A PROFILE OF HOV LANE VEHICLE CHARACTERISTICS ON I-85 PRIOR TO HOV-TO-HOT CONVERSION

A Thesis
Presented to
The Academic Faculty

By

Katie S. Smith

In Partial Fulfillment
Of the Requirements for the Degree
Master of Science in the
School of Civil & Environmental Engineering

Georgia Institute of Technology
December 2011

A PROFILE OF HOV LANE VEHICLE CHARACTERISTICS ON I-85 PRIOR TO HOV-TO-HOT CONVERSION

Approved by:

Dr. Randall L. Guensler, Advisor
School of Civil & Environmental Engineering
Georgia Institute of Technology

Dr. Michael P. Hunter
School of Civil & Environmental Engineering
Georgia Institute of Technology

Dr. Catherine Ross
School of City and Regional Planning
Georgia Institute of Technology

Date Approved: November 14, 2011

ACKNOWLEDGEMENTS

I would like to thank my advisor, Dr. Randall Guensler, for giving me the opportunity to complete this program despite my non-traditional background, and also for his support throughout my time at Georgia Tech. I would also like to thank Dr. Michael Hunter for not only his input on this thesis, but for giving me the opportunity to complete an independent study. I would like to thank Dr. Guensler, Dr. Hunter, and Dr. Ross for their review of this thesis. I am grateful to Vetri Elango for his input and answers to my numerous questions and for assisting me with organizing and processing the data.

I would like to thank my fellow graduate students who have spent many hours assisting with the I-85 HOV-to-HOT data collection and project: Stephanie Box, Felipe Castrillon, Kate Colberg, Kate D'Ambrosio, David Duarte, Sara Khoeini, Laskshmi Peesapati, Maria Roell, Chris Rome, Adnan Sheikh, Chris Toth, Sam Vedala, Trung Vo, and Stephanie Zinner. The data collection would not have been possible without the work of dozens of undergraduate students who spent many hours collecting data out on I-85. Kate D'Ambrosio deserves special recognition for all of her hard work on the HOV-to-HOT project and for giving me the opportunity to work with her on the data processing for her thesis, which set the precedent for the methodology used in my own thesis. Finally, I would like to thank my friends and family for their support not only during the writing of this thesis, but throughout my journey from history to civil engineering.

TABLE OF CONTENTS

LIST OF TABLES

Page

LIST OF FIGURES

Page

LIST OF ABBREVIATIONS

BRR	Beaver Ruin Road
CTR	Chamblee-Tucker Road
GDOT	Georgia Department of Transportation
Georgia Tech	Georgia Institute of Technology
GP	General Purpose (lanes)
GRA	Graduate Research Assistant
GTRI	Georgia Tech Research Institute
HD	High Definition
HDV	Heavy Duty Vehicle
HOT	High-Occupancy Toll
HOV	High-Occupancy Vehicle
JCB	Jimmy Carter Boulevard
LDV	Light Duty Vehicle
OPR	Old Peachtree Road
PHR	Pleasant Hill Road
SOV	Single Occupant Vehicle
SUV	Sport Utility Vehicle
URA	Undergraduate Research Assistant
USDOT	United States Department of Transportation

SUMMARY

The conversion of high-occupancy vehicle (HOV) lanes to high-occupancy toll (HOT) lanes is currently being implemented in metro Atlanta on a demonstration basis and is under consideration for more widespread adoption throughout the metro region. Further conversion of HOV lanes to HOT lanes is a major policy decision that depends on knowledge of the likely impacts, including the equity of the new HOT lane. Rather than estimating these impacts using modeling or surveys, this study collects revealed preference data in the form of observed vehicle license plate data and vehicle occupancy data from users of the HOV corridor. Building on a methodology created in Spring 2011, researchers created a new methodology for matching license plate data to vehicle occupancy data that required extensive post-processing of the data. The new methodology also presented an opportunity to take an in-depth look at errors in both occupancy and license plate data (in terms of data collection efforts, processing, and the vehicle registration database).

Characteristics of individual vehicles were determined from vehicle registration records associated with the license plate data collected during AM and PM peak periods immediately prior to the HOV lanes conversion to HOT lanes. More than 70,000 individual vehicle license plates were collected for analysis, and over 3,500 records are matched to occupancy values. Analysis of these data have shown that government and commercial vehicle were more prevalent in the HOV lane, while hybrid and alternative fuel vehicles were much less common in either lane than expected. Vehicle occupancy data from the first four quarters of data collection were used to create the distribution of occupancy on the HOV and general purpose lane, and then the matched occupancy and license plate data were examined. A sensitivity analysis of the occupancy data established that the current use of uncertain occupancy values is acceptable and that bus and vanpool occupancy should be considered when determining the average occupancy of all vehicles on the HOV lane. Using a bootstrap analysis, vehicle values were compared to vehicle occupancy values and the results found that there is no correlation between vehicle value and vehicle occupancy. A conclusions section suggests possible impacts of the findings on policy decisions as Georgia considers expanding the HOT network. Further research using these data, and additional data that will be collected after the HOT lane opens, will include emissions modeling and a study of changes in vehicle characteristics associated with the HOT lane conversion.

CHAPTER 1: INTRODUCTION

Managed lanes remain a popular topic in transportation planning due to continued increases in congestion, ongoing concerns regarding vehicle emissions, and decreasing funds and available space for highway expansion. High-occupancy vehicle (HOV) lanes have been in existence since 1969, and the introduction of high-occupancy toll (HOT) lanes in the 1990s has added another alternative for highway management [1]. Evaluating the performance of these facilities can include assessment of such factors as effective capacity, travel times, service reliability, vehicle occupancy (person throughput), carpool violation rates, and safety. Beyond these characteristics, many studies have also sought to identify reasons why people choose to carpool or ride express buses on these facilities, usually as a function of various socio-demographic variables and travel time. Another set of analyses that can be conducted is to assess vehicle occupancy and the characteristics of the vehicles that use managed lanes from the perspective of transportation policy. For example, the likelihood of carpool formation may be a function of available vehicle types in participating households. In addition, knowing the number and types of hybrid and exempt vehicles using a facility may help policy makers predict whether allowing these vehicles to access an HOV or HOT lane with a single-occupant will have a detrimental effect on the capacity of the lane.

Metropolitan Atlanta is already home to a limited high-occupancy vehicle (HOV) lane system, and the most congested HOV-equipped corridor is scheduled for conversion to a high-occupancy toll (HOT) lane in October 2011. The purpose of this study is to create a profile of vehicle characteristics of carpoolers that can be compared to the adjacent general purpose lane, as well as an occupancy distribution for both lanes. Individual occupancy records are then matched to the corresponding vehicles to take the analysis a step further. The vehicle characteristics profile and the matched occupancy results can then be used to compare the profile of the HOT lane vehicles after the conversion is complete. Creating a pre-conversion profile of the lane users and the occupancy by vehicle will assist policy makers in evaluating the impact of the lanes on different users. Equity is one often-cited concern when HOT lanes are discussed, and this HOV profile helps to provide data to assess this issue.

Chapter 2 includes a literature review on managed lanes, including performance measures, equity concerns, and carpooling activity. Chapter 3 outlines the methodology for the license plate data collection, occupancy data collection, and the matching process. Chapter 4 describes the data processing steps required to QA/QC the data and then complete the matching process. An in-depth analysis of bias and error is also included. Chapter 5 presents an analysis of the separate data as well as an analysis of the matched records, focusing on creating a profile of HOV lane users that can be compared to future HOT users to assist in answering the questions regarding equity impacts of the lane. Chapter 6 concludes the thesis with recommendations for policy decisions and areas of future research.

CHAPTER 2: LITERATURE REVIEW

The following literature review contains information on the history, operation, and evaluation of managed lanes. In particular, this study examines equity concerns surrounding HOT lanes as well as the potential use of vehicle characteristics to describe carpooling activity.

The HOV lane concept was first introduced in 1969 in New Jersey when a bus lane borrowed a lane from the off-peak direction [1]. Also in 1969, a bus-only lane was created in Virginia to allow buses to operate during a major construction project. The temporary bus lane was so successful that the construction plan was altered to include two permanent HOV lanes [1]. As of 2001, the most popular type of HOV lane was the concurrent-flow lane, and 48% of all HOV lanes are buffered concurrent lanes (separated by a physical barrier) and 28% are non-buffered concurrent lanes [1]. Many HOV lanes initially were used for buses and 3+ carpools, but over time the vehicle occupancy requirements have changed to mainly 2+ [2]. By 2000, because the lanes ran under capacity over 80% of HOV lanes in the United States operated on a 2+ basis, and about half of HOV lanes operated on a 24-hour basis (the 3+ facilities operate in areas with heavy congestion such as San Francisco and Houston) [1]. All of the current HOV lanes in the Atlanta area are non-buffered, and the HOT lanes on I-85 will have the same separation but with fewer weaving zones [3].

2.1 HOV Lane Performance

United States legislation mandates that HOV lanes must operate at 45 miles per hours 90 percent of the time during peak periods, and if this requirement is not met for 180 consecutive days (weekday peak periods) then a policy change must be considered [4]. Individual systems can set specific goals beyond the federal standards. For example, in California additional goals for HOV systems include decreasing emissions and encouraging carpooling [5]. The Georgia Department of Transportation states on their website that the HOV lanes in Georgia "were built to reduce traffic congestion and air pollution by giving a faster travel time for those who carpool, vanpool, or ride buses [6]."

2.1.1 Capacity and Flow

Some researchers have suggested that many HOV lanes do not function properly, in that the lanes operate below capacity or the lanes become congested like their general purpose lane counterparts [7]. Commuters often complain when a carpool lane is moving freely that the lane is underutilized given the low density of vehicles passing by the general purpose lanes [8]. A forthcoming occupancy study conducted on the HOV-to-HOT facility on I-85 by Georgia Tech in 2011 will report that the carpool lane does serve fewer vehicles than the adjacent general purpose lane, but carries significantly more persons per hour than the adjacent lanes. The concept of carpooling implies that multiple people in one vehicle will replace single drivers in multiple vehicles, but this does not work when carpools are composed of related family members ("fampools") who would carpool without any form of incentive [9]. The amount of "fampooling" is hard to quantify, but Georgia Tech is developing a methodology to measure these types of carpools on an Atlanta toll road, GA 400.

The HOV lane can also become congested on a regular basis, but with a congestion onset that is delayed by a short period compared to the general purpose lanes [7]. In this study it was found that the congestion was not necessarily due to the demand of the HOV lane but an unwillingness of drivers on the HOV lane to have a larger speed differential with vehicles on the general purpose lanes (non-barrier separated) [7]. A study in California found that HOV lanes are 20% under capacity in comparison with the general purpose lanes and one highlighted reason is the presence of "snails"—slow vehicles in the HOV lane which hold up the flow of all cars in the lane [5]. Congestion levels can also result from the prevalence of single-occupant vehicle (SOV) violators in the lane, which is estimated to be 13% in metro Atlanta [10]. The net result is that the carpool lane does not exhibit predictable travel times due to the onset of recurring congestion with severity that varies significantly day-to-day. Despite the evidence of variable travel times on HOV lanes, a survey of HOV and general purpose lane users in California found that all types of drivers consistently over-estimated the time savings of the HOV lane; on the four mainline HOV lane facilities included in the survey the average perceived time savings was over nine minutes while the actual time savings was less than three minutes [11].

2.1.2 Enforcement and Safety

There are two main types of violations on an HOV or HOT facility—weaving and occupancy violations. Both of these violations have been a concern on HOV facilities for many years and can impact the performance and safety of the lanes. A 1981 report on HOV enforcement in California outlines enforcement options on the lanes, with a focus on how to curb high violation rates and illegal weaving. The study found that violation rates ranged from 3.8% to 37.7% based on the specific site and time. Also, HOV lane violators were more likely to have additional traffic citations on their driving record than non-violators [11]. A study on the same facilities seven years later found that violation rates still varied greatly across facilities, from 5-32%. This second report found that AM violation rates were much lower than PM violation rates, and violations increased in periods of low light such as dawn, dusk or during the night hours. The report issued a survey to drivers who use the facilities and found that users also overestimate the HOV violation rates, with perceived violations rates above 15% and actual rates from 4-10%. Users overestimate the risk of receiving a ticket at 1-18% while the actual apprehension rate is between 1.5% and 2.8%. The study concludes that violations between 5-10% are acceptable, especially as reducing the rate to below 5% would require extensive investment in enforcement efforts [12]. Higher violation rates can have varied impacts on a facility based on the congestion levels (i.e. a facility that is near capacity will experience more of an adverse effect due to violators than a facility that is 20% under capacity). Non-barrier facilities can make people hesitant to go fast speeds in the managed lane if traffic in the adjacent lane is moving slowly or is stopped completely.

2.1.3 Occupancy Requirements

The goal of the new I-85 Atlanta HOT lane is to provide reliable trips in the managed lane for those who are either willing to form three-person carpools, ride in vanpools or express buses, or to pay for access to the facility. Three-person carpools will be able to use the lane for free given that it is fairly difficult to find a third passenger. The available capacity on the lane will then allow the agency to charge a toll to allow two-person carpools and single occupant vehicles to access the lane to fill available capacity. The toll price will vary in response to demand for lane access, with prices increasing as demand increases. The pricing strategy is to set prices such that demand never exceeds capacity. The HOT lane is expected to improve traffic conditions for the managed lane (because demand will be constrained by price) and improve traffic conditions on the mainline as well, because the HOT lane will actually be able to carry more vehicles per hour uncongested than it was carrying as a congested HOV lane. The main group that is expected to be negatively impacted is current two-person carpools, who will now have to split a toll, unless they can find another passenger to join their carpool. However, this fee may already be acceptable to many of these users given the expected faster trip and more reliable travel time [10]. As mentioned earlier, some argue that current HOV lanes are not very effective at reducing traffic, because 43 percent of carpoolers are related household members [13]. This concept of carpools consisting of only related individuals has been coined “fampooling”[9], and many such carpools may not be amenable to increasing to 3+ occupants. Two-thirds of all unrelated carpoolers always ride or drive in their carpool rather than switching the driving duties with other carpool members, and this inflexibility could also limit users’ carpool formation options [14].

HOV lanes encourage carpooling, but the shift to an HOT lane could not only result in some people switching from carpools to SOVs but could potentially detract from transit ridership along the route. This potential mode shift from transit users to single-occupant vehicles exists when an HOV lane is converted to a HOT lane, but a survey-based study in Houston concludes that transit passengers shifting to SOV vehicles would only impact the occupancy of the lane by 1-2% [15]. The study also examines ridership information from the years immediately preceding and following HOT conversion at other facilities (I-394 in Minneapolis and I-25 in Denver). Neither city experienced a decrease in transit ridership on the HOT corridor, and Minneapolis actually recorded significant increases in ridership [15]. One of the cited reason that transit ridership on I-394 did not decrease is that transit buses benefit from the more reliable trip times and that buses are better able to access the lanes [16].

2.1.4 Evaluation

Previous studies of the effectiveness of HOV lanes typically rely on limited data and are not transparent about the methods used to obtain the data or potential problems in the data. A review of the performance of the QuikRide program on the Katy Freeway in Houston collected manual counts of users for two days before implementation and seven days after implementation, and supplemented this data with automatic vehicle identification data [17]. The Houston study provides no additional details about the data collection (methods, the exact dates of the data collection, etc.). One state report from California calculates speed and volume levels using single data points to represent a facility's effectiveness, and survey questions designed by metropolitan planning organizations regarding HOV lanes in another cited example can be unclear and guided to respondents to giving affirmative answers that may or may not accurately reflect the public's stance on HOV lanes [5]. None of these studies used before and after data to assess changes in household travel behavior and door-to-door commute times.

2.2 Equity Concerns

Eighty years ago, privately-financed road were considered fair and publicly financed roads were considered unfair due to the small percentage of the population that owned automobiles [18]. This view was reversed as vehicle ownership rates increased and a correlation between road use and fuel use determined that using a fuel tax would be fair in place of tolls. The establishment of HOT lanes can raise concerns about the equity of the facility, especially when the HOT lanes are converted from pre-existing HOV or general purpose lanes rather than added as new capacity. Beyond the concern that the cost of the toll may be an unfair burden for low-income individuals, there are several other equity concerns associated with HOT lanes. As many as five types of equity can be associated with managed lanes: geographic equity, income equity, participation equity, opportunity equity, and modal equity [10]. Many issues cut across multiple types of equity, so this section will highlight geographical distribution of equity, income equity, equity across different user classes, and public perceptions of equity.

2.2.1 Geographic Distribution of Benefits and Burdens

Geographic equity is defined by whether improvements and burdens are distributed across various communities in a logical and objective manner [18]. These improvements can refer to the benefits of using the facility or to improvements made with the toll revenues, and the burdens can refer to new congestion on parallel or local routes. HOT lane projects such as I-394 in Minneapolis and I-85 in Atlanta allocate a large portion of toll revenues or initial project funding to expanding transit service along the HOT route [19, 20].

Proposals that enhance regional mobility but place a burden on local accessibility (either directly on the HOT facility or on alternate routes) are not geographically equitable as drivers who are just passing through the corridor may benefit more than local residents [18]. Spatial mismatch of jobs and housing can be a concern, specifically that low-income city dwellers cannot access jobs in suburbs [21]. This mismatch can be addressed by the existence of reverse commute routes on the HOT corridor. For example, transit buses on the HOT corridor in Atlanta do run in the reverse commute direction and the tickets are discounted by 50% [22]. Individuals without a vehicle may still be at a disadvantage unless there are local feeder routes that connect to the express buses.

Another cited concern is that users who live further from the city center and travel along an HOT corridor will benefit more than those who live along the corridor. In Maryland, residents argued that proposed HOT lanes would be inequitable for users that do not utilize the full corridor since the toll on their segment would be made higher by the volume of drivers arriving from farther out on the corridor; the same argument has been made about the transit system (trains are full by the time they reach inner stations [18]). In addition to this concern, in Atlanta the limited access points to the HOT lane could be a concern for people who utilize the corridor but do not live or work close to a legal weaving section. For example, over the sixteen mile stretch of HOV lanes on I-85 in Atlanta, the number of legal entrance/exit zones (delineated by double dashed lines) was reduced in anticipation of the conversion to HOT lanes, leaving one six-mile stretch left without an entry section [23]. In practical terms, any drivers who need to enter the expressway along this six-mile stretch will not be able to fully benefit from the HOT lane. Any driver who needs to enter or exit the lane at points of heavy congestion may also find it difficult to transition to/from slow or stopped traffic in the general purpose lanes to the 50+ mph speeds of the HOT lane.

2.2.2 Concerns for Low-Income Individuals

Income equity is the equal distribution of benefits and burdens of the facility across all income groups with special consideration to protecting the rights of economically disadvantaged communities [18]. The concept of situational value of time (an individual's value time varies based on the trip-type and other factors) means that low income users will sometimes desire to use the lanes but the toll cost will not always outweigh their value of time. A study on SR-91 in California cited the specific example of low-income parents who used the HOT lanes to avoid paying late daycare pick-up fees (i.e. a $5 toll is preferable to a $20 late fee) [18]. While the literal monetary cost of a toll could exclude some participants, sometimes the most significant barrier is the requirement to have a bank account or credit card to obtain a transponder [10]. For the Atlanta HOT lane, a credit card is not required to open an account if the PeachPass will always be toll-exempt (i.e. if the pass is issued to a motorcycle or alternative fuel vehicle) but is necessary for all other users [20].

Another potential income equity issue is that if there is an absence of transit alternatives on an HOT route, low-income individuals without a personal vehicle cannot benefit from the travel time savings. As mentioned previously, expanded transit service on the HOT corridor in Atlanta is available in both the peak and off-peak directions so options do exist for low income individuals. A 2007 Atlanta study found that household incomes of anticipated HOT corridor users were 15% higher than expected while carpooling rates were lower [24]. However, an equity analysis of the potential HOT lanes in Atlanta found that the lanes are not likely to have a negative effect on low-income individuals since the lanes create a new mobility option [10].

2.2.3 Fairness to User Classes

Fairness among different users of the HOT facility can involve issues beyond geography or income. Commuters with inflexible work schedules could be at a disadvantage because it is more difficult for these users to utilize Xpress bus routes or organize carpools, but these commuters would also benefit from the reliable trip times of the HOT lane [10]. Irregular or long hours can also limit employees' access to transit or carpool opportunities. Some argue that HOT lanes do not promote multimodal transportation because people can get the same travel time by paying a toll that others get by doing "the right thing" and carpooling or taking transit [18]. In Seattle, transit advocates argued that the minimum HOT toll on SR-167 should not be lower than the transit fare in the same corridor so that SOVs do not receive an "unfair" advantage [18].

2.2.4 Public Perceptions

Perceived equity concerns are just as important as actual equity concerns because public opposition and opinion have been the deciding factors in the failed implementation of several tolling projects rather than any kind of technical analysis [18]. Public perception of the equality of HOV and HOT lanes can vary by region (no two surveys are ever identical so bias in the survey design could also contribute to differences in the results). As indicated by a survey in California, a sizable portion of drivers (40%) do not consider HOV lanes "fair." Another survey in Texas found that 48% of drivers believe that HOT lanes are unfair [12, 18]. A study in San Diego found that 60% of low-income respondents approve of the HOT concept and 78% of low-income respondents believe that paying a toll on such a facility is fair [18].

Media attention can also influence the public's perception of HOT lanes and be a gauge of public acceptance of a project. The media can fixate on a catchy phrase such as "Lexus lanes" that highlights the income equity concern and leave HOT implementers frustrated; one person described the situation as "the TV media and also other media like sound bites, and we lost the war of the sound bites [21]." In Minneapolis, HOT lanes were first proposed in 1997 but did not pass, but after working with the local media and carefully educating the public the HOT lanes were approved and have since been expanded to an additional corridor [19]. Diverse stakeholders often change positions on HOT projects based on the perceived impacts on their membership or constituents so when planning a new facility all types of equity should be addressed [21].

2.3 HOV Exemptions

The underutilization of HOV lanes has resulted in several policy changes, including conversion to HOT lanes and allowing alternative fuel vehicles (AFVs) access to the HOV lane. Alternative fuel vehicles include cars powered solely by electricity, hydrogen, natural gas, biofuel, propane, fuel cell, or other miscellaneous alternative fuels [25]. Multiple states—California, Florida, Arizona, New Jersey, New York, Utah, and Virginia—have piloted or implemented programs that expand this policy to allow single-occupant hybrid electric vehicles such as a Toyota Prius or Honda Insight) to use HOV lanes [26].

Beginning in 2000, Virginia was one of the first states to allow single-occupant hybrids access to HOV lanes [26]. Hybrid HOV access was found to have a positive correlation with hybrid sales in Virginia as hybrid sales increased 92% after the implementation of the new policy [26]. In 2004, Virginia commissioned a report on the status and future of the hybrid HOV exemption, and the study authors concluded that either the occupancy levels for hybrid vehicle should be increased or that an increase in the issuance fee for the “clean special fuel” plate from $10 to $500 should be implemented so that the extra funds can be used for further enforcement and maintenance of the HOV facilities [27]. Rising congestion levels in the peak periods results in a change in the hybrid exemption policy to maintain the federally-mandated minimum average speed of 45 mph in the HOV lanes. The current policy involves specific rules for each HOV facility. For example, only hybrid vehicles purchased prior to July 1, 2006 can use the I-95/395 HOV lanes during peak periods with fewer than three occupants [28].

California chose a different approach to the hybrid exemption and limited participation to 85,000 hybrid vehicles [29]. Hybrid vehicle owners had to purchase a sticker from the Department of Motor Vehicles that identified their vehicle as “exempt,” and the stickers were required to remain with the vehicle rather than the individual. This has the (perhaps unintentional) consequence of increasing the resale value of any hybrid vehicle with one of the exemption stickers by over $3,000 [30].

Some argue that not all hybrids should be given the same preference, as hybrid cars are much more efficient than hybrid trucks or sport utility models [31]. The long-term implications of allowing hybrids into the lane are also a concern as the sales of hybrid vehicles increase every year [32]. The I-85 corridor in Atlanta is already set for HOT conversion, but other HOV lanes in the metro area may consider implementing exemptions for hybrids (true alternative fuel vehicles already have an exemption in Georgia, but hybrid vehicles do not [33]). A recent report recommends that the alternative fuel vehicles HOV exemption be continued in Georgia but should the program should be monitored on a quarterly basis to ensure that the AFV vehicles are not creating congestion on the lanes. The report does not recommend extending the exemption to hybrid electric vehicles in the Atlanta metro area [34].

2.4 Vehicle Characteristics

Fleet composition varies significantly by time of day. Distributions of vehicle characteristics are used extensively in vehicle emissions modeling to more accurately reflect the local or regional fleet (rather than using national data provided by federal agency emissions rate models such as MOBILE6). A nationwide survey of air pollution control organizations found that most agencies do use local data, and many decode VINs and aggregate the data to the county level [35]. These techniques assume that the registration database is correct, that vehicles are housed at the registration address, and that the data are static (no changes in registration spatially or temporally have occurred). A recent dissertation found that many of these assumptions are erroneous, specifically the assumption regarding vehicle location, as only 67% of vehicles in this study were housed at the registration address [35]. VIN numbers or other vehicle information can be entered incorrectly into the registration database due to confusion of characters such as “O” and “0” and even correctly entered vehicle records do not include information necessary for emissions modeling, such as gross vehicle weight rating [36]. The data reported in this thesis presents the opportunity to analyze the fleet characteristics of I-85 commuters specifically, rather than using county or regional data.

Using county-by-county registration data from Tennessee, researchers found a strong correlation between median vehicle age and average personal income for the corresponding county. The average vehicle age in the highest-income county was 5.9 years and the average vehicle age in the lowest-income county was 10.8 years. Lower-income counties also had 73% more light-duty trucks [37]. Research about the people who choose certain categories of vehicles is another way that vehicle characteristics can tie to demographics. One such study outlines detailed statistics about SUV owners, including gender, marital status, age, household income, and fuel economy expectations, and found that the typical SUV customer is male, married, 45 years old, in a household with an income of $94,400, and at the head of the household [38].

2.4 Carpooling Activity

License plate data provide revealed preference data about users of a transportation corridor. Revealed preference data are preferable to stated preference data which may arise from employee-based surveys. Certain cities have created occupancy mandates for local businesses that penalize larger companies that do not maintain a certain level of carpooling among employees [39]. Data collected in 1987 from one such city, Pleasanton, CA, suggested that employees were most likely to carpool when they commuted long distances, worked for a large company with a single campus, did not participate in flex-time programs, and worked in non-professional or non-management positions [39].

Travel surveys can also be used to obtain carpooling information, however the data may be limited. For example, the largest survey in Atlanta will involve only 10,000 households, and the data are collected only once every ten years for a single travel day per household [40]. Surveys are difficult to undertake due to cost constraints and the respondent burden. A survey was conducted in the Puget Sound region for the purpose of tracking commuters who switch between carpooling and single-occupant vehicles and vice versa. The study was limited by the small sample size (very few people switched from SOV to carpooling within the survey period) and the only significant variable that could be identified as motivating a switch was when respondents moved to a zone with a higher residential density [41]. Another problem is the under-representation of certain groups in surveys. In one survey that attempted to estimate mode choice for travelers on a new HOT facility in Texas, the responses did not represent a true sample of the socioeconomic characteristics of people in the area, so paper-based surveys were issued in low-income areas. The number of low-income and minority responses was still too low to be reliable, so the researchers undertook a weighting process using replicate weights to make the low-income and minority responses equal to population proportions (the end result of the survey found that the percentage of HOV2s and HOV3+ vehicles would only decrease slightly after the conversion to HOT lanes) [9].

A study on SR-91 in California presented carpooling behavior and sought to create discrete choice models to model carpool formation. Overall, carpooling rates were similar on the roadway to comparable roadways without HOT lanes, which indicated that the presence of a SOV toll option did not discourage carpooling overall. People have the option to obtain time savings for the toll price, but by forming a carpool the same benefit can be obtained for no cost [42]. When the QuikRide program started on the Katy Freeway, participation of SOVs and HOV2s leveled off after about two months, and two-thirds of the new participants were HOV2s and one-third were SOVs [17]. The Express Lanes in Atlanta will follow a similar model to the QuikRide program so the QuikRide participation results could be an indication of the make-up of new HOT lane users in Atlanta as well as a guide to the projected time needed for the lanes to operate efficiently.

Many studies have set out to identify socio-demographic variables that correlate with carpooling rates to guide policy decisions, but in many cases only weak correlations are discovered. Factors such as lower income, lower automobile ownership rates, and multiple worker households have been found in previous studies to link back to carpooling [14]. A more recent study examined the factors further using a survey data and nested logistic regression models and found that vehicle occupancy, household income, trip purpose, and age are predictors of HOT lane use [43]. Specifically, there was a positive correlation between household income and HOT lane use (high income households were 18% more likely to use the lane). Each additional passenger in a vehicle increases the likelihood of using the HOT lane by 92%, and travelers who make home-based trips were three times as likely to use the HOT lanes. The study also found that people are more likely to use HOT lanes for afternoon period work-to-home trips [43].

Some studies have attempted to quantify more intangible characteristics to predict carpooling behavior. In one study the researchers wanted to quantify “ideological” preferences and used state-level-per-capita Sierra Club membership as a surrogate for environmental preferences, and per-capita active and reserve military participation as a surrogate for energy security concern [26]. The study estimated that a one standard deviation increase in Sierra Club membership was associated with a 17% in high-fuel economy hybrid vehicles and that a one standard deviation increase in military participation was associated with an 11% increase in the same type of sales [26].

The use of the vehicle characteristics to create a profile of carpool vehicles versus general purpose lane vehicles may help to identify variables that influence carpooling, such as vehicle body type (e.g. larger vehicles) or household vehicle ownership. Such variables may also be correlated with underlying reasons for carpooling and may be more reliable than survey or surrogate data. If public agencies can better understand the type of vehicle that tends to be used for carpools, they may be able to use this information to target these audiences with new policies.

CHAPTER 3: METHODOLOGY

The current HOV-to-HOT Corridor Performance Monitoring project is collecting vehicle occupancy and license plate data. The methods are based upon a 2007 study that collected over 120,000 license plates using spotting scopes and voice recorders. This method successfully captured 20-30% of passing vehicle plates [44]. A second study built on this methodology found that incomes on the anticipated HOT corridor were higher than expected while carpooling rates were lower [24]. The capture rates of the visual/voice recorder method were effective enough for analysis, but recording all the license plates later became possible in 2010 with the increasing quality and lower costs of high definition digital video cameras. A new methodology for vehicle occupancy was developed in 2010, and this methodology was further adjusted in summer 2011 to assist in the process of matching occupancy records to license plate records.

3.1 License Plate Data

License plate videos are now collected quarterly at five different sites along the northeast I-85 corridor (see Figure 1 and Figure 2). At each site, data are collected during the morning (7:00-9:00am) and afternoon (4:30-6:30pm) peak period for at least three days per week. High definition cameras are set-up on overpasses to record traffic in the peak direction only; southbound in the morning and northbound in the afternoon. The videos are then processed by undergraduate students using a purpose-built, custom software program. Students input the plate information, state, vehicle classification, and any comments via an electronic video interface. The vehicle classification (LDV, SUV, or HDV) is only entered for missed license plates and out-of-state plates because the classification for Georgia plates is obtained from the registration database information. The resulting database includes a timestamp that can be tied back to the video image for each license plate record and identifies the individual that processed the data. This report uses only data from the HOV lane (Lane 0) and the adjacent general purpose lane (Lane 1) in the spring data collection effort (May-June 2011).

