EVALUATION OF HIGH OCCUPANCY TOLL LANE USAGE
BY SINGLE OCCUPANCY VEHICLES

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ABSTRACT

High Occupancy Toll (HOT) facilities are effective tools for managing demand and mitigating congestion where construction to expand roadway capacity is not feasible. This paper evaluates paying Single Occupancy Vehicles’ (SOV) responses to toll rates. Due to the unique features of HOT facilities—dynamic toll rates and multiple access points—drivers’ reactions to the change in HOT lane toll rates can differ substantially from traditional toll road drivers’ reactions. This is especially true for paid SOV drivers. This study used toll and traffic data from SR-167 in Washington State in 2008 and 2010. Logistic regression models were used to evaluate the influence of toll rate, volume, speed, and speed reliability on the percentage of paid SOVs in the HOT lane. Results show that both HOT and general-purpose traffic conditions impact SOVs’ choices. Speed, speed reliability, and traffic volumes in the general-purpose lanes are all associated with the percentage of paid SOVs using the HOT lane. Toll rate is only significant for the year 2010, and a ramp-up effect in use is found from the HOT lane’s 2008 opening year to 2010. SOV drivers’ reactions to dependent variables in 2008 differ significantly from reactions found in 2010. This study provides critical information for understanding the factors affecting drivers’ HOT lane use choices, as well as insights into the design of tolling schemes at different stages of a HOT facility.

Keywords: High occupancy toll lanes, toll lanes, toll rates, value of time
INTRODUCTION AND LITERATURE REVIEW

Congestion pricing is an effective travel demand management strategy chosen by many states and local transportation agencies. The premise of toll regulation is to shift traffic on congested corridors during peak hours to other roads, to different departure times, or to other modes of transportation. A considerable number of studies have been conducted to model the response of traffic demand to toll rates. Traditionally, studies have relied on large-scale surveys where the value of time (VOT) is identified and utility functions are used to model the likelihood of travelers’ choice of toll roads. Research has been conducted to investigate various impacts on toll road use, including not only VOT [1-4], but also driver behavior due to road pricing [5-11], and comparisons between results inferred from data obtained by stated preference (SP) and revealed preference (RP) surveys [1, 12, 13].

Previous studies indicate an overall willingness to pay for travel options that will reduce travel time. Lam and Burris et al. [6] studied drivers’ willingness to pay on two express lanes in San Diego and found that travelers are willing to pay a toll even when the VOT is small. Khademi et al. [8] concluded that willingness to pay varies little based on sociodemographics, with the exceptions being the impacts of income and public transport accessibility.

The amount drivers are willing to pay also depends on a number of variables. Gifford and Talkington model daily traffic demand using toll rates, gas price, and the corresponding day-of-week. They found that day-of-week cross elasticity is complementary, and therefore concluded that time-varying prices may be a viable strategy for managing traffic demand [14]. Cain et al. [15] indicate that at the aggregate level, variable pricing program implementation had a minimal impact on the overall distribution of demands. However, disaggregate level analysis showed a significant shift of traffic from peak hour to peak hour shoulders where a discount toll rate was applied.

Variable toll rates can also have a significant effect on traffic congestion. Du et al. [7] showed that the toll change shifted the time-of-day travel demand with an increase in non-peak hour trips and a decrease in peak hour trips. Speed improved significantly after the toll changes, especially over a short-term observation period. Bell et al. [16] studied the diversion of traffic using macroscopic and microscopic simulation and concluded that the diversion of traffic was affected by a combination of factors, such as toll, distance of the alternative route, and level of congestion of both the alternative route and the tolled route.

The High Occupancy Toll (HOT) facilities are toll locations where a High Occupancy Vehicle (HOV) lane is converted to a toll lane for single occupancy vehicle (SOV) drivers, while remaining available to HOVs free of charge. HOT facilities are based on the premise that a majority of the HOV lanes in the U.S. are underused, and in recent years, they have grown in demand [17-19]. The first HOT lane, in California, opened to SOV users in 2001, and as of 2015, approximately 20 HOT facilities are in use in the U.S., with many more under construction. HOT facilities a flexible solution to congestion management and a convenient tool in improving traffic network efficiency without new construction.

