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Final Report

Evaluation and Testing of Regional Models

Sensitivity Analyses of the Best Practice Model (BPM) in the New York Metropolitan Region
(Part I)

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16. Abstract

Activity-based microsimulation models are gaining increasing attention from MPOs around the country. These models earn their reputation by having shown their theoretical superiority over the traditional four-step models. The NYBPM (New York Best Practice Model) model is one of a relatively few operating activity-based microsimulation models in the country and thus provides us a working platform to test their practical advantages over the traditional four-step models. We accomplish this goal by examining the sensitivity of the model in response to changes in the input. More specifically, we conduct a series of sensitivity analysis to the NYBPM by modifying the inputs relating to changes in policy, socioeconomic characteristics, and population and employment levels and comparing the results to those in the 2002 base scenario. The results suggest that the model results are mostly consistent with our expectations, except the total journey productions when we change the population and employment levels in selected locations. While the results provide empirical support to the model and validate its wide applications in the region, they call for further investigation in the journey production aspect.

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1 Introduction

Travel demand forecasting is undergoing a transition. Travel models are used in the United States by Metropolitan Planning Organizations (MPOs) and their consultants to project future traffic and transit volumes, and these projections are in turn used to evaluate future air quality and environmental impacts of regional travel. Most models in current use are viewed as inadequate for future needs, however. MPOs increasingly desire the ability to analyze the effects of various kinds of policy changes, not just expansions of network capacity. Policy analysis requires models that can more closely approximate real travel behavior, taking into account more inputs and producing more outputs than many models now in use are capable of.

Traditional travel models used in government and industry are based on data aggregated at the level of Traffic Analysis Zones (TAZs), and run through the standard four steps of trip generation, trip distribution, mode choice, and route assignment. These four-step aggregate models have a number of limitations. One of the most prominent of these is that they are susceptible to aggregation error, which makes them insensitive to policy changes. By using zonal average values, they ignore the distribution of individual-level variables that influence travel behavior. Beimborn et al (1996) note that such models were designed in an era of freeways and neglect non-auto modes. Other criticisms are that they do not take into consideration the effects of induced demand and development, they have poor handling of non-work and linked trips, and their analysis overemphasizes peak hour congestion while aggregating trips into only a few time periods.

A newer generation of travel models that attempts to address these concerns has been developed mainly in academic circles. According to Vovsha, et al (2003), these models have three main characteristics that distinguish them from four-step models: they are activity-based (rather than trip-based), they are tour-based (rather than trip-based), and they use disaggregate micro-simulation techniques. Among the advantages of these models are their improved modeling of individual behaviors, and their more natural application to analyzing different socioeconomic groups. In theory, this kind of model should be more sensitive than a four-step model and provide outputs that better reflect actual responses to transportation changes.

Many MPOs continue to use traditional four-step aggregate models, and a gap has opened between the academic state of the art and the public-sector state of practice. One of the reasons for this gap may be the greater complexity of microsimulation models and the resulting need for specialized expertise to develop and run them, as Walker (2005) reports. For many planning agencies, the relatively straightforward structure of aggregate four-step models and their familiarity make them and their results more trusted and more accessible compared to newer models. A paucity of research demonstrating clear advantages in direct comparison between the two kinds of models may also be a contributing factor. In the past decade, some planning organizations around the country have begun to move to microsimulation models. The "Best Practice Model" (BPM) developed for the New York Metropolitan Transportation Council is the example studied in this report; other notable examples include models for the Columbus, OH, Portland, and San Francisco areas (Walker 2005). The Federal Highway Administration has also established a Travel Model Improvement Program (TMIP). One notable outcome of the program has been the development of the TRANSIMS model, but TMIP also exists to assist MPOs intending to adopt up-to-date modeling techniques.

There are a few pressing issues facing MPOs as they transition to more advanced regional travel models. The most basic of these is to understand the capabilities and limitations of the various existing, available microsimulation models (current-generation models such as those just listed). As noted, one of the motivations for moving to newer models is the need to conduct analysis of travel demand management and other policies, so it is of foremost importance for any adopted model to be suitable for such policy analysis. MPOs interested in developing the next generation of travel models will need to decide on the kinds of features and structures to incorporate. For example, they may require models with sensitivity to particular kinds of inputs. They might want to adopt a mixed model structure including some microsimulation components and some aggregate ones. The study of current models will be useful for guiding these decisions, and can also provide experience regarding the kinds of computing power requirements, data collection needs, output interpretation methods, and other operational requirements involved in adopting a new model.

In this project, we attempt to address some of the major transition issues by presenting the results of a set of sensitivity analyses performed on three case studies using the NY BPM. BPM is one of a relatively few microsimulation type models in use by an MPO in practice, outside the academy. As such it has the advantage of having a set of input data (for both current and forecast future years) already available. NYMTC's experience as one of the MPOs pioneering application of microsimulation models can take a guiding role in relation to other planning organizations in the midst of similar transitions.

The idea behind sensitivity analysis can be stated quite simply (Bonsall et al 1977). It is a process of testing the model response to changes in inputs. Prior theoretical or empirical results can provide a basis for comparison with the modeled response: if the model outputs seem to behave in accordance with the theoretical predictions or empirical expectations, the model as currently constructed may be considered valid and thus useful for analyzing the particular kind of policy tested. On the other hand, if the response fails to match expectations, this result will identify a starting point for an investigation into possible problems with the model design or implementation, leading to suggestions for improvements in future models. At the extreme, if the model makes a surprising prediction, we could also take it as a sign that there is something wrong with the theory or the empirical studies which shaped our expectations. In essence, when the model produces unexpected results we are asked to weigh established theory and evidence against the model design and the survey instrument it was based on. However, if there is already a large well-established body of literature that we believe describes the real world adequately, we would be inclined to believe the literature rather than the model. One other logical possibility is that even if the model produces results that accord well with prior expectations, it could have done so by a coincidence, such as two errors which canceled each other out.

The project particularly addresses the issue of understanding model capabilities and limitations. The question is whether or not the model outputs are responsive to policy changes, and can thus provide useful information to policy analysts and makers at MPOs. The travel outcomes that would be of interest include such variables as car ownership rates, trip volumes and lengths, mode splits, and time of day distributions. The determinants of travel behavior and travel demand are also of interest. These may include transport policy, the urban and suburban built environment, demographic variables, and various modal characteristics. These and other factors have become increasingly important topics of national discussion in transportation planning, either as potential levers of action for influencing travel behavior, or as trends that will have to be taken into consideration and accommodated in the future. In this project, we designed three types of initiatives that would incur changes in auto ownership and consequent travel behavior. They are: 1) changes in the level of transit fare; 2) increases in neighborhood median income; and 3) increases in population and employment in areas with different levels of transit accessibility. We will report the methods we used to carry out the sensitivity tests for each initiative, their results and our interpretations, and our recommendations for NYMTC to further improve its BPM model.

The remainder of this report has the following structure: after this introduction, a literature review (Section 2) explores the previous research on computer modeling in policy analysis, activity-based microsimulation models, and empirical results regarding the three initiatives. Section 3 describes the methodology used for the sensitivity analysis, and Section 4, 5, and 6 discuss the results from the three case studies. The final section (Section 7) concludes the study.

2 Literature Review

Both academic researchers and MPOs have begun incorporating new frameworks and techniques into their regional transportation demand forecasting models (Vovsha et al 2003; Davidson et al 2007). The most salient distinguishing characteristic of the new generation of models is that they are activity-based. This literature review begins by briefly setting forth the theory of activity-based travel forecasting and reviewing possible variations in model designs.

2-1 Activity-based models: Theory

There have been a number of articles that have explained the motivations, theoretical basis, and historical development of the activity-based approach, describing its important elements and its main distinctions compared to the trip-based approach (Bowman and Ben-Akiva, 1997; Kitamura, 1997; Kurani and Lee-Gosselin, 1996; McNally, 2000; and Bhat and Koppelman, 2002a, 2002b). In the subsequent discussion, we briefly discuss these various elements. We adopt the convention of McNally (2000), and use the abbreviations FSM and ABA to stand for the conventional Four-Step Model and the Activity-Based Approach, respectively.

The motivation for developing activity-based travel models can be succinctly stated: according to Bowman and Ben-Akiva (1997) it is simply that "travel decisions are activity based". Bhat and Koppelman (2002) write that the activity-based approach "views travel as a derived demand; derived from the need to pursue activities distributed in space", and McNally (2000) notes that "travel is [essentially] a physical mechanism to access an activity site for the purpose of participating in some activity". While some researchers, such as Mokhtarian (2005), have explored the possibility of a positive travel utility (which could lead to travel being pursued for its own sake), this possibility is not considered in the ABA.

Conventional trip-based four-step models (FSMs) ignore activity participation decisions. Instead, they consider activities only in their first step, trip generation (through the use of trip purpose), and consequently ignore many attributes of the underlying activities. They also fail to reflect the linkage of trips and activities into patterns, and ignore the constraints and dependencies that drive activity scheduling decisions (McNally 2000). These limitations lead FSMs to be insensitive to many of the behavior-changing policies that governments enact to manage congestion. To illustrate, we use a simple example described by Bowman and Ben-Akiva (1997). Suppose a worker who used to drive alone on his commute changed to transit in response to government incentives. If he also used to make a shopping stop along his work-to-home trip, the shopping activity would still need to be served, perhaps leading to a new drive-alone home-based shopping tour replacing the former trip chain. Bowman and Ben-Akiva (1997) add that people increasingly have non-travel alternatives that can satisfy their activity needs, such as telecommuting and catalog shopping. These possibilities are all examples of activity-travel-pattern decisions that a conventional trip-based model can not account for.

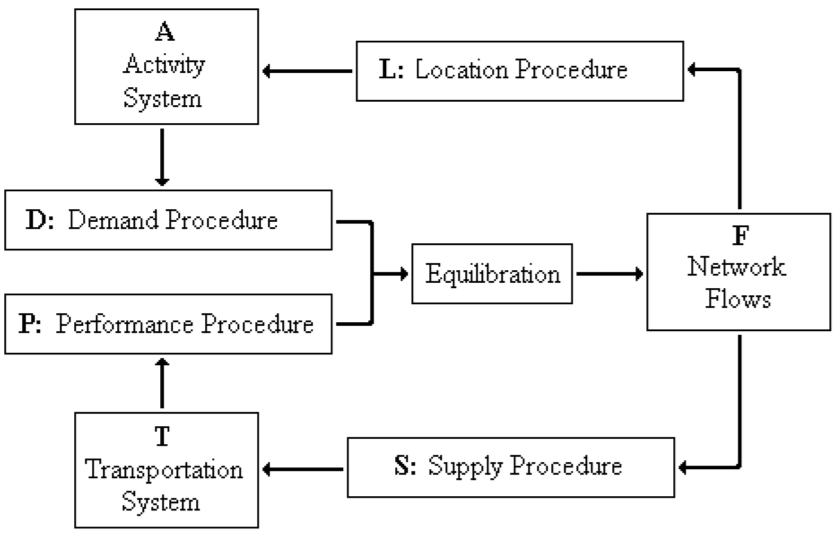
The Clean Air Act Amendments of 1990 also provided an incentive for the development of the activity-based models (Bhat and Koppelman, 2002a, 2002b). This legislation mandated the implementation of Transportation Control Measures (TCMs) including "non-capital improvement measures such as ridesharing incentives, congestion pricing and employer-based demand management schemes", which conventional models could not represent adequately. The more detailed trip information (finer temporal resolution and number of cold start vehicle trips) required for air quality modeling was another reason behind the shift in modeling approaches. Davidson et al (2007) provide the following list of new and emerging analytical needs:

- Pollutant emissions,
- Energy consumption,
- Americans with Disabilities Act requirements,
- Environmental justice analyses,
- FTA [Federal Transit Administration] new-starts benefits calculations,
- High Occupancy Vehicle (HOV) demand, and
- Value pricing and toll facilities, including private investment decisions resulting from legislative and funding requirements that have led to new model developments.

To better illustrate the distinct capabilities and emphases of the FSM and the ABA, it may be useful to consider the contextual frameworks proposed for each. McNally (2000) describes the FSM in the context of what he calls the "Manheim-Florian transportation systems analysis framework", while Bowman and Ben-Akiva (1997) place the activity-based approach in an "Activity and Travel Decision Framework". These two frameworks are quite similar in many respects, but the differences are instructive.

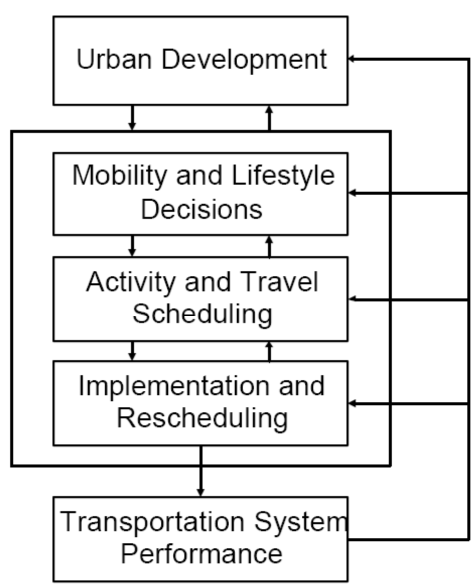
Consider first the Transportation Systems Analysis framework described by McNally (2000), and shown in Figure 2-1. It is a highly symmetrical framework with a supply side and a demand side (the bottom and top halves of the framework as drawn). The FSM occupies the center of the framework, creating an estimate of travel demand (D) and equilibrating it with network performance (P) to obtain the network flows (F) that constitute the model outputs. The activity system (A), characterized by land use and socioeconomic data, and the transportation system (T), comprising transportation infrastructure and services, provide exogenous inputs to the FSM. In most implementations the location or land-use model (L) and the transportation supply decision-making process (S), which take the network flows as inputs, are not integrated into the FSM system or not formally modeled at all. To summarize, the framework represents the FSM as determining the equilibrium flows that balance supply and demand. In contrast, the Activity and Travel Decision Framework described next de-emphasizes supply, and gives demand a more prominent place.

Figure 2-1 Transportation Systems Analysis Framework (McNally 2000)



According to Bowman and Ben-Akiva (1997), activity-travel decisions made by households and individuals take place in the context of a five-part framework (see Figure 2-2). At the top of this framework are the Urban Development decisions undertaken by governments and firms, while the Performance of the Transportation System is at the bottom of the framework. The middle three parts of the framework are household and individual choices, divided into Mobility and Lifestyle Decisions, Activity and Travel Scheduling, and Implementation and Rescheduling of the activity agenda. The first of the three consists of decisions like residential location and car ownership that are made over the long term, whereas the latter two are decisions faced on a daily or even more frequent basis. Household members, by implementing their chosen travel/activity patterns, directly affect the fifth and last level of the framework, Transportation System Performance, which in turn influences the four decision processes just described. Thus, the equilibration and network flows that McNally (2000) depicted as separate parts of the Transportation Systems Analysis framework are given a condensed representation as feedback arrows leading from Transportation System Performance to the upper four framework levels. What McNally represented simply as Activity and Demand are expanded into separate elements, showing the behavioral emphasis of the ABA and making explicit the notion that the decisions that create travel demand are derived from decisions to participate in activities at spatially-separated locations.

Figure 2-2 Activity and Travel Decision Framework (Bowman and Ben-Akiva, 1997)

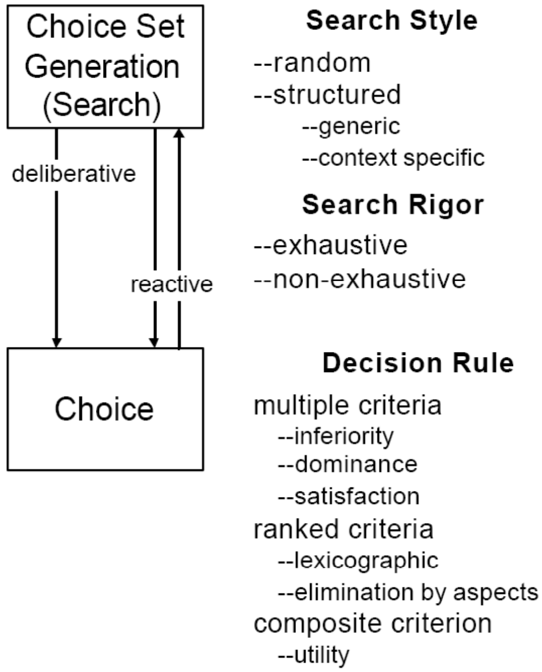


The Activity and Travel Decision framework reflects a number of ideas with implications for modeling. Since travel demand is explicitly recognized as being derived from activity demand, a model of the former must also model the latter. The framework makes clear that activity and travel demand must be analyzed in the context of households and individuals. In particular, characteristics of households and their members (including such factors as household size and type, age, gender, and presence of children) are found to be strongly associated with observed activity and travel patterns. Two further characteristics of activity and travel demand are also noted: not all activities necessarily involve travel, and individuals' activity options are constrained in various ways described below (Bowman and Ben-Akiva 1997). Household dependencies and constraints are both major topics of activity analysis research.

Activity analysis has its roots in Hägerstrand's (1970) space-time prism concept. The prisms demarcate the boundaries in a three-dimensional time-space (two spatial dimensions and one temporal dimension) within which people may perform activities. Three kinds of constraints may limit the activity locations available to an individual, namely constraints of capability, coupling, and authority. Capability constraints are the natural or technological limitations that define how far a person may travel in a given time on the modes available. Coupling constraints refer to the need for some activities to be performed in conjunction with others. Authority constraints are restrictions imposed by someone else or an institution that limit (or require) one's presence at a particular location in time and space. For example, the required arrival time at one's job is an authority constraint on a worker (Kurani and Lee-Gosselin 1996). Each constraint is associated with a certain degree of fixity or flexibility (Bhat and Koppleman 2002a, 2002b).

Even within these constraints, individuals face multi-dimensional choices when creating a daily activity schedule. The problem of modeling the scheduling decision process was described by Bowman and Ben-Akiva (1997) with a decision framework of three elements: a set of alternatives, a decision-maker, and a decision protocol. The decision protocol is in turn broken into a search stage and a choice stage. A decision process in which the choice loops back to search is called a reactive process; while one in which the decision is made in a single choice iteration is termed deliberative (see Figure 2-3). In the search stage, the choice set that will be considered by the decision-maker is generated. The method of generating alternatives may be characterized by its search style, search rigor, and decision rule. A search with a random style lacks a defined method for generating the set of alternatives, whereas a structured search style produces choices systematically (for example, creating a new alternative based on a previous one). Search rigor refers to whether the choice set generated exhausts all possibilities or not. In the choice stage, one alternative from the choice set is selected using a decision rule. The decision rule takes into account one or more criteria based on the attributes of the choices (e.g., travel cost and time). If multiple criteria are used, they may be ranked or unranked, or combined into a composite utility function, allowing trade-offs between attributes.

Figure 2-3 Decision Protocol for Activity Scheduling (Bowman and Ben-Akiva, 1997)



In modeling practice, Bowman and Ben-Akiva (1997) note that a deliberative process with exhaustive search leading to a utility-maximizing choice is commonly assumed. This assumption can be criticized for being an unrealistic portrayal of how real people manage to decide from among large choice sets. Bowman and Ben-Akiva (1997) list a number of alternative decision protocols, which may better represent the “coping mechanisms” people use to make decisions: "(1) non-exhaustive search, (2) selection based on habit, (3) adaptive decisions, which adjust prior decisions in response to changing conditions, (4) satisfaction rules which stop the search when a satisfying alternative is found, and (5) bounded rational decisions, in which a non-exhaustive search generates a manageable choice set, to which a utility-based decision rule is applied." In all cases, the decision process is separated into the two stages of search followed by choice.

In the next section, modeling practice is discussed. Following the outline of Bowman and Ben-

Akiva (1997), the commonalities among activity-based modeling approaches are presented first, followed by a discussion of the differences.

2-2 Activity-based models: Issues of Implementation (Types of Models and Distinguishing Features)

Travel demand models applying the activity-based approach tend to have a number of commonalities. According to Bowman and Ben-Akiva (1997), activity-based models share a common place within the five-part Activity and Travel Decision framework (between urban development and transportation system performance) and a common two-stage decision process, as described above. Davidson et al (2007), describing common features of recent travel demand models, write that they are activity-based, tour-based, and micro-simulation based. These three features are theoretically independent of one another. In practice they are complementary, since tours are an effective unit for analyzing daily activity schedules, and micro-simulation is an effective technique for applying activity and tour concepts in practical regional models. All three are therefore commonly implemented together.

According to Bhat and Koppleman (2002a, 2002b), the use of trips as the unit of analysis in the FSM is "a fundamental conceptual problem". As noted, the FSM thus ignores possible interdependence among trip decisions, as well as the process of organizing and scheduling trips into tours of many stops. The ABA takes a larger unit of analysis, often the tour. The terms "sojourn" and occasionally "journey" are sometimes used synonymously with "tour" to indicate a trip-chain beginning and ending at the same location, or a journey between two anchor points (e.g., home and work).

Micro-simulation is the name often given (sometimes without the hyphen) to describe modeling techniques applied at the disaggregate level. As noted by Davidson et al (2007), this means that the model explicitly predicts the activity and travel behavior for each individual in each household. Sometimes disaggregate models are described as microscopic models, borrowing the terminology used for traffic simulations (e.g., McWethy et al 2007).

Within the overall rubric of activity-based models, however, there are numerous possible variations in terms of modeling approach, unit of analysis, decision mechanism, handling of various input factors and choice dimension outputs. The next few paragraphs describe these sub-categories and distinguishing features of models that use an activity-based approach.

First, models may be classified by their overall modeling approach, employing either structural equations or micro-simulation. Each approach is discussed briefly. Models based on structural equations, a sub-type of econometric models, use equations to relate the variables that reflect mobility and activity participation to exogenous explanatory variables that reflect the characteristics of the individual, household, land use, or network. They do not explicitly model the behavioral mechanisms of activity or travel decision-making (Kitamura, 1997), meaning that these structural equations are not derived from a behavioral framework, such as the utility maximization principle. Rather, they represent associations between two sets of variables, based on the researcher's hypotheses. McNally (2000) goes so far as to say that they are "effectively descriptive".

Models based on micro-simulation, on the other hand, do explicitly model decisions at the household or individual level (Kitamura 1997). Computation process modeling (CPM) is a technique related to micro-simulation, distinguished by the use of heuristic if-then type rules to represent decision-making processes directly (Guo and Bhat 2001).

Second, activity-based models may differ in their unit of analysis. It can be the entire daily activity-travel pattern or schedule, the tour, or the individual activity or stop. Or the model may jointly consider more than one of these units, for instance both pattern and tour. The unit of analysis is related to the distinction between simultaneous and sequential decision structures. For instance, in an activity-based model using a simultaneous decision structure, a synthetic individual decides on an activity-travel pattern for the entire modeled day, by choosing from among a set of possible patterns. In this case, the pattern is the analysis unit. In contrast, in a model with a sequential decision structure, an individual decides on the next activity or stop to travel to given previous activities/stops. In this case, the stop is the unit of analysis.

Third, different decision mechanisms can be employed. Utility-maximizing frameworks may be the most familiar from examples such as the logit model. Bowman and Ben-Akiva (1997) noted that utility functions are simply ways to combine multiple decision criteria into a single composite criterion. Other possible decision rules may have different ways of handling multiple ranked or unranked criteria. Alternatives to utility maximization present in the models reviewed by Guo and Bhat (2001) include satisficing criteria, heuristic rules, and observed probability replication.

There are several factors involved in an activity or activity-pattern choice that models can treat in varied ways. For instance, one model could consider workers and non-workers separately, while another might consider both types in a single framework (Waddell et al 2001). Some models assign higher priority to some activities or tours (e.g., primary vs secondary tours), while others consider some activity start/end times as fixed (and some flexible), and still other models do not apply any concept of priority or fixity. The location choice might take into account space-time constraints, but some models implement no such restrictions. Likewise, models may differ in their sensitivity to inter-stop dependencies and consistency (for example mode consistency between stops on a tour), and interpersonal dependencies (for example joint decision-making within a household) (Guo and Bhat 2001).

Activity-based models may include different choice dimensions as outputs, including activity participation (the choice of whether or not to participate in an activity), activity purpose, timing, duration, location, sequence, and travel mode. A model system may be structured to model activity participation (or other dimensions) for every activity, only for flexible activities, or only for primary stops. The various activity attributes can also be modeled to varying levels of precision or aggregation. For example, activity location could be represented either by a census tract or the actual point location; time of day could be aggregated into a few large periods or represented continuously (Guo and Bhat 2001; Waddell et al 2001).

In summary, the two main approaches to activity-based modeling are econometric models and simulation. Model designs can differ in their units of analysis, decision mechanism, handling of various input factors, and choice dimension outputs. In later sections of this literature review, examples of such models will be presented and classified according to their differences in these characteristics.

2-3 Applications

Regional transportation demand models have a long history, with an origin in the 1950s, but until relatively recently they had been used mainly for "predict and provide"-type planning studies and evaluations of large infrastructure and network capacity improvements (Boyce and Williams, 2005). Over the past few decades, however, there has been an increasing interest in expanding the domain of travel demand modeling applications, together with increasing awareness of the limitations of traditional models. The studies described in this section tend to reflect one or both of these dual interests. Some focus on investigations of policies and model-predicted effects, while others focus on models and their capabilities (especially in recent years with the advent of activity-based approaches).

The use of a large number of model runs for a systematic exploration of the output responses to different input scenarios was pioneered by Bonsall et al (1977) "in order both to investigate extremes of policy and to carry out sensitivity tests" (p.157). This study used a conventional four-step aggregate model for the West Yorkshire Study Area around the city of Leeds, in northern England. The baseline used for comparison was the "Most Likely Future" scenario projected for 1981. In all, 26 kinds of tests were performed, requiring some 70 alternative scenarios to be run.

The tests fell into three broad categories, and examined the effects of changing policies, exogenous inputs, or model form. In the category of policy changes, tests included two contrasting land use patterns; network modifications including a park-and-ride program; and variations in vehicle running costs, parking charges, and public transport fares. For these last three tests, between three and six alternative runs were performed, with values of the modified variables ranging from zero to 10 times the most likely future value. Tests of exogenous inputs changed variables such as transit travel times (access, wait, and in-vehicle), mean car occupancy, value of time, income, car prices, and trip rates. Up to six values of each variable were used. The minor modifications of model form included such experiments as altering parameters, removing network capacity constraints, and using different assignment methods. In all cases, the alternative scenarios were selected not because they might represent a feasible or realistic future condition, but in order to investigate the altered variables' abilities to affect the model outputs.

Bonsall et al (1977) concluded that this study demonstrated the usefulness of computer models and the method of comparison of model outputs with the most likely future. They recommended that increased application of computer models be used to inform urban transportation policy debates. However, they noted that some indicators were particularly sensitive to model design (for example, mean speed was very sensitive to assignment method) and should be used with caution. Additionally, the particular model used produced some results that were "clearly not sensible". This was especially the case for the largest input changes, and was attributed to the fact that "certain aspects of behaviour (such as car occupancy levels) are beyond the predictive scope" of the model. These caveats reinforced for Bonsall et al (1977) the importance of accurate model estimation and empirical studies to examine the "credibility of model-based predictions".

Mannering and Harrington (1981) used a microsimulation model system to evaluate the travel demand impacts resulting from a fuel supply shortage and the contingency plans that might be enacted in response to the shortage. They created a model system of their own design specifically for this purpose. The resulting model incorporated components from previously developed models for the San Francisco and Washington, DC areas. These components included trip generation and destination/mode choice modules for shopping and social/recreation trips, and a mode choice module (including a model for car pool size) for work trips. The only two modes considered were automobile and transit; the possible destinations were limited to ten alternatives. The model did not include any zone structure or network representation; instead, the characteristics of the alternative destinations (including distance from origin) were created with a Monte Carlo procedure.

The submodels were applied at the level of individual pseudo households, which were synthesized according to distributions based on national census and survey data. The model constant terms may be calibrated to match the predicted mode shares to observed mode shares, while the model coefficients were assumed to be perfectly transferable to any geographic region[1]. In the case of Mannering and Harrington's (1981) demonstration, effects of a fuel crisis and policy responses were predicted at a national level. First, the model was run in a loop, adjusting the price of fuel until the fuel demand was equal to a given amount of supply reflecting a shortage. Then various parameters were modified to evaluate the effects of energy contingency plans. These contingency plans included a reduction of speed limits, a four-day work week, and a system of stickers restricting the use of vehicles to certain days of the week. The reported outputs included VMT by trip purpose, work trip modal share, automobile trip length (for shopping and social/recreation trips only), and total fuel consumption. The policies most effective at reducing

[1] This is a usual practice. The BPM model in New York allows users to adjust constant terms but not model coefficients.

fuel consumption were the four-day workweek and the weekday household-vehicle sticker plan, which lowered gasoline demand by 5.9% and 5.7%. The microsimulation model also allowed evaluation of the different impacts across income groups; the shortened work week was found to affect high income groups most, while the sticker scheme distributed the impacts more equally (Mannering and Harrington 1981).

Conventional travel demand forecast models have also been used as simulations to investigate the impact of urban form on travel. A number of such studies were reviewed by Handy (1996). In one example, McNally and Ryan (1994) compared travel statistics for two hypothetical neighborhoods with different street networks but otherwise similar characteristics. One had a suburban "planned unit development" (PUD) layout with multiple cul-de-sacs, and the other had a "traditional neighborhood design" laid out on a grid of streets. The grid layout allowed drivers to take more direct routes, leading to sizeable improvements in mean speed and trip time compared to the traditional PUD-style network. The traditional neighborhood scenario had 4.8% more total trips but 10.6% fewer vehicle-kilometers traveled. Handy (1996) cautioned that since the results from this and similar studies depend on simplifications and assumptions built into the simulation, they are of limited usefulness for understanding the true nature of the link between urban form and travel behavior.

Lewis (1998) documented a notable use of the San Francisco Metropolitan Transportation Commission (MTC) land use and transport model, MTC-FCAST, in 1994. The MTC ran the model using assumptions from Regional Alliance for Transit (RAFT) and compared the results to a run using the assumptions of the Regional Transportation Plan (RTP) as a baseline. The modeled year was 2010. The "RAFT run" tested the impact of three policy changes: parking "cashout", land use changes, and a shift of funds from freeways to transit. Cashout refers to a policy where commuters who do not use employer-provided parking are reimbursed for the monetary value of the parking. The land use changes included greenbelt preservation, transit-oriented neighborhood promotion measures, and brownfield redevelopment. The transit investments included multiple bus and rail projects, added at the expense of most RTP freeway investments.

The RAFT assumptions resulted in a 3% reduction in auto ownership, 6.3% reduction in VMT, and 24% increase in overall transit ridership compared to RTP assumptions. Two additional runs were also performed, one without parking cashout, and one without land use changes, to try to determine the contributions of each individual policy. This sensitivity analysis focused on the reduction in SOV work trips, finding that 45% of the reduction was attributable to parking cashout, and 41% to land use changes. Lewis (1998) notes that synergistic effects are ignored in this analysis; that is, it does not consider whether the policies in combination might have a larger effect than the sum of their individual contributions.

As new models have been developed using an activity-based approach, there have been a number of analyses exploring and demonstrating the new models' sensitivity to policy and behavioral variables lacking in conventional models. Kitamura (1997) describes two examples of such analyses. In the first, a structural equation type model estimated from a survey in Osaka was used to predict the effects of reducing commute time by 10 minutes. The model showed that over 7 minutes of that time savings was spent at home, and almost two minutes were spent at activities outside of home. Only relatively minor effects were observed in terms of increased travel time or higher number of trips (or chains).

The second example described by Kitamura (1997) evaluated two artificial scenarios, comparing the effects of reducing travel time from work to home versus reducing travel time between the work location and an activity center. The model predicted the changes in time allocation between travel and activity participation that would occur in response to the respective travel time reductions, and allowed a comparison between the expected utility for the two scenarios. It was found that an improvement in travel time to the activity center resulted in higher expected utility (0.297) than improvement in travel time between work and home (0.279), though both had increased utility compared to the base case (0.220).

Another demonstration was performed by Pendyala et al (1997) using a small travel-diary sub-sample in Washington, DC area. Their model, called AMOS (Activity Mobility Simulator), uses a neural network for learning and modeling individual decision processes. The alternative scenario tested had a congestion pricing transportation control measure (TCM) with resultant travel time reduction. The study illustrated that AMOS, unlike a conventional model, can predict secondary and tertiary traveler responses. For example: a person making the commute trip by transit instead of auto (in response to a congestion pricing policy) leads to additional home-based trips, instead of chaining on work-to-home.

Policy changes were also the focus of Shiftan and Suhrbier (2002) in their demonstration study using data from Portland, OR. They used an activity-based random-utility model to test three policy changes, implemented separately and in combination, including transit improvements, pricing, and telecommunications changes. Of the three policy changes, doubling the share of telecommuting proved to have the largest impact on the total number of trips, especially AM period work trips to downtown. The model also identified an increase in the number of maintenance and discretionary tours. Transit improvements (halved fares and waiting times) caused the largest mode shift, increasing transit's mode share from 5% to 5.4%. Auto pricing changes (a $1 peak period SOV toll and doubled parking costs in the downtown) were found to cause the greatest reduction in auto trips to downtown. In combination, the three policies reduce drive-alone trips by slightly less than the sum of the individual reductions. The impact on peak period CBD[2]-bound travel is significant, but the impact on overall regional travel is smaller.

Shiftan and Suhrbier (2002) concluded that this analysis demonstrates a number of advantages the activity-based model approach offers over a four-step model for assessment of travel demand management (TDM) strategies. The activity-based approach gives more insight into decision-making processes of travelers, possibly leading to increased predictive accuracy. An activity-based model can describe a greater array of impacts that will occur in response to TDMs, including the prediction of indirect secondary and synergistic effects. For instance, the phenomenon of induced travel (additional demand for trips generated by improved transportation supply) is not modeled by traditional models that do not consider network level of service in the trip generation step. The model actually predicts negative synergistic effects for a mix of policies with the same goal (their combined impact is smaller than the sum of the individual impacts).

In the Dallas-Fort-Worth area, Bhat et al (2004) developed the CEMDAP model and

[2] Central business district.

demonstrated its use to test a policy scenario in which workers were allowed to leave 2.5 hours early, compared to a base scenario (without the work-schedule change). The test included a disaggregate component, which analyzed 50 runs of each scenario for a single random individual. This disaggregate component can be used to show the effect of a policy on specific members of a target population. In the policy scenario, the individual showed an increased tendency to make stops on the work-to-home commute (28% compared to 16%) compared to the base scenario. At the aggregate level, Bhat et al used a subsample of one thousand households to quantify the extent of impact of the policy if 25% of workers were released from work early. These impacts included a higher likelihood of making stops on the work-to-home commute (17.2% compared to 16%) or making additional after-work home-based tours (46.6% compared to 45.8%).

The sensitivity of the Albatross model was comprehensively explored in a range of tests performed by Arentze and Timmermans (2005). Over a dozen scenarios were created, with varying attributes in demographics, work schedules, shopping hours, land use patterns, and travel times and costs. The results were discussed qualitatively only. Albatross was found to be sensitive to variables such as workforce participation, car possession, number of children, and spatial distances. Relatively small or negligible effects were observed from isolated changes concerning socioeconomic class. Some of the tested scenarios, such as those involving young children and elderly persons, led to a response that altered activity patterns while leaving total travel demand unchanged. In some cases the model made interesting or unexpected predictions. For instance, the change in opening hours for shopping facilities led to a decline in car use for non-work activities, attributed to lower car availability during the times of day for these activities. The scenario with increased spatial concentration of shopping facilities surprisingly did not lead to any change in average trip distance, which the authors attributed to a simultaneous substitution of shorter trips for some activities and longer trips for others. Overall, Arentze and Timmermans (2005) found the model results matched expectations and had clear interpretations even in cases when the effects predicted were unanticipated.

Safirova et al (2005) documented the application of the START model to congestion pricing policy in the Washington, DC area. START is described as "a strategic and regional transport planning model" developed by MVA Consultancy and used in a number of locations in the United Kingdom. The model was specifically created to analyze the effects of different policies. It uses a highly simplified representation of transportation supply, with only 40 zones in the DC application, links for only six freeways along major corridors, and rail and "highly stylized" bus networks. The more detailed modeling of demand features a series of nested logit models for trip probability, destination, mode (SOV, HOV, transit, and non-motorized), time of day (from three periods), and route. The model is not activity-based, but does distinguish six trip purposes. It also distinguishes among eight household types by income quartile and auto availability. The run time for this model is relatively short, enabling a large number of runs to be made and compared easily.

In comparing the effects of two (differently-sized) cordon pricing areas with link-based tolls, Safirova et al (2005) first computed the overall benefit for different pricing levels, and selected for closer examination the ones for each policy that maximized net benefits. They found that consumer welfare effects of all schemes were of the same order of magnitude overall: the net gain for society was $179.4m for a $3.50 downtown-only cordon, $243.1m for a larger $2.50 cordon (charged at the Beltway), and $225.6m for inbound link-based tolls of 27 cents per mile. However, the impacts were distributed among income groups differently. The smaller cordon option was most effective at increasing the number of transit trips (by 8.53%), but was also the least equitable. The total distributional effects of the policy would of course depend on how the revenue raised from congestion pricing is used. (Safirova et al 2005)

Walker (2005) compared the sensitivity of model results from aggregate and microsimulation models for Southern Nevada. Both were four-step models, but the microsimulation version used individuals rather than zones as the basic analysis unit. The two models differed most in their trip generation steps, but used the same nested logit models for destination and mode choice, and the same assignment methods for highway and transit. For the sensitivity analysis, auto travel time was changed in 10% increments in a range from -20% to +40%. The resulting percent changes in vehicle-miles traveled (VMT) were quite similar throughout the range (for example, a 40% increase in travel time resulted in a decline in VMT of approximately 6% to 7% for both models). However, in the percent changes in transit trips, the microsimulation results showed greater sensitivity than the aggregate model (i.e., predicted larger increases in transit trips in response to higher auto travel times, approximately 11% versus 8% for the 40% increase of TT). This difference is attributed to aggregation bias. This bias is eliminated in the microsimulation model, which also has the advantage that its simulation error can be understood and quantified.

Following on the work of Walker (2005), McWethy et al (2007) compared the sensitivity of a traditional four-step aggregate model and a microsimulation model (based on the MORPC activity-based model), estimated using data from the Austin, TX area. In addition to a 2000 base scenario, two test scenarios were created, one with expanded capacity (an added lane along two important corridors), and one with centralized employment (shifted from rural and suburban zones to the Austin CBD). The output variables compared included the overall VMT and VHT. In the expanded-capacity scenario, the microscopic model predicted only very minor changes in VMT, due to some estimation problems in the mode and destination choice models. For other variables in both of the tested scenarios, the activity-based model was found to have larger magnitudes of response to input changes. As an example, the microscopic model's walk/bike mode split changed by -13.3% in the centralized employment scenario compared to the base, while the change was only 2.5% for the aggregate model. Thus, in general, the activity-based model had greater sensitivity, which was expected since aggregate models "ignore some important behavioral distinctions". However, McWethy et al (2007) caution that the microscopic model requires more careful estimation and calibration than the aggregate one, and that it is not possible to judge if the modeled responses to input changes are accurate in the absence of real-world data.

In another comparative analysis, Cervenka (2007) compiled results of sensitivity tests from three metropolitan areas. The Seattle-area Puget Sound Regional Council (PSRC), Vancouver-area Southwest Washington Regional Transportation Council (RTC), and the Dallas-Fort-Worth North Central Texas Council of Governments (NCTCOG) all use traditional four-step models. The activity-based CEMDAP model is also being developed and calibrated for the Dallas-Fort-Worth area. The input variable change in all cases was simply an increase by 25% of in-vehicle travel times (auto and transit). The aggregate base year VMT changes for the three traditional models are very similar across the regions, with decreases of 8.4%, 8.2%, and 7.9% reported by PSRC, RTC, and NCTCOG, respectively. In addition to the similarity of the overall level of change predicted by the three traditional models, in all cases the sensitivity was less for AM peak periods compared to PM and off-peak periods (which showed the most VMT change). However, three rather disparate results were also reported: the Dallas-Fort-Worth 2025 scenario produced a larger decrease, 13.9%; CEMDAP also exhibited greater sensitivity of VMT to IVTT, with a 13.5% decrease in the base year; and the Portland region (across the river from RTC) indicated a 10.5% decrease. The interpretation of these differences is not yet resolved.

3 Methodology

3-1 Model and Base Scenario Dataset

This study attempts to address the basic question of validity of advanced travel demand models by presenting three case studies of sensitivity analysis performed using such a model. The example studied in this study is the "Best Practice Model" (BPM) developed for the New York Metropolitan Transportation Council (NYMTC). The BPM is one of a relatively few of the advanced type of models in use by a Metropolitan Planning Organization in practice, outside the academy. As such it has the advantage of having already undergone some validation as part of a complete model development process, including estimation and calibration against a travel survey and traffic counts. This process was documented by Parsons Brinckerhoff (2005a).

In addition, the model area has a set of input data (for both current and forecast future years) already available. The model was most recently recalibrated using data from 2002, and it is the 2002 dataset that was used for the base scenario model run. All other scenarios for the sensitivity analysis were modifications of the 2002 base scenario, and the outputs of modified scenarios were all compared to the corresponding outputs of the base scenario.

3-2 Modified Scenarios

The modified scenarios use the same inputs as those in the base scenario except for a few which are defined according to the requirements in the three case studies to be performed. In the following paragraphs, we describe each of these three case studies briefly.

Sensitivity case A1 is to test the response of BPM model with respect to transit fare changes. This case will test the sensitivity of NYBPM to changes in the transit fares (including bus, train, ferry etc.) in the NYMTC region. It will examine multiple scenarios for transit fare changes for the entire NYMTC region, ranging from -95% to +100% of the current fare.

Sensitivity case A2 is to test the response of BPM model with respect to changes in socioeconomic and demographic (SED) characteristics. This case will test the sensitivity of NYBPM model to increases in neighborhood income. We will identify all neighborhoods with a median household income level of $25,000 or lower (in 1990 dollar) and increase their median incomes to $45,000 and $80,000.

Sensitivity case A3 is to examine the response of BPM model with respect to changes in population and employment. We identify three locations with a descending order of transit accessibility: Jamaica LIRR Hub, the area approximately 6 miles north in Flushing, and the area approximately 6 miles south at the JFK airport. Six scenarios will be run to examine the response of the model after locating 10,000 jobs or people to each of these three locations.

3-3 The NYMTC Best Practice Model

A detailed description of the New York Best Practice Model can be found in Parsons Brinckerhoff (2005a). The BPM's modeled region covers 28 counties across parts of three states (New York, New Jersey, and Connecticut), with a total population of 20 million. It has 3,586 Transportation Analysis Zones (TAZs), a 53-thousand link highway and street network, and a complete transit network. The model as tested was implemented using Caliper’s TransCAD version 4.5, with various procedures and scripts accessed through a Graphical User Interface (GUI) program called CENTRAL4. All software programs and datasets used were obtained from NYMTC.

The flow of data between various model components is shown in Figure 3-1. The BPM takes Socio-Economic Data Forecasts (SEDF) and Highway and Transit Networks (HNET, TNET) as inputs to a model run. This set of three inputs constitutes a complete specification of a BPM scenario. The SEDF consist of population and job data at a zonal level, and vary according to the year of the scenario to be modeled. NYMTC has projections at five-year intervals through 2030. The highway and transit networks also vary based on the year to be modeled, with networks for future years including new links or updated capacity to reflect any projects scheduled to be completed by that time. The demographic data are generally as given to the modeler, while the networks may be modified in order to analyze possible infrastructure changes or policy alternatives.