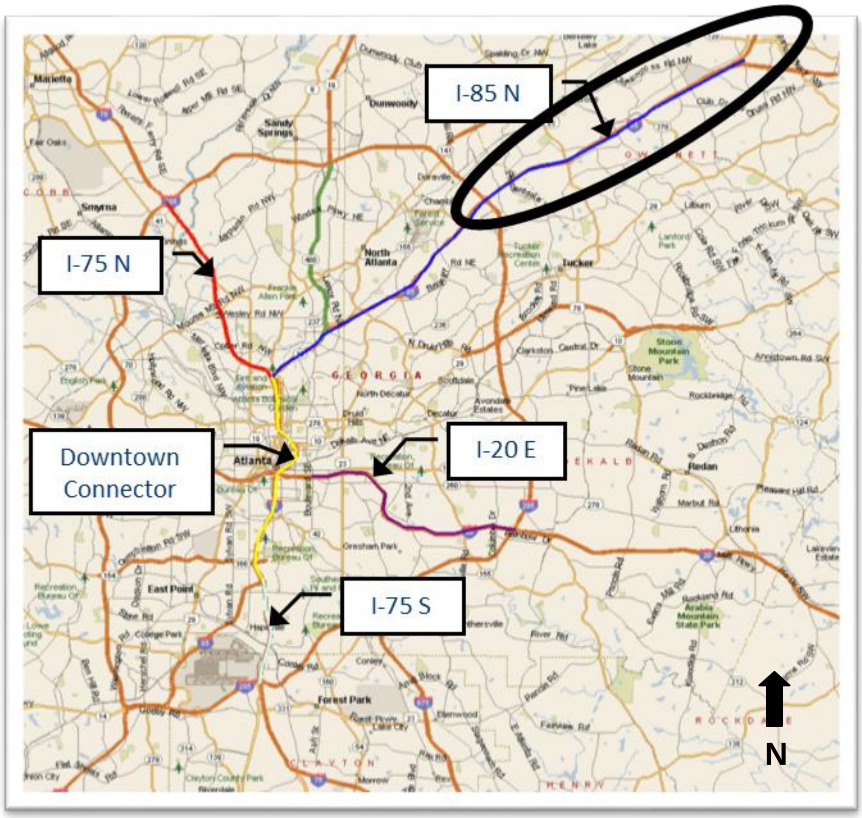


Figure 1: Study Corridor [45]

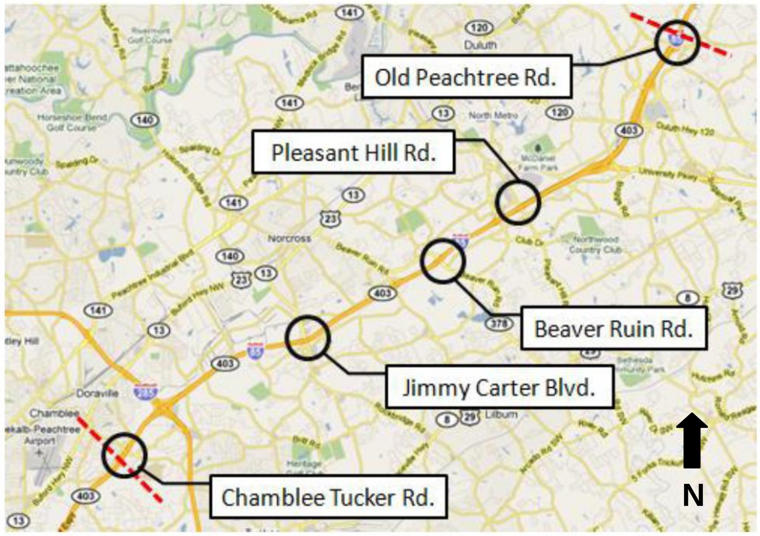


Figure 2: Site Locations on I-85 Corridor [45]

3.2 Occupancy Data

Vehicle occupancy data are collected concurrently with the license plate video data (even though the data are collected at the time the two data streams are not paired in any way). A recent thesis, “Methodology For Collecting Vehicle Occupancy Data On Multi-Lane Interstate Highways: A GA 400 Case Study,” by D’Ambrosio describes in detail the occupancy data collection methods used in this project and how they were developed [45]. The occupancy data are collected using the roadside observation method, with data collectors positioned in the gore area between the highway and the entrance/exit ramp (see Figure 3).

Figure 3: Occupancy Data Collection in Gore Area

Data collectors record occupancy values using electronic keypads, netbooks, and custom software. One data collector is assigned per lane, and the lanes are numbered beginning with the HOV lane as Lane 0 and counting up to the rightmost lane (Lane 4 or Lane 5 depending on the total number of lanes). Each vehicle is assigned a classification of either light duty vehicle (LDV), sport utility vehicle (SUV), or heavy duty vehicle (HDV) in addition to the occupancy values. The LDV category includes all passenger cars and station wagons, the SUV category includes pick-up trucks, crossover vehicles, all sizes of sport utility vehicles, and vans, and the HDV category includes large trucks with at least six wheels and two or more axles. Seven occupancy values are available on the keypad (see Figure 4). The “+” values are intended for use when data collectors can see some passengers but are unsure about the presence of additional passengers due to visual constraints such as tinted windows or high speeds. The clear (“C”) button allows students to clear a record that was entered incorrectly. The “MISS” button is intended for use when observers are unable to enter an occupancy value for a vehicle due to high volumes, low lighting, or other circumstances.

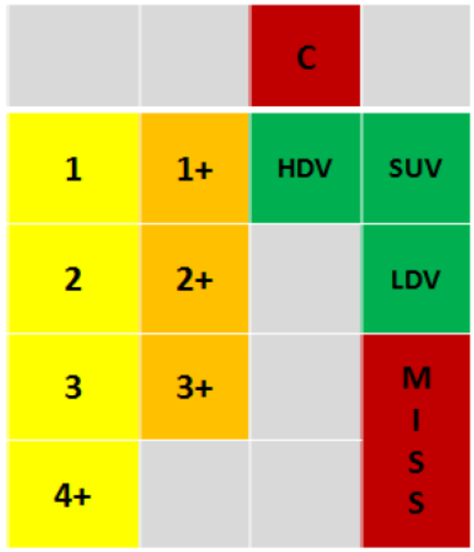


Figure 4: External Keypad for Occupancy Data Collection [45]

To better facilitate matching the occupancy data to the license plate data, a few changes were made to the standard occupancy methodology outlined in D'Ambrosio's thesis. An additional person collects occupancy data on the HOV/HOT lane so that the two occupancy data streams can be compared to one another before being matched with the license plates. A video camera is placed in the gore area with the occupancy data collectors to capture their view of the highway. The occupancy collectors may view the highway before or after the exact location that license plates are recorded, and the gore area video captures vehicles that either change lanes or could be missed due to occlusion by trucks or other vehicles in the general purpose lanes. Figure 5 illustrates the potential distance, approximately one-third of a mile, between the collection points of the two types of data. This is the greatest possible distance between data collection locations, and sometimes the license plate video and occupancy collectors' viewpoints overlap. The extra data collector on the HOV lane records a description of the first and last vehicle in each day's occupancy data file to aid in the matching process (the worksheet is provided in Appendix A and the training document is in Appendix B). The adjusted methodology was only utilized in the spring and summer occupancy data collection, but occupancy data from all four quarters of data collection are used in this report to determine occupancy distributions for error checking purposes.

Figure 5: Data Collection Locations at Old Peachtree Road

3.3 Matching Occupancy to License Plate Data

Occupancy data and license plate data are collected simultaneously in the field, but matching the two data streams after field collection involves extensive data processing and verification. The two data streams for each lane share three common variables that are used for matching: the lane, vehicle classification, and the time gap between vehicles. The license plate video collected from the overpasses is post-processed by undergraduate research assistants (URAs) using the method described in Section 3.1. After the license plates are processed by URAs and the vehicle classification, make, and model are received from the vehicle registration database, the original license plate video is reviewed a second time to verify the accuracy of the license plate data. This second viewing of the video ensures that all vehicles are listed in the license plate stream and that any mistakes made during the original license plate processing can be corrected (on average, 11% of vehicle records were corrected). At the same time, the gore area video associated with vehicle occupancy is watched to verify the order of vehicles. The order of vehicles can be affected by lane changes between the occupancy data collection site and the view of the license plate camera, as well as any potential missed vehicles due to large trucks in the general purpose lanes. A notes column is added to the database to keep track of any discrepancies that could affect the matching process.

After the occupancy and license plate data are verified and adjusted to account for any missed or extra vehicles (mainly due to lane changes), the common variables of time gap and vehicle classification can be used to match up the three data streams. Even though the occupancy and license plate video data have differing time stamps for each record due to differences in camera and netbook clocks or the potential distance between the two collection points, the time gaps between vehicles are fairly consistent given that the furthest distance between the collection points is only one-third of a mile. The other common variable between occupancy and license plate data are the vehicle classification. Occupancy data collectors enter a vehicle classification for each occupancy record, and the license plate video records have the vehicle information either from the license plate data or as entered by the URA during video processing. These fields are used in combination with comments entered during the re-watching of the two videos to match the two occupancy streams with the license plate video. Figure 6 illustrates the matching process in a flow chart.

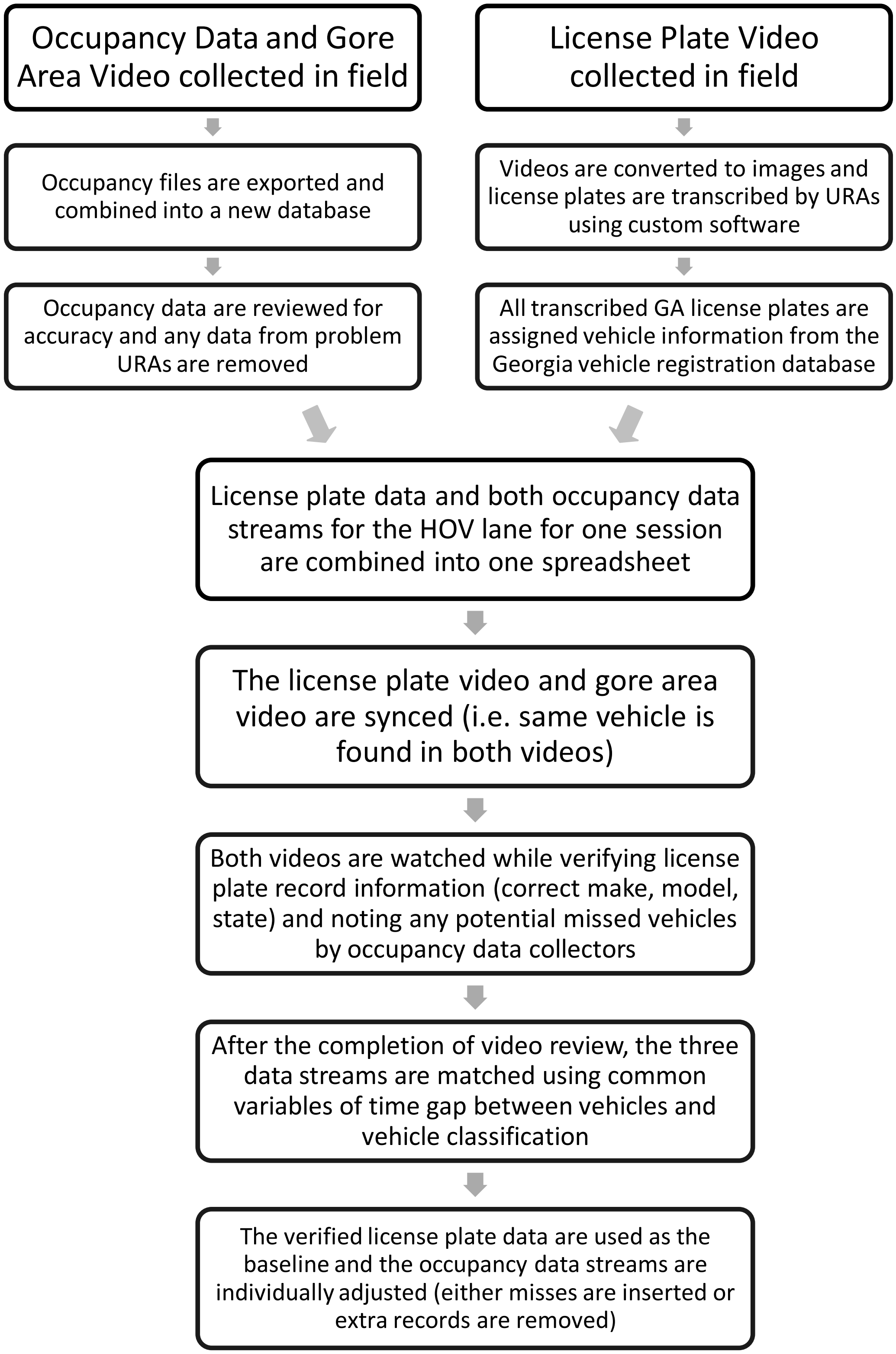


Figure 6: Flow Chart of Matching Process

CHAPTER 4: DATA PROCESSING

Data processing requires that each type of data (license plate and occupancy) is verified before any matching is attempted. The matching process then requires another verification process of the information obtained in the first processing of the data. This chapter will address each process and discuss the data cleaning and error checking issues of each type of information.

4.1 License Plates

Each decoded license plate was assigned a unique key identifier, and Georgia license plates (nearly 80,000 in total) were matched to the motor vehicle registration database by a separate unit at Georgia Tech, the Georgia Tech Research Institute (GTRI), for privacy considerations. The key identifier was carefully designed to include information about the origin of the plate (site, session, period, etc.). Duplicate plates (i.e. multiple sightings of the same vehicle) were left in the data set, and these duplicates accounted for about 25% of the total number of plates. Approximately 80% of the plates that were processed yielded a match in the motor vehicle registration database. The processed results contain vehicle-specific data that exclude any personally identifiable information such as name or physical address. The data sets were then merged using the key identifier. For the final analysis, over 93,000 total license plates were observed in the video, and 60,000 were matched to vehicle records. About 10% of the total plates were out-of-state vehicles, 10% were misses, and the remaining plates did not have a match in the database, either due to transcription errors or errors in the registration database.

4.1.1 Body Type

Several fields returned from the database were recoded for use in analysis. For example, the Georgia registration database employs 25 different body types that were recoded as shown in Table 1. The body types were recoded to correspond with the three body types used in occupancy data collection (LDV, SUV, and HDV).

Table 1: Vehicle Body Type Re-Classification

LDV	**SUV**	**HDV**
2S (2 door sedan)	AM (ambulance)	HR (horse trailer)
3S (3 door sedan)	CT (camper trailer)	TL (trailer)
4S (4 door sedan)	MP (multi-purpose)	UL (trailer)
5S (5 door sedan)	TK (pick-up truck)	BU (bus)
CN (convertible)	TR (pick-up truck)	
CP (coupe)	VN (van)	
LM (limousine)	WK (work truck)	
MC (motorcycle)	JP (jeep)	
RD (roadster)	BT (boat trailer)	

During license plate video processing, URAs assign any missed or out of state license plates a vehicle classification using ten vehicle types: 2-axle single unit truck, 3 or 4-axle single trailer combination, 3-axle single unit truck, 5-axle single trailer combination, light utility truck, MARTA bus, motorcycle, other bus, passenger car, and school bus (flashcards with examples of each vehicle type are included in Appendix D). These ten vehicle types can be recoded to correspond with the three general vehicle types used in the occupancy data collection (LDV, SUV, and HDV). There were 15,000 records with these recoded vehicle classifications.

Table 2: Video Processing Vehicle Classification Recode

LDV	SUV	HDV
Motorcycle Passenger car	2-axle single unit truck Light utility truck	3 or 4-axle single trailer combination 3-axle single unit truck 5-axle single trailer combination MARTA bus Other bus School bus

4.1.2 Fuel Type

The fuel type for each vehicle was also recoded in order to combine like fields (see Table 3). The reason for the use of multiple letters for the same fuel type (i.e. "B" or "H" for hybrid) is not known, and the researcher who provided the registration database information did not have an explanation either.

Table 3: Vehicle Fuel Types

Fuel Code	**Decoded Type**
B	Hybrid
C	Gasoline
D	Diesel
F	Flex fuel
G	Gasoline
H	Hybrid
I	Gasoline
N	Natural Gas
O	Flex fuel
9	N/A (no vehicle model listed)

4.1.3 Vehicle Makes and Models

More than 60,000 vehicles records were returned from the registration database. These records included 194 different vehicle makes and 2,417 different vehicle models. All trailers were excluded from the make and model recoding process due to the diverse models and makes and the fact that the trailer details are not representative of the vehicle that is hauling the trailer. Once the various trailer types were removed from the database, only 84 makes and 2,317 models remained. The vehicle make list includes many uncommon manufacturers such as Hino, Daewoo, and Datsun, but the list did not contain any duplicates. In contrast, the vehicle model list included many different iterations of the same model type. The full list of 2,317 models was reviewed and duplicate fields were combined while still including model variations that reflected different engine types (i.e. an "Accord DX" was changed to simply "Accord "while a "Jetta TDI" remained separate from "Jetta"). Only 858 vehicle models remained after the recoding process. The complete table of recoded vehicle models is available in Appendix C.

4.1.4 Issues During Data Processing

As student assistants enter license plates in the purpose-built program, there is the option to include comments. The comments were recoded to combine similar entries (for example, "Lots of glare" and "Glare" were combined). The five most common comments were "Glare," "Blurry," "Blocked," "No license plate," and "Unsure." For both files, all the names of the student assistants that collected the plate data are also retained and recoded to numeric values for use in analysis.

4.2 Occupancy

The vehicle occupancy data do not require extensive post-processing, and therefore occupancy data from the complete first year of data collection (September 2010-September 2011) are available for analysis. Only the HOV lane occupancy data are processed for matching to license plate data, but an analysis of all the available occupancy data identifies any problems with the data that could affect the matching process.

Occupancy data files for all sessions after fall 2010 contain the name of the URA who collected the data. Over the four quarters of data collection, over 65 different students collected vehicle occupancy field data. Each individual's occupancy distributions can be separated according to session, site, day of the week, time period, and lane. The occupancy distributions are compared across several of these variables to assess the potential accuracy of the data. Several anomalies emerged in the distribution of occupancy values which motivated further analysis of the data. Occupancy distributions are expected to vary slightly, but due to the large sample size, the distributions across different sessions should be comparable. Before analysis of any questionable variations in the data, individual URAs were contacted for further explanation to ensure that there were no extenuating circumstances that could affect the data, such as equipment problems or extreme traffic conditions.

A detailed data analysis revealed that certain URAs show a tendency to over or under-use certain occupancy values. These specific individuals were identified and their data were removed from the dataset. An example of the effect of this bias is the tendency of one URA (URA 44) to use the "1+" occupancy value almost exclusively rather than using the definitive "1" value. The effect of this bias is shown in Figure 7 and Figure 8. Figure 7 illustrates the distribution at Chamblee-Tucker Road across fifteen URAs. Figure 8 shows the distribution with URA 44 removed. The impact of URA 44's classification can clearly be seen on Thursday, where a significant fraction of “1”s are shifted to “1+”.

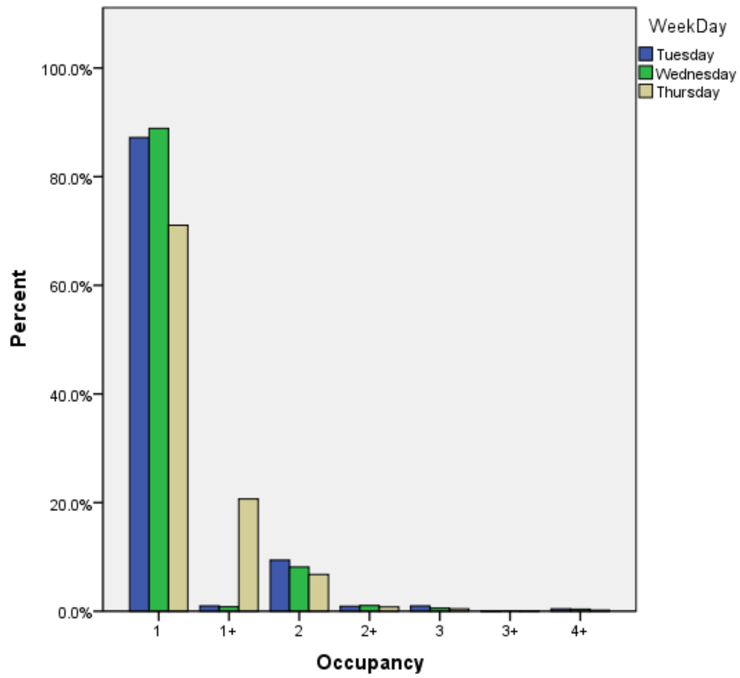


Figure 7: Spring 2011 Occupancy Distribution at CTR, General Purpose Lanes only

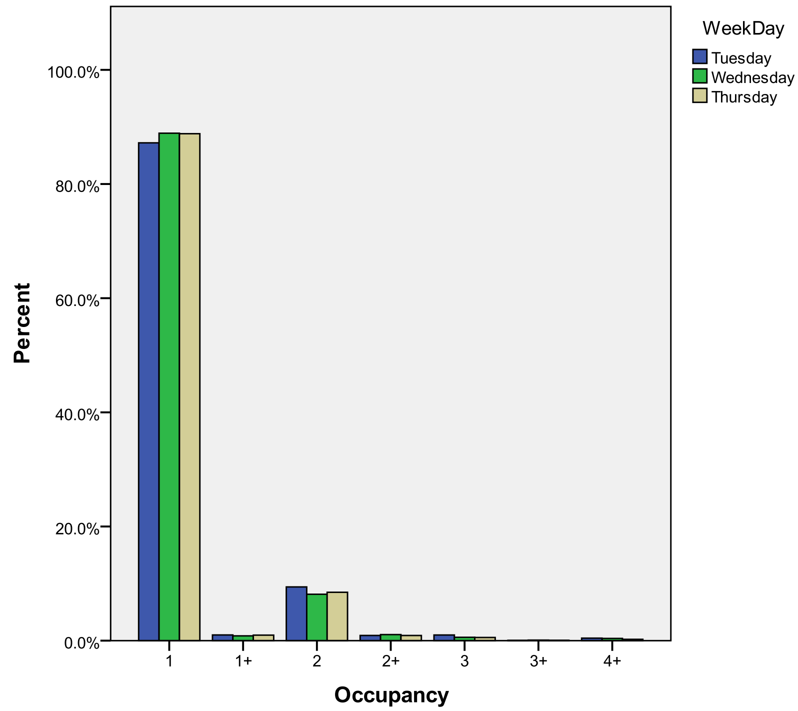


Figure 8: Spring 2011 Occupancy Distribution at CTR, General Purpose Lanes only – URA 44 removed

Some of the HOV lane data reflected an extremely low occurrence of "1" values. One-occupant motorcycles are allowed to utilize the lanes, and motorcycles generally make-up at least 1-2% of all vehicles. The prevalence of motorcycles in combination with HOV lane violators could be expected to result in a "1" percentage of at least 5-10%, with the literature review section suggesting violation rates in excess of 10% in Atlanta [10]. When the URAs who collected the data were contacted, they explained that they were mainly giving observed potential violators the "benefit of the doubt." These URAs did not feel comfortable recording a "1" occupancy reading because they did not think that people would violate the policies of the lane. This was clearly a problem in the training system and was addressed prior to Summer 2011 data collection.

Another problem identified in data analysis is the over-use of the HDV vehicle classification. Despite extensive training, pick-up trucks and sport utility vehicles are sometimes identified as HDVs by certain URAs. HDVs typically comprise less than 5% of all vehicles, but due to this mistake some sessions contained over 20% HDVs. Misclassification of vehicles can be a major concern as vehicle classification is one of only three variables used when matching occupancy records with license plate records. Analysts in post-processing have to be aware of this issue and provide some latitude in using the SUV vs. HDV pairing (vehicles that are likely to be mismatched are identified in the notes section during the second watching of the video).

Table 4 and Table 5 highlight the effect of removing several URAs (URA 44, URA 2, and URA 24) from occupancy data at one site (Beaver Ruin Road) over three quarters of data collection. These three URAs did not collect data on the HOV lane so those percentages are unchanged in Table 5. The only categories that are affected by the changes are Winter AM and Spring PM data for the general purpose lanes. The Winter AM data has 20.6% “1+” values before the problem URAs are removed and only 7.9% “1+” after they are removed. In the Spring 2011 PM data, the “1+” values decrease from 11.7% to 5.2%.

The fall data remain unchanged as names were not collected during field collection (since names were not recorded there was no way to identify and correct any potential problems, but none of the identified problem URAs collected data in the fall session), but other sessions change significantly once the bias is removed. The bias had a greater effect when a problem URA collected data on the same lane over multiple sessions or if a problem URA went out in the field with greater frequency than other URAs.

Table 4: Occupancy Distribution at Beaver Ruin Road – all URAs included

AM	HOV Lanes				General Purpose Lanes		
	Fall 2010	Winter 2011	Spring 2011		Fall 2010	Winter 2011	Spring 2011
1	6.6%	0.9%	9.7%		88.1%	75.3%	86.5%
1+	10.4%	18.8%	17.2%		7.3%	20.6%	6.6%
2	67.4%	42.7%	41.9%		3.8%	2.9%	5.6%
2+	10.2%	33.0%	26.6%		0.5%	1.0%	0.9%
3	2.7%	1.7%	2.3%		0.2%	0.1%	0.2%
3+	0.5%	1.4%	0.4%		0.05%	0.0%	0.1%
4+	2.2%	1.4%	1.9%		0.1%	0.0%	0.1%
PM	**HOV Lanes**				**General Purpose Lanes**		
	Fall 2010	Winter 2011	Spring 2011		Fall 2010	Winter 2011	Spring 2011
1	6.2%	8.8%	5.0%		84.4%	86.8%	79.2%
1+	3.1%	5.2%	7.6%		8.4%	5.7%	11.7%
2	52.8%	73.3%	57.8%		5.8%	6.5%	6.8%
2+	29.8%	5.6%	23.6%		1.0%	0.5%	1.5%
3	4.1%	4.5%	2.6%		0.3%	0.4%	0.4%
3+	1.3%	0.3%	0.9%		0.1%	0.05%	0.1%
4+	2.7%	2.3%	2.6%		0.1%	0.1%	0.2%

Table 5: Occupancy Distribution at Beaver Ruin Road –URAs with bias removed from Spring and Summer 2011

AM	HOV Lanes				General Purpose Lanes		
	Fall 2010	Winter 2011	Spring 2011		Fall 2010	Winter 2011	Spring 2011
1	6.6%	0.9%	9.7%		88.1%	87.7%	86.5%
1+	10.4%	18.8%	17.2%		7.3%	7.9%	6.6%
2	67.4%	42.7%	41.9%		3.8%	3.5%	5.6%
2+	10.2%	33.0%	26.6%		0.5%	0.8%	0.9%
3	2.7%	1.7%	2.3%		0.2%	0.1%	0.2%
3+	0.5%	1.4%	0.4%		0.05%	0.0%	0.1%
4+	2.2%	1.4%	1.9%		0.1%	0.0%	0.1%

PM	HOV Lanes				General Purpose Lanes		
	Fall 2010	Winter 2011	Spring 2011		Fall 2010	Winter 2011	Spring 2011
1	6.2%	8.8%	5.0%		84.4%	86.8%	85.3%
1+	3.1%	5.2%	7.6%		8.4%	5.7%	5.2%
2	52.8%	73.3%	57.8%		5.8%	6.5%	7.4%
2+	29.8%	5.6%	23.6%		1.0%	0.5%	1.3%
3	4.1%	4.5%	2.6%		0.3%	0.4%	0.4%
3+	1.3%	0.3%	0.9%		0.1%	0.05%	0.1%
4+	2.7%	2.3%	2.6%		0.1%	0.1%	0.2%

4.3 The Matching Process

After the occupancy and license plate data were processed individually, the matching process required another round of in-depth processing. The occupancy data only needed minor corrections, such as adding missed vehicles and determining the starting and end point of data collection in relation to the license plates. However, re-watching the license plate video using the information from the registration database exposed errors in the both the initial video processing as well as in the vehicle registration database.

4.3.1 License Plate Transcription Corrections

When the license plate videos are first processed by URAs, each video is converted to still images (two frames per second) and then separated into folders by twenty-minute interval. Every time a URA signs into the processing program, the next available video segment is uploaded from the queue. Because of this queue process, many URAs will process portions of the same day of video, so any errors noted in this section are distributed randomly throughout out the dataset rather than limited to one complete day of data.

4.3.1.1 State Assignment

Only Georgia license plate records are available for this study, so any out of state plates are assigned a vehicle classification during the initial video processing. URAs are given flashcards with examples of different state license plates to assist them in making accurate records (the flashcards were developed by D'Ambrosio and are provided in Appendix D [45]). When the license plate video was reviewed a second time, many out of state plates were incorrectly identified as Georgia or another state altogether. Out-of-state license plates mistakenly assigned a Georgia plate can result in incorrect records from the registration database if there is a vehicle with the same letter/character combination (on average, 3.2% of plates were incorrectly identified as Georgia and 6.2% of these misclassifications returned incorrect GA records). The video processing software requires each URA to enter his or her name before each processing session, so the out of state errors could be analyzed by URA. One specific URA (URA 57) entered all license plates as Georgia, even when they were clearly not Georgia plates.

4.3.1.2 Motorcycles

Motorcycles are the source of several discrepancies in data processing. First, the use of only three vehicle classifications in occupancy data collection (LDV, SUV, and HDV) does not allow motorcycles to be uniquely identified. The majority of motorcycles have only one occupant, so labeling all motorcycles as LDVs can skew the perceived violation rate. The video processing software does not provide a motorcycle classification option either. Adding to this issue is the extremely small physical size of motorcycle license plates, which makes accurate transcription very difficult even when using high definition cameras. Out of the 60,000 records returned from the registration database, only 29 are motorcycles. Reviewing the videos a second time revealed that motorcycles comprise 1.75% of all vehicles in the HOV lane versus the 0.04% that returned records from the registration database. One particular URA completely ignored motorcycles when processing the license plate video, which only added to the problem of missed motorcycle license plates as many of the images during this URA's processing time were clearly visible. Changes to the video processing program and the occupancy data collection equipment could help identify motorcycles in the future. Rather than grouping motorcycles in with all light duty vehicles (LDVs), motorcycles could have a separate category on the occupancy keypad and in the video processing software. This problem could exist in other studies, so unless the issue of motorcycles is specifically addressed violation rates may higher than in reality.

4.3.1.3 Time Stamps

As previously mentioned, the license plate video is converted to images for use in the processing software. Two images are captured for every second of video, and URAs are then able to tab through the images to find the clearest image of each license plate. When vehicles travel very close behind each other, some license plates are only visible for one frame or multiple plates are visible in one screen shot. As an experiment, the Pleasant Hill video was reduced to one frame per second rather than two frames per second. Due to this change, multiple license plates have the same time stamp, and when the data are exported in .CSV format, the two or more records with the same time stamp are sorted alphabetically. The plates do not always occur in alphabetical order, so during the re-watching of the video the records had to be re-ordered. Rarely, a vehicle may be missed during video processing. Some vehicles travel so closely together that the first vehicle may be obscured, and this problem contributed to 1.9% missed vehicles over one session of data.

4.3.1.4 Notes

The notes field also allowed extra comments that assist the matching process. For example, single rider motorcycles and vehicles with higher occupancy rates such as transit buses are flagged so that the occupancy values can be easily verified. These types of vehicles are less likely to result in uncertain occupancy values due to their unique body type and visibility. To obtain accurate occupancy values, express bus occupancy values are handled separately (through surveys) but for the matching process the “4+” values were assigned to all buses. Vehicles may change lanes (illegally since there is not a weaving section) or travel immediately behind other vehicles so that they are obscured from the occupancy data collector’s view. Any license plate corrections are also recorded in the notes section; approximately one-quarter of incorrect plates can be corrected with this method.

