Drive-Access Transit: A Regional Analytical Framework

by

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ABSTRACT

A framework for analyzing drive-access transit at a regional level is developed in this research. This framework is intended primarily for in-house use by regional transit agencies, yet has implications for the regional community at large. This framework serves as a tool for understanding and communicating what drive-access transit is, its significance to the regional transportation system, and the behavior of regional drive-access transit users. This framework emphasizes the utilization of GIS technology for both the analysis and communication of information relating to drive-access transit. It also focuses scholarly attention on drive-access transit in general and on kiss-and-ride in particular.

The framework is applied to the Boston Metropolitan Region as a primary case study. Data from a variety of regional sources are utilized. GIS technology is used to visualize drive-access transit's regional significance in terms of total ridership, mode share, and drive-access transit facilities' utilization rates. A sub-mode choice model and a station choice model are developed for both rapid transit and commuter rail drive-access transit users. These models depend on the CTPS Emme/2 network model and the MIT Boston Regional TransCAD network model for the rapid transit and commuter rail models, respectively. The MIT Boston Regional TransCAD network model is intended to support on-going research, beyond the scope of this thesis, as part of the collaborative MBTA/MIT transit research effort.

As a result of the application of the analytical framework, key findings and specific recommendations related to drive-access transit are reported for the Boston Metropolitan Region. Key findings include:

- approximately 46 percent of the region's population lives beyond normal walking distance of transit services;
- drive-access transit accounts for 69 percent of overall commuter rail ridership and 18 percent of overall rapid transit ridership;
- drive-access transit accounts for 31 percent of rapid transit ridership in the 50 outermost rapid transit stations;
- the MBTA has a significant investment in station parking facilities, parking fees represent an increasingly important part of the MBTA's operating budget, and parking fees in the region evidence no spatial correlation;
71 percent of regional parking facilities reached 85 percent of capacity, many of them filling hours prior to the departure of the last morning peak train;

commuter rail station choice is dependent on access distance, parking capacities, and transit fares, with travelers willing to drive an extra mile if it results in savings of more than $0.90 on their transit fare;

rapid transit station choice is dependent on access distance, parking capacities, and transit trip distances, with travelers willing to drive an extra mile if it results in transit trip reduction of more than 3.3 miles;

sub-mode choice for both commuter rail and rapid transit users depends on access distance, automobile availability, and the number of vehicles owned per capita.

Recommendations included:

- Making drive-access transit and particularly kiss-and-ride a regional transportation priority.
- Utilizing the developed models temporarily for modeling proposed services and policy implications until better data can be collected for a more complete model estimation process.
- Promote drive-access transit, especially kiss-and-ride and carpooling to parking stations, through targeting responsive demographic markets, and through incentives such as reduced transit fares, parking fees, or preferential parking treatment.

This research is an important initial step in assessing drive-access transit and its regional transportation role.

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1. INTRODUCTION

This thesis develops a process, or framework, for analyzing drive-access transit at a regional level. This exploratory research is intended as a potential tool to help transit agencies and other regional transportation stake-holders better understand drive-access transit, its regional significance, and its regional user behavior. Once developed, this framework is then applied to the Boston Metropolitan Region as a primary case study. Drive-access transit's significance is assessed using a variety of methods. GIS technology is used to convey information in its geographical context. Models and tools are developed to describe drive-access transit behavior in the region. Conclusions and recommendations specific to the region are suggested.

1.1 MOTIVATION

A problem facing many regions in the United States is how to increase transit accessibility in a fiscally constrained climate. In an ideal situation with no monetary limitations, transit services would be universally distributed and everyone would have quick, safe, and convenient transit access. However, in the real world, regions are often faced with difficult decisions regarding transit accessibility. In areas with populations dense enough to support the economical provision of a dense transit network, people are often able to walk to nearby transit services and thereby easily access the system. However, as areas grow less dense and transit services become less cost-effective to operate, walking to transit often becomes a difficult proposition.

Several accessibility alternatives to walk-access transit exist. These alternatives include encouraging bicycle access to stations and/or providing bus feeder services. However, in automobile-dependent areas or areas prone to inclement weather, the number of riders willing to use a bicycle to access transit is likely to remain small. Providing bus feeder service may also be difficult due to the additional cost involved. There must also be sufficient concentration of demand, in terms of minimum residential density, along the bus feeder route to make it a viable alternative. Finally, riders may not choose to use the bus feeder service due to both the additional transfer involved and the negative perceptions of bus reliability and service quality.

Another alternative to walk-access transit is drive-access transit. Many individuals, both within the transit industry and without, are unfamiliar with what exactly is meant by drive-access transit. Therefore, a specific and clear definition of drive-access transit is essential to its proper analysis. Unfortunately, a clear definition of drive-access transit is rarely directly stated in the literature. There are, however, a wide range of implicit definitions. There is variation concerning whether or not drive-access transit refers only to individuals who drive to and park at transit stations or also includes people driven to and dropped off at transit stations. There is variation concerning whether or not drive-access transit is considered a mode of travel by itself or is rather a sub-mode of transit. There is variation concerning which transit vehicle types drive-access transit refers to. It is apparent that drive-access transit is concerned with commuter rail, but less apparent is whether or not drive-access transit also includes automobile access to rapid transit, light rail, buses, ferries, etc. In fact, there appear to be as many variations in the
definition of drive-access transit as there are variations in the way park-and-ride is spelled. (Spelling variations include: park-and-ride, Park & Ride, park n' ride, Park and Ride, etc.)

Much of this variation in defining drive-access transit may be explained by the variation between regional transit systems. For example, a high-income region with high levels of automobile dependence and an abundance of free, available parking might experience little or no kiss-and-ride usage. In such a case, the time and effort of identifying and analyzing such a small percentage of the total transit ridership would not be cost-effective. Still other regions might not use certain transit vehicle types. Therefore, regional differences might account for this varying perception of drive-access transit.

In this research, drive-access transit is defined to be any transit access mode where an automobile is used to access a transit station. This primarily refers to transit riders who choose to drive to a station, park their automobile, and access the transit station (park-and-ride); and transit riders that are driven to a station, dropped-off, and then access the transit station (kiss-and-ride). It is considered a viable access mode for all transit vehicle types, including: commuter rail, rapid transit, buses, and ferries.

Drive-access transit is vitally important to regional transportation systems for several reasons. First, drive-access transit is important to transit agencies since it represents choice riders; individuals who, by definition, have access to a car, yet who choose to use transit for (at least) a portion of their trip. In order for transit agencies to be able to fulfill their mandate of providing mobility to a regional population in a cost-effective manner, they must be able to attract choice riders. A better understanding of drive-access transit on a regional level will allow transit agencies to make investments and set policies that best take advantage of opportunities and behaviors specific to their region.

Furthermore, drive-access transit represents an opportunity for long-term ridership growth. As travelers become more familiar with transit facilities, they may be more likely to utilize transit for a greater percentage of their daily trips. As ridership grows over the long-term, this represents additional revenue and political support for the transit agency.

Drive-access transit also helps support transit access in low-density areas, where transit service tends to be less economic, by consolidating transit demand. Transit agencies operate in a fiscally constrained climate. As providing a public good, they must compete with other public goods and services for public attention and funding. By consolidating demand, transit agencies are able to provide more service in a cost-effective manner. This allows them to demonstrate proper and responsible stewardship over the public money they have received and make a stronger case for receiving additional future funds.

Related to proper financial stewardship is the fact that transit agencies have invested a considerable amount of money in drive-access transit-related facilities. Parking lots and parking garages, parking management systems, drop off carousels, parking enforcement, security systems, etc. all represent a significant investment on the part of transit agencies. Also, if parking fees are assessed at these transit stations, drive-access transit might represent a source of considerable additional revenue for the transit agency. By focusing attention on scholarly drive-access transit research, agencies ensure that they might receive a proper return
on their investment. Transit agencies are also better capable of deciding whether or not future investment in such facilities is warranted and/or desirable.

Additionally, as transit agencies better understand drive-access transit users and their behavior, they will be better equipped to meet their mobility needs. They will be able to more effectively target specific services and programs. Agencies will also be better able to predict demand for future or alternative transit services.

Drive-access transit is not only of importance to the transit agency, but is of importance to the regional community at large. To start, since transit agencies are funded in large part by tax dollars, the public has the right to monitor transit agency policies and investments. Therefore, for the same financial reasons mentioned above, the general public also has an interest in seeing drive-access transit perform effectively.

Next, drive-access transit has significant impact on local communities. In highly automobile-dependent communities, drive-access transit might be the only alternative to automobile travel. Another impact is that if parking capacity at transit stations is insufficient to meet drive-access transit demand, the excess vehicles may overflow into surrounding neighborhoods. Also, large drive-access transit facilities might decrease congestion on the overall network, but might increase local congestion in the area immediately surrounding the station. Clearly, understanding drive-access transit is of importance to both regional transit agencies and local communities.

Furthermore, there are several current trends that will make drive-access transit even more important in the future. For example, continued urban sprawl in the United States will only contribute to drive-access transit's significance. Many transit stations, especially those stations located on the outer urban edge or in suburban areas, are strongly dependent on automobiles for station access. Due to both urban form and urban sprawl, potential transit riders in these areas find accessing the station by foot or by bus to be extremely time-consuming, inconvenient, and even dangerous. Cities prone to inclement weather also are more likely to see potential passengers prefer to utilize automobiles to access transit. As the urban form continues to become less dense, drive-access transit can serve the increasingly important role of consolidating demand and allow increased access in automobile-dependent areas.

Another trend that will increase drive-access transit's importance is the rising costs of providing parking infrastructure. As it becomes increasingly expensive to build and maintain parking infrastructure, information to support proper decision-making becomes increasingly important. Properly modeling drive-access transit behavior will allow for more accurate predictions of ridership demand and demand for parking facilities. This in turn can be used in the planning and pricing of transportation services. This information should assist decision-makers in making choices that are both socially responsible and economically sound.

Increased road congestion will also contribute to drive-access transit's future importance. As congestion increases, utilizing transit for at least a portion of their trip will become more attractive to automobile users. Lack of available parking and/or high parking costs at trip destinations, specifically in central business districts, will also increase the attractiveness of drive-access transit. Care will need to be taken to ensure that sufficient capacity exists to meet
this increase in drive-access transit usage and that this increased usage will not create significant negative ramifications for the surrounding community.

One current trend that is of considerable concern is the relatively little scholarly attention that has been focused on drive-access transit, particularly in regard to kiss-and-ride. The apparent academic neglect of drive-access transit in general, and kiss-and-ride specifically, is surprising. For so important a topic to receive so little attention is disconcerting and should be remedied. Technology exists and is readily available, especially Geographic Information Systems (GIS) technology, to perform detailed analysis of both demographic and spatial information. In addition, this technology is capable of visualizing and presenting this information in a manner useful to transit agency personnel and the general public.

Consistent with this lack of academic attention is the scarcity of information available concerning drive-access transit. For example, information concerning drive-access transit is not included in the National Transit Database (NTD, 2005), nor in the American Public Transportation Factbook (APTA, 2004). This scarcity of information and data further compounds the difficulty in exploring and examining drive-access transit at the regional level.

Another difficulty in examining drive-access transit is the need for specific tools and models capable of assessing drive-access transit’s regional significance and explaining regional drive-access transit behavior. There are essentially two traveler decisions of key importance to understanding drive-access transit behavior. The first decision involves station choice. What factors influence an individual’s decision to drive to a station further away from his/her origin? The second decision is what mode of drive-access transit does an individual select. In other words, how does a traveler choose between park-and-ride and kiss-and-ride? In real life, these choices are often made simultaneously. However, in modeling these decisions, developing a decision-making hierarchy is necessary. As a result of this abstraction and the afore-mentioned scarcity of data, developing useful models is fraught with difficulties.

This research is designed to be exploratory in nature. More than anything else, it develops an analytical framework as a way of looking at drive-access transit. It then applies this framework to a real-world case study in an attempt to identify the many difficulties and limitations endemic to such an analysis. The case study analyzes the available information, develops several models specific to drive access transit, makes preliminary conclusions based on this limited data, and makes recommendations about how to obtain better information and apply it in the future. In addition, it serves as an example of the many difficulties inherent to such an analysis, allowing future analysts the ability to streamline this process to better suit their regional needs.

1.2 OBJECTIVES

This research, although exploratory, is meant to help focus academic attention on drive-access transit, especially the kiss-and-ride access mode. The objectives of this research, therefore, are to:

- Develop a framework for analyzing drive-access transit at a regional level.
- Apply this analytical framework to the Boston Metropolitan Region as a case study.
Utilize Geographic Information System (GIS) technology to facilitate analysis and communication of drive-access transit research.

Develop sub-mode choice and station choice models as tools for understanding drive-access transit behavior in the Boston Metropolitan Region.

Provide recommendations and possible future directions regarding drive-access transit policies, practices, and planning.

1.3 Research Method

This thesis seeks to develop a framework to analyze drive-access transit on a regional level. This framework will serve as a tool for conducting regional analyses and presenting the results of these analyses to inform transit agency decision-makers as well as the general public.

The transportation literature is explored to document prior findings on behavior and the potential benefits of drive-access transit. Demographic information and past surveys are also referenced. A critique of GIS technology and transit network models is summarized. Previous definitions and mathematical models of drive-access transit behavior are consulted.

A regional analytical framework is then developed that answers fundamental questions regarding drive-access transit. Care is taken to ensure that the framework is both easy to interpret and easy to communicate to a variety of audiences. An emphasis is placed on regional adaptation of the framework.

The regional analytical framework is then applied to the Boston Metropolitan Region as a primary case study. The background of the region and information on the relevant transportation agencies are presented. GIS technology is utilized to facilitate analysis of various drive-access transit related data sets. This geographic representation of the data allows for the recognition of spatial patterns and relationships, or sometimes more importantly, the absence of spatial patterns and relationships. A regional transportation network model recently developed as part of a collaborative effort of the MIT Transit Research Group is used to gain consistent and accurate trip component information. Using multinomial logit estimation, a sub-mode choice model and a station choice model are developed for both commuter rail and rapid transit travelers.

Finally, key findings, conclusions, and recommendations specific to the study region are reported. Limitations of the framework and its real-world application are discussed.

1.4 Thesis Structure

This thesis has six chapters including this first introductory chapter.

Chapter 2 reviews prior literature and background information relevant to this thesis. Studies and reports documenting drive-access transit benefits, demographics and surveys are
summarized. GIS technology and transit network models are also discussed. Previous attempts at modeling drive-access transit behavior are documented.

The regional analytical framework for drive-access transit research is developed in Chapter 3. Guidelines are presented and emphasis is placed on regional adaptation.

The analytical framework developed in Chapter 3 is then applied to the primary case study in Chapter 4. The background of the Boston Metropolitan Region is presented. The collection, management, coordination, and implementation of various data represented considerable effort on the part of the researcher. Regional drive-access transit significance is assessed by presenting this data in its geographical context using GIS technology.

Chapter 5 documents the development of tools to better analyze the region's drive-access transit behavior. The development of a regional transportation network model, a collaborative effort of the MIT Transit Research Group, is presented as part of on-going research outside the scope of this thesis. The development of models to explain regional drive-access transit behavior is also presented.

Research conclusions are presented and discussed in Chapter 6. General recommendations as well as recommendations specific to the case study region are offered, including possible additional applications of this research. Opportunities for further related research directions are proposed.
2. LITERATURE AND BACKGROUND

This chapter describes the mechanics and benefits of drive-access transit's two modes: park-and-ride and kiss-and-ride. The demographics of drive-access transit users are also described. Previous studies concerning geographic information systems, transit network representations, and information visualization are reviewed. Prior work on mode choice and station choice models is summarized. Park-and-ride and kiss-and-ride marketing studies are analyzed.

2.1 DRIVE-ACCESS TRANSIT BENEFITS

Drive-access transit is typically separated into two access modes, namely park-and-ride and kiss-and-ride. The benefits of these modes are considered separately in Sections 2.1.1 and 2.1.2 below.

2.1.1 Park-and-Ride Benefits

The literature includes several studies that examine the benefits of park-and-ride service. The results of these studies have sometimes been conflicting. For example, some studies conclude that park-and-ride strategies reduce overall traffic congestion, while others claim park-and-ride might actually increase congestion by creating traffic bottlenecks as drivers access stations further upstream. As a result of such conflicting claims, there is still some debate as to what the aims of park-and-ride should be, how it should be implemented, and what benefits result from park-and-ride.

Parkhurst (1996) asserts that park-and-ride "can have one or more differing aims, namely:

- To maintain or increase the number of economically-desirable trips to the city centre,
- To avoid using valuable city centre land for car parks and access roads
- To reduce congestion, noise and pollution." (Parkhurst 1996)

However, Parkhurst (1996) further asserts that from his study of short-range park-and-ride schemes in nine United Kingdom cities, the actual benefits accruing from implementation of park-and-ride are mostly economic. Specifically, Parkhurst cites these cities' ability to retain a relatively smaller supply of parking spaces in their economically valuable central business districts and higher vehicle occupancy rates allowing more trips to the city center without the expected levels of accompanying traffic congestion as the key demonstrable benefits of park-and-ride. Parkhurst could find no correlation between park-and-ride implementation and reductions in overall traffic congestion or pollution. Instead, Parkhurst found "new traffic emerging to fill vacated capacity" (Parkhurst, 1996). This study would suggest that park-and-ride policies, while not reducing total congestion and pollution, may provide additional accessibility and significant economic benefits, without the same levels of accompanying congestion and pollution that one would expect in the absence of park-and-ride.
In contrast, Wang et al (2004) summarized several studies conducted in North America and the United Kingdom that concluded that park-and-ride facilities were in fact effective in reducing traffic congestion. This study also cited a parking demand study conducted in Hong Kong that showed promising results in using park-and-ride facilities to help manage travel demand.

What can be agreed is that park-and-ride helps support transit access in lower-density areas by consolidating transit demand. Additionally, drive-access transit is of vital importance to transit agencies as a source of potential long-term ridership growth, given current suburban development patterns. With most transit systems operating as radial networks, park-and-ride strategies maintain the viability of the region’s downtown central business districts (CBD) by concentrating demand and allowing more individuals the opportunity to access the CBD by transit. Drive-access transit users represent choice riders: individuals with access to an automobile who choose to use transit for at least a portion of their trip. Attracting these choice riders may allow transit agencies to increase ridership, revenue, and most importantly perhaps, regional public and political support.

2.1.2 Kiss-and-Ride Benefits

Kiss-and-ride service offers many of the same benefits as park-and-ride services, along with the added bonus of not requiring investment in parking infrastructure at transit stations.

As transit ridership increases, many areas face severe parking shortages at, and around, transit stations. In these cases parking can often overflow into surrounding neighborhoods. Also, as more drivers vie for a limited number of available parking spaces, traffic congestion around these transit stations increases. Parking fees and resident parking restrictions can help manage this demand, but also run the risk of driving potential riders to choose a non-transit alternative (no pun intended).

Additionally, the cost of supplying parking infrastructure is continually increasing. Parking spaces are expensive to build and maintain. The cost of a suburban parking space in a structure has been estimated at up to $23,600, excluding maintenance costs (Shoup, 1997). One can assume that the cost for parking spaces in urban areas, where available space is at a premium, would be even greater. A range of parking construction cost estimates generated by the Institute of Transportation Engineers is shown in Table 2-1. It is important to note that these estimates are likely significantly lower than the actual cost of constructing parking spaces in the dense urban areas most likely to have extensive transit networks.
Table 2-1. Construction Costs of Parking

<table>
<thead>
<tr>
<th>Range</th>
<th>Surface</th>
<th>Above-ground Structured</th>
<th>Subsurface Structured</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lower Limit</td>
<td>$1,000</td>
<td>$8,000</td>
<td>$20,000</td>
</tr>
<tr>
<td>Upper Limit</td>
<td>$3,000</td>
<td>$15,000</td>
<td>$35,000</td>
</tr>
</tbody>
</table>

Source: ITE Parking Generation (McCourt, 2004).

Given the financial constraints that most transit agencies are continually facing, the capital-intensive strategy of continually building and maintaining additional parking infrastructure at transit stations is difficult at best. Of course this depends on specific transit agency revenues and the relative cost of drive-access transit alternatives.

Kiss-and-ride is a strategy that allows transit modes to increase their ridership and market share without the expense of supplying additional parking spaces. Instead of having to park, the transit rider is driven to the station by another person, dropped off, and then picked up on the return trip.

In addition, kiss-and-ride allows travelers to avoid the need for second or third cars per household. By allowing travelers in the same household to travel together, fewer automobiles per household are necessary. This could result in fewer automobiles on the road and positively affect regional vehicle-hours and vehicle-miles traveled. Reduced automobile ownership can also help create a more transit-oriented populace and a less automobile dependent urban form.

Unfortunately the kiss-and-ride strategy is rarely considered in the literature. No studies or reports were found that deal specifically with the benefits of kiss-and-ride access. It is regrettable that more research into the viability and benefits of kiss-and-ride access has not been performed. Hopefully this research will assist in correcting this omission in the research literature.