The highway network (HNET) is a representation of highways and streets in the region, including all streets classified as major arterials or above and some smaller streets as well. In the course of data preparation for a model run, four copies of the network are produced, one for each assignment period (AM, Mid-Day, PM, and Night-Time). The separate period networks can show time-of-day variant features, such as the number of lanes in each direction, and parking or vehicle-type (HOV, truck) restrictions. They are also pre-loaded with the bus volumes scheduled for the period.

The transit network (TNET) represents the various transit routes in the region, including commuter rail services (Long Island Rail Road (LIRR), Metro-North Railroad (MNR), and New Jersey Transit (NJT)), subways (New York City Transit (NYCT), Port Authority Trans-Hudson (PATH), and Newark City Subway (NCS)), bus lines, and ferries. It also has “access links” representing the walking and driving paths used to reach transit stops. The data describing transit service characteristics include fares, headways, and capacities by period.

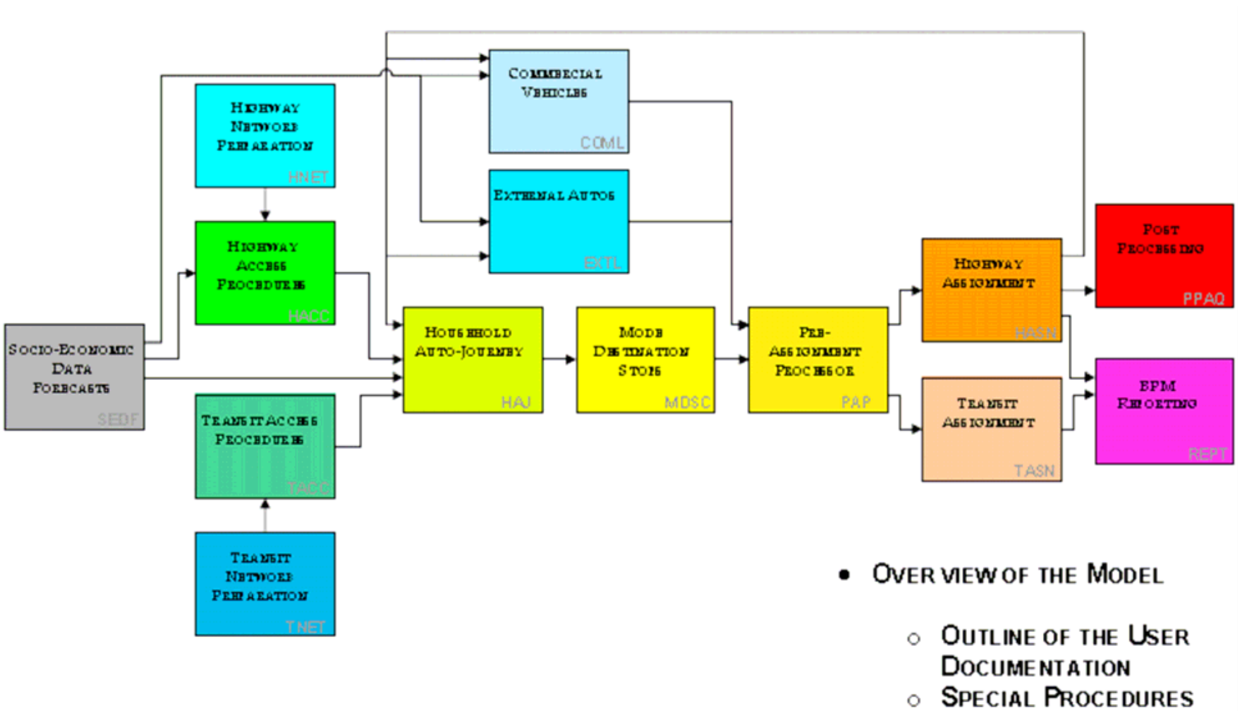
In addition to the three input datasets described above, the model requires a set of “skim” matrices. The skim matrices contain the zone-to-zone travel times and costs that are used as inputs to the core modeling components. Separate matrices are used for SOVs and HOVs, and for peak (congested) and off-peak (free-flow) conditions. As a practical matter, these input skims, called pre-skims, can be taken from the outputs of a previous model run's AM and MD assignment step, respectively. The pre-skims represent an assumption about the level of congestion and therefore the travel times that prevail under the modeled conditions. Thus it is necessary to check that the assumed input travel times are reasonably consistent with the resulting model outputs. The procedure adopted to perform these checks is discussed separately in this chapter.

The three submodels performing Household (population) synthesis, Auto ownership modeling, and Journey generation are run together as a single model component (HAJ), followed sequentially by Mode, Destination, and Stop Choice modeling in a single component (MDSC). The Pre-Assignment Processor (PAP) divides journeys among 4 time periods, and passes the resulting trip matrices to traditional highway and transit assignment procedures built-in to the

TransCAD software program.

The sub-models are described in more detail below, highlighting some of the advanced features that distinguish the BPM from traditional four-step models. Three of the submodels: auto ownership model, journey production model, and mode choice model, are of particular interest in our sensitivity analyses.

Figure 3-1 NYMTC Best Practice Model flow. (Parsons Brinckerhoff, 2005b)



3-4 Auto Ownership Model

The BPM's auto-ownership model uses a standard nested logit structure where the discrete choices being modeled are the alternatives of owning 0, 1, 2, and 3 or more cars. The probabilities resulting from the logit model are then applied using a Monte Carlo procedure that determines the number of automobiles owned by each individual simulated household. The utility function incorporates both household-level and zonal variables. The household variables include income category, and a set of alternative-specific "car sufficiency" variables. The zonal attributes include residential zone density, automobile importance, and accessibility. These variables are explained below.

The car-sufficiency indices are integers in the range 0 to 3 that express whether and to what extent a household owns enough automobiles to meet its needs. The indices are structured so as to favor choices in which households have at least as many cars as the number of working adults. For example, a household with two working adults would have a worker car-sufficiency index of 0, 1, 2, and 2, for the alternatives of owning 0, 1, 2, and 3+ automobiles, respectively; a third car would not have added utility for the two workers. A similar car-sufficiency variable applies to any non-working adults in the household, taking into account the number of workers and the presence or absence of children.

The auto ownership model also takes into account the considerable variability in walking and transit accessibility throughout the New York metropolitan region. Accessibility indexes for walk, transit, and automobile modes are defined for each residential zone as the sum over all possible destination zones of zonal employment divided by the square of travel time between the two zones. Transit accessibility is defined as zero for these purposes if the residential zone is not within half a mile of a transit stop. An auto-importance variable ranging between 0 and 1 is then constructed as the ratio of the auto accessibility index over the sum of all three accessibility indexes. The auto-sufficiency indexes are multiplied by the auto-importance in the utility function, so that they have more influence in zones with little walk and transit accessibility.

In addition, the model includes a density variable (proportional to the number of households plus jobs per square mile) and area-type constants that reflect the intensity of land use in eleven separate area types ranging from CBD to rural.

One deficiency of the model is that it does not include variables of travel time and cost of the trips made by the household. A household may live in a transit-extensive area but still own automobiles, because a household member's work place can only be accessed by automobiles. Empirical studies have found that transit accessibility at the destination (e.g., work) plays a more important role than accessibility at the origin (e.g., home) in determining auto ownership or mode choice decisions (Zhang, 2004; Chen et al., 2008). Even though the main goal of this auto ownership model in BPM is to generate households' demographics, the inclusion of travel time and cost variables (possibly in sketchy forms from previous runs) will make the model more behaviorally sensitive and thus improve its accuracy (Johnston and Rodier, 1994).

3-5 Journey Production Model

The journey production part of the HAJ replaces the trip generation step of a conventional four-step model. The BPM may also be viewed as a tour-based model because of its use of paired journeys rather than elemental trips as the unit of analysis. That is, the BPM journey production model determines the number of "round trips" an individual will make from origin to destination and back to the origin.

The BPM journey production model determines the number of trips by each person in two steps.

First, a set of logit[3] models was developed to model the probabilities of a person's making 0, 1, or 2 or more journeys per day. This set of models contains:

1) home to work journey (worker)
2) home to school journey (worker)
3) home to university journey (worker)
4) home to maintenance journey (worker)
5) home to discretionary journey (worker)
6) at work journey (worker)
7) home to school journey (non-working adult)
8) home to university journey (non-working adult)
9) home to maintenance journey (non-working adult)
10) home to discretionary journey (non-working adult)
11) home to school journey (child)
12) home to maintenance journey (child)
13) home to discretionary journey (child)

The variables included in these models relate to household composition, car ownership, relative auto-sufficiency (equal to 1 if the number of autos owned by the household is larger than the number of workers in the household), household incomes (represented in three dummy variables: high, medium, and low incomes), area type (Manhattan, urban county, suburban county),

[3] In theory, this should be an ordered logit model due to the ordered nature of the dependent variable. In BPM model, this is treated as an unordered logit model.

accessibility to jobs[4], journeys made by the modeled person[5], and journeys made by all members of the household and intra-household interactions. The "no journey" alternative was used as reference alternative.

The second step of the journey production model involves simulation. The probabilities of making 0, 1, or more journeys generated from the previous step are used in the simulation. For instance, in the previous step, the 123,456th person is determined to be a child whose probability of making one school journey is 0.9, ,the probability of making zero school journey is 0.1, and the probability of making other types of journeys are zero. During simulation, a very long list of pseudo-random numbers is generated. The 123,456th number is drawn from this list. If the drawn number is between 0 and 0.9, the child makes one school journey; if the drawn number is between 0.9 and 1, the child made no journey.

3-6 Mode Choice Model

Mode choice in the BPM is modeled in two steps. In the first step, journeys are split between motorized and non-motorized modes using a binary choice model. If motorized modes are chosen, the model will then identify which motorized mode will be selected; if non-motorized model are chosen, the model would go directly to a non-motorized destination choice model, in which only destinations within 3 miles from the origin could be chosen. In general, the only active variable in the nonmotorized destination choice model is distance. The exception is for

[4] There are two types of job accessibility variables: job accessibility by walk and job accessibility by transit. They are calculated by gravity-based model. If the household does not have walk access to transit (i.e., it is not within 0.5 miles of a transit stop), then transit accessibility is set to zero.
[5] The journeys are modeled in order starting with journeys to school for children, then journeys to school for non-workers, then journeys to school for workers, etc. so that if there is a journey to school for a child, there is a possibility of a journey to school by an adult to accompany the child.

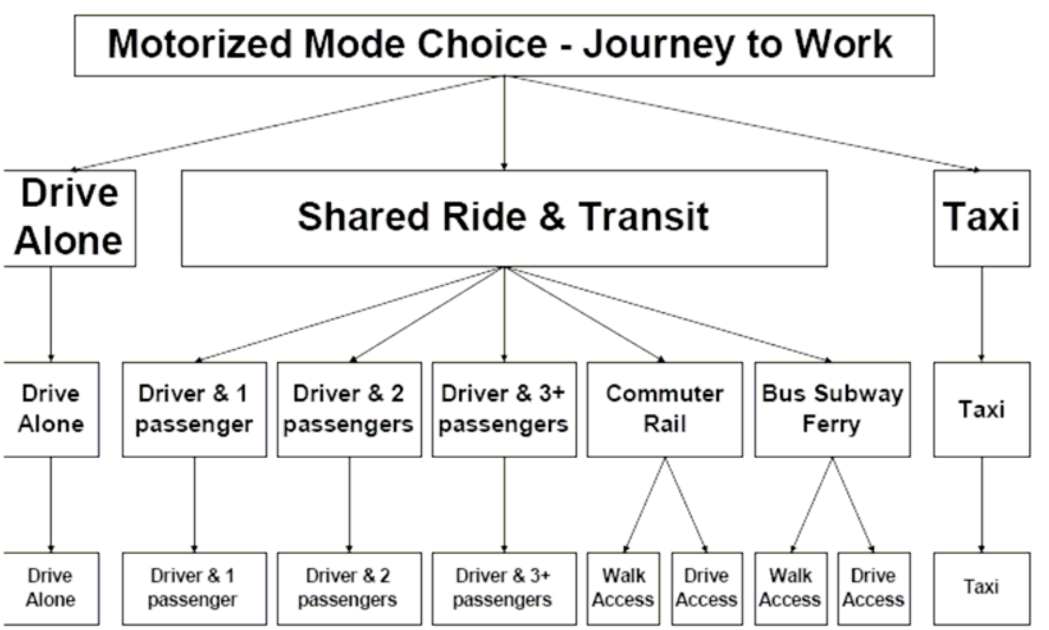
trips to school which also include an intra-school district dummy variable. Distance is included in the destination choice utility function as a power term as follows:

$$U = \ln(ATTR) - \gamma \ln(DIST),$$

where ATTR is the total journey attractions by zone. In all cases, the value of the coefficient γ was found to be close to 2 which means that, as the distance decreased from 3 to 2 miles, the probability of choosing a nonmotorized mode doubled. As the distance decreased from 2 miles to 1 mile, the probability quadrupled.

The model allows ten motorized modes: drive alone, shared ride with one passenger, shared ride with two passengers, shared ride with three or more passengers, commuter rail with walk access, commuter rail with drive access, other transit with walk access, other transit with drive access, taxi cab, and school bus. These modes are estimated in hierarchical nested structures integrated with six travel purposes. Figure 3-2 shows an example of such structure for journeys from home to work.

Figure 3-2 NYMTC Mode Choice Model For Journeys to Work (Parsons Brinckerhoff, 2005a, p. 5-62)



Each one of the six hierarchical nested structures (corresponding to six travel purposes) has a distinct nesting structure and set of variables. Typically, the explanatory variables include six types: travel time, travel cost, highway distance from original and destination, auto ownership, income dummy, journey destination in Manhattan dummy, and parking lot dummy. In some nested structures, certain particular explanatory variables are used. For instance, in the journeys from home to school model, there is one variable which indicates the type of area (CBD high density areas, CBD low density areas, urban and suburban areas, and exurban and rural areas) and types of county.[6] In all six model structures, drive alone is used as the reference utility with all constants equal to zero, which implies that other modes' coefficients indicate relative attractiveness of the corresponding mode compared to drive alone.

[6] Counties are classified into four types. Type 1:New York, NY, Queens, NY, Bronx, NY, Kings, NY, Bergen, NJ, Passaic, NJ, Hudson, NJ, Essex, NJ, Union, NJ; Type 2:Richmond, NY, Nassau, NY, Suffolk, NY, Westchester, NY,

3-7 Procedure for Model Runs

The base scenario used year 2002 socioeconomic and demographic data and highway and transit networks, all of which were provided by NYMTC and served as a standard baseline.

The inputs to the modified scenarios are the same as those in the base scenario, except for a few required by the three case studies to be run. Including the base scenario, a total of twelve model runs were performed for A1 (case study 1). Eleven scenarios have identical input data and networks except for the fares on all transit modes (ferry, commuter rail, light and heavy rail, and bus). Three progressive increases of fares by a factor of 1.1 were performed, as were three progressive decreases. In addition, to test more extreme cases, two runs were performed with larger increases of 65% and 100%, and three runs were performed with fare decreases of 50%, 75%, and 95%.

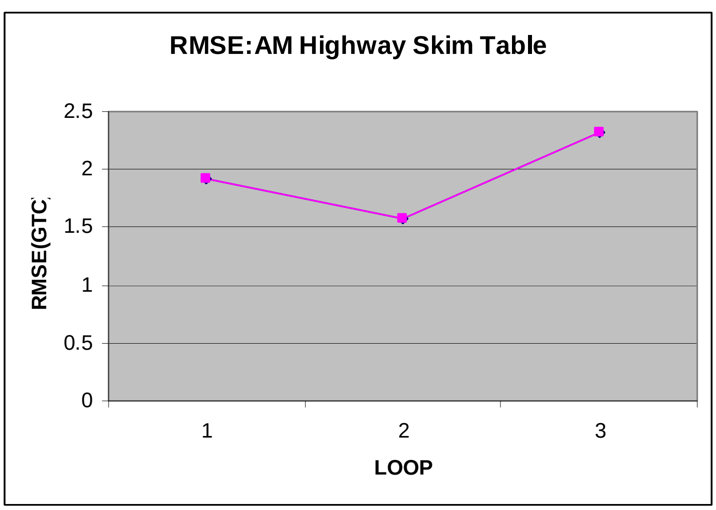
Including the base scenario, a total of three model runs were performed for A2 (case study 2). Similarly, the modified scenarios have identical inputs to those in the base scenario, except those neighborhoods whose median incomes are $25,000 or lower in 1990 dollars. Their levels were raised to $50,000 and $80,000 respectively in the two modified scenarios.

For case study A3, a total of seven model runs were performed including the base scenario. The six modified scenarios have identical inputs to those in the base scenario, except the population and employment levels in three selected locations: Jamaica LIRR Hub, the area approximately 6

Morris, NJ, Somerset, NJ, Middlesex, NJ, Monmouth, NY, Ocean, NJ, Hunterdon, NY, Warren, NJ, Sussex, NJ, miles north in Flushing, and the area approximately 6 miles south at JFK airport. These three areas differ in their transit accessibility, with the first being the most transit accessible. Each modified scenario has either 10,000 people or 10,000 jobs more than the level in the base scenario.

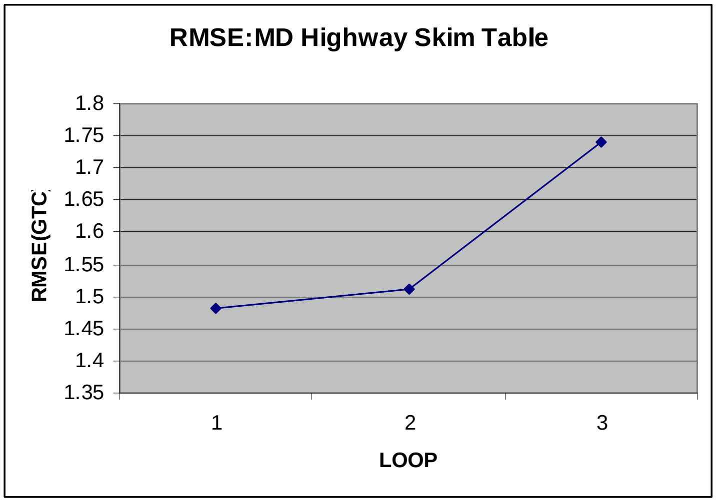
Each scenario was treated to a full model run, starting with network preparation procedures and proceeding through assignment. This includes a complete population synthesis each time. To check for model convergence, the input and output highway skim matrices were compared using the percent root-mean-square error (%RMSE) computed over all cells. We tested the RMSE for one scenario in Case study A3 when locating 10,000 people in JFK with three feedback loops (each loop goes back to transit accessibility procedure in the BPM model). The RMSE for these three loops are shown in Figure 3-3 and Figure 3-4 for AM and MD periods. In general, after three loops, we did not observe a trend of decreasing RMSE. We decided to perform one loop for our case studies.

Figure 3-3 RMSE for AM Skim Table



New Haven, CT, Mercer, NJ; type 3: Rockland, NY; type 4: Putnam, NY, Orange, NJ, Duchess, NY, Fairfield, CT.

Figure 3-4 RMSE for MD Skim Table



3-8 Outputs Examined

We examined various outputs from the BPM model. For Case study A1, these outputs included auto ownership levels, mode share, journeys by purpose and mode, CBD bound by origin region, mean trip length by purpose and mode, and mean highway speed. The results in Case study A1 are all on a regional level since fare changes are made region wide. The results examined in Case studies A2 and A3 are not on a regional level. In Case study A2, TAZs with median incomes less than or equal to $25,000 (in 1990 dollar) are chosen and their median incomes were increased to $50,000 and $80,000. We examined auto ownership, mode share, journeys by purpose and mode, mean trip length by purpose and mode, and mean highway speed in these chosen TAZs[7]. In Case study A3, TAZs in LIRR, Flushing, and JFK are chosen and we allocated an additional 10,000 jobs and 10,000 people in each of these three areas. In Case studies A1 and A2, we mainly focused on journeys originating from the areas under investigation, while in case study A3, we also examined journeys to the areas of interest.

[7] We did not observe changes in those zones whose median incomes are not changed.

3-9 Variability of Outputs

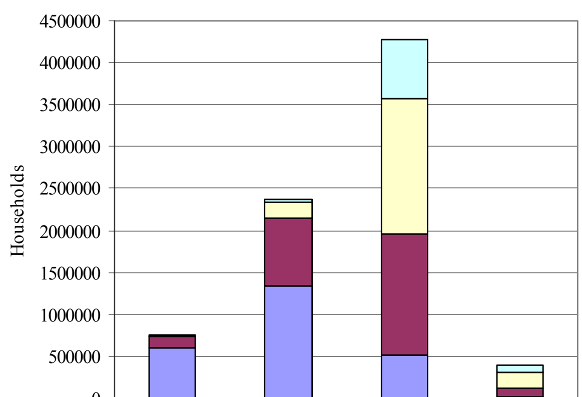
The study looked at changes in forecasting results with respect to certain changes made in the input. One important thing we need to address is how to tell whether the change in results is due to a change from input or due to micro-simulation, which is used in BPM model to generate synthetic households. One key feature of micro-simulation is that the seed for random number generation is varied each time, and consequently the forecasting results of model are also varied. Castiglione et al (2003) applied a micro-simulation base model to investigate how results may vary due to random simulation. It is found that the variation of results could be as high as 6% at the TAZ level. However, the variation of results decreases significantly to less than 1% at the neighborhood and county levels. Therefore, given a certain level of aggregation, we could assume that as long as the change is significantly larger (for instance 10%), it is likely to be due to changes in input.

4 Sensitivity Analysis Results: Case Study A1 – Impact of Transit Fare Changes

4-1 Auto Ownership

In the base scenario, the proportion of households in the region owning 0, 1, 2, and 3 or more automobiles was 31.7%, 32.0%, 25.7%, and 10.6%, respectively. The average household owned 1.19 automobiles. These region-wide figures obscure the large variation in car-ownership within the region. In Manhattan and Urban-type counties (e.g, Queens, Brooklyn, and Bronx), the average auto ownership per household is 0.22 and 0.56, while in Suburban and Rural counties, it is 1.65 and 1.91. The number of households in each auto-ownership category is shown by county type in Figure 4-1.

Figure 4-1 Auto Ownership by County Type

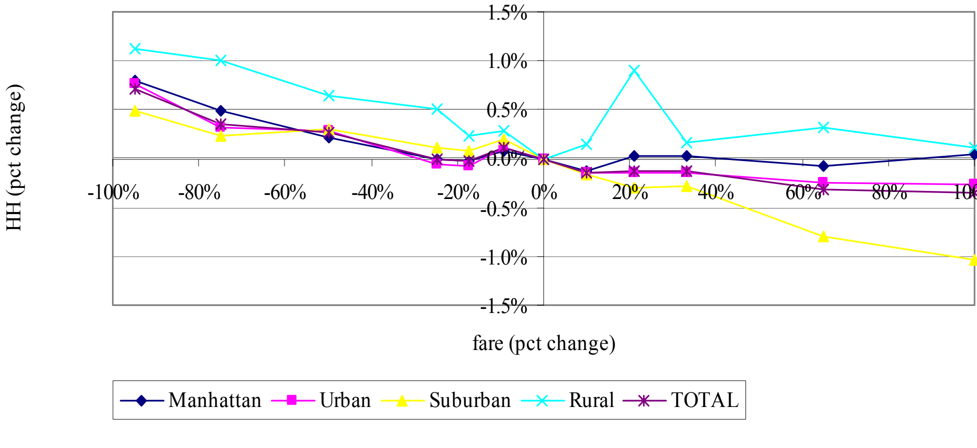


	Manh	Urban	Suburban	Rural
3+	760	45657	693977	81989
2	8243	190290	1625077	180519
1	147553	799556	1436964	107186
0	592726	1341944	513592	21399

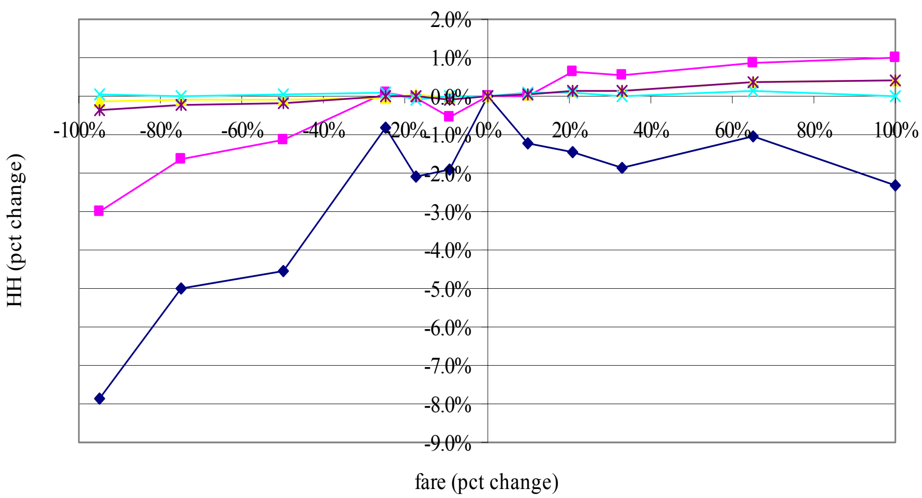
County Type

Figure 4-2 shows the percent change from the base scenario of the number of households with zero and two or more cars, separated by county type. The inherent variability of these model outputs is apparent in the plots' lack of monotonicity: in some cases the "response" to a small change in fares is greater than the response to the next larger change. In a few cases, the response to a small fare decrease is even in the direction opposite to logical expectations. This variability is even more pronounced for the Manhattan and Rural county types, where the relatively small number of households makes the graph appear more volatile.

Figure 4-2 Change in number of (a) zero-car and (b) multiple-car households



(a) 0-car households



(b) 2+car households

Nevertheless, a very small but clear trend can be observed in Urban and Suburban county types. As transit fare increases, the number of carless households decreases, and the number of multiple-car households increases. Since in the base scenario there are relatively few carless suburban households and even fewer multiple-car urban households, the changes appear larger for these county types when expressed in percentage terms, as they are here.

In a region with nearly 8 million households, the addition of some thirty thousand cars has only a minuscule effect on the average auto ownership. Thus these results indicate that the cross-elasticity of car ownership with respect to transit fares is extremely small. The point elasticity for the entire region calculated for a 100% increase in fares is a mere 0.004.

The insensitivity of car ownership to transit fare shown by the model matches common sense: in those parts of the region where it is unnecessary and expensive to own and use an automobile, even a substantial fare change is not sufficient to influence many households on such a major purchase decision. The same thinking applies (in reverse) for those areas that have limited transit access and are thus heavily auto-dependent.

The results are not unexpected given the auto-ownership model specification. Transit fare does not enter the model directly, and the only way fares could affect car ownership is through the auto-importance variable. This variable is calculated for each zone from the modal accessibility indexes, which in turn depend on the zone-to-zone travel times present in the pre-skims input to the model run.

4-2 Mode Choice

The region-wide total number of journeys made by each mode in the base scenario is given in

Table 4-1. Overall, 58.8% of journeys are made by SOV or HOV, and 15.8% by either transit or commuter rail. The great majority of the latter are walk-to-transit (WT) journeys.

Table 4-1 Total Regional Journeys by Mode

Mode	Number	Share
SOV	9,762,946	34.76%
HOV2	4,559,587	16.24%
HOV3	1,560,558	5.56%
HOV4+	625,377	2.23%
WT	3,693,332	13.15%
DT	221,779	0.79%
WC	297,621	1.06%
DC	219,526	0.78%
Taxi	1,673,442	5.96%
Non-Mot	4,671,943	16.64%
SchBus	797,464	2.84%
Total Journeys	28,083,575	100.00%

The percentage change in number of journeys by each mode is plotted against the change in transit fares in Figure 4-3 and Figure 4-4. It is clear that the demand for Commuter Rail is more elastic than demand for other transit modes. Within commuter rail journeys, those employing walk access (WC) are about twice as elastic as those employing drive access (DC). Within non-CR transit modes, the opposite applies: the number of walk-access journeys (WT) is less elastic than that of drive-access (DT) journeys. For the automotive modes, SOV journeys show the smallest response, about half as large as HOV journeys, which in turn change about half as much as Taxi journeys.

Figure 4-3 Change in Number of Journeys by Transit Modes.

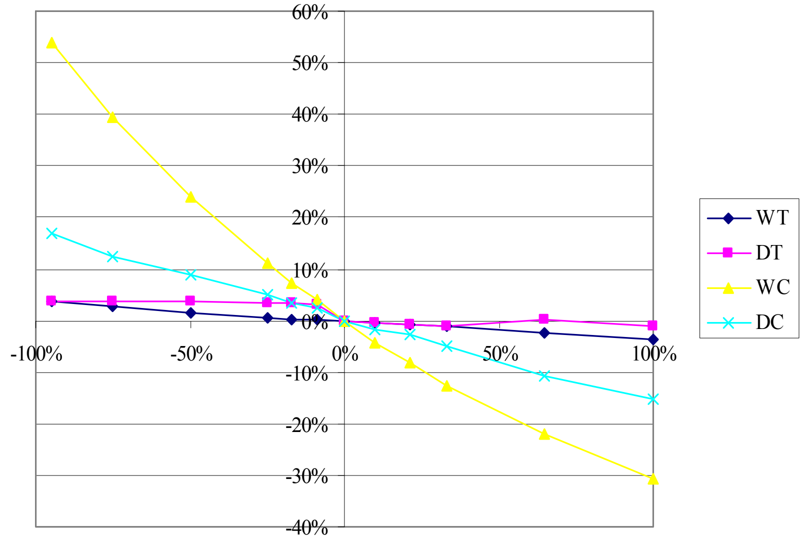
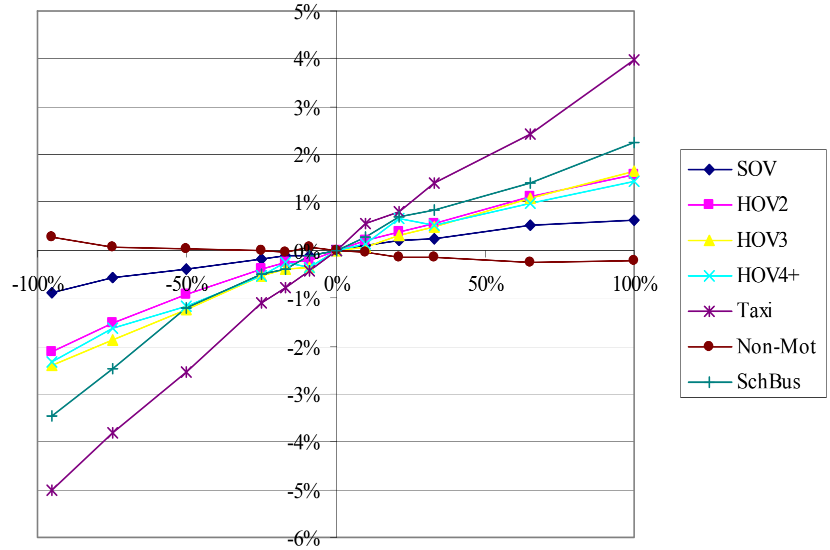


Figure 4-4 Change in number of journeys by non-transit modes.



The New York region may have some characteristics (such as high level of congestion and high parking charges) which lead to the relatively muted response. As noted above, a large proportion of households in the city are carless, which restricts their ability to change to automotive modes. In addition, the scenarios in this sensitivity analysis raise fares on all modes and all providers at once, which reduces the possibility of substitution among transit modes.

4-3 Journeys by Purpose and Mode

Graphs of the percentage change in journeys by purpose and mode are shown in three sets of figures comprising 24 individual figures (Figure 4-5 to Figure 4-28). Each set corresponds to a particular set of modes: Personal vehicle, Transit/CR, and other modes, respectively. The numbers shown next to a particular mode is the number (in thousands) at the base scenario. It should be noted that the vertical scales of the graphs are consistent within each set (consisting of a set of 8 graphs), but not between the three modes. This was done because the sensitivity of transit and CR usage is generally larger than that of the highway and other modes.

