A PROFILE OF CHANGES IN VEHICLE CHARACTERISTICS FOLLOWING THE I-85 HOV-TO-HOT CONVERSION

A Thesis
Presented to
The Academic Faculty

by

David J. Duarte

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

Georgia Institute of Technology
May 2013

A PROFILE OF HOT LANE VEHICLE CHARACTERISTICS ON I-85 POST 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. Jorge A. Laval
School of Civil & Environmental Engineering
Georgia Institute of Technology

Date Approved: April 1, 2013

ACKNOWLEDGEMENTS

I wish to thank everyone who contributed to this thesis. I wish to thank my committee for reviewing this document, which proved to be a huge milestone in my career. I would especially like to thank Dr. Randall Guensler, my advisor, for bringing me on the project as GRA and putting a lot of work to advance his students experience in projects like the HOV-to-HOT conversion.

I wish to thank all my fellow graduate students that I worked with. These individuals made the experience more valuable and I appreciate the time we spent together on a project or in an extracurricular activity. Thank you for all the help I received. Special thanks to Kate D'Ambrosio and Katie Smith for creating a foundation for me to continue in our research field. I also wish to thank the URAs I hired and worked with during my time on the conversion project.

I wish to thank God for giving me the gifts to achieve this milestone. I wish to thank my family for the constant support. A special thanks to Margaret DeGrace for having to put up with my strange work schedule.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF SYMBOLS AND ABBREVIATIONS

BRR	Beaver Ruin Road
CSV	Comma Separated Values
CTR	Chamblee-Tucker Road
GDOT	Georgia Department of Transportation
GP	General Purpose (lanes)
GRA	Graduate Research Assistant
GRTA	Georgia Regional Transportation Authority
GTRI	Georgia Tech Research Institute
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
SRTA	State Road Toll Authority
SUV	Sports Utility Vehicle
URA	Undergraduate Research Assistant

SUMMARY

A 15.5-mile portion of the I-85 high-occupancy vehicle (HOV) lane in the metropolitan area of Atlanta, GA was converted to a high-occupancy toll (HOT) lane as part of a federal demonstration project designed to provide a reliable travel option through this congested corridor. Results from the I-85 demonstration project provided insight into the results that may follow the Georgia Department of Transportation's planned implementation of a $16 billion HOT lane network along metropolitan Atlanta's other major roadways [2]. To evaluate the impacts of the conversion, it was necessary to measure changes in corridor travel speed, reliability, vehicle throughput, passenger throughput, lane weaving, and user demographics. To measure such performance, a monitoring project, led by the Georgia Institute of Technology collected various forms of data through on-site field deployments, GDOT video, and cooperation from the State Road and Toll Authority (SRTA). Changes in the HOT lane's speed, reliability or other performance measure can affect the demographic and vehicle characteristics of those who utilize the corridor. The purpose of this particular study was to analyze the changes to the vehicle characteristics by comparing vehicle occupancy, vehicle classifications, and vehicle registration data to their counterparts from before the HOV-to-HOT conversion.

As part of the monitoring project, the Georgia Tech research team organized a two-year deployment effort to collect data along the corridor during morning and afternoon peak hours. One year of data collection occurred before the conversion date to establish a control and a basis from which to compare any changes. The second year of data collection occurred after the conversion to track those changes and observe the progress of the lane's performance. While on-site, researchers collected data elements including visually-observed vehicle occupancy, license plate numbers, and vehicle classification [25]. The research team obtained vehicle records by submitting the license plate tag entries to a registration database [26]. In previous work, vehicle occupancy data were collected independently of license plate records used to establish the

commuter shed. For the analyses reported in this thesis, license plate data and occupancy data were collected concurrently, providing a link between occupancy records of specific vehicles and relevant demographic characteristics based upon census data. The vehicle records also provided characteristics of the users' vehicles (light-duty vehicle vs. sport utility vehicle, model year, etc.) that the researchers aggregated to identify general trends in fleet characteristics.

The analysis reported in this thesis focuses on identifying changes in vehicle characteristics that resulted from the HOV-to-HOT conversion. The data collected from post-conversion are compared to pre-conversion data, revealing changes in vehicle characteristics and occupancy distributions that most likely resulted from the implementation of the HOT lane. Plausible reasons affecting the vehicle characteristics alterations will be identified and further demographic research will enhance the data currently available to better pinpoint the cause and effect relationship between implementation and the current status of the I-85 corridor.

Preliminary data collection outliers were identified by using vehicle occupancy data. However, future analysis will reveal the degree of their impact on the project as a whole. Matched occupancy and license plate data revealed vehicle characteristics for HOT lane users as well as indications that the tested data collectors are predominantly synchronized when concurrently collecting data, resulting in an argument to uphold the validity of the data collection methods.

Chapter two provides reasons for why HOT lanes were sought out to replace I-85's HOV lanes. Chapter two will also provide many details regarding how the HOT lanes function and it will describe the role the Georgia Institute of Technology played in the assessment the HOV-to-HOT conversion. Chapter three includes the methodologies used to complete this document while chapter four provides results and analysis for the one year period before the conversion and the one year period after the conversion.

CHAPTER 1: INTRODUCTION

Before October 2011, Atlanta maintained a continuous segment of High Occupancy Vehicle (HOV) lanes along the I-85 corridor, one lane per direction. HOV lanes were first conceived in 1969 [18] and have been used since then as a method to manage and improve a facility's effective capacity, travel time, emissions, service reliability, and vehicle occupancy [13] by restricting the lane to vehicles to a minimum amount of passengers, typically two or three passengers.

Over the past 40 years, the built environment and how we travel around it has greatly changed. Many issues like congestion, fuel prices, climate change, environmental concerns, and funding constraints have led to discussions and initiatives to improve upon our transportation system. Funding has slowly evolved into one of the most difficult challenges. A lack of financial resources can postpone any project, even one that is cost effective. It is believed that the current funding mechanism will not serve the U.S's needs as we move into the future [14]. Organizations are looking to adapt to leaner budgets and it is essential for them to systematically prioritize any available funds and implement the most cost effective projects as well as rate their performance to improve them during future opportunities.

High Occupancy/Toll (HOT) lanes are an alternative to HOV lanes in an attempt to more efficiently manage highway traffic while taking into consideration recent funding complications. HOT lanes are similar to HOV lanes but they allow single-occupant vehicles to utilize the facility for a price that is paid through a toll while high-occupant vehicles are either toll-exempt or pay a reduced toll. HOT lanes provide a set of potential benefits that HOV lanes could otherwise not provide. The potential benefits include a source of revenue to fund highway management initiatives and an increased ability to provide reliable travel times [32].

HOT lanes are a viable traffic management option as nine states have implemented at least one of these facilities since 1995. The nine states include California, Colorado, Florida, Georgia, Minnesota, Texas, Utah, Virginia, and Washington [34]. Additional facilities are being opened in many of these same states. Also, the facilities already open to the public are constantly being expanded across more roadway. For example, GDOT has selected the I-75 corridor as a potential location for a new HOT lane facility in Georgia while also having the desire to expand the current I-85 HOT lanes for another additional 11 miles [33]. These new toll lane facilities would form part of a network that GDOT plans to implement.

Atlanta faces many of the same issues that are constricting the transportation systems of metropolitan areas countrywide. Atlanta, seen as an effective and thriving transportation hub thanks to the Hartsfield-Jackson International Airport is also viewed as a city with severe traffic congestion along its heavily used commuter routes. Metropolitan authorities have looked to improve their current managed lane footprint to meet capacity demands and saw HOT lanes as the most feasible option. However, each region is different and all the regional authorities implemented each HOT lane facility differently so despite success in other areas, it does not translate into immediate success for Atlanta. Therefore, it was essential for stakeholders to assess if the lanes worked as intended. This thesis uses portions of the data that will assess whether the lanes were a success.

Substantial quantities of documents have been written about managed lanes and there is no lack of examples pertaining to the lanes on the I-85 corridor. Studies have pinpointed deficiencies in the HOV system while other works have already turned to HOT lanes as the most manageable and feasible strategy. Previous work has also built the foundation to outline the procedure to collect data and quantify the performance of High Occupancy/Toll lanes.

CHAPTER 2: LITERATURE REVIEW

2.1 HOV Lane Inadequacy

When HOV lanes operate as intended, they provide an incentive for carpooling, reducing the number of vehicles using a facility and therefore the resulting congestion on the general purpose lanes. From a policy perspective, the benefits resulting from the lane's incentive for carpool formation and congestion reduction needs to outweigh the potential decline in capacity [12]. HOV lanes run the risk of reducing vehicle capacity and person throughput if the lane is underutilized during peak congestion periods. On the other hand, when demand for a carpool lane exceeds the capacity of the lane, such as was observed on the I-85 corridor [19], the resulting congestion on the HOV lane negates the incentive for carpool use. These congested periods on the I-85 corridor were shorter than the congestion periods in the general purpose lanes, but still long enough to alter the reliability of the lane [19]. This congestion could partially be attributed to the excess demand for vehicles carrying at least two passengers, as also indicated in Ross, et al., 2008 [29]. The HOV lane may have already served its purpose of raising vehicle occupancy but there is no longer any time-savings incentive for people to continue consolidating and using fewer vehicles. While potential benefits might result from raising the required carpool occupancy to 3 persons per vehicle, previous experience in Texas indicates that such a change would significantly reduce carpool demand, potentially resulting in the lane changing from being over-utilized to being under-utilized. In addition, it is unclear whether the HOV lane's person throughput would improve, given the high degree of "Fampooling" suspected of occurring where previous studies have indicated that as many as 43% of carpoolers are related household members [20]. Therefore, it is important for future studies to have more detailed research in this subject area.

2.1.1 Occupancy Violation

The effectiveness of HOV lanes has also been questioned in previous studies due to the level of vehicle occupancy violations [17]. Single Occupant Vehicles, except for specific exempted vehicles, were not allowed to use the I-85 HOV lane, but according to a study by Smith, the violation rate on the HOV lanes was found to be significant with 15% being single-occupant vehicles (SOVs) and another 9.5% of vehicles who were possible violators [17]. Possible violators were vehicles identified as having at least one occupant. Motorcycles were found to only be 1-2% of vehicles on the I-85 HOV study corridor [17]. Violation rates do not solely impact the Atlanta metropolitan area, another study done in California revealed that violation rates can vary between 5% and 32% with ticketed violation rates only between 1.5% and 2.8% [21]. It was very possible that such violation rates are high enough to worsen congestion to a point where the lane began to break down. Simply said, these SOVs can potentially push traffic beyond capacity. It could prove costly to increase enforcement to a point where violation would diminish completely given current low observed apprehension rates. In the same California study, one of the freeways that only allowed carpools of 3 people or more to use HOV lane had one of the higher violation rates. Violation rates were between 25% and 35% because users found it difficult to form a 3-person carpool and instead chose to violate the HOV restriction [21].

2.1.2 Illegal Weaving

Weaving reduces effective capacity and leads to congestion forming at lower traffic volumes because it creates a bottleneck that reduces the flow of traffic. Limiting weaving zones within HOV or HOT lanes is important to restrict the occasions where users complete a weaving maneuver. It is exemplary design to try to concentrate weaving in specific locations and spread weaving over sufficient distances so as to increase flow and reduce bottleneck effects. Enforcement related to illegal weaving activities is difficult to maintain and it is an issue that hinders HOV lanes from being utilized to their full extent. The HOV lanes in the Atlanta area are not barrier-separated from the general purpose lanes, which may result in HOV and HOT lane users being less willing to allow a large speed differential to exist between their lane and the adjacent general purpose lane. A large speed differential involves a level of risk due to the danger if any general purpose vehicle were to merge on to the managed lane last minute [19]. This unwillingness may cause vehicles to drive slower than the speed they would otherwise desire.

In prior decades, a possible effort to mitigate Atlanta's congestion would have been to construct additional lanes, but it was apparent that this form of capacity addition was no longer a feasible prospect to keep up with the evolving nature of transportation needs. For this and any aforementioned reason, authorities in Atlanta decided to take a step forward and implement a new strategy.

2.2 I-85 High Occupancy/Toll Lane

To ensure the healthy performance of a congestion mitigation strategy, manage the rising concern of vehicle emissions, and to enforce the federally mandated requirement of maintaining vehicles at 45 mph, GDOT along with SRTA converted a 15.5-mile stretch of the HOV lane on the I-85 corridor into a High Occupancy/Toll (HOT) lane. A HOT lane is a type of managed lane that has proven to provide transportation agencies around the country with a relatively inexpensive option where demand can be constrained by price to meet various goals like improved traffic conditions in all lanes, including the general purpose lanes [17] [11]. **Error! Reference source not found.** locates the study corridor in relation to the other metropolitan area highways that may undergo similar conversion projects.

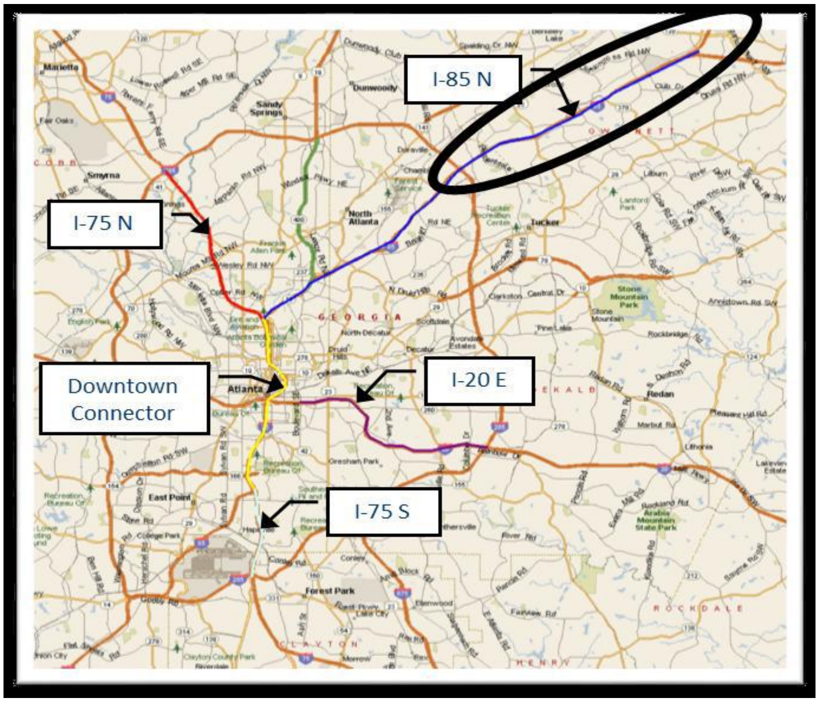


Figure 1: Study Corridor Location [25]

All users are required to obtain a PeachPass Radio Frequency Identification tag for their vehicle. Drivers can establish their the primary commute mode for their account as a payment mode, in which case they will pay a congestion-based toll, or carpool mode, in which they operate a 3-person carpool and travel for free. Users may change their Identification tag mode by using a variety of methods including internet webpage and direct phone call before they begin their trip. Consult sections 2.2.3.1 and 2.4 for the toll-setting process and its evolution after the HOT lanes opened.

2.2.1 Transit on HOT Lane

Transit buses are toll-exempt vehicles because the partnering metropolitan area authorities along with the U.S. Department of Transportation combined the HOT lane conversion initiative with a project to add more commuter buses and bus amenities [1]. This transit project aims to provide a reliable service to as many users as possible to encourage bus ridership and reduce congestion. Users of these express buses do not pay the toll but they enjoy the improved transit travel time. The lane was expected to improve travel time because of the dynamic nature of the toll's price.

Economic equity is a potential concern but anyone, including a non-transit user, is allowed to use the lane. According to a study in South Florida, an HOT lane's benefits were not divided along demographic boundaries [11]. A study from Houston concluded that very few transit users (1% to 2%) would ride in their personal vehicle after HOT implementation [22]. Other metropolitan areas also presented results with little to no adverse effects regarding their transit use after implementing a new toll lane system. The I-394 system in Minneapolis and the I-25 system in Denver saw no drop in transit ridership with Minneapolis experiencing an increase [22]. In Atlanta, authorities were prepared to see an increase in ridership.

2.2.2 Alternative Fuel Vehicles on HOT Lane

Alternative Fuel Vehicles (AFVs) are also toll-exempt. Although hybrids are AFVs [23], they are not toll-exempt because a vehicle is required to be solely powered by electricity, hydrogen, natural gas, biofuel, propane, fuel cell, or other miscellaneous alternative fuels to use the lane for free [17]. Other states have implemented programs where hybrids are allowed to use the HOV lane [24] but many issues prevent this from being a program of interest for Atlanta [7].

2.2.3 HOT Lane Features

Authorities chose the segment slightly south of I-285 and slightly north of the intersection between State Route 316 and I-85 because of the severe congestion conditions. Outside of this 15.5 mile corridor, the managed lane was not functionally altered by the authorities.

2.2.3.1 Toll Price

Gena Evans, executive director of SRTA, recognizes that the HOT lane is an "all-electronic commuting choice" that will provide for a more reliable option [15]. As the amount of users increases at a given time, SRTA assigns a higher price to the time-savings that the HOT provides. As the price continues to rise, this discourages too many users from entering the lane and causing it to surpass capacity. This control will give SRTA the ability to maintain an optimum level of reliability. The resulting price is reflected on digital signs all along this corridor, which drivers will view and use to make a decision to either use the lane or remain on a general purpose lane. Once a user begins to use the lane, the price at their entry point is constant throughout the entire trip until the user exits the HOT lane [3]. This price rate stability attempts to comfort users by demonstrating that there was no intention to exploit the consumer. Figure 2 displays a sample sign.

Figure 2: HOT Entrance Sign [3]

<u>2.2.3.2 Pricing and Weaving</u>

The 15.5 mile stretch is divided into local entrances and exits where vehicles are allowed to weave into or out of the HOT lane. A vehicle that enters the I-85 HOT corridor views both the price to the closest local exit and the final exit. A user that only desires to use half of the corridor may use one of the local exits and will only pay for the extent that they utilized the lane. The conversion consisted of reducing the amount of entrance and exit weaving segments (where the double solid white line striping turns into skipped line striping) and establishing a new enforcement methodology to promote a safer way for the vehicles to maintain an efficient and desired speed [28][16].

2.3 Georgia Tech Research Activities

To measure some of the performance measures of the HOT lane, GDOT entrusted the Georgia Institute of Technology (Georgia Tech) with the Effective Capacity Analysis and Traffic Data Collection for the I-85 HOV to HOT Conversion project. The institute deployed a research team of faculty, post-docs, graduate students, and undergraduate students to collect various forms of data. Graduate Research Assistants (GRAs) refer to graduate students that are funded under an assistantship. Undergraduate Research Assistants (URAs) refer to undergraduate students and graduate students that are paid hourly and do not necessarily have a major in an academic field directly relates to transportation or civil engineering. The data collection schedule was split into quarters named after the seasons (fall, winter, etc.), but was also dependent of the Georgia Tech school calendar so as to accommodate students' schedules. Data collection began in fall 2010 following various preparations and testing of equipment. In previous efforts, researchers used binoculars and voice recorders to obtain license plate records [25]. This equipment was replaced by high definition video cameras that would capture video of the license plates and could be used for playback later in the laboratory. The methodology for collecting vehicle occupancy evolved throughout the study, with preliminary results indicating areas for improvement. These alterations are noted in section 2.3.2 Data Collection Methodology Updates.

2.3.1 Data Collection Methodology

The research team collected occupancy and license plate data for various days (exact days depended on the site, the weather conditions, and varying research needs) during the peak morning and afternoon times along the peak direction for two hours. Morning commute (AM) sessions occurred from 7:00 AM until 9:00 AM while afternoon commute (PM) sessions occurred from 4:30 PM until 6:30 PM. Along this corridor, the AM peak direction was southbound and the PM peak direction was northbound. When the conversion monitoring began in 2010, Monday through Thursday were the days utilized to conduct field data collection. After analysis of the first quarter data, the team assessed that data collection from Tuesday through

Thursday would be employed thereafter. Typically, a quarter of data collection consisted of five to six weeks of activity, and each week focused on a different deployment site. At the end of the study period, deployments usually occurred only on Tuesdays and Thursdays because the Wednesday sessions were revealing no additional variability and were deemed unnecessary in a study by Khoeini [26]. However, the days when the team deployed depended on weather conditions and scheduling conflicts, so Tuesday, Wednesday, and Thursday became interchangeable collection days.

