The impact of a toll reduction for truck traffic using SH 130

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A R T I C L E   I N F O

Article history:
Available online xxx

Keywords:
Toll reduction
Truck toll elasticity
Time series analysis

A B S T R A C T

This research investigated the impact of a toll reduction for trucks on SH 130 and the resulting changes in the number of trucks using the road. SH 130 is a tolled bypass facility, running parallel to Interstate 35 (I-35), around the Austin area. This toll road was constructed, in part, to divert traffic from I-35 which runs through Austin. However, the toll road was only partially successful in attracting truck traffic since many truck drivers felt the toll was high compared to the travel time saved. Hence, beginning on March 1, 2011, Texas Department of Transportation reduced the toll rate by 25% for 5-axle vehicles and 40% for 6 plus-axle vehicles. A toll reduction is relatively rare and there are very few studies on how this may impact truck travel.

A time series analysis of the toll transaction data, along with the local price of diesel fuel, unemployment rate, GDP, and income levels, resulted in a toll-price elasticity of –0.43 for 5-axle vehicles (the vast majority of 5-plus axel vehicles). Thus, the drop in toll was successful in attracting additional trucks – but also resulted in decreased revenues from tolls. The majority (94%) of 5-axle vehicles paid using electronic toll collection (ETC), and the remainder paid manually (MLT). The toll-price elasticity for 5-axle vehicles paying by ETC was –0.39 while it was –1.49 for those paying by MLT. Thus MLT vehicles were much more price sensitive to the toll reduction, possibly indicating new users of the road who had not signed up for ETC before the toll reduction.

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1. Introduction

1.1. Background

State Highway 130 (SH 130) along with SH 45 Southeast combine to form a toll road alternative to I-35 in the Austin area. The two roads run from Georgetown to Creedmoor in Central Texas (see Fig. 1, note at the time of this research the southern end of SH 130 was in Creedmore, but it has since been extended to Seguin). SH 130, running parallel to I-35, was intended to relieve the congestion and improve the mobility by serving as an alternate to the busy I-35 (Geiselbrecht et al., 2008). The Texas Department of Transportation (TxDOT) revealed that I-35 in this area was the fourth-most congested roadway in Texas. In 2010, commuters traveling to work, truckers working to get their shipments to market on-time, and families on vacation experienced more than 4.6 million hours of delay on I-35 (Texas Department of Transportation, 2011a). According to the Capital Area Transportation Coalition, the congestion along the I-35 corridor was costing businesses more than $194 million a year in higher operating costs and lost productivity (San Antonio Business Journal, 2003; NewsOXY, 2015).

TxDOT began the construction of segments 1 through 4 of SH 130 in October 2003 as a controlled access toll road with two lanes in each direction. It is a typical bypass route built to interstate standards and, to date, does not get congested. The road opened in segments, with segments 1 through 4 opening in 2006 and segments 5 and 6 opening in October 2012 (Federal Highway Administration, 2014). SH 45SE, which links SH 130 to I-35, opened to traffic on May 2009 (Texas Transportation Commission, 2012). This research focuses on segments 1 through 4 of SH 130 and SH 45SE.

Due to the congestion on I-35, trucks were expected to shift to SH 130. Even though the total traffic volumes on SH 130 were nearly 18% above projections during the six months ending in February 28, 2009, the revenues were below projections since the truck traffic volume was below the expected projections as well as the truck toll rate was considerably higher compared to that of the automobile toll rate. Most truckers were not inclined to pay for the
toll and fuel cost ($25 in tolls and an extra $12 in diesel) to obtain the travel time savings benefit (about 22 min in the peak period) offered by SH 130 (Austin Contrarian, 2009). More recent analyses indicated that the total revenues still continue to be below projections (Wear, 2011).

To encourage additional truck traffic on SH 130 and SH 45SE, the Texas Transportation Commission agreed to lower the toll rates for trucks having 5 and 6-plus axles beginning on March 1, 2011 (KVUE Television Inc., 2011; Texas Department of Transportation, 2011b). Table 1 presents the previous and current toll rates for SH 130 and SH 45 SE. The toll for the entire 56 miles of SH 130 and SH 45 SE was based on four plazas on SH 130 (4 × $5.40) plus one plaza on SH 45 SE ($4.00) for a total of $25.60. After the discount began, this rate dropped to $19.20, approximately a 25% reduction. The objective of this research was to investigate the elasticity of demand due to this toll rate reduction as well as to understand the related impact on truck traffic.

