Application of Variable Tolls on Congested Toll Road

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Abstract: This paper examines how different price elasticities of travel demand would impact traffic on a toll road with a time-of-day variable toll rate. Price elasticities were derived from data collected on a pair of bridges that currently offer tolls that vary by time of day. Both aggregate traffic data and disaggregate driver data were used to determine a range of probable elasticities. The aggregate method applied the short run price elasticities observed at the operational bridges to a hypothetical toll road. To determine disaggregate elasticity rates, discrete choice models of a driver’s willingness to alter his or her time of travel due to the variable toll were estimated using survey data. Using these models, and varying the socioeconomic and commute characteristics of drivers on the hypothetical toll road, it was possible to determine the impact of different price elasticities on the flow of traffic. Elasticities from $-0.076$ to $-0.15$ caused travel times to improve by 8.8 to 13.3%, respectively.


CE Database subject headings: Traffic analysis; Transportation studies; Pricing; Tolls.

Introduction

Traffic congestion is a significant problem in the United States and around the world during specific, relatively short, periods of the day. Most roads are congested for six or fewer hours per day (Schrank and Lomax 2001) leaving the remainder of the day with excess roadway capacity. In theory, this peak-period traffic congestion occurs when the marginal cost of the trip exceeds the cost perceived by the driver (average variable cost) (Walters 1968; Glaister 1981; Arnott and Small 1994). Increasing the driver’s perceived cost of his or her trip to the marginal cost would discourage drivers from making those trips personally valued to be less than the marginal cost. This would reduce traffic to an economically efficient (optimal) level and reduce peak-period congestion. Although this economic theory has been examined extensively in the literature (Pigou 1920; Hau 1992a,b; Small 1992; Button 1993; Gomez-Ibanez and Small 1994; Johansson and Mattsson 1995) there have been few empirical examples available to substantiate this theory. As of December 2001, only 19 variably priced systems of roads or bridges existed in the world (Burris and Pendyala 2002).

With so few operational systems, many of the previous road pricing studies have relied on stated preference surveys to anticipate drivers’ response to a variable toll (Doxsey 1997; Kuppam et al. 1998; Bhat and Castelar 2002) or assumed a reasonable range of elasticity values (Bhatt 1994; Mohring 1999). In this paper, we refer to this variation in toll rate as variable pricing since the project from which data were obtained is the Lee County Variable Pricing Project. It is also commonly referred to as congestion pricing, road pricing, and value pricing.

The results from stated preference surveys can overstate or provide misleading information on how drivers will respond to change (Couture and Dooley 1981; Wardman 1988). Many researchers are now combining stated and revealed preference data to analyze behavior (Daly et al. 1999; Hensher et al. 1999; Bhat and Castelar 2002). These issues, combined with the fact that respondents overestimated their own actual use of variable pricing in this research, indicate the importance of real world traffic data and revealed preference survey data when determining the impact of a variable toll.

Whether using revealed preference, stated preference, or actual traffic data, the demand for transportation is assumed to follow inverse demand curves such as those shown in Fig. 1. In Fig. 1, the demand for travel is plotted against the generalized cost of travel. These cost curves include only the short run variable and marginal costs. However, adding road maintenance cost and fixed vehicle operating costs by shifting both cost curves upward by a fixed amount for all vehicle flow rates (Hau 1992b) would not alter the concepts presented here. The demand curves may represent total traffic on all roads or on a specific route, during an entire day or a specific time period, or traveling by several different modes or one specific mode. This study focused on automobile traffic using two parallel routes during certain periods of the day. Even limiting the analysis to these narrow conditions the slopes of the demand curves could vary considerably based on the availability of alternate routes and modes. If there were alternate routes available with comparable characteristics to the toll routes then one would expect a high toll-price elasticity of demand for travel on the toll route. Toll-price elasticity of demand is defined here as follows:

$$E_t = \frac{\text{Change in Traffic Volume/Original Traffic Volume}}{\text{Change in Toll Rate/Original Toll Rate}}$$

(1)

where $E_t$ = toll-price elasticity of traffic demand (referred to as the elasticity); when $E_t$ is between $-1$ and $+1$ the relationship is termed inelastic. When $E_t$ is less than $-1$ or greater than $+1$ the relationship is termed elastic. In toll applications it was expected that elasticities would all be negative, indicating a loss of traffic due to an increase in toll price or vice versa.
Similarly, if travelers could choose an alternate mode to the automobile that offered them similar benefits then the toll-price elasticity of mode use would also be high. These are but two of hundreds of factors that influence the slope of the demand curve. Other important factors include the socioeconomic and commute characteristics of the drivers. This study examines how some of these factors influence the relationship between price and demand for transportation.