2.3.1.1 Data Collection Sites

The research team analyzed possible data collection site locations and these efforts resulted in five sites, each associated with a highway exit. Exit 94: Chamblee Tucker Road (CTR) was the most southern and a U-turn bridge prevented data collection on its southern side so the team only deployed to this site for the PM periods. Exits 99, 102, and 104: Jimmy Carter Boulevard (JCB), Beaver Ruin Road (BRR), and Pleasant Hill Road (PHR), respectively, were considered to be very similar in regards to occupancy distributions [26]. Exit 109: Old Peachtree Road (OPR) was the most northern site and was different from the other sites because users moving northbound along the corridor split at the State Route 316 interchange. The user characteristics on the two freeways north of freeway split are different. When observing the peak direction in the mornings, the southbound interchange was a source of congestion due to the sheer volumes merging together. OPR and CTR were very important data collection sites because they were either HOT corridor entrances or exits depending on the time of day. OPR, however, was additionally significant because of the potential difference in demographic characteristics among HOT users entering from OPR and those entering from SR 316.

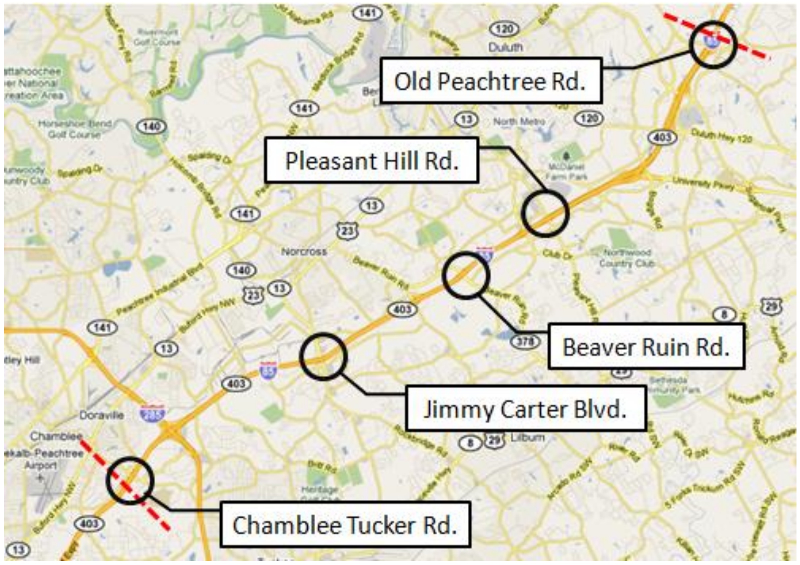


Figure 3: Data Collection Site Location [25]

2.3.1.2 Field Deployment

When deployed, the research team divided into two teams; one collected vehicle occupancy data by visual inspection using an electronic keypad and netbook interface, the other set up high definition cameras to capture videos of the peak direction vehicles and their license plates. Various precautions are taken before and during deployment for safety and liability concerns. All researchers were required to wear a high visibility vest in the field and follow several safety guidelines. Local police authorities were notified of deployment, emergency contact information was brought to the site, and supplies like water and sun block were packaged into a field kit in case they were needed.

2.3.1.2.1 Occupancy Group

A thesis written by D'Ambrosio, "Methodology For Collecting Vehicle Occupancy Data On Multi-Lane Interstate Highways: A GA 400 Case Study," explains the process used to arrive to at the collection methodology in great detail [25]. The data collectors in the vehicle occupancy group sat in the gore area close enough where they could visually inspect each vehicle, but not too close so as to compromise their safety. Data collectors recorded each vehicle's occupancy value, preceded by a simple vehicle classification into a netbook using a customized keypad. An image of the customized keypad's interface is in Figure 4. The vehicle classifications were divided into three categories: LDV for Light Duty Vehicle, SUV for Sports Utility Vehicle and HDV for Heavy Duty Vehicle. Light duty vehicles included passenger cars, hatchbacks, and station wagons; the SUV category included pick-up trucks, crossover vehicles, all sizes of sport utility vehicles, multi-purpose vehicles, and vans. Heavy duty vehicles included large trucks (from panel utility trucks to multi-trailer trucks) and buses. The data collector was required to press a classification button and then an occupancy value; otherwise, an error is recorded. The researcher was notified of a potential error visually as well as audibly. Researchers typically wore ear-bud headphones to hear these notifications due to traffic levels.

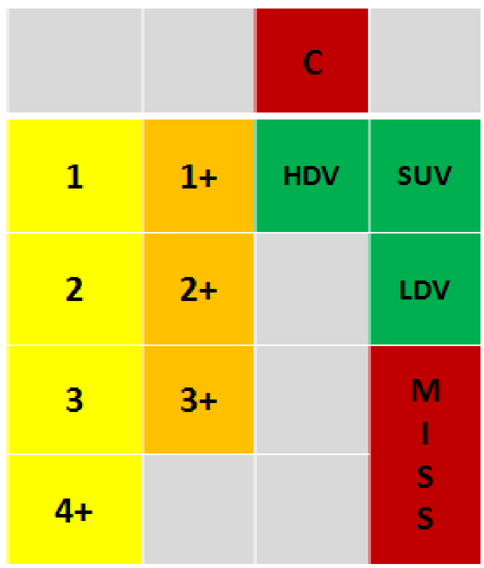


Figure 4: Keypad Configuration for Occupancy Data Collection [25]

2.3.1.2.2 Occupancy Values

The keypad contained three discrete occupancy value buttons: 1, 2, and 3. There were also uncertain values that consisted of these same numbers with a "+" following the digit (e.g. 1+). These values were used for vehicles that, due to visual constraints, could not be assigned a certain occupancy value. If a vehicle has dark tinted windows, an URA was instructed to press "1+" because they knew that the vehicle at the very least carried a driver but they were uncertain if there were additional passengers. Similarly, if the data collector could see two persons in the front seat but could not see into the rear seat, they were instructed to press “2+.” The “4+” button was used when there were at least 4 individuals in a particular vehicle. In the case of transit buses, a bus observation was typically recorded by assigning it a HDV “4+” classification. At times, vehicle speed, light conditions, or vehicle occlusion prevented a researcher from having the opportunity to view the interior of a vehicle. For those occasions, the URA was instructed to press the “Miss” keypad button, which allocated a place marker within the stream of data so that researchers analyzing this data would know that a vehicle was observed but its occupancy or vehicle class was not. Lastly, when the “C” button was pushed, it earmarked the previous entry as being erroneous. A programming script recoded the researcher’s button presses into values in a Comma Separated Values (CSV) file format that were later analyzed.

2.3.1.2.3 Lane Assignment

One Undergraduate Research Assistant (URA) was assigned per lane, except for instances when the research team assigned two URAs to a lane to compare the results for purposes of quality assurance and data reliability. Since Spring 2011, the research team deployed two URAs to record occupancy on the HOT lane. Also, the occupancy team set up a high definition camera to record the researchers’ point of view from the gore area. This methodology update was added so that two HOV lane occupancy data streams could be matched and compared for Smith’s thesis, “A Profile of HOV Lane Vehicle Characteristics on I-85 Prior to HOV-To-HOT Conversion” [17]. A detailed description of the matching process is found in section 3.3 Matching Methodology and additional information referencing all the changes to methodology are in section 2.3.2 Data Collection Methodology Updates. When the research team first employed the parallel occupancy study, there were worries that the URAs would collect data more carefully because they knew they were being compared. An experiment was conducted where four URAs were assigned to the same lane without either of them knowing. Results showed that they all had similar proportions for each occupancy category [17].

During any session when the research group lacked the human resources necessary to field a full team of researchers: a URA for every lane and two for the HOT lane, the second URA doing the parallel study would move to another lane. For this reason, not all data collection sessions had two data streams from the HOT lane. However, it was common to have enough human resources to field a team that included two HOV/HOT data recorders. In fall 2011, an experienced set of URAs were asked to perform supervisory duties to ensure fewer issues during field data collection. All sites except for OPR have 6 lanes; therefore, the vehicle occupancy research group typically consisted of 6 – 10 URAs. OPR has five lanes because it was past the point where SR 316 deviates from I-85.

2.3.1.2.4 License Plate Group

The data collectors on the video camera team capturing license plates sat atop the overpass to ensure the safety of the expensive equipment. Four high definition cameras were set up in the peak direction. Additional equipment taken with the cameras included batteries, SD cards, and tripods. A camera was set up for every two lanes and the fourth camera recorded a general view of the corridor facing the same direction as the other cameras. The lanes are assigned a number, 0 for the HOV or HOT lane, which are the leftmost lanes, and the remaining general purpose lanes were identified as lanes 1 through 5 from left to right (fast lane to slow lane). The rightmost lane at PHR was Lane 5 while the rightmost lane was Lane 4 at OPR. Figure 5 illustrates the numbering scheme. At most sites, a camera was set up for lanes 0 and 1, 2 and 3, and 4 and 5. At OPR, The rightmost camera solely covers lane 4. The researchers focused the cameras on a specific point on the highway where the video would clearly display each license plate for each of the vehicles in both lanes.

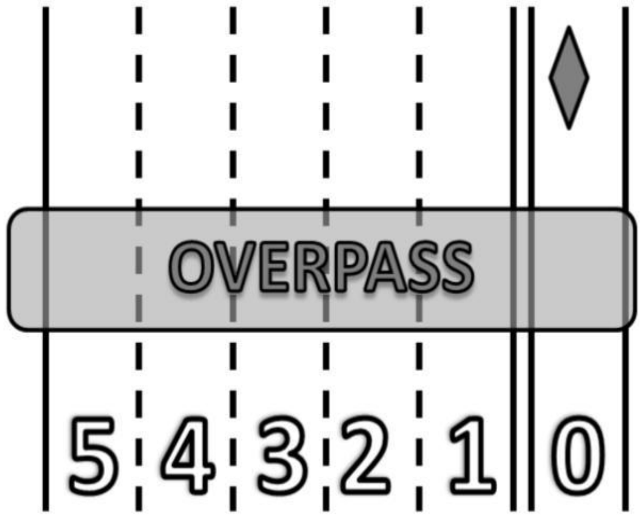


Figure 5: Lane Number Configuration [25]

2.3.1.3 Video Processing for License Plates

Two frames were extracted from every second of the overpass lane video and placed into a proprietary data processing program used by the URAs. These students viewed the sequential frames and manually recorded the alphanumeric license plates into the program. This step of the data collection was coined as Video Processing, irrespective of the fact that the program used images extracted from the video rather than the video itself. Researchers accessed the program at Georgia Tech Civil Engineering computer labs where they could flexibly work on images without a schedule dictating their working hours. The program data entry screens include entry forms for recording vehicle classification, the state of the vehicle plate, and a comment field for use by GRAs to report vehicle-specific issues. At times, the license plates in the video frames were difficult to decipher because of the ambient conditions. For example, low levels of light, sunlight at a glaring angle, or occlusion by trailer hitches prevented the researcher from transcribing license plate digits. When a URA could not accurately transcribe the data, they were instructed to record that vehicle with an “M” for missed. For missed vehicles, and for license plates from a state other than Georgia, data processors were instructed to classify the vehicle using a list of various vehicle types so that at least the vehicle classification would be known for illegible and out-of-state license plates.

2.3.1.4 Post-Video Processing

Once an entire quarter's worth of video frames were processed, each license plate entry was sorted, cleaned (removal missed license plates, missed state tags, and out-of-state tags), assigned a unique key identifier, and sent to the Georgia Tech Research Institute (GTRI) for processing. The plate data were linked to the motor vehicle registration database [17], which contains vehicle ownership names and registration household address. To ensure privacy protection, GTRI processed the plate data remotely and only returned the census block group ID of the registration address, ensuring that no personally identifiable information would be transmitted. Vehicle make, model, model year, and body style were also obtained so that vehicles could be classified accordingly. Not all license plates sent to this database were correct and, therefore, some license plate entries either returned either no information or erroneous information. Correct license plates are not expected to always return accurate household census block identification or vehicle information because: 1) the registration database contains errors, 2) some license plates were previously assigned to different vehicles, and 3) vehicles may be registered to the incorrect address for insurance purposes. In Georgia, a license plate stays with the user instead of the vehicle [27]. With respect to vehicle classification errors, problems can only be identified when researchers verified license plate information for quality assurance during matching efforts. To prepare for matching efforts, the license plate information from the database was compiled with the missed license plates and the out-of-state tags to form a complete list of license plate records that utilized the corridor.

2.3.2 Data Collection Methodology Updates

A bulk of the data collection methodology was prepared by researchers prior to fall 2010.However, the research team regularly altered the data collection plan. Vehicle occupancy data collectors' names became a required input after the Fall 2010 quarter. The team added an extra URA on lane 0 during the Spring 2011 quarter, added a supervisor to each data collection session in Fall 2011, and for the Summer 2012 quarter, researchers attempted to add two more

URAs per session where each one would observe a general purpose lane simultaneously with another researcher to obtain parallel occupancy data that could later be used to match records other than just those in the managed lane. As previously mentioned, the parallel occupancy study analysis done in this thesis used matching methodologies very similar to those conducted in D'Ambrosio's and Smith's studies [25] [17].

Smith concluded that the researchers typically had a preference regarding on what lane they collected occupancy data, adding a potential for data collection bias [17]. For this reason a rotation system was implemented. URAs were rotated through the lanes with the exception of the HOT lane, because at least one experienced URA was always assigned to that lane. New URAs were hired during every Georgia Tech school semester (Fall, Spring, Summer), meaning that new researchers joined the group nearly every quarter. During Fall 2011, hiring methods were changed to recruit a more balanced group of graduate and undergraduate students. Therefore, the research team consisted of many more graduate students after Fall 2011 than prior to that quarter. Another methodology change involved reducing the quantity of data collection sessions. Six sessions per quarter (one AM and one PM from the three centrally located sites) were removed from the deployment plan because Khoeini concluded that the data were sufficiently consistent that it was wasteful of limited resources to continue having as many deployments to the same site [26].

2.4 Initial HOT Lane Performance and Reactions

Immediately after implementation of the HOT lane on October 2nd, 2011, the entire region witnessed the significant performance issues via news media reporting. Initial HOT lane performance results were not desirable as the lane remained predominantly under-utilized. This was an expected result because previous HOT implementation in other metropolitan areas had been successful. Unfortunately, Peach Pass acquisition rates by the traveling public were low prior to project implementation. Acquisition rose significantly over the first few months of lane implementation [30]. From November 2011 to March 2012, the number of issued Peach Pass transponders grew from 100,000 to 150,000 (**Error! Reference source not found.**). HOT lane vehicle volume also rose significantly as more and more I-85 users obtained a Pass and saw the potential time-savings benefit that the lane offered. However, the media did not hesitate to portray disappointing images of an under-utilized HOT lane and general purpose congestion conditions that were worse than before conversion. A national toll publication considered the HOT lane commencement to be the "rockiest start yet of any of the congestion pricing projects around the country" [6].

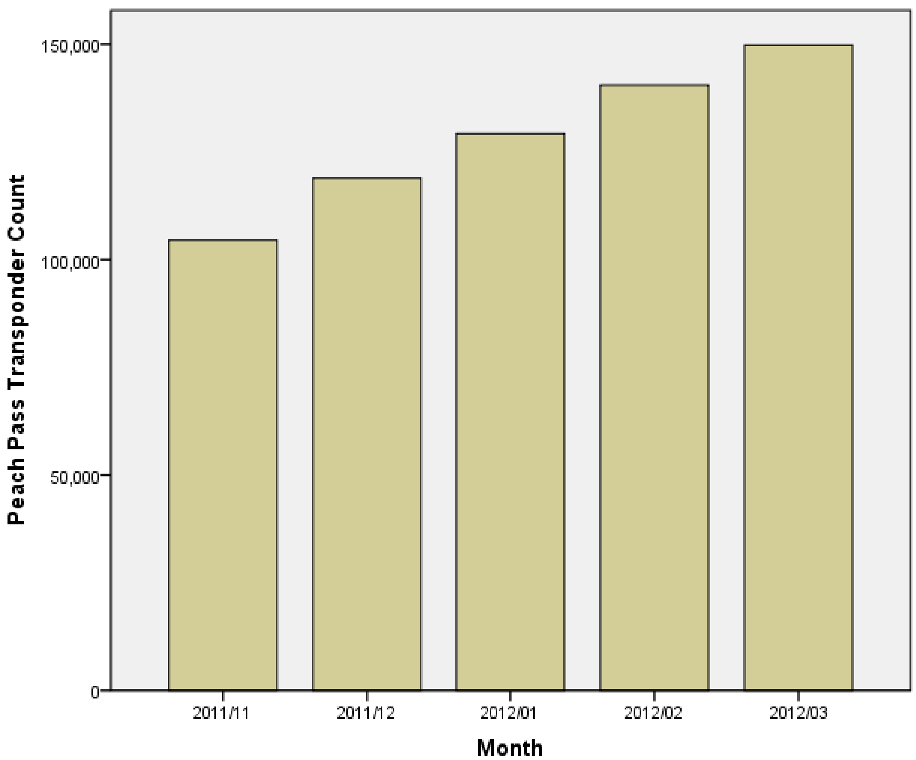


Figure 6: Peach Pass Transponder Count from November 2011 - March 2012 [30]

After the fourth day of implementation, Governor Nathan Deal intervened and lowered the price ceiling on the toll to calm the public and address complaints that he received from various constituents. At that time, HOT lane pricing policy included a minimum price of 10 cents per mile and a maximum price of 90 cents per mile [3]. At the time right before Governor Deal's intervention, the price to use the lane for the entire corridor had risen to $5.50, which represented a per-mile price of 34 cents. Governor Deal lowered the price temporarily to $3.05, which represents a per-mile price of 19 cents [5]. Gena Evans defended SRTA's management of the lane by claiming that they were actively changing the algorithm, which had an issue with the way it weighed current traffic conditions [6]. In the end, various authorities all played a part in influencing the management of the HOT lane causing significant results, but it was difficult to measure just how influential these results may have been in the long term.

2.4.1 Months after Implementation

As the one year anniversary of the conversion has come and passed, the HOT lane has come far from its controversial beginnings. In reality, only a few months were necessary to see a significant amount of improvement regarding volume and revenue performance. On February 28th, the 15.5 mile stretch hit a four month maximum price of $4.75 [8]. At this point, the toll price was not a factor of political intervention, but a testament to the time-savings benefit that the HOT lane rendered to its users. By the following day, February 29th, the state had issued more than 138,000 Peach Passes. On weekdays, HOT lane traffic nearly always exceeded 10,000 trips, and on some days it approached 17,000 trips [2]. However, authorities believed there was still room for improvement. As recently as January, SRTA's governing board lowered the minimum per mile price from 10 cents to 1 cent [10]. The purpose of this reduction was to promote lane usage during off-peak times. The capacity provided by the lane was not really needed during the off peak, but drivers may have appreciated the reduction in traffic density on the general purpose lanes. In March, weekday trips averaged 16.8 thousand, which was 2.3 times greater than the figure seen in October 2011 [9]. The lane was gaining an increased user base, but according to a study by Sheikh, the May 2012 SRTA data indicates that 10% of the HOT lane users account for more than 50% of the total lane trips [31]. These users account for all vehicles including those owned by the government and commercial users, which slightly biased the data due to the nature of their trips. Many of these vehicles regularly transported three or more individuals so they were toll-exempt. Despite not paying a toll, these vehicles had the potential to increase the person throughput and accomplish one of the metropolitan area's goals.

However, it has been difficult to assess the extent to which toll-exempt vehicles, such as transit buses and vanpools, benefitted from the lane conversion because the calculation of an accurate performance measure was still in development. A comprehensive data collection plan was used to collect the necessary data following the HOV-to-HOT conversion for vanpools while data for transit buses was more directly accessible [4]. The results for the research team's findings are found in sections 3.2.5 Buses and Vanpools and section 4.2.3.5 Transit Presence in Matching.

