Temporal Transferability Assessments of Vehicle Ownership Models and Trip Generation Models for Boston Metropolitan Area

by

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Submitted to the Department of Civil and Environmental Engineering and the Department of Urban Studies and Planning in partial fulfillment of the requirements for the degrees of

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Abstract

In the last few decades, travel demand models have undergone tremendous development and, today, are routinely used to support planning and policy decisions. But uncertainty in forecasting with such models is often overlooked, and its impact on forecast accuracy is rarely evaluated. My thesis attempts to understand behavior uncertainty and model uncertainty in travel demand modeling. In particular, I assess the temporal transferability of vehicle ownership models and trip generation models for the Boston metropolitan area from 1990 to 2010.

Through statistical tests, I find significantly changed preferences in household vehicle ownership choice and trip production. For vehicle ownership choice, the effects of most socio-economic and demographic factors, and regional location factor have evolved; while the effects of local built environment factors and transit access are stable. Trip rates have changed over time, with decreased home-based work, home-based shopping, home-based bank and personal business, home-based social, home-based eating and non-home-based work trips; and increased home-based recreational and home-based work-related trips.

The prediction tests suggest that failing to consider preference changes causes significant bias in forecasts. The transferred vehicle ownership model of 1991 under-predicts 0-vehicle households by 42.5%, and over-predicts 2-vehicle households by 14.8% in 2010. The transferred trip rates from 1991 overestimate total trips in 2010 by 7% to 9%. Home-based work-related, home-based pick-up and drop-off, and home-based recreational trips are significantly under-predicted by 34%, 12% and 27%, respectively; while home-based work, home-based shopping, home-based social, and non-home-based work trips are significantly over-predicted by 9%, 20%, 31%, and 69%, respectively.

Different model specifications have shown a modest range of variability in prediction outcomes, suggesting model specification uncertainty has less influence than behavior uncertainty on forecasts. In vehicle ownership modeling, children, seniors, and local built environment variables improve the prediction accuracy for 0-vehicle group. But all model specifications cannot distinguish well between 0- and 1-vehicle households, and between 2- and 3-vehicle households. Household characterization affects the prediction accuracy for certain trip purposes. Including more detailed household information may lead to worse forecasts because of large sampling variance.

Future work is suggested to incorporate behavior uncertainty in forecasts, explore uncertainty in model structure, and evaluate the practical implications of the lack of model transferability.

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Contents

List of Figures

Chapter 1

Introduction

In the last few decades, travel demand models have undergone tremendous improvements, with routine use to support planning and policy decisions. In this general activity, compared to the vast amount of research on demand forecasting, two types of researches are being overlooked. First, evaluations of model forecast accuracy are lacking. Existing studies have consistently shown large discrepancies between forecast and the actual demand. Second, the concept of uncertainty has only received sporadic attention. In typical practices, models generate point estimates according to a single specification and expected values of the parameters, with the assumption that behaviors remain stable over time. However, uncertainty is inherently in model structure, specification and estimation, which translate implicitly to predicted outcomes. Behavior change over time can undermine the transferability of model parameters, and even challenge the assumptions about model structure and specifications. Without understanding the sources of uncertainty, and appropriately characterizing them in modeling, the forecast results would very likely miss the future, and probably misguide the decisions to prepare for such future scenarios.

My thesis aims to understand both the behavior uncertainty and model uncertainty in vehicle ownership modeling and trip generation modeling. I use the Boston metropolitan area from 1990 to 2010 as the empirical setting, in order to answer the following questions:

1) Do preferences change over time? If so, how and what are the underlying reasons?
2) If we assume preferences are stable, yet they do change, what would be the forecasting errors we could make? This is the situation when we stand in the past with no idea of the future behaviors, and make forecasts for the future. How would that forecast compare to the realized outcome?
3) Would different model specifications lead to substantively different prediction outcomes? What would be the range of outcomes due to model uncertainty?

To understand these aspects, I adopt the temporal transferability assessment framework. Through statistical tests and prediction tests, I identify the major preference changes, and assess the influence of model specifications. I also evaluate the magnitude of the population forecast inaccuracy due to behavior and model uncertainty[1].

This thesis is organized as follows.

Chapter 2 reviews the sources of uncertainty in travel demand modeling, temporal transferability assessment methods, and prior findings for the temporal transferability of vehicle ownership models and trip generation models.

Chapter 3 introduces the methods – including details about the model structure and the transferability assessment methods applied in this thesis.

Chapter 4 depicts the major demographic trends and travel behavior changes from 1990 to 2010 in the study area, serving as the background to help understand input and behavior uncertainty.

Chapter 5 evaluates behavior uncertainty and model uncertainty in vehicle ownership models using temporal transferability tests.

Chapter 6 assesses behavior uncertainty and model uncertainty in trip generation models.

Chapter 7 discusses the main findings and proposes directions for future studies.

[1] Please note that input uncertainty (e.g. demographics, economic conditions etc.), though critical, is not the focus of this thesis. But Chapter 4 touches on some aspects of the input uncertainty in the Boston metropolitan area.

Chapter 2

Literature review

Various sources of uncertainty in travel demand modeling can lead to inaccurate forecasts of travel demand. This chapter begins with an overview of travel demand forecast inaccuracies, sources of uncertainty, and general approaches to modeling uncertainty. Then I focus on model transferability—the method applied in this thesis – with an overview of the concepts, methods, and empirical findings from prior studies, in particular, studies of vehicle ownership models and trip generation models.

The topic of uncertainty covers a broad scope of perspectives, concepts and methods, leading to different avenues of researches and applications. This review paints a broader picture of the uncertainty literature than those elements of uncertainty I cover in the scope of my thesis. I do so to clarify terminology and methods, understand the current status of uncertainty research, and identify needs and directions for future studies in this thriving field.

2.1 Travel demand forecast inaccuracy

Transport planning relies heavily on travel demand modeling and forecasting. Inaccurate forecasts can mislead transportation planning, policy-making, and infrastructure investment decisions. Despite the importance of forecast accuracy, the topic has been relatively understudied.

At a project level, a handful of studies have revealed the large discrepancy between actual and forecast demand (Table 2–1). For rail projects, different studies have consistently revealed a tendency to substantially overestimate rail ridership and underestimate costs. Pickrell (1990, 1992) found that, among the 9 fixed guide-way transit projects built between 1971 and 1987, 8 projects' actual ridership was 54% to 85% below the forecast, with only one project's actual demand 28% below forecast. The U.S. Federal Transit Administration (FTA)'s evaluation of 18 transit projects between 2003 and 2007 revealed that actual ridership averaged only 75 % of the predicted ridership (Lewis-Workman et al., 2007). In a broader survey of 27 rail projects in 14 nations, Flyvbjerg et al. (2005) found that for more than 90% of the rail projects, ridership forecasts were overestimated. The actual ridership was, on average 51.4%, lower than forecast, with a 95% confidence interval between −62.9% and −39.8%.

The accuracy of road traffic forecasts is more varied. A multinational study by Flyvbjerg et al. (2005) suggested that road traffic forecasts were not generally overestimated, but were often inaccurate. According to their study, the discrepancy between actual and forecasted traffic was more than ±20% for half of the projects (Flyvbjerg et al., 2005). Muller and Buono (2002)'s study of 23 toll roads in the U.S. showed that only three projects reached or exceeded the forecast demand. The rest had actual traffic ranging from 29% to 67% of the forecast. Naess et al. (2006) found that 13 of 14 U.S. toll roads over-predicted traffic by an average of 42%. Studies of toll routes in Australia (Li and Hensher, 2010; Bain, 2013) yielded similar results; while traffic forecasts for toll roads in Norway were fairly accurate (Welde and Odeck, 2011).

Table 2–1 Prior studies of road and rail forecast accuracy in the U.S. and other countries

Authors	**Year**	**Country**	**Sample**	**Forecasted demand**	**Forecast accuracy (Actual-Forecast)/Forecast**
Pickrell	1990, 1992	U.S.	10 major transit projects	Rail ridership	1 project: 28% below forecast 8 projects: 54% to 85% below forecast.
Muller, and Buono	2002	U.S.	23 toll road projects	Road traffic	7 projects: 61%–67% of forecast; 8 projects: 51%–60% of forecast; 5 projects: 29%–51% of forecast.
Naess et al.	2006	U.S.	14 toll roads	Road traffic	13 out of 14 over-predict demand.
Lewis-Workman et al.	2007	U.S.	18 transit projects	Rail ridership	On average 25% below forecast.
Skamris and Flyvbjerg	1997	Denmark	7 large bridge and tunnel projects	Road traffic	On average 9% below forecast (+27% to -32%)

Flyvbjerg et al.	2005	14 nations	27 rail and 183 road projects	Rail ridership; Road traffic	Rail: 51.4% lower than forecast on average (95%CI: −62.9% to −39.8%) Road: half projects have more ±20% forecast error.
Li and Hensher	2010	Australia	14 major toll road projects	Road traffic	Overestimated by 40 % on average.
Welde and Odeck	2011	Norway	25 toll roads and 25 toll-free road projects	Road traffic	Toll roads: accurate Toll-free roads: under-estimated
Bain	2013	Australia	7 toll road projects	Road traffic	All 7 projects have actual traffic lower than predicted by 40–60 %.

At the regional level in the USA, Long-Range Transportation Plan (LRTP) is required for metropolitan areas of more than 50,000 people by federal law (Chapter 53 of title 49, United States Code). Travel demand forecasts over 20 to 30 years serve as a basis for identifying critical trends and needs for transportation system improvements and land use development. Relative to forecasting for specific projects, forecasting for such a complex system, using tools such as a four-step travel demand model, is exposed to even more varieties of uncertainty, with error propagation across model stages making the final outputs even more uncertain. However, the long-range forecasting accuracies of regional transport models have rarely been evaluated. Table 2–2 provides a list of these studies.

Horowitz and Emsile (1978) compared the forecasts of average daily traffic (ADT) on 78 inter-state highway segments in 55 U.S. cities and towns with the actual traffic volumes in 1975. They found that the 1968 and 1972 forecasts tended to overestimated 1975 ADT by 24% and 21% respectively. They attributed the over-predictions to the 1973-74 gasoline shortage and errors in traffic assignment techniques.

The Institute of Transportation Engineers (ITE, 1980) evaluated the forecast accuracies of population, employment, vehicle ownership, and trips for five metropolitan areas in the U.S. The model inputs data corresponded to the period between 1956 and 1961, and the forecast year was 1975. The discrepancies varied across regions, and were attributed to unanticipated social and economic changes, such as reversed migration patterns, birth rate decline, decentralization of population and employment, higher labor participation rates, higher trip rates, and the downturns of manufacturing industry, among others.

MacKinder and Evans (1981) found the overestimations of population, vehicle ownership, income, trips and traffic flows based on a survey of 44 transport studies undertaken between 1962 and 1971 in the UK.

Niles and Nelson (2001) examined the Puget Sound region (Seattle-Tacoma-Everett area, USA). They found the 1969 forecasts overestimated population and employment for 1975, and the 1967 forecasts underestimated households, employment, vehicles and vehicle miles travelled (VMT) for 1990.

Parthasarathi and Levinson (2010) compared the traffic forecasts produced by the computer-based models in the 1960s in Minnesota with the actual traffic counts around 1980. They found a general trend of underestimating road traffic, with 65% of the critical links showing underestimated values; and that under-prediction was worse for links with higher volumes. They found population was over-predicted by 10% to 12% over a 5- to 25-year span.

Forecasts for the same period of time (about 1970-1980) in the USA seem to share some commonality in the pattern of inaccuracies, implying similar socio-demographic trends and behavioral changes (see Table 2–2). Still, evaluations of long-range regional transport models' forecast accuracy are rare, and mostly done for models from the 1960s. As modeling techniques have been tremendously improved over the last few decades, it is most appropriate to evaluate performance of recent modeling.

Table 2–2 Prior evaluations of forecast accuracies in regional transport models

Author	Area	Base year	Forecast year	Over-estimated	Under-estimated	Sources of inaccuracies
Horowitz and Emsile (1978)	78 interstate highway segments	1968; 1972	1975	Average daily traffic: 21%-24%[a]		Gasoline shortage; Errors in traffic assignment modeling
ITE (1980)	5 metropolitan areas in U.S.	1956-1961	1975	Results varied for different regions	Results varied for different regions	Reversed migration patterns, birth rate decline, suburban growth relative to central cities, decentralization of population and employment, higher labor participation rates, higher trip rates, the downturns of manufacturing industry.
MacKinder and Evans (1981)	44 transport studies in UK	1962-1971		Population: 10% Car ownership and household income: 20% Trips: 30%-35% Traffic flow: 13%		Socioeconomic variables
Niles and Nelson (2001)	Puget Sound Region	1964; 1969; 1967	1975; 1990	(For 1975) Population Employment Speeds	(For 1990) Households: 23% Employment: 31% Vehicles: 32%	Sudden downturn in aircraft industry in the early 1970s; women participation labor force; decreasing household size; and shift of population to suburbs
Parthasarathi and Levinson (2010)	Minnesota	1961, 1964	1980	Population: 10%-20%	Roadway traffic	

a. Percentage error= (Forecasted-Actual)/Actual

2.2 Sources of uncertainty

Sources of forecasting inaccuracies have been discussed both in general and for particular types of projects (Mackie and Preston, 1998; Flyvbjerg et al., 2005; Naess et al., 2006; Lemp and Kockelman, 2009; Hartgen, 2013). Hartgen (2013) summarizes them into technical sources and institutional sources. Technical sources consist of the uncertainty in transport modeling, such as data errors and model errors. Institutional sources refer to the bias induced by institutional or political factors. A classic example is optimism bias—overestimation of ridership and underestimation of costs in rail projects, motivated by getting non-local funds (Flyvbjerg et al., 2005). My thesis focuses on technical sources – uncertainty, which can be quantified and incorporated into transport modeling.

Sources of uncertainty are classified in ways that incorporate various angles, scopes and application purposes (e.g. Mahmassani, 1984; Pradhan and Kockelman, 2002; Bain and Wilkins, 2002; Lemp and Kockelman, 2009; Rasouli and Timmermans, 2012).

Mahmassani (1984) frames the sources of uncertainty with emphasis on its connection to the evaluation of transport alternatives. The sources of uncertainty that he identified include: 1) the unknown or unexpected situations, such as political changes and technological breakthroughs; 2) exogenous events or states, such as economic conditions, and new land development; 3) randomness in the measurement or predicted outcome; 4) imprecise evaluation criteria; and 5) preferential or normative basis of the evaluation. Zhao and Kockelman (2002) focus on the stochastic errors that can be described statistically. Their summary of uncertainty—inherent uncertainty, input uncertainty, and propagated uncertainty, corresponds to type 2) and 3) in Mahmassani (1984)'s definition. Rasouli and Timmermans (2012) summarized uncertainty as input uncertainty and model uncertainty. Based on a synthesis of previous literature, I find it most helpful to categorize sources of uncertainty into three types: exogenous input uncertainty, behavioral uncertainty, and model uncertainty.

2.2.1 Exogenous input uncertainty

Exogenous inputs to transport models include demographic and economic inputs, land use and transport network attributes, and policies. These inputs can be treated as endogenous, if say, a socio-economic model or a land use model is linked to the transport model. But they are typically treated exogenously, as outputs from other forecast models or assumed scenarios, having no interaction with the transport model.

Socio-demographic and economic projections

Socio-demographic inputs, such as population growth rate, household size, family structure, age composition, and income distribution, have a substantial amount of impact on travel demand forecasts. Economic conditions, such as employment rates, gasoline prices, construction costs etc., can also have a large impact on travel forecasts.

Most demographic inputs are more predictable, such as birth rate, and age composition; while others can be more difficult to anticipate, such as migration rate, household size, and family structure. For example in California, population projections from different sources can vary by up to 8.6 million statewide, with the annual growth rate ranging from 0.8% to 4.0%. This variability is mainly due to the different assumptions about migration patterns (Rodier and Johnson, 2002).

Economic conditions in general are more volatile, subject to influences from the regional and global economy. Unanticipated economic downturns can lead to substantial over-estimation of employment and trips. Take the Puget Sound Region for example, where the tremendous growth in the aircraft industry in the late 1960s made the population and employment forecasts for the 1970s high by extrapolation. The sudden downturn in the aircraft manufacturing in the 1970s devastated such forecasts, with the actual regional population being 20% lower than the forecast (ITE, 1980).

What would be the impact of input uncertainty on forecast outcomes? Prior studies answered this question either through historical evidence or Monte-Carlo simulation. Rodier and Johnson (2002) examined the travel demand and emissions models of the Sacramento, CA, USA. They found that within a ±2.0% plausible error range for population and employment, forecasted VMT and trips vary by -12.0% to 13.6% and -16.7 to 19.7% respectively over 10 years; and by -21.8% to 28.5% and -30.2% to 42.5% respectively over 20 years. Harvey and Deakin (1995) showed that plausible ranges of inputs—population growth, fuel price and household income levels in their Short-Range Transportation Evaluation Program (STEP) model—cause VMT to vary from 25% below to 15% above the original prediction. Zhao and Kockelman (2002) explored input (household and employment) uncertainty propagation in a four-step model for Dallas-Fort Worth sub-region in the USA. They found demographic inputs as primary contributors to the uncertainty in predicted VMT and link flows.

Transport networks and services

Future transport network changes are sometimes unknown. For example, traffic forecasts for toll road projects are subject to nearby highway extensions. Future transport service quality, such as frequency, reliability, and fares for rail and bus (Mackie and Preston, 1998), are subject to the resources available for system maintenance and improvements.

Future technological innovations can also bring new types of vehicles and services, such as autonomous cars, car-sharing programs etc. The development of intelligent transportation system can improve roadway capacity and speeds (Niles and Nelson, 2001). All of these can drastically change transportation system. Also, supply-side change can trigger a series of behavioral changes, which are also hard to predict, leading to more complicated dynamics and a new equilibrium. Relevant technological change can also come from outside the transportation sector, specifically, such as the rise of the Internet.

Land use

Land use describes the spatial distribution of activities and urban forms. Actual land use outcomes are a combined result of market forces and public interventions. Land use inputs for transport models come from planning scenarios or land use models. Land use scenarios often include projections for the location, density and diversity of growth (Bartholomew, 2007). Bartholomew (2007)'s review of 80 scenario planning projects in the U.S. showed that the range of density covered by different scenarios was narrow, and biased towards higher densities; and the aspects of land use mix (diversity) and design were not included in many scenario formulations. Land use modeling is an alternative to scenario planning, but it also has a variety of uncertainty (Lemp and Kockelman, 2009; also see e.g. Pradhan and Kockelman, 2002; Krishnamurthy and Kockelman 2003, Clay and Johnston 2006).

Uncertainty in land use inputs has significantly influenced travel forecast. Flyvbjerg et al., 2005) did a survey among project managers and researchers from 26 rail projects and 208 road projects, asking them the causes of inaccuracies in traffic forecasts. The fact that land use implemented often differs from the projected is voted as the 2nd most popular cause for inaccurate road traffic forecasts (with trip generation at the top). For regional planning, unexpected population decentralization in the 1970s resulted in under-prediction of population and vehicles in the suburban Washington D.C. and over-prediction in the District of Columbia (ITE, 1980).

Policy interventions[2]

[2] Transport network and land use changes can be part of the policy. I separate them because transport and land use is also driven by market, thus the uncertainty is not only subject to planning.

Future policies, such as gasoline taxes, congestion fees, subsidies for non-motorized transport, and parking costs, are also inputs that can be uncertain.

2.2.2 Behavior uncertainty

Travel-related behaviors are often represented as model parameters. Behavior uncertainty is sometimes treated as a type of model uncertainty—parameter uncertainty. I distinguish behavior uncertainty from model uncertainty, because behavior changes are real in life, independent from how a model represents them.

The use of models for predicting the future often rests upon the assumption that preferences remain stable over time, so that the parameterized relationships can be transferred from one period to another. But preferences do change over time, as a result of social and environment changes, adoption of new technologies, etc. For example, women participation in labor force grew tremendously over the last 50 years, and as a result, overall work trip rates increased. More recently, working at home has been steadily growing. With the increasing flexibility in work locations and work time (Niles and Nelson, 2001), work trip rates and departure time distribution would change. Other preferences like individuals' values of time, allocation of time, resistance to travel, represented as the friction factors in the trip distribution stage of the four-step model, can also change. Households' preferences for residential and employment space also evolve and can affect land use outcomes (Niles and Nelson, 2001). By comparing travel behavior data from multiple years, Parthasarathi and Levinson (2010) found increases in HBW trip length and trip time by 74% and 29%, respectively; an increase in trips per household by 16%; and a decrease in auto occupancy by 10% from 1970 to 2000 in Minnesota.

2.2.3 Model uncertainty

Every model also has uncertainty since it is a simplified representation of reality. Model uncertainty accumulates from underlying data, model structure, model specification, and/or model estimation.

Data used for model estimation and validation is subject to various errors. Some errors are systematic, caused by biased sampling, improper survey design, and coding errors (Rasouli and Timmermans, 2012). Systematic errors cause bias in model estimates. Some of the errors are random, due to the fact that a sample is used to make inferences for the entire population.

Models can have different structures under different assumptions. For example, the logit and nested logit model incorporate different assumptions regarding the similarity between the alternatives in the choice set. For trip generation, there are alternative structures, such as cross-classification, ordinary least squares, Poisson, negative binomial and ordered logit models.

For a given a structure, model specifications can include different explanatory variables, and variable transformations. For example, model specifications decide how much population heterogeneity and spatial heterogeneity are characterized. Missing predictors, say income levels or life cycle, may result in biased estimates and poor predictions. Selecting a model involves making a tradeoff between bias and variance in the estimates. As more predictors are included, model estimation bias will decrease, but the sampling uncertainty can increase and the model may over-fit observed data, and as a result, cannot generalize well. Alternatively, a simpler model may cause more bias.

Model estimation uncertainty is connected to the estimation procedures. For example, simulation techniques are often used in the estimation of advanced demand models, which allow for flexible error structures. Simulation procedures often use random initializations. Model runs with different initializations will result in different optimal estimates and predictions (Rasouli and Timmermans, 2012).

2.3 Uncertainty analysis approaches

There are two general approaches to analyze uncertainty in transport models: uncertainty propagation and model transferability assessment.

2.3.1 Uncertainty propagation

The main idea behind uncertainty propagation is to probabilistically characterize uncertainty in exogenous inputs and model parameters, perform Monte-Carlo simulations, and generate probabilistic distributions of the outputs. Sensitivity analysis and regression can be applied in the end to assess the impact of different sources of uncertainty on the output variations. This simulation-based approach is a generic tool to explore the future output space given any type of uncertainty. It does not aim to reduce uncertainty; rather it provides richer information on the implications of uncertainty in model outputs, in order to better inform decision-making.

Transport models (e.g., the “four-step” model) typically involve numerous sub-models and modules estimated and implemented sequentially. Any uncertainty from the initial inputs and each modeling stage are thus carried over to the following stages. In such cases, passing only the point estimates (expected values of a random variables) from one stage to the next will bias final estimates, because the models are, in general, not linear. Nonlinear models require distributional information about the inputs (Zhao and Kockelman, 2002), rather than simply expected values.

A number of studies have examined uncertainty propagation in four-step models and integrated land-use and transport models. Table 2–3 contains a summary of these studies. Limitations of prior studies include: 1) the uncertainty characterization of model inputs and parameters are often crude and arbitrarily set to a standard distribution with a certain coefficient of variation; 2) output uncertainty is analyzed often in terms of its spread (coefficient of variation) and its correlation with input uncertainty. And in fact, few studies have examined the impact of output uncertainty on decision-making. For example, Waller et al. (2001) found that using the expected value of the traffic assignment output tends to overestimate performance of the network and could lead to erroneous choice of improvements. They propose a demand inflation approach, which helps selecting improvements with not only lower expected total system travel time, but also significant reductions in the variance associated with this measure. Rodier and Johnson (2002) found that the plausible errors in population and employment projections (within one standard deviation) can result in the region's transportation plan not meeting the conformity test for NOx. Duthie et al. (2010) found that the ranking of roadway improvement projects can be different if uncertainty is considered relative to treating all parameters and data as deterministic.

Table 2–3 Summary of uncertainty propagation studies in transport and land use modeling

	Place	Model	Size	Uncertain inputs	Uncertain parameters	Uncertainty characterization	# of samples	Outputs	Measures of uncertainty	Findings
1	Sacra mento	SACMET 96; DTIM2		Population Employment Fuel price Income	None	Mean and standard deviation of projection errors from historical data		Trips VMT Emissions	Percent change	Population and employment projection errors generate large impact. Household income and fuel prices are not significant sources of uncertainty.
2	Dallas-Fort Worth	TransCA D	25 zones and 818 links 18,000 households	Household Employment	Parameters not described	Multivariate normal and multivariate lognormal. A single coefficient of variation for all inputs and parameters. A single correlation coefficient (of +0.30) relating all demographic data inputs.	100	VMT VHT Link flows Link travel time	Coefficient of variation Sensitivity Standardized regression coefficient	Link flow's uncertainty is greater than input uncertainty; VMT and VHT's uncertainty is smaller than input uncertainty. Average uncertainty is amplified in the first three steps; reduced in the final step; but not below the input uncertainty.
3	Eugen e-Spring field, Orego n	UrbanSim , TransCA D	271 TAZs 2970 links	Population Employment Household and employment mobility	Location choice coefficients Land price coefficients	Growth rates: 1.5, 1, 0.5; Mobility rates: 10%, 20%, 30%; Location choice and land price coefficients: 17th,	81	VMT VHT Link flows Land price Occupanc y rates	Standardized regression coefficient	Population and employment contribute more to output uncertainty. Land use output is more varied than travel output. Inputs that have a cumulative effect are likely

						50th 83rd percentile (Latin Hypercube sampling)		Occupancy densities		to have a significant impact on outputs in the long run.
4	Austin	ITLUP (DRAM /EMPAL) UTPP	1,074 TAZs 16,966 links 700,000 people	Population growth Employment growth	95 parameters	Multivariate normal with variance-covariance matrix estimated from the model	200	VMT VHT Residential and commercial densities	Standardized regression coefficient	Variations were most sensitive to the exponent of the link performance function, the split of trips between peak and off-peak periods, and several trip generation and attraction rates.
5	Sacramento	MEPLAN	70 zones 1.9 million people	Exogenous production (demand for goods and services produced by basic sectors)	Commercial trip rates Perceived cash costs of travel for SOVs Concentration parameter	Exogenous production: ±10% Commercial trip rates: ±25% Concentration: ±50% Driving cost: ±50%; ±100%	239	VMT Mode share of SOV Total SOV trips Spatial spreading of traffic Household and employment location	Regression coefficients	Commercial trip generation rates have the largest impact on model outputs.

6	Not specified	Gravity-based transportation and land use model (ITGLUM)	Not specified	Household and employment totals	Trip generation parameters	Lognormal with a 0.3 coefficient of variation (Antithetic sampling)	200	TSTT VMT Total delay Average and standard deviation of network speed	Difference in performance metrics	Ranking of roadway improvement projects differs when including uncertainty in model parameters and inputs.
7	Grenoble, France	Land use module of TRANUS.	225 zones, 2,413 nodes	None	100 uncertain parameters in land use model	Product of independent Gaussian	100	Land use assignments	Mean squared error	The minimum and maximum amount of land used and elasticity parameter are the main factors for output uncertainty

Note:1. Rodier, Johnson (2002)

2. Zhao, Kockelman (2002)

3. Pradhan, Kockelman (2002)

4. Krishnamurthy, Kockelman (2003)

5. Clay, Johnston (2006)

6. Duthie et al. (2010)

7. Dutta et al. (2012)

2.3.2 Model transferability assessment

Model transferability analysis focuses on whether models estimated from different contexts are equal, or whether a model estimated for one context can be applied to another context. If a model is not transferable, the reasons can be due to differences between the contexts, or poor models. Therefore, transferability is a tool for identifying behavior and model uncertainty. It can also be used to find potential model improvements.

Transferability analysis is model validation oriented. However, simulation can be used to complement transferability analysis. For example, prediction errors from a transferred model can be further propagated to the next model steps, in order to evaluate the impact on the model outputs. Also, predictive testing in transferability analysis can be enhanced by incorporating sampling uncertainty through simulation: the prediction error is measured not only by the difference between the predicted (expected value of the predicted random variable) and the actual value, but by comparing the predicted distribution and the actualized value—e.g., whether a 95% confidence interval of the distribution captures the actual value.

This thesis mainly follows the model transferability assessment approach. And I also use simulations to examine error propagation with sampling uncertainty taken into account.

2.3.2.1 Definitions of model transferability

Theoretical discussion of travel model transferability dates back, at least, to three papers in 1981 (Ben-Akiva, 1981; Hansen, 1981; and Louviere, 1981) at a conference on Spatial, Temporal and Cultural Transferability of Travel-Choice Models. Koppelman and Wilmot (1982) give a broad definition of transferability: "the usefulness of the transferred model, information or theory in the new context".

Ben-Akiva (1981) and Hansen (1981) categorize model transferability into four levels: 1) underlying theory of travel behavior; 2) mathematical model structure; 3) empirical specification; and 4) model parameter estimates. Levels 1, 2 and 3 correspond to model uncertainty, while level 4 corresponds to behavior uncertainty and model data uncertainty. Sikder (2013) gives a detailed elaboration of each level, as summarized in Table 2–4.

Table 2–4 Levels of model transferability

Levels	Contents	Examples: reasons for not transferable
1. Underlying theory of travel behavior	Behavior theory	Utility maximization vs. Satisficing or lexicographic rules
2. Model structure	Mathematical structure	Logit vs. nested logit Linear regression vs. count data
3. Empirical model specification	Explanatory variables. Variable forms	Omitted variables Unspecified population heterogeneity and spatial heterogeneity Inappropriate variable transformation
4. Model parameter estimates	Model coefficients	Preference differences Sampling error Data errors (inconsistency, coding error etc.)

Source: summarized from Sikder (2013)

In practice, perfect transferability is unrealistic, since models are never perfect and can only be developed up to a satisfactory level of performance (Ben-Akiva, 1981). Sikder (2013) gives an operational definition of transferability: *"If a transferred model performs better than (or as good as) a model that can be built using locally available data and resources, then the model could be considered transferable for practical purposes."* Rather than judging transferability in absolute terms (i.e., yes or no), transferability should be assessed in degrees, in light of the ultimate implications for decision-making.

2.3.2.2 Transferability tests

Empirical transferability assessment involves two contexts: the base context, from which a model is estimated; and the transfer context, to which a model is applied. The context can be defined by time or space (temporal transferability or spatial transferability, respectively). The goal is to assess whether the two models are equivalent, or the extent to which a model can be transferred to a different context. There are two kinds of tests to measure model transferability: statistical tests and predictive tests. Table 2–5 shows the metrics for each type.

Statistical tests aim to test the statistical equivalence of the model parameters. Log-likelihood metrics provide a basis for overall model equality assessment. Parameters from the base model β_b and the transferred model β_t are both applied to the transfer context data to compute the log-likelihood: $L_t(\beta_b)$ and $L_t(\beta_t)$. $L_t(\beta_b)$ can never be larger than $L_t(\beta_t)$, the maximized log-likelihood for the transfer context, and will in practice almost always be smaller.

Model Equality Test Statistics (METS), Transferability Test Statistics (TTS), Transfer Index (TI), and Transfer Rho-square primarily test overall model equality. METS is a likelihood ratio test. It compares the unrestricted model (i.e., two contexts' models have completely different parameters) to a restricted model with equal coefficients across contexts. It can be extended to test equality for a partial set of parameters. METS requires datasets for both contexts to estimate a model with combined datasets.

TTS, introduced by Atherton and Ben-Akiva (1976), measures how far the log-likelihood of a transferred model, $L_t(\beta_b)$, is from the log-likelihood of a local model, $L_t(\beta_t)$. TI, proposed by Koppelman and Wilmot (1982), is a standardized TTS, in which the log-likelihood is normalized by subtracting the baseline log-likelihood (usually the constant-only model $L_t(\beta_t^{ASC})$). The closer the TI to 1, the higher the model transferability. Transfer Rho-square is a different normalization than TTS, which mimics the goodness of fit measure, but for a transferred model. Transfer Rho-square is never greater than 1. The larger the value, the better the fit of the transferred model to the application data. Note that TTS, TI and Transfer Rho-square do not need estimation data from the base context, as long as the base model parameters (β_b) are known.

For individual parameter comparisons, the t-test is commonly used. The test statistic is the coefficient difference divided by the standard error of the difference. For logit models, possible underlying differences in the variances of the datasets can be hidden in the model scale parameter; so such possibilities must be taken into account when comparing model coefficients (as discussed in the Chapter 3).

Nonetheless, limitations of these statistical tests exist (Ben-Akiva, 1981; Koppelman and Wilmot, 1982). If the sample size is large enough, very small numerical differences between two coefficients can be identified by statistical tests. But the difference may not be practically important. On the other hand, even if the statistical test does not reject the equal coefficients hypothesis, the numerical difference may still lead to practically important different forecasts (Sikder, 2013). Ultimately, what matters is the impact of the difference in model parameters on the outputs of interest.

Predictive tests offer a direct assessment of forecast accuracy. In contrast to statistical tests, which compare models, predictive tests compare forecasts with actual data (i.e., validation). Shortcomings of predictive tests include the difficulty in locating the source errors, since multiple sources can be at work simultaneously, and judging how much error is acceptable.

Table 2–5 Statistical test and predictive test statistics

	Test name	Type of test	Test statistics
Statistical tests	Model equality test statistics (METS)	Statistical tests of equivalence of parameters	$-2(L_{bt}(\beta_{bt}) - L_t(\beta_t) - L_b(\beta_b))$
	Transferability Test Statistic (TTS)	Statistical tests of equivalence of parameters	$TTS_t(\beta_b) = -2(L_t(\beta_b) - L_t(\beta_t))$
	Transfer Index (TI)	Standardized version of TTS	$TI_t(\beta_b) = \frac{-2(L_t(\beta_b) - L_t(\beta_t^{ASC}))}{-2(L_t(\beta_t) - L_t(\beta_t^{ASC}))}$
	Transfer Rho-square	Measure of "goodness of fit" of transferred model	$\rho_T^2 = 1 - \frac{L_t(\beta_b)}{L_t(C_t)}$
	T-test	Statistical test of individual parameter equivalence	$\frac{\beta_t - \beta_b}{\sqrt{var(\beta_t - \beta_b)}}$
Predictive tests	Relative Error Measure (REM)	Aggregate-level prediction error	$(\mathrm{PS_k} - \mathrm{OS_k})/\mathrm{OS_k}$
	Root-Mean-Square Error (RMSE)	Aggregate-level prediction error	$\left(\frac{\sum_k \mathrm{PS_k} \times \mathrm{REM_k}^2}{\sum_k \mathrm{PS_k}}\right)^{1/2}$
	Relative Aggregate Transfer error (RATE)	Aggregate-level predictive ability	$\frac{\mathrm{RMSE_t}(\beta_b)}{\mathrm{RMSE_t}(\beta_t)}$
	Aggregate Prediction Statistic (APS)	Aggregate-level predictive ability	$\sum_k \frac{(\mathrm{PS_k} - \mathrm{OS_k})^2}{\mathrm{PS_k}}$

Source: adapted from Sikder (2013).

b: base context; t: transfer context. $L_t(\beta_b)$: Log-likelihood of the base model applied to the transfer context. $L_t(\beta_t)$: Log-likelihood of the local model for the transfer context. $L_t(\beta_t^{ASC})$: Log-likelihood of the constant–only local model for the transfer context. $\mathrm{PS_k}$: Predicted share in category k. $\mathrm{OS_k}$: Observed share in category k.

2.4 Empirical findings: temporal transferability of vehicle ownership models and trip generation models

There are not many studies of temporal transferability of travel demand models, especially for vehicle ownership, trip generation and distribution models. However, trip generation (including vehicle ownership in a general sense) and distribution steps are critical in the four-step model, because the total amount of travel (i.e. number of trips by purposes and trip lengths) and the spatial distribution of demand (i.e. production-attraction matrices) will substantially influence the final travel outputs. NCHRP report 716 (2012) and Fox and Hess (2010) review previous temporal transferability studies. Built on their survey, more recent studies have been added.

2.4.1 Temporal transferability of vehicle ownership model

Few studies have examined vehicle ownership preference change over time. Most of them are done in rapidly developing and motorizing countries, where income is increasing and new transport services are becoming available.

Zegras and Hannan (2012) modeled vehicle ownership choice for Santiago metropolitan area in Chile using disaggregated travel survey and multinomial logit models. They found that demographic and built environment variables changed in their effect on vehicle ownership from 1991 to 2001. In particular, the effect of income, number of children and land use mix weakened; the distance to CBD effect strengthened over time; and the residential density effect varied depending on the vehicle ownership category.

Gómez-Gélvez and Obando (2013) examined car ownership preference changes in Bogotá, Colombia from 1995 to 2005, using an ordered logit model. The results showed that the coefficients related to number of household members increased expect for non-working adults. Adults working further than 5 km from their home became more likely to own cars than adults working within 5km from home, contrary to the result in 1995. The effect of population density on car ownership became insignificant in 2005, while it was significantly negative in 1995. The impact of access to new BRT lines on car ownership had mixed results, probably due to the not fully controlled impact of income. They also suggested the changes of social stratum effect is probably due to the increase in car costs, which are not included in the model.

Sanko et al. (2009) conducted a temporal transferability analysis of vehicle ownership models in Nagoya, Japan for the years 1981, 1991 and 2001. They used a bivariate ordered probit model for auto and motorcycle ownership. They found that age and gender had less important effect on car ownership over time as motorization proceeded.

Xiang (2014) found that vehicle ownership preferences in Singapore changed between 1997, 2004 and 2008. Particularly, the likelihood of owning cars declined for all income groups over the years. Chingcuanco and Miller (2014) examined the evolution of alternative specific constants (ASCs) and scale parameters of a multinomial logit model of vehicle ownership using 19 years' data in Ontario, Canada. They varied ASCs, scales, and both for each year, while constraining other coefficients to be the same across years. They found that scale differences were not significant across years when ASCs were allowed to vary temporally, meaning that the temporal differences were mainly reflected in the average effect rather than the variance of the unobserved factors. They also found that the ASCs for the 1 vehicle alternative are not significant across the 19 years, meaning that most of the factors that influence owning 1 vehicle have been captured by the model; but the ASCs for 2 and 3 vehicle alternatives appear to be increasing with time, consistent with the gradual rise in motorization levels observed from the data. By regressing the year-specific ASCs and scales against the macro-economic variables, such as gas price, employment rates etc., they found significant relationships between them. This demonstrated the potential to predict the preference parameters by exogenous variables—a way to connect exogenous uncertainty and behavior uncertainty. However, experiments with the validation data, using forecasted ASCs and scales were similar to or worse than the baseline models.