2.2 Drive-Access Transit Surveys and Demographics

Many factors may play an important role in the behavior and decision-making processes of drive-access transit users and this section reviews available surveys and demographic studies conducted on drive-access transit users.

2.2.1 Park-and-Ride Surveys and Demographics

The Transit Capacity and Quality of Service Manual (2003) summarized the results of a number of park-and-ride user surveys in Sacramento, Northern Virginia, Chicago, Seattle and Phoenix. The Manual cites the following key characteristics of park-and-ride users:
Park-and-ride users are choice users,
Park-and-ride users have significantly higher incomes than local bus riders,
The majority of park-and-ride users are commuters to the area's central business district (CBD),
Parking at the users' ultimate destination is expensive,
Most users originally discovered park-and-ride facilities because they could see them from their regular commute routes.

The Manual also stated that the most successful park-and-ride lots focused on making automobile access as convenient and quick as possible. The Manual further suggested that the transit portion of the patron's trip should, in most cases, "represent more than 50% of the total journey time from the patron's home to final destination" (Transit Capacity and Quality of Service Manual, 2003).

The Chicago Transit Authority (CTA) has invested in detailed marketing surveys of its park-and-ride facility users. These surveys help throw light on the demographics and behavior of typical drive-access transit users.

In September and October of 1993, the CTA conducted surveys at its Cumberland park-and-ride facility. According to these surveys the two primary reasons users indicated for selecting drive-access transit was "expensive parking at destination" and "faster than driving all the way". Approximately 68% of the parking facility users were traveling to work, and 63% indicated that they were regular commuters. 89% of the survey respondents drove alone to the station, 9% were in two-occupant vehicles, and 2% were in vehicles with 3 or more persons. The average drive time to the station was determined to be 16.5 minutes. (CTA O'Hare, 1994)

In late 1998, a customer satisfaction survey was conducted at all of the CTA's park-and-ride facilities. These surveys indicated that the primary reasons why parking facility users use park-and-ride are because it is the fastest way to make their trip, they dislike driving, expensive parking costs at their trip destination, and they dislike expressways. These surveys also concluded that the typical park-and-ride facility user was likely to be female, between the ages of 35 and 50, from households with 2-4 persons, two or more cars, and with incomes of $50,000 or more. These surveys also indicated that while most users lived within 10 miles of the parking facility, some traveled 50 miles or more. (CTA Blue Line, 1998) (CTA Red, Yellow..., 1998) (CTA Summary, 1998)

Hendricks and Outwater (1998) conducted a study in King County, Washington and found that only 5 percent of the trips reported were non-work trips. Additionally, their surveys indicated that parking facility capacity affected both mode choice and station choice decisions. Finally, they found that parking costs, both at the trip destination and at the drive-access transit station significantly affected drive-access behavior.

Johnson and Resnick (2000), conducted a survey at commuter rail facilities focusing on how parking availability might affect traveler's mode choice. Their results indicated that 58 percent of the survey respondents indicated that if the parking lot at their intended station was full, they
would simply park further from the station. Another 24 percent indicated that they would drive to another station, while 18 percent of the respondents stated that they would merely drive the entire distance to their final destination. These results indicate that parking availability had no effect on mode or station choice for more than half of the survey respondents. These findings cast doubt on the effectiveness of utilizing Intelligent Transportation Systems (ITS) technology to provide drivers with real-time parking information. However, the usefulness of these findings is limited by the lack of information given about the areas surrounding these stations. In other words, these findings might be related to the relative cost and availability of parking in the neighborhoods surrounding the commuter rail station. These findings are also limited by their focus only on current transit users; non-users may behave differently.

Additionally, anecdotal evidence suggests that both the mode choice and station choice decisions are affected by several difficult-to-quantify factors. For example, weather may influence station choice as travelers travel further distances to park at stations with covered parking lots. Trip-chaining may also influence mode choice and station choice as travelers must first run various errands either prior to accessing the transit station or following their egress on the return trip. Time of departure may influence drive-access transit behavior as parking availability might be limited later in the day. Time of return may also influence behavior as some stations may be less attractive or perceived as being less safe after dark. The vehicle being driven may also influence behavior, as those with more expensive vehicles may choose to be dropped off or may choose to drive further to a station perceived to have more secure parking.

### 2.2.2 Kiss-and-Ride Surveys and Demographics

Consistent with the little research conducted on kiss-and-ride, there is little information available regarding the demographics of kiss-and-ride users.

Schank (2002) examined the demographics of kiss-and-ride patrons as part of a New York City commuter rail network case study. Commuter rail stations with very different kiss-and-ride characteristics were studied to determine what role, if any, station design, parking problems, and station area demographics played in encouraging kiss-and-ride access. Schank determined that although the direction of causality was uncertain, station factors such as short-term parking availability, adequate curb space, parking enforcement, and separate kiss-and-ride and park-and-ride areas might all contribute to encouraging kiss-and-ride access. Schank’s demographic analysis indicated that factors such as income were not significant in determining the success of kiss-and-ride at nearby stations. The only demographic factor found to be significant was the percentage of females in the population.

As in park-and-ride, anecdotal evidence indicates that kiss-and-ride is also strongly affected by difficult to quantify factors. In addition to the factors listed above, kiss-and-ride also must be concerned about the trip made by whoever dropped off the kiss-and-ride passenger. It is often assumed that this person is most likely a member of the same household as the kiss-and-ride user and that his/her trip is merely to the station and back home again. However, this assumption has never been substantiated in the literature. It is certainly plausible that a large portion of kiss-and-ride passengers may be dropped off by someone on his/her way to a destination outside the home. In this case, the secondary destination would obviously have a
major impact on station choice. These activity-based decisions could present the greatest analytical difficulty, since relatively few transportation agencies have activity-based survey information or models.

2.2.3 Surveys and Demographics Summary

In summary, the literature suggests several factors that may be correlated with drive-access transit usage. These factors can be classified into four main types: demographics, trip and station characteristics, and other factors.

Demographic factors that may influence drive-access transit behavior include:

- gender,
- income,
- automobile ownership,
- household size, and
- age.

Trip characteristics that influence drive-access transit behavior may include among other things:

- times and costs associated with both the automobile and transit portions of the trip,
- trip purpose,
- time of departure, and
- the time of the return trip.

Station characteristics that influence drive-access transit behavior may include:

- station parking capacity,
- station parking costs,
- whether or not the station parking is covered or not,
- lighting around the station, and
- the overall perceived station security.

Finally, other factors that influence drive-access transit behavior may include:

- weather,
- trip-chaining,
- network characteristics, and
- vehicle characteristics.
2.3 **Analytical Background**

This section provides the analytical background for this research. It reviews both geographic information systems and network representation background material. This section also discusses previous attempts to model drive-access transit behavior.

2.3.1 **Geographic Information Systems and Network Representation**

A Geographic Information System (GIS) is “a class of software tools dedicated to the storage and display of spatially referenced information” (Grayson, 1993). GIS technology is used to process and visualize spatial and demographic data, for example transportation networks. Central to GIS technology are relational database systems which process and manage the data. Relational databases organize data in tables and permit a user to generate new tables or queries based on a query language. In addition to processing this data, the visualization of this data allows for superior spatial analysis and better communication of research results. In particular, this visualization of data allows one to recognize and analyze spatial patterns that are not otherwise obvious.

GIS allows for spatial queries, which has tremendous benefits when analyzing choice behavior. Rather than being forced to rely on individual perceptions of travel times, distances, and costs, much of this information can be obtained through these spatial queries. Also, analyzing the spatial aspects of demographic information is greatly facilitated.

GIS technology has proven attractive to transit agencies for many reasons. “The ability to manage large amounts of spatial data holds obvious appeal to transit agency staff ranging from planners who are interested in the spatial distribution of jobs and population to signage crews who maintain thousands of individual bus-stop signs” (Busby, 2004). As a result, most transit agencies have implemented GIS technology of one form or another. However, the effectiveness of this GIS utilization has sometimes been called into question. For example, Grayson (1993) cites Clarke who laments the failure of GIS to expand analytic capabilities, claiming GIS is focused on “technological issues relating to data storage, retrieval, and display” arguing that GIS needs to move “from being an end in itself to becoming an enabling device within a broader decision making environment. This will involve practitioners developing a much broader knowledge of the problems and processes that decision makers are involved in, as well as the incorporation of more powerful, value adding, analytical techniques.” (Clarke, 1990). Although Clarke’s remarks are nearly fifteen years old, one could argue that his criticism remains valid today.

One of the objectives of this thesis is to utilize GIS technology to facilitate both the analysis of drive-access transit behavior and the communication of the analysis’ results. There are several existing software packages that merge representations of transit and road networks with GIS databases. TransCAD, one of the software packages used for analysis in this thesis, was the first such integrated package and uses the trademark “Transportation GIS Software” to describe itself (Caliper, 2002). Competing transportation demand models such as Emme/2, which was
used for a portion of this thesis’ analysis, and Cube have established similar relationships with GIS packages, specifically ENIF and Arc-View, respectively.

The use of GIS technology for these analytical and communicative purposes helps refute Clarke’s criticism that GIS utilization is too focused on data storage and retrieval. Additionally, it should make the results of this research more accessible to all interested parties and stakeholders.

2.3.2 Drive-Access Transit Models

Modeling drive-access transit is inherently difficult. First, one must specify a mode choice model that accurately represents the variables that influence a traveler’s choice of drive-access transit versus other modes. The definition of what constitutes a mode varies. Many agencies classify park-and-ride and kiss-and-ride as separate modes or as sub-modes of transit (Hull, 1998), while other agencies lump them together as drive-access transit (Harrington, 2003). Still other agencies further classify park-and-ride into sub-modes of drive alone park-and-ride and carpool park-and-ride (CTA Blue Line, 1999). Also, the price of parking at the trip destination is a significant factor in the decision to use drive-access transit yet many models do not have reliable parking cost information available (Busby, 2004). Parking availability is extremely difficult to model effectively due to its dependency on station capacity, time of day, and station attractiveness. All of these attributes vary across stations and thus affect the choice of station and the choice of mode. Additionally, modeling drive-access to transit is further complicated by its asymmetry – a vehicle is available on the access end of a transit trip but not on the egress end (Busby, 2004). Furthermore, many models can lead to the unrealistic behavior of driving most of the distance from the origin, parking, and taking a short transit trip to the destination (Busby, 2004). The literature describes several different methods to overcome these modeling difficulties.

In a very early study, Boyce (1973) considered several models for determining station choice among suburban park-and-ride stations. One model consisted of creating hyperbolic shaped market areas, or catchment areas, based on the following deterministic station choice equation:

\[ D_A - D_B = K \]  \hspace{1cm} (2-1)

where \( D_A \) and \( D_B \) are the straight line distances to stations A and B from a point on the market area boundary and \( K \) is the ratio of the difference in the fixed cost of using station A and B to the cost per mile of accessing either station. Boyce used a variety of variables to estimate both the fixed cost and the cost per mile of accessing each station, but concluded that the best deterministic model of station choice could explain only about 60% of observed behavior. Boyce found that the simple deterministic models, i.e. assigning all travelers to the nearest station, performed as well as more elaborate deterministic models. Boyce next developed a probabilistic model using a probit model form. This model allowed travelers to choose between the two closest stations based on cost differentials. This probabilistic model performed marginally better than the deterministic model, but was still simplistic in its choice behavior modeling assumptions.
The Transit Capacity and Quality of Service Manual (2003) indicates that, traditionally, demand for drive-access has been based on the demographics of a fixed and defined market area. These market areas for park-and-ride services often reflect parabolic, circular, or semi-circular catchment areas. This methodology is simplistic and fails to capture much of the complexity of drive-access transit users’ mode and station choice behavior.

Kastrenakes (1988) used a multinomial logit model to develop a station choice model for NJ (New Jersey) Transit’s commuter rail stations. This model sought to allow the agency to forecast rail ridership at specific stations, thereby allowing NJ Transit to fine-tune its park-and-ride program and make strategic decisions regarding possible future service improvements, including the provision of new services on existing rail lines, the creation of new rail lines, the creation of new stations on existing rail lines, and the extension of existing commuter rail lines. While not specifically dealing with drive-access transit, this mode was included in the overall station ridership. This model’s parameters consisted of access time to the station, a dummy variable indicating whether or not the station was located in the same community as the trip origin, the frequency of service at the station, and a generalized cost that included transit fare and a value of in-vehicle travel time based on the average hourly wage rate. The results of this model concluded that access time and frequency of service had the strongest influence on station choice. This model suffered from several limitations, including the neglect of station characteristics such as parking capacity and cost and the neglect of all demographic factors.

Fan et al (1993) analyzed station catchment areas and adopted a nested logit approach for estimating mode choice and station choice behavior in the Toronto (Ontario) region. Their analysis indicated that for commuter rail travelers, 98.8 percent of the observed trip makers used either the closest or second closest access station. For subway travelers, 98 percent of observed trip makers chose one of the five closest access stations. They estimated two nested models, one with the station choice as the upper-level decision and access mode as the lower-level decision and the other model with the inverse nest structure. Their results suggested that the more appropriate model structure was with access mode as the upper-level decision and station choice the lower-level decision. The model parameters for the station choice decision included transit in-vehicle travel time, transit out-of-vehicle time, transit fare, service frequency, automobile travel time, a natural logarithm of the number of parking spaces, and a dummy variable indicating whether or not a station was the station closest to the trip origin. The model parameters for the mode choice decision included age, gender, income level, and access time and distance. The absence of a transportation network model in this study indicates that the researchers relied exclusively on the stated trip characteristics of the survey respondents. These stated trip characteristics are likely to be inaccurate and biased by individual preferences and perceptions.

Blain (1997) suggested modeling drive-access transit station choice by using a logit model that combined the utility of the auto portion of the trip with the utility of the transit portion of the trip. The parameters used in determining these utilities were simplistic, only auto time, auto distance, transit time and transit fare were examined, and were presumably used only for demonstration purposes. This procedure was undoubtedly superior than assigning all drive-access transit trips to the nearest station or neglecting park-and-ride altogether, however, this model has several major limitations. The first is that the utility of the auto portion of a drive-access trip is assumed
Chapter 2

to be the same as the utility of an automobile only trip. The same can be said of the utilities of
the transit portion of the drive-access transit trip. A traveler, planning on transferring from
automobile to transit at some point in their trip, may value the automobile portion or transit
portion of that trip differently than someone choosing to use one mode exclusively. Also, the
variables used in the logit model were simplistic, completely ignoring station characteristics such
as parking capacity and parking costs.

Hendricks and Outwater (1998) used a logit intermediate choice model to explicitly model the
drive-access transit station choice decision as a discrete choice in a multi-step decision
process. In addition to calculating utilities for the automobile and transit portion of the trips, a
station utility, based on parking costs and a security rating, was also calculated. These three
utilities were then combined in a logit model to describe station choice behavior. Additionally,
an iterative process was suggested where a dummy variable was introduced as a multiplier that
increased with each iteration to reflect the added disutility of using a station where demand was
approaching capacity. While this model adds some realism to the model and considers station
characteristics as a factor in the station choice decision, it suffers from many of the same
drawbacks as previous methods. It also treats the utilities for the auto and transit portions the
same as the utilities for those modes when used exclusively. Furthermore, a perceived security
rating is hard to quantify and highly variable from traveler to traveler.

Hull (1998) suggested several refinements to the logit model for park-and-ride usage for the
greater Vancouver (British Columbia) region. In this model it was suggested that adding a
weight to the auto disutility would prevent more “distant origins” from being over-represented in
the model. An iterative method using a dummy variable to represent the additional penalty or
“shadow price” (Hull, 1998) of choosing to park at a station nearing capacity, was also included.
Finally, a bias or penalty was included for park-and-ride trips to ensure that trips from nearby
origins were not over-predicted. Again this method suffers from limitations. Weights and biases
are introduced to make the model “behave.” These weights and biases seem subjective and
somewhat arbitrary. A better understanding of the factors that make these weights and biases
necessary would be preferable.

Busby (2004), while attempting to use an accessibility metric to compare planning alternatives,
encountered the above mentioned problems of asymmetric trip generation and unrealistic travel
behavior. His solution involved arbitrarily designating a 10 mile radius around the CBD where
drive-access transit was not a viable mode choice. Additionally, drive-access trips were limited
to only those with automobile trip portions of less than 15 minutes, and these automobile drive
times were heavily weighted in his generalized cost function. Busby recognized that these
modeling techniques were arbitrary, yet due to insufficient information concerning the factors
affecting drive-access transit, a more rigorous solution was impossible.

Hoogendoorn-Lanser (2005) examined modeling travel behavior in multi-modal networks
primarily for Dutch cities. Her work concluded that activity-based models that took into account
traveler’s knowledge of the transport system, the road network near the traveler’s origin, and the
availability of home-based transport modes provided model performance superior to traditional
directional models. However, directional models provide the opportunity to establish which trip
attributes contribute to the disutility of transferring to another mode. This modal transfer is
essential to modeling drive-access transit. Her research also concluded that drive-access to rail represented a relatively small share of Dutch rail travelers. She therefore recommended that traditional data collection techniques might need to be altered in order to better screen information on this travel mode.

In summary, while several attempts have been made to model drive-access transit behavior, and progress has been made, many limitations can still be observed. First, there has been little use of GIS technology in some of these studies. The application of transportation GIS software should allow for better analysis of the survey data and provide more accurate information on both the origin to transit station and the transit station to destination portions of the drive-access transit trip. Second, most of the attempted models neglect to consider demographic, station, and trip factors as model parameters. Third, most of these studies are directed specifically at commuter rail. While drive-access transit is obviously of tremendous importance to suburban commuter rail operators, drive-access transit can also play a vital role at urban rapid transit stations and their surrounding communities. Finally, these models neglect kiss-and-ride. With kiss-and-ride’s potential for long-term ridership growth in a fiscally constrained climate, a clearer understanding of kiss-and-ride’s underlying behavior is long overdue.

2.4 Literature and Background Summary

This chapter has described the literature and analytical background of this research effort. The literature suggests that the benefits associated with park-and-ride include: relative reductions in traffic congestion and air pollution, the continued economic vitality of central business districts, and the consolidation of transit demand in areas with low population density. Furthermore, kiss-and-ride has the added benefits of needing no additional investment in parking infrastructure at transit stations and contributing to a less automobile-oriented urban form. The literature also suggests several factors correlated with drive-access transit usage. These factors can be organized into four groups: demographics, trip and station characteristics, and other factors. Finally, several previous methods to overcome the inherent difficulties of modeling drive-access transit were reviewed. Many of these models were of limited application due to little use of GIS technology, omission of several important model parameters, focus on only commuter rail, and their neglect of kiss-and-ride.
3. ANALYTICAL FRAMEWORK

In this chapter, a general framework is developed to analyze drive-access transit and its impacts on the region's transportation stakeholders. The overall framework is described in Section 3.1. Section 3.2 discusses methods of assessing drive-access transit's regional significance. Section 3.3 presents several factors, assumptions and techniques useful in modeling drive-access transit behavior. Both the station choice and sub-mode choice models are discussed. These models contribute to a better understanding of drive-access transit behavior, and are perhaps the core elements of this framework. Finally, the chapter finishes with a brief discussion of how this analysis should lead to findings and recommendations that allow decision-makers to better evaluate and select among various drive-access transit related policies and investments.

3.1 OVERALL FRAMEWORK

With little prior research on drive-access transit, especially the kiss-and-ride access mode, the need for an analytical framework becomes obvious. In developing a clear analytical framework, the objective is to be able to address fundamental questions regarding drive-access transit. These fundamental questions include:

- How does drive-access transit contribute to the overall efficiency and effectiveness of a region's transportation system? How significant is this contribution?
- What are the demographics and trip characteristics of typical drive-access transit users?
- What are the factors that influence the decision between drive-access sub-modes, i.e., between park-and-ride and kiss-and-ride?
- What are the factors that influence the drive-access transit station choice decision?

In addition to answering these questions, the ideal analytical framework should produce results that are:

- Easy to interpret. Analytical results should be readily understood by non-technical personnel. These results should also be placed in their correct geographic context.
- Easy to communicate. Analytical results should be presented/communicated in a manner that is easily understood by audiences of varying backgrounds and technical expertise.
- Flexible. It should be applicable to a wide variety of purposes and goals.
- Utilizes data sources efficiently. Data collection and processing is increasingly expensive and time-consuming.

This framework is intended primarily for in-house use by regional transit agencies, yet has implications for the regional community at large. This framework serves as a tool for understanding and communicating what drive-access transit is, its significance to the regional transportation system, and the behavior of regional drive-access transit users. This framework
Chapter 3

emphasizes the utilization of GIS technology for both the analysis and communication of information relating to drive-access transit. In essence, this framework should serve as an example of a possible method of exploring drive-access transit as it relates to any specific region. This framework is shown in Figure 3-1.

