geurs et al. *(Geurs et al. 2010)* propose to use a disaggregated logsum accessibility measure from a land-use transportation interaction model to compute changes in consumer surplus between policy scenarios. While the goal of their research is similar to that of this project in terms of providing an elegant and convenient solution to measure benefits from land-use and/or transportation policies, their consumer surplus metrics are only meaningful for measuring the difference between two scenarios, and thus not suitable for use to monitor accessibility trends over time. It also lacks the capacity to examine the balance aspect across geographic regions and population subgroups.

2.2 ACCESSIBILITY OBSERVATORY

The Accessibility Observatory at the University of Minnesota focuses on the research and application of accessibility-based transportation system evaluation. The Accessibility Observatory builds on earlier work conducted at the University of Minnesota, including the *Access to Destinations* study and the first *Access Across America* series report.

The Access to Destinations *(Owen and Levinson 2012)* study laid the groundwork for their accessibility evaluation. The Observatory uses the methods and tools developed there as the starting point for an integrated, multi-modal accessibility evaluation system that they plan to apply nationwide.

The *Access Across America* series measures accessibility to jobs via various modes of transportation in major metropolitan areas across the United States. Latest release reports are Access Across America: Transit 2014 *(Owen and Levinson 2014)* and Access Across America: Auto 2013 *(Owen and Levinson 2014)*.

2.2.1 Methodology

2.2.1.1 Cumulative Opportunities Accessibility

Owen and Levinson *(Owen and Levinson 2012)* use a cumulative opportunities measure of accessibility. The approach begins by specifying a mode and travel time threshold, and then counts the number of opportunities that can be reached via that mode within the specified travel time threshold. The study examines six time threshold (from 0 to 10 minutes, from 10 to 20 minutes, from 20 to 30 minutes, from 30 to 40 minutes, from 40 to 50 minutes, from 50 to 60 minutes). Accessibility is calculated as:

$$A_{i,co} = \sum_{j=1}^{n} O_J f(C_{ij}) \quad \textbf{(2.1)}$$

A_i, co = cumulative opportunities accessibility from a zone (i) to the considered type of opportunities
O_j = number of opportunities of the considered type in zone j (e.g., employment)
C_{ij} = generalized (or real) time or cost of travel from i to j
$f(C_{ij})$ = impedance function

For the cumulative opportunities measure, $f(C_{ij})$ is defined as 1 if C_{ij} < T and 0 otherwise. T is the pre-specified travel time threshold.

2.2.1.2 Worker-weighted Job Accessibility

To compare accessibility of different level of geography, Owen and Levinson (2012) propose the of a worker-weighted accessibility measure. The cumulative accessibility measure is averaged across all subzones with each subzones' contribution weighted by the number of workers in that subzone.

$$A_{pw} = \frac{\sum_{i=1}^{n} A_i P_i}{\sum_{i=1}^{n} P_i} \quad \textbf{(2.2)}$$

A_{pw} = worker-weighted average accessibility of all subzones
P_i =population in subzones i

2.2.1.3 Weighted Accessibility Ranking

Metropolitan area rankings are based on an average of worker-weighted job accessibility for each metropolitan area over the six travel time thresholds. With the weighted average job accessibility, destinations reachable in shorter travel times are given more weight. Here two time thresholds are used to get a series of "donuts" (e.g., jobs reachable from 0 to 10 minutes, from 10 to 20 minutes, from 20 to 30 minutes, from 30 to 40 minutes, from 40 to 50 minutes, from 50 to 60 minutes).

$$a_w = \sum_t (a_t - a_{t-10}) e^{\beta t} \quad \textbf{(2.3)}$$

a_w = = Weighted accessibility ranking metric for a single metropolitan area
a_t = Worker-weighted accessibility for threshold t
β = -0.08 (calculated through survey data)

2.2.2 Evaluation

This performance measure developed by the Accessibility Observatory is a type of opportunity-based accessibility measures. The chief advantage of the cumulative opportunities measure is its simplicity to interpret and its focus on commuting by a particular mode, but it also has a few limitations. First, cumulative opportunities and weighted opportunities measures of accessibility do not account for differences in preferences among individuals - they imply that all people living in the same location (e.g. traffic analysis zone) will experience the same level of accessibility. For example, it does not differentiate accessibility by income groups. Travelers of different income group people usually have different time constraints, preference and availability of travel modes. Second, it only measures the access to jobs, but not necessary the destinations that travelers travel to. For example, low income households may live in downtown area with the best cumulative opportunities accessibility, but they still have to do long commute to access jobs for which they are qualified. Except for jobs, accessing to other types of activities is not considered, such as shopping, recreation and others. Lastly, a fixed threshold in the impedance function may create cliff effects as a 30-minute cut-off would mean that jobs within 29 minutes will be counted while those 31-minutes away would be excluded.

2.3 TRAVEL MARKET BASKET

The term market basket refers to a fixed list of items used specifically to track inflation in an economy or of a specific market. The most common type of market basket is the basket of goods and services used to define the Consumer Price Index (CPI), which is intended to track the prices of goods and services in the basket. The consumer basket is the base for the definition of the Consumer Price Index (CPI). In this section, we examined the methodology for the CPI. The CPI was first developed to characterize the rapid increases in necessary cost-of-living adjustments (COLA) during World War I (Bureau of Labor Statistics, 2007). Three of the main CPI series include CPI for All Urban Consumers (CPI-U), Chained CPI for All Urban Consumers (C-CPI-U) and CPI for Urban Wage Earners and Clerical Workers (CPI-W).

2.3.1 The CPI Calculation Process

The CPI is built in two stages (Figure 2.1): Low-level aggregation and upper-level aggregation. The technical calculation process is provided in Chapter 17 Consumer Price Index of the Handbook of Methods by the Bureau of Labor Statistics (BLS)[1]. This section provides a brief summary of the process, especially focusing on the construction of market basket with Consumer Expenditure Survey (CES).

[1] U.S. Bureau of Labor Statistics, Handbook of Methods, Chapter 17 The Consumer Price Index, available at http://www.bls.gov/opub/hom/pdf/homch17.pdf

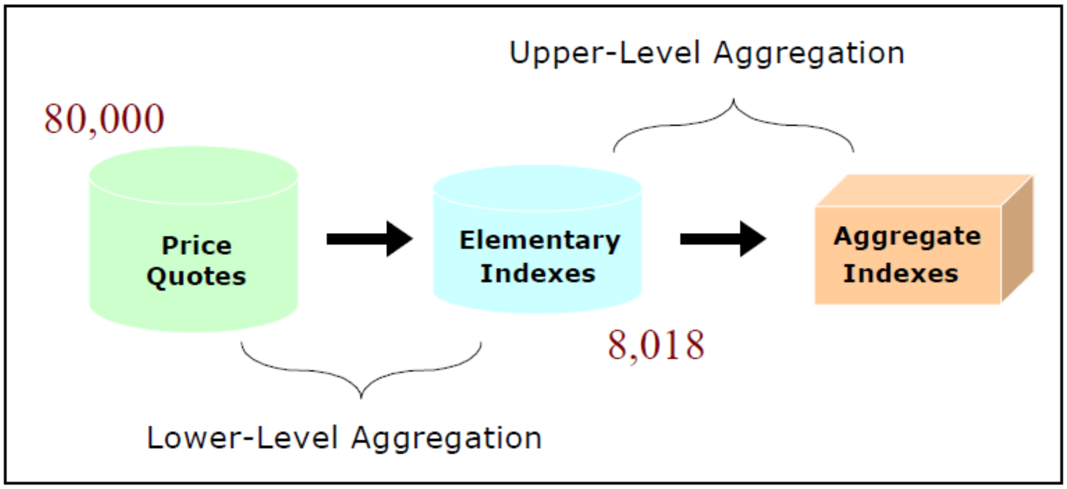

Figure 2.1: 2-Stage Process of the CPI Calculation

The first stage is often referred to as "lower-level aggregation" or "elementary-level aggregation" as it involves averaging the most fundamental component of the index - observed price change for specifically defined consumer goods, services, and products. In this stage, price changes for roughly 80,000 specific items per month are averaged to yield 8,018 estimates of aggregate price change.

In the CPI calculation process, the urban portion of the United States is divided into 38 geographic areas called *index areas*, and the set of all goods and services purchased by consumers is divided into 211 categories called *item strata.* This results in 8,018 (38 x 211) item-area combinations. An elementary-level index is computed for each combination of an item stratum and index area.

The CPI item structure has four levels of classification. The 8 major groups are made up of 70 expenditure classes (ECs), which in turn are divided into 211 item strata. Major groups and ECs do not figure directly in CPI sample selection, although ECs are used in smoothing item stratum expenditure estimates during composite estimation. Within each item stratum, one or more substrata, called entry-level items (ELIs), are defined. There are a total of 305 ELIs, which are the ultimate sampling units for items as selected by the BLS national office. They represent the level of item definition from which data collectors begin item sampling within each sample outlet. Each ELI has a corresponding sampling frame of outlets that sell the ELI. In each there are several unique items. A single selection of a unique item is referred to as a quote. An example of a unique item for the ELI Cookies is a 1-lb. bag of chewy-style chocolate-chip cookies with walnuts, of a particular brand name.

For example, the prices of approximately ten different brands and styles of watches at various locations in Chicago are observed each month, compared to the prices observed in the previous month, and averaged together to produce an index of price change for watches in Chicago. Watches (ITEM=AG01) is one of 211 elementary items, and Chicago (AREA=A207) is one of 38 elementary areas in the current CPI market basket structure. The Chicago-watch index is one of the 8,018 (211 items x 38 areas) elementary indexes produced in the first stage of CPI construction.

In the second stage, the elementary indexes are averaged together to yield various aggregate indexes and ultimately the All-Items, U.S. City Average index of price change.

Aggregation of elementary CPI data into published indexes requires three ingredients: input elementary price indexes, input elementary expenditure to use as aggregation weights, and a price index number formula that uses the expenditures to aggregate the sample of elementary indexes into a published index. More technical details are available in page 33-36 of Chapter 17 Consumer Price Index in the BLS Handbook of Methods.

2.3.1.1 Items in the Market Basket

The CPI market basket is developed from detailed expenditure information provided by families and individuals on what they actually bought. For the current CPI, this information was collected from the Consumer Expenditure (CE) Surveys for 2011 and 2012. In each of those years, about 7,000 families from around the country provided information each quarter on their spending habits in the interview survey. To collect information on frequently purchased items, such as food and personal care products, another 7,000 families in each of these years kept diaries listing everything they bought during a 2-week period.

Over the 2 year period, then, expenditure information came from approximately 28,000 weekly diaries and 60,000 quarterly interviews used to determine the importance, or weight, of the more than 200 item categories in the CPI index structure.

For each of the more than 200 item categories, using scientific statistical procedures, the Bureau has chosen samples of several hundred specific items within selected business establishments frequented by consumers to represent the thousands of varieties available in the marketplace. For example, in a given supermarket, BLS may choose a plastic bag of golden delicious apples, U.S. extra fancy grade, weighing 4.4 pounds to represent the apples category.

To enable the CPI to reflect changes in the marketplace, new item and outlet samples are selected each year, on a rotating basis, for approximately 25 percent of the item strata. Each year, four regional item universes are tabulated from the 2 most recent years of CE data. Independent samples of ELIs are selected from the corresponding regional item universe for each item stratum scheduled for rotation that year. Within each sample, each item sample is based on a systematic probability-proportional-to-size (PPS) sampling procedure, in which each ELI has a probability of selection proportional to the CPI-U population expenditures for the region for the ELI within its stratum.

2.3.1.2 Relative Importance of Items

According to Schmidt *(Schmidt 1995)*, the relative importance based on consumer expenditure data refers to the ratio of expenditure of an item or a group of items to the total expenditures for all items. The patterns of expenditures at major group levels are quite similar over these time periods.

According to Mason and Butler *(Mason and Butler 1987)*, the expenditure weight for each item stratum is an estimate of total expenditure by the index population for that item. It is calculated as the product of estimates of mean expenditures of consumer units and the number of consumer units.

Mason and Butler *(Mason and Butler 1987)* defines relative importance as the share that the base-period expenditure multiplied by the price relative for a particular item stratum of the sum of all base-period expenditures multiplied by their price relatives.

$$\boldsymbol{RI_{t,i}} = \frac{\boldsymbol{E_{0i}(\frac{p_{ti}}{p_{0i}})}}{\boldsymbol{\sum_i E_{oi}(\frac{p_{ti}}{p_{oi}})}} * \mathbf{100} \qquad \textbf{(2.4)}$$

Where

P_{ti} is the price of item I in the comparison period t;
P_{oi} is the price of item I in the base period;
E_{oi} is the expenditure for item i in the base period

2.3.1.3 Consumer Expenditure Survey

The objectives of the CES is to provide the basis for revising weights and associated pricing samples for the CPI and to meet the need for timely and detailed information on the spending patterns of different types of families. Results of the CES are used to select new “market baskets” of goods and services for the index, to determine the relative importance of components, and to derive cost weights for the baskets.

The BLS follows these steps when using CE data in the CPI[2].

1. The BLS combines the spending information from respondents across the country to see how much is spent on each type of item.

2. All reported expenses are used to estimate how much urban households spend on each item.

3. These estimates are used to construct the market basket which contains a representative sample of expenses.

4. The BLS conducts another survey to find out where consumers purchased items in the market basket.

5. BLS data collectors visit housing units and a sample of the identified stores to obtain current price information on about 80,000 items each month across the country.

[2] The CE and the Consumer Price Index, available at http://www.bls.gov/respondents/cex/ceandcpi.htm

6. The BLS combines the information about the items purchased, the expenditures on these items, and their current prices to calculate the CPI.

2.3.2 Travel Market Basket

Inspired by the CPI, Reiff and Gregor *(Reiff and Gregor 2005)* proposed a transportation cost index as a multimodal performance measure of transportation and land use system. To do so, they first define market areas with data and models within the traditional 4-step travel demand modeling framework. The advantage of this approach is that the data for market definitions are readily available from most travel demand models and defining TAZ level travel market areas by trip purpose and income group is very straightforward. Ideally, to be consistent how CPI works, a representative travel market basket would be identified for each travel purpose and perhaps even each income group for the study area. However, various methods of defining reference travel market baskets (varying by income group and trip purpose) via the identification of a reference TAZ were tested, as an analog to a reference market basket of goods and services used by the CPI measure, and there is variation in the sizes of the identified market baskets because of idiosyncrasy. Thus in their study a reference travel market basket is not used; instead travel market areas are identified for each TAZ and for each income group and trip purpose. Even though such an approach would resemble the actual travel cost for each combination more closely, it deviates from the market basket definition used by CPI, which inspired the original idea of creating the TCI. This current project will explore alternative method of defining travel market basket. Details of Reiff and Gregor *(Reiff and Gregor 2005)*'s original approach is available in their final report, below we summarize their approach for contracting and comparison with our approaches later.

Since then, Diana and Mokhtarian *(Diana and Mokhtarian 2009)* have defined "modal baskets" as an individual's transportation modal mix, but we are unable to identify additional research relating to the development of transportation market baskets either on an individual level or based on a geographical region.

The main objective of developing TCIs is for policy makers and stakeholders to be able to understand the distribution of transportation costs for different trips purposes in a specific geographic location. In keeping with this main objective, it is reasonable for the transportation market basket to follow the CPI methodology of including only conditional transportation costs which users of transportation explicitly pay or experience.

2.4 TRANSPORTATION COSTS

Transportation costs are characterized in the economic literature as trade-offs of scarce resources, such as money, time or land. These costs can be categorized into internal costs (also known as private or user costs) and external costs, which can be aggregated to equal the total social cost *(Litman and Doherty 2009)*. Both internal and external costs can then be subdivided into variable costs (incremental costs that are usually associated with level of consumption or miles traveled) and fixed costs (costs that are not affected by level of consumption). Internal costs of transportation typically involve costs that are directly incurred by the user or consumer of transportation, whereas external costs of transportation involve costs that are imposed on other travelers (e.g., congestion costs or crash damages) or others who may not be involved in the provision or consumption of transportation (e.g., air pollution or noise pollution). Litman and Doherty *(Litman and Doherty 2009)* further point out issues associated with choosing a discount rate for future costs, incorporating variability and uncertainty, and the complications associated with 'conservative' cost estimates that only include easily quantifiable costs (such as fuel costs or travel time) and ignore intangible ones (such as environmental impacts of various emissions or social disparities).

Once a travel market basket is defined for a certain trip purpose, transportation costs associated with the transportation market baskets may include costs that are associated directly with travelers who undertake the trip, both internal and external. Researchers such as Bhat *(Bhat 1995; 1998a; 1998b; 2000)*, Hensher *(Hensher 1994)*, Anas *(Anas 1981; 2007)*, Kahn et al. *(Kahn et al. 1981)*, Train and McFadden *(Train and McFadden 1978)*, Train *(Train 1980)*, Gillen *(Gillen 1977)*, Louviere *(Louviere 1988)*, Louviere and Hensher *(Louviere and Hensher 1982)*, Zhao et al. *(Zhao et al. 2013)* and Pinjari et al. *(Pinjari et al. 2011)* have extensively studied transportation choice. User costs of transportation, costs of alternative (substitute) modes and travel time (and other related time spent) have been found to be primary determinants of transportation choice.

Reiff and Gregor *(Reiff and Gregor 2005)* derive travel costs from "access utilities" calculated for the destination choice model. The access utilities measure the perceived "costs" of traveling between TAZs by trip purpose, income group and travel mode. The model-derived costs are converted into monetary units and are aggregated across travel modes and averaged across the market place for the TAZ. The cost by travel mode is then combined into one representative cost to be averaged across each TAZ market place.

In addition to model-derived cost calculation, Litman and Doherty *(Litman and Doherty 2009)* summarized the transportation cost literature between 1975 and 2012.

For travelers who drive private motor vehicles, their transportation cost includes marginal internal costs and marginal external costs. Marginal internal costs can be defined as the costs to the traveler for each mile traveled, such as vehicle operating costs (i.e. fuel costs), vehicle depreciation costs, time costs and parking fees; marginal external costs includes social costs (i.e. congestion, land use alterations, safety/accidents, public infrastructure and energy) and environmental costs (i.e. air pollution, water pollution, noise & vibration pollution and greenhouse gas/climate change) *(Keeler et al. 1975; Hanson 1992; MacKenzie et al. 1992; Lee 1995; Delucchi 1996; Sansom et al. 2001; Quinet 2004; Jakob et al. 2006; Clarke and Prentice 2009; Smith et al. 2009; Becker 1965)*.

Public transportation includes options such as bus, light rail, heavy rail and streetcars. Public transportation marginal internal costs include the same costs as those for motor vehicles, except that vehicle operating costs and depreciation costs are substituted by public transit fares; and marginal external costs also include social costs (i.e. public infrastructure and accidents) and environmental costs depending on the situation *(Keeler et al. 1975; Miller and Moffet 1993; Black et al. 1996; Decoria-Souza and Jensen-Fisher 1997; Ellwanger 2000; NZMOT 2005)*.

Active transportation modes such as walking and bicycling incur marginal internal costs such time costs, bicycle operating cost and health impacts due to environmental exposure or accidents, but do not include the marginal external costs associated with motorized travel such as air pollution or greenhouse gas emissions *(COWI 2009; Land Transport New Zealand 2006)*. Oja et al. *(Oja et al. 2011)* found strong fitness benefits and moderate benefits in reducing cardiovascular risk factors (inconclusive benefits for others) in a review of studies on the health benefits of cycling, while Wanner et al. *(Wanner et al. 2012)* found limited evidence that active transport leads to higher levels of physical activity and lower body weight after screening more than 14,000 references and reviewing 36 unique studies.

It is important to note that the geographic scope, time period evaluated, traffic conditions (i.e. urban/rural, peak/non-peak or overall) and chosen discount rate may significantly influence the magnitude of these costs. Smith et al. *(Smith et al. 2009)* examined several modes of transportation including private car, bus, rail and active modes such as walking and cycling to characterize costs and benefits for the New Zealand Transport Agency, and conducted case studies of urban areas in New Zealand, Australia and the United Kingdom. The authors' conclusion echoes "context specific" nature of transportation costs and provision.

To determine the exact cost of time, the concept of Value of Travel Time (VOT) is essential to be clarified for each mode and travel purpose. Value of travel time refers to the cost of time spent on transport, including waiting as well as actual travel. It includes costs to consumers of personal (unpaid) time spent on travel, and costs to businesses of paid employee time spent in travel.

Jiang and Morikawa *(Jiang and Morikawa 2004)* use the theoretical framework to derive the variation in VOT with respect with travel time, wage, and work time.

Oregon Department of Transportation (ODOT) estimate the hourly value of travel-time for two types of travel with three types of vehicles *(ODOT 2012,* shown in Table 2.1 below*)*. On-the-clock business trips represent travel for work and do not include commute trips. The value of On-the-clock business trips is a reflection of the total cost of the employee's time to the employer and so is a function of total compensation. Personal trips include recreation, shopping, commuting, and other personal travel. Value of personal time reflects the opportunity cost of time spent traveling vs. time that could be spent doing something else and is typically expressed as a fraction of household income. The fraction of the hourly median household income used to value personal time is currently 50% for local trips and 70% for intercity trips, applied equally to drivers and passengers.

Table 2.1: Details of Estimated Value of One Hour of Travel-Time by Vehicle Class, Oregon 2011

Category	Vehicle Category		
	Automobile & Psngr. Truck	Delivery & Med. Trucks	Heavy Trucks
2011 Oregon Median Hourly Wage	$16.90	$14.54	$18.41
2011 Value of Fringe Benefits	$7.35	$7.29	$9.23
Total Hourly On-the-clock Compensation	$24.25	$21.83	$37.64
2011 Oregon Hourly Median Household Income	$24.77	N/A	N/A
Hourly Value Personal Local Travel	$12.39	N/A	N/A
Hourly Value Personal Intercity Travel	$17.34	N/A	N/A

The methodology used by ODOT is based on work done by the USDOT in the Revised Departmental Guidance on Valuation of Travel Time *(U.S. Department of Transportation 2011)*. Table 2.2 illustrates USDOT recommended travel time values. Personal travel is calculated relative to wages, and business travel relative to total compensation, averaging 120% of wages.

Table 2.2: Recommended Value of Travel Time

Time component	Reference	Value
In-Vehicle Personal (local)	Of wages	50%
In-Vehicle Personal (Intercity)	Of wages	70%
In-Vehicle Business	Of total compensation	100%
Excess (waiting, walking, or transfer time) Personal	Of wages	100%
Excess (waiting, walking, or transfer time) Business	Of total compensation	100%

Fosgerau et al *(Fosgerau et al. 2010)* used stated preference survey data to measure the value of travel time for several transport modes (Table 2.3). The stated choice survey includes both an experiment measuring the VOT in the current mode of the respondents, but also a similar experiment for an alternative mode. Consequently, the authors observe the same individual's VOT in different modes, and can thereby disentangle mode effects from user type effects.

Table 2.3: Relative mean Value of Travel Time, after controlling for covariates (bus-none normalized to one)

Current mode	Alternative mode	Experiment Mode		
		Car	Bus	Train
Car	None	1.21		
Car	Bus	1.36	1.25	
Car	Train	1.37		
Bus	None		1.00	
Bus	Car	1.06	0.90	
Bus	Train		0.79	0.71
Train	None			1.36
Train	Car	0.94		1.45
Train	Bus		0.97	0.73

Litman *(Litman 2007)* estimated travel time unit costs with respect to qualitative factors such as comfort, convenience, productivity and security for different types of travelers. Table 2.4 indicates how travel time values vary depending on the quality of conditions, using level-of-service ratings to reflect comfort and convenience factors.

Table 2.4: Travel Time Values Relative to Prevailing Wages

Category	LOS A-C	LOS D	LOS E	LOS F
Commercial vehicle driver	120%	137%	154%	170%
Commercial vehicle passenger	120%	132%	144%	155%
City bus driver	156%	156%	156%	156%
Personal vehicle driver	50%	67%	84%	100%
Adult car passenger	35%	47%	58%	70%
Adult transit passenger-seated	35%	47%	58%	70%
Adult transit passenger-standing	50%	67%	83%	100%
Child (<16 years) - seated	25%	33%	42%	50%
Child (<16 years) – standing	35%	46%	60%	66%
Pedestrians and cyclists	50%	67%	84%	100

3.0 METHODOLOGY

3.1 TRANSPORTATION MARKET BASKET IDENTIFICATION

Besides Reiff and Gregor *(Reiff and Gregor 2005)*'s original model-based approach, in this chapter we discuss 3 alternative methods of defining travel market baskets: cluster-based approach, survey-based approach, and an individual model-based approach. We implemented and tested the cluster-based approach and survey-based approach, but suspended the effort for the individual model-based approach due to its extensive data requirement and poor computational performance. These two approaches implemented have different data requirements and suitable for different types of applications, as we demonstrate later in this report.

3.1.1 Reiff and Gregor's Model-based Approach

Reiff and Gregor's *(Reiff and Gregor 2005)* original approach to market basket definition relies on data and models in traditional 4-step travel demand model. The advantage of their approach is that the data for market definition are readily available and the computation for TAZ level travel market baskets differentiated by trip purpose and income group is very straightforward. Although Reiff and Gregor tested methods of defining reference travel market baskets (varying by income group and trip purpose) via identifying a reference TAZ, as an analog to a reference market basket of goods and services used by the CPI measure, they abandoned the idea due to idiosyncrasy and variation in the sizes of the identified market baskets *(Reiff and Gregor 2005)*. Instead they identified a "travel market area" for each TAZ and for each income group and trip purpose. Even though such an approach would resemble the actual travel cost for each combination more closely, it deviates from the market basket definition used by CPI in that it defines a market area for each location (TAZ) while CPI keeps the same basket of goods and services for all households/locations.

According to Reiff and Gregor's *(2005)* original approach, defining the market basket for TAZ k for income group i and trip purpose p follows these steps:

> **<u>Step 1</u> Determine size terms**. The size terms of the destination choice model utilities measure the perceived attractiveness of TAZs to trips of different types. They are functions primarily of the numbers of jobs and households in a TAZ, but may include other factors. For example, the size term for home-based recreation trips is calculated with this equation:
>
> $$\text{size}_k = \text{emp}_k + 1.175\text{hhs}_k + 7.614\text{park}_k \qquad \textbf{(3.1)}$$
>
> where
>
> emp = number of employees of TAZ *k;*
> hhs = number of households;
> parks = park land in acres.

Step 2 **Identify the potential market area of TAZ *k*** for income group *i* and trip purpose *p*. Reiff and Gregor used a threshold to identify the set of TAZs that is to be included in the market area of the focus TAZ. They tested two different methods: the first method bases the threshold on percentage of the total trips attracted to each TAZ from TAZ *k*, as shown in Equation (3.2); the second method establishes a log sum threshold as in Equation (3.3):

$$J_{pik} = \{j: \frac{\text{Trips}_{pikj}}{\sum_{t \in T} \text{Trips}_{pikt}} \geq \text{cutoff } 1\} \qquad \textbf{(3.2)}$$

$$J_{pik} = \{j: \text{logsum}_{pikj} \geq \text{cutoff } 2\} \qquad \textbf{(3.3)}$$

where

T = the set of all TAZs in the model area;
cutoff = chosen threshold for defining the market area;
trips_{pikj} = the number of trips by income group *i* for purpose *p* between TAZ *k* and TAZ *j*;
logsum_{pikj} = the log sum of the access utilities for travel by income group *i* for purpose *p* between TAZ *k* and TAZ *j*.

Several percentage cutoffs were tested, in particular 75% and 50%. The log sum threshold in Equation (3.3) was chosen by examining ordered plots of log sum values for all TAZs and each trip purpose. For the Medford data, the value of 1 was chosen as the threshold for determining the market area, because the average log sum trends for all zones have inflection points of 1, as log sums increase rapidly to the left of the inflection points and decline gradually to the right *(Reiff and Gregor 2005)*.

Because of the difficulty in describing a market basket defined by using a threshold log sum value in common sense terms, a 50% trip percentage cutoff in Equation (3.2) was used in the Medford case study *(Reiff and Gregor 2005)*.

Step 3 **Create market baskets for each TAZ by income group and by trip purpose.** Once a market area has been identified for TAZ *k* income group *i* and trip purpose *p*, the market basket can be calculated by adding up the size terms for all the TAZs in the market area.

$$\text{MB}_{pik} = \sum_{j \in J_{pik}} \text{size}_j \qquad \textbf{(3.4)}$$

where

MB_{pik} = market basket for TAZ *k* for income group *i* and trip purpose *p*;

J_{pik} = market area for TAZ *k* for income group *i* and trip purpose *p*, as defined in Equation (3.2) or (3.3);

size_j = the size term for TAZ *j*.

Step 4 **Identify a reference TAZ and reference market baskets.** The purpose of identifying a reference TAZ is two-folded: 1.) Through a reference TAZ, reference market baskets (one for each income and trip purpose combination) can be identified as the market area of the reference TAZ; 2.) Once travel market baskets are identified and travel cost aggregated, aggregated travel cost by TAZ are compared with travel cost of the reference TAZ for the same income group and trip purpose (*Reiff and Gregor 2005,* page 50, Equation 4-16).

Identifying the reference TAZ begins with calculating a score for each TAZ:

$$\text{score}_k = \sum_{pi} \frac{\text{MB}_{pik}}{\max_k(\text{MB}_{pik})} \quad \textbf{(3.5)}$$

where

MB_{pik} = market basket for TAZ *k* for income group *i* and trip purpose *p*, as defined in Equation (4).

The reference TAZ is the TAZ with highest score in score_k.

Reiff and Gregor tested different methods for identifying market areas (Equation 3.2 and 3.3) and subsequently identified the reference TAZ. They found the two methods defining market areas resulted in two very different reference TAZs and reference travel market baskets with varying sizes and concluded that there is a practical limitation with this approach of identifying reference travel market baskets, as the market basket for the reference TAZ can be very idiosyncratic. They thus abandoned the idea of identifying reference travel market baskets via the reference TAZ and used the reference TAZ only in indexing the aggregated travel cost.

3.1.2 Survey-based Approach

The cluster-based approach still heavily relies on travel demand models. Although some of the information used in the approach may be available from alternative sources, it would be difficult to adapt it to places without travel demand models and use it to compute historical transportation costs for monitoring purpose. Thus we develop another approach that does not rely on travel demand models.

The travel survey-based approach, or sampling-based approach, computes transportation costs based on travel diaries of a sample of travelers that are assumed to be representative of travel patterns in the region. From the travel diaries in the travel survey, the travel time and associated costs are aggregated by trip purpose, household, income group, and geographies.