CHAPTER 3: METHODOLOGY

3.1 Creating a User Profile

In the months before the HOV-to-HOT conversion occurred on the I-85 metro Atlanta corridor, Smith carried out a study that established a profile of HOV lane users in an effort to provide greater knowledge related to revealed lane use preference. A managed lane, like the HOT lane, required sufficient time after implementation for users' travel behavior to equilibrate. Demographic characteristics of the lane users may vary depending on the operating conditions of the lanes. Now, after more than a year past the implementation of the HOT lane a new profile of vehicle characteristics may be observed. This was done by analyzing occupancy data, reviewing license plate data inputted by the research team as well as demographic information developed from registration census block group information received from GTRI, and finally by matching records from the vehicle occupancy data streams to the license plate and demographic data.

3.2 Managing Occupancy Data

Occupancy distributions were prepared and analyzed to look for trends, changes in averages, and anomalies within each quarter's data set. An analysis of the occupancy distributions across different variables indicated that there was little variability in the occupancy observed on a day to day basis along the I-85 corridor. There were strong similarities in occupancy and license plate data collection distributions for sessions that had similar characteristics. For example, JCB AM and PHR AM had similar distributions because they were data collection sessions located at sites with similar characteristics and both were collected during the morning time period. On the other hand, contradicting attributes for these variables produced distinct trends in the data and were taken into account when bias or poor data collector performance could be identified. A study identified that the three days when the research team collected data did not significantly differ from one another in a demographic sense [26]. Therefore, from that point forward the research team reduced the amount of field deployments by attending each of the middle sites for fewer days. This congruence signified that weekday was not a significant variable as long as only Tuesdays through Thursdays were used. There was no change in regard to the frequency of AM or PM deployments because morning and afternoon peak periods were different due to the highly contrasting trip purposes for those times of day. This study also stated that the three sites located geographically in the middle of the corridor (JCB, BRR, PHR) were similar when comparing their occupancy data, which resulted in site location being one of the important variables.

3.2.1 Identifying Poor Data Collector Performance

Having the level of variable variability in mind, the research team identified outliers from the occupancy distribution. The most important purpose was to flag this data and later remove it if it posed a significant effect on the overall results. Another purpose was to evaluate URA performance and reinstruct them if it was necessary. Researchers identified certain URAs that had tendencies toward over or under using an occupancy value. The “1”, “1+”, “2”, “2+” values were the most commonly misused. A few URAs also had consistent overuse of the “Miss” button, which suggested researchers to question that URA’s data further. The research team compared the vehicle occupancy distributions by lane, session, site, and time period to identify potential outliers.

Researchers responsible for the data anomalies were notified immediately so that they could receive additional training or re-assess their personal interpretation of the research methods. Researchers that were newer to the project, despite training, found it difficult to adapt to the research team’s expectations and often needed retraining. Typically, URAs improved their performance by either fully understanding the purpose and significance of the uncertain values or realizing that they were under an erroneous conception of how they were supposed to record their observations. It was critical for the research team to flag these URAs’ data in an attempt to prevent their recurrent anomalous data from biasing the overall results.

In the winter 2011 quarter, the research team collected 338,240 occupancy records. Of the 41 URAs that collected occupancy during the winter quarter, 12 of those URAs were flagged due to abnormally high rates of uncertain occupancy values. This left the winter 2012 data with 262,830 entries representing 77.71% of the original sample set. URA data were considered to be outliers if their averages for particular occupancy values were vastly higher or lower than the rest of the URAs. If the URA's data differed from the average by more than one standard deviation, then it was categorized as an outlier. However, their data were only compared to other URAs' data with the same similar attributes that were mentioned in the beginning of section 3.2 Managing Occupancy Data. There was no "ground truth" to compare their data with and, therefore, the research team was cautious when assessing occupancy averages. A sense of confidence was required before identifying an URA's data as an outlier. This confidence was affected by the sample size. If a particular URA completed five sessions of data collection and all five of their data collection files were statistically far from the average for their respective attributes, then it was clear that that URA's data were prone to be outliers.

3.2.1.1 Limitations

The research team's occupancy data collection quality control methods were limited. Matching efforts for this study as well as those done in the past by Smith and D'Ambrosio led to positive results in regards to the consistency among the field collectors but D'Ambrosio's study on GA 400 did not yield sufficiently matched data at tollbooths and downstream to establish a ground truth and evaluate data collection accuracy. Parallel occupancy studies were developed with various purposes in mind, one being for the research team to increase confidence that the data were acceptable through a high consistency match rate. However, the scopes of these studies were limited so they did not include the entire data collection crew.

3.2.3 Removal of Duplicates

Most URAs who observed the HOT lane were experienced data collectors that were known to not be outliers within the data; however, even some of the most experienced URAs' data still required to be removed so that lanes being used for parallel occupancy studies were not counted twice. If included, this extra occupancy data could also potentially bias the dataset. A side-by-side comparison was carried out to assess which parallel occupancy URA had data more congruent with the averages seen across the quarter. If both URAs averages were within .01 of the average seen across the quarter then the URA with more records for the two hour period was used.

3.2.2 Removal of URA Occupancy Data

A regression tree analysis is currently being developed by the research team used to detect if any URAs' data biased the dataset. The regression tree will branch out at nodes representing the data files' attributes. The larger the branch, the more files it will contain and the more it will statically affect the average occupancy. The smallest of branches will be the attributes that affect the data the least. The research team intends to not use "1.5" to represent "1+", "2.5" for "2+", and so on. Instead, a value was calculated to represent each uncertain occupancy value (these values do not include "4+") for every URA for each session. These calculated values were produced by taking a weighted average of the certain values (including "4+" as "4.5"). Therefore, if an URA recorded 90 occurrences of "1", 5 occurrences of "1+", and 5 occurrences of "2" then the "1+" would be calculated by using 90/95 and 5/95 as the respective weights for the "1" and "2" values.

3.2.4 Average Occupancy Value

In conducting previous occupancy analyses, it was necessary to choose a discrete value to represent the uncertain occupancy categories so that averages could be reported to the appropriate authorities. The research team chose to use an intermediate value, "1.5", to represent

“1+” because it could accurately represent the likelihood of the vehicle containing one occupant, two occupants, or the more unlikely higher-occupant vehicles [17]. So “2+” was represented with “2.5”, “3+” with “3.5”, and “4+” with “4.5.” Smith carried out a sensitivity analysis using other values and comparing them to this intermediate one. In the sensitivity analyses, she rounded down all the uncertain values (e.g. “1.5” was rounded down to “1”) and then repeated the process rounding up the uncertain values (e.g. “1.5” values were converted to “2”). The fourth average occupancy value used for the sensitivity analysis was calculated to observe the impact of transit. The value of “4.5” was replaced with the actual average occupancy for transit buses. Details for this procedure are mentioned in the 3.2.5 Buses and Vanpools section. The first three sensitivity analysis methods concerned with the uncertain values produced 2.049, 1.998, and 2.074 average occupancies. It was deduced that the original intermediate method was acceptable since the differences between the average occupancies were insignificant. Final results will include uncertain occupancy values that are tailored for each URA performance as mentioned in section 3.2.2 Removal of URA Occupancy Data so as to reduce sample bias.

3.2.5 Buses and Vanpools

To accurately represent the true occupancy on a transit bus, the research team searched for ridership data, which yielded an average of 26 persons per Xpress or Gwinnett County Transit bus from May 2011. Section 4.1.1 Pre-Conversion Occupancy will discuss how replacing “4.5” with 26 affected the matched occupancy average. The research team did not discern any ridership information for vanpools for the pre-conversion period and there was no reliable method to obtain their frequency either. Consequently, these vehicles’ impact could not be assessed. During the post-conversion data collection period, it was important for the researchers to amend this and obtain the necessary data to calculate vanpool occupancy and frequency so as to establish their person throughput.

Surveys collected from the VPSI vanpool company during the post-conversion period revealed the times and occupancy for some of their vehicles. These surveys indicated that a significant portion of vanpools used the corridor before 7 AM, which is when data collection started. Despite, not receiving a response from all the survey recipients, the research team identified a reliable average occupancy value of 8.4 persons per vehicle [4]. Transit bus results for the month of February indicated an increase of 50 buses per week between 2011 and 2012. There was also an increase of 286 transit riders during this comparison period, meaning that each new bus added approximately five more riders [4].

3.2.6 Issues with Uncertain Occupancy Values

From the Winter 2012 quarter on, the amount of uncertain values had declined. This was possibly a serious issue because this potentially signified that the URAs may have been recording discrete occupancy values during opportunities where they were unsure of the occupancy. It uncertain instances they should either select "Miss" or one of the "+" occupancy options. They were instructed to input "Miss" if they did not have the opportunity to see the vehicle or to input an uncertain "+" value when certain vehicle characteristics did not allow the URA to completely view the vehicle's interior. Obvious occasions where URAs deviated from these instructions resulted in the GRAs removing their data due to bias. However, this situation that occurred in the Winter 2012 quarter was an occupancy paradigm shift rather than just outliers tampering with the results. Without "ground truth" occupancy values it was difficult to assess whether the group's interpretation of the methodologies was functioning as intended. Section 4.2.1.1 Explaining the Uncertainty Phenomenon contains the analysis of this dilemma.

3.3 Matching Methodology

The researchers used a very similar methodology to the one described by Smith in her thesis where occupancy values and recorded license plate entries were matched to identify key characteristics about the managed lane's fleet during morning and evening peak hours. This matching process also served as a quality check process due to the scrutiny applied to the data on a record by record basis.

3.3.1 File Preparation

The Section 2.3.1.4 Post-Video Processing mentioned a list of license plate entries, which consisted of Georgia tags, missed tags, and out-of-state license plates. The list's entries were sorted by session. Data from a PM and AM session from every site, except CTR because the team did not deploy there in the mornings, was selected and each session was placed into a separate file. In total, there were nine files. Each of the nine files was processed independently.

Data from the two URAs recording parallel occupancy values for each of the nine sessions were added to each file alongside the license plate data. Each of these nine files encompassed the three data streams that were matched together. Although all data were originally collected at the same time, issues regarding varying equipment clock time, vehicle weaving, vehicle occlusion, human error, and inconsistencies inserted by the Georgia registration database required researchers to conduct a quality assurance and matching procedure that would synchronize and correct the data available. All the cameras and netbooks had their times configured on an individual basis but they drifted apart from one another creating a difference in the data's time stamps that encumbered the matching process. Time synchronization did not occur frequently enough to avoid this drift.

The next step was to configure the data into an intuitive and consistent format that would facilitate side by side comparison. This format later allowed the research team to identify the beginning and end of the data streams where some license plate entries and occupancy records were removed because there was insufficient data to match these marginal entries. This typically occurred when one research group (license plate or occupancy group) would begin collecting data a few minutes earlier or later than the other research group. The research team eliminated 278 data points from the matching dataset. However, this is a small number compared to the 18,571 vehicles that were used for the nine sessions (1.5%).

3.3.2 Reviewing License Plate Data

The next step was to use the frames extracted from the overpass video to review the license plate information entered by URAs and any information that was retrieved from the registration database. The license plate entries were compiled and sorted in chronological order by using the time stamps given to them from the original video. Because more than one vehicle's license plate information could be entered per frame, many entries had the same time stamp and were occasionally out of order. It was the matching researcher's responsibility to manually order the entries as they were seen in the frames and video.

3.3.2.1 Correcting Vehicle Classification

Each plate entry was deemed to be in either of the following categories: Correct with accurate vehicle registration data, correct plate with no vehicle registration data, incorrect with no vehicle registration data, or incorrect with incorrect vehicle registration data. The vehicle classification was one of the variables used to properly match the data streams. These variables will be explained in section 3.3.4 Essential Variables for Matching. The vehicle classification was either extracted from the registration database information or manually inputted by the URA, which were both reviewed by a researcher using the frame images.

Whenever a license plate returned vehicle make a model information, it facilitated the reviewing process because it gave the researcher a quick clue as to whether the license plate was entered correctly or incorrectly. If an URA that inputted an incorrect license plate and it returned a vehicle description that did not match the vehicle in the video image, the researcher was made aware that there was an issue with that entry. Then the matching researcher would look at the alphanumeric tag and realize that a mistake was made by the URA. Consequently, this misclassification facilitated the identification of the incorrect license plate entry because the vehicle registration database returned a vehicle make and model that was easier to distinguish than the series of numbers and letters of the license plate. Typically, the difference between the observed and the described vehicles was very distinct and clear, which made it even easier for the researcher. If the plate had been entered correctly then the vehicle make and model would most likely have matched with the image.

Despite cases where the two vehicles being compared were vastly different, the researcher reviewing the plates needed to be very knowledgeable of vehicle makes and models. At times it was necessary for the researcher to conduct an image search of certain vehicles to identify the subtle physical differences from one vehicle to another. Expert knowledge, however, was not required since 42.2% of the vehicles on the HOV lane consisted of the 25 most popular models [17]. As a result of this vehicle identification, every entry that returned vehicle information accelerated the reviewing process.

3.3.2.2 Issues when Reviewing License Plate Data

The QA/QC process revealed that the nature of the video processing software and the methodology used to collect this data was not fully effective at contending with certain limitations of this research endeavor. The following sections describe issues that were encountered.

3.3.2.2.1 URAs Transitioning between Video Processing Files

Some vehicles were double counted or missed during the video processing stage. URAs transcribed license plates from images that were extracted from the overpass video. These images were grouped in folders representing 20 minutes of video. When an URA decided to stop working, they closed the program and the image at which they stopped was placed into a queue of files for the next URA to pick up from. When the second URA logged into the program, the next image from the queue of images was opened but this URA was not able to observe the list of recorded license plates. Therefore, the second researcher could not know which license plate was entered last and can only assume the previous URA’s finishing point, which left the matching researchers to fill in any gaps or remove any duplicates. This was a minor issue when comparing the amount of plates requiring attention to the entire dataset.

3.3.2.2.2 Duplicate Vehicle Registration Information

A further video processing issue that was addressed during the reviewing period so as to not affect the outcome of the matching process was the existence of duplicate motor vehicle registration records. Records should have only returned for vehicles who registered their tags in the state of Georgia. However, there were instances where database information was assigned to vehicles that were out-of-state or that were designated as “Missed.” The URAs designated a plate’s state of origin as “Missed” when they could not read the state’s name or did not recognize the plate. The existence of these duplicates appeared to be a sparsely intermittent issue where vehicle information from a Georgia license plate was assigned to a nearby record. It was thought to be an error caused during the joining of the various datasets. Like any other erroneous registration data entry, it was marked as incorrect to calculate the quantity of accurate records in the dataset.

In a similar fashion, a pair of vehicles’ records located nearby would also have duplicate entries where one entry had the correct registration database information and the other entry had the second license plate’s information. In these instances the license plates affected were accurately transcribed Georgia tags. Figure 7 demonstrates this scenario. The records in question are highlighted. When the videos were consulted, the “XXXX042” license plate was identified as the Pontiac G6 GTP while the “XXXX184” license plate was identified as the Toyota 4 Runner. When the correct records were identified, the duplicates were removed from the dataset.

0:00:02	XXXXHM	SUV	SUV	GA	ACUR	MDX	2010	MP
0:00:01	XXXX484	SUV	SUV	GA	MAZD	CX-9	2010	MP
0:00:02	XXXX242	LDV	LDV	GA	NISS	ALTIMA BAS	2004	4S
0:00:02	XXXX311	SUV	SUV	GA	FORD	EXPLORER	1999	MP
0:00:03	XXXXANA	SUV	SUV	GA	DODG	RAM TRUCK	2008	TK
0:00:00	XXXX042	SUV	SUV	GA	TOYT	4 RUNNER	2005	MP
0:00:01	XXXX042	LDV	LDV	GA	PONT	G6 GTP	2006	4S
0:00:00	XXXX184	SUV	SUV	GA	TOYT	4 RUNNER	2005	MP
0:00:06	XXXX184	LDV	LDV	GA	PONT	G6 GTP	2006	4S
0:00:01	XXXX318	LDV	LDV	GA	PONT	GRAND PRIX	2006	4S
0:00:02	XXXXVA	SUV	SUV	GA	FORD	LGT CONVTN	2009	TK
0:00:05	XXXX954	LDV	LDV	GA	BUIC	LUCERNE C)	2008	4S
0:00:18	XXXX741	SUV	SUV	GA	FORD	ECONOLINE	2009	TK
0:00:00	XXXX123	HDV	HDV	GA	MCIB	D4500	2010	BU

Figure 7: Example of Vehicle Registration Duplicates

3.3.2.2.3 Erroneous State Designation

It was not uncommon for URAs to have identified a specialty Georgia license plate as a "Missed" plate due to the large variety of plates that all had distinct features. On the other hand, URAs may not have noticed when a plate was from out-of-state and they may have inputted the alphanumeric tag while leaving the default option of recording it as a Georgia plate. When that record was sent to GTRI, it could have potentially returned an erroneous record. The matching process sought to identify all these state designation errors but the large sample size proved challenging and some were undoubtedly missed.

3.3.3 Using the License Plate Data Stream

Once the license plates and vehicle classification were verified and corrected, the data stream provided insight into what specific vehicles used the HOT lane during the two hours of data collection. This reviewed license plate information was much more accurate and reliable than the occupancy data. The overpass video captured every vehicle that passed its focal point with very few instances of vehicle occlusion while the gore video captured fewer vehicles because there were at least four other lanes of traffic between the camera and the HOT lane. The URAs had an almost identical point of view as the gore camera. Therefore, it was typical for the occupancy data to be missing vehicles due to issues like occlusion. As a result, the license plate information was used as a reference for the occupancy data to find discrepancies and identify the vehicles that were not observed by the URAs.

3.3.4 Essential Variables for Matching

Correctly matching all the data streams together would have been futile without the license plate data stream. More specifically, there were aspects of this data stream that served the purpose of being an essential variable to correctly match the data. At times, the occupancy value was also a helpful clue to discern the correct layout of the data streams.

3.3.4.1 Time Gap

A time gap variable, created from two successive vehicles' time stamps, identified an approximate spacing between vehicles. This variable was calculated for all three data collection streams. It was used to assess whether one or more vehicles were not viewed by the field data collector. When examining synchronized portions of the data streams, a larger time gap in the occupancy data streams than the license plate stream was a strong indicator that a vehicle was missed. This suspicion was confirmed by using the gore area video, which often showed larger vehicles occluding the vehicle in question. Once the occupancy data stream was rearranged to add missing vehicle(s) and resynchronize time gaps.

3.3.4.2 Vehicle Class

Another essential variable was the vehicle class. Researchers classified vehicles during occupancy data collection under a 3-category system (LDV, SUV, and HDV). This system was maintained for simplicity during the matching process. The license plate information had two different formats for vehicle classification that needed to be recoded into the 3-category system.

3.3.4.2.1 Recoding Registration Database Vehicle Body Styles

When a record was sent and returned with information from the database, the various two-letter body style codes seen in Table 1 were re-coded into the 3-category system. During data processing, researchers observed additional body types not included in the pre-conversion study's classification table [17]. The code, SW, represents station wagons and form part of the LDV category. However, there were inconsistencies in the database regarding assignment of body types. For example, Honda CR-Vs can show up in the registration database entered as 4S, MP, or SW. This inconsistency indicated that matching researchers were required to acknowledge the potential error and correct it when necessary. There was one occurrence of the TG body style code, which was not a pre-conversion body style code, and it was a Mazda CX-7. The HC, TV, and AT body style codes were also added to the table for the post-conversion period. When the body style information was not returned, then a researcher added a vehicle classification (LDV, SUV, or HDV) during the quality assurance check.