Figure 3-1. Analytical Framework

An analysis of drive-access transit begins with an assessment of drive-access transit's regional significance. This entails the collection of available drive-access transit data, the placement of this data into its proper geographic context, and the interpretation of this data. Relevant
information might include: total drive-access transit ridership, mode share, prior investment in facilities and their current utilization, regional accessibility goals, etc. Placing this information in its geographic context is most easily accomplished using some form of GIS technology.

Next, one should consider how to explain and model drive-access transit behavior. As mentioned previously, the two key drive-access transit decisions are 1) station choice and 2) sub-mode choice. Observing regional travel behavior is a difficult task. A method must be developed to ensure that these observations are consistent and accurate. Once a sufficient number of observations are recorded, these observations can be used to estimate sub-mode choice and station choice models.

Both the assessment of drive-access transit’s regional significance and the tools developed to explain drive-access transit behavior, contribute to findings and recommendations specific to the region. These findings are then presented to decision-makers to inform their evaluation and selection of investments, policies, and practices.

3.2 Assessing Drive-Access Transit Significance

Drive-access transit could be regionally significant for many of the same reasons that transit is significant. Transit results in reduced street congestion. It is a more sustainable and environmentally attractive transportation alternative than automobile usage. Transit provides access to economic opportunities in a socially equitable manner. Drive-access transit could be significant since it plays a major role in encouraging individuals to choose transit for at least a portion of their trip.

Quantifying the “significance” of drive-access transit is difficult for many reasons. To begin, there is a scarcity of available information. Data is increasingly expensive to collect and process. Many agencies do not have specific facilities dedicated to drive-access transit. Those agencies that do, often disagree as to the nature of drive-access transit and what does or does not constitute drive-access transit. As a result, drive-access transit data is often difficult to find and once found, is often incomplete.

Despite these difficulties, there are definite methods an agency can employ in order to gain a greater understanding of drive-access transit’s regional significance. The first method is to examine the region’s total transit ridership. This can be accomplished using a comprehensive ridership survey or recent census data. With this information, an agency can get ballpark figures of how many trips are taken within their region daily, what percentage of these trips are by transit, and what percentage of transit trips utilize drive-access. GIS technology is helpful in both analyzing and presenting this information in a straight-forward manner. GIS technology also allows an agency to better understand which areas utilize drive-access transit more than others. These total numbers can act as “back of the envelope" figures to help illustrate drive-access transit’s significance to other travel modes in the region.

In addition to total drive-access transit ridership, it would be significant to assess drive-access transit ridership as part of the total transit mode share. In some cases, transit market share might be small compared to other travel modes. This might be misleading in determining drive-
access transit's regional significance, since although total transit market share may be small, drive-access transit may account for a large portion of that transit market share. Again, GIS technology would be beneficial in analyzing this data and presenting the percentage of drive-access transit compared to other transit access modes.

Both the total and relative drive-access transit numbers should be analyzed by geographical area, transit line, vehicle mode, etc. These analyses are not only helpful in determining drive-access transit's regional significance, but also may assist in refining how the region looks at drive-access transit. For example, should these analyses suggest that drive-access transit plays a negligible role in the provision of bus services, a region may decide not to expend the time and effort to collect and analyze drive-access transit data for buses.

Furthermore, another method to assess drive-access transit's regional significance, would be to analyze the region's investment in drive-access transit facilities. Drive-access transit facilities include: park-and-ride lots, parking garages, drop off facilities, etc. Understanding recent investments in these facilities may help agencies understand how important drive-access transit is from a budgetary standpoint, in terms of investment and operating cost per transit user for instance. Another important aspect is the revenue, if any, that is generated from these drive-access transit facilities. In some transit systems, drive-access transit facilities generate large daily revenues, which might be of special importance given the fiscal crises currently affecting many United States' transit agencies.

In addition to the regional investment in drive-access transit facilities, understanding the current utilization rates of these facilities is also important. High utilization rates indicate that the existing facilities are popular and represent potential for increased ridership and revenue. Also, if drive-access transit facilities are reaching capacity early in the peak period, one can assume that latent demand for these facilities exists. The existence and extent of such latent demand has a significant effect on several transportation policies, including:

- commuter programs,
- transit fare pricing,
- station parking pricing,
- the expansion of existing parking facilities,
- parking enforcement, etc.

Finally, a transit agency must also integrate current regional transportation goals into its assessment of drive-access transit's significance. Future goals or needs might provide drive-access transit with significance that it currently cannot rightly claim. For example, if a region's transportation goals include increasing transit ridership in rural or suburban areas, then drive-access transit might be considered potentially significant, even if current drive-access transit is not.

Determining specific values and performance measures again should be based on the principle of regional adaptation. With regions varying in terms of demographics, urban form, transit network configuration, transit ridership, and regional transportation goals, it is impossible to give
general guidance as to what does or does not constitute “significant” levels of drive-access transit. For example, what a small, poorly funded transit agency might consider a significant investment in drive-access transit facilities might just be a drop in the bucket to a larger, better funded transit agency. Also, the performance measures that a region uses will largely be based on the availability of data that the agency has collected. This follows the logic that if something cannot be properly measured, then it cannot be properly managed. Agencies that can afford comprehensive ridership surveys and market studies will have a larger choice of possible performance measures than those agencies that, due to limited funding or resources are unable to perform such surveys. Therefore, regional adaptation is important when determining the significance of a region’s drive-access transit. Ideally, a transit agency would be able to apply this analytical framework and specifically define what it considers “significant” for its region and why.

3.3 UNDERSTANDING DRIVE-ACCESS TRANSIT BEHAVIOR

An understanding of drive-access transit’s regional significance allows an agency to begin to examine regional drive-access transit behavior. Understanding drive-access transit behavior is perhaps the core of this framework. An understanding of who is choosing to utilize drive-access transit and what factors influence their decisions is necessary for proper demand modeling of alternative transit services. This understanding also helps local stakeholders understand the impacts such proposed services might bring.

The behavior of drive-access transit users is quite different than the behavior of most other transit users. As described previously, this behavior is dependent on four types of factors: demographics, station and trip characteristics, and other factors. These four types of factors interact to influence drive-access transit behavior, and only by examining these factors and modeling their relative impact on drive-access transit user’s decisions, can an agency properly make policy decisions regarding drive-access transit. Examples of each of these four types of factors are shown in Table 3-1.
### Table 3-1. Examples of Drive-Access Transit Behavioral Factors

<table>
<thead>
<tr>
<th>Type of Factor</th>
<th>Examples</th>
</tr>
</thead>
<tbody>
<tr>
<td>Demographics</td>
<td>Age, Gender, Income Level, Household Size, Automobile Availability, Number of Vehicles per Household, Number of Wage-earners per Household, Number of Licensed Drivers per Household</td>
</tr>
<tr>
<td>Station Characteristics</td>
<td>Parking Capacity, Parking Fees, Station Design, Station Environment</td>
</tr>
<tr>
<td>Trip Characteristics</td>
<td>Trip Purpose, Time of Day, Time of Return Trip, Automobile Travel Time, Transit In-Vehicle Time, Transit Wait Time, Transit Fare, Number of Transit Transfers, Transfer Penalties</td>
</tr>
<tr>
<td>Other Factors</td>
<td>Weather Conditions, Trip-chaining Activities, Perceived Station Safety and Security</td>
</tr>
</tbody>
</table>

In order to gain a greater understanding of the relative influence of these factors on drive-access transit in a specific region, information on these factors must be collected. This information may be gleaned from a variety of sources, but the most reliable would be information obtained from a comprehensive transit passenger survey. Admittedly a survey of this type only gives information on passengers currently utilizing drive-access transit and fails to take non-transit users preferences into account. However, understanding current drive-access
transit passengers' behavior is an important first step in understanding the entire drive-access transit market.

From such surveys, information on demographic factors can be determined directly. Additionally, by asking survey respondents to indicate trip purpose, trip time of day, trip origin and destination, as well as their trip's boarding and alighting station, one can utilize GIS technology and transit network models to determine each trip's various trip components and station characteristics. Finally, a section of the survey could be devoted to determining how much, if at all, other factors influence individual drive-access transit decisions.

Furthermore, GIS technology allows an agency to better analyze drive-access transit behavior. For example, one can determine the various catchment areas of the different drive-access transit stations. One can also determine the average automobile access time and distance on a station by station basis. One can compare these access times between park-and-ride and kiss-and-ride users at the same station, to see what difference, if any, exists between sub-modes. This information is helpful in developing models to explain drive-access transit behavior.

With this information, one can utilize demand modeling techniques to develop models which explain drive-access transit behavior. There are two key interrelated decisions that affect drive-access transit behavior: the decision between choosing park-and-ride and kiss-and-ride, and the decision as to which transit station is selected. These two decisions can be modeled as a sub-mode choice model and a station choice model.

The sub-mode choice model attempts to explain which factors influence the choice between park-and-ride and kiss-and-ride. A variety of factors might influence this decision, including:

- Automobile access time and distance: The greater the access time and distance, the more likely a decision-maker is to choose park-and-ride. This assumes that for kiss-and-ride, the person dropping off the drive-access transit user will return to the trip origin, making long access trips less attractive. The initial wait time at the station and the terminal time at the station might also be included as part of this access time.

- Automobile availability: If an individual has little or no access to an automobile, he/she will be more likely to choose kiss-and-ride.

- Parking capacity: The greater the capacity at a station, the more likely someone is to choose park-and-ride.

- Parking fees: As parking fees increase, more individuals will choose kiss-and-ride as a way to avoid them.

- Household size, number of licensed drivers per household and number of vehicles owned per household: Larger households with fewer available automobiles would be more likely to choose kiss-and-ride.

- Age: Younger users and elderly users might be more likely to have someone drop them off.

- Gender: The literature indicates that females are more likely to choose kiss-and-ride than males.
Chapter 3

- **Income level**: Individuals with lower income levels might choose kiss-and-ride as a way to avoid paying parking fees. Conversely, individuals with high income levels are more likely to own an automobile and therefore be more likely to choose park-and-ride.

- **Trip frequency and trip purpose**: Daily commuters traveling to work might prefer the flexibility of park-and-ride rather than regularly needing someone to pick them up on the return trip.

- **Trip time of day**: Trips beginning later in the day might be more likely to be kiss-and-ride as parking availability at many stations becomes limited.

The station choice model attempts to explain which factors influence the choice between various transit stations. A variety of factors might influence this decision, including:

- **Automobile access time and distance**: An individual will, all else being equal, choose the station closest to him/her. Variations of this factor may include some sort of proximity dummy variable, a closest station dummy variable, distance relative to the shortest automobile access distance, etc.

- **Automobile trip cost**: An individual will seek to minimize the cost of accessing the transit station.

- **Transit wait time**: A traveler might drive to a further station if the expected wait time at that station is less.

- **Transit in-vehicle travel time**: A traveler will select a station that helps minimize total trip time, of which transit in-vehicle travel time would be a part.

- **Transit fare**: Again, a traveler might travel further in order to reduce the cost of the transit portion of the trip.

- **Number of transfers and transfer penalties**: A traveler might choose a station based on how direct the transit portion of the trip and how onerous those transfers are deemed to be.

- **Parking capacity**: A station with greater parking capacity might influence a traveler's station choice.

- **Parking fees**: A traveler might travel to a station with lower parking fees.

These lists of variables that might be included in both the sub-mode choice and the station choice drive-access transit models are by no means exhaustive: there are many other variables and factors that may be considered relevant depending on the specific characteristics of the region.

In modeling these decisions, it is clear that both decisions are related. The choice of transit station directly influences an individual's choice between park-and-ride and kiss-and-ride and vice versa. For example, an individual might choose the closest station, which happens to have an abundance of free parking, and therefore choose park-and-ride. Conversely, an individual might have no access to a car and choose kiss-and-ride, and therefore choose a different station since it is easier to access from the freeway. Ideally, one would model both decisions simultaneously. However, this modeling structure is extremely complex, and, to the researcher's knowledge, no such model has ever been successfully estimated.
An alternative would be to attempt to model the two decisions using a nested model structure where one decision acts as an input for the other decision. In such a model, it is unclear which decision would be made first, and therefore both possible nested model structures should be analyzed to see which structure best reflects the regional drive-access transit users’ revealed behavior. Both possible nest structures are shown in Figure 3-2.

**Figure 3-2. Alternative Model Nest Structures**

![Diagram of Nest Structure 1](image)

![Diagram of Nest Structure 2](image)

Another modeling alternative would be to model the two decisions separately. While less realistic than the nested model alternatives, two separate models might still evidence some explanatory power.
In choosing which type of model best fits a region, several guidelines or “rules-of-thumb” are suggested. To begin, an agency should assess its technical and data capacity and resources. Complex simultaneous models might be beyond the region’s current technical abilities. Also, in order to facilitate transparency of calculation, selecting the simplest model that adequately explains real-life drive-access transit behavior is important. Like Occam’s Razor, the simplest solution is often the best. Therefore, if a simple, deterministic model can be demonstrated to be statistically equivalent to a more complex, probabilistic model, selecting the simpler model makes sense.

3.4 DRIVE-ACCESS TRANSIT FINDINGS AND RECOMMENDATIONS

The findings of both the significance assessment and the behavioral analysis should then be summarized and presented in an easily understood format. Based on these findings, recommendations specific to the region should be made in accordance with regional transport goals. These recommendations could include specific policies that should be implemented, the application of the developed models to various projects, etc. It is highly probable that, due to the scarcity of drive-access transit information, these initial recommendations are likely to include better data collection.

With this information in hand, decision-makers at the transit agency and in the community at large can make better informed decisions regarding drive-access transit policies and procedures.

3.5 FRAMEWORK SUMMARY

This chapter has developed a four-step analytical framework for drive-access transit. The first step involves assessing drive-access transit’s regional significance. This should involve analysis of drive-access transit’s total ridership, transit mode share, drive-access transit facilities, investments and revenue, utilization rates, and finally how drive-access transit relates to regional transportation goals and objectives. Again, GIS technology is emphasized throughout the process, both as an analytical tool and as a means of conveying analytical results to a wide and varied audience. The second step of the analytical framework involves gathering information on the factors that influence drive-access transit behavior and then using these factors to develop explanatory models. Behavioral factors were divided into four categories: demographics, station and trip characteristics, and other factors. The third step involves summarizing research findings and developing regionally specific recommendations. Finally, this information would be presented to decision-makers to aid in their evaluation and selection of drive-access transit related policies and investments.
4. THE BOSTON CASE STUDY: DRIVE-ACCESS TRANSIT CHARACTERIZATION AND SIGNIFICANCE

In this chapter, the first step of the analytical framework is applied to drive-access transit in the Boston Metropolitan Region. The case study area and its background are introduced in Section 4.1. The significance of drive-access transit to the region is assessed in several different ways, including: ridership, mode share, facilities and utilization, monetary impacts, and accordance with relevant regional transport goals. This assessment is presented in Section 4.2.

4.1 CASE STUDY BACKGROUND

The study area defined for this case study includes all communities defined as part of the Boston Metropolitan Planning Organization (MPO). This area is referred to as the Boston Metropolitan Region. The communities included in this region are shown in Figure 4-1.

Figure 4-1. Boston Metropolitan Study Region

Source: CTPS Website, Accessed April 2005

The Boston Metropolitan Region was selected as the primary case study for several reasons. To begin, Boston has a long history of transit provision and innovation. Furthermore, the Massachusetts Bay Transportation Authority (MBTA), the foremost transit agency in the region, is a high profile, nationally recognized transit agency. In 2004, the MBTA was ranked the nation's 6th largest mass transit system in terms of passenger miles (APTA, 2004). It also serves a diverse population of approximately 2.6 million people in 175 cities and towns.
To carry out its mission, the MBTA offers a wide range of transportation services including: bus, subway, ferry, streetcar, bus rapid transit, and commuter rail service.

Of particular relevance to this thesis are the MBTA’s rapid transit and commuter rail lines. The MBTA has five major rapid transit lines: the Red, Blue, Green, Orange, and Silver Lines. The Green Line is light rail service, the Silver Line is bus rapid transit service, and the other three lines are subway service. Together these five lines serve 131 stations and have a route length of over 60 miles. A map of these rapid transit lines is shown in Figure 4-2.

Figure 4-2. MBTA Rapid Transit Lines Map

Source: MBTA Website, Accessed April 2005
The MBTA's commuter rail service is also extensive, including 13 lines serving 124 stations and covering over 336 route miles. A map of these commuter rail lines is shown in Figure 4-3.

**Figure 4-3. MBTA Commuter Rail Lines Map**

As stated previously, according to the 2004 Congestion Management Report, the MBTA transit system carries approximately 1,090,000 unlinked trips each weekday. Table 4-1 shows average daily unlinked trip information on the transit system.
Table 4-1. MBTA Daily Unlinked Ridership

<table>
<thead>
<tr>
<th></th>
<th>Approximate Average Daily Ridership</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rapid Transit</td>
<td>630,000</td>
</tr>
<tr>
<td>Green Line</td>
<td>183,000</td>
</tr>
<tr>
<td>Blue Line</td>
<td>50,000</td>
</tr>
<tr>
<td>Orange Line</td>
<td>174,000</td>
</tr>
<tr>
<td>Red Line</td>
<td>223,000</td>
</tr>
<tr>
<td>Silver Line</td>
<td>14,000</td>
</tr>
<tr>
<td>Commuter Rail</td>
<td>110,000</td>
</tr>
<tr>
<td>Commuter Boat (Ferry)</td>
<td>5,000</td>
</tr>
<tr>
<td>Bus</td>
<td>310,000</td>
</tr>
</tbody>
</table>


In the ten years between 1992 and 2002, the daily ridership on the MBTA system increased 9 percent to over one million, mostly due to increases in commuter rail ridership. About one-third of the daily ridership uses buses, approximately 60 percent is on the rapid transit and light rail lines, and 10 percent uses the commuter rail system. (CTPS Congestion Report, 2004)

Working in conjunction with the MBTA is the Central Transportation Planning Staff (CTPS), which "provides technical and policy-analysis support" (CTPS Website, 2005) to the Boston Metropolitan Planning Organization (MPO) and various transportation agencies including the MBTA.

The CTPS Website (2005) describes the agency staff as being, “multidisciplinary and includes transportation analysts, planners, and engineers, as well as other professionals working in the areas of geographic information systems, cartography, graphic design, technical editing, computer systems operation, and administrative services.”

CTPS is responsible for providing a variety of services for the region’s transportation agencies, including: travel modeling and forecasting; transportation planning and analysis; certification activities; and data, maps, and graphics. As part of this work, CTPS has conducted the on-board passenger surveys used in this thesis. Additionally, CTPS has developed a transportation network model of the region using the EMME/2 transportation demand modeling software. The 1995 version of this network was utilized to obtain some of the travel trip information used in this study. The on-board surveys, the EMME/2 model, and the trip information obtained from that model will be described in greater detail in a subsequent chapter of this thesis.

There were several other factors that help make the Boston Metropolitan Region attractive as the primary case study. First, utilizing such a well-known and well-recognized transit system not only allows for proper assessment of the framework’s validity, but allows other agencies to more easily apply the framework. The agency’s wide range of vehicle types also contributes to its attractiveness as a primary case study.
The transit system's predominantly radial network form is also significant. Drive-access transit plays a far more important role in radial networks than in other transit system configurations, since people commuting into the downtown area often only have one viable direct route. The trade-off between driving further in exchange for shorter transit trip is also more pronounced in a radial network. This means that understanding these trade-offs takes on added importance.

In common with many transit agencies around the country, the MBTA faces the challenge of attempting to expand and improve its services within tight fiscal constraints. The authority is burdened with the highest debt load of any transit agency in the nation (Daniel, 2005), and also faces a $10 million deficit in the upcoming fiscal year. The MBTA directly controls over 34,000 parking spaces on its system (MBTA Website, 2005), representing a significant investment in parking infrastructure. Research into how to obtain the greatest return on this investment is of continued importance to the agency. It also serves as an example to other agencies facing similar financial challenges.

4.2 Drive-Access Transit Significance

This section uses various data sources to assess the significance of drive-access transit in the Boston Metropolitan Region. Limited data on ridership, mode share, facilities and utilization, monetary impacts, and relevance to regional transport goals is presented. Whenever possible, GIS technology is used to communicate this information visually.

4.2.1 Drive-Access Ridership and Mode Share

An understanding of total drive-access transit ridership in relation to total regional trips is an important starting point in assessing drive-access transit's regional significance. It serves as a "back-of-the-envelope" number, allowing one to put drive-access transit in its proper perspective.

According to CTPS 2004 Congestion Management Report and the 2000 U.S. Census data, if one assumes ¾ mile as maximum transit walk distance, approximately 54 percent of the population within the Boston Metropolitan Region lives within walking distance of MBTA transit service. This means that nearly half the population cannot easily walk to transit service, emphasizing the importance of drive-access to transit.

Also according to 2000 Census data, approximately 6.8 percent of all work trips made in the Boston Metropolitan Region are by transit. In many regions, especially in the auto-dependent United States, transit usage may not account for a large percentage of total transportation trips. However, drive-access transit, if it accounts for a large portion of those transit trips, may still be highly significant to the transit agency. Assessing the role that drive-access plays in transit mode share is vital to understanding its significance.