Figure 4-5 Percentage Change in Work (Low-income) Journeys by Transit/CR

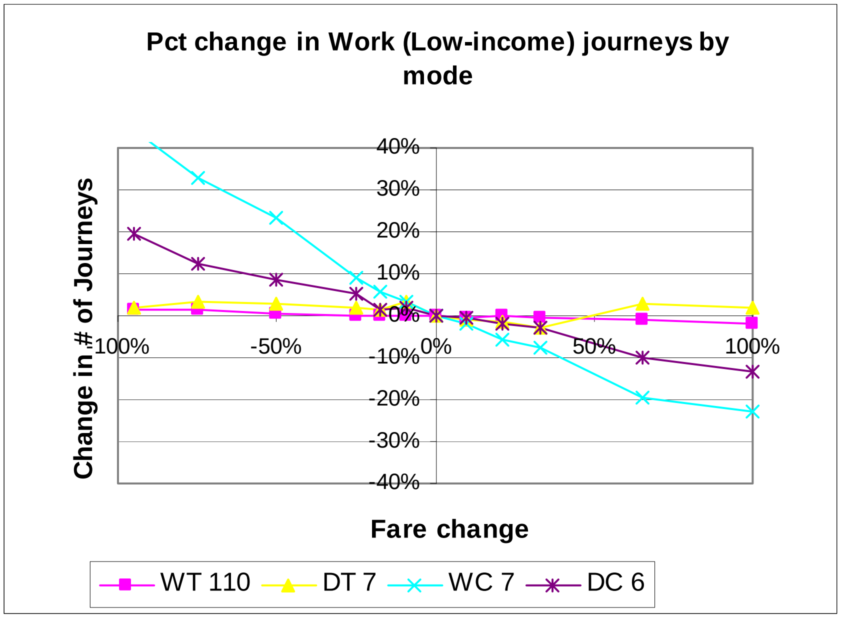


Figure 4-6 Percentage Change in Work (Med-income) Journeys by Transit/CR

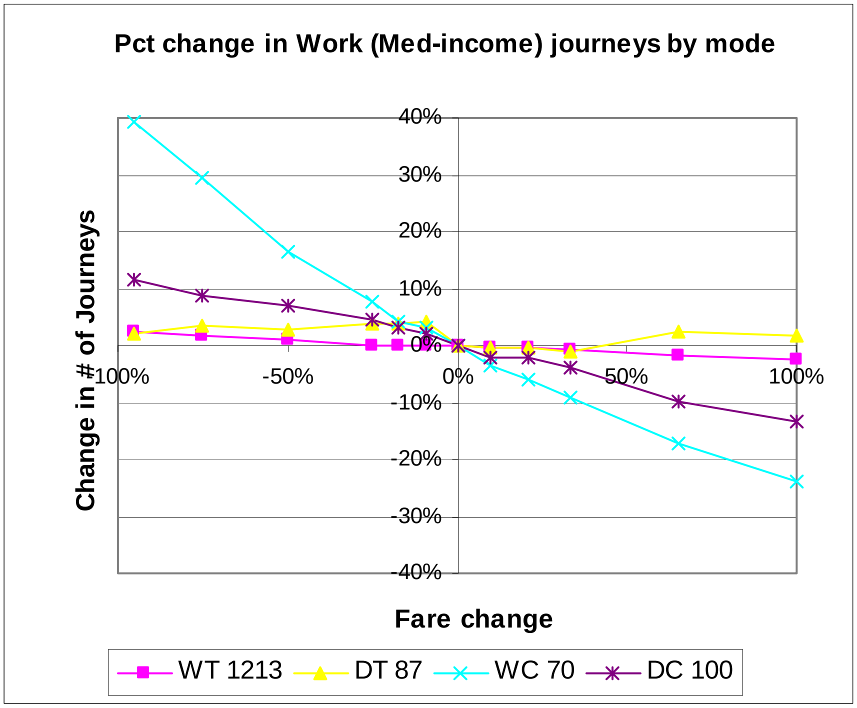


Figure 4-7 Percentage Change in Work (High-income) Journeys by Transit/CR

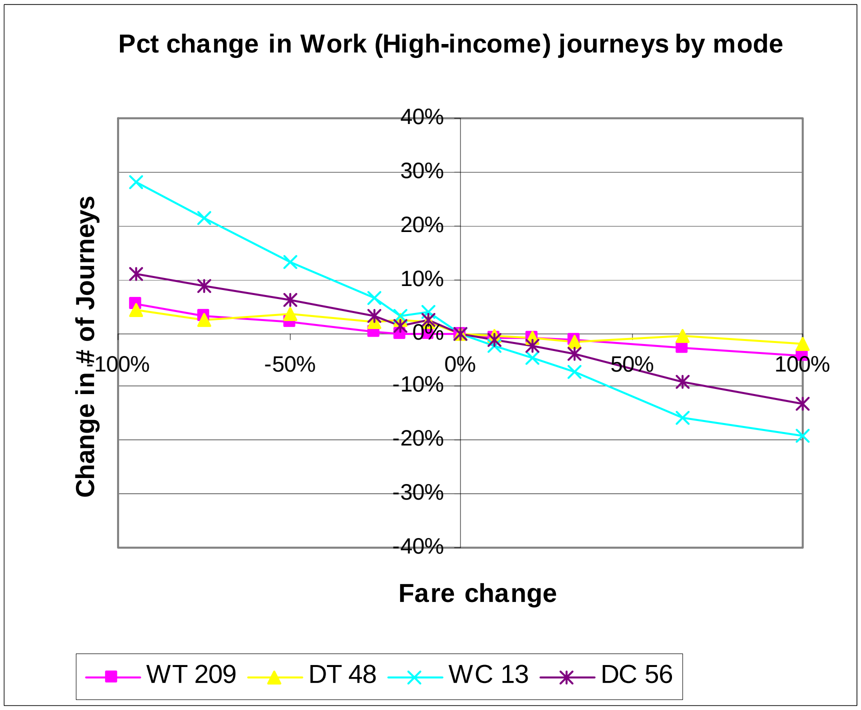


Figure 4-8 Percentage Change in School Journeys by Transit/CR

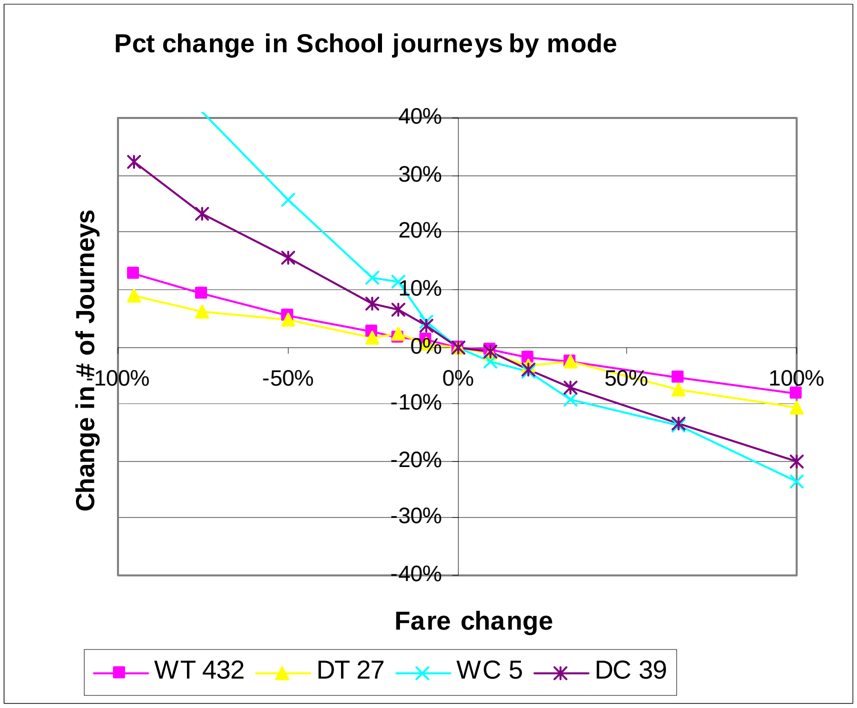


Figure 4-9 Percentage Change in University Journey by Transit/CR

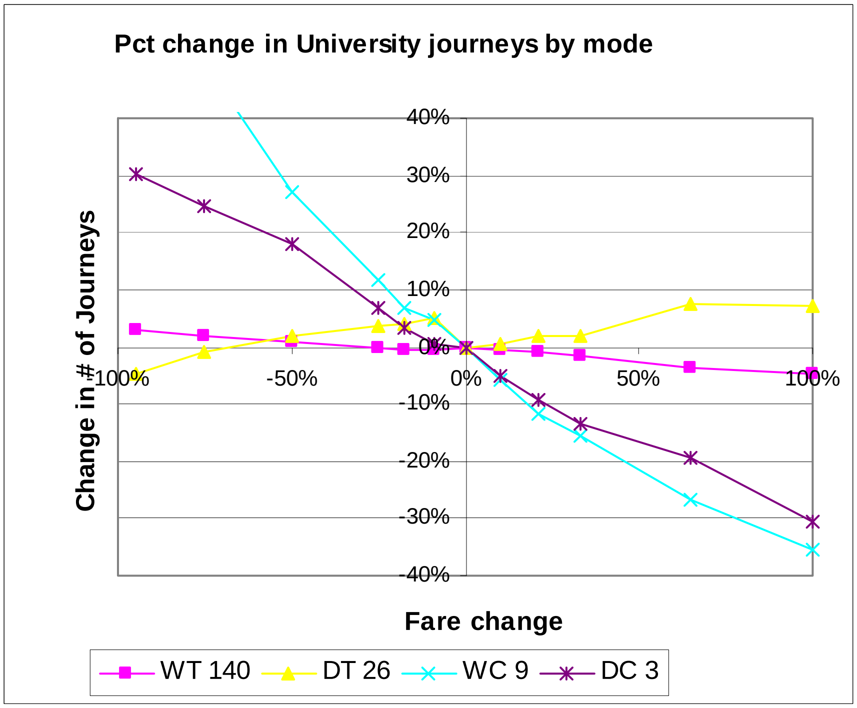


Figure 4-10 Percentage Change in Maintenance Journey by Transit/CR

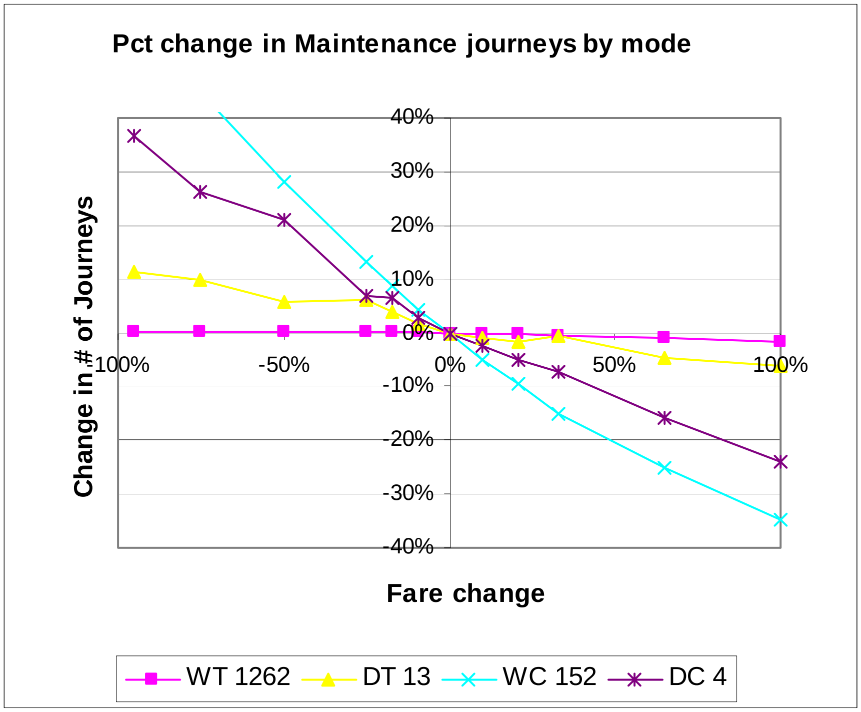


Figure 4-11: Percentage Change in Discretionary Journey by Transit/CR

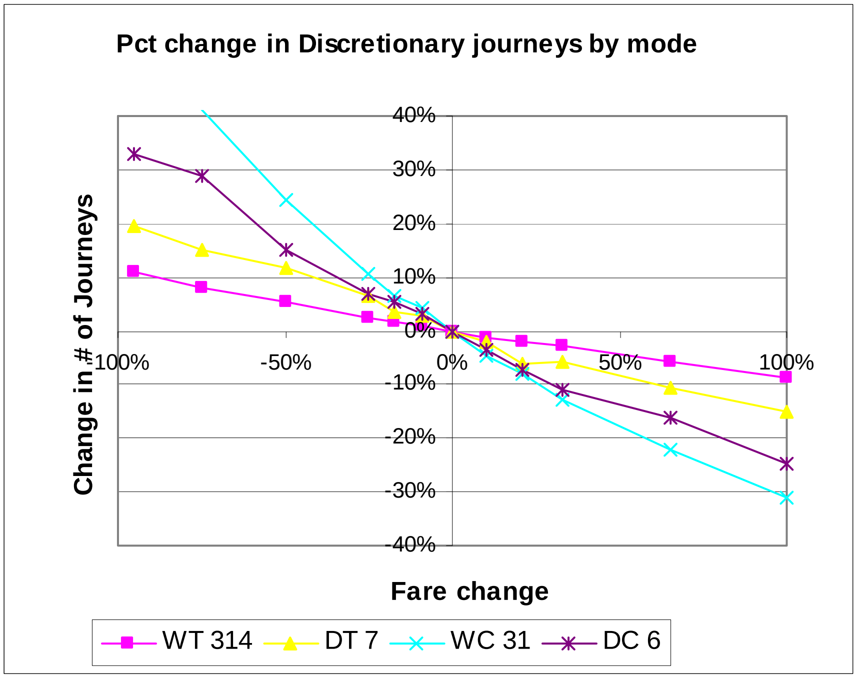


Figure 4-12 Percentage Change in At-work Journey by Transit/CR

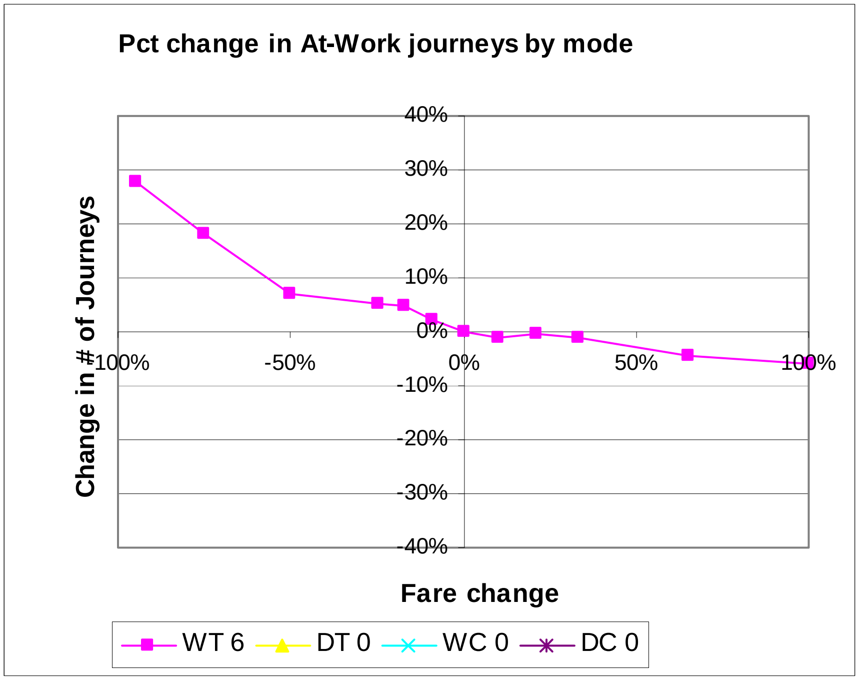


Figure 4-13 Percentage Change in Work (Low-income) Journey by Personal Vehicles

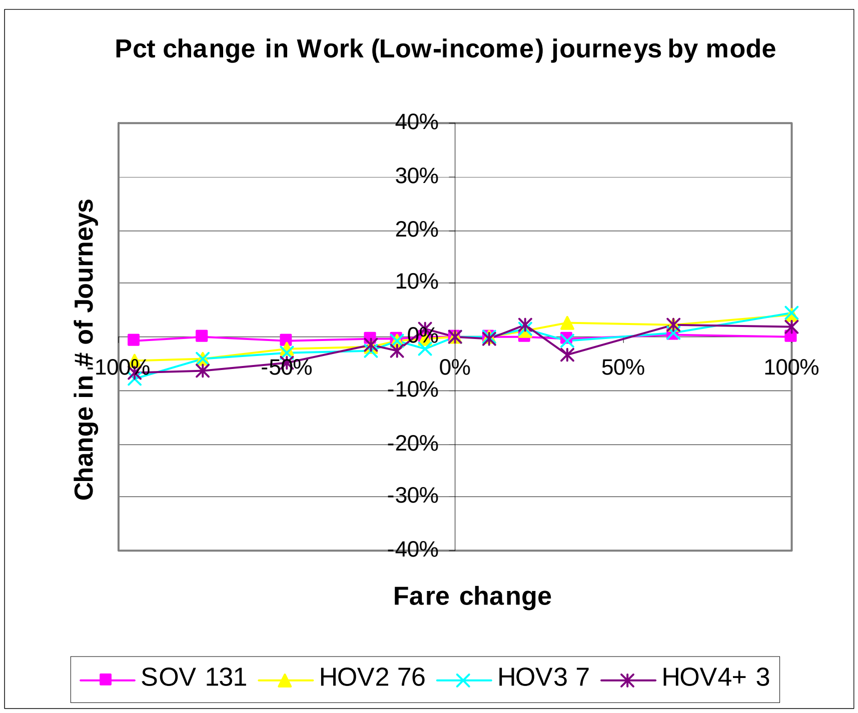


Figure 4-14 Percentage Change in Work (Med-Income) Journeys by Personal Vehicles

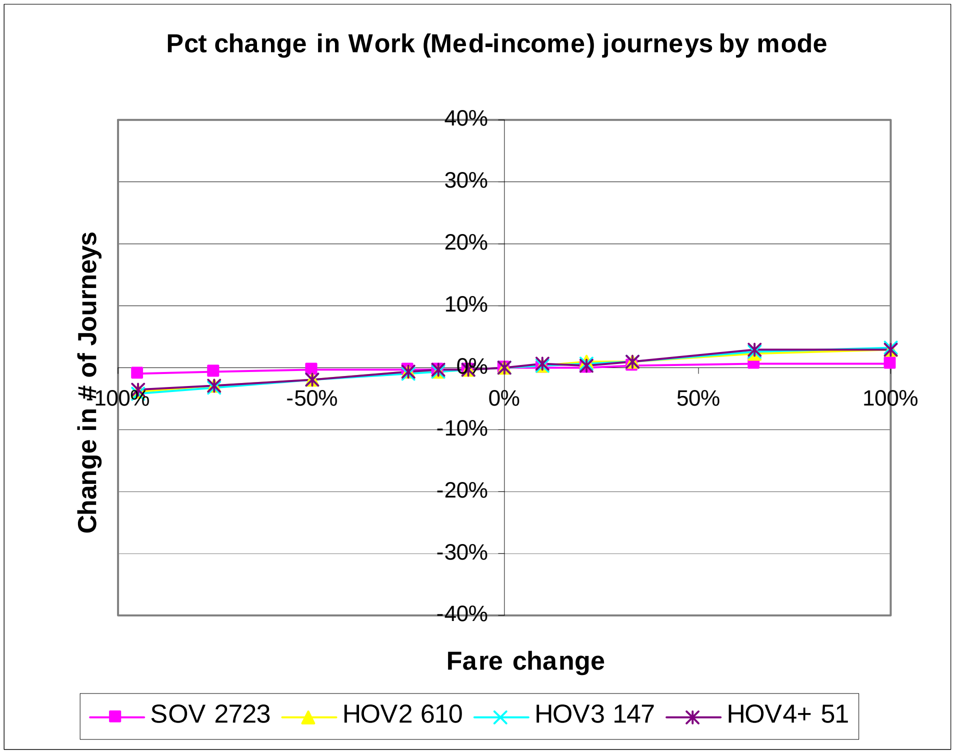


Figure 4-15 Percentage Change in Work (High-Income) Journeys by Personal Vehicles

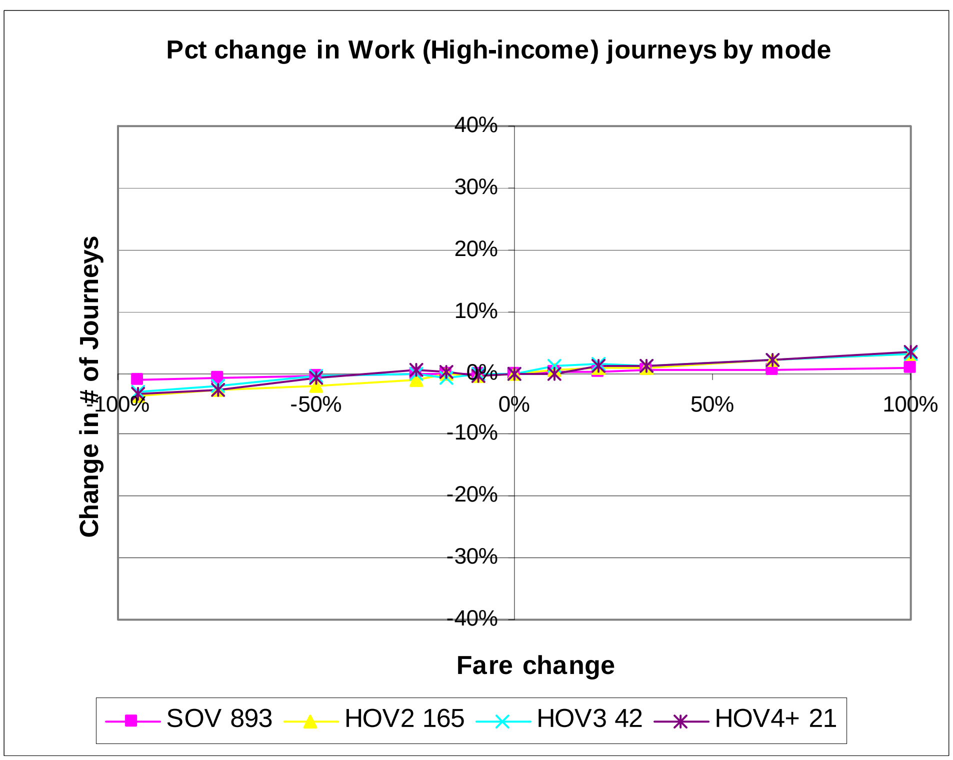


Figure 4-16 Percentage Change in School Journeys by Personal Vehicles

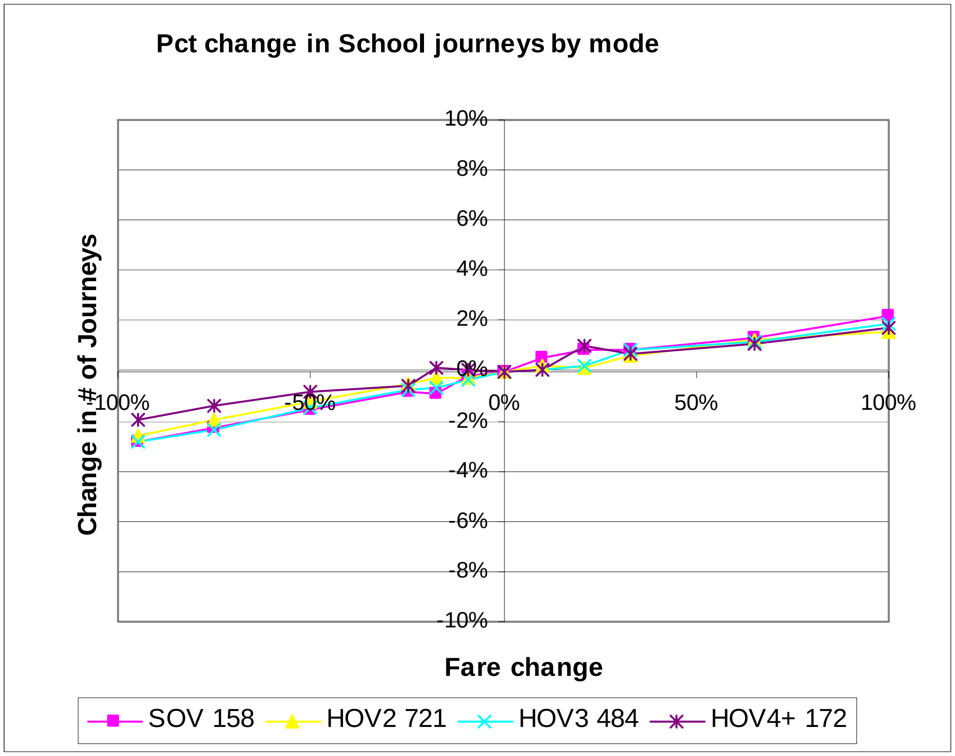


Figure 4-17 Percentage Change in University Journeys by Personal Vehicles

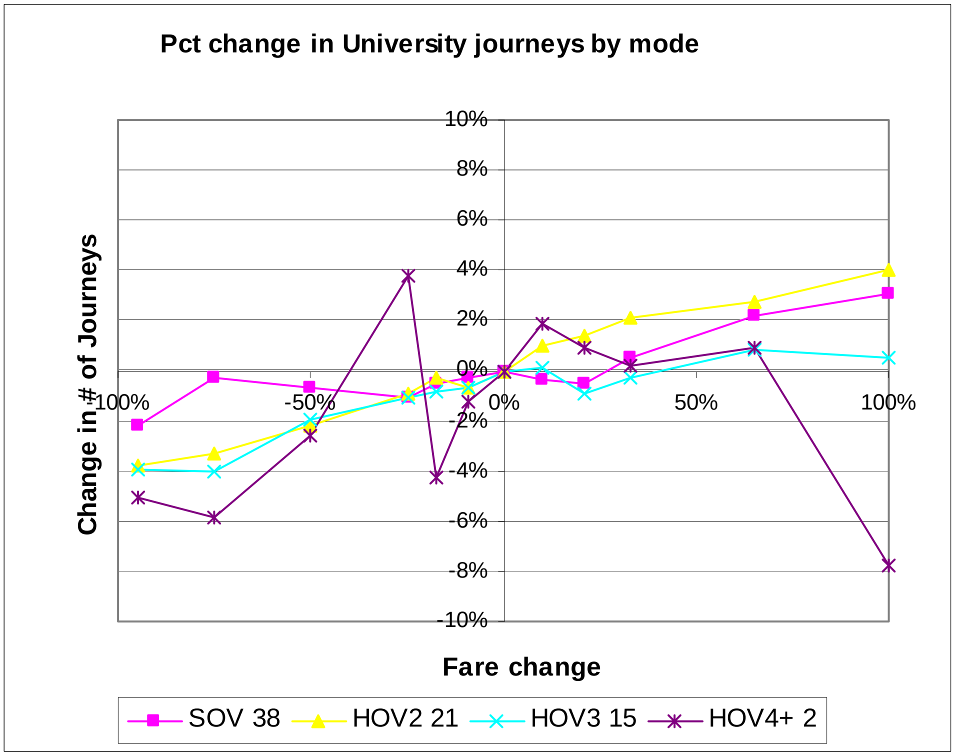


Figure 4-18 Percentage Change in Maintenance Journeys by Personal Vehicles

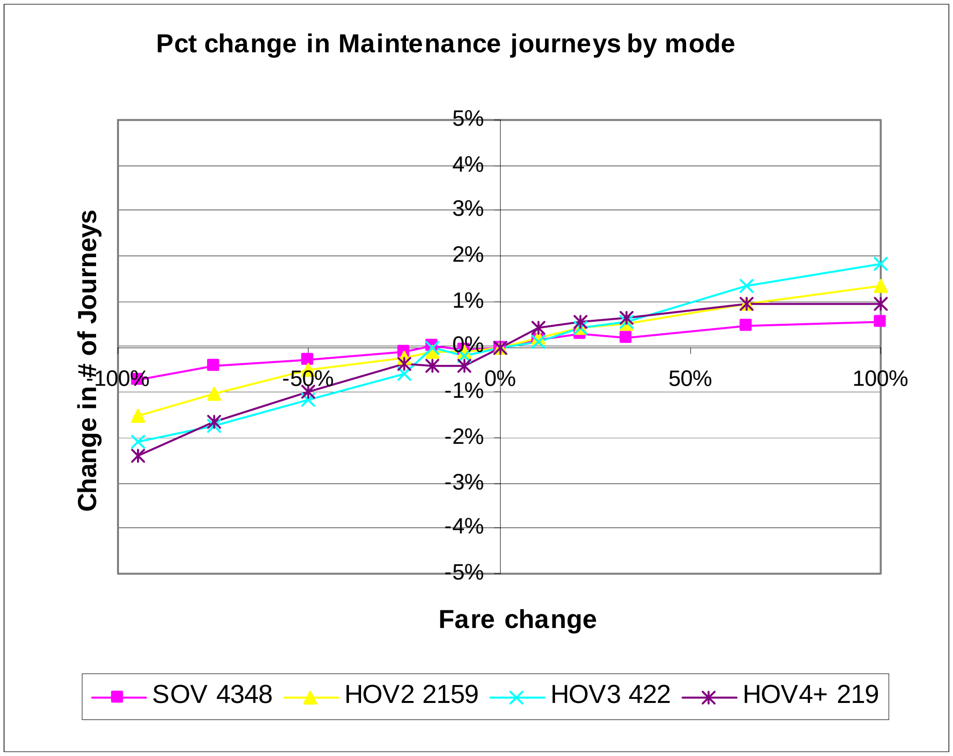


Figure 4-19 Percentage Change in Discretionary Journeys by Personal Vehicles

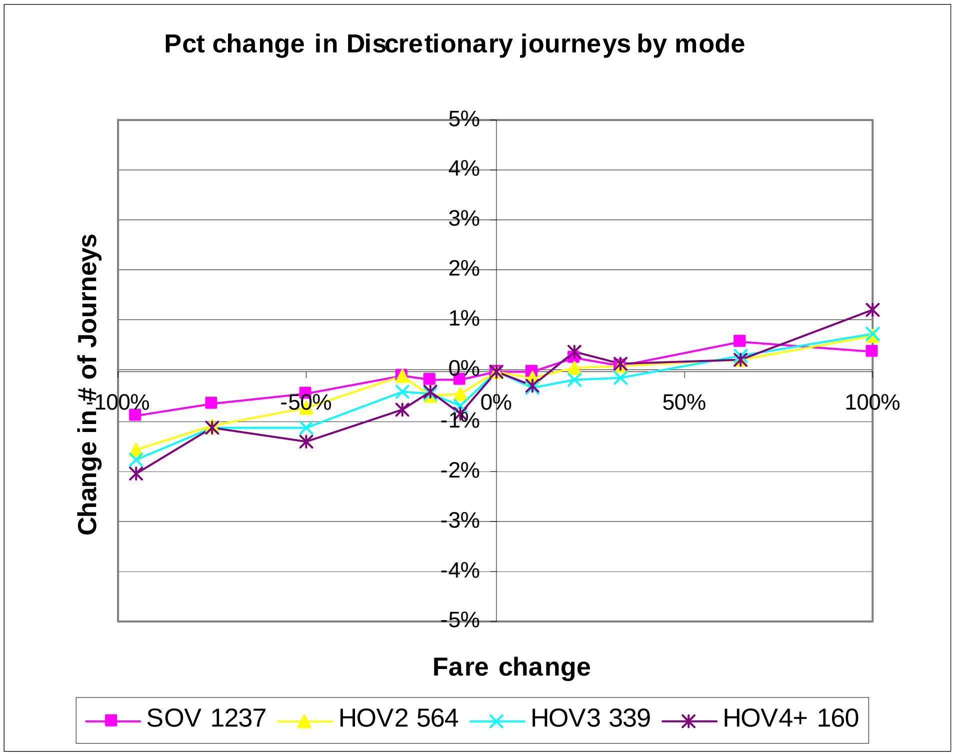


Figure 4-20. Percentage Change in At-work Journeys by Personal Vehicles

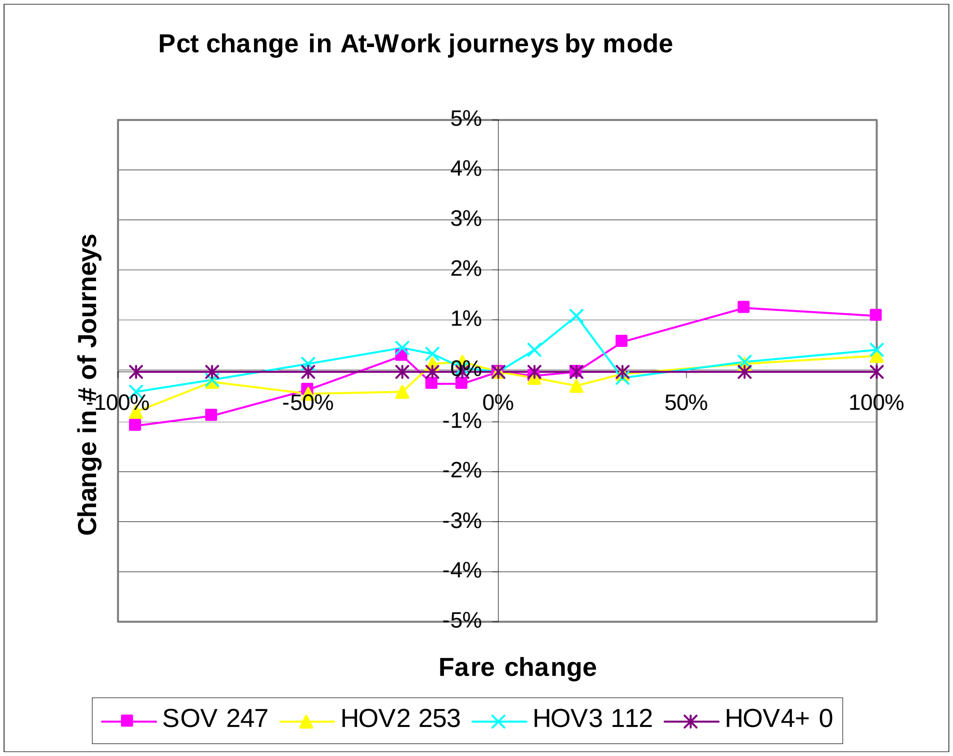


Figure 4-21 Percentage Change in Work (Low-income) Journeys by Other Modes

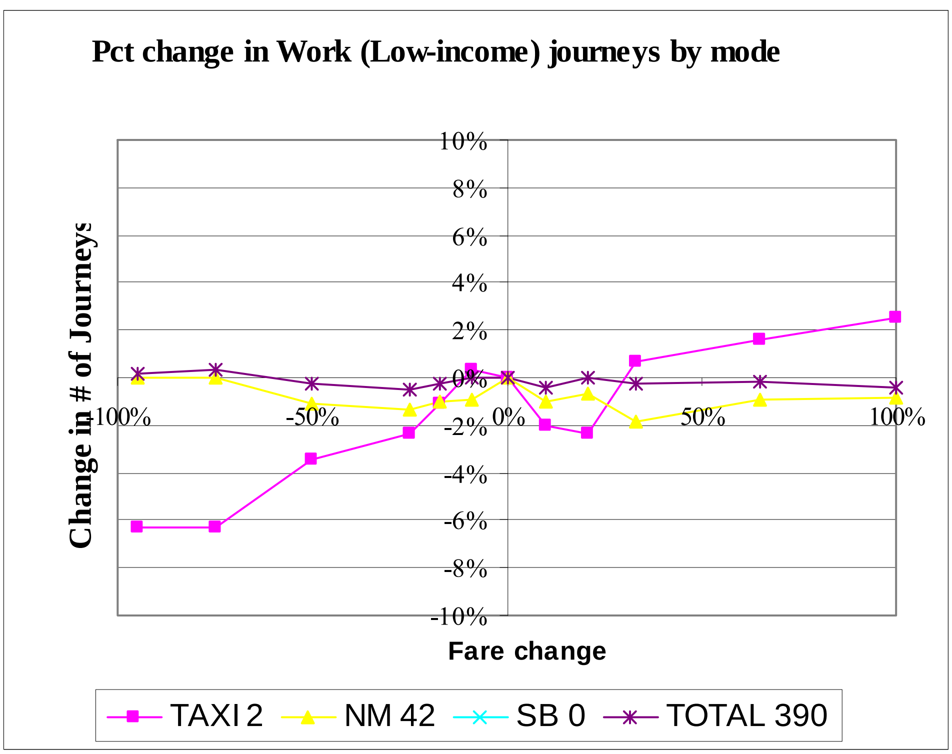


Figure 4-22 Percentage Change in Work (Med-income) Journeys by Other Modes

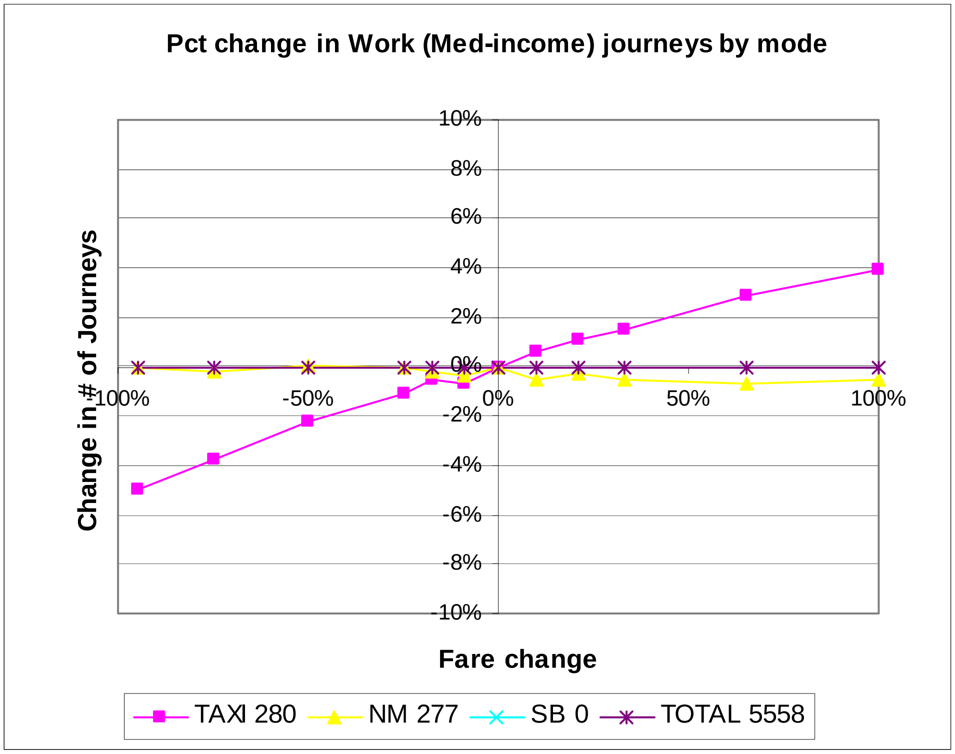


Figure 4-23 Percentage Change in Work (High-income) Journeys by Mode

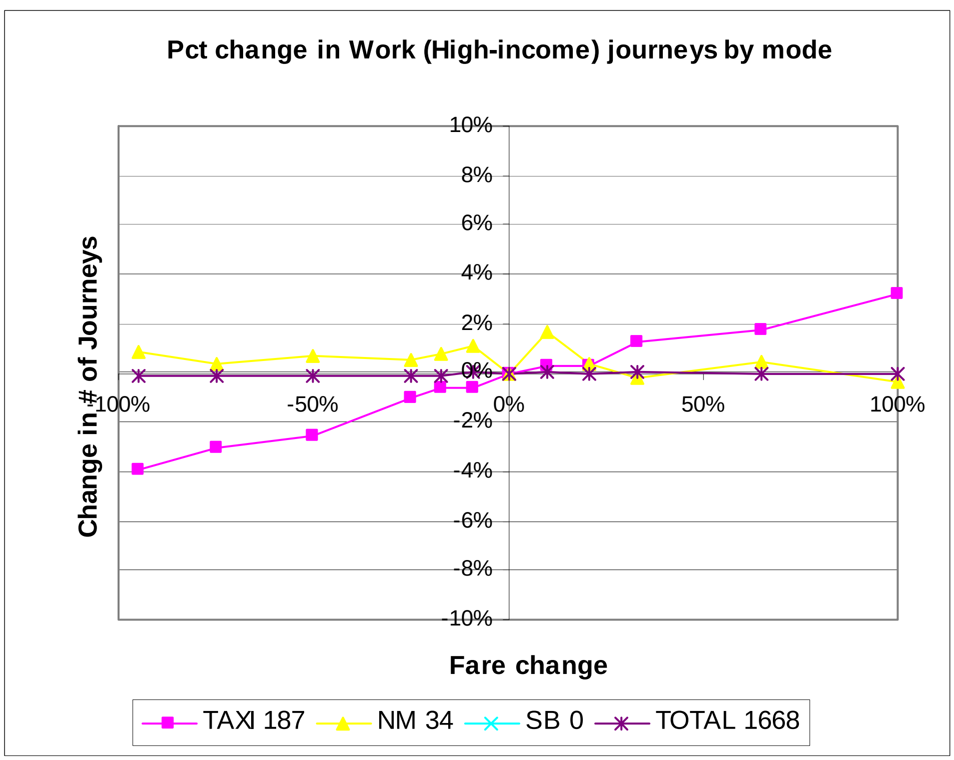


Figure 4-24 Percentage Change in School Journeys by Other Modes

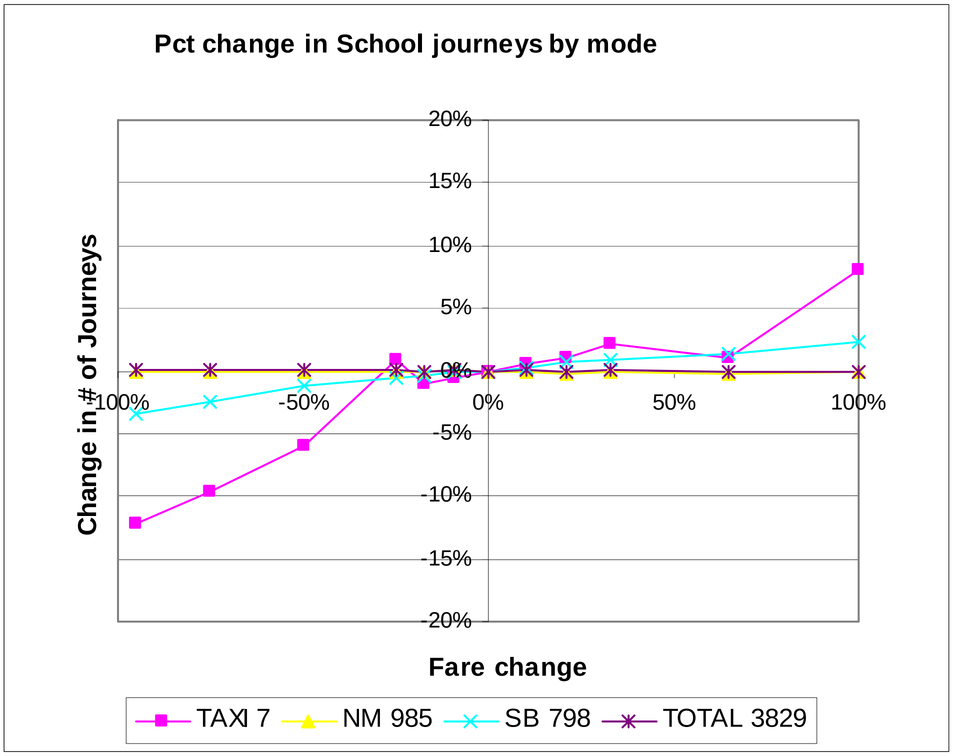


Figure 4-25 Percentage Change in University Journeys by Other Modes

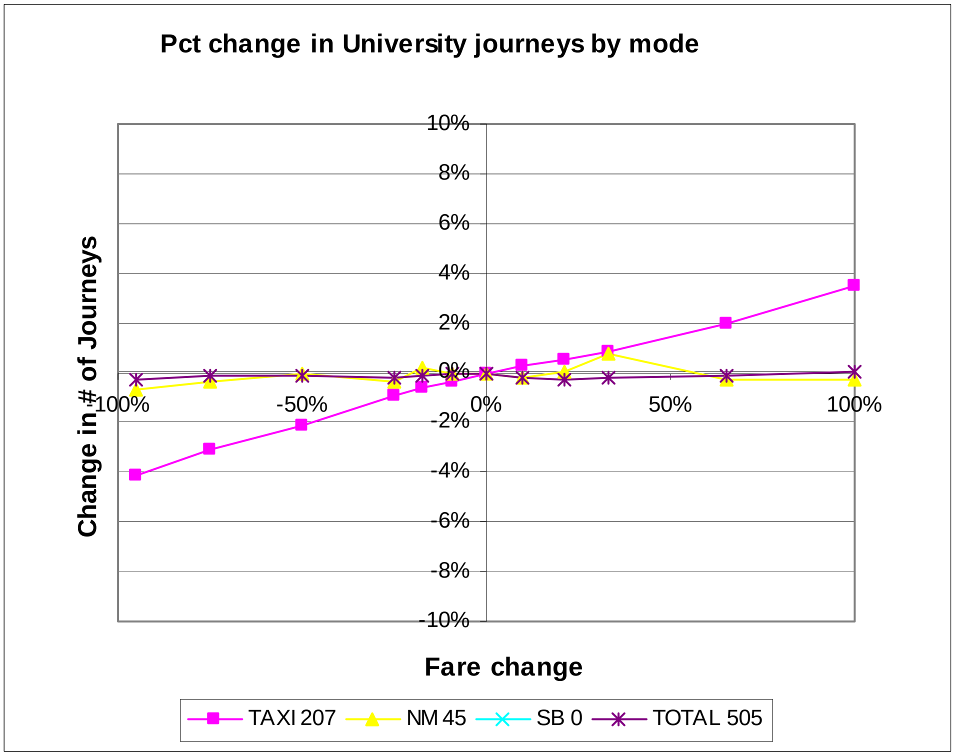


Figure 4-26 Percentage Change in Maintenance Journeys by Other Modes

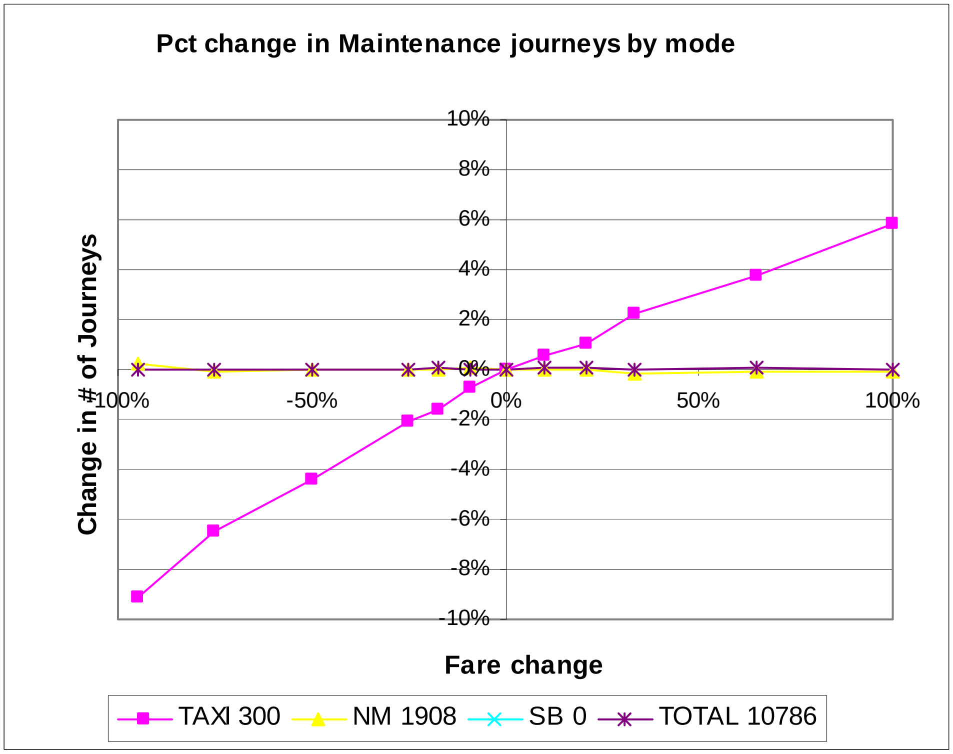


Figure 4-27 Percentage Change in Discretionary Journeys by Other Modes

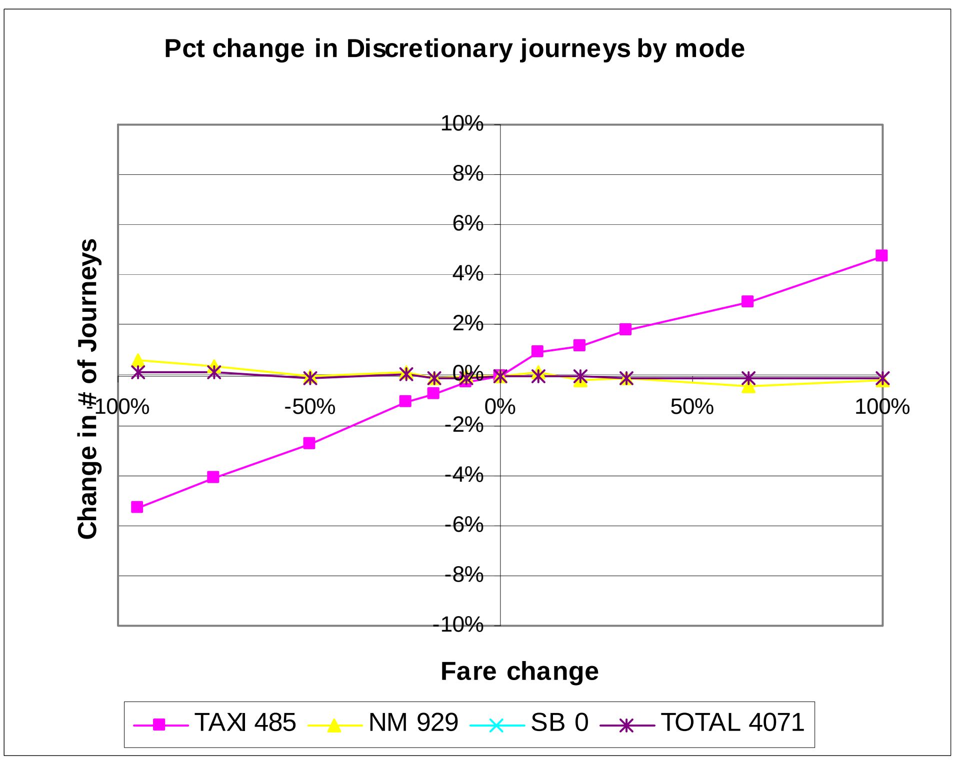
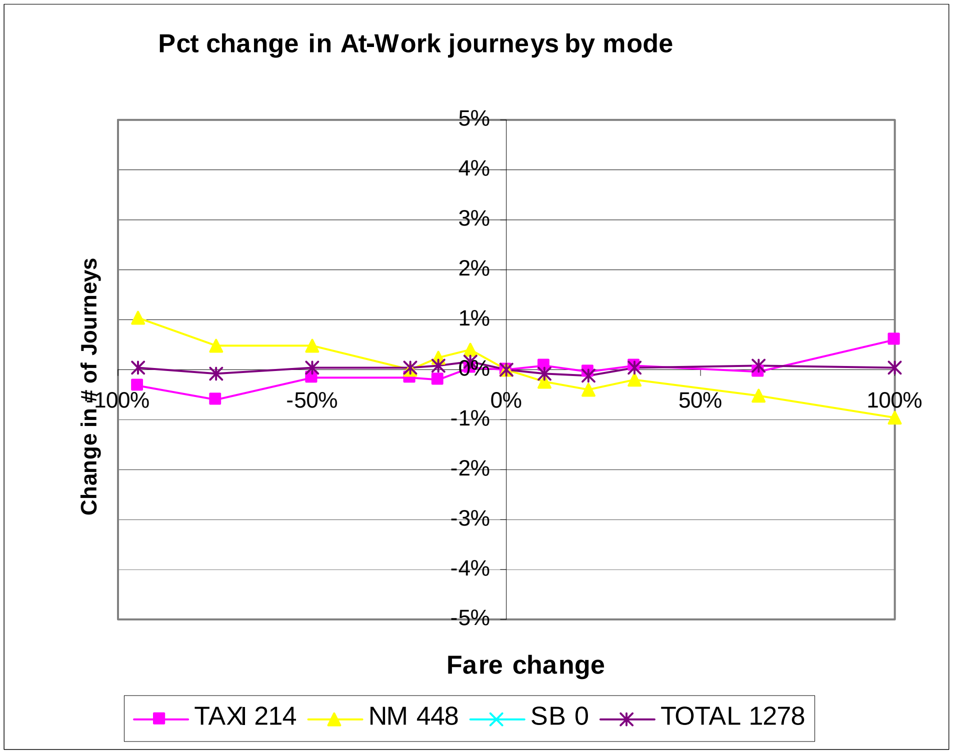


Figure 4-28 Percentage Change in At-work Journeys by Other Modes



It can be generally observed that among the highway modes that employ personal vehicles, SOV journeys show the least sensitivity and higher-occupancy modes (HOV2, HOV3, and HOV4+) show more. This holds except for the School journey-purpose, in which SOV journeys are understandably relatively rare, since these journeys are made mostly by children without driver's licenses. The number of HOV3 and HOV4+ journeys is quite small, especially in the categories of low-income work and university purposes. In these cases, the number of journeys on these two modes is noticeably more volatile than for lower-occupancy modes.

Commuter rail journeys accessed by walking are the most elastic of the four transit/CR modes, followed by drive-access CR journeys. This result is reasonable, since the CR mode is a more expensive transit mode, and an equal-percentage fare increase causes a larger absolute fare hike, thus causing a larger percentage mode shift. This is true across all journey purposes except for the At-work purpose, which does not create any commuter rail journeys at all (and only about 6 thousand walk-to-transit journeys). The At-work purpose also shows the highest elasticity of non-CR transit journeys (for example, a 95% fare reduction leads to walk-to-transit At-work journeys to increase by almost a third). The relatively large elasticity of these walk-to-transit At-work journeys is probably due to the flexible nature of these trips: many of them are non-essential trips. For other purposes, the number of WT and DT journeys is less sensitive to fares than WC and DC, as expected. An interesting anomaly can also be observed in the results for drive-to-transit (DT) University journeys. This curve is slightly upward-sloping, indicating that the number of such journeys actually grows when their price is increased. It is possible that this trend is the result of substitution of drive-to-transit for drive-to-commuter-rail journeys.