While considered an effective and powerful tool, the complex operating characteristics of HOT lanes pose a challenge for researchers and practitioners to forecast traffic and revenues [20,21]. To accurately estimate traffic and revenue for HOT facilities, it is critical to accurately quantify SOV drivers’ responses to tolls and to decide optimum toll rates for HOT lanes [22-27]. Several factors complicate the relationship between drivers’ responses and toll rates.

- The HOT lane is typically adjacent to general-purpose (GP) lanes with multiple access points.
- The decision to use the HOT facility can thus be made and also changed in the middle of traveling.
- Toll rates change dynamically in accordance with the congestion level of HOT lanes.
- Studies have shown that drivers’ responses to the increase of HOT toll rates are not necessarily a monotonic downward curve [28, 29].

Travel time saving and toll rate are only two of many factors affecting decision making [6, 32]. In fact, Bonsall et al. found that the response of road users to a complex or highly differentiated toll system is so complicated that the impacts of complex price signals are likely to be blunted [30]. In addition there
could be many contributing factors including VOT, trip purposes, departure time and arrival time
resilience, configuration of access points, local economic conditions, traffic compositions, population
distribution, and gas cost [10]. Devarasetty et al. suggested that the estimation of managed lane usage
should include the reliability of travel time [31]. As far as increasing HOT lane use, De Palma and
Lindsay argued that tolling could affect travel decisions and thus tolling is effective only if travelers can
be made aware of tolls sufficiently in advance [32]. Lou et al. and Yin et al. used a self-learning approach
to evaluate the impacts of lane-changing behavior to determine dynamic pricing strategies for HOT lanes
to maximize the freeway’s throughput [22, 27, 33]. Clearly, there is a great deal to consider when
determining best HOT facility use strategies.

The dynamic toll rate method is a commonly used pricing approach for HOT lanes. Under the
dynamic toll method, the toll rate is not only a tool to control upcoming traffic entering the HOT lane, but
also the result of current and near-future traffic conditions. Therefore, drivers are not only responding to
toll rate, but may also use the toll rate as an indicator of congestion levels. The majority of the previous
research discussed here either modeled HOV and SOV traffic as integrated parts or optimized the toll
rates by treating the aggregated volume as one target.

The goal of this study is to investigate the impacts that dynamic tolls have on individual drivers’
choices in HOT facilities by studying the patterns of SOVs in the HOT lane. The study focuses on the
responses of the subset of users who actually pay to use the managed lane. Also studied in this paper is
the difference between the opening year of the HOT facility as compared to an established year in order to
examine drivers’ acceptance of the HOT lane and the potential change in drivers’ behaviors at different
stages of HOT facilities’ implementations.

This paper is organized as follows: following the introduction is a section stating the research
problem; data used in this paper are described in the next section; methodology and modeling results are
presented next; and the last section contains conclusions and discussions.

PROBLEM STATEMENTS

One of the most important characteristics of the HOT facility is that only SOVs pay the toll. Subsequently,
only the number of SOVs will affect the HOT lanes’ revenue. To accurately predict traffic flow and
revenue for HOT facilities, it is critical to understand SOV users’ reactions. One key forecasting
procedure component is the diversion curve. Diversion curves describe the percentage of SOV drivers
who are likely to divert from GP lanes and pay for using the HOT lane. Diversion curves are developed
based on potential factors that will affect traffic demand. Those factors may include, but are not limited to,
regional and road-user socioeconomic characteristics, class of toll roads, magnitude of congestion, and
available alternative travel modes. Diversion curves need to be determined before a HOT facility is open
to public and are the basis for forecasting and estimating traffic demand and revenue. Therefore, the
accuracy of these curves is the key to accurate estimation of revenue and traffic for HOT facilities.

HOT facilities typically have a dynamic toll rate calculation system that aims at maintaining a
target level of service (LOS) in the HOT lane. Previous studies have suggested that trip purposes, trip
makers, and trip distances should all be taken into consideration as factors affecting the VOT and
resultant choices of SOV drivers. However, in the case of HOT lanes, the dynamic toll rate is updated in a
very short time period and obtaining such detailed data in real time is unrealistic. The toll rate and
diversion rate for HOT lanes, therefore, will be more sensitive and vary more rapidly. Traffic density and
speed, two primary LOS indicators, are key factors in determining toll rate; at the same time, toll rate has
a direct impact on traffic density and speed. The interaction between toll rate, level of service, and
percentage of SOVs in the HOT lane makes the conventional method of using VOT to model the
willingness to pay—originally intended for fixed toll rate facilities—a questionable approach.