Fig. 1 shows two demand curves representing two elasticities of demand. Demand Curve 1 assumes a less elastic response by traffic to a toll than does demand curve number two. The two curves both intersect the average variable cost at the actual flow ($q_{actual}$). Based on standard economic theory, the optimal traffic flow occurs when the driver’s cost of travel equals the marginal cost of travel. To achieve this optimal flow of traffic an optimal toll, equal to the difference between the marginal cost and the average variable cost, would have to be applied to all vehicles. For Demand Curve 1, the optimal toll is the difference between $c_1$ and $c_3$, while the optimal toll based on Demand Curve 2 would be the difference between $c_2$ and $c_4$. Thus, both the optimal toll rate and traffic flow directly depend on the toll-price elasticity of demand.

This paper first derives short run price elasticities of demand based on traffic volume changes on two bridges with variable tolls as well as relationships between the socioeconomic and commute characteristics of drivers and their toll-price elasticity of demand. Next, based on those data, the paper examines how varying the elasticities of demand impact traffic flow. Two elasticities were based on traffic volumes collected at the two bridges and ten other elasticities were derived from population sets with different socioeconomic and commute characteristics. Each population set had a different toll-price elasticity and therefore a different predicted change in traffic demand due to the variable toll.

Data Source

The data used in these analyses were obtained from numerous studies conducted on a pair of toll bridges with variable pricing in Lee County, Fla. (Burris 2000; Burris 2001). Starting in August 1998, both the Midpoint Memorial Bridge and the Cape Coral Bridge implemented variable pricing programs. These programs offered participants a 50% reduction on their tolls if they traveled during specific off-peak hours. The off-peak hours included 6:30 a.m. to 7:00 a.m., 9:00 a.m. to 11:00 a.m., 2:00 p.m. to 4:00 p.m., and 6:30 p.m. to 7:00 p.m. Lee County, Fla., has an electronic toll collection system called LeeWay. It was installed in late 1997 and during the study had over 77,000 tags in circulation in a county of only 440,000 people. Only those people who paid their tolls using LeeWay were eligible for the variable pricing toll discount. In 1999, approximately 26% of the total bridge traffic was eligible for the discount.

During the study, the standard toll for two-axle vehicles on each bridge was $1.00. However, Lee County offered several different payment options for its electronic toll collection customers. One option allowed drivers to pay $330 per year and drive across the bridges toll free for one year. Those drivers were not eligible for any variable pricing toll discount. A second option charged drivers a yearly fee of $40 and reduced the standard toll to $0.50. These users saved an additional $0.25 when traveling during the discount periods. Finally, for no charge, drivers could obtain a transponder that allowed them to participate in the variable pricing program but did not alter the regular toll. These users saved $0.50 during discount periods. Of those drivers who obtained a variable pricing toll discount, approximately 94% received a $0.25 discount and 6% received a $0.50 discount.

This particular study setting had several inherent advantages. The first was that, unlike the other operational systems, drivers experienced minimal congestion on the Lee County toll bridges even during peak periods. Traffic speeds on the bridges remained close to free flow speed during all hours of the day, and queues at the tollbooths were only slightly longer during peak periods. In 1999, the average daily traffic volumes crossing the four-lane Midpoint Memorial and Cape Coral bridges were 32,000 and 36,000 vehicles, respectively. The level of service on both bridges in 1999 during the peak hour of the peak season was C. In March 2000, the average queue length in the automated lanes on the Midpoint Memorial Bridge in the peak direction during the peak period (7 a.m. to 9 a.m.) was 2.3 vehicles, and during the discount periods (6:30 a.m. to 7:00 a.m. and 9 a.m. to 11 a.m.) the average queue length was 1.2 vehicles. The additional 1.1 vehicles per lane resulted in approximately 6 s of extra delay during the peak period, which was a 0.4% increase in average travel time based on the average commute length of 23.1 min in Fort Myers and Cape Coral (Census 2000). This lack of congestion on the toll bridges simplified the analysis of toll-price elasticity since drivers were not factoring in travel time savings when making their decisions regarding what time of day to travel.

Another advantage of the Lee County project was that the alternative routes to these two bridges were inconvenient, and surveys of drivers indicated no significant changes in routes traveled due to the variable toll (Burris 2001). Also, travel across the bridges was dominated by automobile. LeeTran, the local transit agency, carried less than 0.7% of the total person trips across the bridges. Additionally, the variable toll had no significant impact on transit use or the use of carpools (Burris 2001). Therefore, this project had the advantage of examining toll-price elasticity of travel behavior variance with respect to time, while travel time, route, and mode were all held constant. Travelers did not have to contemplate benefits derived from improved travel time, alternate routes, or alternate modes when choosing to alter their times of travel due to the variable toll.