The sampling-based approach requires these steps:

1. **Identify linked trips in the travel survey diaries**.

2. **Identify home-based trips**. as travel costs will be attributed to households' residence geography, much like the cluster-based approach;

3. **Identify home-based trips by trips purpose and income group**. Home-based trips are classified into the same four trip purposes: HBW, HBS, HBR, HBO.

4. **Summarize the costs of making the trips** for various purposes at the household-level and use the information as an approximation for household-level travel costs of the study area.

The survey-based approach calculates observed travel costs. It is informative to describe the current "burden" of traveling for households in the sample and the distribution of travel costs for households in various groups (income groups, racial/ethnic groups, geographical locations, etc). However, it may not be a fare benchmark when comparing travel costs across groups for policy-making purpose, as the observed travel behavior may be the result of households' coping strategies. For example, a household may forego recreation trips on weekdays, because the residence is in such a bad location that those trips are too costly, even though recreation trips are desirable. A household may also chain their trips of different purposes, because making an individual trip for each purpose is too expensive, even though trip chaining may mean that they cannot use the ideal mode for each trip purpose. It is equivalent to defining a travel market basket for each household, which includes all the trips the household made during the day of the survey. A household's costs of making ("purchasing") the trips in the basket approximate their true transportation costs. Thus it would useful to use the survey-based TCI to monitor the pattern of transportation cost distribution. For the purpose of evaluating policy scenarios, it would be better to have a fixed travel market basket that is shared by all households.

3.1.3 Cluster-based Approach

The cluster-based approach identifies activity centers in a study area with spatial clustering of activities and uses them as travel market baskets. The rationale is that, when properly identified, these activity centers represent common destinations for various types of trips and keeping track of the transportation costs accessing these destinations in the baskets could serve as a measure for the performance of transportation and land use systems. This approach needs to balance the tradeoffs between computational complexities, data requirements and accurately capturing activity centers (i.e. for employment, recreation and shopping), the following spatial clustering approaches present alternatives to the identification of trip destinations that form transportation market baskets.

3.1.3.1 Center Business district (CBD)

For this methodology, a mono-centric city is assumed in which CBD (or TAZ which contain the CBD) is where all employment opportunities, entertainment and shopping options are concentrated *(Anas et al. 1998)* describes this standard urban spatial structure based on the bid-rent theory). The data requirements for this method are low, and a mono-centric city may sufficiently describe very small cities where most businesses are concentrated on a small geographical scale.

Helsley and Sullivan *(Helsley and Sullivan 1991)* and Chen *(Chen 1996)* theorize that the diseconomies of transportation and congestion as CBDs experience growth combined with technological advances in transportation (which lower transportation costs) may lead to more polycentric urban spatial trends. In addition, Giuliano and Small *(Giuliano and Small 1991)*, Giuliano et al. *(Giuliano et al. 2007)*, McDonald and McMillen *(McDonald and McMillen 2000)* and Greene *(Greene 2008)* have empirically documented the existence of multiple employment centers within US metropolitan areas. For most modern metropolitans, assuming a mono-centric city with a central CBD may be unrealistic and over-simplistic for the purposes of calculating a transportation cost index. However, the mono-centric CBD approach provides a straightforward baseline for a minimalist transportation cost index calculation. Therefore, we propose additional methodologies that take this complexity into account.

3.1.3.2 Spatial Employment Enter Identification

To better describe the reality, poly-centric city model is extended from mono-centric model. And various forms of spatial analysis are applied to identify the centers. Although most of the research in the literature examines employment centers specifically, the methodology is applicable to identify other types of travel destinations such as recreation or shopping. Some of the methods of identify spatial centers include:

- Spatial cluster analysis – This methodology has been used mainly in identifying crime hotspots within metropolitan areas, and is built into many geographical information system (GIS) packages.

- Employment density thresholds – McDonald *(McDonald 1989)* and Giuliano and Small *(Giuliano and Small 1993)* agree that "employment, not population, is the key to understanding the formation of urban centers; and that a center is best identified by finding a zone for which gross employment density exceeds that of its neighbors" *(Giuliano and Small 1993)*. Empirically, Giuliano and Small *(Giuliano and Small 1993)* and Giuliano et al. *(Giuliano et al. 2007)* identify urban centers by employing "a density cutoff of 10 employees per acre, and a minimum total employment of 10,000" in their analysis. Redfearn *(Redfearn 2007)* expands upon this idea by mapping employment densities, identifying peaks in the densities, and testing these peaks for significance.

- Nonparametric identification – McMillen *(McMillen 2001)* utilizes a two-stage non-parametric procedure to identify employment centers. In the first step, a nonparametric locally weight regression (LWR or also known as geographically weighted regression) is conducted to smooth employment densities over space to create a benchmark. Next, actual employment densities are compared to the estimated (smoothed) densities to identify candidates for subcenters. McMillen also clusters nearby significant residuals together (within a 3 mile radius) to avoid counting nearby sites as multiple candidates for employment centers. A semiparametric regression is conducted during the second stage to identify which candidates subcenters display "significant local effects on the overall employment density".

3.1.3.3 Cluster-based Approach for Activity Center Identification

For our purpose, the method proposed in Giulinao *(Giulinao 1991)* and Giuliano and Small *(Giuliano and Small 1993)* maintains a good balance between reasonableness, data requirements and computing complexity and is what we implement for our cluster-based approach of travel market definition. Specifically, for each trip purpose (HBW, HBS, HBR and HBO), we identify activity centers for as a cluster of activities. A center is defined as a continuous set of zones: 1.) each zone in the center has a density of activities above cutoff *D* and all the immediately adjacent zones outside the center have a density below *D;* 2.) the center has at least *E* total activities.

The detailed steps are as follows:

1. Calculate TAZ level employment density for HBW and size terms[3] density for HBR, HBS, and HBO;

2. Identify TAZs with densities greater than cutoff *D*;

3. Group spatially contiguous TAZs identified in step 2 into centers;

4. Calculate total employment or size terms for each center identified in step 3;

5. Eliminate centers with total employment or size terms below cutoff E from centers identified in step 3. The remaining are activity centers.

All data needed for the center identification process, such as TAZ, employment by sector group, households, acreage of park areas etc (vary depending on the formula for the size terms), are available from the travel demand model, or alternative data sources such as the Longitudinal Employer-Household Dynamics (LEHD) and population census data. If data from external sources are needed, they are aggregated to TAZ. LEHD releases LEHD Origin-Destination Employment Statistics (LODES) annually. Workplace Area Characteristics in the LEHD provide information of jobs totaled by work Census Block.

The cutoff *D* and *E* should match the theoretical concept of centers, to be able to analyze commuting to centers, and to end with a manageable number suitable for statistical analysis. Giuliano et al. *(Giuliano et al. 2007)* identify employment centers by employing a density cutoff of 10 employees per acre, and a minimum total employment of 10,000 in their analysis for the Los Angeles area, based their selection on expert opinion. Figures 3.1 – 3.4 show the histogram of log of TAZ activity density for the Portland area. For some trip purpose like HB Shopping (HBS), there is a threshold with clear discontinuity in their distribution that can be used as cutoff *D*; while for some other such a cutoff is not apparent, for example the density distribution for HBW resembles a normal distribution rather closely and lacks of a threshold with clear discontinuity in its distribution.

[3] Size terms measure the perceived attractiveness of TAZs to trips of different types. And size terms calculation formulas are taken from travel demand model, for example Metro's 2013 Trip-Based Travel Demand Model or Corvallis' JEMnR model.

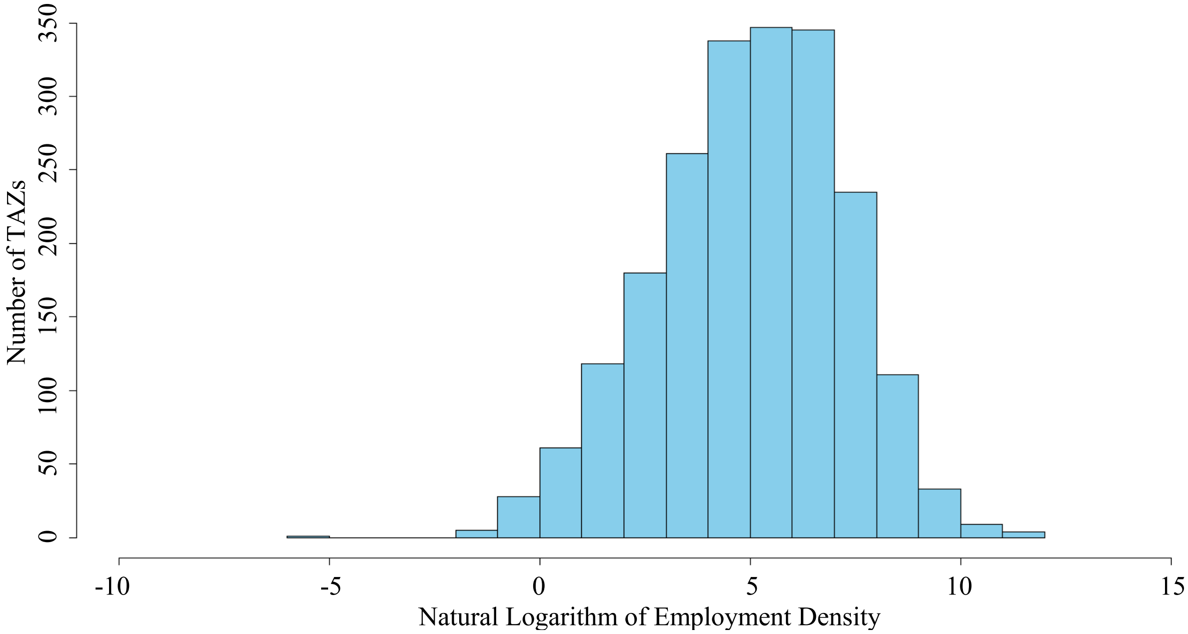

Figure 3.1: Employment density distribution of HBW

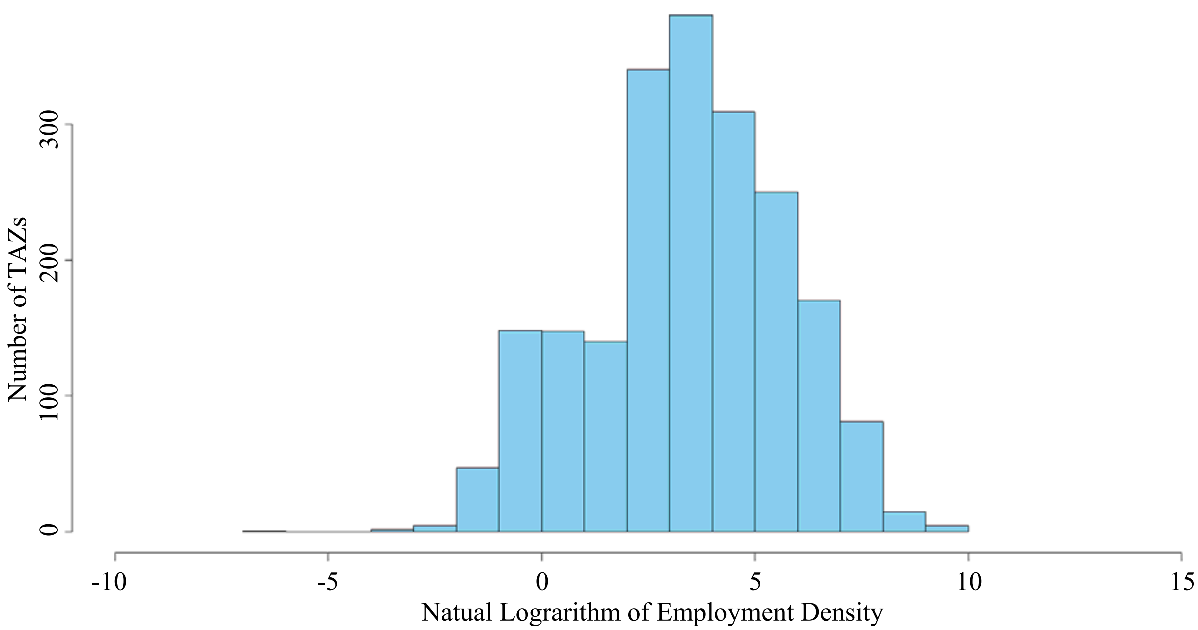

Figure 3.2: Size terms density distribution of HBS

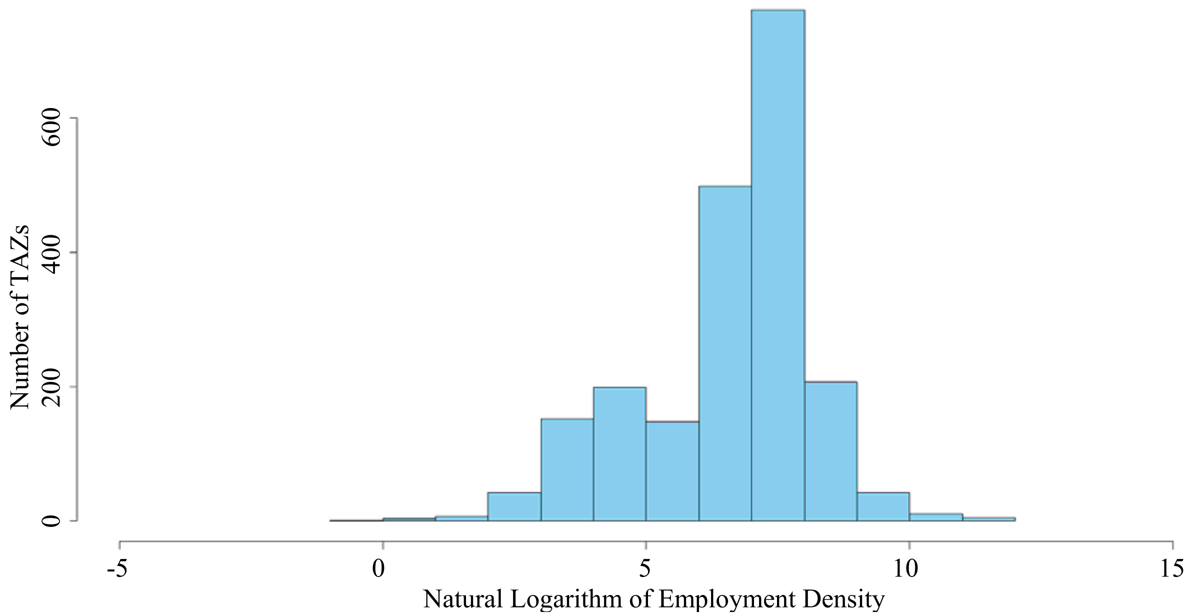

Figure 3.3: Size terms density distribution of HBR

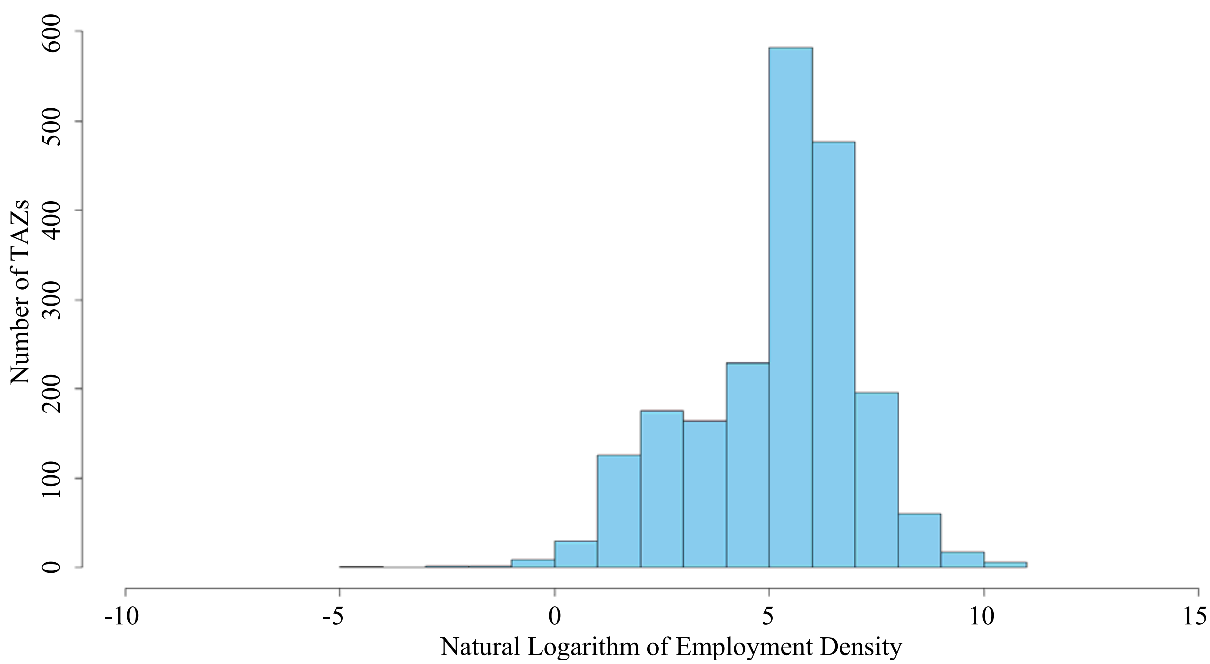

Figure 3.4: Size terms density distribution of HBO

For our purpose, we aim for these cutoffs to be more objective and to make them easily applicable to areas of different sizes. However, by looking at the statistical distribution of activity density, there does not seem to be clear choice for cutoffs for all the cases. We thus conduct sensitivity analysis to select these two cutoffs. The details of the analysis are provided in Chapter 4.

3.1.4 Individual-level Model-based Approach

This approach is similar to Reiff and Gregor's travel market area approach in that they both rely on models, but this approach works at the individual level and can incorporate detailed socio-economic and demographic characteristics of individual households as well as spatial and travel information at fine resolution. With trip generation model and destination choice model, the approach can theoretically approximate the travel needs, thus travel market basket, of any individual household. The disadvantage of this approach is that it has much higher data requirement and is more computation intensive.

Another theoretical limitation is that this individual-level approach relies on first estimating travel behavior models for individual households, as these models may not be readily available in traditional travel demand model system, and then applying the estimated model specification to simulate travel needs for individual households. Besides the land use and accessibility information used in Reiff and Gregor's approach, model estimation requires individual household level observations, such as Household Activity Survey data, while model application needs synthesized population (households) data, usually from a population synthesizer.

<u>Step 1</u> **Determine trip rates for households by trip purpose with trip generation models**. Various models have been used to determine the trip rates for households. Cross-classification analysis and linear regression model are commonly used in 4-step travel demand model *(Martin et al. 1998)*. In a linear regression model, trip rates for household *n* are modeled with:

$$\text{trips}_n = \alpha + X_n\beta \qquad \textbf{(3.6)}$$

Where

trips_n = trip rates for a select trip purpose for household *n*;
X_n = socio-economic and demographic characteristics of household n, including household size, income, number of vehicles, etc;
α, β = parameters in the model to be estimated.

Once the model parameters are estimated from observed data, the model can be applied to predict trip rates for any household for which we have information. The advantage of an individual-level approach is that households don't need to be segmented by income, like in the Reiff and Gregor's approach, or other variables.

<u>Step 2</u> **Simulate trip destinations for household by trip purpose**. Destination choice model is a commonly used method in determining trip destination. Take HBW trips as an example, the destination of HBW trips can be modeled with a workplace location choice model *(Wang et al. 2011)*. Let the probability that worker *n* chooses workplace location *i* from the set C_n of potential workplace locations, conditional on variables including personal characteristics and locational attributes X_{ni}, be given by the following multinomial logit form:

$$\mathrm{P}_n(i|X_n) = \Pr\left(U_{ni} \geq U_{nj}, i, j \in C_n\right) = \frac{\exp(\beta X_{ni})}{\sum_{j \in C_n} \exp(\beta X_{nj})} \qquad \textbf{(3.7)}$$

where

> X_{ni} is a vector of variables associated with workplace location i for individual n, including socio-economic and demographic characteristics of household n (interacting with origin and/or destination attributes), attributes of origin and destination (choice), as well as accessibility between origin and destination.
>
> β is a parameter vector to be estimated.

Once the model parameters are estimated from observed data, Equation (3.7) can be applied to simulate trip destination for any household. It is possible to predict the probabilities of a household choosing any destination in alternative set C_n or predict a single destination for a trip via a Monte Carlo process. Either method should produce similar results when examined at aggregated level (by TAZ or by income group etc.). For simplicity, a single destination will be predicted.

Step 1 and 2 together identifies travel market baskets of a given trip purpose for any household by predicting its trip frequency and destination. Coupling with a mode choice model and using skims data from travel demand model, it is possible to calculate trip-level transportation cost for the household, which can be aggregated to total transportation costs by household or further to any summary information useful, such as average transportation costs by TAZ or by household income group.

3.2 TRANSPORTATION COST CALCULATION METHODOLOGY

Reiff and Gregor *(Reiff and Gregor 2005)* calculate transportation costs with a utility-based approach, which we summarize in the first subsection. However, such an approach is limited by the formula and quality of the mode choice model in the travel demand modeling system. Through literature review, we determined that conditional transportation costs are the appropriate costs to include within a transportation cost index calculation. These costs include costs that are explicitly charged to the users of transportation, such as operating, maintenance and ownership costs of various transportation modes and the cost of travel/wait/delay time. Research by Bhat *(Bhat 2000, 1998a, 1998b, 1995)*, Hensher *(Hensher 1994)*, Anas *(Anas 2007, 1981)*, Kahn et al. *(Kahn et al. 1981)*, Train and McFadden *(Train and McFadden 1978)*, Train *(Train 1980)*, Gillen *(Gillen 1977)*, Louviere *(Louviere 1988)*, Louviere and Hensher *(Louviere and Hensher 1982)*, Zhao et al. *(Zhao et al. 2013)* and Pinjari et al. *(Pinjari et al. 2011)* has shown that these costs are the primary determinants of transportation choice. The transportation cost calculation methodologies and potential data sources for automobile, public transportation and non-motorized modes (walking and cycling) are detailed below.

3.2.1 Utility-based Travel Cost Calculation

In Reiff and Gregor *(Reiff and Gregor 2005)*'s approach, once travel market areas for each TAZ are defined, average costs to access the market areas are calculated for each TAZ. The costs are calculated from the travel model access utilities, which measure the perceived ease of travel between every pair of TAZs for each trip purpose, income group and mode of travel. The utilities are calculated from linear utility equations that were statistically estimated from household activity surveys. The terms of the equations are factors that affect people's perceptions of the ease of travel. The coefficients for the terms indicate the strength of each factor. Some examples of factors included in the utility equations are:

- The time spent traveling in a vehicle,
- The time to walk to get to the vehicle (e.g. walk time to a bus stop),
- The time spent waiting, and
- The money cost of the trip (i.e. operating cost).

Since the utilities are unit-less quantities in preference space, they are not intuitive to understand. They can be easily converted into understandable monetary units in willingness-to-pay space by dividing them by the coefficient of a monetary cost factor, such as operating cost:

$$MC_{pimkj} = \frac{U_{pimkj}}{OC_{pi}} \qquad \textbf{(3.8)}$$

where

MC_{pimkj} is the cost for traveling by mode *m* between TAZs *k* and *j* for purpose *p* by income group *i* in monetary term;

U_{pimkj} is the utility for traveling by mode *m* between TAZs *k* and *j* for purpose *p* by income group *I*;

OC_{pi} is the cost coefficient for purpose *p* and income group *i.*

A composite approach of calculating travel costs across all modes is to compute a cost from a composite of the access utilities for the travel modes. This is done in the standard traveling modeling approach by calculating the log sum of the mode choice model. It can be thought of as a measure of travel opportunities rather than travel cost. The composite cost for traveling between two TAZs *k* and *j* by a household of income group *i* for purpose *p* is calculated as follows:

$$TC_{pikj} = \ln(\textstyle\sum_{m'} \exp(U_{pim'kj})) \qquad \textbf{(3.9)}$$

The average cost to access the market basket for a TAZ *k* can be computed as a weighted average of the travel costs from TAZ *k* to each TAZ *j* in the market areas for that TAZ *k*. The weighting factor in calculating the average is the proportion of the size term of each TAZ. Thus the weighted average cost to access the market areas for income group *i* and purpose *p* from zone *k* is calculated as follows:

$$AC_{pik} = \frac{\sum_{j \in J_{pik}} TC_{pikj} * size_{pij}}{\sum_{j \in J_{pik}} size_{pij}} \quad \textbf{(3.10)}$$

where

J_{pik} - the market areas for TAZ *k*;

TC_{pikj} is the equivalent cost for traveling between TAZ *k* and TAZ *j* for income group *i* and purpose *p*;

$size_{pij}$ is the size term for income group *i* for purpose *p* in TAZ *j*.

3.2.2 Travel Costs by Mode

3.2.2.1 Automobiles

For travel by private automobiles, the transportation cost is characterized by operating costs (fuel cost and tire usage), ownership costs (maintenance, repair, etc.), parking costs and the value of travel time. The cost of automobile travel for a trip between a TAZ or a household location and a travel destination is defined as follows:

$$C_{auto} = D \cdot f_{auto} + D \cdot O_{auto} + Parking + w \cdot TT_{auto} \quad \textbf{(3.11)}$$

where

D = distance between origin and destination (miles);

f_{auto} = per mile fuel and tire costs;

O_{auto}= per mile ownership costs including maintenance and repair;

Parking = parking cost for trip (and/or toll costs);

w = value of travel time per hour;

TT_{auto} = estimated travel time for trip.

Potential Data Sources for each of cost components are discussed in turn.

1. Fuel and tire costs (f_{auto}) – Per mile fuel costs are calculated as the price per gallon of gasoline divided by fuel economy of vehicles (miles per gallon). Although American Automobile Association's (AAA) reports average per mile driving cost for the entire country, it is preferable to obtain regional fuel prices and regional vehicle fleet fuel economy data because both of these components may vary significantly depending on the region or state.

Estimated city and highway fuel economies can be obtained from Environmental Protection Agency's (EPA) fuel economy data. Alternatively, if regional or state-level Department of Transportation maintains more detailed data on fleet composition, more accurate average fuel economy may be estimated. Per mile fuel cost data may be obtained from AAA's Fuel Gauge Report on average fuel prices or the Energy Information Administration's (EIA) regional gasoline price series.

For tires, AAA estimates the cost to be $0.01 per mile based on tires of similar quality as those that came with the car. IntelliChoice (IntelliChoice, 2002) also estimates tire costs based on an estimated lifetime of 45,000 miles for each set of tires, without the assumption that car owners continue to purchase the same tires as the original set.

2. Ownership costs (O_{auto}) - Assuming vehicles are driven for 15,000 of miles per year and maintained at manufacturer's recommended maintenance schedule, AAA estimates a maintenance average cost per mile of $0.497 which is consistent with the average maintenance cost of $0.54 found by Polzin, Chu, and Roman *(Polzin et al. 2008)*. AAA estimates average maintenance cost for small, medium, and larger sedans while Polzin, Chu, Roman *(Polzin et al. 2008)* estimated averages for both older and newer cars. Since vehicle age is the main determinant of maintenance and required repairs, the costs estimated by Polzin, Chu, and Roman *(Polzin et al. 2008)* may be more applicable for our purposes.

Following Barnes and Langworthy *(Barnes and Langworthy 2004)*, we will utilize estimated repair costs from IntelliChoice *(IntelliChoice 2002)*. Similarly, we will also assume that 50% of 5-year repair costs occur in the first 4 years, 50% occurs in the 5th year, and the same amount of repair (as the 5th year) occurs for every year thereafter. Marginal per mile depreciation costs can be estimated using data from the National Automobile Dealers Association, Edmunds or Kelley Blue Book.

3. Parking - Direct parking cost for commute and non-commute purposes in different destinations would be estimated using parking meter rates and annual commute and non-commute mileages. Other fixed costs such as tolls will also be considered within this category.

4. Value of travel time ($\boldsymbol{w \cdot TT_{auto}}$) - ODOT *(ODOT 2012)* estimates the value of travel time associated with both business and personal travel by vehicle type following guidelines from USDOT. The most recent estimated weighted average value of travel time on automobile and passenger trucks is equal to $23.68 per hour.

Ozbay et al. *(Ozbay et al. 2001)* use a regression-based approach to estimating marginal costs associated with vehicles. The authors separate user costs into two categories: self-vehicle operating costs ("car ownership, fuel and oil consumption, regular or unexpected maintenance, and so forth") and user interaction costs ("accident- and congestion-related costs"). For the purposes of estimating the transportation cost index, we are particularly interested in the estimated self-vehicle operating costs (C_{opr}), formulated as a function of depreciation, gas cost, oil cost, tire cost, maintenance cost, insurance cost and parking fees and tolls. Ozbay et al. *(Ozbay et al. 2001)* estimate the marginal vehicle operating cost per mile as

$$\boldsymbol{MC_{opr} = 0.1227 + \frac{0.104}{a}} \tag{3.12}$$

where *a* is equal to the vehicle age (years). When necessary regional data associated with vehicle operation and ownership is unavailable, this methodology represents a reasonable alternative. In this case, the cost of automobile travel for a trip between a TAZ or a household location and a travel destination is defined as:

$$C_{auto} = D \cdot MC_{opr} + w \cdot TT_{auto} \tag{3.13}$$

where

D = distance between origin and destination (miles);

MC_{opr} = per mile cost of vehicle operation (including gas, oil, maintenance, etc.);

w = value of travel time per hour;

TT_{auto} = estimated travel time for trip.

3.2.2.2 Public Transportation

Costs for travel via public transit include transit user fares and value of travel/wait time. Specific data for the study area would be obtained from the appropriate source. Transit fares would be obtained from the regional public transit agency while transit travel time would be based on… The cost of travelling on public transportation for a trip between a TAZ or a household location and a travel destination is defined as follows:

$$\boldsymbol{C_{public} = fare + w \cdot TT_{public}} \tag{3.14}$$

where

fare = transit fares;

w = value of travel time per hour;

TT_{public} = estimated travel time (including wait time) for trip.

Potential Data Sources:

1. Transit fares For the Portland Metro area, we use the formula in the Metro's travel demand model for estimates of transit fares, which are based on the average fares charged by the region's transit providers *(Metro Research Center and Transportation Research and Modeling Services 2013)*. The average fares for all transit providers providing a transit pass option were estimated at 73% of the cash fare price, which is the 2010 ratio for TriMet.

2. Transit travel time Transit travel time including accessing and transferring can be retrieved from travel skims when they are available. When travel skims are not available, it may be possible to approximate travel time from transit network *(Krizek et al. 2007)*,network with GTFS *(Gandavarapu 2012)*, or query transit travel time from online APIs like Google Maps.