Table 1: Recoded Vehicle Registration Body Styles

LDV	SUV	HDV
2S (2 door sedan) 3S (3 door sedan) 4S (4 door sedan) 5S (5 door sedan) CN (convertible) CP (coupe) LM (limousine) MC (motorcycle) RD (roadster)	CT (camper trailer) MP (multi-purpose) TK(pickup truck) TR (pickup truck) VN (van) WK (work truck) JP (jeep) BT (boat trailer) TG (Mazda CX-7)	HR (horse trailer) AM (ambulance) TL (trailer) UL (trailer) BU (bus) HC (motor home) TV(motor home) AT (horse trailer)

3.3.4.2.2 Recoding Manual Vehicle Classification

If an observed license plate record was not sent to the GTRI database (if it was a missed license plate, missed state identification, or an out-of-state tag), the file format automatically recoded the URA's manual vehicle classification into the 3-category system. The URAs' vehicle classification options are displayed in Table 2. As mentioned before, the quality assurance process verified that the URAs' original vehicle classification was correct. For example, a hatchback like the Kia Soul was commonly classified by the URAs as a light utility truck but it should have been classified as a passenger car, which would have then changed the recoded classification from a SUV to a LDV. The 2-axle single unit truck classification was the only vehicle type that was classified under two categories in the 3-category classification system. Most 2-axle single unit trucks were large pickup trucks with altered, industrial or commercially-specific cargo areas and were classified as SUVs. Examples of these vehicles may be observed in the Appendix A.

Table 2: Recoded Manual Vehicle Classification

LDV	SUV	HDV
passenger car motorcycle	light utility truck 2-axle single unit truck	MARTA bus school bus other bus 5-axle single trailer combination 3 or 4-axle single trailer combination 3-axle single unit truck 2-axle single unit truck

3.3.4.3 Occupancy Value

The last essential variable was the occupancy value. Section 3.2.1 Identifying Irregular URA Performance mentioned that some URAs underperformed or simply had a misunderstanding of the data collection methods. To mitigate this issue, the research team decided to use the most experienced URAs to collect occupancy on the HOT lane, provided there were no human resource limitations. This began in the Fall 2011 quarter Since they were reliable URAs it was useful to use the occupancy value as a matching variable. It was common for the two URAs to have long successions of equal occupancy values, which aided the research team to identify where certain portions matched with one another. Figure 8, demonstrates this concept. Two “SUV 2” occupancy records at either side of the highlighted area are from the same vehicle. Other variables like time gap and vehicle classification aid in identifying a match but the equal occupancy values also give a clue as to which records align with one another.

4:42:24 PM	0:00:05	URA 18	SUV	1		#		4:42:55 PM	0:00:02	URA 36	LDV	1	#
4:42:29 PM	0:00:06	URA 18	SUV	1		#		4:42:57 PM	0:00:04	URA 36	SUV	1	#
4:42:35 PM	0:00:02	URA 18	LDV	1		#		4:43:02 PM	0:00:04	URA 36	SUV	1	#
4:42:37 PM	0:00:01	URA 18	SUV	1		#		4:43:06 PM	0:00:03	URA 36	LDV	1	#
4:42:38 PM	0:00:02	URA 18	LDV	1		#		4:43:09 PM	0:00:02	URA 36	LDV	1	#
4:42:39 PM	0:00:02	URA 18	SUV	1	wrong	#		4:43:11 PM	0:00:01	URA 36	SUV	2	#
4:42:41 PM	0:00:03	URA 18	SUV	1		#		4:43:12 PM	0:00:06	URA 36	LDV	1	#
4:42:44 PM	0:00:04	URA 18	SUV	1		#		4:43:17 PM	0:00:16	URA 36	LDV	1	#
4:42:48 PM	0:00:04	URA 18	LDV	1		#		4:43:33 PM	0:00:01	URA 36	SUV	1	#
4:42:52 PM	0:00:01	URA 18	LDV	1		#		4:43:34 PM	0:00:01	URA 36	SUV	1	#
4:42:53 PM	0:00:01	URA 18	SUV	2		#		4:43:35 PM	0:00:02	URA 36	SUV	1	#
4:42:54 PM	0:00:06	URA 18	LDV	1		#		4:43:38 PM	0:00:11	URA 36	LDV	1	#
4:43:00 PM	0:00:17	URA 18	LDV	1		#		4:43:48 PM	0:00:01	URA 36	SUV	1	#
4:43:16 PM	0:00:01	URA 18	SUV	1		#		4:43:50 PM	0:00:01	URA 36	SUV	2	#
4:43:17 PM	0:00:01	URA 18	SUV	1		#		4:43:50 PM	0:00:03	URA 36	SUV	1	#
4:43:18 PM	0:00:02	URA 18	SUV	1		#		4:43:53 PM	0:00:02	URA 36	LDV	1	#
4:43:20 PM	0:00:11	URA 18	LDV	1		#		4:43:56 PM	0:00:07	URA 36	LDV	1	#
4:43:32 PM	0:00:01	URA 18	SUV	1		#		4:44:03 PM	0:00:02	URA 36	LDV	1	#
4:43:33 PM	0:00:01	URA 18	SUV	2		#		4:44:05 PM	0:00:01	URA 36	LDV	1	#

Figure 8: Example of Occupancy Value in Matching Process

3.3.5 Matching Missed Vehicles

Once the research team had three data streams with directly comparable vehicle classification formats, the matching process began. By using the variables mentioned, a researcher attempted to match every record of license plate information with two occupancy values, one from each occupancy data collector. As mentioned, there were many times when one or no occupancy values were attributed to a license plate because the URAs had not observed the vehicle. When gap, vehicle classification, or occupancy value discrepancies indicated that an URA missed a vehicle, then a blank line was inserted in the data stream to represent said missed vehicle. Since the gore camera video was taken from the point of view of the occupancy data collectors, it frequently revealed which vehicles were most likely missed due to occlusion from larger vehicles.

3.3.6 Tracking Vehicles

Researchers took notes on the images and videos observed to record any significant vehicle sightings or events (e.g. illegal weaving) that occurred. Significant vehicle sightings included motorcycles to identify the frequency of these vehicles on the corridor since there was no separate classification for them. Out of 60,000 records that returned from the database for the Spring 2011 quarter, only 29 (.04%) were motorcycles. However, when the research team reviewed the video camera frames for the vehicles being matched, 123 motorcycles were observed in the HOV lane, which represented 1.75% of that dataset. The research team deemed it more reasonable to use 1.75% as the proportion of motorcycles in the entire dataset as well.

Transit buses and vanpools were also kept track of to visually count the appearances of these vehicles during the two hour periods. The research team took note of some government vehicles as well so as to identify the intensity of their presence along the HOT route. Results for these values are found in section 4.2.3.5 Transit Presence in Matching.

While making notes of specific observed vehicles, the research team took advantage of the opportunity and tracked the frequency of the different types of vehicle classification errors in the occupancy data streams. The results are discussed in section 4.2.3.7 Vehicle Classification errors. Results were only available for the post-conversion period.

3.3.7 Matching Limitations

There were various difficulties encountered when matching the three data streams together. These processes involved many data records and many instances for errors to arise. The variability involved with the different sessions, site locations, time periods, and data collectors provided unique difficulties for researchers to match. However, the research team took note of any anomaly to outline methodology limitations and improve future methodologies.

3.3.7.1 Successive Misses in Occupancy Data Stream

Strange occurrences in the vehicle occupancy data provoked researchers to segregate large portions of data. For example, this occurred with excessive quantities of successive misses. Misses were typically instances when a data collector made a mistake or when they observed a vehicle but were not certain enough to assign it an occupancy value. Occasions when there were several successive misses led the matching researcher to assume that there was an equipment malfunction due to the unlikely nature of a URA making so many successive errors or missing so many successive vehicles. During the weeks of field data collection, supervisors or GRAs reported any incidents and it was common for equipment to falter temporarily, which potentially caused small errors in the data. In such a case, the entries were not included in the matching analysis. In fact, when most of these “false” misses were removed, a matching researcher observed that the URA continued to collect data accurately without actually missing any vehicles.

3.3.7.2 URA Data Collection Techniques

There was a limitation to the degree of accuracy that could be reached while matching. At times it was very challenging to discern which occupancy record aligned with each license plate record, even when using time gaps, vehicle classifications, gore videos, video camera still images, and occupancy values. URAs data entry techniques in the field could have had an impact, at any point, as they recorded vehicles. For example, an URA could have memorized the series of vehicles while he or she readjusted their bodies to a more comfortable position and then entered the records at one time, affecting the time gaps in the data stream. They may also have forgotten a particular vehicle record in that process. such errors would have misguided the matching process because the time gaps and the amount of vehicles observed would not have resembled the pattern seen in the license plate stream, the gore video, license plate images, or the other URA's occupancy stream.

3.3.7.3 Legal Weaving Zones

The gore video revealed lane changes that occurred in the short distance (approximately one-third of a mile) [17] between the point where the gore camera captured video and the point where the overpass camera captured video. Figure 9 represents this distance visually when collecting data in the northbound direction. Cases where the vehicle weaved out of the HOT lane required a line to be inserted in the license plate data stream because that vehicle was not observed in lane 0 during video processing. Cases where the vehicle weaved into the HOT lane required a line to be inserted in the occupancy data streams. Due to the increased enforcement involving illegal lane weaving, there were fewer vehicles making weaving movements than before the HOV-to-HOT conversion.

Figure 9: Location of Data Collection Views [17]

There were, however, sites where legal weaving zones were within the observation area. So, within the maximum distance of one-third mile between occupancy and license plate collection points, vehicles legally weaved from lane to lane. Drivers had limited opportunities to legally weave into or out of the HOT lane so users may have felt strongly inclined to use the local exit/entrance in an attempt to minimize their usage of the lane to only the portion they desired. Weaving added an additional level of difficulty during the matching process, because every weaving maneuver noticed by the URAs required another vehicle to be inserted in either the occupancy or license plate information data streams and some weaves may have been missed. More complications arose in situations where it was difficult to identify which vehicle had made the weaving maneuver. If the view from the gore area camera was occluded by another vehicle, then it became increasingly difficult to pinpoint the unaccounted for vehicle. Three of the nine types of sessions occurred at a site with a legal weaving zone. In the gore area video for BRR in both the morning and afternoon sessions, it was possible to observe vehicles switching lanes over the skipped striping. CTR also had this characteristic.

3.3.7.4 Short Time Gaps Between Vehicles

It was easier for GRAs to match records at sites with lower volumes because the scarcity of longer gaps limited the quantity of unique time gap values. Each time gap was used as a matching indicator, so the greater the variety of time gap values, the easier it was to utilize these indicators. When a series of vehicles all had two seconds, one second, or less than one second time gaps between them, it was more difficult to identify the vehicles that either URA missed. Table 3 provides insight into this concept. The 20+ second time gaps were easily matched across the data streams because of the wide variety of time gaps including these long pauses. If all the time gaps were two seconds or less, then it would be more difficult to match the data entries together.

Table 3: Example of Time Gap Use in Matching Process [17]

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

Previous work from other research team contributors helped establish the basis for the methodology used for the analysis in this thesis. A variety of datasets that range from one season to the next and that consist of vehicle occupancy, license plate, and matched data allowed the team to identify preliminary data collection outliers that will be used by future bias-identifying studies. The subsequent chapter will demonstrate how the matched occupancy and license plate data revealed vehicle characteristics for HOT lane users as well as indications that the HOT data collectors are consistent with one another when concurrently collecting data, aiding to validate the data collection methods.

CHAPTER 4: DATA ANALYSIS

4.1 Pre-Conversion User Profile

The various forms of data collected for this project enabled the research team to examine user characteristics and assess potential factors affecting effective capacity along this corridor. This section provides an overview of the user characteristics identified for the HOV lane using occupancy values, license plate registration information, and results found from matching efforts. The HOV lane predominantly consisted of two-person carpools because results indicated that 61.5% of vehicles in this lane had two occupants [17]. In a later section, results from the post-conversion period will reveal that vehicle occupancy in the managed lane has dropped considerably, while occupancy in the general purpose lanes has increased. since the conversion in October 2011. The original HOV lane was a carpool lane, so the changes in vehicle occupancy and changes in the user profile of the lane was expected.

4.1.1 Pre-Conversion Occupancy

Over the first four quarters, 65 different students collected vehicle occupancy. These students collected well over a million records that were used to develop occupancy distributions. This section reflects the research team's principal findings. Smith, who conducted a significant portion of analysis, expected a combined rate of SOV violators and single-occupant motorcycles in the HOV lane to be at least between of 5-10%. Results for the HOV lane exceeded this expectation as 15% of vehicles in the carpool lane were SOVs with as many as 9.5% being possible violators in cases where the URAs selected the "1+" option. Of that combined 24.5%, 1.75% was attributed to motorcycles, which was a figure provided from reviewing the license plate data. Taking all the percentages into consideration, SOV frequency was still consistent with values that were seen in literature..

On the general purpose lanes, SOVs were the vastly predominant vehicle with nearly 90% of vehicles on these lanes only carrying one passenger. The HOV lane processed more carpoolers with 61.5% of its users having two occupants. On the general purpose lanes, two person carpools represented less than 10% of the vehicles. The other occupancy categories did not make up a significant portion of the data. “2+”, “3”, “3+”, and “4+” together made up less than two percent of the vehicles on lanes 1 - 5. These higher occupancy values, however, had more of a presence in the HOV lane.

There was no doubt that the carpool lane was carrying more individuals per vehicle than the general purpose lanes. However, more complete studies will assess the effective capacity of these lanes through closer examination of changes to vehicle throughput and travel time reliability. Section 4.2.1 Post-Conversion Occupancy will present the updated occupancy results illustrating how the occupancy distribution has shifted after the HOV-to-HOT conversion, which enabled single occupant users to pay a toll and utilize the lane. The HOT lane opened to a new market, potentially affecting the characteristics of the users along the entire corridor.

4.1.2 Pre-Conversion License Plate Data

More than 60,000 vehicle records returned information from the registration database for the HOV lane and general purpose GP1 (the adjacent fast lane). During Smith’s license plate review, she identified an average of 3.2% of plates that were incorrectly identified as a Georgia tag, with 6.2% of these misclassifications returning incorrect vehicle registration information. When reviewing the alphanumeric portion of the plates, she was able to correct 25% of the incorrect plates. The error mentioned in section 3.3.2.1 Correcting Vehicle Classification in which the registration database returned incorrect information for correctly transcribed license plates contributed to less than 1% of Smith’s data. However, 20% of plates that were fairly visible did not return a registration database record at all.

4.1.2.1 Resubmitting Plates

After resubmitting 20,000 plates that did not return a record, over 5,000 of them returned a record after correction. Before sending the resubmitted list of plates, the research team converted all the entries to upper case letters, which appears to have been the driving factor for a quarter of those entries being able to retrieve information that previously did not warrant any. Revising the license plate dataset by converting all the records including the letter “O” to the number “0” also improved the return rate Because Georgia license plates employ the number instead of the letter in every circumstance, even on vanity plates. This piece of information was used to inform URAs in future training sessions. Because the field research team was notified of this issue, the appearance of the letter “O” in post-conversion plates was very minor.

4.1.2.2 Makes and Models

The registration database returned records including information for 194 different makes and 2,417 different vehicle models. These quantities included towed trailers, which, when removed, reduced the data to 84 vehicle makes and 2,317 models. However, the research team found that the model list included many different iterations of the same model type. After recoding all the iterations into one type, 858 models remained [17].

4.1.2.3 URA Video Processing Comments

The five most common URA comments were “glare”, “blurry”, “blocked”, “no license plate” and “unsure”. Occlusion contributed to 1.9% of entries to be missed in one particular session. Continuous training to improve the research team’s video camera capturing techniques during field deployments was employed but there were many environmental elements like sunlight levels that did not allow clear visibility of all the plates. “Glare” and “blurry” were two comments that could have been avoided by deploying during time periods with an adequate level of sunlight. Too much light hitting the plates directly caused glare, while the blurriness could be partially attributed to low levels of sunlight in the mornings. However, it was more important for the research team to deploy during peak periods.

4.1.2.4 Variable Independence for the HOV lane and General Purpose Lane 1

The following were results obtained to discern the independence of different variables for HOV lane and GP1. Comparisons made for vehicle ownership, vehicle classification, vehicle fuel source, and model year used the data returned from the registration database. The state of origin was information collected directly from the URAs' data entry during Video Processing. Chi-square tests were performed with a 95% confidence level.

4.1.2.4.1 Vehicle Ownership

Vehicles utilizing HOV lane and GP1 were divided among three categories for vehicle ownership. Approximately 9% were owned commercially, less than 1% owned by the government, and 90% were privately owned. Commercial ownership for the HOV lane was 11%, which was higher than the expected value, while commercial ownership in the general purpose lane was 8%. Although there were very few government vehicles in proportion to the other categories, an 79.8% of them traveled on the HOV lane.

4.1.2.4.2 Vehicle Classification

Buses used the HOV lane at a rate of 49:1 compared to general purpose lane 1. Results revealed that the frequency of HDVs in the HOV lane, excluding buses, was twice as high as in general purpose lane 1. HDVs accounted for 0.8% of all vehicles in the HOV lane while only 0.2% of vehicles in GP1 classified as HDV. The team attributed the frequent presence of HDVs other than transit buses to the fact that work crews in large trucks were also a common occurrence on the HOV corridor. Another important finding was that a significantly larger percentage of SUVs populate the HOV lane than GP1. Smith proposed a hypothesis that larger passenger capacity, like the capacity in a SUV compared to a LDV, was a variable that related vehicles to the HOV lane. However, after comparing vehicle sizes and their frequencies in HOV lane and GP1, her results were inconclusive. Larger LDVs like 5-door hatchbacks were compared against more intermediately sized 4-door sedans and 2-door coupes. Despite a large enough dataset of LDVs in the HOV lane, the chi-square test was not significant enough to prove the hypothesis involving LDV sub-classifications. Similar inconclusive results were developed while studying SUV sub-classifications.

4.1.2.4.3 Vehicle Fuel Source

Alternative Fuel Vehicles (AFVs) were not prevalent along this corridor but even fewer of these vehicles actually carried a license plate with the “AFV” designation. It was not a mandatory designation but it would have aided the research team in flagging some of the vehicles that use alternative fuels. The results indicated that 2,016 vehicles on the two lanes were AFVs, which only represented 3.32% of the entire dataset. Natural gas was the least common fuel source. Diesel fuel was more frequent in the HOV lane than GP1, which was attributed to the greater proportions of commercial and heavy duty vehicles on the HOV lane. There were sufficient diesel vehicles in the HOV lane that it was the second highest fuel source. Hybrids’ presence was approximately 0.9% for both lanes, which demonstrated their small vehicle market share. Vehicles with gasoline as their fuel type were an overwhelming majority with 93% of them occupying both lanes. For this reason, Smith conducted another analysis to evaluate the other fuel types while excluding gasoline [17]. This exclusion revealed that hybrids were expected in larger quantities in the HOV lane than what was observed empirically.

4.1.2.4.4 Vehicle Model Year

The pre-conversion examination of the vehicle model years included dividing the range of years into nine divisions or bins so that the chi-square test could be used. Despite the dependency significance, no practical difference was observed between HOV lane and GP1. The largest differential between the two lanes occurred in the 1995-1999 year bin with an additional 1.6% favoring the HOV over GP1.

4.1.2.4.5 State of Origin

When examining in-state vs. out-of-state license plate records across the two lanes, Smith encountered a higher percentage of out-of-state vehicles in the HOV lane than in the adjacent general purpose lane. The observed out-of-state count for the HOV lane was about 20% higher than the expected count from the chi-square test.

4.1.3 Pre-Conversion Occupancy and License Plate Matching

Matching efforts for the pre-conversion period involved matching five data collection sessions with over 7,000 occupancy records to individual vehicles. About 5,780 or 82.2% of those records had a consistent occupancy value, and of these matched and accurate records, 3,570 (61.8%) yielded parallel license plate data. Table 4 defines what constitutes as a consistent occupancy value, which was used in both the pre-conversion and the post-conversion matching efforts. The most common inconsistent pairing was “2” and “1”, with 373 occurrences that represent 5.63% of all matched records. The inconsistent values were 15.4% of the total matched records. The five matched sessions were representative of the entire license plate dataset with the exception of any Beaver Ruin Road (BRR) or Tuesday data. Post-conversion matching efforts had the purpose of including all sessions, days, and time periods to present an even more representative sample.