Resulting Traffic Elasticities-Aggregate

Research on the toll-price elasticity of demand for traffic has found elasticities ranging from −0.03 to −0.52, including:

![Fig. 1. Demand for transportation assuming different elasticities](image-url)
• The Transportation Research Board (1994) found elasticities from 0.1 to 0.4.
• Oum et al. (1992) found elasticities ranging from 0.09 to 0.52.
• The Urban Transportation Monitor (2000) found elasticities near 0.2 for toll increases of approximately 100 percent, and
• Wuestefeld and Regan (1981) found elasticities ranging from 0.03 to 0.31.

However, these elasticities were primarily based on total traffic changes throughout the day. For example, the total number of daily trips forgone due to a toll increase. In contrast, this project examines the toll-price elasticity of traffic shifting to an alternate time of travel. As shown in this project (see Table 1) these elasticities can vary significantly based on the time of day and the mix of traffic. Note that since there was no toll change during the peak periods it was not possible to determine toll-price elasticities for those time periods. However, the change in traffic during those periods (−7.5 and −3.8% for the morning peak periods) was used to analyze the impact of a variable pricing program on peak-period traffic.

When examining the change in traffic from January to July 1998 (the period prior to the introduction of variable tolls) as compared to January to July 1999 (the period five months after the introduction of variable tolls) traffic during the morning discount periods was more elastic than during the afternoon discount periods (see Figs. 2 and 3). Additionally, since traffic patterns of drivers not eligible for the variable pricing toll discount did not change significantly in most time periods (changes in traffic during a half-hour period of less than approximately 2.5% were not significant at the 0.05 level) (Cain et al., 2001), the changes observed in the travel behavior of eligible drivers was attributed to the toll discount. Considering that most eligible users received a discount of only $0.25, the change in travel patterns and resulting elasticities proved that drivers were inclined to modify their times of travel for even a small monetary incentive. Alternatively, it was possible that some frequent drivers took a long-term perspective and realized that the $0.25 per trip discount could total over $100 in annual savings, and this aggregate savings inspired their changes in travel behavior.

Elasticities were higher in the morning (from −0.11 to −0.36)

### Table 1. Impact of Variable Pricing on Distribution of Daily Travel Demand

<table>
<thead>
<tr>
<th>Time period</th>
<th>Midpoint Bridge</th>
<th></th>
<th>Percent of daily demand</th>
<th></th>
<th>Cape Coral Bridge</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Prevariable pricing</td>
<td>Variable pricing</td>
<td>Percent demand shift</td>
<td>Elasticity</td>
<td>Prevariable pricing</td>
</tr>
<tr>
<td>Pre-A.M. peak discount (6:30 a.m.–7:00 a.m.)</td>
<td>4.1</td>
<td>4.8</td>
<td>17.8</td>
<td>−0.36</td>
<td>3.1</td>
<td>3.4</td>
</tr>
<tr>
<td>A.M. peak (7:00 a.m.–9:00 a.m.)</td>
<td>19.5</td>
<td>18.0</td>
<td>−7.5</td>
<td>NA</td>
<td>16.9</td>
<td>16.3</td>
</tr>
<tr>
<td>Post-A.M. peak discount (9:00 a.m.–11:00 a.m.)</td>
<td>8.6</td>
<td>9.1</td>
<td>5.6</td>
<td>−0.11</td>
<td>10.1</td>
<td>10.6</td>
</tr>
<tr>
<td>Off-peak (11:00 a.m.–2:00 p.m.)</td>
<td>13.3</td>
<td>13.4</td>
<td>0.6</td>
<td>NA</td>
<td>15.6</td>
<td>15.3</td>
</tr>
<tr>
<td>Pre-P.M. peak discount (2:00 p.m.–4:00 p.m.)</td>
<td>11.9</td>
<td>12.5</td>
<td>5.6</td>
<td>−0.11</td>
<td>12.5</td>
<td>13.2</td>
</tr>
<tr>
<td>P.M. peak (4:00 p.m.–6:30 p.m.)</td>
<td>23.1</td>
<td>22.2</td>
<td>−4.0</td>
<td>NA</td>
<td>21.4</td>
<td>20.9</td>
</tr>
<tr>
<td>Post-P.M. peak discount (6:30 p.m.–7:00 p.m.)</td>
<td>2.9</td>
<td>3.0</td>
<td>2.7</td>
<td>−0.05</td>
<td>2.9</td>
<td>2.9</td>
</tr>
</tbody>
</table>

Note: NA = not applicable. Prevariable pricing indicates traffic data from January to July 1998. Variable pricing indicates traffic data from January to July 1999. Traffic data include every vehicle crossing either bridge that was eligible for the variable toll, approximately 26% of total traffic.