4.3.2 Registration Database Corrections

A small number (less than 1%) of license plates returned incorrect vehicle information even though the license plate was transcribed correctly. In Georgia, a license plate stays with the individual rather than the vehicle, and an individual has 30 days to transfer an existing license plate to a new vehicle [46]. The frequency of updates to the registration database is unknown, so the incorrect records are assumed to be out-of-date information due to new vehicle purchases or stolen license plates.

Nearly 20% of transcribed license plates did not return a record from the database despite being extremely clear in the video. No specific trend explained the lack of records, and the records were re-submitted to GTRI to test if the lack of records was due to a problem in the initial query. Of the 20,000 plates that were re-submitted, 25% (over 5,000) returned a record. The only change made to the license plate data prior to the request was to convert entries to all upper case letters. Several weeks later, researchers discovered a major error in the initial license plates request due to a conversation with a URA. The URA pointed out that the state of Georgia always uses zero in place of the letter “O” on license plates, even in the case of vanity plates (i.e. ZOOM would be written as Z00M). Several hundred license plate records contained “o’s”. This issue was not resolved in time to add these missing plates to the analysis for this thesis, but moving forward all future license plate requests will convert any “o’s” to zeroes. The impact on the data should not be significant since the license plates with zeroes are randomly distributed).

As previously mentioned in Section 4.1.1, all vehicles are classified as 25 distinct body types in Georgia's vehicle registration database. After the body types are recoded to match the three basic vehicle classifications used in occupancy data collection, the vehicle classification can be used as a variable for matching. Unfortunately, the body type classification is inconsistent even among the same vehicle model, so many of these vehicles were re-classified by hand while re-watching the video. An example of this body type classification inconsistency is the Honda CR-V, which is entered in the registration base as 4S (four door sedan), MP (multi-purpose), and SW (sports wagon).

4.3.3 Occupancy Data Collection Corrections

Vehicles in general purpose lanes 1-5 (all lanes between the HOV lane and the gore area) may also obstruct the occupancy collector's view of the HOV lane and result in missed vehicles. Data collectors in the field are able to watch each vehicle for a further distance than is captured in the gore area video, but potential misses can be noted in the database and then compared to any discrepancies between the occupancy and license plate streams. Figure 9 shows an example of occlusion due to a tractor-trailer.

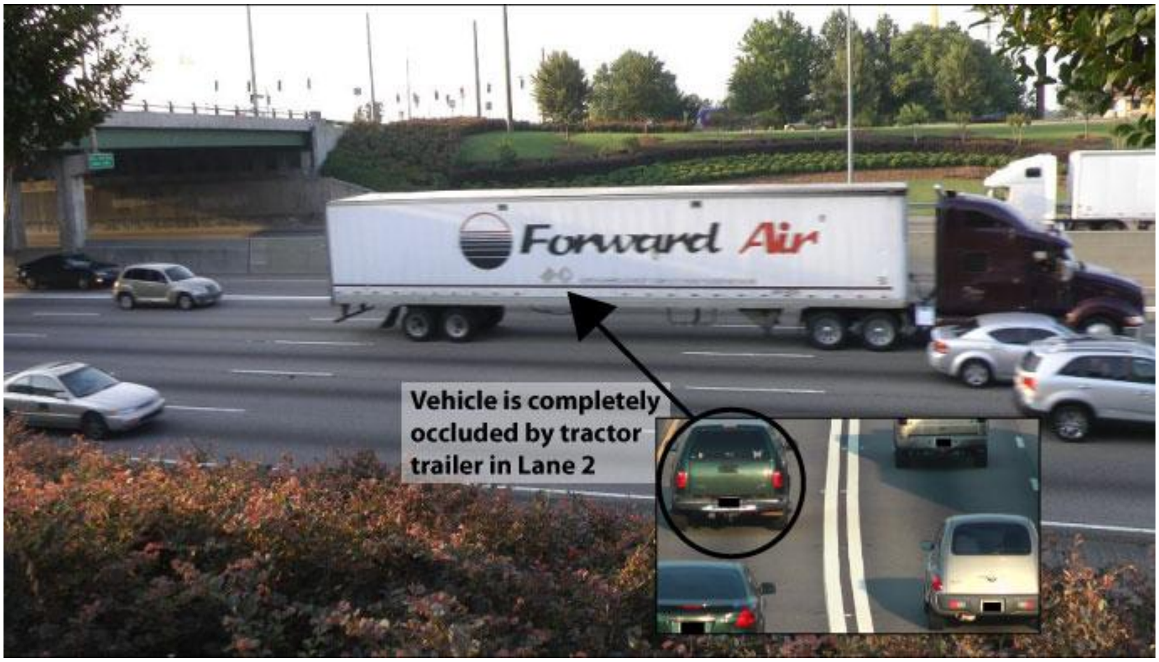


Figure 9: Occupancy Data Collection Occlusion Example

4.4 Actions to Improve Methodologies

Many of the issues discussed in this chapter are preventable, and knowledge of all of the potential issues is very beneficial for the analysis of the data. Researchers took immediate action to address many of these issues to improve future data collection efforts.

4.4.1 Methodology Improvements

The changes to the occupancy data collection started for the spring data collection are now integrated into the standard data collection procedure. Every session, two URAs record occupancy for the HOV lane and a camera is set-up in the gore area. In previous data collection sessions, URAs chose their own lane assignments. Many URAs expressed a strong preference for one lane and collected data on this lane every session.

The bias of one URA can greatly affect the data if no one else ever has the opportunity to collect accurate data on that particular lane. To reduce the impact of bias on one lane, URAs are now rotated to a different lane for each session (some repetition still occurs as there are only six lanes and many URAs work at least two sessions per week). One URA is also designated the occupancy area supervisor for each session; this supervisor works with each URA to make sure he or she is entering the data correctly, observing the correct lane, and not taking any extended breaks. The supervisor can also quickly deal with any equipment malfunctions in the field so that other data collectors do not have to stop recording occupancy data.

Beginning in the summer session, more frequent data checks were performed for completed video and occupancy files. If any files are deemed inaccurate (either due to bad occupancy or bad video quality), a make-up data collection was scheduled as soon as possible.

4.4.2 URA Training

Many URAs work multiple semesters on the HOV-to-HOT project, but there is still a large amount of turnover due to factors such as class schedule conflicts and student graduation. All new URAs receive detailed training before beginning the occupancy data collection or video processing. The potential mistakes discovered in the processing of data for this thesis are now integrated into the new training materials to minimize the likelihood of new URAs making the same mistakes. Any returning URAs also received training so that they maintain good data collection methods, and occupancy data is cross-compared across URAs as part of QA/QC to verify that the trainings are effective.

Several URAs with extremely poor performance (bias or errors) were terminated, and URAs with minor errors received individual training in addition to the group sessions.

CHAPTER 5: DATA ANALYSIS

The license plate and occupancy data are analyzed independently and then together. License plates from Lane 0 and Lane 1 collected in the Spring 2011 session are compared to highlight differences between carpoolers and single-occupant vehicles on the general purpose lanes. Occupancy data from the first four quarters of data collection (September 2010-September 2011) are used to develop distributions for the HOV lane and the general purpose lanes to identify any variances due to site, time, or day of the week. Finally, matched occupancy and license plate records from Spring 2011 are studies to create a profile of current users of the HOV lane prior to the conversion at a HOT lane.

5.1 License Plates

Chi-square tests were performed to compare the independence of different variables for Lane 0 (the managed lane) and Lane 1(the adjacent general purpose lane). A 95% confidence level was used in the analysis. Due to the large sample size, almost all tests were significant.

5.1.1 Vehicle Ownership

The vehicle registration database assigns one of three ownership values for each vehicle: commercial, government, and private. Approximately 9% of vehicles were commercial, less than 1% government, and 90% private. The percentage of commercial vehicles in the managed lane was 11% while the percentage in the general purpose lane was only 8%. The percentage of commercial vehicles in Lane 0 was also higher than expected, and commercial vehicles also showed a greater variation in vehicle registration addresses, which may indicate that these vehicles are not traveling to or from the registered address or are being used for personal trips. Although the total number and percentage of government vehicles on the road was small (only 460 government vehicles were observed), the percentage of government vehicle using the carpool lane was nearly seven times higher than in the adjacent general purpose lane. The chi-square test results show significance at the 95% confidence level and the full results of the test are shown in Table 6.

Table 6: Vehicle Ownership and Lanes Chi-Square Results

Vehicle Ownership * Lane Crosstabulation

			Lane		Total
			HOV	GP 1	
Vehicle Ownership	Commercial	Count	2445	3066	5511
		Expected Count	2000	3511	5511
		% within Lane	11.1%	7.9%	9.1%
	Government	Count	367	93	460
		Expected Count	167	293	460
		% within Lane	1.7%	0.2%	0.8%
	Private	Count	19235	35531	54766
		Expected Count	19880	34886	54766
		% within Lane	87.3%	91.8%	90.2%
Total		Count	22047	38690	60737

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	564.051	2	.000
Likelihood Ratio	548.564	2	.000

The distribution of the cities attached to the vehicle's registration reflects significant differences. Nearly 25 percent of all vehicles in the HOV lane are registered in the nearby city of Lawrenceville, yet only 12 percent of commercial vehicles are registered in Lawrenceville. Commercial vehicles in the managed lane were just as likely to be registered in Atlanta as Lawrenceville, while only 5% of all vehicles are registered in Atlanta. This indicates that commercial vehicles are registered and used in different locations. A recent dissertation found that household travel behavior is very different when a commercial vehicle is present in the household (these households have higher trip rates than households without a commercial vehicle with all other major demographic variables being equal [47]). A travel survey could provide more conclusive evidence about the trip origins and destinations of these commercial vehicles, as well as the trip purposes.

5.1.2 Vehicle Classification

Vehicle classifications were included as body type in the registration database, and as discussed in the data processing chapter the twenty-five different body types were recoded to the three vehicle classifications used in occupancy data collection (refer to Table 1). The actual count of heavy duty vehicles in the HOV lane was twice the expected count, and the reverse trend was observed in Lane 1 as the actual count of HDVs was only 40% of the expected count. Even though HDV vehicles were more prevalent in the carpool lane, they are still less than one percent (0.8%) of all vehicles (compared to 0.2% on Lane 1). SUVs account for nearly 60% of vehicles in the carpool lane but less than 50% of vehicles in Lane 1.

Although the higher number of heavy duty vehicles (HDVs) using the carpool lane may be counter to initial expectation, this may make some sense as a large number of work trucks with crews were observed using the carpool lane. Buses were excluded from the vehicle classification and fuel type analyses (a total of 230 bus license plates were recorded with 98% of these buses observed in the carpool lane). The biggest finding with respect to lane use is that a significantly larger percentage of SUVs are using the carpool lane than are using the adjacent general purpose lane.

Table 7: Vehicle Classification and Lane Chi-Square Results

VehicleClass * Lane Crosstabulation					
			Lane		Total
			HOV	GP 1	
VehicleClass	HDV	Count	171	65	236
		Expected Count	85.1	150.9	236.0
		% within Lane	0.8%	0.2%	0.4%
	LDV	Count	8978	20200	29178
		Expected Count	10523	18655	29178
		% within Lane	41.1%	52.2%	48.2%
	SUV	Count	12672	18421	31093
		Expected Count	11213	19880	31093
		% within Lane	58.1%	47.6%	51.4%
Total		Count	21821	38686	60507

Chi-Square Tests			
	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	787.011	2	.000
Likelihood Ratio	784.167	2	.000

The vehicles types can be further subdivided to examine the tendencies of different types of SUVs and LDVs to utilize the carpool lane. The expectation was that larger vehicles, such as full-size sedans or SUVs, would be more likely to use the carpool lane than smaller two door coupes or small SUVs. Two door, four door, and five door sedans were analyzed using the body type variable from the vehicle registration database. Five door sedans (hatchbacks) were the least common sedan type on either lane with only

21 total observations. The five door sedan expected counts were different from the actual counts but due to the extremely small sample size these results were not conclusive. The counts for two door and four door sedans were not significantly different from the expected counts. Contrary to the hypothesis that smaller sedans (two door) would be less prevalent in the carpool lane, the results of the chi-square test for LDV sub-classifications were not significant despite the large number of HOV observations (Table 5).

Table 8: Sedan Body Types and Lanes Chi-Square Results

Sedans * Lane Crosstabulation					
			Lane		Total
			HOV	GP 1	
Sedans	2 Door	Count	304	726	1030
		Expected Count	325.4	704.6	1030.0
		% within Lane	3.8%	4.2%	4.0%
	4 Door	Count	7753	16735	24488
		Expected Count	7736	16752	24488
		% within Lane	96.1%	95.8%	95.9%
	5 Door	Count	11	10	21
		Expected Count	6.6	14.4	21.0
		% within Lane	0.1%	0.1%	0.1%
Total		Count	8068	17471	25539

Chi-Square Tests			
	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	6.310	2	.043
Likelihood Ratio	6.014	2	.049

Next, the different categories of SUV s were examined. This analysis was somewhat hindered by the unclear body type assignments employed in the registration database. For example, the “SW” category included a wide variety of vehicle body types, from station wagons, to small SUV sports wagons, to crossover vehicles. As expected, the majority (over 90%) of large passenger vans observed were in the HOV lane. Small passenger vans also were disproportionately observed in the carpool lane, representing 26% of the vehicles in the HOV lane and only 14% of the adjacent general purpose lane. The use of pickup trucks differed only slightly across these lanes. However, large SUVs represented a much lower percentage of HOV traffic than in the general purpose lane (35% vs. 49%), indicating that the large passenger carrying capacity of these vehicles is probably not a driving factor in commute choice.

Table 9: SUV Body Types and Lane Chi-Square Results

SUVTypes * Lane Crosstabulation					
			Lane		Total
			HOV	GP 1	
SUVTypes	Camper/Trailer	Count	7	3	10
		Expected Count	4	6	10
		% within Lane	0.1%	0.0%	0.0%
	Passenger Van/ Non-Transit Bus	Count	121	28	149
		Expected Count	61	88	149
		% within Lane	1.0%	0.2%	0.5%
	Pick-Up Truck	Count	3888	6075	9963
		Expected Count	4061	5902	9963
		% within Lane	30.7%	33.0%	32.0%
	Sports Wagon/Crossover/ Small SUV	Count	494	773	1267
		Expected Count	516	751	1267
		% within Lane	3.9%	4.2%	4.1%
	SUV	Count	5122	9005	14127
		Expected Count	5759	8368	14127
		% within Lane	40.4%	48.9%	45.4%
	Van	Count	3044	2537	5581
		Expected Count	2275	3306	5581

		% within Lane	24.0%	13.8%	17.9%
Total		Count	12676	18421	31097

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	676.234	5	.000
Likelihood Ratio	669.962	5	.000

5.1.3 Fuel Type

Alternative fuel vehicles are slowly gaining popularity in the United States, and this data set provided an excellent opportunity to take closer look at the prevalence of these vehicles in the I-85 commute fleet. The strict federal definition of alternative fuel vehicle, which is also used by the State of Georgia, does not include gasoline hybrids like the popular Toyota Prius [25]. Alternative fuel vehicles under the federal definition qualify for Georgia AFV plates, which allow drivers to use the carpool lane.

Five different fuel types are recorded in the registration database: diesel, flex fuel, gasoline, hybrid, and natural gas. Diesel vehicles accounted for 4.5% of vehicles in the carpool lane but only 1.8% of vehicles in Lane 1. The high proportion of diesel vehicles in the HOV lane correlates back to the high number of commercial and heavy duty vehicles in the lane. Flexfuel vehicles are eligible for official "AFV" license plates in Georgia, but the actual count of these vehicles in the HOV lane was slightly less than expected (3%). Not all flexfuel vehicles have the AFV license plate, and only 93 total vehicles with the official Georgia "AFV" license plate were observed (0.9% of vehicle observed). Only 71 of these AFV plates returned records from the vehicle registration database. Of the 72, there were only 22 unique vehicles (most vehicles were observed on more than one day). AFV vehicles are simply not very prevalent in the NE I-85 corridor fleet (natural gas vehicles were the least common AFV fuel type with only eleven total records). Gasoline vehicles represent such a large majority (over 90%) that the test was repeated with this category excluded to highlight the differences in the other categories (see Table 11).

Hybrid vehicles are much more prevalent than official AFV vehicles, with 544 records from the registration database. As mentioned in the literature review, a previous study used uncommon variables such as Sierra Club membership levels to examine the relationship between environmentalism and propensity to carpool (the study did find a positive correlation). Based on this previous work, researchers hypothesized that hybrid vehicle owners would be more likely to carpool. While the results of the first chi-square test for fuel type as well as the test results with gasoline excluded were significant, there was no practical difference between the percentage of hybrid vehicles on the carpool lane and Lane 1. In fact, once gasoline was excluded the actual count of hybrid vehicles in the carpool lane was over twenty percent lower than the expected count. The second test increased the difference between the expected and actual counts of flexfuel vehicles as well. Natural gas and diesel vehicles were the only non-gasoline fuel types that had greater actual percentages in the carpool lane than expected.

Table 10: Fuel Type and Lane Chi-Square Results

FuelType * Lane Crosstabulation					
			Lane		Total
			HOV	GP 1	
FuelType	Diesel	Count	991	686	1677
		Expected Count	606	1071	1677
		% within Lane	4.5%	1.8%	2.8%
	Flexfuel	Count	752	1253	2005
		Expected Count	725	1280	2005
		% within Lane	3.4%	3.2%	3.3%
	Gasoline	Count	19922	36332	56254
		Expected Count	20336	35918	56254
		% within Lane	91.1%	94.1%	93.0%
	Hybrid	Count	192	352	544
		Expected Count	197	347	544
		% within Lane	0.9%	0.9%	0.9%
	Natural Gas	Count	11	0	11
		Expected Count	4	7	11
		% within Lane	0.1%	0.0%	0.02%
Total		Count	21868	38623	60491

Chi-Square Tests			
	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	416.845	4	.00
Likelihood Ratio	400.538	4	.00

Table 11: Fuel Type and Lane Chi-Square Results (gasoline excluded)

FuelType * Lane Crosstabulation					
			Lane		
			0	1	Total
FuelType	Diesel	Count	991	687	1678
		Expected Count	770.5	907.5	1678.0
		% within Lane	50.9%	30.0%	39.6%
	Flexfuel	Count	752	1253	2005
		Expected Count	920.7	1084.3	2005.0
		% within Lane	38.6%	54.7%	47.3%
	Hybrid	Count	192	352	544
		Expected Count	249.8	294.2	544.0
		% within Lane	9.9%	15.4%	12.8%
	Natural Gas	Count	11	0	11
		Expected Count	5.1	5.9	11.0
		% within Lane	.6%	.0%	.3%
Total		Count	1946	2292	4238
		Expected Count	1946.0	2292.0	4238.0
		% within Lane	100.0%	100.0%	100.0%

Chi-Square Tests			
	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	211.483	3	0.000
Likelihood Ratio	216.636	3	0.000

5.1.4 Model Year

Vehicle model year can be a useful indication of a fleet's emissions impact (this will be done in the future using this data set). Vehicle model years were binned so that the chi-square test could be applied, but no category showed any practical difference (despite the significance indicated by the low p-value). A subsequent analysis will examine the breakdown of vehicle model years by engine certification grouping for use in enhanced vehicle emissions impact research.

Table 12: Model Years and Lane Chi-Square Results

			Lane		Total
			0	1	
YearBins	1989 and earlier	Count	174	293	467
		Expected Count	170.8	296.2	467.0
		% within Lane	0.7%	0.7%	.7%
	1990-1994	Count	590	951	1541
		Expected Count	563.5	977.5	1541.0
		% within Lane	2.5%	2.3%	2.3%
	1995-1999	Count	3223	4924	8147
		Expected Count	2979.3	5167.7	8147.0
		% within Lane	13.4%	11.8%	12.4%
	2000-2002	Count	4193	7138	11331
		Expected Count	4143.7	7187.3	11331.0
		% within Lane	17.4%	17.1%	17.2%
	2003-2004	Count	3743	6668	10411
		Expected Count	3807.3	6603.7	10411.0
		% within Lane	15.6%	16.0%	15.8%
	2005-2006	Count	4375	7705	12080
		Expected Count	4417.6	7662.4	12080.0
		% within Lane	18.2%	18.5%	18.4%
	2007-2008	Count	4371	7751	12122
		Expected Count	4433.0	7689.0	12122.0
		% within Lane	18.2%	18.6%	18.4%
	2009-2010	Count	2769	5289	8058
		Expected Count	2946.8	5111.2	8058.0
		% within Lane	11.5%	12.7%	12.3%
	2011-2012	Count	616	1003	1619
		Expected Count	592.1	1026.9	1619.0
		% within Lane	2.6%	2.4%	2.5%
Total		Count	24054	41722	65776
		Expected Count	24054.0	41722.0	65776.0
		% within Lane	100.0%	100.0%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	56.557	8	.000
Likelihood Ratio	53.357	8	.000

5.1.5 In-State vs. Out-of-State Vehicles

Out-of-state vehicles observed in this data collection effort may just be passing through the region. However, since the collection only took places during peak commuting periods it is likely that many of these vehicles are garaged in Georgia but registered in another state (this could also apply to vehicles registered in distant Georgia counties). Previous research in the Atlanta area found that approximately 67% of vehicles have the registration database address as the point of origin [35]. The percentage of out-of-state vehicles in the HOV lane is slightly higher than in the adjacent general purpose lane, and also about 20% higher than the expected count from the chi-square test (see Table 13).

Table 13: In-State Registration and Lane Chi-Square Results

StateGAvsOut * Lane Crosstabulation					
			Lane		Total
			HOV	1	
StateGAvsOut	GA	Count	32163	53372	85535
		Expected Count	32425	53110	85535
		% within Lane	94.9%	96.1%	95.6%
	Out of State	Count	1746	2168	3914
		Expected Count	1484	2430	3914
		% within Lane	5.2%	3.9%	4.4%
Total		Count	33909	55540	89449

Chi-Square Tests			
	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	78.069	1	.000
Continuity Correction	77.771	1	.000
Likelihood Ratio	76.636	1	.000

5.2 Occupancy

The processed occupancy data for all four quarters were analyzed to examine the impact of factors such as site, day, and time on the occupancy distributions. Because two data collectors recorded occupancy on the HOV lane beginning in late May 2011, one set of HOV lane records was removed on each of these sessions to eliminate intra-correlation of the data. The vehicle occupancy, vehicle classification, URA name, and a time stamp are recorded with the occupancy (LDV, SUV, and HDV) but no other vehicle information is included in each record.

5.2.1 Overall HOV vs. General Purpose

Over four quarters, 1,562,034 occupancy records were collected at the five sites on I-85. After the duplicate HOV lane values were removed from the database, 1,434,634 unique occupancy records remained. The problem URA data were also removed. The overall distributions of the HOV lane and the general purpose lanes (Lanes 1-5) are seen in Figure 10 and Figure 11. Nearly 90% of vehicles in the GP lanes have only one occupant and 61.5% of vehicles in the HOV lane have two occupants. The HOV lane has about 15% single-occupant vehicles and another 9.5% of possible violators ("1+" records). One should note that motorcycles are not separated out from the distribution even though they are legal lane users with only one occupant. Motorcycles were observed to make-up slightly less than two percent of all vehicles, so the actual violation is a little lower than the graph illustrates. The higher occupancy categories (2+ and above) represent less than two percent of vehicles on the general purpose lanes (the counts are so small that these categories are barely visible in Figure 11).

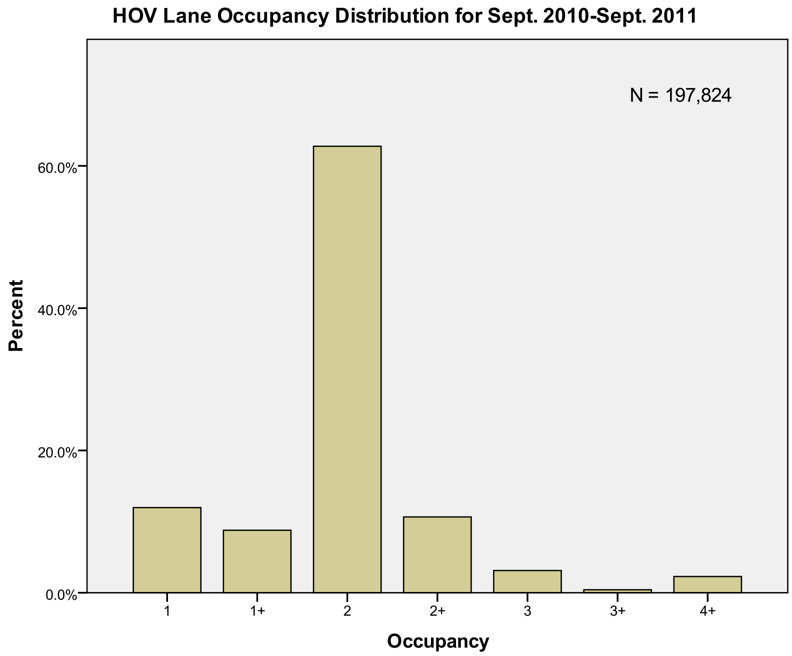


Figure 10: HOV Lane Occupancy Distribution for Sept. 2010-Sept. 2011

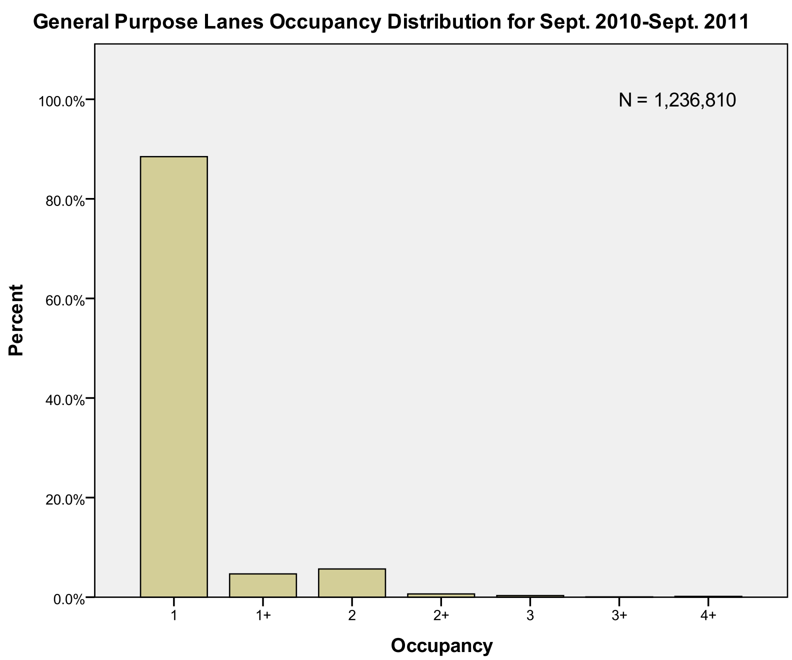


Figure 11: GP Lanes Occupancy Distribution for Sept. 2010-Sept. 2011

Two URAs record data on the HOV lane, but the observers receive additional training and know that their results are being compared and. To test the accuracy of URAs on one of the general purpose lanes, five URAs were assigned to record on Lane 4 without knowing that the results would be compared. Figure 12 illustrates the occupancy distributions of each URA, and all five URAs recorded more than 85% “1” values. The percentages of each occupancy category are very similar, but URA 10 recorded half as many total occupancy records.

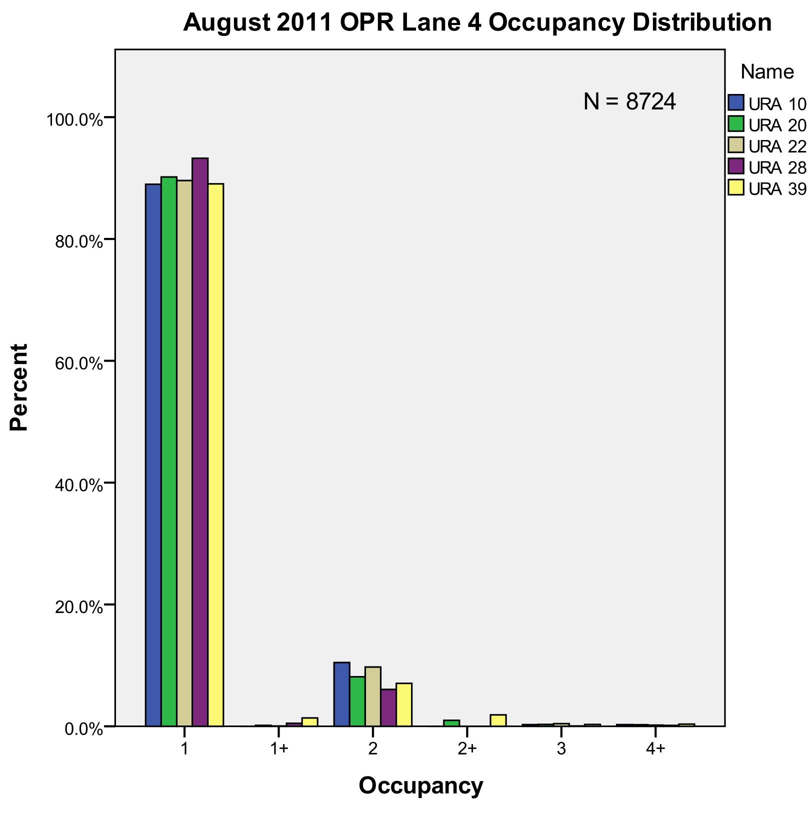


Figure 12: Comparison of Five URAs on One GP Lane

In order to see the difference in the other occupancy categories, the“1” values were excluded and the distribution for the higher occupancy values is shown in Figure

13. URA 20 and URA 39 record slightly more “2+” values than the other URAs, but the actual counts of these values were less than 40 (out of about 1800 records per URA). The other three URAs recorded zero “2+” values.

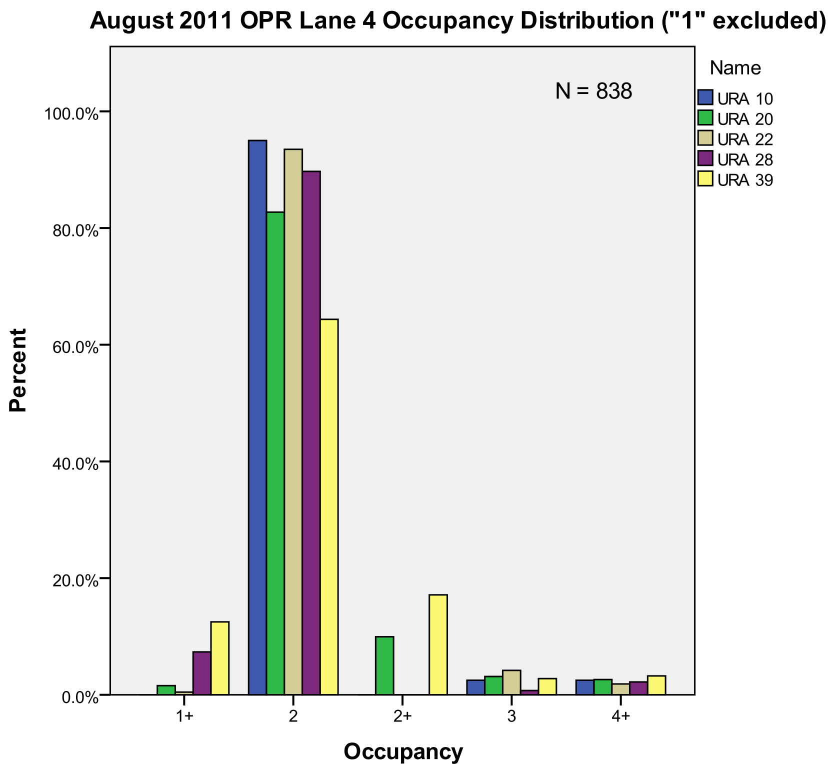


Figure 13: Comparison of Five URAs on One GP Lane (“1” values removed)

<u>5.2.2 Variance due to Time and Site</u>

Only a limited number of sessions were matched due to the extensive processing time, so the variance of occupancy by site, day, and time were examined to ensure that the chosen sessions would not reflect any particular bias. No Tuesday or Beaver Ruin Road data were matched (the full details of the matched data are included in Section 5.3). The updated occupancy methodology was not implemented until the second week of spring data collection, so no Beaver Ruin data was matched. Table 14 includes the percentages of each occupancy value by day of the week. Fall 2010 data included a few Monday sessions, but these data were excluded for consistency with the other data collection sessions. As in earlier analysis, data from the problem URAs are excluded. Since URA names were not included in the fall 2010 files, any potential data from problem URAs from that session could not be removed. Thursday HOV lane AM data have nearly 10% less "2" values than Tuesday or Wednesday, but the percentages of the "2+" and higher values are very similar to the other days of the week. The only general purpose lane day to reflect less than 89% "1" values is Tuesday AM.