2. Literature review

2.1. Impact of toll changes and related elasticities

To begin, the available literature regarding the toll price elasticity of truck traffic especially due to toll changes was examined. The related impacts on truck traffic due to toll changes were also reviewed. Of particular interest were any examples of the impact of lowering tolls.

McKnight (1992) estimated the toll elasticities for the Triborough Bridge and Tunnel Authority (TBTA) crossings in New York City. They found the elasticity of demand varying between −0.61 to −0.29 for medium trucks and −0.93 to −0.27 for heavy trucks. Hirschman et al. (1995) determined the impact of toll increases on traffic volume and revenue at TBTA crossings in New York City. They developed multiple regression models that estimated traffic volume on each TBTA bridge and tunnel based on toll levels and other explanatory variables. They found the toll elasticities for the light trucks and heavy trucks ranged from −0.54 to −0.07 and −0.60 to 0.20, respectively. The toll elasticities for truck traffic were inelastic and larger than the auto elasticities on average (McKnight, 1992). Lake and Ferreira (2002) calculated the average toll elasticity for trucks in Brisbane and they found it to be in the range of −0.30 to −0.20.

The Massachusetts Turnpike Authority raised their toll rate by an average of 51% for the commercial vehicles in March 1990. This resulted in a 7% decrease in commercial vehicle traffic; of which 4.4% was attributed to this toll increase. The rest was attributed to an overall decline in truck traffic due to a recession. The estimated elasticity was −0.086 indicative of a highly inelastic response. Similarly, the toll increase for New Jersey Turnpike in 1991 resulted in toll elasticity of about −0.09 for commercial vehicles (Wilbur Smith Associates, 1995).

<table>
<thead>
<tr>
<th>Table 1</th>
<th>Toll rates on Austin Area Toll Roads (Realty, 2010; Texas Department of Transportation, 2011c).</th>
</tr>
</thead>
<tbody>
<tr>
<td>Axle</td>
<td>SH 130 toll rates (toll per plaza)</td>
</tr>
<tr>
<td></td>
<td>Tag (ETC)</td>
</tr>
<tr>
<td>5</td>
<td>$5.40</td>
</tr>
<tr>
<td>6+</td>
<td>$6.75</td>
</tr>
<tr>
<td>Axle</td>
<td>SH 45 southeast toll rates (toll per plaza)</td>
</tr>
<tr>
<td></td>
<td>Tag (ETC)</td>
</tr>
<tr>
<td>5</td>
<td>$4.00</td>
</tr>
<tr>
<td>6+</td>
<td>$5.00</td>
</tr>
</tbody>
</table>


Fig. 1. Map of Central Texas Turnpike System (CTTS) (Central Texas Turnpike System, 2006).
The Ohio Department of Transportation (ODOT) decreased the toll rate for trucks in January 2005 on the Ohio Turnpike. The cross-state trip rate for one of the more common classes of trucks (65,001–80,000-pound vehicles) was dropped from $42.45 to $31.00. As a result, the truck traffic increased by 4% due to this 27% drop in toll rate and the resulting toll elasticity was −0.15 (Geiselbrecht et al., 2008).

In 1996, part of the Florida Turnpike lowered its truck toll rate approximately 33% to attract truck traffic from the toll-free parallel route, I-95. However, data revealed that there was no change in truck traffic due to this toll change, resulting in an elasticity of 0. The reason for this low elasticity was attributed to the need to take the shortest route (I-95) because of not having a direct route between the origins and destinations from the turnpike; also the additional travel time required to get to the turnpike compared to the relative toll savings was not economically lucrative for the truckers to switch routes (Geiselbrecht et al., 2008) – which was the reason of such a low elasticity.