Fortunately, since multiple HOT facilities have been in operation for years, it is now feasible to
look at historical data to examine the mechanisms working behind the scenes. In this study, we will
investigate the impact of dynamic tolls on the choices of SOV drivers using data collected on SR-167 in
Washington State in its opening year of 2008 and during the operational year of 2010. Although the
congestion level in the HOT lane primarily determines the HOT toll rate, we do not believe that HOT traffic conditions are the sole factor in SOV user decision-making. The prevailing traffic conditions in GP lanes also play a critical role in decision-making, and modeling should take the traffic conditions of both GP and HOT lanes into consideration.

**METHODOLOGY AND MODEL DEVELOPMENT**

**Study Site**

SR-167 opened to traffic in May, 2008, and runs northbound and southbound for approximately 10 miles between Renton and Auburn. Since HOV lanes on SR-167 operate at under capacity during peak hours, the HOT lane was used as a tool to increase vehicle throughput without reducing the level of service for carpools and transit users. There are two GP lanes in each direction, which are free and open to all traffic at all times. The HOT lane runs side-by-side with the GP lanes. Access in and out of the HOT lanes is restricted at designated exits. HOVs can use the HOT facility free of charge at any time. SOVs must pay a toll when traffic is congested [34]. The toll rate updates periodically to maintain a free flow condition in the HOT lane, and may change as frequently as every five minutes to ensure a satisfactory LOS. The location and configuration of SR-167 is shown below (FIGURE 1).

![SR-167 Configuration](http://www.wsdot.wa.gov/NR/rdonlyres/C198671E-7B2F-4186-9912-A41A0B274103/0/SR167_AnnualPerformanceSummary_113011_FINAL_WEB.pdf)

**Data Descriptions**

The SR-167 HOT lane uses a dynamic tolling system. Toll rates ranged from $0.50 to $9.50 in 2008, and from $0.50 to $4.50 in 2010. The research team contacted two data providers in the Washington State Department of Transportation (WSDOT) and acquired two sets of data:

1. Loop detector data where the GP and HOV traffic volumes and speed data extracted from WSDOT’s Compact disk Data Retrieval (CDR) utility are aggregated to five-minute intervals;
2. Transponder data where the HOT lane data are obtained from SR-167’s HOT management authority.

One challenge in processing traffic data is missing values. Observations with zero traffic volume could either indicate zero traffic flow or could indicate a malfunction of data collecting tools. We validated observations showing zero traffic volume using occupancy, defined as the percentage of time the loop detector was activated. The rule is that whenever there is non-zero occupancy data, there should be a valid larger-than-zero traffic count. Zero traffic volume is only accepted as valid when the occupancy is simultaneously zero. Transponder data include the following information at the resolution of five minutes: toll rate, number of SOVs paying to use the HOT lane, number of HOVs using the HOT lane for free, and the spot speed of vehicles driving in the HOT lane. Since they are from two different sources, the two sets of data were first compared to ensure consistency and filter out errors.

Consistency of Loop Detector Data and HOT Data
Since the transponder data only included HOT lane information, only the HOT lane traffic data from loop detectors is examined against it. Traffic volumes for 2008 and 2010 from the two data sources on the northbound lanes of section six are averaged and plotted below as an example of the data comparison. The discrepancy between the two data sources is minimal, with both data sources indicating a morning peak from 6:00 a.m. to 8:00 a.m. northbound on SR-167 (FIGURE 2).

![Average Hourly Traffic Volume NB Section 6](image)

**FIGURE 2 Data Consistency**

Exploratory Data Analysis
The percentage of SOV users in the HOT lane is investigated from two perspectives: 1) the mean percentage of valid automatic vehicle identification (AVI) (i.e., the percentage of SOVs in the HOT lane’s traffic), and 2) the percentage of paid SOVs across all three lanes of the roadway section’s traffic. The following graphics show the relationship of SOV usage in HOT lanes only along with toll rate in the years 2008 and 2010, respectively (FIGURE 3). Results show that in 2008, the percentage of paid SOVs increases with a toll rate increase from zero to $2.50. The percentage of paid SOVs stays stable from the range of $2.00 to $3.00 and then starts to decrease after the toll rate increases to above $3.00. A similar
pattern is observed in the year 2010. The stabilized portion for the SOV percentages in 2010, however, extends further with increasing toll rates.