Table 4: Definition of Consistent Occupancy Values [17]

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

4.1.3.1 Match Rate

The pre-conversion analysis suggested that the match rate was higher at sites with lower volumes, likely because the slower pace of data collection increased the quality of the URAs' data. Match rates at the lower volume sites ranged between 85.7% and 88.3% compared to the higher volume sites that ranged between 76.1% and 77.2%. Smith found that at JCB and PHR 97% of the time gaps between vehicles were less than ten seconds while only 66% of the time gaps at OPR were less than 10 seconds, which made it easier to match at OPR than JCB or PHR.

4.1.3.2 Occupancy Distribution

Table 5 displays the occupancy distribution for the pre-conversion matched records. The combination of SOVs and potential lane violators (received a "1+" from the URAs) contributed 8.9% of all vehicles, which was also within the expected range. Reviewing the video data streams allowed the research team to acquire the exact quantity of buses that utilized the HOV lane. There were 73 bus observations in the matching data, all of which were given an average occupancy of 26 as mentioned in section 3.2.5 Buses and Vanpools. This occupancy value adjustment did not significantly affect the overall corridor throughput since buses were not nearly as common as privately owned vehicles. Transit buses were, however, approximately half of all “4+” vehicles, which represented 2.6% of the total matched dataset. Vehicles and their license plates could not be assigned an occupancy value when both observers recorded a miss, which happened 2.6% of the time.

Table 5: Pre-Conversion Matched Occupancy Distribution

		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	

4.1.3.3 Comparing Datasets

The research team compared the vehicle classifications of the matched records to those from the rest of the HOV records. This investigation concluded that both set of vehicle classifications strongly resemble one another. HDVs were slightly more frequent in the matched records but this was the only minor difference between the two. The top 25 vehicle models from both data sets were also compared. The research team assigned a make and model to 663 vehicles without database information. About 260 vehicles without database information were assigned a make only. These assignments were done to search for any potential bias in the non-database vehicles. No bias was identified [17].

4.1.3.4 Vehicle Classification across Pre-Conversion Occupancy

LDVs and SUVs were most commonly found within the “2” occupancy value group. The majority of HDVs were found within the “4+” group. LDVs and SUVs had noticeable presences in most of the other occupancy categories, except the “3+” and “4+” categories. LDVs had a greater proportion of SOVs while SUVs had a slightly larger proportion of 2-person carpoolers. Figure 10 exhibits these proportions.

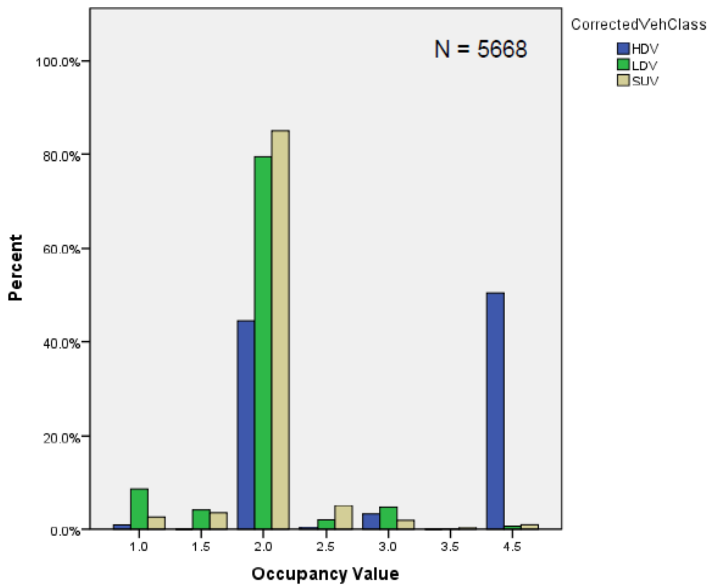


Figure 10: Vehicle Classification across Occupancy

4.1.3.5 Ownership across Pre-Conversion Occupancy

A vehicle ownership analysis yielded a strong presence of government and commercial vehicles in the HOV lane. An overwhelming majority of government vehicles fell under the “4+” category. Many of these included transit buses but when these buses were removed from the analysis, a significant amount of government vehicles still carried four occupants or more. Vehicles under private ownership had slightly more 2 occupants that those with commercial purposes. However, commercial vehicles had more vehicles in the “2+” and “4+” categories.

4.2 Post-Conversion User Profile

Quarterly data collection deployments for the post-conversion period generated important data that would allow the research team to identify user characteristics and compare them to those already identified for the pre-conversion period. This comparison was then used to establish potential factors impacting effective capacity for the HOT lane and the adjacent general purpose lanes. The general public observed the poor initial performance of the lane through media reports. When enough time was allowed for demand to increase and the tolling price to adjust to demand, the lane's volume increased. However, it is also important to observe what was specifically occurring to the SOVs, the carpoolers, and the transit users.

4.2.1 Post-Conversion Occupancy

The field team included 85 students that collected occupancy during the second year of data collection. Twenty additional students were needed to obtain the various data than the previous year. During the post-conversion period, more URAs were deployed during a single data collection session to conduct parallel occupancy studies, but there were also fewer sessions conducted per week. Personnel turnover was much higher during the second year, because many of the students that were hired during the first year were graduating or accepting internships. This turnover could have affected the occupancy results because many of the students collecting data were never able to gain enough experience to become highly experienced data collectors. The impact of these students with potential sample bias is currently being examined through a variability analysis and results will be included in the final HOV-to-HOT conversion monitoring report. All of the supervisors that the research team deployed were hired during the pre-conversion period.

These 85 students collected 1,524,480 records. Table 6 displays the distribution of occupancy values for all sites across the two different lane types and across each quarter. These values include all the data that were collected, even the potential biased data. Fall 2011 has higher percentages of uncertain values because of the issue explained in section 3.2.6 Issues with

Uncertain Occupancy Values. The managed lane changed drastically and became more similar to the general purpose lanes in terms of carpooling rates. Results indicated that 85.9% of vehicles in the morning were SOVs when including the "1+" entries, which was a steep increase when compared to an overall SOV rate of 24.5% for the HOV lane. Motorcycles were not a significant portion of the SOVs because matching results yielded motorcycles to make up a little over 1% of vehicles on the HOT lane. In terms of carpoolers, the quantity of vehicles with exactly two occupants declined substantially. The HOV lane had over 61.5% 2 person carpoolers while HOT lane continuously saw a decline in two-person carpoolers, even months after the conversion. The most recent quarter, Summer 2012, indicated 10.7% of vehicles in the morning and 11.7% of vehicles in the afternoon were two-person carpools. The presence of buses and higher occupant vehicles allowed the HOT lane to have an average of 2.3% of "4+" vehicles.

On the general purpose lanes, SOVs were the vastly predominant vehicle with most quarters reporting over 80% of vehicles on these lanes carrying exactly one passenger. This percentage was very similar to the values observed in the pre-conversion period. However, the "1" percentage in the pre-conversion era could have been greater but the proportions of uncertain values was higher during that period. On the general purpose lanes, two-person carpools represented 10.9% of the vehicles in the AM and 13.9% of vehicles in the PM for the Summer 2012 quarter. Pre-conversion GP lanes had less than 10% of vehicles with two occupants. The other occupancy categories did not make up a significant portion of the data. "2+", "3", "3+", and "4+" together made up less than two percent of the vehicles on lanes 1 - 5. These higher occupancy values, however, had more of a presence in the HOT lane.

Table 6: Post-Conversion Occupancy Distribution

AM	**HOT Lane**					**General Purpose Lanes**			
	Fall 2011	Winter 2012	Spring 2012	Summer 2012		Fall 2011	Winter 2012	Spring 2012	Summer 2012
1	56.6%	81.7%	86.5%	83.6%		73.2%	88.6%	88.4%	86.1%
1+	27.2%	4.8%	0.5%	2.4%		18.9%	2.2%	1.4%	2.1%
2	12.4%	11%	10.6%	10.7%		6.7%	8.9%	9.8%	10.9%
2+	1.4%	0.2%	0.1%	0.4%		1.0%	0%	0%	0.3%
3	0.8%	0.7%	0.7%	0.8%		.2%	0.2%	0.3%	0.4%
3+	0.3%	0.1%	0%	0.1%		0%	0%	0%	0%
4+	1.4%	1.4%	1.6%	1.8%		0%	0.1%	0.1%	0.2%
PM	**HOT Lane**					**General Purpose Lanes**			
	Fall 2011	Winter 2012	Spring 2012	Summer 2012		Fall 2011	Winter 2012	Spring 2012	Summer 2012
1	63.4%	81.6%	82.3%	81.4%		81.9%	81.7%	84%	83.9%
1+	16.5%	2.2%	1.8%	3.3%		5%	5.2%	1.3%	0.8%
2	14.7%	12.7%	12.8%	11.7%		11.8%	11.8%	13.4%	13.9%
2+	1.6%	0.3%	0.1%	0.4%		0.5%	0.6%	0.2%	0.3%
3	1.1%	0.8%	0.9%	0.8%		0.5%	0.4%	0.7%	0.7%
3+	0.1%	0.1%	0%	0.1%		0%	0.1%	0%	0%
4+	2.6%	2.3%	2.1%	2.3%		0.3%	0.3%	0.4%	0.4%

The HOV lane carried significantly more individuals per vehicle than the HOT lane [give values here]. However, the new carpool lane does still have a higher average occupancy compared to the general purpose lanes. Also, although the general purpose lanes had a smaller proportion of carpoolers, when aggregated, the quantity could reflect an increase in carpooling. Figure 11 and Figure 12 is a graphical representation of the average occupancy value when using “1.5” for “1+” and so on as a base estimate until final analyses are conducted. Although all eight quarters remain relatively similar, the post-conversion quarters are the lowest means. Future studies will utilize a methodology similar to section 3.2.2 Removal of URA Occupancy Data to manage the uncertain values more accurately and, therefore, reflect more appropriate performance results. In addition, other more robust studies will assess the effective capacity of the conversion through closer examination of changes to vehicle throughput and travel time reliability.

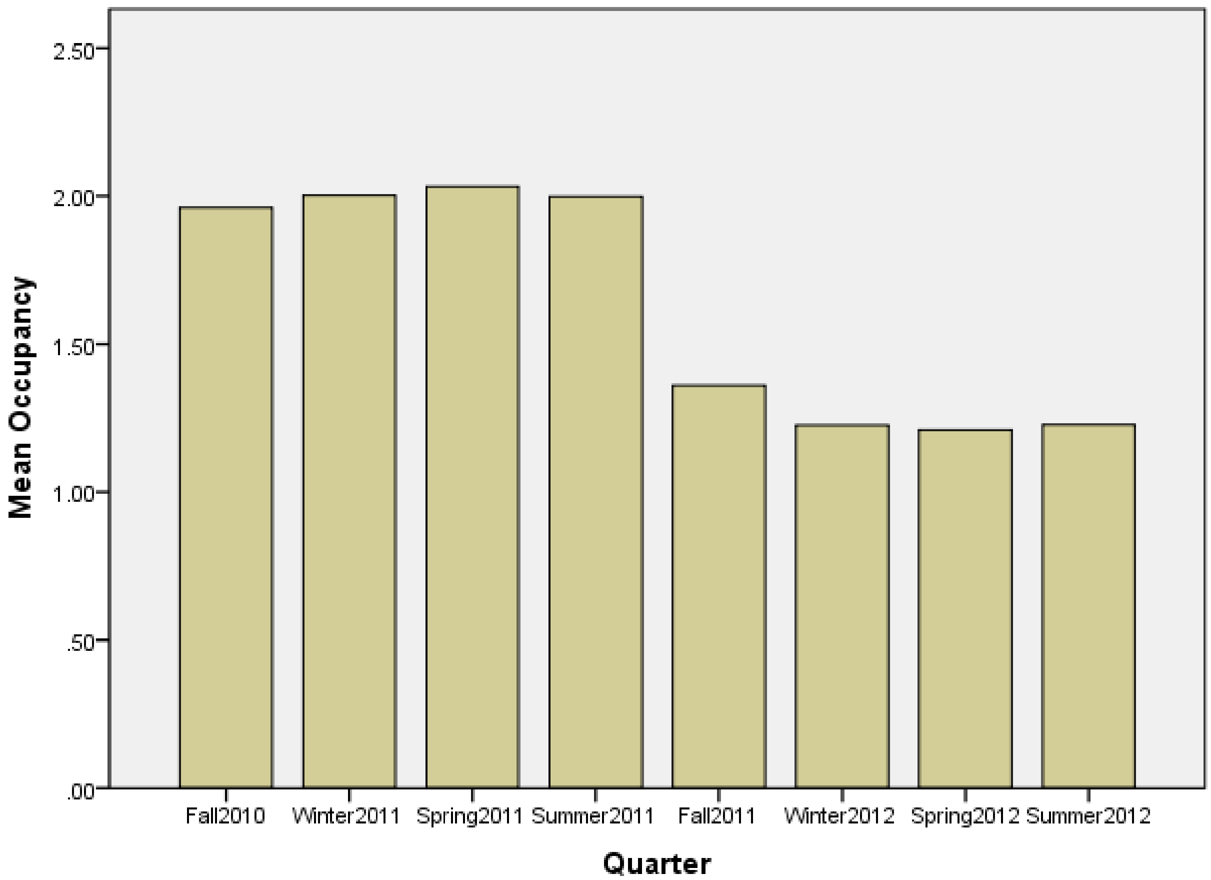


Figure 11: HOV/HOT Quarterly Average Occupancy

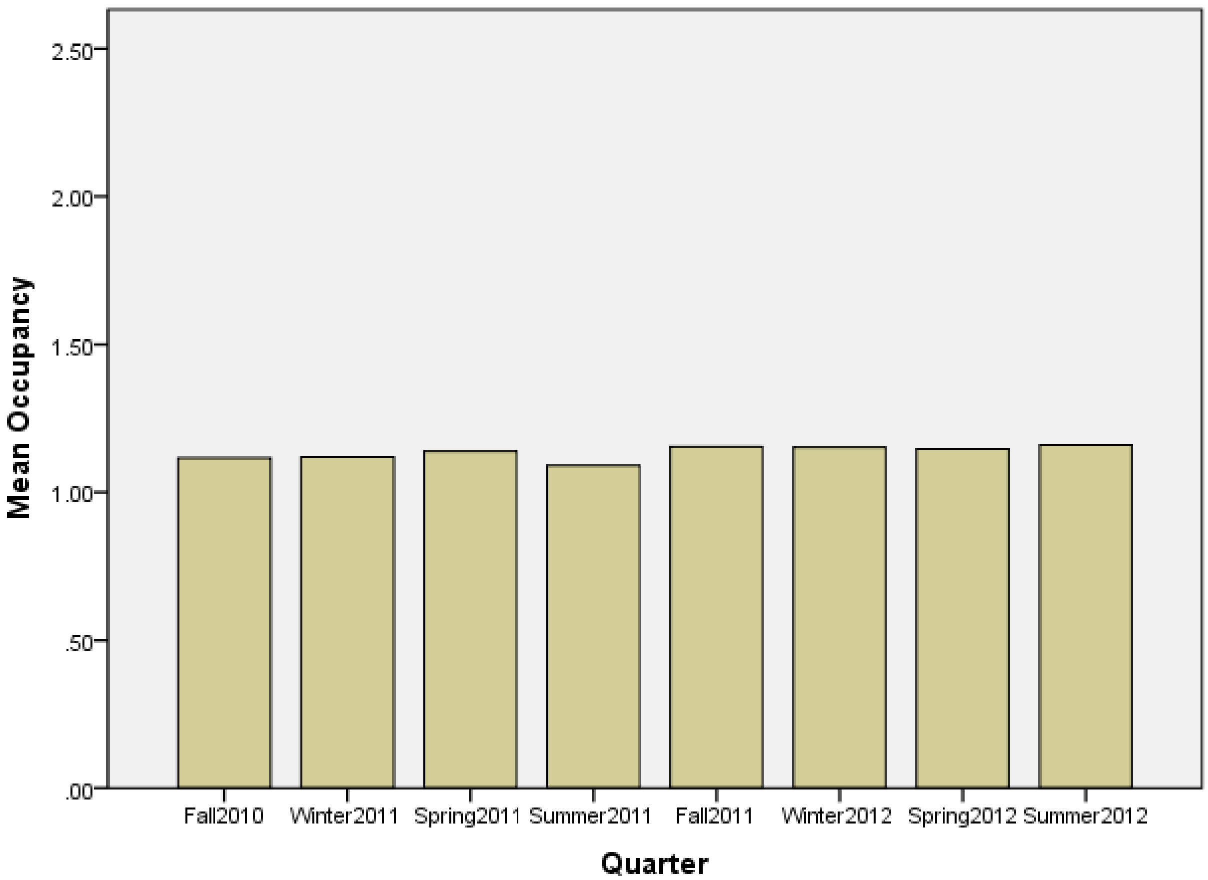


Figure 12: GP Quarterly Average Occupancy

<u>4.2.1.1 Explaining the Uncertainty Phenomenon</u>

The shift in uncertain occupancy values first mentioned in section 3.2.6 Issues with Uncertain Occupancy Values was a phenomenon that required the research team's attention. Figure 13 represents this issue graphically. The "1+" and "2+" areas can be viewed for the first five quarters but they taper off in the last quarters. It was important to identify a hypothesis that reasonably explained the shift. The research team believed that if the URAs who had been deemed reliable were recording consistent or even identical vehicle occupancy data then that was an indication that they had become more accurate. Matching results showed that the occupancy value consistency rate decreased from 82.2% in the pre-conversion period to 77.4% the post-conversion period. This decrease was not substantial and both percentages took into account all vehicles during the two-hour sessions, including the vehicles that were not seen by either URA. Therefore, a match rate within a few percentage points of 80% was a positive outcome.

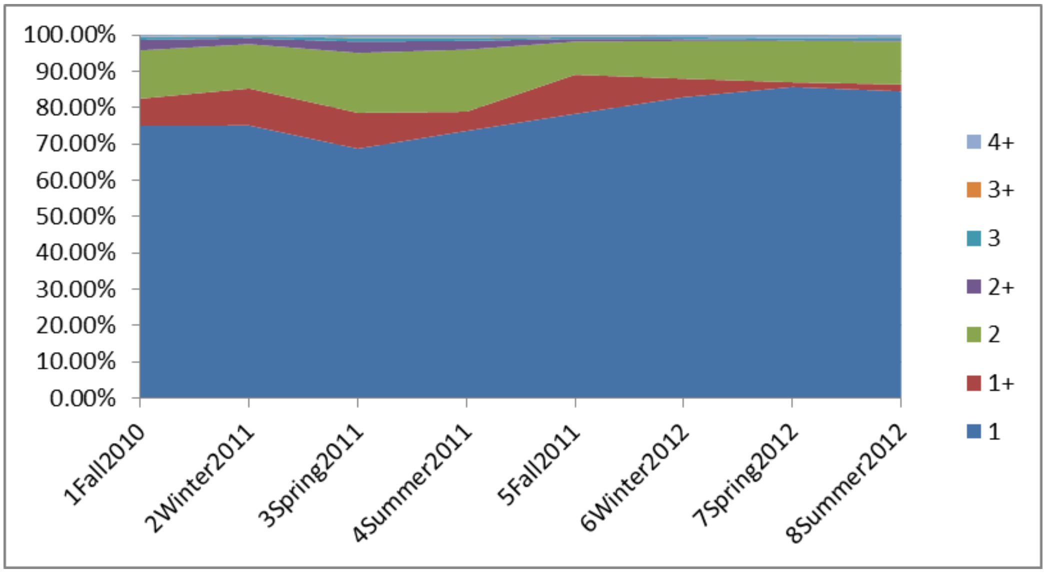


Figure 13: Area Plot of Quarterly Occupancy Distribution

Many of the URAs stated that they changed their approach to data collection based off the research team's feedback. In fact, instructions to refrain using uncertain "+" values during dark hours were sent out at the beginning of the Winter 2012 quarter. There was no doubt that this had an effect on the occupancy distributions since that was message's intention. However, the effect of these renewed instructions was more far-reaching than intended. The research team intended to reduce the amount of uncertain values due to darkness but it produced a trickle-down affect where subsequent quarters, more brightly-lit quarters, also saw a decline in reporting of uncertain values. Another hypothesis is that the URAs were inclined to put forward more effort to increase their accuracy since they were told to not depend on the uncertain values as a "crutch".