To summarize, previous studies have all found preference changes in vehicle ownership choice over time. The results seem to be somewhat context-specific. But above all, we have too few studies to reach a conclusion. Although we may assume ownership preference stability in a highly motorized, industrialized economy, Chingcuanco and Miller (2014) did find strong correlations between model parameters and macro-economic variables in an already highly motorized area. This seems to suggest that people do adjust behaviors to macro economic changes. Assuming that parameters remain the same over the long run is naive. Lastly, I found no evaluations of the impact of vehicle ownership behavior and model uncertainty on a regional travel forecast scale. In the end, vehicle forecasts for the population matter, as they directly affect trip generation and mode choice in a four-step model. This becomes a judgment call for practical implications.

2.4.2 Temporal transferability of trip generation model

Few studies have focused on temporal transferability in the context of trip generation (NCHRP, 2012). Most have found models are not transferable over time.

Kannel and Heathington (1972) used the 1964 and 1971 household travel survey data in Indianapolis to develop linear regression models for household-level trip generation. Household size and auto-ownership were included in the model. They observed that the effect auto-ownership had changed, while the effect of household size was stable. When they applied the 1964 model to the 357 households in 1971, the total number of predicted trips is within 2% error.

Doubleday (1976) used an individual-level linear regression model of the cross-classification type. He included employment status, profession, presence and age of children, and household car ownership in the model. He found that the transferred model predicted well for employed males, but not so, for retired individuals, homemakers, and employed females. This interesting result indicates behavior uncertainty varies across groups of population and trip purposes.

Badoe and Steuart (1997) did a comprehensive test of the temporal transferability of linear regression trip generation models at the household level. They employed data from the Greater Toronto area from 1964 and 1986, and included household size, workers, licensed drivers and number of vehicles in their models. At the disaggregated level, models satisfactorily predicted total home-based trips and home-based work trips, but poorly predicted home-based non-work trips. They attributed this to the model's lack of explanatory power for the home-based non-work trip production, and to not considering trip-chaining. When they aggregated trips to the zonal level, the bias was narrowed, but over-prediction still existed for all purposes, being greatest for social and recreational, shopping, and personal business trips. Shams et al. (2014) also found that a commute trip model was transferable; while a shopping trip model was not.

Mwakalonge et al. (2012) investigated the temporal transferability of linear-regression trip generation models using national level data in the U.S.. Their main focus is non-motorized travel and total travel. They found that for non-motorized travel, only the coefficient for single-adult households with no children was stable across all of the analysis years. For both non-motorized and total travel, most model parameter estimates were stable in the short term (5 to 10 years) but not over the long term (15 to 20 years). The models' ability to predict travel in future contexts decreased with increasing time gap between the contexts.

In addition to linear regression models, other trip generation model structures have been examined. Cotrus et al. (2005) studied the transferability of linear-regression and Tobit trip generation models from 1986 to 1997 in Tel Aviv and Haifa, Israel. The regression models and Tobit models are both statistically different over time. They attributed the changes to economic conditions, structure and development of the metropolitan areas (i.e., land use and spatial structure), changes in lifestyle and socio-economic variables not included in the model, and inconsistencies across the travel surveys. They also suggested that Tobit models perform better than regression or discrete choice models in predicting non-travelers (i.e., trip rate 0).

In contrast to Cortus et al.'s findings, Badoe (2007) found that linear regression models out-performed truncated normal models (i.e., Tobit), Poisson models, negative binomial models, and an ordered logit models. He assessed these models' performance at the individual and zonal level, using estimation data for 1986 and validation data for 1996 collected from the Toronto Region. In another study, Mwakalonge and Badoe (2012) found the traditional cross-classification method out-performed multiple classification models, using data from San Francisco Bay Area in 1965, 1981, 1990, 1996 and 2000.

However, a study by Lim and Srinivasan (2011) found that ordered probit models are able to replicate the trip generation patterns better than linear-regression, log-linear, and negative-binomial models for home-based work, home-based other, and non-home-based trip purposes. They used 2001 NHTS data for estimation, and applied these models to 2009 NHTS data. Since these few studies are based on different locations and time, there has not been a clear answer about which model structure is the most transferable over time.

In summary, the majority of studies have found that trip generation model parameters are not transferable over time. Most have not offered concrete explanations of behavioral change, except for a few mentioning behavioral response to energy crises or economic conditions (Cotrus et al., 2005; Mwakalonge et al. 2012). There seems to be a consensus that work trip production is more stable over time, while non-work trips are far less stable. Notably, the explanatory power of the models for non-work trips is not high, which means that they need to be improved.

The gaps in our understanding include: 1) the exogenous conditions associated with trip-making behavioral changes, and how to incorporate the relations into future scenario formulation; 2) the uncertainty of model predictions for different trip purposes (i.e. work vs. non-work); 3) how the lack of temporal transferability could influence the subsequent model stages in a four-step model.

Table 2–6 Temporal transferability studies of trip generation models

Author	Area	Model types	Variables	Time	Findings
Ashford, Holloway (1971)	Pittsburgh	Zonal-level linear regression; household level cross-classification		1958; 1967	Substantial differences in the estimated coefficients
Kannel, Heathington (1972)	Indianapolis	Household-level linear regression	Household size; auto ownership	1964, 1971	The effect of auto-ownership changed
Doubleday (1976)	Reading, England	Individual-level linear regression	Employment status and profession; presence and age of children; household car ownership	1962, 1971	Predictions are not good for retired individuals, homemakers, and employed females.
Badoe and Steuart (1997)	Greater Toronto, Canada	Household-level linear regression	Household size; vehicles; licensed drivers; employed persons	1964, 1986	Good transferability for total home-based trips, and home-based work trips; and poor prediction for home-based non-work trips
Cotrus et al. (2005)	Tel Aviv and Haifa, Israel	Individual-level linear regression and Tobit	Age; car; driver's license; employment, education, and status in the household.	1984; 1996/97	Regression and Tobit model are statistically different over time
Badoe (2007)	Toronto Region	Individual-level linear regression; Tobit; Poisson; negative binomial; and ordered logit model	Age, gender, employment, licensed driver, vehicles	1986; 1996	Linear regression model is more transferable than other models

Mwakalonge et al. (2012)	U.S. national travel surveys (NPTS; NHTS)	Linear regression		1990, 1995, 2001, 2009	Only the coefficient for single-adult households with no children was stable. Most model parameter estimates were stable in the short term but not in the long term
Shams et al. (2014)	New York metropolitan region	Individual level multinomial logit model	Income, age, employment, gender, household size, licensed driver, household vehicles	1998; 2010	Commute trip model is transferable. Shopping trip model is not.

2.5 Summary

Based on this review of the literature, I derive the following areas for further research.

First, there is a clear need for systematic evaluations of long-range regional transport models. Existing studies that I have found all assess models developed in the 1960s. We do not yet know whether advanced modeling techniques have improved forecast accuracies.

Second, uncertainty characterization needs to better represent reality. In particular, there is lack of systematic characterization of the nature, magnitudes and correlations of the sources of uncertainty in the real world. For example, how much variability is there in migration rate? What is the range of, and how volatile is, the gas price?

Also, relationships among exogenous inputs and behavior deserve further study. For example, gas prices can influence vehicle ownership preferences and travel frequency. Understanding the correlation between different sources of uncertainty is important for formulating scenarios and assessing uncertainty propagation.

Prior uncertainty propagation analysis has put greater emphasis on simulation and sensitivity analysis, while simplifying uncertainty representation. Inputs and parameters are assumed to follow certain probability distributions, with a correlation structure arbitrarily specified. In future analysis, these probabilistic distributions should be inferred from historical data.

Ultimately, we need to translate uncertainty experienced in the past into knowledge of uncertainty in the future, to make simulation results more relevant and informative for future decision-making.

Transferability studies can be enriched in a number of ways, and complemented by simulation methods. Not many studies have assessed the predictive performance of the transferred model on population-level forecasts, and the error propagation through later model stages. Also, sampling uncertainty needs to be considered in the assessment of transferability. The uncertainty propagation approach can be used to study error propagation and include sampling uncertainty.

My thesis addresses a few of above aspects. It contributes towards a better understanding of preference stability in vehicle ownership choice and trip-making behavior, using the Boston metropolitan area from 1990 to 2010 as the case. Beyond the traditional transferability assessment, I consider uncertainty in model specifications, and in sampling. Furthermore, I apply models to make population forecasts in a four-step model, and let errors propagate from the vehicle ownership model to the trip generation step.

Chapter 3

Methods

This chapter describes the basics of the models and statistical tests used in this thesis. Chapters 5 and 6 provide detailed demonstrations of the applications.

3.1 The Logit model

The logit model is a type of model structure used for discrete choice analysis. I adopt it in this thesis for modeling vehicle ownership choice by household. For a comprehensive description of the logit model, and other model structures for discrete choice analysis, the reader may wish to consult Ben-Akiva and Lerman (1985).

In a discrete choice setting, individual n needs to select from a set of mutually exclusive and collectively exhaustive alternatives, defined as choice set C_n of size J_n (Eq. 3.1).

$$C_n = \{j: 1,2, \dots J_n\} \tag{3.1}$$

In the general formulation of a random utility model, individual n is assumed to select the alternative i with the highest utility from the choice set C_n, which can be written as:

$$P(i|C_n) = P(U_{in} \geq U_{jn}, \forall j \in C_n) \tag{3.2}$$

The random utility of an alternative is expressed as a sum of observable systematic components (V_{in}) and unobservable components (ε_{in}) (Eq. 3.3).

$$U_{in} = V_{in} + \varepsilon_{in} \tag{3.3}$$

The logit model structure is distinguished from other random utility models by its assumptions of the error term ε_{in}: 1) ε_{in} are independently and identically distributed (i.i.d.); and 2) ε_{in} follow Extreme Value (0, μ) distribution. These assumptions imply that the variances of the random components of the utilities are equal across alternative i and across individual n (homogenous across individuals).

$$\varepsilon_{in} \sim EV(0, \mu) \tag{3.4}$$

The choice probability for alternative i is:

$$P_n(i|C_n) = \frac{e^{\mu V_{in}}}{\sum_{j \epsilon C_n} e^{\mu V_{jn}}} \tag{3.5}$$

Note the scale parameter μ in each of the terms of Equation 3.5. This parameter is usually not identifiable, and the usual procedure is to set it arbitrarily to a convenient value, such as 1.

The systematic utility component V_{in} is estimated by a group of predictors, which can include the attributes of alternatives for individual n, which is z_{in}, and social-economic variables of individual n, which is S_n. z_{in} and S_n can be transformed, and $x_{ink} = h(z_{in}, S_n)$ are the final predictor variables appearing in the systematic utility V_{in} (Eq. 3.6 and Eq. 3.7).

V_{in} is linear in its parameters. The alternative specific constant Asc_i is specified for $J - 1$ alternatives, leaving one alternative as the reference group. It measures the average unobserved effect on the utility of alternative i. β measures the effect of the predictor variable on the systematic utility of the alternative. It can be *alternative-specific*, meaning distinct β_{ik} is associated with alternative i; or it can be *generic*, meaning β_k is the same for all alternatives (drop i).

$$V_{in}(z_{in}, S_n|\beta) = Asc_i + \sum_{k=1}^{K} \beta_{ik} x_{ink} \tag{3.6}$$

$$x_{ink} = h(z_{in}, S_n) \tag{3.7}$$

All the parameters are estimated by maximizing the log-likelihood of the observed choice (Eq. 3.8 and Eq. 3.9)

$$\mathcal{L}(\boldsymbol{\beta}) = \sum_{n=1}^{N} \sum_{i=1}^{J_n} y_{in} \ln P_n\,(i|x_n, \boldsymbol{\beta}) \tag{3.8}$$

$$\widehat{\boldsymbol{\beta}} = argmax_{\boldsymbol{\beta}}(\mathcal{L}(\boldsymbol{\beta})) \tag{3.9}$$

3.2 Scale parameter

The scale parameter μ in a logit model is the scale parameter in the Extreme Value distribution of the random error term (see Eq. 3.4). The variance of the random error term is:

$$Var(\varepsilon_{in}) = \frac{\pi^2}{6\mu^2} \tag{3.10}$$

As shown in Eq. 3.10, the bigger the scale, the smaller the variability in the unobserved error. The scale parameter is not identifiable for a single dataset, and is usually set to 1. The coefficients can be identified only after fixing this scale. So the magnitude of the coefficient in the logit model is subject to the scale parameter.

When models are estimated separately on different datasets (from different time periods, or different locations, or revealed preference data vs. stated preference data), the magnitude of the estimated coefficients are not directly comparable, because the scale, or in other words, the variability in the unobserved preference, can differ across datasets.

To compare model coefficients from multiple data sources, a joint estimation should be performed on the pooled data with one data set's scale set to 1, and the others' scales to be estimated. The estimated scale parameter can be tested against the null hypothesis that the scale is one, meaning no significant scale difference between the corresponding dataset and the reference dataset. This is explained in more detail in section 3.4.

3.3 Likelihood ratio test of preference stability

The Model Equality Test (METS) mentioned in Chapter 2(section 2.3.2.2), is a Likelihood Ratio (LR) test. It examines if the model parameters of two models can be considered as statistically equal.

Eq. 3.11 and 3.12 show the general formulation of the LR test. The test statistic T is -2 times the difference in the log-likelihood between the restricted model and the unrestricted model. It follows a Chi-square distribution with a degree of freedom equal to the difference in the number of parameters.

$$T = -2(\mathcal{L}_R - \mathcal{L}_{UR}) \tag{3.11}$$

$$T \sim {\chi^2}_{K_{UR}-K_R} \tag{3.12}$$

In the context of preference stability, suppose there are two contexts: the base year context denoted as b, and the application year (or transfer) context denoted as t. And we have data for both contexts. The unrestricted model can be estimated separately for each data set. The log-likelihood of the unrestricted model is the sum of the log-likelihood from the two separate models ($\mathcal{L}_{UR} = L_t(\beta_t) + L_b(\beta_b)$). The restricted model can be estimated on the pooled data with certain restrictions. The LR test statistics is in Eq. 3.13.

$$T = -2(L_{pooled}(\beta) - L_t(\beta_t) - L_b(\beta_b)) \tag{3.13}$$

There can be different kinds of restrictions, depending on the specific preference stability of interest. Some commonly tested restrictions include:

1) all parameters are the same;
2) all parameters are the same except the scale parameter; and
3) all parameters are the same except the scale parameter and the ASCs.

From 1) to 3), the restriction becomes weaker. If 1) cannot be rejected, it means the two models are the same. If 2) is not rejected, it means the two models are different only in terms of scale (i.e., underlying variance). After adjusting the scale, the preference coefficients are the same. In other words, the ratios of the coefficients have not changed from one context to another. If 3) is not rejected, it means there are only changes in scale and ASCs between the contexts, which are the variance and the average of the unobserved effects. All the observed effects have not changed over time. When restriction 3) is rejected, we can conclude that at least some of the observed preferences have changed from one year to another, meaning that preferences are not stable across years.

This framework can be extended further to explore the stability of a subgroup of preference parameters, not only the scale and ASCs. And the unrestricted model can be a pooled model with certain parameters restricted to be equal across contexts; and that a more restricted model can be tested against it.

In Chapter 5, I first test the three basic preference stability hypotheses in vehicle ownership choice; and then extend the analysis to explore which sets of preferences have changed.

3.4 T-test of preference stability

A T-test is used for testing the equivalence of individual parameter estimates. Note that the result from a LR test may be different from t-test in terms of preference change. The LR test detects changes in the effect of a group of variables *together*; while the t-test measures the change in the expected value of an individual parameter, without considering its interactions with some other predictors and their joint effect on the choice. It is possible that a t-test does not show any significant change for individual parameters, yet the joint effect of these parameters differs across the contexts according to the LR test.

The null hypothesis in a t-test is: $\hat{\beta}^t = \hat{\beta}^b$. The t-test statistic is shown in Eq. 3.14. For large samples, the test statistic Z follows the standard normal distribution $N(0,1)$.

$$Z = \frac{\hat{\beta}^t - \hat{\beta}^b}{\sqrt{Var(\hat{\beta}^t - \hat{\beta}^b)}} \qquad (3.14)$$

As mentioned in section 3.2, the individual coefficients cannot be directly compared across models estimated on different data sets, because the apparent difference can be due to the scale difference. To avoid this fallacy, a model should be estimated on pooled data from the two contexts. Suppose the scale of the base context is set to 1, estimate scale of the transfer context μ (Eq. 3.15-3.18)

Base context:

$$U_{in}^{b} = \boldsymbol{\beta}_{i}^{b} x_{n}^{b} + \varepsilon_{in}^{b} \tag{3.15}$$

$$P_{n}^{b}(i) = \frac{\exp(\boldsymbol{\beta}_{i}^{b} x_{n}^{b})}{\sum_{j} \exp(\boldsymbol{\beta}_{j}^{b}\, x_{n}^{b})} \tag{3.16}$$

Transfer context:

$$U_{in}^{t} = \mu(\boldsymbol{\beta}_{i}^{t} x_{n}^{t} + \varepsilon_{in}^{t}) \tag{3.17}$$

$$P_{n}^{t}(i) = \frac{\exp(\mu(\boldsymbol{\beta}_{i}^{t} x_{n}^{t}))}{\sum_{j} \exp(\mu(\boldsymbol{\beta}_{j}^{t}\, x_{n}^{t}))} \tag{3.18}$$

Note: $\boldsymbol{\beta}$ is a vector of coefficients. The superscript identifies the context.

$$\frac{Var(\varepsilon_{in}^{t})}{Var\left(\varepsilon_{in}^{b}\right)} = \frac{1}{\mu^{2}} \tag{3.19}$$

If the $\hat{\mu}$ is not significantly different from 1, a pooled model with the same scale can be estimated, and the t-test can be performed directly. Otherwise, the t-test should be performed between $\mu\hat{\beta}^{t}$ (coefficient adjusted by scale) and $\hat{\beta}^{b}$. The null hypothesis will thus be: $\hat{\beta}^{b} = \mu\hat{\beta}^{t}$.

Chapter 4

Greater Boston’s demographic and travel behavior trends

This chapter depicts the major demographic trends from 1980 to 2010 and travel behavior changes from 1990 to 2010 in the Greater Boston Area. As discussed in Chapter 2, demographics are a main source of input uncertainty. However, as this chapter describes, different aspects of demographics can have different degrees of uncertainty: some are highly predictable, while others are more surprising. Although in this thesis I will not model any input uncertainty, this evidence provides a valuable backdrop to my assessment and can be of value to future studies on input uncertainty.

For behavioral changes, shifts in aggregate-level behavior can be a result of demographic changes and/or individual preference changes. In Chapters 5 and 6, I will test disaggregated preference changes in the case of vehicle ownership choice and trip generation. However, as behaviors are often interconnected, changes at different levels (population and individual) and of different behavioral aspects should tell a consistent story. This chapter provides the background to facilitate the understanding of all these changes.

4.1 Study area and data

The study area comprises 986 Traffic Analysis Zones (TAZ) that are covered by the Central Transportation Planning Staff (CTPS)’s regional travel demand model for the Boston Metropolitan Area (Figure 4-1 and Figure 4-2). It consists of 164 cities or towns with about 4.5 million people and 1.7 million households in 2010.

Demographic data is mainly from Geolytics Neighborhood Change Database (NCDB), a database of U.S. Census data from 1970, 1980, 1990, 2000, and 2010 at the census tract level normalized to 2010. A total of 974 census tracts are selected for the study area.

Census Transportation Planning Products (CTPP) data from 1990, 2000, and 2010 are used to describe journey-to-work. It is part of the census and covers the population. Two travel surveys, the 1991 Boston Household Travel Survey (BTS) and the 2010-2011

Massachusetts Travel Survey (MTS) are used for general travel behavior statistics. The surveys contain about 4,000 and 10,000 households respectively, with detailed information about the households, individuals, and a workday travel-activity journal.

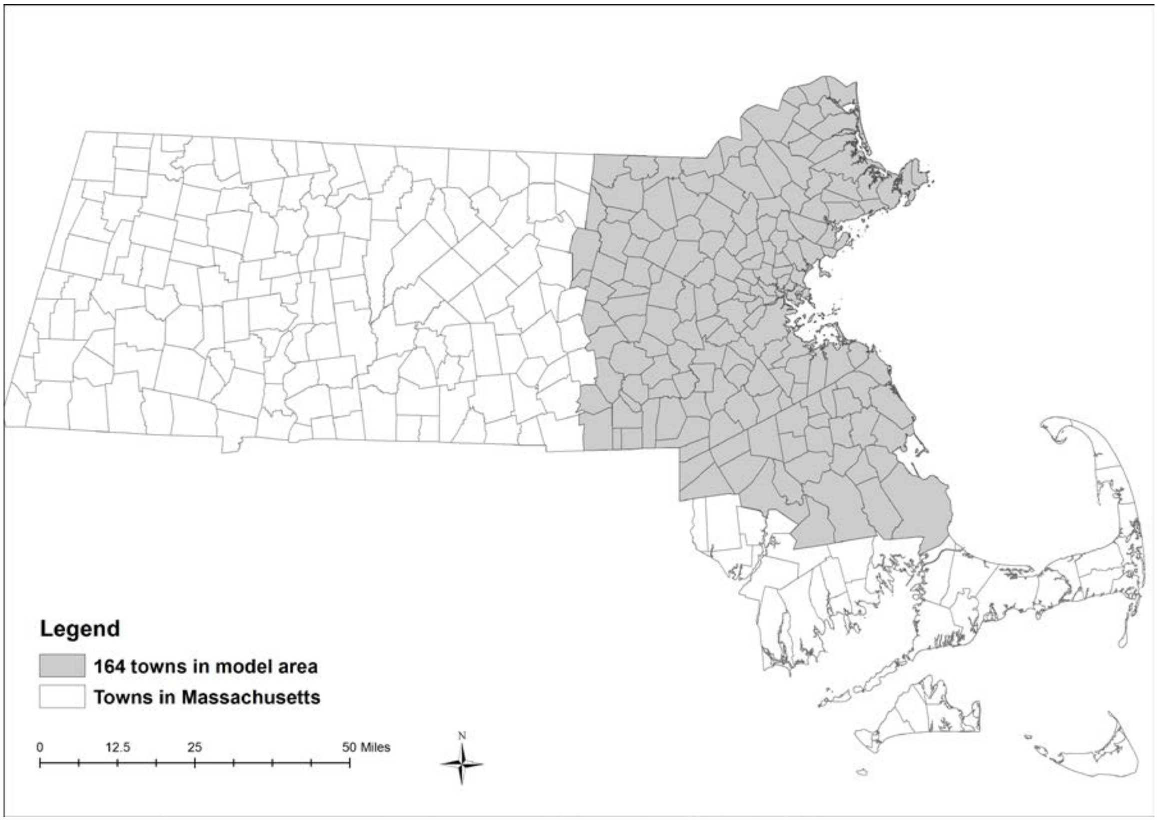


Figure 4-1 Location of the study area in Massachusetts

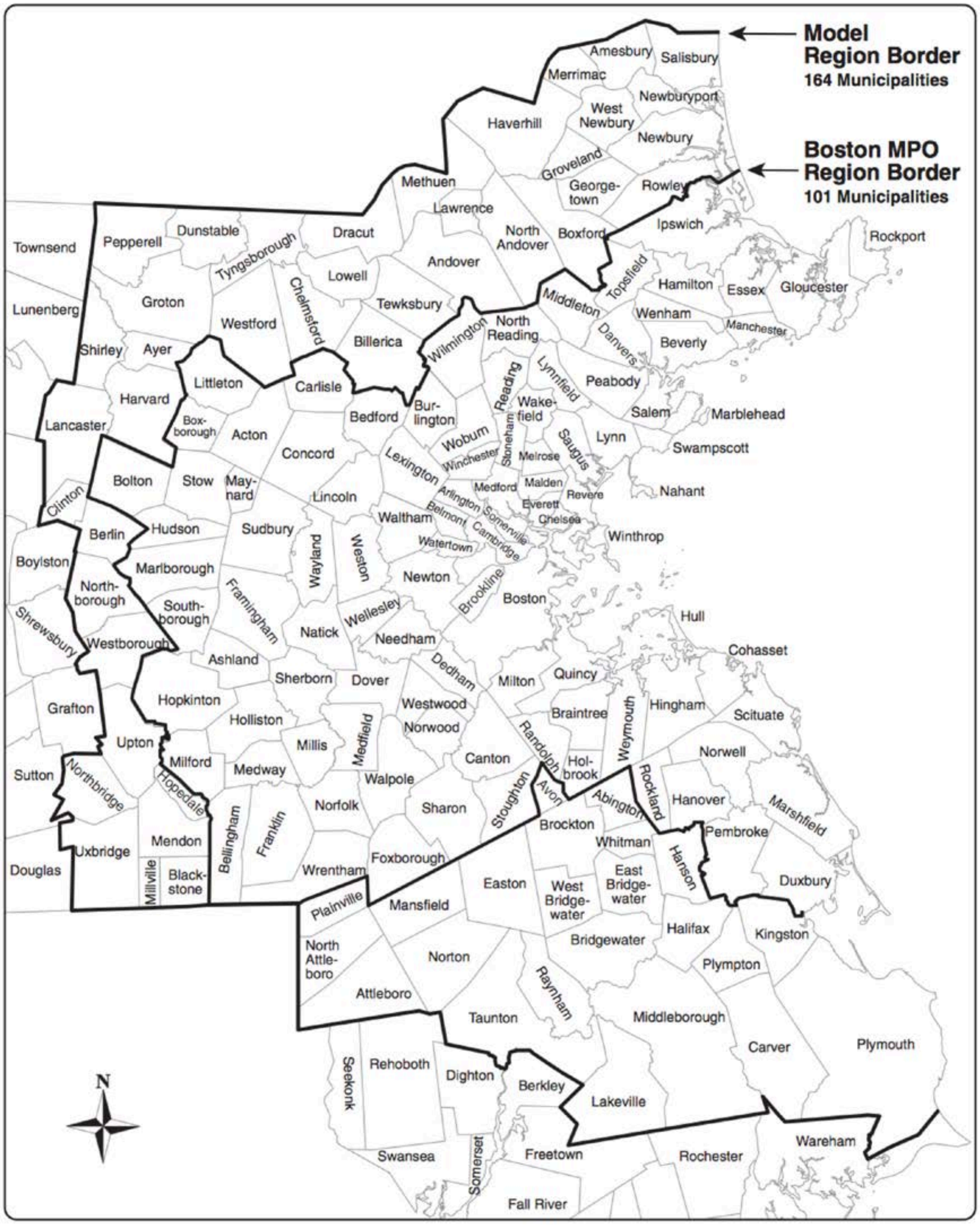


Figure 4-2 Geographic boundary of the regional four-step model by CTPS.

Source: Kuttner et al. 2014. *Exploring the 2011 Massachusetts Travel Survey* http://www.ctps.org/Drupal/data/pdf/studies/other/Exploring_2011_Travel_Survey.pdf accessed on May 21, 2015.

4.2 Demographic characteristics

Total population, households, and workers

The area's population growth rate has been relatively stable, ranging from 4.0% to 6.2% over every decade since 1980 (Table 4–1). Growth in the number of workers is more surprising. From 1980 to 1990, total workers increased by 13.7%, while in the next two decades, the growth rate stabilized at around 4%. This can be related to the large increase in female participation in the labor force during the 1980s. Work trips can be largely under-estimated if such an increase was not foreseen. This can also be due to data inconsistency (see note for Table 4–1)

Table 4–1 Total population, total number of households and average household size

Year	1980	1990	2000	2010	80-90	90-00	00-10
Population	3,846,964	3,999,967	4,247,202	4,457,728	4.0%	6.2%	5.0%
Households	1,354,501	1,483,626	1,618,669	1,718,099	9.5%	9.1%	6.1%
Workers	1,799,287	2,044,974	2,117,656	2,211,714	13.7%	3.6%	4.4%
Persons/HH	2.84	2.70	2.62	2.59			
Workers/HH	1.33	1.38	1.31	1.29			

Source: NCDB 1980, 1990, 2000 and 2010.

Note: The variable "Workers 16+ years old" is not directly available from NCDB 1980. I computed the workers by summing workers working at home (WKHOME8), and workers working outside the home (TRVLPB8D). For the others census years, the total number of workers is directly taken from the variable "Workers 16+ years old."

Household size

Household size in the study area has been shrinking, from 2.84 in 1980 to 2.59 in 2010 (Table 4–2). The share of 1-person households expanded from 25.8% in 1990 to 28.6% in 2010, while households with 4 or more persons dropped to 23.8% from 26.2%.

Smaller household sizes can be a result of more people staying single or not having children. It is also related to the growth in the number of older adults. Changes in household size may affect housing choices. Smaller households may prefer the city rather than the suburbs. Population density increases and gentrification in central cities since the 1990s may be related to this shift in household size. Household size could also affect household modal use. Small households of younger people may prefer fewer vehicles, and car-pool, while small senior households may keep their cars even if they do not use them as often.

Table 4–2 Percent of households by household size

HH size	1980	1990	2000	2010
1-person		25.8	27.8	28.6
2-person		30.5	30.8	31.2
3-person		17.5	16.4	16.4
4-person		15.4	14.8	14.3
5-person		7.2	6.8	6.2
6-person		2.4	2.3	2.1
7+person		1.2	1.1	1.2
Total		100.0	100.0	100.0
Average household size	2.84	2.70	2.62	2.59

Source: NCDB 1980, 1990, 2000 and 2010.
Note: 1980 household size composition is not available from NCDB 1980.

Household income distribution

The income gap among households in the study area has widened. The share of the two highest income groups expanded from 32% to 34% from 1990 to 2010. The lowest income group slightly decreased in the 1990s, and increased again from 2000 to 2010. The total share of the two lowest income groups ended up with a net increase from 24% to 26%. Income groups in the middle decreased.

This trend of relative income polarization is consistent with other evidence. For example, Goodman and Nakosteen (2011), in the report *Diverging Destinies: The Commonwealth's Relatively Robust but Imbalanced Economic Recovery*, show the widening income inequality in Massachusetts and its sub-regions. The study divided households into 5 income quintiles and measured the median income for each quintile from 1980 to 2008. During the 1980s and 1990s, all five quintiles experienced real income growth, but the top group had considerably stronger growth, while growth for the bottom 40% was significantly lower. Between 1999 and 2008, income growth for the highest group slowed down but stayed positive, while households below the state median income experienced a net fall in income. They also observed that the steepest rise in the state's inequality has been in the Greater Boston region, where in 2008 the median family income in the top fifth of families was 10 times that of their counterparts in the bottom fifth, while in 1979, this ratio was only 6.6.

This income distribution change could directly affect vehicle ownership choices and mode choices. If preferences for each income segment stay the same, there would be more 0-vehicle and 2-and-more vehicle households. But car purchases also depend on automobile market trends, as the cost of cars relative to income would also affect these decisions. This would require analysis of the changes in the costs of vehicles over time (including the used car market).

Table 4–3 Household income distributions from 1990 to 2010

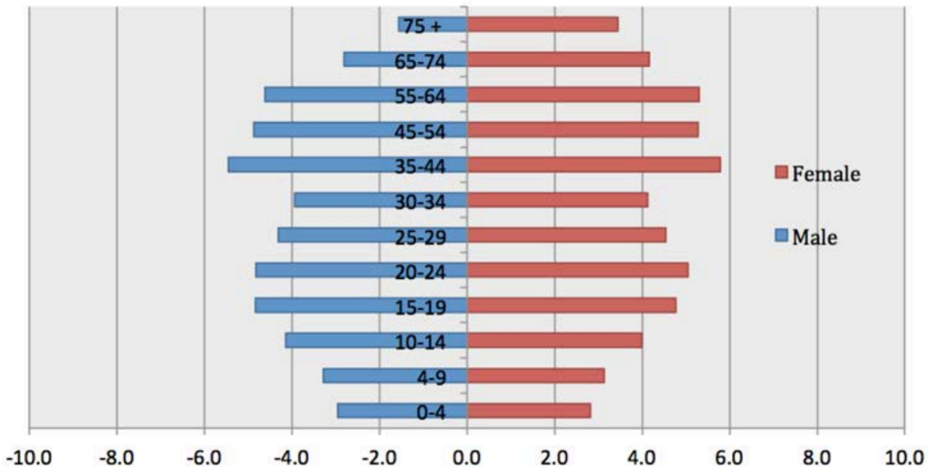
Household income	1990	2000	2010
Less than $15,000	10.5%	9.9%	11.1%
$15,000-$34,999	13.4%	18.4%	14.7%
$35,000-$49,999	10.8%	10.1%	10.5%
$50,000-$74,999	18.7%	13.5%	16.5%
$75,000-$99,999	14.7%	13.8%	13.3%
$100,000-$149,999	16.1%	16.7%	17.6%
$150,000 or more	15.7%	17.5%	16.3%
Total HH	1,507,077	1,642,229	1,689,349

Data source: CTPP 1990, 2000, and 2010. 1990 and 2000 income is converted to 2009 dollars.

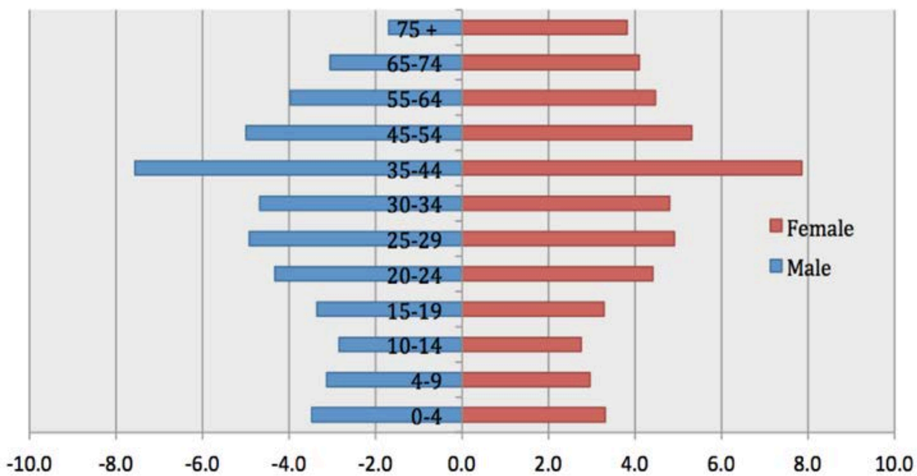
Age structure

Age pyramids display an apparent aging trend (Figure 4-3). Over time the biggest age group is steadily moving upward into the older age bracket. Baby-boomers (born in the 1946-1964 time period), were in the 16-34 year old age group in 1980, with the first of them approaching 64 years old by 2010. The population age structure clearly reflects this generation.

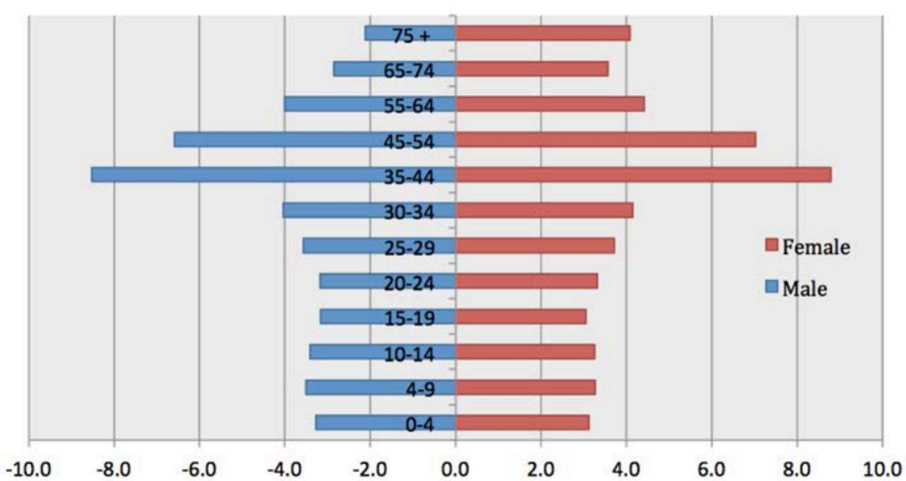
Age, on the one hand, affects individual's travel behavior (such as trip frequency), and on the other hand, is linked to household lifecycle and longer-term decisions (such as residential location choice, vehicle ownership choice etc.). The shift in age composition can trigger a series of changes in various aspects of travel outcomes. Models should be sensitive to the shift in age structure and be able to reflect its impacts.



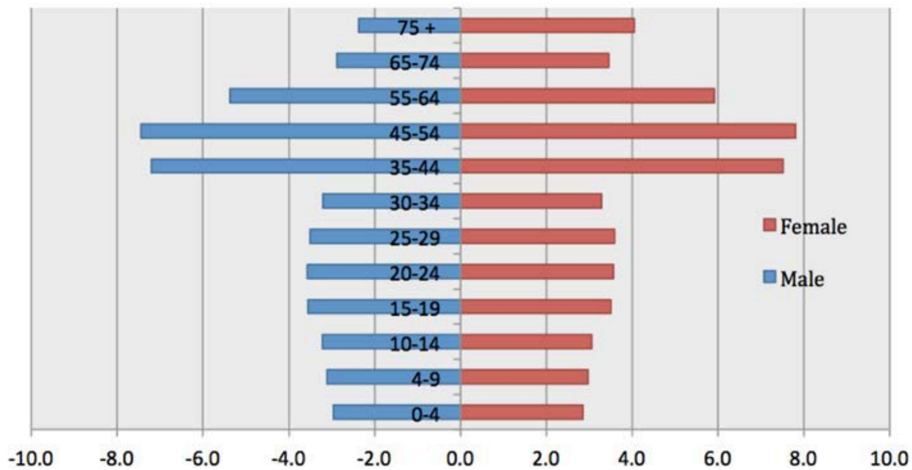
1980



1990



2000



2010

Figure 4-3 Population age structure by gender (1980 -2010)
(Length of the bar is percentage in the population)

Racial and ethnic composition

Another relevant demographic trend is the steady increase in the minority racial and ethnic groups (Table 4–4 Population by racial and ethnic group). The share of the study area's black population increased from 4.6% to 8.6% from 1980 to 2010. The Hispanic population increased more rapidly, surpassing the black population by 2010. The Asian population is also catching up, approaching the levels of the Black population. The percentage of foreign-born population jumped to 16.7% in 2010 from 9.2% in 1980.

The non-white population growth can contribute to behavior uncertainty, since models rarely represents racial differences in preference. Whether these groups' preferences differ should be tested; although "why" they differ cannot be revealed in models alone.