![Fig. 2. Change in travel patterns of eligible drivers on midpoint memorial bridge](image1)

![Fig. 3. Change in travel patterns of ineligible drivers on midpoint memorial bridge](image2)
and considerably lower (from −0.03 to −0.11) in the afternoon. Similar results were found on State Route 91 in California (Parkan 1999; Sullivan 2000). This may indicate that travelers had more flexibility in altering the time of their morning trips (for example, the ability to arrive at work early) but less flexibility in the afternoon.

### Resulting Traffic Elasticities-Disaggregate

The differences in elasticities during various periods of the day (as shown in Table 1) were hypothesized to be related to the different socioeconomic and commute characteristics of the drivers during those periods of the day. Therefore, to improve the accuracy of any predictions of toll-price elasticity, disaggregate models of drivers altering their times of travel due to the variable toll were estimated. The data for these models were obtained from a survey conducted on the toll bridges in Lee County, Fla., in 1999 (see Burris 2000 for a full description of the survey).

Using logit modeling techniques (Ben-Akiva and Lerman 1985) two models were developed (see Burris and Pendyala 2002 for additional information regarding model development). The first was a binomial logit model based on responses from all survey respondents who were eligible for variable pricing and had heard of the program. Each respondent indicated if he or she had ever changed his or her time of travel due to the toll discount. Using that response as the dependent variable, the model of participation in variable pricing was developed (see Table 2). The probability of a driver altering his or her time of travel due to the toll discount is shown in Eq. (2).

\[
P_p = \frac{e^{u_p}}{e^{u_p} + e^{u_m}}
\]

where \(P_p\) = probability of participation (altering time of travel due to the toll discount); \(u_p\) = the utility derived from participation: \(-0.66 + 0.71*ATT + 1.10*Ret + 0.93*Flex - 0.74*HHI - 0.48*TPComm; ATT = 1 if the driver had the ability to alter his or her time of travel on the trip the driver received the survey and 0 if the driver had no flexibility; Ret = 1 if the respondent was retired and 0 if not; Flex = 1 if the respondent had flextime at his or her place of employment and 0 if not; HHI = 1 if the respondent had a household income in excess of $75,000 and 0 if not; TPComm = 1 if the respondent was on a commute trip and 0 if not; and \(u_{mp}\) = the utility derived from not participating. This option was set as the reference alternative and equaled 0.

A second model was then developed including only those respondents who had changed their times of travel at least once per month due to the toll discount (Table 3). This model estimated the frequency with which a driver would alter his or her time of travel due to the variable toll as follows:

\[
P_{fx} = \frac{e^{u_{fx}}}{e^{u_{fx}} + e^{u_{fm}}}
\]

where \(P_{fx}\) = probability of the driver altering his or her time of travel due to the toll discount with a frequency of \(x\); \(u_{fx}\) = utility derived from participation in the program with a frequency of \(x\). These utilities can be written in a similar manner to those in Eq. (2) using the coefficients shown in Table 3. The utility for once per month participation was the reference alternative and was set equal to 0. \(X = 1\) for once per week participation; \(X = 2\) for two to five times per week participation; \(X = 3\) for more than 5 times per week participation; and \(X = m\) for once per month participation.

With these two models it was possible to estimate the average

### Table 2. Model of Participation in Variable Pricing

<table>
<thead>
<tr>
<th>Variable name</th>
<th>Coefficient</th>
<th>t-stat</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>−0.66</td>
<td>−4.00a</td>
</tr>
<tr>
<td>Ability to alter time of travel on current trip</td>
<td>0.71</td>
<td>4.50a</td>
</tr>
<tr>
<td>Retired</td>
<td>1.10</td>
<td>4.85a</td>
</tr>
<tr>
<td>Flextime available</td>
<td>0.93</td>
<td>4.53a</td>
</tr>
<tr>
<td>Household income exceeded $75,000</td>
<td>−0.74</td>
<td>−3.08a</td>
</tr>
<tr>
<td>Commute trip</td>
<td>−0.48</td>
<td>−2.74a</td>
</tr>
<tr>
<td>N</td>
<td>764</td>
<td></td>
</tr>
<tr>
<td>Log likelihood</td>
<td>−470.16</td>
<td></td>
</tr>
<tr>
<td>Restricted log likelihood</td>
<td>−520.38</td>
<td></td>
</tr>
<tr>
<td>(p^2)</td>
<td>0.097</td>
<td></td>
</tr>
<tr>
<td>Percent correct</td>
<td>66.8</td>
<td></td>
</tr>
</tbody>
</table>

\(^a\)Significant at the 0.05 level.