A more in depth assessment was necessary to assess this uncertainty phenomenon. The numerical difference between the two URAs at each matched session was calculated and aggregated. This difference only included entries where both URAs had observed the vehicle. The average difference was 0.0106, which was a better result than the pre-conversion difference of -.049. The percentage of exact matches in the post-conversion study was 91.1%, which represented a large increase given that pre-conversion exact matches did not even attain 60%.

There was no occupancy difference value other than “0” that exceeded 3.5% while the pre-conversion results indicated that differences of “0.5” and “-0.5” both exceeded 10%. Figure 14 is a visual representation of the difference between the two URAs for all of the nine matched sessions. Hence, the team believes that the field researchers improved their ability to identify vehicle occupancy in the second year.

Table 7: Statistics for the Difference between Occupancy A and Occupancy B

	Statistic	Std. Error
N	15750	
Mean	0.0106	0.0025
Median	0.0000	
Std. Deviation	0.3090	
Skewness	0.052	0.020
Kurtosis	29.947	0.039

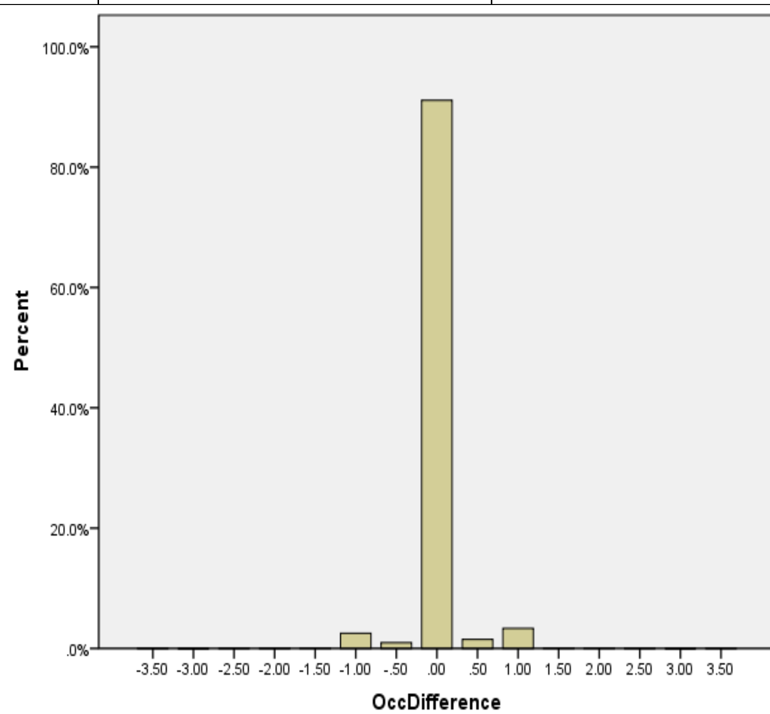


Figure 14: Distribution for URA A and URA B Occupancy Difference

4.2.2 Post-Conversion License Plate Data

From the 252,681 license plate entries sent to GTRI for the Spring 2012 quarter, which only included Georgia license plates that were legible to the URAs, 215,189 (85.2%) returned information from the registration database. Limitations to the quantity of vehicle records were the accuracy of license plate transcription, correct identification of tag's state of origin, and other errors involving the retrieval process from GTRI. If these limitations were corrected then more than the 252,681 plates would have been sent to GTRI and, proportionally, more plates would have returned motor vehicle records.

4.2.2.1 Transcription Errors

When reviewing the license plate information, rough estimates were calculated for the prevalence of transcription and state identification errors. At least 0.1% of license plate entries were incorrectly designated as a Georgia vehicle. These entries were sent to the registration database but the database only managed Georgia tags and, as a result, those plates did not return any vehicle information. Also, it was highly likely that many plates were incorrectly identified as a "Missed" state plate when it should have been designated as a Georgia tag. Georgia uses a wide variety of specialty plates and it was difficult for the research team to be visually familiar with all of them. Therefore, some plates from Georgia were not sent to the database because their state of origin was unknown. The license plate reviewing procedure also revealed that 11.8% of vehicles' plates were initially transcribed incorrectly. Incorrectly transcribed plates include alpha numeric entries where one or many of the digits were mistaken or when a clearly legible plate was designated as missed. The team is working on future protocols and methods to reduce data transcription errors and re-investigating the use of updated automated license plate reader technologies.

4.2.2.2 Makes and Models

Table 8 provides information comparing the amount of vehicle records, the various vehicle makes, and the different vehicle models that were found for the pre-conversion and post-conversion periods. It is important to note that the pre-conversion quantities only account for HOT lane and GP1.

Table 8: Comparison of Vehicle Makes and Models

	Pre-Conversion (HOV Lane, GP1)	Post-Conversion (HOT Lane, GP1)	Post-Conversion (All Lanes)
vehicle records	60,737	86,113	215,189
different makes with trailers	194	165	492
different vehicle models with trailers	2,417	2,537	4,363
different makes with no trailers	84	94	143
different vehicle models with no trailers	2,317	2,468	3,664

4.2.2.3 URA Video Processing Comments

The five most common URA comments for the post-conversion period were comments relating to the tag being blocked, blurry, unclear, temporary or new, and having glare. These same types of comments were also seen during the pre-conversion period. About 54.5% of the comments were issues relating to the license plate being too blurry. During the data collection quarters, the research team underwent training to improve various data collection tasks, including camera set up. However, during the review process it was possible to observe when a video camera was set up incorrectly, which resulted in fewer legible plates. There were also factors that were difficult to avoid. At certain points the video images from the overpass would become blurry. No evidence of a probable cause was seen in the images. It was possible that vibrations from the overpass distorted the cameras' focus as these vibrations were very noticeable while sitting on the overpass sidewalk, adjacent to the cameras.

4.2.2.4 Variable Independence for HOT and General Purpose Lanes

The following were results obtained to discern the independence of different variables for the HOT lane and the general purpose lanes. Comparisons made for vehicle ownership, vehicle classification, vehicle fuel source, and model year used the 215,189 records returned from the registration database for all six lanes. The state of origin was information collected directly from the URAs' data entry video processing. Chi-square tests were performed with a 95% confidence level for two sets of tests with varying lane combinations, one set compared HOT lane and GP1 while the other compared HOT lane and all the general purpose lanes.

4.2.2.4.1 Vehicle Ownership: HOT vs. General Purpose Lane 1

Vehicles utilizing HOT lane and GP1 were divided among three categories for vehicle ownership. It ownership. It was indicated that 1.9% of vehicles in the HOT lane were owned by the government compared government compared to 0.2% in GP1. This overwhelming presence of government vehicles in the managed the managed lane rather than GP1 was a trend that continued across the HOV-to-HOT conversion. Results conversion. Results indicated that 8.3% of vehicles were commercially owned in this dataset. This represents This represents a 0.8% decrease compared to a similar test in the pre-conversion period.

Table 9 indicates that there were proportionally more commercial vehicles in GP1 than the HOT lane, which is represented in the HOT lane's higher expected value. On average, 90.9% of vehicles in these lanes were privately owned. There were fewer observed private vehicles in the managed lane than expected, which was also observed in the pre-conversion period. However, the difference between observed and expected was larger in the pre-conversion period.

Table 9: HOT vs. GP 1 Ownership

			Lane		Total
			HOT	GP 1	
Ownership	Government	Count	516	104	620
		Expected Count	234.6	385.4	620
		% within Lane	1.9%	0.2%	0.8%
	Commercial	Count	2084	3970	6054
		Expected Count	2290.4	3763.6	6054
		% within Lane	7.5%	8.7%	8.3%
	Private	Count	25150	41525	66675
		Expected Count	25225	41450	66675
		% within Lane	90.6%	91.1%	90.9%
Total		Count	27750	45599	73349

Chi-Square Tests			
	Value	Df	Asymp. Sig. (2-sides)
Pearson Chi-Square	573.452	2	0.000
Likelihood Ratio	571.793	2	0.000

4.2.2.4.2 Vehicle Ownership: HOT vs. General Purpose Lanes

Table 10 displays results from a test for ownership dependence between the HOT lane and all the general purpose lanes. The results yielded very similar indications as the comparison between HOT lane and GP1. Government vehicles were 0.4% of the entire Spring 2012 vehicle registration dataset. Commercial ownership was 8.8% and 90.8% were privately owned. The similar results between the two tests indicate that general purpose lane 1 was not very different from the other general purpose lanes regarding vehicle ownership.

Table 10: HOT vs. All GP Ownership

			Lane		Total
			HOT	GP 1-5	
Ownership	Government	Count	516	371	887
		Expected Count	114.4	772.6	887
		% within Lane	1.9%	0.2%	0.4%
	Commercial	Count	2084	16765	18849
		Expected Count	2430.7	16418.3	18849
		% within Lane	7.5%	8.9%	8.8%
	Private	Count	25150	170303	195453
		Expected Count	25204.9	170248.1	195453
		% within Lane	90.6%	90.9%	90.8%
Total		Count	27750	187439	215189

Chi-Square Tests			
	Value	df	Asymp. Sig. (2-sides)
Pearson Chi-Square	1675.790	2	0.000
Likelihood Ratio	1069.829	2	0.000

4.2.2.4.3 Vehicle Classification: HOT vs. General Purpose Lane 1

Results revealed that the frequency of HDVs in the HOT lane, including buses, was twice as high as as high as the expected count. About 1.9% of vehicles in the HOT lane were HDVs while only 0.4% of 0.4% of vehicles in GP1 were classified as heavy duty vehicles. However, because many of these vehicles were vehicles were transit buses, another chi-square test was conducted excluding buses (

Table 12). The chi-square value indicated that this test was not as dependently significant as the bus-inclusive test with a difference of 0.005 between the two values.

Although the proportions of LDVs and SUVs in HOT lane and GP1 for both Table 11 and

Table 12 were very similar, each classification is "preferred" in one lane over the other. The slightly higher percentage of SUVs in the HOV lane did not extend into the post-conversion period as there were more SUVs in GP1 than the HOT lane. Both tables indicate expected LDV counts higher than the observed counts for GP1. Within the SUV vehicle classification, the expected count was more than 300 vehicles greater than what was observed in GP1 as is demonstrated in Table 11. The proportions for HDVs in both lanes waned to 0.2%, indicated by comparing the two tables. These results demonstrate that HOT lane and GP1 were composed of vehicles with very similar classifications except for the presence of transit in the HOT lane.

Table 11: HOT vs. GP 1 Vehicle Classification Including Buses

			Lane		Total
			HOT	GP 1	
Vehicle Class	HDV	Count	514	156	670
		Expected Count	253.5	416.5	670
		% within Lane	1.9%	0.3%	0.9%
	LDV	Count	14819	24161	38980
		Expected Count	14757.2	24232.8	38980
		% within Lane	53.4%	53%	53.1%
	SUV	Count	12417	21282	33699
		Expected Count	12749.3	20949.7	33699
		% within Lane	44.7%	46.7%	45.9%
Total		Count	27750	45599	73349

Chi-Square Tests			
	Value	df	Asymp. Sig. (2-sides)
Pearson Chi-Square	445.195	2	0.000
Likelihood Ratio	434.865	2	0.000

Previous studies indicated that passenger capacity was not a prevailing factor for higher carpooling rates but it was important to note that the research team obtained results suggesting a decrease in the average passenger occupancy and the frequency of SUVs for the post-conversion period in the HOT lane. The HOV lane carried 58.1% SUVs when buses were excluded from the study. A similar test without buses for the HOT lane revealed that only 46% of vehicles were SUVs.

Table 12: HOT vs. GP 1 Vehicle Classification Excluding Buses

			Lane		Total
			HOT	GP 1	
Vehicle Class	HDV	Count	57	90	147
		Expected Count	55.1	91.9	147
		% within Lane	0.2%	0.2%	0.2%
	LDV	Count	14819	24161	38980
		Expected Count	14608.5	24371.5	38980
		% within Lane	54.3%	53.1%	53.5%
	SUV	Count	12417	21282	33699
		Expected Count	12629.4	21069.6	33699
		% within Lane	45.5%	46.7%	46.3%
Total		Count	27293	45533	72826

Chi-Square Tests			
	Value	df	Asymp. Sig. (2-sides)
Pearson Chi-Square	10.667	2	0.005
Likelihood Ratio	10.671	2	0.005

4.2.2.4.4 Vehicle Classification: HOT vs. General Purpose Lanes

The research team generated a second set of vehicle classification comparisons between the HOT lane and all the general purpose lanes. By incorporating lanes 2-5 into the comparison the two lane types became even more similar to one another than what the first set of chi-square tests indicated, also indicating that there are significant differences between the composition of general purpose lane 1 and other general purpose lanes.. The lane types were more similar in the second set of comparisons because the percentages of HDVs were more similar. Proportionally, there were more HDVs in all of the general purpose lanes than just in general purpose lane 1. A possible explanation for this was that slower moving HDVs like 5 axle trailer combinations preferred lanes 2-5.

Table 13: HOT vs. All GP Vehicle Classification Including Buses

			Lane		Total
			HOT	GP 1-5	
Vehicle Class	HDV	Count	514	2221	2735
		Expected Count	352.7	2382.3	2735
		% within Lane	1.9%	1.2%	1.3%
	LDV	Count	14819	99582	114401
		Expected Count	14752.8	99648.2	114401
		% within Lane	53.4%	53.1%	53.2%
	SUV	Count	12417	85635	98052
		Expected Count	12644.5	85407.5	98052
		% within Lane	44.7%	45.7%	45.6%
Total		Count	27750	187438	215188

Chi-Square Tests			
	Value	df	Asymp. Sig. (2-sides)
Pearson Chi-Square	89.731	2	0.000
Likelihood Ratio	80.793	2	0.000

Buses were removed from the subsequent chi-square test to assess the impact of busses on the HOT lane. The results were more significantly dependent than when comparing HOT lane and GP1. Since most of the HDVs in the HOT lane were buses, the vast majority of the remaining HDVs were proportionally more common in the general purpose lanes than the HOT. Continuing with the trends observed when comparing HOT lane to GP1, LDVs still exceeded expected counts in the HOT lane and SUVs continued to exceed expected counts in the general purpose lanes.

Table 14: HOT vs. All GP Vehicle Classification Excluding Buses

			Lane		Total
			HOT	GP 1-5	
Vehicle Class	HDV	Count	57	1964	2021
		Expected Count	257.2	1763.8	2021
		% within Lane	0.2%	1%	0.9%
	LDV	Count	14819	99582	114401
		Expected Count	14558.2	99842.8	114401
		% within Lane	54.3%	53.2%	53.3%
	SUV	Count	12417	85635	98052
		Expected Count	12477.7	85574.3	98052
		% within Lane	45.5%	45.7%	45.7%
Total		Count	27293	187181	214474

Chi-Square Tests			
	Value	df	Asymp. Sig. (2-sides)
Pearson Chi-Square	184.229	2	0.000
Likelihood Ratio	256.171	2	0.000

4.2.2.4.5 Vehicle Fuel Source: HOT vs. General Purpose Lane 1

Alternative Fuel Vehicles (AFVs) are toll exempt vehicles and for this reason it was expected that AFVs would take advantage of the HOT lane's benefits. There were very few vehicles fueled by anything other than gasoline in the pre-conversion period. The post-conversion period saw a very increase in alternative fuel vehicles in the fleet. To obtain the results, chi square tests were conducted for the registration database information. However, the database used one-letter codes to identify fuel sources. Table 15 displays what each letter signified. The number “9”, one of these codes, represented the vehicles that had unknown vehicle models and, therefore, their fuel source was unknown. All the vehicles with a “9” fuel code were joined with the “E” and “P” fuel codes into the unknown fuel source category. It is believed that these unknown fuel codes are registration errors. These errors represented less than 0.1% of the dataset so it affected the analysis to a minimal degree.

Table 15: Vehicle Registration Fuel Source Codes

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

Table 16 presents the following results. The presence of toll-exempt AFVs increased from 3.3% to 4.5%. There were fewer vehicles fueled by natural gas so Flex Fuel was a much more popular choice among HOT and GP1 users. Due to the increase in Flex Fuel vehicles, diesel no longer commanded second place among the managed lane’s fuel sources. However, diesel still remained a more common fuel source in the HOT lane than GP1. In fact, all fuel sources were more common in the HOT lane except for gasoline. Hybrid vehicles were more common in the post-conversion period, where 1.2% of vehicles on these two lanes used hybrid technology compared to the pre-conversion’s 0.9%.

Table 16: HOT vs. GP 1 Fuel Source Including Gasoline

			Lane		Total
			HOT	GP 1	
Fuel Type	Diesel	Count	856	871	1727
		Expected Count	653.4	1073.6	1727
		% within Lane	3.1%	1.9%	2.4%
	Flex Fuel	Count	1343	1975	3318
		Expected Count	1255.4	2062.6	3318
		% within Lane	4.8%	4.3%	4.5%
	Gasoline	Count	25043	42223	67266
		Expected Count	25449.8	41816.2	67266
		% within Lane	90.4%	92.8%	91.9%
	Hybrid	Count	441	442	883
		Expected Count	334.1	548.9	883
		% within Lane	1.6%	1%	1.2%
	Natural Gas	Count	10	0	10
		Expected Count	3.8	6.2	10
		% within Lane	0%	0%	0%
	Unknown	Count	8	4	12
		Expected Count	4.5	7.5	12
		% within Lane	0%	0%	0%
Total		Count	27701	45515	73216

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sides)
Pearson Chi-Square	197.072	5	0.000
Likelihood Ratio	195.217	5	0.000

Chi square tests were conducted a second time with the exclusion of gasoline fueled vehicles in order to remove their bias. For diesel, the expected counts were slightly closer to observed counts. The removal of gasoline allowed the research team to obtain results indicating that Flex Fuel was more common GP1 than the HOT lane. This is somewhat contrary to expectations since the HOT lane offers a time-savings benefit for these AFVs. Of all the vehicles owned by businesses and government that were powered by Flex Fuel, 13.2% of them were commercially owned compared to 15.6% that were owned by the government. Similar to diesel vehicles, hybrid expected counts were also more similar to the observed counts. Changes to results for natural gas fueled vehicles and unknown fuel sources were not significant due to their low counts.

Table 17: HOT vs. GP 1 Fuel Source Excluding Gasoline

			Lane		Total
			HOT	GP 1	
Fuel Type	Diesel	Count	856	871	1727
		Expected Count	771.5	955.5	1727
		% within Lane	32.2%	26.5%	29%
	Flex Fuel	Count	1343	1975	3318
		Expected Count	1482.2	1835.8	3318
		% within Lane	50.5%	60%	55.8%
	Hybrid	Count	441	442	883
		Expected Count	394.5	488.5	883
		% within Lane	16.6%	13.4%	14.8%
	Natural Gas	Count	10	0	10
		Expected Count	4.5	5.5	10
		% within Lane	.4%	.0%	.2%
	Unknown	Count	8	4	12
		Expected Count	5.4	6.6	12
		% within Lane	.3%	.1%	.2%
Total		Count	2658	3292	5950

Chi-Square Tests			
	Value	df	Asymp. Sig. (2-sides)
Pearson Chi-Square	65.028	4	.000
Likelihood Ratio	68.789	4	.000

4.2.2.4.6 Vehicle Fuel Source: HOT vs. General Purpose Lanes

The second set of chi square tests, which used all the lanes in the dataset, suggested a strong gasoline predominance in this corridor's vehicles. Gasoline use among these vehicles was 92.9% , which almost matched the rate of gasoline presence in the pre-conversion period. About 2.2% of vehicles use diesel in all six lanes compared to 2.4% in the HOT lane and general purpose lane 1. Flex Fuel was also not as common in this larger dataset. Only 3.8% of vehicles consumed Flex Fuel. Hybrids were only 1% of this larger dataset compared to 1.2% of the HOT vs. General Purpose Lane 1 dataset. The natural gas and unknown categories were only faintly affected by the addition of lanes 2 – 5 into the comparison. When comparing the HOT lane to all the general purpose lanes, the HOT lane again had an upper hand on all fuel sources except for gasoline.