Table 14: Occupancy Distributions by Day of the Week

AM	**HOV Lanes**				**General Purpose Lanes**		
	Tuesday	Wednesday	Thursday		Tuesday	Wednesday	Thursday
1	6.7%	8.7%	14.5%		84.1%	89.1%	91.6%
1+	9.9%	9.4%	14.3%		9.8%	6.1%	2.7%
2	68.1%	62.3%	51.5%		5.5%	4.2%	4.6%
2+	11.2%	14.6%	15.5%		0.4%	0.3%	0.7%
3	2.2%	2.6%	1.8%		0.1%	0.2%	0.2%
3+	0.2%	0.4%	0.5%		0.03%	0.03%	0.06%
4+	1.7%	2.0%	1.8%		0.02%	0.1%	0.1%
TOTAL	100.0%	100.0%	100.0%		100.0%	100.0%	100.0%
PM	**HOV Lanes**				**General Purpose Lanes**		
	Tuesday	Wednesday	Thursday		Tuesday	Wednesday	Thursday
1	9.7%	8.6%	9.1%		90.4%	89.2%	89.8%
1+	8.0%	6.0%	6.8%		2.9%	3.0%	2.3%
2	68.4%	70.3%	70.9%		5.9%	6.5%	6.8%
2+	7.2%	7.4%	5.7%		0.3%	0.6%	0.5%
3	3.8%	4.2%	4.3%		0.3%	0.5%	0.4%
3+	0.5%	0.5%	0.3%		0.0%	0.1%	0.0%
4+	2.6%	2.9%	2.8%		0.2%	0.2%	0.2%
TOTAL	100.0%	100.0%	100.0%		100.0%	100.0%	100.0%

Next, the occupancy distributions were compared by site (still separated by AM and PM). As a reminder, only PM data are collected at Chamblee-Tucker so AM data are not available. Many of the differences in the occupancy distributions across different days of the week were between "certain" and "uncertain" values (1 vs. 1+), so the table for the site comparison includes the combined category percentages. Jimmy Carter Boulevard had over 15% "1" occupancy records in the HOV lane AM data (compared to 6-8% at other sites), but the combined "1" and "1+" values at JCB are 24% which is comparable to the other sites.

Table 15: HOV Lane Occupancy Distributions by Site

AM	**HOV Lanes**									
	CTR (%)		JCB (%)		BRR (%)		PHR (%)		OPR (%)	
1	N/A		15.5	23.7	6.6	20.5	5.9	16.6	7.7	25.8
1+			8.2		13.9		10.7		18.1	
2			59.5	72.5	57.1	74.0	66.2	79.0	57.1	69.9
2+			13.0		16.9		12.8		12.8	
3			1.8	2.0	2.8	3.4	2.2	2.6	2.1	2.5
3+			0.2		0.6		0.4		0.4	
4+			1.7	1.7	2.1	2.1	1.8	1.8	1.8	1.8
Total			100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
PM	**HOV Lanes**									
	CTR (%)		JCB (%)		BRR (%)		PHR (%)		OPR (%)	
1	6.8	20.3	10.3	14.3	7.7	12.6	9.3	16.3	12.0	19.9
1+	13.5		4.0		4.9		7.0		7.9	
2	68.7	71.9	74.4	77.7	65.9	80.8	72.3	76.8	64.5	72.6
2+	3.2		3.4		14.9		4.5		8.1	
3	4.2	4.6	4.7	5.0	3.3	4.0	4.1	4.4	4.1	4.5
3+	0.4		0.3		0.7		0.3		0.4	
4+	3.2	3.2	2.9	2.9	2.5	2.5	2.5	2.5	2.8	2.8
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0

Table 16: General Purpose Lanes Occupancy Distributions by Site

AM	General Purpose Lanes									
	CTR (%)		JCB (%)		BRR (%)		PHR (%)		OPR (%)	
1	N/A		87.1	94.6	90.2	94.4	94.2	96.2	89.0	92.0
1+			7.5		4.2		2.4		3.0	
2			4.9	5.2	4.6	5.2	2.9	3.1	6.5	7.6
2+			0.3		0.6		0.2		1.1	
3			0.2	0.2	0.2	0.3	0.2	0.2	0.2	0.3
3+			0.0		0.1		0.0		0.1	
4+			0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
Total			100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
PM	**General Purpose Lanes**									
	CTR (%)		JCB (%)		BRR (%)		PHR (%)		OPR (%)	
1	88.3	90.6	92.3	93.9	88.7	93.4	91.3	93.7	86.9	90.2
1+	2.3		1.6		3.7		2.4		3.3	
2	7.8	8.5	5.1	5.5	6.4	7.0	5.4	5.8	8.5	9.0
2+	0.7		0.4		0.6		0.4		0.5	
3	0.6	0.6	0.4	0.4	0.4	0.4	0.3	0.3	0.5	0.5
3+	0.0		0.0		0.0		0.0		0.0	
4+	0.3	0.3	0.2	0.2	0.2	0.2	0.2	0.2	0.3	0.3
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0

5.3 Matched Occupancy and License Plates

Due to the time-intensive processing, only five of the eighteen available data collection sessions were matched. Over 7,000 occupancy values were matched to vehicles from the license plate video. 5,780 (82.2%) had consistent occupancy records, and of these matched and accurate records 3,570 (61.8%) had license plate data.

Table 17 defines consistent and inconsistent occupancy values. If both observers record a miss (this happened 2.6% of the time), no occupancy values can be entered into the final database. The definitions of consistent are modified from D'Ambrosio's thesis to exclude the match of values such as "1" and "1+" as consistent [45].

Table 17: Definition of Consistent Occupancy Values

Occupancy Value A	Occupancy Value B	Result
1	1	Consistent
1	1+, 2, 2+, 3, 3+, 4+	Not consistent
1+	1+, 2, 2+, 3, 3+, 4+	Consistent
1+	1	Not consistent
2	1+, 2	Consistent
2	1, 2+, 3, 3+, 4+	Not consistent
2+	1+, 2+, 3, 3+, 4+	Consistent
2+	1, 2	Not consistent
3	1+, 2+, 3	Consistent
3	1, 2, 3+, 4+	Not consistent
3+	1+, 2+, 3+, 4+	Consistent
3+	1, 2, 3	Not consistent
4+	1+, 2+, 3+, 4+	Consistent
4+	1, 2, 3	Not consistent

The details of the inconsistent occupancy values are shown in Table 18. The inconsistent pairs are shown separately by Observer A and Observer B, so each pair of inconsistent is shown twice (e.g. Observer records "2" while Observer B records "1" is listed separately than Observer A records "1" while Observer records "2"). The most common inconsistent pairing was "2" and "1", with 373 occurrences that represent 5.63% of all matched records. The inconsistent values are 15.4% of the total matched records. If the definition of consistent values from D'Ambrosio's thesis was used instead of the more strict exclusion of values such as “2” and “2+”, an additional 5.54% of the inconsistent values could have been labeled as consistent.

Table 18: Occurrence of Inconsistent Occupancy Records

Observer A	Observer B	Count	% of Total Records
2	1	238	3.59%
2	2+	149	2.25%
1	2	135	2.04%
3	2	103	1.55%
2+	2	89	1.34%
1	1+	85	1.28%
2	3	80	1.21%
1+	1	39	0.59%
4+	2	26	0.39%
2	4+	20	0.30%
3	4+	17	0.26%
2	3+	9	0.14%
1	2+	7	0.11%
3	1	6	0.09%
2+	1	5	0.08%
3+	2	5	0.08%
3+	3	4	0.06%
1	3	3	0.05%
3	3+	1	0.02%
1	3+	0	0.00%
1	4+	0	0.00%
3+	1	0	0.00%
4+	1	0	0.00%
TOTAL		**1021**	**15.4%**

The matched sample is representative of the entire license plate dataset despite the omission of any Beaver Ruin Road or Tuesday data. A socio-demographic analysis of the data showed that Monday-Wednesday data and data from the three middle corridor sites (BRR, JCB, and PHR) had no significant difference [48]. 123 motorcycles, all with occupancy of 1, were observed in the sample. Motorcycles therefore account for 1.8% of all vehicles and 5.0% of light duty vehicles (LDVs).

Table 19: Details of Matched Records

Site	JCB	OPR	OPR	PHR*	CTR	TOTAL
Date	6/1/2011	6/8/2011	6/23/2011	5/25/2011	6/16/2011	
Day	Wednesday	Wednesday	Thursday	Wednesday	Thursday	
Period	AM	AM	PM	PM	PM	
URA A	URA 36	URA 21	URA 26	URA 36	URA 48	
URA B	URA 21	URA 22	URA 22	URA 5	URA 39	
Matched Records	2524	747	1263	796	1697	7027
Consistent Occupancy	1948 (77.2%)	660 (88.3%)	1082 (85.7%)	606 (76.1%)	1484 (87.4%)	5780 (82.3%)
LP Data	1097 (43.4%)	427 (57.2%)	612 (48.5%)	404 (50.8%)	1024 (60.3%)	3564 (50.7%)

**Only forty-five minutes of video were matched for this session*

The match rate is higher at sites with lower volumes. Specifically, the occupancy matching rates are higher at Old Peachtree Road and Chamblee-Tucker Road (88.3%, 85.7%, and 87.4% versus 77.2% and 76.1% at the two other sites). At JCB and PHR, vehicle volumes are on average nearly twice the average volumes at OPR and CTR and 97% of time gaps between vehicles are less than ten seconds (by comparison, only 66% of time gaps are less than ten seconds at OPR). On average, URAs at the high volume sites took one or two 15-20 second breaks over each data collection session, even a 15 second break once or twice in the two hour period can result in dozens of missed vehicles. Also, the time stamp difference between vehicles is one of the variables used to match not only occupancy to license plates but also to match the two occupancy streams. The higher prevalence of time gaps greater than ten seconds at CTR and OPR make the matching process much easier than matching the time gaps at the sites with higher volumes and more regular time gaps. This concept is demonstrated in Table 20, which includes a sample of the three data streams from a session at Old Peachtree Road. The longer time gaps (approximately 23 and 27 seconds) assist in matching the three data streams accurately.

Table 20: Example of Time Gap Use in Matching Process

Gap A (s)	Vehicle Class. A	Occupancy A	Gap B (s)	Vehicle Class. B	Occupancy B	Video Gap (s)	Vehicle Class. Video
0:00:02	LDV	2	0:00:01	LDV	2	00:00.0	LDV
0:00:10	LDV	1	0:00:13	LDV	1	00:12.0	LDV
0:00:08	SUV	1.5	0:00:07	SUV	2	00:07.0	SUV
0:00:23	SUV	2	0:00:23	SUV	2	00:24.0	SUV
0:00:02	SUV	2	0:00:01	SUV	2	00:00.0	SUV
0:00:01	SUV	2	0:00:01	SUV	2	00:01.0	SUV
0:00:04	SUV	2.5	0:00:03	SUV	2	00:04.0	SUV
0:00:02	LDV	2	0:00:02	LDV	2	00:02.0	LDV
0:00:03	LDV	2	0:00:04	LDV	2	00:03.0	LDV
0:00:10	LDV	1	0:00:10	LDV	1	00:11.0	LDV
0:00:25	SUV	2	0:00:28	SUV	2	00:27.0	SUV
0:00:10	LDV	1	0:00:07	LDV	2	00:09.0	LDV
0:00:12	SUV	2	0:00:12	SUV	2	00:13.0	SUV
0:00:05	SUV	2	0:00:04	SUV	2	00:03.0	SUV
0:00:01	LDV	2	0:00:01	LDV	2	00:01.0	LDV

5.3.1 Matched Occupancy Sensitivity Analysis

A sensitivity analysis of the occupancy data assesses sensitivity to recorder errors and inconsistent match errors. As mentioned in the previous section, the two recorded occupancy values were compared and only the consistent occupancy values are used in the final analysis.

Table 17 contains definitions of consistent and inconsistent occupancy values between observers. The designations “Observer A” and “Observer B” were randomly assigned to the URAs for each data collection session. The definition of consistent values differs from a previous analysis of the project’s occupancy data because pairs such as “2” and “2+” are not considered to be consistent for this analysis [45].

The uncertain, or “+” occupancy values, are changed to numeric values that are 0.5 more than the certain value (i.e. “1+” becomes “1.5”) to facilitate analysis of the data. Using the values listed in Table 22, the average occupancy for the matched records is 2.049. If all the uncertain values are rounded up (“1.5” to “2”), the average occupancy increases very slightly to 2.074. If the uncertain values are truncated (“1.5” to “1”), the average occupancy only decreases slightly to 1.998. The changes are very slight due to the high percentage of “2” occupancy values in the data. The negligible effect on the overall average indicates that using 0.5 in place of the “+” is acceptable for the majority of vehicles.

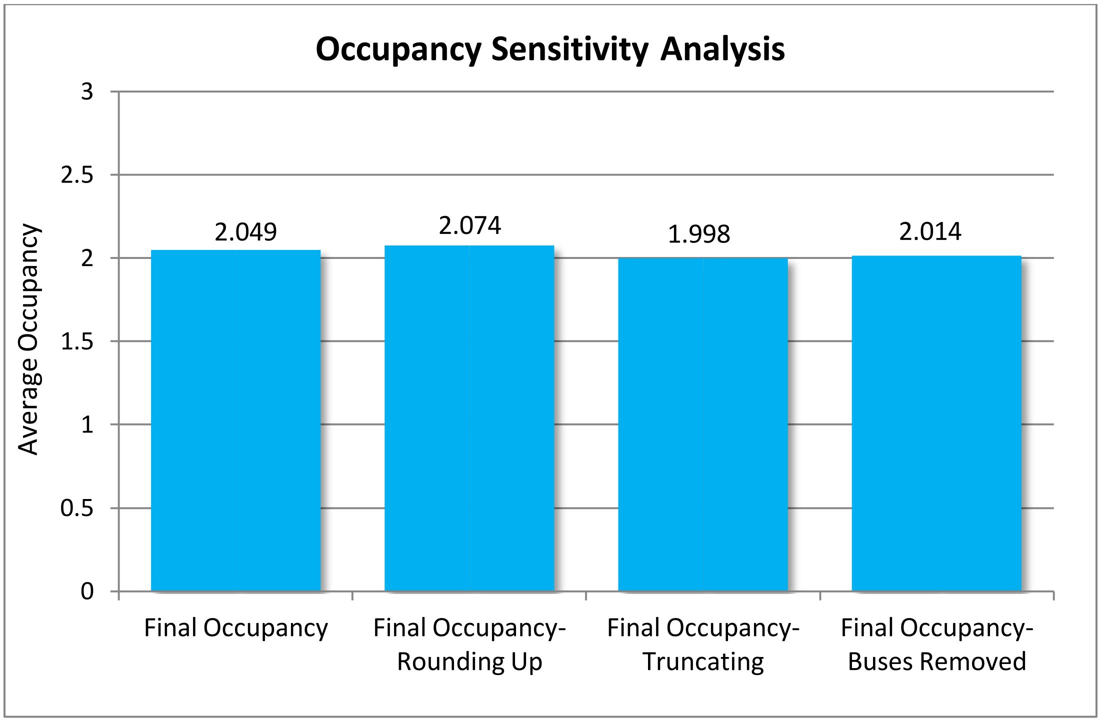


Figure 14: Occupancy Sensitivity Analysis

After the sensitivity analysis concluded that assigning uncertain values an additional “0.5” was reasonable, the difference between the consistent records was examined. Observer B’s occupancy records were subtracted from Observer A’s records to obtain the difference between them. The results are shown in Figure 15 and the details of the distribution are in Table 21. The mean difference is -0.049, or 0.02%, which indicates that the occupancy methodology is producing good results. The distribution is nearly symmetrical and nearly 60% of the records are an exact match. The lowest and highest difference are both 3; this value can result from one URA recording a “1+” while the other enters a “4+” value. The specific URAs designated as “A” and “B” are listed in Table 19.

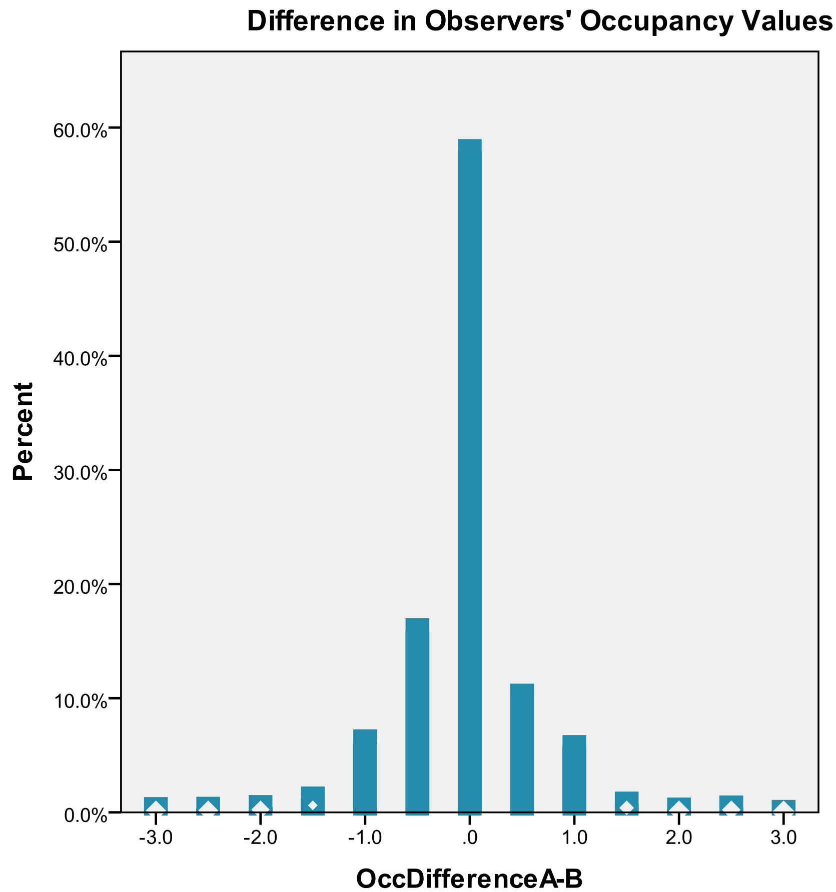


Figure 15: Difference in Observers' Occupancy Values for all Sessions

The average difference is only -0.049, which as mentioned earlier indicates a good match between the occupancy data streams.

Table 21: Descriptives of Occupancy Difference Distribution

		Statistic	Std. Error
Occupancy A-Occupancy B	Mean	-.049	.0074
	Median	.000	
	Std. Deviation	.5806	
	Skewness	-.219	.031
	Kurtosis	5.130	.063

5.3.2 Occupancy of Buses and Vanpools

The other potential bias in the occupancy values is the use of "4+" for school and transit buses. Two additional average occupancy values are calculated, one with all the buses removed and one with the higher bus occupancy included. Using ridership data from the two regional transit agencies, GRTA Xpress buses and Gwinnett County Transit buses, the average bus occupancy is 26 persons for routes that utilize the study corridor. Exact counts for May 2011 for each site were obtained to maximize the accuracy of the average occupancy per bus. A total of 73 buses were observed and had consistent occupancy records. Once the estimated bus occupancy values of "4+" are replaced with the actual occupancy value of 26, the average occupancy for the dataset increases to 2.324 persons per vehicle. Vanpools could also have an effect on the overall occupancy rate, but there are no available data regarding occupancy or frequency of these vehicles.

Buses are expected to make up a larger percentage of vehicles on the HOT lanes than the HOV lanes due to the expanded transit service included in the project funding, so the "4+" values may produce a much lower average occupancy than in reality. If possible, researchers should obtain bus and vanpool ridership information for the HOT lane after the conversion in order to determine changes in occupancy and overall person throughput of the lane. The complete breakdown of occupancy values is shown in Table 22. The 73 transit buses account for approximately half of all "4+" vehicles in the sample.

Table 22: Occupancy Values for Matched Records

		Frequency	Percent	Valid Percent
Valid	1.0	300	4.3	5.2
	1.5	213	3.0	3.7
	2.0	4701	66.9	81.3
	2.5	216	3.1	3.7
	3.0	185	2.6	3.2
	3.5	17	.2	.3
	4.5	148	2.1	2.6
	Total	5780	82.3	100.0
Missing	System	1247	17.7	
Total		7027	100.0	

5.3.3 Comparison to Larger Sample

Two variables—vehicle classification, vehicle model—were compared for the matched records and all HOV records to further assess that the sample is representative. The vehicle classification distributions are nearly identical, with the matched records including slightly more HDVs than the entire data set.

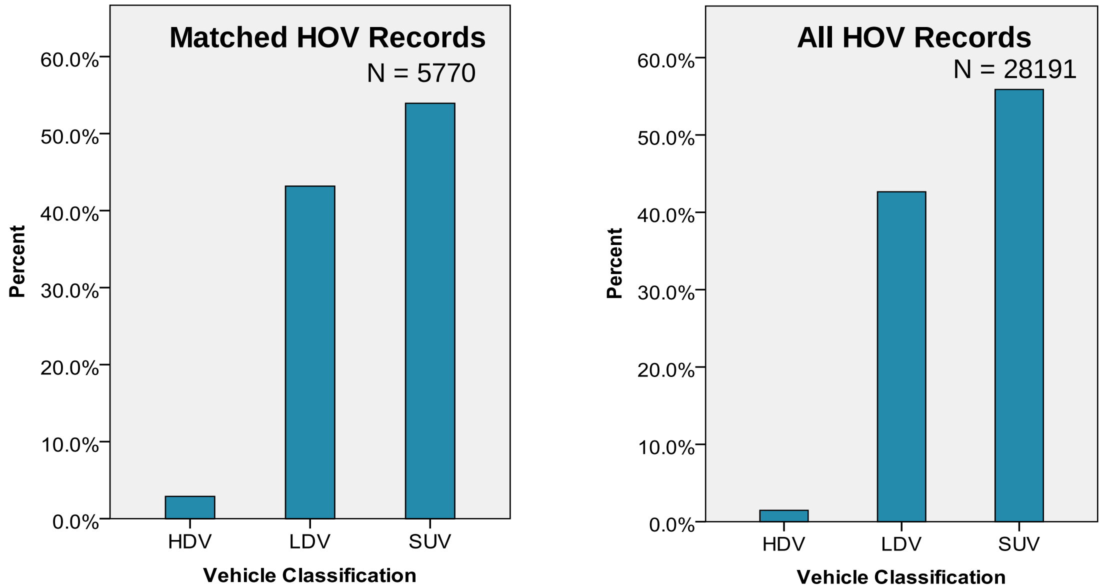


Figure 16: Vehicle Classification Distribution of HOV Matched Records and All HOV Records

The top 25 vehicle models were also compared and the paired records include almost all of the common vehicles found in the entire dataset. The percentages of each vehicle model are out of the records that returned vehicle information from the registration database (so 4.2% of all HOV records with registration information were Honda Accords). Considering the large number of possible vehicle models, the high percentage of the top few models is somewhat surprising. Under the assumption that the license plates returned from the registration database were randomly distributed (i.e. transcription errors or other problems were not biased towards one type of car), approixmatel one in 25 vehicles on the HOV lane is a Honda Accord. Note that an MCIB D4500 is a transit bus used by both regional express bus providers (Gwinnett County Transit and GRTA Xpress buses).

Table 23: Comparison of Top 25 Vehicle Models

Matched Records					All HOV Records			
Make	**Model**	**Count**	**%**		**Make**	**Model**	**Count**	**%**
Honda	Accord	164	3.8		Honda	Accord	947	4.2
Ford	F-150	138	3.2		Toyota	Camry	806	3.6
Toyota	Camry	133	3.1		Ford	F-150	740	3.3
Chevrolet	Silverado	129	3.0		Chevrolet	Silverado	616	2.7
Honda	Civic	96	2.2		Honda	Civic	551	2.5
Honda	Odyssey	85	2.0		Honda	Odyssey	452	2.0
Ford	Econoline	84	1.9		Toyota	Corolla	400	1.8
Ford	F-350	82	1.9		Ford	Explorer	399	1.8
Toyota	Corolla	81	1.9		Ford	F-350	390	1.7
Dodge	Ram	77	1.8		Chevrolet	Express	366	1.6
Nissan	Altima	74	1.7		Ford	Econoline	359	1.6
Ford	Expedition	70	1.6		Toyota	Sienna	348	1.6
Chevrolet	Express	67	1.5		Dodge	Ram	347	1.5
Ford	Explorer	66	1.5		Nissan	Altima	337	1.5
Toyota	Sienna	57	1.3		Ford	Expedition	297	1.3
Chevrolet	Tahoe	55	1.3		Chevrolet	Tahoe	266	1.2
Toyota	4 Runner	54	1.2		Toyota	4 Runner	261	1.2
Toyota	Tacoma	49	1.1		Toyota	Tacoma	249	1.1
Dodge	Grand Caravan	48	1.1		Nissan	Maxima	242	1.1
Chrysler	Town & Country	46	1.1		Dodge	Grand Caravan	219	1.0
Honda	CR-V	45	1.0		Honda	CR-V	218	1.0
Nissan	Maxima	45	1.0		MCIB	D4500	218	1.0
MCIB	D4500	44	1.0		Toyota	Tundra	214	1.0
Ford	Ranger	42	1.0		Chrysler	Town & Country	213	0.9
TOTAL		**1831**	**42.2**		**TOTAL**		**9455**	**42.2**

During processing, any errors in license plate transcriptions were noted as well as details about out-of-state vehicles of those with incorrect data or missing Georgia license plates. In total, 663 vehicles without license plate records were assigned a make and model and 260 vehicles without license plate data were assigned a make only. Vehicles were only assigned a specific model when the researcher was certain, otherwise only a make was assigned. If the video was blurry or the vehicle was blocked, information was not recorded. The goal of noting all the visible makes and models was to compare the distribution of these vehicles with the overall distribution to identify any potential bias (i.e. are most out-of-state vehicles luxury models). Several luxury brands—BMW, Lexus, and Mercedes—appeared in the top five makes, but no luxury models appear in the top 25 models.

Table 24: Makes and Models Assigned in Video Comments

Make	Frequency	Percent
BMW	26	10.0
Chevrolet	24	9.2
Ford	18	6.9
Lexus	17	6.5
Mercedes	17	6.5
Dodge	15	5.8
Hyundai	14	5.4
Jeep	12	4.6
Buick	10	3.8
Infiniti	10	3.8
Kia	8	3.1
Volvo	8	3.1
Acura	7	2.7
Cadillac	7	2.7
Audi	6	2.3

Model	Frequency	Percent
Accord	42	6.3
Odyssey	41	6.2
F-150	36	5.4
Camry	34	5.1
Sienna	29	4.4
Civic	25	3.8
Altima	19	2.9
CR-V	17	2.6
Silverado	17	2.6
D4500	16	2.4
Corolla	14	2.1
Sierra	14	2.1
E-350	12	1.8
Tahoe	10	1.5
Explorer	8	0.8

Pilot	6	2.3
Prius	6	2.3
Malibu	5	1.9
Mercury	5	1.9
Pontiac	5	1.9
Toyota	5	1.9
Chrysler	4	1.5
Scion	4	1.5
Impala	3	1.2
Lincoln	3	1.2
TOTAL	245	94

Focus	8	8
Quest	8	8
Taurus	8	8
Tundra	8	8
HHR	7	7
Sequoia	7	7
Yukon	7	7
Avalon	6	6
Edge	6	6
Fusion	6	6
TOTAL	405	57.1

5.3.4 Profile of HOV Lane Users

The goal of matching occupancy to license plate records was to obtain an accurate profile of users of the HOV lane using vehicle characteristics. The matched records are examined and new information is used (vehicle valuation for specific matched models).

Beyond the matched records themselves, information learned over the completion of processing can also be used to obtain more accurate information about HOV users than the license plate data alone. For instance, the vehicle classification obtained from the body type field in the license plate processing can be compared to the classification note during the second review of the video. The most significant shift was the number of HDVs that were misclassified using information from the registration database and video processing.

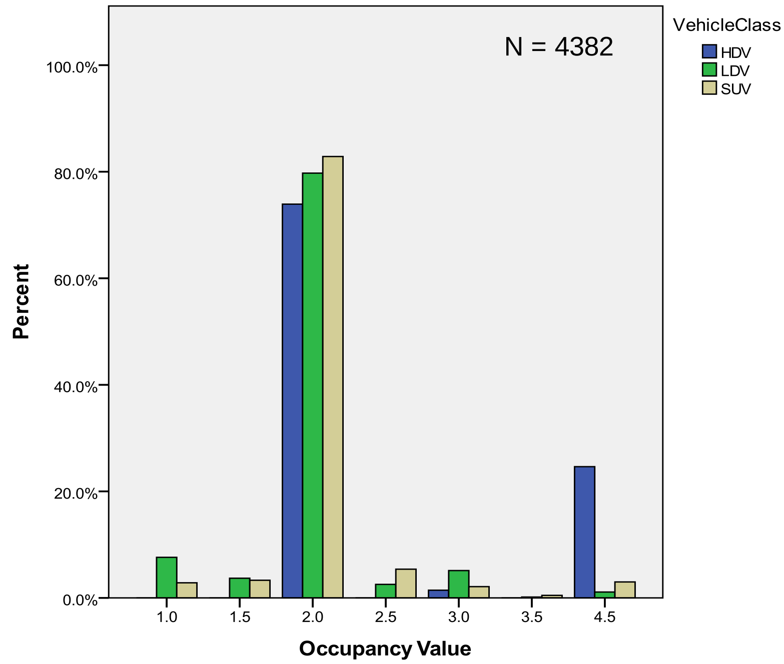


Figure 17: Vehicle Classification from Video Processing and Database

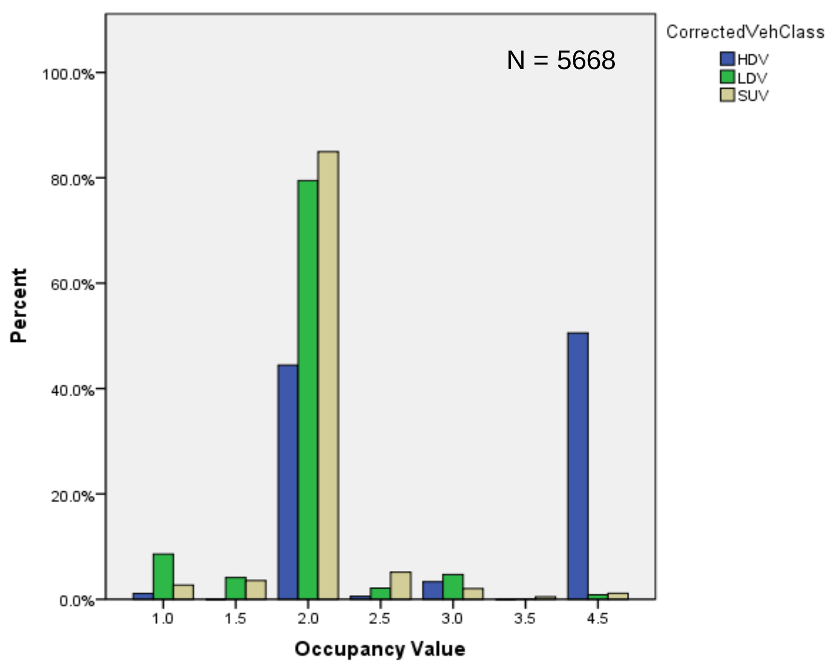


Figure 18: Corrected Vehicle Classification from Matching Process

5.3.4.1 Vehicle Ownership

In the license plate analysis section, vehicle ownership distributions were examined and government and commercial vehicles were found to have a large presence in the HOV lane. The occupancy values of the matched records are shown in Figure 19.