The analysis of drive-access transit's mode share was divided into three groups, organized by service type. These three groups are: commuter rail, rapid transit, and bus and ferry.
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Commuter Rail

To analyze drive-access’s role for commuter rail, two data sources were primarily used: the MBTA 1993 Commuter Rail Survey and the MBTA 1998 Old Colony Commuter Rail Survey. Surveys were distributed on board all weekday commuter rail trains throughout the service day, with the aim of distributing a survey to every passenger on every train. Control counts were made at the same time and the survey responses were expanded accordingly.

To begin, we examine the drive-access mode share for all commuter rail trips. Since, drive-access transit is a strategy specifically aimed at concentrating transit demand in areas with low population densities; one would expect that commuter rail would be highly dependent on drive-access. All 88 commuter rail stations within the Boston Metropolitan Region were examined.

The combined results indicated that 69 percent of all commuter rail trips utilized drive-access, with 56 percent park-and-ride and 13 percent kiss-and-ride.

For further analysis, these commuter rail lines are divided into north and south areas, with the north including the Rockport/Ipswich, Haverhill, Lowell, and Fitchburg Lines and the south including the Framingham, Needham, Providence, Stoughton, Middleborough, and Plymouth (Old Colony) Lines.

The 42 stations on north side had an overall drive-access mode share of 60 percent (45% park-and-ride and 15% kiss-and-ride).

Figures 4-4 and 4-5 show the drive-access mode share for all the north side stations. This visual representation makes two things very clear. First, commuter rail ridership pales in comparison to rapid transit ridership. Second, one can clearly recognize that drive-access transit is responsible for well over 50 percent of all passengers boarding at nearly all commuter rail stations. It is important to note that this data is limited to only the responses of the aforementioned surveys and is therefore partial at best. This information is also shown in tabular format in Appendix D.
Figure 4-4. MBTA North Commuter Rail Stations Transit Access Mode Shares

There are also 46 stations on south commuter rail lines within the Boston Metropolitan Region. These 46 stations evidenced an overall drive-access transit mode share of 74 percent (60% park-and-ride and 14% kiss-and-ride).

This suggests that while all commuter rail in the Boston Metropolitan Region is highly dependent on drive-access, the south lines are most heavily dependent. This difference between north and south commuter rail lines could be due to differences in population density, income levels, relative ease of automobile travel, etc. Park-and-ride typically represents between 40-60 percent of the total transit trips, while kiss-and-ride accounts for 13-15 percent of the total trips at an average commuter rail station. This information is presented graphically in Figure 4-6.
**Rapid Transit**

Rapid transit refers to the MBTA's Red, Green, Blue and Orange Lines. To analyze drive-access to rapid transit, the MBTA 1994 Rapid Transit Passenger Survey was the primary data source. Similar to the commuter rail surveys, this passenger survey was conducted on typical weekdays between 6:00 AM and 3:30 PM. Survey forms were distributed at station entrances to ensure that the sample was not biased toward longer trips. This survey strategy was designed so that 85 percent of the passengers on any given line would have the opportunity to complete a survey. Concurrent passenger volume counts were conducted and the survey responses were expanded to represent the total number of passengers using each station during this time period.

Since rapid transit stations are typically located in areas with dense populations and relatively little parking availability, one would expect drive-access to play a much smaller role here than at commuter rail stations. For this reason, most of the literature on drive-access transit has
focused on commuter rail stations, and relatively little emphasis has been placed on the significance of drive-access transit at rapid transit stations. In all, 125 rapid transit stations within the Boston Metropolitan Region were included in the surveys.

The combined results of these stations indicated that, overall, 18 percent of the rapid transit trips utilized drive-access, with 12 percent park-and-ride and 6 percent kiss-and-ride. These mode shares are indeed much smaller than those for commuter rail, however 18 percent or nearly one-fifth of the total transit ridership relying on drive-access is still highly significant. This is even more significant when one recognizes that most of these stations have no dedicated parking or drop-off facilities.

Furthermore, by examining the outermost rapid transit stations, those stations where one would expect drive-access to play a more significant role, the significance of drive-access transit is indeed even greater. Taking the 50 outermost rapid transit stations, which include all rapid transit stations with parking facilities, one finds that the drive-access accounts for 31 percent of all trips, with 24 percent park-and-ride and 7 percent kiss-and-ride.

This information is presented graphically in Figures 4-7 and 4-8. One can clearly see how drive-access transit plays a role at all rapid transit stations, even those located in the downtown area. The greater percentage of drive-access transit at the outer rapid transit stations is also readily apparent. Again, this information is also presented in tables in Appendix D.
Figure 4-8. MBTA South Rapid Transit Stations Transit Access Mode Shares


**Buses and Ferries**

The analysis of drive-access on buses and ferries is limited by the lack of data on these modes. However, there is some evidence suggesting that drive-access transit also plays a significant role for these services. To begin, the CTPS 2004 Congestion Management Report reported that the parking lot at the Hingham Shipyard was observed to have had 1699 vehicles parked there on a typical weekday. Assuming that each of these vehicles represented one ferry service passenger, this would mean that 34 percent of all ferry passengers used drive-access from this one terminal.

For buses, it is more difficult to determine the significance of drive-access. It is likely that drive-access also plays a significant role for bus service, particularly at route terminals and bus stops that service several different routes. However, the only data found for the region was the MBTA 1998 Bus Passenger Survey, which had 789 respondents who indicated that they used drive-access transit to get to bus service. Of these 789 respondents, 454 respondents (57.5%) used park-and-ride and 335 respondents (42.5%) used kiss-and-ride. It makes sense that kiss-and-
ride would play a larger role in drive-access for buses since there is no dedicated parking associated with bus stops in the region.

**Transit Mode Share Summary**

In summary, drive-access transit clearly represents a significant portion of transit ridership in the region. It accounts for nearly 70 percent of the overall commuter rail ridership and 18 percent of the total rapid transit ridership. There is also limited evidence that suggests that drive-access transit plays an important role for both bus and ferry services. Of some surprise is the fact that drive-access transit accounts for 31 percent of transit ridership in the 50 outermost rapid transit stations.

**Table 4-2. Summary Table of Drive-Access Mode Share**

<table>
<thead>
<tr>
<th></th>
<th>Number of Stations</th>
<th>% Park-and-ride</th>
<th>% Kiss-and-ride</th>
<th>% Drive-access Transit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Commuter Rail Overall</td>
<td>88</td>
<td>56%</td>
<td>13%</td>
<td>69%</td>
</tr>
<tr>
<td>North Commuter Rail</td>
<td>42</td>
<td>45%</td>
<td>15%</td>
<td>60%</td>
</tr>
<tr>
<td>South Commuter Rail</td>
<td>46</td>
<td>60%</td>
<td>14%</td>
<td>74%</td>
</tr>
<tr>
<td>Rapid Transit Overall</td>
<td>125</td>
<td>12%</td>
<td>6%</td>
<td>18%</td>
</tr>
<tr>
<td>Rapid Transit Outermost Stations</td>
<td>50</td>
<td>24%</td>
<td>7%</td>
<td>31%</td>
</tr>
</tbody>
</table>

**4.2.2 Drive-Access Facilities and Utilization**

Another way to measure the significance of drive-access transit is through the drive-access transit facility utilization rates. Drive-access transit facilities include: park-and-ride lots, parking structures, kiss-and-ride drop-off areas, carousels, etc. The utilization rates of these facilities help demonstrate demand for drive-access transit. While, there are few facilities dedicated to kiss-and-ride, park-and-ride facilities are closely monitored both as a congestion management tool and as a source of revenue for the transit agency. Massachusetts state agencies together operate over 43,000 parking spaces dedicated to park-and-ride in the Boston Metropolitan Region. The MBTA alone operates over 34,000 parking spaces at its transit stations. Utilization of these parking spaces is usually monitored using two measures: station parking usage compared to station parking capacity, and time of day that the parking lot fills up.

**Parking Capacity and Usage**

In the Boston Metropolitan Region, 86 commuter rail park-and-ride facilities and 28 rapid transit park-and-ride facilities were observed in 2004 as part of the CTPS Congestion Management System Report. Of these facilities, 71 percent filled to 85 percent of capacity or more. Several facilities were filled to greater than capacity as cars were parked in spaces not formally designated as parking spaces. Furthermore, 46 percent of these facilities reached capacity prior to the departure of the last train in the morning peak period.
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This information is presented graphically in Figures 4-9 through 4-11. It is again important to note that the information presented is limited to the stations considered in the Congestion Management Report.

Figure 4-9. MBTA North Stations Parking Capacity and Usage

Data Source: CTPS 2004 Congestion Management Report. Note: Percent full is given in bold to the left of the station.
Figure 4-10. MBTA South Stations Parking Capacity and Usage

Data Source: CTPS 2004 Congestion Management Report. Note: Percent full is given in bold to the left of the station.
From the figures above one can quickly identify several stations that have underutilized parking facilities. For example, in the north, Newburyport, Lynn, Bradford, and (especially) Anderson RTC commuter rail stations use less than half their available parking. In the south, the Route 128, Ashland and Needham Heights commuter rail stations are also less than half full. Almost all rapid transit stations appear to be heavily utilized, except for Wonderland and Riverside stations with 80 percent and 75 percent lot utilization rates, respectively. One would expect that both Wonderland and Riverside, being outer terminals, would fill up completely, especially since as terminals, they would be among the stations most accessible to commuters living beyond the end of the rail line.

Another way to examine drive-access transit utilization is to compare the number of park-and-ride and kiss-and-ride users determined from the MBTA 1994 Rapid Transit Passenger Survey with the 1995 parking lot capacities. This method has at least three benefits that are lacking in the 2004 Congestion Management Report data. First, it takes kiss-and-ride into account. While, kiss-and-ride obviously does not require parking spaces, measuring kiss-and-ride may give an indication of latent demand at a station. Second, it examines the effect of parking near stations...
without dedicated parking facilities. This is of particular importance to neighborhoods surrounding these stations, for obvious reasons. Third, this method allows one to see the total number of park-and-ride users at each station. One of the disadvantages of only looking at MBTA parking lot data, is that park-and-ride users using other nearby parking facilities are not represented. The following two figures present this information graphically. Again, it is important to note that this information presented is limited to the responses generated from the various passenger surveys.

Figure 4-12. Drive-Access Transit Usage and Capacity for North Rapid Transit Stations

For example, from Figure 4-12, one can quickly recognize that there are significant numbers of both park-and-ride and kiss-and-ride users at Davis Station which has no dedicated parking facilities. This would suggest that these park-and-ride transit users are parking in the neighborhoods surrounding the transit station, a point of concern for local residents. Similar conclusions can be made for the Maverick and Suffolk Downs stations. One can also see that there are far more park-and-ride users than there are parking spaces at the Sullivan Square Station, indicating that these park-and-ride users are most likely parking at nearby parking facilities in addition to the MBTA parking lot. Another point of interest is Wonderland Station. The 2004 Congestion Management Report observed that this station never reaches capacity, however, these survey results indicate that there are far more park-and-ride users using Wonderland than there are parking spaces. Unfortunately, since these studies were not conducted at the same time, it is impossible to tell whether this incongruency is due to a change
in utilization over time, a large amount of parking turnover at Wonderland Station, or more park-and-ride users parking at facilities other than the MBTA parking facility.

Figure 4-13. Drive-access Transit Usage and Capacity for South Rapid Transit Stations

If parking lot data and passenger surveys were conducted during the same time frame, this information would be even more valuable. One could compare MBTA lot utilization and total drive-access transit usage and determine what percentage of drive-access transit users utilize MBTA parking lots. Unfortunately since the lot utilization data and the passenger survey data used in this analysis were collected nearly a decade apart, such a comparison here is not reliable.

Time of Day that Parking Facilities Fill Up

This measure of utilization is another indicator of whether latent demand for parking facilities exists, an important input into parking related policy decisions. For example if station parking facilities fill early, additional parking facilities might be worth investing in or an increase in the parking fee might be warranted. Figures 4-14 and 4-15 show the time of day that MBTA parking facilities fill.
One might expect that outer stations would fill earlier and then inner stations would also fill up. However this is not always the case. For example, Wakefield station on the Haverhill Commuter Rail Line fills up by 7:26, while the stations on either side of it, Greenwood and Reading, do not fill until 9:10 and 9:26, respectively.
For rapid transit stations, several inner stations also fill earlier than might be expected. For example, Wollaston Station on the Red Line and Sullivan Square on the Orange Line fill much earlier than other nearby stations, most likely due to their small parking capacity.

One of the benefits of utilizing GIS technology is the ability to represent data in a variety of graphical formats. A more qualitative representation of this data is presented as a color map in Figure 4-16.
In conclusion, the fact that so many of these facilities are reaching capacity so early would seem to suggest a large amount of latent demand for more park-and-ride facilities. This information is vital to several different types of policy decisions. For example, with large latent demand, the MBTA may choose to increase the parking fee at stations that are filling up early and offer parking fee discounts at underutilized stations as a way to manage demand for parking. For stations that are filling up early, the MBTA might also consider constructing convenient drop off points for kiss-and-ride users. Also, for those stations where parking is overflowing into surrounding neighborhoods, traffic mitigation methods and parking enforcement policies should be re-evaluated. Something else to consider is the fact that once full, these stations cannot accommodate parking for other transit trips during the day. This means that these stations serve only early morning commuters. By designating certain parking spaces to have parking time limits, the MBTA might be able to encourage additional parking turnover, generating additional parking revenue and serving more trip purposes. Such a strategy would have to be carefully implemented to ensure that it did not negatively affect transit trip totals at stations.
4.2.3 Drive-Access Monetary Impacts

There are several ways to examine the monetary impacts of drive-access transit. In this case study, these monetary impacts are analyzed in terms of prior investment in parking infrastructure and the percentage of parking revenues to total operating revenues in the MBTA's annual budget. A spatial analysis of parking fees at transit stations is also presented.

As mentioned before, the MBTA operates over 34,000 parking spaces at its transit stations, representing a significant investment in drive-access transit facilities. The cost of building and maintaining these spaces is difficult to calculate. Still, using a very conservative estimate of $2,000 per space, based on the ITE parking space construction cost estimates (see Table 2-1), this would mean that the MBTA alone has invested $68 million in parking infrastructure. This is almost certainly a low estimate and does not include maintenance and management costs.

The revenue generated by these parking facilities is also significant. The MBTA annual budget includes parking revenue as part of line item entitled: Revenue from Real Estate Operation. This line item generated over $26.2 million in FY2003 and is expected to generate nearly $31.5 million in FY2004, due in large part to a parking fee increase (see Figure 4-17). This $31.5 million represents approximately 9 percent of the MBTA's total operating revenue. Over the past five years, the Revenue from Real Estate Operation has risen at an average annual rate of 12 percent, and has grown from 7 percent of the MBTA's total operating revenue in FY1999 to a predicted 9 percent in FY2004.

Figure 4-17. Annual MBTA Revenue from Real Estate Operations, FY1999 to FY2004*

With such a large investment in parking facilities and with real estate operations (consisting largely of parking fee revenue) representing nearly a tenth of total operating revenue, drive-access transit facilities represent an important part of the MBTA's regional transportation system. As such, it is deserving of proper attention, to ensure that the maximum possible return on investment is achieved.

Since parking fees represent an increasingly significant part of the MBTA's total operating revenue, a spatial analysis of the region's parking fee policy is important. Utilizing GIS technology, one can graphically represent the region's transit stations with dedicated parking facilities and these facilities' associated parking fees. These graphical fare representations are presented in Figures 4-18 through 4-20.

*Figure 4-18. MBTA North Commuter Rail Parking Fees*

Figure 4-19. MBTA South Commuter Rail Parking Fees

There appears to be little relationship between parking fees and geographical location in the north commuter rail stations. For example, on the Lowell Commuter Rail Line, parking fees fluctuate between $0-$5 along the line, indicating that these parking fees have little to do with station location.

Figure 4-21 shows the relationship between percent parking capacity filled and parking fees at stations. In accordance with the economics of supply and demand, one would expect that stations which exceed their parking capacity (thereby evidencing high parking demand) would have the highest associated parking fees. However, Figure 4-21 shows that this is not the case. Instead, there is no clear correlation between percent capacity filled and parking fees. It is therefore more likely that the perceived quality of these parking facilities and the costs associated with operating each parking facilities are what dictate parking prices in the region.
In addition to the methods mentioned here, there are several other methods of assessing the monetary impacts of drive-access transit that were not attempted as part of this thesis. For example, one could include an analysis of the economic benefits accrued to the central business district as a result of drive-access transit. One might also want to collect data concerning the costs associated with operating a region’s drive-access facilities. This cost data would be especially helpful in budgetary decisions regarding existing parking facilities and decisions concerning the construction of additional parking facilities.
4.2.4 Relevant Regional Transportation Goals

Understanding how drive-access transit relates to regional transportation goals is a qualitative measure to assess the regional significance of drive-access transit. Such qualitative measures help take into account regional priorities and values that might not be represented in a strictly quantitative analysis.

There are two goals listed in the MBTA’s mission statement that relate to drive-access transit. The first relevant goal is the MBTA’s service goal. This goal states that the MBTA will “provide clean, safe, and reliable public transportation, accessible to everyone, and a clean and safe environment for employees (MBTA Website, 2005).” Making transit accessible to everyone is an ambitious undertaking, especially when 46 percent of the regional population does not live within walking distance of transit service. In order to meet this goal of universal accessibility, drive-access transit must be a regional priority.

Additionally, drive-access transit accessibility may tap one of the region’s primary growth areas. According to the 2000 U.S. Census, the population of the City of Boston was 589,141 people, representing only about 19 percent of the 3,066,394 people living in the Boston Metropolitan Region. With the lower population density of the suburban regions, drive-access transit may provide greater transit accessibility to regional residents living outside the City of Boston. With the world-class services and leisure activities currently available in downtown Boston, increasingly regional transit accessibility to the downtown may take advantage of a promising growth opportunity for public transport.

The MBTA’s financial goal is also relevant to a discussion of drive-access transit’s regional significance. This MBTA goal states that the MBTA will “provide affordable transit for the public and work toward reducing the burden to taxpayers through efficient operations, innovative fare policies, and the generation of non-fare revenues (MBTA Website, 2005).” A thorough understanding of drive-access transit allows decision-makers to truly assess how policy changes might affect the transportation system. For example, how raising parking fees (a non-fare revenue) might affect service demand. Another example would be a better understanding of how “innovative fare policies” might affect both mode choice and station choice behavior.

From a policy standpoint, one may be faced with contradictory choices, where information on drive-access transit trade-offs would be extremely helpful. For example, one might choose to raise parking fees at transit stations to encourage greater kiss-and-ride usage. But one runs the risk of perhaps decreasing total public transit mode share.

These regional goals of universal transit accessibility and financial responsibility suggest that an examination of drive-access transit should be a priority for the Boston Metropolitan Region.
5. THE BOSTON CASE STUDY: DRIVE-ACCESS TRANSIT BEHAVIOR

In this chapter, the second step of the analytical framework is applied to drive-access transit in the Boston Metropolitan Region. The existing drive-access transit modeling practices used by CTPS are reviewed. The background of the modeling approach used in this case study is presented. The drive-access transit behavior of commuter rail and rapid transit travelers are considered separately. Station choice and sub-mode choice models are developed for both commuter rail and rapid transit travelers.

5.1 CURRENT MODELING PRACTICES

When assessing the quality of a region’s drive-access modeling practices, there are several important questions to consider, including:

- What data are the models based on?
- How reliable is this data?
- Do the models accurately reflect revealed traveler behavior?
- Do the models take into account important parameters?

In the Boston Metropolitan Region, drive-access transit has been classified as a travel mode. The region’s other travel modes include: walk-access transit, single-occupancy automobile, high-occupancy automobile, and walk. The specifications of these travel modes and the related mode choice model is beyond the scope of this thesis.

In applying this mode-choice model, all trips that are determined to be drive-access transit are assigned to an access station based on a utility equation with the following parameters:

- station parking capacity
- total transit impedance (consisting of a linear combination of in-vehicle time, initial wait time, boarding time, auxiliary time, transfer time, number of transfers, and transit fare), and
- automobile drive time.

The selection of these parameters and their coefficients for this station choice model represent a “best estimate” on the part of the CTPS modeling staff. Due to limited time and resources, these modeling practices have never been substantiated by rigorous research or analysis. Since this model was not estimated from an actual data set, it is impossible to know how well it reflects revealed traveler behavior. The parameters used and their respective coefficients are also unreliable, especially for use in planning and policy decisions.

Once all drive-access transit trips are assigned to stations, 15 percent of these trips are assumed to be kiss-and-ride and the rest are assumed to be park-and-ride. This arbitrary sub-mode choice assignment also represents a “best estimate” on the part of CTPS modelers.
The confidence one can place in these modeling practices is seriously undermined by the lack of validation and verification. Even a cursory analysis of actual observed drive-access transit behavior further erodes one's confidence in these measures. For example, according to the passenger surveys, kiss-and-ride accounts for about 22 percent of drive-access transit use, not 15 percent. Additionally, kiss-and-ride usage varies greatly from station to station, so that any arbitrary percentage assignment significantly misrepresents actual traveler behavior.