3.2.2.3 Non-motorized Modes (Bicycle and Walking)

Bicycle - Litman *(Litman 2009)* estimates the annual cost per mile of a bicycle to range between \$0.47 to \$0.56, including ownership, maintenance, value of travel time and parking cost estimations, depending on urban/rural travel and peak/off-peak hours. .

$$\boldsymbol{C_{bicycle} = D \cdot f_{bicycle}} \tag{3.15}$$

where

D = distance between origin and destination (miles);

$f_{bicycle}$ = per mile cost of bicycling.

Walking – Walking is estimated to cost \$1.37 per mile *(Litman 2009)*. This cost is primarily consists of the value of travel time, particularly because walking usually incurs very little out-of-pocket costs.

$$\boldsymbol{C_{walk} = D \cdot f_{walk}} \tag{3.16}$$

where

D = distance between origin and destination (miles);

f_{walk} = per mile cost of walking.

Potential Data Sources for calculating travel costs for non-motorized modes:

Biking and Walking Distance MPOs including the Metro have started to incorporate biking and walking into their travel demand models, and thus the distance matrices may be available from travel model skims. When such skims are not available, it may be possible to approximate travel time from bicycle and pedestrian network *(Krizek et al. 2007)* or via online APIs like Google Maps.

3.2.3 A Generic Travel Cost Calculation Algorithm

Although it may be desirable to follow the travel costs by mode approaches discussed above, their data requirements are very high. To reduce the data requirement and simply calculation while retaining as much realism as possible, we propose a generic travel cost calculation algorithm that works for all modes, and capture the travel costs with two major components:

- The time costs, including the time spent traveling in a vehicle, the time to walk to get to the vehicle (e.g. walk time to a bus stop), the time spent waiting, and

- The monetary cost of the trip (i.e. operating cost, ownership cost, fares).

Generalized costs that include both components may be available from travel demand models. If they are not, they can be approximated:

$$\boldsymbol{TC_{pimkj} = C_m + TTime_{pimkj} * VOT_{pim} + TDist_{pimkj} * MC_m} \qquad \textbf{(3.17)}$$

Where

C_m A constant for mode *m,* which could be the fare for a fixed fare transit system;

$TTime_{pimkj}$ and $TDist_{pimkj}$ is the travel time and distance by travelers from income group *i* using mode *m* from original TAZ k to access to TAZ j in for purpose *p*;

VOT_{pim} is the value of time for travelers from income group *i* using mode *m* for purpose *p*. We use the 2012 VOT values recommended by ODOT (Table 3.1), which is closer to the time when the data we are using in this project (2011 for the survey-based approach; 2010 for the cluster-based approach), even though more recent values are available.

MC_m is distance-based monetary cost for mode *m*. Monetary costs per mile is estimated from various sources described in Table 3.2.

Table 3.1: Recommended Value of Time by Mode Relative to 2011 Oregon Hourly Wage

Mode	Percent of Wage Rate
Walk	50%
Bike	50%
Auto/Van/Truck Driver	50%
Auto/Van/Truck Passenger	35%
Bus	35%
Rail	35%
Dial-A-Ride/Paratransit	35%
Taxi	35%
Carpool/Vanpool	35%
Other (Specify)	50%

Data sources: Litman *(Litman 2007)*; ODOT *(ODOT 2012)*

Table 3.2: Monetary Costs per Mile by Travel Mode

Mode	Monetary Costs per Mile ($)	Sources
Driving	.592	(American Auto Association (AAA))
Bus	1.01	(Portland Facts)
Rail	1.38	(Portland Facts)
Taxi	2.60	(Portland Taxi Cab Company)
Bike / Walk	0.0	

Note that the accounting of travel costs can use dollars or minutes. We adopt the practice that is commonly applied in calculating generalized costs in the modeling community. When measuring travel costs in dollars, the time cost component of transportation needs to be converted to dollars through value of time and then combine with the monetary cost component. On the other hand, when calculating travel costs in minutes, the VOT will be set to 1, and the monetary component will be converted to time, i.e. how long it takes the traveler to earn the monetary costs of traveling – by dividing the total monetary costs by wage rate, or, alternatively, dividing the total monetary costs by value of time. These two units are both valid and, from our perspective, should make little difference in results as long as one unit is used consistently. For convenience, we use minutes as our unit of choice.

Dollars and minutes can be easily switched in the current implementations. To switch travel cost accounting to minutes, the VOT parameter is set to 1, and MC_m is set to the time-equivalent monetary costs. The unit.name parameter in the code can be set to "dollars" or "minutes" to switch between these two units. It is also possible to set either VOT or MC to 0 to include only the time costs or monetary costs of traveling for diagnostic purpose.

3.3 TRANSPORTATION COST AGGREGATION

Once transportation market baskets are defined for an urban area and transportation costs have been identified for both motorized and non-motorized modes for each TAZ or household location to destinations within a market basket, the total cost can be calculated across mode, trip purpose, and income group to get aggregated travel costs. Below are a few approaches described by Reiff and Gregor *(Reiff and Gregor 2005)* and adopted in this current project as well.

There are a few different approaches to incorporating varying costs by mode. The simplest is to pick the least costly mode:

$$\boldsymbol{TC_{pikj} = \min_m(TC_{pimkj})} \quad \textbf{(3.18)}$$

An alternative approach would be average costs weighted by mode probabilities:

$$TC_{pikj} = \textstyle\sum_m (TC_{pimkj} * P_{pimkj}) \text{ and} \quad \textbf{(3.19)}$$

$$P_{pimkj} = \frac{\exp(U_{pimkj})}{\sum_{m'} \exp(U_{pim'kj})}$$

The travel costs are weighted by trips and mode probabilities from each TAZ to destinations in travel market baskets:

$$TC_{pimk} = \frac{\sum_{j \in C_p} TC_{pimkj} * Trips_{pimkj}}{\sum_{j \in C_p} Trips_{pimkj}} \quad \textbf{(3.20)}$$

and

$$TC_{pik} = \frac{\sum_{j \in C_p} TC_{pimkj} * Trips_{pimkj} * P_{pimkj}}{\sum_{j \in C_p} Trips_{pimkj} * P_{pimkj}} \quad \textbf{(3.21)}$$

with

$$P_{pimkj} = \frac{\exp(U_{pimkj})}{\sum_{m'} \exp(U_{pim'kj})} \quad \textbf{(3.22)}$$

Where

$j \in C_p$ the set of TAZs belonging to the travel market basket for purpose *p*;

$Trips_{pimkj}$ the number of trips from TAZ k to TAZ j by income group *i* using mode *m* t from TAZ *k* to TAZ *j* for purpose *p;*

P_{pimkj} is the probability that mode m is used by income group *i* for trip purpose *p* from TAZ *k* to TAZ *j;*

U_{pimkj} is the utility for traveling by mode *m* between TAZ *k* and *j* for purpose p by income group *i*.

Following similar logic of how weighted average travel costs are calculated, it is possible to suppress income group or trip purpose dimension and summarize the average costs by TAZ and other dimensions:

$$TC_{pk} = \frac{\sum_i TC_{pik} * \mathrm{hhs}_{ik}}{\sum_i hhs_{ik}} \quad \textbf{(3.23)}$$

$$\boldsymbol{TC_{ik}} = \frac{\sum_p \boldsymbol{TC_{pik}} * \mathbf{trips}_{pik}}{\sum_p \boldsymbol{trips_{pik}}} \quad \textbf{(3.24)}$$

where

hhs_{pik} is the number of households of income group *i* in TAZ *k*;

trips_{pik} is the number of trips made by income group *i* for purpose *p* in TAZ *k*.

A similar process can be used to aggregate average travel costs to geographic units larger than TAZs such as districts, cities and the whole region. In this process, the proportions of trips occurring among the zones within each larger geographic area are used as weights. The average cost *AC* to access the market basket for all TAZs in district *d* for purpose *p* and income group *i* is calculated as follows:

$$\boldsymbol{TC_{pid}} = \frac{\sum_{k \in d} \boldsymbol{TC_{pik}} * \mathbf{trips}_{\boldsymbol{pik}}}{\sum_{k \in d} \boldsymbol{trips_{pik}}} \quad . \qquad \textbf{(3.25)}$$

4.0 IMPLEMENTATIONS AND THE PORTLAND APPLICATION

Two approaches of travel market baskets definitions are implemented in R for this project. The scripts are available on github at https://github.com/cities-lab/tci. This chapter describes the implementations and the applications of the both approaches to the Portland area.

4.1 SURVEY-BASED APPROACH

The survey-based approach calculates travel costs primarily with a travel survey dataset, in Portland's case, the Oregon Travel Activity Survey (OTAS) data. The survey was conducted in 2011 covering the whole state of Oregon. The home-based trips are classified into four different types, including home-based work (HBW), home-based shopping (HBS), home-based recreation (HBR), and home-based other (HBO), while non-home-based trips are excluded. Households are classified into 3 income groups: low income, middle-income, and high income. To be consistent with the classification used in Metro's travel demand model, data from which is used in the cluster-based approach, we use the same classification thresholds of $25K, $25-50K, and $50K+ in 1994 dollars. All steps of the survey-based approach are implemented in tci/code/survey directory. The inputs for the survey-based approach are listed in Appendix A.

Step 1. Prepare the survey data for TCI computation: classify income groups for each household and identify household characteristics and trip purpose

Total 2010 household income (the INCOME field in the OTAS data) is used to classify households into three income groups: low income (<$35K), middle-income ($35-75K), and high income ($75K+)[4]. Two additional household characteristics are used for the Portland application include traffic district of household residence and household size, both of which is available in the 2011 OTAS data. We directly use the trip purpose information processed and prepared by ODOT TPAU staff and consultants. We also retain the household weights (HHWGT) provided in the OTAS data for later use.

Step 2. Calculate generalized costs for each trip

Generalized costs that include both travel time cost and monetary cost components are aggregated for each trip (and thus for each trip purpose, mode and income level) using Equation (3.17) described in section 3.2.3

In the 2011 OTAS data, trip duration (TRPDRE) and trip distance (TRPDST) provides information for travel time and travel distance. Value of travel time and monetary cost per mile parameters are specified in Table 3.1 and Table 3.2 in Chapter 3. C_m is set to 0 for the Portland application. Those parameters are specified in settings.R.

[4] Those cutoffs in 2010 dollars are the brackets closest to $25K, $25-50K, and $50K+ in 1994 dollars.

Step 3. Compute travel costs by trip, person, household and districts

From the trip-level travel costs computed in step 3, we can apply HHWGT and compute travel costs for different units. Trip-level travel costs can be compared across different income group and/or different trip purpose. They can also be aggregated over persons and households. Person- and household-level travel costs can be summarized and examined by income group, trip purpose, residence district, or a combination of these characteristics using aggregation methods described in section 3.3. Although it is possible to aggregate household-level travel costs by residence TAZ, there are usually few surveyed households per TAZ (some TAZs may not have any household observations at all), the aggregated travel costs at the TAZ level is not robust and thus not used.

Step 4. Generate plots and maps

Plots and maps can be generated from the results of step 3.

Figure 4.1 – 4.4 demonstrates the results from the survey-based approach for the Portland area using 2011 OTAS data.

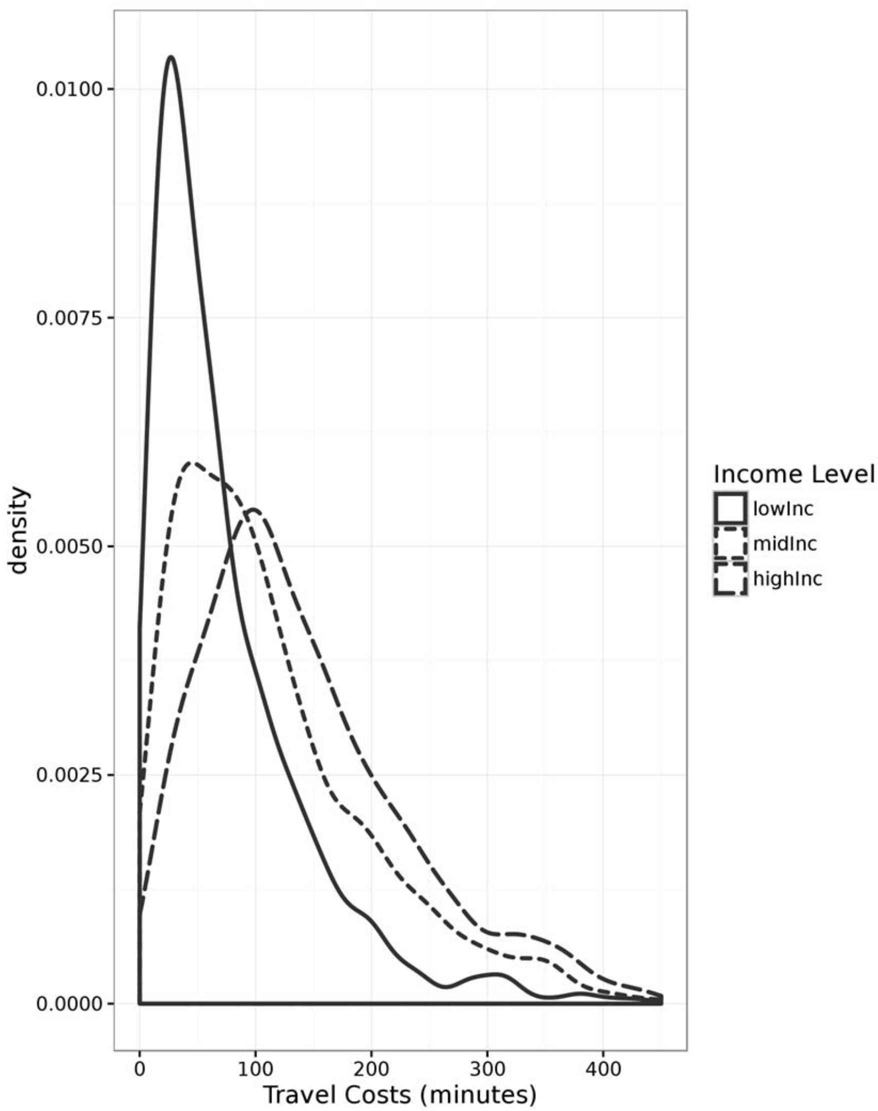

Figure 4.1: Density distributions of household-level travel costs by income level for Portland with 2011 OTAS data

Figure 4.1 shows the distributions of household-level travel costs by income level. Without considering other factors, low income households in general spend less than mid-income and high income households on traveling. Other factors may confound the pattern, for example, if household size is correlated with income. Since the income level of low, mid and high is categorized by household income regardless of household size, household size is highly likely correlated with income, which may explain the pattern observed in Figure 4.1.

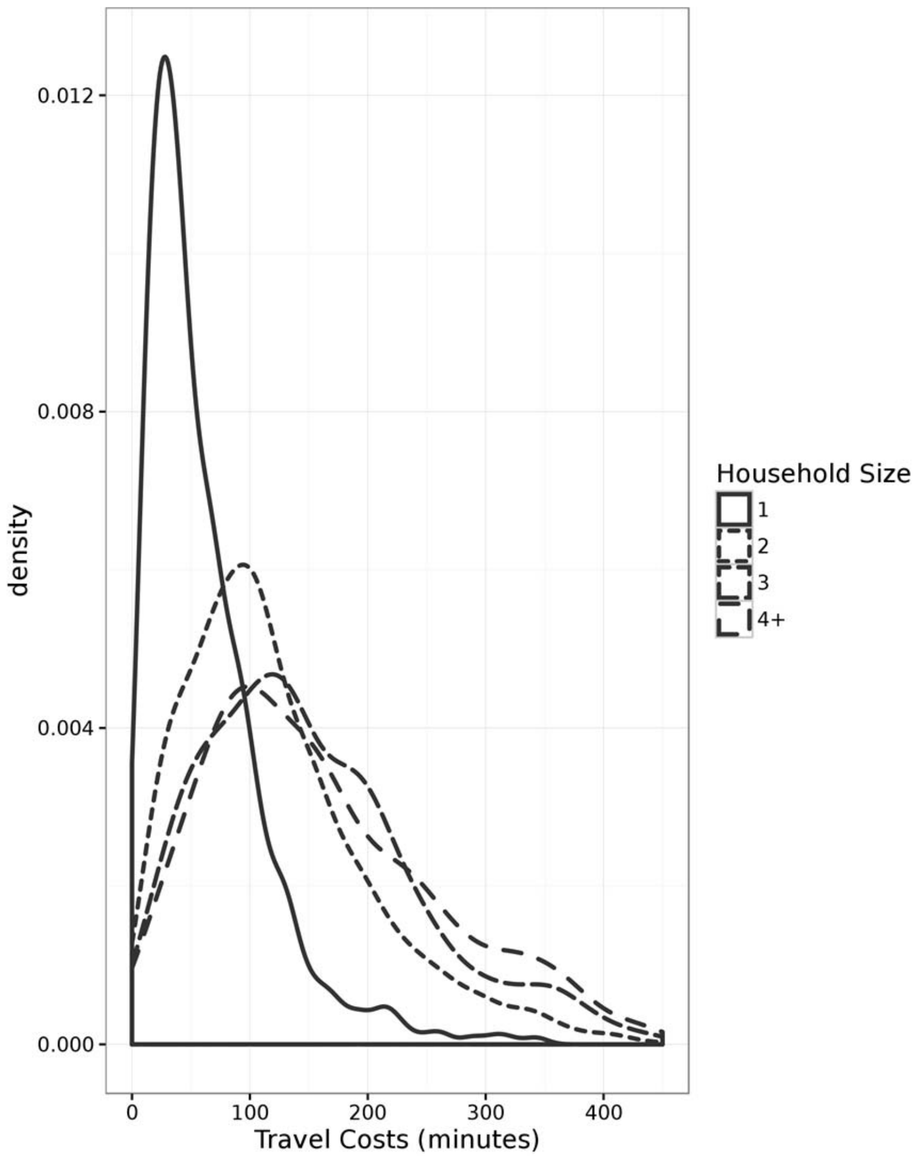

Figure 4.2: Density distributions of household-level travel costs by household size for Portland with 2011 OTAS data

Figure 4.2 displays the distributions of household-level travel costs by household size. It makes sense that smaller households have lower travel costs than larger households, as the household-level travel costs sum travel costs over all household members. The travel cost distributions for households with 3 and 4+ members are very similar.

In addition to income and household size, travel costs can be compared across other household characteristics. For example, Figure 4.3 shows household-level travel costs for households with and without children (at least one household member younger than 16). It seems to make sense that households with children have higher travel costs, as they may be larger and have to make trips with and for the children. Because detailed household information is available, the possibility is limitless how the travel costs can be plotted against household's social-demographic characteristics and related other information, such as land use, transportation infrastructure, etc.

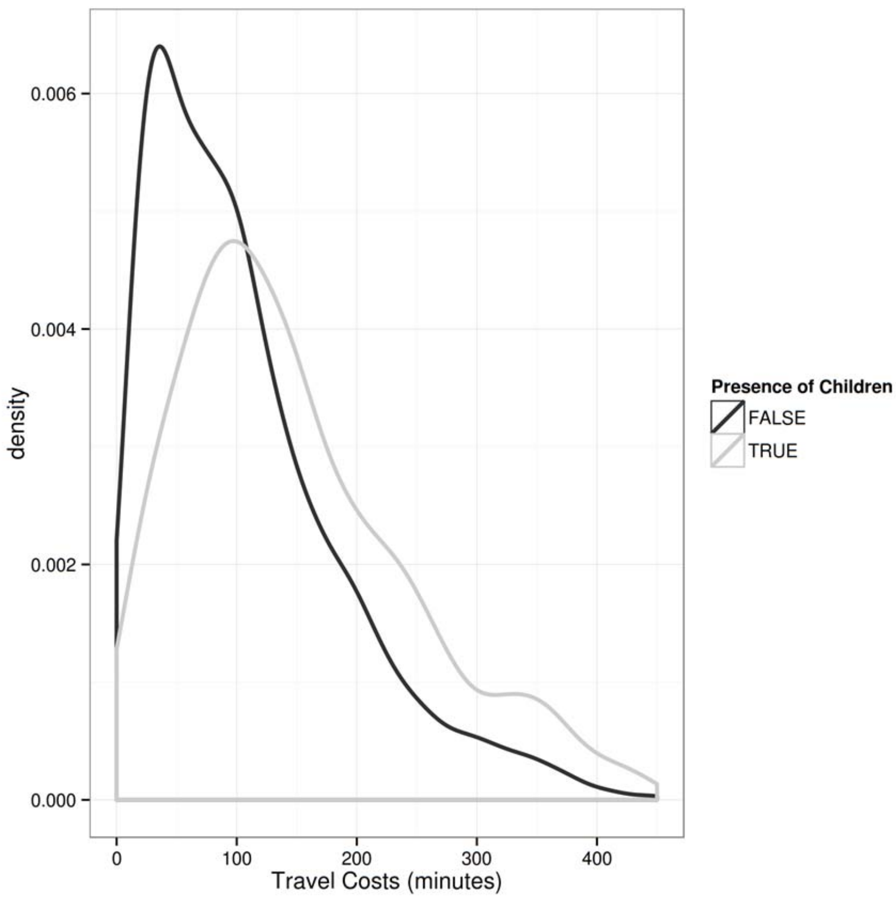

Figure 4.3: Density distributions of household-level travel costs by presence of children for Portland with 2011 OTAS data

Given the relationship between household-level travel costs and household size shown in Figure 4.2, it may be useful to examine the average travel costs per person. Figure 4.4 shows the average household-level travel costs per person for Portland (household-level travel costs divided by household size). The difference in travel costs across income categories becomes much smaller once household size is factored in.

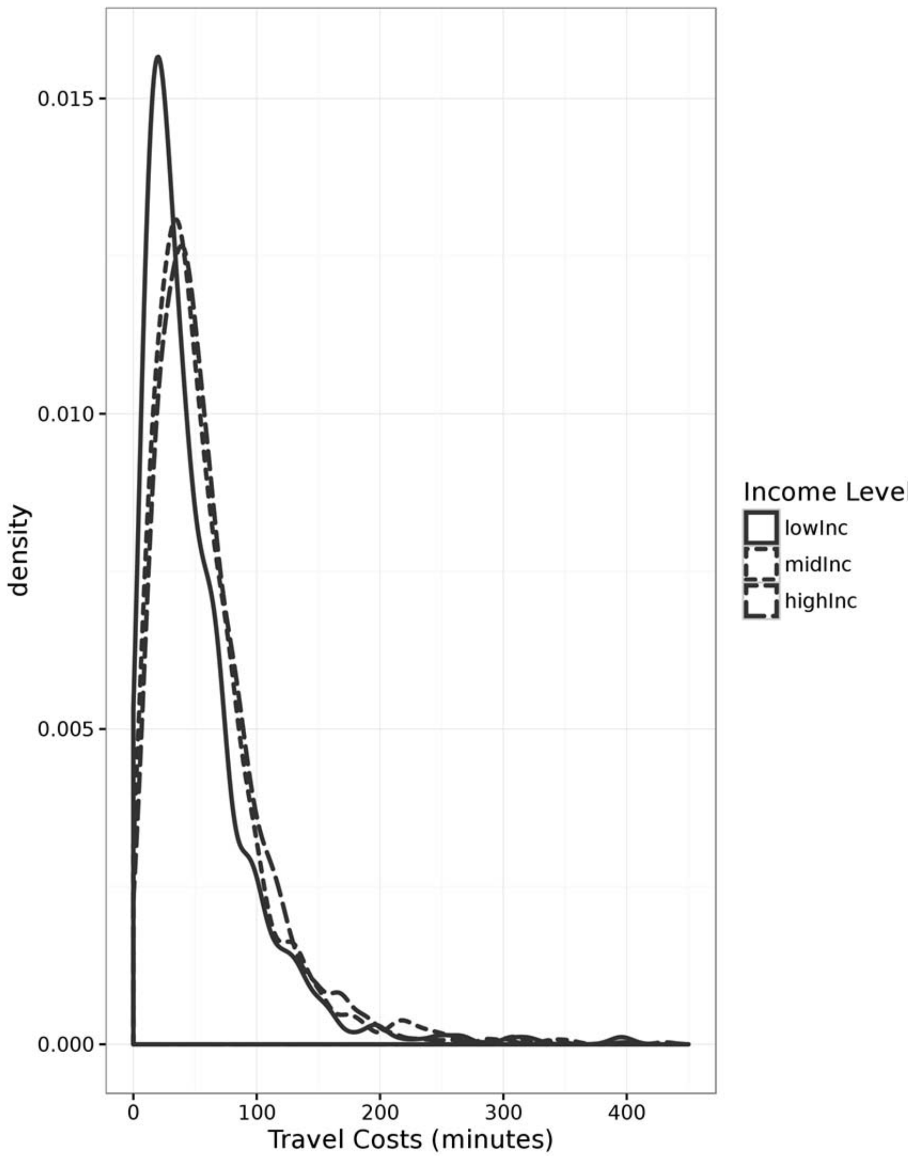

Figure 4.4: Density distributions of average travel costs per person by income for Portland with 2011 OTAS data

Besides household-level travel costs, it is possible to examine travel costs at other levels with the survey-based approach. Figure 4.5 shows trip-level travel costs by trip purpose and the traveler's household income.

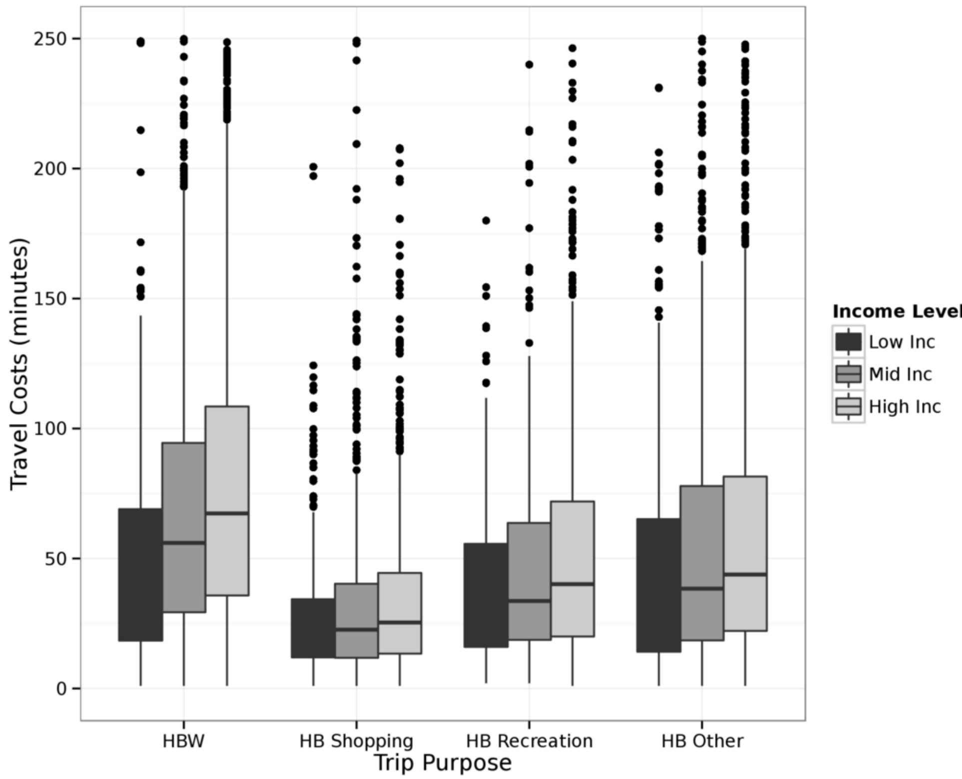

Figure 4.5: Box plot of trip-level travel costs by trip purpose and traveler's household income level for Portland with 2011 OTAS data

Finally, travel costs can be summarized geographically and plotted as maps. Figure 4.6 demonstrates mapping average household-level travel costs at the traffic district level by income and trip purpose. Maps on the first row plot average household-level travel costs making HBW, HBS, HBR, and HBO at district level for low, mid, high income, and all households. Areas without data are shown in white (blank). Since the value for each district is calculated by averaging household-level travel costs over all corresponding households living in the district, there are anomalies where trips of certain purpose produce higher values than all trips. For example, for low income households living in east Portland, the costs for HB Recreation trips (the high value area in the first map on the fourth row) are much higher than those for all trips. This does not make sense, but it is caused by the fact that very few low income household making HB recreation trips in the district.

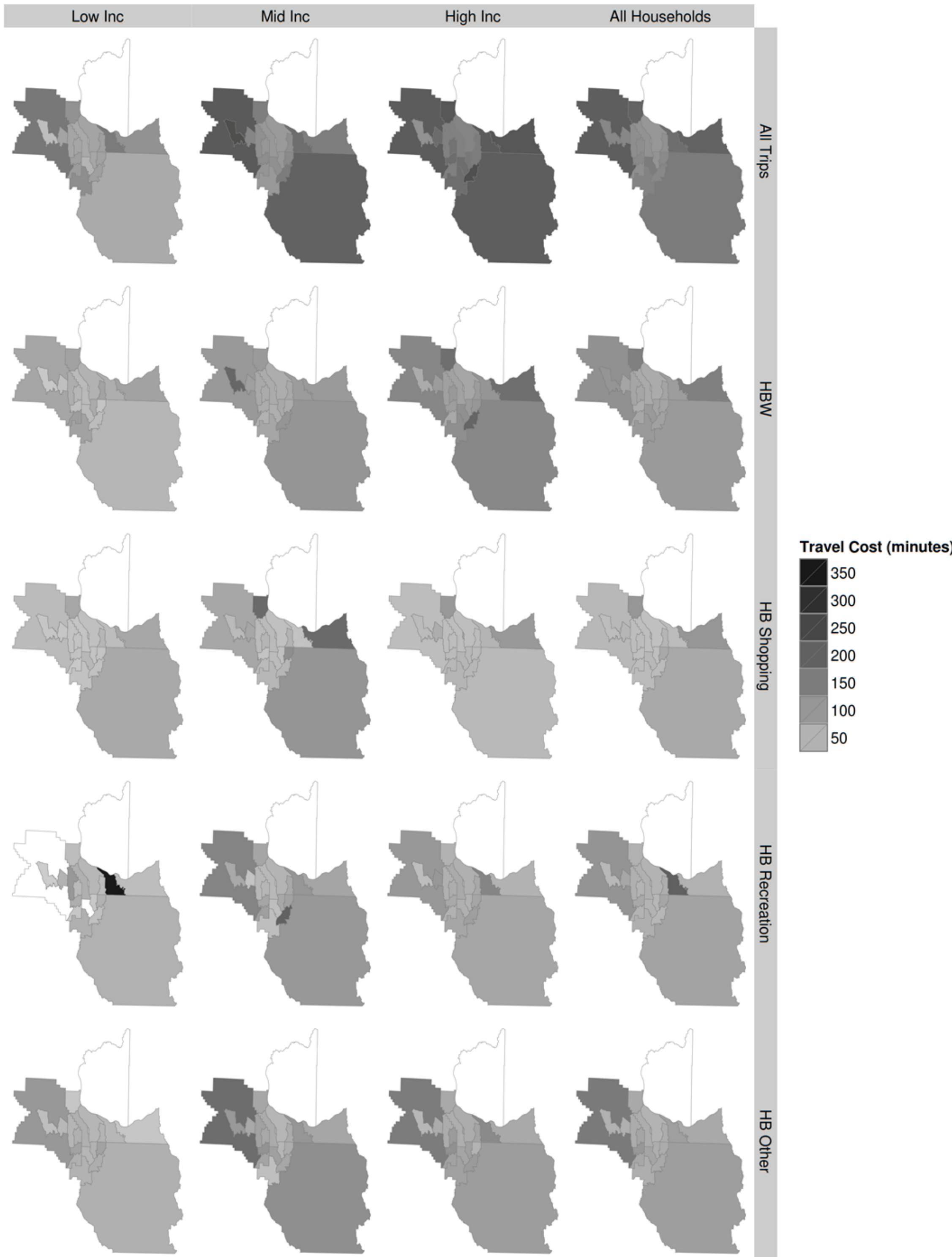

Figure 4.6: District level average household travel costs by income level and trip purpose for Portland with 2011 OTAS data

Due to the problem of the inconsistent result described above and of potential modifiable areal unit problem (MAUP) in aggregating by geography, we test extrapolating per person travel costs (log scale) to grid cells and plotting the extrapolated values in each grid cell as a heat map (Figure 4.7; see script code/misc/plot_heatMap.R for details of how it is created).