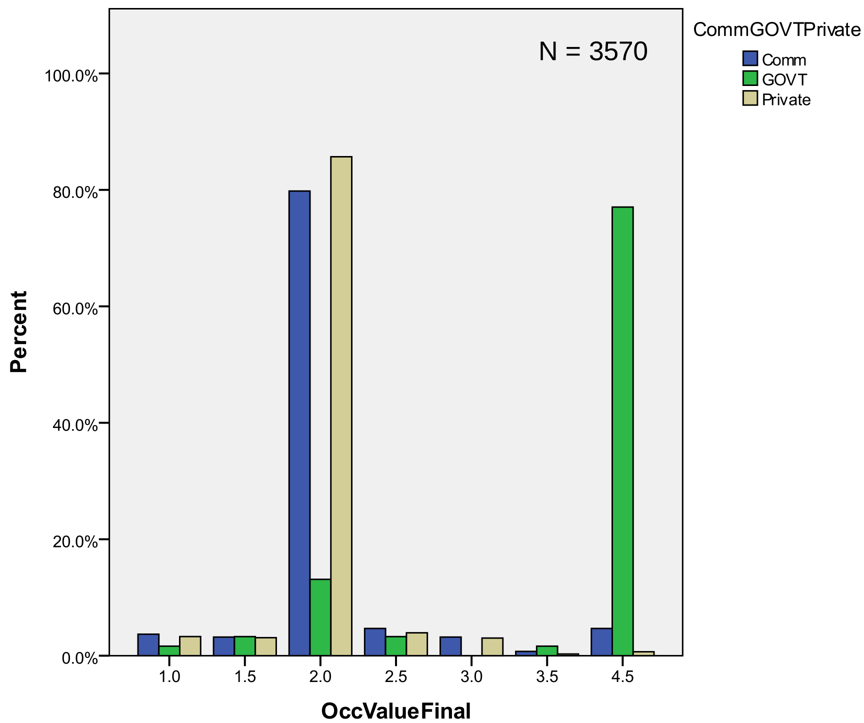


Figure 19: Vehicle Ownership Distribution

At first glance, the overwhelming majority of government vehicles are 4+ occupant vehicles. The reason for the government prevalence in this category is mainly due to transit buses. To better evaluate the distribution, transit buses were then excluded (see Figure 20). Surprisingly, over thirty percent of government vehicles are still in the 4+ category. Only the buses with correct license plate information could be removed from the data, so the remaining 4+ records are most likely still buses that either did not return information from the registration database or did not have the license plate information entered correctly.

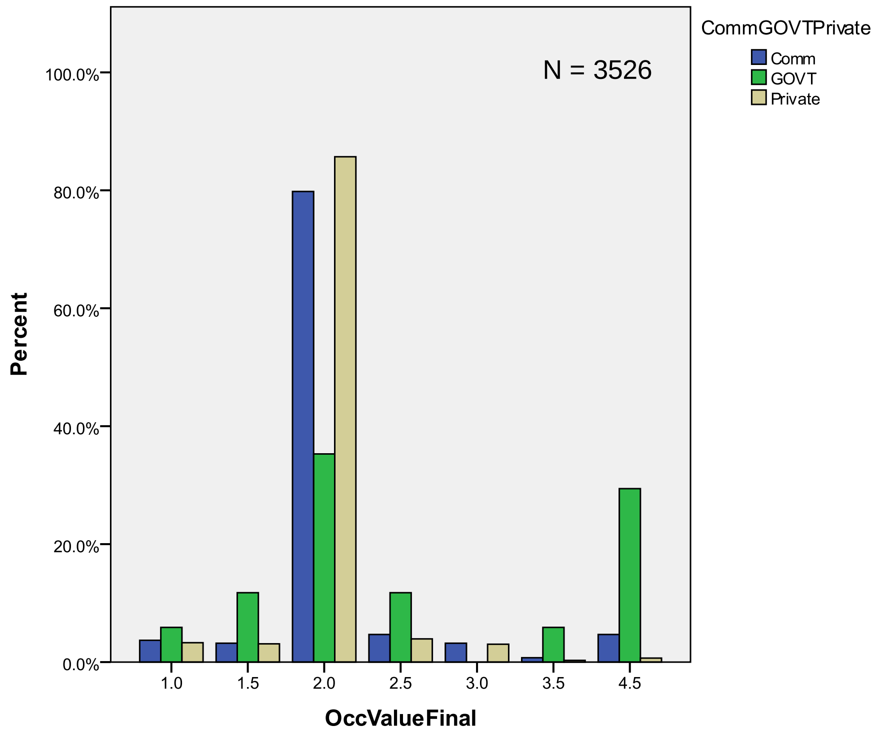


Figure 20: Vehicle Ownership Distribution – Buses Removed

5.3.4.2 Vehicle Values

There are 1612 unique vehicles (categorized using make, model, and year) in the matched records database. Car values were retrieved manually from Kelley Blue Book (www.kbb.com) for all 3564 matched records, with the exception of model years older than 1990. All vehicles older than 1990 were assigned a value of $500 based on the value of the vehicle for salvage, as the depreciation from the initial purchase price eventually approaches the salvage value (see Figure 21). The vehicle value decreases at the fastest rate in the first few years after the initial purchase of a new vehicle, and this conceptual graph is compared to results from Kelly Blue Book (using vehicle value data from the 1991-2011 Toyota Camry).

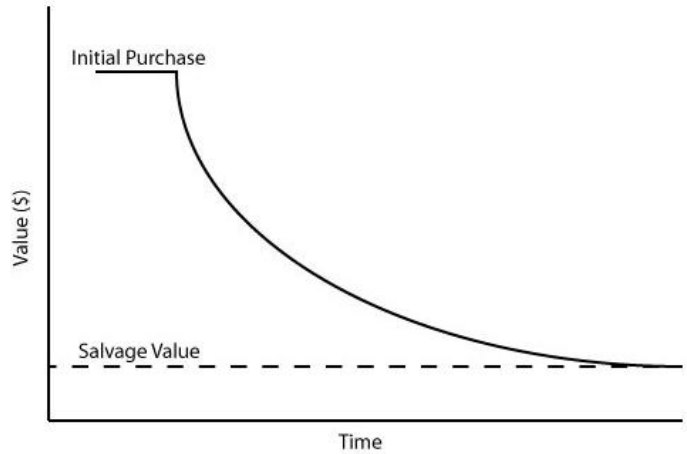


Figure 21: Car Depreciation Conceptual Graph [49]

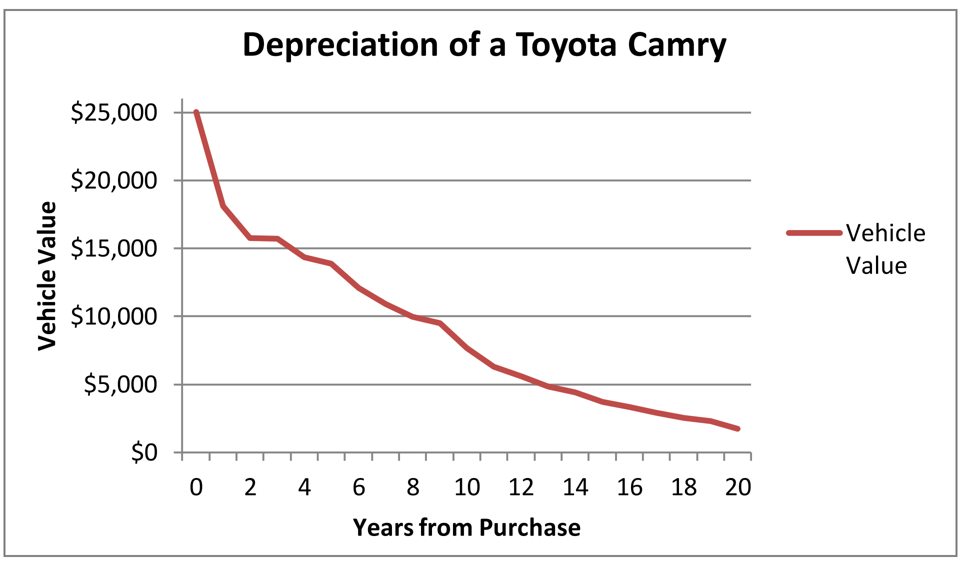


Figure 22: Depreciation Curve Using Kelley Blue Book Data

Trailers, heavy duty vehicles, and transit buses are excluded from the vehicle value analysis due to the difficulty in obtaining these values and their potential impact on biasing the results since they can pulled by any type of vehicle. HDVs and buses are not relevant to this analysis of personal vehicle use in the lane and links to demographic analysis. Transit buses are fairly expensive and including them would be counter-productive as the goal of the analysis is to use vehicle value as an approximate substitute for household income to examine the income equity of the HOV lane. Once these vehicles were removed, 3442 vehicles values were entered into the database. The lowest value was $500 (base salvage) and the most expensive vehicle was valued at $93,100 (Mercedes S550). When the KBB website included a range of prices for a vehicle, the low and high value were recorded and then the average value was calculated for each vehicle. Default or base model values were used for factors such as transmission and luxury level (i.e. LX, DX, etc.) as this information was not available from the vehicle registration database. Figure 23 contains findings of the distribution of vehicle values on the HOV lane. The mean vehicle value is $12, 744 and the median value is $11,005. The values are not normally distributed.

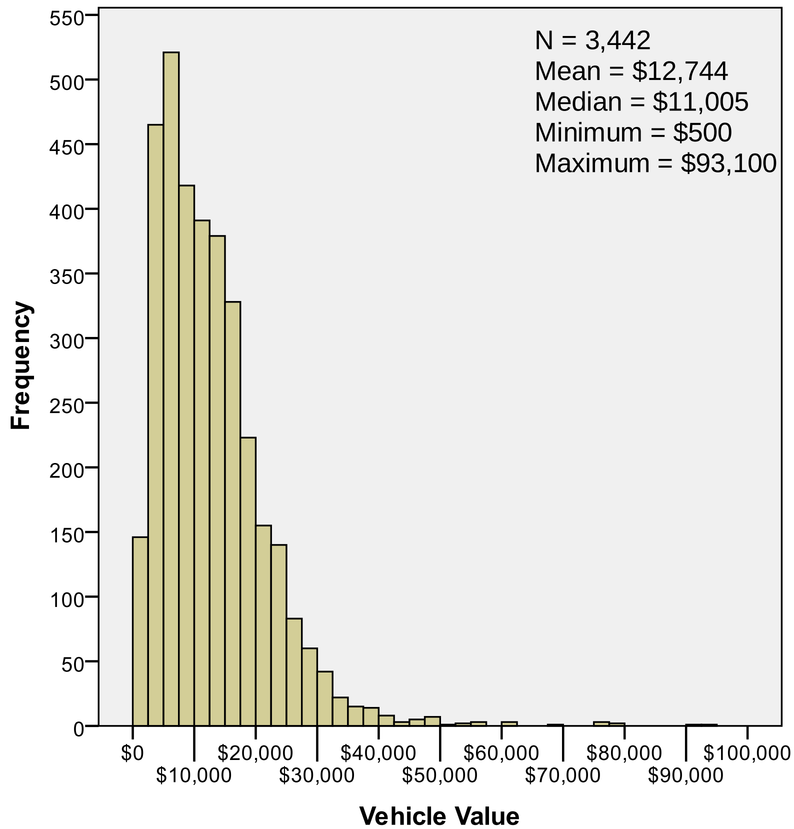


Figure 23: Distribution of Average Vehicle Values

A previous study in Tennessee found a strong positive correlation between vehicle age and average household income (county-level data were used in the study [37]). A San Francisco study also found that the cost of a vehicle is positively correlated with household income [50]. All of the average vehicle values have corresponding occupancy values, so the next step in the analysis was to examine the relationship between occupancy and vehicle value (and by proxy, household income). First, the vehicle values were binned into three categories: low vehicle values (<$5,000), middle vehicle values ($5,001-$20,000), and high vehicle values ($20,000+). The occupancy distributions of each vehicle value category are shown in Figure 24, Figure 25, and Figure 26. The middle vehicle value has the most records at 2,263 while the low income category has the least records with 612. The occupancy distributions for HOV users appear similar and the mean values only differ by 0.02 across the three categories (2.03 for the low category, 2.04 for the middle category, and 2.05 for the high category). Comparing the means does not provide evidence that the two variables are not related, so in order to assess if vehicle value and occupancy are correlated a more robust statistical analysis is required.

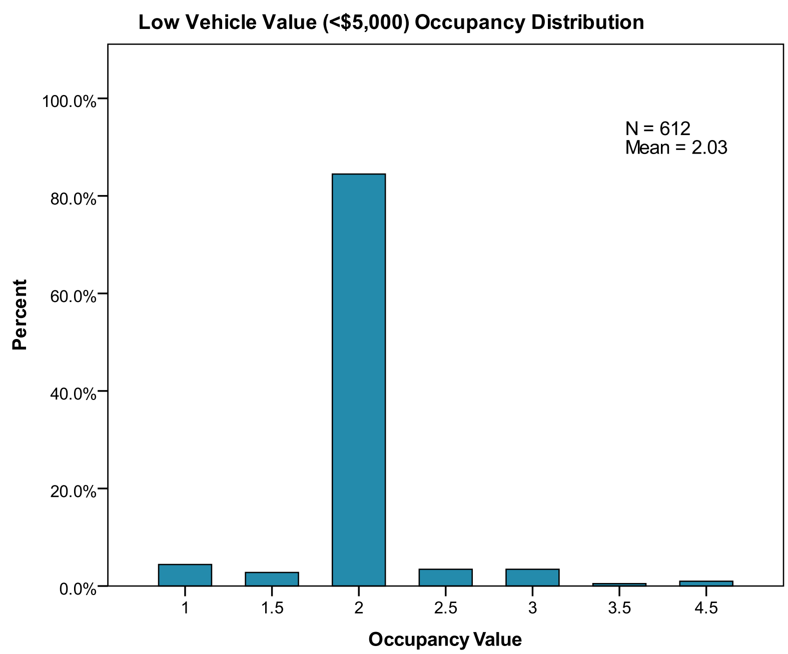


Figure 24: Occupancy Distributions of Low Vehicle Values

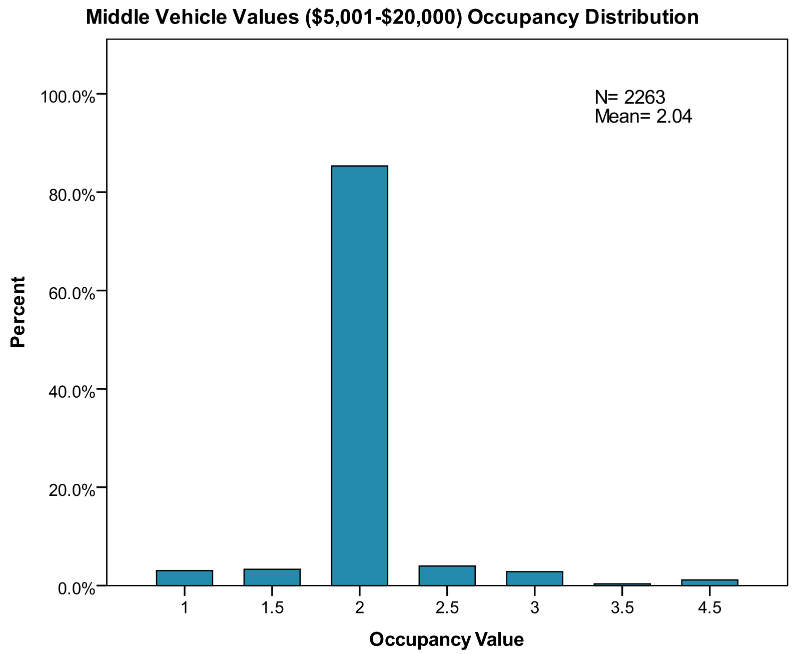


Figure 25: Occupancy Distributions of Middle Vehicle Values

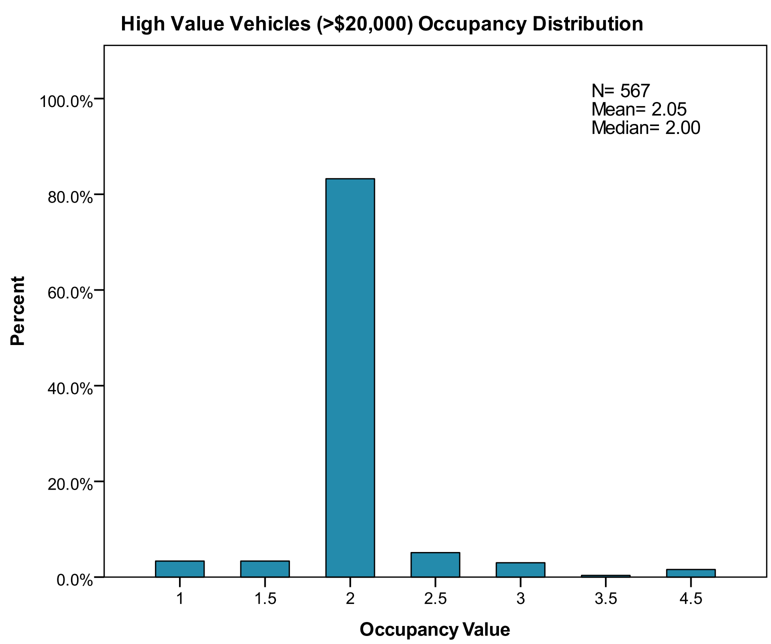


Figure 26: Occupancy Distributions of High Vehicle Values

Because the average vehicle values are not normally distributed, a nonparametric statistical test was employed. The bootstrap test was selected to assess whether the differences in the mean vehicle value for each occupancy category were statistically significant. The bootstrap test is a data-based simulation method for statistical inference that draws sample with replacement over 1000 replications and then calculates the mean of each replication for each variable [51]. Table 25 contains the number of records and mean vehicle values for each occupancy value. There were only 13 occurrences of "3+" occupancy records, so this category was combined with the "4+" category for the bootstrap analysis.

Table 25: Details of Vehicle Values by Occupancy

Occupancy Value	Mean Vehicle Value	Number of Records
1	$11,734.69	115
1+	$12,962.81	111
2	$12,769.67	2,920
2+	$12,889.40	140
3	$12,684.59	102
3+	$12,457.04	13
4+	$12,959.87	41

The original distributions of the vehicle values for each occupancy category are available in Appendix E. None of the original vehicle value graphs have a normal distribution regardless of the number of records. Even after combining the "3+" and "4+" values, there are only 54 of these higher occupancy records. In contrast to this small sample, the "2" group has nearly 3,000 records.

The list of 1000 means from the bootstrap replications is ranked from smallest to largest, and the median value is the average for the original sample. The 95% confidence intervals are the 25th and 975th largest values from the 1000 bootstrap replications [51]. Table 26 shows these values for each occupancy category. All of the median values are very similar and all of the confidence bounds overlap. The median values are not perfectly centered within the confidence bounds, but the values are shifted less than $100 above or below the center point. The confidence intervals are graphed in Figure 27 and Figure 28. Figure 27 shows the confidence bounds in the context of the entire vehicle value range of the data, and Figure 28 zooms in on the intervals so that the reader can see the differences in the size of the intervals by variable. As expected, the confidence interval is the smallest for the "2" occupancy value due to the large number of records. At the 95% confidence level, all confidence intervals overlap hence there is no statistically significant difference between the vehicle values for each occupancy category.

Table 26: Results of Bootstrapping

Occupancy Category	**Median of 1,000 Means**	**25th Ranked Value**	**975th Ranked Value**
1	$11,697	$10,341	$13,247
1.5	$13,003	$11,451	$14,797
2	$12,769	$12,450	$13,079
2.5	$12,933	$11,645	$14,294
3	$12,692	$10,767	$14,830
3.5	$12,333	$8,271	$16,792
4.5	$12,965	$10,983	$14,944
3.5 & 4.5	$12,822	$10,975	$14,822

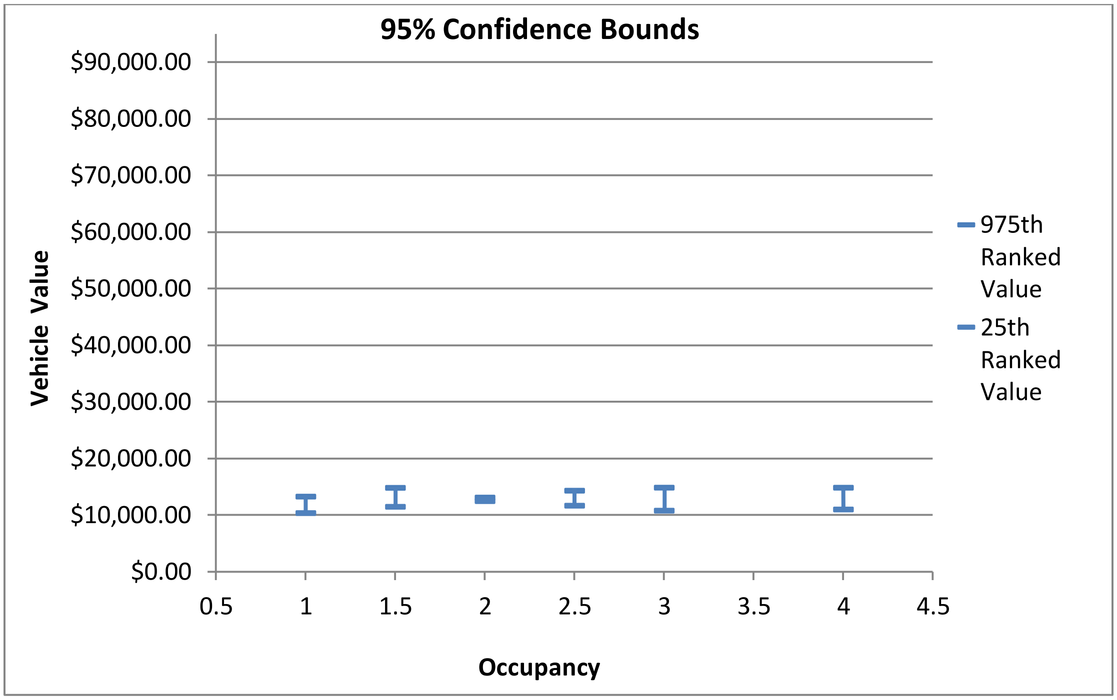


Figure 27: 95% Confidence Bounds for Bootstrap Results

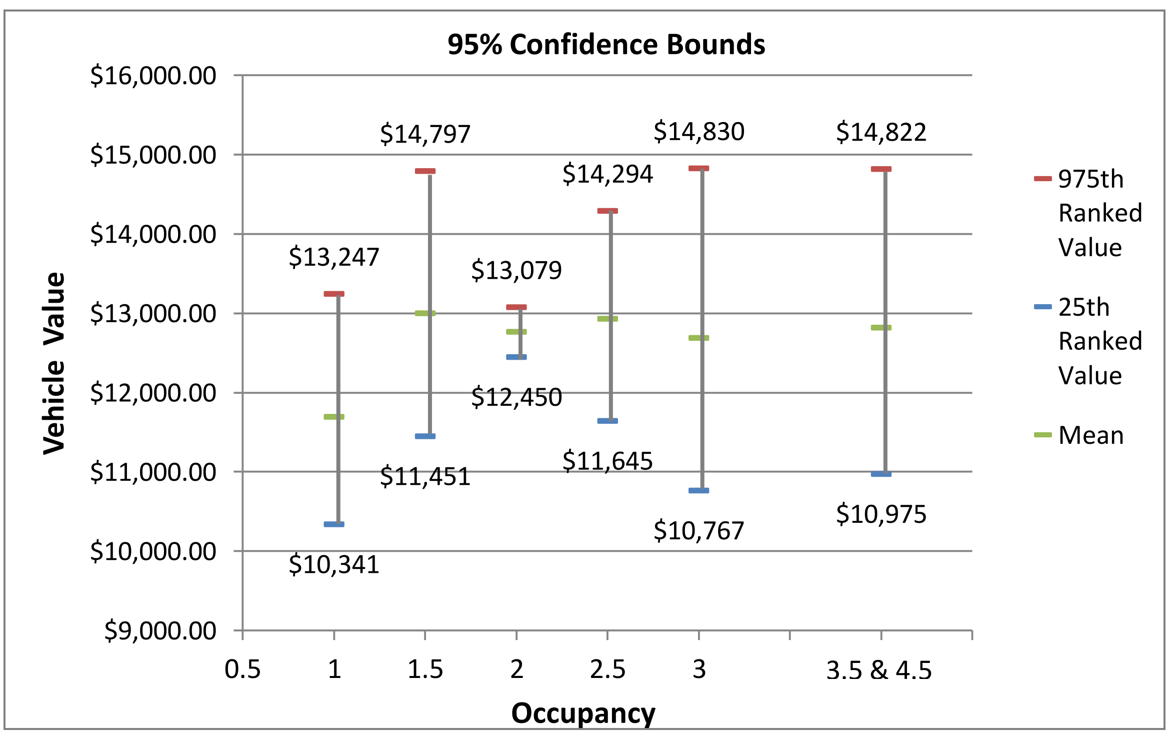


Figure 28: 95% Confidence Bounds from Bootstrap Results (zoomed in)

The final data presented for the profile of HOV lane users are the distribution of vehicle models from the matched occupancy and license plate records. Using only the matched records, a frequency table of the vehicle makes demonstrates that while Lexus, Mercedes, and other luxury make vehicles do utilize the HOV lane they are a very small percentage of the overall users. Based on the numbers in Table 27, the HOV lanes on the I-85 pre-conversion corridor in Atlanta could be coined "Ford lanes" or "Ford and Toyota lanes" and the post-conversion HOT lane analysis will show if this distribution changes to reflect the media's "Lexus lane" claim.

Table 27: Distribution of Vehicle Models on the HOV Lane

Vehicle Make	Frequency	Percent	Cumulative Percent
Ford	592	17.2	17.2
Toyota	519	15.1	32.3
Chevrolet	455	13.2	45.5
Honda	371	10.8	56.3
Nissan	228	6.6	62.9
Dodge	182	5.3	68.2
GMC	111	3.2	71.4
Lexus	99	2.9	74.3
Chrysler	89	2.6	76.9
Mercedes	62	1.8	78.7
Jeep	57	1.7	80.3
Hyundai	56	1.6	82.0
Acura	55	1.6	83.6
BMW	54	1.6	85.1
Mazda	49	1.4	86.5
Kia	48	1.4	87.9
Infiniti	45	1.3	89.3
Pontiac	43	1.2	90.5
Mitsubishi	41	1.2	91.7
Volkswagen	40	1.2	92.9

Buick	31	0.9	93.8
Lincoln	30	0.9	94.6
Volvo	30	0.9	95.5
Cadillac	29	0.8	96.3
Saturn	18	0.5	96.9
Isuzu	16	0.5	97.3
Mercury	16	0.5	97.8
Audi	13	0.4	98.2
Oldsmobile	13	0.4	98.5
Land Rover	11	0.3	98.9
Subaru	9	0.3	99.1
Suzuki	8	0.2	99.4
Jaguar	6	0.2	99.5
Plymouth	6	0.2	99.7
Porsche	4	0.1	99.8
Hummer	2	0.1	99.9
Mini	2	0.1	99.9
Saab	2	0.1	100.0
Total	3442	100.0	

CHAPTER 6: CONCLUSION

The goal of research effort reported in this thesis is to establish a profile of HOV lane users on the HOV-to-HOT conversion corridor on I-85 in metro Atlanta using license plate and vehicle occupancy data. This profile can then be compared to a profile of HOT lane users after the lane conversion in fall 2011. Establishing a profile of the vehicles pre-conversion can help answer questions regarding the equity of the HOT lane. In order to establish the profile, a new methodology was developed to match license plate records to occupancy records. A thorough analysis of each type of data as well as the matched data provides valuable information about the current users of the carpool lane.

One aspect of this study examines the differences and similarities in vehicle characteristics of the HOV lane and the adjacent general purpose lane in I-85. Specific variables were selected for analysis, and the end result is a profile for each lane that can be used in a future comparison with the post-conversion corridor. Government and commercial vehicle were surprisingly prevalent in the HOV lane, while hybrid and alternative fuel vehicles were much less common in either lane than expected. The distribution of the registration address of the commercial vehicles contained more occurrences of addresses outside the corridor area than the distribution of all observed vehicles, indicating that the commercial vehicles may not be garaged at the registration address (as expected from the earlier study by Granell [35]). The percentage of out-of-state vehicles was higher than anticipated in the HOV lane, and this information is helpful in regard to the upcoming HOT lane administration. Many of the out-of-state vehicles most likely reside within Georgia (such as college students) and could be repeat observations of the same vehicle. Information about the lane conversion could be made available on neighboring state's information or media websites. Other characteristics such as the body types of sedans were found to be no different in the carpool lane than the adjacent general purpose lane. These characteristics alone cannot predict carpooling behavior directly, but the fleet composition information may help policy makers target potential carpoolers in the future. The information also indicates levels of participation in programs such as the AFV-exempt group, especially if policy makers consider expanding the exemption to hybrid vehicles.

Vehicle occupancy data from the first four quarters of data collection were used to create the distribution of occupancy on the HOV and general purpose lanes. Analysis of the data revealed the significant bias of three individual data collectors, but after the removal of these data there were no significant differences in the distribution on different days of the week, different sites, and different sessions of data collection (spring vs. summer, etc.).

Finally, the matched occupancy and license plate data were examined. A sensitivity analysis of the occupancy data established that the current use of uncertain values is acceptable and that bus and vanpool occupancy should be considered when determining the average occupancy of all vehicles on the HOV lane. Vehicle values were obtained for the matched records based upon make, model, and year, and the median vehicle value of HOV lane users was just over $11,000. Using a bootstrap analysis, vehicle values were compared to vehicle occupancy values and the results found that there is statistically significant difference in vehicle value across vehicle occupancy categories. Further research could expand this analysis to the pre-conversion general purpose lanes and the post-conversion HOT lanes. The final note about the profile of HOV lane users on the Atlanta I-85 corridor is that luxury makes and models comprise only a small percentage of overall lane users.