This set of graphs also shows which journey purposes are most sensitive to fare changes. A slight trend across income categories of work journeys is visible, with low-income workers showing a larger response and high-income workers a smaller one, especially as fares on commuter rail decrease to almost zero or increase to almost double the base fare. Similarly, the University journey purpose is dominated by students who have relatively low incomes, and shows even greater price sensitivity. Also, it can be seen that the number of discretionary journeys on transit (especially by non-CR transit modes) is more sensitive to fares than mandatory-purpose journeys.

The final set of graphs shows journeys made by other modes including taxi, non-motorized modes, and school bus. Taxi journeys serve to some extent as a substitute for transit journeys, so the upward-sloping lines seen in these plots accords with our intuition. Again, categories with only a small number of journeys (here the low-income work and school purposes) show more volatility (reflected in "bumpier" lines) than larger categories. School buses also serve as a substitute mode for transit journeys to school, and the graph reflects this. By way of contrast, walking and bicycling are minor modes and not generally viewed as acceptable substitutes for motorized modes. The model results reflect this, with very little change in the number of these journeys. Possible exceptions may apply for at-work and high income work journeys, where the non-motorized journeys trend very slightly downward as fares increase.

It is useful to note that the total journey production for each purpose is quite stable across all fare scenarios. The BPM journey frequency models do include transit accessibility and walk accessibility indices for the maintenance- and discretionary-purpose journeys by non-workers, but with relatively small coefficients (the largest being just 0.0007). Since travel costs such as fare do not directly appear in these models, we can safely conclude that changes in journey rates reflect only random variation and not any systematic trend. The change in number of journeys (all modes) was no more than 0.51% across all purposes and all fare scenarios. Those purposes with relatively few journeys (low-income work and university) had the greatest variation, while the larger purposes (such as median-income work and maintenance) exhibited more stability. The fact that the totals do not change greatly makes it possible to interpret the resulting percent change in the number of journeys as equivalent to the percent change in mode share. In other words, for this model the responses to change in transit prices are mainly manifested in mode and destination shifts rather than altered journey-frequency. Destination shifts are investigated indirectly below, through examinations of the number of CBD[8]-bound journeys and mean trip lengths.

4-4 CBD-bound Journeys by Sub-Region of Origin

Journeys to the CBD (defined to include the Lower, Valley, and Midtown Manhattan districts) number slightly over 3 million in the base case. The total number of journeys destined to the CBD sub-region from all other sub-regions shows only a small response to transit fare changes, increasing by 1.24% for nearly-free transit and falling by 0.88% for doubled fares. The direction of these changes seems intuitively correct. Also in accordance with expectation, journeys from New Jersey and the outer boroughs of New York City follow a similar trend, falling by a few percent as fares increase. The upward trend in journeys from the rest of Manhattan to the CBD has a more subtle interpretation. It may be that very low transit costs cause some travel originating in non-CBD Manhattan to be redirected away from the CBD to other destinations in Manhattan or the other boroughs that are also served by transit. (There is a corresponding increase in the number of such journeys, not shown on the graph). The number of journeys from Other New York State (i.e., “upstate”), Connecticut, and Long Island origins to the CBD is relatively small. For the northern suburbs and Connecticut, there is again an upward trend in the number of CBD-bound journeys as fares rise, and in the case of Long Island, the number of such journeys appears to fluctuate in response to fare changes. It is also not clear how one should interpret the increase in journeys from Connecticut to the CBD as transit fares rise. The O/D table shows that these journeys seem to be mainly replacing journeys from Connecticut to New Jersey. In any case, the absolute difference is less than three

[8] Central Business District.

thousand journeys between the 95% decrease and the 100% increase scenarios.

Figures 4-29, 4-30, and 4-31 show CBD bound journeys for Work, School/University, and Other purposes. (The Work category includes Low, Median, and High Income groups, and the Other category includes Maintenance, Discretionary, and At-Work purposes, but a further breakdown is not available in the summary report produced by BPM.) Work journeys make up over half of the total CBD-bound travel, and this graph closely resembles the one for all purposes, with some exceptions. The line for Other NYC is completely flat for Work and School/University journeys, showing that the downward trend in overall CBD-bound travel from the rest of the city is completely accounted for by travel for Other purposes (up by over 10% for nearly-free transit, and down by 6% for doubled fares, compared to the base case). Similarly, for journeys originating from New Jersey, greater sensitivity is shown in the Other purpose category than Work or School/University purposes. As for the northern suburbs (Other NYS), Connecticut, and Long Island, the two non-work purpose categories show large responses with the expected downward trend, but appear somewhat erratic because of the small number of such journeys. Because of these limited samples, the line for Connecticut has been omitted from the graphs.

Figure 4-29 Percentage Change in Work CBD-bound Journeys by Origin Region

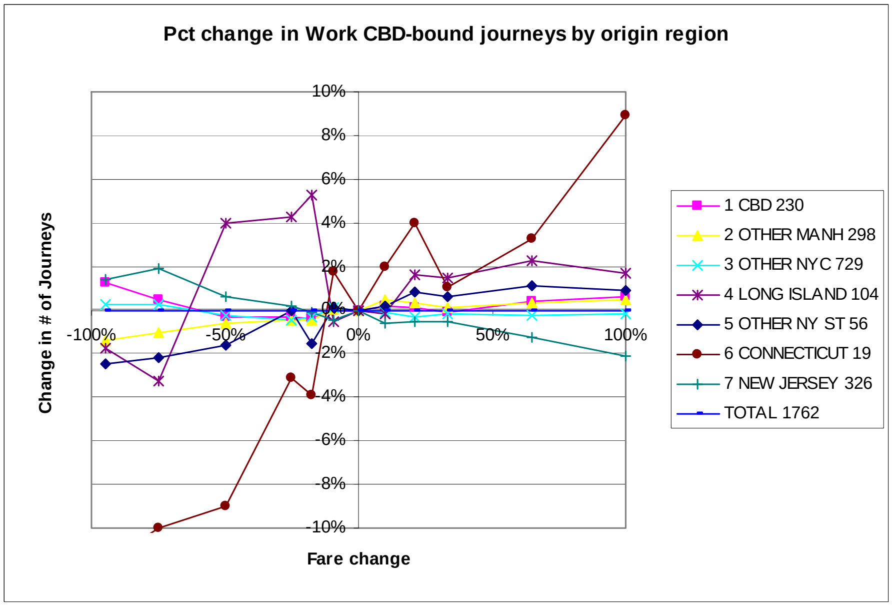


Figure 4-30 Percentage Change in School and University CBD-bound Journeys by Origin Region

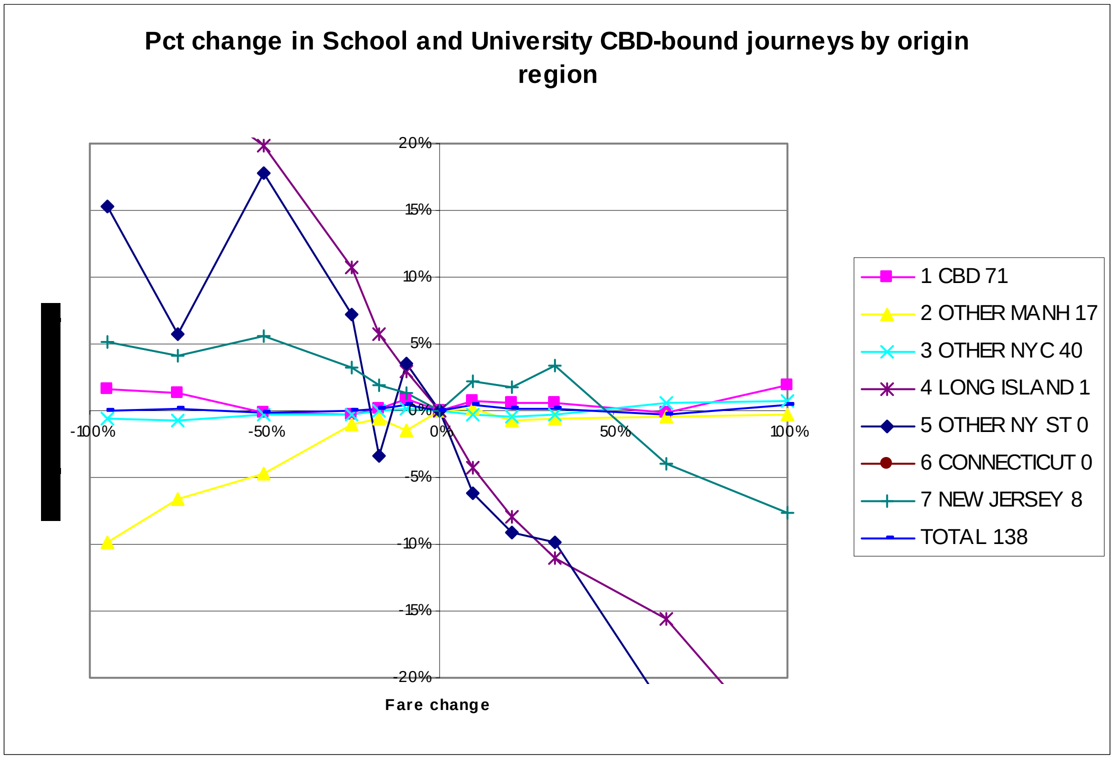
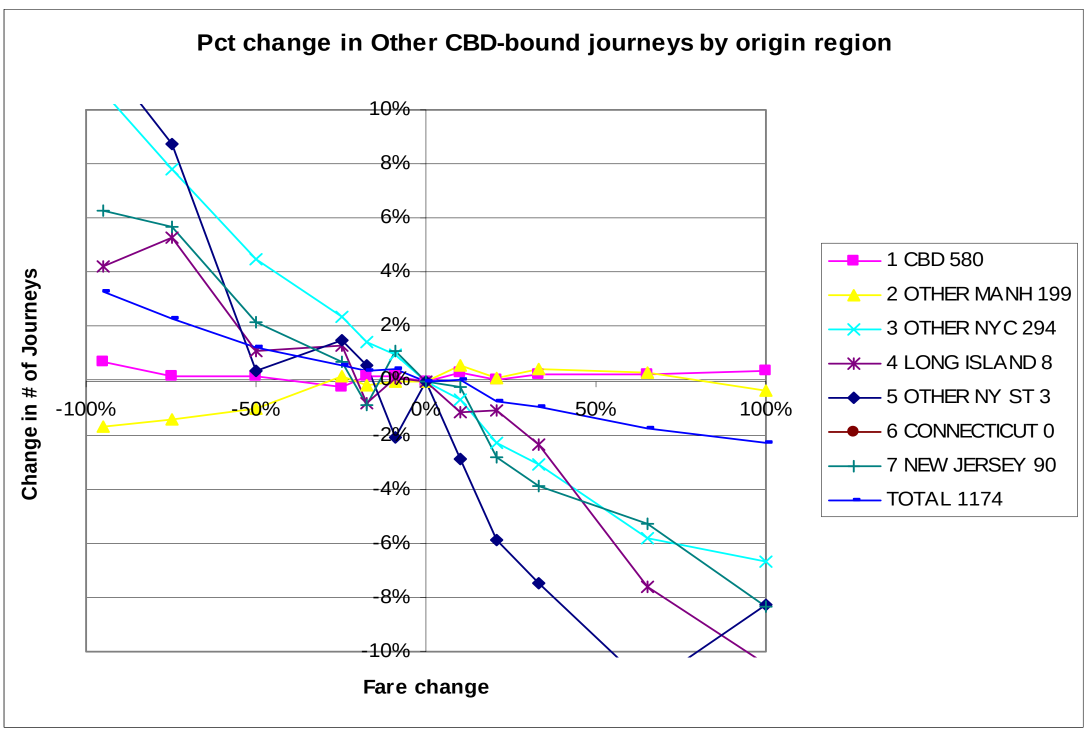


Figure 4-31 Percentage Change in Other CBD-bound Journeys by Origin Region



A set of six graphs in Figures 4-32 to 4-36 shows the change in number of CBD-bound trips by SOV, HOV, Taxi, Transit, and Commuter Rail modes (The aggregate O/D tables for separate HOV occupancy categories and Transit and CR access modes are not produced by the BPM reporting procedures). These illustrate the expected effects, with transit and CR journeys from all sub-regions generally declining as fares increase, and journeys on other modes rising. As noted above, these is little fare-sensitivity exhibited for transit journeys from New York City to the CBD, not unexpected since many of these journeys have few alternative modes, and the sheer volume of such journeys is quite large. Also, Commuter Rail journeys are more sensitive than non-CR transit. Especially of note are CBD-bound CR journeys originating from within New York City and within Manhattan. For instance, a doubling of fares causes a 69% decline in Other Manhattan-to-CBD journeys, and a 46% decline in other NYC-to-CBD journeys.

Figure 4-32 Percentage Change in SOV CBD-bound Journeys by Origin Region

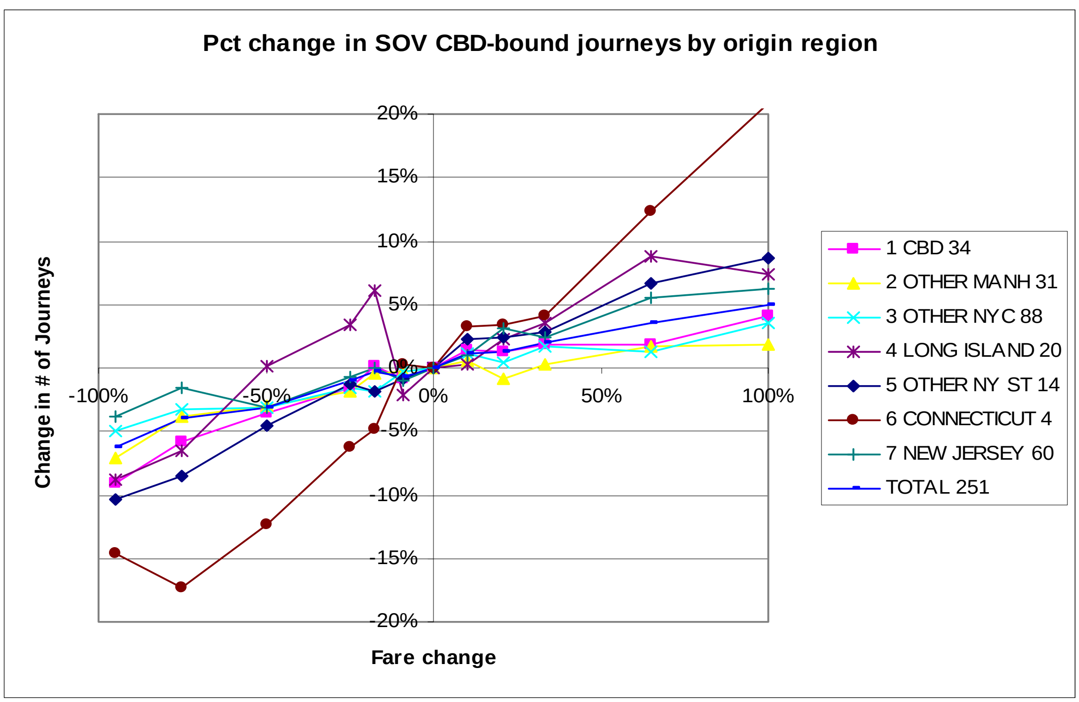


Figure 4-33 Percentage Change in HOV CBD-bound Journeys by Origin Region

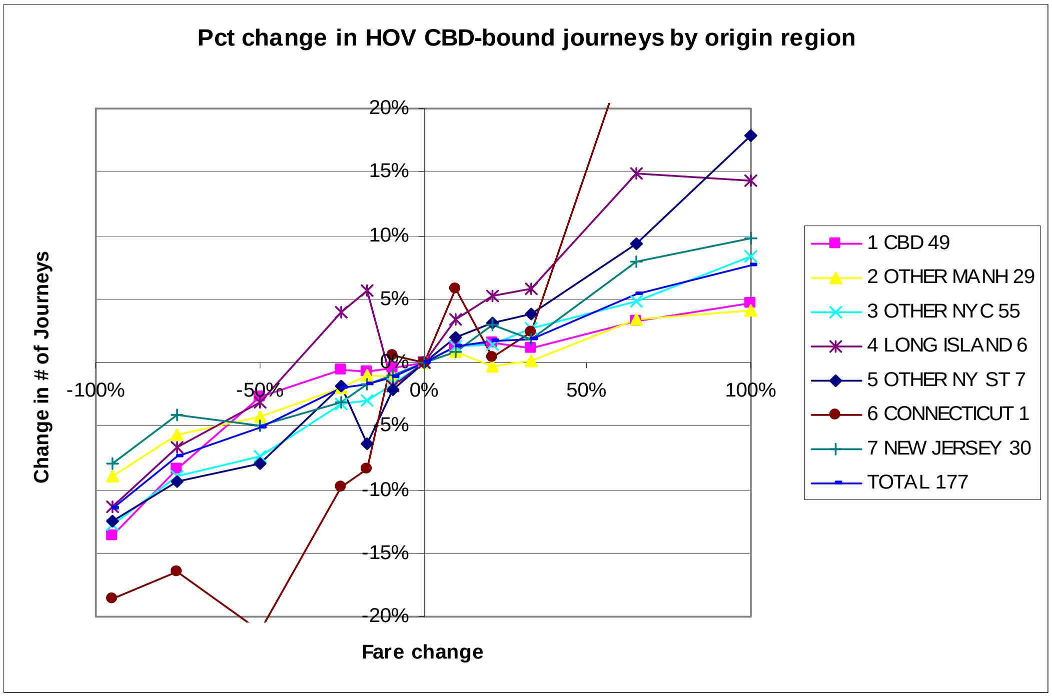


Figure 4-34 Percentage Change in Taxi CBD-bound Journeys by Origin Region

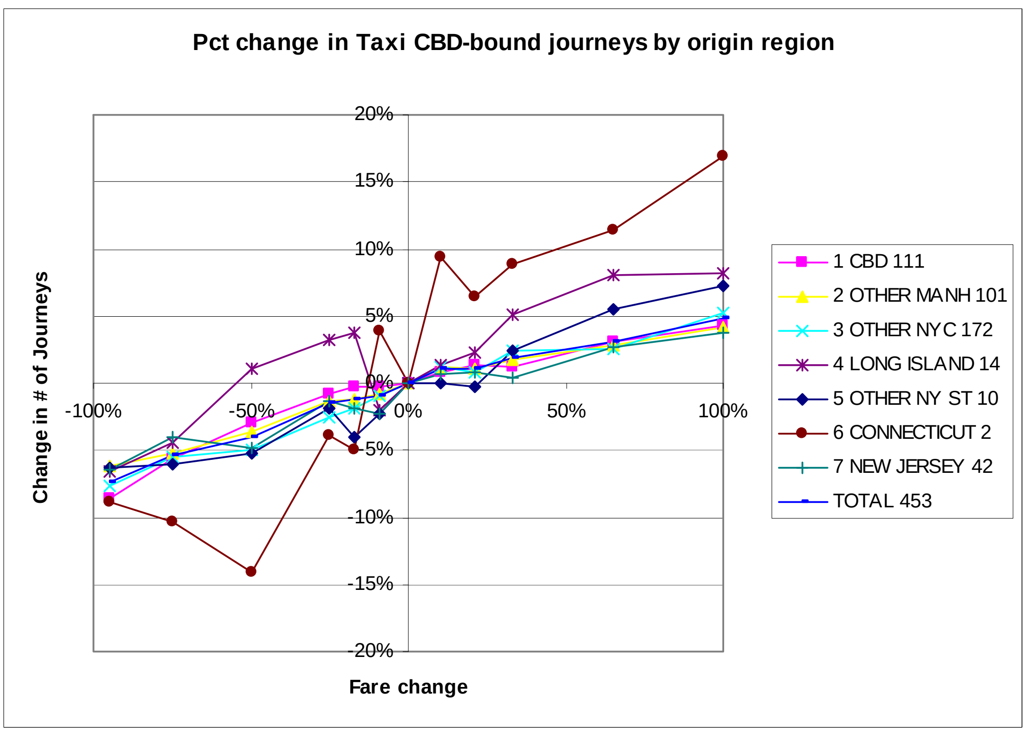


Figure 4-35 Percentage Change in non-CR Transit CBD-bound Journeys by Origin Region

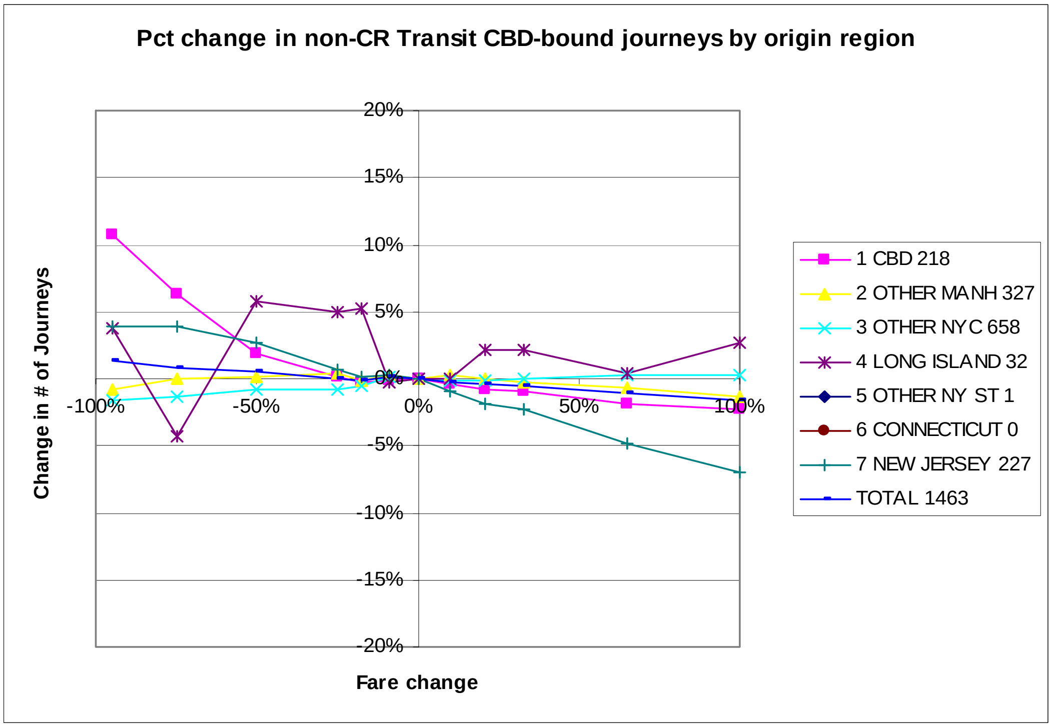
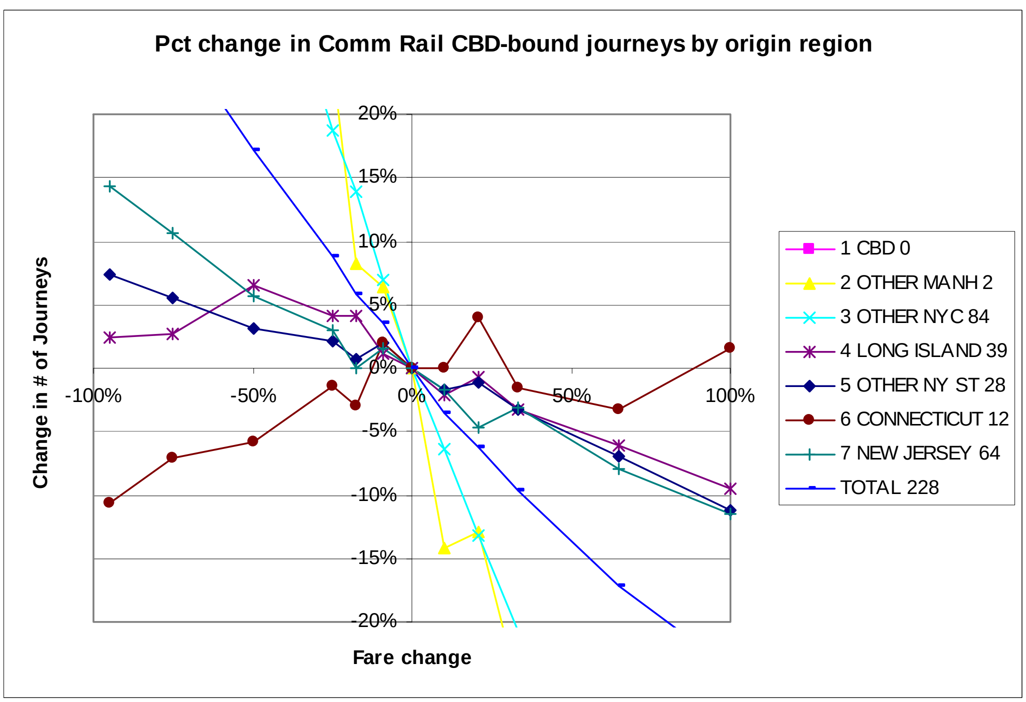


Figure 4-36 Percentage Change in Commuter Rail CBD-bound Journeys by Origin Region



4-5 Mean Trip Length by Mode and Purpose

Mean trip lengths of many purposes for different modes are shown in Figures 4-37 to 4-48. For many mode/purpose combinations, these graphs are very volatile and show no identifiable trend. This is especially the case for the minor modes that represent very small numbers of journeys, such as HOV4 (Shared Ride with 4 occupants). Interpretation of these results is further clouded by a quirk of the BPM reporting software. Mean trip length is reported in the output report files to the nearest 0.1 mile. This low level of precision makes it difficult to observe small changes, especially if average trip lengths are short. For example, the mean trip length for non-motorized journeys is given as 0.9 mi. If a different scenario reports a mean trip length of 1.0mi, this results in a calculated increase of 11%, even though the actual change could be as little as 1% (0.94 mi to 0.95 mi) or as much as 22% (0.85 mi to 1.04 mi).