However, the problem with the heat map is that it is not conducive to show much of a pattern in the distribution of per person travel costs.

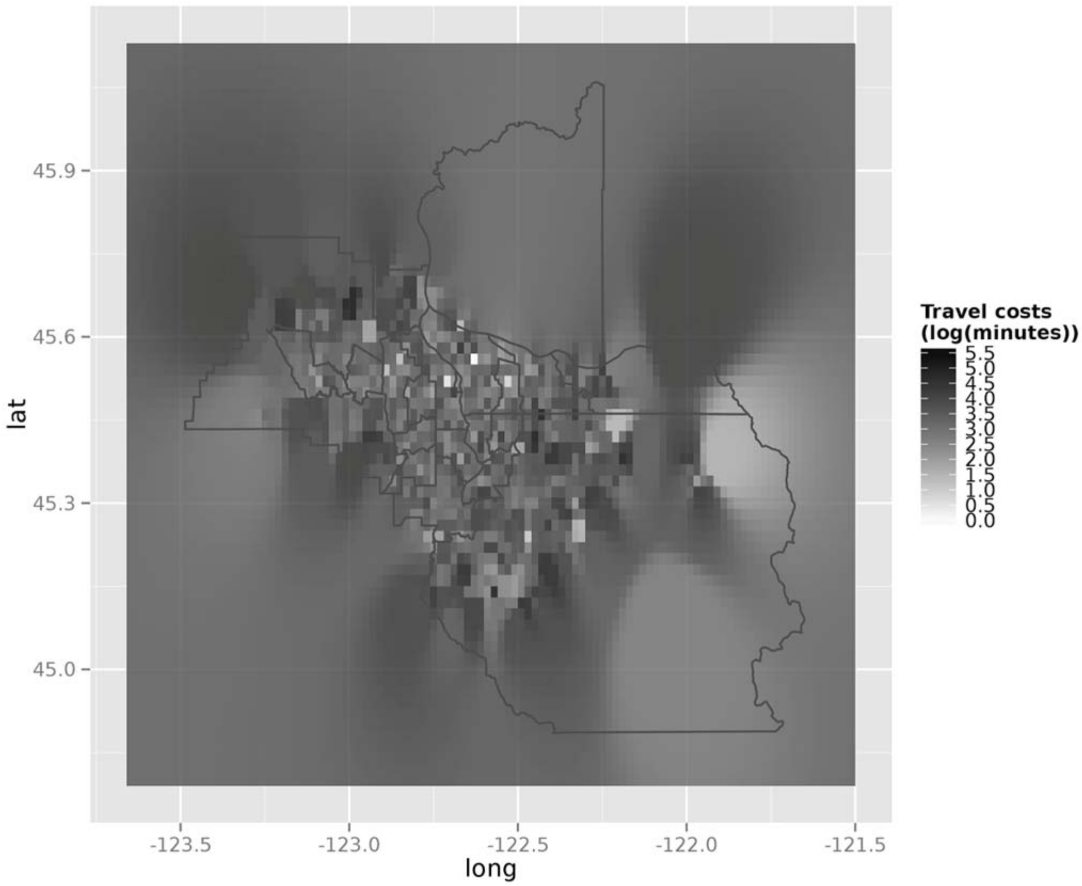

Figure 4.7: Heat map of per person travel costs for Portland with 2011 OTAS data (grid cell size = 0.02′* 0.02′, overlaid with traffic district boundaries)

4.2 CLUSTER-BASED APPROACH

Section 3.1.3 describes the cluster-based approach. The approach is implemented in R and the code is in `tci/code/cluster` directory. Steps for implementing the cluster-based approach are described below. Inputs for the cluster-based approach are listed in Appendix B.

One of the unresolved issues in chapter 3 is to determine the cutoffs for center identification. Sensitivity testing is conducted to test how sensitive the identified spatial distribution of centers and the resulted travel costs are in response to different cutoffs. The results of the sensitivity analysis for Portland are included in Appendix C. What we found from the sensitivity testing is that the identified centers and TCI results are very stable when the cutoffs are set at 50 – 70 percentiles. For applications of cluster-based approach covered in the report, we use 50 percentiles as cutoffs. The parameter for cutoffs can be changed by users in R scripts.

1. Calculate sizeterm density

This step calculates employment density for HBW and size terms density for HBR, HBS, and HBO. For HBW, employment used here is the total employment of all sectors. For the Portland application, size terms for HBR, HBS and HBO are calculated as follows:

HBSsizeterms = RetEmp +.008396*NonRet + .022126*Hhold
HBRsizeterms = TotEmp + 1.278*Hhold + 4.6833*ParkAcres
HBOsizeterms = 0.2393*Hhold + RetEmp + 0.6419*SvcEmp + 0.6109*GvtEmp
+ 06802*NonRetSvcGvt

where

RetEmp = retail trade (NAICS 44, 45, 72)
NonRet = all employment other than retail
Hhold = Number of households in attraction TAZ
TotEmp = Total employment of attraction TAZ
ParkAcres = Park acres in attraction TAZ
SvcEmp = service (NAICS 51, 54, 56, 61, 62, 71, 81)
GvtEmp = government ownership service (NAICS 92)
NonRetSvcGvt = all employment other than retail, service, and government

2. Identify centers

This step adds size term density data to the TAZ shape file and identifies centers in a spatial clustering process. This step identifies centers for each of the four trip purposes: HBW, HBS, HBR and HBO. Based on the results of the sensitivity analysis, a density cutoff of 50% and a total cutoff of 50% are used.

3. Calculate trips by purpose, income, mode and time of day

Since trips by purpose, income, mode and time of day were not provided to us (only trip distribution by purpose and income are available), we calculate them from mode choice utilities. This step calculates mode choice probabilities and trips by mode:

$$MT_{pikjm} = MT_{pikj} * MP_{pikjm}$$
$$MP_{pikjm} = \exp\left(U_{pikjm}\right) / \sum_m (U_{pikjm}) \qquad \textbf{(4.1)}$$

where

MT_{pikjm} is the number of trips of income group *i* from TAZ *k* to TAZ *j* for trip purpose p by mode *m*

MT_{pikj} is the number of trips of income group *i* for trip purpose from TAZ *k* to TAZ *j*

MP_{pikjm} is the probability that mode m is used by income group *i* for trip purpose *p* from TAZ *k* to TAZ *j*

U_{pikjm} is the utility for traveling by mode m between TAZ k and j for purpose p by income group i

4. Calculate travel time and distance

This step calculates travel time and distance from each TAZ to activity centers. The travel time is weighted by number of trips from an origin TAZ to TAZs in the centers.

5. Calculate trip-level generalized costs

Generalized costs that include both travel time cost and monetary cost components are aggregated for each mode in the same way as step 2 in the survey-based approach.

6. Aggregate travel costs

Similar to step 3 in the survey-based approach, the distribution of the travel costs computed in step 5 can be aggregated across various dimensions, such as mode, income group, trip purpose, home location or a combination of these characteristics following methods discussed in section 3.3.

7. Generate plots and maps

Plots and maps can be generated from the results of step 3.

Figure 4.8 – 4.11 show results from the cluster-based approach for Portland with data from Metro's 2010 travel demand model.

Figure 4.8 shows the density distributions of household-level travel costs by income level with the cluster-based approach. Low income households have much higher travel costs with a very different distribution than other households. This plot is theoretically comparable to Figure 4.1, but the results from the survey-based approach and the cluster-based approach may not be directly comparable for a few reasons. First, the two approaches measure different things (see discussion in section 3.1.2). The survey-based approach depicts the travel costs given households' current travel pattern, while the cluster-based approach describes what the travel costs would be if households had similar travel pattern. Second, the unit of analysis for the survey-based approach is individual households on the survey day, while that for the cluster-based approach is aggregated households at TAZ level (theoretically an average low-, mid- or high-income household living in a TAZ when the income is used for segmentation).

Nevertheless, Figure 4.8 shows that if all households share the same travel market baskets defined as activity centers in the cluster-based approach, low-income households tend to have higher transportation costs than mid- and high-income households. This makes sense as low-income households are more likely to reside in locations (TAZs) with worse regional accessibility and it would cost them more to travel to regional activity centers. Figure 4.8 also shows that high-income households have higher costs than mid-income households, although the difference is less drastic than that the difference to low-income households.

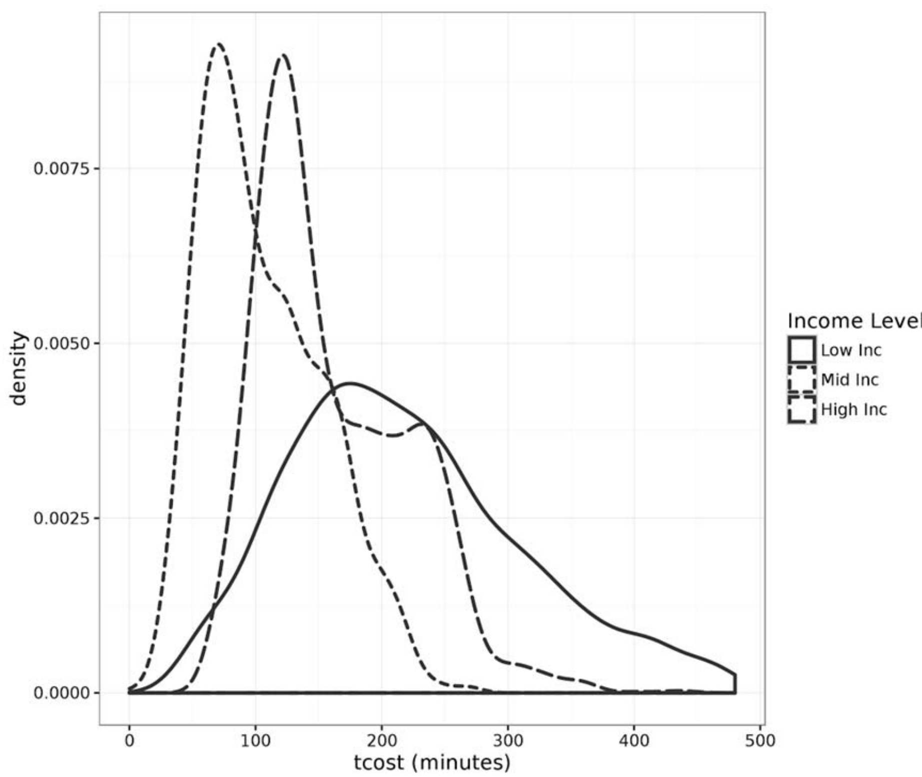

Figure 4.8: Density distributions of travel costs by income level for Portland with the 2010 travel demand model data

Just like the survey-based approach, there are many ways to present the results from the cluster-based approach, although there is some difference between the results from these two approaches. There is more flexibility in ways to describe the transportation costs distribution against household attributes in the survey-based approach because of the use of microdata as inputs. In the cluster-based approach, the household attributes available for analysis is limited by what are available in the travel demand model that provides the most of the inputs for the cluster-based approach. In a common 4-step model, the household data are usually aggregated by income and sometime income alone, which limits ways to examine the transportation costs distribution. When TCI takes inputs from an activity-based travel model (ABM) (beyond the scope of this project and thus untested, but it is feasible), such limitations will be eliminated, as the inputs will again be microdata from the ABM.

Because of this reason, we cannot plot some of the same graphs as we do for the survey-based approach, for example, travel costs by household size or presence of children, or per person travel costs. But there are plenty of other attributes that can be used for analysis. For example, Figure 4.9 shows the distribution of travel costs by trip purpose, and Figure 4.9 the distribution of travel costs by trip purpose and income.

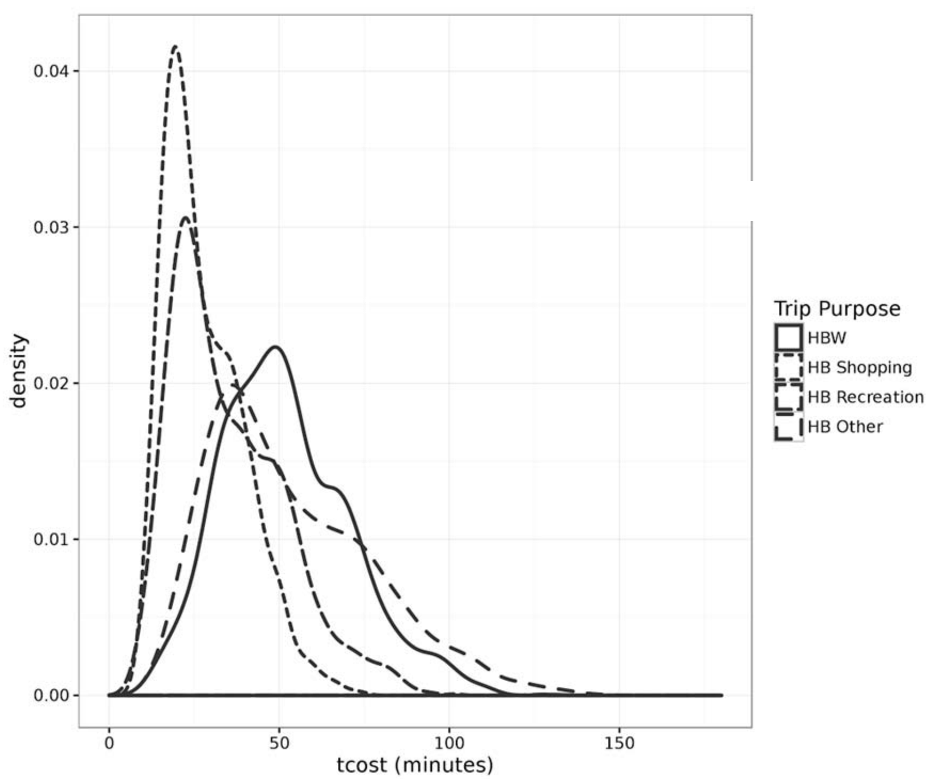

Figure 4.9: Density distributions of travel costs by trip purpose for Portland with the 2010 travel demand model data

Comparing Figure 4.10 with Figure 4.5, it is easy to note that, with the exception of HB shopping trips by low-income households, the range of travel costs by trip purpose and income from the cluster-based approach is smaller than that from the survey-based approach (as indicated by the height of the boxes in the two box plots). This is likely due to the fact that Figure 4.9 (the cluster-based approach) reflect variation across TAZs, while Figure 4.5 (the survey-based approach) reflects the variation among households.

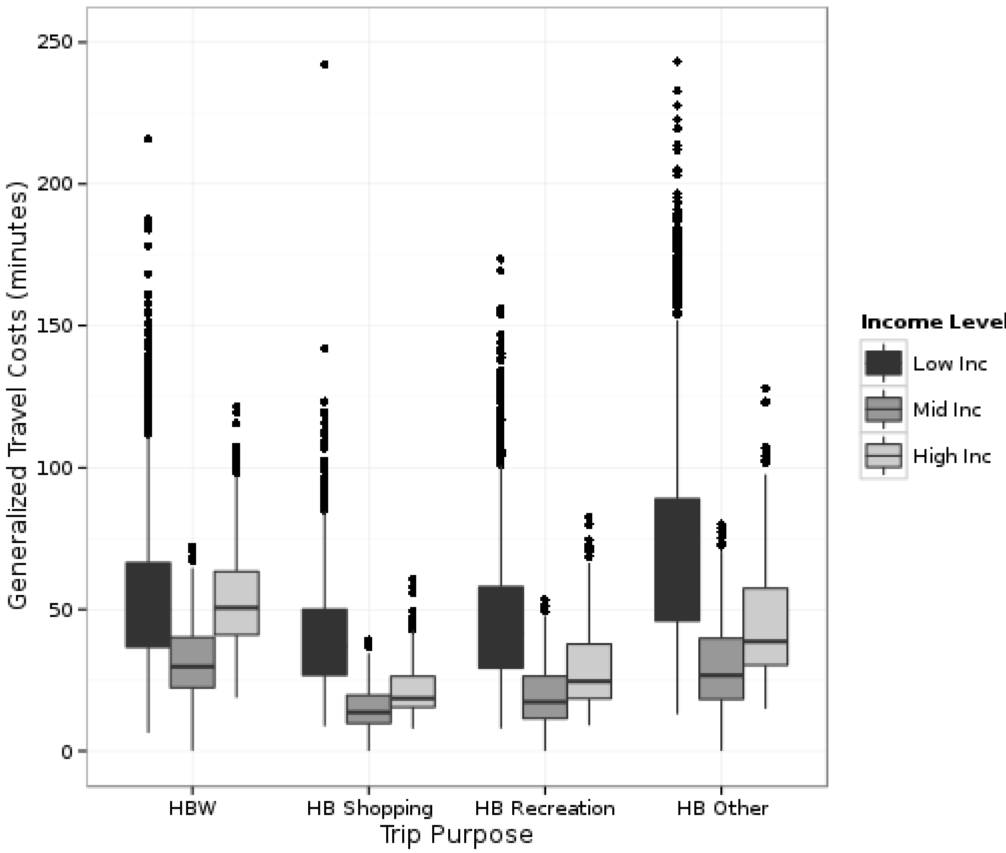

Figure 4.10: Box plot of travel costs by income level and trip purpose for Portland with the 2010 travel demand model data

Just like for the survey-based approach, it is possible to plot the spatial distribution of transportation costs with maps. Figure 4.11 shows the TAZ level spatial distribution of travel costs by trip purpose and income level. Maps in the first row are total costs for All Trips per household, while those in other rows are costs per trip.

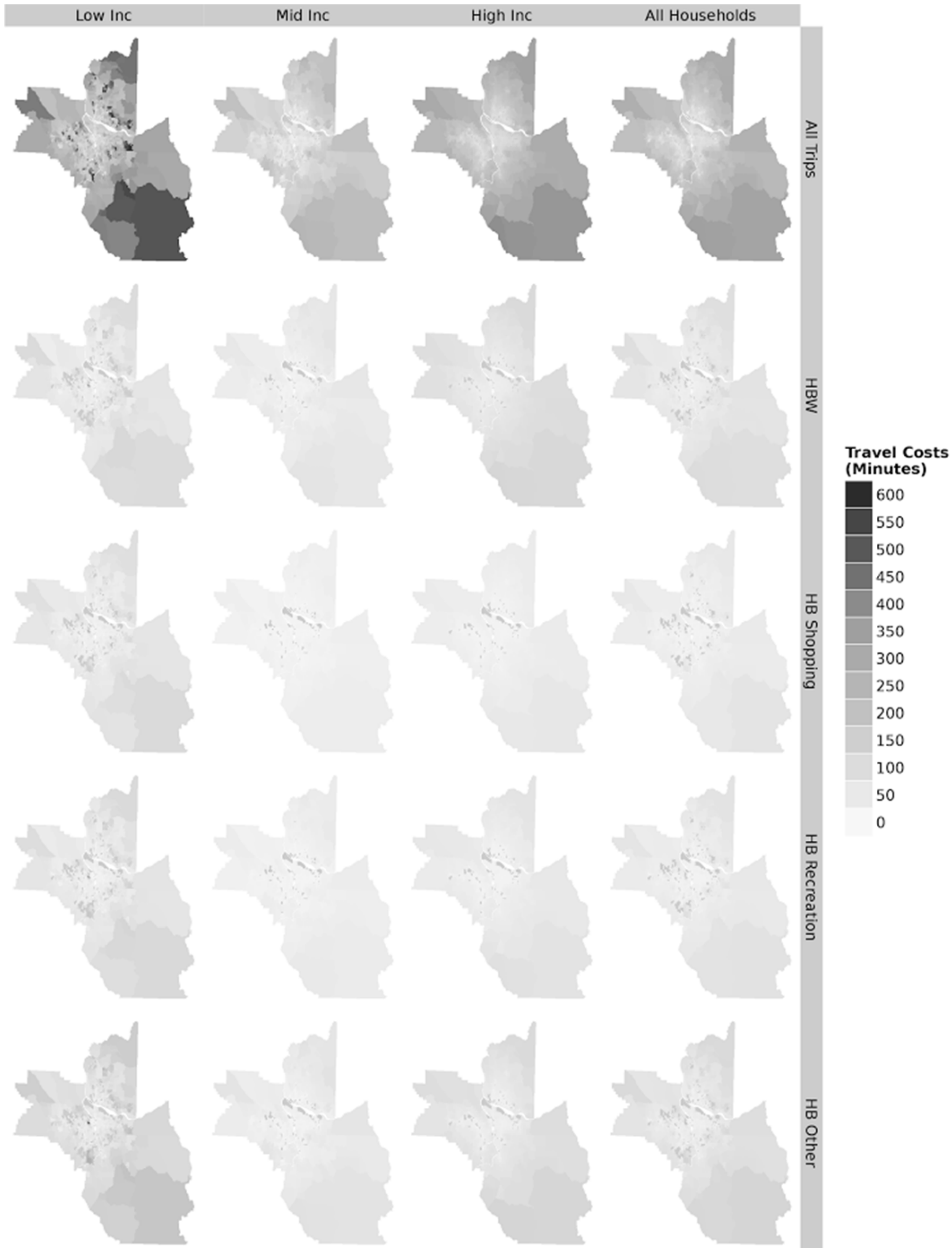

Figure 4.11: TAZ level spatial distribution of travel costs by income level and trip purpose for Portland with 2010 travel demand model data

5.0 SCALABILITY TESTING WITH THE CORVALLIS APPLICATION

This chapter documents Task 5 - application of the travel market definitions to a mid-sized metropolitan area, Corvallis, in addition to Portland for testing of their scalability. The purpose of this task is to determine whether the travel market definitions are meaningful at all level geographic levels, as the market basket definitions likely pose the most substantial scale issues. Besides, the tests may provide understanding of the consequence of applying methods to areas where the availability and quality of data may not be as good as that for Portland. This chapter summarizes the testing of these two methods for Corvallis.

5.1 SURVEY-BASED APPROACH

The survey-based approach utilizes the survey data like the OTAS data to calculate travel costs for each trip and each household, and then aggregates trip-level and household-level costs by geography (e.g. TAZ, district), trip purpose and/or income group. Figure 5.1 – 5.3 shows the results of the survey-based approach for Corvallis. Even though there are much fewer observations for Corvallis in the OTAS data (n=348 versus n=4,106 for the Portland area)5, the results are still reasonable, which attests to the robustness and scalability of the survey-based approach.

[5] n – Number of households who reported at least one HBW/HBS/HBR/HBO trip during the day of the survey.

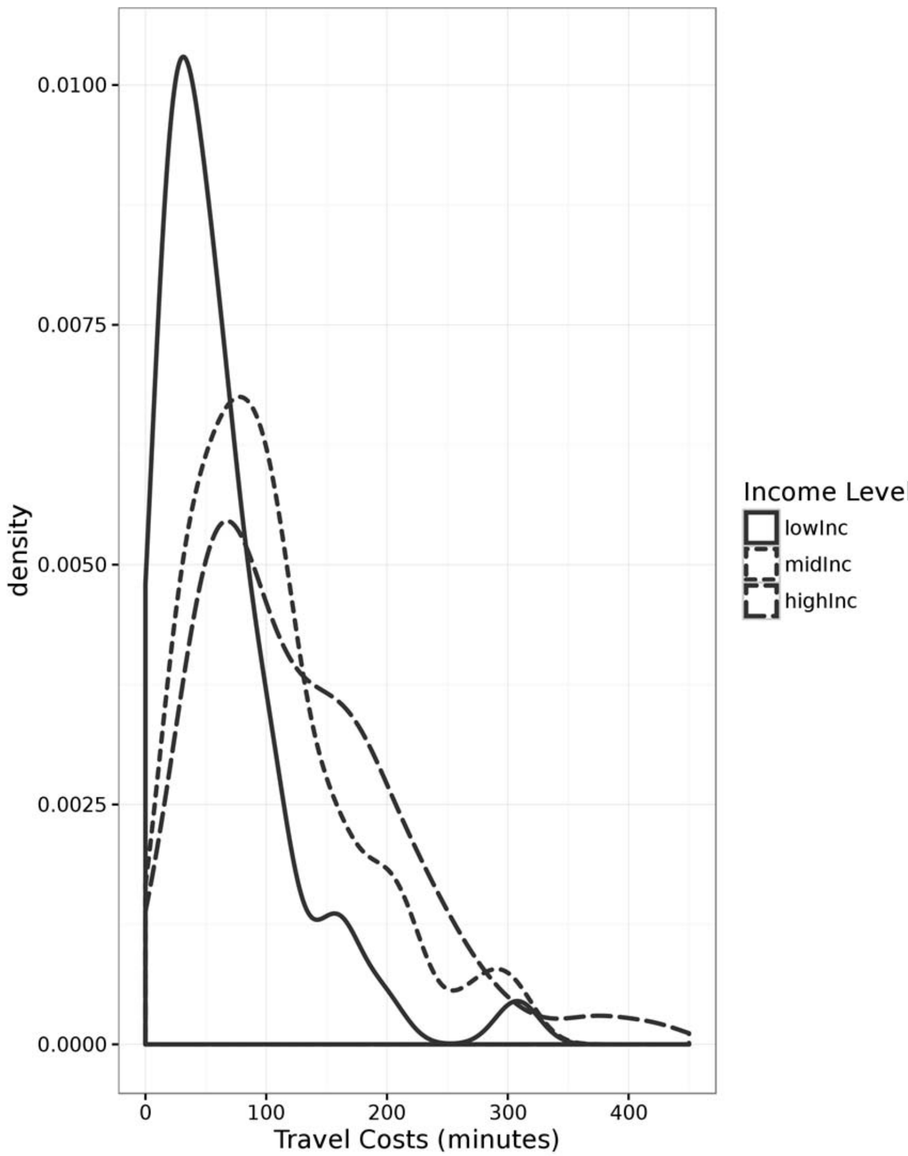

Figure 5.1: Density distributions of household-level travel costs by income level for Corvallis with 2011 OTAS data

Compared to Portland (Figure 4.1), households in the Corvallis area on average have lower travel costs with a mean household-level travel cost of 105 minutes versus 119 minutes for Portland. However, the difference in means masks the subtle difference in the distribution of household-level travel costs between these two areas: in Corvallis there is a larger share of low income households who enjoy low travel costs (<100 minutes), but their travel costs are higher than those for low income households in Portland, as demonstrated by the wider peak in Figure 5.1. This is probably due to the fact that since Portland is a much bigger region, some households there would have to make very long trips. On the other hand, there are more transportation options available in Portland, a substantial share of low-income households are taking the advantage to enjoy lower travel costs.

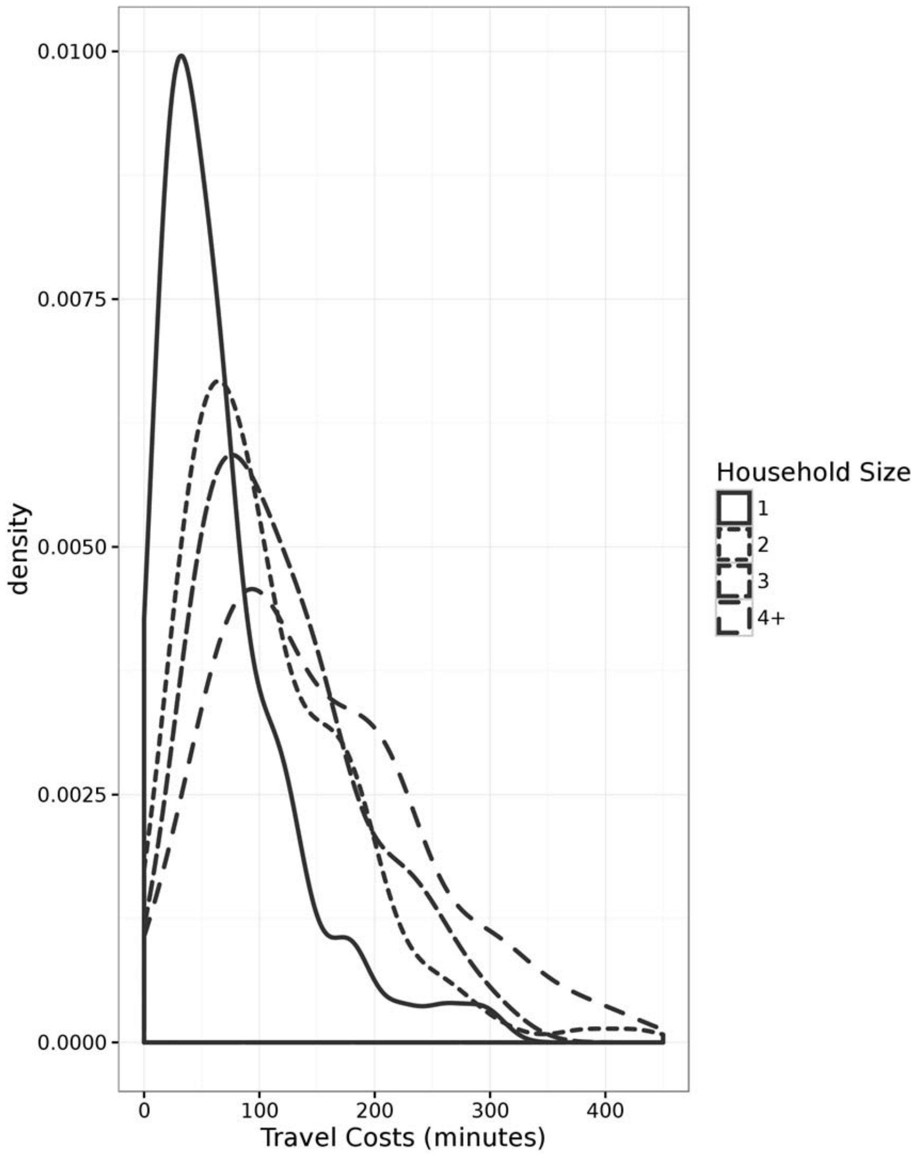

Figure 5.2: Density distributions of household-level travel costs by household size for Corvallis with 2011 OTAS data

In Corvallis a similar pattern occurs across distributions of household-level travel costs by household size: as households get larger, their travel costs increase (Figure 5.2). But the difference between households with 3 members and those with 4+ members in Corvallis is larger than the difference in Portland (Figure 4.2).