Future research will include using the vehicle characteristics for emissions modeling, creating targeted travel surveys to learn more about trip purposes and origins/destinations, and a comparison with the vehicle characteristics and profile post-HOT conversion. The post-conversion HOT profile is expected to reflect an increase in commercial vehicles due to the increased number of private vanpools and the time savings offered to company vehicles. Another expectation is a decrease in out-of-state vehicles, since registration is required to access the Express lane (i.e. less tourists or business travelers in the lane). Finally, the average vehicle value is expected to increase as people with a high value of time choose to pay a toll to access the lane as single-occupant vehicles.

APPENDIX A: HOV LANE NOTES WORKSHEET

Additional HOV Lane Data Collection

Record the description of the first vehicle in the occupancy data collection and the last vehicle for the session. If there are gaps or lulls in traffic, please make notes about additional vehicles.

Site: ______________________________ Date: ____________________ AM/PM (circle one)

Notes: ____

Time	Classification	Occupancy	Description
7:00am	*LDV*	*1+*	*Blue PT Cruiser*

APPENDIX B: I-85 OCCUPANCY MATCHED RECORDS DEPLOYMENT TRAINING

B.1 Background

This specific deployment will be in conjunction with the larger HOV to HOT data collection, but will have the specific goal of matching the vehicle occupancy with vehicle license plates on the HOV lane. The recent GA 400 field deployment tested the standard occupancy methods and found them to be accurate, with over 95% of passing vehicles recorded by occupancy observers. The GA 400 field deployment also developed estimates for the uncertain "+" values that can be applied to the HOV lane data.

In this deployment, the Georgia Tech team will collect data via the standard manual roadside observation method, with an additional camera placed at the occupancy collection site to aid in matching vehicles with the overpass camera. The HOV occupancy observer will be in addition to the standard occupancy team (i.e. two observers will collect occupancy for the HOV lane). The team will use the data to match vehicle occupancy values with vehicle license plates of the HOV lane.

B.2 Vehicle Classifications

The GA 400 deployment data analysis showed some confusion regarding certain vehicle classifications. Pick-up trucks and passenger vans are SUVs, not HDVs. Crossover vehicles such as a Nissan Murano or Honda Element are SUVs, while station wagons (including PT Cruisers) are LDVs. Data collectors will receive additional training to address any possible inconsistencies in classification. For this deployment, every vehicle's occupancy data should be recorded or indicated as a "MISS".

Figure 29: Nissan Murano

Figure 30: Honda Element

B.3 Start/Stop Records

The HOV occupancy collector has a clipboard to record the characteristics of the first recorded HOV occupancy (i.e. red hatchback) to aid in the matching process, along with the last vehicle. If there are any large gaps in traffic, additional vehicles and time stamps can be recorded (i.e. 5:05pm, blue minivan).

B.4 Video Camera View

Before the camera is set-up, the clock should be set to match the netbook's clock. This should be done in the field to maximize the time synching between the camera and netbook. The camera should capture the same approximate view as the HOV lane occupancy recorder. The tripod should be set back a safe distance from the roadway but with an unobstructed view (i.e. no data collector heads in the way). The camera and tripod are secured to a metal stake using one of the metal cables (same as those used for the cameras on the bridge) and a cable tie. The camera can be placed at an angle (see Figure 2) away from observers but should not be close to the roadway (the freeway or the exit ramp).

Figure 31: View of Occupancy Observers from Gore Area

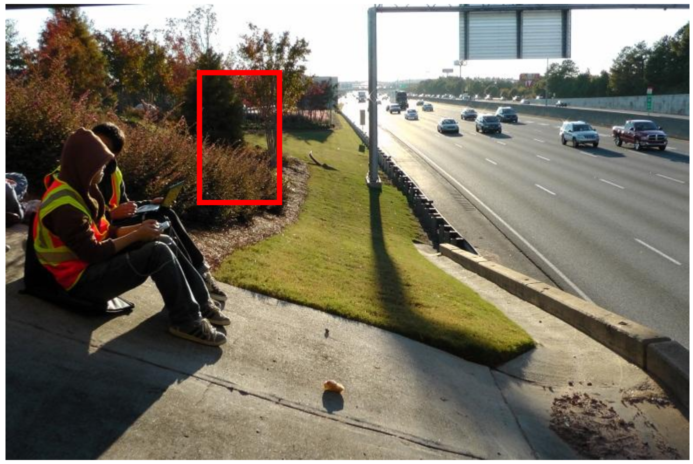


Figure 32: Potential Camera Placement in Gore Area

APPENDIX C: VEHICLE MODEL RECODES

Current	Recode	Frequency
3	MAZDA3	6
5	MAZDA5	25
6	MAZDA6	3
150	F-150	1
1500	SILVERADO	8
1500 PICKUP	SILVERADO	1
1K15S1	RABBIT	1
1N6AA06A64N	TITAN	4
1ZT69	MALIBU	1
200SX SE-R	200SX /SE	1
240 240/240DL	240	6
240SX SE	240SX	1
240SX SX/SE	240SX	5
3 MAZDA3HATCH	MAZDA3	43
3 MAZDA3I	MAZDA3	155
3 MAZDA3S	MAZDA3	54
3.5 RL	3.5RL	1
3.5RL SE	3.5RL	1
300 DT	300 D	3
300 E 2.6	300 E	1
300 LX	300	1
300 SERIES	300	2
3000 SERIES 380	3000 SERIES	2
300C HEMI LXCS	300M	1
300ZX 2 PLUS 2	300ZX	4
318I (U.S.)	318I	1
318I AUTOMATIC	318I	2
318IS AUTOMATI	318IS	1
323CIC	323CI	1
323I AUTOMATIC	323I	3
323IS AUTOMATI	323I	1
325I AUTOMATIC	325I	9
325I/325IS	325IS	10
325I/325IS AUT	325IS	2
325IS SULEV	325IS	1
328I AUTOMATIC	328I	17
328I SULEV	328I	8
328IC AUTOMATI	328IC	1
328IS AUTOMATI	328IS	1
328XI SULEV	328XI	2
335I SEDAN	335I	1
335I SULEV	335I	1
3500 W35042	3500	7
350Z ZCOUPE	350Z	23
350Z ZROADSTER	350Z	16
3572L2	PASSAT	1
3B3455	PASSAT	1
4000 W4S042	4000 SERIES	1
4300 SBA 4X2	4000 SERIES 43	1
4500 W45042	4000 SERIES	1
525I AUTOMATIC	525I	30
525IT AUTOMATI	525IT	5
528I AUTOMATIC	528I	37
528IT AUTOMATC	528I	1
530I AUTOMATIC	530I	34
535I SEDAN	535I	3
540I AUTOMATIC	540I	10
540IT AUTOMATI	540IT	1
540IT AUTOMATIC	540IT	1
545I AUTOMATIC	545I	9
5D2.4DOHC	CR-V	1
5N1AA08A14N	ARMADA	1
5N3ZA0ND2AN	QX56	1
6 MAZDA6I	MAZDA6	104
6 MAZDA6S	MAZDA6	33
6 SPEED	MAZDA6	1
6220C	COROLLA	1
626 DX/LX	626	1
626 LX	626	1
626 U.S. DX/LX	626	33
626 U.S. ES	626	1
626 U.S. ES/LX	626	21
626 U.S. LX	626	9

633CSI AUTOMAT	633CSI	1
645CI AUTOMATI	645CI	11
6DP69	CTS	1
6EB26	SRX	1
740 GLE	740	1
740/740 GL	740	1
740I IAUTOMATI	740I	8
740I IAUTOMATIC	740I	1
740I IL	740I	37
740I ILAUTOMAT	740I	2
740IL	740I	1
740LI	740I	1
745LI	745I	37
750IL	750I	4
750LI	750I	42
850 850/GLT	850 GLT	12
850 R	850	1
850/GLT	850 GLT	1
88 /LS	88	2
88 50TH ANNIVER	88	1
88 ROYALE LS	88 ROYALE	3
88 ROYALE LS/LS	88 ROYALE	1
8PA52X	A3	1
9/5 2.3T	9/5 AERO	1
9/5 LINEAR	9/5	5
9/5 SE	9/5	4
900 S	900	8
900 SE TURBO	900	6
9000 /S	9000	4
9000 CSE TURBO	9000	1
911 CARRERA S	911 CARRERA	5
911 CARRERA/4/	911 CARRERA	2
911 CARRERA2/4	911 CARRERA	4
911 NEW CARRER	911 CARRERA	1
911 NEW GEN CA	911 CARRERA	1
911 TURBO	911 CARRERA	1
93 BASE	93	1
93 S	93	4
93 SE	93	6

98 REGENCY BRO	98 REGENCY	7
98 REGENCY ELI	98 REGENCY	1
9M24H3	JETTA	1
9PAAE1	CAYENNE	1
A3 2.0 PREMIUM	A3 2.0	3
A4 1.8 CABRIOL	A4	5
A4 1.8T	A4	26
A4 1.8T AVA QU	A4	1
A4 1.8T AVANT	A4	6
A4 1.8T QUAT/S	A4	7
A4 1.8T QUATTR	A4	6
A4 1.8T/SPECIA	A4	3
A4 2	A4	1
A4 2.0	A4	3
A4 2.0T	A4	20
A4 2.0T AVANT	A4	6
A4 2.0T CABRIO	A4	7
A4 2.0T PREMIU	A4	13
A4 2.0T QUA PR	A4	15
A4 2.0T QUATTR	A4	22
A4 2.8 QUATTRO	A4	2
A4 3.0	A4	1
A4 3.0 AVANT Q	A4	1
A4 3.0 QUATT/S	A4	1
A4 3.0 QUATTRO	A4	9
A4 3.2 QUATTRO	A4	1
A4 SERIES	A4	1
A4 S-LINE 2.0T	A4	2
A5 QUATTRO	A5	3
A5 QUATTRO PRE	A5	1
A52.OT	A5	1
A6 2.7TQUATTRO	A6	3
A6 2.8QUATTRO	A6	1
A6 3.0	A6	1
A6 3.0 AVANT Q	A6	5
A6 3.0 QUATTRO	A6	10
A6 3.2	A6	2
A6 3.2 QUATTRO	A6	16
A6 3.2Q	A6	2

A6 4.2QUATTRO	A6	1
A6 AVANT QUA A	A6	1
A6 QUATTRO	A6	1
A6 QUATTRO2.8	A6	1
A6 S-LINE 3.2	A6	2
A6 S-LINE QUAT	A6	1
A8 4.2 QUATTRO	A8	1
A8 L QUATTRO	A8	2
A8 L QUATTRO A	A8	4
A8 QUATTRO	A8	3
ACADIA ACADIA	ACADIA	66
ACCENT BLUE/GS	ACCENT	1
ACCENT GL	ACCENT	16
ACCENT GLS	ACCENT	25
ACCENT GS	ACCENT	8
ACCENT GS/GL	ACCENT	1
ACCENT GT	ACCENT	2
ACCENT GT/GLS/	ACCENT	3
ACCENT L	ACCENT	2
ACCORD EX	ACCORD	3
ACCORD 4S	ACCORD	7
ACCORD CROSSTO	CROSSTOUR	30
ACCORD DX	ACCORD	6
ACCORD DX/LX	ACCORD	1
ACCORD EX	ACCORD	118
ACCORD EX V6	ACCORD	1
ACCORD EX VL	ACCORD	2
ACCORD EX/EX-R	ACCORD	4
ACCORD EX/SE	ACCORD	3
ACCORD EX-L	ACCORD	295
ACCORD LX	ACCORD	90
ACCORD LX/EX	ACCORD	6
ACCORD LXI	ACCORD	1
ACCORD LX-P	ACCORD	86
ACCORD LX-S	ACCORD	2
ACCORD SDN	ACCORD	3
ACCORD SE	ACCORD	111
ACCORD SED	ACCORD	3
ACCORD U.S. 10	ACCORD	1

ACCORD U.S. 10T	ACCORD	1
ACCORD U.S. DX	ACCORD	29
ACCORD U.S. EX	ACCORD	1366
ACCORD U.S. EX/	ACCORD	23
ACCORD U.S. LX	ACCORD	788
ACCORD U.S. LX/	ACCORD	39
ACCORD U.S. SE	ACCORD	147
ACCORD U.S. VA	ACCORD	40
ACCORD U.S. VAL	ACCORD	1
ACCORD VALUEPA	ACCORD	1
ACCORD4DREX	ACCORD	1
ACCORD4DREX-L	ACCORD	1
AERIO PREMIUM	AERIO	3
AERIO S/LX	AERIO	5
AERIO SX	AERIO	3
AEROSTAR AEROS	AEROSTAR	8
ALERO GL	ALERO	20
ALERO GLS	ALERO	3
ALERO GX	ALERO	3
ALLROAD 2.7	ALLROAD	1
ALTIMA 2.5	ALTIMA	3
ALTIMA 2.5 SED	ALTIMA	5
ALTIMA 2.5/2.5	ALTIMA	337
ALTIMA 2.5S	ALTIMA	47
ALTIMA 3.5SE	ALTIMA	12
ALTIMA 3.5SE/3	ALTIMA	24
ALTIMA BASE SL	ALTIMA	1
ALTIMA BASE/S/	ALTIMA	160
ALTIMA GXE	ALTIMA	2
ALTIMA GXE/GLE	ALTIMA	122
ALTIMA GXE/GLE/	ALTIMA	33
ALTIMA S/SL	ALTIMA	225
ALTIMA SE	ALTIMA	23
ALTIMA SE/SL	ALTIMA	5
ALTIMA SE/SL/S	ALTIMA	43
ALTIMA XE/GXE/	ALTIMA	27
ASTRO VAN	ASTRO	95
ASTRO VAN ASTR	ASTRO	78
AURA XE	AURA	7

AURA XR	AURA	5
AURORA 4.0	AURORA	3
AVALANCHE AVAL	AVALANCHE	17
AVALANCHE_____	AVALANCHE	2
AVALON U.S. XL	AVALON	252
AVALON U.S. XL/	AVALON	18
AVALON U.S. XLS	AVALON	1
AVALON UBASE/L	AVALON	5
AVALON XL	AVALON	5
AVALON XL XLS	AVALON	1
AVALON XL/XLS/	AVALON	55
AVALON XLS	AVALON	4
AVENGER	AVENGER	4
AVENGER ES	AVENGER	9
AVENGER R/T	AVENGER	7
AVENGER SE	AVENGER	18
AVENGER SXT	AVENGER	18
AVEO BASE/LS	AVEO	18
AVEO LS	AVEO	9
AVEO LS/LT	AVEO	12
AVEO LT	AVEO	2
AZERA GLS	AZERA	1
AZERA LIMITED/	AZERA	14
B2200 B2200 SH	B2200	2
B2300	B2300	1
B2300 B2300 CA	B2300	2
B2300 B2300 RE	B2300	5
B2300 B2300 REG	B2300	2
B2500 B2500 CA	B2500	1
B2600 CAB PLUS	B2600	1
B3000 B3000 CA	B3000	4
B3000 B3000 CAB	B3000	2
B3000 CA	B3000	1
B4000 B4000 CA	B4000	4
B4000 B4000 CAB	B4000	6
BN716TA	TITAN	1
BONNEVILLE LE	BONNEVILLE	4
BONNEVILLE SE	BONNEVILLE	18
BONNEVILLE SLE	BONNEVILLE	3

BONNEVILLE SSE	BONNEVILLE	6
BOXSTER S	BOXSTER	7
BREEZE /EXPREE	BREEZE	3
BRONCO BRONCO	BRONCO	6
C10 C10	C10	2
C15 SUBURBAN	SUBURBAN	3
C1500 C1500 (P	C 1500	2
C1500 SUBURBAN	SUBURBAN	13
C230 C230KSPOR	C230	20
C230 GEN 2006	C230	37
C230WZ	C230	2
C2500 SUBURBAN	SUBURBAN	1
C280 4MATIC AW	C280	1
C280 GEN 2006	C280	2
C280W	C280	1
C300 4MATIC AW	C300	1
C300W	C300	2
C320 4M AWD	C320	1
C350W	C350	4
C4500 C4C042	C4500	2
C4500 C4E042	C4500	3
C5500 C5C042	C5500	6
C5500 C5E042	C5500	2
C6000 (C6D) C6D	C6000	1
C70 HPT	C70	8
C70 LPT	C70	12
C70 TURBO	C70 T5	8
CALIBER R/T FW	CALIBER	4
CALIBER SXT	CALIBER	48
CAMARO /CAMRS	CAMARO	6
CAMARO LS	CAMARO	14
CAMARO LT	CAMARO	22
CAMARO RS	CAMARO	4
CAMARO SS	CAMARO	5
CAMARO Z28	CAMARO	14
CAMERO	CAMARO	1
CAMRY BASE/SE/	CAMRY	460
CAMRY CE	CAMRY	14
CAMRY CE/LE/XL	CAMRY	94

CAMRY DLX	CAMRY	4
CAMRY DX/LE/XL	CAMRY	3
CAMRY DX/LE/XLE	CAMRY	6
CAMRY LE	CAMRY	39
CAMRY LE/XLE	CAMRY	99
CAMRY LE/XLE/S	CAMRY	100
CAMRY NEW GEN	CAMRY	308
CAMRY SE	CAMRY	1
CAMRY SOLARA	SOLARA	10
CAMRY SOLARA S	SOLARA	5
CAMRY SOLARA U	SOLARA	162
CAMRY SOLARA U.	SOLARA	10
CAMRY U.S. CAMR	CAMRY	3
CAMRY U.S. CE	CAMRY	2
CAMRY U.S. CE/	CAMRY	265
CAMRY U.S. CE/L	CAMRY	84
CAMRY U.S. DLX	CAMRY	2
CAMRY U.S. DX/	CAMRY	13
CAMRY U.S. DX/L	CAMRY	13
CAMRY U.S. LE	CAMRY	95
CAMRY U.S. LE/	CAMRY	705
CAMRY U.S. LE/X	CAMRY	11
CAMRY U.S. SE	CAMRY	7
CAMRY U.S. XLE	CAMRY	6
CAMRY U.S./DX	CAMRY	6
CAMRY XLE	CAMRY	5
CANYON CANYON	CANYON	32
CAPRICE CL	CAPRICE	1
CAPRICE CLASSI	CAPRICE	14
CAPRICE CLASSIC	CAPRICE	2
CARAVAN	GRAND CARAVAN	426
CARAVAN GRAND	GRAND CARAVAN	3
CARAVAN(CANAD A	GRAND CARAVAN	3
CAVALIER CAVAL	CAVALIER	50
CAVALIER CAVALI	CAVALIER	7
CAVALIER LS	CAVALIER	23
CAVALIER LSSPO	CAVALIER	13
CAVALIER RS/VL	CAVALIER	2

CAVALIER Z24	CAVALIER	3
CAYENNE ENNE S	CAYENNE	2
CAYMAN CAYMAN	CAYMAN	4
CC LUXURY	CC	5
CC SPORT	CC	5
CELICA GT (FWD	CELICA	49
CELICA GT/GT-S	CELICA	2
CELICA GTS	CELICA	1
CELICA GTS (FW	CELICA	12
CELICA ST (FWD	CELICA	6
CENTURY CUSTOM	CENTURY	79
CENTURY LIMITE	CENTURY	2
CENTURY LIMITED	CENTURY	2
CENTURY SPECIA	CENTURY	9
CENTURY SPECIAL	CENTURY	1
CG11405	EXPRESS CARGO	2
CG13405	EXPRESS CARGO	5
CG21405	EXPRESS CARGO	1
CG23405	EXPRESS CARGO	5
CHALLENGER R/T	CHALLENGER	5
CHALLENGER SE	CHALLENGER	6
CHALLENGER SRT	CHALLENGER	7
CHARGER R/T	CHARGER	32
CHARGER RALLYE	CHARGER	1
CHARGER SE/SXT	CHARGER	46
CHARGER SRT-8	CHARGER	4
CHARGER SXT	CHARGER	23
CHEROKEE CHERO	CHEROKEE	27
CHEROKEE CLASS	CHEROKEE	1
CHEROKEE COUNT	CHEROKEE	3
CHEROKEE COUNTR	CHEROKEE	4
CHEROKEE LARED	CHEROKEE	2
CHEROKEE LIMIT	CHEROKEE	1
CHEROKEE LIMITE	CHEROKEE	6
CHEROKEE PIONE	CHEROKEE	3
CHEROKEE SE	CHEROKEE	6
CHEROKEE SPORT	CHEROKEE	43

CHEROKEE SPORT/	CHEROKEE	21
CHEV010	EXPRESS CARGO	2
CHRYSLER 300	300	30
CHRYSLER 300 3	300	19
CHRYSLER 300 C	300	2
CHRYSLER 300 L	300	27
CHRYSLER 300 T	300	74
CHRYSLER 300M	300	21
CIRRUS LX/LXI	CIRRUS	1
CIRRUS LXI	CIRRUS	1
CIVC	CIVIC	8
CIVIC EX	CIVIC	2
CIVIC (CANADA)	CIVIC	5
CIVIC CIV	CIVIC	2
CIVIC DEL SOL	DEL SOL	5
CIVIC DEL SOL S	DEL SOL	1
CIVIC DX	CIVIC	6
CIVIC EX	CIVIC	34
CIVIC EX/EX-V	CIVIC	7
CIVIC EX-L	CIVIC	49
CIVIC EXS	CIVIC	1
CIVIC GX	CIVIC	1
CIVIC LX	CIVIC	67
CIVIC SI	CIVIC	36
CIVIC U.S. CIV	CIVIC	18
CIVIC U.S. CIVI	CIVIC	8
CIVIC U.S. CX	CIVIC	3
CIVIC U.S. DX	CIVIC	107
CIVIC U.S. EX	CIVIC	525
CIVIC U.S. GX	CIVIC	9
CIVIC U.S. HX	CIVIC	24
CIVIC U.S. LX	CIVIC	717
CIVIC U.S. LX-	CIVIC	22
CIVIC U.S. SI	CIVIC	24
CIVIC U.S. SI/	CIVIC	43
CIVIC U.S. SI/E	CIVIC	9
CIVIC U.S. SI/S	CIVIC	3
CIVIC VP	CIVIC	1

CK15543	SILVERADO	1
CLK320 CLK320C	CLK320	7
CLK350A	CLK350	1
CLK430A	CLK430	1
COBALT COBALT	COBALT	121
COLORADO COLOR	COLORADO	131
COMMANDER BASE	COMMANDER	35
COMMANDER LIMI	COMMANDER	45
COMPASS LIMITE	COMPASS	5
COMPASS SPORT	COMPASS	9
CONCORDE LIMIT	CONCORDE	4
CONCORDE LX	CONCORDE	13
CONCORDE LX/LX	CONCORDE	2
CONCORDE LXI	CONCORDE	12
CONTOUR /GL/SP	CONTOUR	3
CONTOUR LX/SPO	CONTOUR	8
CONTOUR LX/SPOR	CONTOUR	3
CONTOUR SE	CONTOUR	7
CONTOUR SE/COM	CONTOUR	4
CONV R10	R10	1
COOPER COOPER	COOPER	1
COOPER S	COOPER	12
COPPER S	COOPER	1
COROLLA (U.S.)	COROLLA	676
COROLLA /DX	COROLLA	2
COROLLA BASE/L	COROLLA	36
COROLLA BASE/S	COROLLA	277
COROLLA CE/LE	COROLLA	68
COROLLA DLX (F	COROLLA	14
COROLLA DLX (FW	COROLLA	1
COROLLA DLX 4X	COROLLA	1
COROLLA DX	COROLLA	4
COROLLA LE	COROLLA	1
COROLLA LE (FW	COROLLA	1
COROLLA LE/DX	COROLLA	5
COROLLA MATRIX	MATRIX	153
COROLLA S	COROLLA	1
COROLLA U.S.	COROLLA	1

CORSICA LT	CORSICA	1
CORVETTE GRAND	CORVETTE	1
CORVETTE Z06	CORVETTE	1
COUGAR I4	COUGAR	1
COUGAR V6	COUGAR	3
COUGAR V6/SPOR	COUGAR	1
COUGAR XR7	COUGAR	11
COUGAR XR7/30	COUGAR	5
CR V	CR-V	1
CRESSIDA LUXUR	CRESSIDA	1
CROSSFIRE LTD	CROSSFIRE	7
CROWN VIC	CROWN VICTORIA	1
CRV	CR-V	3
CR-V 2WDEX-L	CR-V	1
CRV EX	CR-V	2
CRV EXL	CR-V	1
CR-V5DR2WDLX	CR-V	1
CS10516	BLAZER	1
CTS CTS HI FEA	CTS	44
CTS CTS-V	CTS	6
CTS HI FEATURE	CTS	1
CTS LUXURY COL	CTS	4
CTS LXY COLLEC	CTS	1
CTS PRFORMNCE	CTS	1
CTS V	CTS	5
CUTAWAY VAN	E-SERIES	45
CUTAWAY VAN E3	E-350	22
CUTAWAY VAN E4	E-450	3
CUTAWAY VAN G3	EXPRESS	1
CUTLASS CIERA B	CUTLASS CIERA	1
CUTLASS CIERA S	CUTLASS CIERA	1
CUTLASS CIERA/	CUTLASS CIERA	1
CUTLASS SUPREM	CUTLASS SUPREME	7
CX7	CX-7	2
DAKOTA DAKOTA	DAKOTA	45
DAKOTA LARAMIE	DAKOTA	1
DAKOTA QUAD	DAKOTA QUADCAB	1

DAKOTA SLT	DAKOTA	15
DAKOTA ST	DAKOTA	16
DAKOTA SXT	DAKOTA	6
DELTA 88 ROYAL	88 ROYALE	1
DELTA 88 ROYALE	88 ROYALE	1
DENALI DENALI	DENALI	15
DEVILLE CONCOU	DEVILLE	1
DEVILLE D'ELEGA	DEVILLE	1
DEVILLE DEVILL	DEVILLE	48
DEVILLE DEVILLE	DEVILLE	6
DEVILLE DHS	DEVILLE	7
DEVILLE DTS	DEVILLE	3
DIAMANTE ES	DIAMANTE	3
DIAMANTE LS	DIAMANTE	9
DIAMANTE VRX	DIAMANTE	1
DISCOVERY II L	DISCOVERY II	1
DISCOVERY II S	DISCOVERY II	13
DRW SUPER DUTY	F-350	133
E 250 VAN	E-250	2
E150	E-150	4
E15C	E-150	1
E250	E-250	12
E250 ECONOLINE	E-250	1
E250 SD	E-250	2
E250 VAN	E-250	4
E25C	E-250	1
E320 /SPECIAL E	E320	2
E320 E320 4M A	E320	2
E320 E320 4MAT	E320	1
E320W	E320	1
E320W/SPECIAL	E320	1
E35	E-350	3
E350 4M AWD	E350	1
E350 E350 4M A	E350	2
E350 E350 WAGO	E350	2
E350 ECONOLINE	E350	1
E-350 SD CUTAW	E-350	1
E3500 VAN	E-350	2
E350A	E350	3

E350W	E350	1
E3BH	E-350	1
E420 /SPECIAL E	E420	1
ECLIPSE GS	ECLIPSE	28
ECLIPSE GT	ECLIPSE	12
ECLIPSE RS	ECLIPSE	22
ECLIPSE SPYDER	ECLIPSE	12
ECONOLINE CLUB	ECONOLINE	2
ECONOLINE CLUBW	ECONOLINE	1
ECONOLINE E250	E-250	1
ECONOLINE VAN	ECONOLINE	558
ECONOLINE VAN E	ECONOLINE	48
ECONOLINE WAGO	ECONOLINE WAGON	155
ECONOLINE WAGON	ECONOLINE WAGON	1
ECONOLN VAN SU	E-350	7
ECONOLN VAN SUP	E-350	11
EL DORADO	ELDORADO	2
ELANTRA /GL	ELANTRA	2
ELANTRA BAS/GT	ELANTRA	2
ELANTRA BLUE/G	ELANTRA	31
ELANTRA GLS	ELANTRA	23
ELANTRA GLS/GT	ELANTRA	56
ELANTRA GLS/SE	ELANTRA	36
ELANTRA GT	ELANTRA	4
ELDORADO TOURI	ELDORADO	1
ELEMENT EX	ELEMENT	1
ENDEAVOR LTD	ENDEAVOR	1
ENVOY ENVOY XU	ENVOY	4
ENVOY ENVOYXL	ENVOY	36
ENVOY XL	ENVOY	6
ENVOY XU	ENVOY	1
ENVOYDENALI EN	ENVOY	13
EOS 2.0T W/LUX	EOS	2
EOS 3.2L W/SPT	EOS	3
EOS BASE/2.0T	EOS	1
EOS LUX	EOS	1
EOS TURBO/KOMF	EOS	14
EQUINOX FWD LS	EQUINOX	2

EQUINOX LT	EQUINOX	2
ES300	ES 300	211
ES330	ES 330	101
ES350	ES 350	148
ESCALADE ESCAL	ESCALADE	15
ESCALADE EXT	ESCALADE	4
ESCORT LX	ESCORT	5
ESCORT LX/SPOR	ESCORT	7
ESCORT LX/SPORT	ESCORT	1
ESCORT SE	ESCORT	8
ESCORT SE/SPOR	ESCORT	1
ESCORT SE/SPORT	ESCORT	1
ESCORT ZX2	ESCORT	4
ESCORT ZX2/COO	ESCORT	5
ESCORT ZX2/COOL	ESCORT	2
ESCORT ZX2/SPO	ESCORT	9
ESCORT ZX2/SPOR	ESCORT	2
ESTEEM GL/GLX	ESTEEM	2
ESTEEM GL/GLX/	ESTEEM	5
EXPLOR SPTRAC	EXPLORER	1
EXPLORER SERIE	EXPLORER	1
EXPR	EXPRESS	1
EXPR 3500	EXPRESS	1
EXPRESS CARGO	EXPRESS	1
EXPRESS CUTAWA	EXPRESS CUTAWAY TRUCK	38
EXPRESS CUTAWAY	EXPRESS CUTAWAY TRUCK	2
EXPRESS RV G10	EXPRESS RV	1
EXPRESS RV G15	EXPRESS RV	1
EXPRESS RV G20	EXPRESS RV	3
EXPRESS RV G30	EXPRESS RV	3
EXPRESS RV G35	EXPRESS RV	1
EXPRESS VAN	EXPRESS	187
EXPRESS VAN G1	EXPRESS	63
EXPRESS VAN G10	EXPRESS	1
EXPRESS VAN G2	EXPRESS	251
EXPRESS VAN G20	EXPRESS	14
EXPRESS VAN G3	EXPRESS	41

EXPRESS VAN G30	EXPRESS	2
EXPRESSG	EXPRESS	1
EX-V6	CROSSTOUR	3
F 150	F-150	3
F 150XL RC	F-150	1
F 250 4X2 CREW	F-250	4
F 250 SD	F-250	8
F 350	F-350	4
F100	F-100	4
F150	F-150	195
F150 4X	F-150	1
F150 PICKUP	F-150	2
F150 SC	F-150	1
F-150 SC	F-150	1
F150 SUPERCAB	F-150	2
F-150ONVTNL 'F	F-150	1
F250	F-250	25
F250 SD	F-250	7
F-250 SD	F-250	1
F250 SPR DUTY	F-250	1
F250 SUPE	F-250	3
F250 SUPERDUTY	F-250	2
F250SD	F-250	3
F-250SD	F-250	3
F350	F-350	10
F350 DUALLY	F-350	3
F350 PICKUP	F-350	1
F350 SD	F-350	8
F-350 SD	F-350	1
F350 SUPERDUTY	F-350	4
F350SUPER DUTY	F-350	1
F450	F-450	1
F550	F-550	2
F-550SD	F-550	1
F650	F-650	2
F750	F-750	1
FIESTA SEL	FIESTA	1
FIESTA SES	FIESTA	1
FIREBIRD FIREBI	FIREBIRD	1