Table 4–4 Population by racial and ethnic group

Year	Black	%	Hispanic	%	Asian	%	Foreign born	%
1980	175,211	4.6	94,138	2.5			352,564	9.2
1990	233,821	5.8	184,440	4.6			430,877	10.8
2000	303,120	7.1	283,481	6.7	222,391	5.2	604,591	14.2
2010	381,285	8.6	417,355	9.4	329,947	7.4	744,055	16.7

Source: NCDB 1980, 1990, 2000 and 2010.

Occupation

Occupation types have undergone a drastic change since 1980. The most remarkable shift is the boom in “Executives, managers, and administrators” and “Professional and technical occupations”; and the decline in “Operators, assemblers, transportation, and material moving workers” and “Administrative support and clerical workers” (Table 4–5, Table 4–6). This shift is consistent with relative de-industrialization and a continued shift towards a “knowledge-based” and service-oriented economy.

Note that the trends are not linear for some occupation categories. The growth in professional and managerial workers has slowed down recently. Sales workers increased by 41% in the 1980s, slightly decreased in the 1990s, and increased again in the 2000s. We can observe fluctuations for Sales workers, Service workers, and Precision production, craft, and repair workers (Figure 4-4).

Changes in the composition of occupation types may affect long-term job location and commute distance, as workers of different occupations may have significantly different distance to work. They can also relate to more flexible working hours, which could change departure times and/or more flexible workplaces, which could change trip distribution. These changes could also cascade into other trips and activity patterns (e.g., trip chaining).

Table 4–5 Numbers of workers by occupation (1980-2010)

					Percentage change			
Occupation	**1980**	**1990**	**2000**	**2010**	**80-90**	**90-00**	**00-10**	**80-10**
Professional and technical occupations	369,040	476,180	583,110	629,000	29%	22%	8%	70%
Executives, managers, and administrators	215,940	329,960	373,720	410,760	53%	13%	10%	90%
Sales workers	167,860	236,040	227,830	241,340	41%	-3%	6%	44%
Administrative support and clerical workers	362,150	369,200	332,460	302,670	2%	-10%	-9%	-16%
Precision production, craft, and repair workers	197,950	190,540	266,240	237,440	-4%	40%	-11%	20%
Operators, assemblers, transportation, and material moving workers	207,360	149,860	54,792	54,988	-28%	-63%	0%	-73%
Nonfarm laborers	62,451	56,425	32,334	31,457	-10%	-43%	-3%	-50%
Service workers	239,340	253,170	282,730	358,000	6%	12%	27%	50%
Farm workers or in forestry and fishing	11,498	14,641	4,233	3,491	27%	-71%	-18%	-70%

Table 4–6 Percentages of workers by occupation (1980-2010)

Occupation	1980	1990	2000	2010
Professional and technical occupations	20.1	22.9	27.0	27.7
Executives, managers, and administrators	11.8	15.9	17.3	18.1
Sales workers	9.2	11.4	10.6	10.6
Administrative support and clerical workers	19.8	17.8	15.4	13.3
Precision production, craft, and repair workers	10.8	9.2	12.3	10.5
Operators, assemblers, transportation, and material moving workers	11.3	7.2	2.5	2.4
Nonfarm laborers	3.4	2.7	1.5	1.4
Service workers	13.1	12.2	13.1	15.8
Farm workers or in forestry and fishing	0.6	0.7	0.2	0.2
Total	100	100	100	100

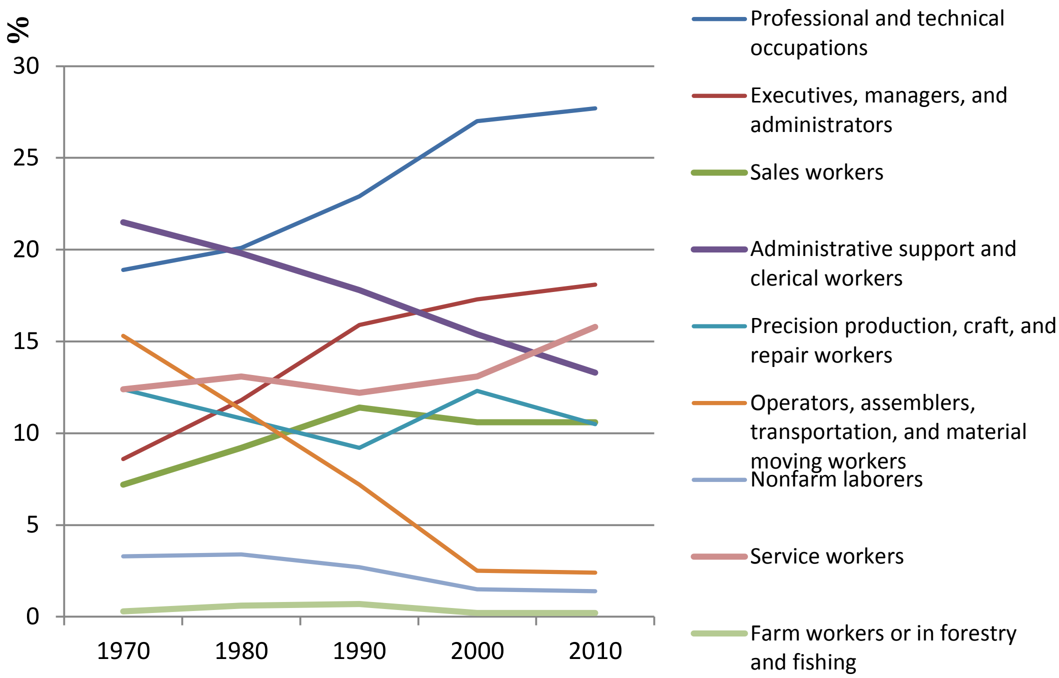


Figure 4-4 Changes in the percentage of occupation types (1970-2010)

Housing

The housing stock has been growing, with the highest growth rate in the 1980s (Table 4–7). Percentage growth of owned housing units is faster than that of rental units. The total amount of rental units increased by 6% in the 1980s, and has not changed much since then. Owned units have expanded by 16%, 11% and 12% respectively in the 1980s, 1990s and 2000s. The share of rental housing has declined from 44% in 1980 to 37% in 2010. Share of vacant units (rental and owned) is volatile, ranging from 3.5% to 6.6%.

Table 4–7 Housing units, growth rates, and vacancy rate

Year	Total units		Owned units		Rental units		Rental share	Share of total vacant units
	Total units	Growth rate	Owned units	Growth rate	Rental units	Growth rate		
1980	1,418,494		791,520		626,974		44.2%	4.5%
1990	1,582,228	11.5%	917,692	15.9%	664,536	6.0%	42.0%	6.1%
2000	1,677,262	6.0%	1,014,744	10.6%	662,518	-0.3%	39.5%	3.5%
2010	1,809,543	7.9%	1,132,774	11.6%	676,769	2.2%	37.4%	6.6%

4.3 Vehicle ownership

Vehicle ownership has also been increasing. From 1980 to 2010, the share of 0-vehicle and 1-vehicle households decreased from 17.8% to 13.4% and from 41.0% to 35.4%; while the share of 2- and 3+vehicle households increased from 30.6% to 36.8% and from 10.6% to 14.4%. In terms of the numbers of households, 0-vehicle households slightly decreased while 2-vehicle and 3-vehicle households increased by 50.0% and 69.3% respectively from 1980 to 2010 (Table 4–8). Total number of vehicles increased by 8.5% and 5.8% respectively in the last two decades. Vehicles per household and vehicles per licensed driver stayed about the same over time; while vehicles per worker slightly increased (Table 4–9).

Overall, these vehicle ownership increases can be attributed to different hypotheses. For example, the increasing population of older adults may have a path-dependence effect, meaning as people age they may keep their cars even when, according to other characteristics, such as income or household structure, we may not expect them to have the same vehicle demands. Relative income may also play a role; if income increases relative to the cost of a car, we would not be surprised to see increased vehicle ownership. In addition, the relative attractiveness of a car may increase due to changes in the spatial structure of the metropolitan area and/or the service quality of alternatives, especially public transport.

Also, the dynamics of car ownership have a lot of variations across space. I select the Metropolitan Core Communities defined by Metropolitan Area Planning Council (MAPC)[3] as an example. As shown in Table 4–10 and Table 4–11, since 1980 the city of Boston has experienced a decrease in the share of 0-vehicle households. From 1990 to 2010, while the total number of households grew by 8%, the total vehicle fleet increased by 13%. This big change in vehicle ownership in Boston is consistent with the *Boston Transportation Fact Book and Neighborhood Profiles (2002),*[4] which also noted that auto registrations in the city increased by 36% from 1990 to 2001 despite a population growth of just 3%. It attributed this growth to new residents, with high-level income moving into the resurging city.

Interestingly, Cambridge reflects the opposite of Boston, showing a somewhat remarkable reduction in vehicles per households. In contrast, Chelsea, Revere, Malden and Everett seemed to be rapidly motorizing in the last two decades. Further analysis is needed to find a proper explanation. Demand models should be able to predict these changes by capturing the underlying causes.

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[3] Massachusetts Community Types
http://www.mapc.org/sites/default/files/Massachusetts_Community_Types_-_July_2008.pdf

[4] Boston Transportation Fact Book and Neighborhood Profiles
http://www.cityofboston.gov/transportation/accessboston/pdfs/front.pdf

Table 4–8 Number of occupied housing units by number of vehicles

Year	0-VEH	1-VEH	2-VEH	3+-VEH	Total occupied housing unit
1980	240,671	555,521	414,528	143,585	1,354,305
1990	225,779	532,609	524,568	202,491	1,485,447
2000	219,570	591,781	605,139	201,413	1,617,903
2010	227,120	597,566	621,787	243,061	1,689,534
% Change					
80-90	-6.2%	-4.1%	26.5%	41.0%	
90-00	-2.8%	11.1%	15.4%	-0.5%	
00-10	3.4%	1.0%	2.8%	20.7%	
Total 80-10	*-5.6%*	*7.6%*	*50.0%*	*69.3%*	
Share					
1980	17.8%	41.0%	30.6%	10.6%	100.0%
1990	15.2%	35.9%	35.3%	13.6%	100.0%
2000	13.6%	36.6%	37.4%	12.4%	100.0%
2010	13.4%	35.4%	36.8%	14.4%	100.0%

Source: NCDB 1980, 1990, 2000 and 2010.

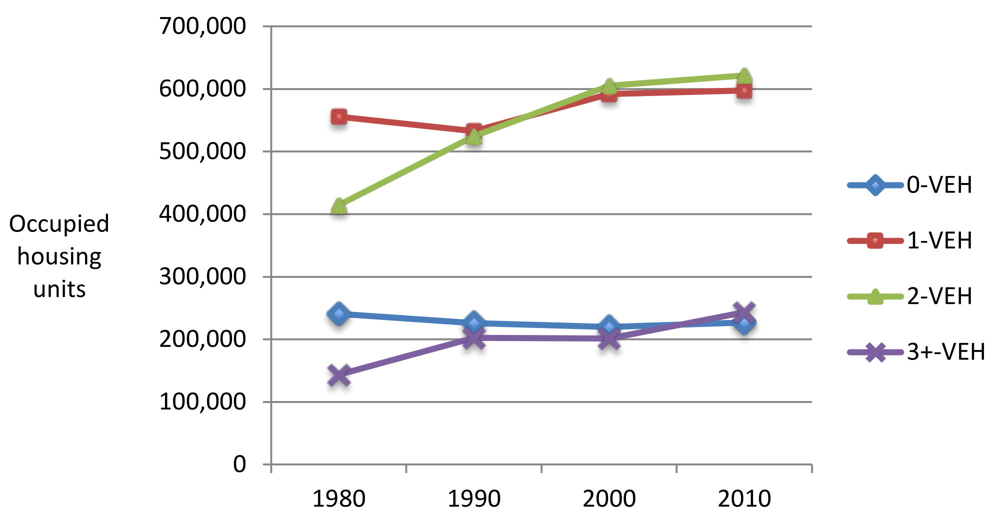

Figure 4-5 Changes in occupied housing units by vehicle ownership from 1980 to 2010

Table 4–9 Total cars, cars per household and worker in 1990, 2000 and 2010

Year	Total vehicles	% Change	Licensed drivers	Cars per household	Cars per worker	Cars per licensed driver
1990	2,312,803		2,662,018	1.54	1.16	0.87
2000	2,508,585	8.5%		1.53	1.19	
2010	2,653,793	5.8%	3,057,313	1.54	1.20	0.87

Source: Licensed driver data is from BTS and MTS. Rest of the data is from CTPP.

Note: Total households and total workers used to calculate cars per HH and cars per worker are from CTPP, which are slightly different from the totals from Geolytics.

Table 4–10 Share of vehicle ownership in Metropolitan Core Communities (1990 vs. 2010)

	Veh0		Veh1		Veh2		Veh3+	
Town	**1990**	**2010**	**1990**	**2010**	**1990**	**2010**	**1990**	**2010**
Boston	37.3%	35.9%	41.9%	42.0%	16.6%	17.6%	4.1%	4.4%
Cambridge	27.8%	32.0%	51.5%	48.8%	17.4%	16.4%	3.2%	2.9%
Chelsea	38.0%	32.2%	39.0%	44.7%	18.0%	18.9%	4.9%	4.3%
Everett	20.7%	17.8%	44.8%	44.4%	26.5%	26.5%	7.9%	11.2%
Malden	19.2%	19.6%	43.9%	40.9%	28.7%	28.6%	8.1%	10.8%
Revere	20.7%	17.1%	45.3%	45.0%	25.4%	29.5%	8.6%	8.5%
Somerville	24.2%	24.0%	47.1%	46.1%	21.2%	22.6%	7.6%	7.3%

Source: CTPP 1990, 2010

Table 4–11 Total vehicles and total households changes in Metropolitan Core Communities

	Total cars		Total households		Cars per household			
	1990	**2010**	**1990**	**2010**	**1990**	**2010**	**% Change in cars**	**% Change in HH**
Boston	201,448	227,706	226,257	244,534	0.89	0.93	13%	8%
Cambridge	38,635	41,968	39,807	46,321	0.97	0.91	9%	16%
Chelsea	9,371	11,464	10,333	11,823	0.91	0.97	22%	14%
Everett	18,126	20,736	14,559	15,174	1.25	1.37	14%	4%
Malden	27,889	31,532	21,624	23,520	1.29	1.34	13%	9%
Revere	21,195	25,165	16,992	18,869	1.25	1.33	19%	11%
Somerville	34,108	36,924	29,656	31,828	1.15	1.16	8%	7%

Source: CTPP 1990, 2010

4.4 Trip characteristics

Data used to describe trip characteristics come mainly from the 1991 Boston Household Travel survey (BTS) [5]and the 2010-2011 Massachusetts Travel Survey (MTS)[6].

Trip definition

Note an important distinction between the BTS and MTS on how trips were recorded. BTS was a trip-based survey, while MTS was an activity-based survey. In BTS, each trip is a record, with no detailed information for each leg of a trip, except for the modes used within the trip. For MTS, on the other hand, each activity place is a record, with information on the start and end time of the stay, and the trip information recorded in-between the stays. By connecting two consecutive stays, the leg of a trip is formed. But this leg is not directly comparable with a trip in BTS. For comparability, I consolidated the legs of the same trip and made a trip table consistent with the BTS. I identified a leg within a trip by checking the destination purpose: a “transition” (between modes) represents a leg of the trip. A trip is completed when reaching a non-transition destination. To represent the population for each year, I used the respective expansion factors as provided in the surveys. Table 4–12 summarizes the statistics for the sample and its expansion to the population.

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[5] http://www.surveyarchive.org

[6] http://www.massdot.state.ma.us/planning/Main/MapsDataandReports/Reports/TravelSurvey.aspx

Table 4–12 Summary statistics for BTS and MTS

	1991		2011		% Change (1991-2011)
	Sample	Population	Sample	Population	
Households	3,906	1,509,050	10,408	1,702,907	12.8%
Persons	10,003[a]	3,870,730[b]	26,182	4,507,604	16.5%
Age 16+	7,923	3,009,616	20,890	3,596,211	19.5%
Workers	5,872	2,181,339	13,894	2,324,114	6.5%
(% of persons)	58.7%	56.4%	53.1%	51.6%	
(% of age16+)	74.1%	72.5%	66.5%	64.6%	
Students	2,474	985,891	7,182	1,328,478	34.7%
Licensed drivers	7,196	2,662,018	18,596	3,057,313	14.8%
Vehicles	6,488	2,318,211	18,124	2,736,237[c]	18.0%
Total trips	39,934	15,764,745	95,407	15,752,164	-0.1%
Trips/person	4.0	4.1	3.6	3.5	-14.6%
Trips/household	10.2	10.5	9.2	9.3	-11.4%

a. The difference between the number of persons in the Person table in BTS (9,256) and that in the household table (sum of household size=10,003) is mainly due to the absence of children under 5 years old and guests. (e.g. 835 persons under 5; only 86 appear (birth year>=1986) in the Person table. b. Expanded from Household table using household expansion weight, because of the reason in note a. c. Note that this is about 100K more (or 3% more) than the total vehicles from CTPP (Table 4–9).

Trip frequency

Overall, people made fewer trips in 2010 than in 1991. From 1991 to 2010, total trips stayed about the same, while households and population increased by 12.8%[7] and 16.5%. Trips per person decreased by 14.6% and trips per household decreased by 11.4% (Table 4–12).

Trip frequency by purpose shows a decline in home-based work (HBW) trips (Table 4–13, Figure 4-6). The total of HBW and home-based work-related (HBWR) trips had a net decrease of 10%. Since the non-home-based work (NHBW) trip rates also declined, the

[7] This is based on expanded survey data. Survey data is not as reliable in terms of total numbers.

decline in HBW and HBWR trips was unlikely due to more trip-chaining (i.e., fewer direct HBW trips) within the commute. Several hypotheses may explain this: 1) fewer workers going to work (e.g., working from home); 2) more flexible work schedules; and 3) less travel during work time. Most home-based non-work trips (HBNW) decreased except home-based recreation (HBRec) trips, and home-based pick-up and drop-off trips (HBPuDo).

Table 4–13 Trip frequency by origin-destination purposes

	1991			2011			
	Total trips	**Trips /person**	**Trips /hh**	**Total trips**	**Trips /person**	**Trips /hh**	**% Change in trips/hh**
HBW	2,552,980	0.66	1.69	2,470,854	0.55	1.45	-14%
HBWR	219,259	0.06	0.15	348,712	0.08	0.20	38%
HBW&HBWR	*2,772,239*	*0.72*	*1.84*	*2,819,566*	*0.63*	*1.65*	*-10%*
HBSc	1,298,129	0.34	0.86	1,437,981	0.32	0.84	-2%
HBPuDo	1,153,038	0.30	0.76	1,488,843	0.33	0.87	14%
HBSh	1,644,829	0.42	1.09	1,527,740	0.34	0.9	-17%
HBBPB	1,441,760	0.37	0.96	1,547,371	0.34	0.91	-5%
HBEat	569,177	0.15	0.38	593,402	0.13	0.35	-7%
HBSo	959,022	0.25	0.64	793,764	0.18	0.47	-26%
HBRec	826,890	0.21	0.55	1,247,419	0.28	0.73	33%
HBO	74,355	0.02	0.05	72,693	0.02	0.04	-19%
NHBW	2,456,111	0.63	1.63	1,522,718	0.34	0.89	-45%
NHBO	2,521,553	0.65	1.67	2,691,840	0.6	1.58	-5%
Home-home[8]	13,179	0.00	0.01	8,828	0.00	0.01	15%
Total	15,730,282	4.06	10.42	15,752,164	3.49	9.25	-11%

HBW: home-based work; HBWR: home-based work-related; HBSc: home-based school; HBPuDo: home-based pick-up and drop-off; HBSh: home-based shopping; HBBPB: home-based bank and personal business; HBEat: home-based eating; HBSo: home-based social; HBRec: home-based recreation; HBO: home-based other; NHBW: non-home-based work; NHBO: non-home-based other.

[8] Trip from home to home.

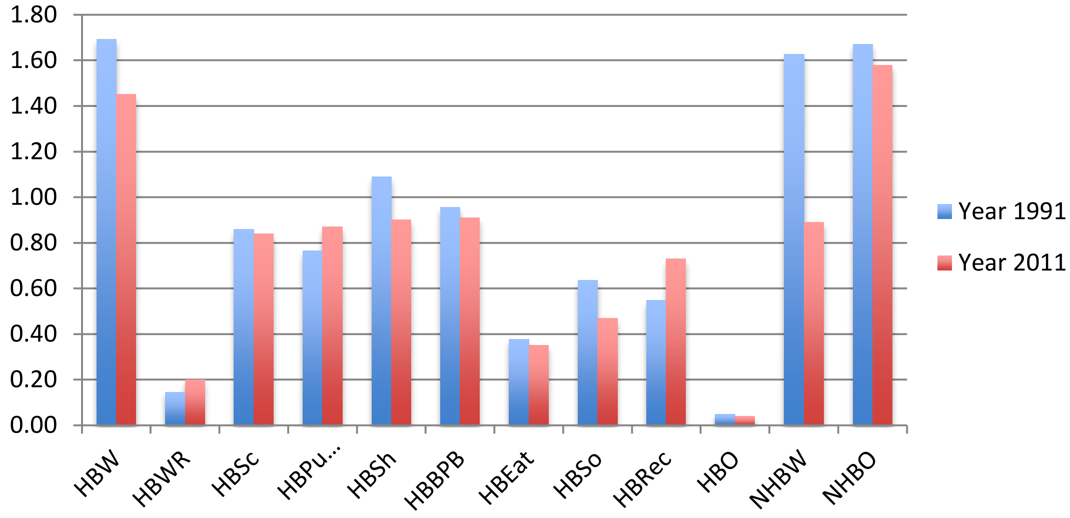


Figure 4-6 Average daily trips per household by trip purpose (1991 vs. 2011)

Trip distances

Here I measure travel distance by the Euclidean distance between the origin and destination, geocoded at the census block centroids (resulting in calculated distances which are shorter than the actual travel distances).

The longest trips are HBW and HBWR, which increased by 1.8 km and 3.1km, respectively between 1991 and 2011. Home-based recreational, home-based work-related, non-home-based work and work-related trips, home-based social trips have the largest relative increases in distances.

Table 4–14 Trip origin-destination Euclidean distance (1991 vs. 2011)

	Mean (KM)			Standard Deviation		Expanded sample size	
Purpose	**1991**	**2011**	**%Change**	**1991**	**2011**	**1991**	**2011**
HBW	11.2	13.0	17%	11.6	13.2	2,419,421	2,414,440
HBWR	10.0	13.1	32%	11.2	16.2	203,187	330,253
HBSc	4.6	4.8	5%	7.2	7.6	870,100	1,429,411
HBPuDo	4.4	4.4	-1%	6.1	6.6	1,144,124	1,471,588
HBSh	4.3	4.5	5%	5.8	6.1	1,582,028	1,477,979
HBBPB	5.0	6.4	28%	6.8	10.1	1,384,720	1,518,959
HBEat	5.9	6.2	5%	9.3	9.4	544,702	581,605
HBSo	6.2	8.1	31%	8.9	14.7	906,690	768,479
HBRec	5.1	6.9	37%	6.6	12.1	796,728	1,208,522
NHBW	6.5	8.6	32%	9.1	12.9	2,301,205	1,461,121
NHBO	5.0	5.4	9%	7.2	9.4	2,391,116	2,599,711

Source: BTS1991 and MTS2010

Trip times

Travel time for all trip purposes except for home-based pick-up/drop-off trips increased. Home-based work trip time increased from 26 to 33 minutes. Travel time for HBWR, HBBPB, and HBSo trips increased by more than 50%. Note that the increase in travel time is in general greater than the increase in distance, implying worsened congestion.

Table 4–15 Travel time by trip purpose (1991 vs. 2011)

	Mean (minutes)			Standard Deviation	
PURPOSE	**1991**	**2011**	**%Change**	**1991**	**2011**
HBW	26	33	27%	20	24
HBWR	23	36	57%	18	50
HBSc	20	22	10%	17	19
HBPuDo	13	13	0%	19	12
HBSh	13	16	23%	11	15
HBBPB	14	21	50%	14	29
HBEat	16	19	19%	14	19
HBSo	16	24	50%	13	44
HBRec	15	22	47%	12	30
NHBW	17	23	35%	14	27
NHBO	14	17	21%	23	23

Source: BTS1991 and MTS2010

Modes

For all trip purposes, auto mode share slightly decreased from 77.8% to 75.9%, while transit (including transit mixed with others) share increased from 5.0% to 7.6%. The share of “walk-only” trips decreased by 2 percent (Table 4–16)

Table 4–16 Mode share for trips of all purposes

	1991		2010	
	Frequency	**Share**	**Frequency**	**Percent**
Walk only	1,889,897	12.6	1,652,464	10.5
Bike only	136,439	0.9	215,829	1.4
Car only	*11,638,426*	*77.8*	*11,960,329*	*75.9*
Car driver only			8,718,011	55.3
Car passenger only			3,242,318	20.6
Public transit	*734,820*	*5.0*	*1,194,945*	*7.6*
Bus only	234,533	1.6	397,034	2.5
Rail only	278,048	1.9	403,759	2.6
Rail & bus	97,732	0.7	162,672	1.0
Rail & car	93,332	0.6	188,894	1.2
Bus & car	24,484	0.2	23,775	0.2
Rail, bus and car	6,691	0.0	18,811	0.1
School bus	434,726	2.9	517,547	3.2
Other	118,773	0.8	209,972	1.3
Total	14,953,081	100	15,751,085	100

For HBW trips, auto share decreased from 81% to 73%; while transit share grew from 11% to 18%. Among the transit modes, rail only and rail & car increased the most (Table 4–17). The usual mode to work self-reported by workers is consistent with the mode share of HBW trips observed on the survey day (Table 4–18). The decrease in auto share for commute trips is potentially a result of the resurgence of jobs and residents in the urban core (see section 4.5).

Table 4–17 Mode share for HBW trips

	1991		2011	
Mode	**N**	**Percent**	**N**	**Percent**
Walk only	140,159	5.5	121,540	4.9
Bike only	31,489	1.2	51,223	2.1
Car only	*2,062,764*	*81.2*	*1,799,784*	*72.8*
Car driver only			1,658,850	67.1
Car Passenger only			140,934	5.7
Public transit	*276,910*	*10.9*	*451,031*	*18.3*
Bus only	63,362	2.5	83,260	3.4
Rail only	84,948	3.3	159,823	6.5
Bus&rail	54,047	2.1	71,922	2.9
Bus&car	16,047	0.6	10,019	0.4
Rail&car	52,919	2.1	116,017	4.7
Bus&rail&car	5,587	0.2	9,991	0.4
School bus	1,066	0.0	2,928	0.1
Other	27,565	1.1	44,123	1.8
Total	2,539,953	100.0	2,470,629	100.0

Table 4–18 Usual mode to *work* in 2011 (self-reported in MTS)

	Frequency (Expanded population)	**Percent**
Total	2,324,114	100.0
Work at home	158,862	6.8
Go to work	2,165,253	93.2
Walk	119,915	5.2
Bike	47,983	2.1
Auto/Van/Truck Driver	1,481,627	63.8
Auto/Van/Truck Passenger	78,357	3.4
Bus/Public Transit	377,175	16.2
Dial-A-Ride/Para-transit	3,381	0.1
Taxi	3,868	0.2
Motorcycle Driver	1,433	0.1
Motorcycle Passenger	181	0.0
Other	40,063	1.7
Don't know or refused	11,270	0.5

Working-at-home

A home-based worker is defined as a worker who works at home for the majority of days in a week. According to census data, the percentage of home-based workers increased from 1.4% in 1980 to 4.0% in 2011 (Table 4–19).

The MTS estimation of home-based workers in 2011 is 6.8%, higher than the 4.0% from the census. MTS also surveyed the percentage of workers that occasionally telecommute. This share is 23.6% (Table 4–20).

Surprisingly, 24% of the workers in MTS did not travel to work on the survey day. Among workers not travelling to work, 18.0% travel without going to work; 5.8% stay at home, with no travel at all.[9] Part of reason for this is that workers who occasionally worked at home are not classified as home-based workers. They may stay at home on the survey day for various reasons. Work trips per worker decreased from 1.1 to 0.8. Work-related trips per worker stayed the same (Table 4–21).

Table 4–19 Percentages of working-at-home workers from 1980 to 2010

Year	Total workers	Percentage of workers that usually worked at home in the last week
1980	1,799,287	1.4%
1990	2,044,974	2.4%
2000	2,117,656	3.2%
2010	2,211,714	4.0%

Source: NCDB 1980, 1990, 2000 and 2010

[9] In 1991 BTS: among 2,044,088 workers, 87% go to work. The rest 13% travelled somewhere but not to work. Note that 1991BTS does not include people with 0 trips.

Table 4–20 Percentage of workers who usually work from home and workers who telecommute in 2011 (MTS)

	Sample		Population	
	Frequency	Percentage	Frequency	Percentage
Workers	13,892	100.0%	2,324,114	100.0%
Usual mode to work is "Work from home"	1,079	7.8%	158,862	6.8%
Tele commute	3,715	26.7%	549,135	23.6%

Note: No survey data for 1991

Table 4–21 Work and work-related trips per worker

	Sample		Population	
	1991	2011	1991	2011
Work trips	6,388	11,186	2,393,516	1,839,990
Work trips per worker	1.19	0.81	1.10	0.79
Work trips per worker who actually went to work	1.35	1.05	1.26	1.04
Work-related trips	1,197	3,265	435,829	498,762
Work-related trips per worker	0.22	0.24	0.20	0.21
Work-related trips per worker who went to work	0.25	0.31	0.23	0.28

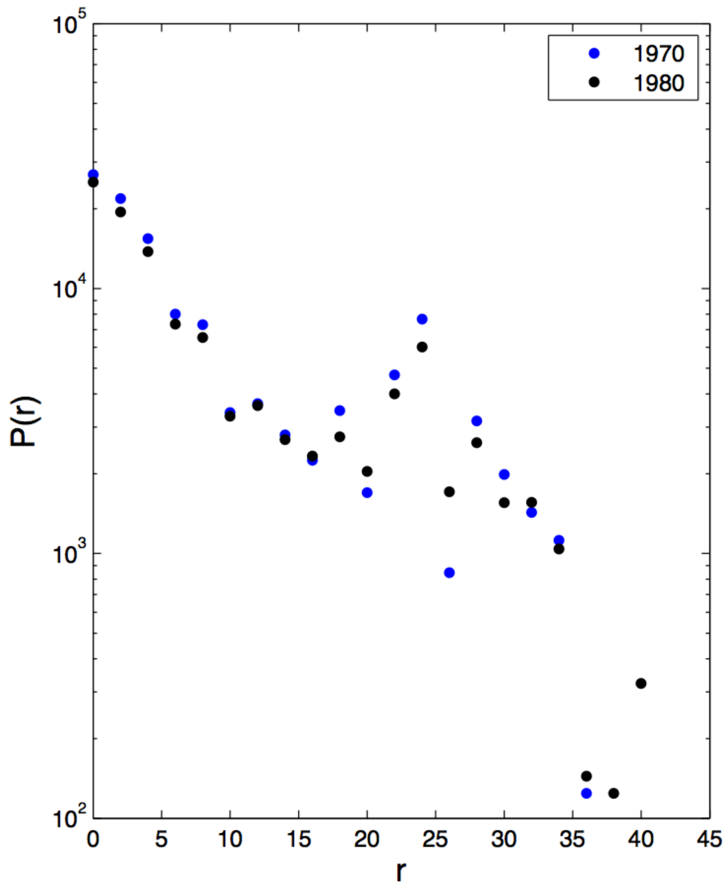
Source: MTS2010 and BTS1990

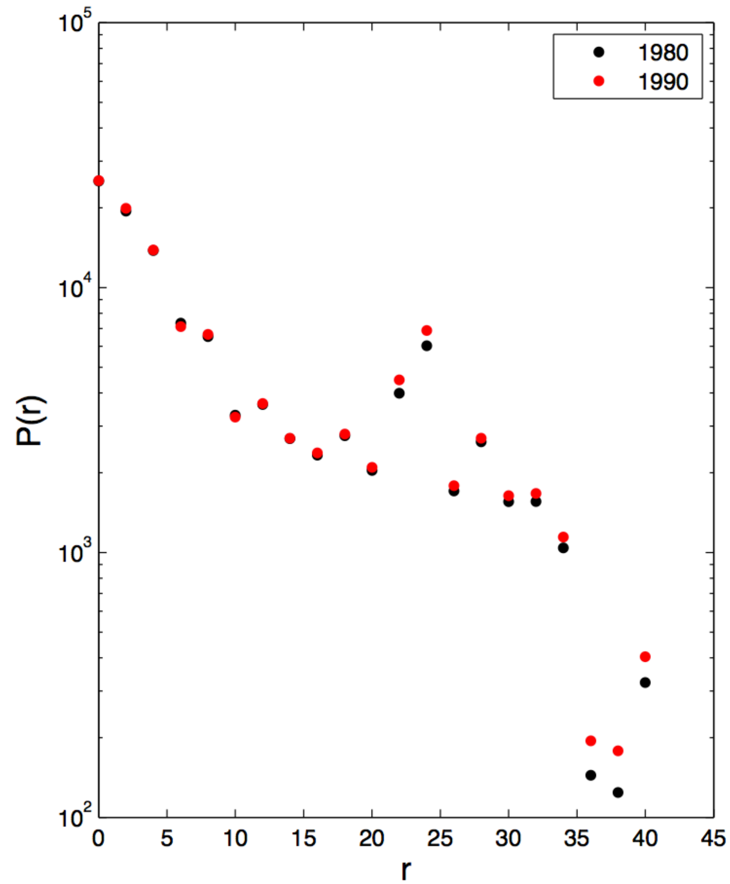
4.5 Land use: population and job density

Major trends in population density changes at different distances from the CBD are summarized as (Figure 4-7):

- 1970-1980: population density significantly decreased in the center and sub-centers (both the inner core and the suburban centers). Population density increased on the periphery of these centers.
- 1980-1990: density only increased in the outer cities and suburbs about 25 miles from the CBD.
- 1990-2000: Density in the historic center started to grow.
- 2000-2010: Density in the historic center significantly increased.

Job density has been increasing since 1990 in the urban core and outer suburbs (Figure 4-8). The resurgence of the inner core neighborhoods may not have been expected 20 years ago. This trend may have impacted travel patterns, such as the observed increases in commute distance and time, as more people commute from suburbs to the inner cores. The shift of commute travel mode to transit can also be related to this. Increased roadway congestion and the slower speeds of transit may have contributed to the travel time increase for the journey to work.


1970
1980
P(r)
r


1980
1990
P(r)
r

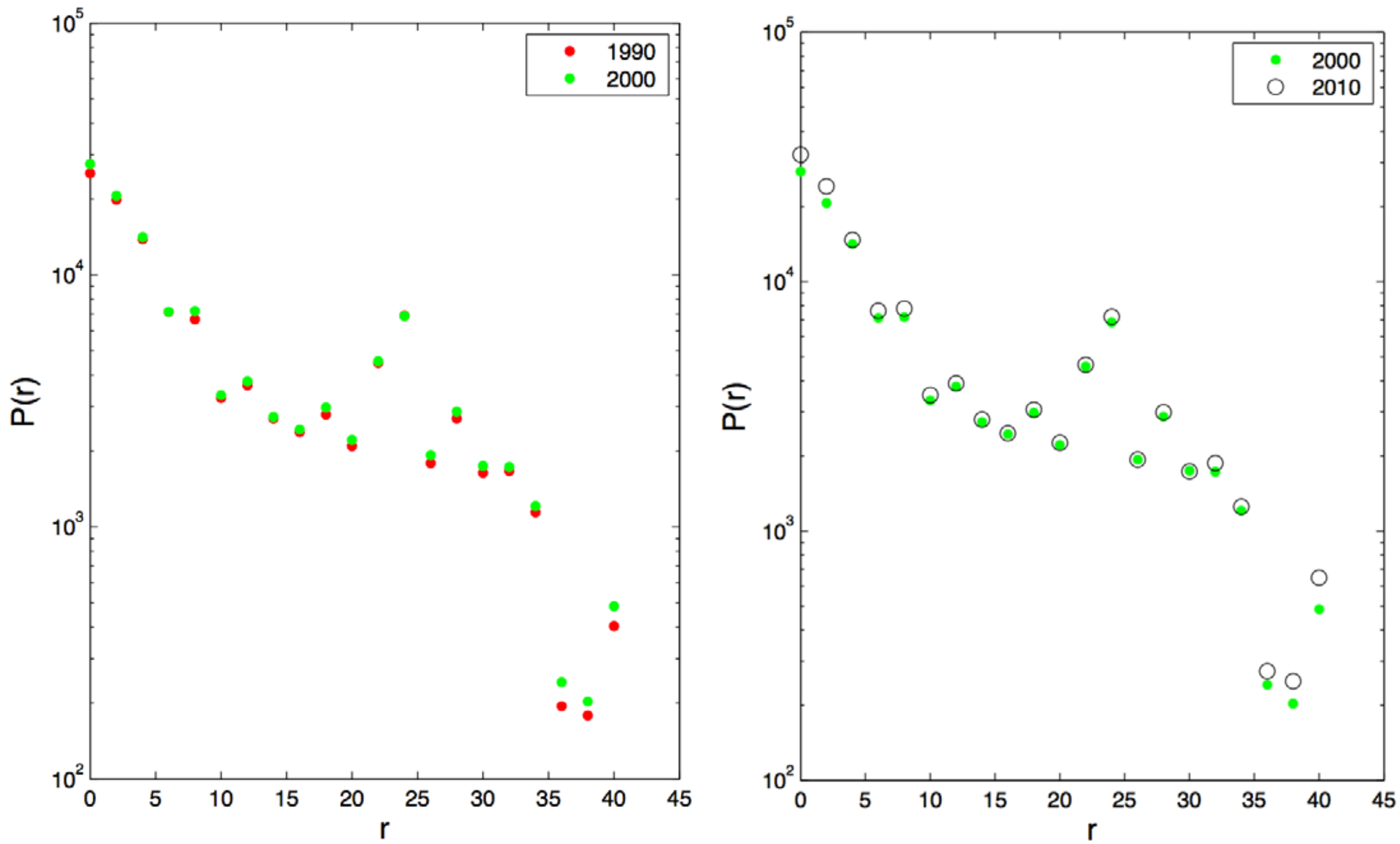


Figure 4-7 Population density changes at different distances to CBD (1980-2010)

Note: r is the distance to CBD measured in miles. Y-axis is the population density measured in persons per square miles plotted on logarithm scale.