URS Corporation and Vollmer Associates (URS Corporation, 2005) estimated toll elasticity for SH 130 depending on time of day. This elasticity varied between −0.698 and −0.691, which according to the study indicates that trucks were sensitive to the increase in toll rate. The estimated truck toll-price elasticities (using survey data) on SH 130 would be 0.68. This was comparable to the −0.60 elasticity for trucks of Dallas North Tollway. These elasticities were based on logit models of route choice based on a survey of trucks and appeared to be considerably larger than many of the other results including the results we developed in this research. This could be due to erroneous survey responses from the truckers – many of whom we found to be vehemently against toll roads in our research and surveys (Geiselbrecht et al., 2008). More truckers may have indicated that they would not use the toll road in the event of a toll increase than the number that would really stop using the toll facility. Therefore, we feel that the actual truck data in response to the toll change, which was used in the analysis of this paper, provides a better estimate of elasticity of demand. The elasticities found in different studies mentioned above are summarized in Table 2 below.

Ozbay et al. (2006) evaluated the impact of the time-of-day pricing program initiated on March 25th, 2001 by the Port Authority of New York and New Jersey (PANYNJ). The researchers used a dataset consisting of routinely collected traffic data at all toll lanes prior to September 11, 2001. The value pricing program established higher toll levels during peak hours and lower toll levels during off-peak hours. Results indicated that there was a statistically significant shift of weekday truck traffic to the morning prepeak (5–6 a.m.) and afternoon post peak hours (7–8 p.m.) after implementing the time-of-day pricing. However, the weekend truck traffic percentage shares did not indicate any statistically significant changes during the shoulder hours (11 a.m.–2 p.m. and 8–9 p.m.). These findings were supported by the findings of Muriello and Jiji (2004) which indicated that truck traffic during 6–7 a.m. decreased 5.7% from 2000 to 2001 due to the value pricing program initiated by the PANYNJ. Ozbay et al. (2006) mentioned that even though PANYNJ time-of-day pricing gave truckers an incentive to shift their travel periods, it was not the only factor affecting the truckers’ travel pattern. The declining truck traffic during the peak period might be due to the recession that began in the New York–New Jersey region in 2001. Commercial surveys indicated that truck dispatchers consider other factors such as on-time delivery, customer needs, and various operational constraints while deciding to shift to off-peak hours to save tolls. Truckers stated that they would shift to the off-peak hours if the customers/receivers were willing to accept off-peak deliveries. Holguin-Veras et al. (2003) indicated that 70% of the carriers did not change route after the 2001 PANYNJ toll increase; the customers’ requirement was indicated as being the top priority which led many truckers not to change their delivery schedule.

2.2. Trucking industry’s perspective regarding usage of toll facilities

Zhou et al. (2009) used interviews and survey data to better understand trucker’s use of toll roads, particularly the use of SH 130 near Austin. From the interviews, they found that private carriers were most likely to use the toll road as they can more often pass the cost of the toll onto their customers. When the drivers face a tight schedule for delivery, they tend to take the toll road to avoid a congested toll-free road. For the independent owner-operators, the shippers usually offer a specific amount to transport a good and the independent owner–operator can accept the price or choose not to take the shipment. The toll related cost during the transportation is an additional cost to the independent owner–operators and they cannot shift the toll related cost on to their customers. Hence, the independent owner operators are least likely to take the toll road.

If the intraregional and local area shippers are aware of the recurring congestion situation in an area, they can adjust their trip schedule as well as can decide on whether to use the toll facility. For instance, intraregional and local area shippers in Austin area are aware of the congestion situation and they often adjusted their operations to ensure timely delivery of shipments without utilizing the toll facilities. This is especially true for those truckers who have a wide delivery window with their shipment. The researchers found that the customers in Austin area are also aware of the traffic condition and may accept late delivery of goods or products.

2.3. Summary

Based on previous studies, the toll elasticity of demand for trucks is highly inelastic and hence, it will be difficult to impact the route choice by altering the toll. The vast majority of these estimates were based on toll increases. Very few studies of the impact of toll decreases (like the one examined in this paper) are available. The drop in toll rates, in this case, provides a useful opportunity to better understand the impact of tolls on truck travel. If results from SH 130 are similar to those found in the literature, it can be expected that elasticities will be negative and highly inelastic and this would also result in a revenue loss for SH 130.