Very similar patterns in the distributions of travel costs are observed in Corvallis as in Portland. As shown in Figure 5.3, households with children have higher travel costs than those without in Corvallis, the same as shown in Figure 4.3 for Portland, although the difference is smaller in Corvallis, indicated by the fact that the two density lines are closer to each other in Figure 5.3.

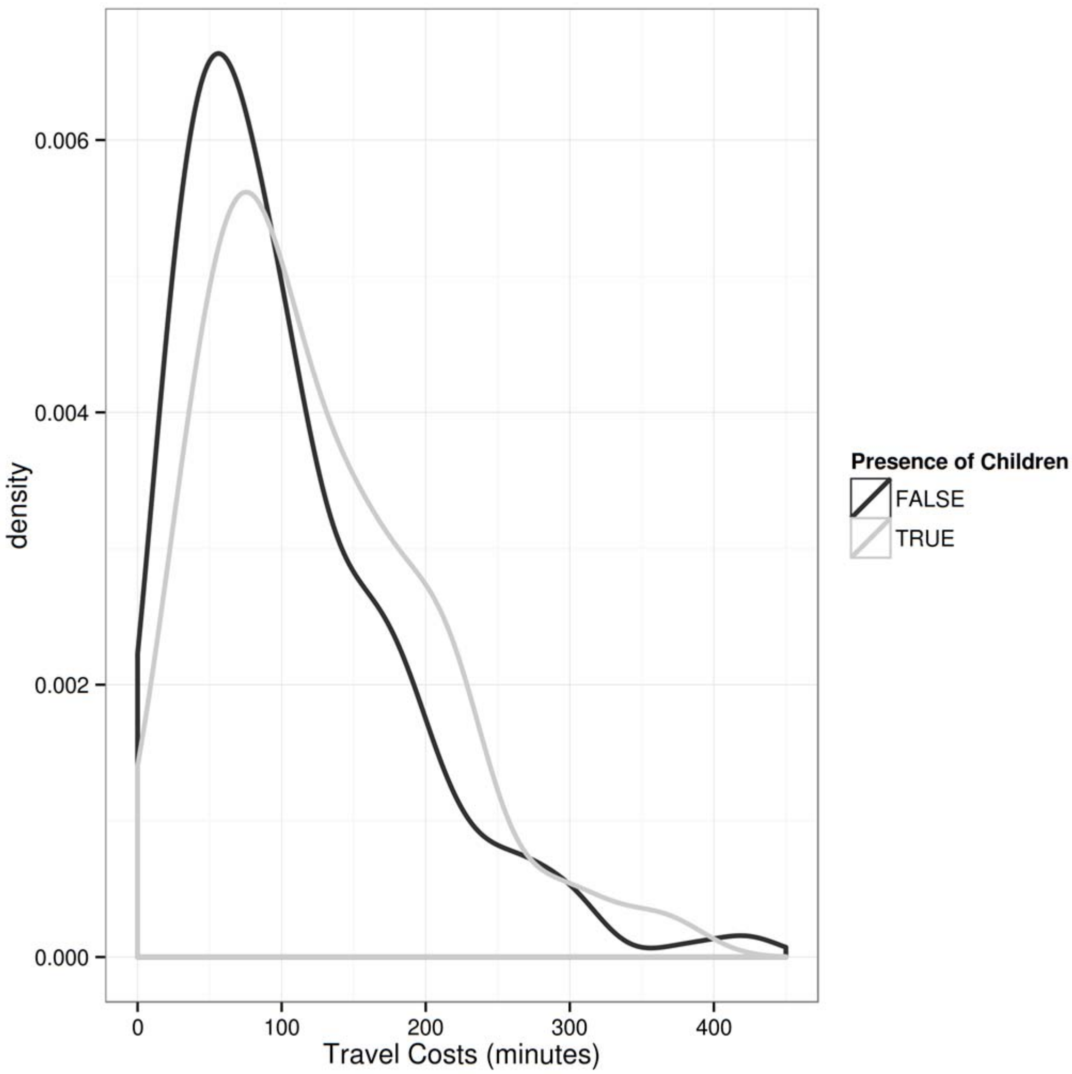

Figure 5.3: Density distributions of household-level travel costs by presence of children for Corvallis with 2011 OTAS data

Again similar to the pattern observed for Portland, the difference in travel costs across income groups becomes much smaller once household size is factored in for Corvallis as well (Figure 5.4).

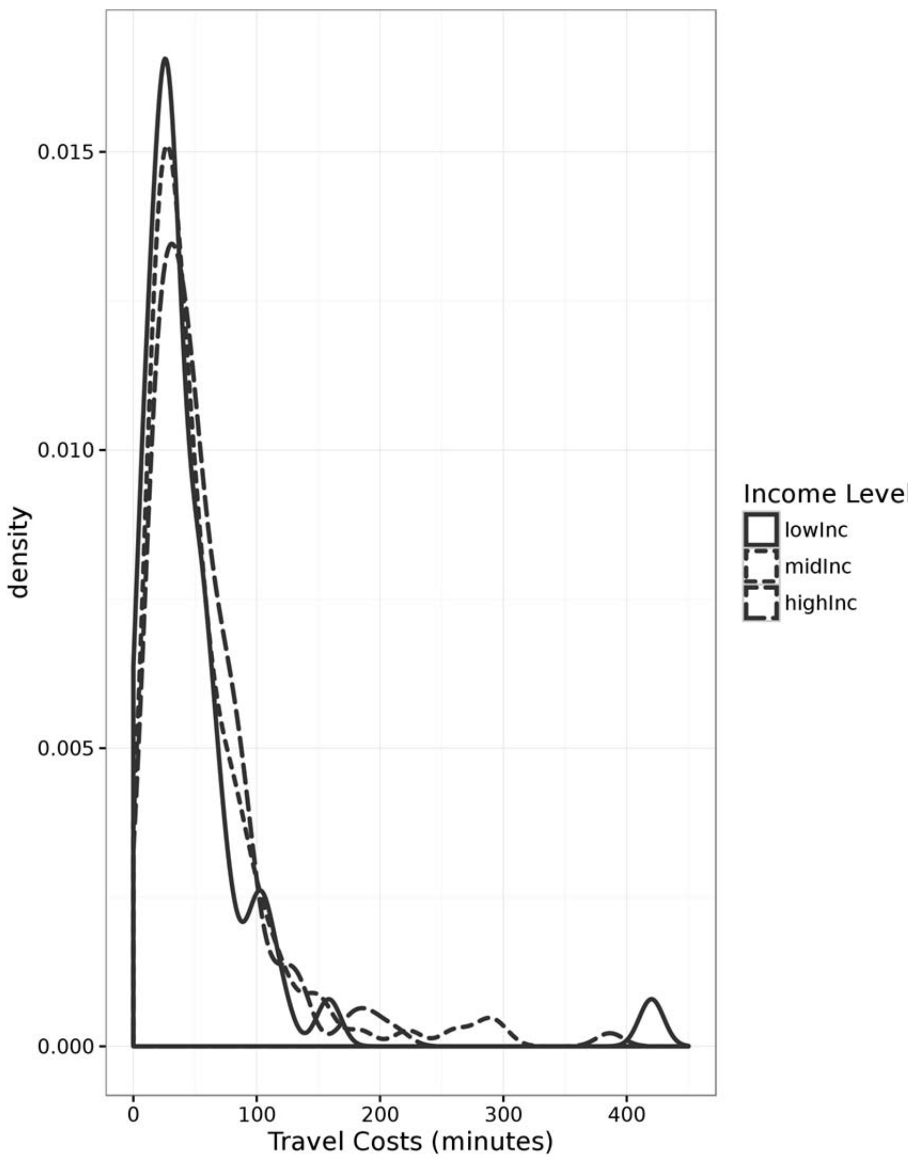

Figure 5.4: Density distributions of average travel costs per person by income for Corvallis with 2011 OTAS data

Figure 5.5 shows trip-level travel costs by trip purpose and the traveler's household income for Corvallis.

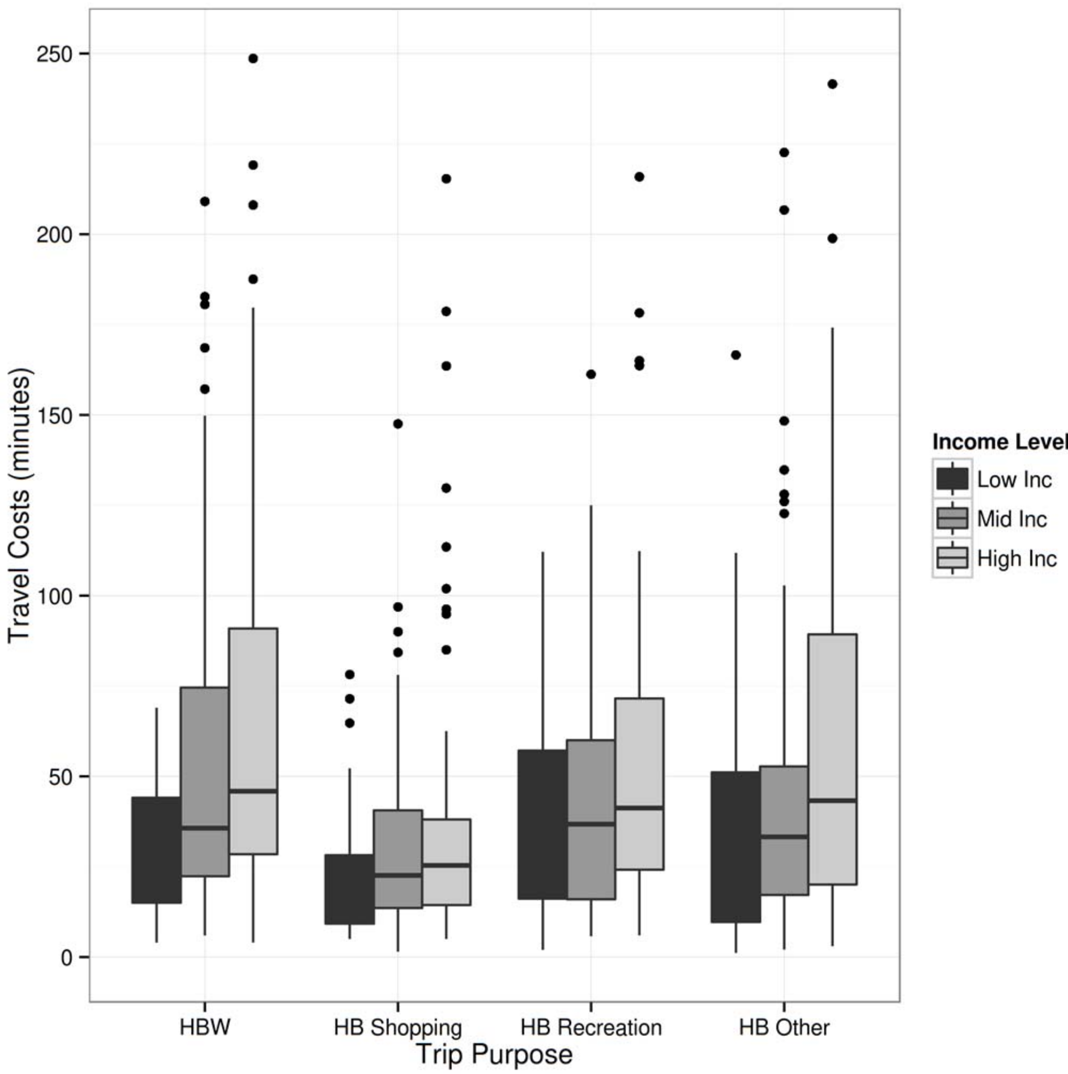

Figure 5.5: Box plots of trip-level travel costs by income level and trip purpose for Corvallis with 2011 OTAS data

5.2 CLUSTER-BASED APPROACH

The cluster-based approach has been described in early chapters of this report. This method defines a travel market for each of the four trip purposes: Home Based Work (HBW), Home Based Shopping (HBS), Home Based Recreation (HBR) and Home Based Others (HBO). For each trip purpose, the travel market basket is a set of geographic clusters that represent activity centers identified with the algorithm proposed by Giulinao *(Giulinao 1991*).

The cluster-based approach uses the travel demand model (TDM) data, including household and employment by TAZ, size terms in the destination choice model utility function and travel time skims. This task uses data from the Corvallis JEMnR (Jointly Estimated Model in R) TDM, which has similar model structure to the Portland TDM, although the size terms formulas are different.

The steps to define travel markets are as follows.

Step 1. Calculate TAZ level employment density for HBW and size terms density for HBR, HBS, and HBO;

Employment density is employment divided by the Traffic Analysis Zone (TAZ) area , and size terms density is size terms divided by the TAZ area. For each TAZ in Corvallis, the size terms are calculated as follows.

HBS: RetEmp + 0.025*NonRet + 0.019*Hhold

HBR: NonRet +1.175*Hhold + 7.614*ParkAcres

HBO: 0.404*GvtEmp + RetEmp + 0.537*SvcEmp + 0.114*NonRetSvcGvt + 0.260*Hhold

where RetEmp = Retail trade employment

NonRet = All employment other than retail

Hhold = Number of households

ParkAcres = Park Acres

GvtEmp = government employment

SvcEmp = service employment

NonRetSvcGvt = all employment other than service and government

Step 2. Identify TAZs with densities greater than cutoff D;

Step 3. Group contiguous TAZs identified in step 2 into clusters;

Step 4. Calculate total employment or size terms for each cluster identified in step 3;

Step 5. Eliminate cluster with total employment or size terms below cutoff E from centers identified in step 3. The remaining are activity centers.

There are two cutoffs in the algorithm above. The density cutoff (cutoff D) selects TAZs to form centers and the total cutoff (cutoff E) selects activity centers to form a travel market basket. In order to define a reasonable travel market basket, the cutoff values are crucial. Unfortunately there is no theoretical ground for determining these cutoffs, as Giulinao *(Giulinao 1991)* relied on expert opinion when determining them in their study. Sensitivity analysis has been done to determine reasonable cutoff values. Figure 5.6 below shows travel market baskets for trip purpose HBW with various cutoff values. Non-center area is in red color. In the left-upper graph, the area in blue color is identified as the HBW travel market basket with density cutoff set at the 50th percentile and total cutoff the 75th percentile; the area in blue color and light blue color is HBW travel market for density cutoff of the 50th percentile and total cutoff of the 50th percentile.

The travel market basket becomes smaller as the density cutoff increases. The right-lower graph shows HBW travel market for density cutoff of the 95th percentile (employment densities less than the 95th percentile are eliminated). It is much smaller than the model area.

The process is repeated for other trip purposes (HBS, HBR and HBO) and the graphs are not included here due to space limit.

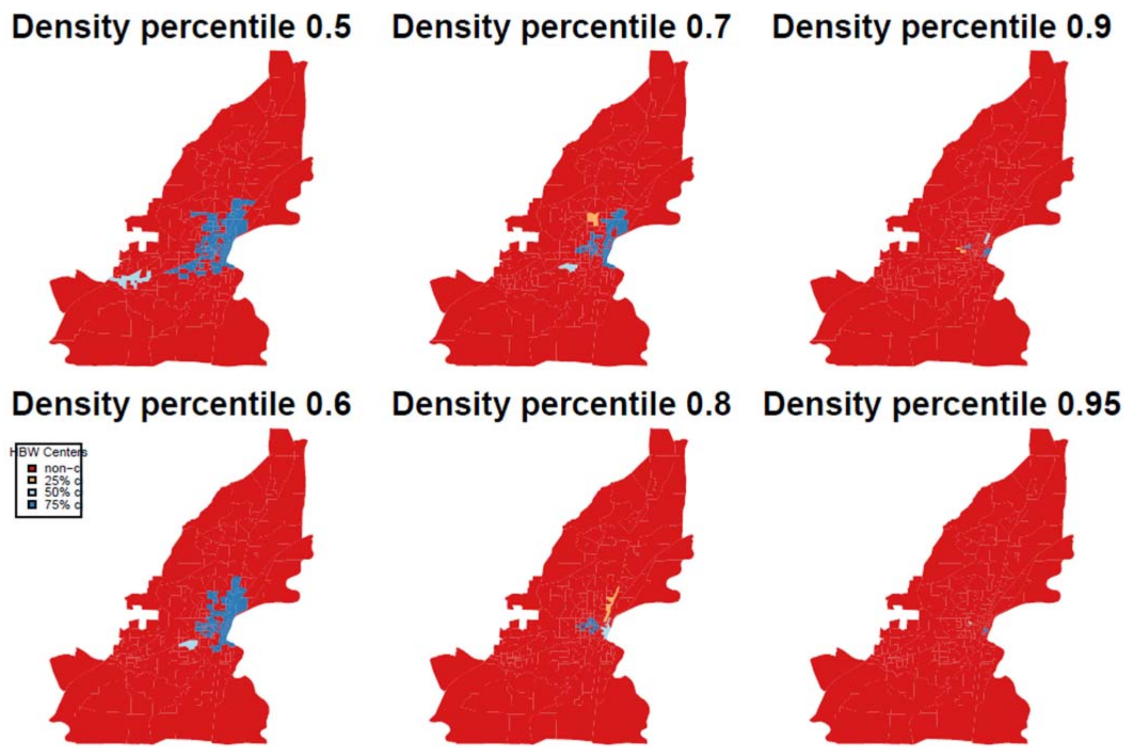

Figure 5.6: Sensitivity analyses of cutoff values for HBW trips

In addition to the travel market baskets, the travel costs (TC) accessing the basket identified with various cutoff values have been calculated, and are listed in Table 5.1. This also provides information to verify reasonable cutoff values. Each TAZ's TC has been aggregated by trip purposes and income groups. The calculation process is the same as PSU's Portland study, so results are comparable.

In Table 5.1, when the density cutoff increases, the TC mean, median, and the 3rd quartile are stable while the minimum and the 1st quartile significantly decrease; and the maximum slightly increase. The density cutoff has significant effect on the TC minimum and the 1st quartile. From the analysis, density cutoff larger than the 60 percentile is not suitable for Corvallis.

TC is not sensitive to the total cutoff because it changes little as the total cutoff increases. This is also observed from PSU's Portland results listed in Appendix C. Further, Portland's TC has little change when the density cutoff increases from the percentile of 50 to 70. This is different from Corvallis. 50 percentile are used for both density and total cutoffs.

The sensitivity analysis helps planners to determine reasonable cutoff values.

Table 5.1: Travel costs with various cutoff values

Cutoff		Descriptive statistics					
Density	Total	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
50%	25%	0.59	0.77	1.00	1.24	1.63	3.84
	50%	0.59	0.77	1.01	1.24	1.63	3.84
	75%	0.57	0.76	0.99	1.24	1.62	3.83
60%	25%	0.49	0.72	0.97	1.20	1.64	3.86
	50%	0.49	0.72	0.97	1.20	1.64	3.86
	75%	0.48	0.71	0.97	1.20	1.63	3.87
70%	25%	0.44	0.69	0.99	1.18	1.62	3.90
	50%	0.44	0.69	0.99	1.19	1.62	3.90
	75%	0.42	0.68	0.98	1.18	1.62	3.90
80%	25%	0.37	0.65	0.96	1.16	1.61	3.93
	50%	0.36	0.63	0.96	1.16	1.62	3.96
	75%	0.39	0.61	0.97	1.15	1.63	3.98
90%	25%	0.27	0.55	0.95	1.10	1.52	4.04
	50%	0.25	0.54	0.91	1.07	1.46	4.03
	75%	0.22	0.50	0.93	1.06	1.45	4.08
95%	25%	0.19	0.49	0.97	1.08	1.54	4.11
	50%	0.19	0.49	0.97	1.08	1.54	4.11
	75%	0.21	0.48	0.95	1.07	1.52	4.10

Figure 5.7 shows maps of activity centers for each of the trip purpose with the density cutoff of 50% and total cutoff of 50%.

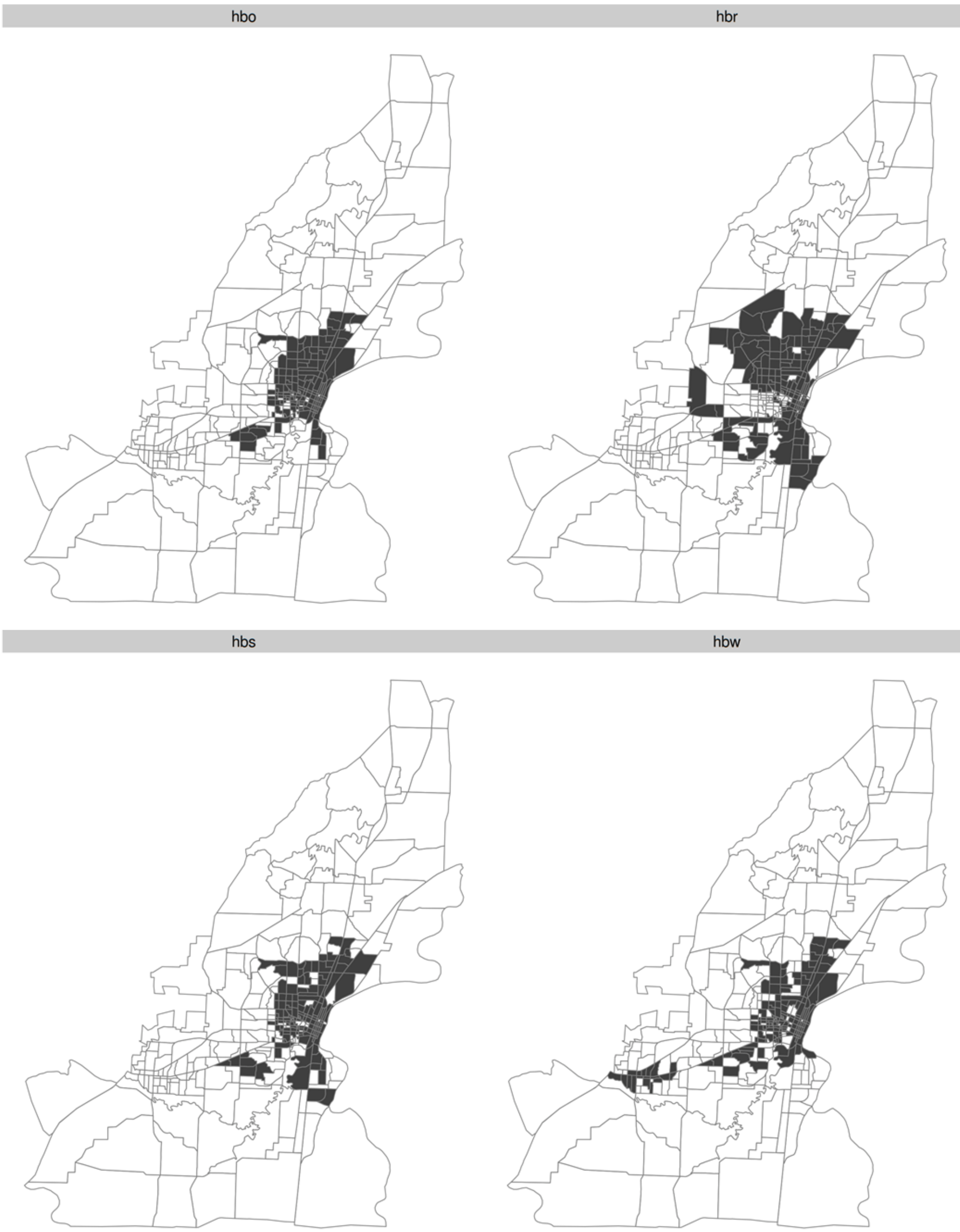

Figure 5.7: Activity centers by trip purpose for Corvallis identified with the cluster-based approach

Figure 5.8 - 5.11 show the results from the cluster-based approach for Corvallis. In Figure 5.8, the similar pattern observed in Portland emerges for Corvallis: with the cluster-based approach, low income households have higher travel costs, reversing the pattern in the results from the survey-based approach.

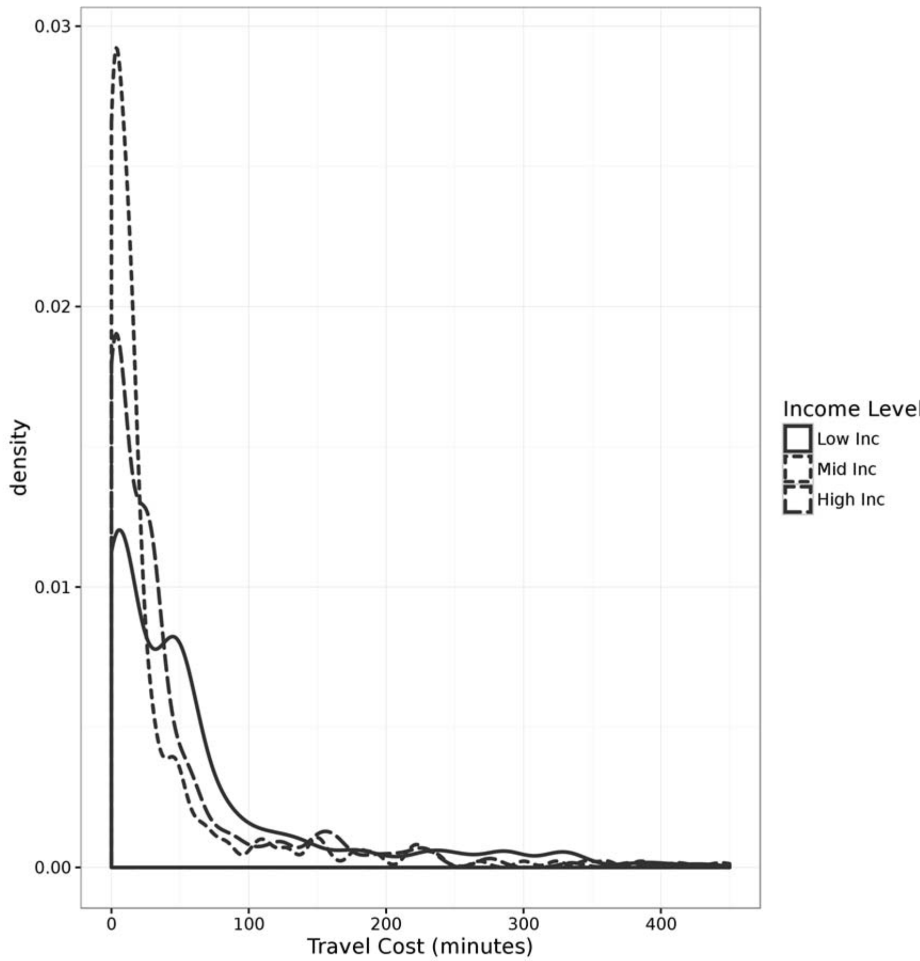

Figure 5.8: Density distributions of travel costs by income level for Corvallis with the 2010 CAMPO JEMnR model data

Unlike the distributions of travel costs by trip purpose in Portland, the difference across trip purpose is much smaller in Corvallis (Figure 5.9), likely due to the fact that the centers identified for different purposes largely overlap with each other (Figure 5.7). Figure 5.9 corroborates this pattern.