### Table 3. Frequency of Variable Pricing Participation Model

<table>
<thead>
<tr>
<th>Variable name</th>
<th>Once per week</th>
<th>2 to 5 times per week</th>
<th>Over 5 times per week</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>−1.00</td>
<td>−1.15</td>
<td>−3.76</td>
</tr>
<tr>
<td>Commute trip</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Weekly crossings on Cape Coral and Midpoint bridges</td>
<td>0.06</td>
<td>0.10</td>
<td>0.11</td>
</tr>
<tr>
<td>Retired</td>
<td>1.30</td>
<td>1.33</td>
<td>1.42</td>
</tr>
<tr>
<td>Household income exceeds $75,000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Flextime available</td>
<td>0.96</td>
<td>1.08</td>
<td>1.12</td>
</tr>
<tr>
<td>Ability to alter time of travel</td>
<td>0.51</td>
<td>0.91</td>
<td>0.73</td>
</tr>
<tr>
<td>N</td>
<td>335</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log likelihood</td>
<td>−4139</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Restricted log likelihood</td>
<td>−4907</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(p^2)</td>
<td>0.157</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Percent correct</td>
<td>34.9%</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

\(^a\)Significant at the 0.05 level.
number of trips altered due to variable pricing on any given day assuming:

- The average number of trips altered by drivers who indicated they altered two to five trips per week due to variable pricing was three per week, and
- the average number of trips altered by drivers who indicated they altered more than five trips per week was seven per week.

For any given set of driver characteristics, Eq. (2) was used to determine if the driver had altered his or her time of travel due to variable pricing. If yes, Eq. (3) was used to predict the number of weekly trips altered by the variable toll. Applying these models to the survey data resulted in the models underestimating the number of trips altered by the survey respondents by only 4.4%.

To calibrate the discrete choice models the socioeconomic and commute characteristics of Lee County toll bridge drivers eligible for the variable toll discount (as determined from the driver survey) were entered into the models. These characteristics included 56% of drivers on commute trips, 14% with household incomes exceeding $75,000, 20% with flextime available at their place of employment, 16% were retired, and 48% had the ability to alter the time of his or her current trip. The models’ predicted number of altered trips averaged approximately 9.0%. Comparing this to the 7.5 and 3.8% change in eligible morning peak-period traffic that occurred on the bridges, it was found that the model overestimated the number of trips altered due to variable pricing by approximately 37.5%. Therefore, model predictions were reduced by 37.5% to better reflect actual traffic volume changes observed on the Lee County toll bridges.

Since the model accurately determined the number of trips that survey respondents claimed to have altered due to variable pricing it appeared that survey respondents overstated the true impact of variable pricing on their travel behavior. The signs and magnitudes of the model coefficients for both models were as expected. Therefore, despite the overstatement of the number of trips, it was assumed that the driver characteristics found in the models correctly indicated a greater or lesser likelihood of altering one’s time of travel due to the variable toll. This overstatement is likely due to travelers’ ex-post rationalization of their trips altered due to the toll discount.

Application of Price Elasticities of Travel Demand

Introduction

Next, an investigation of how the aggregate elasticities and the disaggregate models developed here could be applied by an agency contemplating the introduction of a variable toll was undertaken. To perform this analysis, traffic behavior on a congested toll road was modeled and analyzed before and after the introduction of a variable toll. Although a significant shift in travel behavior occurred on the bridges in Lee County, the uncongested conditions rendered the impact of these changes on the overall flow of traffic negligible (Burris 2001).

The hypothetical toll road example developed in the next section examines traffic during a morning peak period. Therefore, the two changes in morning peak-period traffic observed in Lee County, –7.5% on the Midpoint Memorial Bridge and –3.8% on the Cape Coral Bridge, were used in the toll road example. Since these percentages were obtained on facilities offering a 50% off-peak toll discount, the example problem also assumed an off-peak toll discount equal to 50%.

Base Case Scenario

This example considered 10,000 vehicles traveling in the peak direction on a turnpike during the morning peak period (from 7:00 a.m. to 9:00 a.m.). The section of turnpike under investigation included a ten-kilometer stretch of road built to interstate standards terminated by a toll plaza. The time between vehicle arrivals at the toll plaza was assumed to follow a negative exponential distribution pattern (Drew 1968). All of the 10,000 vehicles were eligible for the variable pricing toll discount.