Figure 4-37 Mean Trip Lengths by DA Mode

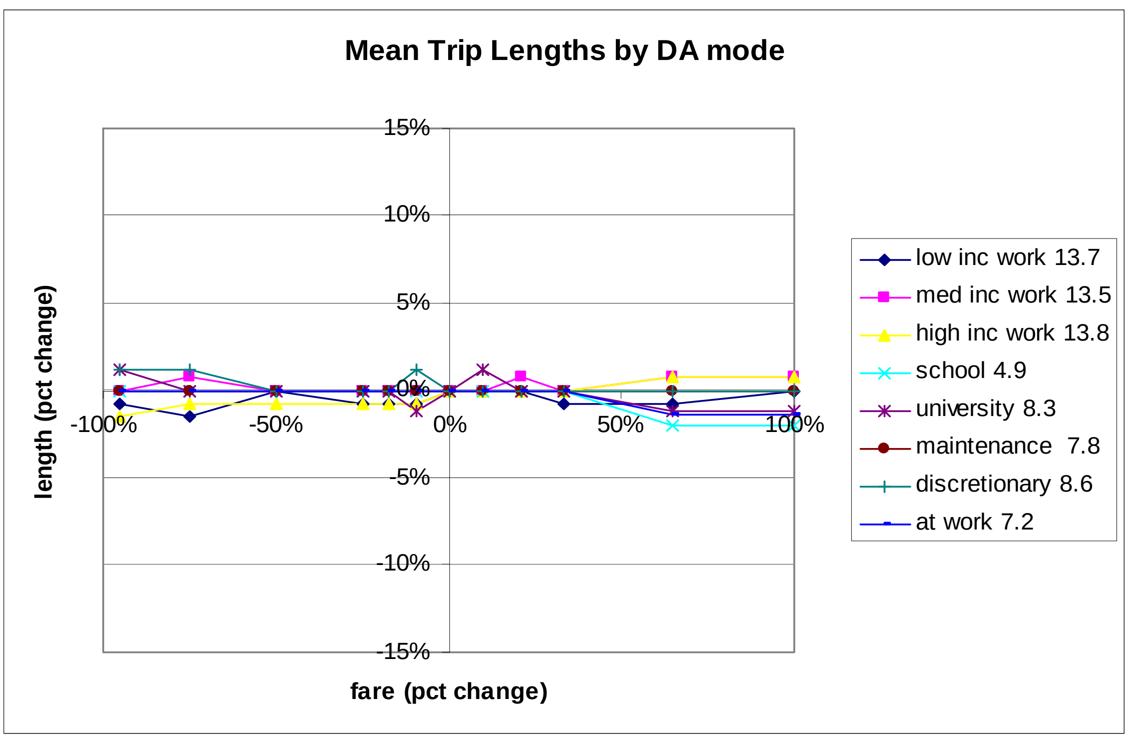


Figure 4-38 Mean Trip Lengths by SR2 Mode

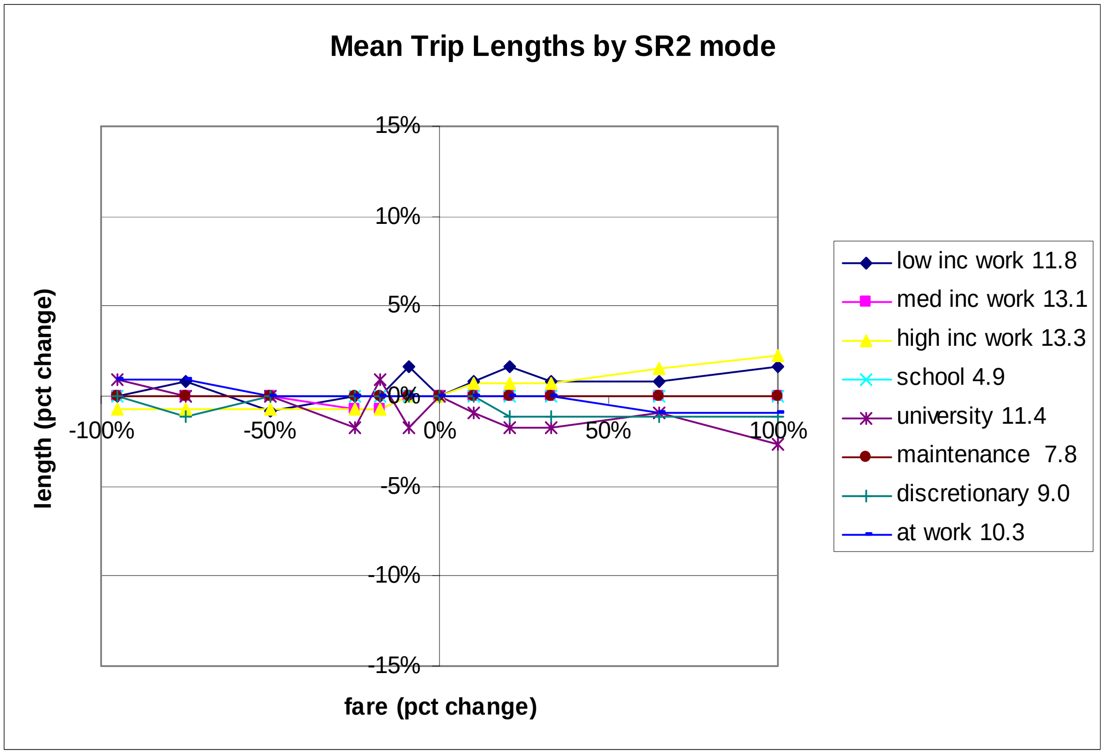


Figure 4-39 Mean Trip Lengths by SR3 Mode

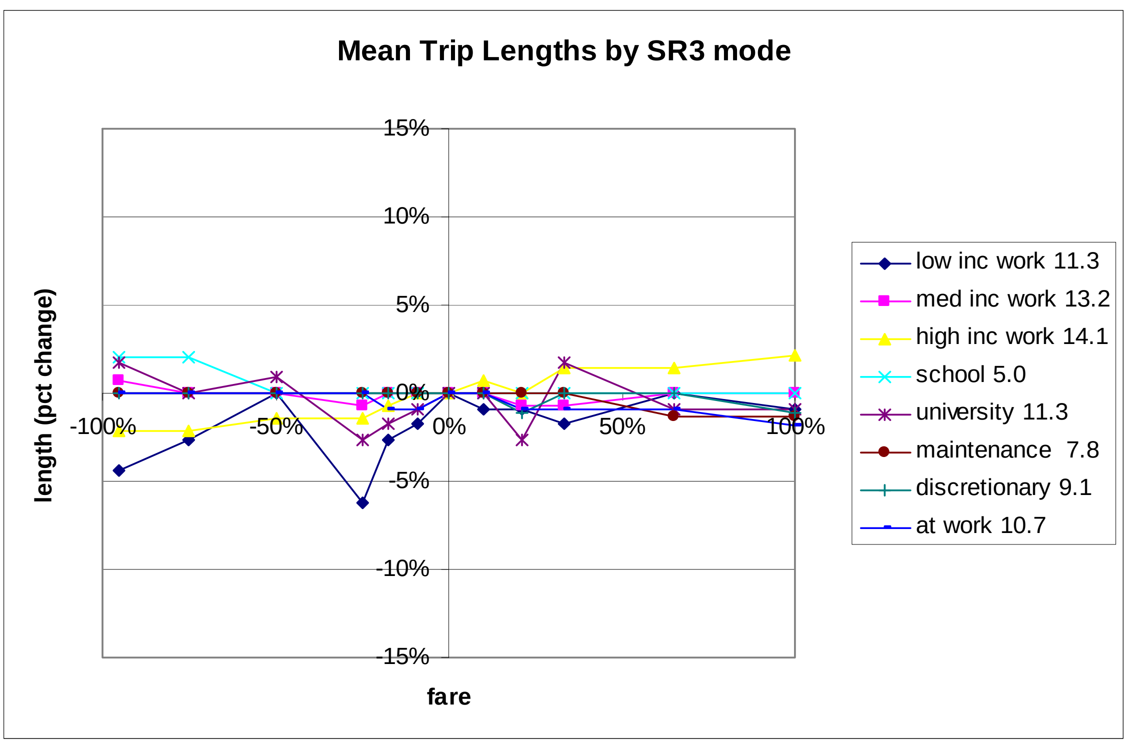


Figure 4-40 Mean Trip Lengths by SR4 Mode

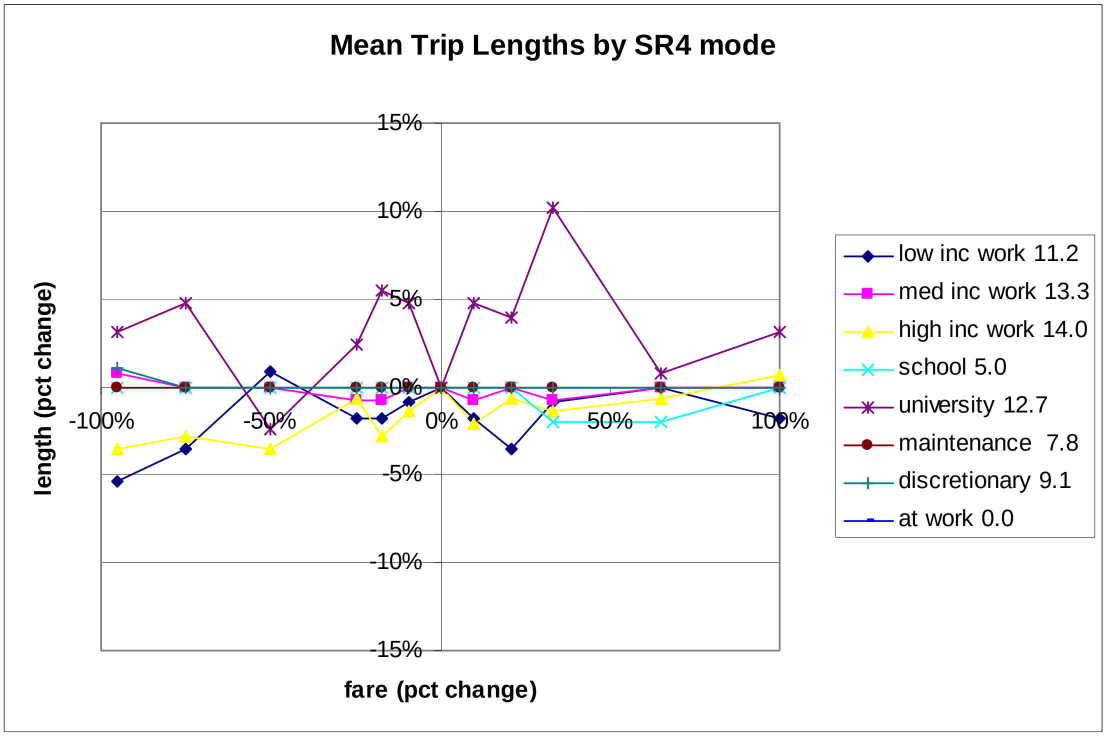


Figure 4-41 Mean Trip Lengths by WT Mode

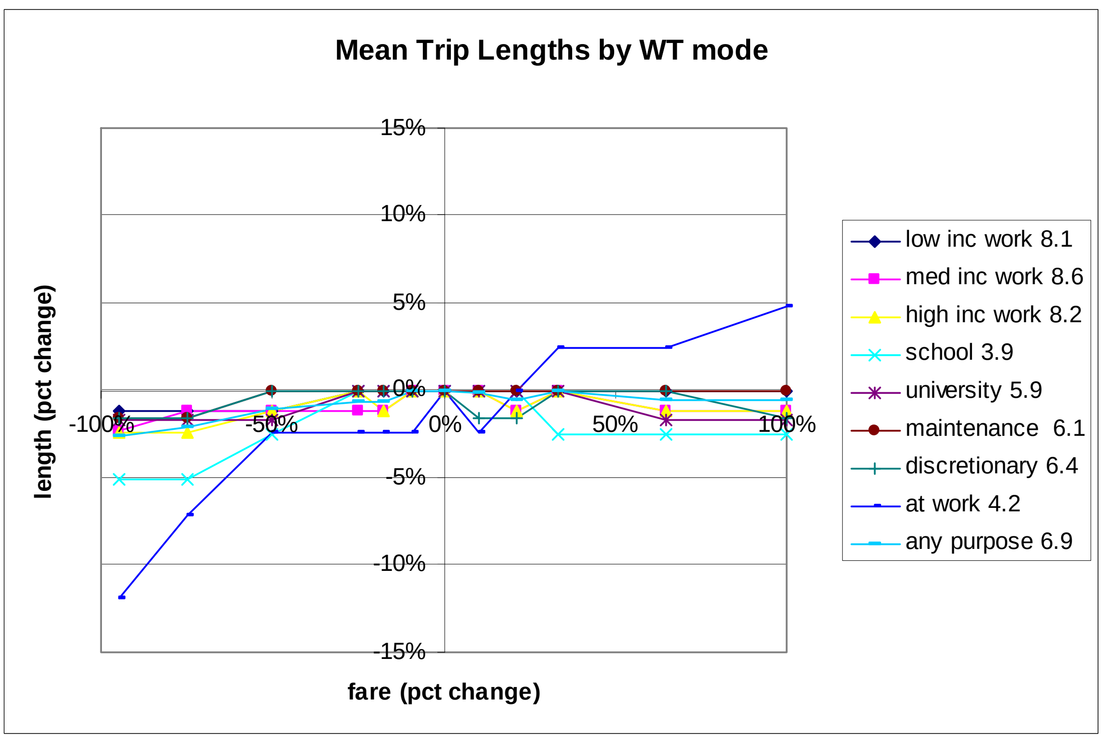


Figure 4-42 Mean Trip Lengths by DT Mode

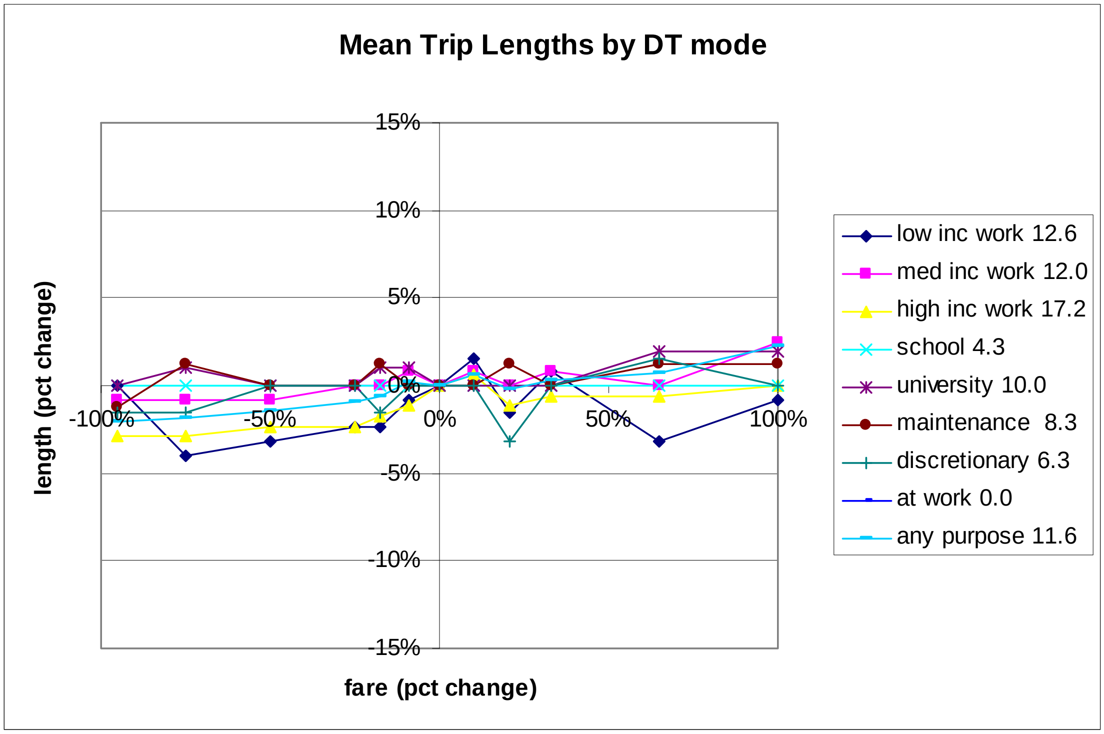


Figure 4-43 Mean Trip Lengths by WC Mode

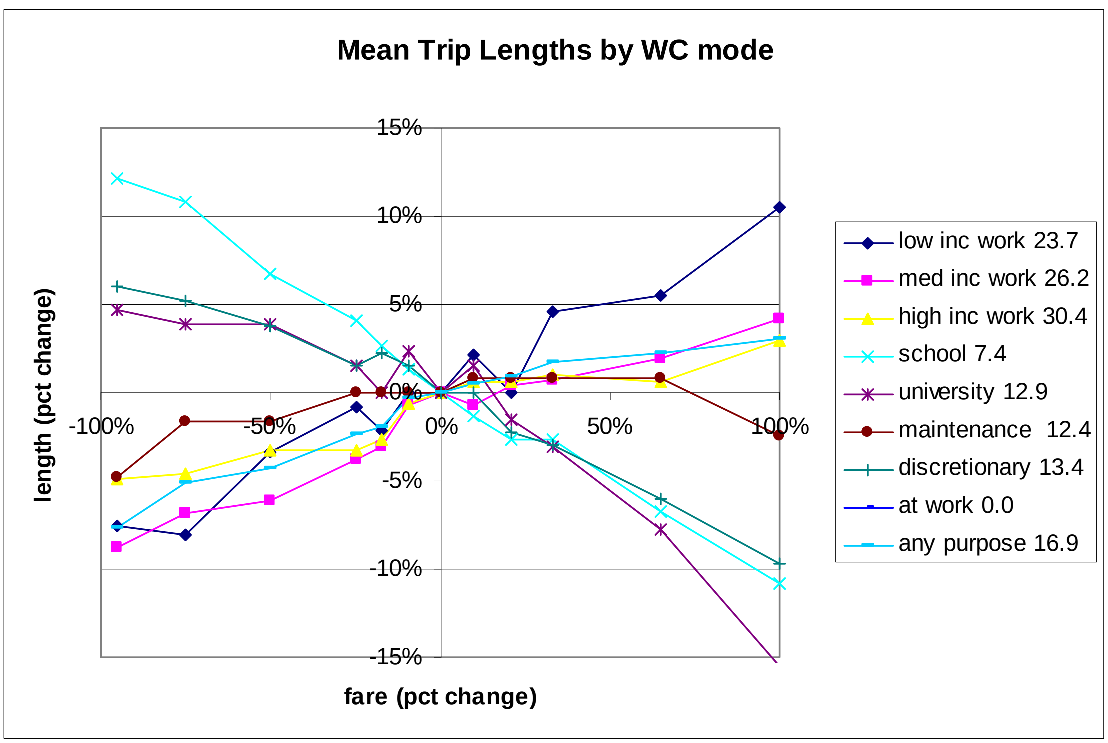


Figure 4-44 Mean Trip Lengths by DC Mode

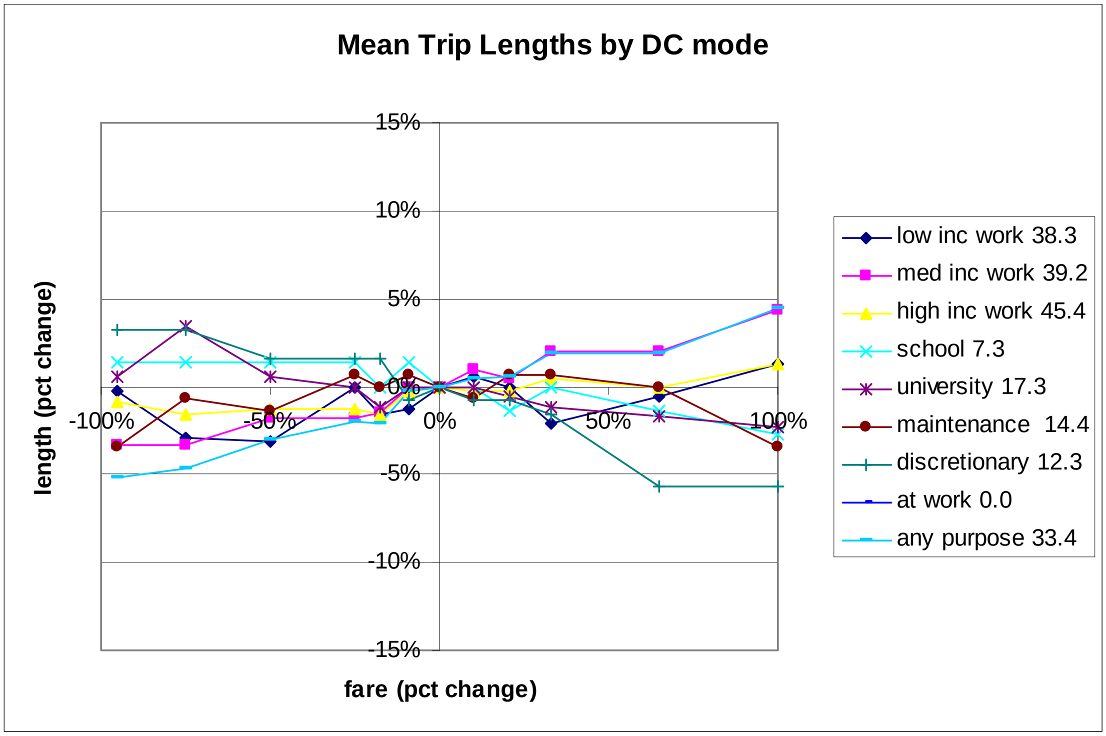


Figure 4-45 Mean Trip Lengths by TX Mode

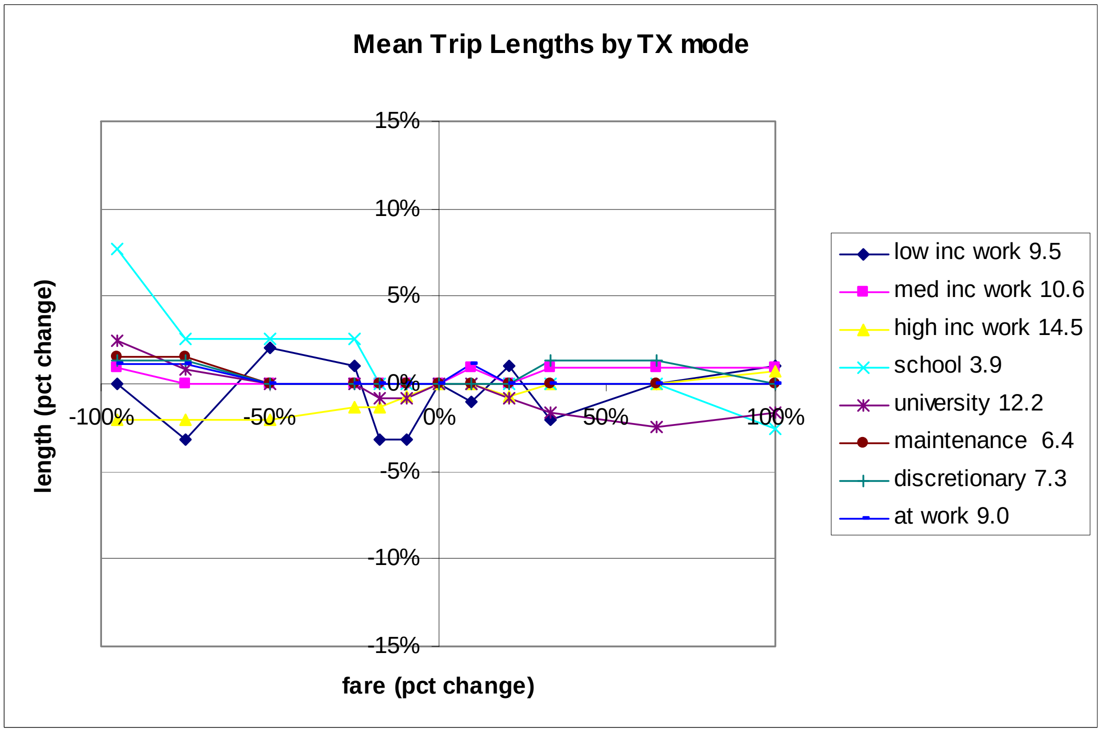


Figure 4-46 Mean Trip Lengths by NM Mode

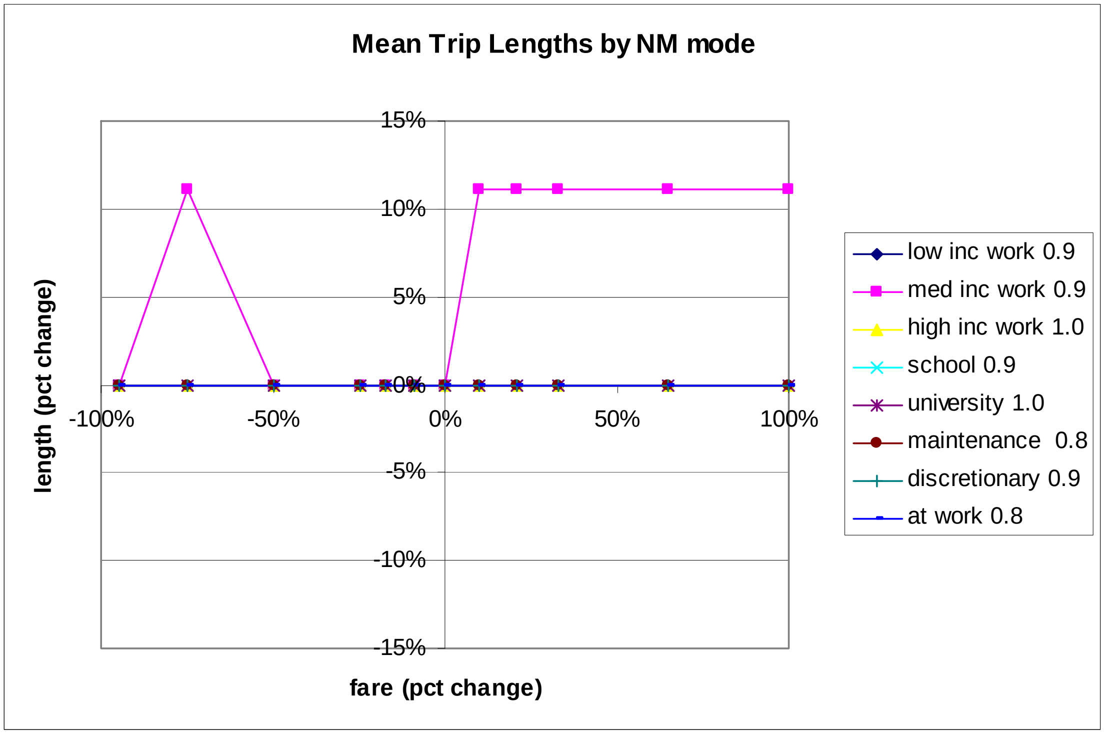


Figure 4-47 Mean Trip Lengths by SB Mode

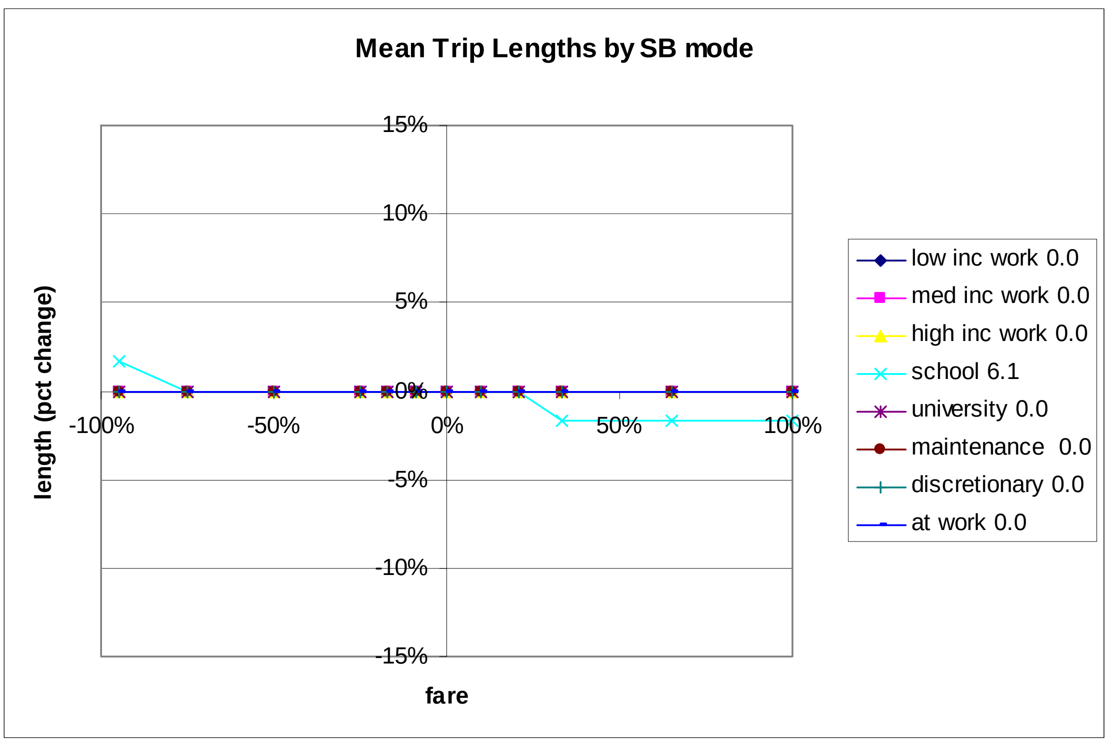
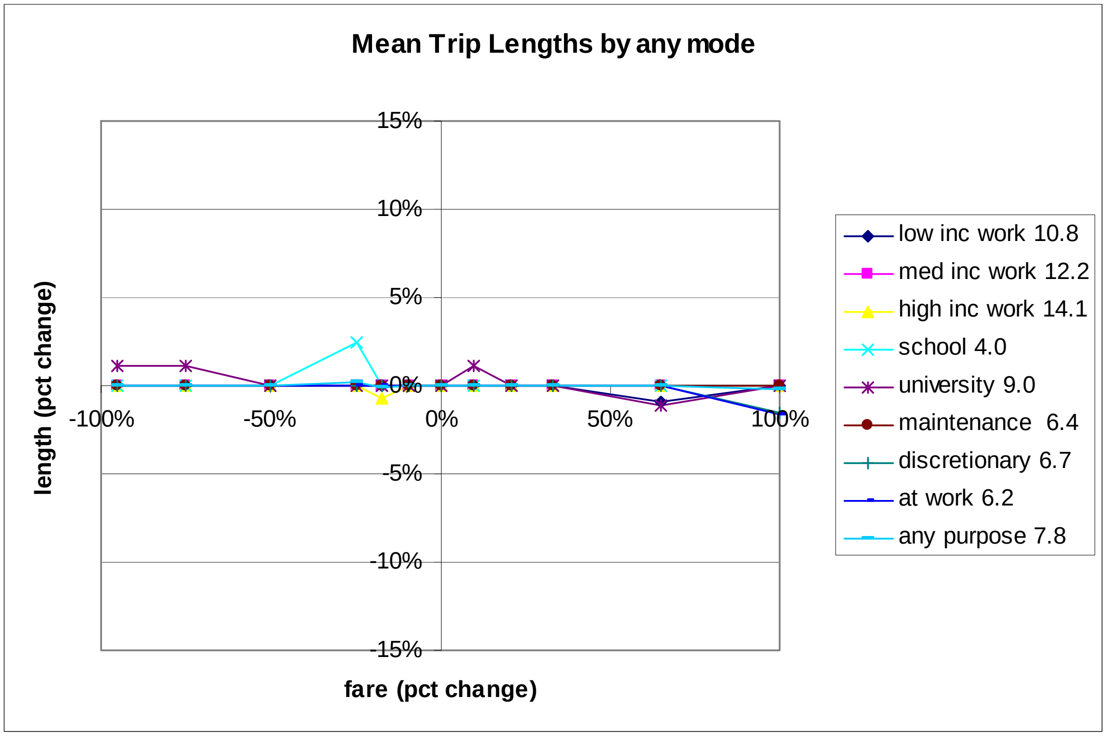


Figure 4-48 Mean Trip Lengths by Any Mode



A few noteworthy trends that are visible in the graphs pertain to the WT and WC modes. It appears that as transit fare decreases, people are more willing to make short At-work journeys on transit (see above section). This effectively pulls down the average trip length for lower-fare scenarios. In higher-fare scenarios the decreased willingness to spend money on short transit journeys results in longer average non-motorized trip lengths, as only trips of a significant distance warrant taking transit.

A similar process may be occurring for WC trip lengths, but in the opposite direction. Here, the average trip length is increased when fares are lowered, as people become more willing to spend for long commuter-rail trips (keeping in mind that zone-based fares roughly correspond to distance as well). This applies to School, University, and discretionary mean trip lengths.

However, for Work and Maintenance journeys, the mean trip length on the WC mode increases with increasing fares: some shorter trips are taken on an alternative mode (such as non-CR transit), resulting in a higher average trip length.

4-6 Mean Highway Speed

The BPM Highway network includes not only highways but also many local streets classified as arterials. The TransCAD assignment procedure loads trips onto the network, and produces summary statistics including demand, vehicle-time-traveled, and vehicle-distance-traveled for each of six assignment “modes”: Drive Alone, HOV 2 and Taxi, HOV 3+, Externals, Trucks, and Other Commercial. Average speed on the loaded networks is computed by dividing total VMT by total VHT. The assignment is performed separately for each one of the four periods (AM, MD, PM, NT), so separate plots can be made. A graph for all periods is also provided (Figures 4-49 to 4-52).

Figure 4-49 Highway Assignment Average Speeds

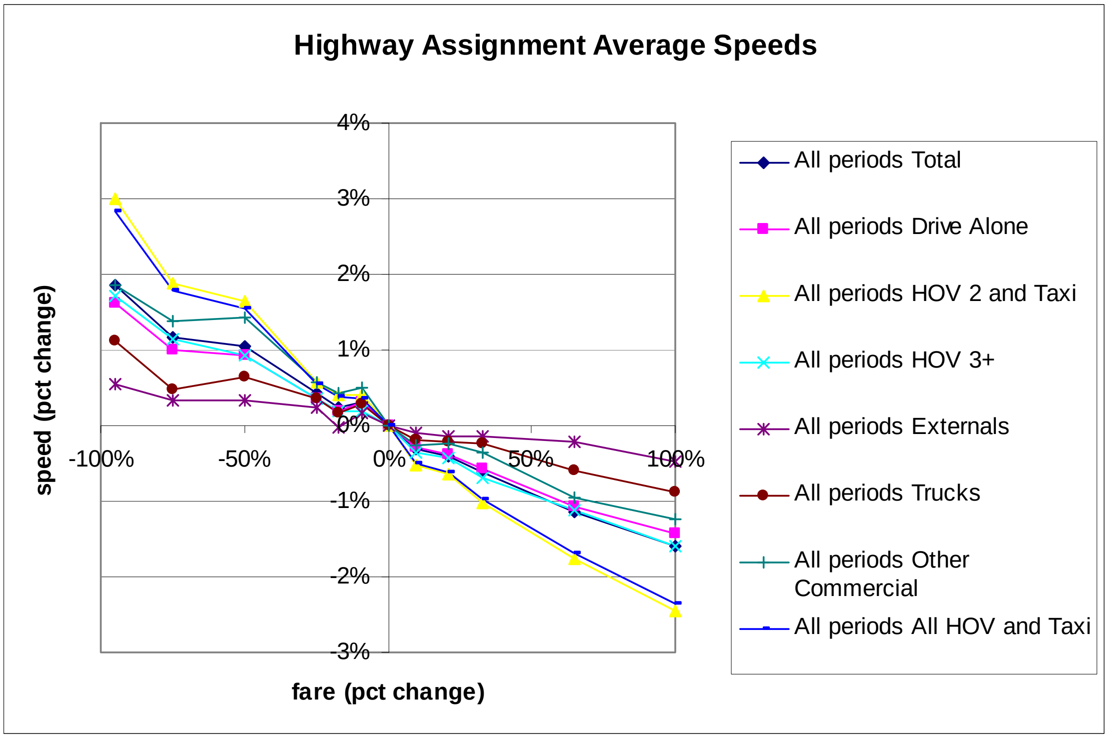


Figure 4-50 Highway Assignment Average Speeds (AM Peak)

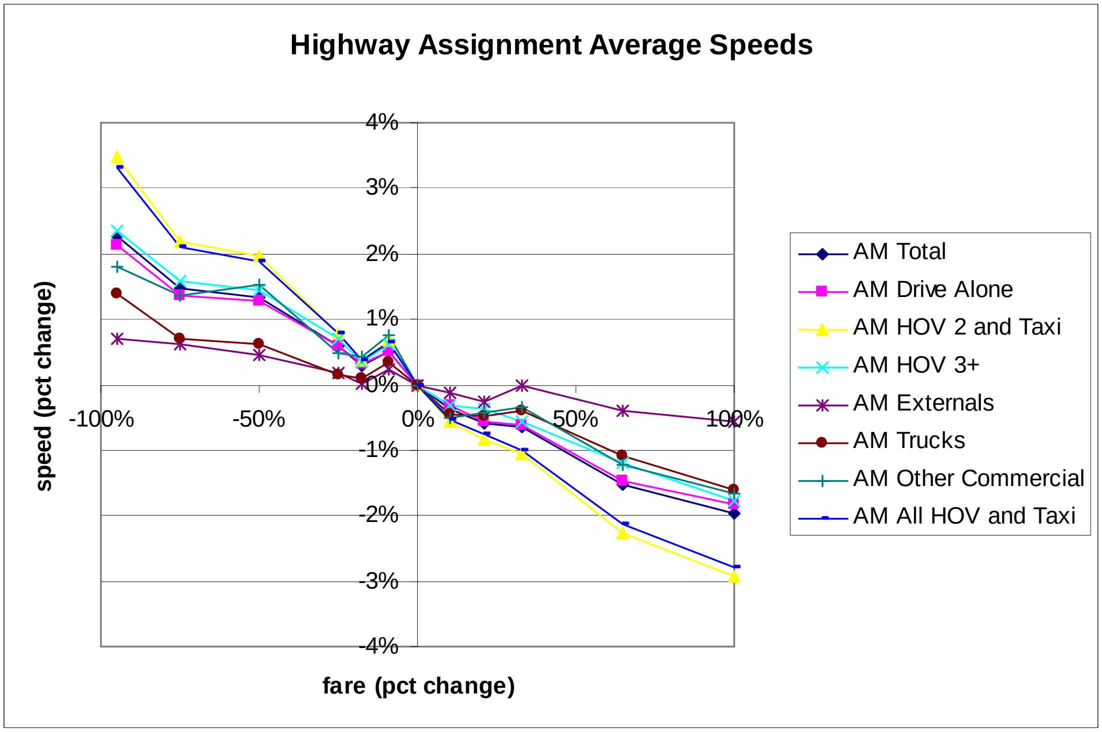


Figure 4-51 Highway Assignment Average Speed (Mid-day)

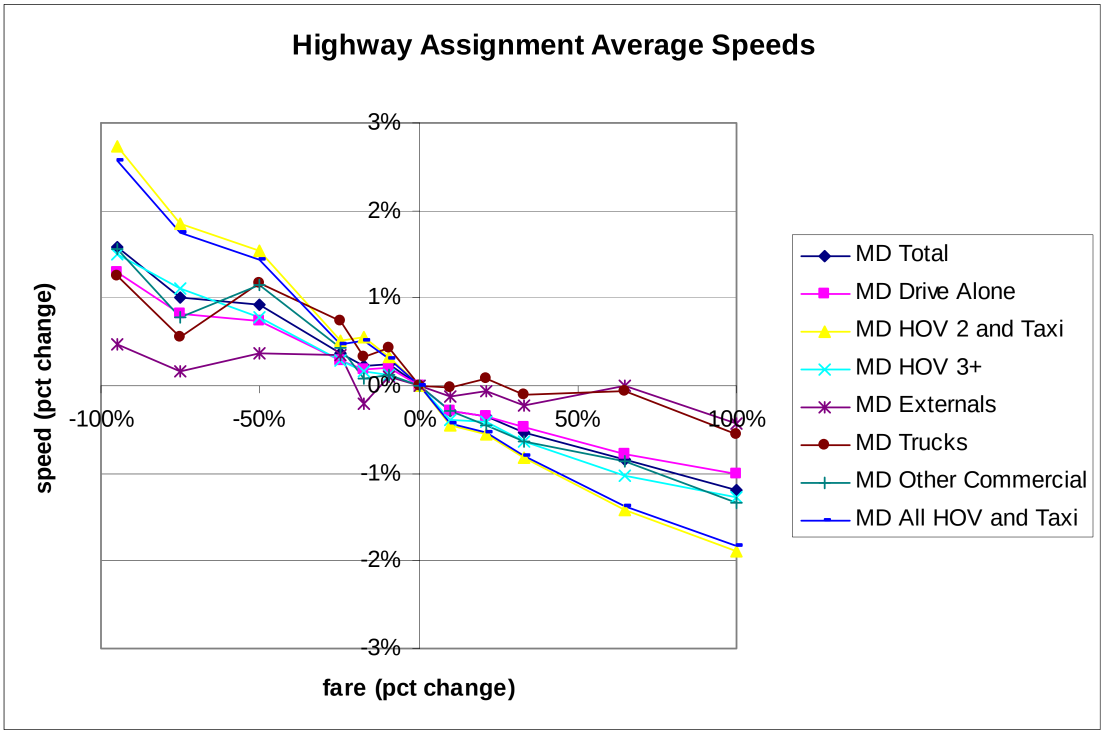
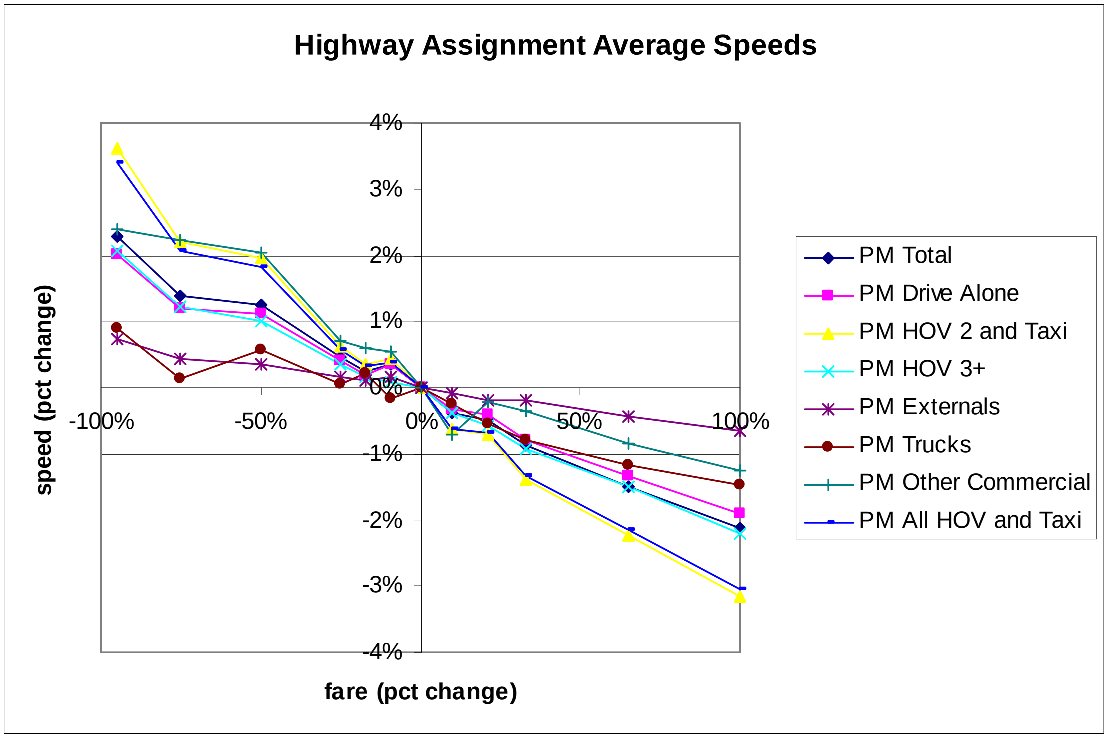


Figure 4-52 Highway Assignment Average Speed PM Peak



The general trend, which applies to all modes and all periods, is that speeds decline as transit fares rise. Compared to the base scenario, overall average highway speed increases by 1.85% for the nearly-free transit scenario, and declines 1.58% for the doubled-fare scenario. This agrees with intuition, which suggests that as fares increase, a shift will occur from transit modes to highway modes, leading to greater congestion and lower average speed throughout the highway network. Intuition also suggests that the degree to which each of the highway assignment modes is affected should vary with the geographical distribution of modal VMT. For instance, long-distance travel, which originates from and/or is destined to locations outside the BPM region, should have a larger proportion of travel taking place on outlying highways that bypass the congested core area most affected by a shift to or from transit modes. Indeed, the assignment modes for Externals and Trucks show the smallest change in average speeds. On the other hand, travel by Taxi, which tends to have shorter trips and occur on local streets in denser areas, should be more strongly affected by transit fare changes. The results of the assignment reflect this expectation as well, with HOV2 and Taxi speeds showing the greatest sensitivity to the fare change scenarios. Finally, note that the AM and PM period assignment speeds are more heavily affected by transit fares, changing by about 2% (all modes) in the extreme cases. In the relatively free-flowing NT period, overall speeds change by less than 1% (all modes) even when fares are nearly free or doubled.

5 Sensitivity Analysis Results: Case Study A2 - Impact of A Change in Median Income

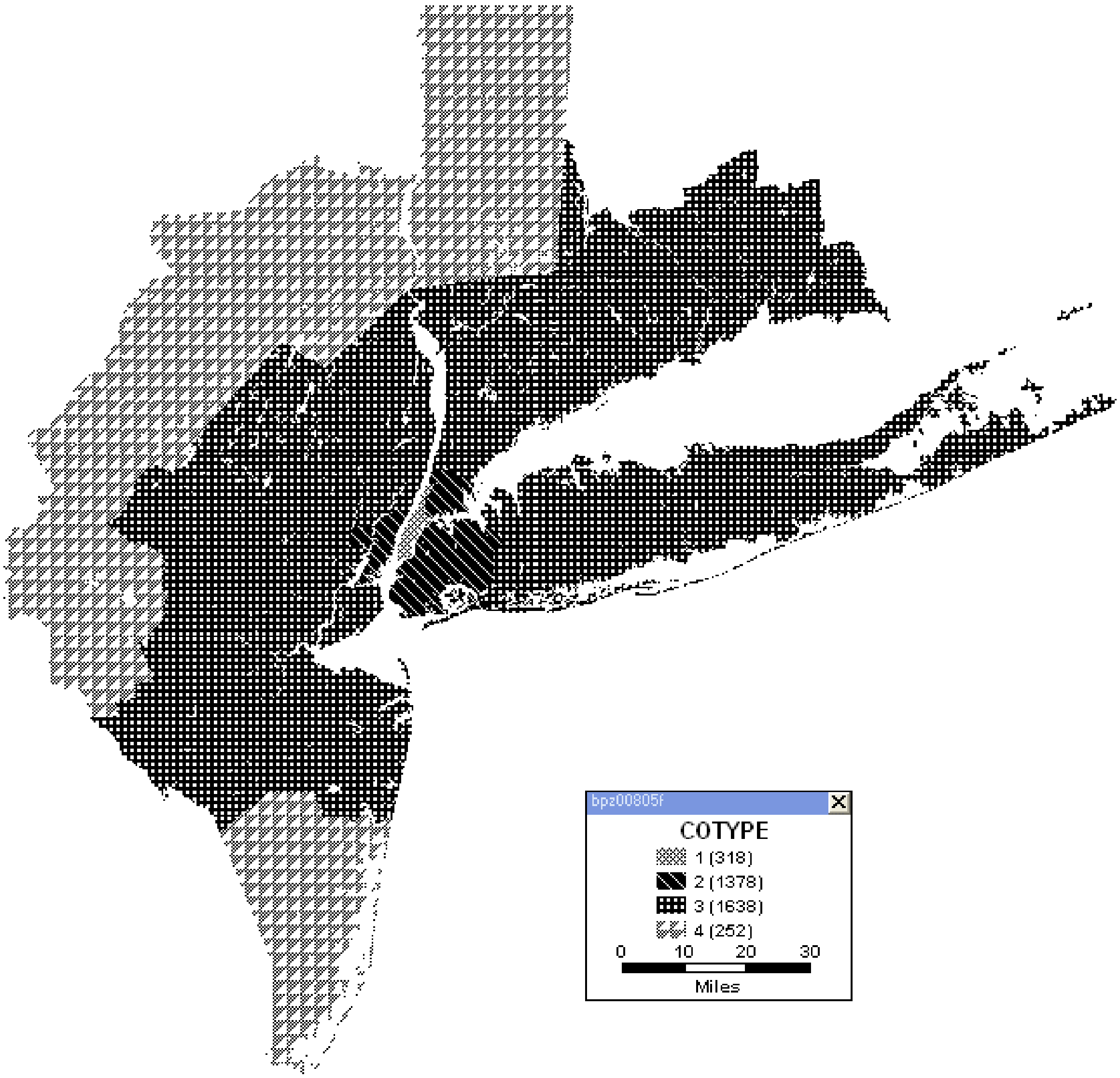
5-1 Overview

Household income is an important variable in travel behavior research. Household income is thought to be positively related to auto ownership, which then affects travel choices, such as mode choice, destination choice and vehicle miles traveled. In case study A2, we tested how the BPM model responds to income changes. All neighborhoods (defined as at the TAZ level) with a median household income of $25,000 or lower in 1990 dollars had their median incomes be increased to two levels: $50,000 and $80,000. Thus, there were three scenarios in this case study. S1 represents the base scenario, which is year 2002; S2 refers to the scenario where all neighborhoods with a median income of $25,000 or lower in 1990 dollars have their median incomes be increased to $50,000; and S3 refers to the scenario where all neighborhoods with a median income of $25,000 or lower in 1990 dollars have their median incomes be increased to $80,000.

There are a total of 3,586 Traffic Analysis Zones (TAZs) in the BPM model, which are divided into four county types: Manhattan (county type 1), Urban areas (county type 2), Suburbs (county type 3) and Rural areas (county type 4). The county types within the study region are shown in Figure 5-1. Urban areas contain those TAZs located in Bronx, Brooklyn, Queens, and the part of New Jersey closest to Manhattan. TAZs categorized as suburban are located in Long Island, Staten Island, and parts of New Jersey, New York, and Connecticut surrounding New York City. The TAZs in New Jersey, New York, and Connecticut which are farthest from New York City are categorized as rural. The numbers of TAZs falling into each county type (1

– Manhattan; 2 – Urban; 3 – Suburbs; and 4 – Rural) are shown in the legend of Figure 5-1.

Figure 5-1 County Types of the BPM Region



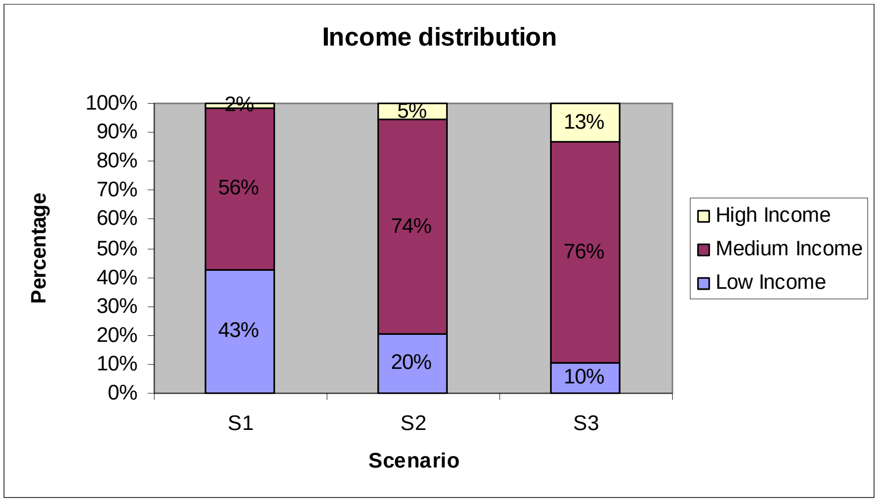
Out of the 3,572 TAZs, 52 TAZs have median household incomes equal to or lower than $25,000. Among these 52 zones, 9 of them are located in Manhattan, 33 of them are categorized as urban, and the other 10 TAZs are in the Suburbs. In the rest of this section, we call these 52 TAZs "change zones" and the other 3,524 TAZs "control zones". Table 5-1 compares the change zones with the control zones in terms of their socioeconomic and demographic attributes. The average median household income of the control zones is much higher than that of change zones ($77,980 vs. $20,428). The population density and job density of the change zones are much higher than those of the control zones. The average household size between the two groups is similar.

Table 5-1 A Comparison between Change Zones and Control Zones (S1 Scenario)

	Control Zones		**Change Zones**	
Number of TAZs	3,524		52	
	Mean	Std.	Mean	Std.
Median household income ($)	77,980	45,548	20,428	4,897
Population density(persons/sq. miles)	26,891	34,993	34,945	36,779
Household size	2.69	0.54	2.60	0.67
Job density(jobs/sq. miles)	16,348	73,189	45,775	155,840

In the BPM model, the household income variable can only take three values: low income, medium income, or high income. 15% of households are categorized as low income. Another 15% of households are categorized as high income. The remaining 70% are in the medium income group. Figure 5-2 shows the income distributions of change zones for scenario S1, S2, and S3. In scenario S1, 43% of the households in the change zone are low-income households; 56% are medium income households and only 2% are high income households. This is compared to 15% for both low- and high-income households and 70% for medium income households as regional averages. After we increase the median income of the change zones to $50,000 (S2), the percentage of low income households decreases to 20%, while the percentages of medium and high income households increase to 74% and 5%, respectively. After we increase the median income of the change zones to $80,000 (S3), the percentage of low income households further decreases to 10%, while the percentages of medium and high income household increase to 76% and 13%, respectively.

Figure 5-2 Income Distributions in Change Zones in the Three Scenarios



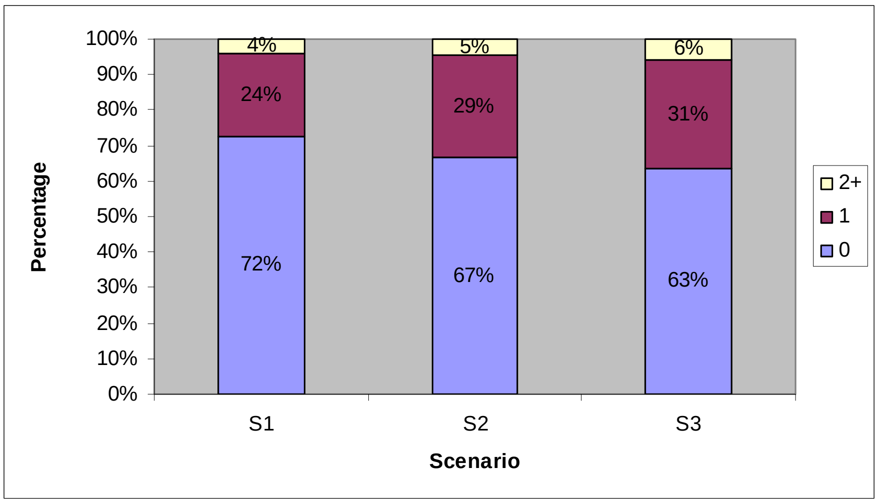
5-2 Auto Ownership Changes in Change Zones

5-2-1 Aggregate Auto Ownership Changes for 52 Selected TAZs

The correlation between household income, auto ownership, and average household vehicle mile traveled is reported in many household travel surveys and reports (National Household Travel Survey, 2001; Transportation Statistics Annual Report, 2006; Memmott, 2007). Almost all have reported a positive relationship between the three – a higher income results in more autos owned and thus a higher level of household vehicle miles traveled (Pucher and Renne, 2003).

Figure 5-3 shows the distributions of auto ownership for the change zones in the three scenarios. In scenario S1, 72% of the households do not have a private vehicle; 24% of the households own one vehicle; and 4% of the households own two or more vehicles. After the median income of these TAZs is increased to $50,000, the percentage of zero-vehicle households decreases to 67%, the percentage of one-vehicle households increases to 29%, and the percentage of multiple-vehicle households increases to 5%. After the median income increases to $80,000, the split becomes 63% for zero-vehicle households, 31% for one-vehicle households, and 6% for multiple-vehicle households.

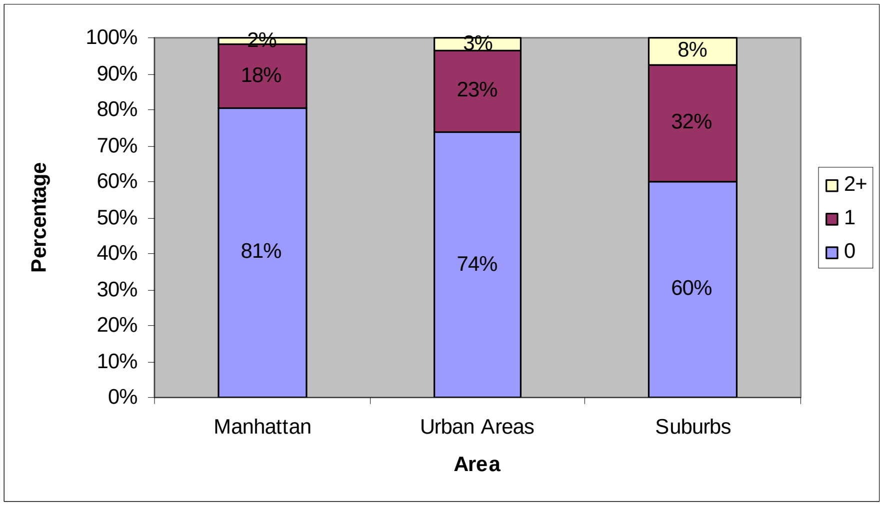
Figure 5-3 Distributions of Auto Ownership in Change Zones in the Three Scenarios



5-2-2 Auto Ownership Changes in Different Areas

Auto ownership is closely related to the geographical distribution of residential locations, due to different levels of population density and levels of accessibility. Figure 5-4 shows the distributions of auto ownership for Manhattan, Urban Areas, and Suburbs for the 52 TAZs in the base scenario. Intuitively, we expect that households in Manhattan would have the lowest auto ownership due to the extensive availability of transit service in Manhattan. The results are consistent with our expectation. 81% of the Manhattan households do not own a private vehicle, 18% of them have one private vehicle, and only 2% of them have more than one vehicle. For households living in Urban Areas, auto ownership is slightly higher than that in Manhattan. 74% of the households do not own a vehicle, 23% of household have one vehicle, and only 3% have more than one vehicle. Suburban households have the highest auto ownership rates. 60% of the households do not own a private vehicle and 40% of households (32% with one vehicle and 8% with more than one) own at least one vehicle.

Figure 5-4 Distributions of Auto Ownership in Different Areas in the Change Zones in the Base Scenario



The distributions of auto ownership for households living in Manhattan in the three scenarios (S1, S2, S3) are shown in Figure 5-5. The overall trend is that auto ownership increases as the median income increases. The share of households without vehicles decreases from 81% to 76% when the median income increases to $50,000 and to 73% when median income increases to $80,000. The share of households with at least one vehicle increases from 20% in scenario S1 (of this 20%, 18% is for one vehicle households and 2% is for multiple vehicle households) to 24% in scenario S2 (of this 24%, 22% is for one vehicle households and 2% is multiple vehicle households); and it further increases to 25% in scenario S3 (of this 25%, 24% is for one vehicle households and 3% is for multiple vehicle households).