The percentage of paid SOVs in all three lanes across the roadway section versus total traffic volume is illustrated below (FIGURE 4). A four stage trend is observed: first, when the overall volume stays low, the diversion rate stays stable and low; second, when the overall volume increases to capacity, the diversion rate increases dramatically; third, during the period when the traffic volume is around capacity, the diversion rate remains high; and lastly, when traffic conditions reach the over-saturated stage, the diversion rate drops. The following illustration shows that when the traffic volume is high, the percentage of SOVs choosing the HOT lane is significantly higher in 2010 than in 2008. The percentage of paid SOVs doubled when the traffic flow rate was above 1,400 vehicles per hour per lane.
The previous section illustrated that the percentage of SOVs in the HOT lane does not continuously decrease with the increase in toll rates as has been observed on a regular toll road. Previous research found that travelers are likely to choose the HOT lane even when travel time savings are insignificant, or even nonexistent [6, 35]. In this section, we explore the factors that affect the choices of SOVs in the HOT lane by modeling the percentage of SOVs in the total HOT lane traffic. A logistic regression model is used to compute the probability of SOVs selecting the HOT lane. Explanatory factors, including traffic volume, toll rate, speed in GP lanes, and buffer index of speed on GP lanes, are investigated as well.

For exploratory analysis, the percentage of vehicles that paid tolls in a time period $i$ is calculated as

$$\text{PercSOV}_i = \frac{SOV_i}{SOV_i + HOV_i + VOL_{GP_i}}$$

where $SOV_i$ is the number of SOVs in the HOT lane, $HOV_i$ is the number of HOVs in the HOT lane, and $VOL_{GP_i}$ is the traffic volume in GP lanes.

The data collected in this research do not include microscopic trip information, such as origin and destination or aggregated average travel time. Instead, available spot-detected speeds for both GP and HOT lanes are used. We define a speed buffer index $SpdBI_i$ at time window $i$ as

$$SpdBI_i = 90\text{th percentile of speed}_i - \text{mean speed}_i$$

The speed buffer index is similar to a travel time buffer index. It measures the range of variation of speed and is adopted as a measure of travel time reliability. The smaller the speed buffer index, the more reliable the traffic time. The mean values of the variables for both years are illustrated below (TABLE 1). As shown, there is a 76% increase in average percentage of SOV uses along with a modest 7% increase in overall average traffic volume per lane. Consistent with high increases in the percentage of SOV users, the HOT lane traffic volume increases by 12%. Although increased traffic volume has a
minor impact on the mean travel speed (1%~3% increase), the speed buffer index shows a substantial
decrease of 22% and 10%. This result indicates that by converting a HOV lane to a HOT lane, both GP
and HOT lanes have improved travel time reliability and throughput. It also implies that speed variation
and travel time reliability are sensitive to the traffic volume increase and could potentially affect SOV
users’ decisions.

**TABLE 1 Summary Statistics**

<table>
<thead>
<tr>
<th>Year</th>
<th>SOV %</th>
<th>Traffic Volume (V/H/Lane)</th>
<th>GP Volume (V/H/Lane)</th>
<th>HOT VOL (V/H/Lane)</th>
<th>GP Speed</th>
<th>HOV speed</th>
<th>SpdBI GP</th>
<th>SpdBI HOT</th>
<th>Toll ($)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2008</td>
<td>0.69%</td>
<td>980</td>
<td>1269</td>
<td>403</td>
<td>57.2</td>
<td>54.8</td>
<td>0.54</td>
<td>0.30</td>
<td>0.70</td>
</tr>
<tr>
<td>2010</td>
<td>1.21%</td>
<td>1047</td>
<td>1344</td>
<td>452</td>
<td>58.8</td>
<td>55.9</td>
<td>0.42</td>
<td>0.27</td>
<td>0.64</td>
</tr>
<tr>
<td>Changes</td>
<td>76%</td>
<td>7%</td>
<td>6%</td>
<td>12%</td>
<td>3%</td>
<td>1%</td>
<td>-22%</td>
<td>-10%</td>
<td>-8%</td>
</tr>
</tbody>
</table>