To determine both vehicle speed along this section of turnpike and the amount of delay caused by the toll plaza, it was necessary to make several assumptions, including: there were three lanes in each direction on the turnpike; six toll plaza lanes per direction all with electronic toll collection; 3.6 m wide lanes; no lateral obstructions; no interchanges; a free-flow speed of 120 km per hour, a peak-hour factor of 0.92; 10% trucks and buses; and level terrain.

The Highway Capacity Manual (Transportation Research Board 2000, p. 23-4) was used to estimate the average speed of the vehicles on the turnpike. The 10,000 vehicles using this turnpike experienced an average travel speed of 97.2 kilometers per hour (kph). Therefore, traveling the entire ten kilometers would require 370.3 s. The flow rate was calculated to be 1,902 vehicles per hour per lane, and the level of service on the turnpike from 7:00 a.m. to 9:00 a.m. was D.

Basic queuing theory was used to calculate the delay experienced by the 10,000 vehicles at the toll plaza. Each vehicle was assumed to pay the toll electronically and was eligible for the variable toll. Using data from Lee County’s electronic toll collection system, the average electronic transaction required 4.2 s per vehicle. Pietrzyk and Mierzejewski (1993) found transaction times for electronic toll payment in a dedicated electronic toll collection lane was approximately three seconds. If the lanes were controlled by gates, which was the case on the Cape Coral and Midpoint bridges, this increased the transaction times by one to 1.5 s. Therefore, the 4.2 s transaction times assumed here correspond well to typical transaction times for gated facilities. Transaction times followed a negative exponential distribution pattern.

Each of the 10,000 vehicles experienced an average delay of 23.3 s, and there was an average of 32.4 vehicles in the queues under this base case scenario. Therefore, the average vehicle travel time in the base case was 397.8 (370.3 + 23.3 + 4.2) s.

Variable Pricing Scenarios

Next, it was assumed that the turnpike authority implemented a variable pricing program similar to the Lee County variable pricing program. This program included a 50% off-peak discount for electronically paying customers for short time periods before and after the peak traffic periods. This toll discount encouraged some of the 10,000 drivers traveling during the 7:00 a.m. to 9:00 a.m. time period to switch to the discount periods. Note that the exact time of these discount periods would be selected based on traffic volumes. The selected discount periods would have low-traffic volumes allowing for increased traffic during those periods without causing congestion.

It was also necessary to assume that drivers along this congested turnpike reacted in a similar manner as Lee County drivers when the variable toll was introduced. Since the elasticities found in the Lee County project were within the range of elasticities found in the literature, this assumption was reasonable. However, in congested conditions, one may expect additional drivers to alter their time of travel from the peak period into the discount
period due to the travel time savings. Conversely, under extremely congested conditions, some travelers who traditionally drove during the off-peak period to avoid traffic congestion might change their time of travel to the peak period once traffic congestion lessened. For these drivers, the benefit of improved travel time during the peak period would more than offset the off-peak toll discount.

To determine the number of trips altered by the toll discount, it was necessary to consider the socioeconomic and commute characteristics of those 10,000 travelers. These characteristics included those independent variables used in the discrete choice models of travelers' likelihood and frequency of altering their time of travel due to the variable toll. These characteristics included:

- Commute trip purpose,
- Flexibility in the time of travel,
- Retirement,
- Number of weekly trips across the bridges with variable tolls,
- Flextime availability at the workplace, and
- Household income greater than $75,000.

Using data from the Nationwide Personal Transportation Survey, the Bureau of Labor Statistics, and the 1999 Lee County bridge traveler survey, the traffic streams shown in Table 4 were developed. Next, a spreadsheet was developed containing 10,000 toll road drivers with randomly distributed characteristics that, in aggregate, matched the characteristics found in Table 4. Using Eqs. (2) and (3) the number of weekly trips each driver altered due to the variable toll was estimated. To determine the number of daily trips, the number of weekly trips was simply divided by five. The number of daily trips was then split evenly between the morning and evening peak periods. Finally, to accurately reflect the changes observed in peak-period traffic in Lee County these results were reduced by 37.5%.