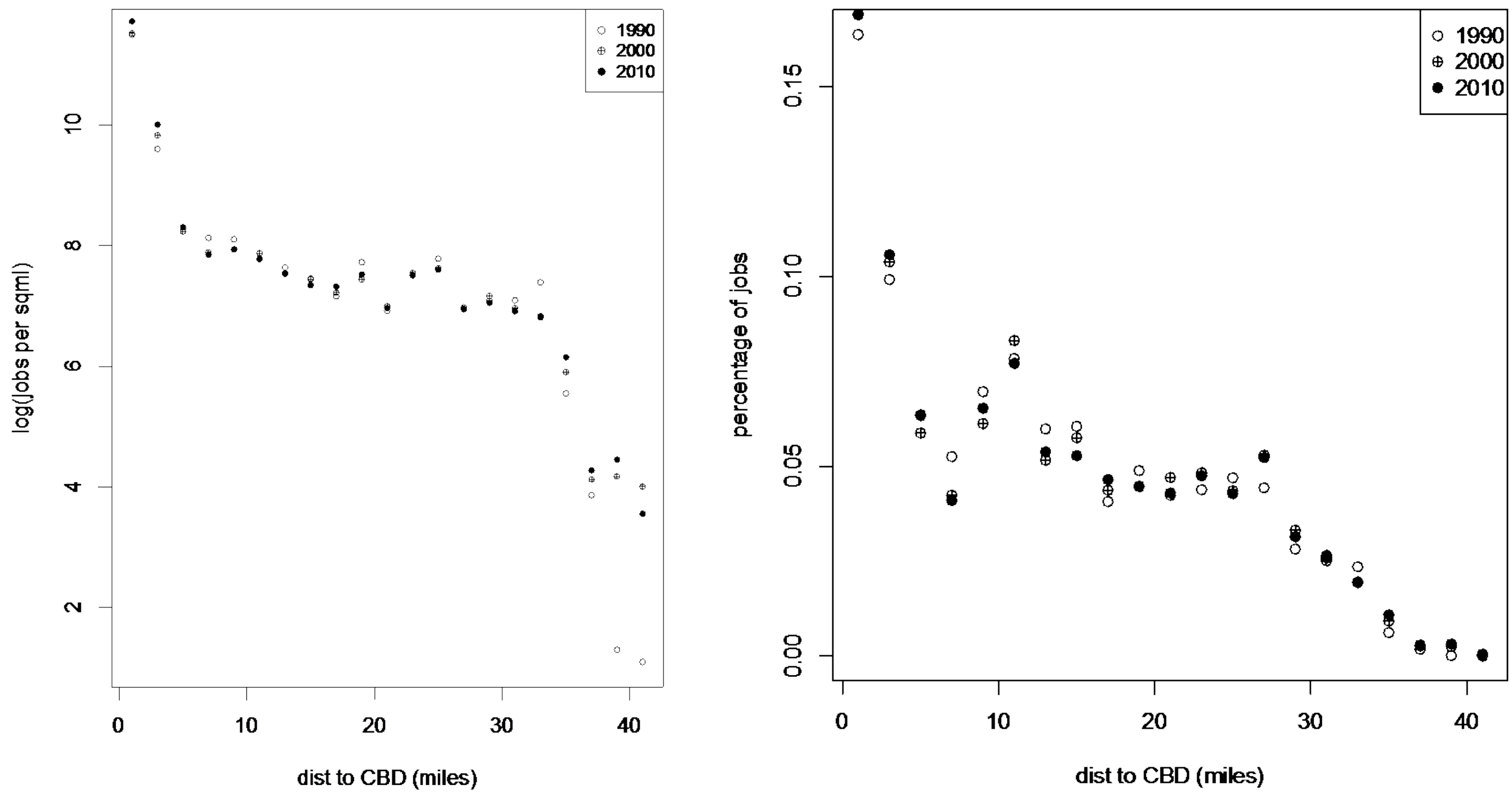


Figure 4-8 Changes in job density and percentage of jobs at different distances to CBD (1990-2010)

4.6 Summary

This chapter has depicted changes in various aspects of the demographic inputs and travel behaviors. Changes in the number of workers, household size, income, racial composition, occupation, and density seem more unexpected compared to population growth rate and age structure. Future studies should compare the historical forecasts with the reality, and quantitatively describe the degree of uncertainty associated with each input and their correlations. Such knowledge should be incorporated into future scenario formulations.

Changes in aggregate behavior are often a result of changed demographic inputs and/or preferences. A qualitative description can hardly tell the underlying causes. I can only propose hypothesis for further analysis. However, a transferable model given accurate input projections should be able to replicate the observed changes. If not, it would be either because preferences have changed or the models are insufficient (for example, when certain important aspects are omitted from the model). In the next two chapters, I focus on the transferability of vehicle ownership and trip generation models, and the underlying behavior and model uncertainty.

Chapter 5
Temporal transferability of vehicle ownership models

This chapter evaluates behavior uncertainty and model uncertainty in vehicle ownership models using temporal transferability tests. Statistical tests of model equality and parameter differences between 1991 and 2011 models reveal preference changes over time; that is, behavioral uncertainty. I perform prediction tests at two levels. At a disaggregate level, I compare the transferability of various model specifications, examining the uncertainty in model specification. At an aggregate forecast level, I apply a single model specification form with parameter estimates from two different years' survey data to the population in 2010. The predicted vehicle ownership shares are compared with those observed from Census Journey to Work (CTPP) data. I also examine the sampling distribution of the prediction to reveal the sampling uncertainty from the survey data.

5.1 Data summary

I use the Massachusetts Travel Survey 2010-2011 (MTS) and the Boston Household Travel Survey 1991 (BTS) for vehicle ownership modeling. The two surveys have comparable household information and vehicle ownership data. The household observations are geocoded at the center of the census block. I select households within the study area – 986 Traffic Analysis Zones (TAZ) (see Section 4.1), resulting in a total of 3,502 and 9,660 observations in BTS and MTS, respectively. Table 5–1 summarizes household characteristics and vehicle ownership from the two surveys.

Table 5–1 Summary of sample statistics of BTS91 and MTS11

		BTS91		MTS11	
		Count	**Percent**	**Count**	**Percent**
Total HH		3,502	100.0	9,660	100.0
Cars					
	0	368	10.5	1,026	10.6
	1	1,208	34.5	3,037	31.4
	2	1,438	41.1	3,803	39.4
	3+	488	13.9	1,794	18.6
Size					
	1	804	23.0%	2,531	26.2%
	2	1,245	35.6%	2,987	30.9%
	3	596	17.0%	1,706	17.7%
	4	542	15.5%	1,648	17.1%
	5+	315	9.0%	788	8.2%
Workers					
	0	488	13.9%	1,950	20.2%
	1	1,312	37.5%	3,462	35.8%
	2	1,335	38.1%	3,457	35.8%
	3+	367	10.5%	791	8.2%
Children					
	0	2,669	76.2%	6,425	66.5%
	1	423	12.1%	1,339	13.9%
	2+	410	11.7%	1,896	19.6%
Seniors					
	0	2,862	81.7%	7,788	80.6%
	1	414	11.8%	1,248	12.9%
	2+	226	6.5%	624	6.5%
Income[a] *(In 2010 dollars)*	<35K	508	14.5%	2,005	20.8%
	35-50K	994	28.4%	888	9.2%
	50-75K	896	25.6%	1,563	16.2%
	75-100K	561	16.0%	1,455	15.1%
	100-150K	244	7.0%	1,937	20.1%
	>150K	299	8.5%	1,812	18.8%
Race	White	n.a.	n.a.	8,311	86.0%
	Black	n.a.	n.a.	474	4.9%
	Asian	n.a.	n.a.	224	2.3%
	Others	n.a.	n.a.	651	6.7%

a. The original income categories in BTS91 are: Less than 20; 20-40K; 40-60K; 60-80K; 80-100K and more than 100K. It is roughly comparable with the combined categories in MTS10.

Built environment and location characteristics come from a range of other data sources (Table 5–2). I calculate the accessibility ratio as the ratio of transit accessibility over auto accessibility, using a gravity-based measure (Eq. 5-1). A_i^m denotes TAZ i's (household's "home TAZ") potential access to all job opportunities in the metropolitan area by mode m. w_j denotes TAZ j's share of all jobs in the metropolitan area.

The impedance function (f_{ij}) selected is gamma function (Eq. 5-2). Impedance t_{ij} is free flow travel time between TAZ OD pair i and j, derived from a base year four-step model for Boston metropolitan area. I obtained values for the parameters (b= –0.503 and c= –0.078) from those recommended for home-based work trips for large MPO's in the USA (NCHRP Report 716, 2012, pp.47, Table 4-5). Parameter a is not used since it will be cancelled in the ratio of the accessibility. Ideally, the gamma function parameters should be calibrated for the study area in the trip distribution step. Since the Boston four-step model[10] is still in the process of updating for 2010, I used the NCHRP recommended parameter values instead.

$$A_i^m = \sum_{j \epsilon L} w_j * f_{ij} * 100 \tag{5-1}$$

$$f_{ij} = a * t_{ij}^b * e^{c * t_{ij}} \tag{5-2}$$

[10] A four-step model implemented in Cube Voyager is developed by Mikel Murga for the study area.

Table 5–2 Measurements for built environment and location characteristics

BE variables	Specifics	Geographical level or precision	Data sources
Distance to CBD	CBD: Government Center Subway Station. Unit: km	Household geocoded at the centroid of census block	
Access to subway	Dummy: 1 if within 800 meters to any subway station; 0 otherwise.		Subway system GIS shape files
Access to commuter rail	Dummy: 1 if within 800 meters to any commuter rail station; 0 otherwise.		Commuter rail system GIS shape files
Population density	Persons/square miles $*10^{-3}$	TAZ	Census Journey-to-work (CTPP)
Job-worker balance (JWR)	Total jobs/total workers	TAZ	Census Journey-to-work (CTPP)
Accessibility ratio	$\frac{Job\ accessibilty\ by\ transit}{Job\ accessibilty\ by\ auto}*100$	TAZ	Census Journey-to-work (CTPP); Free-flow travel time skim from Boston 4-step transport model
Percentage of 4-way intersections		TAZ	MassGIS TIGER files for 1990 and 2010.
Road intersections per kilometer		TAZ	MassGIS TIGER files for 1990 and 2010.

5.2 Model specifications and estimation

The vehicle ownership model has a logit model structure (see Chapter 3 for details). The choice set consists of 0, 1, 2, 3+ vehicles as alternatives. Predictors include household characteristics and built environment variables. Table 5–3 shows the different model specifications. The variable representing the household's race (categorical variable for race composition in the household) is only available for 2010. I estimated models of different specifications for 1991 and 2010, including a specification directly implementable in a four-step model in Cube (MCube). Note that by sequentially adding sets of variables, the complexity increases. Table 5–4 and Table 5–5 show the coefficients estimates for 1991 and 2010. Table 5–6 lists the model estimates for the Cube model specification (MCube) separately, as it is a simplified version. Table 5–7 and Table 5–8 summarize the model fit for all specifications.

Table 5–3 Vehicle ownership model specifications

	Explanatory variables	**M1[b]**	**M2**	**M3**	**M4**	**M5**	**M6**	**M7**	**M Cube**
Socio-demographics	Household size	✓	✓	✓	✓	✓	✓	✓	✓
	Number of workers	✓	✓	✓	✓	✓	✓	✓	✓
	Income level (6 levels)	✓	✓	✓	✓	✓	✓	✓	
	Income level (4-levels)								✓
	Number of children		✓	✓	✓	✓	✓	✓	
	Number of seniors		✓	✓	✓	✓	✓	✓	
	Race[a]							✓	
Transit access	Within 800m to subway	✓	✓	✓	✓	✓	✓	✓	✓
	Within 800 m to commuter rail	✓	✓	✓	✓	✓	✓	✓	✓
	Accessibility ratio: transit/auto			✓	✓	✓	✓	✓	✓
Built environment	Distance to CBD (km)				✓	✓	✓	✓	✓
	Distance to CBD squared				✓	✓	✓	✓	✓
	LN: Population density					✓	✓	✓	✓
	LN: Jobs/workers					✓	✓	✓	✓
	Road intersections per km						✓	✓	
	% of 4-way intersections						✓	✓	

a. Race in MTS is the racial category of the household. It consists of 7 categories: White Alone; Black or African American Alone; American Indian or Alaskan Native Alone; Asian Alone; Native Hawaiian, Pacific Islander Alone; Some Other Race Alone; and Two or More Races.

b.

Model 1: basic demographic characteristics and transit access.

Model 2: add number of children, and senior people

Model 3: add job accessibility measure (transit VS auto)

Model 4: add distance to CBD and squared distance to CBD

Model 5: add population density and job-worker ratio.

Model 6: add road intersection density and percentage of 4-way intersections

Model 7: add race (only for 2010)

Model Cube: a simplified model version implemented in a four-step model in Cube.

Table 5–4 Vehicle ownership model estimation results for 1991 (BTS)

	M1			M2			M3			M4			M5			M6		
	B	SE		B	SE		B	SE		B	SE		B	SE		B	SE	
1:(intercept)	0.936	0.163	***	0.639	0.208	**	0.722	0.210	***	-0.657	0.373		-0.117	0.514		-0.337	0.596	
2:(intercept)	-2.210	0.268	***	-2.411	0.301	***	-2.185	0.304	***	-4.576	0.471	***	-3.356	0.608	***	-3.606	0.719	***
3:(intercept)	-2.836	0.415	***	-3.429	0.449	***	-3.160	0.452	***	-5.992	0.626	***	-4.687	0.758	***	-4.661	0.926	***
1:Size: 2-pers	0.594	0.180	***	0.400	0.198	*	0.367	0.201		0.414	0.203	*	0.406	0.204	*	0.409	0.204	*
2:Size: 2-pers	2.638	0.234	***	2.536	0.249	***	2.523	0.253	***	2.599	0.257	***	2.571	0.258	***	2.572	0.258	***
3:Size: 2-pers	1.329	0.353	***	1.129	0.369	**	1.121	0.372	**	1.204	0.375	***	1.177	0.376	**	1.183	0.376	**
1:Size: 3-pers	1.296	0.328	***	1.426	0.380	***	1.349	0.382	***	1.363	0.386	***	1.340	0.391	***	1.358	0.392	***
2:Size: 3-pers	3.889	0.361	***	4.301	0.410	***	4.254	0.415	***	4.295	0.419	***	4.255	0.424	***	4.275	0.425	***
3:Size: 3-pers	3.694	0.437	***	4.205	0.484	***	4.165	0.488	***	4.205	0.492	***	4.166	0.497	***	4.188	0.497	***
1:Size: 4-pers	0.726	0.379		0.945	0.468	*	0.824	0.468		0.832	0.476		0.822	0.479		0.847	0.480	
2:Size: 4-pers	3.820	0.401	***	4.549	0.490	***	4.445	0.494	***	4.490	0.502	***	4.490	0.506	***	4.519	0.507	***
3:Size: 4-pers	3.346	0.475	***	4.457	0.559	***	4.357	0.562	***	4.405	0.570	***	4.413	0.573	***	4.441	0.574	***
1:Size: 5-pers+	1.652	0.583	**	1.866	0.665	**	1.739	0.695	*	1.772	0.696	*	1.707	0.691	*	1.729	0.691	*
2:Size: 5-pers+	4.308	0.600	***	5.168	0.684	***	5.037	0.714	***	5.126	0.717	***	5.047	0.712	***	5.075	0.713	***
3: Size: 5-pers+	3.864	0.653	***	5.308	0.738	***	5.196	0.767	***	5.287	0.769	***	5.210	0.766	***	5.239	0.766	***
1:Workers1	0.528	0.181	**	0.786	0.203	***	0.795	0.204	***	0.830	0.208	***	0.825	0.210	***	0.831	0.211	***
2:Workers1	0.862	0.230	***	1.057	0.254	***	1.051	0.257	***	1.112	0.263	***	1.118	0.265	***	1.127	0.266	***
3:Workers1	0.302	0.343		0.764	0.368	*	0.768	0.369	*	0.832	0.374	*	0.846	0.375	*	0.853	0.376	*
1:Workers2	-0.292	0.251		0.086	0.275		0.150	0.277		0.165	0.280		0.176	0.283		0.181	0.284	
2:Workers2	0.470	0.280		0.747	0.311	*	0.817	0.316	**	0.868	0.321	**	0.900	0.325	**	0.912	0.325	**
3:Workers2	0.471	0.376		1.129	0.413	**	1.206	0.417	**	1.264	0.421	**	1.305	0.424	**	1.314	0.424	**
1:Workers3+	-0.544	0.558		-0.419	0.559		-0.426	0.573		-0.362	0.571		-0.386	0.569		-0.387	0.569	
2:Workers3+	-0.327	0.572		-0.376	0.574		-0.437	0.591		-0.328	0.591		-0.343	0.589		-0.339	0.589	
3:Workers3+	1.729	0.617	**	1.908	0.630	**	1.848	0.645	**	1.972	0.647	**	1.968	0.645	**	1.967	0.645	**
1:INC35-50K	0.886	0.169	***	0.888	0.173	***	0.923	0.175	***	0.934	0.177	***	0.921	0.178	***	0.915	0.179	***

2:INC35-50K	1.682	0.228	***	1.670	0.230	***	1.741	0.234	***	1.784	0.238	***	1.739	0.240	***	1.733	0.240	***
3:INC35-50K	1.449	0.346	***	1.461	0.351	***	1.514	0.354	***	1.556	0.356	***	1.509	0.357	***	1.506	0.357	***
1:INC50-75K	1.672	0.232	***	1.700	0.235	***	1.747	0.239	***	1.765	0.240	***	1.754	0.242	***	1.735	0.243	***
2:INC50-75K	3.014	0.278	***	3.006	0.280	***	3.073	0.287	***	3.143	0.290	***	3.092	0.292	***	3.070	0.293	***
3:INC50-75K	2.842	0.376	***	2.846	0.382	***	2.889	0.387	***	2.960	0.389	***	2.904	0.390	***	2.886	0.390	***
1:INC75-100K	2.222	0.339	***	2.295	0.342	***	2.427	0.348	***	2.454	0.347	***	2.423	0.348	***	2.380	0.351	***
2:INC75-100K	4.011	0.373	***	4.051	0.376	***	4.274	0.386	***	4.343	0.387	***	4.247	0.388	***	4.195	0.391	***
3:INC75-100K	3.725	0.455	***	3.837	0.461	***	4.053	0.470	***	4.119	0.470	***	4.016	0.471	***	3.971	0.473	***
1:INC100-150K	2.191	0.570	***	2.227	0.571	***	2.406	0.584	***	2.385	0.581	***	2.417	0.583	***	2.415	0.583	***
2:INC100-150K	4.381	0.589	***	4.378	0.589	***	4.578	0.613	***	4.611	0.608	***	4.554	0.611	***	4.552	0.612	***
3:INC100-150K	4.369	0.652	***	4.366	0.657	***	4.534	0.679	***	4.566	0.675	***	4.497	0.677	***	4.493	0.678	***
1:INCMT150K	3.559	0.745	***	3.580	0.747	***	3.884	0.754	***	3.815	0.753	***	3.841	0.757	***	3.782	0.758	***
2:INCMT150K	5.587	0.762	***	5.568	0.763	***	5.978	0.779	***	5.934	0.776	***	5.850	0.781	***	5.781	0.782	***
3:INCMT150K	5.640	0.809	***	5.624	0.814	***	5.999	0.828	***	5.953	0.826	***	5.854	0.831	***	5.785	0.832	***
1:Child: 1				-0.310	0.359		-0.333	0.364		-0.332	0.374		-0.375	0.379		-0.392	0.380	
2:Child: 1				-0.882	0.371	*	-0.995	0.379	**	-1.009	0.389	**	-1.067	0.394	**	-1.087	0.395	**
3:Child: 1				-1.377	0.397	***	-1.504	0.405	***	-1.510	0.414	***	-1.570	0.418	***	-1.587	0.419	***
1:Child: 2+				-0.448	0.505		-0.414	0.510		-0.390	0.519		-0.367	0.517		-0.391	0.518	
2:Child: 2+				-1.141	0.509	*	-1.174	0.517	*	-1.209	0.527	*	-1.198	0.525	*	-1.229	0.526	*
3:Child: 2+				-1.956	0.529	***	-2.001	0.539	***	-2.046	0.547	***	-2.046	0.546	***	-2.073	0.547	***
1:Senior: 1				0.388	0.224		0.393	0.226		0.398	0.230		0.361	0.232		0.356	0.233	
2:Senior: 1				0.291	0.265		0.232	0.269		0.247	0.274		0.168	0.276		0.163	0.277	
3:Senior: 1				1.036	0.304	***	0.974	0.308	**	0.998	0.312	***	0.918	0.314	**	0.914	0.315	**
1:Senior: 2+				1.399	0.420	***	1.396	0.424	***	1.391	0.428	***	1.384	0.431	***	1.366	0.432	**
2:Senior: 2+				1.122	0.445	*	1.063	0.450	*	1.072	0.456	*	1.032	0.460	*	1.013	0.461	*
3:Senior: 2+				1.767	0.508	***	1.700	0.513	***	1.713	0.519	***	1.668	0.523	***	1.650	0.523	**
1:Subway	-2.042	0.155	***	-2.009	0.159	***	-1.222	0.239	***	-0.875	0.240	***	-0.804	0.242	***	-0.772	0.244	**
2:Subway	-3.293	0.190	***	-3.318	0.194	***	-1.325	0.286	***	-0.852	0.288	**	-0.774	0.290	**	-0.738	0.292	*

3:Subway	-3.671	0.270	***	-3.790	0.279	***	-1.610	0.384	***	-1.078	0.390	**	-0.994	0.392	*	-0.976	0.394	*
1:CommRail	-0.551	0.153	***	-0.528	0.154	***	-0.217	0.172		-0.347	0.174	*	-0.293	0.176		-0.297	0.176	
2:CommRail	-0.997	0.188	***	-0.970	0.189	***	-0.297	0.210		-0.490	0.213	*	-0.375	0.215		-0.384	0.215	
3:CommRail	-1.107	0.248	***	-1.109	0.251	***	-0.377	0.271		-0.582	0.274	*	-0.459	0.276		-0.459	0.277	
1:AccRatio							-0.111	0.025	***	-0.041	0.030		-0.011	0.032		-0.010	0.032	
2:AccRatio							-0.308	0.033	***	-0.164	0.038	***	-0.113	0.040	**	-0.115	0.040	**
3:AccRatio							-0.353	0.048	***	-0.171	0.054	**	-0.117	0.056	*	-0.117	0.056	*
1:DISTCBD (km)										0.113	0.028	***	0.098	0.031	***	0.106	0.032	***
2:DISTCBD (km)										0.171	0.030	***	0.132	0.033	***	0.140	0.035	***
3:DISTCBD (km)										0.199	0.034	***	0.157	0.038	***	0.161	0.040	***
1:DISTCBD_SQ										-0.002	0.000	***	-0.002	0.001	**	-0.002	0.001	**
2:DISTCBD_SQ										-0.002	0.001	***	-0.002	0.001	***	-0.002	0.001	***
3:DISTCBD_SQ										-0.003	0.001	***	-0.002	0.001	***	-0.003	0.001	***
1:LN(DENPOP)													-0.266	0.122	*	-0.313	0.137	*
2:LN(DENPOP)													-0.507	0.131	***	-0.566	0.154	***
3:LN(DENPOP)													-0.543	0.146	***	-0.536	0.186	**
1:LN(JWR)													-0.232	0.084	**	-0.240	0.085	**
2:LN(JWR)													-0.275	0.096	**	-0.285	0.097	**
3:LN(JWR)													-0.281	0.111	*	-0.286	0.113	*
1:inters. per km																0.021	0.040	
2:inters. per km																0.016	0.057	
3:inters. per km																-0.021	0.088	
1: % 4-way inters.																0.578	0.670	
2: % 4-way inters.																1.012	0.861	
3: % 4-way inters.																0.247	1.289	

Notes: *JWR*: job-worker ratio. *DENPOP*: $1*10^{-3}$ persons/square miles; *inters. per km*: $1*10^{-3}$ intersections per road kilometer. AccRatio: job accessibility by transit/auto*100. Significance level: *0.05; **0.01; ***0.001. See Table 5–7 for summary statistics of the models.

Table 5–5 Vehicle ownership model estimation results for 2010 (MTS)

	M1			M2			M3			M4			M5		
	B	SE		B	SE		B	SE		B	SE		B	SE	
1:(intercept)	0.552	0.069	***	0.173	0.084	*	0.259	0.085	**	-0.801	0.183	***	0.726	0.250	**
2:(intercept)	-2.487	0.135	***	-2.979	0.152	***	-2.761	0.153	***	-5.819	0.268	***	-3.279	0.328	***
3:(intercept)	-3.896	0.221	***	-4.467	0.241	***	-4.169	0.242	***	-8.411	0.362	***	-5.286	0.414	***
1:Size: 2-pers	0.193	0.108		0.024	0.122		0.020	0.124		0.080	0.125		0.127	0.126	
2:Size: 2-pers	2.994	0.141	***	2.869	0.153	***	2.878	0.155	***	3.034	0.159	***	3.143	0.162	***
3:Size: 2-pers	2.662	0.199	***	2.617	0.210	***	2.622	0.212	***	2.815	0.216	***	2.957	0.219	***
1:Size: 3-pers	0.261	0.160		-0.179	0.231		-0.244	0.234		-0.189	0.239		-0.099	0.240	
2:Size: 3-pers	2.926	0.186	***	3.285	0.251	***	3.223	0.255	***	3.369	0.263	***	3.579	0.266	***
3:Size: 3-pers	3.206	0.233	***	4.179	0.290	***	4.122	0.294	***	4.301	0.302	***	4.563	0.306	***
1:Size: 4-pers	0.315	0.224		-0.548	0.386		-0.634	0.387		-0.550	0.390		-0.370	0.387	
2:Size: 4-pers	3.612	0.238	***	4.290	0.399	***	4.255	0.401	***	4.455	0.409	***	4.798	0.409	***
3:Size: 4-pers	3.376	0.278	***	5.661	0.429	***	5.636	0.432	***	5.876	0.441	***	6.284	0.443	***
1:Size: 5-pers+	0.013	0.283		-0.928	0.446	*	-1.005	0.446	*	-0.863	0.454		-0.678	0.454	
2:Size: 5-pers+	3.295	0.294	***	4.011	0.457	***	3.930	0.462	***	4.225	0.475	***	4.547	0.478	***
3: Size: 5-pers+	3.245	0.329	***	5.919	0.489	***	5.828	0.495	***	6.168	0.509	***	6.549	0.513	***
1:Workers1	0.312	0.094	***	0.576	0.100	***	0.608	0.101	***	0.631	0.102	***	0.640	0.104	***
2:Workers1	0.472	0.123	***	0.891	0.134	***	0.933	0.136	***	1.026	0.140	***	1.044	0.143	***
3:Workers1	0.608	0.168	***	0.968	0.182	***	1.032	0.184	***	1.146	0.188	***	1.174	0.191	***
1:Workers2	0.582	0.175	***	0.981	0.184	***	1.046	0.186	***	1.039	0.186	***	0.995	0.187	***
2:Workers2	1.300	0.187	***	1.782	0.200	***	1.890	0.203	***	2.009	0.207	***	1.991	0.209	***
3:Workers2	1.627	0.219	***	1.976	0.236	***	2.119	0.239	***	2.288	0.244	***	2.302	0.246	***
1:Workers3+	0.715	0.505		1.303	0.522	*	1.481	0.525	**	1.544	0.528	**	1.508	0.534	**
2:Workers3+	1.436	0.502	**	1.670	0.522	***	1.956	0.529	***	2.145	0.533	***	2.085	0.540	***
3:Workers3+	3.739	0.511	***	3.189	0.535	***	3.517	0.543	***	3.785	0.549	***	3.750	0.555	***
1:INC35-50K	1.377	0.133	***	1.336	0.135	***	1.319	0.136	***	1.336	0.137	***	1.250	0.139	***
2:INC35-50K	1.786	0.167	***	1.682	0.171	***	1.621	0.173	***	1.682	0.177	***	1.491	0.181	***

3:INC35-50K	1.773	0.225	***	1.694	0.233	***	1.601	0.235	***	1.696	0.240	***	1.446	0.243	***
1:INC50-75K	1.555	0.129	***	1.568	0.130	***	1.579	0.132	***	1.590	0.132	***	1.484	0.134	***
2:INC50-75K	2.458	0.155	***	2.463	0.158	***	2.460	0.160	***	2.537	0.163	***	2.305	0.166	***
3:INC50-75K	2.639	0.199	***	2.749	0.204	***	2.729	0.206	***	2.849	0.210	***	2.558	0.213	***
1:INC75-100K	1.870	0.170	***	1.883	0.171	***	1.964	0.174	***	1.949	0.173	***	1.876	0.176	***
2:INC75-100K	3.110	0.190	***	3.112	0.192	***	3.190	0.197	***	3.227	0.199	***	2.998	0.203	***
3:INC75-100K	3.315	0.227	***	3.451	0.231	***	3.508	0.236	***	3.595	0.239	***	3.274	0.243	***
1:INC100-150K	2.278	0.213	***	2.330	0.214	***	2.463	0.219	***	2.435	0.216	***	2.368	0.219	***
2:INC100-150K	3.802	0.227	***	3.880	0.229	***	4.024	0.235	***	4.066	0.235	***	3.822	0.239	***
3:INC100-150K	4.099	0.256	***	4.359	0.261	***	4.479	0.267	***	4.583	0.268	***	4.236	0.273	***
1:INCMT150K	2.349	0.240	***	2.374	0.240	***	2.617	0.248	***	2.537	0.244	***	2.484	0.248	***
2:INCMT150K	4.029	0.251	***	4.085	0.252	***	4.365	0.263	***	4.392	0.261	***	4.130	0.266	***
3:INCMT150K	4.560	0.277	***	4.819	0.281	***	5.079	0.292	***	5.232	0.291	***	4.823	0.297	***
1:Child: 1				0.328	0.207		0.359	0.210		0.356	0.215		0.297	0.216	
2:Child: 1				-0.684	0.218	**	-0.706	0.223	**	-0.733	0.229	***	-0.855	0.232	***
3:Child: 1				-1.486	0.230	***	-1.534	0.236	***	-1.582	0.242	***	-1.728	0.246	***
1:Child: 2+				0.962	0.347	**	0.984	0.347	**	0.999	0.352	**	0.908	0.350	**
2:Child: 2+				-0.709	0.357	*	-0.757	0.360	*	-0.821	0.369	*	-1.010	0.369	**
3:Child: 2+				-2.750	0.371	***	-2.815	0.375	***	-2.917	0.384	***	-3.154	0.385	***
1:Senior: 1				0.797	0.108	***	0.788	0.109	***	0.763	0.110	***	0.648	0.113	***
2:Senior: 1				0.854	0.147	***	0.851	0.148	***	0.896	0.151	***	0.717	0.153	***
3:Senior: 1				0.874	0.174	***	0.902	0.176	***	0.993	0.179	***	0.814	0.181	***
1:Senior: 2+				1.334	0.269	***	1.372	0.273	***	1.365	0.274	***	1.252	0.278	***
2:Senior: 2+				1.605	0.275	***	1.614	0.280	***	1.661	0.285	***	1.445	0.290	***
3:Senior: 2+				1.337	0.299	***	1.357	0.304	***	1.449	0.309	***	1.199	0.315	***
1:Subway	-1.364	0.089	***	-1.327	0.090	***	-0.614	0.132	***	-0.396	0.131	**	-0.300	0.131	*
2:Subway	-3.195	0.116	***	-3.189	0.117	***	-1.374	0.170	***	-0.855	0.170	***	-0.694	0.171	***
3:Subway	-3.955	0.157	***	-4.004	0.162	***	-1.475	0.218	***	-0.792	0.228	***	-0.586	0.230	*
1:CommRail	-0.526	0.096	***	-0.471	0.098	***	-0.233	0.104	*	-0.256	0.105	*	-0.168	0.105	
2:CommRail	-1.004	0.122	***	-0.956	0.124	***	-0.401	0.132	**	-0.438	0.134	***	-0.301	0.136	*
3:CommRail	-1.248	0.148	***	-1.226	0.152	***	-0.461	0.162	**	-0.452	0.165	**	-0.256	0.167	

1:AccRatio	-0.124	0.017	***	-0.061	0.019	***	-0.008	0.020	
2:AccRatio	-0.338	0.023	***	-0.143	0.026	***	-0.053	0.027	
3:AccRatio	-0.523	0.034	***	-0.206	0.037	***	-0.090	0.037	*
1:DISTCBD_KM				0.069	0.014	***	0.033	0.015	*
2:DISTCBD_KM				0.178	0.016	***	0.110	0.018	***
3:DISTCBD_KM				0.223	0.018	***	0.135	0.020	***
1:DISTCBD_SQ				-0.001	0.000	***	-0.001	0.000	*
2:DISTCBD_SQ				-0.002	0.000	***	-0.002	0.000	***
3:DISTCBD_SQ				-0.002	0.000	***	-0.002	0.000	***
1: LN(DENPOP)							-0.623	0.061	***
2: LN(DENPOP)							-1.010	0.072	***
3: LN(DENPOP)							-1.240	0.081	***
1: LN(JWR)							-0.230	0.053	***
2: LN(JWR)							-0.309	0.066	***
3: LN(JWR)							-0.325	0.076	***
1:inters_per_km									
2:inters_per_km									
3:inters_per_km									
1: % inters.4									
2: % inters.4									
3: % inters.4									
1:Black									
2:Black									
3:Black									
1:Asian									
2:Asian									
3:Asian									
1:Others									
2:Others									
3:Others									

See Table 5–8 for summary statistics of the models. See footnotes of Table 5-4 for variables specifications

Table 5–5 cont'd

	M6			M7		
	B	SE		B	SE	
1:(intercept)	0.894	0.308	**	0.928	0.256	***
2:(intercept)	-2.778	0.405	***	-3.05	0.334	***
3:(intercept)	-4.613	0.517	***	-5.024	0.419	***
1:Size: 2-pers	0.132	0.126		0.248	0.129	
2:Size: 2-pers	3.153	0.162	***	3.283	0.164	***
3:Size: 2-pers	2.966	0.219	***	3.103	0.221	***
1:Size: 3-pers	-0.1	0.24		0.049	0.243	
2:Size: 3-pers	3.579	0.266	***	3.751	0.27	***
3:Size: 3-pers	4.56	0.306	***	4.744	0.31	***
1:Size: 4-pers	-0.351	0.389		-0.23	0.392	
2:Size: 4-pers	4.829	0.41	***	4.99	0.415	***
3:Size: 4-pers	6.312	0.444	***	6.505	0.449	***
1:Size: 5-pers+	-0.676	0.454		-0.453	0.461	
2:Size: 5-pers+	4.563	0.479	***	4.841	0.488	***
3: Size: 5-pers+	6.56	0.514	***	6.88	0.522	***
1:Workers1	0.637	0.104	***	0.643	0.106	***
2:Workers1	1.043	0.143	***	1.056	0.144	***
3:Workers1	1.173	0.191	***	1.199	0.192	***
1:Workers2	0.992	0.187	***	0.956	0.189	***
2:Workers2	1.989	0.209	***	1.955	0.212	***
3:Workers2	2.301	0.246	***	2.27	0.248	***
1:Workers3+	1.503	0.533	**	1.536	0.536	**
2:Workers3+	2.079	0.539	***	2.131	0.544	***
3:Workers3+	3.747	0.555	***	3.793	0.559	***
1:INC35-50K	1.251	0.139	***	1.156	0.141	***
2:INC35-50K	1.482	0.181	***	1.375	0.183	***
3:INC35-50K	1.434	0.243	***	1.331	0.245	***
1:INC50-75K	1.489	0.134	***	1.38	0.135	***
2:INC50-75K	2.306	0.166	***	2.173	0.168	***
3:INC50-75K	2.555	0.214	***	2.429	0.215	***
1:INC75-100K	1.877	0.176	***	1.707	0.178	***
2:INC75-100K	2.984	0.203	***	2.786	0.205	***
3:INC75-100K	3.254	0.243	***	3.052	0.246	***
1:INC100-150K	2.372	0.22	***	2.167	0.222	***
2:INC100-150K	3.807	0.24	***	3.577	0.243	***
3:INC100-150K	4.212	0.273	***	3.981	0.276	***
1:INCMT150K	2.498	0.249	***	2.226	0.251	***
2:INCMT150K	4.129	0.267	***	3.816	0.269	***
3:INCMT150K	4.812	0.298	***	4.503	0.3	***
1:Child: 1	0.294	0.217		0.375	0.219	
2:Child: 1	-0.859	0.233	***	-0.764	0.236	***
3:Child: 1	-1.73	0.246	***	-1.624	0.249	***
1:Child: 2+	0.902	0.351	**	0.972	0.353	**
2:Child: 2+	-1.026	0.369	**	-0.973	0.373	**
3:Child: 2+	-3.168	0.386	***	-3.135	0.389	***
1:Senior: 1	0.643	0.113	***	0.618	0.114	***
2:Senior: 1	0.711	0.153	***	0.683	0.155	***
3:Senior: 1	0.81	0.181	***	0.777	0.182	***
1:Senior: 2+	1.24	0.278	***	1.199	0.285	***
2:Senior: 2+	1.426	0.29	***	1.371	0.298	***

3:Senior: 2+	1.177	0.315	***	1.118	0.322	***
1:Subway	-0.304	0.132	*	-0.354	0.133	**
2:Subway	-0.725	0.171	***	-0.758	0.173	***
3:Subway	-0.624	0.231	**	-0.645	0.232	**
1:CommRail	-0.165	0.106		-0.105	0.108	
2:CommRail	-0.282	0.136	*	-0.222	0.138	
3:CommRail	-0.229	0.168		-0.175	0.169	
1:AccRatio	-0.006	0.02		-0.014	0.02	
2:AccRatio	-0.047	0.027		-0.06	0.027	*
3:AccRatio	-0.082	0.038	*	-0.098	0.038	**
1:DISTCBD_KM	0.032	0.015	*	0.026	0.015	
2:DISTCBD_KM	0.107	0.018	***	0.104	0.018	***
3:DISTCBD_KM	0.13	0.02	***	0.127	0.02	***
1:DISTCBD_SQ	-0.001	0	*	0	0	
2:DISTCBD_SQ	-0.002	0	***	-0.002	0	***
3:DISTCBD_SQ	-0.002	0	***	-0.002	0	***
1: LN(DENPOP)	-0.578	0.076	***	-0.572	0.062	***
2: LN(DENPOP)	-0.871	0.094	***	-0.94	0.073	***
3: LN(DENPOP)	-1.06	0.11	***	-1.167	0.082	***
1: LN(JWR)	-0.213	0.056	***	-0.251	0.054	***
2: LN(JWR)	-0.263	0.07	***	-0.327	0.067	***
3: LN(JWR)	-0.273	0.079	***	-0.34	0.076	***
1:inters_per_km	-0.034	0.033				
2:inters_per_km	-0.075	0.045				
3:inters_per_km	-0.096	0.058				
1: % inters.4	-0.173	0.517				
2: % inters.4	-1.326	0.696				
3: % inters.4	-1.862	0.93	*			
1:Black				-0.682	0.136	***
2:Black				-0.928	0.208	***
3:Black				-1.402	0.334	***
1:Asian				-0.535	0.265	*
2:Asian				-0.929	0.306	**
3:Asian				-1.991	0.401	***
1:Others				-0.917	0.133	***
2:Others				-1.278	0.173	***
3:Others				-1.329	0.213	***

Table 5–6 Vehicle ownership model for Cube model implementation (MCube)

	1991			2010		
	B	S.E.		B	S.E.	
1:(intercept)	0.315	0.486		0.504	0.252	*
2:(intercept)	-3.005	0.573	***	-3.822	0.324	***
3:(intercept)	-3.966	0.706	***	-5.773	0.401	***
1:SIZE2-pers	0.530	0.185	**	0.944	0.116	***
2:SIZE2-pers	2.492	0.241	***	4.299	0.156	***
3:SIZE2-pers	1.133	0.362	**	4.154	0.212	***
1:SIZE3-pers	1.680	0.340	***	1.232	0.171	***
2:SIZE3-pers	4.637	0.377	***	4.574	0.205	***
3:SIZE3-pers	4.410	0.454	***	5.047	0.251	***
1:SIZE4-pers+	1.388	0.348	***	1.207	0.193	***
2:SIZE4-pers+	4.685	0.382	***	5.148	0.220	***
3:SIZE4-pers+	4.180	0.458	***	5.142	0.264	***
1:WORKERS1	0.614	0.186	***	0.329	0.100	**
2:WORKERS1	1.063	0.236	***	0.635	0.131	***
3:WORKERS1	0.498	0.342		0.830	0.175	***
1:WORKERS2	-0.170	0.256		0.655	0.175	***
2:WORKERS2	0.803	0.288	**	1.671	0.191	***
3:WORKERS2	0.796	0.376	*	2.116	0.224	***
1:WORKERS3+	-0.262	0.540		1.097	0.506	*
2:WORKERS3+	0.039	0.558		2.222	0.507	***
3:WORKERS3+	2.108	0.601	***	4.713	0.519	***
1:IncGrpMid-low	0.880	0.175	***	1.213	0.108	***
2:IncGrpMid-low	1.779	0.212	***	2.015	0.136	***
3:IncGrpMid-low	1.503	0.256	***	1.986	0.167	***
1:IncGrpMid-high	1.871	0.229	***	2.014	0.129	***
2:IncGrpMid-high	3.185	0.265	***	3.272	0.159	***
3:IncGrpMid-high	3.082	0.303	***	3.410	0.186	***
1:IncGrpHigh	2.727	0.397	***	2.589	0.172	***
2:IncGrpHigh	4.572	0.416	***	4.173	0.201	***
3:IncGrpHigh	4.615	0.444	***	4.543	0.224	***
1:Subway1	-0.850	0.238	***	-0.331	0.130	*
2:Subway1	-0.830	0.285	**	-0.742	0.168	***
3:Subway1	-0.995	0.383	**	-0.656	0.223	**
1:CommRail1	-0.325	0.172	.	-0.183	0.105	.
2:CommRail1	-0.437	0.210	*	-0.332	0.134	*
3:CommRail1	-0.498	0.270	.	-0.285	0.162	.
1:AccRatio	-0.00546	0.0310		0.00241	0.0200	
2:AccRatio	-0.0975	0.0393	*	-0.0398	0.0267	
3:AccRatio	-0.103	0.055	.	-0.0768	0.0364	*

1:DISTCBD_KM	0.0930	0.0305	**	0.0334	0.0154	*
2:DISTCBD_KM	0.126	0.0330	***	0.107	0.0177	***
3:DISTCBD_KM	0.152	0.0374	***	0.129	0.0196	***
1:DISTCBD_SQ	-0.00152	0.000510	**	-0.00054	0.000262	*
2:DISTCBD_SQ	-0.00201	0.000544	***	-0.00157	0.000292	***
3:DISTCBD_SQ	-0.00240	0.000605	***	-0.00173	0.000314	***
1:LN (DENPOP)	-0.309	0.121	*	-0.663	0.0616	***
2:LN (DENPOP)	-0.546	0.130	***	-1.053	0.0718	***
3:LN (DENPOP)	-0.566	0.144	***	-1.249	0.0794	***
1:LN (JWR)	-0.219	0.082	**	-0.239	0.0535	***
2:LN (JWR)	-0.254	0.093	**	-0.322	0.0658	***
3:LN (JWR)	-0.264	0.109	*	-0.343	0.0744	***

See Table 5–7 and Table 5–8 for summary statistics of the models.