Table 18: HOT vs. All GP Fuel Source Including Gasoline

			Lane		Total
			HOT	GP 1-5	
Fuel Type	Diesel	Count	856	3851	4707
		Expected Count	611.6	4095.4	4707
		% within Lane	3.1%	2.1%	2.2%
	Flex Fuel	Count	1343	6853	8196
		Expected Count	1064.9	7131.1	8196
		% within Lane	4.8%	3.7%	3.8%
	Gasoline	Count	25043	173059	198102
		Expected Count	25738.5	172363.5	198102
		% within Lane	90.4%	93.3%	92.9%
	Hybrid	Count	441	1722	2163
		Expected Count	281	1882	2163
		% within Lane	1.6%	.9%	1%
	Natural Gas	Count	10	2	12
		Expected Count	1.6	10.4	12
		% within Lane	.0%	.0%	.0%
	Unknown	Count	8	19	27
		Expected Count	3.5	23.5	27
		% within Lane	.0%	.0%	.0%
Total		Count	27701	185506	213207

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sides)
Pearson Chi-Square	381.177	5	.000
Likelihood Ratio	328.638	5	.000

In order to more effectively compare the less used fuel sources, another test was conducted excluding gasoline. Diesel was a more common fuel source than Table 16 had indicated. Results indicated that 31.2% of gasoline-less vehicles used diesel compared to 29% in Table 17. In addition, 54.3% and 14.3% of gasoline-less vehicles used Flex Fuel and hybrid technology, respectively. Therefore, the concentration of Flex Fuel and hybrid vehicles was greater in the HOT lane and general purpose lane 1 than in all six lanes. The HOT lane remained dominant in the diesel and hybrid categories while the general purpose lanes had a greater ratio of Flex Fuel powered vehicles. However, 55.1% is lesser than the 60% of gasoline-less vehicles that used Flex Fuel in general purpose lane 1. This could suggest that lane 1 has the highest percentage of Flex Fuel vehicles than any other lane.

Table 19: HOT vs. All GP Fuel Source Excluding Gasoline

			Lane		Total
			HOT	GP 1-5	
Fuel Type	Diesel	Count	856	3851	4707
		Expected Count	828.3	3878.7	4707
		% within Lane	32.2%	30.9%	31.2%
	Flex Fuel	Count	1343	6853	8196
		Expected Count	1442.2	6753.8	8196
		% within Lane	50.5%	55.1%	54.3%
	Hybrid	Count	441	1722	2163
		Expected Count	380.6	1782.4	2163
		% within Lane	16.6%	13.8%	14.3%
	Natural Gas	Count	10	2	12
		Expected Count	2.1	9.9	12
		% within Lane	.4%	.0%	.1%
	Unknown	Count	8	19	27
		Expected Count	4.8	22.2	27
		% within Lane	.3%	.2%	.2%
Total		Count	2658	12447	15105

Chi-Square Tests			
	Value	df	Asymp. Sig. (2-sides)
Pearson Chi-Square	59.494	4	.000
Likelihood Ratio	47.783	4	.000

4.2.2.4.7 Vehicle Model Year: HOT vs. General Purpose Lane 1

The registration database used by GTRI was not updated since the fourth quarter of 2011, meaning that no vehicles within the 2013 vehicle fleet were in the dataset. For this reason the research team continued to use the same nine vehicle year bins that were utilized in the pre-conversion analysis. The HOT lane fleet contained a larger proportion of newer model year vehicles than the general purpose lanes (more observed newer model vehicles than expected). Consequently, the HOT lane was used by newer vehicles. These results are important for a follow-up study that will analyze the distribution of the vehicles' monetary values given that newer vehicles were typically more costly than older vehicles [17].

Table 20: HOT vs. GP 1 Vehicle Model Year

			Lane		Total
			HOT	GP 1	
Bin Years	1989 and earlier	Count	125	321	446
		Expected Count	168.7	277.3	446
		% within Lane	.5%	.7%	.6%
	1990 – 1994	Count	280	989	1269
		Expected Count	480.1	788.9	1269
		% within Lane	1%	2.2%	1.7%
	1995 – 1999	Count	1899	4750	6649
		Expected Count	2515.5	4133.5	6649
		% within Lane	6.8%	10.4%	9.1%
	2000 – 2002	Count	3372	6947	10319
		Expected Count	3904	6415	10319
		% within Lane	12.2%	15.2%	14.1%
	2003 – 2004	Count	3814	6875	10689
		Expected Count	4044	6645	10689
		% within Lane	13.7%	15.1%	14.6%
	2005 – 2006	Count	5105	8136	13241
		Expected Count	5009.4	8231.6	13241
		% within Lane	18.4%	17.8%	18.1%
	2007 – 2008	Count	5597	8188	13785
		Expected Count	5215.3	8569.7	13785
		% within Lane	20.2%	18%	18.8%
	2009 – 2010	Count	4155	5141	9296
		Expected Count	3516.9	5779.1	9296
		% within Lane	15%	11.3%	12.7%
	2011 – 2012	Count	3403	4252	7655
		Expected Count	2896.1	4758.9	7655
		% within Lane	12.3%	9.3%	10.4%
Total		Count	27750	45599	73349

Chi-Square Tests			
	Value	df	Asymp. Sig. (2-sides)
Pearson Chi-Square	909.867	8	.000
Likelihood Ratio	927.256	8	.000

4.2.2.4.8 Vehicle Model Year: HOT vs. General Purpose Lanes

A comparison between the HOT lane and the general purpose lanes yielded very similar results to those from Table 20. The same trends were seen from the previous comparison. The bin with the most vehicles in the general purpose lanes was 2005 – 2006, while the 2007 – 2008 bin still had the most HOT vehicles of any other lane.

Table 21: HOT vs. All GP Vehicle Model Year

			Lane		Total
			HOT	GP 1-5	
Bin Years	1989 and earlier	Count	125	1500	1625
		Expected Count	209.6	1415.4	1625
		% within Lane	0.5%	0.8%	0.8%
	1990 – 1994	Count	280	4885	5165
		Expected Count	666.1	4498.9	5165
		% within Lane	1%	2.6%	2.4%
	1995 – 1999	Count	1899	23341	25240
		Expected Count	3254.9	21985.1	25240
		% within Lane	6.8%	12.5%	11.7%
	2000 – 2002	Count	3372	31171	34543
		Expected Count	4454.5	30088.5	34543
		% within Lane	12.2%	16.6%	16.1%
	2003 – 2004	Count	3814	28032	31846
		Expected Count	4106.7	27739.3	31846
		% within Lane	13.7%	15%	14.8%
	2005 – 2006	Count	5105	31911	37016
		Expected Count	4773.5	32242.5	37016
		% within Lane	18.4%	17%	17.2%
	2007 – 2008	Count	5597	31419	37016
		Expected Count	4773.5	32242.5	37016
		% within Lane	20.2%	16.8%	17.2%
	2009 – 2010	Count	4155	19699	23854
		Expected Count	3076.1	20777.9	23854
		% within Lane	15%	10.5%	11.1%
	2011 – 2012	Count	3403	15481	18884
		Expected Count	2435.2	16448.8	18884
		% within Lane	12.3%	8.3%	8.8%
Total		Count	27750	187439	215189

Chi-Square Tests			
	Value	df	Asymp. Sig. (2-sides)
Pearson Chi-Square	2335.988	8	.000
Likelihood Ratio	2440.814	8	.000

4.2.2.4.9 State of Origin: HOT vs. General Purpose Lane 1

The overall presence of out-of-state vehicles increased after the conversion from 4.4% to 4.7%. The results from the pre-conversion period indicated that it was more common to find out-of-state vehicles in the HOV lane than GP1. However, for the HOT lane, the opposite was true. About 6.4% of vehicles in GP1 were from out-of-state, while only 1.9% of vehicles in the HOT lane have tags from another state. The HOT lane's expected count was more than twice the observed count. The requirement of owning a Peach Pass to use the HOT lane seems the likely reason for this changed user characteristic.

Table 22: HOT vs. GP 1 State of Origin

			Lane		Total
			HOT	GP 1	
State Origin	GA	Count	35630	56234	91864
		Expected Count	34615.6	57248.4	91864
		% within Lane	98.1%	93.6%	95.3%
	Out of State	Count	708	3863	4571
		Expected Count	1722.4	2848.6	4571
		% within Lane	1.9%	6.4%	4.7%
Total		Count	36338	60097	96435

Chi-Square Tests			
	Value	df	Asymp. Sig. (2-sides)
Pearson Chi-Square	1006.385	1	.000
Likelihood Ratio	1005.393	1	.000

4.2.2.4.10 State of Origin: HOT vs. General Purpose Lanes

There were very few differences for this State of Origin comparison when compared to the results presented in Table 22. The sum of all the general purpose lanes had proportionally more Georgia vehicles than just GP1 but the expected count of out-of-state vehicles in the HOT lane increased by over 250 (13%). However, the differences in the percentages within each lane between the two results were very subtle.

Table 23: HOT vs. All GP State of Origin

			Lane		Total
			HOT	GP 1-5	
State Origin	GA	Count	35630	237462	273092
		Expected Count	34359.1	238732.9	273092

		% within Lane	98.1%	94.1%	94.6%
	Out of State	Count	708	15021	15729
		Expected Count	1978.9	13750.1	15729
		% within Lane	1.9%	5.9%	5.4%
Total		Count	36338	252483	288821
Chi-Square Tests					
		Value	df	Asymp. Sig. (2-sides)	
Pearson Chi-Square		987.496	1	0.000	
Likelihood Ratio		986.719	1	0.000	

4.2.3 Post-Conversion Matching

The sample size for the post-conversion matching was considerably larger than the pre-conversion. Nine sessions were matched as opposed to five from the pre-conversion period. One session was matched for each time period at every site. Note that matching occurred for only one Chamblee-Tucker Road session because data was only collected for the afternoon time period. Table 24 presents the individual session results. The sample size also included at least two sessions from each of the weekdays used for data collection, however, it has already been stated that Tuesdays, Wednesdays, and Thursdays were very similar to one another in regards to data significance.

A little over 7,000 vehicles formed part of the matching efforts prior to the conversion. For the post-conversion period, the research team attempted to match 18,573 vehicles. About 94.6% of those vehicles (17,576) had at least one vehicle occupancy record, 14, 378 (77.4%) vehicles had two occupancy records that were consistent according to the research team's consistency requirements, and 77.3% of vehicles had two occupancy records with exact same occupancy record. Refer to Table 4 in the Pre-Conversion Matching section for what constitutes as consistent occupancy entries. The research team received 10,005 license plate records from the registration database from the 18,573 vehicles, which represented 53.9% of the dataset. When only considering the 14,350 exact occupancy matches, 7,770 (54.1%) of those vehicles received registration data. Of the 7,770 exact occupancy matches with registration database information 7,097 (91.3%) of them received accurate data. Accurate data was isolated from the inaccurate data by rejecting any record returned from an incorrectly transcribed license plate as well as rejecting a correctly transcribed license plate with an erroneous vehicle make and model. The most common inconsistent pairing was when one data collector selected “2” for their vehicle occupancy and the other data collector selected “1” for the same vehicle, with 841 occurrences that represent 4.5% of all matched records.

Table 24: Results for Nine Matched Sessions

Site	Date	Day	Period	URA A	URA B	Matched Vehicles	Consistent Occupancy	LP Data
PHR	April 3	Tuesday	AM	12	14	1892	80.7%	44.9%
PHR	April 3	Tuesday	PM	12	18	1711	79.1%	56.9%
OPR	April 10	Tuesday	AM	29	14	853	67.3%	34%
OPR	April 10	Tuesday	PM	24	10	862	79.2%	68.9%
JCB	April 18	Wednesday	PM	2	9	2745	72.4%	65.2%
BRR	April 19	Thursday	AM	18	14	3231	77.1%	58.3%
BRR	April 19	Thursday	PM	24	10	2393	76.9%	63.2%
JCB	April 24	Tuesday	AM	5	18	2903	80%	28.3%*
CTR	May 2	Wednesday	PM	18	36	1983	80.8%	65%
Total						18573	77.4%	53.9%

*A significant portion (19.7%) of the license plate entries were unavailable data

4.2.3.1 Match Rate

Incidentally, the consistent occupancy match rates in the post conversion period did not appear to be as dependent on vehicle volume as was identified for the pre-conversion data. First of all, these results suggested that the volumes in the data collection sites fluctuated. For sessions that were matched in the before and after periods, the pre-conversion vehicle counts were not equal to their post-conversion counterparts. However, the sites with the lowest volumes remained as the lowest in the post-conversion period. Therefore, OPR, PHR, and CTR had lower volumes than JCB and BRR for both study periods.

The gap time between each vehicle observation was affected by the difference in vehicle volumes. On average, OPR had approximately eight seconds between each vehicle, PHR and CTR had four-second average gap times while JCB and BRR had either three-second or two-second average gap times. Short gaps may have been a factor making data collection more difficult, but vehicle volume did not have sufficient weight as a variable to prominently affect their consistency match rate. For example, OPR PM and JCB AM had very different volume scenarios yet their match percentage was very similar (79.2% compared to 80%). This possibly indicated that consistency was more dependent on URA performance. For example, URA 29 and URA 14 collected occupancy during the lowest consistent occupancy session, OPR AM. URA 14 collected occupancy with other URAs for this study and during those sessions, URA 14 collected much more consistent occupancy. Hence, it is possible that URA 29's performance was not optimal. The influence of individual URA's on occupancy results is currently being assessed by the research team.

4.2.3.2 Occupancy Distribution

Table 25 displays the occupancy distribution for the post-conversion matched records. All valid values were from exact occupancy matches. All missing values were instances when either URA missed a vehicle or when their occupancy was inconsistent or not exactly identical. These results provide another layer of data certainty indicating that a large majority of HOT vehicles have one occupant.

Table 25: Post-Conversion Matched Occupancy Distribution

	Occupancy Value	Frequency	Percent	Valid Percent
Valid	1.0	12572	67.7	87.6
	1.5	1	0.0	0.0
	2.0	1440	7.8	10.0
	2.5	1	0.0	0.0
	3.0	62	0.3	0.4
	3.5	0	0.0	0.0
	4.5	274	1.5	1.9
	Total	14350	77.3	100.0
Missing	System	4223	22.7	
Total		18573	100.0	

4.2.3.3 License Plate Error Identification

About 11.8% of vehicles' license plates were identified incorrectly. A significant portion of the incorrect plates were plates that were clearly visible by the matching researcher but had been recorded by the researcher as a miss. More plates may have been incorrectly transcribed but only the ones where the reviewer was certain of a discrepancy were flagged as incorrect. About 85.5% of the 2,460 incorrect plates were corrected. Corrections were only made when the research team was confident in the updated plate value. From the total attempted license plates, 3.3% of them were incorrect yet returned a record from the GTRI database.

4.2.3.4 Matched Registration Database Records

According to the matching results, 56.8% of plates manually inputted by the URAs returned a record from the database. However, when the missed, unknown state, or out-of-state plates were removed from the data, 78% of plates returned a record from the database. This rate was similar to the rate of the overall legible Georgia Spring 2012 plates that returned information as well as the 80% rate of legible Georgia Spring 2011 plates that returned information. According to matching and reviewing efforts, 3.1% of the registration database information was incorrect despite being retrieved by a correctly transcribed license plate. During the pre-conversion period the rate of incorrect registration database information with correct tags was lesser than the Spring 2012 figure. This was expected because GTRI's motor vehicle registration database had been more recently updated for the pre-conversion study than the post-conversion study. 9,133 records or 91% of the returned records for the nine matched sessions were transcribed correctly and had accurate vehicle information. It was assumed that these proportions would remain consistent regardless if the entire dataset was used. For example, if matching efforts had been extended to all sessions during the Spring 2012 quarter then results would likely indicate similar return rates.

4.2.3.5 Transit Presence in Matching

Of the 18,573 vehicles, 237 (1.3%) were transit buses, which included buses with the GRTA Xpress and Gwinnett County Transit logos. This result is somewhat expected since the percentage of vehicles with a body style code of “BU” was 1.4%. Vanpools were less than half as common as buses with only 103 appearances of VPSI, Rideshare, and Groome vanpools. It was possible that more vanpools used the corridor during the data collection times; however, if the vehicle was not clearly marked as such then it was not noted during video review.

Results from a vanpool study for VPSI vanpools suggested that a significant portion of vanpools during in the morning peak would not be picked up during the two-hour videos used for matching. Frequencies for this vanpool company during three-hour morning peaks indicated a range of 23-28 vehicles per day [4]. The reported VPSI value is significantly higher than what was observed during the two-hour video reviews. This study also mirrored the methodology to obtain a pre-conversion frequency. Pre-conversion frequency was 7/8 of the post-conversion VPSI frequency resulting in only a slight increase in throughput if occupancy did not increase. The study also suggested that the increase in passenger throughput by vanpools was likely to be negligible.

According to the same study, transit buses were less common in the early morning when compared to the pre-conversion period [4]. There was an overall increase in bus frequency, 50 additional buses per week, but a large portion of this increase was due to more buses in later morning hours. Therefore, it is more likely that the license plate observations for buses are more useful to determine a transit profile than the vanpool observations. This study also deemed the passenger throughput increase of 286 occupants per week to be insignificant in comparison to the overall corridor throughput.

4.2.3.6 Motorcycle Presence in Matching

An accurate count of motorcycles were no longer necessary to calculate the SOV violation rate since single occupant vehicles were allowed to use the lane as long as they paid a toll or had a toll-exempt vehicle. However, it was in the interest of the research team to count the number of motorcycles; 210 (1.1% of observed vehicles. The proportion of motorcycle decreased from 1.75% in pre-conversion matching efforts to 1.1% post-conversion matching efforts.

4.2.3.7 Vehicle Classification Errors

Between the two URAs that collected occupancy at each session, 33,328 vehicle classification records were assembled. Most of these were for the same vehicles. However, there were times when a particular vehicle was not classified correctly. Yet, the URAs for the most part performed well given that only 1.8% of the vehicles were classified incorrectly. The most common mistake was classifying LDVs as SUVs. A common example of this error was classifying any of the Toyota Scion vehicles as a SUV.

4.2.3.8 Comparing Datasets

When the research team compared the vehicle classifications and the top 25 vehicle models of the matched records to those from the rest of the HOV records, the results indicated that both sets of data strongly resembled one another. HDVs were slightly more frequent in the matched records but this was the only minor difference between the two. Surprisingly to Smith, most of the top 25 vehicle models were found in both datasets [17]. The post-conversion matching results were more representative of the entire Spring 2012 dataset than the pre-conversion of the entire Spring 2011 dataset. So, the research team expected to find results in the two datasets where the vehicle class distributions were more similar. However, there were more HDVs, fewer SUVs, and more LDVs in the matched results, although the differences were slight. For example, HDV frequency was greater by 0.08% in the matched records, which represented a 4.1% increase. These discrepancies are so small that they could result due to errors mentioned in section 3.3.4.2.1 Recoding Registration Database Vehicle Body Styles where the vehicle registration database was inconsistent in its classification process.

4.2.3.9 Vehicle Class across Post-Conversion Occupancy

Figure 15 demonstrates the distribution of vehicle classes across the vehicle occupancy values. As was expected, LDVs and SUVs dominated the SOVs while "4+" vehicles were almost entirely HDVs. The chart suggests that SUVs lend themselves to be used more for carpooling than LDVs. There was a very low presence of vehicles within the "1+", "2+", and "3+" occupancies because the URAs predominantly had exact occupancy matches when they were also certain of what they had observed.