These trips were combined to determine the total number of trips altered for all 10,000 drivers. Since the logit models based their results on probability, a total of 20 trials using the same socioeconomic and commute characteristics were run and the average number of altered trips was entered into Table 5. In this manner, the unique toll-price elasticity for each of these different populations can be found in Table 5 as follows:

\[
E_t = \frac{\text{Change in Traffic Volume/Original Traffic Volume}}{\text{Change in Toll Rate/Original Toll Rate}} = \frac{10,000 - \text{Number of A.M. Peak Trips}/10,000}{-50}\%
\]  

(4)

<table>
<thead>
<tr>
<th>Scenario number</th>
<th>Number of A.M. peak trips</th>
<th>Average speed (kph)</th>
<th>Queue length (vehicles)</th>
<th>Queue delay (s)</th>
<th>Total trip time (s)</th>
<th>Time saved versus base case (s)</th>
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<tr>
<td>Initial condition without variable tolls</td>
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<tr>
<td>Base case 10 000.0</td>
<td>97.2</td>
<td>32.35</td>
<td>23.29</td>
<td>397.8</td>
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<td>Disaggregate (logit model) elasticity results</td>
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<td>9 535.7</td>
<td>104.0</td>
<td>9.9</td>
<td>7.5</td>
<td>357.8</td>
<td>40.0</td>
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<td>2</td>
<td>9 546.4</td>
<td>103.9</td>
<td>10.1</td>
<td>7.6</td>
<td>358.4</td>
<td>39.4</td>
</tr>
<tr>
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<td>9 554.1</td>
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<td>10.2</td>
<td>7.7</td>
<td>358.8</td>
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<td>9 555.3</td>
<td>103.8</td>
<td>10.3</td>
<td>7.7</td>
<td>358.9</td>
<td>38.9</td>
</tr>
<tr>
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<td>9 562.5</td>
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<td>7.8</td>
<td>359.3</td>
<td>38.5</td>
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<tr>
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<td>104.8</td>
<td>8.8</td>
<td>6.7</td>
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<td>43.4</td>
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<tr>
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<td>104.7</td>
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<td>43.1</td>
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<tr>
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<td>6.8</td>
<td>354.8</td>
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<tr>
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<td>104.6</td>
<td>9.0</td>
<td>6.8</td>
<td>355.1</td>
<td>42.7</td>
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<tr>
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<td>9 491.8</td>
<td>104.5</td>
<td>9.1</td>
<td>6.9</td>
<td>355.5</td>
<td>42.3</td>
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<td>Aggregate elasticity results</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Cape Coral (−3.8%)</td>
<td>9 620.0</td>
<td>102.9</td>
<td>11.6</td>
<td>8.7</td>
<td>362.7</td>
<td>35.1</td>
</tr>
<tr>
<td>Midpoint (−7.5%)</td>
<td>9 250.0</td>
<td>107.2</td>
<td>6.1</td>
<td>4.7</td>
<td>344.6</td>
<td>53.2</td>
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<tr>
<td>Average of all ten scenarios plus two aggregate elasticity results</td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average</td>
<td>9 502.2</td>
<td>104.4</td>
<td>9.4</td>
<td>7.1</td>
<td>356.3</td>
<td>41.5</td>
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</table>

**Table 4.** Percent of Drivers with Specified Characteristics

<table>
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<th>Scenario number</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percent on a commute trip</td>
<td></td>
<td>40</td>
<td>50</td>
<td>60</td>
<td>70</td>
<td>80</td>
<td>40</td>
<td>50</td>
<td>60</td>
<td>70</td>
<td>80</td>
<td>60</td>
</tr>
<tr>
<td>Percent with time of travel flexibility</td>
<td></td>
<td>30</td>
<td>30</td>
<td>30</td>
<td>30</td>
<td>30</td>
<td>40</td>
<td>40</td>
<td>40</td>
<td>40</td>
<td>40</td>
<td>35</td>
</tr>
<tr>
<td>Percent who are retired</td>
<td></td>
<td>4</td>
<td>4</td>
<td>4</td>
<td>4</td>
<td>4</td>
<td>4</td>
<td>4</td>
<td>4</td>
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<td>4</td>
<td>4</td>
</tr>
<tr>
<td>Number of weekly trips</td>
<td></td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td>Percent with flextime available</td>
<td></td>
<td>15</td>
<td>15</td>
<td>15</td>
<td>15</td>
<td>15</td>
<td>25</td>
<td>25</td>
<td>25</td>
<td>25</td>
<td>25</td>
<td>20</td>
</tr>
<tr>
<td>Percent with household incomes over $75,000</td>
<td></td>
<td>12</td>
<td>12</td>
<td>12</td>
<td>12</td>
<td>12</td>
<td>12</td>
<td>12</td>
<td>12</td>
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</tr>
</tbody>
</table>
Results

In addition to the disaggregate results described above, the change in trips calculated using the aggregate percentage changes in peak-period traffic (−7.5% and −3.8%) was applied to the hypothetical toll and road traffic. After the application of the variable toll, the two-hour traffic volumes on the toll road ranged from 9,250 to 9,620 vehicles. Applying the same highway capacity and queue analysis to these derived peak-period traffic volumes resulted in increased travel speeds and decreased delays (see Table 5). The vehicles that left the peak period, from 380 to 750 vehicles, were assumed to travel during the uncongested discount periods.