Table 5–7 Summary of model estimation for 1991

1991	M1	M2	M3	M4	M5	M6	M7	Cube
Null Log-Likelihood	-4357	-4357	-4357	-4357	-4357	-4357	n.a.	-4357
Final log-Likelihood	-2996	-2955	-2897	-2867	-2853	-2852	n.a.	-2915
Rho-square[a]	0.312	0.322	0.335	0.342	0.345	0.345	n.a.	0.331
Adjusted rho-square[b]	0.302	0.309	0.321	0.327	0.329	0.327	n.a.	0.319
Likelihood ratio[c]	2721	2804	2919	2980	3007	3009	n.a.	2883
Degree of freedom	45	57	60	66	72	78	n.a.	51

a. $1 - (L(\beta)/L(0))$

b. $1 - (L(\beta) - K)/L(0)$

c. $-2\,(L(0)-L(\beta))$

Table 5–8 Summary of model estimation for 2010

2010	M1	M2	M3	M4	M5	M6	M7	Cube
Null Log-Likelihood	-12380	-12380	-12380	-12380	-12380	-12380	-12380	-12380
Final Log-Likelihood	-8498	-8246	-8076	-7879	-7748	-7743	-7694	-8000
Rho-square	0.314	0.334	0.348	0.364	0.374	0.375	0.379	0.354
Adjusted rho-square	0.310	0.329	0.343	0.358	0.368	0.368	0.372	0.350
Likelihood ratio	7764	8268	8608	9004	9265	9274	9375	8761
Degree of freedom	45	57	60	66	72	78	81	51

Model specification tests

A series of LR tests (see section 3.3 for details of LR test) for the 1991 model show that household income, a range of demographic characteristics (e.g., number of children, older adults, workers), and some relative location (accessibility ratio, distance to CBD, and squared distance to CBD) and local built environment variables (population density and job-to-worker ratio) are significantly different from zero. The impacts of road intersections per kilometer and proportion of 4-way intersections are not significant. The final preferred model for 1991 is M5. Results of the likelihood ratio tests are shown in Table 5–9.

Table 5–9 Model specification tests for model 1991

Restricted model	M1	M2	M3	M4	M5
Unrestricted model	M2	M3	M4	M5	M6
Coefficients restricted to 0	Child; Senior	AccRatio	Distance to CBD; squared distance to CBD	Ln(Pop density); Ln(JWR)	% 4-way intersection; intersections per km
LR test statistics $-2(\mathcal{L}(\hat{\beta}_R) - \mathcal{L}(\hat{\beta}_U))$	82	116	60	28	2
Degree of freedom	12	3	6	6	6
P-value	0.000	0.000	0.000	0.000	0.920
Reject H_0	Yes	Yes	Yes	Yes	No
Preferred model	M2	M3	M4	M5	M5

Table 5–10 Model specification tests for model 2010

Restricted (H_0)	M1	M2	M3	M4	M5	M5
Unrestricted (H_a)	M2	M3	M4	M5	M6	M7
Coefficients restricted to 0	Child; Senior	AccRatio	Distance to CBD; squared distance to CBD	Ln(Pop density); Ln(JWR)	% 4-way intersection; Intersections/km	Race
LR test statistics $-2(\mathcal{L}(\hat{\beta}_R) - \mathcal{L}(\hat{\beta}_U))$	504	340	394	262	10	108
Degree of freedom	12	3	6	6	6	9
P-value	0.000	0.000	0.000	0.000	0.125	0.000
Reject H_0	Yes	Yes	Yes	Yes	No	Yes
Preferred model	M2	M3	M4	M5	M5	M7

The specification test results for 2010 are in general similar to 1991, with one more specification, M7, which includes race (Table 5–10). Race turns out to have significant impact on vehicle ownership. Note that the race variable reduces the residual deviance by 108 with 9 degrees of freedom, which is a remarkable improvement of the model. The final preferred model for 2010 is M7.

Model interpretations

Based on the preferred model specifications for each year, the model estimates suggest the following:

- Larger households own more cars. Note the difference between 1991 and 2010: In 2010, household size only affects the probability of having 2 and 3+ cars relative to no car, but not the probability of having 1 car versus none; but in 1991, household size also plays a role in increasing the likelihood of having 1 car relative to no car. For example, in 1991, the probability of having 1 car over the probability of having no car ($\frac{P1}{P0}$) for a 2-person household is 1.5 times ($e^{0.406} = 1.5$) that ratio for a 1-person household; P1/P0 for a 3-person household is 3.8 ($e^{1.34} = 3.8$) times as much as that ratio for a 1-person household. But in 2010, there is no significant difference. This suggests that the first car decision in 2010 is not affected much by the number of persons in the household. Other factors may play a more important role.

- The higher the number of workers in a household, the higher the probability of having more cars. Note that in 1991, the coefficients “1:Workers2”, “1:Workers3+”, and “2:Workers3+” are not significantly different from 0. It means that there is no significant difference between 2-worker household and 1-worker household, and between 3+worker household and 1-worker household in terms of the probability of owning 1 car versus no car (P1/P0); and there is no difference between 3+-worker household and 1-worker household in term of the probability of having 2 car vs. no car (P2/P0), all else equal.

- Higher income households are more likely to own more cars. As the number of cars increases from 1 to 3+, the gap between the lower income household and the higher income household in the likelihood of having cars becomes wider.

- Number of children lowers the chance to own 2 or 3+ cars, all else equal. The rationale is that given the total household size and workers controlled, more children imply fewer other adults and therefore fewer cars[11]. More children also imply lower net income, as children might be more costly and restrict the financial resources to own more cars.

- Households with senior members have higher probability to own more cars. There can be different reasons for this. First, walk or transit is usually not a friendly mode choice for senior people given their physical conditions. It could also be the path-dependence effect. Once people get used to car, they may find it hard to live without it, even if they do not drive as much.

- Proximity to a subway station reduces the likelihood of owning cars; while proximity to commuter rail does not show significant impact. For example, in 2010 (specification M7), the probability of having one car over the probability of having no cars (P1/P0) for a household within 800 meters to the subway station is 0.70 of that

[11] I also tried excluding household size, and including the exact number of children, workers, seniors and other adults. But this specification has much lower log-likelihood compared to the model with dummies for size, workers, children and seniors. In a 4-step model application, the exact composition of the household in the population is often unknown, categorical representation for these variables are more applicable, and can capture the non-linear effect.

ratio for a household with no subway close by. P2/P0 for a household with subway access is 0.47 of that ratio for households without subway access (see Table 5–11).

Table 5–11 Effect of subway on vehicle ownership in 1991 and 2010

Coefficients	2010 (M7)	2010 (M5)	1991 (M5)	Probability ratio conditional on subway proximity	2010 (M7)	2010 (M5)	1991 (M5)
1 car: Subway	-0.35	-0.30	-0.80	$\frac{\mathrm{P(1car)/P(0car)}_{\mid subway}}{\mathrm{P(1car)/P(0car)}_{\mid no\ subway}}$	0.70	0.74	0.45
2 car: Subway	-0.76	-0.69	-0.77	$\frac{\mathrm{P(2car)/P(0car)}_{\mid subway}}{\mathrm{P(2car)/P(0car)}_{\mid no\ subway}}$	0.47	0.50	0.46
3+car: Subway	-0.65	-0.59	-0.99	$\frac{\mathrm{P(3+car)/P(0car)}_{\mid subway}}{\mathrm{P(3+car)/P(0car)}_{\mid no\ subway}}$	0.52	0.56	0.37

- The accessibility ratio reduces the chances of owning 2 and 3+ cars. However, it does not affect the probability of having 1 car relative to the probability of having no cars.
- The relationship between Distance to CBD and the utility of owning a number of cars is quadratic: as the household moves away from the CBD, the utility of owning cars first increases till it reaches the quadratic peak, and then decreases. The linear term Distance to CBD captures the slope of the increase in vehicle ownership as it gets further from CBD. The quadratic term captures the vehicle ownership decrease in the sub-centers of the metropolitan area. In sub-centers, the higher residential density, higher concentration of jobs and commercial services relative to the surrounding suburbs, and access to transit can lower vehicle ownership.
- Higher population density lowers the need for a car. Higher density indicates more walkability, more accessibility to shops or other amenities, which reduces the need for a car. Higher density also implies more expensive parking, which lowers the incentives to buy cars.
- Local job access (Job per worker within TAZ) decreases the need for cars.
- Compared to White people, Asian, Black, and other racial groups have lower preference for a car. This effect is significant for all levels of vehicle ownership, all else equal. Understanding this apparent racial effect deserves further research.

5.3 Statistical tests of temporal transferability

5.3.1 Likelihood ratio test of preference stability

To see if preferences have changed over time, I first perform a LR test (see Chapter 3 section 3.3 for details about the method). I choose model specification M5 for the test since it is the best specification given common data available for both years.

The fully unrestricted model – that is, with all coefficients different across the two periods – is considered the base line. Then, I estimate its opposite extreme—a pooled model with all coefficients restricted to be equal across the two years (Pooled 1). Then I estimate a pooled model with all coefficients except for the alternative specific constants (ASC) restricted to be equal across the two years (Pooled 2). In these two models, I estimate the scale for 2010 and fix the 1991 scale to 1. The results (Table 5–12) show that both the Pooled 1 and Pooled 2 models are rejected; the unrestricted model is preferred, indicating preference changes from 1991 to 2010, not just due to changes in the unobserved factors (ASC).

Table 5–12 Likelihood ratio test for model equality

	Unrestricted	Pooled 1	Pooled 2
Log-likelihood	-10601	-10760	-10711
Degree of freedom	144	73	76
LR tests			
H_0 (Restrictions)		$\boldsymbol{\beta}^{91} = \boldsymbol{\beta}^{10}$ $ASC^{91} = ASC^{10}$	$\boldsymbol{\beta}^{91} = \boldsymbol{\beta}^{10}$
H_a		Unrestricted	Unrestricted
LR test statistic		318	221
Degree of freedom		71	68
P-value		0.000	0.000
Reject H_0		Yes	Yes
Preferred model		Unrestricted	Unrestricted

To identify which preference parameters have changed and which have not, I conduct a sequence of LR tests. I start from the fully unrestricted model (UR), impose a group of constraints at a time (i.e., semi-restricted), and conduct the LR test. If the LR test indicates rejection of the null hypothesis, I return to the unrestricted version and try a new set of constraints; otherwise, I keep the semi-restricted model, and add new constraints. In this fashion, a group of variables are tested together to decide whether they should be the same across years, or year-specific. Table 5–13 presents the results.

Table 5–13 Likelihood ratio test results for preference stability

Model	L(β)	df	H_0 (Equal coefficients[1])	H_a[2]	LR test	df	p-value	Reject H_0
Unrestricted								
UR	-10600.7	144						
Restricted								
R1	-10601.4	142	Population density	UR	1.3	2	0.528	No
R2	-10605.7	136	Subway; Commuter Rail	R1	8.7	6	0.192	No
R3	-10610.9	130	Job/worker; AccRatio	R2	10.3	6	0.112	No
R4	-10630.3	124	Distance to CBD; squared Distance to CBD	R3	38.8	6	0.000	Yes
R5	-10626.3	115	Income	R3	30.8	15	0.009	Yes
R6	-10632.4	118	Household size	R3	43.0	12	0.000	Yes
R7	-10633.6	121	Workers	R3	45.4	9	0.000	Yes
R8	-10617.5	124	Child	R3	13.3	6	0.039	No
R9	-10626.6	118	Senior	R8	18.2	6	0.006	Yes

1. Equality restriction: the coefficients are set to be equal for 1991 and 2010 in the pooled model.
2. This is the unrestricted model to compare with.

The stability tests suggest that the relationship between vehicle ownership likelihood and the local built environmental factors (population density and job-worker ratio) have not changed over time. In general, these effects are stable. The effects of transit accessibilities have not changed either. The Regional location factor has changed, however, as indicated by the distance to CBD measure. Most change appears to relate to the role of household socioeconomic and demographic factors, with the exception being a household's number of children. The final best model is R8, with population density, access to subway, access to commuter rail, job-worker ratio, job accessibility ratio, and number of children sharing the same coefficients across years. However, it should be noted that the sequence of these LR tests might affect the results.

The distance to CBD, in general, captures the effect of regional accessibility to jobs and other activities on vehicle ownership for a mono-centric city structure. It may also capture the unobserved parking cost and built environment effects. Changes in the effect of distance to CBD can have various causes, such as changes in the regional distribution of jobs and other opportunities. It may also reflect the change in many unmeasured factors, such as transit service quality, walkability, land use diversity, or the relative costs of car ownership in different locations of the region. If these aspects become more homogenous between locations at different distance to CBD, the coefficient will become weaker.

The instability of household socioeconomic and demographic factors is a little surprising because it contradicts the conventional assumption that preferences for households of certain characteristics remain stable. One possible explanation is the imperfect description of household lifecycle, which household size, number of workers, age and number of children can only partially capture. It can also suggest real changes in behavior, as a manifestation of general life-style change. This can be further explored through cohort analysis of preference change.

5.3.2 Individual parameter tests of preference change

While the LR test indicates whether a group of variables together have the same effect over years, a t-test can be used to detect changes in individual parameter estimates. The t-test result is shown in Table 5–14. Note I use model specification R8 for the t-tests. The stable parameters in the LR test from above are constrained to be the same.

Table 5–14 T-test of coefficient change

	2010			1991			Difference		
	B	S.E.		B	S.E.		B10-B91	S.E.	
V1_ASC	0.808	0.249	**	-0.444	0.319		1.252	0.405	**
V1_SIZE2	0.143	0.127		0.361	0.197		-0.218	0.234	
V1_SIZE3	-0.00818	0.234		1.06	0.34	**	-1.068	0.413	*
V1_SIZE4	-0.193	0.370		0.413	0.396		-0.606	0.542	
V1_SIZE5P	-0.481	0.437		1.17	0.596		-1.651	0.739	*
V1_WORKER1	0.642	0.122	***	0.82	0.206	***	-0.178	0.239	
V1_WORKER2	0.989	0.209	***	0.196	0.277		0.793	0.347	*
V1_WORKER3	1.441	0.548	*	-0.267	0.557		1.708	0.781	*
V1_SENIOR1	0.644	0.129	***	0.451	0.227		0.193	0.261	
V1_SENIOR2	1.220	0.302	***	1.48	0.42	***	-0.260	0.517	
V1_CHILD1	0.118	0.123							
V1_CHILD2	0.426	0.198	*						
V1_INC35-50K	1.263	0.188	***	0.921	0.175	***	0.342	0.257	
V1_INC50-75K	1.501	0.199	***	1.73	0.237	***	-0.229	0.310	
V1_INC75-100K	1.909	0.257	***	2.39	0.343	***	-0.481	0.429	
V1_INC100-150K	2.407	0.322	***	2.29	0.575	***	0.117	0.659	
V1_INCMT150K	2.540	0.350	***	3.68	0.75	***	-1.140	0.828	

V1_SUBWAY	-0.240	0.079	**						
V1_COMRAIL	-0.139	0.061	*						
V1_AccRatio	-0.007	0.011							
V1_DISTCBD_KM	0.026	0.015		0.132	0.0223	***	-0.106	0.027	***
V1_DISTCBD_SQ	-0.00044	0.000		-0.0021	0.00041	***	0.00168	0.00048	***
V1_LogDENPOP	-0.848	0.110	***						
V1_LogJWR	-0.354	0.077	***						
V2_ASC	-3.121	0.468	***	-4.01	0.471	***	0.889	0.664	
V2_SIZE2	3.154	0.345	***	2.52	0.252	***	0.634	0.427	
V2_SIZE3	3.635	0.432	***	3.99	0.375	***	-0.355	0.572	
V2_SIZE4	4.847	0.596	***	4.2	0.422	***	0.647	0.730	
V2_SIZE5P	4.615	0.624	***	4.7	0.616	***	-0.085	0.877	
V2_WORKER1	1.051	0.176	***	1.11	0.262	***	-0.059	0.316	
V2_WORKER2	2.009	0.286	***	0.922	0.318	**	1.087	0.427	*
V2_WORKER3	2.058	0.576	***	-0.226	0.576		2.284	0.815	**
V2_SENIOR1	0.720	0.171	***	0.259	0.272		0.461	0.321	
V2_SENIOR2	1.423	0.324	***	1.13	0.45	*	0.293	0.554	
V2_CHILD1	-0.568	0.141	***						
V2_CHILD2	-0.646	0.211	**						
V2_INC35-50K	1.502	0.234	***	1.74	0.237	***	-0.238	0.333	
V2_INC50-75K	2.324	0.282	***	3.07	0.286	***	-0.746	0.402	
V2_INC75-100K	3.038	0.360	***	4.19	0.382	***	-1.152	0.525	*
V2_INC100-150K	3.868	0.448	***	4.41	0.599	***	-0.542	0.748	
V2_INCMT150K	4.200	0.488	***	5.65	0.771	***	-1.450	0.912	
V2_SUBWAY	-0.443	0.105	***						
V2_COMRAIL	-0.223	0.079	**						
V2_AccRatio	-0.047	0.016	**						
V2_DISTCBD_KM	0.099	0.021	***	0.184	0.0262	***	-0.085	0.033	*
V2_DISTCBD_SQ	-0.00143	0.000	***	-0.00286	0.000454	***	0.00143	0.00056	*
V2_LogDENPOP	-1.390	0.151	***						
V2_LogJWR	-0.468	0.093	***						
V3_ASC	-5.163	0.682	***	-5.11	0.623	***	-0.053	0.924	
V3_SIZE2	2.971	0.359	***	1.12	0.373	**	1.851	0.517	***
V3_SIZE3	4.615	0.525	***	3.91	0.456	***	0.705	0.695	
V3_SIZE4	6.275	0.704	***	4.23	0.503	***	2.045	0.865	*
V3_SIZE5P	6.524	0.759	***	5.07	0.679	***	1.454	1.018	
V3_WORKER1	1.185	0.224	***	0.822	0.374	*	0.363	0.436	
V3_WORKER2	2.324	0.335	***	1.34	0.419	**	0.984	0.537	
V3_WORKER3	3.768	0.672	***	2.07	0.632	**	1.698	0.923	
V3_SENIOR1	0.828	0.203	***	0.992	0.311	**	-0.164	0.371	
V3_SENIOR2	1.192	0.340	***	1.72	0.515	***	-0.528	0.617	
V3_CHILD1	-1.080	0.167	***						
V3_CHILD2	-1.880	0.260	***						

V3_INC35-50K	1.457	0.282	***	1.52	0.356	***	-0.063	0.454	
V3_INC50-75K	2.573	0.329	***	2.88	0.386	***	-0.307	0.507	
V3_INC75-100K	3.303	0.403	***	3.98	0.466	***	-0.677	0.616	
V3_INC100-150K	4.266	0.496	***	4.33	0.666	***	-0.064	0.831	
V3_INCMT150K	4.880	0.558	***	5.62	0.821	***	-0.740	0.993	
V3_SUBWAY	-0.413	0.137	**						
V3_COMRAIL	-0.208	0.096	*						
V3_AccRatio	-0.066	0.022	**						
V3_DISTCBD_KM	0.125	0.024	***	0.202	0.0302	***	-0.078	0.038	
V3_DISTCBD_SQ	-0.00164	0.000	***	-0.00317	0.000513	***	0.00153	0.00063	*
V3_LogDENPOP	-1.680	0.177	***						
V3_LogJWR	-0.485	0.105	***						
Scale _1991	1	Fixed							
Scale_2010	1.66	0.162	***						

Significance level: *** 0.001; ** 0.01; * 0.05

The T-test suggests that the distance to CBD effect has weakened. The increase in the likelihood of having 1 and 2 relative to no vehicle have all flattened out as distance to CBD increases in 2010 compared to 1991. This is consistent with the empirics in Chapter 4 that the City of Boston’s vehicle ownership has significantly increased. Though the phenomenon is attributed to the resurgence in residential and commercial development, which has attracted many high-income people to move into Boston (City of Boston et al., 2002), the model here seems to suggest preference change in addition to the population input change, since income is controlled. Also, the rapid vehicle growth in a few Metropolitan Core towns − Chelsea, Revere, Everett, and Malden, as discussed in Chapter 4, also resonates with this flattening out phenomenon.

All else equal, 2-worker and 3-worker households’ preferences for 1 car and 2 cars have increased. The effect of household size on 1-vehicle and 3+vehicle ownership has changed. 2-person households and 4-person households’ preference for three cars has increased. 1-person households and 5+ person households’ preference for 1 car has declined. Households with monthly income 75,000 to 100,000 dollars prefer 2 cars less in 2010 than they did in 1991.

5.4 Prediction tests on disaggregated data

Section 5.2 compared a variety of model specifications within a given year (1991 or 2011); Section 5.3 assessed the stability of the model parameter estimates (preferences) across the two years. The latter approach still does not measure the performance of transferring from one year to another. In this section, I test model predictive performance, assessing how well a model estimated for one year predicts based on another year's data. This provides a measure of the overall magnitude of model and behavioral uncertainty in an aggregate manner, unlike statistical tests, which indicate where the differences may come from. I test the transferred model and the locally estimated model, across different model specifications. I use the naïve transfer method -- without adjusting any parameters.

5.4.1 Misclassification error

Misclassification error is used to evaluate forecast performance. It is defined as the fraction of misclassified sample:

$$\frac{1}{N_s}\sum_{i=1}^{N_s}[[\hat{y}_i \neq y_i]]$$

where y_i is the observed choice, and $\hat{y}_i$ is the estimated choice for household i and $[[\hat{y}_i \neq y_i]]$ is the indicator function, equal to 1 if the statement is true, and 0 otherwise. I compare different specifications according to misclassification errors, using the 1991 travel survey data as the training data, and the 2010 data as the test data. According to the model estimation context and the application context, three types of errors are measured: *base* error (1991 model applied to 1991 data), *forecast* error (1991 model applied to 2010 data), and *local* error (2010 model applied to 2010 data[12]).

Forecast error is often inflated compared to base error because of: 1) changes in behavior; 2) model specification error; 3) changes in unobserved factors; and 4) data measurement error. Local error is usually lower than forecast error because it is based on models estimated on contemporaneous data. The gap between forecast error and local error reflects the temporal transferability of a model from 1991 to 2010.

Table 5–15 and Figure 5-1 show the misclassification error levels for different model specifications. In all specifications, base error is the lowest and forecast error is the highest, with local error in between the two. Overall the differences are relatively modest, 1% to

[12] The 2010 data is the same data set used for model estimation.

3% in error rates. Base error decreases when households' number of children and seniors, distance to CBD, squared distance to CBD, and accessibility ratio are included (i.e., moving from M1 to M4). Population density, job-worker balance, road configurations do not make much difference in lowering the error rates.

When model 1991 is transferred to predict vehicle ownership in 2010, the forecast error is 2.3 to 3.4 percent higher than the local error, depending on the specification. Forecast error also decreases from M1 to M4, and then remains about the same among M4, M5 and M6.

The difference between forecast error and local error is small, from 0.7 to 2.8 percent. Again M4, M5, and M6 have similar forecasting performance − around 37% error rate, about 2.8% away from the best locally estimated model. The household's race is not available in the 1991 data. However, it noticeably reduces local error for 2010 model.

Overall, the transferred model performs quite close to the local model in terms of misclassification error rates.

Table 5–15 Misclassification errors for multiple model specifications

All households	**M1**	**M2**	**M3**	**M4**	**M5**	**M6**	**M7**	**MCube**
Base error (1991→1991)	36.2%	35.4%	34.6%	33.7%	33.8%	33.7%	−	34.8%
Forecast error (1991→2010)	38.5%	38.4%	37.6%	37.1%	37.0%	36.9%	−	37.9%
Local error (2010→2010)	37.8%	36.0%	35.3%	34.9%	34.2%	34.3%	33.8%	36.0%

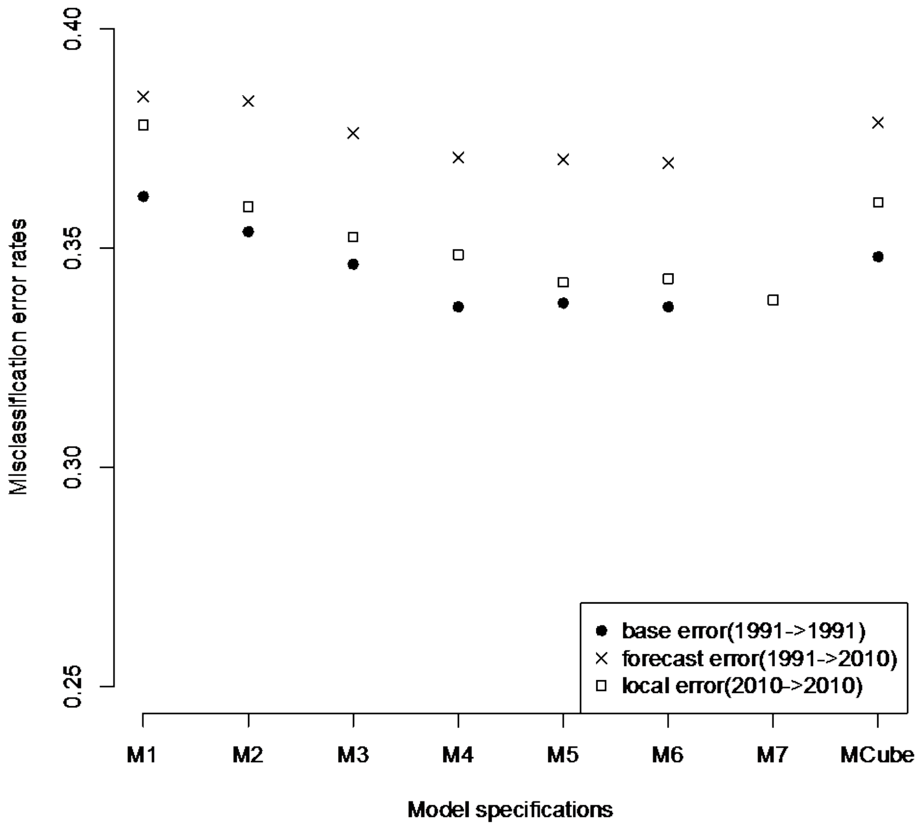


Figure 5-1. Misclassification error rates for different model specifications

5.4.2 Sensitivity for household subgroups

Sensitivity measures a model's ability to identify a condition correctly. In this case, sensitivity is the ratio of the number of households correctly predicted to own J vehicles over the number of households that actually own J vehicles:

$$Sensitivity = \frac{\#\ members\ in\ class\ J\ correctly\ classified\ to\ class\ J}{\#\ members\ in\ class\ J}$$

Table 5–16 shows the model sensitivity for households in different vehicle ownership categories. In general, the models have much lower sensitivity for 0-vehicle and 3-vehicle households than 1-vehicle and 2-vehicle households.

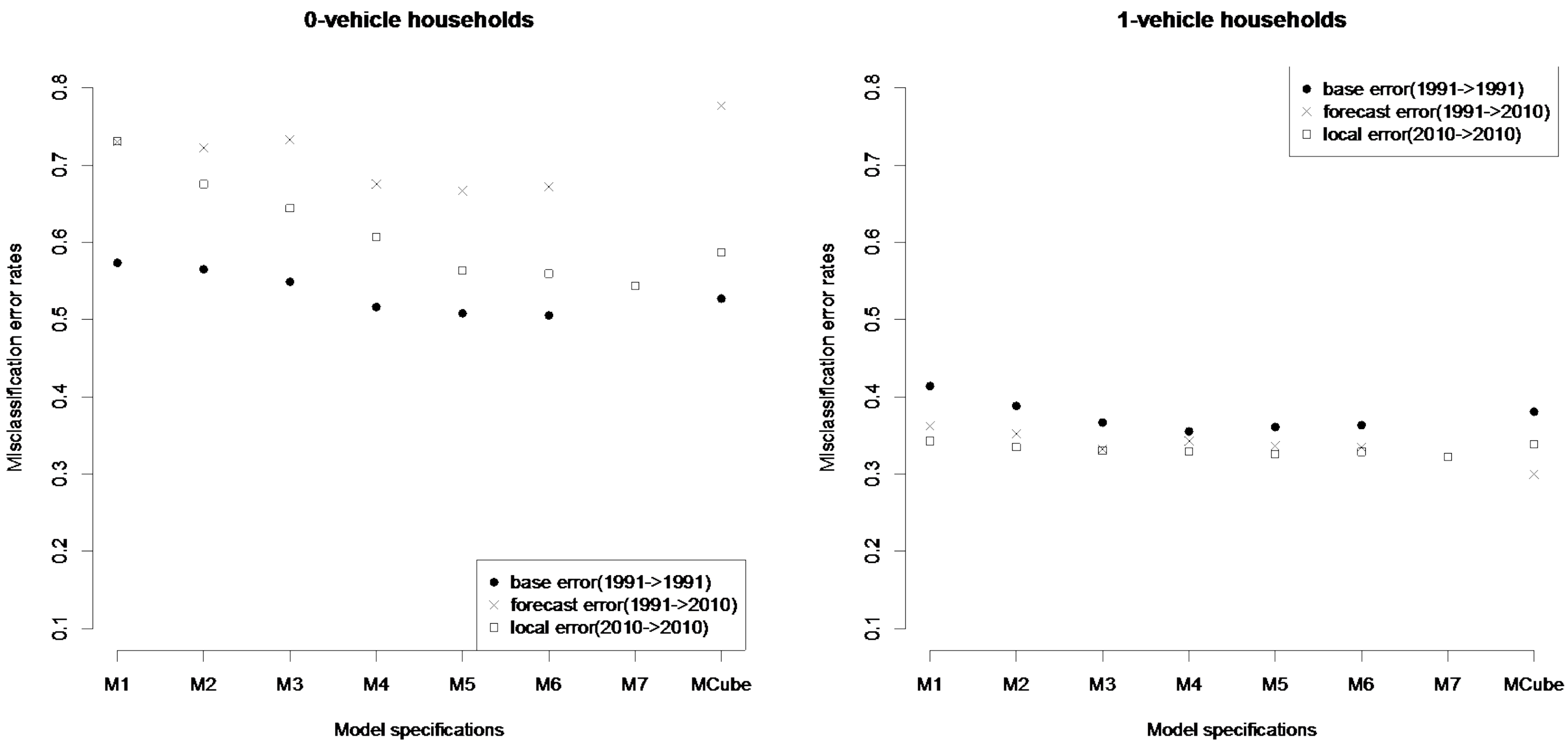
For 0-vehicle households, the local model (2010→2010) correctly identifies only 27% to 46% of them. The transferred model (1991→2010) performs worse, only predicting 22%--33% of these households correctly. Built environment variables contribute to improving the ability to identify 0-vehicle households, since the sensitivity keeps improving as more built environment variables are added.

For the 3-vehicle group, the local model's (2010→2010) sensitivity ranges from 31% to 42%. Including the number of children and seniors improves the sensitivity for the local model. The transferred model's sensitivity to 3-vehicle group is very low and does not vary much across specifications. Surprisingly, sensitivity of the base model (1991->1991) is relatively high (around 46%). It suggests that the 1991 model is more capable of correctly identifying the 3-vehicle group in 1991.

Misclassification errors for the 2- and 3-vehicle ownership groups are much lower. Sensitivities of the forecast model and the local model are close, implying higher temporal transferability for these two groups.

Table 5–16 Prediction sensitivity of different model specifications

				Sensitivity				
0-veh HH	M1	M2	M3	M4	M5	M6	M7	MCube
1991→1991	42.7%	43.5%	45.1%	48.4%	49.2%	49.5%	NA	47.3%
1991→2010	27.0%	27.8%	26.7%	32.5%	33.3%	32.7%	NA	22.3%
2010→2010	26.9%	32.5%	35.6%	39.3%	43.7%	44.1%	45.6%	41.3%
1-veh HH	M1	M2	M3	M4	M5	M6	M7	MCube
1991→1991	58.6%	61.2%	63.3%	64.5%	63.9%	63.7%	NA	61.9%
1991→2010	63.8%	64.8%	66.7%	65.7%	66.3%	66.6%	NA	70.0%
2010→2010	65.7%	66.5%	66.9%	67.1%	67.5%	67.1%	67.8%	66.2%
2-veh HH	M1	M2	M3	M4	M5	M6	M7	MCube
1991→1991	79.6%	79.0%	78.5%	79.1%	79.1%	79.5%	NA	78.9%
1991→2010	83.4%	82.4%	83.0%	83.6%	83.0%	83.2%	NA	81.3%
2010→2010	83.6%	82.7%	82.9%	82.3%	81.9%	81.9%	81.9%	83.2%
3+veh HH	M1	M2	M3	M4	M5	M6	M7	MCube
1991→1991	46.3%	46.7%	46.9%	46.7%	46.9%	46.9%	NA	46.5%
1991→2010	31.1%	31.8%	31.6%	31.7%	31.7%	31.7%	NA	31.0%
2010→2010	31.0%	38.4%	39.3%	40.4%	41.3%	41.4%	41.9%	32.4%


0-vehicle households
1-vehicle households
Misclassification error rates
Model specifications
M1 M2 M3 M4 M5 M6 M7 MCube
base error(1991->1991)
forecast error(1991->2010)
local error(2010->2010)

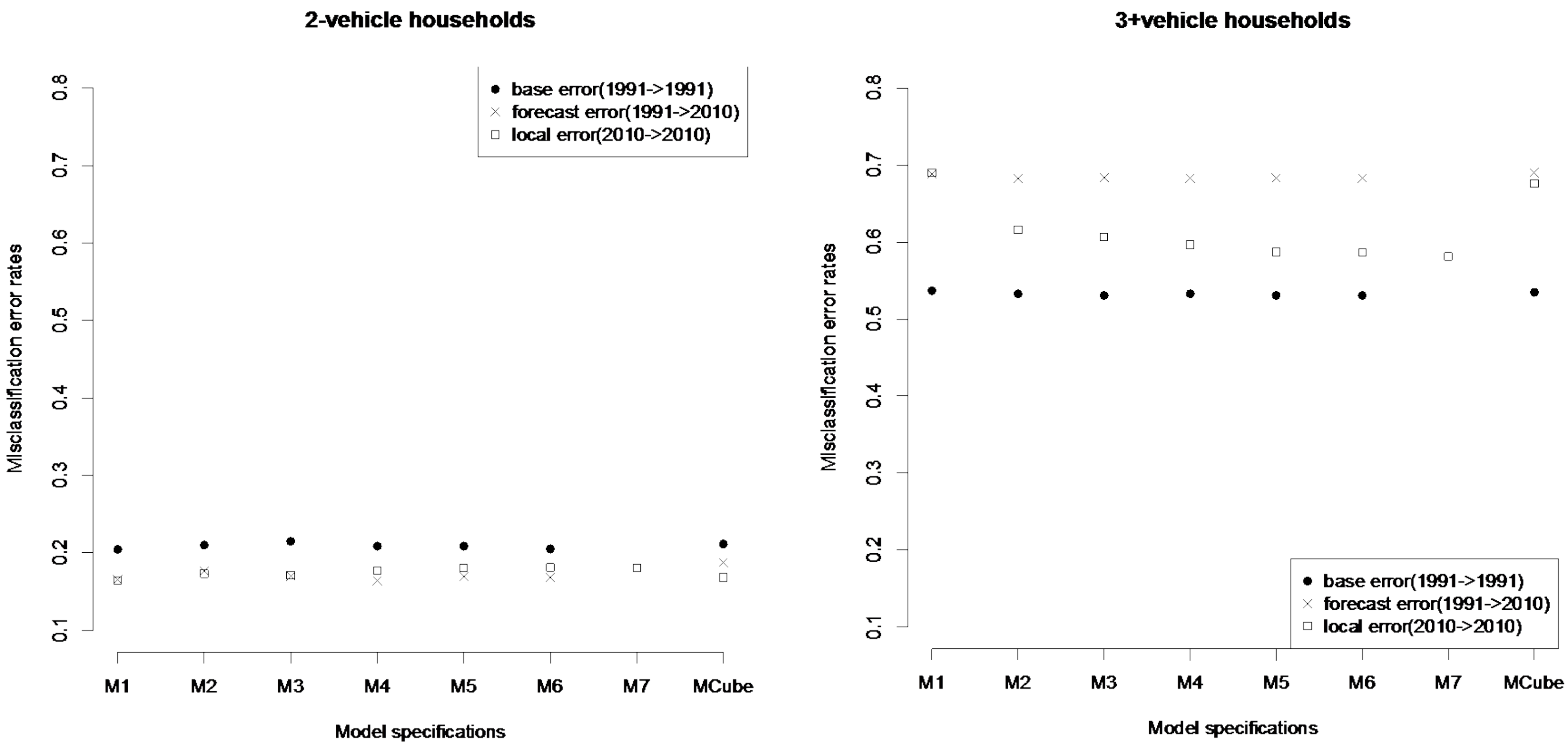


Figure 5-2 Prediction error (=1-sensitivity) for households by number of vehicles

The main type of misclassification made for each subgroup is further examined and summarized as below.