As previously stated, toll rates are highly correlated to the traffic status, and conversely, traffic
conditions will impact toll rate updates. Multiple variables are compared pairwise to identify the inter-
correlations of the variables. The results are shown in TABLE 2 and TABLE 3. As can be seen, the
correlation among all the factors is much stronger in 2010. This implies a better acceptance of the HOT
system by the public and a more sensitive response to the changes in variables. The largest change is
observed for the speed buffer index on the GP lane “SpdBI_GP”. The correlation between the “SpdBI_GP”
with the “SOV Perc” was 0.58 in 2008 and increased to 0.72 in 2010. This shows that speed reliability in
the GP lane is a key factor in SOV drivers’ decision making. The correlations of “SpdBI_HOT” and “Toll”
with the percentage of SOV drivers are much higher in 2010 as well. This indicates a higher sensitivity of
the public to traffic conditions in the HOT facility and also indicates that users care more about toll rates.
This occurs even though the tolls in 2010 were lower than those in 2008.

The toll rate is positively correlated with the percentage of SOV users (0.36 in 2008 and 0.56 in
2010). While seemingly counter-intuitive, this is caused by the toll rate setting mechanism. The toll rate is
dynamically updated based on the variation in traffic demand, so the more congested the roadway, the
higher the toll rate will be. Consequently, a higher percentage of SOV users were generally associated
with higher toll rates because they will choose HOT lanes to avoid GP lane congestion. The SOV user
percentage is negatively associated with speed in the GP and HOT lanes: the lower speed indicates a
higher traffic volume and thus will promote SOV usage of the HOT lane. The higher speed buffer index
indicates an increased travel time uncertainty, and thus a higher SOV lane usage, which implies that
reliability is another critical factor in SOV usage. One notable observation is that the correlation of
percentage of SOV users and toll is among the lowest correlation values compared to other variables.
Another interesting observation is that the correlation between “SpdBI_HOT” and the “SOV Perc” is
much weaker than the case of “SpdBI_GP,” indicating that users were more sensitive to traffic conditions
in the GP lane than the HOT lane.

The results also show that there are relatively high correlations among factors, which prohibits
the use of all factors in a model-based analysis. As suggested from the results, the percentage of SOV
users are highly correlated with overall traffic volume, traffic volume in the GP and HOT lanes. speed of
the GP lane, and speed buffer index of the GP lane. Those variables, therefore, are selected for the models
to be illustrated in the next section.
TABLE 2 Correlation Table for 2008

<table>
<thead>
<tr>
<th></th>
<th>SOV Perc.</th>
<th>Traffic Volume</th>
<th>GP Volume</th>
<th>HOT Volume</th>
<th>GP Speed</th>
<th>H0V Speed</th>
<th>SpdBI GP</th>
<th>SpdBI HOT</th>
<th>Toll</th>
</tr>
</thead>
<tbody>
<tr>
<td>SOV Perc.</td>
<td>1.00</td>
<td>0.55</td>
<td>0.45</td>
<td>0.70</td>
<td>-0.70</td>
<td>-0.33</td>
<td>0.58</td>
<td>0.23</td>
<td>0.36</td>
</tr>
<tr>
<td>Total volume</td>
<td>0.55</td>
<td>1.00</td>
<td>0.98</td>
<td>0.83</td>
<td>-0.62</td>
<td>-0.36</td>
<td>0.56</td>
<td>-0.13</td>
<td>0.35</td>
</tr>
<tr>
<td>GP volume</td>
<td>0.45</td>
<td>0.98</td>
<td>1.00</td>
<td>0.70</td>
<td>-0.60</td>
<td>-0.34</td>
<td>0.54</td>
<td>-0.19</td>
<td>0.29</td>
</tr>
<tr>
<td>HOT volume</td>
<td>0.70</td>
<td>0.83</td>
<td>0.70</td>
<td>1.00</td>
<td>-0.53</td>
<td>-0.33</td>
<td>0.49</td>
<td>0.09</td>
<td>0.44</td>
</tr>
<tr>
<td>GP speed</td>
<td>-0.70</td>
<td>-0.62</td>
<td>-0.60</td>
<td>-0.53</td>
<td>1.00</td>
<td>0.42</td>
<td>-0.85</td>
<td>-0.13</td>
<td>-0.38</td>
</tr>
<tr>
<td>HOV speed</td>
<td>-0.33</td>
<td>-0.36</td>
<td>-0.34</td>
<td>-0.33</td>
<td>0.42</td>
<td>1.00</td>
<td>-0.38</td>
<td>-0.49</td>
<td>-0.20</td>
</tr>
<tr>
<td>SpdBI HOT</td>
<td>0.58</td>
<td>0.56</td>
<td>0.54</td>
<td>0.49</td>
<td>-0.85</td>
<td>-0.38</td>
<td>1.00</td>
<td>0.16</td>
<td>0.32</td>
</tr>
<tr>
<td>Toll</td>
<td>0.36</td>
<td>0.35</td>
<td>0.29</td>
<td>0.44</td>
<td>-0.38</td>
<td>-0.20</td>
<td>0.32</td>
<td>0.12</td>
<td>1.00</td>
</tr>
</tbody>
</table>