This case study includes preliminary attempts to estimate both station choice models and sub-mode choice based on actual observed traveler behavior. The development of these models should not only provide a better understanding of regional drive-access transit behavior, but should also suggest possible future modeling approaches for CTPS.

5.2 MODEL BACKGROUND

After assessing drive-access transit's regional importance, one must also examine drive-access transit user behavior within the region. As mentioned previously, this behavior depends on four categories of factors: demographics, station and trip characteristics, and other factors. In order to gather information on these factors, passenger surveys and market studies are required. Unfortunately, due to the cost of collection, data of this type is often limited. In this research, two prior passenger surveys are used to analyze drive-access behavior for commuter rail users and for rapid transit users, respectively.

The following sections will first examine commuter rail drive-access behavior and then rapid transit drive-access behavior. The passenger surveys will be analyzed in terms of demographics. The process of determining individual trip characteristics from transportation network models will be described. Finally, station choice and sub-mode choice models will be formulated and estimated for drive-access for both rapid transit and commuter rail users.

The probabilistic models used in this research are binomial or multinomial logit discrete choice models. Discrete choice models represent the choice of an individual among several options. For example, in the sub-mode choice model, the rider can choose between park-and-ride and kiss-and-ride (a binary choice), and in the station choice model, the rider can choose among several different transit stations (a multinomial choice). These models assume that the individual will choose the option that provides the highest expected utility, where the utility is a function of the factors described previously. The model is based on comparisons between these utilities.

\[ U_{in} = V_{in} + \varepsilon_{in} \quad \{i \in C_n\} \]  \hspace{1cm} (5-1)

Where \( C_n \) is the choice set, \( V_{in} \) is the observable, or systematic, component of the total utility, and \( \varepsilon_{in} \) is the unobservable component of the total utility. The choice probability of option \( i \) is equal to the probability that the utility of option \( i \), \( U_{in} \), is greater than or equal to the utilities of all other options in the choice set.
The Boston Case Study: Drive-Access Transit Behavior

\[ P(i / C_n) = Pr(U_{in} >= U_{jn}, \text{all } j \in C_n) \quad (5-2) \]

Dividing the utility of each alternative into its deterministic and random components, one finds the probability of choosing \( i \) becomes

\[ P_n(i) = Pr(\alpha V_{in} + \alpha \varepsilon_{in} >= \alpha V_{jn} + \alpha \varepsilon_{in}, \text{all } j \in C_n, j \neq i) \]

If \( \varepsilon_n = \varepsilon_{in} - \varepsilon_{jn} \) is logistically distributed, namely

\[ F(\varepsilon_n) = \frac{1}{1 + e^{-\mu \varepsilon_n}}, \quad \mu > 0, \quad -\infty < \varepsilon_n < \infty \]

Then,

\[ P_n(i) = \frac{e^{\alpha V_{in}}}{\sum_j e^{\alpha V_{jn}}}, \text{all } j \in C_n \quad (5-3) \]

This simplifies to the binary logit model when there are only two alternatives, as in the case of the sub-mode choice model.

\[ P_n(i) = \frac{e^{\alpha V_{in}}}{(e^{\alpha V_{in}} + e^{\alpha V_{jn}})} \quad (5-4) \]

There are several assumptions that underly multinomial models, including: 1) that the rider will choose the alternative with the greatest expected utility, 2) that the random component of the utility is logistically distributed, and 3) that the choice set demonstrates independence from irrelevant alternatives. (Ben-Akiva, 1985)

Due to the limited time and resources available for this research, only one nested model structure was attempted. This nest structure has station choice as the upper level decision and sub-mode choice as the lower level decision. (This structure was previously referred to as “Nested Structure 1” in Figure 3-2). Given additional time, models could be estimated using the inverse nest structure and these nested models could be compared to determine which structure best reflects Boston regional drive-access behavior.

Unfortunately, all attempts to nest the station choice and sub-mode choice models developed in this research were unsuccessful. As a result, the models are presented separately.

### 5.3 Commuter Rail

Since drive-access is of greatest importance for commuter rail, it is a logical place to begin the analysis of regional drive-access behavior with commuter rail.

In order to analyze drive-access transit behavior for commuter rail, various commuter rail passenger surveys were examined. Unfortunately, only the MBTA 1998 Old Colony Commuter Rail Passenger Survey contained sufficiently detailed information on origin and destination addresses. The methods used to conduct this survey were described in Section 4.2.1. This survey resulted in records with origin and destination information for 3236 trips, so all trip ends could be geo-coded using GIS software. It also provides information on where people board, transfer, and egress the commuter rail system. The actual transit path can be defined
accurately, and all associated characteristics, such as in-vehicle time, transfer time, and waiting
time can be estimated accurately. One of the limitations of this data, is that since the data only
reflects trips made by those already using the transit system, it can not be used to predict
possible effects of service changes on traveler's not presently using the transit system.

This section will analyze the demographics of these drive-access transit survey respondents. It
will also combine these demographic factors with station and trip characteristics, and other
factors in an attempt to estimate models of both commuter rail drive-access station choice and
sub-mode choice.

5.3.1 Drive-Access User Demographics

To understand the demographic factors that may influence drive-access behavior in this region,
the MBTA 1998 Old Colony Commuter Rail Passenger Survey's drive-access transit users'
demographic information is analyzed in this section. Of the total of 3236 respondents, about
89.5 percent (2896 respondents) indicated that they used drive-access. The drive-access
respondents were further divided into 2590 (89.4 percent of total drive-access respondents)
respondents who chose park-and-ride and 406 (10.6 percent) respondents who chose kiss-and-
ride. This section summarizes the results in terms of: age, gender, income, automobile
availability, household size, and automobile ownership.

Age

In this survey, respondents were asked to place themselves in one of six age groups; "17 and
Under", "18-24", "25-34", "35-44", "45-64", and "65 and Older". The age group distribution for
park-and-ride respondents and kiss-and-ride respondents are shown in Figures 5-1 and 5-2,
respectively.
The Boston Case Study: Drive-Access Transit Behavior

Figure 5-1. Commuter Rail Park-and-ride Users by Age Group

Data Source: MBTA 1998 Old Colony Commuter Rail Passenger Survey

Figure 5-2. Commuter Rail Kiss-and-ride Users by Age Group

Data Source: MBTA 1998 Old Colony Commuter Rail Passenger Survey
Both graphs evidence fairly normal age distribution with the vast majority of the riders being adults between the ages of 25 and 64. Of some interest is the low number of young park-and-ride respondents. It is expected that these young adults and children, with their limited access to automobiles and generally lower incomes, would be more likely to use kiss-and-ride than park-and-ride.

**Gender**

Tables 5-1 and 5-2 summarize respondents’ gender, again by park-and-ride and kiss-and-ride respectively.

*Table 5-1. Commuter Rail Park-and-ride Users by Gender*

<table>
<thead>
<tr>
<th>GENDER</th>
<th>Number of Respondents</th>
<th>Percent of Answered</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male</td>
<td>1137</td>
<td>46.6%</td>
</tr>
<tr>
<td>Female</td>
<td>1304</td>
<td>53.4%</td>
</tr>
<tr>
<td>No Answer</td>
<td>49</td>
<td></td>
</tr>
</tbody>
</table>

Data Source: MBTA 1998 Old Colony Commuter Rail Passenger Survey

*Table 5-2. Commuter Rail Kiss-and-ride Users by Gender*

<table>
<thead>
<tr>
<th>GENDER</th>
<th>Number of Respondents</th>
<th>Percent of Answered</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male</td>
<td>189</td>
<td>48.0%</td>
</tr>
<tr>
<td>Female</td>
<td>205</td>
<td>52.0%</td>
</tr>
<tr>
<td>No Answer</td>
<td>12</td>
<td></td>
</tr>
</tbody>
</table>

Data Source: MBTA 1998 Old Colony Commuter Rail Passenger Survey

These tables indicate that for both park-and-ride and kiss-and-ride respondents, female respondents were slightly more common than male respondents. However, this may be due to a higher percentage of females using the transit system or merely a higher percentage of females choosing to respond to the survey.

**Income**

Graphs of the income level distribution for park-and-ride respondents and kiss-and-ride respondents are shown in Figures 5-3 and 5-4, respectively.
The Boston Case Study: Drive-Access Transit Behavior

Figure 5-3. Commuter Rail Park-and-ride Users by Income Level

![Bar chart showing the number of respondents for each income level for park-and-ride users.](chart)

Data Source: MBTA 1998 Old Colony Commuter Rail Passenger Survey

Figure 5-4. Commuter Rail Kiss-and-ride Users by Income Level

![Bar chart showing the number of respondents for each income level for kiss-and-ride users.](chart)

Data Source: MBTA 1998 Old Colony Commuter Rail Passenger Survey
Both park-and-ride and kiss-and-ride respondents tended to have annual incomes greater than $40,000. Individuals with annual incomes greater than $80,000 made up the largest income level group for both kiss-and-ride and park-and-ride. However, the difference between this group and the other groups is far more pronounced for park-and-ride. This income information might be an important factor in the overall mode split model. This information might also be useful in targeting marketing information to potential drive-access transit users.

**Automobile Availability and Licensed Drivers**

Automobile availability and whether or not one has a valid driver's license may have an effect on the choice between park-and-ride and kiss-and-ride. In this survey, 99.1 percent of the park-and-ride respondents stated they had access to an automobile for their trip, compared with only 62.2 percent of the kiss-and-ride respondents. Additionally, 99.6 percent of the park-and-ride respondents stated they had a valid driver's license versus 86.5 percent of the kiss-and-ride respondents. These results suggest that automobile availability plays an important role in choosing between park-and-ride and kiss-and-ride, more so than having a valid driver's license.

**Household Size**

The average household size for park-and-ride users in this survey was 2.93 compared with 3.29 kiss-and-ride users. It is expected that kiss-and-ride users might come from larger households, since it would be easier for them to find someone to drop them off at the rail station. This data supports that assumption.

**Automobile Ownership**

The average number of vehicles owned per household for park-and-ride users in this survey was 3.13 vehicles versus 2.93 for kiss-and-ride users. The average number of vehicles owned per capita for park-and-ride users in this survey was 1.21 vehicles versus 0.97 vehicles for kiss-and-ride users. This data is in accordance with a priori expectations. One would expect that park-and-ride users would own more vehicles per household and per capita than kiss-and-ride users. This could indicate that kiss-and-ride users do not feel the need to purchase additional vehicles since they already have someone dropping them off. It could also represent the fact that people with more vehicles will likely have a higher income and therefore are less concerned with the additional cost associated with parking on a daily basis. Or more simply, car ownership might affect sub-mode choice.

**5.3.2 Trip Characteristics**

In order to analyze drive-access behavior, accurate and consistent trip characteristics are needed for each survey response. The trip information provided by the survey respondent should not be used since these responses are often inaccurate and biased by individual perceptions. Therefore, it is advisable to use a transportation network model to estimate consistent trip information for each respondent. In the case of this commuter rail survey, the MIT Boston Regional TransCAD network model was used.
The Boston Case Study: Drive-Access Transit Behavior

This model is being developed as part of an on-going, collaborative research effort which extends well beyond the scope of this thesis. It has the benefits of being transparent in terms of data inputs and outputs, and highly accessible by research personnel. At the time of this analysis, the model consisted of 182,427 links, of which 175,020 were walk accessible and 180,662 were automobile accessible. The rapid transit and commuter rail route networks were developed and calibrated collaboratively as part of this research.

In order to use this network model, first the origin addresses indicated on the survey responses had to be geo-coded into the network using the TransCAD GIS software. Only 223 of the survey responses had origin addresses detailed enough to be properly geo-coded. This low success rate is due to a lack of emphasis placed on collecting accurate address location. Many survey respondents omitted this information or provided information too vague to be properly geo-coded. The locations of the trip origins that were successfully geo-coded are shown graphically in Figure 5-5. The locations are color-coded by boarding station in order to gain a better understanding of where these trips are heading.
Using the transportation network model, automobile costs and distances were calculated and matched up with the corresponding survey response. In all, automobile trip characteristics were generated for 166 survey responses. Again, the low success rate is due to insufficiently detailed survey responses. Analysis of these 166 automobile trips indicates that the average automobile trip for park-and-ride users was 3.6 miles and took 7.4 minutes. The average automobile trip for kiss-and-ride users was 2.1 miles and took 4.6 minutes.

The vast majority of drive-access transit users also chose their closest station. Tables 5-3 and 5-4 break down the station choice information by time and by distance.
The Boston Case Study: Drive-Access Transit Behavior

Table 5-3. Commuter Rail Station Choice By Time

<table>
<thead>
<tr>
<th></th>
<th># of Survey Responses</th>
<th>Percentage</th>
<th>Cumulative Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Closest Station</td>
<td>124</td>
<td>74.7%</td>
<td>74.7%</td>
</tr>
<tr>
<td>2nd Closest</td>
<td>28</td>
<td>16.9%</td>
<td>91.6%</td>
</tr>
<tr>
<td>3rd Closest</td>
<td>10</td>
<td>6.0%</td>
<td>97.6%</td>
</tr>
<tr>
<td>&gt; 3rd Closest</td>
<td>4</td>
<td>2.4%</td>
<td>100.0%</td>
</tr>
<tr>
<td>Total</td>
<td>166</td>
<td></td>
<td>100%</td>
</tr>
</tbody>
</table>

Table 5-4. Commuter Rail Station Choice By Distance

<table>
<thead>
<tr>
<th></th>
<th># of Survey Responses</th>
<th>Percentage</th>
<th>Cumulative Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Closest Station</td>
<td>129</td>
<td>77.7%</td>
<td>77.7%</td>
</tr>
<tr>
<td>2nd Closest</td>
<td>25</td>
<td>15.1%</td>
<td>92.8%</td>
</tr>
<tr>
<td>3rd Closest</td>
<td>8</td>
<td>4.8%</td>
<td>97.6%</td>
</tr>
<tr>
<td>&gt; 3rd Closest</td>
<td>4</td>
<td>2.4%</td>
<td>100.0%</td>
</tr>
<tr>
<td>Total</td>
<td>166</td>
<td></td>
<td>100%</td>
</tr>
</tbody>
</table>

Nearly 75 percent of the survey respondents chose the transit station closest to them by time and nearly 78 percent of the survey respondents chose the transit station closest to them by distance. In both cases, over 91 percent of the survey respondents chose either the closest or the next closest station, and nearly 98% chose one of the three closest stations.

Tables 5-5 and 5-6 show station choice for just park-and-ride respondents, while Tables 5-7 and 5-8 show station choice for kiss-and-ride respondents.

Table 5-5. Commuter Rail Park-and-ride Station Choice By Time

<table>
<thead>
<tr>
<th></th>
<th># of Survey Responses</th>
<th>Percentage</th>
<th>Cumulative Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Closest Station</td>
<td>103</td>
<td>72.5%</td>
<td>72.5%</td>
</tr>
<tr>
<td>2nd Closest</td>
<td>26</td>
<td>18.3%</td>
<td>90.8%</td>
</tr>
<tr>
<td>3rd Closest</td>
<td>10</td>
<td>7.0%</td>
<td>97.8%</td>
</tr>
<tr>
<td>&gt; 3rd Closest</td>
<td>3</td>
<td>2.1%</td>
<td>100.0%</td>
</tr>
<tr>
<td>Total</td>
<td>142</td>
<td></td>
<td>100%</td>
</tr>
</tbody>
</table>

Table 5-6. Commuter Rail Park-and-ride Station Choice By Distance

<table>
<thead>
<tr>
<th></th>
<th># of Survey Responses</th>
<th>Percentage</th>
<th>Cumulative Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Closest Station</td>
<td>107</td>
<td>75.3%</td>
<td>75.3%</td>
</tr>
<tr>
<td>2nd Closest</td>
<td>24</td>
<td>16.9%</td>
<td>92.2%</td>
</tr>
<tr>
<td>3rd Closest</td>
<td>8</td>
<td>5.6%</td>
<td>97.8%</td>
</tr>
<tr>
<td>&gt; 3rd Closest</td>
<td>3</td>
<td>2.1%</td>
<td>100.0%</td>
</tr>
<tr>
<td>Total</td>
<td>142</td>
<td></td>
<td>100%</td>
</tr>
</tbody>
</table>
Table 5-7. Commuter Rail Kiss-and-ride Station Choice By Time

<table>
<thead>
<tr>
<th></th>
<th># of Survey Responses</th>
<th>Percentage</th>
<th>Cumulative Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Closest Station</td>
<td>20</td>
<td>83.3%</td>
<td>83.3%</td>
</tr>
<tr>
<td>2nd Closest</td>
<td>2</td>
<td>8.3%</td>
<td>91.7%</td>
</tr>
<tr>
<td>3rd Closest</td>
<td>0</td>
<td>0%</td>
<td>91.7%</td>
</tr>
<tr>
<td>&gt; 3rd Closest</td>
<td>2</td>
<td>8.3%</td>
<td>100.0%</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>24</strong></td>
<td><strong>100%</strong></td>
<td></td>
</tr>
</tbody>
</table>

Table 5-8. Commuter Rail Kiss-and-ride Station Choice By Distance

<table>
<thead>
<tr>
<th></th>
<th># of Survey Responses</th>
<th>Percentage</th>
<th>Cumulative Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Closest Station</td>
<td>21</td>
<td>87.5%</td>
<td>87.5%</td>
</tr>
<tr>
<td>2nd Closest</td>
<td>1</td>
<td>4.2%</td>
<td>91.7%</td>
</tr>
<tr>
<td>3rd Closest</td>
<td>0</td>
<td>0%</td>
<td>91.7%</td>
</tr>
<tr>
<td>&gt; 3rd Closest</td>
<td>2</td>
<td>8.3%</td>
<td>100.0%</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>24</strong></td>
<td><strong>100%</strong></td>
<td></td>
</tr>
</tbody>
</table>

A comparison of these tables shows that a slightly higher percentage of kiss-and-ride users chose the closest station than did park-and-ride users. This is consistent with the expectation that long access trips are less attractive to kiss-and-ride users.

Once the origin information had been geo-coded and the trip characteristics had been generated and analyzed for the automobile access portion of the trip, the next step in the process was to geo-code the trip destinations into the transportation network model. Only 352 of the survey responses had destination addresses detailed enough to be properly geo-coded. Most of these trip destinations are located in the Boston central business district (CBD) (Figure 5-6).

Unfortunately, since automobile access trip characteristics could only be generated for 166 survey responses, this severely limited the total number of observations that could be used to estimate sub-mode choice and station choice models.
5.3.3 Station Choice Model

Since only a small number of survey responses had origin and destination information detailed enough to accurately geo-code them, the total number of observations available for model estimation was only 166 individual responses. Of these 166 observations, 142 (86%) were park and ride users, 24 (14%) were kiss and ride users.

Based on the demographic analysis conducted on the commuter rail passenger survey and the trip characteristics generated from the transportation network model, the following sub-mode choice model was developed and estimated. Biogeme, a free object-oriented software package designed for the maximum likelihood estimation of generalized extreme value models, was used to estimate this model (Biogeme Website, 2005).

There were a total of nine possible stations that could be chosen along the Old Colony Commuter Rail Line. The choice set for each response included the three stations closest to the origin by distance.
As in the commuter rail sub-mode choice model, the Biogeme software package was used to estimate this model. In specifying models to estimate station choice behavior, the following variables were analyzed:

- automobile trip times and distances,
- transit total trip times and distances, in-vehicle travel times, initial wait times, fares,
- parking capacity,
- parking fees, and
- dummy variables for whether or not a station was the closest station to the origin both by time and distance to account for possible bias towards the closest station.

Using these variables, several different models were specified and tested. According to the statistical t-test values several variables were insignificant in every model examined including transit total trip times and distances, transit in-vehicle travel times, and the closest station dummy variables. Based on this data set, one cannot conclude that these variables play a significant role in determining station choice behavior.

Automobile distances were determined to be more statistically significant than automobile travel times and were therefore included in the recommended model. Both variables had the expected sign, indicating that travelers are less likely to choose stations further away. Surprisingly, some model specifications indicated that initial wait time at the station was also significant. However, the sign indicated that the longer the wait, the more likely a traveler is to choose that station. This hardly seems likely, and could be explained by lack of variation in the sample. For that reason, initial wait times were excluded from the recommended model. Parking fees were also statistically significant in some model specifications, however, they too had the incorrect sign, indicating that travelers were more likely to choose a station with a higher parking fee. This could be due to better parking conditions associated with the higher fee, but without more information, this variable would be misleading in the model. Therefore, the parking fee variable was also excluded from the recommended model.

The other two variables that were included in the model were the parking capacity variable and the transit fare variable. The signs of the variables indicate that travelers are more likely to choose stations with more parking capacity and less likely to choose stations with higher transit fares. Parking capacity is not significant at the 90% confidence level, but was considered significant enough for inclusion in the recommended model.