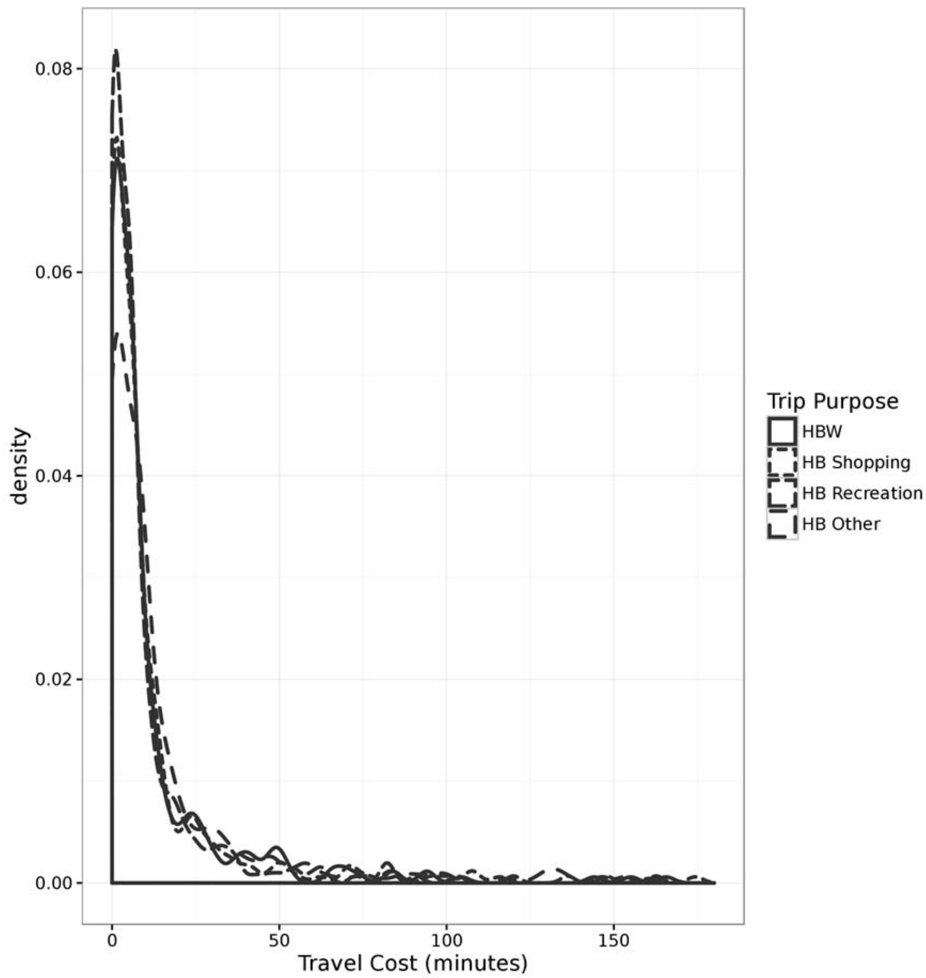

Figure 5.9: Density distributions of travel costs by trip purpose for Corvallis with the 2010 CAMPO JEMnR model data

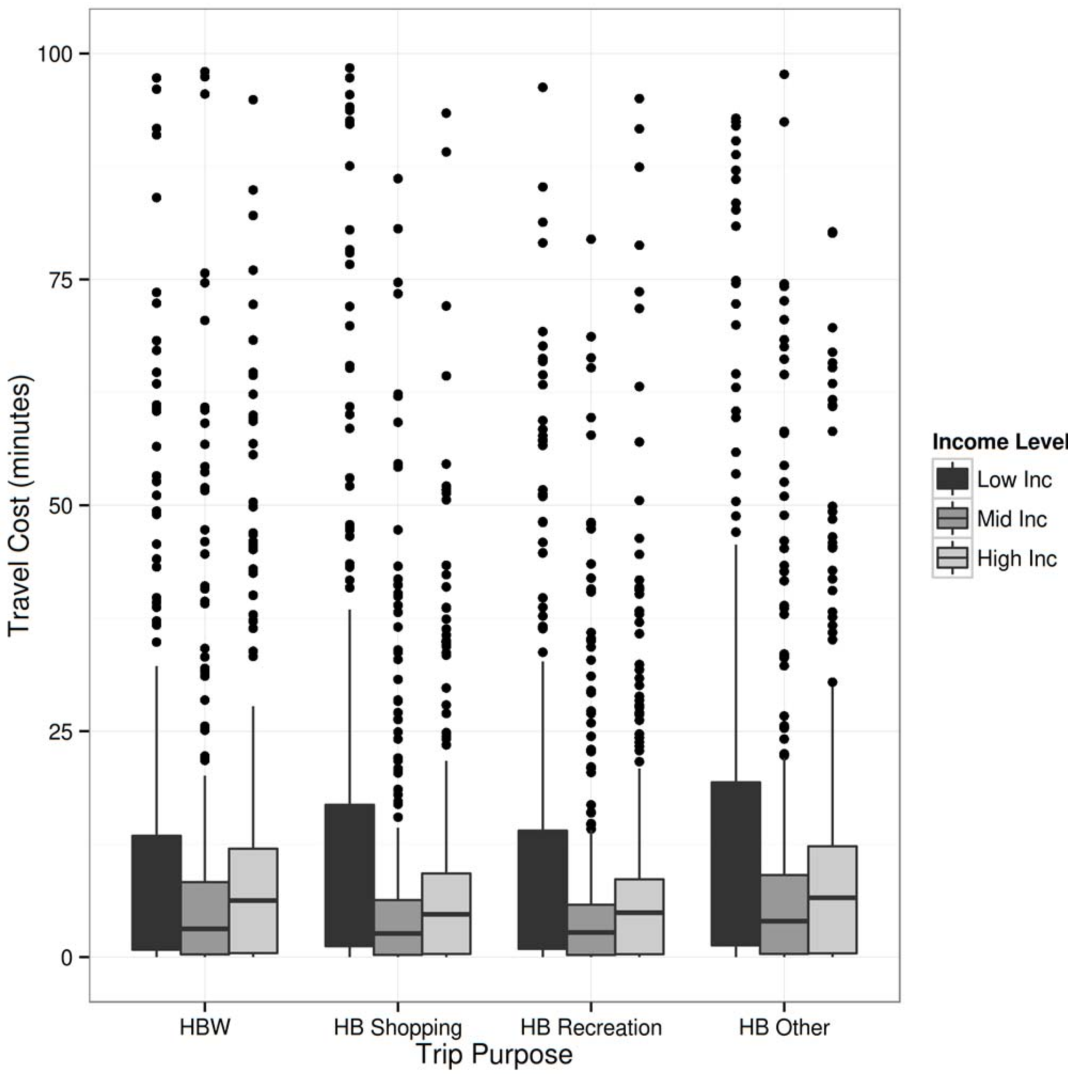

Figure 5.10: Box plot of travel costs by income level and trip purpose for Corvallis with the 2010 CAMPO JEMnR model data

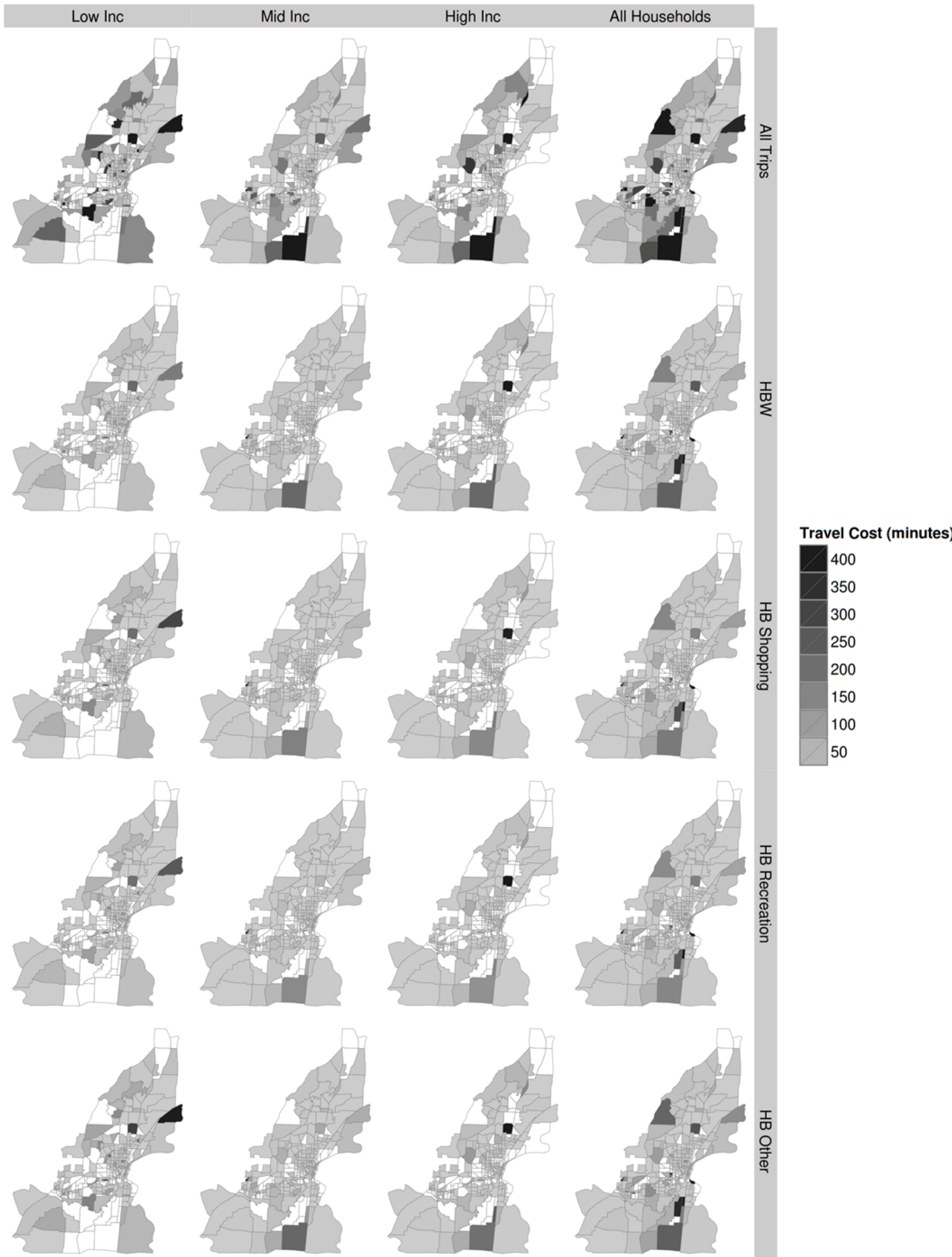

Figure 5.11: TAZ level travel costs by income level and trip purpose for Corvallis with the 2010 CAMPO JEMnR model data

6.0 APPLICATABILITY TESTING

We set out to develop TCI to handle different application contexts including trend monitoring, policy screening, and scenario assessments. The survey-based approach can be used to do trend monitoring, while the cluster-based approach is more geared towards the latter two types of applications. To demonstrate TCI in different types of applications and its applicability, we apply the two approaches in two sample applications, first to monitor the trend of travel costs between 1994 and 2011 for Portland, and then to evaluate outcomes from transportation scenarios for Corvallis.

6.1 TREND MONITORING

Since the survey-based approach primarily relies on travel survey data as inputs, it can be easily applied to different time periods or regions for which a travel survey dataset is available. To showcase a trend monitoring application, we apply the survey-based approach to Portland with 1994 travel survey data.

To do this, we use the same steps described in section 4.1, but with the 1994 travel survey data. When classifying households into low-, mid-, and high- income group, we use the $25K, $25-50K, and $50K thresholds (instead of the thresholds that are adjusted for inflated in the 2011 application). We use the same 2011 per distance monetary costs by mode and wage rate. Ideally, we would use these per distance monetary costs and the wage rates for 1994, however, such information is hard to find. An alternative is to adjust those 2011 parameters for inflation back to 1994, but because of the way we calculate monetary costs and the fact that we use minutes as the units for travel costs, it does not make a difference whether we adjust for inflation or not. To demonstrate this point, consider equation (14) in section 3.2.5:

$$\boldsymbol{TC_{pimkj} = C_m + TTime_{pimkj} * VOT_{pim} + TDist_{pimkj} * MC_m} \qquad \textbf{(6.1)}$$

Where

C_m A constant for mode *m,* which could be the fare for a fixed fare transit system;

$TTime_{pimkj}$ and $TDist_{pimkj}$ is the travel time and distance by travelers from income group *i* using mode *m* from original TAZ *k* to access to TAZ *j* in for purpose *p*;

VOT_{pim} is the value of time for travelers from income group *i* using mode *m* for purpose *p*.

MC_m is distance-based monetary cost for mode m. Monetary costs per mile is estimated from various sources described in section 3.2.

Sine we use minutes as the units for travel costs accounting, VOT_{pim} is set to 1 and time costs component does not need to be adjusted for inflation. Since we use distance-based monetary costs calculation, $C_m$is set to 0 and the monetary costs component will compute the monetary costs from distance traveled $TDist_{pimkj}$ and then convert them to minutes with wage rate:

$$MC_m = \frac{DC_m}{W}, \qquad \textbf{(6.2)}$$

where DC_m is per distance monetary costs (dollars/mile) for mode m, and W the wage rate (dollars/hour). If we were to get these parameters for 1994 from 2011 by adjusting for inflation, we will need to apply the adjustment factor to both the numerator and the denominator, and it will cancel out.

The 1994 travel survey includes trip diaries for two days (the 2011 OTAS includes only one-day diary). We use the trips in one of these two days (the weekday if the other day is a weekend or day one if both days are weekdays).

One difference between the 2011 and 1994 survey data is that the household-level weights is available for the 2011 survey data, but not for 1994. Thus the 2011 results described in section 4.1 are after applying the weights in computation, while the 1994 results below are not. Because of this difference, it is hard to assess how much of the trend we observed is the real trend, and how much is due to weighting (or the lack of).

Figures 6.1 – 6.5 show the results for Portland with 1994 travel survey data. Figure 6.1 shows the distributions of 1994 household-level travel costs by income level. Compared to 2011, the difference of travel costs between income groups is smaller in 1994, as the peaks of these distributions largely overlap in 1994.

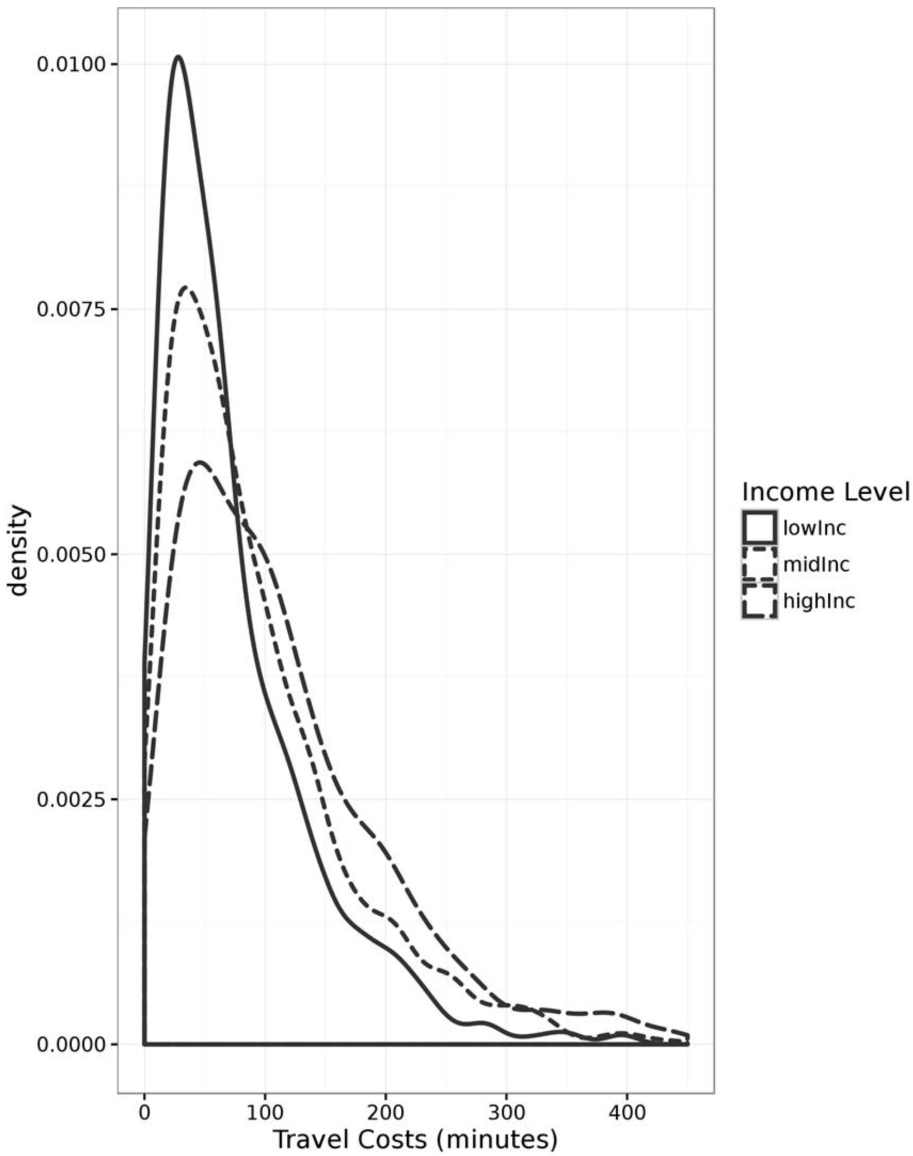

Figure 6.1: Density distributions of household-level travel costs by income level for Portland with 1994 travel survey data

Same as in 2011, the household-level travel costs are highly correlated with household size (Figure 6.2) and influenced by the presence of children (Figure 6.3).

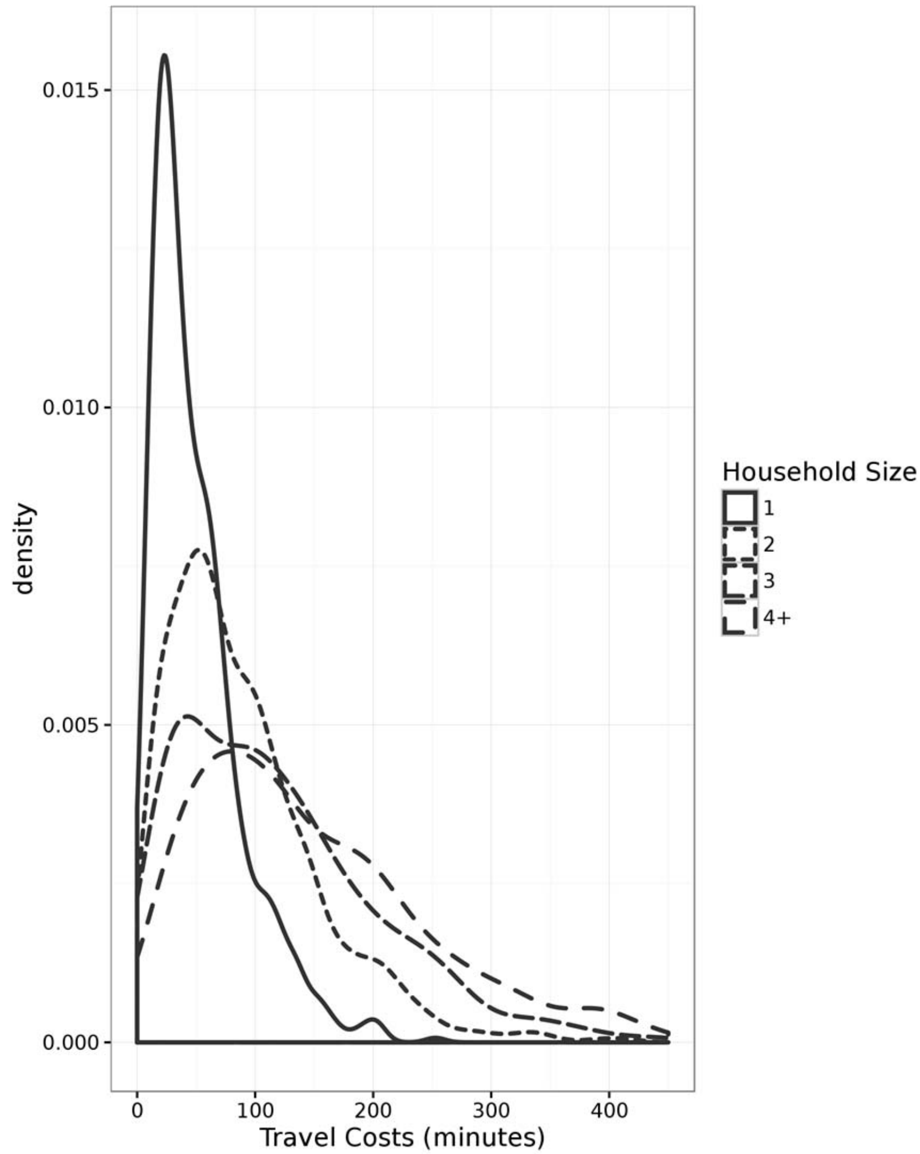

Figure 6.2: Density distributions of household-level travel costs by household size for Portland with 1994 travel survey data

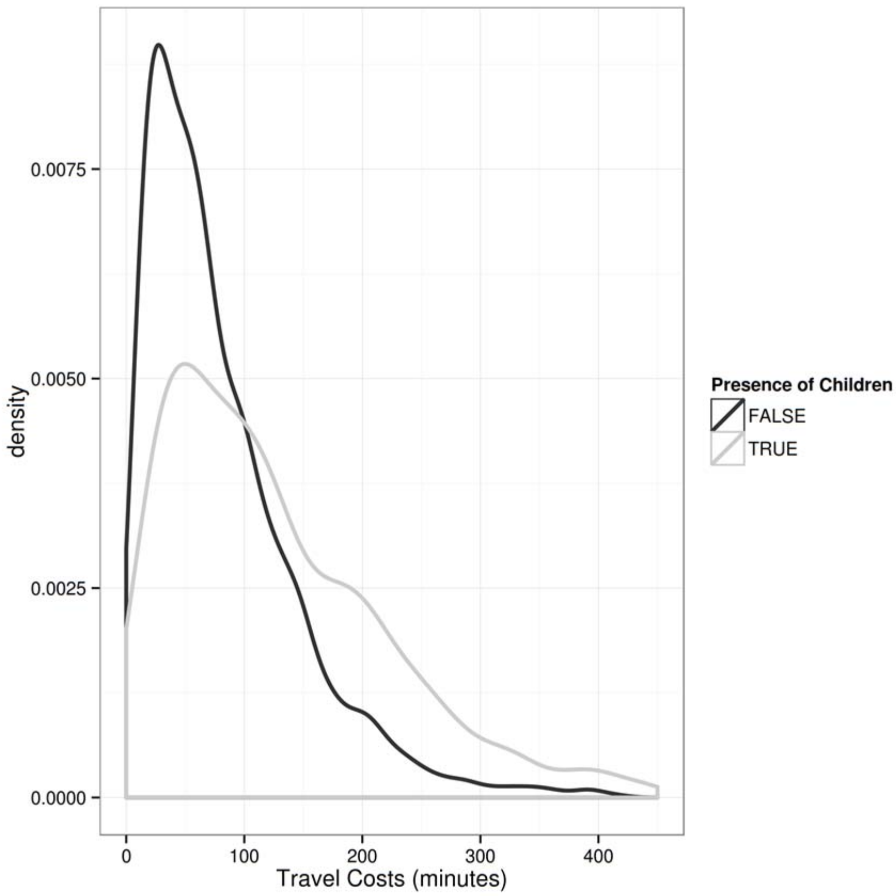

Figure 6.3: Density distributions of household-level travel costs by presence of children for Portland with 1994 travel survey data

Similarly, the difference in household-level travel costs across income groups almost disappears when household size is factored in (Figure 6.4). The distributions of average travel costs per person for the 3 income groups are almost identical in 1994; their difference grew bigger in 2011 (Figure 4.4 in Chapter 4 on page 40).

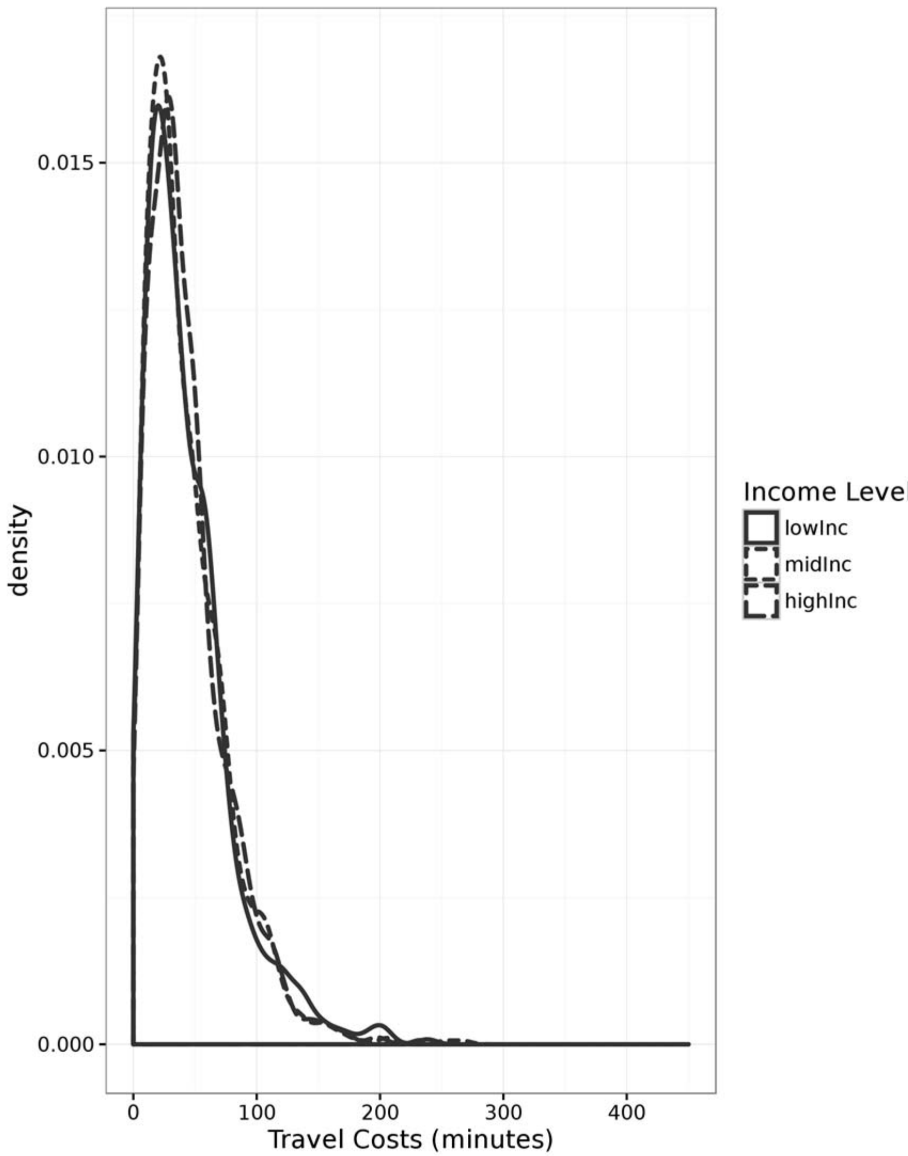

Figure 6.4: Density distributions of average travel costs per person by income for Portland with 1994 travel survey data

Figure 6.5 shows trip-level travel costs by trip purpose and the traveler's household income and Figure 6.6 the spatial distribution of average household travel costs at the traffic district level by income and trip purpose in 1994. Comparing 1994 to 2011, the variations in the trip-level travel costs (measured by the height by the shaded boxes in Figure 6.5 and Figure 4.5 (Chapter 4 page 41), respectively) vary between the two years, but the relationship across income groups is stable.

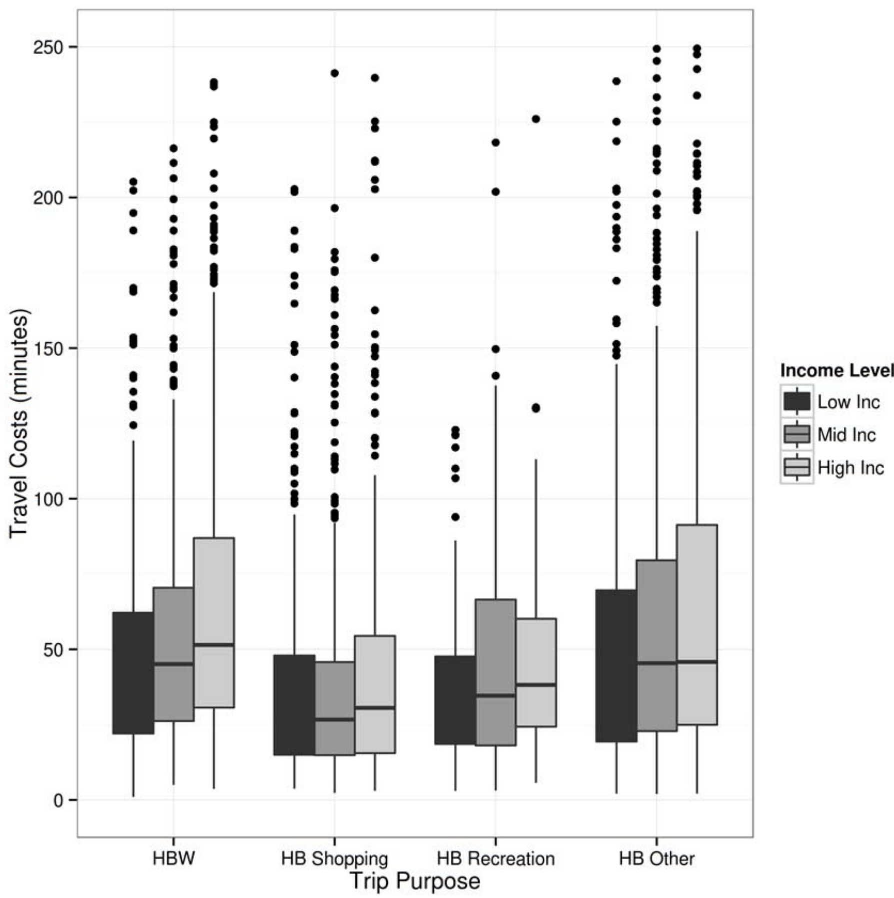

Figure 6.5: Box plots of trip-level travel costs by income level and trip purpose for Portland with 1994 travel survey data

6.2 SCENARIO EVALUATION

We expect that there are two types of application contexts that involve scenario evaluation: 1.) Evaluating the effects of potential transportation network and/or land use changes in a screening or rapid response approach that does not entail running a travel demand model; and 2.) Estimating the effects of potential transportation network and/or land use changes in a more comprehensive analysis approach involving the use of a travel demand model (potentially with a land use model). In this subsection, we demonstrate the application of TCI in both application contexts. Since the applications of TCI in these two contexts are almost limitless, the demonstrations serve as examples how TCI could be used in such contexts, instead of an exhaustive study of all potential applications. For the rapid response approach, we demonstrate the application of the cluster-based approach in two hypothetical scenarios for Corvallis that are set up in a way that is common in rapid response evaluations; while for comprehensive analysis, we apply TCI to evaluate two 2030 transportation scenarios for Corvallis.

6.2.1 Rapid Response Application

In a rapid response application, it is common to set up a scenario by making assumptions of how a certain input (or a set of inputs) would change and to apply performance measures or evaluation models to assess the impacts of such changes. Two hypothetical scenarios are created based on the 2010 Corvallis data: in scenario A, the auto travel time is reduced by half while everything else remains the same; in scenario B, the transit travel time is reduced by half while everything else remains the same. Since auto is the predominate mode of travel in Corvallis, we expect to see larger impacts of scenario A on TCI, and since there is difference in mode shares spatially and across socio-demographical groups, we expect the effects of scenario B to vary – because we have not assumed households would shift mode in response to the travel time deduction.