TABLE 3 Correlation Table for 2010

<table>
<thead>
<tr>
<th></th>
<th>SOV Perc.</th>
<th>Traffic Volume</th>
<th>GP Volume</th>
<th>HOT Volume</th>
<th>GP Speed</th>
<th>H0V Speed</th>
<th>SpdBI GP</th>
<th>SpdBI HOT</th>
<th>Toll</th>
</tr>
</thead>
<tbody>
<tr>
<td>SOV Perc.</td>
<td>1.00</td>
<td>0.51</td>
<td>0.39</td>
<td>0.70</td>
<td>-0.73</td>
<td>-0.33</td>
<td>0.72</td>
<td>0.27</td>
<td>0.56</td>
</tr>
<tr>
<td>Total volume</td>
<td>0.51</td>
<td>1.00</td>
<td>0.98</td>
<td>0.80</td>
<td>-0.51</td>
<td>-0.30</td>
<td>0.51</td>
<td>-0.11</td>
<td>0.36</td>
</tr>
<tr>
<td>GP volume</td>
<td>0.39</td>
<td>0.98</td>
<td>1.00</td>
<td>0.65</td>
<td>-0.46</td>
<td>-0.27</td>
<td>0.45</td>
<td>-0.16</td>
<td>0.26</td>
</tr>
<tr>
<td>HOT volume</td>
<td>0.70</td>
<td>0.80</td>
<td>0.65</td>
<td>1.00</td>
<td>-0.52</td>
<td>-0.30</td>
<td>0.57</td>
<td>0.08</td>
<td>0.56</td>
</tr>
<tr>
<td>GP speed</td>
<td>-0.73</td>
<td>-0.51</td>
<td>-0.46</td>
<td>-0.52</td>
<td>1.00</td>
<td>0.43</td>
<td>-0.89</td>
<td>-0.27</td>
<td>-0.40</td>
</tr>
<tr>
<td>HOV speed</td>
<td>-0.33</td>
<td>-0.30</td>
<td>-0.27</td>
<td>-0.30</td>
<td>0.43</td>
<td>1.00</td>
<td>-0.43</td>
<td>-0.58</td>
<td>-0.21</td>
</tr>
<tr>
<td>SpdBI HOT</td>
<td>0.72</td>
<td>0.51</td>
<td>0.45</td>
<td>0.57</td>
<td>-0.89</td>
<td>-0.43</td>
<td>1.00</td>
<td>0.34</td>
<td>0.44</td>
</tr>
<tr>
<td>Toll</td>
<td>0.56</td>
<td>0.36</td>
<td>0.26</td>
<td>0.56</td>
<td>-0.40</td>
<td>-0.21</td>
<td>0.44</td>
<td>0.23</td>
<td>1.00</td>
</tr>
</tbody>
</table>