The recommended model is shown in Table 5-9. This model has three parameters and the log-likelihood value indicates that it is superior to any naïve model. Also, in discrete choice models, the adjusted $\rho^2$ value serves as an informal goodness-of-fit index that measures the fraction of the initial log likelihood value explained by the model. Usually a value between 0.3 to 0.4 is a good result for the model specification, which is equivalent to an adjusted $R^2$ value of 0.7 to 0.85 for a linear regression model (Chu, 2002). The model recommended below has an adjusted $\rho^2$ value of 0.629, which is considered a good result.
Table 5-9. Recommended Commuter Rail Station Choice Model

<table>
<thead>
<tr>
<th>Independent Variable</th>
<th>Estimated Coefficient</th>
<th>Standard Error</th>
<th>t-statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Automobile distance</td>
<td>-1.595</td>
<td>0.215</td>
<td>-7.407</td>
</tr>
<tr>
<td>Parking capacity</td>
<td>0.00166</td>
<td>0.00117</td>
<td>1.426</td>
</tr>
<tr>
<td>Transit fare</td>
<td>-1.770</td>
<td>0.502</td>
<td>-3.523</td>
</tr>
</tbody>
</table>

Model Statistics:

Valid Cases: 162 (138 park-and-ride (85.2%) and 24 kiss-and-ride (14.8%))

Initial Log-likelihood: -179.361
Final Log-likelihood: -66.4837
Likelihood Ratio Test: 225.756
Rho-square Value: 0.629

It would also be possible to estimate separate models for park-and-ride and kiss-and-ride separately. This would be especially useful if attempting to nest the models in such a way that sub-mode choice was the upper-level decision and station choice was the lower-level decision. Such models were not attempted as part of this thesis.

5.3.4 Sub-Mode Choice Model

Utilizing the same survey responses as the station choice model estimation process, a sub-mode choice model was developed and estimated for commuter rail passengers. In specifying models to estimate sub-mode choice behavior, the following variables were analyzed:

- automobile travel times and distances to the chosen station,
- auto availability,
- whether or not the respondent had a valid driver's license,
- parking capacity at the chosen station,
- parking fees at the chosen station,
Chapter 5

- trip purpose (divided into home-based work trips, home-based other trips, and non-home-based trips),
- trip frequency,
- household size,
- number of vehicles owned per household and per capita,
- income levels,
- age, and
- gender.

Using these variables, several different models were specified and tested. According to the statistical t-test values, several variables were insignificant in every model examined. These insignificant variables included whether or not the respondent had a valid driver's license or not, trip purpose, household size, number of vehicles owned per household, income level, age, and gender. Again, based on this data set, one cannot conclude that these variables significantly affect travelers' sub-mode choice decision.

Both automobile travel time and distance were determined to be statistically significant in several model specifications, however, only automobile distance had the expected sign. Not surprisingly, the models indicated that the greater the distance to a station the more likely an individual was to choose park-and-ride. This is consistent with the expectation that long distances might be considered too burdensome for the driver dropping someone off, and therefore act as a disincentive to choosing the kiss-and-ride alternative. However, the opposite sign on the automobile travel time coefficient indicated that the longer the drive time, the more likely an individual was to choose kiss-and-ride. The reasons behind such contradictory results are unclear. Therefore, the automobile travel time variable was dropped from the recommended model.

Besides the automobile distances, other variables that were statistically significant included parking capacity, number of vehicles owned per capita, and trip frequency. These variables all had parameters with the expected sign and were significant statistically. The model also indicated that the greater the trip frequency (the number of days per week that this individual makes this commuter rail trip) the more likely that individual is to choose kiss-and-ride instead of park-and-ride. This may be due to the fact that paying a parking fee everyday represents a greater disincentive than occasionally paying parking fees. Parking fees were not shown to have significance at a high confidence level. However, it was decided that they were significant enough to include in the recommended model.

The recommended model is shown in Table 5-10. This model has six parameters, one of which is an alternative specific constant, and its final log-likelihood value indicates that it is superior to any naive model. The model recommended below has a $p^2$ value of 0.620, which is considered a good result.
### Table 5-10. Recommended Commuter Rail Sub-Mode Choice Model

<table>
<thead>
<tr>
<th>Independent Variable</th>
<th>Estimated Coefficient</th>
<th>Standard Error</th>
<th>t-statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>ASC (Park-and-ride)</td>
<td>13.531</td>
<td>8.595</td>
<td>1.574</td>
</tr>
<tr>
<td>Automobile distance</td>
<td>0.508</td>
<td>0.241</td>
<td>2.106</td>
</tr>
<tr>
<td>Parking capacity</td>
<td>0.007</td>
<td>0.003</td>
<td>2.511</td>
</tr>
<tr>
<td>Parking fees</td>
<td>-1.798</td>
<td>1.668</td>
<td>-1.078</td>
</tr>
<tr>
<td>Number of vehicles owned per capita</td>
<td>2.363</td>
<td>7.597</td>
<td>3.110</td>
</tr>
<tr>
<td>Trip frequency</td>
<td>-2.447</td>
<td>1.219</td>
<td>-2.008</td>
</tr>
</tbody>
</table>

**Model Statistics:**

Valid Cases: 162 (138 park-and-ride (85.2%) and 24 kiss-and-ride (14.8%))

- Initial Log-likelihood: -112.29
- Final Log-likelihood: -42.7019
- Likelihood Ratio Test: 139.176
- Rho-square Value: 0.620
5.4 Rapid Transit

To analyze drive-access behavior for rapid transit, the MBTA 1994 Rapid Transit Passenger Survey was the primary data source. The methods used to conduct this survey were described in Section 4.2.1. The survey resulted in records for more than 38,800 trips, with the origin and destination for each trip, so all trip ends can be geo-coded using GIS software. It also provides information on where people board, transfer, and egress the subway system. The actual transit path can be defined, and all associated characteristics, such as in-vehicle time, transfer time, and waiting time can be estimated accurately. One of the limitations of this data though, is that since the data only reflects trips made by those already using the transit system, it can not be used to predict possible effects on traveler's not using the transit system.

5.4.1 Drive-Access User Demographics

To understand the demographic factors that may influence drive-access behavior in this region, the MBTA 1994 Rapid Transit Passenger Survey's drive-access users' demographic information is analyzed in this section. This survey had a total of 38,874 respondents. Of these respondents, about 29 percent (11,321 respondents) indicated that they used drive-access, including 8442 (75 percent) who chose park-and-ride and 2879 (25 percent) who chose kiss-and-ride. This section will look at demographics in terms of: age, gender, income, automobile availability, and household size.

Age

This survey had the same six age groups as the commuter rail survey. The age group distribution for park-and-ride and kiss-and-ride respondents is shown in Figures 5-7 and 5-8, respectively.
Figure 5-7. Rapid Transit Park-and-ride Users by Age Group

Data Source: MBTA 1994 Rapid Transit Passenger Survey

Figure 5-8. Rapid Transit Kiss-and-ride Users by Age Group

Data Source: MBTA 1994 Rapid Transit Passenger Survey
Both graphs indicate that the age distribution follows the expected normal distribution, with the vast majority of the respondents being adults between the ages of 25 and 64. As with commuter rail, more younger riders chose kiss-and-ride than did older riders.

**Gender**

Tables 5-11 and 5-12 summarize respondents’ gender, again for park-and-ride and kiss-and-ride groups respectively.

**Table 5-11. Rapid Transit Park-and-ride Users by Gender**

<table>
<thead>
<tr>
<th>GENDER</th>
<th>Number of Respondents</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male</td>
<td>3505</td>
<td>41.9%</td>
</tr>
<tr>
<td>Female</td>
<td>4862</td>
<td>58.1%</td>
</tr>
<tr>
<td>No Answer</td>
<td>75</td>
<td></td>
</tr>
</tbody>
</table>

Data Source: MBTA 1994 Rapid Transit Passenger Survey

**Table 5-12. Rapid Transit Kiss-and-ride Users by Gender**

<table>
<thead>
<tr>
<th>GENDER</th>
<th>Number of Respondents</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male</td>
<td>987</td>
<td>34.7%</td>
</tr>
<tr>
<td>Female</td>
<td>1854</td>
<td>65.3%</td>
</tr>
<tr>
<td>No Answer</td>
<td>38</td>
<td></td>
</tr>
</tbody>
</table>

Data Source: MBTA 1994 Rapid Transit Passenger Survey

These tables indicate that female respondents were more common than male respondents for park-and-ride, however, this imbalance was much greater for kiss-and-ride. This propensity for females to be more likely to choose drive-access transit than males is supported by the literature. However, it is unclear if this is due to a higher percentage of females using the transit system, a higher number of females choosing drive-access transit (particularly kiss-and-ride), or merely a higher percentage of females choosing to respond to the survey.

**Income**

Graphs of the income distribution for park-and-ride respondents and kiss-and-ride respondents are shown Figures 5-9 and 5-10, respectively.
These graphs suggest that the majority of drive-access users have an annual household income of over $40,000. Higher income levels are better represented in the case of park-and-ride, perhaps suggestive of the extra cost of parking fees attracting only those with sufficient incomes, or perhaps an effect of automobile ownership.
Automobile Availability and Licensed Drivers

In this survey, 96.7 percent of the park-and-ride respondents stated they had access to an automobile for their trip, versus only 57.9 percent of the kiss-and-ride respondents. Similarly, 98.3 percent of the park-and-ride respondents stated they had a valid driver’s license, versus 88.6 percent of the kiss-and-ride respondents. As with commuter rail, this would seem to indicate that automobile availability and kiss-and-ride usage are strongly correlated.

Household Size

The average household size for park-and-ride users in this survey was 2.74 people compared with 2.97 for kiss-and-ride users. Again, similar to commuter rail, the larger average household size for kiss-and-ride users is in accordance with a priori expectations.

Automobile Ownership

The average number of vehicles owned per household for park-and-ride users in this survey was 2.92 vehicles versus 2.60 vehicles for kiss-and-ride users. The average number of vehicles owned per capita for park-and-ride users in this survey was 1.25 vehicles versus 0.99 vehicles for kiss-and-ride users. This data is also in accordance with a priori expectations. The fact that even kiss-and-ride users have nearly one automobile per person in their household is an interesting comment on the high levels of United States’ automobile ownership.

5.4.2 Trip Characteristics

Accurate trip information is vital to an understanding of drive-access transit behavior. Stated trip information is often inaccurate and is largely based on individual perceptions. In order to avoid this bias, the trip origin address, boarding station, and destination address were used as inputs into transportation network models. These models then generated consistent and accurate trip information for both the automobile and transit portions of the trip. In the case of this analysis, it was decided to use two different transportation network models to generate the trip characteristic information, the CTPS Emme/2 network model and the MIT Boston Regional TransCAD network model. Behavioral models could then be estimated for both model outputs and comparisons between the models could be made.

The CTPS Emme/2 Network Model

Prior to this research, CTPS had already used the origin and destination addresses listed in the survey to assign many of the survey’s observations to specific origin and destination zones within their Emme/2 transportation network model. This model also had specific park-and-ride nodes for transit stations with park-and-ride facilities. Therefore, CTPS was able to create skims of this network to collect trip information. For the automobile portion of the trip, the 1995 AM peak automobile network was used to obtain automobile distances, times and costs from all origin zones to all park-and-ride nodes. The 1995 network was used since it was the network closest (in time) to the survey date. A similar skim was then performed using the 1995 AM peak
transit network to obtain transit trip information from all park-and-ride nodes to all destination zones. This transit trip information included transit wait time, in-vehicle travel time, fare, number of transfers, and transfer penalties. From the analysis of drive-access transit's significance we know that not all drive-access transit behavior occurs at stations with dedicated parking facilities, especially kiss-and-ride behavior. Therefore, similar skims were performed for both the automobile and transit trip portions using the traffic analysis zone (TAZ) in which the station was used as the intermediate destination rather than a park-and-ride node. This trip information was then appended to the survey observations using Microsoft Access database software.

There were several limitations to the utility of this data. The first was that it was hard to visualize. Therefore skim errors and computational errors were difficult to catch. The other limitation was that some of the automobile to park-and-ride node skims returned information inconsistent with the actual road network. This made it impossible to quickly compare travel times from the origin to several different transit stations. It also raised doubts concerning the accuracy of travel times for the entire road network. Also, since the survey responses were assigned to zones rather than specific addresses, it was difficult to determine whether these zones were sufficiently detailed to provide adequate travel information. Perhaps the greatest limitation however was the limited familiarity of the researcher with this Emme/2 model and its outputs.

The MIT Boston Regional TransCAD Network Model

The MIT Boston Regional TransCAD network model was developed as part of on-going research by the MIT Transit Research Group. Using the origin addresses, survey observations were geo-coded into the network. Skims similar to those described above were then used to collect trip information for both the automobile and transit portions of each trip. This information was then appended to the survey responses.

The data produced from this model also had several limitations. For example, this modeling process resulted in a smaller sample size than the CTPS Emme/2 model. This is due to the fact that the TransCAD model could only geo-code origins and destinations with actual street addresses or intersections, whereas the Emme/2 model relied on aggregate zonal information. The TransCAD model was also in a state of continual refinement and calibration, requiring extra time and effort. The ability to visualize the data using TransCAD’s GIS capabilities however, proved invaluable in verifying and calibrating the model outputs.

As with commuter rail, relatively few survey responses had geo-codable origin and destination address information. Specifically, only 1148 of the survey responses had origin addresses detailed enough to be properly geo-coded. This low success rate for geo-coding represents one of the serious limitations to the application of this research’s results. The locations of these trip origins are shown in Figure 5-11. The locations are color-coded by rapid transit line in order to better visualize where these trips are heading.
Using the transportation network model, automobile costs and distances were calculated and matched with the corresponding survey responses. In all, automobile trip characteristics were generated for 444 survey responses. Analysis of these 444 automobile trips indicates that the average automobile trip for park-and-ride users was 7.1 miles and took 14.5 minutes. The average automobile trip for kiss-and-ride users was 4.0 miles and took 9.2 minutes.

The majority of drive-access users also chose the station closest to their origin as shown in Tables 5-13 and 5-14.
Table 5-13. Rapid Transit Station Choice By Time

<table>
<thead>
<tr>
<th># of Survey Responses</th>
<th>Percentage</th>
<th>Cumulative Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Closest Station</td>
<td>226</td>
<td>50.9%</td>
</tr>
<tr>
<td>2nd Closest</td>
<td>125</td>
<td>28.2%</td>
</tr>
<tr>
<td>3rd Closest</td>
<td>34</td>
<td>7.7%</td>
</tr>
<tr>
<td>4th Closest</td>
<td>18</td>
<td>4.1%</td>
</tr>
<tr>
<td>5th Closest</td>
<td>17</td>
<td>3.8%</td>
</tr>
<tr>
<td>6th Closest</td>
<td>8</td>
<td>1.8%</td>
</tr>
<tr>
<td>&gt;6th Closest</td>
<td>16</td>
<td>3.6%</td>
</tr>
<tr>
<td>Total</td>
<td>444</td>
<td>100%</td>
</tr>
</tbody>
</table>

Table 5-14. Rapid Transit Station Choice By Distance

<table>
<thead>
<tr>
<th># of Survey Responses</th>
<th>Percentage</th>
<th>Cumulative Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Closest Station</td>
<td>254</td>
<td>57.2%</td>
</tr>
<tr>
<td>2nd Closest</td>
<td>100</td>
<td>22.5%</td>
</tr>
<tr>
<td>3rd Closest</td>
<td>31</td>
<td>7.0%</td>
</tr>
<tr>
<td>4th Closest</td>
<td>20</td>
<td>4.5%</td>
</tr>
<tr>
<td>5th Closest</td>
<td>18</td>
<td>4.1%</td>
</tr>
<tr>
<td>6th Closest</td>
<td>5</td>
<td>1.1%</td>
</tr>
<tr>
<td>&gt;6th Closest</td>
<td>16</td>
<td>3.6%</td>
</tr>
<tr>
<td>Total</td>
<td>444</td>
<td>100%</td>
</tr>
</tbody>
</table>

Over 50 percent of the survey respondents chose the transit station closest to them by time and over 57 percent of the survey respondents chose the transit station closest to them by distance. In both cases, over 90 percent of the survey respondents chose one of the four closest stations and over 96 percent of the respondents chose one of the six closest stations.

Tables 5-15 and 5-16 show station choice for park-and-ride respondents, while Tables 5-17 and 5-18 show station choice for kiss-and-ride respondents.

Table 5-15. Rapid Transit Park-and-ride Station Choice By Time

<table>
<thead>
<tr>
<th># of Survey Responses</th>
<th>Percentage</th>
<th>Cumulative Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Closest Station</td>
<td>160</td>
<td>47.5%</td>
</tr>
<tr>
<td>2nd Closest</td>
<td>102</td>
<td>30.3%</td>
</tr>
<tr>
<td>3rd Closest</td>
<td>27</td>
<td>8.0%</td>
</tr>
<tr>
<td>4th Closest</td>
<td>15</td>
<td>4.5%</td>
</tr>
<tr>
<td>5th Closest</td>
<td>16</td>
<td>4.7%</td>
</tr>
<tr>
<td>6th Closest</td>
<td>7</td>
<td>2.1%</td>
</tr>
<tr>
<td>&gt;6th Closest</td>
<td>10</td>
<td>3.0%</td>
</tr>
<tr>
<td>Total</td>
<td>337</td>
<td>100%</td>
</tr>
</tbody>
</table>
Table 5-16. Rapid Transit Park-and-ride Station Choice By Distance

<table>
<thead>
<tr>
<th></th>
<th># of Survey Responses</th>
<th>Percentage</th>
<th>Cumulative Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Closest Station</td>
<td>184</td>
<td>54.6%</td>
<td>54.6%</td>
</tr>
<tr>
<td>2nd Closest</td>
<td>80</td>
<td>23.7%</td>
<td>78.3%</td>
</tr>
<tr>
<td>3rd Closest</td>
<td>26</td>
<td>7.7%</td>
<td>86.0%</td>
</tr>
<tr>
<td>4th Closest</td>
<td>15</td>
<td>4.5%</td>
<td>90.5%</td>
</tr>
<tr>
<td>5th Closest</td>
<td>18</td>
<td>5.3%</td>
<td>95.8%</td>
</tr>
<tr>
<td>6th Closest</td>
<td>4</td>
<td>1.2%</td>
<td>97.0%</td>
</tr>
<tr>
<td>&gt;6th Closest</td>
<td>10</td>
<td>3.0%</td>
<td>100%</td>
</tr>
<tr>
<td>Total</td>
<td>337</td>
<td>100%</td>
<td></td>
</tr>
</tbody>
</table>

Table 5-17. Rapid Transit Kiss-and-ride Station Choice By Time

<table>
<thead>
<tr>
<th></th>
<th># of Survey Responses</th>
<th>Percentage</th>
<th>Cumulative Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Closest Station</td>
<td>66</td>
<td>62.3%</td>
<td>62.3%</td>
</tr>
<tr>
<td>2nd Closest</td>
<td>23</td>
<td>21.7%</td>
<td>84.0%</td>
</tr>
<tr>
<td>3rd Closest</td>
<td>7</td>
<td>6.6%</td>
<td>90.6%</td>
</tr>
<tr>
<td>4th Closest</td>
<td>3</td>
<td>2.8%</td>
<td>93.4%</td>
</tr>
<tr>
<td>5th Closest</td>
<td>1</td>
<td>0.9%</td>
<td>94.3%</td>
</tr>
<tr>
<td>6th Closest</td>
<td>1</td>
<td>0.9%</td>
<td>95.2%</td>
</tr>
<tr>
<td>&gt;6th Closest</td>
<td>5</td>
<td>4.7%</td>
<td>100%</td>
</tr>
<tr>
<td>Total</td>
<td>106</td>
<td>100%</td>
<td></td>
</tr>
</tbody>
</table>

Table 5-18. Rapid Transit Kiss-and-ride Station Choice By Distance

<table>
<thead>
<tr>
<th></th>
<th># of Survey Responses</th>
<th>Percentage</th>
<th>Cumulative Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Closest Station</td>
<td>70</td>
<td>66.0%</td>
<td>66.0%</td>
</tr>
<tr>
<td>2nd Closest</td>
<td>20</td>
<td>18.9%</td>
<td>84.9%</td>
</tr>
<tr>
<td>3rd Closest</td>
<td>5</td>
<td>4.7%</td>
<td>89.6%</td>
</tr>
<tr>
<td>4th Closest</td>
<td>5</td>
<td>4.7%</td>
<td>94.3%</td>
</tr>
<tr>
<td>5th Closest</td>
<td>0</td>
<td>0%</td>
<td>94.3%</td>
</tr>
<tr>
<td>6th Closest</td>
<td>1</td>
<td>0.9%</td>
<td>95.2%</td>
</tr>
<tr>
<td>&gt;6th Closest</td>
<td>5</td>
<td>4.7%</td>
<td>100%</td>
</tr>
<tr>
<td>Total</td>
<td>106</td>
<td>100%</td>
<td></td>
</tr>
</tbody>
</table>

As with commuter rail, we again see that kiss-and-ride users are slightly more likely to choose a closer station than are park-and-ride users.