3. Data collection

Several data sources were required to determine the impact of the March 1, 2011 toll reduction on truck (5 and 6-plus axle vehicles) traffic. Most importantly, TxDOT provided a detailed

<table>
<thead>
<tr>
<th>Facility/location</th>
<th>Type of vehicle</th>
<th>Elasticity</th>
</tr>
</thead>
<tbody>
<tr>
<td>TBT crossings, NY</td>
<td>Medium truck</td>
<td>−0.61 to −0.29</td>
</tr>
<tr>
<td></td>
<td>Heavy truck</td>
<td>−0.93 to −0.27</td>
</tr>
<tr>
<td></td>
<td>Automobile</td>
<td>−0.26 to 0.19</td>
</tr>
<tr>
<td></td>
<td>Light truck</td>
<td>−0.54 to −0.07</td>
</tr>
<tr>
<td></td>
<td>Heavy truck</td>
<td>−0.60 to 0.20</td>
</tr>
<tr>
<td></td>
<td>Truck</td>
<td>−0.30 to −0.20</td>
</tr>
<tr>
<td>Brisbane</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Massachusetts Turnpike</td>
<td>Commercial vehicle</td>
<td>−0.086</td>
</tr>
<tr>
<td>New Jersey Turnpike</td>
<td>Commercial vehicle</td>
<td>−0.09</td>
</tr>
<tr>
<td>Ohio Turnpike</td>
<td>Truck</td>
<td>−0.15</td>
</tr>
<tr>
<td>Florida Turnpike</td>
<td>Truck</td>
<td>0.00</td>
</tr>
<tr>
<td>SH 130</td>
<td>Truck</td>
<td>−0.698 to −0.691, −0.68</td>
</tr>
<tr>
<td>Dallas North Tollway</td>
<td>Truck</td>
<td>−0.60</td>
</tr>
</tbody>
</table>

Table 2: Truck elasticities from previous studies.

dataset regarding SH 130 toll transactions. The dataset had hourly toll transactions for each day of each month from January 2007 to October 2011. The toll transaction data was categorized by number of axles and payment type (electronic toll collection (ETC) and manual lane terminal (MLT)). Only the trucks having five or more axles were considered in this analysis. Besides the toll transaction information, other variables such as income data, diesel price, population data, and gross domestic product (GDP) information were considered and included as key exogenous variables in the time series analysis that may have impacted the truck traffic volumes although none had an obvious impact on truck traffic (see Fig. 2). The quarterly personal income data for all of Texas and the price of diesel fuel were obtained from the website of the Texas Comptroller of Public Accounts (Texas Comptroller of Public Accounts, 2011) and U.S. Energy Information Administration (EIA) (U.S. EIA, 2011), respectively. The population of Travis, Williamson, Hays, Bastrop, and Caldwell Counties, the location of SH 130 and the City of Austin, was obtained from the U.S. Census Bureau. The population data was used as a surrogate measure for number of vehicles registered in the area as the registration data was only available up to 2008. Data regarding the economic indicator, gross domestic product (GDP), was obtained for the period from 2008 to 2011 for the Austin-Round Rock Metropolitan Statistical Area. The data were for the Austin area as the majority of SH 130 traffic, approximately 80%, were local trips while only approximately 20% of SH 130 traffic were through trips.

SH 130 has four segments from North to South: Georgetown/ Round Rk, Pflugerville/Cam, Decker/Long Lake, and Bergstrom Airport which are abbreviated as ML 5, ML 6, ML 7, and ML 8, respectively. Each segment has a mainline (ML) toll plaza and the toll transactions recorded at these four mainline plazas were used in the following analyses. Each of these toll plaza facilities has two types of transaction options: MLT and ETC. Note that for consistency we did not include transactions from the one plaza located on SH 455E.

3.1. Toll transactions on SH 130

The number of toll transactions by number of axles (2, 3, 4, 5 and 6-plus) using both payment types (MLT and ETC) for each segment was computed for each day starting with January 1st 2007 until October 31st 2011. The average of the number of toll transactions (by number of axles) over a given month represented the monthly number of toll transactions for each of the four segments (ML 5–ML 8). Then the monthly toll transactions on the four segments were combined to obtain the total number of toll transactions on SH 130 for the entire month, including weekends and holidays. Note that this could be as much as four times the actual traffic volumes since each vehicle could use up to 4 toll plazas on each trip. Average daily toll transactions (ADTT) were obtained by dividing this total number of monthly toll transactions by the number of days in that month (see Fig. 3).