Regression Analysis

A logistic regression is developed to model the relationship between the percentage of SOVs in the HOT lane and potential impact factors. The model setup is as follows. Let $Y_i$ be the number of SOVs in the HOT lane for time window $i$. We assume $Y_i$ follows a binomial distribution:

$$Y_i \sim \text{Binomial}(N_i, P_i),$$

where $N_i$ is the total number of vehicles in the HOT lane in time window $i$; $P_i$ is the probability of a randomly selected vehicle in the HOT lane being a SOV. The $P_i$ is directly related to SOV users who are willing to pay to use the HOT lane and is the key parameter of interest. We used a logit link function to link the $P_i$ with the set of covariates:

$$\text{logit}(P_i) = \beta_0 + \beta_1 X_{i1} + \cdots + \beta_K X_{Ki}$$

where $\beta_0, \ldots, \beta_K$ are regression coefficients and $X_{i1}, \ldots, X_{Ki}$ are $K$ covariates for time window $i$.

As indicated in the correlation analysis in the previous section, there are strong correlations among variables. To prevent them from being included simultaneously in the model to avoid multicollinearity problems, we propose two models, each including a different set of carefully selected covariates:
1. The first model includes the total traffic volume as measured by the number of vehicles per hour per lane, toll rate, and average speed in the GP lane;

2. The second model includes total traffic volume as measured by the number of vehicles per hour per lane, toll rate, and speed buffer index in the GP lane.

Data from 2008 and 2010 are used to fit the model, respectively. Results are shown below (TABLE 4). Based on the AIC values, both models provide insights into the influence of factors on HOT lane usage by SOV drivers. All the independent variables in both models are significant, except the toll rate using the 2008 data. The results from 2008 indicated that overall traffic demand and average speed in the GP lane significantly impacted the probability of SOV drivers choosing the HOT lane. For model 1, an increase in traffic volume and decrease in the average speed in the GP lane, increases the probability of choosing a HOT lane. The toll rate, however, has no significant impact on the probability of using the HOT lane. For model 2, with the increase in the speed buffer index, and thus a decrease in travel time reliability, SOV drivers are more likely to pay into the HOT facility. As was the case with model 1, the total traffic volume has a positive impact on the probability while the toll rate has a minimal impact on the results.

TABLE 4 Logistic regression model coefficients

<table>
<thead>
<tr>
<th></th>
<th>Estimate</th>
<th>Standard Error</th>
<th>P-Value</th>
<th>Estimate</th>
<th>Standard Error</th>
<th>P-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Model 1</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Intercept)</td>
<td>-2.85</td>
<td>0.69</td>
<td>&lt;0.001</td>
<td>-2.85</td>
<td>0.44</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Traffic Volume (V/H/Lane)</td>
<td>0.14</td>
<td>0.03</td>
<td>&lt;0.001</td>
<td>0.14</td>
<td>0.02</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Toll ($)</td>
<td>0.04</td>
<td>0.09</td>
<td>0.697</td>
<td>0.36</td>
<td>0.08</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>General Purpose Lane Speed</td>
<td>-0.07</td>
<td>0.01</td>
<td>&lt;0.001</td>
<td>-0.06</td>
<td>0.01</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td><strong>Model 2</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Intercept)</td>
<td>-7.59</td>
<td>0.27</td>
<td>&lt;0.001</td>
<td>-6.93</td>
<td>0.21</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Traffic Volume (V/H/Lane)</td>
<td>0.18</td>
<td>0.03</td>
<td>&lt;0.001</td>
<td>0.15</td>
<td>0.02</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Toll ($)</td>
<td>0.11</td>
<td>0.09</td>
<td>0.209</td>
<td>0.37</td>
<td>0.08</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Speed Buffer Index in GP Lanes</td>
<td>0.83</td>
<td>0.13</td>
<td>&lt;0.001</td>
<td>0.88</td>
<td>0.08</td>
<td>&lt;0.001</td>
</tr>
</tbody>
</table>

The most noticeable change in results for the year 2010 is that the toll rate is a statistically significant factor in both models. The magnitude of the point estimate for toll rate also increases substantially. All other parameters are very similar to those of 2008. This result implies that the overall traffic volume, GP speed, and GP travel time reliability are still good indicators of the likelihood of SOV drivers choosing the HOT lane. Results also show that drivers are more responsive to the toll rate after the HOT facility has been in operation for some time. The parameters for tolls are both positive in the two models, which is compatible with previous research showing that HOT users are not deterred by tolls. On the contrary, they might see tolls as an indicator of upcoming congestion and decide to opt in.
CONCLUSIONS AND DISCUSSION