Once the origin information had been geo-coded and the trip characteristics had been generated and analyzed for the automobile access portion of the trip, the next step in the process was to geo-code the trip destinations into the transportation network model. Only 1355 of the survey responses had destination addresses detailed enough to be properly geo-coded. The majority of the trip destinations are located in the Boston central business district (CBD) as shown in Figure 5-12.
5.4.3 Station Choice Model Based on CTPS Emme/2 Data

Microsoft Access computer software was utilized to appropriately join the survey data with the station data and the trip information generated by the CTPS Emme/2 model. This resulted in 2969 valid drive-access transit observations. Of these observations, 2303 (78%) were park and ride users, 666 (22%) were kiss and ride users. 509 observations (17%) were on the Blue Line, 777 (26%) were on the Orange Line, 1414 (48%) were on the Red Line, and 269 (9%) were on the Green Line.

The station choice model was estimated using the multinomial logit estimation function in the TransCAD software. In specifying models to estimate station choice behavior, the following variables were analyzed:

- automobile trip times, distances and cost;
- transit trip times, fares, in-vehicle times, auxiliary times, first wait times, transfer times, number of transfers, boarding times,
Parking capacity,
parking fees, and
a dummy variable for whether or not the station is a terminal.

Station choice models were estimated for all drive-access transit users, and for park-and-ride and kiss-and-ride users separately. In all, 42 rapid transit stations were included in this model.

Unfortunately, in none of these models are any of these variables determined to be statistically significant. Also none of the models evidence a likelihood value statistically better than a naive model. This suggests that the information we have available is inadequate to describe regional drive-access transit station choice behavior. There are several possible reasons for this failure. First, the non-observed factors discussed earlier could play such a vital role in this region, that their absence from the model makes model estimation infeasible. Alternatively, the trip characteristics generated by the network model might not be sufficiently accurate to properly model behavior. Also, errors in data manipulation and/or application on the part of the researcher could have contributed to this result. Possible errors in the model formulation could also have produced these inconclusive results.

5.4.4 Sub-Mode Choice Model Based on CTPS Emme/2 Data

In specifying models to estimate sub-mode choice behavior, the following variables were analyzed:
- automobile drive times, distances and costs to the chosen station,
- transit initial wait times at the chosen station,
- auto availability,
- whether the respondent had a valid driver's license or not,
- parking capacity at the chosen station,
- parking fees at the chosen station,
- trip purpose (divided into home-based work trips, home-based other trips, and non-home-based trips),
- trip frequency,
- trip time of day,
- household size,
- number of vehicles owned per household and per capita,
- income levels,
- age, and
- gender.
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Using these variables, several models were specified and tested. According to the statistical t-test values several variables were insignificant in every model examined, including: trip purpose, trip frequency, trip time of day, and age. From these models, there is no evidence that these variables play a significant role in determining the sub-mode choice between park-and-ride and kiss-and-ride.

Of income levels, only the dummy variable representing individuals with annual household income of under $20,000 was ever significant, and this significance varied dramatically according to the model specification. Typically, a t-test value of 1.96 is considered significant at a 90% confidence level. In some models, the low income variable had a t-test value slightly above 1.96 and in other models, it was deemed highly insignificant. Therefore, because of the unstable nature of this variable, it is not recommended for use in the final model.

Both the automobile drive time and the initial wait time were highly significant in every model specification. The initial wait time was included in the model since it was thought that this is sometimes considered as part of the total time it takes to access a station. Additionally, since individuals often perceive wait time differently than travel time, wait time was included as a separate variable. Not surprisingly, the models indicated that the greater the automobile drive time to a station the more likely an individual was to choose park-and-ride. This is consistent with the expectation that long drive times might be considered too burdensome for the driver dropping someone off and therefore acts as a disincentive to kiss-and-ride. However, in contrast, the models also indicated that the larger the initial wait time, the more likely for kiss-and-ride to be chosen. This might be explained by the reasoning that the longer one has to wait at the station, the less concerned they are of arriving on time and therefore the additional hassle of having someone drop you off seems less onerous. Regardless, this is a surprising result and deserves additional research to determine if this behavioral interpretation is correct and why.

Besides the automobile travel times and initial wait times, other variables that were significant included parking capacity, parking fees, number of vehicles owned per household, household size, and gender. All these variables had highly significant parameters with the expected sign. Of interest, while both number of vehicles owned per household and household size were significant by themselves, the number of vehicles owned per capita was more significant than either separately. This can be explained by the hypothesis that fewer cars per person would result more strongly in an individual choosing kiss-and-ride over park-and-ride.

Also of interest, gender was highly significant in all models, with men being less inclined to choose kiss-and-ride than women. This result is consistent with Schank’s (2002) finding that the percentage of females in the population surrounding the station was correlated with kiss-and-ride usage.

The recommended model is shown in Table 5-19. This model has eight parameters, one of which is an alternative specific constant, and its final log-likelihood value indicates that it is superior to any naïve model. The model has an adjusted $R^2$ value of 0.407.
Table 5-19. Recommended Rapid Transit Sub-Mode Choice Model Using Emme/2 Data

<table>
<thead>
<tr>
<th>Independent Variable</th>
<th>Estimated Coefficient</th>
<th>Standard Error</th>
<th>t-statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>ASC (Park-and-ride)</td>
<td>1.778</td>
<td>0.316</td>
<td>5.633</td>
</tr>
<tr>
<td>Automobile travel time</td>
<td>0.0119</td>
<td>0.00330</td>
<td>3.624</td>
</tr>
<tr>
<td>Transit initial wait time</td>
<td>-0.189</td>
<td>0.0594</td>
<td>-3.175</td>
</tr>
<tr>
<td>Automobile availability</td>
<td>3.071</td>
<td>0.169</td>
<td>18.174</td>
</tr>
<tr>
<td>Parking capacity</td>
<td>0.000452</td>
<td>0.0000960</td>
<td>4.723</td>
</tr>
<tr>
<td>Parking fees</td>
<td>-0.482</td>
<td>0.0939</td>
<td>-5.133</td>
</tr>
<tr>
<td>Number of vehicles owned per capita</td>
<td>0.928</td>
<td>0.117</td>
<td>7.906</td>
</tr>
<tr>
<td>Gender (Male)</td>
<td>0.332</td>
<td>0.109</td>
<td>3.037</td>
</tr>
</tbody>
</table>

Model Statistics:

Valid Cases: 2969 (2303 park-and-ride (77.6%) and 666 kiss-and-ride (22.4%))

Maximum likelihood reached at iteration 11.

Log-likelihood at zero: -2057.953979
Log-likelihood at end: -1211.266877
-2 (LL(zero) - LL(end)): 1693.374204
Asymptotic rho squared: 0.411422
Adjusted rho squared: 0.407
5.4.5 Station Choice Model Based on MIT TransCAD Data

As described above, the MIT Boston Regional TransCAD network model is being developed as part of on-going, collaborative research.

Joining the survey responses for which automobile trip characteristics could be generated with the survey responses for which transit trip characteristics could be generated resulted in 444 total observations. Of these 444 observations, 337 (75.9 percent) used park-and-ride and 107 (24.1 percent) used kiss-and-ride. Utilizing these survey responses, a station choice model was developed and estimated for rapid transit passengers. There were a total of 27 possible stations that could be chosen.

Again, the Biogeme software package was used to estimate this model. In specifying models to estimate station choice behavior, the following variables were analyzed:

- automobile trip times and distances,
- transit total trip times and distances, in-vehicle travel times, and number of transfers needed,
- parking capacity,
- parking fees, and
- dummy variables for whether or not a station was the closest station to the origin both by time and distance to account for possible bias towards the closest station.

Using these variables, several different models were specified and tested. Several variables were insignificant in every model examined including total transit times, transit in-vehicle travel times, the number of transfers on the transit portion of the trip, and the closest station dummy variables. From these models, there is no evidence to suggest that these variables play a significant role in determining station choice behavior.

As in the commuter rail station choice model, automobile distances again were determined to be more statistically significant than automobile travel times. Therefore the automobile distance to the station was included in the recommended model. The automobile travel time variable's coefficient had the correct sign, indicating that travelers are less likely to choose stations further away, however it was not statistically significant in several model specifications. Similar to the commuter rail station choice model, parking fees were also statistically significant in some model specifications, but with the incorrect sign. This would suggest that travelers were more likely to choose a station with a higher parking fee. As stated before, this could be due to better parking conditions associated with the higher fee, but without more information, this variable would be misleading in the model. Therefore, the parking fee variable was excluded from the recommended model.

Other than the automobile distance variable, the other two variables that were included in the model were parking capacity and transit trip distance. The signs on the variables indicate that travelers are more likely to choose stations with more parking capacity and less likely to choose stations with longer transit distances to their destination.
Chapter 5

The recommended model is shown in Table 5-20. This model has three parameters, and its final log-likelihood value indicates that it is superior to any naïve model. The model recommended below has an adjusted $R^2$ value of 0.403.

*Table 5-20. Recommended Rapid Transit Station Choice Model Using TransCAD Data*

<table>
<thead>
<tr>
<th>Independent Variable</th>
<th>Estimated Coefficient</th>
<th>Standard Error</th>
<th>t-statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Automobile distance</td>
<td>-1.476</td>
<td>0.125</td>
<td>-11.774</td>
</tr>
<tr>
<td>Parking capacity</td>
<td>0.00104</td>
<td>0.000146</td>
<td>9.989</td>
</tr>
<tr>
<td>Transit trip distance</td>
<td>-0.444</td>
<td>0.0752</td>
<td>-5.898</td>
</tr>
</tbody>
</table>

**Model Statistics:**

Valid Cases: 406

Initial Log-likelihood: -573.986

Final Log-likelihood: -342.895

Likelihood Ratio Test: 462.183

Rho-square Value: 0.403

### 5.4.6 Sub-Mode Choice Model Based on MIT TransCAD Data

Since only a limited number of survey responses had "geo-codable" origin and destination information, the total number of observations available for model estimation was limited to only 458 observations. Again, the Biogeme software package was used to estimate this model.

In specifying models to estimate sub-mode choice behavior, the following variables were analyzed:

- automobile travel times and distances to the chosen station,
- auto availability,
- whether the respondent had a valid driver's license or not,
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- parking capacity at the chosen station,
- parking fees at the chosen station,
- trip purpose (divided into home-based work trips, home-based other trips, and non-home-based trips),
- trip frequency,
- household size,
- number of vehicles owned per household and per capita,
- income levels,
- age, and
- gender.

Using these variables, several models were specified and tested. Variables which were insignificant in every model examined included: automobile travel times, whether or not the respondent had a valid driver’s license, parking capacities, parking fees, trip purpose, trip frequency, household size, number of vehicles owned per household, income levels, age, and gender. From these models, one cannot conclude that these variables play a significant role in determining the sub-mode choice behavior for rapid transit users.

Variables that were deemed statistically significant included: automobile availability, automobile distances, and vehicles owned per capita. The positive sign of the vehicles owned per capita and the automobile distance variables' coefficients indicates that travelers are more likely to choose park-and-ride when the distance to a station is greater and when their household owns more cars per capita. Also, if individuals have an automobile available, they are more likely to choose park-and-ride.

The recommended model is shown in Table 5-21. This model has four parameters, one of which is an alternative specific constant. Its final log-likelihood value indicates that it is superior to any naive model. The model recommended below has a $R^2$ value of 0.462.
### Table 5-21. Recommended Rapid Transit Sub-Mode Choice Model Using TransCAD Data

<table>
<thead>
<tr>
<th>Independent Variable</th>
<th>Estimated Coefficient</th>
<th>Standard Error</th>
<th>t-statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>ASC (Park-and-ride)</td>
<td>3.602</td>
<td>0.677</td>
<td>5.318</td>
</tr>
<tr>
<td>Automobile distance</td>
<td>0.147</td>
<td>0.0376</td>
<td>3.913</td>
</tr>
<tr>
<td>Automobile availability</td>
<td>3.437</td>
<td>0.426</td>
<td>8.065</td>
</tr>
<tr>
<td>Number of vehicles owned per capita</td>
<td>0.699</td>
<td>0.333</td>
<td>2.100</td>
</tr>
</tbody>
</table>

**Model Statistics:**

Valid Cases: 458 (347 park-and-ride (75.8%) and 111 kiss-and-ride (24.2%))

- Initial Log-likelihood: -317.461
- Final Log-likelihood: -170.747
- Likelihood Ratio Test: 293.428
- Rho-square Value: 0.462
6. FINDINGS AND RECOMMENDATIONS

In this chapter, findings of this research are reported. These findings include data and model findings specific to the case study as well as overall findings relevant to the real-world application of the framework. Recommendations specific to the Boston Metropolitan Region are proposed. Opportunities for possible related future research are discussed.

6.1 FINDINGS

In applying the analytical framework to the Boston Metropolitan Region, there were several key findings specific to the Boston case study. Additionally, there were some conclusions reached relating to the overall effectiveness of the framework and its implementation. These findings are summarized in Sections 6.1.1 and 6.1.2, respectively.

6.1.1 Case Study Findings

As the first step of the analytical framework, the regional significance of drive-access transit was assessed using a variety of data sources and GIS technology. Key findings included:

- Drive-access transit accounts for 1.2 percent of the total daily trips in the Boston Metropolitan Region.
- Approximately 46 percent of the region's population does not live within walking distance (3/4 mile) of transit service. Providing better drive-access transit to these individuals has tremendous ridership growth potential for regional public transport.
- Passenger surveys indicate that drive-access accounts for 69 percent of commuter rail trips (56 percent park-and-ride, 13 percent kiss-and-ride).
- Passenger surveys indicate that drive-access accounts for 18 percent of total rapid transit trips (12 percent park-and-ride, 6 percent kiss-and-ride), and 31 percent of rapid transit trips at the 50 outermost transit stations (24 percent park-and-ride, 7 percent kiss-and-ride).
- The MBTA is responsible for over 34,000 parking spaces. These spaces generate revenue that in recent years has become an increasingly larger percentage of the MBTA's total operating revenue.
- A recent study indicated that 71 percent of the MBTA parking facilities reached 85 percent or more of capacity, many of them filling prior to the departure of the last morning peak train. This is an indication of latent demand for parking facilities in the region.
- Parking fees in the region do not have a clear spatial relationship. There is also no apparent correlation between parking capacity filled and parking fee prices. Instead, these fees appear to have been determined on a station-by-station basis.
The behavior of regional drive-access transit users was also examined. Passenger surveys were analyzed with respect to demographics, and then geo-coded into transportation network models. These network models were used to develop accurate and consistent trip characteristics for each survey response. These demographic and trip information were then combined with available station information to create variables for multinomial logit model estimation. Models were then estimated to explain sub-mode choice and station choice behavior. Due to the limited data available, this behavioral analysis was confined solely to commuter rail and rapid transit in the region.

To begin, the only commuter rail passenger survey with detailed origin and destination addresses, necessary for the accurate generation of trip characteristics, was the 1998 MBTA Old Colony Commuter Rail Passenger Survey. Therefore, these commuter rail results are limited in application. A more complete analysis would involve looking at all commuter rail lines in the region.

Demographically, these commuter rail drive-access users demonstrated normal age and gender distributions. Income levels seemed rather high with the vast majority of drive-access transit users coming from households with annual incomes exceeding $40,000. Of interest is that automobile availability varied greatly between park-and-ride users and kiss-and-ride users. Over 99 percent of park-and-ride users had access to an automobile, while only 62 percent of kiss-and-ride users had access to an automobile, suggesting that automobile availability is a key determinant in travelers' sub-mode decision.

Using the MIT Boston Regional TransCAD network model, automobile and transit trip characteristics were generated for a total of 166 survey responses. These responses were then used to estimate an access mode choice model for commuter rail riders. Several model specifications were tested. The recommended model had a $R^2$ value, which measures model goodness-of-fit, of 0.620. This model indicated that variables that significantly affected the commuter rail traveler’s sub-mode choice decision included automobile distance to the chosen station, parking capacity and fees at the chosen station, the vehicles per person ratio of the traveler’s household, and the frequency with which the traveler makes such trips.

These survey responses also indicated that nearly 98 percent of the commuter rail drive-access users chose to access one of the three stations closest to the trip origin both by time and distance. A station choice model was also estimated using the commuter rail survey responses, with the recommended model having a $R^2$ value of 0.629. This recommended model included three variables that had a significant effect on commuter rail drive-access users' station choice: automobile distance, parking capacity, and transit fare from the station to the destination. Comparing the estimated coefficients for automobile distance and transit fare, one can estimate that, on average, a driver is willing to drive an extra mile to a further transit station, if it results in a decrease of more than $0.90 in their transit fare. This result has direct implications for fare zone policies and station location decisions. It also is vital to a proper understanding of commuter rail station catchment areas.

Next, rapid transit drive-access users' behavior was analyzed using the 1994 Rapid Transit Passenger Survey information. Demographically, the rapid transit drive-access users were similar to the commuter rail drive-access users. They too showed a normal distribution of age groups. Again, automobile availability for park-and-ride users (nearly 97 percent) was much higher than for kiss-and-ride users (58 percent).
Sub-mode choice and station choice model estimations were attempted using both the trip characteristic data generated by the CTPS Emme/2 network model and the MIT TransCAD network model, however, data generated by both network models had serious limitations. The Emme/2 data allowed for a much larger set of observations to be used, however the inability to visualize and verify the generated data led to complications and computational difficulties. The TransCAD data, although more detailed and easier to visualize and verify, resulted in a much smaller sample set, since detailed “geo-codable” address information was required.

Using the Emme/2 data, several sub-mode choice model specifications were tested. The recommended model had a $p^2$ value of 0.407. This model indicated that several variables that significantly affected the commuter rail traveler’s sub-mode choice decision also affected the rapid transit traveler’s sub-mode choice decision. These variables included automobile travel time to the chosen station, parking capacity and fees at the chosen station, and the vehicle per person ratio of the traveler’s household. This model also found that automobile availability, initial transit wait time, and gender also affected the sub-mode choice decision. Several attempts were made at estimating a station choice model using this data, but no model generated was statistically superior to a naïve model, and none of the variables tested were found to be statistically significant.

Using the TransCAD data, several sub-mode choice model specifications were also tested. The recommended model had a $p^2$ value of 0.462. This model indicated that the variables that significantly affected the rapid transit traveler’s sub-mode choice decision included automobile distance to the chosen station, automobile availability, and the vehicle per person ratio of the traveler’s household. These findings were consistent with the other sub-mode choice findings.

These survey responses indicated that over 96 percent of the rapid transit drive-access transit users chose to access one of the six stations closest to the trip origin both by time and distance. Several station choice model specifications were tested. The recommended model had a $p^2$ value of 0.402. This recommended model included three variables that had a significant effect on commuter rail drive-access users’ behavior: automobile distance, parking capacity, and transit distance from the station to the destination. Unlike commuter rail trips, nearly all rapid transit trips cost the same fare (with the exception of some Red Line and Green Line trips), and therefore transit fare does not play a significant role in the rapid transit station choice decision. However, by comparing the estimated coefficients for automobile distance and transit distance, one can estimate that, on average, a driver would be willing to drive an extra mile to a further transit station, if it resulted in a decrease of more than 3.3 miles off their transit trip distance. This seems plausible if one considers that for rapid transit, someone might drive slightly further to access a station on the same line as their destination.

It is interesting to compare the commuter rail and rapid transit results. To begin, let us compare the demographics of these two surveys. Both surveys demonstrated a fairly normal distribution of age group levels, with the majority of respondents being between ages 24 and 65. There was greater disparity between the surveys in terms of gender, as shown in Table 6-1.
Table 6-1. Gender Comparison of Commuter Rail and Rapid Transit Survey Responses

<table>
<thead>
<tr>
<th></th>
<th>Percent Male</th>
<th>Percent Female</th>
</tr>
</thead>
<tbody>
<tr>
<td>Commuter Rail Park-and-ride Respondents</td>
<td>46.6%</td>
<td>53.4%</td>
</tr>
<tr>
<td>Rapid Transit Park-and-ride Respondents</td>
<td>41.9%</td>
<td>58.1%</td>
</tr>
<tr>
<td>Commuter Rail Kiss-and-ride Respondents</td>
<td>48.0%</td>
<td>52.0%</td>
</tr>
<tr>
<td>Rapid Transit Kiss-and-ride Respondents</td>
<td>34.7%</td>
<td>65.3%</td>
</tr>
</tbody>
</table>

Rapid transit had a higher percentage of female respondents for both park-and-ride and kiss-and-ride. Of particular note is the fact that over 65 percent of the rapid transit kiss-and-ride users were female. In terms of income levels, both surveys indicated that drive-access transit users predominately had annual incomes exceeding $40,000. However, the commuter rail survey showed an even greater response rate of individuals with even higher income levels.