Figure 5-5 Distributions of Auto Ownership in the Change Zones in the Three Scenarios for Households in Manhattan

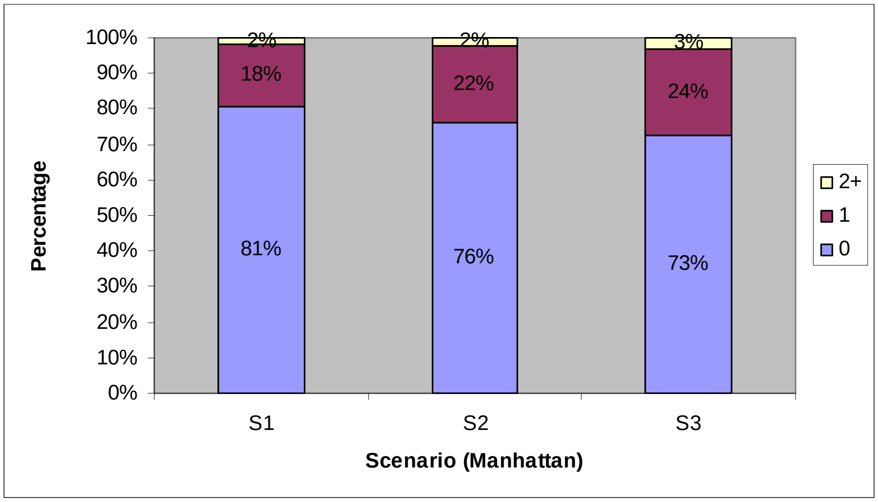


Figure 5-6 shows distributions of auto ownership in the three scenarios for households living in Urban Areas. The overall trend is quite similar to that of Manhattan. The share of households without vehicles decreases from 74% (S1) to 69% (S2) and 66% (S3). On the other hand, the share of households with at least one vehicle increases from 26% (23% is for households with one vehicle and 3% is for households with more than one vehicle) in scenario 1 (S1) to 31% (27% is for households one vehicle and 4% is for households with more than one vehicle) in scenario 2 (S2), and 34% (29% is for households with one vehicle and 5% is for households with more than one vehicle) in scenario 3 (S3).

Figure 5-6 Distributions of Auto Ownership for Households in the Urban Change Zones (Other Than Manhattan) in the Three Scenarios

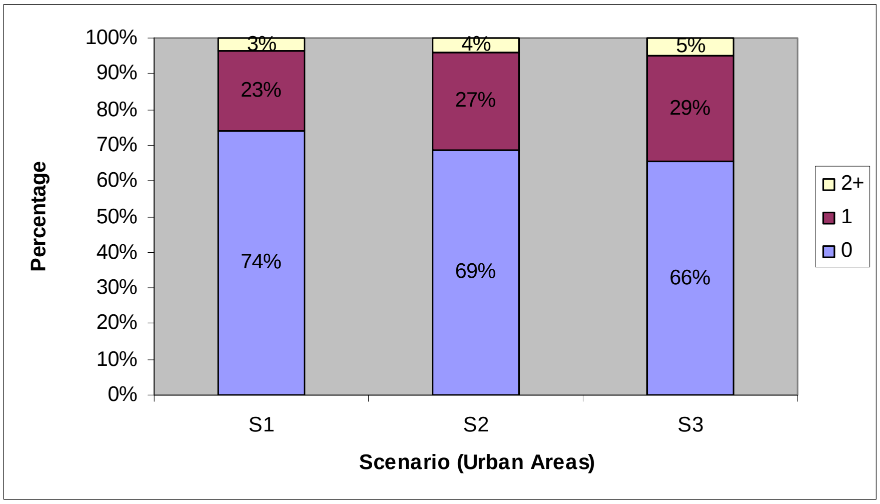
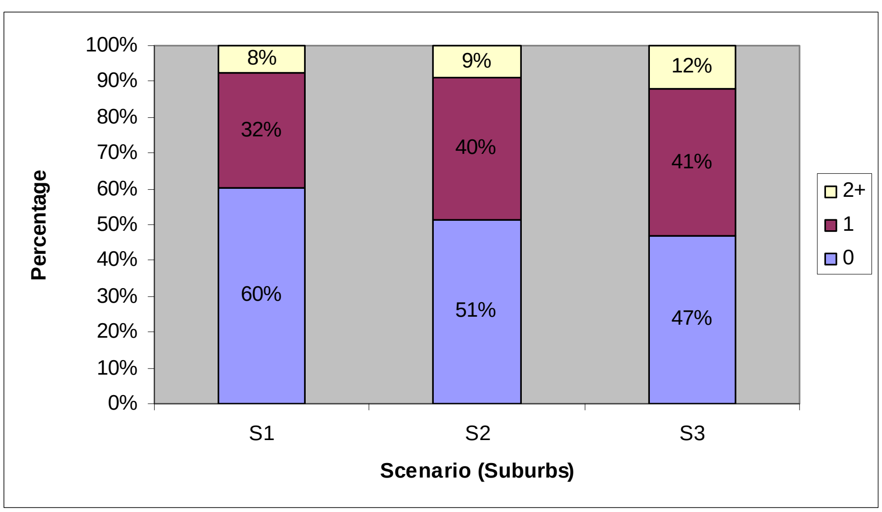


Figure 5-7 shows the distributions of auto ownership for households living in the Suburbs in the three scenarios. The overall trend is similar to that of Manhattan. The share of households without vehicles decreases from 60% in scenario 1 (S1) to 51% in scenario 2 (S2), and to 47% in scenario S3. The share of households with at least one vehicle increases from 40% in the base scenario, to 49% in scenario 2 (S2), and to 53% in scenario 3 (S3).

Figure 5-7 Distributions of Auto Ownership for Households in the Suburban Change Zones in the Three Scenarios



We found that the elasticity of auto ownership with respect to income (defined as the percentage change of auto ownership divided by the percentage change of income) is the highest for suburban households. When the median income increases to $50,000 and $80,000, the decrease in the share of Manhattan households without vehicles is 4% and 7%, respectively. At the same time, the share of households without vehicles in the Urban Areas decreases by 5% and 8% and the share of suburban households without vehicles decreases by 9% and 13%, respectively. The above-noted differences are within our expectations – within New York City the automobile is not viewed as much a necessity as it is in the suburbs. Thus, the extra income obtained can well be spent on other items, instead of acquiring a car, in order to enhance life quality.

5-3 Change in Journeys by Mode

5-3-1 Mode Share Change in the Change Zones (52 Selected TAZs)

The relationship of income and auto ownership suggests that low-income householda tend to use public transportation due to their lower level of auto ownership and their tendency to live in central cities, where public transit service is denser than in the suburbs (Pucher and Renne, 2003).

The mode shares of 52 TAZs in the change zones are shown in Table 5-2. About 22% of the trips are made by auto, 29% of the trips are made by commuter rail (CR) or other transit, and the rest are made by other modes.

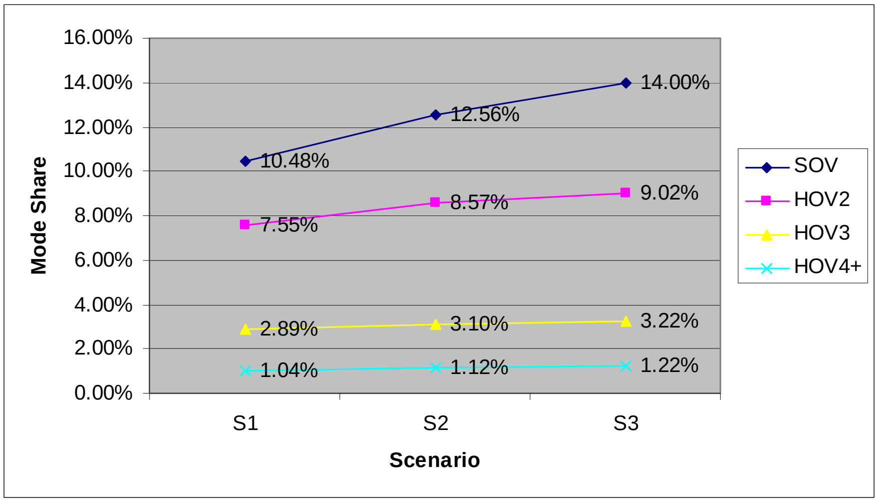
Table 5-2 Mode Shares in the Change Zones (52 Selected TAZs)

Mode	**Number**	**Share**
Drive alone	19,030	10.48%
HOV2	13,714	7.55%
HOV3	5,248	2.89%
HOV4+	1,886	1.04%
Total Auto	39,878	21.96%
Walk to Transit (WT)	49,222	27.11%
Drive to Transit (DT)	1,290	0.71%
Walk to Commuter Rail (WC)	1,739	0.96%
Drive to Commuter Rail (DC)	164	0.09%
Total **Transit and CR**	52,415	28.87%
Taxi	13,554	7.47%
Non-Mot	72,384	39.87%
SchBus	3,329	1.83%
Total for other **Modes**	89,267	49.17%
Total Journeys	181,560	100.00%

When the median household income increases, more people are expected to use private vehicles, due to an expected increase in auto ownership. This is observed in our results. The changes in the mode shares of private vehicles in the three scenarios are shown in Figure 5-8. The mode shares of the four private vehicle modes (SOV, HOV2, HOV3, HOV4+) increase when the median income increases. The more median income increases the greater the observed increase in the mode share of those private vehicle modes. SOV has the largest increase, about a 2.07% increase when the median income increases to $50,000, and a 3.52% increase when the median income increases to $80,000. HOV4+ has the smallest increase, about 0.08% and 0.18% respectively. Overall, the share of private vehicle modes increases by

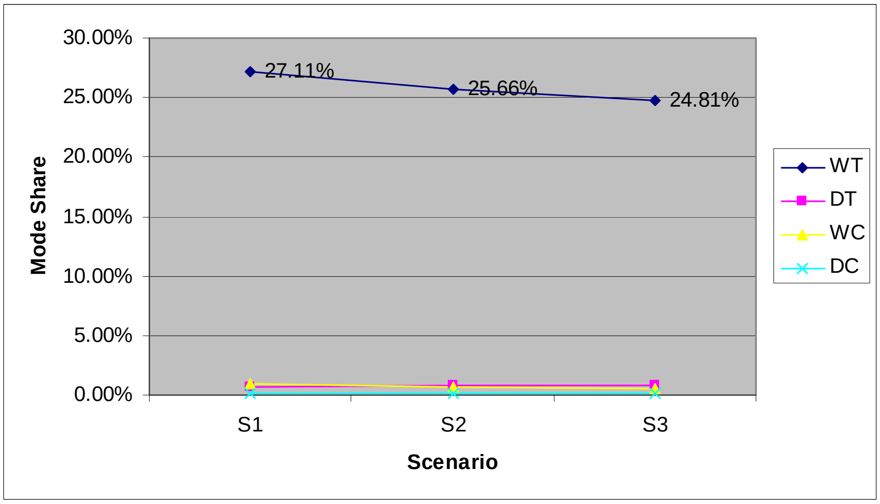
3.38% when the median income increases to $50,000, and by 5.49% when the median income increases to $80,000.

Figure 5-8 Shares of the Four Private Vehicle Modes in the Change Zones in the Three Scenarios



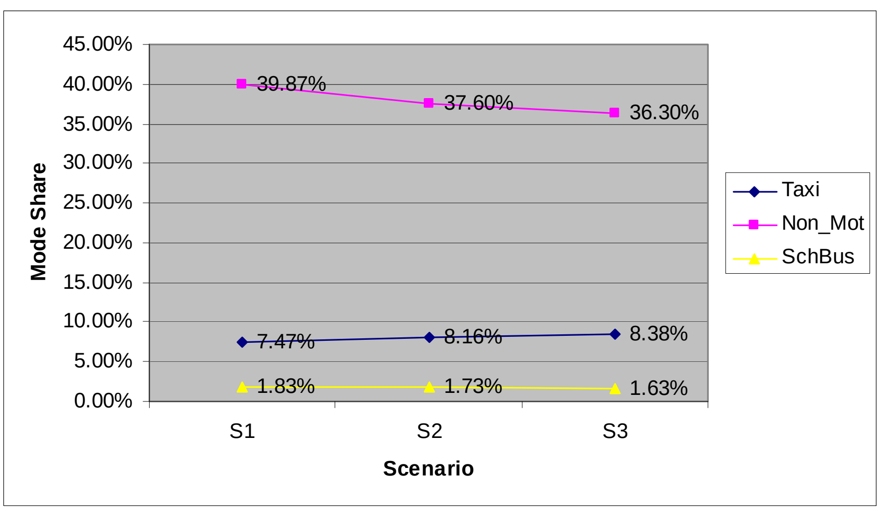
On the other hand, the mode share of public transit is expected to decrease when the median income increases. This is also observed in our results (Figure 5-9). Of all four public transit modes (walk to transit, drive to transit, walk to commuter rail, and drive to commuter rail), walk to transit is the most dominant; its mode share decreases by 1.45% and 2.30% respectively when the median household income increases to $50,000 and $80,000. It should be noted that the mode shares of drive to transit and drive to commuter rail increase though in very small magnitudes. Overall, public transit decreases by 1.71% and 2.64% when the median income increases to $50,000 and $80,000.

Figure 5-9 Shares of the Four Public Transit Modes in the Change Zones in the Three Scenarios



In addition, the share of non-motorized modes experiences a decrease, from 39.87% to 37.60% and 36.30%, respectively when the median household income increases to $50,000 and $80,000. The mode share of taxi experiences an increase, from 7.47% to 8.16% and 8.38% respectively. The school bus mode also experiences a small decrease (see Figure 5-10).

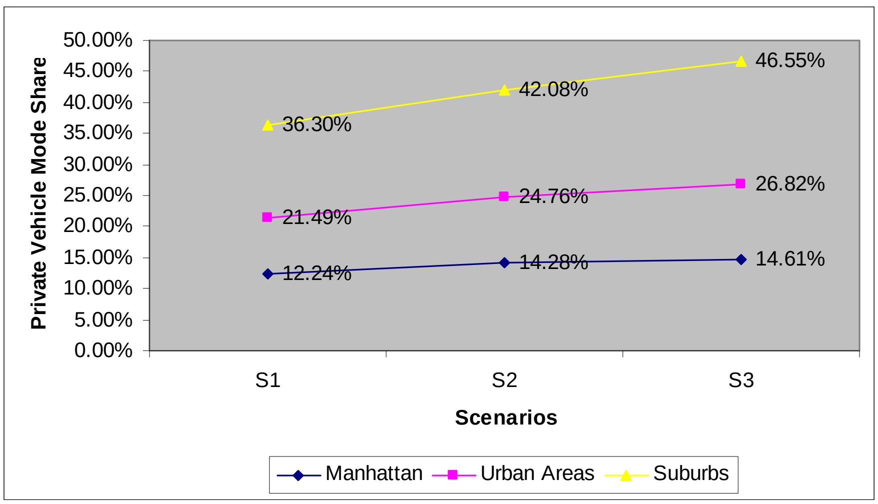
Figure 5-10 Shares of Other Modes (Taxi, Non-motorized Modes, and School Bus) in the Change Zones in the Three Scenarios



5-4 Change in Mode Share in Areas with Different Levels of Accessibility

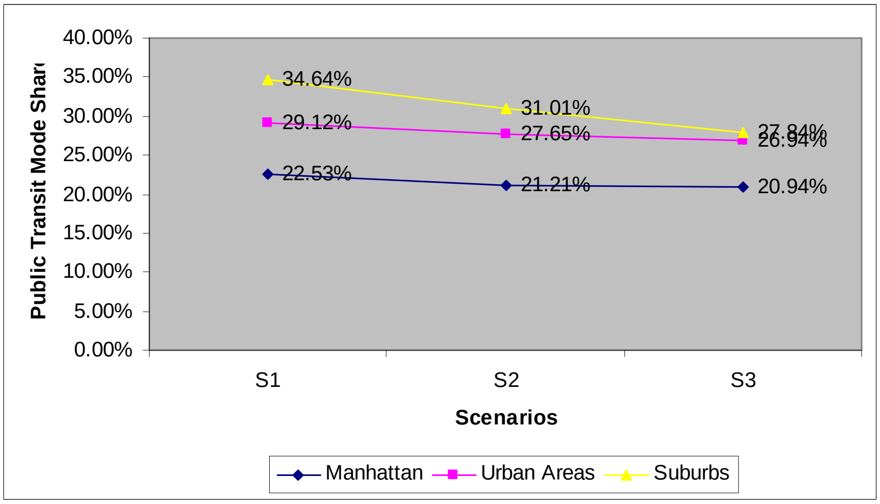
Figure 5-11 shows the mode shares of private vehicles in the three scenarios. The share of Manhattan households using private vehicles experiences the smallest increase, 2.03% and 2.37% when the median household income increases to $50,000 and $80,000. For households living in the Urban Areas, the increases are about 3.27% and 5.33% respectively. The highest increase in the mode share of private vehicles occurs in the Suburbs, about 5.78% and 10.25% respectively.

Figure 5-11 Mode Shares of Private Vehicles in the Change Zones in the Three Scenarios



For public transit, we also observe consistent results. The share of public transit modes in Manhattan experiences the smallest decrease (-1.33% and -1.60%, respectively), while those in the Suburbs experiences the highest decrease (-3.63% and -6.80%, respectively), see Figure 5-12.

Figure 5-12 Mode Shares of Public Transit in the Change Zones in Three Scenarios



The mode shares of taxi, non-motorized, and school bus in the three scenarios are shown in Figure 5-13, 14, and 15. The magnitude of change for Taxi and school bus is small, less than 1% after the median income is increased. The mode share of the non-motorized modes decreases when the median household income is increased. The decrease for Manhattan households is the smallest.

Figure 5-13 Mode Shares of Taxi in the Change Zones in Three Scenarios

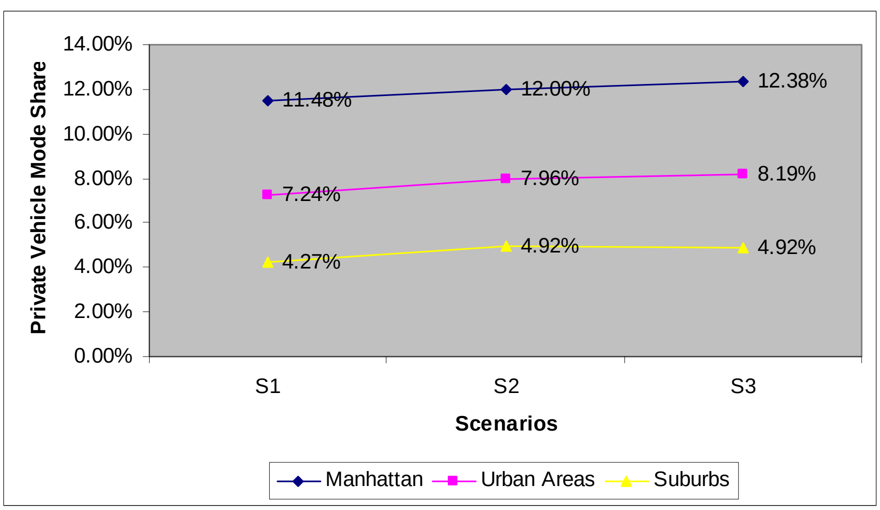


Figure 5-14 Mode Shares of Non-Motorized Modes in the Change Zones in the Three Scenarios

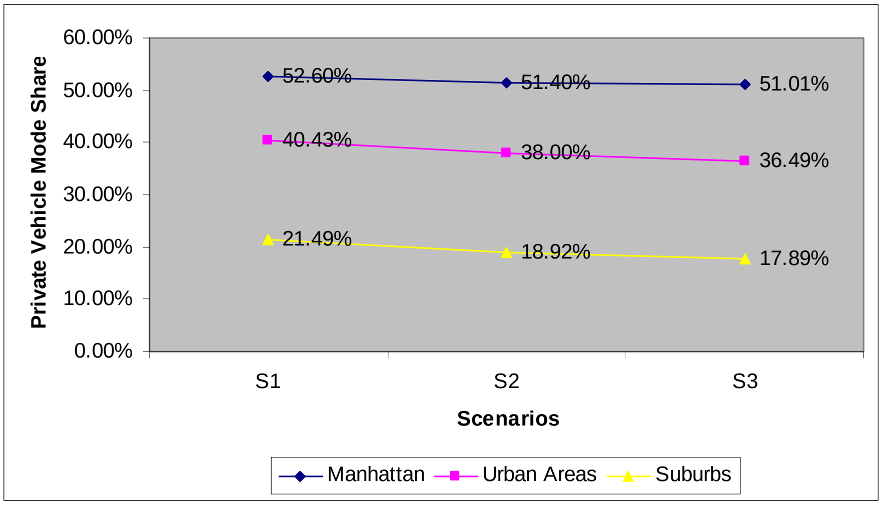
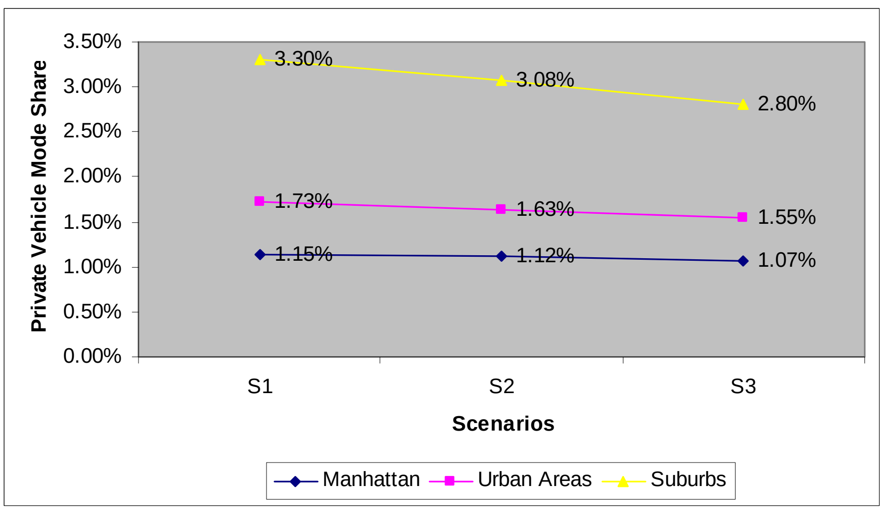


Figure 5-15 Mode Shares of School Bus in the Change Zones in the Three Scenarios



5-5 Change in Number of Journeys by Purpose

5-5-1 Change in the Number of Journeys by Purpose in the Change Zones (52 Selected TAZs)

The numbers of journeys by purpose and their percentage changes are shown in Table 5-3. For comparison purposes, the table is stratified by income. Overall, the total journey productions of the three scenarios are quite stable, with a mere 1.10% increase when the median household income increases to $50,000, and a slightly higher 1.69% increase when the median household income increases to $80,000.

When the median household income increases, it is observed that the total number of work journeys increases. This can be explained in two ways. First, the extra income is probably the result of more people going to work and,second, higher income people tend to make more work journeys. Other journeys that experience an increase include journeys for maintenance, discretionary and at work. School and university journeys witness a drop, probably because students are generally a lower-income group.

Table 5-3 Changes in the Numbers of Journeys by Purpose and Their Percentage Changes in the Three Scenarios in the Change Zones (52 Selected TAZs)

	Number of journeys			**% chg. against S1**	
Purpose	**S1***	**S2**	**S3**	**(S2-S1)/S1**	**(S3-S1)/S1**
Work -Low income	3,772	1,483	739	-60.68%	-80.41%
Work - Medium income	19,674	20,877	19,619	6.11%	-0.28%
Work - High income	866	2,296	5,061	165.13%	484.41%
Total Work	**24,312**	**24,656**	**25,419**	**1.41%**	**4.55%**
School	26,211	23,640	22,606	-9.81%	-13.75%
University	4,317	4,153	4,030	-3.80%	-6.65%
Maintenance	77,983	81,186	82,337	4.11%	5.58%
Discretionary	30,192	31,366	31,821	3.89%	5.40%
At work	18,545	18,561	18,412	0.09%	-0.72%
Total	**181,560**	**183,562**	**184,625**	**1.10%**	**1.69%**

Table 5-3 Changes in the Numbers of Journeys by Purpose and Their Percentage Changes in the Three Scenarios in the Change Zones (52 Selected TAZs) (cont'd)

Household	Number of Household			% chg. against S1	
Low income	22,888	10,936	5,557	-52.22%	-75.72%
Medium income	29,999	39,937	40,973	33.13%	36.58%
High income	852	2,866	7,209	236.38%	746.13%
Total	53,739	53,739	53,739	0.00%	0.00%

5-5-2 Changes in the Number of Journeys by Trip Purpose in Areas with Different Levels of Accessibility

Table 5-4 shows that the increase in the total number of work journeys in Manhattan (11.18%) is higher than that in the Urban Areas (3.62%) and in the Suburbs (3.57%), when the median income is increased to $80,000. Some work journeys (e.g., by high income) experience higher than expected changes (e.g., over 400%); which is probably caused by the relatively small number of journeys in the base scenario.

Table 5-4 Numbers of Work Journeys in Three Scenarios in Different Areas in the Change Zones

	Number of journeys			% chg. against S1	
52 Selected TAZs					
Purpose	**S1***	**S2**	**S3**	**(S2-S1)/S1**	**(S3-S1)/S1**
Work -Low income	3,772	1,483	739	-60.68%	-80.41%
Work - Median income	19,674	20,877	19,619	6.11%	-0.28%
Work - High income	866	2,296	5,061	165.13%	484.41%
Total Work	**24,312**	**24,656**	**25,419**	**1.41%**	**4.55%**
Manhattan					
Purpose	**S1***	**S2**	**S3**	**(S2-S1)/S1**	**(S3-S1)/S1**
Work -Low income	561	211	95	-62.39%	-83.07%
Work - Median income	2,389	2,564	2,551	7.33%	6.78%
Work - High income	64	235	705	267.19%	1001.56%
Total Work	**3,014**	**3,010**	**3,351**	**-0.13%**	**11.18%**
Urban Areas					
Purpose	**S1***	**S2**	**S3**	**(S2-S1)/S1**	**(S3-S1)/S1**
Work -Low income	2,606	1034	534	-60.32%	-79.51%
Work - Median income	14,539	15,402	14,301	5.94%	-1.64%
Work - High income	706	1,737	3,663	146.03%	418.84%
Total Work	**17,851**	**18,173**	**18,498**	**1.80%**	**3.62%**

Table 5-4 Numbers of Work Journeys in Three Scenarios in Different Areas in the Change Zones (cont'd)

Suburbs					
Purpose	**S1***	**S2**	**S3**	**(S2-S1)/S1**	**(S3-S1)/S1**
Work -Low income	605	238	110	-60.66%	-81.82%
Work - Median income	2,746	2,911	2,767	6.01%	0.76%
Work - High income	96	324	693	237.50%	621.88%
Total Work	**3,447**	**3,473**	**3,570**	**0.75%**	**3.57%**

Table 5-5 shows the distributions of non-work journeys in three different areas in the three scenarios. In sum, the number of school and university journeys decreases when the median household income increases, while the number of journeys for other non-work purposes increases. The decrease is the largest for the Suburbs and the smallest for Manhattan. Interestingly, the increase appears to be the largest for Manhattan for maintenance and discretionary journeys. The number of at work journeys in the Suburbs experiences a small decrease.

Table 5-5 Numbers of Non-Work Journeys in Three Different Areas in the Three Scenarios

	Number of journeys			% chg. against S1	
Purpose	**S1***	**S2**	**S3**	**(S2-S1)/S1**	**(S3-S1)/S1**
52 Selected TAZs					
School	26,211	23,640	22,606	-9.81%	-13.75%
University	4,317	4,153	4,030	-3.80%	-6.65%
Maintenance	77,983	81,186	82,337	4.11%	5.58%
Discretionary	30,192	31,366	31,821	3.89%	5.40%
At work	18,545	18,561	18,412	0.09%	-0.72%
Manhattan					
School	2,880	2,687	2,525	-6.70%	-12.33%
University	486	463	425	-4.73%	-12.55%
Maintenance	5,277	5,754	5,795	9.04%	9.82%
Discretionary	1,708	1,852	1,845	8.43%	8.02%
At work	11,246	11,274	11,291	0.25%	0.40%
Urban Areas					
School	19,757	17,841	17,114	-9.70%	-13.38%
University	3,502	3,379	3,264	-3.51%	-6.80%
Maintenance	62,409	64,618	65,860	3.54%	5.53%
Discretionary	25,606	26,457	26,639	3.32%	4.03%
At work	6,657	6,661	6,482	0.06%	-2.63%
Suburbs					
School	3,574	3,112	2,967	-12.93%	-16.98%
University	329	311	341	-5.47%	3.65%
Maintenance	10,297	10,814	10,682	5.02%	3.74%
Discretionary	2,878	3,057	3,337	6.22%	15.95%
At work	642	626	639	-2.49%	-0.47%

5-6 Change in Number of Journey by Purpose and Mode

The numbers of journeys by purpose and mode and their percentage changes are shown in Table 5-6. In general, low income work journeys by all modes experience very large decreases, while high income work journeys by all modes experience very large increases. In contrast, changes in medium income work journeys are not nearly as large, most of which are below 10%. It should be noted that some of the large changes in high income work journeys are likely caused by the small numbers for this group of travel in the base scenario (e.g., HOV4+, WC, DC).

When the median household income increases, more school journeys are made by auto (SOV, HOV2, HOV3), drive to transit (DT), and drive to commuter rail (DC). At the same time, fewer school journeys are made by school bus, taxi, non-motorized, and walk to transit (WT). Note that the school bus mode is only available for school journeys.

When the median household income increases, more university journeys are made by DT and taxi and fewer of them are made by WT and the non-motorized modes. When the median household income increases, more maintenance journeys are made by private vehicles and taxi and fewer of them are made by public transit or non-motorized modes. A similar observation applies to discretionary journeys. Walk to Transit (WT) discretionary journeys also experience an increase, while discretionary journeys made by non-motorized modes decrease.

For journeys at work, only SOV, HOV2+, HOV3+, WT, taxi, and non-motorized modes are feasible. Most of these journeys are made by taxi and non-motorized, which experience almost no change after the income change.

Table 5-6 Numbers of Journeys by Purpose and Mode

Purpose: Work – Low Income					
mode	**S1**	**S2**	**S3**	**(S2-S1)/S1**	**(S3-S1)/S1**
SOV	279	146	71	-48%	-75%
HOV2	515	206	97	-60%	-81%
HOV3	48	23	15	-52%	-69%
HOV4+	37	16	3	-57%	-92%
WT	2,090	778	369	-63%	-82%
DT	100	48	29	-52%	-71%
WC	14	8	4	-43%	-71%
DC	4	4	0	0%	-100%
Taxi	54	10	6	-81%	-89%
Non-Mot	631	244	145	-61%	-77%

Table 5-6 Numbers of Journeys by Purpose and Mode (cont'd)

Purpose: Work – Medium Income					
SOV	4,179	4,503	4,146	8%	-1%
HOV2	1,532	1,603	1,476	5%	-4%
HOV3	377	390	399	3%	6%
HOV4+	150	150	140	0%	-7%
WT	8,887	9,458	8,952	6%	1%
DT	497	477	442	-4%	-11%
WC	146	163	134	12%	-8%
DC	111	117	115	5%	4%
Taxi	1,848	1,973	1,868	7%	1%
Non-Mot	1,947	2,043	1,947	5%	0%
Purpose: Work – High Income					
SOV	256	551	1,285	115%	402%
HOV2	80	195	473	144%	491%
HOV3	15	39	72	160%	380%
HOV4+	6	21	39	250%	550%
WT	258	728	1,573	182%	510%
DT	43	111	228	158%	430%
WC	2	8	12	300%	500%
DC	1	11	11	1000%	1000%
Taxi	175	509	1,116	191%	538%
Non-Mot	30	123	252	310%	740%

Table 5-6 Numbers of Journeys by Purpose and Mode (cont'd)

Purpose: School					
SOV	196	248	275	27%	40%
HOV2	1,394	1,628	1,723	17%	24%
HOV3	1,080	1,198	1,299	11%	20%
HOV4+	439	409	446	-7%	2%
WT	6,931	5,634	5,080	-19%	-27%
DT	94	135	173	44%	84%
WC	15	19	11	27%	-27%
DC	31	47	57	52%	84%
Taxi	59	46	38	-22%	-36%
Non-Mot	12,643	11,102	10,491	-12%	-17%
SchBus	3,329	3,174	3,013	-5%	-9%
Purpose: University					
SOV	78	80	104	3%	33%
HOV2	55	76	68	38%	24%
HOV3	55	50	37	-9%	-33%
HOV4+	4	1	1	-75%	-75%
WT	1,933	1,754	1,628	-9%	-16%
DT	391	435	404	11%	3%
WC	44	16	29	-64%	-34%
DC	4	3	0	-25%	-100%
Taxi	1,013	1,023	1,059	1%	5%
Non-Mot	740	715	700	-3%	-5%

Table 5-6 Numbers of Journeys by Purpose and Mode (cont'd)

Purpose: Maintenance					
SOV	9,391	12,096	13,937	29%	48%
HOV2	6,777	8,119	8,719	20%	29%
HOV3	1,814	1,956	2,097	8%	16%
HOV4+	798	962	1,053	21%	32%
WT	23,519	22,863	22,219	-3%	-6%
DT	116	105	95	-9%	-18%
WC	1,352	803	610	-41%	-55%
DC	4	9	7	125%	75%
Taxi	2,671	3,314	3,421	24%	28%
Non-Mot	31,541	30,959	30,179	-2%	-4%
Purpose: Discretionary					
SOV	2,993	3,874	4,573	29%	53%
HOV2	1,480	1,826	2,202	23%	49%
HOV3	971	1,180	1,153	22%	19%
HOV4+	452	501	568	11%	26%
WT	5,487	5,780	5,881	5%	7%
DT	49	75	91	53%	86%
WC	166	155	165	-7%	-1%
DC	9	7	5	-22%	-44%
Taxi	5,584	5,942	5,765	6%	3%
Non-Mot	13,001	12,026	11,418	-7%	-12%

Table 5-6 Numbers of Journeys by Purpose and Mode (cont'd)

Purpose: At Work					
SOV	1,658	1,550	1,451	-7%	-12%
HOV2	1,881	2,079	1,898	11%	1%
HOV3	888	852	869	-4%	-2%
WT	117	111	99	-5%	-15%
Taxi	2,150	2,153	2,201	0%	2%
Non-Mot	11,851	11,816	11,894	0%	0%

5-7 Change in Mean Trip Length by Purpose

5-7-1 Trip Length in the Change Zones (52 Selected TAZs)

Many studies (Taylor and Ong, 1995; Johnston, 2000; McLafferty and Preston, 1997; Sastry et al., 2002) have found that higher income households often have longer commute distances. The underlying hypothesis relates to suburban sprawl and the willingness to exchange long commute distance for higher earnings.

That higher income households have longer commute distances is observed in the BPM results (see Table 5-7). In the three scenarios, the average commute distances for low income households are 6.33, 6.24, and 5.91 miles, shorter than those of medium and high income households[9]. The average commute distance for high income households is always the highest in all three scenarios.

[9] Note that low income households having shorter average commute distances does not necessarily imply that they have shorter average commute times. Shen (2000) compares commute times across intra-city neighborhoods and finds that residents of lower income and lower education neighborhoods have greater average commute times.

Table 5-7 Average Trip Lengths in the Change Zones in Three Scenarios (miles)

purpose	S1	S2	S3	S2-S1/S1	S3-S1/S1
Work -Low income	6.33	6.24	5.91	-1.43%	-6.55%
Work - Medium income	7.02	6.91	6.97	-1.56%	-0.61%
Work - High income	7.15	7.30	7.36	2.10%	2.92%
All	6.91	6.90	7.02	-0.16%	1.53%
School	2.41	2.47	2.51	2.24%	4.14%
University	7.21	6.94	7.06	-3.74%	-2.14%
Maintenance	3.83	3.89	3.95	1.36%	3.03%
Discretionary	3.82	3.98	4.14	4.19%	8.58%
At work	2.14	2.15	2.11	0.21%	-1.52%

The average trip length for school and university trips decreases, as the median income increases, while the trip length for maintenance and discretionary trips increases when the median household income increases.

5-7-2 Trip Lengths in Three Different Areas

Table 5-8 shows the average trip lengths for eight purposes in Manhattan, Urban Areas, and Suburbs. The observation that higher income households have longer commute distances is no longer the case in Manhattan. In the Urban Areas and the Suburbs, we still observe that trend, but the commute distances for higher income households is not that much longer.

In scenarios S1 and S2, the average commute distance of medium income households is the shortest. The average commute distance of Manhattan households is shorter than for households residing elsewhere. Suburban households have the longest trip lengths.

For non-work trips, the trip length for trips to school is quite similar in all three areas, probably due to the fact that children tend to go to local schools. The trip length for university trips is the longest for households living in the Urban Areas. The trip lengths of maintenance and discretionary trips for Manhattan households are the shortest, followed by those living in the Urban Areas and the Suburbs. Trip lengths for at work trips are also short for Manhattan households.

Table 5-8 Average Trip Lengths (Miles) in Three Different Areas in the Three Scenarios

Trip Purpose	**S1**	**S2**	**S3**
Manhattan			
Work -Low income	5.39	5.99	4.84
Work - Medium income	5.10	4.93	4.91
Work - High income	5.39	5.16	5.53
School	2.15	2.34	2.27
University	4.57	4.94	4.53
Maintenance	2.93	2.98	3.02
Discretionary	3.10	3.17	3.44
At work	0.92	0.93	0.91

Table 5-8 Average Trip Lengths (Miles) in Three Different Areas in the Three Scenarios (cont'd)

Urban Areas			
Work -Low income	6.24	5.98	5.57
Work - Medium income	6.82	6.67	6.77
Work - High income	6.94	7.09	7.22
School	2.27	2.32	2.32
University	7.80	7.26	7.52
Maintenance	3.55	3.63	3.71
Discretionary	3.72	3.88	4.01
At work	3.74	3.74	3.66
Suburbs			
Work -Low income	7.56	7.58	8.50
Work - Medium income	9.74	9.88	9.90
Work - High income	9.88	9.99	9.97
School	3.38	3.43	3.84
University	4.89	6.46	5.78
Maintenance	6.02	5.87	5.94
Discretionary	5.13	5.32	5.58
At work	6.88	7.05	7.55

5-8 Changes in Trip Length by Mode

5-8-1 Changes in Trip Length by Mode in the Change Zones (52 Selected TAZs)

Table 5-9 shows the average trip lengths by mode and their respective percentage changes from scenario S1 to S2 and S3. No clear trend can be identified. For instance, the average trip length for drive to transit (DT) decreases when the median household income increases to $50,000 and increases when the median income increases to $80,000. The same contradiction also appears for walk to commuter rail (WC), drive to commuter rail (DC), and non-motorized modes.

Table 5-9 Average Trip Lengths by Mode in the Change Zones in the Three Scenarios

Mode	S1	S2	S3	S2-S1/S1	S3-S1/S1
Auto					
Drive alone	6.15	6.06	6.15	-1.61%	-0.07%
HOV2	5.99	5.82	5.91	-2.69%	-1.24%
HOV3	5.84	5.59	5.74	-4.27%	-1.57%
HOV4+	5.72	5.70	5.57	-0.22%	-2.55%
Public Transit					
Walk to Transit (WT)	5.67	5.72	5.74	0.85%	1.28%
Drive to Transit (DT)	7.02	6.99	7.15	-0.30%	1.91%
Walk to Commuter Rail (WC)	14.14	13.91	14.14	-1.60%	0.04%
Drive to Commuter Rail (DC)	9.86	10.38	9.11	5.27%	-7.68%
Others					
Taxi	6.65	6.49	6.53	-2.42%	-1.77%
Non-Mot	0.73	0.74	0.73	0.20%	-1.11%
SchBus	5.39	5.40	5.55	0.12%	2.99%

5-8-2 Changes in Trip Length by Mode in Three Different Areas

Table 5-10 shows average trip lengths by mode in Manhattan, Urban Areas, and Suburbs. For the auto mode, the trip lengths are the shortest for Manhattan households, followed by households living in Urban Areas, and then those in the Suburbs.

For public transit, the average trip lengths for walk and drive to transit are the shortest for

Manhattan households, followed by households living in Urban Areas, and then those in the Suburbs. However, the average trip length of walk to commuter rail is the longest for Manhattan households. This pattern is understandable, as commuter rail trips made by Manhattan households are often reverse commute trips. For drive to commuter rail, the average trip length for suburban households is longer than for those living in Urban Areas. No Manhattan households make drive to commuter rail trips.

For trips made by modes other than private vehicle and public transit, taxi trips made by Manhattan households are the shortest. In terms of non-motorized trips, the average trip length is similar for all households, probably due to the fact that non-motorized trips are primarily physically constrained.

Table 5-10 Average Trip Lengths by Mode in the Change Zones in the Three Different Areas

Mode	S1	S2	S3	S2-S1/S1	S3-S1/S1
Manhattan					
Drive alone	4.82	4.61	4.66	-4.28%	-3.29%
HOV2	3.57	3.83	3.77	7.43%	5.70%
HOV3	3.56	4.03	3.86	13.04%	8.27%
HOV4+	4.47	5.35	5.12	19.62%	14.63%
Walk to Transit (WT)	4.17	4.08	4.25	-2.16%	1.94%
Drive to Transit (DT)	4.29	4.72	4.48	9.83%	4.32%
Walk to Commuter Rail (WC)	28.00	24.66	18.94	-11.94%	-32.36%
Drive to Commuter Rail (DC)	/	/	/	/	/
Taxi	3.14	3.19	3.27	1.48%	4.14%
Non-Mot	0.70	0.70	0.70	0.12%	-1.02%
SchBus	4.83	5.21	5.19	7.77%	7.40%
Urban Areas					
Drive alone	5.90	5.84	5.86	-1.07%	-0.70%
HOV2	6.05	5.79	5.88	-4.38%	-2.90%
HOV3	5.92	5.56	5.64	-6.05%	-4.68%
HOV4+	5.61	5.53	5.32	-1.44%	-5.10%
Walk to Transit (WT)	5.79	5.81	5.82	0.39%	0.43%
Drive to Transit (DT)	6.75	6.68	6.84	-0.99%	1.37%
Walk to Commuter Rail (WC)	15.33	14.11	15.32	-7.98%	-0.11%
Drive to Commuter Rail (DC)	8.26	8.14	7.19	-1.45%	-13.00%
Taxi	7.48	7.17	7.23	-4.14%	-3.38%
Non-Mot	0.73	0.73	0.72	0.45%	-0.70%
SchBus	5.07	5.30	5.21	4.56%	2.85%

Table 5-10 Average Trip Lengths by Mode in the Change Zones in the Three Different Areas (cont'd)

Suburbs					
Drive alone	7.32	7.18	7.47	-1.88%	2.05%
HOV2	7.10	7.08	7.21	-0.35%	1.49%
HOV3	6.87	6.68	7.23	-2.78%	5.24%
HOV4+	6.54	6.60	6.83	0.86%	4.41%
Walk to Transit (WT)	6.28	6.63	6.74	5.43%	7.30%
Drive to Transit (DT)	9.61	9.76	9.68	1.52%	0.74%
Walk to Commuter Rail (WC)	13.38	13.59	13.18	1.58%	-1.50%
Drive to Commuter Rail (DC)	12.96	13.84	13.53	6.78%	4.44%
Taxi	8.65	8.90	8.80	2.88%	1.68%
Non-Mot	0.91	0.90	0.88	-0.41%	-3.21%
SchBus	6.71	5.82	6.93	-13.29%	3.22%

5-9 Mean Highway Speed

Table 5-11 shows the mean highway speeds (measured as the average travel length from one TAZ to other TAZs divided by travel time) for the 52 selected TAZs in the Change Zones and the mean speeds in the sub-regions for the three scenarios. In the Change Zones, the mean highway speed is the lowest in Manhattan and the highest in the suburbs. The same pattern appears when the median income increases. However, when comparing mean speeds among the scenarios, no discernable pattern can be identified.