The different elasticities, and therefore percentage change in traffic volumes, had a measurable impact on overall traffic flow on the toll road. Peak-period travelers benefited from the reduced congestion, and discount-period travelers benefited from both the reduced toll rate and increased travel speed in the off-peak period. As discussed earlier, these benefits varied with the toll-price elasticity of travel demand determined in this research. At the same time, discount-period travelers lost the benefits they derived from traveling at their preferred time.

To determine monetary benefits of this proposal several additional assumptions were made. These assumptions included:

- 250 days per year that the toll road was congested and the variable toll was offered.
- A regular toll of $1.00 with variable pricing participants paying $0.50 during the discount periods.
- Drivers valued their travel time in congested traffic at $11.77 and $7.05 per hour in congested conditions. Passengers were not included in the calculation. The value of travel time during uncongested conditions was assumed to be 50% of the average wage rate (Small 1992; Waters 1992). During congested periods (level of service D) the calculated value of travel time was increased by a factor of 1.67 (a compromise based on the estimates found in Waters 1992; Small et al. 1999). To determine the wage rate, the 1998 average earnings per job were obtained from the 2000 Florida Statistical Abstract (University of Florida 2000), converted to year 2000 dollars and divided by 2,080 hours per work year.
- Travel speed remained at the free flow speed of 115.2 kph during the discount periods despite the influx of vehicles. Comparing the base case (no variable pricing) to the average result drawn from the 12 variable pricing scenarios, the following travel time savings were calculated.

Prior to implementation of variable pricing

\[
C_1 = V_1 \cdot TT_1 \cdot VOT_1 \cdot \text{Days} = \frac{10,000 \cdot 397.8 \cdot $11.77 \cdot 250}{3,600 \text{ s/h}}
\]

\[
= $3,251,462
\]

After implementation of variable pricing

\[
C_p = V_p \cdot TT_p \cdot VOT_p \cdot \text{Days} = \frac{9,502 \cdot 356.3 \cdot $11.77 \cdot 250}{3,600 \text{ s/h}}
\]

\[
= $2,767,227
\]

\[
C_d = V_d \cdot TT_d \cdot VOT_d \cdot \text{Days} = \frac{498 \cdot 318.7 \cdot $7.05 \cdot 250}{3,600 \text{ s/h}} = $77,703
\]

\[
\Delta C = C_1 - (C_p + C_d) = $406,532
\]

\[
\Delta TR = V_d \cdot \Delta \text{Toll} \cdot \text{Days} = 498 \cdot 0.5 \cdot 250 = $62,250
\]

where \(C_r\) = cost of travel time for period \(x\); \(V_r\) = volume of vehicles during period \(x\); \(TT_r\) = travel time for vehicles during period \(x\), in seconds; \(VOT_r\) = value of travel time for vehicles during period \(x\), in dollars per hour; \(x\) = 1 for the prevariable pricing period; \(P\) for the peak period after variable pricing was implemented; \(D\) for the discount, or off-peak, period after variable pricing was implemented; Days = 250 days per year; and \(TR\) = toll revenue.

Therefore, drivers gained over $400,000 in travel time savings while $62,250 per year in toll revenue was transferred from the toll authority to the drivers.

Conclusions

The Lee County variable pricing project offered a unique opportunity to investigate the impact on travel behavior of a toll that varied by time of day, absent of several confounding factors. A lack of congestion, inconvenient alternative routes, and no change in mode use all indicated that a driver’s decision to alter his or her time of travel due to the variable toll was primarily a monetary decision.

Using data from this project, price elasticities of travel demand were calculated by time of day in one case and based on the socioeconomic and commute characteristics of drivers in the second. Aggregate elasticities were found to range between −0.36 and −0.03 dependent on the time of day. Disaggregate elasticities varied based on the driver’s employment, household income, trip purpose, availability of flextime at work, and flexibility of his or her current trip. Applying the results from the Lee County project to a congested toll road resulted in a reduction in travel times between 8.8 and 13.3% and an average yearly savings in the value of reduced travel times of over $400,000.

Acknowledgments

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References