For *0-vehicle households*, the major mistake is classifying them into the 1-vehicle group. Error rates range from 46% to 72% (Table 5–17).

Table 5–17 Misclassification rate: 0-veh to 1-veh households /total 0-veh households

	M1	**M2**	**M3**	**M4**	**M5**	**M6**	**MCube**
Base error	51%	50%	49%	46%	46%	46%	48%
Forecast error	65%	65%	67%	62%	62%	62%	72%
Local error	66%	59%	58%	54%	52%	51%	54%

For *1-vehicle households*, the major mistake is classifying them in the 2-vehicle group. About 23% to 32% of 1-vehicle households are misclassified to have 2-vehicles (Table 5–18).

Table 5–18 Misclassification rate: 1-veh to 2-veh households /total 1-veh households

	M1	**M2**	**M3**	**M4**	**M5**	**M6**	**MCube**
Base error	32%	30%	28%	27%	27%	27%	29%
Forecast error	29%	28%	27%	28%	27%	27%	25%
Local error	28%	27%	26%	25%	23%	24%	25%

For *2-vehicle households*, the mistake rate is the lowest. The major type of error is classifying them in the 1-vehicle group. The error rate ranges from 10%-14% (Table 5–19).

Table 5–19 Misclassification rate: 2-veh to 1-veh households /total 2-veh households

	M1	**M2**	**M3**	**M4**	**M5**	**M6**	**MCube**
Base error	13%	14%	14%	14%	14%	13%	14%
Forecast error	11%	12%	12%	11%	12%	12%	14%
Local error	11%	10%	10%	11%	11%	11%	11%

Finally, for *3+vehicle households* the major mistake is classifying them in the 2-vehicle group. The error rate ranges from 45% to 63% (Table 5–20).

Table 5–20 Misclassification rate: 3-veh to 2-veh households /total 3-veh households

	M1	M2	M3	M4	M5	M6	MCube
Base error	46%	45%	45%	45%	45%	45%	46%
Forecast error	63%	62%	62%	63%	62%	62%	63%
Local error	63%	57%	56%	54%	54%	53%	62%

The higher error rates for 0-vehicle and 3-vehicle group suggest that the current features (X) included in the model are not enough to distinguish between 0-vehicle and 1-vehicle, and between 2-vehicle and 3-vehicle group. For example, households in the 0-vehicle group and in the 1-vehicle group may look very similar in terms of the distributions of the predictive features (X). In other words, when two clusters are highly overlapped in feature space, there is more uncertainty in classifying them to the correct group. If a given model structure cannot separate similar observations, it will assign them to the majority group (with higher prior probability), to lower the total error rates. The result is that the minority market segment has higher error rates. In this case, 1-vehicle and 2-vehicle households (about 70% of the market) are the majority groups, so 0-vehicle household tends to be misclassified into the 1-vehicle group, and 3-vehicle household tends to be misclassified to the 2-vehicle group.

Such prediction bias towards the majority group may not have great impact on the market share for the entire population in the region, since the poor performance for the minority group may not change the overall picture. But it would lead to large bias in prediction at a smaller spatial level (e.g., TAZ), since the market share is not homogenously distributed in space. For zones with large shares of 0-vehicle or 3-vehicle households, the predicted market shares would be largely biased. This can translate into uncertainty in predicting number of trips, mode choice, and traffic at the local level.

The potential solutions include: 1) adding more features, or transforming the current feature space to a higher dimensional space, to give the model more freedom to fit the data; and 2) changing to a model structure that can separate the classes given the same features.

5.4.3 Predicted share versus observed share

Model specifications are also evaluated by comparing predicted shares with observed shares. I transfer the 1991 models to make prediction for the *2010 survey data*. The transferred models, in general, under-predict 0-vehicle and 3-vehicle households, and over-predict 1-vehicle and 2-vehicle households (Table 5–21).

Table 5–21 Observed shares of vehicle ownership in 2010MTS versus predicted shares by 1991 model

		0 vehicle	1 vehicle	2 vehicles	3+ vehicles
	Observed	***10.6***	***31.4***	***39.4***	***18.6***
Model 1					
	Predicted	8.9	32.8	43.9	14.4
	Relative Error	-0.160	0.045	0.114	-0.226
Model 2					
	Predicted	9.3	33.3	44.2	13.2
	Relative Error	-0.123	0.061	0.122	-0.290
Model 3					
	Predicted	8.7	33	45.1	13.3
	Relative Error	-0.179	0.051	0.145	-0.285
Model 4					
	Predicted	8.5	32.9	45.2	13.4
	Relative Error	-0.198	0.048	0.147	-0.280
Model 5					
	Predicted	8.7	33.2	44.9	13.3
	Relative Error	-0.179	0.057	0.140	-0.285
Model 6					
	Predicted	8.6	33.4	44.9	13.1
	Relative Error	-0.189	0.064	0.140	-0.296
Model Cube					
	Predicted	7.4	35.4	43.5	13.8
	Relative Error	-0.302	0.124	0.104	-0.258

Since the predicted share is not only a point estimation, but has a sampling distribution, I compute the distribution of the predicted share for the specification MCube, and check whether the observed shares fall into the confidence interval of the predicted share.

I draw 1000 random samples from the joint distribution of the coefficients of the logit model MCube for 1991. For each draw of parameters, the model predicts the shares for the 2010 sample. Table 5–22 and Figure 5-3 depict the results.

The observed share for all household groups falls outside the 95% confidence interval of the predicted share, meaning the discrepancy between observed and predicted share is statistically significant.

Table 5–22 Predicted shares vs. observed shares of vehicle ownership
(Model: MCube. Model year: 1991. Prediction year: 1991 and 2010)

Year	Vehicle ownership	Predicted mean share	95% Confidence Interval (CI)		Coefficient of variation (CV)	Observed share
1991→ 1991	0-veh	0.106	0.098	0.114	0.039	0.105
	1-veh	0.344	0.332	0.357	0.019	0.345
	2-veh	0.410	0.396	0.423	0.017	0.411
	3+veh	0.140	0.130	0.149	0.034	0.139
1991→ 2010	0-veh	0.075	0.067	0.083	0.055	0.106
	1-veh	0.352	0.337	0.366	0.021	0.314
	2-veh	0.434	0.420	0.449	0.018	0.394
	3+veh	0.138	0.127	0.150	0.042	0.186

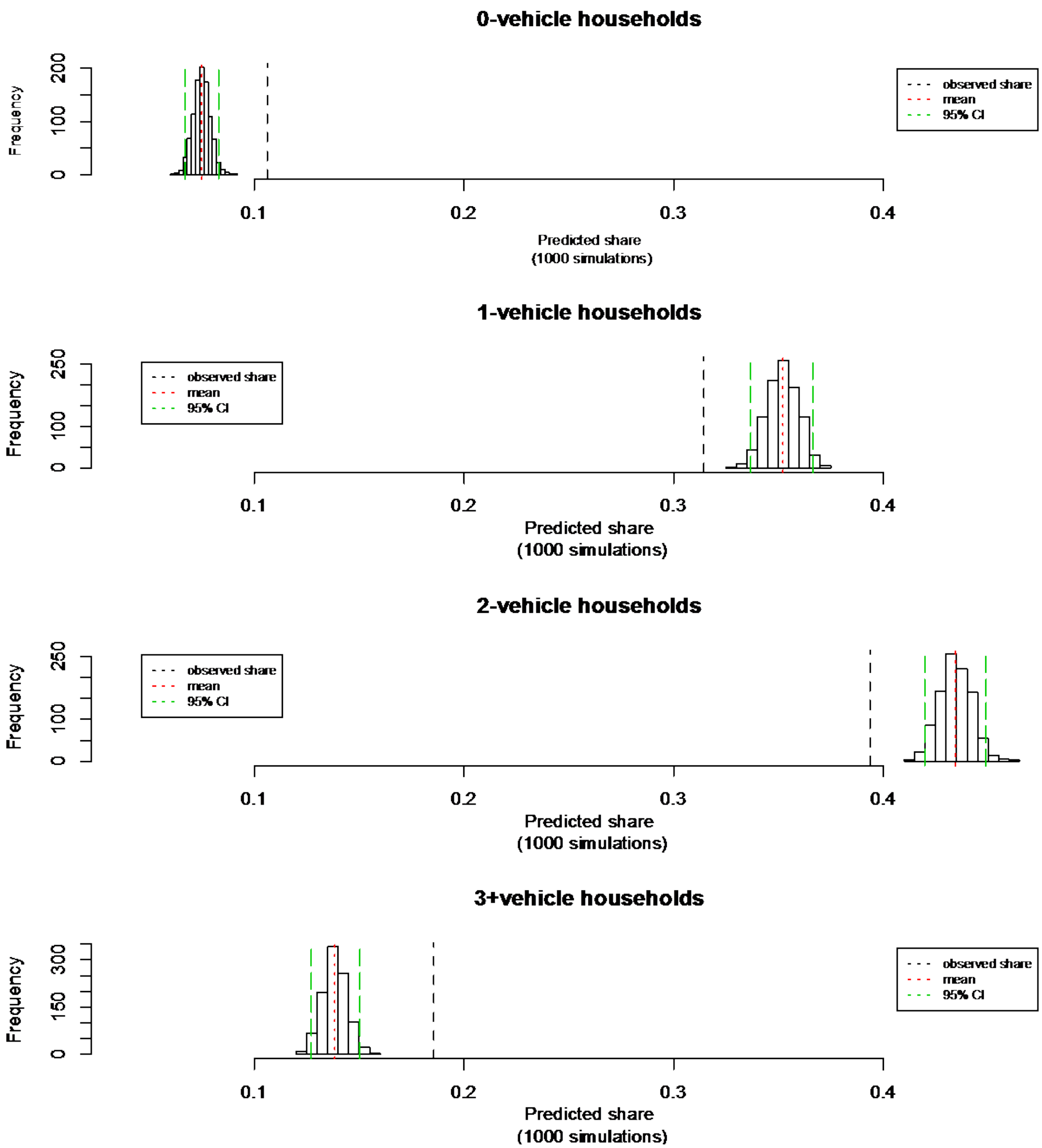


Figure 5-3 Sampling distribution of predicted shares of households by number of vehicles (1991 model applied to 2010 MTS. Model specification MCube. 1000 draws of model parameters)

5.5 Prediction test in population vehicle forecast

This section evaluates the uncertainty when applying the model to the entire population. Aggregate vehicle ownership data for the population are available at the TAZ level, from Census Journey-to-Work data (CTPP). I compare the predicted vehicle ownership with that observed in CTPP. I use model MCube for this forecast, due to the limited information available to characterize the population in CTPP. Table 5–23 lists the inputs and outputs.

Table 5–23 Inputs and outputs for population vehicle ownership forecast for 2010
(Model specification: MCube)

Input	• Model estimated with 1991 BTS (M91) • Model estimated with 2010 MTS (M10) • Number of households characterized by the cross-classification of size, worker, income group in each TAZ (CTPP2010) • TAZ locational attributes
Output	• Expectation of predicted share of car ownership in each TAZ • Sampling distribution of predicted share of car ownership in each TAZ • Comparison of predicted to actual share of car ownership

5.5.1 Predicted and observed vehicle ownership

When the 1991 model is applied to the 2010 CTPP population, 0-vehicle households are under-estimated by 42.5%, 1-vehicle households are slightly over-predicted by 3.8%, 2-vehicle households are over-predicted by 14.8%, and 3-vehicle households are under-predicted by 7.3% (Table 5–24).

Compared to the earlier application of the same 1991 model for 2010 MTS (see Section 5.4.3), prediction performance for the 0-vehicle and 2-vehicle groups gets worse, while predictions for 1-vehicle and 3-vehicle group get better. This may be due to the uncertainty in the travel survey data, which may not well represent the CTPP-estimated population[13].

The locally estimated model (using 2010MTS), when applied to 2010CTPP population, overestimates 3-vehicle households by 22.1%. Prediction errors for other groups are relatively small (≤10%).

[13] The CTPP 'population' is also based on a sample, for which margins of error are also provided.

Compared to the observed 2.64 million vehicles in total, the transferred model and the local model both over-predict, by 5.5% and 6.0% respectively, mainly due to the over-prediction of 2-vehicle and 3-vehicle households, and the under-prediction of 0-vehicle households.

Table 5–24 Observed shares of vehicle ownership in 2010CTPP versus predicted shares by 1991 model and 2010 model

	0-veh	1-veh	2-veh	3+veh	Total HH	Total vehicles[a]
Observed (2010CTPP)						
Count	226,034	594,736	619,171	242,097	1,682,038	2,642,408
Share	13.4%	35.4%	36.8%	14.4%	100%	
1991→2010CTPP						
Count	129,901	617,306	710,604	224,227	1,682,038	2,788,172
Share	7.7%	36.7%	42.2%	13.3%	100%	
Error	-5.7%	1.3%	5.4%	-1.1%		
Relative error	-42.5%	3.8%	14.8%	-7.3%		5.5%
2010 →2010CTPP						
Count	201,916	555,619	629,108	295,396	1,682,038	2,801,432
Share	12.0%	33.0%	37.4%	17.6%	100%	
Error	-1.4%	-2.4%	0.6%	3.2%		
Relative error	-10.7%	-6.6%	1.6%	22.1%		6.0%

a. 3+vehicle households are considered to have 3.343 cars on average when calculating the total vehicles. This number is derived based on the average number of cars for household with 3+ cars from CTPP.

5.5.2 Sampling distribution of predicted vehicle ownership

Because of sampling uncertainty, the difference between the expected value of the observed and predicted shares may not be statistically significant. To explore the distribution of the output, 1000 random sets of coefficients are drawn from their joint distribution. For each draw, the coefficients are applied to predict the ownership shares for the 2010 population. Table 5–25, Table 5–26, Figure 5-4 and Figure 5-5 show the results.

The 1991 model significantly under-predicts 0-vehicle households, and over-predicts 2-vehicle households. For both 1-vehicle and 3+vehicle households, the 95% confidence intervals of the predicted households contains the observed number, meaning the prediction is not statistically different from the observed.

The locally estimated 2010 model significantly under-predicts 0-vehicle and 1-vehicle households, and over-predicts 3-vehicle households. For 2-vehicle households, the prediction is accurate. Overall, local model prediction closely matches the observed share.

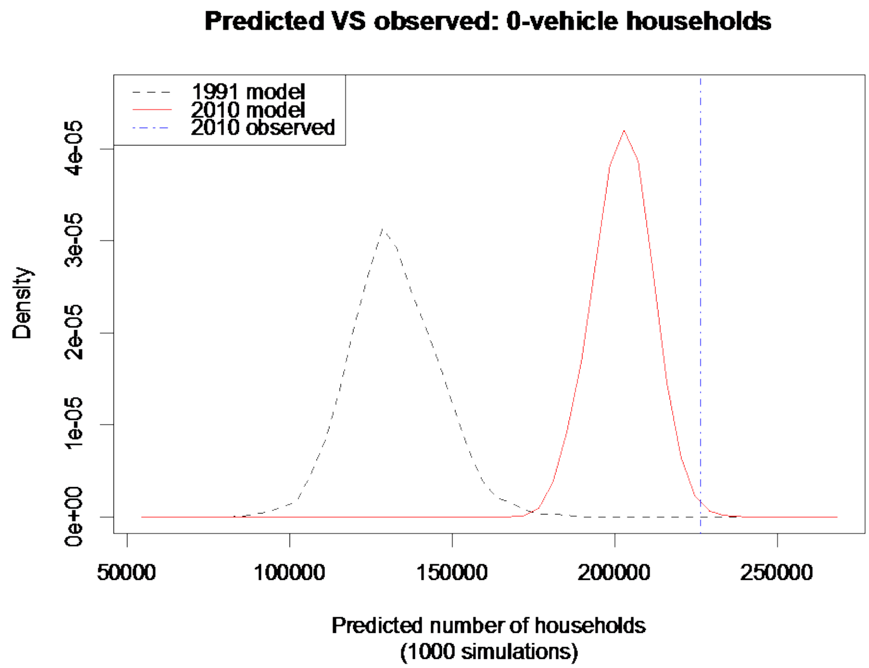
Table 5–25 Summary of sampling distribution of predicted households by vehicle ownership

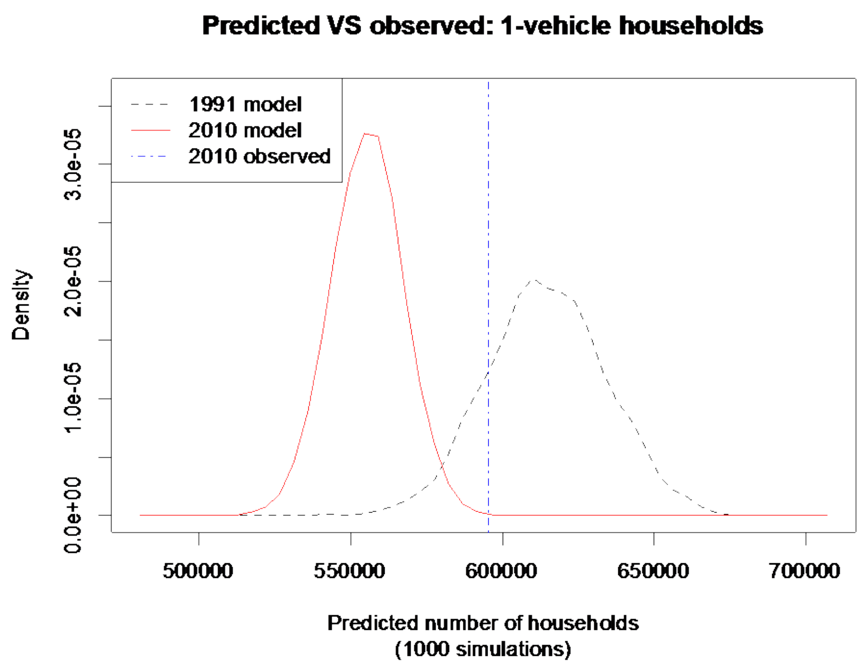
Model	Mean	S.D.	CV	Confidence Interval		Observed in 2010[14]
1991						
V0	132,271	13,509	0.102	107,921	158,916	226,034
V1	614,565	19,382	0.032	576,285	651,987	594,736
V2	708,948	18,462	0.026	673,729	745,576	619,171
V3	226,255	12,447	0.055	202,818	252,431	242,097
2010						
V0	202,332	8,907	0.044	184,776	219,638	226,034
V1	555,393	11,338	0.020	532,626	576,818	594,736
V2	628,757	9,123	0.015	610,469	646,301	619,171
V3	295,556	6,822	0.023	282,281	309,478	242,097

Table 5–26 Summary of vehicle fleet prediction with sampling uncertainty

	Mean	S.D.	CV	Confidence interval		Observed
1991	2,788,831	31,869	0.011	2,728,718	2,852,149	2,642,408
2010	2,800,951	16,990	0.006	2,768,388	2,834,224	2,642,408

[14] Note that the population data 2010 CTPP is also based on survey with various expansion and imputation employed. See http://www.fhwa.dot.gov/planning/census_issues/ctpp/faq/ Ideally, the confidence interval of the prediction should be compared to the observed confidence interval from CTPP. But due to time limit, I only used the CTPP mean.


Predicted VS observed: 0-vehicle households
1991 model
2010 model
2010 observed
Density
0e+00
1e-05
2e-05
3e-05
4e-05
50000
100000
150000
200000
250000
Predicted number of households
(1000 simulations)


Predicted VS observed: 1-vehicle households
1991 model
2010 model
2010 observed
Density
0.0e+00
1.0e-05
2.0e-05
3.0e-05
500000
550000
600000
650000
700000
Predicted number of households
(1000 simulations)

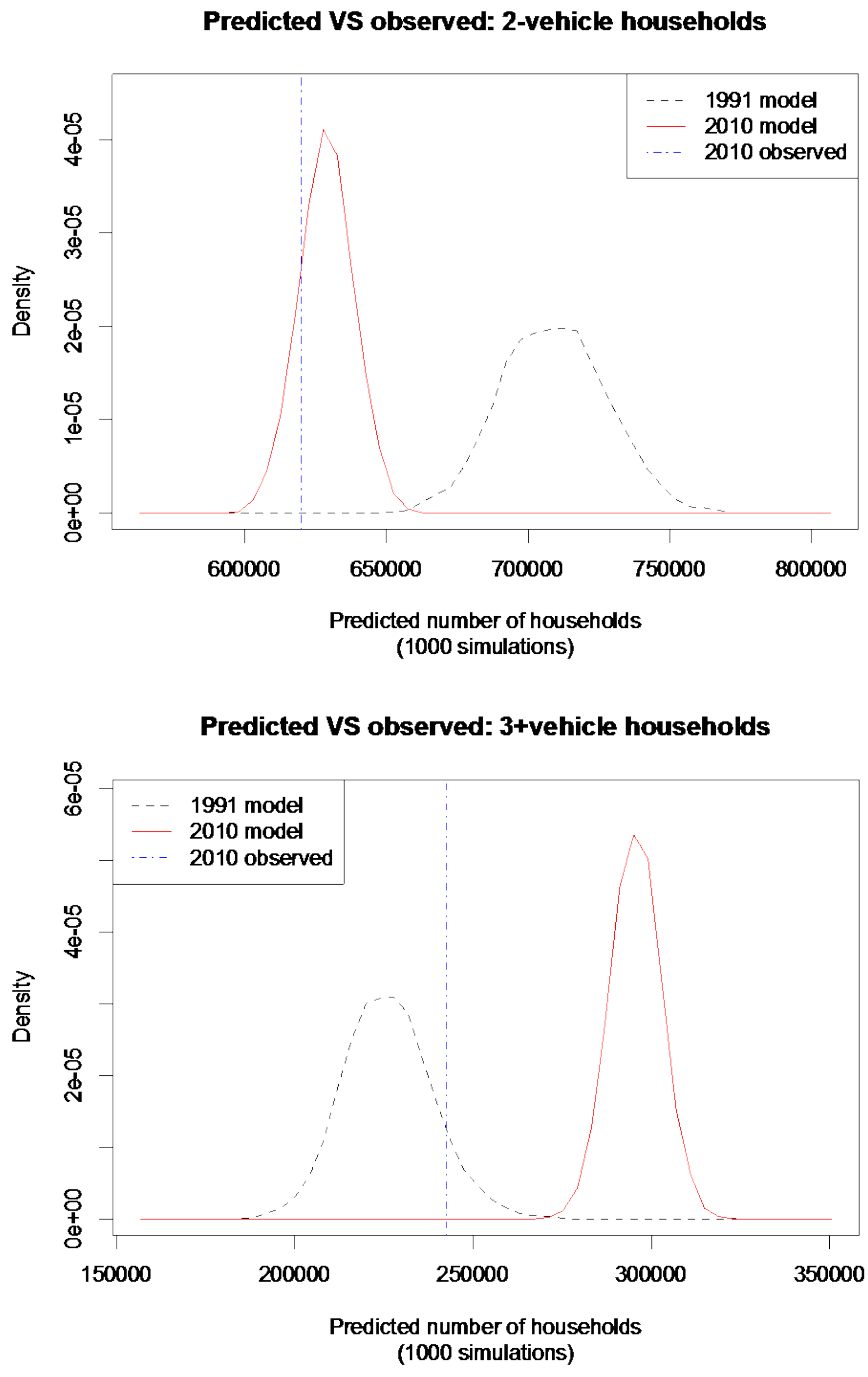


Figure 5-4 Sampling distribution of predicted households by number of vehicles

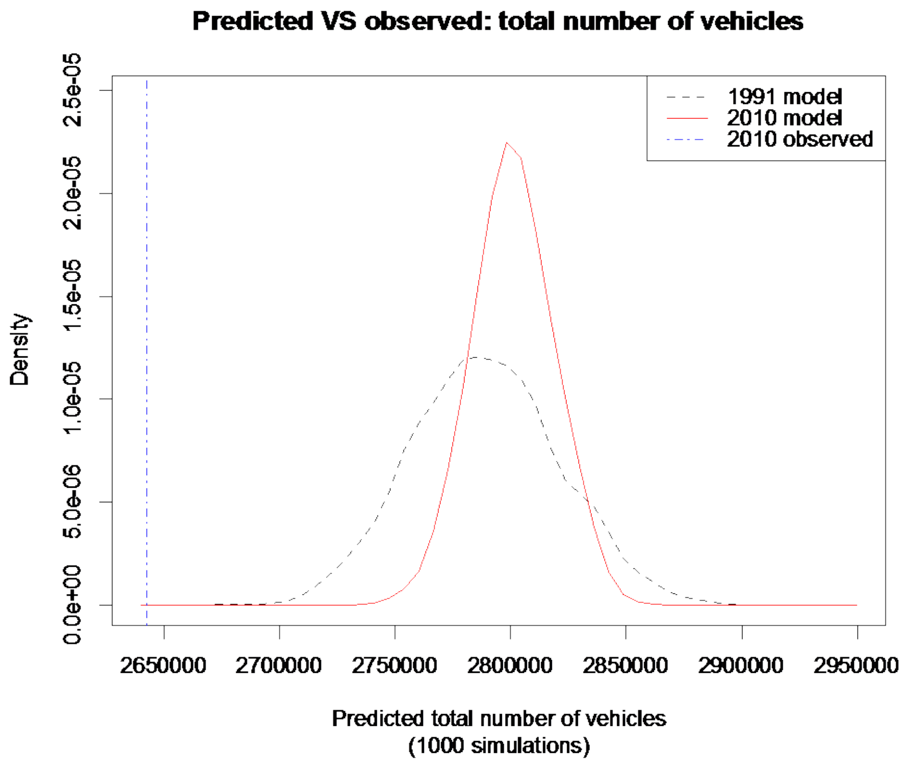


Figure 5-5 Sampling distribution of predicted total vehicles

5.6 Summary

This chapter shows that Boston area households' vehicle ownership choice preferences are not entirely stable over time. Preference parameters for local built environment factors and transit access are stable, while the effects of regional location factor and most socio-economic and demographic factors have evolved.[15]

Given preference changes over time, how can we incorporate this implied behavior uncertainty in forecasting, since we cannot know such preference change ex-ante? One way would be to infer a future based on past preference changes, such as by modeling the relationship between influencing exogenous factors (such as oil prices, employment rates etc.) and preferences, and predicting future preferences given projected future conditions. Chingcuanco and Miller (2014) demonstrate this approach. But this approach introduces

[15] Note, however, that these conclusions are conditioned on the logit model structure and the model specifications explored in this thesis.

the uncertainty in modeling preference change. Another option would be to formulate behavior change scenarios, informed at least partly by the preference change analysis, instead of predicting behavior change. This poses the challenge of sensibly translating the scenarios into changes in preference parameters. With sufficient computational power, one could possibly run forecasts with multiple preference variations, drawing from the distributions for key preference parameters, as identified in the historical models.

The model specifications examined have shown different degrees of prediction performance. Not including households' number of children, number of seniors, and some local built environment variables can lead to higher prediction errors. However, in general the models have high error rates, primarily due to the fact that the models cannot distinguish well between 0- and 1-vehicle households, and between 2- and 3-vehicle households. Forecast errors for 0-vehicle and 3-vehicle group are usually higher, which can cause significantly biased predictions at local level. Alternative model structures should be explored in the future to improve prediction performance.

The transferred models have shown large prediction errors for the population vehicle forecasts, especially for the 0-vehicle and 3-vehicle group. Ultimately understanding the importance of these for transportation systems modeling would require an examination of their propagation to subsequent stages of the four-step model.

Chapter 6

Temporal transferability of trip generation models

This chapter examines the uncertainty related to behavioral change and model specification in trip generation modeling. It also evaluates uncertainty propagation from the vehicle ownership model to trip generation.

6.1 Cross-classification approach and household characterization

Cross-classification is a widely used approach for trip generation in the four-step model (NCHRP, 2012), due to its relative simplicity and ease of application using population data typically available from a census. I initially tried other trip generation model structures, including linear regression, Tobit, Poisson regression, negative binomial, and ordered logit models. But the forecast performances of these models turn out no better than the traditional cross-classification approach for the Boston data. So I proceeded with the cross-classification structure for the uncertainty analysis given the limited available time, and leave the model structure uncertainty to future work.

The classification approach divides households into categories based on their socioeconomic and demographic characteristics, with trip rates then computed for each category, and subsequently applied in the forecasts.

Household categories can be defined in various ways, the most common being size, number of workers, income and the number of motor vehicles. I choose three variations in characterizing households – size-worker-vehicle, size-worker-income, and size-worker-income-vehicle – and calculate trip rates for each approach. I then test if household characterization significantly affects trip generation forecasts, providing an example of uncertainty in model specification.

Table 6–1 shows the values for each categorical variable and the number of household categories for each characterization approach. Note that some categories have zero or too few observations in the surveys. I combine such small groups with their neighboring group to enlarge the sample size. After this consolidation, the “size-worker-vehicle” and “size-worker-income” categorizations have 22 and 50 categories respectively, with at least 10 observations from the surveys for each category. These two household characterizations are denoted as HH22 and HH50.

The most complex “size-worker-income-vehicle” characterization is dealt with differently. Originally it has 224 categories, many of which have fewer than 5 observations. Instead of consolidating them, I replace their trip rates with those from the upper-level group that the household belongs to. “Size-worker-income” – HH50 – is used as the upper-level backup. For example, household group P1W1I1C2 (P1: 1-person, W1: 1-worker, I1: low-income, and C2: 2-car) with fewer than 5 observations inherits the trip rates of its parent in the HH50, which is P1W1I1.

I define and assign the four income levels based on the survey’s original income categories and household size, since for households of different sizes, the four income levels should correspond to different income thresholds (Table 6–2). Table 6–3 shows the income level distribution for the 2010 CTPP population based on this definition.

Table 6–1 Household characterization details

Household characteristics	**Values**
Size (P)	1, 2, 3, 4+
Worker (W)	0, 1, 2, 3+
Income (I)	Low, mid-low, mid-high, high
Vehicles (C)	0, 1, 2, 3+
Household characterization	**Number of household categories**
Size-worker-vehicle (HH22)	22
Size-worker-income (HH50)	50
Size-worker-income-vehicle (HH224)	224

Table 6–2 Household income level definitions (K: 1000 dollars in 2010)

Income levels	1-person	2-person	3-person	4+person
Low	<15K	<35K	<50K	<50K
Mid-low	15K-35K	35K-75K	50K-100K	50K-100K
Mid-high	35K-75K	75K-150K	100K-150K	100K-150K
High	75K+	150K+	150K+	150K+

Table 6–3 Four-level income level distribution for 2010 CTPP population

P: persons W: workers	Low	Mid-Low	Mid-High	High	Total	Low	Mid-Low	Mid-High	High	Total
1P0W	106,632	73,840	37,858	11,295	229,625	46.4%	32.2%	16.5%	4.9%	100.0%
1P1W	17,532	50,007	114,167	73,748	255,454	6.9%	19.6%	44.7%	28.9%	100.0%
2P0W	58,727	39,714	18,439	5,589	122,469	48.0%	32.4%	15.1%	4.6%	100.0%
2P1W	36,163	65,149	50,748	21,250	173,310	20.9%	37.6%	29.3%	12.3%	100.0%
2P2W	10,620	52,983	112,577	57,630	233,810	4.5%	22.7%	48.1%	24.6%	100.0%
3P0W	17,540	4,448	1,372	869	24,229	72.4%	18.4%	5.7%	3.6%	100.0%
3P1W	31,464	29,625	13,763	11,323	86,175	36.5%	34.4%	16.0%	13.1%	100.0%
3P2W	13,825	37,770	33,443	31,939	116,977	11.8%	32.3%	28.6%	27.3%	100.0%
3P3W	3,247	13,035	15,735	14,605	46,622	7.0%	28.0%	33.8%	31.3%	100.0%
4P0W	14,740	3,680	1,057	1,132	20,609	71.5%	17.9%	5.1%	5.5%	100.0%
4P1W	28,872	33,598	23,106	27,586	113,162	25.5%	29.7%	20.4%	24.4%	100.0%
4P2W	17,644	54,060	48,644	52,768	173,116	10.2%	31.2%	28.1%	30.5%	100.0%
4P3W	2,944	16,578	20,098	18,345	57,965	5.1%	28.6%	34.7%	31.6%	100.0%
4P4W	1,179	7,100	11,214	15,085	34,578	3.4%	20.5%	32.4%	43.6%	100.0%
Total	361,129	481,587	502,221	343,164	1,688,101					

Data source: 2010 CTPP. See income level definition in Table 6–2.

6.2 Statistical test of trip rate change

I apply independent sample t-tests to compare the differences in average trip rates for all trip purposes. Table 6–4 to Table 6–15 show the test results. I use the HH22 categorization for statistical tests because the fewer number of household types allows for more observations in each category, and makes it easier to summarize the changes.

Households overall make fewer trips than 20 years ago. Total trip rates have significantly declined for many household types by 12% to 37%. Only households in the P3W1C2 and P3W0C2 groups generate more trips in total (Table 6–4).

HBW trips have decreased for most household groups; while HBWR trips have in general increased (Table 6–5 and Table 6–6). This suggests a shift from HBW trips to HBWR trips. But the sum of HBW and HBWR has decreased. The increase in HBWR relative to HBW may indicate more flexible employment schedules or work settings; while the overall decrease in the sum of both may be attributed to the growing trend of working at-home, and/or more trip chaining within the work commute tour: more people may stop for other activities during their commute tours. This is an area for further study.

Home-based school trips by 3+person households, in which children are mostly like to appear, have increased. For the other groups, home-based school trips have in general declined (Table 6–7). The results seem to suggest at least some measurement inconsistency or coding error in the 1991 BTS, since P1W1 (1-person-1-worker) and P2W2 (2-person-2-worker) households, without children, have unusually high home-based school trip rates. Alternatively or additionally, this may imply that workers nowadays are less likely to also go to school.

Home-based pick-up and drop-off (HBPuDo) trip rates have stayed stable for most household groups, except for P2W0C2, P3W1 and P3W2 households. Households in the P2W0C2 group are likely to be senior households. The decline in HBPuDo trip implies persons in such households more often drive independently. The P3W1 and P3W2 groups are more likely to have children. Having more pick-up and drop-off trips implies that parents more often accommodate their children on trips (e.g., to day-care or school) in 2010 than 1991.

Home-based shopping trips (HBShop) have substantially decreased, especially for the majority of the households with workers. This suggests changes in the mode of shopping: workers may go shopping less frequently, but spend more time on each shopping trip (associated, with, for example, larger shopping centers); people may also shifted more shopping to weekends, which are not covered by the survey. Finally, this change may reflect the impacts of online-shopping becoming popular.

In contrast to households with workers, 0-worker households' shopping trip rates have not changed. This may be because the non-working persons in the households can have more time and flexibility for shopping. The exception among this group is P2W0C2—very likely to be senior households, whose shopping trip rate also decreased.

Most other home-based trips, including home-based bank and personal business trips (HBBPB), home-based social trips (HBSo), and home-based eating (HBEat) trips, have declined. Only home-based recreational trips have increased. Decreased HBBPB trips are mostly likely attributed to the automation of services, for example, online banking. Less HBSo and HBEat trips could be a sign of people spending more time working and less time socializing during the week and eating out less often (perhaps ordering more meals for delivery).

Non-home-based work (NHBW) trips have decreased by a great amount. These are trips between work and activities other than home. Almost all household groups with workers have a 30% to 57% decline in NHBW trip rate. Several changes may be underlying this. First, it may be due to more workers working at home. As HBW trip rates have declined for a majority of the household groups, less presence at work place will lead to less NHBW travel. Second, workers may travel less during their work time. This is supported by my other comparisons of the tour characteristics between 2010MTS and 1991BTS not included in this thesis. I find that workers make fewer trips within their work-based tours in 2010 than 1991. The third hypothesis is that workers may have less trip chaining during their commutes. In other words, commutes consist of more non-stop travel between home and work, which are HBW trips. However, since HBW trips also have declined, this hypothesis is unlikely. More rigorous analysis is needed to disentangle and identify the effect of different behavior mechanisms underlying the trip rate change.