Table 5-11 Mean Highway Speeds in the Change Zones

	Mean	Std.	Min	Max
Scenario S1				
52 Selected TAZs	38.55	12.03	3.24	61.98
Manhattan	36.18	12.97	5.68	61.33
Urban Areas	38.01	12.28	3.24	61.27
Suburbs	42.50	9.15	8.19	61.98
Scenario S2				
52 Selected TAZs	38.52	12.06	3.24	61.98
Manhattan	36.17	12.95	5.68	61.26
Urban Areas	37.85	12.27	3.24	61.35
Suburbs	42.84	9.14	8.12	61.98
Scenario S3				
52 Selected TAZs	38.57	11.98	3.24	62.13
Manhattan	36.21	12.97	5.68	62.12
Urban Areas	38.07	12.22	3.24	61.35
Suburbs	42.35	9.11	8.13	61.98

6 Sensitivity Analysis Results: Case Study A3 - Impact of Changes in Population and Employment

6-1 Overview

Population and employment exert an important influence on travel behavior. In case study A3, we tested the sensitivity of the BPM model in response to changes in population and employment in the region. More specifically, we examined the impact of locating 10,000 additional jobs or people[10] in three locations which differ by their accessibility to transit services. These three locations are: the Jamaica LIRR hub, an area that is approximately 6 miles north in Flushing, and an area that is approximately 6 miles south from the Jamaica LIRR hub, near the JFK airport. The Jamaica LIRR hub has the densest transit service, followed by the area approximately 6 miles north of the LIRR hub in Flushing, and the area approximately 6 miles south of the LIRR hub around the JFK airport. These three locations are shown in Figure 6-1. In addition to the base scenario, the BPM model was run on six scenarios, each associated with a particular area and an increase in population or employment. In the rest of this chapter, we use the following names for the scenarios:

- 10,000 jobs in Jamaica LIRR hub – EMP_LIRR
- 10,000 people in Jamaica LIRR hub – POP_LIRR
- 10,000 jobs in Northern Flushing – EMP_FLUSHING
- 10,000 people in Northern Flushing – POP_FLUSHING
- 10,000 jobs in JFK area – EMP_JFK
- 10,000 people in JFK area – POP_JFK

[10] The additional employment or population is assumed to have the same distribution as the existing ones.

Figure 6-1 Locations of Jamaica LIRR Hub, Flushing, and JFK

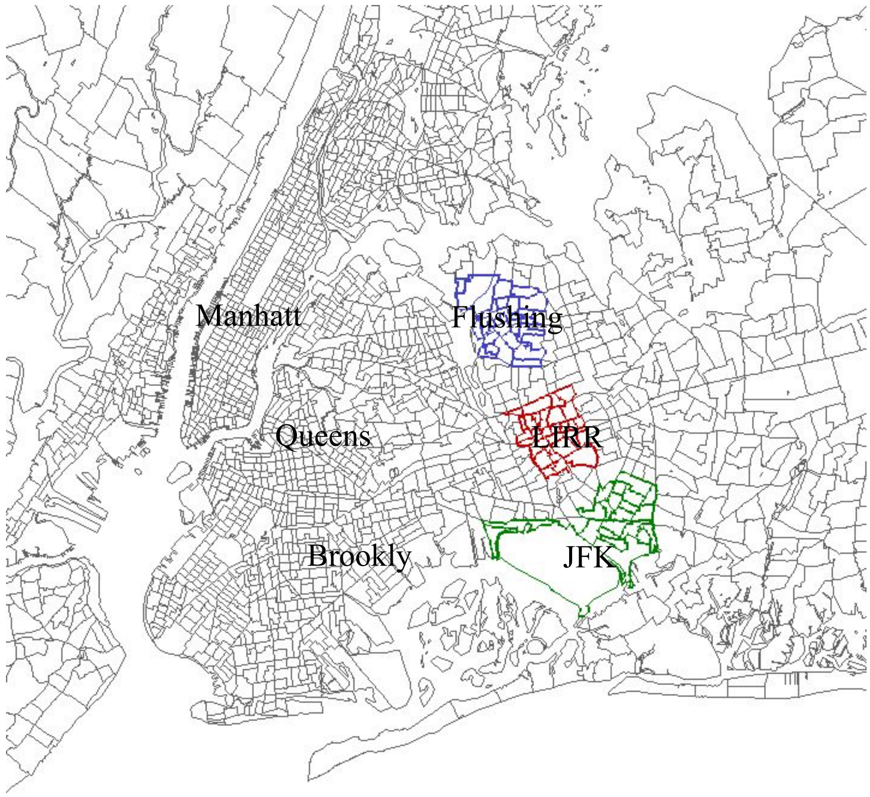


Table 6-1 shows various statistics for the three selected locations. On average, population density is the highest in Flushing and smallest in JFK. Median household income is the highest in JFK. Jamaica LIRR Hub has the best transit accessibility (measured as bus stop density and number of rail and subway stations).

Table 6-1 Socio-demographic Attributes and Transit Accessibilities of LIRR, JFK, and Flushing

Area	Jamaica LIRR Hub		6 Miles North in Flushing		JFK and Surrounding Areas	
Zip Codes	11432	11433	11354	11355	11422	11413
Population density (per mile^2)	25,930	17,997	24,583	40,824	4,872	12,973
Average household size	2.97	3.11	2.67	2.88	3.23	3.18
Median household income ($)	42,414	31,869	37,155	36,973	58,396	56,726
Total number of bus stops	192	120	150	136	92	92
Bus density (number per mile^2)	87	76	68	67	15	30
Total number of rail stations (including subway and LIRR)	5	3	1	0	0	0
Transit Share for Commute Trips	52%	55%	38%	45%	34%	39%

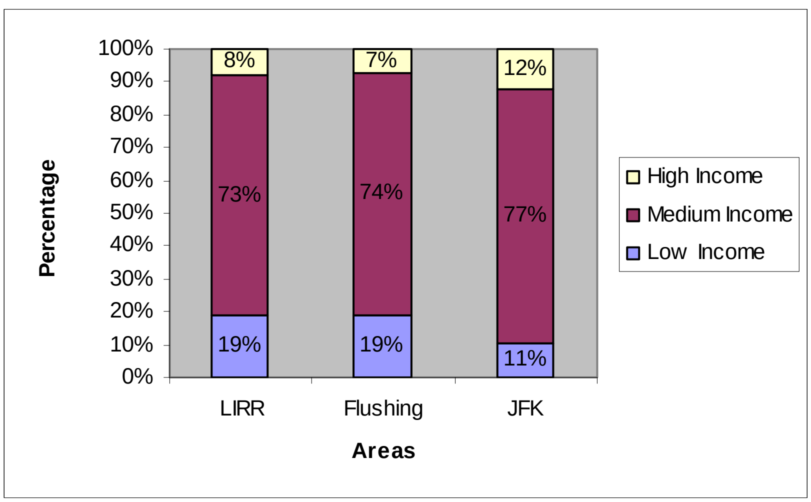
Table 6-2 shows the percentage changes in population and employment when we put 10,000 jobs or people in each of these three locations. The increases in population in LIRR, Flushing, and JFK are 9.20%, 6.31%, and 13.36%, respectively. Job increases are higher: 22.20%, 22.15%, and 17.20%, respectively.

Table 6-2 Distributions of Population and Employment in Seven Scenarios (including 2002 Base Scenario) in Three Locations

Population	Scenario		Percentage increase
	Base	POP	
LIRR	108,644	118,644	9.20%
Flushing	158,500	168,500	6.31%
JFK	74,835	84,835	13.36%
Jobs	**Scenario**		**Percentage increase**
	Base	**EMP**	
LIRR	45,050	55,050	22.20%
Flushing	45,147	55,147	22.15%
JFK	58,139	68,139	17.20%

Since adding 10,000 jobs or people does not affect the income distribution in the area, we only plot the income distributions across three scenarios for base scenario in Figure 6-2. On average, fewer high income households reside in LIRR and Flushing than those in JFK.

Figure 6-2 Income Distributions of Three Areas in Base Scenario



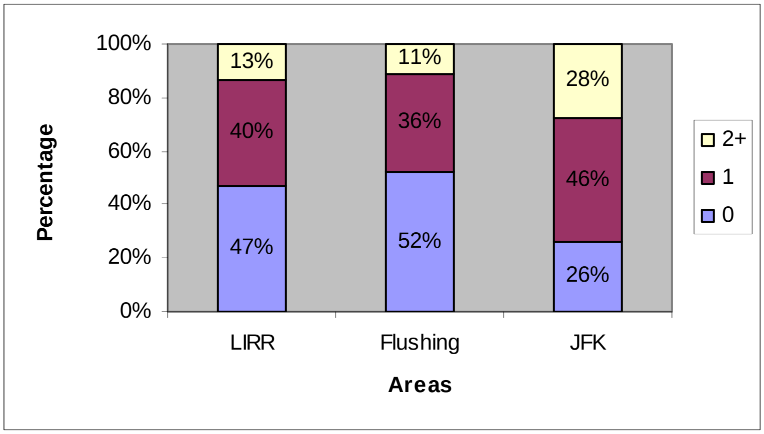
6-2 Changes in Auto Ownership

The distributions of auto ownership in the three selected locations are shown in Figure 6-3. In LIRR, 47% of the households do not own a vehicle; 40% of the households have one vehicle, and rest 13% of the households own more than one vehicle. In Flushing, 52% of the households do not own a vehicle; 36% of the households have one vehicle, and the remaining11% have more than one vehicle. In JFK, only 26% of the households do not have a vehicle; 46% of the households have one vehicle; and the remaining 28% of them have more than one vehicle. The higher auto ownership level in JFK is likely the result of both higher household income level and poorer transit accessibility than in Flushing or LIRR. Note that the share of medium and high income households in JFK is only 8% more than those in LIRR or Flushing, but the share of the households with at least one vehicle is 25% more than those in LIRR or Flushing. Transit accessibility appears to play an important role in suppressing auto ownership.

Given that the income distributions in Flushing and LIRR are similar and the transit accessibility in LIRR is slightly better than that in Flushing, we expect a relatively lower auto ownership level in the LIRR area. The results (Figure 6-3), however, suggest that the opposite is true.

Given that auto ownership is highly affected by income, we expect little change in auto ownership since the addition of 10,000 jobs or people does not appear to affect income distribution.

Figure 6-3 Distributions of Auto Ownership in Three Areas in Base Scenario



6-3 Change in the Number of Journeys by Mode

6-3-1 Outbound Journeys by Mode

Outbound journeys refer to the trips originating from each of the three selected areas and back to the starting location. Table 6-3 shows the number of outbound journeys by mode originating from LIRR. About 30% of journeys are made by auto and the remaining 70% are made by other modes. Mode shares do not change significantly after we add 10,000 more people or jobs in the LIRR area. The difference for the same mode between scenarios is less than 2%, likely a result of random seeds used in microsimulation.

Table 6-3 Numbers of Outbound Journeys from LIRR and their Respective Mode Shares in the Three Scenarios

LIRR	**Base**	**Emp***	**PoP***	**Base**	**Emp***	**PoP***
Drive alone	22,676	22,577	23,307	17.23%	17.23%	16.45%
HOV2	12,595	12,312	13,286	9.57%	9.39%	9.38%
HOV3	4,469	4,448	5,058	3.40%	3.39%	3.57%
HOV4+	1,824	1,881	2,081	1.39%	1.44%	1.47%
Auto	**41,564**	**41,218**	**43,732**	**31.58%**	**31.45%**	**30.87%**
Walk to Transit (WT)	32,902	32,819	35,067	25.00%	25.04%	24.76%
Drive to Transit (DT)	3,089	3,143	3,358	2.35%	2.40%	2.37%
Walk to Commuter Rail (WC)	6,063	6,171	6,399	4.61%	4.71%	4.52%
Drive to Commuter Rail (DC)	71	67	77	0.05%	0.05%	0.05%
Transit	**42,125**	**42,200**	**44,901**	**32.01%**	**32.20%**	**31.70%**
Taxi	8,164	8,348	8,755	6.20%	6.37%	6.18%
Non-Mot	37,703	37,262	41,915	28.64%	28.43%	29.59%
SchBus	2,077	2,040	2,350	1.58%	1.56%	1.66%
Total	**131,633**	**131,068**	**141,653**	**100.00%**	**100.00%**	**100.00%**

* Here Emp refers to scenario EMP_LIRR, and Pop refers to scenario POP_LIRR.

Table 6-4 shows changes in the number of outbound journeys originating from LIRR by mode in the three scenarios. After adding 10,000 jobs in the LIRR area, the total number of outbound journeys remains almost the same as that in the base scenario. After adding 10,000 people in the LIRR area, the total number of outbound journeys experiences a 7.61% increase, or 10,020 journeys in absolute number.

Table 6-4 Changes in the Numbers of Outbound Journeys Originating from LIRR by Mode in the Three Scenarios

LIRR	Base	Emp*	PoP*	(EmP-Base)/ Base	(PoP-Base)/ Base	PoP-Base
Drive alone	22,676	22,577	23,307	-0.44%	2.78%	631
HOV2	12,595	12,312	13,286	-2.25%	5.49%	691
HOV3	4,469	4,448	5,058	-0.47%	13.18%	589
HOV4+	1,824	1,881	2,081	3.13%	14.09%	257
Auto	**41,564**	**41,218**	**43,732**	**-0.83%**	**5.22%**	**2,168**
Walk to Transit (WT)	32,902	32,819	35,067	-0.25%	6.58%	2,165
Drive to Transit (DT)	3,089	3,143	3,358	1.75%	8.71%	269
Walk to Commuter Rail (WC)	6,063	6,171	6,399	1.78%	5.54%	336
Drive to Commuter Rail (DC)	71	67	77	-5.63%	8.45%	6
Transit	**42,125**	**42,200**	**44,901**	**0.18%**	**6.59%**	**2,776**
Taxi	8,164	8,348	8,755	2.25%	7.24%	591
Non-Mot	37,703	37,262	41,915	-1.17%	11.17%	4,212
SchBus	2,077	2,040	2,350	-1.78%	13.14%	273
Total	**131,633**	**131,068**	**141,653**	**-0.43%**	**7.61%**	**10,020**

* Emp refers to scenario EMP_LIRR, and Pop refers to scenario POP_LIRR.

We summarize our findings here. Adding 10,000 people or jobs in LIRR does not affect the mode split. The total number of outbound journeys (originating from LIRR) increases when we add 10,000 people, but not 10,000 jobs. The total numbers of outbound journeys originating from Flushing and JFK are shown in Tables 6-5, 6-6, 6-7, and 6-8. We can draw similar conclusions from these tables.

Table 6-5 Numbers of Outbound Journeys from Flushing and their Respective Mode Shares in the Three Scenarios

Flushing	Base	Emp*	PoP*	Base	Emp*	PoP*
Drive alone	30,861	30,464	31,739	16.07%	15.73%	15.51%
HOV2	16,323	16,047	16,805	8.50%	8.29%	8.21%
HOV3	5,703	5,813	6,247	2.97%	3.00%	3.05%
HOV4+	2,374	2,410	2,684	1.24%	1.24%	1.31%
Auto	**55,261**	**54,734**	**57,475**	**28.78%**	**28.26%**	**28.09%**
Walk to Transit (WT)	43,466	43,818	45,527	22.64%	22.62%	22.25%
Drive to Transit (DT)	4,424	4,397	4,597	2.30%	2.27%	2.25%
Walk to Commuter Rail (WC)	13,433	13,595	14,322	7.00%	7.02%	7.00%
Drive to Commuter Rail (DC)	914	897	995	0.48%	0.46%	0.49%
Transit	**62,237**	**62,707**	**65,441**	**32.42%**	**32.37%**	**31.99%**
Taxi	12,915	13,141	13,720	6.73%	6.78%	6.71%
Non-Mot	59,036	60,448	65,119	30.75%	31.21%	31.83%
SchBus	2,554	2,654	2,860	1.33%	1.37%	1.40%
Total	**192,003**	**193,684**	**204,615**	**100.00%**	**100.00%**	**100.00%**

* Here Emp refers to scenario EMP_Flushing, and Pop refers to scenario POP_ Flushing.

Table 6-6 Changes in the Numbers of Outbound Journeys Originating from Flushing by Mode in the Three Scenarios

Flushing	Base	Emp*	PoP*	(EmP-Base)/ Base	(PoP-Base)/ Base	PoP-Base
Drive alone	30,861	30,464	31,739	-1.29%	2.85%	878
HOV2	16,323	16,047	16,805	-1.69%	2.95%	482
HOV3	5,703	5,813	6,247	1.93%	9.54%	544
HOV4+	2,374	2,410	2,684	1.52%	13.06%	310
Auto	**55,261**	**54,734**	**57,475**	**-0.95%**	**4.01%**	**2214**
Walk to Transit (WT)	43,466	43,818	45,527	0.81%	4.74%	2061
Drive to Transit (DT)	4,424	4,397	4,597	-0.61%	3.91%	173
Walk to Commuter Rail (WC)	13,433	13,595	14,322	1.21%	6.62%	889
Drive to Commuter Rail (DC)	914	897	995	-1.86%	8.86%	81
Transit	**62,237**	**62,707**	**65,441**	**0.76%**	**5.15%**	**3204**
Taxi	12,915	13,141	13,720	1.75%	6.23%	805
Non-Mot	59,036	60,448	65,119	2.39%	10.30%	6083
SchBus	2,554	2,654	2,860	3.92%	11.98%	306
Total	**192,003**	**193,684**	**204,615**	**0.88%**	**6.57%**	**12612**

* Here Emp refers to scenario EMP_Flushing, and Pop refers to scenario POP_ Flushing.

Table 6-7 Numbers of Outbound Journeys from JFK and their Respective Mode Shares in the Three Scenarios

JFK	Base	Emp*	PoP*	Base	Emp*	PoP*
Drive alone	23,580	23,535	25,044	26.51%	26.29%	24.84%
HOV2	11,911	11,996	13,309	13.39%	13.40%	13.20%
HOV3	4,192	4,258	4,924	4.71%	4.76%	4.88%
HOV4+	1,821	1,877	2,221	2.05%	2.10%	2.20%
Auto	**41,504**	**41,666**	**45,498**	**46.66%**	**46.55%**	**45.13%**
Walk to Transit (WT)	17,663	17,365	19,602	19.86%	19.40%	19.44%
Drive to Transit (DT)	1,757	1,703	1,909	1.98%	1.90%	1.89%
Walk to Commuter Rail (WC)	2,348	2,260	2,645	2.64%	2.52%	2.62%
Drive to Commuter Rail (DC)	1,035	1,012	1,131	1.16%	1.13%	1.12%
Transit	**22,803**	**22,340**	**25,287**	**25.64%**	**24.95%**	**25.07%**
Taxi	5,539	5,791	6,379	6.23%	6.47%	6.33%
Non-Mot	17,017	17,654	21,036	19.13%	19.72%	20.87%
SchBus	2,080	2,062	2,616	2.34%	2.30%	2.59%
Total	**88,943**	**89,513**	**100,816**	**100.00%**	**100.00%**	**100.00%**

* Here Emp refers to scenario EMP_JFK, and Pop refers to scenario POP_ JFK.

Table 6-8 Changes in the Numbers of Outbound Journeys Originating from JFK by Mode in the Three Scenarios

JFK	Base	Emp*	PoP*	(EmP-Base)/ Base	(PoP-Base)/ Base	PoP-Base
Drive alone	23,580	23,535	25,044	-0.19%	6.21%	1464
HOV2	11,911	11,996	13,309	0.71%	11.74%	1398
HOV3	4,192	4,258	4,924	1.57%	17.46%	732
HOV4+	1,821	1,877	2,221	3.08%	21.97%	400
Auto	**41,504**	**41,666**	**45,498**	**0.39%**	**9.62%**	**3994**
Walk to Transit (WT)	17,663	17,365	19,602	-1.69%	10.98%	1939
Drive to Transit (DT)	1,757	1,703	1,909	-3.07%	8.65%	152
Walk to Commuter Rail (WC)	2,348	2,260	2,645	-3.75%	12.65%	297
Drive to Commuter Rail (DC)	1,035	1,012	1,131	-2.22%	9.28%	96
Transit	**22,803**	**22,340**	**25,287**	**-2.03%**	**10.89%**	**2484**
Taxi	5,539	5,791	6,379	4.55%	15.17%	840
Non-Mot	17,017	17,654	21,036	3.74%	23.62%	4019
SchBus	2,080	2,062	2,616	-0.87%	25.77%	536
Total	**88,943**	**89,513**	**100,816**	**0.64%**	**13.35%**	**11873**

* Here Emp refers to scenario EMP_JFK, and Pop refers to scenario POP_ JFK.

We observe that the newly generated journeys in the modified scenarios have a different mode distribution from those in the base scenario (Table 6-9). The mode with the largest share is the non-motorized journeys, which are 42% in LIRR, 48% in Flushing and 33% in JFK. These numbers are much higher than those in the base scenarios (28.64% in LIRR, 30.75% in Flushing, and 19.13% in JFK, see Tables 6-3, 6-5, 6-7). In contrast, the mode shares of auto or transit are lower than those in the base scenario. For instance, in LIRR auto takes about 31.58% in the base scenario, while only 21.64% of new generated journeys are made by auto. In the context of the BPM model, this is expected. Adding population to an area without changing employment level means that the added population are mostly non-workers. This results in an increase in trips with purposes other than work and the modes tend to be non-motorized.

Table 6-9 Numbers and Mode Shares of Increased Journeys as a Result of Adding 10,000 People to a Location

	PoP_ LIRR	**PoP_ Flushing**	**PoP_ JFK**	**PoP_ LIRR**	**PoP_ Flushing**	**PoP_ JFK**
	Increase in number against base			**Mode share of the increased journeys**		
Drive alone	631	878	1464	6.30%	6.96%	12.33%
HOV2	691	482	1398	6.90%	3.82%	11.77%
HOV3	589	544	732	5.88%	4.31%	6.17%
HOV4+	257	310	400	2.56%	2.46%	3.37%
Auto	**2,168**	**2,214**	**3,994**	**21.64%**	**17.55%**	**33.64%**
Walk to Transit (WT)	2,165	2,061	1,939	21.61%	16.34%	16.33%
Drive to Transit (DT)	269	173	152	2.68%	1.37%	1.28%
Walk to Commuter Rail (WC)	336	889	297	3.35%	7.05%	2.50%
Drive to Commuter Rail (DC)	6	81	96	0.06%	0.64%	0.81%
Transit	**2,776**	**3,204**	**2,484**	**27.70%**	**25.40%**	**20.92%**
Taxi	591	805	840	5.90%	6.38%	7.07%
Non-Mot	4,212	6,083	4,019	42.04%	48.23%	33.85%
SchBus	273	306	536	2.72%	2.43%	4.51%
Total	**10,020**	**12,612**	**11,873**	**100.00%**	**100.00%**	**100.00%**

6-3-2 Inbound Journeys by Mode

Inbound journeys refer to journeys to one of the three selected locations. The number of inbound journeys to LIRR in the base and two modified scenarios are shown Table 6-10. There is very little change in mode share across the scenarios.

Table 6-10 Numbers of Inbound Journeys to LIRR and their Respective Mode Shares in the Three Scenarios

LIRR	**Base**	**Emp***	**PoP***	**Base**	**Emp***	**PoP***
Drive alone	32,634	32,737	33,532	26.02%	26.22%	25.46%
HOV2	14,878	14,882	15,502	11.86%	11.92%	11.77%
HOV3	4,985	4,921	5,140	3.97%	3.94%	3.90%
HOV4+	2,048	2,017	2,210	1.63%	1.62%	1.68%
Auto	**54,545**	**54,557**	**56,384**	**43.49%**	**43.70%**	**42.81%**
Walk to Transit (WT)	19,614	19,468	20,014	15.64%	15.59%	15.20%
Drive to Transit (DT)	606	592	606	0.48%	0.47%	0.46%
Walk to Commuter Rail (WC)	548	556	544	0.44%	0.45%	0.41%
Drive to Commuter Rail (DC)	623	572	585	0.50%	0.46%	0.44%
Transit	**21,391**	**21,188**	**21,749**	**17.06%**	**16.97%**	**16.51%**
Taxi	7,288	7,352	7,325	5.81%	5.89%	5.56%
Non-Mot	40,113	39,709	44,084	31.98%	31.80%	33.47%
SchBus	2,088	2,051	2,166	1.66%	1.64%	1.64%
Total	**125,425**	**124,857**	**131,708**	**100.00%**	**100.00%**	**100.00%**

* Here Emp refers to scenario EMP_LIRR, and Pop refers to scenario POP_LIRR.

Adding 10,000 jobs in LIRR would naturally mean that more journeys will be attracted to

LIRR. However, the results in Table 6-11 do not show much increase. Adding 10,000 people in LIRR appears to result in more inbound journeys than adding 10,000 jobs.

Table 6-11 Changes in the Numbers and Percentages of Journeys Travel to LIRR by Mode in the Three Scenarios

LIRR	**Base**	**Emp***	**PoP***	**(EmP-Base)/ Base**	**(PoP-Base)/ Base**	**EmP -Base**	**PoP-Base**
Drive alone	32,634	32,737	33,532	0.32%	2.75%	103	898
HOV2	14,878	14,882	15,502	0.03%	4.19%	4	624
HOV3	4,985	4,921	5,140	-1.28%	3.11%	-64	155
HOV4+	2,048	2,017	2,210	-1.51%	7.91%	-31	162
Auto	**54,545**	**54,557**	**56,384**	**0.02%**	**3.37%**	**12**	**1,839**
Walk to Transit (WT)	19,614	19,468	20,014	-0.74%	2.04%	-146	400
Drive to Transit (DT)	606	592	606	-2.31%	0.00%	-14	0
Walk to Commuter Rail (WC)	548	556	544	1.46%	-0.73%	8	-4
Drive to Commuter Rail (DC)	623	572	585	-8.19%	-6.10%	-51	-38
Transit	**21,391**	**21,188**	**21,749**	**-0.95%**	**1.67%**	**-203**	**358**
Taxi	7,288	7,352	7,325	0.88%	0.51%	64	37
Non-Mot	40,113	39,709	44,084	-1.01%	9.90%	-404	3,971
SchBus	2,088	2,051	2,166	-1.77%	3.74%	-37	78
Total	**125,425**	**124,857**	**131,708**	**-0.45%**	**5.01%**	**-568**	**6,283**

The mode distributions of inbound journeys to Flushing and JFK are shown in Tables 6-12 and 6-13. Similar to those inbound journeys to LIRR, we do not observe significant changes.

Table 6-12 Numbers of Inbound Journeys to Flushing and their Respective Mode Shares in the Three Scenarios

Flushing	Base	Emp*	PoP*	Base	Emp*	PoP*
Drive alone	36,262	40,020	37,106	24.01%	25.17%	23.31%
HOV2	17,554	18,359	17,998	11.62%	11.55%	11.31%
HOV3	6,023	6,326	6,425	3.99%	3.98%	4.04%
HOV4+	2,480	2,726	2,550	1.64%	1.71%	1.60%
Auto	**62,319**	**67,431**	**64,079**	**41.26%**	**42.42%**	**40.26%**
Walk to Transit (WT)	18,884	19,789	19,319	12.50%	12.45%	12.14%
Drive to Transit (DT)	687	749	682	0.45%	0.47%	0.43%
Walk to Commuter Rail (WC)	613	683	651	0.41%	0.43%	0.41%
Drive to Commuter Rail (DC)	499	490	529	0.33%	0.31%	0.33%
Transit	**20,683**	**21,711**	**21,181**	**13.69%**	**13.66%**	**13.31%**
Taxi	6,085	6,440	6,153	4.03%	4.05%	3.87%
Non-Mot	59,218	60,661	64,984	39.21%	38.16%	40.83%
SchBus	2,725	2,734	2,765	1.80%	1.72%	1.74%
Total	**151,030**	**158,977**	**159,162**	**100.00%**	**100.00%**	**100.00%**

* Here Emp refers to scenario EMP_Flushing, and Pop refers to scenario POP_ Flushing.

Table 6-13 Numbers of Inbound Journeys to JFK and their Respective Mode Shares in the Three Scenarios

JFK	Base	Emp*	PoP*	Base	Emp*	PoP*
Drive alone	14,784	18,818	15,887	25.12%	28.38%	24.19%
HOV2	8,537	9,416	9,280	14.50%	14.20%	14.13%
HOV3	3,284	3,470	3,478	5.58%	5.23%	5.30%
HOV4+	1,377	1,466	1,524	2.34%	2.21%	2.32%
Auto	**27,982**	**33,170**	**30,169**	**47.54%**	**50.03%**	**45.93%**
Walk to Transit (WT)	8,003	9,000	8,550	13.60%	13.57%	13.02%
Drive to Transit (DT)	410	427	403	0.70%	0.64%	0.61%
Walk to Commuter Rail (WC)	118	136	134	0.20%	0.21%	0.20%
Drive to Commuter Rail (DC)	110	189	102	0.19%	0.29%	0.16%
Transit	**8,641**	**9,752**	**9,189**	**14.69%**	**14.71%**	**13.99%**
Taxi	2,389	2,679	2,484	4.06%	4.04%	3.78%
Non-Mot	17,650	18,509	21,459	29.99%	27.92%	32.67%
SchBus	2,199	2,192	2,382	3.74%	3.31%	3.63%
Total	**58,861**	**66,302**	**65,683**	**100.00%**	**100.00%**	**100.00%**

* Here Emp refers to scenario EMP_JFK, and Pop refers to scenario POP_ JFK.

For newly generated journeys, the observed results again conflict with our expectations in JFK and Flushing (Tables 6-14 and 6-15). Instead of little change in the number of inbound journeys, the number of inbound journeys increases. In Flushing, the total number of in-bound journeys increases by about 5% in the two modified scenarios. In JFK, the total number of in-bound journeys increases by about 12% in the two modified scenarios.

Note that although the increased total numbers of journeys are similar for EMP_Flushing and POP_Flushing, variations are observed across modes. The percentage increases are higher in auto, drive to transit, walk to commuter rail and taxi in the EMP_Flushing scenario, while the percentage increases are higher in non-motorized mode in the POP_Flushing scenario. This difference is also observed in JFK related scenarios.

Table 6-14 Changes in the Numbers of Inbound Journeys to Flushing by Mode in the Three Scenarios

Flushing	Base	Emp*	PoP*	(EmP-Base)/Base	(PoP-Base)/Base	EmP-Base	PoP-Base
Drive alone	36,262	40,020	37,106	10.36%	2.33%	3758	844
HOV2	17,554	18,359	17,998	4.59%	2.53%	805	444
HOV3	6,023	6,326	6,425	5.03%	6.67%	303	402
HOV4+	2,480	2,726	2,550	9.92%	2.82%	246	70
Auto	**62,319**	**67,431**	**64,079**	**8.20%**	**2.82%**	**5112**	**1760**
Walk to Transit (WT)	18,884	19,789	19,319	4.79%	2.30%	905	435
Drive to Transit (DT)	687	749	682	9.02%	-0.73%	62	-5
Walk to Commuter Rail (WC)	613	683	651	11.42%	6.20%	70	38
Drive to Commuter Rail (DC)	499	490	529	-1.80%	6.01%	-9	30
Transit	**20,683**	**21,711**	**21,181**	**4.97%**	**2.41%**	**1028**	**498**

Table 6-14 Changes in the Numbers of Inbound Journeys to Flushing by Mode in the Three Scenarios (cont'd)

Taxi	6,085	6,440	6,153	5.83%	1.12%	355	68
Non-Mot	59,218	60,661	64,984	2.44%	9.74%	1443	5766
SchBus	2,725	2,734	2,765	0.33%	1.47%	9	40
Total	**151,030**	**158,977**	**159,162**	**5.26%**	**5.38%**	**7947**	**8132**

Table 6-15 Changes in the Numbers of Inbound Journeys to JFK by Mode in the Three Scenarios

JFK	Base	Emp*	PoP*	(EmP-Base)/Base	(PoP-Base)/Base	EmP -Base	PoP-Base
Drive alone	14,784	18,818	15,887	27.29%	7.46%	4,034	1,103
HOV2	8,537	9,416	9,280	10.30%	8.70%	879	743
HOV3	3,284	3,470	3,478	5.66%	5.91%	186	194
HOV4+	1,377	1,466	1,524	6.46%	10.68%	89	147
Auto	**27,982**	**33,170**	**30,169**	**18.54%**	**7.82%**	**5,188**	**2,187**
Walk to Transit (WT)	8,003	9,000	8,550	12.46%	6.83%	997	547
Drive to Transit (DT)	410	427	403	4.15%	-1.71%	17	-7
Walk to Commuter Rail (WC)	118	136	134	15.25%	13.56%	18	16
Drive to Commuter Rail (DC)	110	189	102	71.82%	-7.27%	79	-8
Transit	**8,641**	**9,752**	**9,189**	**12.86%**	**6.34%**	**1,111**	**548**
Taxi	2389	2679	2484	12.14%	3.98%	290	95
Non-Mot	17650	18509	21459	4.87%	21.58%	859	3,809
SchBus	2199	2192	2382	-0.32%	8.32%	-7	183
Total	**58,861**	**66,302**	**65,683**	**12.64%**	**11.59%**	**7,441**	**6,822**

6-4 Changes in Journeys by Purpose

6-4-1 Outbound Journeys by purpose

The numbers of outbound journeys by purpose and their respective percentage changes are shown in Table 6-16. After adding 10,000 people in each of the three selected locations, we observe an increase in the number of outbound journeys from these locations. This is expected, although most of the newly generated outbound journeys are for purposes such as school, maintenance, and discretionary activities rather than work. In terms of percentage change, trips to school registers the highest percentage of increase; they increase by 16.39% in LIRR, 13.78% in Flushing, and 30.50% in JFK. In terms of the number of outbound journeys, maintenance trips register the highest increase. After adding 10,000 jobs in LIRR, Flushing, and JFK, only at work journeys experience increases – a 23.39% from Flushing and an 84.29% from JFK. Journeys for other purposes remain stable. These large increases are likely due to the small number in the base scenario.

Table 6-16 Numbers of Outbound Journeys by Purpose and their Respective Changes in the Three Scenarios

LIRR						
	Base	**Emp**	**Pop**	**(Emp-Base)/ Base**	**(Pop-Base)/ Base**	**(Pop-Base)/ Base**
Work -Low income	2,662	2,792	2,467	5.27%	-7.33%	-195
Work - Medium income	26,520	26,596	27,041	0.28%	1.96%	521
Work - High income	4,275	4,276	4,302	0.02%	0.63%	27
Work all	**33,457**	**33,664**	**33,810**	**0.61%**	**1.06%**	**353**
School	15,932	15,785	18,543	-0.79%	16.39%	2,611
University	3,264	3,335	3,673	1.93%	12.53%	409
Maintenance	48,936	48,611	53,594	-0.61%	9.52%	4,658
Discretionary	24,490	24,265	26,548	-0.85%	8.40%	2,058
At work	5,554	5,408	5,485	-2.66%	-1.24%	-69
ALL	**131,633**	**131,068**	**141,653**	**-0.40%**	**7.61%**	**10,020**

Table 6-16 Numbers of Outbound Journeys by Purpose and their Respective Changes in the Three Scenarios (cont'd)

Flushing						
	Base	**Emp**	**Pop**	**Emp-Base**	**Pop-Base**	**Pop-Base**
Work -Low income	4,038	4,069	3,791	0.82%	-6.12%	-247
Work - Medium income	40,743	40,717	40,791	-0.06%	0.12%	48
Work - High income	5,794	6,000	6,011	3.43%	3.75%	217
Work all	**50,575**	**50786**	**50593**	**0.42%**	**0.04%**	**18**
School	21,416	21,430	24,368	0.06%	13.78%	2,952
University	5,099	5,072	5,533	-0.49%	8.51%	434
Maintenance	72,091	72,013	77,623	-0.10%	7.67%	5,532
Discretionary	37,443	37,762	41,188	0.77%	10.00%	3,745
At work	5,379	6,621	5,310	23.39%	-1.28%	-69
ALL	**192,003**	**193,684**	**204,615**	**0.82%**	**6.57%**	**12,612**

Table 6-16 Numbers of Outbound Journeys by Purpose and their Respective Changes in the Three Scenarios (cont'd)

JFK						
	Base	**Emp**	**Pop**	**Emp-Base**	**Pop-Base**	**Pop-Base**
Work -Low income	1,416	1,349	1,177	-5.69%	-16.88%	-239
Work - Medium income	19,879	19,883	19,936	0.02%	0.29%	57
Work - High income	4,454	4,301	4,612	-3.32%	3.55%	158
Work all	**25,749**	**25,533**	**25,725**	**-0.84%**	**-0.09%**	**-24**
School	11,202	11,254	14,619	0.36%	30.50%	3,417
University	2,304	2,188	2,567	-4.52%	11.41%	263
Maintenance	31,417	31,056	36,759	-0.98%	17.00%	5,342
Discretionary	16,745	16,706	19,663	-0.20%	17.43%	2,918
At work	1,526	2,776	1,483	84.29%	-2.82%	-43
ALL	**88,943**	**89,513**	**100,816**	**0.57%**	**13.35%**	**11,873**

6-4-2 Inbound Journeys by purpose

The numbers of inbound journeys by purpose and their respective percentage changes are shown in Table 6-17. After adding 10,000 jobs in LIRR, contrary to our expectations, the number of inbound work journeys does not change. After adding 10,000 jobs to Flushing and JFK, the number of inbound work journeys increases by about 7,000. After adding 10,000 people in LIRR, Flushing, and JFK, the number of inbound journeys increase, but most of them are not for work purposes. Instead, the purposes of the newly generated journeys include school, university, maintenance, or discretionary activities. This is likely due to the fact that the added people are mostly non-workers.

Table 6-17 Numbers of Inbound Journeys by Purpose and their Respective Percentage Changes in the Three Scenarios

LIRR							
	Base	Emp	Pop	(Emp-Base)/ Base	(Pop-Base)/ Base	Emp-Base	Pop-Base
Work -Low income	2,583	2,627	2,585	1.70%	0.08%	44	2
Work - Medium income	25,075	25,041	25,059	-0.14%	-0.06%	-34	-16
Work - High income	4,922	4,908	4,921	-0.28%	-0.02%	-14	-1
Work all	**32,580**	**32,576**	**32,565**	**-0.01%**	**-0.05%**	**-4**	**-15**
School	15,238	15,143	16,497	-0.58%	8.26%	-95	1,259
University	6,958	6,972	6,982	0.20%	0.34%	14	24
Maintenance	43,727	43,389	47,090	-0.72%	7.69%	-338	3,363
Discretionary	21,380	21,289	23,177	-0.39%	8.41%	-91	1,797
At work	5,542	5,488	5,397	-1.00%	-2.62%	-54	-145
ALL	**125,425**	**124,857**	**131,708**	**-0.43%**	**5.01%**	**-568**	**6,283**

Table 6-17 Numbers of Inbound Journeys by Purpose and their Respective Percentage Changes in the Three Scenarios (cont'd)

Flushing							
	Base	Emp	Pop	Emp-Base	Pop-Base	Emp-Base	Pop-Base
Work -Low income	2,441	2,979	2,441	22.04%	0.00%	538	0
Work - Medium income	24,896	30,373	24,875	22.02%	-0.08%	5,477	-21
Work - High income	5,006	6,115	5,013	22.12%	0.14%	1,109	7
Work all	**32,343**	**39,467**	**32,329**	**22.04%**	**-0.04%**	**7,124**	**-14**
School	20,566	20,476	22,395	-0.40%	8.89%	-90	1,829
University	1,869	1,874	1,869	0.27%	0.00%	5	0
Maintenance	60,976	61,009	64,626	0.05%	5.99%	33	3,650
Discretionary	29,709	30,131	32,188	1.31%	8.34%	422	2,479
At work	5,567	6,020	5,755	7.87%	3.38%	453	188
ALL	**151,030**	**158,977**	**159,162**	**4.99%**	**5.38%**	**7,947**	**8,132**

Table 6-17 Numbers of Inbound Journeys by Purpose and their Respective Percentage Changes in the Three Scenarios (cont'd)

JFK							
	Base	Emp	Pop	Emp-Base	Pop-Base	Emp-Base	Pop-Base
Work -Low income	655	1196	656	82.47%	0.15%	541	1
Work - Medium income	6,721	12,263	6,717	82.51%	-0.06%	5,542	-4
Work - High income	1,358	2,486	1,363	82.76%	0.37%	1,128	5
Work all	**8,734**	**15,945**	**8,736**	**82.54%**	**0.02%**	**7,211**	**2**
School	12,813	12,904	14,650	0.62%	14.34%	91	1,837
University	788	792	792	0.51%	0.51%	4	4
Maintenance	22,653	22,487	25,806	-0.64%	13.92%	-166	3,153
Discretionary	12,319	12,208	14,089	-0.79%	14.37%	-111	1,770
At work	1,554	1,966	1,610	25.59%	3.60%	412	56
ALL	**58,861**	**66,302**	**65,683**	**11.33%**	**11.59%**	**7,441**	**6,822**

6-5 Journey by mode and purpose

6-5-1 Outbound Journey by Purpose and Mode

The changes in outbound journey by purpose and mode in Flushing are shown in Table 6-18. In general, the largest portion of work journeys by the low income population in Flushing is made by walk to transit (WT). After locating 10,000 jobs or people in Flushing, we only observe small changes in the number of outbound work journeys. Walk to Transit (WT) has the largest mode share, followed by HOV2, non-motorized modes and SOV. This order changes for the medium income population in Flushing; WT still has the largest share, followed by SOV, which seems to be due to the increase in car ownership. Changes in the number of outbound work journeys are very small. For example, the numbers of outbound work journeys by WT or SOV are less than 3%[11]. Similar conclusions can also be made about the high income population in Flushing.

Most of the school journeys are made by non-motorized, WT, school bus, HOV2, and HOV3 modes. After adding 10,000 people in Flushing, school journeys by non-motorized, WT, school bus, and HOV3 modes all experience large increases (larger than 10%). This is an expected result. Such increases however are not observed after locating 10,000 jobs in Flushing. University journeys are mainly made by WT, taxi, and DT modes. After locating 10,000 people in Flushing, a large increase (20%) is observed for WT.

Journeys for maintenance activities are mainly made by non-motorized, SOV, WC, WT, and HOV2 modes. After adding 10,000 people in Flushing, an increase in the number of outbound journeys by non-motorized modes is observed (10%). After adding 10,000 people in Flushing, very little increase could be detected. Journeys for discretionary activities are mainly made by non-motorized, SOV, WT, and HOV2 modes. After adding 10,000 people in Flushing, the numbers of outbound journeys by non-motorized and WT modes increased (13% and 11%). Again, very little change was observed in the number of outbound discretionary journeys after locating 10,000 jobs in Flushing. Finally, journeys at work at are mainly done by non-motorized modes. After adding 10,000 people in Flushing, very little change is observed. After adding 10,000 jobs in Flushing, a large increase (23%) is observed for non-motorized modes.

[11] The percentage changes for some modes are quite large due to small number in the base scenario.