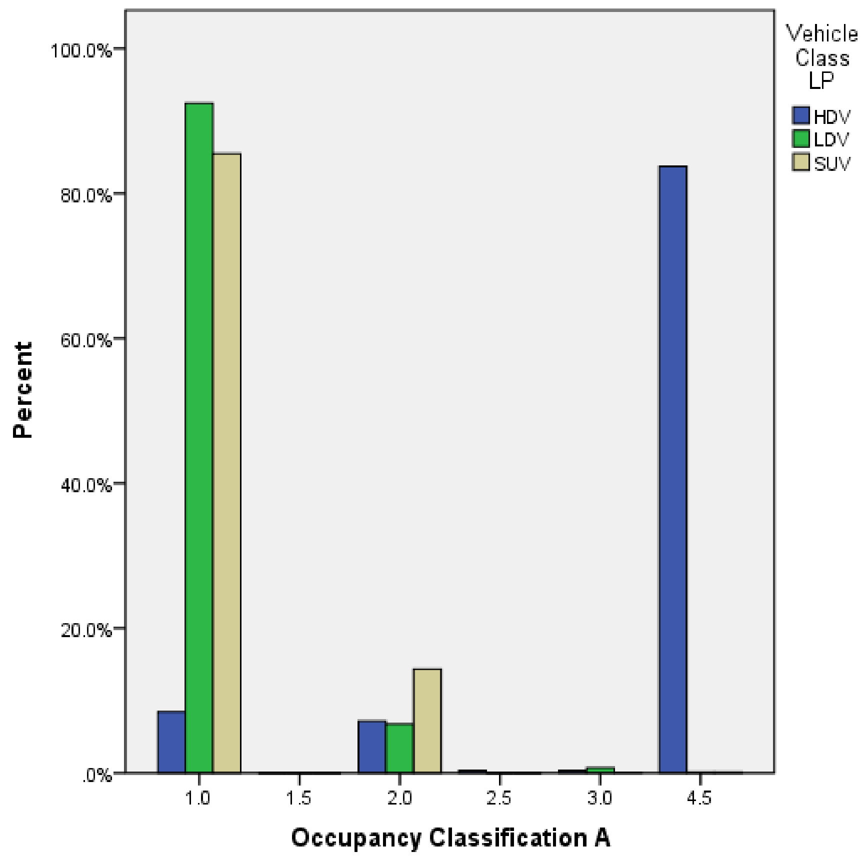


Figure 15: Vehicle Classification across Occupancy Distribution for Matched HOT Data

CHAPTER 5: CONCLUSIONS

The ultimate goal of this thesis was to set up a framework for future demographic studies so that the research team could target HOT users or non-users. Sending travel surveys can be "difficult to undertake due to cost constraints and the respondent burden" [17]. However, the more informed the survey effort is of its target audience, the better the response rate will be. The license plate and vehicle occupancy data was a step forward in assessing these important user traits for a corridor that went through a significant conversion. The managed lane had undergone the transformation from being a HOV lane to a HOT lane that changed lane demand. The scope of Georgia Tech's monitoring project was not only able to identify these preliminary characteristics, but it was also able to compare characteristics from periods of time immediately before and after said conversion.

License plate data including records from a motor vehicle registration database provided insight into I-85 users' vehicles. A continuously improving occupancy data collection methodology provided real-time occupancy data that would have been distorted had surveys been used to collect the data. A proven matching methodology was used to link license plate and vehicle occupancy data together, which complemented the analysis for either forms of data. Measures were taken to verify, correct, and improve the data and the methodologies that were used over the two-year period.

The research team identified occupancy records that were potentially not fit for data analysis. A process was outlined for future studies to identify biased sources of data and remove them from the analysis. Transportation authorities had a large stake in the HOV-to-HOT conversion and one of their principal concerns was how passenger throughput was going to evolve and vehicle occupancy was essential for this. Vehicle occupancy decreased in the managed lane since the conversion but a more in-depth occupancy analysis could reveal the greater impact on the entire corridor.

Comparisons were made for the motor vehicle registration information obtained from the labor-intensive license plate transcription process. The analysis consisted of comparisons of the HOT lane fleet to the adjacent general purpose lane as well as across all general purpose lanes. Using data and similar comparisons made during a pre-conversion time period, it was possible to assess how these distributions changed over time. The analysis revealed characteristics such as the most frequent vehicle model years and fuel types. This information that will be critical in future studies. The vast majority of vehicles on the corridor were privately owned both before and after the conversion. Government vehicles were more concentrated in both the HOV and the HOT lane than any other lane, while the conversion saw a proportional decrease in commercial vehicles on the HOT lane, which was contrary to pre-conversion expectations. However, more information was needed to conclude whether or not all lanes saw a decrease in commercial vehicles. HDVs were more concentrated in the HOV and HOT lanes while the conversion introduced more LDVs into the managed lane. The HOT lane consisted of 53.4% of SUVs, while only consisting of 44.7% of LDVs. Many of the same fuel type trends were seen before and after conversion. Despite an increase in fuel types that could classify a vehicle as toll-exempt, there was little evidence that a significant portion of users were in the HOT lane and benefitting from this exemption. The distribution of vehicle age was similar between the HOV lane and general purpose lane 1; however, after conversion, the HOT lane was composed of newer model year vehicles. As expected, post-conversion results included proportionally fewer out-of-state vehicles in the HOT lane due to the Peach Pass registration requirement in order to utilize the lane.

Nine data collection sessions of the occupancy and license plate data were matched together. This procedure provided the research team with the assurance that data collectors were becoming more consistent with one another, leading to a higher probability of accurate data. The distribution of matched records also provided a form of comparing occupancy distributions and vehicle variables like vehicle classification. SUV was the most common vehicle classification for vehicles in two-person carpools. During the matching procedure, the data entries were reviewed for error rates and special vehicles frequencies. As a consequence, the research team identified URA license plate transcription error rate to be 11.8% and motorcycle frequency to be 1.1%.

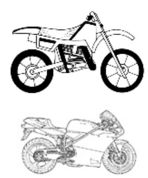
The HOT lane was expected to improve traffic conditions by more efficiently moving vehicles, which would have alleviated congestion in the general purpose lanes and moved more vehicles through that passage [17]. However, the research team observed a slight decrease in overall corridor average occupancy, which the conversion might have caused by provoking users to part from their carpools and drive separately. Additional measures might have been necessary to promote groups of carpoolers to consider splitting the toll as there was, apparently, insufficient benefit to continue carpooling proactively. However, it was difficult to measure the significance of the carpooling data because “fampools” or carpools made up of family members were difficult to distinguish from carpools that that would have otherwise reduced congestion.

The HOT lane’s tumultuous introduction and the additional non-carpooling vehicles caused more congestion than existed before conversion for the first few months of operation. Once past the lane’s “growing pains,” the congestion decreased but it was difficult to identify what caused the reduction in users. It was unknown whether a significant number of users chose an alternate route, whether the peak period widened past the peak hours established in pre-conversion times, whether other non-transportation related issues caused this reduction, or if all three were contributing factors. Although not originally intended, route dispersion could have been a beneficial impact while an extended peak period would have inconvenienced some users’ schedules.

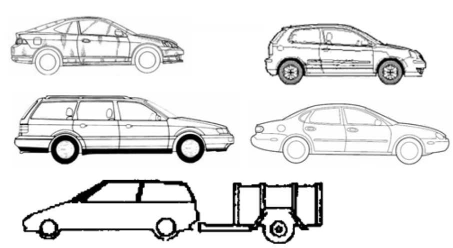
Therefore, transportation stakeholders will be interested in building upon the aforementioned user vehicle traits to identify additional revealed information as to what specific factors led to users making their specific travel choice. Demographic data needs to be collected to bring to bear analytical variables that were not available for this thesis. Examples of additional variables include income, geographic location, transit access, etc. Therefore, future studies could be used to respond to a variety of HOT lane questions. A future study could investigate the accuracy of a 2007 study that predicted that Atlanta HOT users would have 15% higher incomes [29]. That study was already correct in its prediction that the managed lane's carpooling rates would be lower.

APPENDIX A: VEHICLE CLASSIFICATION FLASH CARDS

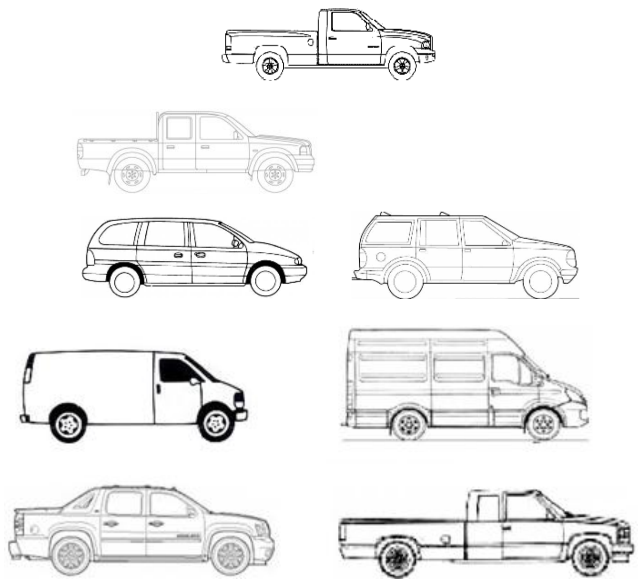
Motorcycle



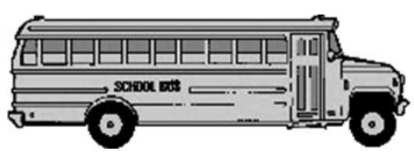
Light Utility Automobile (Passenger Car)



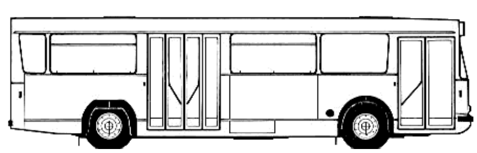
Light Utility Trucks (SUV)



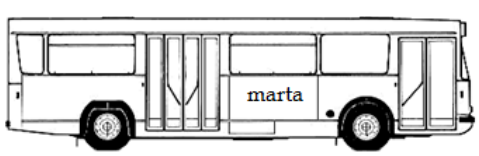
School Bus



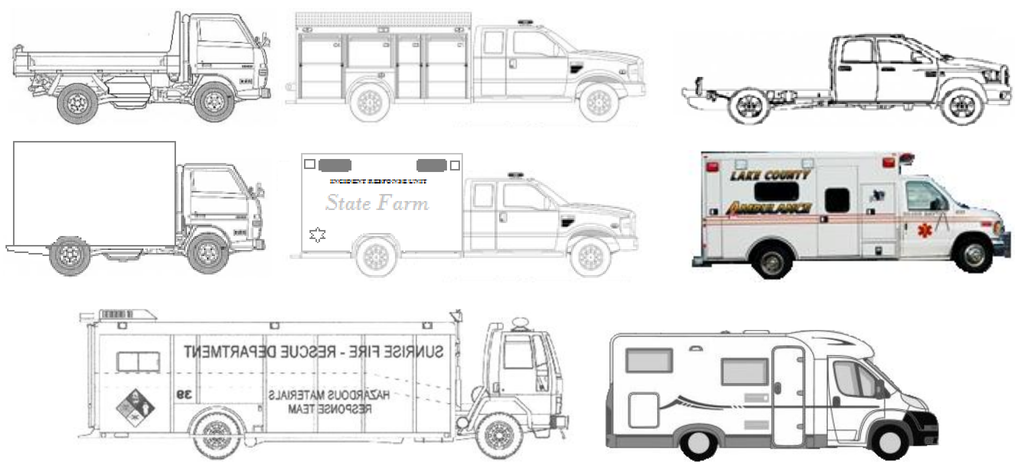
Other Buses



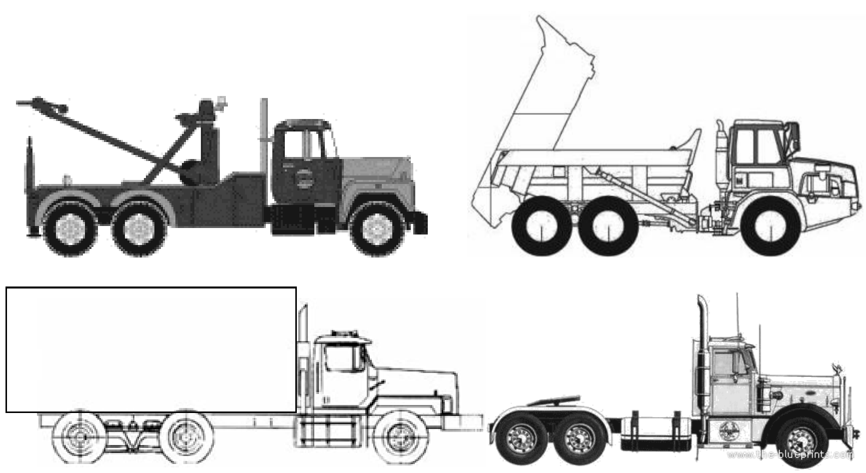
MARTA BUSES -- Bus with MARTA vehicle markings



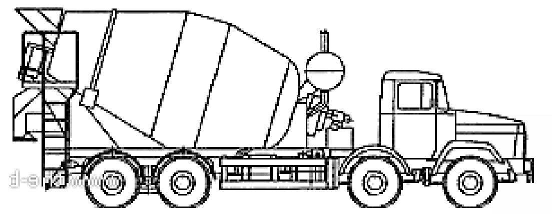
TWO AXLE, SINGLE UNIT TRUCK(s) -- All vehicles on a single frame including trucks, camping and recreational vehicles, motor homes, etc., with two axles and DUAL REAR WHEELS.

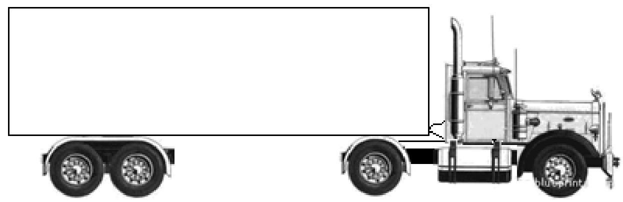


THREE AXLE SINGLE-UNIT TRUCK(s) -- All vehicles on a single frame including trucks, camping and recreational vehicles, motor homes, etc., with three axles.

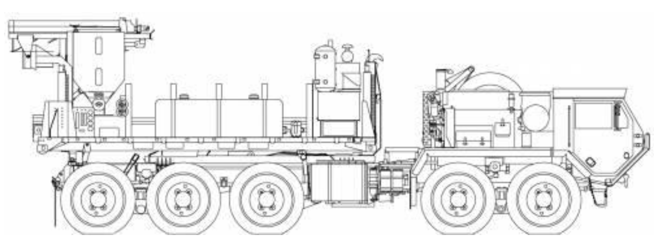


THREE/ FOUR-AXLE Single Trailer Combination -- All trucks on a single frame with three or four axles & a single trailer combination.





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



REFERENCES

1. USDOT. *Atlanta-Area Congestion Reduction Demonstration ("CRD") Description.* [cited 2012 December 6]; Available from: http://www.upa.dot.gov/crd/agreements/atlanta.htm

2. AJC. *HOT Lanes Pick Up Momentum, Critics.* 2012. [cited 2012 December 6]; Available from: http://www.ajc.com/news/hot-lanes-pick-up-1367020.html

3. Gwinnett Daily Post. *Transition Begins to HOT Lanes on I-85.* 2011. [cited 2012 December 6]; Available from: http://www.gwinnettdailypost.com/news/2011/sep/18/transition-begins-to-hot-lanes-on-i-85/#h36454-p13

4. Roell, M., et al., *The I-85 HOT Lane's Impact on Atlanta's Commuter Bus and Vanpool Occupancy*. 2012, Georgia Institute of Technology.

5. AJC. *Deal Lowers Tolls on I-85 HOT Lanes.* 2011. [cited 2012 December 6]; Available from: http://www.ajc.com/news/deal-lowers-tolls-on-1196014.html

6. Toll Roads News. *GA.I-85 Toll Express Lanes Do Better in 2nd Week – but Not Peachy Yet (REVISED). 2011. [cited 2012 December 6];* Available from: http://www.tollroadsnews.com/node/5560

7. 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.

8. AJC. *Cost to Use I-85 HOT Lane Hits New High.* 2012. [cited 2012 December 6]; Available from: www.ajc.com/news/cost-to-use-i-1365649.html

9. Toll Roads News. *GA/I-85 Toll Lanes Lookin' Peachier – Strong Growth in Traffic at 6th Month.* 2012. [cited 2012 December 6]; Available from: http://www.tollroadsnews.com/node/5903

10. Atlanta Business Chronicle. *State Lowers Tolls Again on I-85 Express Lanes.* 2012. [cited 2012 December 6]; Available from:

http://www.bizjournals.com/atlanta/news/2012/01/20/state-lowers-tolls-again-on-i-85.html

11. 95 Express. *About 95 Express.* [cited 2012 December 6]; Available from: http://www.95express.com/pdf/htmlversions/faq_08-0304.html

12. Mallinckrodt, Jack. *Frequently Asked Questions About HOV Lanes.* 2012. [cited 2012 December 6]; Available from: http://urbantransport.org/hovfaq.pdf

13. WSDOT. *Washington State Freeway HOV System.* 2012. [cited 2012 December 6]; Available from: http://www.wsdot.wa.gov/HOV/

14. Fitch Ratings. *U.S. Surface Transportation Funding: Pitted with Potholes.* 2011. [cited 2012 December 6]; Available from: http://www.ibtta.org/files/PDFs/US%20Surface%20Transportation%20Funding-%20Pitted%20with%20Potholes.pdf

15. Atlanta Business Chronicle. *Interstate 85 Toll Lanes to Open Next Month.* 2011. [cited 2012 December 6]; Available from: http://www.bizjournals.com/atlanta/print-edition/2011/09/23/interstate-85-toll-lanes-to-open-next.html

16. Vu, P. et al, *Enforcement Strategies for High-Occupancy Toll Lanes*, in *Transportation Research Board 2008 Annual Meeting.* 2008, Transportation Research Board: Washington, DC.

17. Smith, K.*, A Profile of HOV Lane Vehicle Characteristics on I-85 Prior to HOV-To-HOT Conversion*, in *Civil and Environmental Engineering*. 2011, Georgia Institute of Technology

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

19. 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.

20. 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.

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

22. 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.

23. GSA. *Alternative Fuel Vehicles (AFVs)*. 2012 December 4, 2012; Available from: http://www.gsa.gov/portal/content/104442.

24. 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.

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

26. 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.

27. GeorgiaDepartmentofRevenue. *When, where and what is needed to transfer my Georgia license plate to another vehicle I've purchased or acquired?* 2011 [cited 2012 December 4]; Available from: http://motor.etax.dor.ga.gov/motor/RegistrationSection/rs_TagTransfer.aspx

28. Atlanta Regional Commission. *I-85 HOT Lanes: Modeling Techniques.* 2009. [cited 2012 December 6]; Available from: http://www.atlantaregional.com/File%20Library/Transportation/Travel%20Demand%20Model/tp_mug_1-85hovhotmodel_120409.pdf

29. 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.

30. Guensler, Randall. *Peach Pass Transponder Sales.* Personal interview. 17 Dec. 2012.

31. Sheikh, Adnan. *CDF of HOT Lane User Trips*. Personal interview. 14 Dec. 2012.

32. California Performance Review. *INF05 Need for High-Occupancy/Toll Facilities to Reduce Traffic Congestion and Generate Revenue to Cover Project Costs*. 2007. [cited 2013 January 5]; Available from: http://cpr.ca.gov/cpr_report/Issues_and_Recommendations/Chapter_4_Infrastructure/INF05.html

33. Kish, Phillip. *Ga. DOT plans HOT lanes expansion*. Fox Atlanta. 2012. [cited 2013 January 5]; Available from: http://www.myfoxatlanta.com/story/19599285/ga-dot-plans-to-expand-hot-lanes

34. Metro. *HOT Lanes in the U.S.* 2012. [cited 2013 January 5]; Available from: http://www.metro.net/projects/expresslanes/expresslanes_us/