Figure 6.6 and 6.7 show the travel costs by income groups for scenario A and scenario B, respectively. Compared with the base line (2010 in Figure 5.6), halving auto travel time (scenario A) drastically reduces the travel costs, while halving bus travel time (scenario B) has little effects on travel costs, which makes sense given the low bus mode share. Similar pattern is observed in travel costs by trip purpose and income group (Figure 6.8 and Figure 6.9)

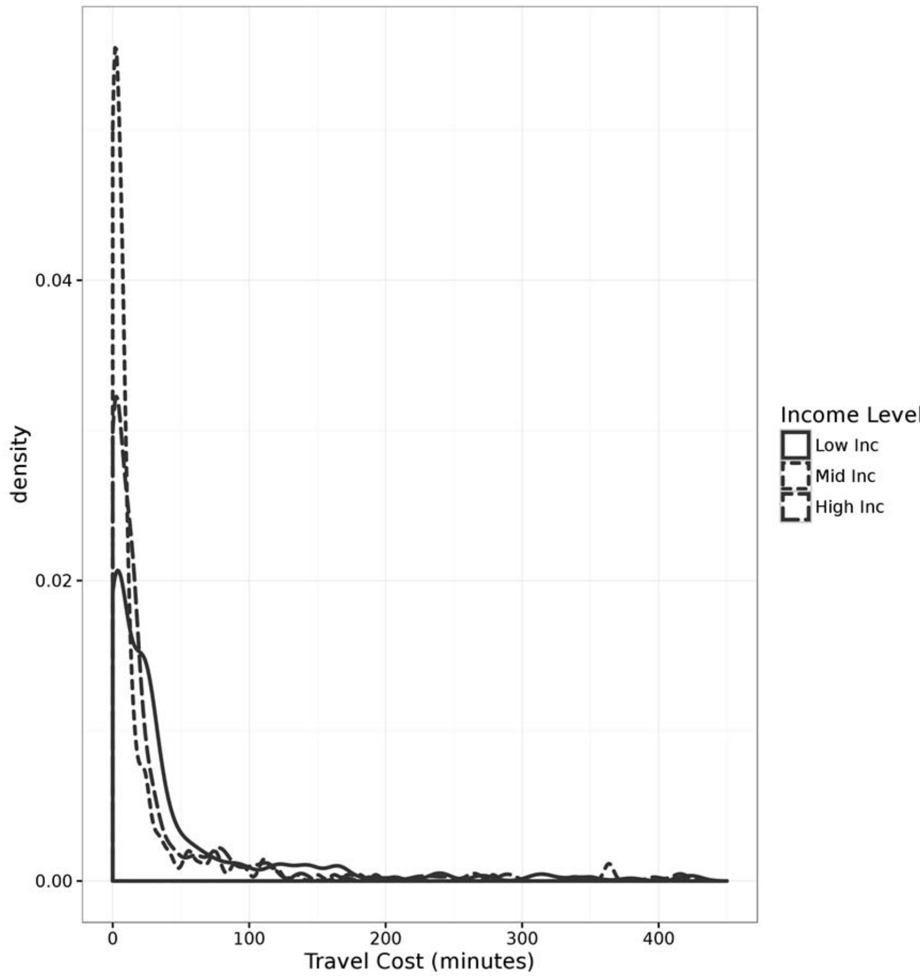

Figure 6.6: Density distributions of travel costs by income level for Corvallis Scenario A (halving auto travel time and all other data from the 2010 CAMPO JEMnR model)

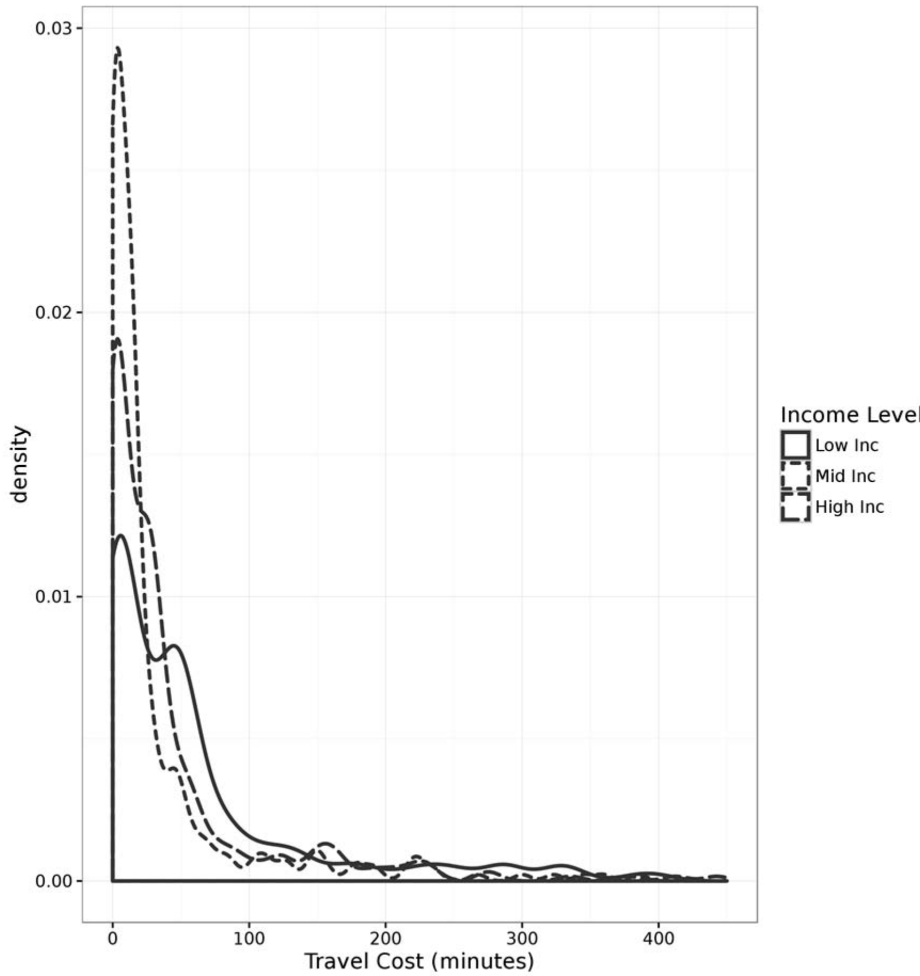

Figure 6.7: Density distributions of travel costs by income level for Corvallis Scenario B (halving bus travel time and all other data from the 2010 CAMPO JEMnR model)

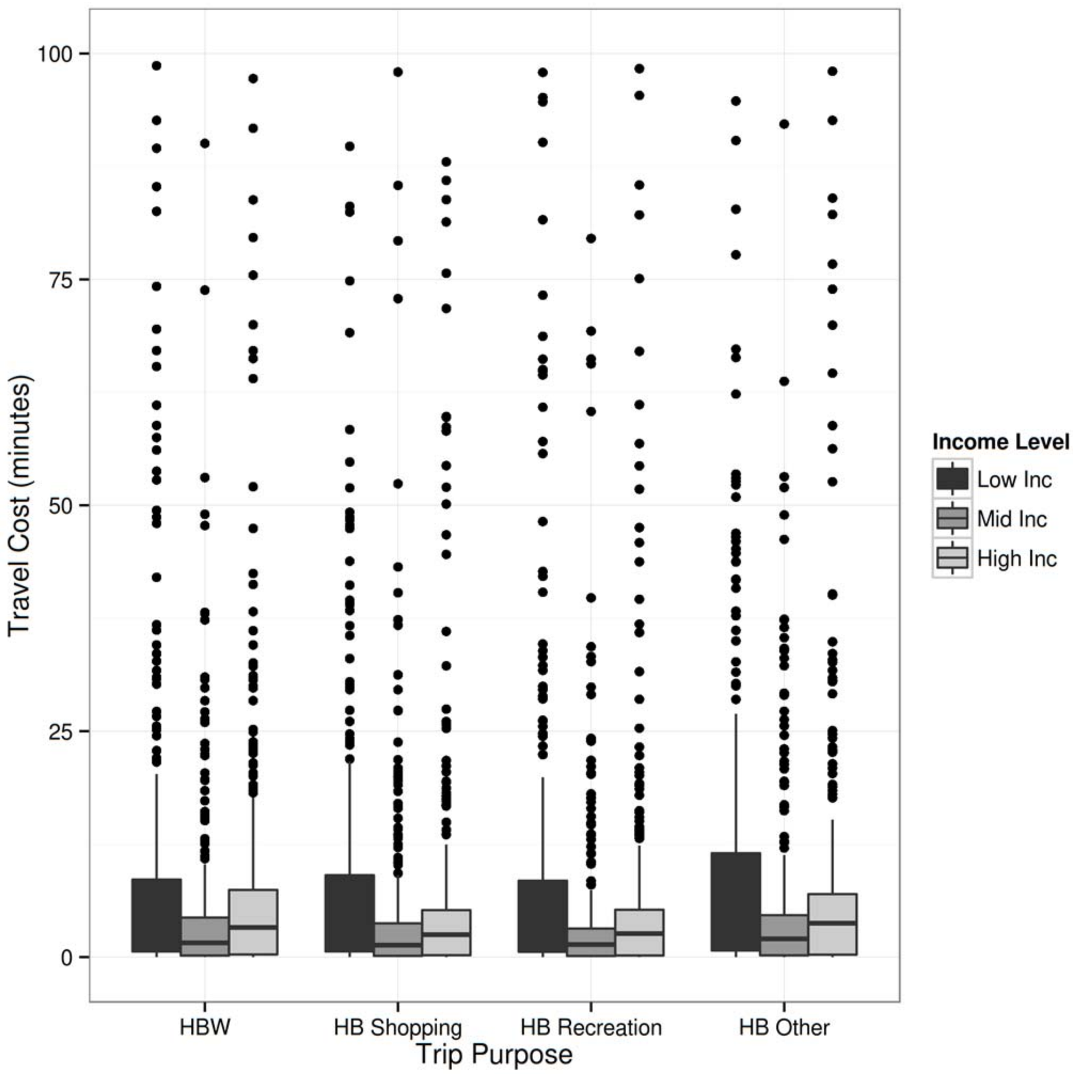

Figure 6.8: Box plot of travel costs by trip purpose and income level for Corvallis Scenario A (halving auto travel time and all other data from the 2010 CAMPO JEMnR model)

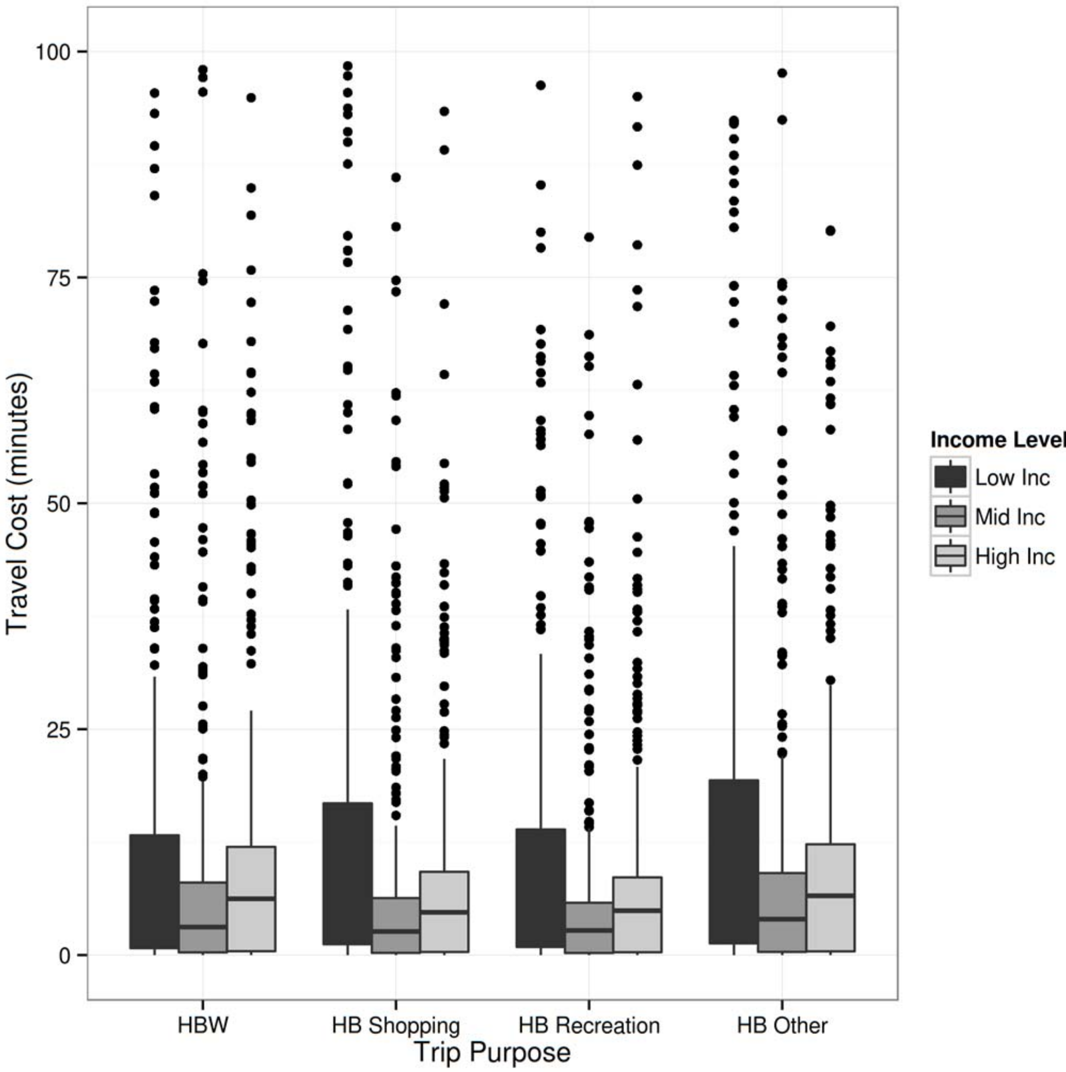

Figure 6.9: Box plot of travel costs by trip purpose and income level for Corvallis Scenario B (halving bus travel time and all other data from the 2010 CAMPO JEMnR model)

In term of spatial pattern, scenario A almost halves the travel costs universally (Figure 6.10), while there is little discernable reduction of travel costs in scenario B results (Figure 6.11).

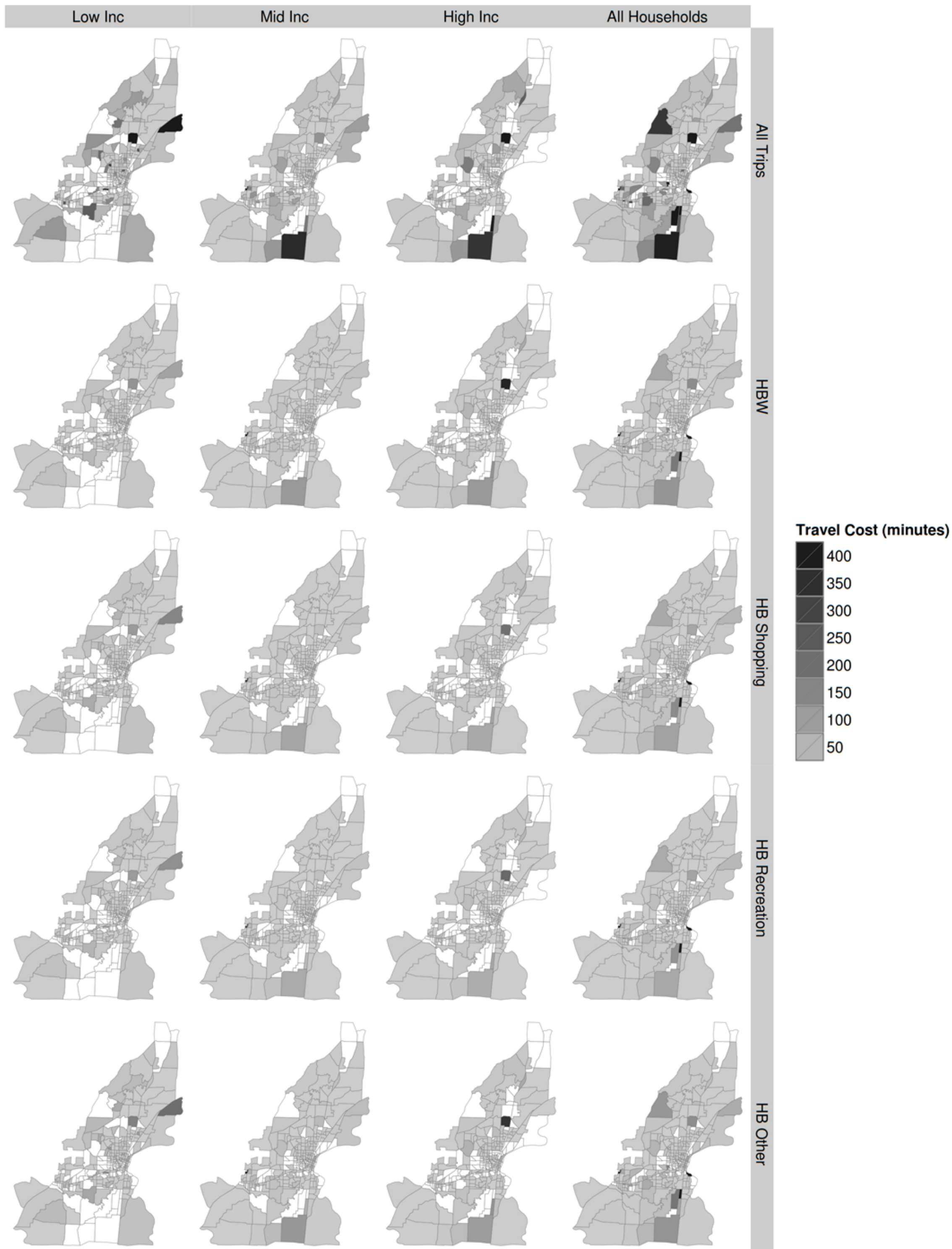

Figure 6.10: TAZ level travel costs by income level and trip purpose for Corvallis Scenario A (halving auto travel time; all other data from the 2010 CAMPO JEMnR model)

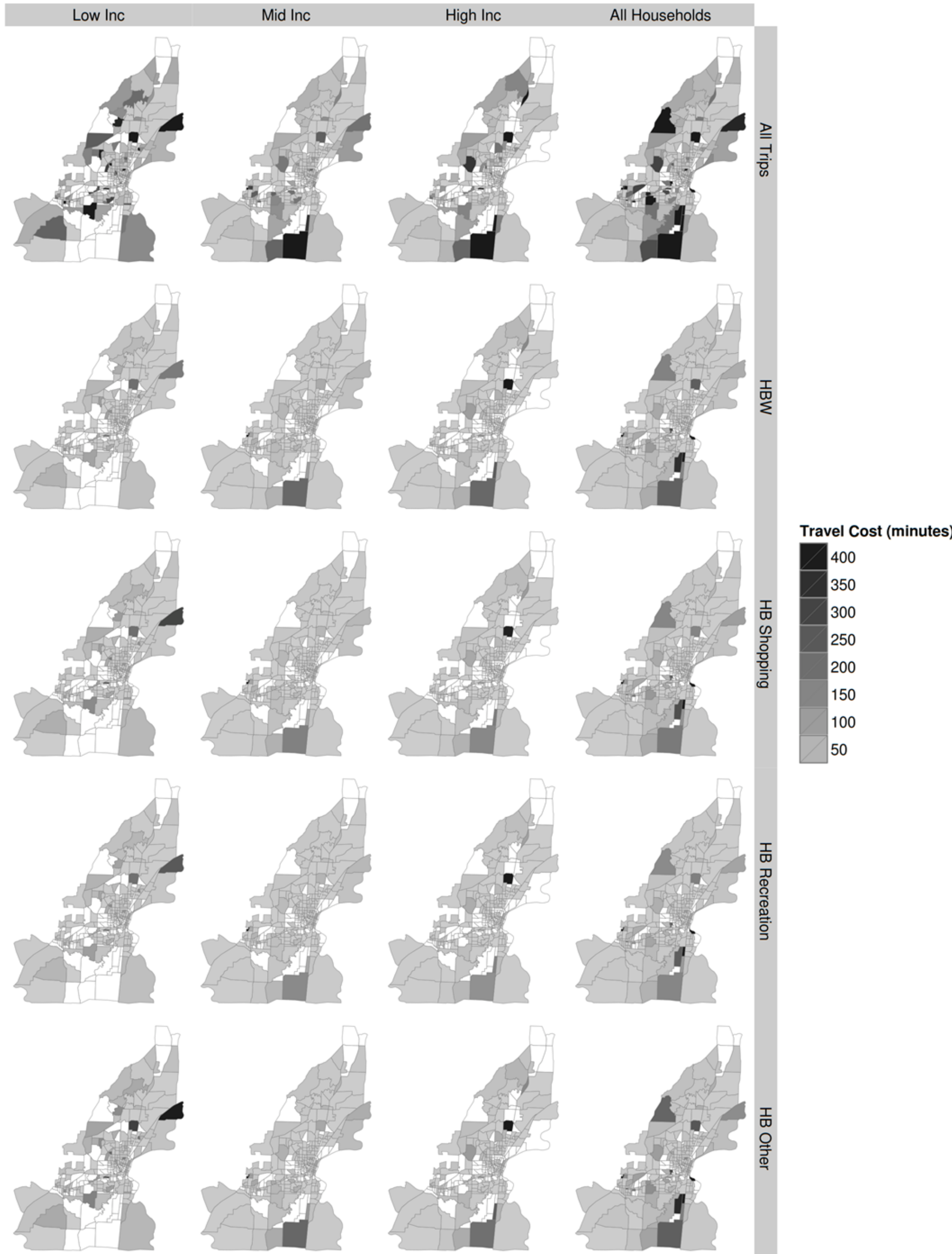

Figure 6.11: TAZ level travel costs by income level and trip purpose for Corvallis Scenario B (halving bus travel time; all other data from the 2010 CAMPO JEMnR model)

6.2.2 Comprehensive Analysis

In a comprehensive analysis application, users evaluate the effects of various scenarios on travel costs via working with simulation models. TCI reads in results from travel demand model (TDM) simulations and generates analysis for TDM outputs for each scenario. TDMs, usually integrated with land use models, enables evaluations of a large set of possible scenarios that may have impacts on travel costs.

As an example of such applications, we use TCI to evaluate the impacts of two future scenarios considered in Corvallis' last RTP process: 2030 Preferred scenario (2030Preferred) and an altered 2030 Preferred scenario (2030Preferred_Scen1). In these scenarios, both transportation system and land use system change from the base year (2010). The difference between the two scenarios is subtle, as 2030Preferred_Scen1 was derived from 2030Preferred. We assess their impacts following a similar procedure we use for rapid response applications.

In both scenarios, the travel costs for low-income households decrease, while those for high-income households increase somewhat (Figure 6.12 and 6.13, comparing with Figure 5.6), as density curve for low-income households moves closer to 0, while that for high-income households moves away from 0. If these effects can be verified, it is a laudable improvement in transportation equity, despite of a small one. The difference in effects between the two scenarios is small because of how the two scenarios are set up.

Looking into travel costs by trip purpose and income group (Figure 6.14 and 6.15), the two scenarios are effective at reducing travel costs of HB shopping, HB Recreation, and HB other trips for low-income households, while they experience a small increase in travel costs of HB Work trips. High-income households see a small increase in travel costs for all trip purposes, while mid-income households have largely stable travel costs. Again, the impacts are very similar between the two scenarios.

Geographically the impacts of the scenarios vary greatly due to change in both transportation and land use systems. Note that TAZs with fewer households (less than 3) and thus fewer home-based trips are excluded to avoid produce results with abnormal values. There are fewer low-income households in 2030, thus there are many more TAZs without travel costs values (drawn in blank) for low-income households (top left sub-figure in Figure 6.16). Some TAZs experience a reduction in travel costs while some others see an increase. The effects vary spatially, by income and trip purpose. The difference between the two scenarios is again subtle: for example, the 2030Preferred_Scen1 (Figure 6.17) produces some different impacts for TAZ 330-332.

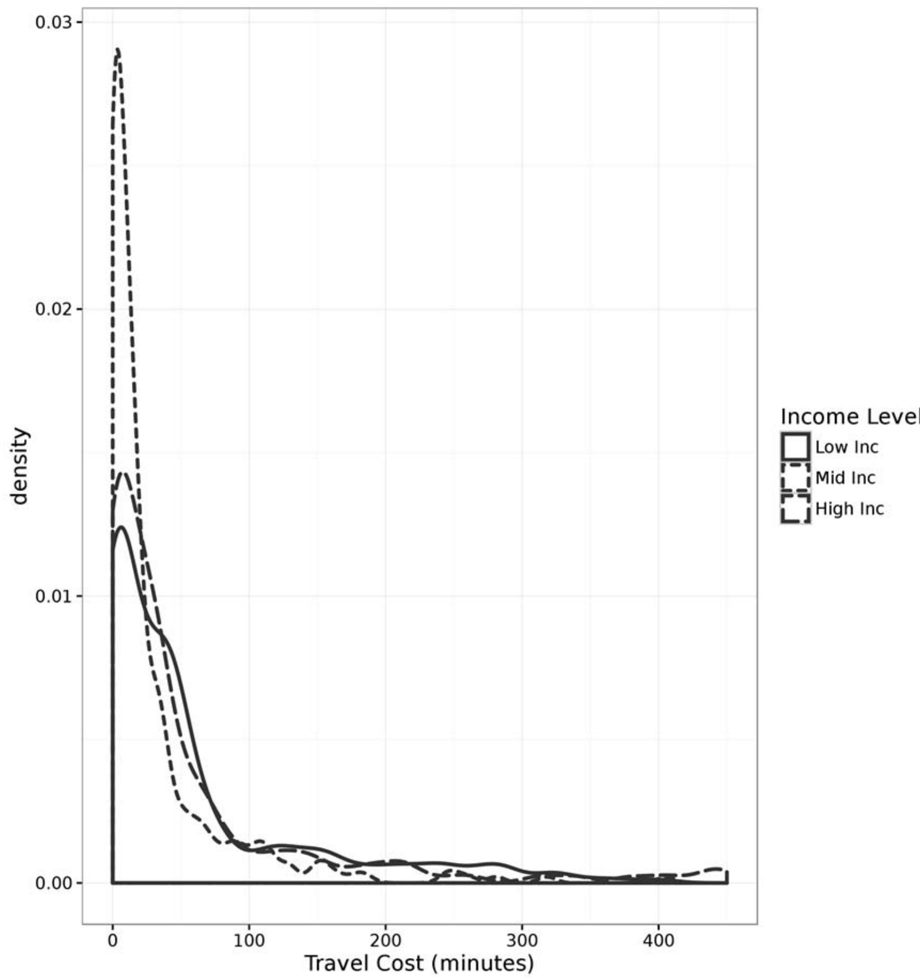

Figure 6.12: Density distributions of travel costs by income group for 2030Preferred Scenario

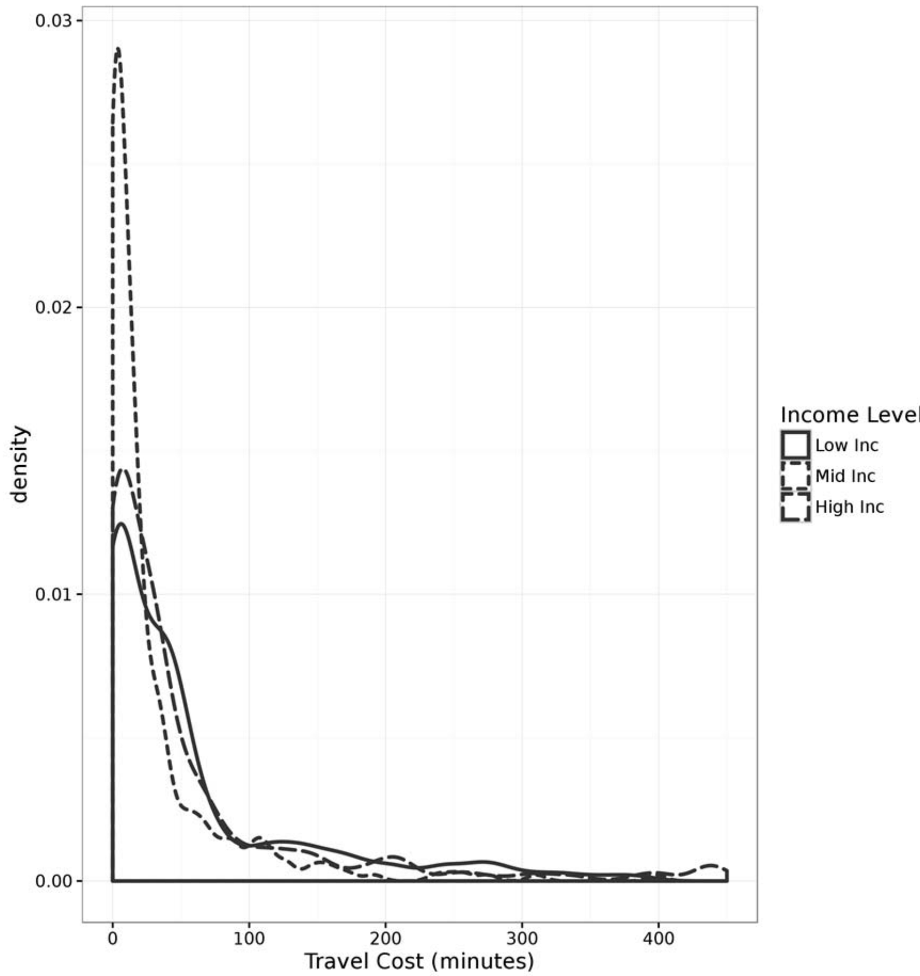

Figure 6.13: Density distributions of travel costs by income group for Corvallis 2030 Preferred Scenario 1 (2030Preferred_Scen1)