Table 6-18 Numbers of Outbound Journeys by Purpose and Mode in Flushing

Purpose: Work – Low Income					
mode	**Base**	**EMP_ Flushing**	**POP_ Flushing**	**(EMP-Base)/Base**	**(POP-Base)/Base**
SOV	398	373	355	-6%	-11%
HOV2	535	524	457	-2%	-15%
HOV3	55	62	38	13%	-31%
HOV4+	27	20	32	-26%	19%
WT	1,760	1,793	1,695	2%	-4%
DT	150	152	121	1%	-19%
WC	287	274	288	-5%	0%
DC	67	64	61	-4%	-9%
Taxi	35	28	32	-20%	-9%
Non-Mot	492	557	520	13%	6%
Purpose: Work – Medium Income					
SOV	9,075	8,820	8,873	-3%	-2%
HOV2	2,380	2,327	2,396	-2%	1%
HOV3	549	569	583	4%	6%
HOV4+	220	190	201	-14%	-9%
WT	18,126	18,251	18,329	1%	1%
DT	2,014	1,984	2,026	-1%	1%
WC	844	884	843	5%	0%
DC	213	235	238	10%	12%
Taxi	2,550	2,525	2,549	-1%	0%
Non-Mot	3,656	3,845	3,707	5%	1%

Table 6-18 Numbers of Outbound Journeys by Purpose and Mode in Flushing (cont'd)

Purpose: Work – High Income					
SOV	1,589	1,684	1,678	6%	6%
HOV2	332	313	311	-6%	-6%
HOV3	59	70	65	19%	10%
HOV4+	29	43	32	48%	10%
WT	1,876	1,930	1,889	3%	1%
DT	794	849	852	7%	7%
WC	76	79	54	4%	-29%
DC	42	31	34	-26%	-19%
Taxi	877	878	965	0%	10%
Non-Mot	193	201	201	4%	4%
Purpose: School					
SOV	301	271	328	-10%	9%
HOV2	1,830	1,729	1,973	-6%	8%
HOV3	1,248	1,267	1,395	2%	12%
HOV4+	447	464	528	4%	18%
WT	5,234	5,266	5,894	1%	13%
DT	289	258	326	-11%	13%
WC	5	4	7	-20%	40%
DC	76	60	98	-21%	29%
Taxi	27	24	30	-11%	11%
Non-Mot	8,670	8,638	10,062	0%	16%
SchBus	2,502	2,614	2,810	4%	12%

Table 6-18 Numbers of Outbound Journeys by Purpose and Mode in Flushing (cont'd)

Purpose: University					
SOV	122	116	129	-5%	6%
HOV2	108	91	112	-16%	4%
HOV3	33	43	45	30%	36%
HOV4+	11	6	9	-45%	-18%
WT	1,419	1,525	1,696	7%	20%
DT	744	750	805	1%	8%
WC	671	649	669	-3%	0%
DC	134	124	122	-7%	-9%
Taxi	1,162	1,086	1,192	-7%	3%
Non-Mot	488	480	552	-2%	13%
Purpose: Maintenance					
SOV	13,233	12,966	13,990	-2%	6%
HOV2	7,200	7,030	7,469	-2%	4%
HOV3	1,355	1,302	1,378	-4%	2%
HOV4+	700	746	805	7%	15%
WT	8,908	8,913	9,476	0%	6%
DT	221	216	246	-2%	11%
WC	10,009	10,160	10,890	2%	9%
DC	360	354	408	-2%	13%
Taxi	1,205	1,191	1,319	-1%	9%
Non-Mot	26,421	26,507	28,942	0%	10%

Table 6-18 Numbers of Outbound Journeys by Purpose and Mode in Flushing (cont'd)

Purpose: Discretionary					
SOV	5,328	5,229	5,507	-2%	3%
HOV2	2,993	2,873	3,176	-4%	6%
HOV3	1,994	1,974	2,231	-1%	12%
HOV4+	902	907	1,045	1%	16%
WT	4,614	4,748	5,102	3%	11%
DT	130	102	135	-22%	4%
WC	523	522	503	0%	-4%
DC	20	11	26	-45%	30%
Taxi	5,886	6,077	6,441	3%	9%
Non-Mot	13,710	13,978	15,560	2%	13%
Purpose: At Work					
SOV	870	1,042	837	20%	-4%
HOV2	859	978	769	14%	-10%
HOV3	340	459	394	35%	16%
WT	36	46	36	28%	0%
Taxi	633	826	667	30%	5%
Non-Mot	2,559	3,155	2,525	23%	-1%

The changes in the numbers of outbound journeys by purpose and mode for JFK and LIRR are shown in Tables 6-19 and 6-20. In general, the change patterns are similar to those in Flushing. The number of outbound work journeys is relatively stable, and journeys for school, university, maintenance, and discretionary activities increased after adding 10,000 people in these two areas. After adding 10,000 jobs in JFK and LIRR, the only observed increase is in journeys at work.

Table 6-21 shows mode shares of outbound journeys by purpose and mode in the base scenario in the three selected locations[12]. For the low income population, transit is more frequently used than private vehicle modes for work journeys in all three areas. For medium and high income populations, a private vehicle is more likely to be used in work journeys than transit in JFK. In LIRR and Flushing, the mode share of transit is still larger in work journeys than private vehicle modes, probably reflecting larger transit accessibility in these two areas.

For school journeys, both LIRR and Flushing have more than 40% journeys made by non-motorized modes while in JFK it is only about 30%. Again, this is likely a reflection of the difference in transit service between the areas. In JFK, about 18% of school journeys are made by school bus, while it is about 12% in Flushing and LIRR. For university journeys, transit commands a dominate share in all three areas.

Maintenance journeys are likely to be made by SOV in JFK, while in Flushing and LIRR they are likely to be made by non-motorized modes. Discretionary and journeys at work are most likely to be made by non-motorized modes in all three areas.

[12] The mode splits are quite similar between the base scenario and the modified scenarios. Thus, we only display the results from the base scenario.

Table 6-19 Numbers of Outbound Journeys by Purpose and Mode in JFK

Purpose: Work – Low Income					
Mode	**Base**	**EMP_ JFK**	**POP_ JFK**	**(EMP-Base)/Base**	**(POP-Base)/Base**
SOV	294	261	245	-11%	-17%
HOV2	273	291	233	7%	-15%
HOV3	23	19	19	-17%	-17%
HOV4+	16	8	4	-50%	-75%
WT	563	491	470	-13%	-17%
DT	44	30	27	-32%	-39%
WC	33	34	18	3%	-45%
DC	81	71	63	-12%	-22%
Taxi	6	15	11	150%	83%
Non-Mot	83	129	87	55%	5%
Purpose: Work – Medium Income					
SOV	7,258	7,116	7,017	-2%	-3%
HOV2	1,658	1,626	1,697	-2%	2%
HOV3	356	401	355	13%	0%
HOV4+	131	130	134	-1%	2%
WT	7,085	7,035	7,213	-1%	2%
DT	715	702	703	-2%	-2%
WC	153	165	161	8%	5%
DC	358	346	381	-3%	6%
Taxi	1,177	1,165	1,251	-1%	6%
Non-Mot	988	1,197	1,024	21%	4%

Table 6-19 Numbers of Outbound Journeys by Purpose and Mode in JFK (cont'd)

Purpose: Work – High Income					
SOV	1,643	1,615	1,663	-2%	1%
HOV2	276	281	283	2%	3%
HOV3	74	70	73	-5%	-1%
HOV4+	53	33	32	-38%	-40%
WT	1,119	1,031	1,128	-8%	1%
DT	444	452	495	2%	11%
WC	29	20	18	-31%	-38%
DC	74	73	79	-1%	7%
Taxi	668	642	767	-4%	15%
Non-Mot	74	84	74	14%	0%
Purpose: School					
SOV	224	226	346	1%	54%
HOV2	1,546	1,459	1,875	-6%	21%
HOV3	985	1,012	1,206	3%	22%
HOV4+	325	403	450	24%	38%
WT	2,526	2,491	3,158	-1%	25%
DT	0	183	277	~	~
WC	195	1	0	-99%	-100%
DC	161	180	224	12%	39%
Taxi	12	11	18	-8%	50%
Non-Mot	3,148	3,226	4,449	2%	41%
SchBus	2,080	2,062	2,616	-1%	26%

Table 6-19 Numbers of Outbound Journeys by Purpose and Mode in JFK (cont'd)

Purpose: University					
SOV	93	88	93	-5%	0%
HOV2	88	96	104	9%	18%
HOV3	39	41	36	5%	-8%
HOV4+	7	9	8	29%	14%
WT	864	777	941	-10%	9%
DT	216	185	242	-14%	12%
WC	62	41	56	-34%	-10%
DC	116	136	114	17%	-2%
Taxi	739	735	854	-1%	16%
Non-Mot	80	80	119	0%	49%
Purpose: Maintenance					
SOV	10,316	10,229	11,575	-1%	12%
HOV2	5,580	5,528	6,300	-1%	13%
HOV3	1,044	1,066	1,299	2%	24%
HOV4+	627	561	762	-11%	22%
WT	4,069	4,041	4,959	-1%	22%
DT	98	101	103	3%	5%
WC	1,954	1,904	2,305	-3%	18%
DC	211	173	233	-18%	10%
Taxi	647	659	812	2%	26%
Non-Mot	6,871	6,794	8,411	-1%	22%

Table 6-19 Numbers of Outbound Journeys by Purpose and Mode in JFK (cont'd)

Purpose: Discretionary					
SOV	3,466	3,489	3,851	1%	11%
HOV2	2,242	2,218	2,556	-1%	14%
HOV3	1,548	1,450	1,842	-6%	19%
HOV4+	662	733	831	11%	26%
WT	1,430	1,484	1,722	4%	20%
DT	45	50	62	11%	38%
WC	117	95	87	-19%	-26%
DC	34	33	37	-3%	9%
Taxi	2,088	2,218	2,490	6%	19%
Non-Mot	5,113	4,936	6,185	-3%	21%
Purpose: At Work					
SOV	286	511	254	79%	-11%
HOV2	248	497	261	100%	5%
HOV3	123	199	94	62%	-24%
WT	7	15	11	114%	57%
Taxi	202	346	176	71%	-13%
Non-Mot	660	1,208	687	83%	4%

Table 6-20 Numbers of Outbound Journeys by Purpose and Mode in LIRR

Purpose: Work – Low Income					
Mode	**Base**	**EMP_ JFK**	**POP_ JFK**	**(EMP-Base)/Base**	**(POP-Base)/Base**
SOV	204	243	236	19%	16%
HOV2	364	329	362	-10%	-1%
HOV3	29	41	39	41%	34%
HOV4+	18	19	17	6%	-6%
WT	1256	1,329	1,251	6%	0%
DT	138	130	105	-6%	-24%
WC	87	78	82	-10%	-6%
DC	2	1	1	-50%	-50%
Taxi	27	23	18	-15%	-33%
Non-Mot	301	323	329	7%	9%
Purpose: Work – Medium Income					
SOV	6468	6,381	6,472	-1%	0%
HOV2	1701	1,709	1,828	0%	7%
HOV3	409	460	439	12%	7%
HOV4+	140	151	156	8%	11%
WT	15183	15,413	15,378	2%	1%
DT	1801	1,792	1,843	0%	2%
WC	331	327	306	-1%	-8%
DC	11	7	7	-36%	-36%
Taxi	1904	2,001	1,938	5%	2%
Non-Mot	2503	2,475	2,594	-1%	4%

Table 6-20 Numbers of Outbound Journeys by Purpose and Mode in LIRR (cont'd)

Purpose: Work – High Income					
SOV	1502	1,431	1,371	-5%	-9%
HOV2	272	277	298	2%	10%
HOV3	62	53	56	-15%	-10%
HOV4+	22	25	29	14%	32%
WT	1944	1,893	1,915	-3%	-1%
DT	794	775	840	-2%	6%
WC	30	19	29	-37%	-3%
DC	1	0	1	-100%	0%
Taxi	763	762	869	0%	14%
Non-Mot	149	143	151	-4%	1%
Purpose: School					
SOV	278	270	281	-3%	1%
HOV2	1540	1,650	1,698	7%	10%
HOV3	1104	1,151	1,245	4%	13%
HOV4+	409	429	433	5%	6%
WT	4224	4,851	5,062	15%	20%
DT	283	279	344	-1%	22%
WC	12	5	13	-58%	8%
DC	4	6	4	50%	0%
Taxi	24	15	22	-38%	-8%
Non-Mot	6834	7,426	7,744	9%	13%
SchBus	2047	2,313	2,339	13%	14%

Table 6-20 Numbers of Outbound Journeys by Purpose and Mode in LIRR (cont'd)

Purpose: University					
SOV	105	99	90	-6%	-14%
HOV2	80	81	80	1%	0%
HOV3	32	22	25	-31%	-22%
HOV4+	7	8	4	14%	-43%
WT	1406	1,406	1,450	0%	3%
DT	782	729	740	-7%	-5%
WC	212	167	154	-21%	-27%
DC	0	0	0	~	~
Taxi	873	918	1,003	5%	15%
Non-Mot	402	380	392	-5%	-2%
Purpose: Maintenance					
SOV	9580	10,542	10,791	10%	13%
HOV2	6233	6,212	6,474	0%	4%
HOV3	1239	1,329	1,315	7%	6%
HOV4+	729	720	784	-1%	8%
WT	9247	9,710	9,942	5%	8%
DT	181	174	186	-4%	3%
WC	4730	4,794	4,734	1%	0%
DC	26	39	33	50%	27%
Taxi	1444	1,517	1,460	5%	1%
Non-Mot	17571	19,194	19,780	9%	13%

Table 6-20 Numbers of Outbound Journeys by Purpose and Mode in LIRR (cont'd)

Purpose: Discretionary					
SOV	3457	3,539	3,754	2%	9%
HOV2	2076	2,151	2,201	4%	6%
HOV3	1473	1,460	1,499	-1%	2%
HOV4+	659	732	738	11%	12%
WT	3457	3,819	3,963	10%	15%
DT	103	115	95	12%	-8%
WC	445	455	455	2%	2%
DC	0	1	2	~	~
Taxi	4389	4,502	4,472	3%	2%
Non-Mot	9124	10,665	10,906	17%	20%
Purpose: At Work					
SOV	493	598	517	21%	5%
HOV2	510	578	520	13%	2%
HOV3	208	211	245	1%	18%
WT	34	34	36	0%	6%
Taxi	367	417	397	14%	8%
Non-Mot	1525	1,870	1,526	23%	0%

Table 6-21 Mode Shares of Outbound Journeys in the Base Scenario in JFK, Flushing, and LIRR

Mode	Flushing	JFK	LIRR
Purpose: Work – Low Income			
SOV	10%	21%	8%
HOV2	14%	19%	15%
HOV3	1%	2%	1%
HOV4+	1%	1%	1%
WT	46%	40%	52%
DT	4%	3%	6%
WC	8%	2%	4%
DC	2%	6%	0%
Taxi	1%	0%	1%
Non-Mot	13%	6%	12%
Purpose: Work – Medium Income			
SOV	23%	37%	21%
HOV2	6%	8%	6%
HOV3	1%	2%	1%
HOV4+	1%	1%	0%
WT	46%	36%	50%
DT	5%	4%	6%
WC	2%	1%	1%
DC	1%	2%	0%
Taxi	6%	6%	6%
Non-Mot	9%	5%	8%

Table 6-21 Mode Shares of Outbound Journeys in the Base Scenario in JFK, Flushing, and LIRR (cont'd)

Purpose: Work – High Income			
SOV	27%	37%	27%
HOV2	6%	6%	5%
HOV3	1%	2%	1%
HOV4+	0%	1%	0%
WT	32%	25%	35%
DT	14%	10%	14%
WC	1%	1%	1%
DC	1%	2%	0%
Taxi	15%	15%	14%
Non-Mot	3%	2%	3%
Purpose: School			
SOV	1%	2%	2%
HOV2	9%	14%	9%
HOV3	6%	9%	7%
HOV4+	2%	3%	2%
WT	25%	23%	25%
DT	1%	0%	2%
WC	0%	2%	0%
DC	0%	1%	0%
Taxi	0%	0%	0%
Non-Mot	42%	28%	41%
Sch-Bus	12%	19%	12%

Table 6-21 Mode Shares of Outbound Journeys in the Base Scenario in JFK, Flushing, and LIRR (cont'd)

Purpose: University			
SOV	2%	4%	3%
HOV2	2%	4%	2%
HOV3	1%	2%	1%
HOV4+	0%	0%	0%
WT	29%	38%	36%
DT	15%	9%	20%
WC	14%	3%	5%
DC	3%	5%	0%
Taxi	24%	32%	22%
Non-Mot	10%	3%	10%
Purpose: Maintenance			
SOV	19%	33%	19%
HOV2	10%	18%	12%
HOV3	2%	3%	2%
HOV4+	1%	2%	1%
WT	13%	13%	18%
DT	0%	0%	0%
WC	14%	6%	9%
DC	1%	1%	0%
Taxi	2%	2%	3%
Non-Mot	38%	22%	34%

Table 6-21 Mode Shares of Outbound Journeys in the Base Scenario in JFK, Flushing, and LIRR (cont'd)

Purpose: Discretionary			
SOV	15%	21%	14%
HOV2	8%	13%	8%
HOV3	6%	9%	6%
HOV4+	2%	4%	3%
WT	13%	9%	14%
DT	0%	0%	0%
WC	1%	1%	2%
DC	0%	0%	0%
Taxi	16%	12%	17%
Non-Mot	38%	31%	36%
Purpose: At Work			
SOV	16%	19%	16%
HOV2	16%	16%	16%
HOV3	6%	8%	7%
WT	1%	0%	1%
Taxi	12%	13%	12%
Non-Mot	48%	43%	49%

6-5-2 Inbound Journeys by Purpose and Mode

The numbers of inbound journeys by purpose and mode for Flushing, JFK, and LIRR are shown in Tables 6-22, 6-23, and 6-24. In general, after adding 10,000 jobs in Flushing and JFK, we observe increases in work journeys by all type of modes for the three income groups. The only exception is LIRR. Very little increase is observed for work journeys.

We do not observe much change in the number of inbound work journeys after adding 10,000 people in the three selected locations. For non-work journeys, very little change was observed after adding 10,000 jobs in Flushing, JFK, and LIRR. This may be unreasonable, job increases in one area will likely stimulate other retail businesses (e.g., delis, coffee shops). One interesting phenomenon relates to the mode shares for inbound and outbound work journeys. As we discussed in Section 6-5-1, transit is more likely or equally likely to be used in outbound work journeys for people living in Flushing, JFK, and LIRR. However, for people who work in Flushing, JFK, and LIRR, private vehicles are more likely to be used than transit.

Table 6-22 Number of Inbound Journeys by Purpose and Mode in Flushing

Purpose: Work – Low Income					
mode	**Base**	**EMP_ Flushing**	**POP_ Flushing**	**(EMP-Base)/Base**	**(POP-Base)/Base**
SOV	637	854	643	34%	1%
HOV2	555	628	536	13%	-3%
HOV3	55	69	57	25%	4%
HOV4+	26	36	31	38%	19%
WT	516	606	499	17%	-3%
DT	21	25	22	19%	5%
WC	34	39	31	15%	-9%
DC	32	34	36	6%	13%
Taxi	7	20	10	186%	43%
Non-Mot	518	619	536	19%	3%

Table 6-22 Number of Inbound Journeys by Purpose and Mode in Flushing (cont'd)

Purpose: Work – Medium Income					
SOV	11,563	14,295	11,501	24%	-1%
HOV2	2,801	3,470	2,742	24%	-2%
HOV3	661	868	699	31%	6%
HOV4+	244	303	241	24%	-1%
WT	3,843	4,727	3,795	23%	-1%
DT	197	237	161	20%	-18%
WC	143	202	172	41%	20%
DC	221	221	235	0%	6%
Taxi	903	1,233	932	37%	3%
Non-Mot	3,914	4,321	3,991	10%	2%
Purpose: Work – High Income					
SOV	3,140	3,833	3,170	22%	1%
HOV2	584	715	579	22%	-1%
HOV3	142	183	132	29%	-7%
HOV4+	66	103	58	56%	-12%
WT	265	307	251	16%	-5%
DT	25	51	28	104%	12%
WC	26	32	29	23%	12%
DC	99	107	93	8%	-6%
Taxi	379	461	363	22%	-4%
Non-Mot	199	224	228	13%	15%

Table 6-22 Number of Inbound Journeys by Purpose and Mode in Flushing (cont'd)

Purpose: School					
SOV	373	366	322	-2%	-14%
HOV2	1,876	1,894	2,009	1%	7%
HOV3	1,290	1,287	1,437	0%	11%
HOV4+	461	488	505	6%	10%
WT	4,467	4,377	4,755	-2%	6%
DT	304	295	331	-3%	9%
WC	8	15	13	88%	63%
DC	113	98	133	-13%	18%
Taxi	13	9	13	-31%	0%
Non-Mot	8,713	8,697	9,836	0%	13%
SchBus	2,726	2,730	2,778	0%	2%
Purpose: University					
SOV	63	81	64	29%	2%
HOV2	57	53	64	-7%	12%
HOV3	32	22	30	-31%	-6%
HOV4+	2	9	2	350%	0%
WT	603	586	589	-3%	-2%
DT	1	0	1	-100%	0%
WC	6	7	6	17%	0%
DC	2	0	0	-100%	-100%
Taxi	679	686	660	1%	-3%
Non-Mot	373	379	401	2%	8%

Table 6-22 Number of Inbound Journeys by Purpose and Mode in Flushing (cont'd)

Purpose: Maintenance					
SOV	14,040	14,067	14,537	0%	4%
HOV2	7,749	7,703	7,989	-1%	3%
HOV3	1,556	1,609	1,650	3%	6%
HOV4+	847	855	857	1%	1%
WT	6,865	6,685	7,013	-3%	2%
DT	57	63	71	11%	25%
WC	169	160	189	-5%	12%
DC	1	1	3	0%	200%
Taxi	942	905	898	-4%	-5%
Non-Mot	26,580	26,747	29,092	1%	9%
Purpose: Discretionary					
SOV	4,841	4,938	5,070	2%	5%
HOV2	2,717	2,664	2,790	-2%	3%
HOV3	1,781	1,792	1,854	1%	4%
HOV4+	811	860	811	6%	0%
WT	2,031	2,185	2,137	8%	5%
DT	81	74	75	-9%	-7%
WC	193	199	186	3%	-4%
DC	20	21	21	5%	5%
Taxi	2,263	2,267	2,373	0%	5%
Non-Mot	13,888	14,043	15,681	1%	13%

Table 6-22 Number of Inbound Journeys by Purpose and Mode in Flushing (cont'd)

Purpose: At Work					
SOV	848	805	957	-5%	13%
HOV2	885	901	945	2%	7%
HOV3	386	384	429	-1%	11%
WT	28	34	28	21%	0%
Taxi	731	693	750	-5%	3%
Non-Mot	2,539	3,043	2,502	20%	-1%

Table 6-23 Number of Outbound Journeys by Purpose and Mode in JFK

Purpose: Work – Low Income					
Mode	**Base**	**EMP_JFK**	**POP_JFK**	**(EMP-Base)/Base**	**(POP-Base)/Base**
SOV	227	439	234	93%	3%
HOV2	188	313	181	66%	-4%
HOV3	17	31	21	82%	24%
HOV4+	9	10	6	11%	-33%
WT	110	208	98	89%	-11%
DT	4	8	4	100%	0%
WC	14	17	12	21%	-14%
DC	10	24	9	140%	-10%
Taxi	1	3	8	200%	700%
Non-Mot	75	143	83	91%	11%

Table 6-23 Number of Outbound Journeys by Purpose and Mode in JFK (cont'd)

Purpose: Work – Medium Income					
SOV	3442	6,489	3,446	89%	0%
HOV2	814	1,523	807	87%	-1%
HOV3	170	382	183	125%	8%
HOV4+	63	136	71	116%	13%
WT	865	1,605	856	86%	-1%
DT	42	84	46	100%	10%
WC	16	40	21	150%	31%
DC	42	89	36	112%	-14%
Taxi	237	496	236	109%	0%
Non-Mot	1030	1,419	1,015	38%	-1%
Purpose: Work – High Income					
SOV	868	1,662	889	91%	2%
HOV2	162	291	171	80%	6%
HOV3	42	84	41	100%	-2%
HOV4+	13	36	18	177%	38%
WT	56	102	50	82%	-11%
DT	13	18	6	38%	-54%
WC	6	8	7	33%	17%
DC	18	33	19	83%	6%
Taxi	95	170	89	79%	-6%
Non-Mot	85	82	73	-4%	-14%

Table 6-23 Number of Outbound Journeys by Purpose and Mode in JFK (cont'd)

Purpose: School					
SOV	300	299	350	0%	17%
HOV2	1777	1,786	1,977	1%	11%
HOV3	1237	1,194	1,194	-3%	-3%
HOV4+	423	451	466	7%	10%
WT	3147	3,152	3,336	0%	6%
DT	272	263	290	-3%	7%
WC	3	1	2	-67%	-33%
DC	33	41	32	24%	-3%
Taxi	9	9	9	0%	0%
Non-Mot	3413	3,516	4,612	3%	35%
SchBus	2199	2,192	2,382	0%	8%
Purpose: University					
SOV	47	40	38	-15%	-19%
HOV2	38	26	32	-32%	-16%
HOV3	14	16	15	14%	7%
HOV4+	4	0	2	-100%	-50%
WT	238	246	226	3%	-5%
DT	0	0	0	#DIV/0!	#DIV/0!
WC	1	2	1	100%	0%
DC	0	0	0	#DIV/0!	#DIV/0!
Taxi	365	385	368	5%	1%
Non-Mot	81	77	110	-5%	36%

Table 6-23 Number of Outbound Journeys by Purpose and Mode in JFK (cont'd)

Purpose: Maintenance					
SOV	7160	7,104	7,953	-1%	11%
HOV2	3914	3,878	4,340	-1%	11%
HOV3	793	748	889	-6%	12%
HOV4+	423	414	485	-2%	15%
WT	2780	2,825	3,069	2%	10%
DT	41	31	28	-24%	-32%
WC	41	42	58	2%	41%
DC	0	0	1	#DIV/0!	#DIV/0!
Taxi	383	382	411	0%	7%
Non-Mot	7118	7,063	8,572	-1%	20%
Purpose: Discretionary					
SOV	2457	2,541	2,743	3%	12%
HOV2	1381	1,362	1,496	-1%	8%
HOV3	905	904	1,023	0%	13%
HOV4+	442	419	476	-5%	8%
WT	802	857	907	7%	13%
DT	38	23	29	-39%	-24%
WC	37	26	33	-30%	-11%
DC	7	2	5	-71%	-29%
Taxi	1100	1,041	1,166	-5%	6%
Non-Mot	5150	5,033	6,211	-2%	21%

Table 6-23 Number of Outbound Journeys by Purpose and Mode in JFK (cont'd)

Purpose: At Work					
SOV	283	244	234	-14%	-17%
HOV2	263	237	276	-10%	5%
HOV3	106	111	112	5%	6%
WT	5	5	8	0%	60%
Taxi	199	193	197	-3%	-1%
Non-Mot	698	1,176	783	68%	12%

Table 6-24 Numbers of Inbound Journeys by Purpose and Mode in LIRR

Purpose: Work – Low Income					
Mode	**Base**	**EMP_ JFK**	**POP_ JFK**	**(EMP-Base)/Base**	**(POP-Base)/Base**
SOV	435	421	371	-3%	-15%
HOV2	364	345	360	-5%	-1%
HOV3	31	34	35	10%	13%
HOV4+	16	17	17	6%	6%
WT	323	335	318	4%	-2%
DT	14	14	17	0%	21%
WC	42	37	47	-12%	12%
DC	27	32	26	19%	-4%
Taxi	8	5	11	-38%	38%
Non-Mot	236	282	298	19%	26%

Table 6-24 Numbers of Inbound Journeys by Purpose and Mode in LIRR (cont'd)

Purpose: Work – Medium Income					
SOV	6,965	6,980	6,913	0%	-1%
HOV2	1,673	1,632	1,676	-2%	0%
HOV3	404	400	392	-1%	-3%
HOV4+	161	145	152	-10%	-6%
WT	2,315	2,337	2,341	1%	1%
DT	135	110	112	-19%	-17%
WC	143	161	175	13%	22%
DC	203	225	186	11%	-8%
Taxi	574	608	553	6%	-4%
Non-Mot	2,340	2,289	2,395	-2%	2%
Purpose: Work – High Income					
SOV	1,823	1,854	1,900	2%	4%
HOV2	338	332	311	-2%	-8%
HOV3	88	86	74	-2%	-16%
HOV4+	51	42	49	-18%	-4%
WT	150	138	159	-8%	6%
DT	27	19	32	-30%	19%
WC	23	40	32	74%	39%
DC	82	86	77	5%	-6%
Taxi	214	224	192	5%	-10%
Non-Mot	164	129	133	-21%	-19%

Table 6-24 Numbers of Inbound Journeys by Purpose and Mode in LIRR (cont'd)

Purpose: School					
SOV	255	256	243	0%	-5%
HOV2	1,446	1,410	1,475	-2%	2%
HOV3	1,004	978	1,070	-3%	7%
HOV4+	369	351	370	-5%	0%
WT	3,587	3,617	3,599	1%	0%
DT	224	248	272	11%	21%
WC	16	19	12	19%	-25%
DC	77	83	86	8%	12%
Taxi	12	10	8	-17%	-33%
Non-Mot	6,802	6,802	7,057	0%	4%
SchBus	2,021	2,025	2,032	0%	1%
Purpose: University					
SOV	269	279	256	4%	-5%
HOV2	189	194	191	3%	1%
HOV3	88	99	87	13%	-1%
HOV4+	13	9	12	-31%	-8%
WT	2,337	2,318	2,316	-1%	-1%
DT	2	1	3	-50%	50%
WC	22	17	16	-23%	-27%
DC	1	1	3	0%	200%
Taxi	2,336	2,360	2,385	1%	2%
Non-Mot	522	515	528	-1%	1%

Table 6-24 Numbers of Inbound Journeys by Purpose and Mode in LIRR (cont'd)

Purpose: Maintenance					
SOV	11,037	11,095	11,108	1%	1%
HOV2	6,075	6,136	6,165	1%	1%
HOV3	1,174	1,191	1,221	1%	4%
HOV4+	672	691	644	3%	-4%
WT	5,849	5,631	5,881	-4%	1%
DT	62	69	55	11%	-11%
WC	147	159	176	8%	20%
DC	2	3	1	50%	-50%
Taxi	706	717	662	2%	-6%
Non-Mot	19,081	18,804	19,674	-1%	3%
Purpose: Discretionary					
SOV	3,887	3,793	3,900	-2%	0%
HOV2	2,215	2,117	2,234	-4%	1%
HOV3	1,405	1,452	1,455	3%	4%
HOV4+	655	661	711	1%	9%
WT	1,770	1,727	1,872	-2%	6%
DT	84	66	65	-21%	-23%
WC	185	181	171	-2%	-8%
DC	19	22	11	16%	-42%
Taxi	1,882	1,846	1,918	-2%	2%
Non-Mot	10,498	10,415	10,676	-1%	2%

Table 6-24 Numbers of Inbound Journeys by Purpose and Mode in LIRR (cont'd)

Purpose: At Work					
SOV	491	517	532	5%	8%
HOV2	582	486	512	-16%	-12%
HOV3	217	235	219	8%	1%
WT	11	28	28	155%	155%
Taxi	398	420	411	6%	3%
Non-Mot	1,478	1,542	1,427	4%	-3%

6-6 Change in Mean Trip Length by Purpose

Table 6-25 shows average trip lengths[13] by purpose in LIRR, Flushing, and JFK for each of the three scenarios. On average, most of the trip lengths remain the same regardless scenarios. The only change that is larger than 10% is for journey at work after we add 10,000 jobs in JFK. Theoretically, after putting 10,000 additional people or jobs in one area, we would expect an increase in the total number of journeys while the mean trip length may not change significantly. Therefore the results are consistent with our expectations.

[13] Note that a journey in BPM consists of a sequence of trips.

Table 6-25 Trip Lengths by Purpose (miles)

LIRR					
	Base	**Emp**	**Pop**	**(Emp-Base)/Base**	**(Pop-Base)/Base**
Work -Low income	10.78	10.58	10.27	-1.86%	-4.73%
Work - Medium income	10.03	10.18	9.87	1.50%	-1.60%
Work - High income	15.4	14.87	14.99	-3.44%	-2.66%
Work all	12.07	11.88	11.71	-1.60%	-2.98%
School	2.99	3.05	2.86	2.01%	-4.35%
University	6.61	6.57	6.47	-0.61%	-2.12%
Maintenance	3.89	3.85	3.77	-1.03%	-3.08%
Discretionary	3.94	3.97	3.82	0.76%	-3.05%
At work	4.03	4.02	3.9	-0.25%	-3.23%
Flushing					
	Base	**Emp**	**Pop**	**(Emp-Base)/Base**	**(Pop-Base)/Base**
Work -Low income	13.07	13.33	12.12	1.99%	-7.27%
Work - Medium income	10.9	11.12	10.68	2.02%	-2.02%
Work - High income	17.7	17.37	16.91	-1.86%	-4.46%
Work all	13.89	13.94	13.24	0.36%	-4.70%
School	2.45	2.45	2.32	0.00%	-5.31%
University	5.98	5.97	6.08	-0.17%	1.67%
Maintenance	3.69	3.67	3.59	-0.54%	-2.71%
Discretionary	3.78	3.75	3.6	-0.79%	-4.76%
At work	4.55	4.1	4.71	-9.89%	3.52%

Table 6-25 Trip Lengths by Purpose (miles) (cont'd)

JFK					
	Base	**Emp**	**Pop**	**(Emp-Base)/Base**	**(Pop-Base)/Base**
Work -Low income	13.15	14	13.02	6.46%	-0.99%
Work - Medium income	10.88	11.48	10.85	5.51%	-0.28%
Work - High income	13.28	13.89	13.79	4.59%	3.84%
Work all	12.44	13.12	12.55	5.52%	0.94%
School	3.52	3.51	3.17	-0.28%	-9.94%
University	8.02	8.15	7.82	1.62%	-2.49%
Maintenance	5.22	5.22	5.13	0.00%	-1.72%
Discretionary	4.93	4.89	4.66	-0.81%	-5.48%
At work	4.92	3.51	4.52	-28.66%	-8.13%

6-7 Change in Trip Lengths by Mode

Table 6-26 shows the average trip lengths by mode and percentage change in the different scenarios. Only a few types of trips show much change in mean trip length, such as drive to transit after adding 10,000 jobs in Flushing and drive alone after adding 10,000 jobs in JFK. Conceptually, we would expect trip lengths not to change much after adding 10,000 people or jobs in one area. These results are consistent with our expectations. For those modes which do show a change in trip length, further investigation is required to understand the phenomenon. It is possible that work trips tend to be longer than trips for other purposes. Therefore, if the number of jobs in an area is increased, it would be reasonable to expect the number of work trips to increase resulting in an increase in average trip length. The modes most likely to be taken to work – drive alone and drive to transit – could reasonably be expected to show an increase in average length.

Table 6-26 Trip Lengths by Mode

LIRR					
	Base	**Emp**	**Pop**	**(Emp-Base)/Base**	**(Pop-Base)/Base**
Drive alone	9.74	9.72	9.44	-0.21%	-3.08%
HOV2	7.53	7.52	7.52	-0.13%	-0.13%
HOV3	6.94	7.07	6.91	1.87%	-0.43%
HOV4+	6.77	6.8	6.62	0.44%	-2.22%
Walk to Transit (WT)	5.8	5.76	5.72	-0.69%	-1.38%
Drive to Transit (DT)	5.37	5.29	5.14	-1.49%	-4.28%
Walk to Commuter Rail (WC)	20.27	20.37	18.97	0.49%	-6.41%
Drive to Commuter Rail (DC)	32.37	32.11	30.27	-0.80%	-6.49%
Taxi	7.73	7.79	7.58	0.78%	-1.94%
Non-Mot	0.73	0.74	0.71	1.37%	-2.74%
SchBus	5.39	5.6	5.44	3.90%	0.93%

Table 6-26 Trip Lengths by Mode (cont'd)

Flushing					
	Base	**Emp**	**Pop**	**(Emp-Base/Base**	**(Pop-Base)/Base**
Drive alone	10.63	11.1	10.22	4.42%	-3.86%
HOV2	8.12	8.34	7.97	2.71%	-1.85%
HOV3	7.33	7.47	7.23	1.91%	-1.36%
HOV4+	7.51	7.34	7.12	-2.26%	-5.19%
Walk to Transit (WT)	5.36	5.48	5.32	2.24%	-0.75%
Drive to Transit (DT)	4.58	4.96	4.59	8.13%	0.07%
Walk to Commuter Rail (WC)	15.74	16.31	16.47	3.62%	4.64%
Drive to Commuter Rail (DC)	31.64	34.3	31.82	8.41%	0.57%
Taxi	7.8	8.3	7.69	6.41%	-1.41%
Non-Mot	0.6	0.59	0.59	-1.67%	-1.67%
SchBus	4.65	4.62	4.39	-0.65%	-5.59%

Table 6-26 Trip Lengths by Mode (cont'd)

JFK					
	Base	**Emp**	**Pop**	**(Emp-Base/Base**	**(Pop-Base)/Base**
Drive alone	9.49	10.48	9.32	10.43%	-1.79%
HOV2	7.59	8.15	7.56	7.38%	-0.40%
HOV3	6.85	7.23	6.96	5.55%	1.61%
HOV4+	6.95	7.26	6.77	4.46%	-2.59%
Walk to Transit (WT)	6.2	6.56	6.19	5.81%	-0.16%
Drive to Transit (DT)	4.9	4.82	4.34	-1.63%	-11.43%
Walk to Commuter Rail (WC)	20.56	19.43	18.46	-5.50%	-10.21%
Drive to Commuter Rail (DC)	31.98	34.93	32.44	9.22%	1.44%
Taxi	8.9	9.33	8.6	4.83%	-3.37%
Non-Mot	0.55	0.56	0.53	1.82%	-3.64%
SchBus	5.41	5.56	5.13	2.77%	-5.18%

6-8 Mean Highway Speeds

Table 6-27 shows mean highway speeds (measured as the average travel length from one TAZ to another TAZ divided by travel time) in the base and modified scenarios in LIRR, Flushing, and JFK. In all three scenarios, mean highway speed is stable. No discernable change pattern can be identified.

Table 6-27 Mean Highway Speeds in Three Scenarios

	Mean	Std.	Min	Max
LIRR				
Base	37.74	12.53	11.16	62.17
Pop	37.96	12.48	11.08	62.44
Emp	37.71	12.71	11.01	62.44
Flushing				
Base	39.33	12.45	10.96	62.65
Pop	39.09	12.47	11.36	62.86
Emp	39.36	12.50	11.36	62.85
JFK				
Base	39.56	11.36	11.31	61.77
Pop	39.53	11.25	11.30	61.77
Emp	38.78	11.46	11.33	61.77

7 Conclusions

In this study, we attempt to address whether the BPM model outputs are responsive to changes in policy, socioeconomic and demographic characteristics, and changes in population and employment. The results of this study can provide useful information to policy analysts and makers at MPOs. Three types of initiatives that would incur changes in auto ownership and consequent travel behavior are designed. They are: 1) changes in the level of transit fare (Case study A1); 2) increases in neighborhood median income (Case study A2); and 3) increases in population and employment in areas with different levels of transit accessibility (Case study A3). The results from the modified scenarios are compared against those in the base scenario to determine whether model responses are consistent with theoretical expectations or empirical evidence. In particular, we compare the results of different scenarios in terms of auto ownership, number of journeys (inbound and outbound), trip lengths, mode share, and highway speed. The conclusions pertaining to the results from three case studies are summarized separately in the following paragraphs.

7-1 Case Study A1

Case study A1 investigates how changes in transit fare may affect travel outcomes. We find that car ownership is insensitive to the change of transit fare, which is consistent with our expectation. In those parts of the region where it is unnecessary and expensive to own and use an automobile, even a substantial fare reduction is not sufficient to influence many households to increase their car ownership. Conversely, in those parts of the region where automobiles are a necessity, even a substantial fare reduction will not make households give up their automobiles.

When transit fare increases, the numbers of journeys by transit (drive to commuter rail, walk to commuter rail, drive to transit, walk to transit) decrease, while the numbers of journeys by other modes (auto, taxi, school bus) increase. This is consistent with theoretical expectation regarding utility maximization. With an increased transit fare, some transit users may switch mode choice.

For highway speeds, the general trend is that speeds decline as transit fares rise. This result suggests that, as fares increase, a shift will occur from transit modes to highway modes, leading to greater congestion and lower average speed throughout the highway network.

7-2 Case Study A2

Case study A2 investigates how income may affect travel outcomes. Median incomes of the neighborhoods (represented by TAZs) with incomes less than or equal to \$25,000 (in 1990 dollars) are increased to \$50,000 and \$80,000 in the two modified scenarios. We observe that auto ownership increases as median income increases. TAZs located in Manhattan experienced the least increase. The literature shows that households living in areas with higher transit accessibility are less likely to own vehicles than those living in areas not well served by transit. The results are consistent with the literature.

When income increases, more journeys are made by auto and fewer journeys are made by transit. The largest increase in auto journeys is in the suburbs and the smallest one is in Manhattan. This result is also in accordance with our expectations.

Overall, the total journey productions remain stable when income increases. This is a slightly unexpected result, as one would expect a positive relationship between income and trip production. The numbers of journeys by purpose show different trends. When the median household income increases, the total number of work journeys increases. Other journeys that experience an increase include journeys for maintenance, discretionary and at work. School and university journeys witness a drop, probably because students are generally a lower-income group.

In terms of trip length, we observe that higher income households have longer commute distances, which is consistent with the results from a number of empirical studies (Taylor and Ong, 1995; Johnston, 2000; McLafferty and Preston, 1997; Sastry et al., 2002). Finally, no discernable change pattern can be identified for mean highway speed change when income increases.

7-3 Case Study A3

Case study A3 investigates how an increase in population and employment in areas with different levels of transit accessibility may result in different travel outcomes. We examine the impacts of adding 10,000 jobs or people in one of the three locations: Jamaica LIRR hub, the area approximately 6 miles north in Flushing, and the area approximately 6 miles south around JFK airport.

No significant changes in average auto ownership levels by household are observed after adding 10,000 jobs or people in LIRR, Flushing, and JFK. This is consistent with our expectations. Auto ownership is highly affected by income, which is not affected by the addition of 10,000 people in an area, since we assume the added population possesses the same income distribution as the existing population.

We also do not observe much change in mode share, after adding 10,000 people or jobs in these three locations. The changes in the number of journeys originating from each of these three locations (outbound journeys) exhibit different patterns in the three locations. After adding 10,000 jobs in these locations, the total number of outbound journeys remains stable. However, after adding 10,000 people in these locations, the total number of outbound journeys (journeys from these locations) experiences an increase, most of which are for school, university, maintenance, and discretionary activities. The changes in the number of inbound journeys (journeys to these locations) tell different stories from the outbound journeys. After adding 10,000 jobs in JFK and Flushing (LIRR is the exception, which we will discuss in following paragraph), the total number of inbound journeys experiences an increase, most of which are for work purposes. After adding 10,000 people in these areas, inbound journeys to these areas for school, university, maintenance, or discretionary activities also increase.

One surprising result is the change in work journeys to LIRR after adding 10,000 jobs. We find the number of work journeys remains stable regardless of the increased job opportunities. This contradicts our expectations. Since the BPM model successfully reports the increases in the number of work journeys to JFK and Flushing after adding 10,000 jobs, the mystery why this is not happening to LIRR remains to be investigated.

Adding 10,000 jobs or people in LIRR, Flushing, or JFK seems not to affect trip lengths significantly for most purposes and modes. There are some modes which show changes in trip lengths, further investigation is required to understand the phenomenon. The modes which show an increase in trip length tend to be those which are most likely to be used for trips to work and work trips tend to be longer than those for other purposes. Finally no discernable change pattern can be identified for highway speed.

7-4 Summary

The general conclusion from this study is that the results of the sensitivity analysis of NYBPM model are mostly consistent with our expectations. They provide support to the model and validate its applications in a variety of projects in the New York Metropolitan Region. However, unexpected results do appear. After adding 10,000 jobs in one area, we expect to observe an increase of work journeys to this area. We do observe this pattern in Flushing and JFK. However, we do not observe the expected increases in LIRR. This calls for future investigations.

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