Approximately 94% of the 5-plus axle vehicles paid by ETC. The 5-axle vehicles were by far the most common among those vehicles that received the toll discount (only vehicles with 5 or more axles). The 5-axle vehicles comprised approximately 94% of the 5-plus axle vehicle on SH 130. Therefore, the results for the 5-axle vehicles that paid by ETC dominated any combined results and were the most reliable due to the large sample size. Analysis of the 6-plus axle vehicles resulted in findings which were not statistically significant. This, combined with the small sample size, led us to not include these analyses in this paper.

During the time of this study, the volume of 5+ axle vehicles on SH 130 was fairly small. As shown in Fig. 2, the ADTT ranged from approximately 700 to 1500, from 2008 to 2011. Since each truck could have multiple transactions, the average daily truck volumes were closer to 350–700 trucks per day (note that based on ETC reads, the average number of toll transactions (plazas) passed by each truck was 2.01). If 20% of trucks traveled during morning peak hours on SH 130 (data shows that this is on the high end) and if 70% of that was in the peak direction, it would be a total of 98 trucks per
hour (700 × 20% to 70%). Therefore, even if the amount of truck traffic on SH 130 were to double it would only be 100 more peak-hour, peak-direction trucks from I-35. Average daily traffic on I-35 is approximately 225,000 vehicles per day, with approximately 10% of those are trucks, and thus moving an additional 100 trucks off of I-35 would have minimal impact on congestion.

As shown in Fig. 3, 5-plus axle vehicles represent a small percentage (just over two percent) of transactions on this highway. Also shown in Fig. 3, a vertical line is drawn corresponding to March 1st, 2011 when the toll reduction was implemented. There was a considerable increase in truck traffic starting in March. However, there was also a considerable increase in automobile traffic in March and there was no change in the toll rate for automobiles. Therefore, traffic trends will be investigated further using time series analysis for factors other than the toll rate that may have caused significant changes in the volume of vehicles on SH 130.

4. Data analysis and results

4.1. Data modeling and results of time series regression

The average daily truck toll transactions (ADTT) per month from September 2008 to October 2011 were used for analysis. Historical toll rates (see Table 1) were collected from the website of the operating agency (the only change during this time period was the toll reduction for 5-plus axle vehicles), and have been adjusted by the consumer price index (CPI) for all urban consumers to reflect the real value of these costs to the travelers (obtained from the Bureau of Labor Statistics, www.bls.gov). Data prior to September 2008 was not used as Segment 4 opened at the end of April 2008, thus starting with September 2008 will minimize the impact of this opening on the analysis. To capture the impact of monthly changes on the use of SH 130, monthly dummy variables were included in the specification to account for seasonality in the monthly ADTT data.

4.2. Autoregressive distributed (lag) (ADL) time series model

An autoregressive distributed lag (ADL) time series model was used to calculate the elasticity estimates with respect to toll cost and diesel price. The autoregressive lag model of order p and n, ADL (p,n) (see Eq. (1)), is defined as

\[ y_t = c + \sum_{i=1}^{p} \alpha_i y_{t-i} + \sum_{j=0}^{n} \beta_j x_{t-j} + u_t \]
\[ E(u_t) = 0, \; (t = 1, \ldots, N) \]
\[ \text{Cov}(u_t, u_s) = \delta_{|t-s|}, \; (s, t = 1, \ldots, N) \]

Where \( y_t \) is a scalar variable, \( c \) the regression intercept, \( u_t \) a scalar zero mean error term and \( x_t \) a vector of explanatory variables observed at time \( t \). \( p \) and \( n \) are the number of order of lags for \( y \) and \( x \), respectively. \( u_t \) and \( u_s \) are the error term at time \( t \) and \( s \), respectively. \( \alpha_i \) and \( \beta_j \) are coefficient estimates. This class of rational distributed lag function was first defined by Jorgenson (1966). The autoregressive lag model is a dynamic single-equation regression and is a member of the class of rational distributed lag functions. This model is particularly attractive for its error-correction (EC) in applied time series econometrics.