Non-home based other (NHBO) trip rates have significantly decreased for a few household groups, and increased only for P3W1C2 group. This change is hard to directly explain, as it is subject to other primary home-based or work-based travel. Nevertheless, the there are fewer trips.

In addition to all the possible explanations for trip rate changes, measurement errors or inconsistent definitions between the two surveys can also play a role (see more details in section 4.4). Nevertheless, given the best effort to make the data consistent, trip generation behaviors do show significant changes over the years, which may be due to new communication technologies, changed life-styles, changes in the transportation system, and changing economic conditions. Uncertainty in data and in behaviors can together contribute to the differences between forecasted and actual number of trips, as assessed in the next section.

Table 6–4 T tests of trip rate equality: total trips

HH22	1991	2010	Diff.	% Diff	P-value	
P1W0C0	3.7	2.8	-0.8	-24.3%	0.009	**
P1W1C0	4.8	3.7	-1.1	-22.9%	0.000	***
P1W0C1	4.3	3.9	-0.5	-9.3%	0.064	
P1W1C1	5.3	4.1	-1.3	-22.6%	0.000	***
P2W0C0	6.0	5.1	-0.9	-15.0%	0.207	
P2W0C1	6.8	6.1	-0.7	-10.3%	0.170	
P2W0C2	9.4	7.3	-2.1	-22.3%	0.001	***
P2W1C0	8.3	5.2	-3.1	-37.3%	0.001	***
P2W1C1	7.5	6.9	-0.6	-8.0%	0.096	.
P2W1C2	7.8	7.4	-0.3	-5.1%	0.397	
P2W2C0	8.8	7.1	-1.7	-19.3%	0.041	*
P2W2C1	8.9	7.2	-1.7	-19.1%	0.000	***
P2W2C2	8.9	7.3	-1.6	-18.0%	0.000	***
P3W0C0/1	9.9	11.3	1.4	14.1%	0.313	
P3W0C2	8.9	11.4	2.5	28.1%	0.064	.
P3W1C0/1	11.5	12.0	0.5	4.3%	0.521	
P3W1C2	11.9	15.0	3.1	26.1%	0.000	***
P3W2C0/1	13.1	13.4	0.3	2.3%	0.734	
P3W2C2	14.3	14.1	-0.1	-1.4%	0.735	
P3W3C0/1	14.9	12.6	-2.3	-15.4%	0.136	
P3W3C2	17.0	14.9	-2.1	-12.4%	0.015	*
P3W3C3	17.3	14.3	-3	-17.3%	0.000	***

Note: P: persons; W: workers; C: cars. C3 includes 3 or more cars.

Table 6–5 T tests of trip rate equality: HBW (home-based work)

HH22 (Only HH with workers)	1991	2010	Diff.	% Diff	p-value	
P1W1C0	1.2	0.8	-0.4	-31.2%	0.000	***
P1W1C1	1.1	1.0	-0.1	-8.5%	0.045	*
P2W1C0	0.9	1.2	0.3	33.1%	0.148	
P2W1C1	1.1	1.0	-0.1	-4.6%	0.588	
P2W1C2	1.2	1.1	-0.1	-5.2%	0.462	
P2W2C0	1.8	1.9	0.1	3.9%	0.793	
P2W2C1	2.4	2.1	-0.2	-9.9%	0.064	.
P2W2C2	2.3	2.1	-0.2	-6.6%	0.038	*
P3W1C0/1	1.2	1.1	-0.1	-8.7%	0.282	
P3W1C2	1.3	1.2	-0.2	-12.8%	0.004	**
P3W2C0/1	2.3	1.9	-0.4	-15.8%	0.022	*
P3W2C2	2.1	1.9	-0.2	-7.5%	0.013	*
P3W3C0/1	2.8	3.2	0.4	14.2%	0.332	
P3W3C2	3.8	3.0	-0.8	-20.1%	0.002	**
P3W3C3	3.9	3.8	-0.1	-3.7%	0.343	

Table 6–6 T tests of trip rate equality: HBWR (home-based work related)

HH22 (Only HH with workers)	1991	2010	Diff.	% Diff	P-value	
P1W1C0	0.09	0.14	0.05	53.8%	0.255	
P1W1C1	0.12	0.17	0.04	34.8%	0.092	.
P2W1C0	0.06	0.03	-0.03	-49.2%	0.570	
P2W1C1	0.14	0.12	-0.02	-12.9%	0.730	
P2W1C2	0.10	0.19	0.09	91.2%	0.013	*
P2W2C0	0.05	0.36	0.31	671.6%	0.013	*
P2W2C1	0.12	0.33	0.21	182.6%	0.000	***
P2W2C2	0.20	0.39	0.19	91.9%	0.000	***
P3W1C0/1	0.14	0.09	-0.05	-33.5%	0.308	
P3W1C2	0.13	0.14	0.01	6.1%	0.783	
P3W2C0/1	0.18	0.30	0.12	65.8%	0.068	.
P3W2C2	0.20	0.32	0.12	61.1%	0.000	***
P3W3C0/1	0.28	0.57	0.28	100.3%	0.111	
P3W3C2	0.35	0.38	0.04	11.1%	0.655	
P3W3C3	0.36	0.53	0.17	47.6%	0.008	**

Table 6–7 T tests of trip rate equality: HBSc (home-based school)

HH22	1991	2010	Diff.	% Diff	P-value	
P1W0C0	0.37	0.03	-0.34	-91.5%	0.002	**
P1W1C0	0.13	0.04	-0.09	-70.6%	0.066	.
P1W0C1	0.13	0.02	-0.11	-83.8%	0.040	*
P1W1C1	0.04	0.00	-0.04	-93.8%	0.002	**
P2W0C0	1.39	0.37	-1.02	-73.1%	0.005	**
P2W0C1	0.11	0.10	-0.01	-5.4%	0.912	
P2W0C2	0.08	0.01	-0.06	-81.5%	0.128	
P2W1C0	1.42	0.38	-1.04	-73.0%	0.003	**
P2W1C1	0.32	0.35	0.03	7.9%	0.732	
P2W1C2	0.13	0.07	-0.06	-48.0%	0.140	
P2W2C0	0.45	0.09	-0.37	-81.2%	0.005	**
P2W2C1	0.24	0.06	-0.18	-73.5%	0.004	**
P2W2C2	0.08	0.02	-0.06	-79.6%	0.000	***
P3W0C0/1	1.48	1.48	0.00	0.1%	0.996	
P3W0C2	0.91	0.85	-0.06	-7.0%	0.834	
P3W1C0/1	1.28	1.38	0.1	8.1%	0.610	
P3W1C2	0.87	1.45	0.58	66.2%	0.000	***
P3W2C0/1	1.18	1.54	0.36	30.4%	0.041	*
P3W2C2	1.12	1.46	0.35	31.0%	0.000	***
P3W3C0/1	1.74	0.89	-0.85	-49.0%	0.061	.
P3W3C2	1.37	1.12	-0.24	-17.7%	0.228	
P3W3C3	0.93	0.70	-0.23	-24.8%	0.044	*

Table 6–8 T tests of trip rate equality: HBPuDo (home-based pick-up drop-off)

HH22	1991	2010	Diff	% Diff	P-value	
P1W0C0	0.02	0.02	0.00	-9.9%	0.927	
P1W1C0	0.03	0.04	0.01	44.1%	0.596	
P1W0C1	0.19	0.10	-0.09	-48.1%	0.083	.
P1W1C1	0.11	0.09	-0.03	-23.9%	0.192	
P2W0C0	0.22	0.29	0.06	28.6%	0.664	
P2W0C1	0.43	0.34	-0.09	-20.4%	0.427	
P2W0C2	0.58	0.24	-0.34	-58.9%	0.028	*
P2W1C0	0.18	0.15	-0.03	-15.4%	0.816	
P2W1C1	0.55	0.65	0.11	19.5%	0.319	
P2W1C2	0.29	0.28	-0.01	-2.6%	0.920	
P2W2C0	0.17	0.11	-0.07	-38.1%	0.549	
P2W2C1	0.52	0.36	-0.16	-31.4%	0.067	.
P2W2C2	0.24	0.17	-0.06	-26.7%	0.064	.
P3W0C0/1	1.19	1.62	0.43	36.3%	0.374	
P3W0C2	0.48	0.80	0.32	65.6%	0.187	
P3W1C0/1	1.38	1.82	0.45	32.7%	0.055	.
P3W1C2	1.62	2.36	0.75	46.1%	0.000	***
P3W2C0/1	1.48	1.95	0.47	31.7%	0.035	*
P3W2C2	1.58	1.85	0.27	17.0%	0.007	**
P3W3C0/1	0.63	0.92	0.29	46.6%	0.356	
P3W3C2	1.60	1.74	0.14	8.9%	0.603	
P3W3C3	0.97	0.91	-0.07	-6.8%	0.603	

Table 6–9 T tests of trip rate equality: HBShop (home-based shopping)

HH22	1991	2010	Diff	% Diff	P-value	
P1W0C0	0.77	0.74	-0.03	-3.8%	0.815	
P1W1C0	0.35	0.47	0.13	37.0%	0.066	.
P1W0C1	0.75	0.70	-0.05	-6.3%	0.571	
P1W1C1	0.50	0.37	-0.12	-24.9%	0.003	**
P2W0C0	1.17	1.02	-0.14	-12.4%	0.671	
P2W0C1	1.57	1.28	-0.28	-18.2%	0.1	.
P2W0C2	2.03	1.36	-0.66	-32.6%	0.008	**
P2W1C0	0.82	0.69	-0.13	-15.4%	0.607	
P2W1C1	1.05	0.84	-0.21	-19.7%	0.111	
P2W1C2	1.19	0.96	-0.23	-19.5%	0.048	*
P2W2C0	0.72	0.89	0.17	24.3%	0.478	
P2W2C1	0.69	0.61	-0.08	-11.6%	0.441	
P2W2C2	0.73	0.64	-0.09	-12.2%	0.122	
P3W0C0/1	1.56	1.31	-0.25	-15.9%	0.475	
P3W0C2	1.64	1.83	0.19	11.9%	0.632	
P3W1C0/1	1.39	0.99	-0.4	-28.8%	0.026	*
P3W1C2	1.35	1.30	-0.05	-3.8%	0.632	
P3W2C0/1	0.94	0.93	-0.01	-1.1%	0.946	
P3W2C2	1.32	0.98	-0.34	-25.7%	0.000	***
P3W3C0/1	1.59	0.83	-0.76	-47.7%	0.018	*
P3W3C2	1.38	1.12	-0.26	-18.7%	0.202	
P3W3C3	1.55	1.24	-0.31	-19.9%	0.018	*

Table 6–10 T tests of trip rate equality: HBBPB (home-based bank and personal business)

HH22	1991	2010	Diff	% Diff	P-value	
P1W0C0	0.59	0.73	0.13	22.7%	0.282	
P1W1C0	0.31	0.32	0.01	3.1%	0.895	
P1W0C1	1.11	0.84	-0.26	-23.9%	0.017	*
P1W1C1	0.45	0.33	-0.12	-26.1%	0.004	**
P2W0C0	0.78	1.12	0.34	44.1%	0.188	
P2W0C1	1.38	1.17	-0.21	-15.2%	0.261	
P2W0C2	1.91	1.59	-0.32	-16.9%	0.237	
P2W1C0	0.91	0.62	-0.29	-32.3%	0.246	
P2W1C1	0.75	0.58	-0.17	-23.2%	0.120	
P2W1C2	1.14	1.04	-0.09	-8.3%	0.461	
P2W2C0	0.75	0.45	-0.30	-40.4%	0.145	
P2W2C1	0.54	0.52	-0.03	-5.1%	0.770	
P2W2C2	0.72	0.62	-0.11	-14.6%	0.077	.
P3W0C0/1	1.15	1.65	0.50	43.6%	0.245	
P3W0C2	1.55	2.00	0.45	29.4%	0.339	
P3W1C0/1	0.94	1.30	0.36	38.6%	0.053	.
P3W1C2	1.22	1.42	0.20	16.7%	0.078	.
P3W2C0/1	0.91	0.82	-0.09	-10.0%	0.588	
P3W2C2	1.11	0.95	-0.16	-14.4%	0.033	*
P3W3C0/1	1.35	0.68	-0.67	-49.6%	0.050	*
P3W3C2	1.09	1.12	0.04	3.4%	0.864	
P3W3C3	1.25	1.00	-0.25	-19.9%	0.032	*

Table 6–11 T tests of trip rate equality: HBSo (home-based social)

	1991	2010	Diff	% Diff	P-value	
P1W0C0	0.38	0.22	-0.16	-42.1%	0.077	.
P1W1C0	0.17	0.18	0.02	11.8%	0.735	
P1W0C1	0.30	0.37	0.07	23.3%	0.280	
P1W1C1	0.30	0.18	-0.12	-40.0%	0.001	***
P2W0C0	0.64	0.37	-0.27	-42.2%	0.234	
P2W0C1	0.47	0.39	-0.07	-14.9%	0.534	
P2W0C2	0.78	0.66	-0.11	-14.1%	0.467	
P2W1C0	0.36	0.20	-0.16	-44.4%	0.319	
P2W1C1	0.48	0.30	-0.18	-37.5%	0.044	*
P2W1C2	0.51	0.40	-0.12	-23.5%	0.186	
P2W2C0	0.42	0.13	-0.29	-69.0%	0.023	*
P2W2C1	0.36	0.18	-0.17	-47.2%	0.017	*
P2W2C2	0.34	0.27	-0.07	-20.6%	0.089	.
P3W0C0/1	1.56	0.81	-0.74	-47.4%	0.152	
P3W0C2	0.91	0.52	-0.39	-42.9%	0.170	
P3W1C0/1	0.69	0.48	-0.20	-29.0%	0.180	
P3W1C2	0.76	0.80	0.04	5.3%	0.680	
P3W2C0/1	0.70	0.59	-0.11	-15.7%	0.458	
P3W2C2	0.85	0.61	-0.24	-28.2%	0.001	***
P3W3C0/1	0.96	0.55	-0.41	-42.7%	0.319	
P3W3C2	1.12	0.64	-0.47	-42.0%	0.006	**
P3W3C3	1.11	0.80	-0.31	-27.9%	0.008	**

Table 6–12 T tests of trip rate equality: HBRec (home-based recreational)

HH22	1991	2010	Diff	% Diff	P-value	
P1W0C0	0.13	0.18	0.05	41.0%	0.362	
P1W1C0	0.24	0.19	-0.05	-19.5%	0.484	
P1W0C1	0.11	0.34	0.22	199.7%	0.000	***
P1W1C1	0.19	0.23	0.05	26.4%	0.117	
P2W0C0	0.19	0.29	0.09	46.9%	0.487	
P2W0C1	0.30	0.52	0.22	71.3%	0.045	*
P2W0C2	0.63	0.60	-0.02	-3.6%	0.881	
P2W1C0	0.15	0.31	0.16	103.1%	0.281	
P2W1C1	0.29	0.49	0.20	70.6%	0.021	*
P2W1C2	0.26	0.60	0.34	133.4%	0.000	***
P2W2C0	0.28	0.68	0.40	142.1%	0.076	.
P2W2C1	0.34	0.42	0.08	24.2%	0.321	
P2W2C2	0.30	0.41	0.11	37.5%	0.008	**
P3W0C0/1	0.74	0.64	-0.10	-14.0%	0.740	
P3W0C2	0.61	1.31	0.70	116.1%	0.031	*
P3W1C0/1	0.83	1.14	0.31	37.6%	0.111	
P3W1C2	0.83	1.59	0.76	92.3%	0.000	***
P3W2C0/1	1.03	1.21	0.17	16.7%	0.464	
P3W2C2	0.94	1.27	0.32	34.2%	0.000	***
P3W3C0/1	0.72	0.89	0.17	23.6%	0.609	
P3W3C2	1.13	1.15	0.03	2.6%	0.897	
P3W3C3	0.92	0.84	-0.07	-8.1%	0.514	

Table 6–13 T tests of trip rate equality: HBEat (home-based eating)

HH22	1991	2010	Diff	% Diff	P-value	
P1W0C0	0.30	0.14	-0.16	-54.2%	0.035	*
P1W1C0	0.26	0.20	-0.06	-24.2%	0.322	
P1W0C1	0.37	0.20	-0.17	-46.1%	0.008	**
P1W1C1	0.26	0.19	-0.07	-27.2%	0.019	*
P2W0C0	0.25	0.18	-0.07	-29.7%	0.695	
P2W0C1	0.61	0.38	-0.23	-37.3%	0.066	.
P2W0C2	0.59	0.53	-0.06	-10.6%	0.674	
P2W1C0	0.42	0.29	-0.13	-31.1%	0.481	
P2W1C1	0.40	0.27	-0.14	-33.8%	0.074	.
P2W1C2	0.34	0.40	0.07	19.9%	0.359	
P2W2C0	0.52	0.43	-0.09	-17.5%	0.637	
P2W2C1	0.38	0.41	0.03	8.0%	0.719	
P2W2C2	0.40	0.33	-0.06	-16.2%	0.191	
P3W0C0/1	0.30	0.21	-0.09	-29.5%	0.582	
P3W0C2	0.27	0.85	0.57	209.9%	0.011	*
P3W1C0/1	0.47	0.34	-0.13	-28.5%	0.372	
P3W1C2	0.32	0.51	0.18	57.1%	0.005	**
P3W2C0/1	0.17	0.36	0.20	119.6%	0.016	*
P3W2C2	0.36	0.44	0.09	24.2%	0.086	.
P3W3C0/1	0.46	0.26	-0.19	-42.1%	0.299	
P3W3C2	0.54	0.45	-0.09	-16.2%	0.587	
P3W3C3	0.62	0.60	-0.02	-3.5%	0.817	

Table 6–14 T tests of trip rate equality: NHBW (non-home-based work)

HH22 (Only HH with workers)	1991	2010	Diff	% Diff	P-value	
P1W1C0	1.37	0.60	-0.77	-56.5%	0.000	***
P1W1C1	1.50	0.80	-0.70	-46.4%	0.000	***
P2W1C0	0.97	0.48	-0.49	-50.8%	0.077	.
P2W1C1	1.11	0.74	-0.37	-33.3%	0.005	**
P2W1C2	1.09	0.72	-0.37	-34.1%	0.003	**
P2W2C0	1.75	1.02	-0.73	-41.6%	0.015	*
P2W2C1	2.29	1.33	-0.96	-42.1%	0.000	***
P2W2C2	2.59	1.39	-1.19	-46.1%	0.000	***
P3W1C0/1	1.00	0.61	-0.39	-39.2%	0.007	**
P3W1C2	1.21	0.72	-0.49	-40.8%	0.000	***
P3W2C0/1	2.04	1.36	-0.68	-33.2%	0.000	***
P3W2C2	2.32	1.54	-0.78	-33.6%	0.000	***
P3W3C0/1	2.26	2.09	-0.17	-7.4%	0.779	
P3W3C2	2.66	1.82	-0.85	-31.8%	0.005	**
P3W3C3	3.33	1.89	-1.44	-43.3%	0.000	***

Table 6–15 T tests of trip rate equality: NHBO (non-home-based other)

HH22	1991	2010	Diff	%Diff	P-value	
P1W0C0	1.07	0.71	-0.36	-33.8%	0.030	*
P1W1C0	0.69	0.66	-0.03	-3.9%	0.839	
P1W0C1	1.32	1.24	-0.08	-6.0%	0.562	
P1W1C1	0.73	0.62	-0.10	-14.4%	0.102	
P2W0C0	1.28	1.19	-0.09	-7.1%	0.762	
P2W0C1	1.84	1.78	-0.06	-3.0%	0.828	
P2W0C2	2.66	2.18	-0.48	-18.0%	0.154	
P2W1C0	2.12	0.65	-1.48	-69.5%	0.002	**
P2W1C1	1.29	1.34	0.06	4.4%	0.751	
P2W1C2	1.50	1.60	0.11	7.1%	0.530	
P2W2C0	1.80	1.00	-0.80	-44.3%	0.057	.
P2W2C1	1.02	0.73	-0.28	-27.6%	0.045	*
P2W2C2	1.02	0.90	-0.12	-11.8%	0.131	
P3W0C0/1	1.85	2.62	0.76	41.2%	0.223	
P3W0C2	2.33	2.89	0.55	23.7%	0.376	
P3W1C0/1	2.03	2.09	0.06	3.1%	0.840	
P3W1C2	2.21	2.81	0.60	27.1%	0.001	***
P3W2C0/1	2.21	1.94	-0.27	-12.2%	0.378	
P3W2C2	2.27	2.04	-0.23	-10.0%	0.089	.
P3W3C0/1	2.02	1.38	-0.64	-31.9%	0.154	
P3W3C2	1.92	1.78	-0.14	-7.2%	0.632	
P3W3C3	2.24	1.79	-0.46	-20.4%	0.018	*

6.3 Prediction test on disaggregated data

To assess the temporal transferability of trip rate models, I apply models estimated for 1991 to predict trips by individual households in 2010 MTS. I then expand these predicted trips using the 2010 survey household expansion factors to estimate total trips for the population. These prediction results are compared with the 2010MTS observed trips (also expanded to population) to measure the magnitude of the errors from transferring 1991 trip rates to the 2010 population (expanded from the survey). I also examine how household characterizations can make a difference in predicting the number of trips. Table 6–16 shows the results.

Table 6–16 Comparisons of prediction errors by different HH categorizations

	Observed (2010MTS)	HH22	% Error	HH50	% Error	HH224	% Error
Total	15,183,718	16,254,006	7.0%	16,436,889	8.3%	16,567,267	9.1%
HBW	2,306,875	2,517,518	9.1%	2,466,436	6.9%	2,460,592	6.7%
HBWR	349,916	229,570	-34.4%	243,933	-30.3%	244,141	-30.2%
HBSc	963,268	957,751	-0.6%	946,335	-1.8%	981,895	1.9%
HBSh	1,500,200	1,805,305	20.3%	1,819,836	21.3%	1,835,797	22.4%
HBPuDo	1,422,844	1,248,832	-12.2%	1,307,877	-8.1%	1,296,385	-8.9%
HBBPB	1,509,155	1,612,330	6.8%	1,641,356	8.8%	1,655,770	9.7%
HBSo	760,004	1,000,243	31.6%	984,150	29.5%	1,013,974	33.4%
HBEat	586,823	636,659	8.5%	650,665	10.9%	655,369	11.7%
HBRec	1,211,414	881,469	-27.2%	901,192	-25.6%	914,870	-24.5%
NHBW	1,500,248	2,532,476	68.8%	2,573,180	71.5%	2,603,009	73.5%
NHBO	2,574,732	2,747,647	6.7%	2,815,084	9.3%	2,817,755	9.4%

The patterns of over- or under-predictions are, overall, consistent across different household characterizations and similar to the changes in trip rates analyzed above. Applying 1991 trip rates overestimates total trips in 2010 by 7% to 9%. Home-based work-related, home-based pick-up and drop-off, and home-based recreational trips are substantially under-predicted; while home-based social, home-based shopping, and non-home-based work trips are over-predicted by a large proportion.

Household characterizations do affect prediction accuracy for some trip purposes. HH50 and HH224 predict better than HH22 for HBW, HBWR, HBPuDo and HBRec trips. This suggests that trip generation for such trip purposes is sensitive to income levels. Including income in household characterization can improve the transferability of trip rates, and reduce prediction errors. For example, using HH50 or HH224 (both having income), the over-prediction of HBW trip is 6.9% and 6.7%, lower than the 9.1% over-prediction by the HH22 characterization.

But for other home-based trip purposes, and non-home-based trip purposes, the HH50 and HH224 perform worse than the HH22. This may be because trip making for such purposes is less affected by income. There are few observations for these trip purposes, and a more detailed household characterization makes observations even sparser for each household category. Also note that there is little difference between HH50 and HH224 in terms of prediction performance. This means that, for these trip purposes, adding additional vehicle ownership information will not help improve prediction accuracy if income level is already included in the household categorization.

Therefore, adding more household characteristics does not necessarily reduce forecast error, since the increase in sampling variance (due to fewer observations in each household category) may overwhelm the decrease in bias. A simpler household characterization may work as well as, and even better than, a more complicated one, at least for some trip categories. In practice, we can potentially adopt a multi-level household characterization strategy: using more detailed household characteristics for certain trip purposes if these purposes are sensitive to certain characteristics; and using higher-level household characteristics for other purposes to reduce sampling variance.

Figure 6-1 shows the magnitude of the trips over- or under-predicted in 2010 applying the 1991 trip rates. NHBW accounts for the greatest amount of over-prediction.

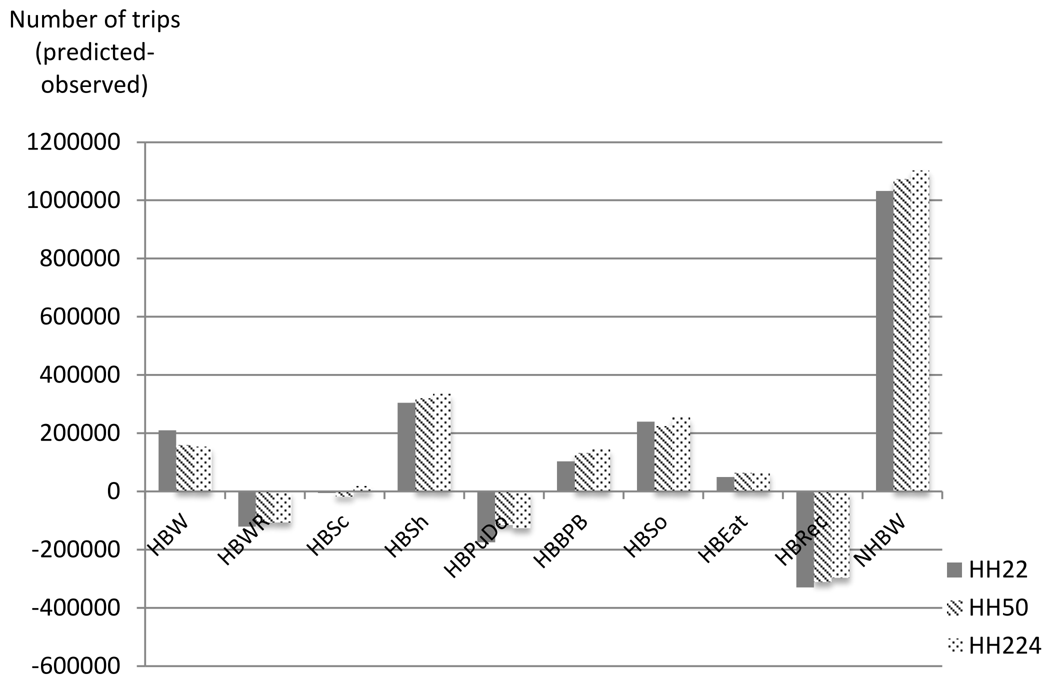


Figure 6-1 Difference between predicted and observed trips in 2010

6.4 Prediction tests for the population

I apply 1991 trip rates to the 2010 CTPP population (rather than 2010MTS, as in section 6.3) for population trip generation. Since uncertainty in vehicle ownership modeling can propagate to the trip generation stage, I divide the uncertainty analysis scenarios for trip generation into two groups: 1) trip production with the actual vehicle ownership in 2010; and 2) trip production with predicted vehicle ownership.

6.4.1 Trip generation uncertainty with actual vehicle ownership

In this case, only the HH22 specification is tested. CTPP 2010 provides the estimated number of households by workers and by cars. The estimated population data for HH224 (the tabulation for the number of households by workers, cars and income group) is not available from CTPP. HH50 does not contain vehicle ownership in its characterization.

Vehicle ownership status matters for subsequent mode choice modeling, as the Boston Cube model implementation has separate model choice models, distinguishing between "choice" versus "captive" users, the latter being without car access and thus "captive" to public transport for motorized trips. In the trip generation step of the Boston Cube model, trips are first generated based on the household characteristics and the trip rates. Then household trips are assigned to "choice" and "captive" riders according to the number of vehicles relative to the number of persons in the households. These separate "choice" and "captive" trips will affect the mode choice step.

I define the two scenarios by trip rate year. Table 6–17 shows the predicted outcomes for the 2010 estimated population.

Table 6–17 Trip production for 2010 population using 1991 and 2010 trip rates for HH22

	Predicted trips for 2010 CTPP population		
Trip purpose	**Trip rate 1991**	**Trip rate 2010**	**% Diff**
HBW	1,984,802	2,148,195	8.2%
HBWC	248,353	275,040	10.7%
HBWR	303,112	202,084	-33.3%
HBWRC	37,859	19,631	-48.1%
HBS	219,088	168,442	-23.1%
HBSC	725,880	764,253	5.3%
HBPUDO	848,272	769,959	-9.2%
HBPUDOC	528,802	422,355	-20.1%
HBSHOP	991,172	1,216,448	22.7%
HBSHOPC	486,822	568,281	16.7%
HBBPB	994,664	1,133,770	14.0%
HBBPBC	481,640	464,399	-3.6%
HBSO	514,307	658,018	27.9%
HBSOC	229,082	331,265	44.6%
HBEAT	421,193	445,320	5.7%
HBEATC	166,770	186,669	11.9%
HBREC	800,047	563,686	-29.5%
HBRECC	394,499	285,347	-27.7%
HBO	56,261	55,515	-1.3%
HBOC	19,757	28,044	41.9%
NHBW	1,316,757	2,194,005	66.6%
NHBWC	156,897	258,231	64.6%
NHBO	1,718,596	1,822,735	6.1%
NHBOC	817,749	877,524	7.3%

Note: trip purpose with ending ‘C’ denotes Captive riders.

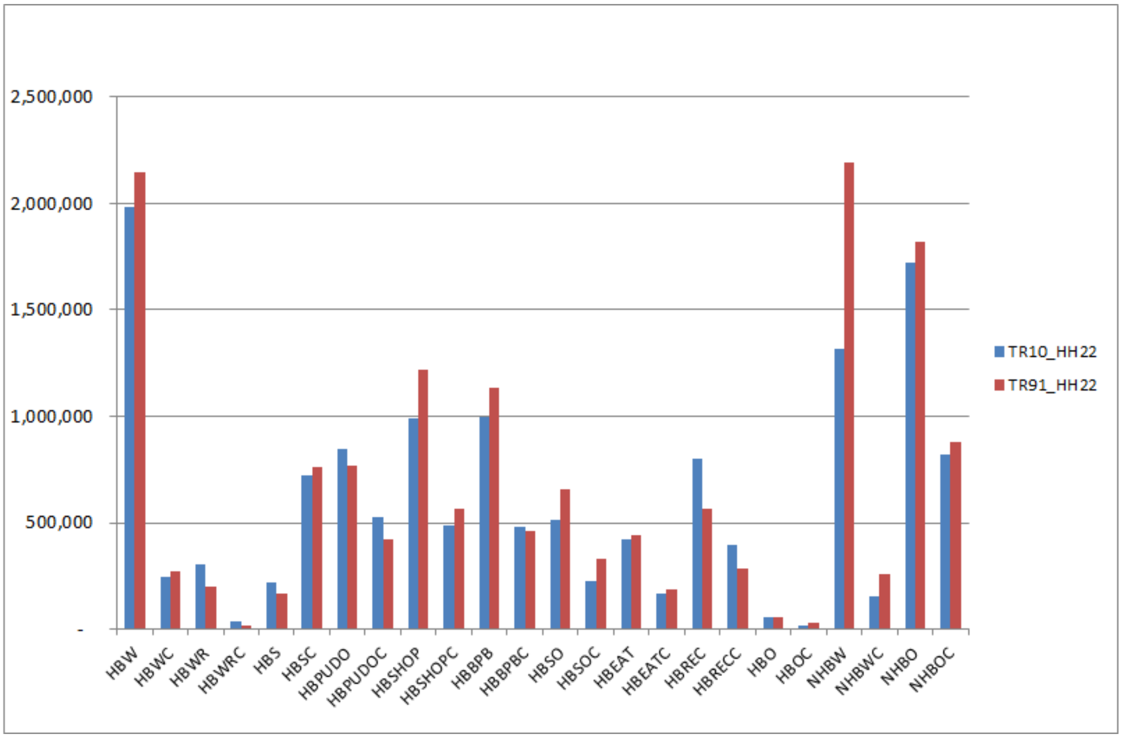


Figure 6-2 Predicted trips for 2010 population using 1991 and 2010 trip rates
(HH22, using Actual vehicle ownership)

I examine sampling uncertainty in forecasting the number of trips through 1000 bootstrap simulations. In each simulation, I randomly sample (with replacement) households from the survey, compute the trip rates for each household category, and apply the trip rates to generate forecasts for the 2010 population. The simulated sampling distributions of the predicted number of trips by trip purpose are displayed in Figure 6-3.

Predictions using 1991 survey data have higher sampling uncertainty than those using 2010MTS, because of the 1991 survey's smaller sample size. Comparing the sampling distributions of the forecasted number of trips can tell whether the differences (in Table 6–17) are indeed significant. Based on Figure 6-3, predicted HBSc, HBEat, HBBPB and NHBO trips are not significantly different between the two scenarios, while predictions for other trip purposes are.