FIREBIRD FORMU	FIREBIRD	11
FIREBIRD FORMUL	FIREBIRD	7
FIT S	FIT	24
FIT SPORT	FIT	64
FIT5DR	FIT	1
FIVE HUNDRED L	FIVE HUNDRED	20
FIVE HUNDRED S	FIVE HUNDRED	43
FLEETWOOD FLEE	FLEETWOOD	9
FLEETWOOD FLEET	FLEETWOOD	1
FLHRCI	FLHR	1
FOCUS LX	FOCUS	16
FOCUS S	FOCUS	2
FOCUS S/SE/SES	FOCUS	57
FOCUS SE	FOCUS	29
FOCUS SE CMFRT	FOCUS	15
FOCUS SE/SE CM	FOCUS	20
FOCUS SE/SE CO	FOCUS	13
FOCUS SE/SE SP	FOCUS	8
FOCUS SE/SEL/S	FOCUS	9
FOCUS SEL	FOCUS	11
FOCUS SES	FOCUS	11
FOCUS ZTS	FOCUS	17
FOCUS ZTW	FOCUS	1
FOCUS ZX3	FOCUS	10
FOCUS ZX4	FOCUS	70
FOCUS ZX4ST	FOCUS	2
FOCUS ZX5	FOCUS	18
FORENZA BSE/CO	FORENZA	32
FORENZA FORENZ	FORENZA	32
FORTE EX	FORTE	30
FORTE SX	FORTE	4
FORTWO PASSION	FORTWO	2
FORTWO PURE/PA	FORTWO	3
FREELANDER SE	FREELANDER	1
FREESTAR VAN	FREESTAR	3
FRONTIER /XE	FRONTIER	6
FRONTIER CREW	FRONTIER	122
FRONTIER KING	FRONTIER	79

FRONTIER KING C	FRONTIER	7
FRONTIER XE	FRONTIER	4
FUSION FUSION	FUSION	271
FUSION SE	FUSION	1
G 1500	G1500	2
G35 AWD	G35	25
G37 BASE/JOURN	G37	49
G37 BASE/SPORT	G37	32
G5 GT	G5	1
G6 BASE/SE	G6	20
G6 GT	G6	57
G6 GTP	G6	11
G6 SE	G6	6
G6 SE 1	G6	1
G6 SE1	G6	14
G6 T	G6	4
G6 VALUELEADER	G6	11
G8 GT	G8	16
GALANT DE (U.S	GALANT	10
GALANT ES	GALANT	2
GALANT ES (U.S	GALANT	37
GALANT ES PREM	GALANT	1
GALANT ES/GTZ	GALANT	17
GALANT ES/GTZ (	GALANT	1
GALANT ES/LS	GALANT	4
GALANT ES/LS (	GALANT	30
GALANT ES/LS (U	GALANT	1
GALANT ES/LS M	GALANT	30
GALANT ES/LS/G	GALANT	1
GALANT ES/SE	GALANT	1
GALANT FE	GALANT	1
GALANT GTS	GALANT	1
GALANT LS (	GALANT	3
GALANT S (	GALANT	1
GCII	E-450	1
GMC SPRINT	SPRINT	1
GMT-400 C1500	GMT-400	87
GMT-400 C2500	GMT-400	9
GMT-400 C3500	GMT-400	6

GMT-400 C3500-H	GMT-400	1
GMT-400 K1500	GMT-400	49
GMT-400 K2500	GMT-400	5
GOLF GL	GOLF	2
GOLF GLS	GOLF	3
GOLF GLS TDI	GOLF TDI	3
GOLF III CITY	GOLF	1
GOLF III GL	GOLF	1
GOLF III GL/GO	GOLF	1
GOLF III SPORT	GOLF	1
GRAND AM GT	GRAND AM	13
GRAND AM GT1	GRAND AM	4
GRAND AM LE	GRAND AM	1
GRAND AM SE	GRAND AM	61
GRAND AM SE1	GRAND AM	37
GRAND PRIX GT	GRAND PRIX	57
GRAND PRIX GT2	GRAND PRIX	18
GRAND PRIX GTP	GRAND PRIX	22
GRAND PRIX GXP	GRAND PRIX	5
GRAND PRIX SE	GRAND PRIX	7
GRAND PRIX SE (	GRAND PRIX	4
GRAND VITARA X	GRAND VITARA	9
GS300	GS 300	66
GS300 GEN 2006	GS 300	29
GS300GENER2006	GS 300	5
GS350	GS 350	43
GS350 AWD	GS 350	3
GS400	GS 400	20
GS430	GS 430	9
GS430 GEN 2006	GS 430	4
GS430GENER2006	GS 430	3
GS450H	GS 450	2
GS460	GS 460	1
GTI 20TH ANN E	GTI	1
GX460	GX 460	10
GX470	GX 470	72
GXE	ALTIMA	1
HALF TONE	HALF TON	1

HATCHBACK	CALIBER	1
HHR PANEL LS	HHR	1
HHR-LS	HHR	1
HIGHLANDER LTD	HIGHLANDER	2
HLFTN PKUP U.S	HALFTON PICKUP	5
HLFTN PKUP U.S.	HALFTON PICKUP	1
HUMMER	H2	6
HUMMER H2	H2	17
HUMMER H2 SUT	H2	3
HUMMER H3	H3	18
I280 I280	I280	1
I290 I290	I290	1
IMPALA 1LT	IMPALA	17
IMPALA 2LT	IMPALA	1
IMPALA LS	IMPALA	154
IMPALA LT	IMPALA	100
IMPALA LTZ	IMPALA	6
IMPALA POLICE	IMPALA	19
IMPALA SS SUPE	IMPALA	2
IMPALA SUPER S	IMPALA	12
IMPREZA 2.5I	IMPREZA	7
IMPREZA 2.5I P	IMPREZA	2
IMPREZA OUTBAC	OUTBACK	4
IMPREZA OUTBACK	OUTBACK	1
IMPREZA RS AWD	IMPREZA	1
IMPREZA WRX	IMPREZA	1
IMPREZA WRX 4X	IMPREZA	1
IMPREZA WRX AW	IMPREZA	3
IMPREZA WRX ST	IMPREZA	8
IMPREZA WRX/LI	IMPREZA	2
IMPREZA WRX/VT	IMPREZA	5
INSIGHT EX	INSIGHT	16
INSIGHT LX	INSIGHT	8
INTEGRA GS	INTEGRA	6
INTEGRA GS/LS	INTEGRA	3
INTEGRA GSR	INTEGRA	5
INTEGRA LS	INTEGRA	37
INTEGRA RS	INTEGRA	5

INTEGRA SE	INTEGRA	2
INTEGRA TYPE R	INTEGRA	10
INTREPID ES	INTREPID	13
INTREPID R/T	INTREPID	4
INTREPID SE	INTREPID	20
INTRIGUE GL	INTRIGUE	8
INTRIGUE GX	INTRIGUE	9
ION LEVEL 1	ION	6
ION LEVEL 2	ION	35
ION LEVEL 3	ION	17
ION REDLINECOU	ION	3
IS250	IS 250	92
IS250 AWD	IS 250	1
IS300	IS 300	43
IS350	IS 350	39
JETTA 2.0L GLI	JETTA	1
JETTA 2.0T W/O	JETTA	1
JETTA 2.5 W/OP	JETTA	9
JETTA 2.5L W/L	JETTA	2
JETTA GL (U.S.	JETTA	23
JETTA GL (U.S.)	JETTA	5
JETTA GL TDI (	JETTA TDI	11
JETTA GLI (U.S	JETTA	1
JETTA GLI W/OP	JETTA	1
JETTA GLS	JETTA	36
JETTA GLS (U.S	JETTA	92
JETTA GLS 1.8	JETTA	1
JETTA GLS TDI	JETTA TDI	30
JETTA GLX	JETTA	1
JETTA GLX (U.S	JETTA	4
JETTA III CITY	JETTA	1
JETTA III GL	JETTA	2
JETTA III GLS	JETTA	6
JETTA S	JETTA	13
JETTA SE/SEL	JETTA	10
JETTA SEL	JETTA	1
JETTA TDI	JETTA TDI	44
JETTA TDI W OP	JETTA TDI	3
JETTA VALUE ED	JETTA	3

JETTA WOLFSBUR	JETTA	17
JIMMY (CANADA)	JIMMY	4
JIMMY JIMMY	JIMMY	25
JIMMY/ENVOY JI	JIMMY	1
K10 PICKUP	K10	1
K15 SUBURBAN	SUBURBAN	2
K150 4WD PICK	K15	1
K1500 4WD PICK	K1500	2
K1500 SURBURB	SUBURBAN	1
K2500 SUBURBAN	SUBURBAN	1
K3500 4WD PICK	K3500	1
KING CAB	TITAN	1
KOMPRSLK CLASS	SLK	1
LACROSSE CX	LACROSSE	13
LACROSSE CXL	LACROSSE	17
LACROSSE CXS	LACROSSE	13
LANCER DE	LANCER	3
LANCER ES	LANCER	36
LANCER ES/ES S	LANCER	6
LANCER EVOLUTI	LANCER	2
LANCER GTS	LANCER	4
LANCER LS	LANCER	3
LANCER OZ RALL	LANCER	3
LANCER RALLIAR	LANCER	2
LAND CRUISER W	LAND CRUISER	26
LAND CRUISER WA	LAND CRUISER	4
LAREDO	WRANGLER	1
LEGACY 2.5GT S	LEGACY	2
LEGACY 2.5I	LEGACY	1
LEGACY 2.5I AW	LEGACY	16
LEGACY 2.5I LI	LEGACY	2
LEGACY 2.5I PR	LEGACY	4
LEGACY 30TH OU	LEGACY	1
LEGACY BRIGHTON	LEGACY	1
LEGACY GT LIMI	LEGACY	6
LEGACY L	LEGACY	1
LEGACY L AWD	LEGACY	1
LEGACY L AWD (	LEGACY	1
LEGACY L SPECI	LEGACY	2
LEGACY LS SPEC	LEGACY	2
LEGACY LS/LSI	LEGACY	4
LEGACY OUTBACK	OUTBACK	15
LEGACY OUTBK 2	OUTBACK	7
LEGACY OUTBK H	OUTBACK	3
LEGACY OUTBK/S	OUTBACK	1
LEGEND GS	LEGEND	1
LEGEND L	LEGEND	18
LEGEND LS	LEGEND	8
LESABRE CUSTOM	LESABRE	78
LESABRE LIMITE	LESABRE	35
LESABRE LIMITED	LESABRE	6
LEXUS ES330	ES 330	1
LEXUS RX 400H	RX 400H	1
LGT CONVTNL 'F	F-150	1547
LGT CONVTNL 'F'	F-150	149
LIB SPT	LIBERTY	1
LIBERTY LIMITE	LIBERTY	35
LIBERTY RENEGA	LIBERTY	4
LIBERTY SPORT	LIBERTY	79
LIBERTY SPORT/	LIBERTY	1
LR2 SE	LR2	4
LR2 SE W/TECH	LR2	5
LR3 HSE	LR3	4
LR3 SE	LR3	8
LR4 HSE	LR4	1
LR4 HSE LUXURY	LR4	1
LS 2000	LS	1
LS400	LS 400	72
LS430	LS 430	106
LS460	LS 460	32
LS460L	LS 460	8
LTD CROWN VICT	CROWN VICTORIA	1
LUCERN	LUCERNE	1
LUCERNE CX	LUCERNE	7
LUCERNE CXL	LUCERNE	24
LUCERNE CXS	LUCERNE	2

LUMINA EURO	LUMINA	3
LUMINA LS	LUMINA	2
LUMINA LUMINA/	LUMINA	16
LUMINA LUMINA/L	LUMINA	10
LW300 LEVEL 3	LW300	1
LX470	LX 470	39
LX570	LX 570	12
M ROADSTER (U.S	M ROADSTER	1
M3 AUTOMATIC	M3	3
M35 SEDAN/SPOR	M35	64
M3CI	M3	1
M3S	MAZDA3	3
M45 SEDAN/SPOR	M45	21
M45X	M45	2
MALIBI SEDAN	MALIBU	1
MALIBU SE	MALIBU	2
MALIBU 1LT	MALIBU	38
MALIBU 2LT	MALIBU	29
MALIBU CLASSIC	MALIBU	4
MALIBU LS	MALIBU	121
MALIBU LS/LT M	MALIBU	7
MALIBU LT	MALIBU	40
MALIBU LTZ	MALIBU	20
MALIBU MAXX LS	MALIBU	1
MALIBU MAXX LT	MALIBU	5
MARK LT MARK L	MARK	9
MARK VII LSC	MARK	3
MARK VIII	MARK	2
MARK VIII /LSC	MARK	1
MARK VIII LSC	MARK	2
MARQUIS	GRAND MARQUIS	1
MARQUIS GRAND	GRAND MARQUIS	103
MARQUIS GRAND G	GRAND MARQUIS	5
MARQUIS GRAND L	GRAND MARQUIS	13
MAXIMA GL	MAXIMA	4
MAXIMA GLE/SE	MAXIMA	49
MAXIMA GXE	MAXIMA	9

MAXIMA GXE/GLE	MAXIMA	270
MAXIMA GXE/GLE/	MAXIMA	65
MAXIMA S/SV	MAXIMA	80
MAXIMA SE	MAXIMA	8
MAXIMA SE/SL	MAXIMA	215
MAXIMA SV	MAXIMA	1
MAZDA 3	MAZDA3	1
MAZDA 5	MAZDA5	1
MAZDA3 M3H	MAZDA3	1
MAZDA3I	MAZDA3	4
MDX RECH	MDX	1
MDX TECH	MDX	1
MDX TOURNAVR	MDX	1
MED.HVY.CONVNT	F-250	1
METRO METRO/LS	METRO	1
METRO METROLSI	METRO	7
MILAN MILAN	MILAN	10
MILAN MILAN AW	MILAN	3
MILAN MILAN PR	MILAN	25
MILAN PREM	MILAN	2
MILLENIA /L	MILLENIA	7
MILLENIA S	MILLENIA	2
MIN COOPER	COOPER	44
MIN COOPER COO	COOPER	48
MIN COOPER S C	COOPER	2
MIRAGE DE	MIRAGE	38
MIRAGE ES	MIRAGE	1
MIRAGE LS	MIRAGE	6
MIRAGE S	MIRAGE	14
MKZ AWD	MKZ	7
MONTANA LUXURY	MONTANA	1
MONTANA/TRANS	MONTANA	5
MONTANNA	MONTANA	1
MONTE CARLO LS	MONTE CARLO	34
MONTE CARLO LT	MONTE CARLO	13
MONTE CARLO SS	MONTE CARLO	15
MONTE CARLO Z3	MONTE CARLO	2
MONTE CARLO Z34	MONTE CARLO	2

MONTEGO LUXURY	MONTEGO	3	NEW BEETLE TDI	NEW BEETLE TDI	3
MONTEGO PREMIE	MONTEGO	6	NEW JETTA 2.5	JETTA	8
MONTEROSPORT	MONTERO	76	NEW JETTA TDI	JETTA	8
MPV 4X2	MPV	1	NEW SPORTAGE	SPORTAGE	9
MURANO LE	MURANO	1	NEWJETTA 2.5	JETTA	2
MURANO MURANO	MURANO	5	NEWJETTA 2.5 W	JETTA	3
MUSTANG COBRA	MUSTANG	1	NEWJETTA GLI W	JETTA	1
MUSTANG GT	MUSTANG	127	NEWJETTA TDI W	JETTA TDI	1
MUSTANG GT/COB	MUSTANG	3	NEWJETTA VALUE	JETTA	3
MUSTANG GT/GTS	MUSTANG	1	NPR NPR	NPR	58
MUSTANG LX	MUSTANG	7	NQR NQR	NQR	2
MUSTANG MACH I	MUSTANG	4	NRR NRR	NRR	1
MX-5 MIATA	MIATA	50	ODYSSEY (U.S.)	ODYSSEY	718
MX-5 MIATA /LS	MIATA	10	ODYSSEY EX	ODYSSEY	5
NAVIGATOR L	NAVIGATOR	1	ODYSSEY EXL	ODYSSEY	2
NEON /ES	NEON	9	OPTIMA EX/SX	OPTIMA	1
NEON /EX	NEON	2	OPTIMA LX	OPTIMA	6
NEON /LX	NEON	5	OPTIMA LX/EX	OPTIMA	112
NEON BASE/SE	NEON	6	OPTIMA LX/SE	OPTIMA	8
NEON ES	NEON	4	OPTIMA/MAGENTI	OPTIMA	5
NEON HIGHLINE	NEON	7	OUTBACK 2.5I	OUTBACK	10
NEON HIGHLINE/	NEON	6	OUTBACK 2.5I L	OUTBACK	2
NEON HIGHLN/SP	NEON	1	OUTBACK 2.5I P	OUTBACK	5
NEON HIGHLN/SPR	NEON	1	PARK AVENUE UL	PARK AVENUE	2
NEON R/T	NEON	6	PASSAT (CANADA	PASSAT	1
NEON SE	NEON	6	PASSAT 2.0 VAL	PASSAT	8
NEON SE/ES	NEON	15	PASSAT 2.0T	PASSAT	2
NEON SPORT	NEON	1	PASSAT 2.0T/2.	PASSAT	8
NEON SRT-4	NEON	11	PASSAT 2.0T/WO	PASSAT	2
NEON SXT	NEON	35	PASSAT 2.OT W/	PASSAT	1
NEON SXT/SPORT	NEON	2	PASSAT 3.6L W	PASSAT	2
NEW BEETLE 2.5	NEW BEETLE	2	PASSAT 3.6L W/	PASSAT	3
NEW BEETLE CON	NEW BEETLE	17	PASSAT 3.6L WA	PASSAT	1
NEW BEETLE GL	NEW BEETLE	4	PASSAT GL	PASSAT	4
NEW BEETLE GLS	NEW BEETLE	49	PASSAT GLS	PASSAT	74
NEW BEETLE GLX	NEW BEETLE	3	PASSAT GLS 4MO	PASSAT	1
NEW BEETLE S	NEW BEETLE	2	PASSAT GLS/GLS	PASSAT	5
NEW BEETLE S/S	NEW BEETLE	1	PASSAT GLX	PASSAT	16

PASSAT GLX 4MO	PASSAT	6
PASSAT GLX S	PASSAT	1
PASSAT GLX V6	PASSAT	23
PASSAT KOMFORT	PASSAT	9
PASSAT LUX	PASSAT	3
PASSAT S3.6L W	PASSAT	1
PASSAT TURBO	PASSAT	3
PASSAT WAGON	PASSAT	2
PASSAT WAGON K	PASSAT	4
PATHFINDER LE	PATHFINDER	1
PATHFINDER S/L	PATHFINDER	1
PATRIOT LIMITE	PATRIOT	12
PATRIOT SPORT	PATRIOT	53
PICKUP 4 X 4 R	4RUNNER	3
PILOT EX	PILOT	2
PRELUDE 2.0SI/	PRELUDE	5
PRELUDE S	PRELUDE	1
PRELUDE SH	PRELUDE	2
PRELUDE SI/SR	PRELUDE	1
PRERUNNER	TACOMA	2
PRIZM LSI	PRIZM	2
PRIZM PRIZM/LS	PRIZM	36
PRIZM PRIZM/LSI	PRIZM	2
PRIZM/LS	PRIZM	4
PROBE GT	PROBE	10
PROBE LX	PROBE	1
PROTEGE DX	PROTEGE	3
PROTEGE DX/LX	PROTEGE	34
PROTEGE DX/LX/	PROTEGE	24
PROTEGE DX/LX/S	PROTEGE	1
PROTEGE ES	PROTEGE	2
PROTEGE ES/LX	PROTEGE	2
PROTEGE LX	PROTEGE	5
PROTEGE PR5	PROTEGE	21
PROTEGE SPEED	PROTEGE	1
PT CRUISER GT	PT CRUISER	1
PT CRUISER TOU	PT CRUISER	11
PT CRUISER_	PT CRUISER	1
Q45 /Q45T	Q45	10

QUAD	RAM	1
QUAD CAB	RAM	1
QUEST S/SE/SL	QUEST	4
R15 CONV R1500	SUBURBAN	1
R350	R 350	24
R500	R 500	3
RAIDER LS	RAIDER	2
RALLY WAGON G3	RALLY WAGON	1
RALLY WAGON/VA	RALLY WAGON	1
RAM 3500	RAM	1
RAM 1500	RAM	25
RAM 1500 QUA	RAM	2
RAM 1500 SLT	RAM	1
RAM 2500	RAM	4
RAM 3500	RAM	2
RAM B3500	RAM	1
RAM SLT 4X4	RAM	1
RAM TRUCK	RAM	301
RAM TRUCK 1500	RAM	494
RAM TRUCK 2500	RAM	80
RAM TRUCK 3500	RAM	26
RAM TRUCK 4500	RAM	2
RAM TRUCK 5500	RAM	2
RAM TRUCK SRT-	RAM	2
RAM VAN	RAM	24
RAM VAN B1500	RAM	13
RAM VAN B250	RAM	5
RAM VAN B2500	RAM	4
RAM VAN B3500	RAM	1
RAM WAGON	RAM	16
RAMCHARGER AD1	RAM	1
RAMCHARGER AW15	RAM	5
RANGE R	RANGE ROVER	1
RANGE ROVER 4.	RANGE ROVER	1
RANGE ROVER HS	RANGE ROVER	23
RANGE ROVER SP	RANGE ROVER	34
RANGE ROVER SU	RANGE ROVER	1
RANGER RANGER	RANGER	167

RANGER SUPER	RANGER	148
RAV4 NEWGENER	RAV4	182
REGAL CUSTOM (	REGAL	2
REGAL CUSTOM (F	REGAL	6
REGAL GRAN SPOR	REGAL	1
REGAL GS	REGAL	7
REGAL LS	REGAL	16
REGAL LS/LSE	REGAL	3
RENO BASE/CONV	RENO	7
RENO RENO BASE	RENO	4
RENO RENO S	RENO	2
RIDGELINE RT	RIDGELINE	5
RIDGELINE RTL	RIDGELINE	47
RIDGELINE RTS	RIDGELINE	11
RIDGELINE RTX	RIDGELINE	6
RIO 5	RIO	3
RIO 5 SX	RIO	7
RIO BASE/LX/SX	RIO	17
ROADMASTER EST	ROADMASTER	2
ROADMASTER LIM	ROADMASTER	3
ROADSTERSLK230	ROADMASTER	2
RONDO BASE/LX/	RONDO	6
RONDO LX/EX	RONDO	11
RSX HATCHBACK	RSX	2
RSX TYPE-S	RSX	10
RX 330 LUV	RX 330	4
RX 350 SUV	RX 350	1
RX 400H	RX 400	2
RX300	RX 300	123
RX330	RX 330	169
RX350	RX 350	128
RX350 SUV	RX 350	1
RX400	RX 400	6
RX400H	RX 400	11
RX450H	RX 450	2
RX7 12A	RX7	1
RX7 13B	RX7	1
S 10 PICKUP	S-10	1
'S'10	S10	1

S10 BLAZER	S10	11
S10 TRUCK	S10	2
S1500 JIMMY	JIMMY	3
S314 15 PASS	S314	5
S350W	S350	1
S4 2.7 T Q	S4	1
S4 CARB QUATTR	S4	3
S4 QUATT PREST	S4	3
S40 1.9T	S40	19
S40 2.4I	S40	41
S40 T5	S40	1
S40 T5 FWD	S40	2
S430	S430	38
S430 S4M AWD	S430	3
S5 QUATTRO	S5	1
S5 QUATTRO PRE	S5	2
S500 SEDAN4M A	S500	2
S500V	S500	1
S60 2.4T	S60	15
S60 2.5T	S60	1
S60 2.5T FWD	S60	46
S60 FWD	S60	17
S60 R	S60	5
S60 T5	S60	1
S70 /SE	S70	5
S70 AWD	S70	1
S70 GLT	S70	7
S80 2.5T FWD	S80	20
S80 2.5TAWD	S80	2
S80 3.2 FWD	S80	29
S80 3.2L	S80	2
S80 T6/EXECUTI	S80	2
S80 T6TURBO	S80	2
S80 TURBOT6	S80	4
SABLE GS	SABLE	20
SABLE GS/GS PL	SABLE	9
SABLE GS/LS	SABLE	1
SABLE LS	SABLE	17
SABLE LS PREMI	SABLE	26

SABLE LS/LTS	SABLE	1
SABLE LUXURY F	SABLE	1
SABLE PREMIER	SABLE	3
SAFARI SAFARI	SAFARI	37
SAFARI SAFARI X	SAFARI	3
SAVANA G1500	SAVANA	21
SAVANA G2500	SAVANA	61
SAVANA G3500	SAVANA	21
SAVANA G3500 L	SAVANA	2
SAVANA RV	SAVANA RV	2
SAVANA RV G150	SAVANA RV	7
SAVANA RV G1500	SAVANA RV	1
SAVANA RV G250	SAVANA RV	2
SCION SCIONTC	SCION	108
SCION SCIONXA	SCION	23
SCION TC	SCION	13
SCION XA	SCION	2
SCION XB	SCION	79
SCION XB 6200A	SCION	1
SCION XB XB	SCION	7
SCION XD	SCION	25
SCIOTC SCIONTC	SCION	1
SCIOXB	SCION	14
SEBRING GTC	SEBRING	12
SEBRING JX	SEBRING	3
SEBRING JXI	SEBRING	14
SEBRING LIMITE	SEBRING	38
SEBRING LX	SEBRING	74
SEBRING LXI	SEBRING	41
SEBRING TOURIN	SEBRING	44
SENTRA 1.8	SENTRA	3
SENTRA 1.8/1.8	SENTRA	102
SENTRA 1.8S	SENTRA	2
SENTRA 2.0	SENTRA	3
SENTRA 2.0/2.0	SENTRA	162
SENTRA 2.5S	SENTRA	1
SENTRA BASE/S/	SENTRA	29
SENTRA BASE/XE	SENTRA	26
SENTRA BASE/XE/	SENTRA	2

SENTRA E/XE (U	SENTRA	3
SENTRA E/XE/GX	SENTRA	7
SENTRA E/XE/GXE	SENTRA	6
SENTRA E/XE/SE	SENTRA	4
SENTRA GXE (U.	SENTRA	1
SENTRA SE	SENTRA	6
SENTRA SE R	SENTRA	1
SENTRA SENTRAS	SENTRA	14
SENTRA U.S. SE	SENTRA	5
SENTRA U.S. SEN	SENTRA	1
SENTRA XE	SENTRA	1
SENTRA XE/GXE	SENTRA	62
SENTRA XE/GXE (	SENTRA	1
SEPHIA /LS	SEPHIA	15
SEVILLE SLS	SEVILLE	10
SEVILLE STS	SEVILLE	13
SHADOW ES	SHADOW	2
SIENNA LIMITED	SIENNA	1
SIERRA 15	SIERRA	3
SIERRA 1500	SIERRA	1
SIERRA C1500	SIERRA	45
SIERRA C1500 D	SIERRA	6
SIERRA C1500 H	SIERRA	2
SIERRA C1500 S	SIERRA	77
SIERRA C1500SI	SIERRA	2
SIERRA C1500SIE	SIERRA	9
SIERRA C2500	SIERRA	2
SIERRA C2500 H	SIERRA	14
SIERRA C2500 S	SIERRA	1
SIERRA C3500	SIERRA	4
SIERRA C3500 S	SIERRA	7
SIERRA K1500	SIERRA	31
SIERRA K1500 D	SIERRA	5
SIERRA K1500 H	SIERRA	1
SIERRA K1500 S	SIERRA	45
SIERRA K1500SI	SIERRA	2
SIERRA K2500	SIERRA	2
SIERRA K2500 H	SIERRA	31
SIERRA K2500 S	SIERRA	1

SIERRA K3500	SIERRA	2
SIERRA K3500 S	SIERRA	4
SILHOUETTE SIL	SILHOUETTE	1
SILVERADO 1500	SILVERADO	5
SILVERADO 2500	SILVERADO	1
SILVERADO 4X4	SILVERADO	1
SILVERADO C150	SILVERADO	430
SILVERADO C1500	SILVERADO	8
SILVERADO C250	SILVERADO	115
SILVERADO C350	SILVERADO	28
SILVERADO K150	SILVERADO	149
SILVERADO K1500	SILVERADO	15
SILVERADO K-25	SILVERADO	1
SILVERADO K250	SILVERADO	103
SILVERADO K350	SILVERADO	37
SILVERADO.	SILVERADO	2
SKY RED LINE	SKY	2
SKYLARK CUS/LI	SKY	2
SL	SL1	9
SL500R	SL500	2
SLK230KOMPRESS	SLK230	6
SOLSTICE GXP	SOLSTICE	5
SONATA LX	SONATA	1
SONATA BASE/GL	SONATA	19
SONATA GL	SONATA	21
SONATA GLS	SONATA	150
SONATA GLS/LS/	SONATA	10
SONATA GLS/LX	SONATA	90
SONATA SE/LIMI	SONATA	91
SONOMA SONOMA	SONOMA	19
SORENTO EX	SORENTO	1
SORENTO EX V6	SORENTO	3
SORENTO/LX	SORENTO	2
SORRENTO	SORENTO	1
SPECTRA /LS	SPECTRA	24
SPECTRA EX	SPECTRA	1
SPECTRA EX/LX	SPECTRA	5
SPECTRA EX/LX/	SPECTRA	46
SPECTRA GS/GSX	SPECTRA	9

SPECTRA NEW SP	SPECTRA	17
SPECTRA5 SX	SPECTRA	5
SPEED3	MAZDA3	14
SPORT VAN	SPORTVAN	3
SPORTVAN/VAN	SPORTVAN	1
SPORTVAN/VAN G	SPORTVAN	8
SPORTVAN/VAN G2	SPORTVAN	1
SPRINTER 2500	SPRINTER	56
SPRINTER 3500	SPRINTER	11
SPRINTER SPRIN	SPRINTER	5
SRW SUPER DUTY	F-350	517
STRATUS ES	STRATUS	2
STRATUS SE	STRATUS	35
STRATUS SE PLU	STRATUS	5
STRATUS SE/SXT	STRATUS	2
STRATUS SXT	STRATUS	34
'STRUCK	S10	60
'STRUCK S 14	S14	1
'STRUCK S10	S10	100
'STRUCK S15	S15	2
STS V6	STS	1
S-TYPE 4.2	S-TYPE	4
S-TYPE SPORT	S-TYPE	4
SUBURBAN K25	SUBURBAN	4
SUNFIRE GT	SUNFIRE	1
SUNFIRE SE	SUNFIRE	25
SUPERCAB	F-250	1
SUPERCREW F150	F-150	3
SUPRA W/SPRTRF	SUPRA	6
SURBURBAN	SUBURBAN	1
SX4 AWD	SX4	1
SX4 BASE/CONVE	SX4	4
SX4 SPORT	SX4	3
SX4 SPORT AWD	SX4	7
SX4 TOURING	SX4	1
SX4 TOURING AW	SX4	1
T100 /DX	T100	2
T100 XTRACAB	T100	10
T100 XTRACAB SR	T100	2