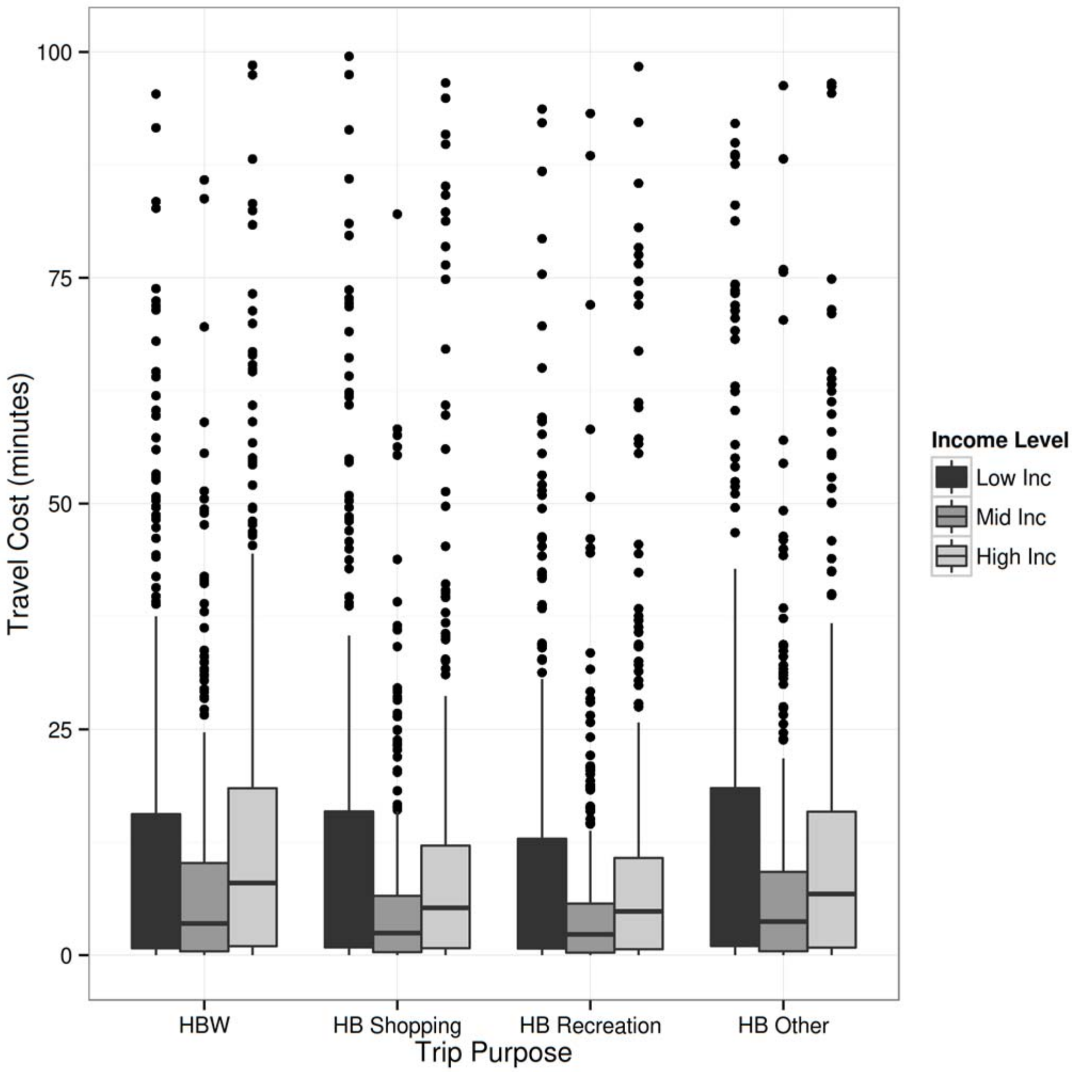

Figure 6.14: Box plot of travel costs by income level and trip purpose for Corvallis 2030Preferred Scenario

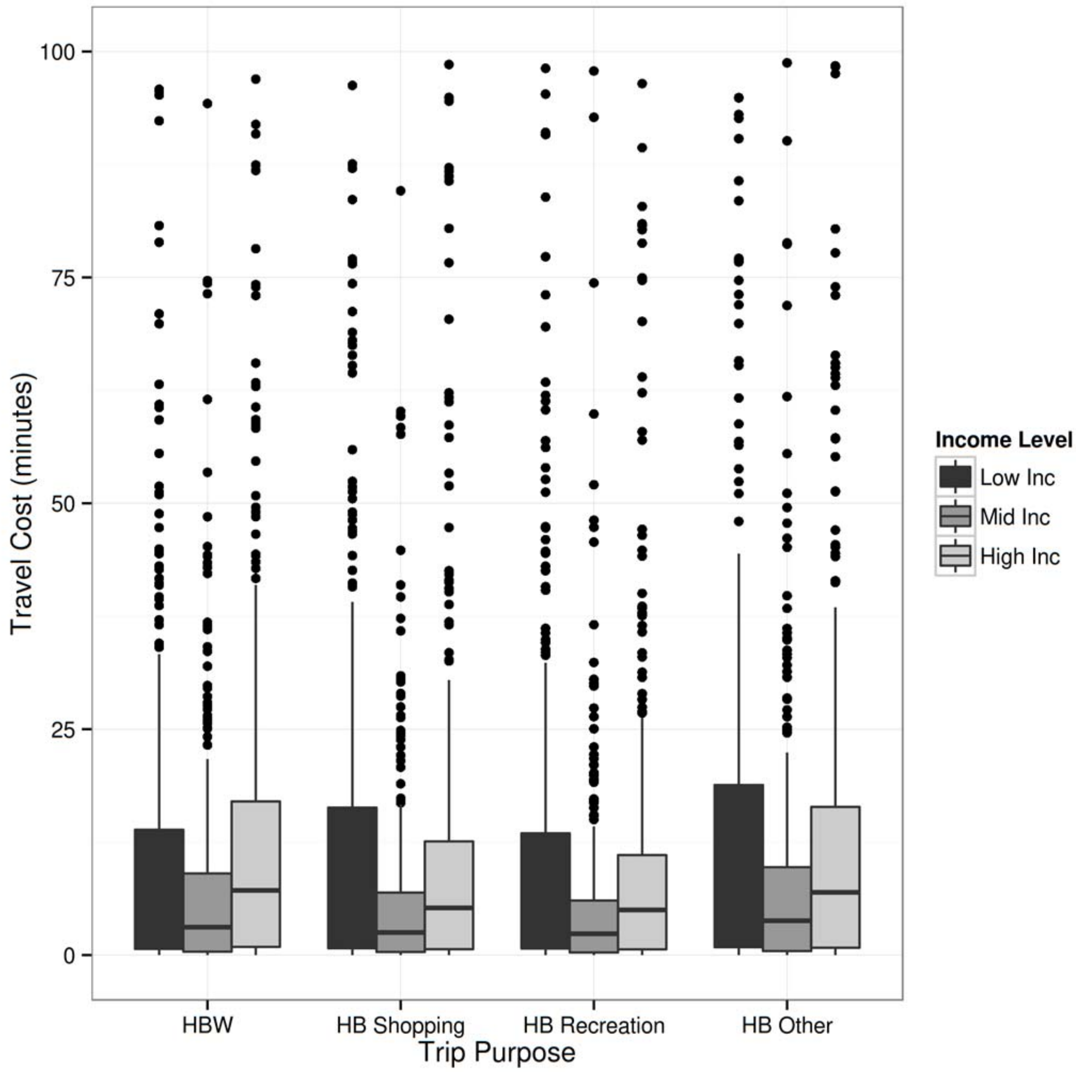

Figure 6.15: Box plot of travel costs by income level and trip purpose for Corvallis 2030 Preferred Scenario 1 (2030Preferred_Scen1)

Figure 6.16: TAZ level travel costs by income level and trip purpose for Corvallis 2030 Preferred Scenario

Figure 6.17: TAZ level travel costs by income level and trip purpose for Corvallis 2030 Preferred Scenario 1 (2030Preferred_Scen1)

7.0 CONCLUSION AND FUTURE RESEARCH

Transportation Cost Index is a performance measure for transportation and land use systems originally proposed and piloted by Reiff and Gregor *(Reiff and Gregor 2005)*. It fills important niches of existing similar measures in term of policy areas covered and type of applications. The goal of this research project is to move TCI from prototype towards implementation and application by establishing robust definitions of travel market baskets and robust methods for calculating transportation costs. After reviewing relevant literature, we propose two methods of defining travel market baskets, namely the cluster-based approach and the survey-based approach, and one method of calculating travel costs, all of which are based on theoretic and empirical research and recommended practice. We develop these methods and implement them in R as an open source project. Furthermore, we demonstrate the applications of TCI with various datasets, in particular with those from Portland and Corvallis in Oregon. With these applications, we show that both approaches work for regions of different size, that is, they have good scalability. We further test applying TCI to two types of applications: trend monitoring and scenario evaluation. The applicability testing demonstrates that the survey-based approach and the cluster-based approach can be used for trend monitoring and scenario evaluation applications, respectively. Overall the project shows that the methods are robust in that they are well justified by theory, scalable across communities large and small, and suitable for various applications.

There are a few limitations of the current TCI implementations. First, the data requirements for both approaches are rather intensive. The survey-based approach requires a travel survey dataset. To have confidence on the TCI results, especially when used to examine travel costs in details, the survey needs to have sufficient number of observations. And since travel surveys have not been done frequently for most regions in the US, relying on them as inputs limits the ability of using TCI to do continuous trend monitoring and to investigate very long term trend. While the cluster-based approach works well for areas with functioning travel demand models, it would be almost impossible to apply it to places without them. Second, the tests of TCI with the Portland and Corvallis applications may not be sufficient to demonstrate robustness, as they may not demonstrate how (or whether) TCI would work in extreme cases, for example, whether the cluster-based approach would still work when land use is more homogenous. Lastly, the results from the survey-based approach and the cluster-based approach are not directly comparable. As discussed earlier in this report, the two approaches measure different things and their inputs have different levels of aggregation. Ideally we would prefer comparable results as applications move between trend monitoring and scenario evaluation, but given the data available for different types of application, it is a trade-off we have to make. The aggregation issue may alleviate as regions move to activity-based travel models.

One issue that can be addressed in future research is to improve household income classification. The current classification scheme we use assigns households to income group regardless of the household size, but it is likely that household income is correlated with household size. As we show in this report, this could confound the analysis using TCI. A better practice would be to take household size into consideration when classifying households, especially for low-income households. For example, federal poverty guideline varies poverty line by number of persons in a household.

Some of these limitations may be addressed in another related ongoing research project led by the same PSU project team. The project is sponsored by National Institute for Transportation and Communities (NITC) and is aimed to make the TCI more generic and easily applicable to other regions of the US. That project will build on this SPR-760 project, put the current implementations through more testing in Utah and Florida, and further refine the algorithms and code. The NITC project will put some focus on handling cases where some of the required data are unavailable. It will likely benefit the TCI by further improving the code-base and documents and by doing more testing in other parts of the US.

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APPENDIX A

INPUT DATA FOR THE SURVEY-BASED APPROACH

APPENDIX A: INPUT DATA FOR THE SURVEY-BASED APPROACH

Travel Survey Data

- Household Characteristics:
  - Residence location (X, Y coordinate or TAZ)
  - Income level
  - Household size
  - Presence of children (optional)
  - Place type (optional)
- Trip Attributes:
  - Mode
  - Trip Duration
  - Trip Distance

GIS shape files

- Traffic Districts (optional)

APPENDIX B

INPUT DATA FOR THE CLUSTER-BASED APPROACH

APPENDIX B: INPUT DATA FOR THE CLUSTER-BASED APPROACH

Land Use Data

- Employment counts by TAZ by employment type:
- Household counts by TAZ by income level
- Park acres by TAZ
- Other variables that are used in size term

Trips and Skims from Travel Demand Model

- Trips by trip purpose, mode, time-of-day and income level
- Travel time skims by mode and time-of-day
- Travel distance by mode and time-of-day
- Mode utilities matrix by trip purpose, mode and income level (optional)

GIS shape files

- Traffic Analysis Zone
- Traffic Districts (optional)

APPENDIX C: SENSITIVITY ANALYSIS OF CUTOFFS FOR THE CLUSTER-BASED APPROACH FOR PORTLAND

APPENDIX C: SENSITIVITY ANALYSIS OF CUTOFFS FOR THE CLUSTER-BASED APPROACH FOR PORTLAND

50, 60, 70, 80, 90 and 95 percentiles for density cutoff are tested in the sensitivity analysis. For each density cutoff, 25, 50 and 75 percentiles for total cutoff are tested. Figure C.1 – C.4 show maps of the identified centers with different cutoffs. With density cutoffs ranging from 50 to 70 percentile, the spatial pattern of centers is persistent across all trip purposes. Only when the cutoffs are above 80 percentile, especially when it is as high as 90 or 95 percentile, the identified center is restricted to a few groups of TAZs. From this observation, it seems that cutoffs with 50-70 percentiles are appropriate.

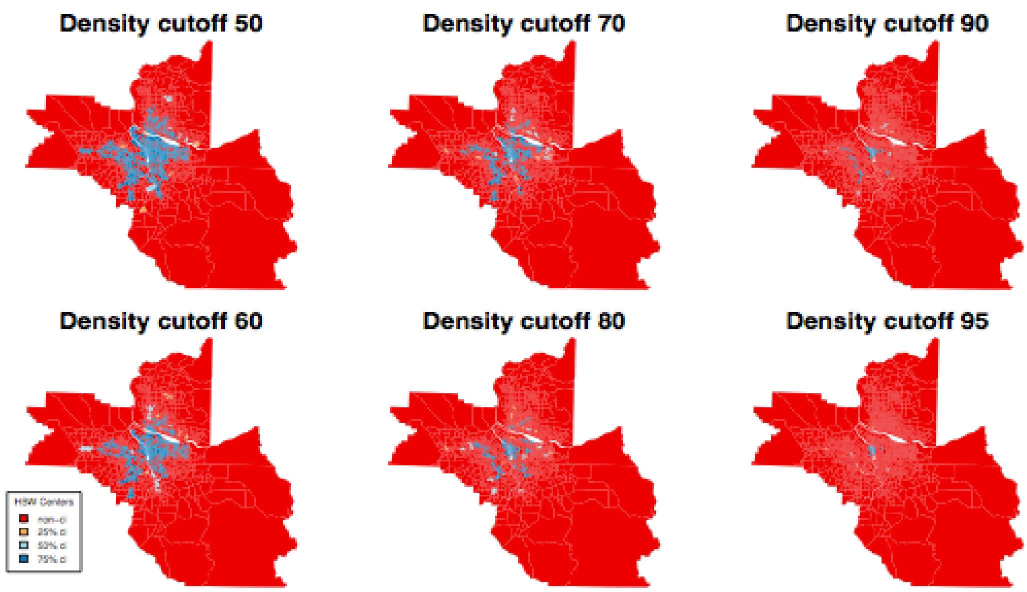

Figure C.1: Maps of identified centers for HB Work with different cutoffs

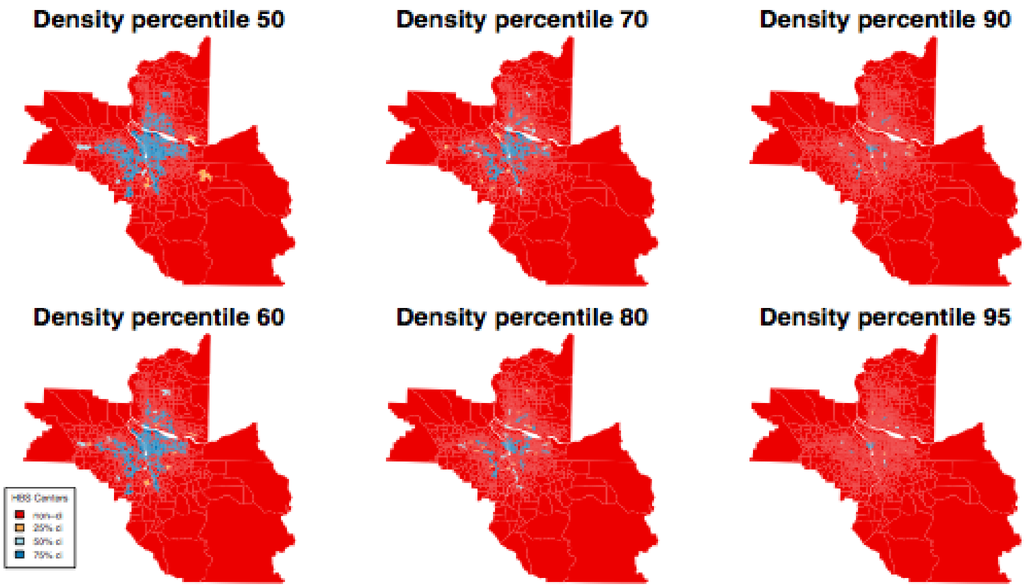

Figure C.2: Maps of identified centers for HB Shopping with different cutoffs

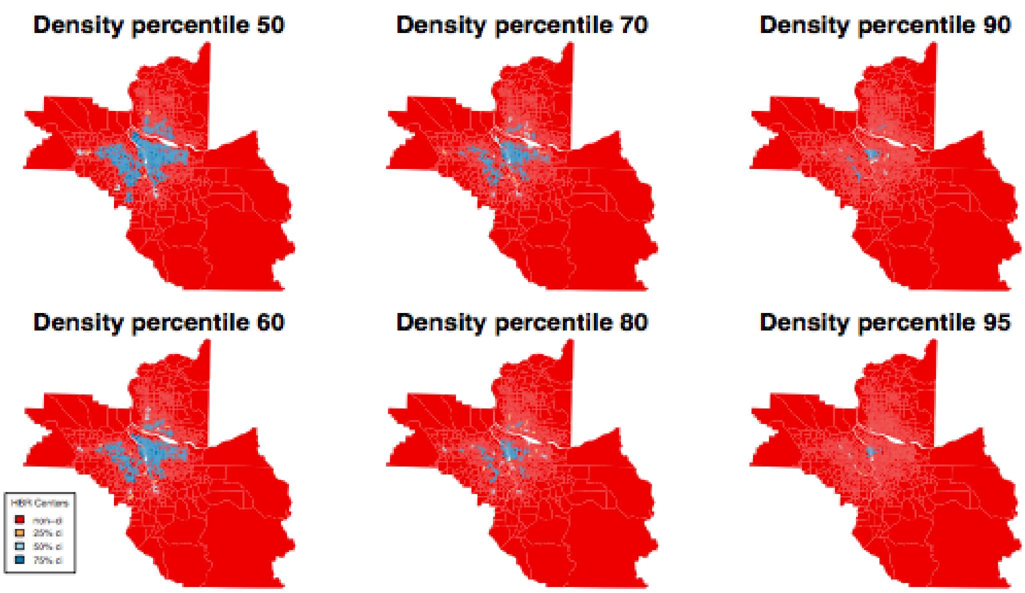

Figure C.3: Maps of identified centers for HB Recreation with different cutoffs

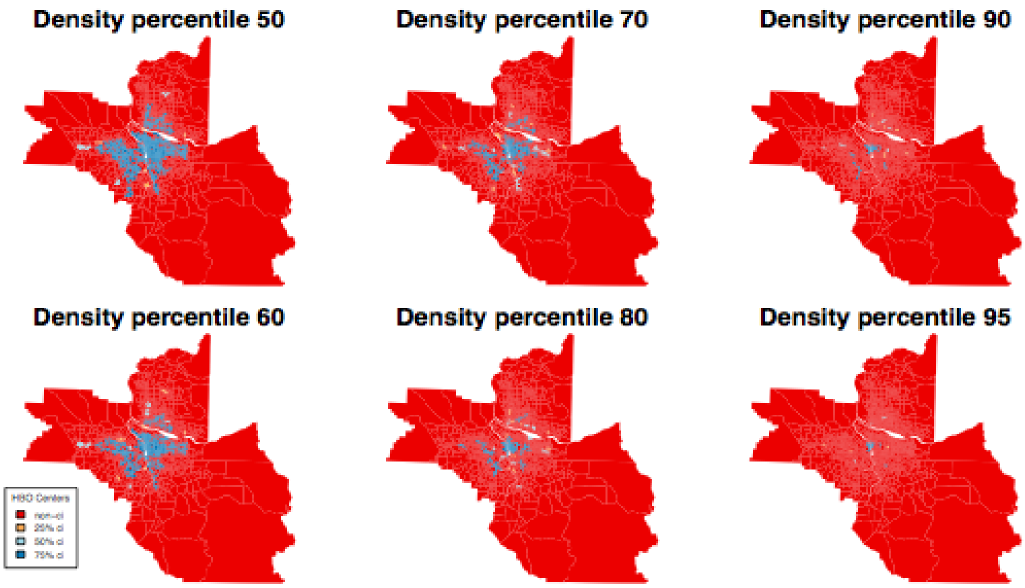

Figure C.4: Maps of identified centers for HB Other with different cutoffs

Next, we calculate the travel costs based on different cutoffs. Table C.1 – C.3 show the minimum, 1st quartile, median, mean, 3rd quartile, and maximum travel costs with different cutoffs. The aggregated travel costs are stable as the cutoffs range between 50-80 percentiles.

Table C.1: Weighted TAZ-level aggregated travel costs for peak period with different cutoffs

Cutoff		Descriptive statistics					
Density	Total	Min	1st Qu.	Median	Mean	3rd Qu.	Max
70%	1000[a]	2.113	3.332	3.910	4.163	4.815	10.820
50%	25%	2.217	3.194	3.580	3.903	4.434	10.400
50%	50%	2.214	3.190	3.582	3.921	4.463	10.440
50%	75%	2.211	3.185	3.592	3.972	4.597	10.570
60%	25%	2.195	3.204	3.640	3.955	4.509	10.620
60%	50%	2.191	3.199	3.637	3.992	4.593	10.620
60%	75%	2.182	3.211	3.699	4.098	4.779	10.980
70%	25%	2.160	3.238	3.752	4.064	4.706	10.600
70%	50%	2.153	3.237	3.810	4.126	4.817	10.650
70%	75%	2.140	3.371	4.076	4.340	5.082	11.570
80%	25%	2.108	3.318	4.015	4.105	4.871	10.690
80%	50%	2.101	3.424	4.140	4.333	5.059	10.720
80%	75%	2.077	3.604	4.453	4.602	5.453	11.850
90%	25%	2.026	3.585	4.430	4.532	5.286	11.800
90%	50%	2.020	3.702	4.554	4.697	5.582	11.880
90%	75%	2.003	4.440	5.450	5.529	6.566	12.200
95%	25%	1.975	4.110	4.990	5.109	6.032	12.380
95%	50%	1.967	4.402	5.433	5.492	6.516	12.440
95%	75%	1.956	4.982	6.060	6.056	7.100	12.920

[a] 1000 is the absolute amount of employment or sizeterms

Table C.2: Weighted TAZ-level aggregated travel costs for off-peak period with different cutoffs

Cutoff		Descriptive statistics					
Density	Total	Min	1st Qu.	Median	Mean	3rd Qu.	Max
70%	1000[a]	2.027	2.997	3.474	3.689	4.165	9.886
50%	25%	2.202	2.927	3.244	3.508	3.905	9.590
50%	50%	2.199	2.921	3.240	3.522	3.930	9.675
50%	75%	2.189	2.914	3.249	3.563	4.031	9.681
60%	25%	2.172	2.930	3.277	3.543	3.969	9.736
60%	50%	2.160	2.922	3.277	3.571	4.030	9.741
60%	75%	2.137	2.927	3.315	3.653	4.163	9.774
70%	25%	2.135	2.943	3.370	3.623	4.080	9.784
70%	50%	2.122	2.943	3.411	3.670	4.187	9.814
70%	75%	2.078	3.035	3.576	3.831	4.392	9.987
80%	25%	2.059	3.005	3.556	3.721	4.217	9.813
80%	50%	2.023	3.076	3.627	3.814	4.356	9.836
80%	75%	1.959	3.203	3.855	4.016	4.657	10.030
90%	25%	1.916	3.197	3.741	3.960	4.514	10.030
90%	50%	1.885	3.273	3.924	4.081	4.746	10.270
90%	75%	1.946	3.789	4.582	4.685	5.474	10.620
95%	25%	1.967	3.585	4.271	4.379	5.076	10.610
95%	50%	1.960	3.765	4.539	4.663	5.439	10.500
95%	75%	1.949	4.161	5.028	5.074	5.823	10.940

[a] 1000 is the absolute amount of employment or sizeterms

Table C.3: Weighted TAZ-level aggregated travel costs with different cutoffs

Cutoff		Descriptive statistics					
Density	Total	Min	1st Qu.	Median	Mean	3rd Qu.	Max
70%	1000[a]	2.055	3.052	3.542	3.759	4.259	10.010
50%	25%	2.204	2.967	3.295	3.564	3.977	9.686
50%	50%	2.201	2.961	3.293	3.578	4.007	9.774
50%	75%	2.198	2.956	3.298	3.621	4.106	9.780
60%	25%	2.183	2.972	3.331	3.691	4.046	9.838
60%	50%	2.178	2.966	3.328	3.630	4.112	9.843
60%	75%	2.169	2.971	3.367	3.715	4.252	9.882
70%	25%	2.148	2.985	3.420	3.684	4.160	9.889
70%	50%	2.141	2.988	3.464	3.734	4.265	9.922
70%	75%	2.112	3.085	3.649	3.901	4.477	10.110
80%	25%	2.089	3.052	3.616	3.788	4.304	9.926
80%	50%	2.056	3.129	3.696	3.886	4.456	9.951
80%	75%	1.990	3.264	3.936	4.095	4.757	10.250
90%	25%	1.943	3.254	3.924	4.038	4.626	10.230
90%	50%	1.914	3.334	4.005	4.165	4.859	10.420
90%	75%	1.968	3.870	4.705	4.795	5.641	10.780
95%	25%	1.968	3.657	4.366	4.478	5.195	10.780
95%	50%	1.961	3.855	4.668	4.774	5.576	10.740
95%	75%	1.950	4.270	5.153	5.200	5.988	11.140

[a] 1000 is the absolute amount of employment or sizeterms

APPENDIX D

SOURCE CODE AND INSTRUCTIONS

APPENDIX D: SOURCE CODE AND INSTRUCTIONS

Source Code

The source code that implements the survey-based approach and the cluster-based approach in R is available as an open source project under GPL License at https://github.com/cities-lab/tci. Since it has more than 10,000 lines of code and will keep evolving as the NITC project progresses, it has not been included in this report but we refer anyone who wants to access a copy of the code to download it from https://github.com/cities-lab/tci/releases. As of the writing of this report, the current version is 0.4.

Instructions

Prerequisites

Before running the TCI R scripts, R and the prerequisite R packages have to be installed. R can be downloaded and installed for most operating systems from http://cran.us.r-project.org/. The prerequisite R packages are specified in `code/installation.R`, which can be installed by sourcing `code/ installation.R` in R command line terminal or by running `Rscript code/installation.R` in a terminal of the operating system.

Code Organization

The `code` subdirectory contains R code organized by different approaches of computing TCI, including `survey` (for the survey-based approach), `cluster` (for the cluster-based approach) and individual (for individual-based approach, unfinished due to extensive data requirements and poor computation performance). The scripts shared across different approaches are directly inside the `code` subdirectory, including:

- `settings.R` – defines common settings for all projects and approaches; some of the settings may be overridden for a specific approach or project;
- `functions.R` – defines common functions that are used throughout the TCI project;
- `installation.R` – Specifies and installs prerequisite R packages.

Other subdirectories inside the `code` directory contain scripts that are auxiliary to TCI computation:

- `code/tests` subdirectory – includes unittest scripts;
- `code/misc` subdirectory – miscellaneous scripts;
- `code/thirdparty` subdirectory – open source scripts that come from a third party.

The `data` subdirectory is where the input data will be read into R by default. It is assumed that the input data is organized inside the `data` subdirectory following [project.name]/[year] structure. These default settings can be overridden by changing in the INPUT_DIR variable.

The `output` subdirectory is where the outputs will be saved by default. The outputs will be organized inside the `output` subdirectory following [project.name]/[year]/[method.name]/[unit.name] structure. Again these default settings can be overridden by changing the OUTPUT_DIR variable.

Survey-based Approach

For each approach, the process of computing TCI can be started by sourcing a `start_[project][year].R` script in `code/cluster` or `code/survey` subdirectory. Below is a description of what each of the scripts does in the process of computing TCI:

- `start_[project][year].R` – invokes the TCI computation for a specific project and year;
- `code/settings.R` – default common settings for all projects and approaches;
- `settings_[project.name].R` (optional) – approach or project specific settings that override those defined in code/settings.R
- `prepare_[project.name][year].R` (optional) – prepares inputs for TCI computation;
- `compute.R` – computes TCI and saves outputs
- `plot.R` – plots and saves graphs and maps for computed TCI

Take the Portland 2011 project as an example. `code/survey/start_Portland2011.R` calculates TCI for Portland with the survey-based approach using the 2011 Oregon Travel Activity Survey (OTAS) data. Sourcing this R script file in R will automatically read required inputs from data/Portland/2011 directory, compute and plot travel costs, and save results and plots in output/survey/Portland/2011 directory (default input and output directory location can be changed by users).

`start_Portland2011.R` first defines project.name, method.name, year, unit.name and abbreviation, before it sources relevant R script files in sequence to compute and plot travel costs:

- project.name – name of the project;
- method.name – name of the approach used to calculate TCI;

- year– year for the input data; used for specifying the default input and output directory with scenario.name;

- unit.name – determines the unit (“minutes” or “dollars”) for transportation cost results;

- abbreviations – defines abbreviations for income groups, trip purposes, travel modes, time periods;

- Directories (optional) – Customize input directory, output directory and directory for intermediate outputs. By default, the input directory (INPUT_DIR) would be in data/[project.name]/[year], while the output directory in output/[project.name]/[year]/[method.name]/[unit.name]. These default setting can be overridden by users in the start_[project.name][year].R script.

`settings_OHAS.R` stores settings shared among projects using the OTAS dataset (note that OHAS, an alternative name for OTAS, is used). Since both Portland and Corvallis projects using the same dataset, the settings common to the OTAS dataset are kept in `settings_OHAS.R`, such as the value of time parameters by mode, so that they don’t have to be specified in two separate files.

`prepare_Portland2011.R` transforms the OTAS data set from the original format to the format required by `compute.R`, including:

- converts trip duration to hours and trip distance to miles;

- reclassifies income into low, middle and high categories (low income: $0- $24,999; mid income: $25,000 - $49,999; high income: $50,000 or more, all in 1994 dollars);

- identifies Transportation Analysis Zone (TAZ) and geographical districts of residence location of households.

`compute.R` then computes trip-level transportation costs and then aggregate them by household, trip purposes, income groups, TAZs and/or districts. It also saves the numeric results into a R image file `tcost.RData` in the output directory.

Finally `plot.R` plots transportation cost results in plots of various form, including density line plots, boxplots, line chart plots and maps for appropriate outputs.

Other projects in the survey subdirectory, such as Corvallis, NHTS, and WFRC, provide more examples of how the survey-based approach is applied to these projects. Users can create their own `start_[project][year].R` script by modeling these examples, customizing settings, and preparing inputs for their project.

Cluster-based Approach

Similarly, `code/cluster/start_Portland2010.R` calculates TCI for Portland with the cluster-based approach using data from Metro's 2010 travel demand model. Although the approach and corresponding inputs are different, the code is organized in the same way as the survey-based approach. A user should be able to understand and customize the scripts following the process described above for the survey-based approach.

One feature specific to the cluster-based approach is the capability to compute TCI for different scenarios. In a start script for the cluster-based approach, a vector of scenario.names will be iterated to calculate transportation costs for each scenario specified. Scenarios are handled in a way similar to how year is handled in the survey-based approach, in term of default input and output directory location.