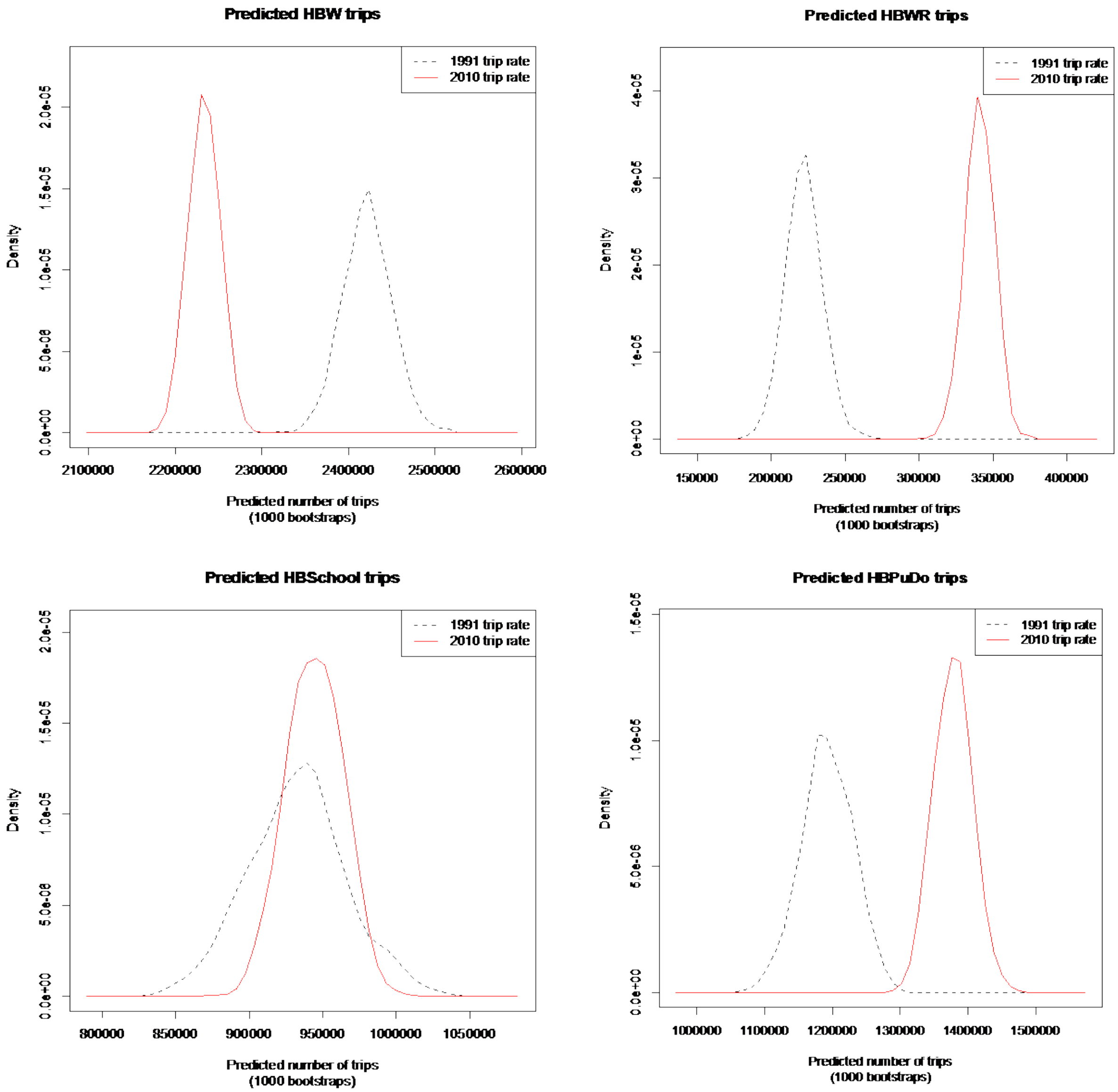


Figure 6-3 Probability density plots of predicted number of trips in 2010 using 1991 and 2010 trip rates

(1000 bootstraps. “captive” and “choice” riders’ trips are combined)

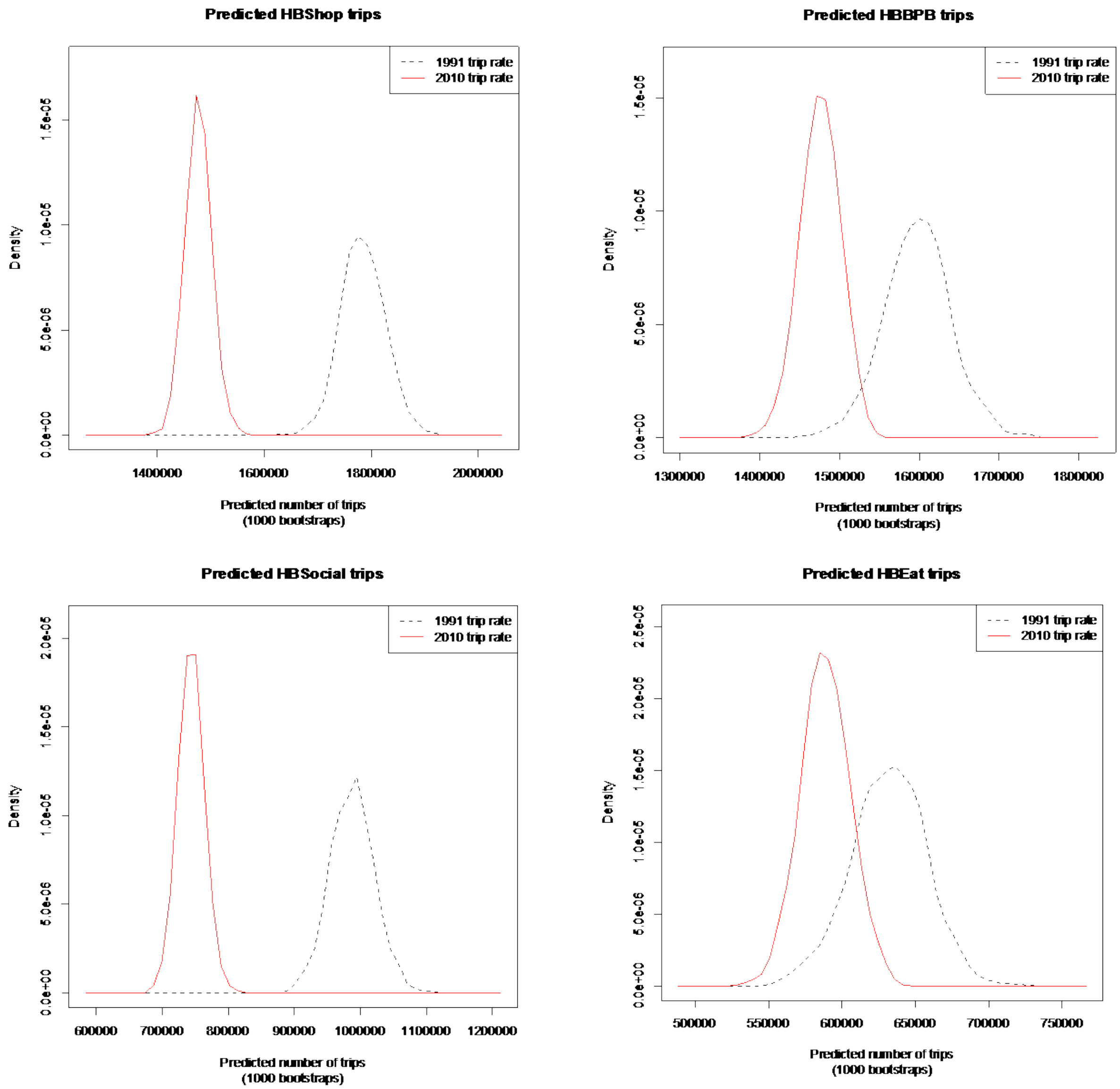


Figure 6-3 cont'd

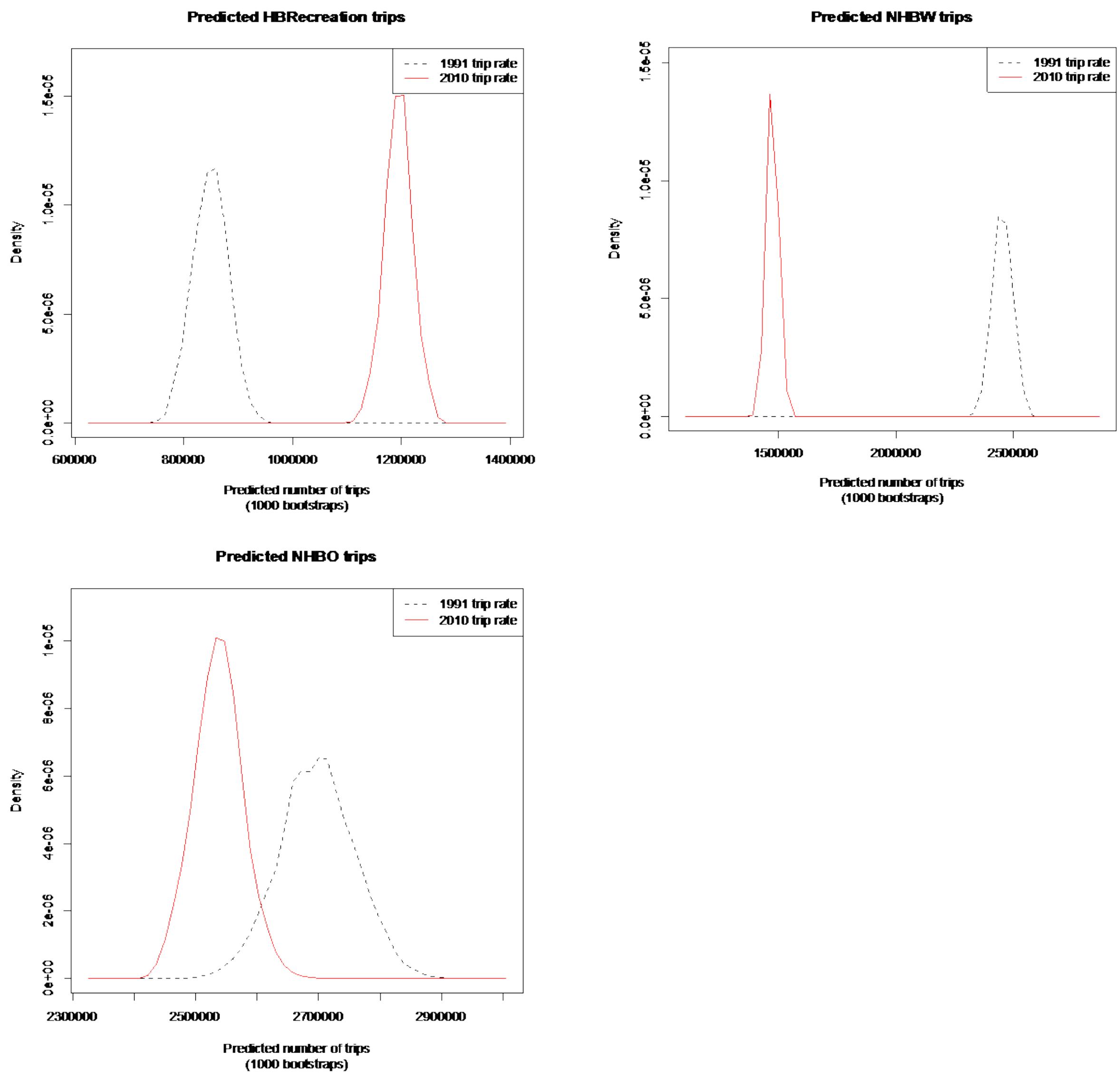


Figure 6-3 cont'd

6.4.2 Trip generation with predicted vehicle ownership

To examine uncertainty propagation between vehicle ownership and trip generation, I use the output of the vehicle ownership model as an input to the trip generation model. The uncertainty in the vehicle ownership model can affect the number of households in each category of the cross-classification-based trip generation model, if vehicle ownership is used in defining household types.

I develop 24 scenarios to examine uncertainty propagation from household vehicle ownership modeling to trip production (trips by purpose for the 2010 population). Table

6–18 and Table 6–19 specify the modeling scenarios. Vehicle model scenarios are defined by 2 specifications and 2 model years. The base model includes household size, workers, income levels, and access to transit and commuter rail stations as predictors. The extended model has additional location and built environment attributes: distance to CBD, population density, job-worker ratio, and job accessibility ratio. This is the same specification as MCube in Chapter 5.

Table 6–18 Scenarios for vehicle ownership prediction

		Vehicle model	
		Base	**Extended**
Model year	**1991**	VehBase91	VehEx91
	2010	VehBase10	VehEx10

Base model: predictors include household size, workers, income levels, and access to transit and commuter rail stations. Extended model: predictors from base model and adding distance to CBD, population density, job-worker ratio, and job accessibility ratio (MCube specification in Chapter 5).

Table 6–19 Scenarios for trip generation

		Household characterization		
		HH22	**HH50**	**HH224**
Trip rate year	**1991**	TR91_HH22	TR91_HH50	TR91_HH224
	2010	TR10_HH22	TR10_HH50	TR10_HH224

Note: TR denotes trip rate.

Table 6–20 (a-d) show the results of the 24 scenarios. Each of the four tables corresponds to a vehicle model scenario (vehicle model year & vehicle model specification). Within each table, there are 6 scenarios for trip rates (trip rate year & household characterization).

Table 6–20 Predicted total trip productions in 2010 by trip purpose of the 24 modeling scenarios

a. Vehicle model 2010: base

	Trip rates 1991			Trip rates 2010		
	TR91_224	**TR91_50**	**TR91_22**	**TR10_224**	**TR10_50**	**TR10_22**
HBW:	2,129,805	2,107,018	2,150,985	1,978,891	1,969,462	1,986,617
HBWC:	290,076	293,543	280,394	263,260	273,825	246,824
HBWR:	212,083	205,814	201,385	304,732	300,065	305,853
HBWRC:	21,260	25,707	21,692	39,587	43,336	35,358
HBS:	307,494	362,478	297,015	352,591	396,249	374,030
HBSC:	582,297	553,044	609,679	581,465	543,814	558,782
HBPUDO:	731,471	759,983	751,322	770,144	798,504	823,839
HBPUDOC:	493,564	495,212	439,098	580,029	554,067	545,827
HBSHOP:	1,236,729	1,169,425	1,216,918	995,714	978,647	995,414
HBSHOPC:	580,052	606,432	567,930	482,061	499,849	487,037
HBBPB:	1,160,388	1,067,050	1,142,983	997,431	957,265	1,006,534
HBBPBC:	489,000	541,833	464,686	487,848	520,231	482,710
HBSO:	640,956	629,673	655,117	514,074	485,794	513,695
HBSOC:	326,341	340,225	331,618	251,605	275,343	236,068
HBEAT:	444,625	444,134	443,289	417,285	405,597	422,944
HBEATC:	180,473	194,061	185,843	167,641	182,099	173,193
HBREC:	552,068	558,852	552,110	744,851	746,476	792,636
HBRECC:	319,803	320,916	296,583	410,767	417,297	406,617
HBO:	61,688	54,593	55,301	53,169	51,076	56,643
HBOC:	35,138	31,632	28,763	19,449	21,715	20,500
NHBW:	2,243,580	2,228,885	2,206,553	1,327,736	1,316,438	1,319,388
NHBWC:	270,963	276,304	259,655	156,326	165,480	153,186
NHBO:	1,809,330	1,792,216	1,817,813	1,687,825	1,635,162	1,725,401
NHBOC:	926,763	951,796	879,409	838,863	897,683	823,680

Table 6-20 cont'd

b. Vehicle model 2010: extended

	Trip rates 1991			Trip rates 2010		
	TR91_224	TR91_50	TR91_22	TR10_224	TR10_50	TR10_22
HBW:	2,122,412	2,099,679	2,143,630	1,972,237	1,962,846	1,979,529
HBWC:	296,959	300,882	286,816	269,079	280,441	252,369
HBWR:	211,306	205,127	200,717	303,362	298,985	304,787
HBWRC:	21,903	26,394	22,250	40,514	44,417	36,123
HBS:	305,044	358,616	294,144	351,312	392,493	369,598
HBSC:	587,625	556,906	615,070	587,673	547,570	564,766
HBPUDO:	728,147	756,964	748,361	769,314	794,924	818,863
HBPUDOC:	496,400	498,231	443,600	583,547	557,647	551,816
HBSHOP:	1,236,418	1,166,633	1,214,317	992,553	976,131	992,005
HBSHOPC:	583,514	609,224	570,618	482,481	502,365	488,767
HBBPB:	1,157,449	1,064,603	1,141,547	994,686	954,055	1,003,974
HBBPBC:	490,793	544,280	466,378	490,683	523,441	485,144
HBSO:	638,219	626,415	653,115	512,536	483,987	512,341
HBSOC:	330,138	343,484	334,792	252,644	277,150	237,708
HBEAT:	444,145	443,666	442,818	416,247	404,809	421,035
HBEATC:	181,472	194,529	186,794	167,527	182,887	173,472
HBREC:	551,854	556,865	550,171	744,026	744,491	788,635
HBRECC:	322,757	322,903	299,535	411,623	419,282	409,041
HBO:	61,196	54,309	55,039	53,243	51,030	56,620
HBOC:	35,220	31,917	28,753	19,548	21,761	20,609
NHBW:	2,236,484	2,223,016	2,198,652	1,323,743	1,312,898	1,315,015
NHBWC:	276,803	282,172	265,416	158,734	169,020	156,632
NHBO:	1,805,270	1,788,810	1,813,664	1,683,872	1,630,137	1,719,486
NHBOC:	930,966	955,202	884,237	842,705	902,707	829,064

Table 6-20 cont'd

c. Vehicle model 1991: base

	Trip rates 1991			Trip rates 2010		
	TR91_224	TR91_50	TR91_22	TR10_224	TR10_50	TR10_22
HBW:	2,109,096	2,087,585	2,126,065	1,946,994	1,947,435	1,959,759
HBWC:	309,587	312,976	295,984	282,294	295,852	268,207
HBWR:	211,206	205,598	200,031	293,922	296,312	298,737
HBWRC:	21,366	25,922	21,113	42,546	47,090	40,011
HBS:	293,351	353,928	91,041	343,407	384,856	367,594
HBSC:	581,754	561,594	613,881	591,253	555,207	574,735
HBPUDO:	731,662	742,723	747,147	780,403	782,153	825,823
HBPUDOC:	522,379	512,472	461,886	613,777	570,418	568,435
HBSHOP:	1,204,560	1,155,314	1,191,584	975,132	969,290	982,660
HBSHOPC:	596,150	620,543	584,616	494,020	509,205	497,357
HBBPB:	1,120,134	1,057,748	1,124,138	970,580	953,295	988,275
HBBPBC:	502,924	551,136	482,417	486,267	524,201	483,943
HBSO:	622,955	622,147	643,667	503,509	482,697	504,225
HBSOC:	328,241	347,751	336,471	259,918	278,439	239,627
HBEAT:	439,828	438,918	440,246	403,775	397,095	412,754
HBEATC:	190,179	199,277	192,011	177,413	190,601	183,751
HBREC:	542,650	548,882	538,877	735,647	731,651	783,838
HBRECC:	330,766	330,886	303,807	435,372	432,122	428,226
HBO:	57,631	53,636	55,193	51,454	49,929	55,314
HBOC:	35,267	32,590	29,745	20,609	22,863	21,528
NHBW:	2,227,802	2,216,003	2,182,710	1,324,940	1,305,367	1,310,660
NHBWC:	275,268	289,186	268,364	165,728	176,551	164,431
NHBO:	1,770,098	1,773,631	1,790,249	1,657,345	1,617,226	1,706,677
NHBOC:	939,164	970,380	900,555	870,433	915,619	848,900

Table 6-20 cont'd

d. Vehicle model 1991: extended

	Trip rates 1991			Trip rates 2010		
	TR91_224	TR91_50	TR91_22	TR10_224	TR10_50	TR10_22
HBW:	2,140,785	2,118,487	2,158,222	1,976,519	1,976,806	1,989,791
HBWC:	279,992	282,074	266,866	254,622	266,482	240,616
HBWR:	213,433	208,151	203,080	299,766	301,119	304,378
HBWRC:	19,676	23,369	19,390	37,771	42,283	35,622
HBS:	299,176	360,393	296,420	349,922	391,727	374,045
HBSC:	572,630	555,129	598,411	581,522	548,335	565,217
HBPUDO:	739,608	753,495	756,796	788,098	792,188	835,113
HBPUDOC:	511,392	501,700	452,933	603,995	560,383	558,469
HBSHOP:	1,229,406	1,176,016	1,215,304	994,330	986,991	1,001,582
HBSHOPC:	576,980	599,841	566,219	476,245	491,505	480,569
HBBPB:	1,142,994	1,077,254	1,148,532	990,302	970,290	1,009,440
HBBPBC:	485,272	531,629	466,961	471,089	507,207	470,288
HBSO:	634,957	632,689	655,224	513,344	490,518	514,284
HBSOC:	320,049	337,210	327,217	254,747	270,619	234,137
HBEAT:	447,253	447,531	448,784	411,629	404,533	421,034
HBEATC:	181,463	190,664	183,880	170,003	183,162	177,251
HBREC:	550,698	557,213	547,650	747,129	743,447	797,401
HBRECC:	322,067	322,555	295,741	422,444	420,326	417,197
HBO:	58,343	54,561	56,027	52,586	50,917	56,602
HBOC:	34,058	31,664	28,775	19,999	21,874	21,028
NHBW:	2,260,410	2,248,821	2,219,556	1,346,437	1,324,668	1,331,124
NHBWC:	244,069	256,367	240,308	147,798	157,251	147,413
NHBO:	1,801,577	1,804,896	1,823,981	1,688,409	1,644,931	1,739,351
NHBOC:	904,160	939,116	868,906	845,949	887,913	826,202

Comparing these scenarios can help understand the impact of uncertainty in vehicle ownership model specification, vehicle ownership model estimation year, trip rate year and household characterization on the trip production results. Due to the difficulty in comparing the four dimensions at the same time, I evaluate them one dimension at a time while controlling the others.

1) Vehicle ownership model specification

The difference between the base and extended vehicle ownership model (with and without built environment variables) in their aggregate forecast of households by number of vehicles, is very small (Table 6–21).

For the 2010 vehicle ownership model, the performance of the base and the extended models are very close. For the 1991 model, the base and extended model under-predict 0-vehicle households, and over-predict 2-vehicle households by a substantial amount. The base model is worse than the extended model for both 0- and 2-vehicle households (Table 6–21).

Table 6–21 Predicted vs. observed vehicle ownership for 2010 population by 1991 and 2010 vehicle model

	Vehicle model 2010				Vehicle model 1991				Actual in 2010	
	Base		Extended		Base		Extended			
Veh0	198,397	11.8%	201,963	12.0%	129,937	7.7%	142,438	8.5%	226,034	13.4%
Veh1	556,206	33.1%	555,758	33.0%	617,444	36.7%	642,325	38.2%	594,736	35.4%
Veh2	629,341	37.4%	629,307	37.4%	710,833	42.2%	678,407	40.3%	619,171	36.8%
Veh3+	298,637	17.7%	295,555	17.6%	224,369	13.3%	219,412	13.0%	242,097	14.4%

To see the impact on trip generation forecast, I select two pairs of scenarios for comparison: 1) the 2010 vehicle ownership model base vs. extended with the same trip rates (TR10_HH22); and 2) the 1991 vehicle ownership model base vs. extended with the same trip rates (TR10_HH22).

The differences in predicted trips between the extended and base models are very small for the 2010 vehicle ownership model, and much bigger for the 1991 vehicle ownership models (Figure 6-4 and Figure 6-5). The extended 1991 vehicle model consistently leads to more trips by choice riders, and fewer trips by captive riders compared to the base model. This is mainly because the 1991 extended vehicle ownership model predicts more 0-vehicle households, and fewer 2- and 3+ vehicle households than the base model.

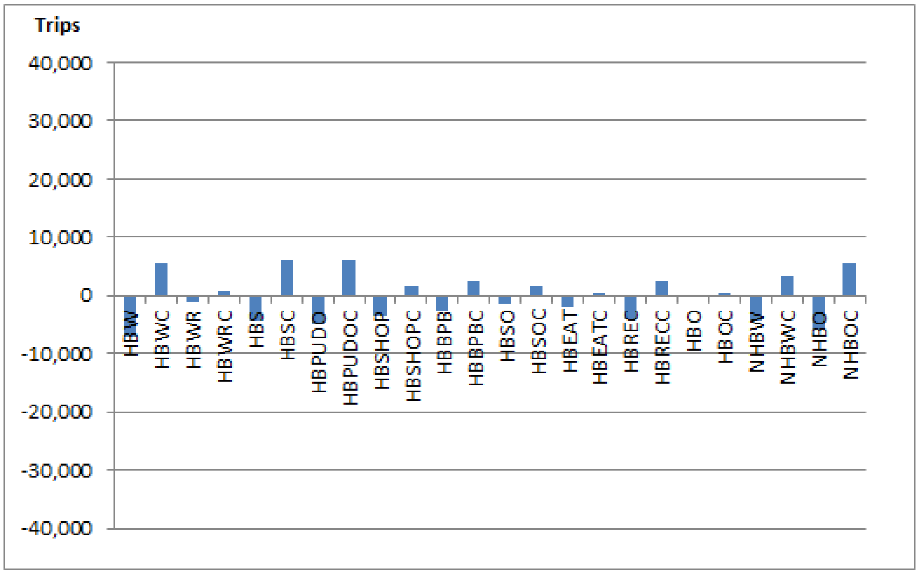


Figure 6-4 Differences in predicted trips: extended - base model

(Vehicle ownership model 2010. 2010 trip rates for HH22)

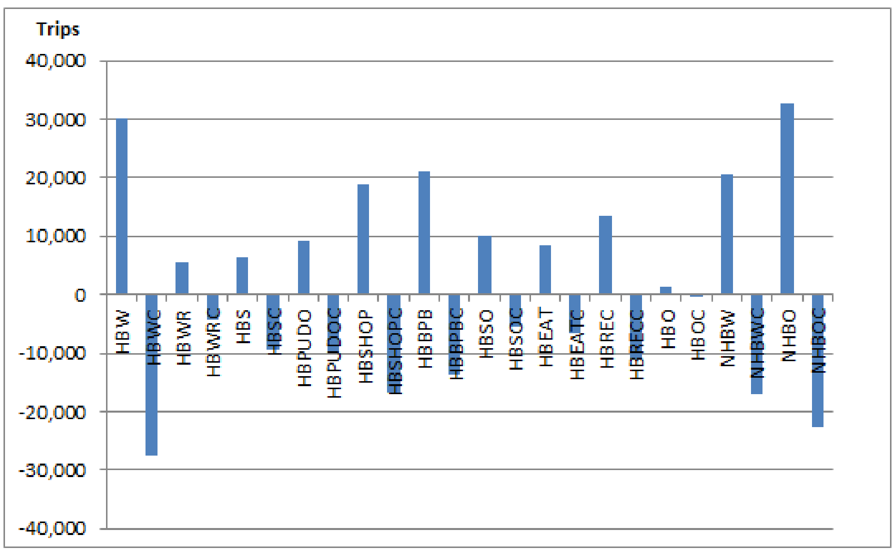


Figure 6-5 Differences in predicted trips: extended - base model

(Vehicle ownership model 1991. 2010 trip rates for HH22)

2) Vehicle ownership model year

Using vehicle ownership models estimated for different years leads to big differences in vehicle ownership forecasts (as shown in Table 6–21), which then can carry over to trip generation. I examine the implications by using the extended vehicle ownership model, and TR10_HH22, and varying vehicle ownership model year. The difference in household trip production between vehicle models in the two years is very small, all else equal (within

1%), with no systematic over/under-prediction of the choice or captive riders (as shown in Figure 6-6).

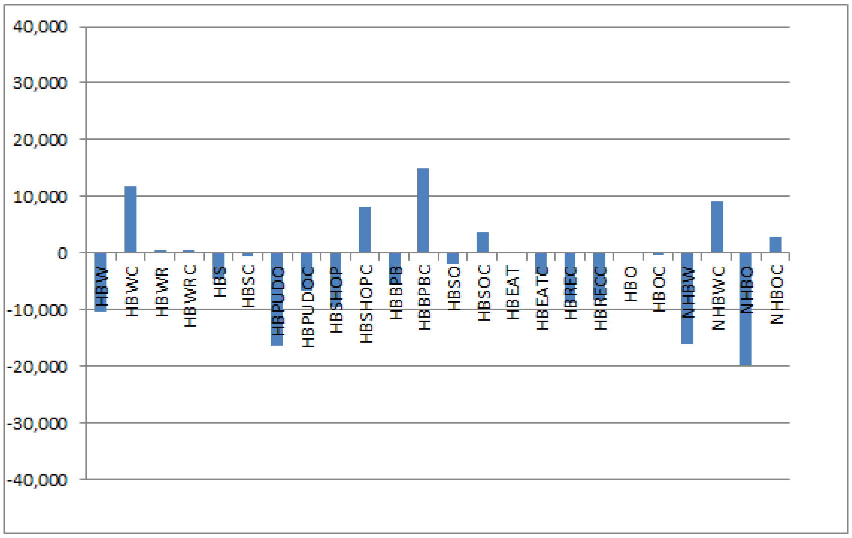


Figure 6-6 Differences in predicted trips: vehicle ownership model 2010 vs. vehicle ownership model 1991

(Extended vehicle ownership model. 2010 trip rates for HH22)

3) Trip rate specification (household characterization)

Given the same vehicle ownership model year (2010) and specification (extended), and the same trip rate year (TR2010), I compare trip forecasts by HH22, HH50 and HH224 trip rates. The differences are, in general small, within 5%. In Figure 6-7, the bars show the number of trips predicted by HH224 trip rates (or HH50) minus trips predicted by HH22 trip rates.

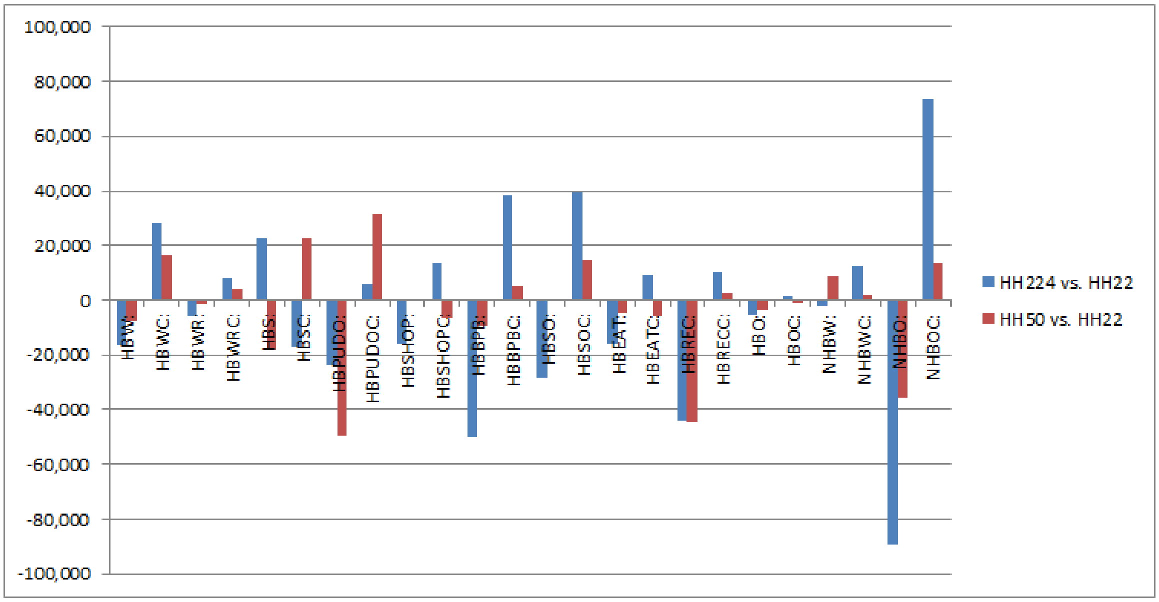


Figure 6-7 Differences in forecasted trips by HH224 vs. HH22, and HH50 vs. HH22.
(Blue bar: $\text{trips}_{\text{HH224}}$-$\text{trips}_{\text{HH22}}$. Red bar: $\text{trip}_{\text{HH50}}$-$\text{trips}_{\text{HH22}}$)

4) Trip rate year

Among all the sources of uncertainty examined here, the temporal change in trip rates causes the biggest difference for trip generation forecasting. I fix the vehicle ownership model as the 2010 extended and household characterization as HH22.

Figure 6-8 shows the trips predicted by 2010 trip rates minus those predicted by the 1991 trip rates. The predicted HBWR, HBPUDO, and HBREC trips by 2010 trip rates are more than those by the 1991 rates; while the predicted NHBW, HBSHOP, HBW, HBBPB, and HBSO trips by 2010 trip rates are less than those predicted by the1991 trip rates. Other household characterizations (HH50 and HH224) show similar results.

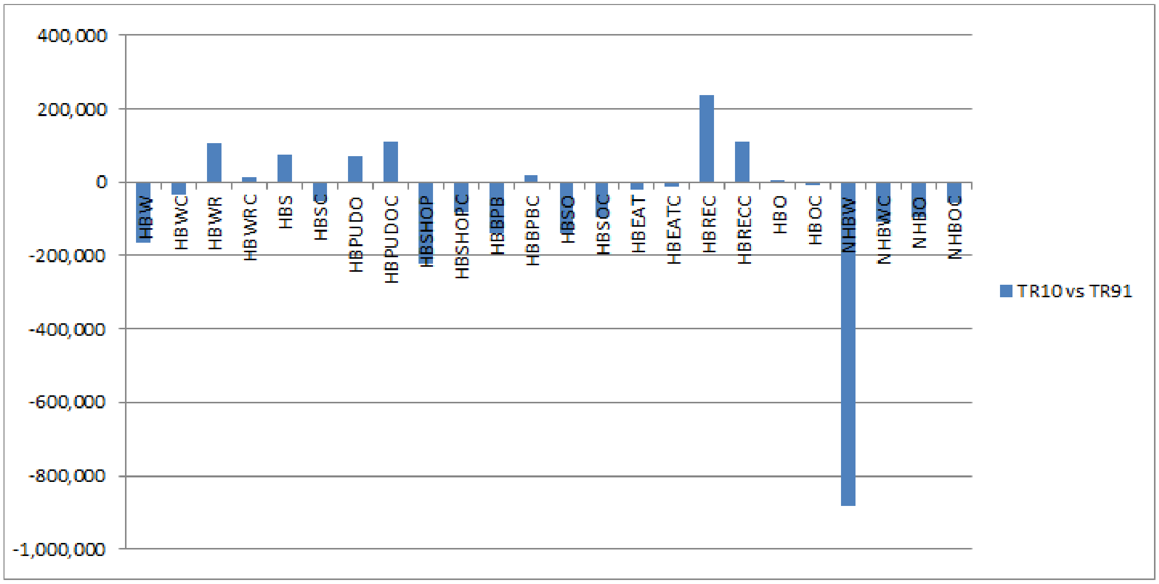


Figure 6-8 Difference in predicted trips between 2010 trip rates and 1991 trip rates
(2010 extended vehicle ownership model. HH22)

5) Totally transferred model vs. 2010 model
Finally, suppose we estimate the vehicle ownership model and trip rates both with the 1991 data and transfer these to the 2010 population, using the extended vehicle model and household type HH22. Figure 6-9 shows the predicted numbers of trips.

Compared to the prediction based on the 2010 vehicle ownership model and 2010 trip rates, the transferred models under-predict HBWR and HBWRC trips by 33% and 46%, HBREC and HBRECC trips by 31% and 28%, HBS by 20%, and HBPUDOC trips by18%. These are the trip purposes with increased trip rates over the years.

On the other hand, the transferred models over-predict NHBW and NHBWC by 69% and 53%, HBSHOP and HBSHOPC by 23% and 16%, HBSO and HBSOC by 28% and 38%, and HBBPB by 14%. These are the trip purposes with declining trip rates. The other trip purposes are within ±10%.

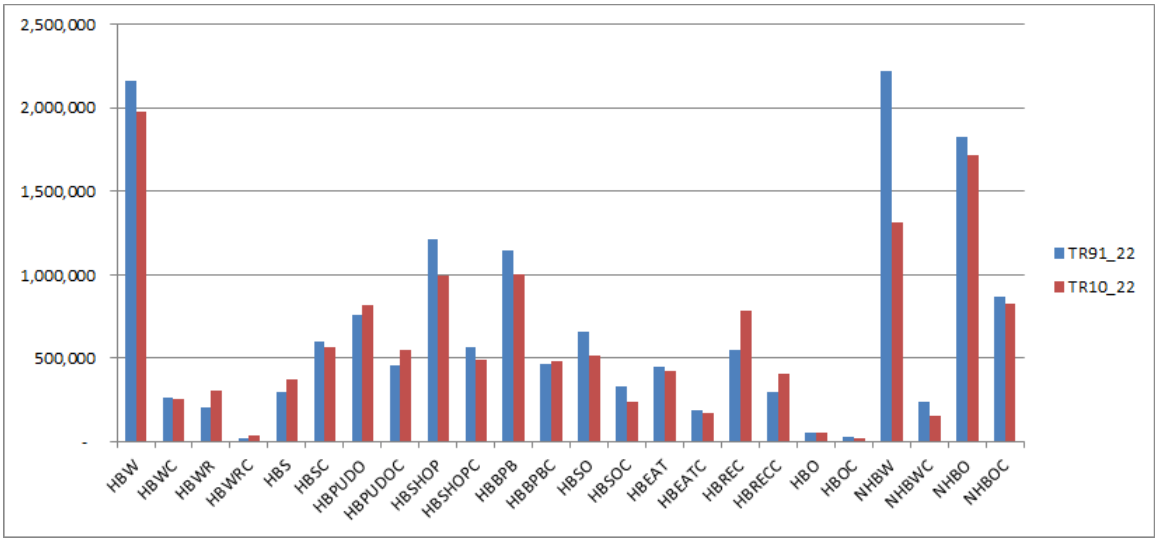


Figure 6-9 Trips predicted by 1991 vehicle ownership model and 1991 trip rates vs. trips predicted by 2010 vehicle ownership model and 2010 trip rates.

6.5 Summary

In summary, the analysis presented here suggests significant trip rates changes over the last 20 years in Boston metropolitan area. I offer hypothetical behavior explanations for the trip rate changes, but more rigorous studies are needed to exactly identify which aspects of behavior are actually evolving and causing the trip rate change.

Comparing across 24 scenarios of uncertainty in trip generation, I find the biggest uncertainty in trip generation comes from the changed trip rates over time. Compared to the 2010 model, the 1991 model over-predicts HBW, HBSHOP, HBBPB, HBSO, NHBW and NHBO trips for 2010 and under-predicts HBWR, HBS, HBPUDO, and HBREC trips for 2010. Ultimately, however, the validity of the trip generation forecasts needs to be tested in terms of the impacts on model outputs as compared with actual road counts, transit ridership etc., to evaluate the accuracy of the transferred model.

Although uncertainty in vehicle model specification, vehicle model year, and household characterization seems unimportant compared with the trip rate change over years, their impact on trip forecast for particular geographic areas, or subgroups of the population can still be large, an area for further research. Also, how much these differences in trip forecasts matter requires an evaluation of their impacts on the overall outcomes forecast with the four-step model.

Chapter 7

Conclusions

I conclude with reference to the three questions raised in the beginning.

1) Through temporal transferability assessment of the models from 1991 to 2010 for Boston metropolitan area, I have found significant preference changes in household vehicle ownership choice and trip generation.

In household vehicle ownership choice, preference parameters for local built environment factors and transit accessibility are stable, while the effects of regional location factor – distance to CBD, and most socio-economic and demographic factors have evolved in the last 20 years. The weakened effect of distance to CBD suggests households further away from CBD have become less inclined to own cars, and households closer to the CBD have become more inclined to own cars, all else equal. This change is consistent with the observed resurgence of vehicles in Boston, and rapid motorization of a few Metropolitan Core towns. Change in this parameter may imply changes in the regional distribution of opportunities, unobserved changes in built environment and transit services, and/or unobserved changes in the characteristics of households in different locations. The instability detected in the socio-economic and demographic factors may be due to lifestyle change across generations and/or poorly measured household life-cycle characteristics.

The instability of trip generation behaviors is revealed in the changed trip rates. HBW trips have declined, most likely due to the increased popularity of working at home and flexible work schedule. HBPuDo trips have decreased for senior households and increased for 3-person households with children. HBShop trips have substantially decreased, possibly reflecting the popularity of online shopping, and other changes in shopping habits. Most other home-based trips, including HBBPB, HBSo, and HBEat trips have declined, mostly likely due to the automation of services, and changes in time allocation between work and non-work activities. NHBW trips have substantially decreased, mostly likely due to more people working at home, and less travel during work. Besides the underlying influences of technology and lifestyle changes, data inconsistency and coding errors may contribute to the changed trip rates.

2) Failing to incorporate preference changes over time (using a naïve transfer) can cause significant bias in the forecast results.

In the case of the vehicle ownership model, when the 1991 model is applied to the estimated 2010 population, 0-vehicle households are under-estimated by 42.5%, 2-vehicle households are over-predicted by 14.8%, and 3-vehicle households are under-predicted by 7.3%.

In the case of the trip generation model, the transferred trip rates from 1991 overestimate total trips in 2010 by 7% to 9%. Home-based work-related, home-based pick-up and drop-off, and home-based recreational trips are substantially unpredicted by 34%, 12% and 27% respectively; while home-based work, home-based shopping, home-based social, and non-home-based work trips are significantly over-predicted by 9%, 20%, 31%, and 69%.

3) Model specifications examined in this thesis have shown some differences in prediction performances, but the variability in the predicted outcome is modest, not as large as the uncertainty caused by behavior changes.

In vehicle ownership modeling, including households' number of children, number of seniors, and local built environment variables can improve the prediction accuracy for 0-vehicle group. However, all model specifications have high prediction errors for 0-vehicle and 3-vehicle segments, suggesting a fundamental problem with the model structure − it cannot distinguish well between 0- and 1-vehicle households, and between 2- and 3-vehicle households, and assign households to the majority group to minimize total errors. Alternatives model structures (e.g., non-linear classification methods) should be explored in the future to tackle this problem.

For the cross-classification approach used for trip generation, household characterization affects the prediction accuracy for certain trip purposes. Including income information can lower prediction errors for HBW, HBWR, HBPuDo and HBRec trips. But more complicated household characterization can predict worse for certain trip purposes because of the increased sampling variance due to sparser observations in certain categories. In practice, I suggest a multi-level household characterization: using more detailed household characteristics for certain trip purposes if such purposes are sensitive to some characteristics and have sufficient amount of observations; and applying higher-level household characteristics for trip purposes that do not have many observations in order to reduce sampling error.

Based on the findings and limitations of this thesis, I suggest a few areas for further research.

1) The linkage between behavior uncertainty and exogenous uncertainty

As behavior changes do happen and significantly affect forecast outcomes, a question remains: how to incorporate behavior uncertainty in forecasting when we cannot know preference change ex-ante? One possibility is to examine the relationship between exogenous uncertainty and behavior uncertainty based on historical evidence, in order to forecast behavior change conditioned on the projection of exogenous inputs. Understanding this relationship is important, because behaviors can be highly dependent on exogenous factors, like energy prices, economic conditions, or technology changes. But a practical problem though is sample size. We need parameters from many years to see how they vary based on exogenous changes. A more qualitative approach is through traditional scenario planning methods – describing plausible evolution in behavior rather than exactly modeling.

2) Model structure uncertainty

This thesis does not analyze model structure uncertainty. As I have found, model specification improvement can only improve prediction to a certain level. For structural problems, we have to change model structure to significantly improve model performance. For example, non-linear classifiers, such as kernel methods, can be estimated and compared with the logit model for vehicle ownership modeling.

3) Error propagation and impact evaluation

Although I estimate the magnitude of mis-prediction in vehicle ownership and trip generation forecasting, whether the statistically significant difference have any practically meaningful implications should be further investigated through error propagation. Ultimately, the impact on predictions of overall transport system performance should be evaluated to best judge the importance of each source of uncertainty. The uncertainty propagation approach can strengthen the current temporal transferability analysis, which focuses on individual models.

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