T100 XTRACAB/DX	T100	1
TACOMA 4X	TACOMA	3
TACOMA 4X2	TACOMA	1
TACOMA ACCESS	TACOMA	24
TACOMA DOUBLE	TACOMA	269
TACOMA PRERUN	TACOMA	10
TACOMA PRERUNN	TACOMA	4
TACOMA REG CAB	TACOMA	7
TACOMA REGULAR	TACOMA	59
TACOMA XRUNNER	TACOMA	3
TACOMA XTRACAB	TACOMA	122
TAHOE	TAHOE	48
TAHOE C1500	TAHOE	394
TAHOE K1500	TAHOE	158
TAHOE/AVAL	TAHOE	1
TALON DL	TALON	1
TALON TSI	TALON	1
TAURUS GL	TAURUS	28
TAURUS GL/SE	TAURUS	2
TAURUS L	TAURUS	1
TAURUS LIMITED	TAURUS	19
TAURUS LX	TAURUS	22
TAURUS LX/SE	TAURUS	8
TAURUS SE	TAURUS	161
TAURUS SE COMF	TAURUS	2
TAURUS SE COMFO	TAURUS	1
TAURUS SE/COMF	TAURUS	9
TAURUS SE/COMFO	TAURUS	2
TAURUS SEL	TAURUS	80
TAURUS SEL AWD	TAURUS	5
TAURUS SES	TAURUS	86
TAURUS X	TAURUS	12
TERCEL CE	TERCEL	4
TERCEL DX	TERCEL	2
TERCEL STD	TERCEL	5
TERCEL STD/DX	TERCEL	2
TERRAIN SLE	TERRAIN	3
TERRAIN SLT	TERRAIN	4

TERRAZA TERRAZ	TERRAZA	1
TG33705	SAVANA	1
THUNDERBIRD LX	THUNDERBIRD	7
THUNDERBIRD SU	THUNDERBIRD	1
TIBURON BASE/G	TIBURON	2
TIBURON GS	TIBURON	4
TIBURON GT	TIBURON	16
TIBURON GT/SE/	TIBURON	5
TITAN CREW CAB	TITAN	38
TITAN KING CAB	TITAN	35
TITAN LE	TITAN	1
TITAN SE	TITAN	2
TITAN XE	TITAN	3
TITAN XE/SE/LE	TITAN	69
TL AT NAV	TL	2
TL AWD	TL	6
TL TYPE-S	TL	35
TL4DRNAVI	TL	1
TL-TECH	TL	1
TOUAREG 2	TOUAREG	6
TOWN CAR CARTI	TOWN CAR	13
TOWN CAR CARTIE	TOWN CAR	1
TOWN CAR DESIG	TOWN CAR	3
TOWN CAR EXEC	TOWN CAR	4
TOWN CAR EXECU	TOWN CAR	48
TOWN CAR EXECUT	TOWN CAR	1
TOWN CAR SIG/D	TOWN CAR	3
TOWN CAR SIG/J	TOWN CAR	1
TOWN CAR SIG/SP	TOWN CAR	4
TOWN CAR SIG/TO	TOWN CAR	10
TOWN CAR SIGNA	TOWN CAR	69
TOWN CAR SIGNAT	TOWN CAR	2
TOWN CAR ULTIM	TOWN CAR	14
TRACER LS/SPOR	TRACER	1
TRAILBLAZER LT	TRAILBLAZER	2
TRIBUT	TRIBUTE	1
TRIBUTE DX	TRIBUTE	2
TROOPER TROOPER	TROOPER	1

TRUCK KING CAB	TITAN	20
TT 2.0T	TT	4
TT QUATTRO	TT	1
TT QUATTRO 3.2	TT	1
TT QUATTRO AWD	TT	5
TUNDRA 4X4	TUNDRA	10
TUNDRA ACC CAB	TUNDRA	11
TUNDRA ACCESS	TUNDRA	57
TUNDRA CREWMAX	TUNDRA	63
TUNDRA DOUBLE	TUNDRA	265
TUNDRA REGULAR	TUNDRA	161
TUNDRA SR5	TUNDRA	1
UPLANDER UPLAN	UPLANDER	24
V70 2.4T	V70	4
V70 2.5T	V70	1
V70 3.2 FWD	V70	2
V70 FWD	V70	7
V70 GLT/AWD	V70	1
V70 TURBOT5	V70	4
V70 V70RAWD/20	V70	2
V70 V70XCAWD X	V70	11
V70 V70XCAWD XC	V70	1
V70 XCAWD X	V70	2
VDPVANDEN PLAS	VDP	5
VEERSA	VERSA	1
VENTURE VENTUR	VENTURE	9
VERONA EX	VERONA	1
VERONA LUXURY	VERONA	1
VERONA S/LX	VERONA	1
VERSA S/SL	VERSA	111
VERSA SL	VERSA	6
VIBE AWD	VIBE	6
VIBE GT	VIBE	10
VIGOR GS	VIGOR	3
VIGOR LS	VIGOR	2
VOYAGER VOYAGE	VOYAGER	27
VOYAGER VOYAGER	VOYAGER	10
VUE FWD	VUE	1

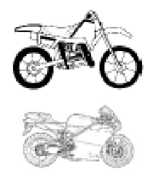
VUE-FWD V6	VUE	1
W4500 W45042	W4500	3
WAGON	MAZDA6	44
WINDSTAR LX	WINDSTAR	9
WINDSTAR SE	WINDSTAR	2
WINDSTAR SEL	WINDSTAR	1
WINDSTAR WAGON	WINDSTAR	4
WRANGLER NGLER	WRANGLER	23
WRANGLER SAHAR	WRANGLER	18
WRANGLER UNLIM	WRANGLER	1
WRANGLER WRANG	WRANGLER	40
WRANGLER/TJ	WRANGLER	16
WRANGLER/TJ SA	WRANGLER	2
WRANGLER/TJ SAH	WRANGLER	4
WRANGLER/TJ SE	WRANGLER	23
WRANGLER/TJ SP	WRANGLER	9
WRANGLER/TJ SPO	WRANGLER	13
WRANGLER/TJ UN	WRANGLER	12
WRANGLER/TJ WR	WRANGLER	4
WRANGLER/YJ WR	WRANGLER	5
WRANGLER/YJ WRA	WRANGLER	4
WRANGLERUNLIMI	WRANGLER	55
X3 2.5I	X3	2
X5 3	X5	8
X5 XDR 35I	X5	2
X5XDR35	X5	5
X5XDRIVE30I	X5	1
XF LUXURY	XF	3
XF PREMIUM LUX	XF	4
XF SUPERCHARGE	XF	11
XG350 BASE/L	XG350	1
XJ VANDEN PLAS	XJ XJ6	1
XJ XJ8L	XJ XJ8	1
XJ-8 VAND	XJ XJ8	2
XTERRA S	XTERRA	1
XTERRA XTERRAS	XTERRA	3
X-TYPE 2.5	X-TYPE	13
X-TYPE 3.0	X-TYPE	4

X-TYPE 3.0 AWD	X-TYPE	7
X-TYPE SPORT 2	X-TYPE	1
X-TYPE SPORT 3	X-TYPE	1
YUKON DENALI	YUKON	4
YUKON XL	YUKON	7
YUKON YUKON	YUKON	244
YUKON YUKON DE	YUKON	49
YUKON YUKON SL	YUKON	7
YUKON YUKON XL	YUKON	47
YUKON/DENALI Y	YUKON	1

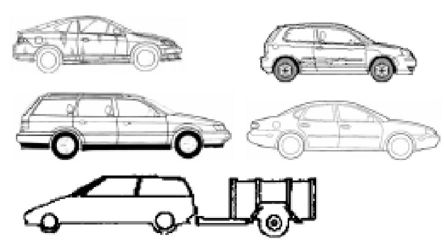
Z3 (U.S.)	Z3	2
Z3 2.8	Z3	1
Z3 2.8 (U.S.)	Z3	1
Z3 ROADSTER	Z3	1
Z3 ROADSTER___	Z3	1
Z4 2.5 (U.S.)	Z4	12
Z4 3.0 (U.S.)	Z4	16
Z4 3.0SI (U.S.	Z4	1
ZR14526	OUTLOOK	1

APPENDIX D: VEHICLE CLASSIFICATION FLASHCARDS FOR LICENSE PLATE VIDEO PROCESSING [45]

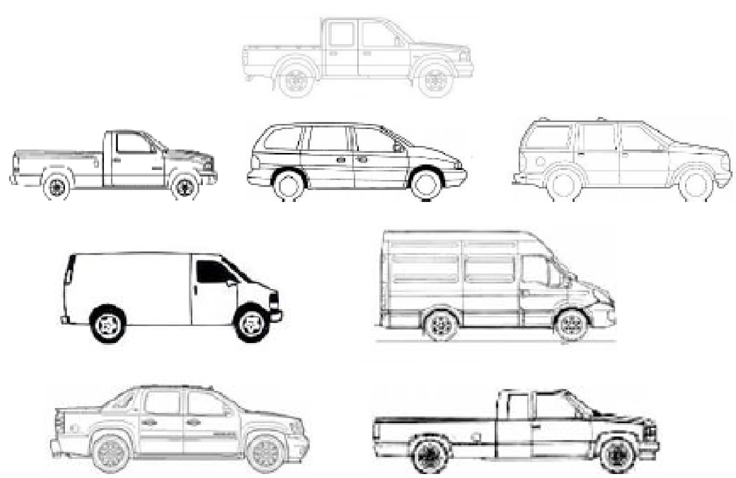
Motorcycle



Light Utility Automobile (Passenger Car)

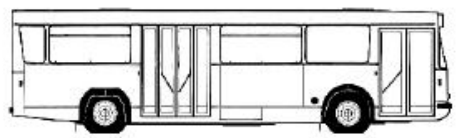


Light Utility Trucks (SUV)

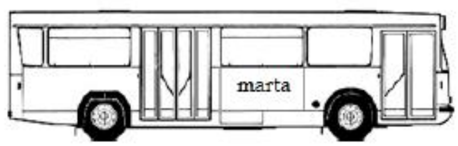


School Bus

Other Buses

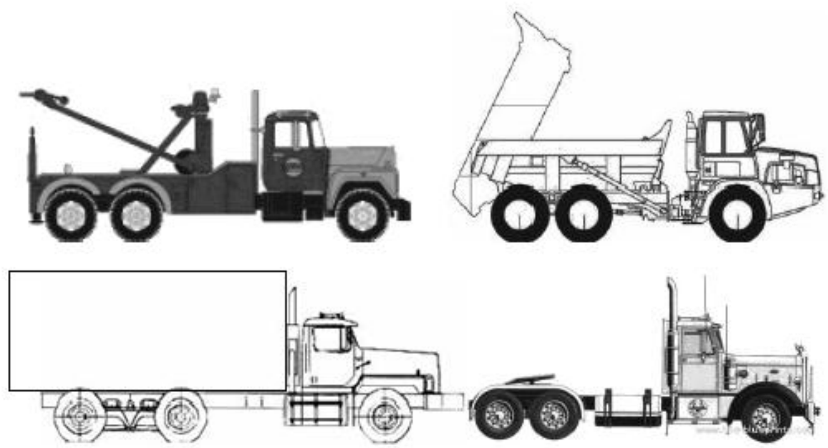


MARTA BUSES -- Bus with MARTA vehicle markings

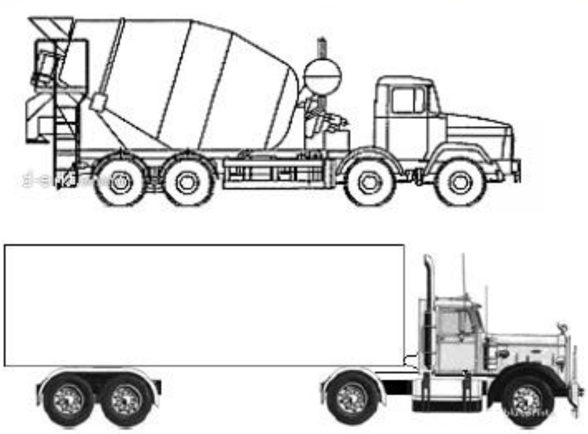


TWO AXLE, SINGLE UNIT TRUCK(s) -- All vehicles on a single frame including trucks, camping and recreational vehicles, motor homes, etc., with two axles and DUAL REAR WHEELS.

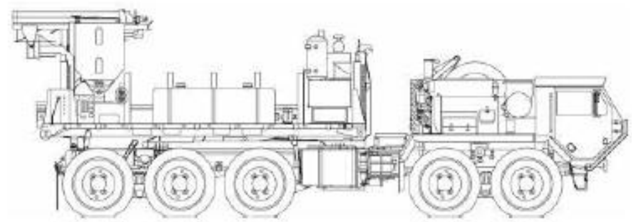
THREE AXLE SINGLE-UNIT TRUCK(s) -- All vehicles on a single frame including trucks, camping and recreational vehicles, motor homes, etc., with three axles.



THREE/ FOUR-AXLE Single Trailer Combination -- All trucks on a single frame with three or four axles & a single trailer combination.



FIVE-AXLE Single Trailer Combination -- All five-axle vehicles consisting of two units, one of which is a tractor or straight truck power unit.



APPENDIX E: AVERAGE VEHICLE VALUE DISTRIBUTIONS BY OCCUPANCY VALUE

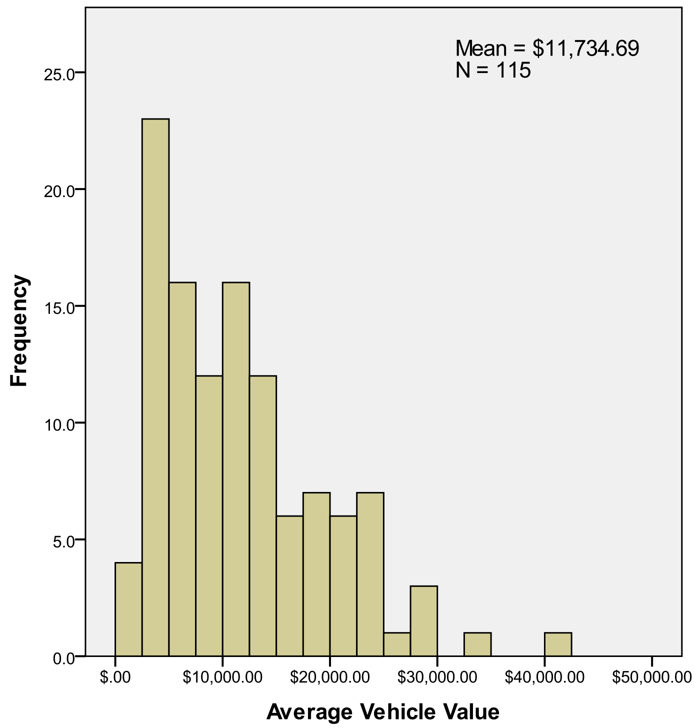


Figure 33: Average Vehicle Values for Occupancy = 1

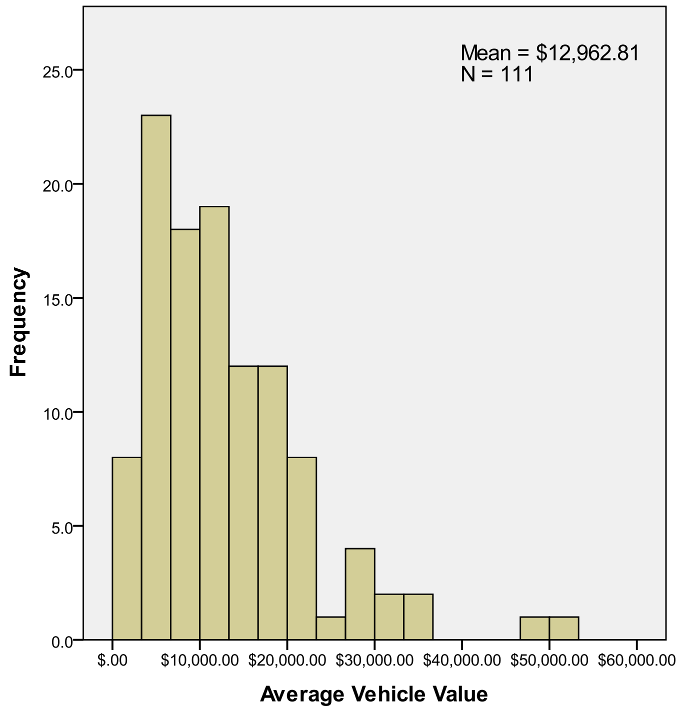


Figure 34: Average Vehicle Values for Occupancy = 1.5

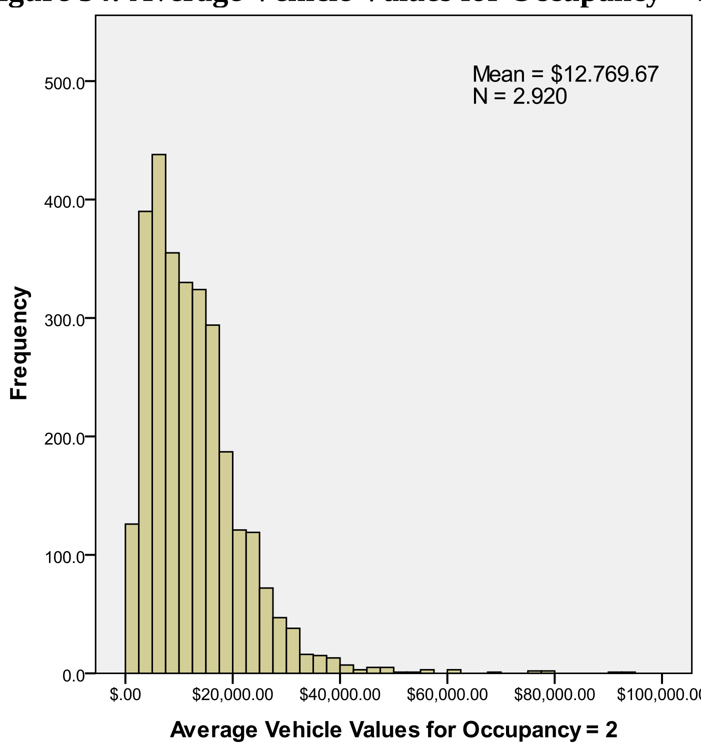


Figure 35: Average Vehicle Values for Occupancy = 2

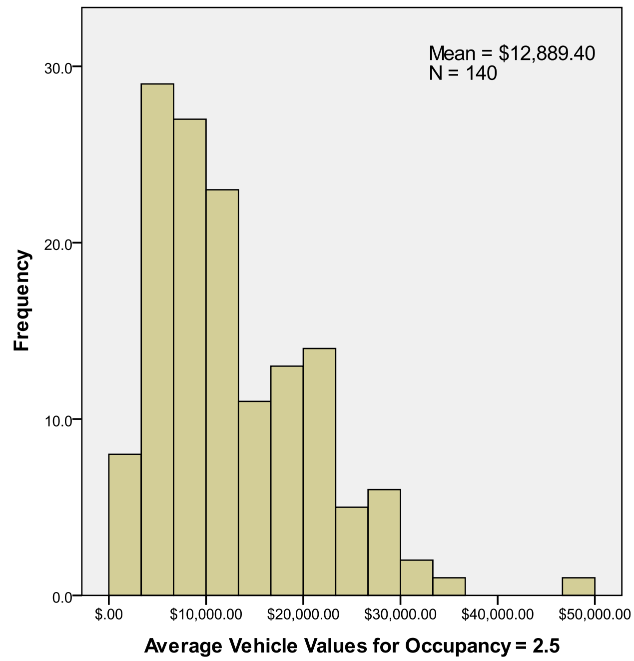


Figure 36: Average Vehicle Values for Occupancy = 2.5

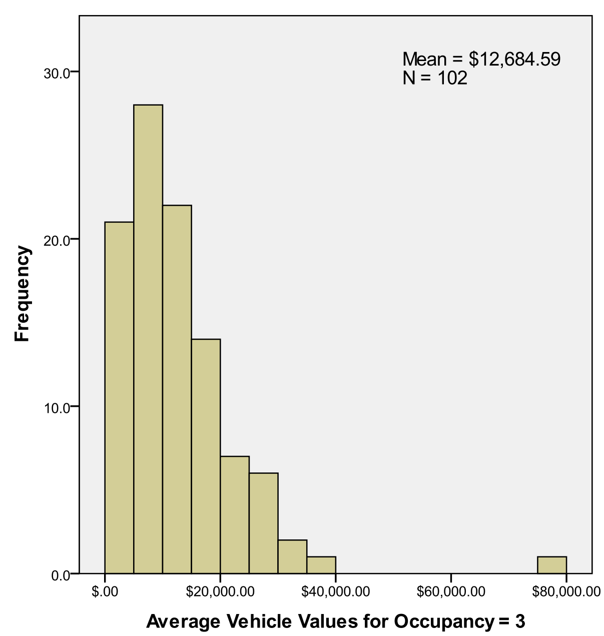


Figure 37: Average Vehicle Values for Occupancy = 3

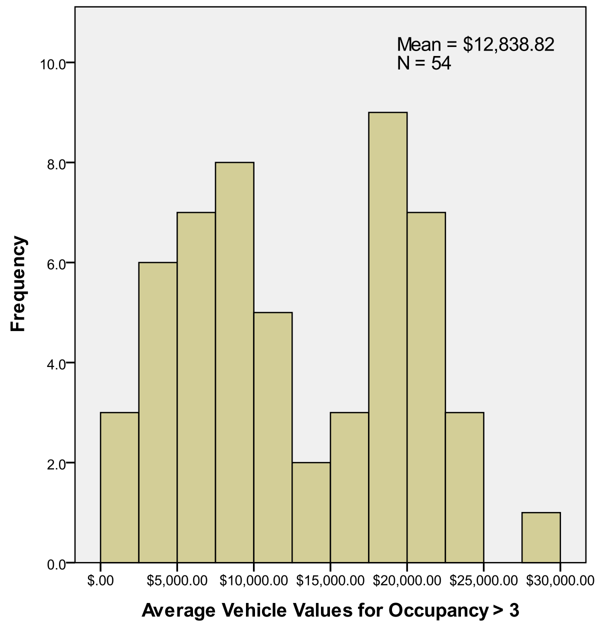


Figure 38: Average Vehicle Values for Occupancy ≥ 3.5

REFERENCES

1. Fuhs, C. and J. Obenberger, *Development of High-Occupancy Vehicle Facilities.* Transportation Research Record, 2002. **1781**: p. 1-9.

2. *Federal-Aid Highway Program Guidance on High-Occupancy Vehicle (HOV) Lanes*, F.H. Administration, Editor. 2008.

3. GDOT, *Plan of Proposed I-85 HOV to HOT Lane Conversion Dekalb and Gwinnett Counties*. 2011, Georgia Department of Transportation: Atlanta, GA.

4. *23 U.S.C. Sec. 166 HOV facilities*. 2011, Office of the Law Revision Counsel, U.S. House of Representatives: Washington, DC.

5. Kwon, J. and P. Varaiya, *Effectiveness of California's High Occupancy (HOV) system.* Transportation Research Record Part C, 2007. **16**: p. 98-115.

6. GDOT. *LUV-the-HOV*. 2010 [cited 2011 October 23]; Available from: http://www.dot.state.ga.us/travelingingeorgia/expresslanes/hovlanes/Pages/LUV-the-HOV.aspx.

7. Guin, A., M. Hunter, and R. Guensler, *Analysis of Reduction in Effective Capacities of High-Occupancy Vehicle Lanes Related to Traffic Behavior.* Transportation Research Record, 2008. **2065**: p. 47-53.

8. Hart, A., *Atlanta traffic: HOT lanes mostly empty on first commute*, in *Atlanta Journal-Constitution*. 2011: Atlanta.

9. Burris, M.W., et al., *Investigating the Impact of Tolls on High-Occupancy-Vehicle Lanes Using Managed Lanes.* Transportation Research Record, 2009. **2099**: p. 113-122.

10. Zuyeva, L., *Equity Issues in HOV-to-HOT Conversion on I-85 North in Atlanta*, in *School of Civil and Environmental Engineering*. 2009, Georgia Institute of Technology: Atlanta.

11. Systan, *Transportation System Management (TSM) Project Violation Rates: Final Report*. 1981, Department of the California Highway Patrol and CALTRANS: Los Altos.

12. Systan, *HOV Lane Violation Study: Final Report*. 1990, California Department of Transportation: Los Altos.

13. Fielding, G.J. and D.B. Klein, *High Occupancy/Toll Lanes: Phasing in Congestion Pricing a Lane at a Time*. 1993, Reason Foundation: Washington, DC. p. 1-11.

14. Teal, R.F., *Carpooling: Who, How and Why.* Transportation Research Record Part A, 1987. **21A**(3): p. 203-214.

15. Chum, G.L. and M.W. Burris, *Potential Mode Shift from Transit to Single-Occupancy Vehicles on a High-Occupancy Toll Lane.* Transportation Research Record, 2008. **2072**: p. 10-19.

16. University_of_Minnesota, *I-394 MnPass: A New Choice for Commuters*. 2006: Minneapolis, MN.

17. Shin, S.W. and M. Hickman, *Effectiveness of the Katy Freeway HOV-Lane Pricing Project.* Transportation Research Record, 1998. **1659**.

18. Ungemah, D.H., *This Land is Your Land, This Land is My Land.* Transportation Research Record, 2007. **2013**: p. 13-20.

19. MnDOT. *MnPass Express Lanes Background*. 2010 [cited 2011 October 23]; Available from: http://www.mnpass.org/394/index.html.

20. SRTA. *Frequently Asked Questions*. 2011 [cited 2011 October 23]; Available from: http://www.peachpass.com/faq.

21. Weinstein, A. and G.-C. Sciara, *Unraveling Equity in HOT Lane Planning.* Journal of Planning Education and Research, 2006. **26**: p. 174-184.

22. GRTA. *Xpress Bus Ticket Information*. 2011 November 2, 2011]; Available from: http://www.grta.org/xpressga/fares.htm.

23. Williams, B., *I-85 Lanes to Change More Than Access Rules*, in *Duluth Patch*. 2011.

24. Ross, C.L., et al., *Section III: Demographic/Travel Profiles*, in *Congestion Pricing Response: Study for Potential Implementation in the Metropolitan Atlanta Area*. 2008, Center for Quality Growth and Regional Development & School of Civil and Environmental Engineering at the Georgia Institute of Technology.

25. GSA. *Alternative Fuel Vehicles (AFVs)*. 2011 October 31, 2011]; Available from: http://www.gsa.gov/portal/content/104442.

26. Gallagher, K.S. and E. Muehlegger, *Giving green to get green? Incentives and consumer adoption of hybrid vehicle technology.* Journal of Environmental Economics and Management, 2011. **61**: p. 1-15.

27. Morrison, D.C. and M. Counts, *Second Report of the High-Occupancy Vehicle Enforcement Task Force*, V.D.o. Transportation, Editor. 2005: Richmond.

28. VDOT. *High Occupancy Vehicle (HOV) Lanes - Rules and FAQs*. 2011 November 2, 2011]; Available from: http://www.virginiadot.org/travel/hov-rulesfaq.asp.

29. Robbins, E., *Cruising Down the HOV Lane: Federal and Local Incentives Steer Drivers to Purchase Hybrid Vehicles.* Villanova Environmental Law Journal, 2009. **20**(1): p. 75-83.

30. Kaffine, D., et al., *Unintended Consequences of Allowing Solo Hybrid Drivers into HOV Lanes: Evidence from the Clean Air Stickers Program in California*, in *World Congress of Environmental and Resource Economists*. 2010: Montreal.

31. Ramish, D., *Government Regulatory Initiatives Encouraging the Development and Sale of Gas/Electric Hybrid Vehicles: Transforming Hybrids from a Curiosity to an Industry Standard.* William & Mary Environmental Law & Policy Review, 2006. **30**(231): p. 231-272.

32. Breiland, C., L. Chu, and H. Benouar. *Operational Effect of Allowing Single Occupant Hybrid Vehicles into High Occupancy Vehicle Lanes*. in *Transportation Research Board Annual Meeting*. 2006. Washington, DC.

33. GDOT. *Alternative Fuel Vehicles (AFV)*. 2010 [cited 2011; Available from: http://dot.ga.gov/travelingingeorgia/hovlanes/Pages/AlternativeFuelVehicles.aspx .

34. Guensler, R., et al., *Evaluation of Transportation-Related Emissions Control Measures for Metropolitan Atlanta*. 2005, Prepared for the Georgia Department of Transportation, Atlanta, GA. Georgia Institute of Technology; Atlanta, GA.

35. Granell, J., *Model Year Distribution and Vehicle Technology Composition of the Onroad Flett as a Function of Vehicle Registration Data and Site Location Characteristics*, in *Civil and Environmental Engineering*. 2002, Georgia Institute of Technology: Atlanta. p. 250.

36. Bachman, W., et al., *Research Needs for Determining Spatially Resolved Subfleet Characteristics.* Transportation Research Record, 1998. **1625**: p. 139-146.

37. Miller, T.L., et al., *Effect of County-Level Income on Vehicle Age Distributions and Emissions.* Transportation Research Record, 2002. **1815**: p. 47-53.

38. Davis, S.C. and L.F. Truett, *An Analysis of the Impact of Sport Utility Vehicles in the United States*. 2000, Oak Ridge National Laboratory: Oak Ridge, Tennessee. p. 1-33.

39. Cervero, R. and B. Griesenbeck, *Factors Influencing Commuting Choices in Suburban Labor Markets: A Case Analysis of Pleasanton, California.* Transportation Research Record Part A, 1987. **22A**(3): p. 151-161.

40. *Transportation: Studies*. 2011 [cited 2011; Available from: http://www.atlantaregional.com/transportation/studies.

41. Wang, T. and C. Chen, *Attitude, Built Environment, and Mode Switchign Behavior*, in *Transportation Research Board 90th Annual Meeting*. 2011, Transportation Research Board: Washington, DC. p. 1-16.

42. Parkany, E., *Can High-Occupancy/Toll Lanes Encourage Carpooling? Case Study of Carpooling Behavior on the 91 Express Lanes.* Transportation Research Record: Journal of the Transportation Research Board, 1999. **1682**(TRB): p. 46-54.

43. Li, J., *Explaining high-occupancy-toll lane use.* Transportation Research Record Part D, 2001. **6**: p. 61-74.

44. Nelson, J.I., et al., *A SocioDemographic Analysis of Northeast Atlanta I-85 Peak Period Commuters Likely to be Affected by Implementation of Value Pricing Along the Corridor,* in *Transportation Research Board 2010 Annual Meeting*. 2010, Transportation Research Board: Washington, DC.

45. D'Ambrosio, K., *Methodology for Collecting Vehicle Occupancy Data on Multi-Lane Interstate Highways*, in *Civil and Environmental Engineering*. 2011, Georgia Institute of Technology.

46. GeorgiaDepartmentofRevenue. *When, where and what is needed to transfer my Georgia license plate to another vehicle I've purchased or acquired?* 2007 [cited 2011 October 7]; Available from: http://motor.etax.dor.ga.gov/motor/registration/tagtransfer.asp.

47. Xu, Y., *Effective GPS-Based Panel Survey Sample Size for Urban Travel Behavior Studies*, in *School of Civil and Environmental Engineering*. 2010, Georgia Institute of Technology: Atlanta.

48. Khoeini, S., et al., *Sensitivity of Commuters' Demographic Characteristics to License Plate Data Collection Specifications: A Case Study for HOV 2 HOT Project in I-85 Corridor*, in *Transportation Research Board Annual Meeting*. 2012: Washington, DC.

49. Rodgers, M.O., *Interview*. 2011.

50. Choo, S. and P.L. Mokhtarian, *What Type of Vehicle Do People Drive? The Role of Attitude and Lifestyle in Influencing Vehicle Type Choice.* Transportation Research Part A, 2004. **38**(3): p. 201-222.

51. Efron, B. and R.J. Tibshirani, *An Introduction to the Bootstrap*. 1993, New York: Chapman & Hall, Inc.

52. Argyrous, G., *Statistics for Research with a Guide to SPSS*. Third ed. 2011, London: SAGE Publications Ltd. 585.