The HOT tolling scheme has initiated many discussions and research interests as follows. 1) The tolls are not a fixed value. Typically, toll rate are updated every few minutes according to traffic conditions. Traffic management authorities monitor traffic conditions in the HOT lane and set a goal of maintaining either a desired speed or a desired traffic density by varying toll rates. When conditions become congested and speed or density measures exceed the threshold, toll rates are raised to limit SOVs’ HOT lane usage. Consequently, tolling rates is not only the reason for, but also the result of, varied traffic conditions. Due to these circumstances, the mechanisms behind the inter-correlation of traffic flow, toll rate, and willingness to pay are more complicated. 2) The HOT lane usually runs side-by-side with GP lanes with access points designed en-route to ensure easy ins and outs of the lane. Opportunities are continuously available along the road for SOVs to opt in or opt out of the HOT lane based on perceived traffic conditions on the road and the toll rate shown on the signing board. This flexibility further complicates the relationship of drivers’ decisions, toll rates, and the traffic conditions. 3) As previous research proved, studies found that drivers might choose to pay for HOT services even when travel time savings are not significant, and sometimes even with negative travel time savings.

In this study, the likelihood of SOV drivers using the HOT lane is investigated using data from SR-167’s HOT lane facility using data from 2008 and 2010. The goal of this research is to study how the dynamic tolling system of a HOT facility will affect SOV drivers’ behavior. Two logit models using different dependent variables are fit for the 2008 and 2010 data. The results showed that:

1. The possibility of SOV drivers choosing HOT lanes is positively correlated with traffic volumes in GP lanes.
2. The possibility of choosing a HOT lane has a negative correlation with the average GP speed, indicating that the slower the GP average speed, the higher the possibility that SOV drivers will buy their way into the HOT lane facility.
3. The possibility of choosing the HOT lane has a much larger correlation with speed reliability, as illustrated using the speed buffer index, compared to absolute speed measures. In fact, the speed buffer index is the strongest explanatory variable across the board.
4. The toll amount is not a significant factor in 2008, but is significant in 2010. This confirms the ramp-up effects of toll facilities. Users’ degree of acceptance was low in the opening year, where the toll rate did not affect SOV drivers’ choices. After the HOT lane was in operation for two years, drivers became more familiar with the facility and were more willing to pay for HOT lane use.
5. The parameter for toll rate is positive using 2010 data. This illustrates a positive relationship between the probabilities of SOV drivers buying their way into the HOT lane with toll rates. This makes sense as the toll rate of a HOT lane is a function of congestion. SOV drivers use the toll rate as an indicator of upcoming congestion after they become familiar with the facility, and respond by choosing HOT lanes to avoid possible travel time fluctuations in GP lanes.

This preliminary study of drivers’ responses to the dynamic HOT lane tolling system has many potential future research directions, as follows:

1. It has been proven that drivers’ willingness to pay is not fixed. It will usually be affected by trip purpose and time of the trip. Also shown is that the toll rate has a varied relationship with the percentage of SOVs willing to pay when the demand changes. Next the data can be categorized into peak and nonpeak time periods or different demand levels to model the effects dependent variables have on the probability of SOVs choosing the HOT lane.
2. Varied by the goals of the HOT facility, different parameters may play different roles. For example, the toll rate may be set differently depending on whether the goal is to maximize throughput or to maximize revenue. The tolling scheme will be changed to fit the managing authority’s purpose. Simulation models can be run to help design tolling plans for the HOT lanes. For example, data obtained from the newly-opened Washington D.C. Beltway can be used to make recommendations through interpretations of simulation results.

3. Data from other locations will be collected and used to verify the variations of model fittings. Because previous research has found that income level in the area will affect willingness to pay, it will be interesting to see how this variation will affect the model fittings.

4. The results show that drivers’ reactions to tolls were dramatically different in 2008 versus 2010. This is a good predictor for setting different tolling schemes for HOT facilities in the opening year and then for adjusting them after the public becomes familiar with the facility. The results from this study can be further generalized to incorporate ramp-up effects to provide insights and suggestions for management authorities in their toll rate decision-making system.

ACKNOWLEDGEMENTS

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