A comparison of the two surveys in terms of automobile availability, percentage of licensed drivers, household size, and number of vehicles owned per household and per capita is summarized in the table below.
Table 6-2. Summary Comparison of Commuter Rail and Rapid Transit Survey

<table>
<thead>
<tr>
<th></th>
<th>Park-and-ride</th>
<th>Kiss-and-ride</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percent Automobile Availability</td>
<td>99.1%</td>
<td>62.2%</td>
</tr>
<tr>
<td></td>
<td>99.6%</td>
<td>86.5%</td>
</tr>
<tr>
<td>Percent Licensed Drivers</td>
<td>99.1%</td>
<td>98.3%</td>
</tr>
<tr>
<td></td>
<td>62.2%</td>
<td>57.9%</td>
</tr>
<tr>
<td>Average Household Size</td>
<td>2.93</td>
<td>3.29</td>
</tr>
<tr>
<td></td>
<td>2.74</td>
<td>2.97</td>
</tr>
<tr>
<td>Average Number of Vehicles Owned Per Household</td>
<td>3.13</td>
<td>2.92</td>
</tr>
<tr>
<td></td>
<td>2.93</td>
<td>2.60</td>
</tr>
<tr>
<td>Average Number of Vehicles Owned Per Capita</td>
<td>1.21</td>
<td>0.97</td>
</tr>
<tr>
<td></td>
<td>1.25</td>
<td>0.99</td>
</tr>
</tbody>
</table>

These values are in accordance with what one would expect. Commuter rail users show greater automobile availability, which is no doubt correlated with the more automobile-dependent regions surrounding commuter rail stations. Also, commuter rail users had slightly larger household sizes and owned more vehicles per household. Of some surprise is the fact that rapid transit users, on average, owned more vehicles per capita, and that even kiss-and-ride users showed almost one vehicle owned for every person in their individual households.

The geo-coded survey responses were then used to calculate average automobile trip characteristics for park-and-ride and kiss-and-ride users. These average trip characteristics are shown in the following table.

Table 6-3. Comparison of Commuter Rail and Rapid Transit Geo-coded Automobile Trip Characteristics

<table>
<thead>
<tr>
<th></th>
<th>Distance (miles)</th>
<th>Time (minutes)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Commuter Rail Park-and-ride</td>
<td>3.6</td>
<td>7.4</td>
</tr>
<tr>
<td>Rapid Transit Park-and-ride</td>
<td>7.1</td>
<td>14.5</td>
</tr>
<tr>
<td>Commuter Rail Kiss-and-ride</td>
<td>2.1</td>
<td>4.6</td>
</tr>
<tr>
<td>Rapid Transit Kiss-and-ride</td>
<td>4</td>
<td>9.2</td>
</tr>
</tbody>
</table>

Rapid transit users, on average, drove longer, in terms of both time and distance, than their commuter rail counterparts. This is reflective of individuals' willingness to drive further for the perceived better service and frequency of rapid transit, as well as its lower fares.
In terms of station choice, commuter rail users were far more likely to choose a closer station. Of the geo-coded survey responses, 97.6 percent of commuter rail users chose one of the three closest commuter rail stations versus only 86.7 percent of the geo-coded rapid transit users. 96.4 percent of the geo-coded rapid transit users chose one of the six closest rapid transit stations. This likely reflects the greater density of rapid transit stations compared with commuter rail. Future research using the inverse nested structure and/or incorporating the overall mode choice model might clarify the reasons for these differences in station choice behavior.

A comparison of the various sub-mode choice and station choice models are summarized in the Tables 6-4 and 6-5.

**Table 6-4. Comparison of Estimated Behavioral Models**

<table>
<thead>
<tr>
<th></th>
<th>Number of Observations</th>
<th>Goodness-of-fit</th>
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</thead>
<tbody>
<tr>
<td><strong>Sub-Mode Choice Models</strong></td>
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<tr>
<td>Commuter Rail Sub-Mode Choice Model</td>
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<td>0.620</td>
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<td>0.407</td>
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<tr>
<td>Rapid Transit TransCAD Sub-Mode Choice Model</td>
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<td><strong>Station Choice Models</strong></td>
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Table 6-5. Matrix of Model Variables

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<th>Station Choice Models</th>
<th></th>
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<tr>
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<td>Rapid Transit</td>
<td>Rapid Transit TransCAD</td>
<td>Commuter Rail</td>
</tr>
<tr>
<td></td>
<td>Sub-Mode Choice Model</td>
<td>Sub-Mode Choice Model</td>
<td>Sub-Mode Choice Model</td>
<td>Station Choice Model</td>
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<tr>
<td>Automobile Distance</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Automobile Travel Time</td>
<td></td>
<td>X</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Automobile Availability</td>
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<td>X</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Parking Capacity</td>
<td>X</td>
<td></td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Parking Fees</td>
<td></td>
<td>X</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of Vehicles Owned per Capita</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Initial Transit Wait Time</td>
<td></td>
<td>X</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Trip Frequency</td>
<td>X</td>
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</tr>
<tr>
<td>Gender</td>
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<tr>
<td>Transit Fare</td>
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<tr>
<td>Transit Distance</td>
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</table>

The commuter rail models evidenced a much better goodness of fit, likely due to the smaller sample size, simpler network, and compactness of destinations. In all the sub-mode choice models, either the automobile distance or time variable was significant. The number of vehicles owned per capita variable was significant in all three sub-mode choice models. In both station choice models, the automobile distance and parking capacity variables were significant.

6.1.2 Framework Findings

Overall, several key findings concerning the implementation of the framework resulted from the case study application.

First, the analysis is only as good as the underlying data. Many assumptions had to be made and often the analysis was incomplete due to insufficient data. In order to truly understand, analyze, and manage any system, data of sufficient quantity and quality must be collected. Obviously, this framework is meant as an exploratory tool and can serve to better illustrate an agency’s data needs.

Second, GIS technology is essential to making this framework work. The GIS technology aids in analysis by allowing for easy recognition of spatial patterns and connections. It can combine many different types of data and allows for easy verification. It also aids in conveying and
communicating the results of this analysis, especially to a non-technical audience. For example, the mode share data represents nearly five pages of tables, yet the main concepts of the mode share were presented in three figures. This consolidation of information was considered extremely useful.

Finally, the framework was very successful in achieving its stated purposes. It collected drive-access transit information from myriad sources and combined them in a logical and useful way. It produced results that were easy to understand and convey. It utilized existing data sources and provided input as to how future data collection could be improved. It generated tools that help explain regional drive-access behavior.

6.2 RECOMMENDATIONS

This section suggests several policy and methodology recommendations specific to the Boston Metropolitan Region.

6.2.1 Policy Recommendations

First, this case study represents an important initial step by focusing more attention on drive-access transit. With the region's transportation focus on improved accessibility and mobility, drive-access transit should be made a higher priority. It is recommended that additional time and resources be allocated to research this access mode.

Also, park-and-ride should be recognized as a revenue source that needs to be optimized. Consideration should be given to expanding parking facilities where economically feasible, adjusting parking fees to reflect parking demand and station location, and providing parking spaces with time limits to allow for more non-commuter trip purposes.

The MBTA and CTPS should consider strategies to promote additional kiss-and-ride usage. With many of the system's parking facilities already filled to capacity, promoting kiss-and-ride usage could provide additional ridership and revenue. Potential strategies include specific and separate kiss-and-ride drop-off zones, favorable parking policies and enforcement at and around transit stations, and/or promotional campaigns. There is already evidence elsewhere that promotional campaigns can result in rapid increase in net drive-access transit usage.

In September and October of 1993, the Chicago Transit Authority (CTA) conducted a drive-access promotional campaign at the Cumberland station along the CTA Blue Line. Two surveys conducted in November 1993 were designed to assess the effectiveness of this promotional campaign and to monitor the characteristics of drive-access transit users. The results of these surveys indicated that a net increase in usage of 8 percent was directly attributable to the marketing promotion. (CTA O'Hare, 1994)

Additionally, the MBTA and CTPS should consider strategies and investments to promote carpooling to transit stations. Carpooling to stations would allow the transit system to serve more people without additional parking infrastructure investment. Such strategies could include
preferential parking for carpools at transit station parking facilities, fare discounts for carpools, and/or promoting carpooling through advertising and marketing campaigns.

6.2.2 Methodology Recommendations

It is also recommended that the MBTA and CTPS coordinate an effort to conduct rigorous on-board passenger surveys at more frequent intervals. Much of the data used in this analysis was over a decade old (e.g. the MBTA 1994 Rapid Transit Passenger Survey). Recent data is essential to proper analysis. Additionally, passenger surveys and parking utilization studies should be conducted concurrently to allow a better understanding of their interrelationships. Clearly, the cost associated with such surveys can be prohibitive, especially with the financial pressures facing these agencies. Methods of reducing this data collection cost could include: investing in automatic data collection technology such as automatic passenger counters, allowing some of the surveys to be conducted on-line to reduce data input costs, and/or collaborating with institutions with similar transportation research goals.

Furthermore, the questionnaires used to conduct these surveys should be redesigned. One of the limitations of the behavioral analysis is that few responses gave detailed “geo-codable” addresses. This could be due to poor emphasis placed on these addresses and individuals reluctance to share this address information. Therefore, the importance of this address information should be better emphasized in the questionnaire, and individuals should be reassured that the information they provide will not be used for any untoward purpose. Additionally, explaining that the closest major street intersection can be used as a substitute for an actual address might also be helpful. The questionnaires also fail to take into account trip-chaining activities both to and from the transit station. Information on other factors such as perceived station security and security, as well as weather conditions might also be helpful.

Realistically, it is understood that the limited finances available to transit agencies might make such an intensive data collection effort infeasible. In the absence of such data, the models developed in this thesis could act as an interim method of better defining station catchment areas, predicting drive-access transit demand, and setting prices. It should be noted, however, that the small sample sizes used in estimating these models are a severe limitation to their long-term applicability. Notwithstanding this, they represent a significant improvement over the “best estimate” modeling approach currently in use.

The MBTA and CTPS should also work together to conduct surveys and market analyses of potential drive-access transit users. One of the disadvantages of using passenger surveys to analyze traveler behavior is that it only accounts for current transit users and fails to account for non-users’ perceptions and travel behavior. Market studies focusing on areas where drive-access transit is a viable transportation option could close this gap.
6.3 Future Research Directions

This research was primarily exploratory in nature. It has many limitations that may be addressed through future research. These future research directions include:

- Apply framework to other regional transit systems. In this research, the framework was applied only to the Boston Metropolitan Region. Applying the framework to other regions, especially regions with different urban forms and different socioeconomic demographics, would allow for better assessment of the framework’s validity. It would also allow for regional comparisons.

- Nest the sub-mode choice and station choice models and incorporate them into the upper transportation mode choice model. Various nesting structures could be developed and compared. Developing separate park-and-ride and kiss-and-ride station choice models could be a part of this alternate nesting structure. In this thesis, only separate sub-mode choice models and station choice models were estimated. Nesting and incorporating this information into the upper transportation mode choice model would be a logical next step.

- Analyze drive-access transit as it relates to buses and ferries. Due to limited data collected on this subject, drive-access transit usage on buses and ferries was neglected in this thesis. The collection and analysis of such data would add to this research’s completeness. Additionally, it is expected that particular drive-access transit usage on buses would evidence travel behavior unlike drive-access transit usage on commuter rail and rapid transit. For example, kiss-and-ride might be more popular than park-and-ride since no dedicated parking is provided at bus stops.

- Incorporate station environmental factors into analysis. For example, only parking capacity at the station is analyzed, not parking in the neighborhood surrounding the station. Also, the attractiveness and safety of the surrounding environment might significantly affect drive-access transit behavior.

- Conduct further analysis on commuter rail lines where data is currently not available. Only the Old Colony commuter rail line was analyzed in this study. As future passenger surveys are conducted on other commuter rail lines, analyzing this data and comparing it to the Old Colony commuter rail results would be of interest.

- Conduct market studies to examine non-transit users’ perceptions of drive-access transit. As mentioned above, passenger surveys only examine current riders’ perceptions and behaviors. Market studies would allow a better understanding of drive-access transit attitudes and behaviors in the general population.

- Examine the return on investment in station parking facilities. Obtain construction costs for regional parking facilities. Factor in the costs of maintaining and operating the parking facilities over their construction lifecycles. Determine the parking demand and revenue generated over the lifecycles of the parking facilities and estimate an expected return on investment.
Findings and Recommendations

- Examine how ITS might influence drive-access transit. For example, how might providing parking information to drivers en route alter their drive-access transit behavior. Also, ITS holds the promise of greatly reducing the cost of data collection and the cost of operating parking facilities.

- Analyze the impacts of various parking fee policies. Perform sensitivity analyses on how different parking fee strategies/policies affect demand for parking facilities. Such an analysis could help clarify whether or not encouraging additional non-commuter trips has a negative impact on transit trip totals.

- Further refine the MIT Boston Regional TransCAD network model. All models need continual refinement and calibration. As a newly developed model, the MIT Boston Regional TransCAD model could be further refined by someone familiar with the region's transportation network.

- Incorporate U.S. Census data more fully into the analysis. Determine methods to exploit this census data to better examine transit users in census tracts far from transit services, and thus requiring drive-access transit.
APPENDIX A: BIBLIOGRAPHY


Caliper Corporation. Travel Demand Modeling with TransCAD. 2002.


Chicago Transit Authority (CTA). O’Hare Line Park & Ride Surveys: Phase II. April, 1994.


Appendix A


# APPENDIX B: LIST OF ACRONYMS

<table>
<thead>
<tr>
<th>Acronym</th>
<th>Definition</th>
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<tbody>
<tr>
<td>CBD</td>
<td>Central Business District</td>
</tr>
<tr>
<td>CTA</td>
<td>Chicago Transit Authority</td>
</tr>
<tr>
<td>CTPP</td>
<td>Census Transportation Planning Package</td>
</tr>
<tr>
<td>CTPS</td>
<td>Central Transportation Planning Staff</td>
</tr>
<tr>
<td>DAT</td>
<td>Drive-Access Transit</td>
</tr>
<tr>
<td>GIS</td>
<td>Geographic Information System</td>
</tr>
<tr>
<td>ITE</td>
<td>Institute of Transportation Engineers</td>
</tr>
<tr>
<td>KNR</td>
<td>Kiss-and-Ride</td>
</tr>
<tr>
<td>MBTA</td>
<td>Massachusetts Bay Transportation Authority</td>
</tr>
<tr>
<td>MPO</td>
<td>Metropolitan Planning Organization</td>
</tr>
<tr>
<td>PNR</td>
<td>Park-and-Ride</td>
</tr>
<tr>
<td>TAZ</td>
<td>Traffic Analysis Zone</td>
</tr>
<tr>
<td>VHT</td>
<td>Vehicle-hours Traveled</td>
</tr>
<tr>
<td>VMT</td>
<td>Vehicle-miles Traveled</td>
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APPENDIX C: BIOGEME MODEL FILES

Commuter Rail Sub-Mode Choice Model File
// File crmodechoice6.mod

//
[DataFile]
$COLUMNS = 32
[Choice]
Acc_mode
[Beta]
// Name Value LowerBound UpperBound status (0=variable, 1=fixed)
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ASC_K 0 -10000 10000 1
VC 0 -10000 10000 0
FR 0 -10000 10000 0
AD 0 -10000 10000 0
PC 0 -10000 10000 0
PF 0 -10000 10000 0

[Utilities]
// Id Name Avail linear-in-parameter expression (beta1*x1 + beta2*x2 + ... )
  2 KNR one ASC_K * one
  3 PNR one ASC_P * one + VC * VEH_CAP + AD * audst + PC * Park_Cap + PF * Park_Fee + FR * Freq

[Expressions]
// Define here arithmetic expressions for name that are not directly available from the data
one = 1

[Mu]
// The scale parameter mu is generally normalized to equal 1
Value LowerBound UpperBound Status(1=fixed)
1 0 1 1

[Model]
// Currently, only $MNL (multinomial logit), $NL (nested logit), $CNL
// (cross-nested logit) and $NGEV (Network GEV model) are valid keywords
//
$MNL
Appendix C

**Commuter Rail Station Choice Model File**

// File crstachoice9.mod

//

[DataFile]
$COLUMNS = 105

[Choice]
B_Sta

[Beta]
// Name Value LowerBound UpperBound status (0=variable, 1=fixed)
PC 0 -10000 10000 0
TF 0 -10000 10000 0
AD 0 -10000 10000 0

[Utilities]
// Id Name Avail linear-in-parameter expression (beta1*x1 + beta2*x2 + ...)  
1 ABIN ABIN_AVA PC * ABIN_PC + TF * ABIN_TFARE + AD * ABIN_AUDST
2 BROCBROC_AVA PC * BROC_PC + TF * BROC_TFARE + AD * BROC_AUDST
3 CAMP CAMP_AVA PC * CAMP_PC + TF * CAMP_TFARE + AD * CAMP_AUDST
4 HANS HANS_AVA PC * HANS_PC + TF * HANS_TFARE + AD * HANS_AUDST
5 HOLBHOLB_AVA PC * HOLB_PC + TF * HOLB_TFARE + AD * HOLB_AUDST
6 MONT MONT_AVA PC * MONT_PC + TF * MONT_TFARE + AD * MONT_AUDST
7 QCTR QCTR_AVA PC * QCTR_PC + TF * QCTR_TFARE + AD * QCTR_AUDST
8 SWEYSWEY_AVA PC * SWEY_PC + TF * SWEY_TFARE + AD * SWEY_AUDST
9 WHITWHIT_AVA PC * WHIT_PC + TF * WHIT_TFARE + AD * WHIT_AUDST

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// available from the data
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// (cross-nested logit) and $NGEV (Network GEV model) are valid keywords
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Rapid Transit Sub-Mode Choice Model File

// File rtmodechoice9.mod

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[Beta]
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ASC_K 0 -10000 10000 1
AA 0 -10000 10000 0
AD 0 -10000 10000 0
VC 0 -10000 10000 0

[Utilities]
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  2 KNR one ASC_K * one
  3 PNR one ASC_P * one + AA * AUTOAVA + AD * AUDST + VC * VEH_CAP

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// Define here arithmetic expressions for name that are not directly available from the data
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// The scale parameter mu is generally normalized to equal 1
// Value LowerBound UpperBound Status(1=fixed)
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// Currently, only $MNL (multinomial logit), $NL (nested logit), $CNL
// (cross-nested logit) and $NGEV (Network GEV model) are valid keywords
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### Rapid Transit Station Choice Model File

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STA_NUM

[Beta]
// Name Value LowerBound UpperBound status (0=variable, 1=fixed)
PC 0 -10000 10000 0
L 0 -10000 10000 0
AD 0 -10000 10000 0

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2 ASHM ASHM_AVA PC * ASHM_PC + L * ASHM_length + AD * ASHM_AD
3 BEAC BEAC_AVA PC * BEAC_PC + L * BEAC_length + AD * BEAC_AD
4 BRNT BRNT_AVA PC * BRNT_PC + L * BRNT_length + AD * BRNT_AD
5 BROH BROH_AVA PC * BROH_PC + L * BROH_length + AD * BROH_AD
6 BROV BROV_AVA PC * BROV_PC + L * BROV_length + AD * BROV_AD
7 CHIL CHIL_AVA PC * CHIL_PC + L * CHIL_length + AD * CHIL_AD
8 DAVS DAVS_AVA PC * DAVS_PC + L * DAVS_length + AD * DAVS_AD
9 ELIO ELIO_AVA PC * ELIO_PC + L * ELIO_length + AD * ELIO_AD
10 FORE FORE_AVA PC * FORE_PC + L * FORE_length + AD * FORE_AD
11 GREE GREE_AVA PC * GREE_PC + L * GREE_length + AD * GREE_AD
12 KEND KEND_AVA PC * KEND_PC + L * KEND_length + AD * KEND_AD
13 LECH LECH_AVA PC * LECH_PC + L * LECH_length + AD * LECH_AD
14 MALD MALD_AVA PC * MALD_PC + L * MALD_length + AD * MALD_AD
15 MILT MILT_AVA PC * MILT_PC + L * MILT_length + AD * MILT_AD
16 NQCY NQCY_AVA PC * NQCY_PC + L * NQCY_length + AD * NQCY_AD
17 OAKG OAKG_AVA PC * OAKG_PC + L * OAKG_length + AD * OAKG_AD
18 ORNT ORNT_AVA PC * ORNT_PC + L * ORNT_length + AD * ORNT_AD
19 QADM QADM_AVA PC * QADM_PC + L * QADM_length + AD * QADM_AD
20 QCTR QCTR_AVA PC * QCTR_PC + L * QCTR_length + AD * QCTR_AD
21 RIVE RIVE_AVA PC * RIVE_PC + L * RIVE_length + AD * RIVE_AD
22 SUFF SUFF_AVA PC * SUFF_PC + L * SUFF_length + AD * SUFF_AD
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// The scale parameter mu is generally normalized to equal 1
// Value LowerBound UpperBound Status(1=fixed)
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## Rapid Transit Stations (continued)

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<th>% PNR</th>
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