Autocorrelation plots of our collected toll transaction data suggest the presence of a nonstationarity variable in the time series data, and regression with nonstationary process violates the Ordinary Least Square (OLS) assumptions and is subject to spurious regression (Granger and Newbold, 1974). However, it turned out for nonstationary variables that cointegration is equivalent to an EC mechanism as formalized by Engle and Granger (1987). Nonstationary series are called integrated of order \( k \) if the series becomes stationary when differenced \( k \) times. A set of series, all integrated of order \( k \), are cointegrated if and only if a linear combination of the nonstationary series (with nonzero weights only) is integrated of order less than \( k \). Preliminary data statistics reveal that the monthly toll transactions and monthly diesel prices are integrated of order one, \( I(1) \), and a cointegration test indicated that there was a cointegrating relationship between the dependent and independent variables. Then our model can be viewed as a cointegrating regression model as long as the residuals are stationary. In such a case, the parameters are super-consistent and they converge at a speed of \( T \) instead of root-\( T \) (Stock, 1987). A partial-adjustment (PA) model similar to the one in this study can be found in Hughes and Knittel (2008).

Many factors, for example, psychological, income level, vehicle occupancy level, urgency of the trip, traffic congestion level, etc. may have a significant impact on the decision to use the toll road. However, information on many of those factors is difficult to collect and quantify. Excluding these factors in the analysis may generate an inaccurate estimation of elasticity of toll road use with respect to the change in toll costs and diesel prices. By introducing the lagged dependent variable (previous number of toll transactions) in the equation, the impact of most excluded factors could be captured as the coefficient of the previous months’ toll transactions for near-term future time periods. Because the variation of gas price, toll rate, unemployment, and population may have lagged effect on the use of toll road, this study also tested models with lagged independent variables but did not generate reasonable results. This specification (model with a lagged dependent variable) also provides estimates of short-run and long-run elasticities as long as the coefficient for the lagged dependent variable is less than 1.0 (Greene, 2003). Serial correlation in time series regression is not an unusual problem. The presence of serial correlation in regression residuals violates the standard assumption of regression theory that disturbances are not correlated with other disturbances. To account for the presence of serial correlation, as a preliminary treatment, the regression with autoregressive process of order \( p \) error is added in the regression. Therefore, our ADL model is shown in Eq. (2):

\[
\begin{align*}
\ln(\text{TollVol}_t) &= c + \alpha_1 \ln(\text{TollTransaction}_{t-1}) + \beta_1 \ln(\text{Diesel}_t) + \beta_2 \ln(\text{Gas}_t) + \beta_3 \ln(\text{Income}_t) + \beta_4 \ln(\text{GDP}_t) + \beta_5 \ln(\text{Pop}_t) + \delta_1 \text{Jan} + \delta_2 \text{Feb} + \delta_3 \text{Mar} + \ldots + \delta_n \text{Nov} + u_t \\
&= c + \sum_{i=1}^{p} \alpha_i \ln(\text{TollVol}_{t-i}) + \sum_{j=0}^{n} \beta_j \ln(x_{t-j}) + u_t
\end{align*}
\]

Where \( \text{Jan}, \text{Feb}, \ldots, \text{Nov} \) are dummy variables for each month except December.
\( \ln(\text{TollTransaction}_t) \) denotes the natural logarithm of number of toll transactions in period \( t \),
\( \ln(\text{TollTransaction}_{t-1}) \) denotes the 1st lag of \( \ln(\text{TollTransaction}_t) \) (the number of toll transactions in the month prior to \( t \)),
\( \ln(\text{Diesel}) \) denotes the natural logarithm of CPI-adjusted retail price of diesel in period \( t \) for the U.S.,
\( \ln(\text{Toll}_t) \) denotes the natural logarithm of the CPI-adjusted toll cost in period \( t \),
\( \text{UEMP} \) denotes the unemployment rate in month \( t \) for the state of Texas,
\( \ln(\text{Income}) \) denotes the natural logarithm of the real personal income (in 1996 real dollars) in period \( t \),
\( \ln(\text{Pop})_t \) denotes the natural logarithm of the population of Travis, Williamson, Hays, Bastrop and Caldwell Counties in period \( t \),
\( \ln(GDP_t) \) denotes the natural logarithm of the gross domestic product of the Austin-Round Rock area in period \( t \),
\( jan, feb, mar, . . . , nov \) denote the eleven monthly dummy variables,
\( \omega_i \) is a disturbance term with zero mean,
\( \gamma_iu_{t-1} \) is the auto-regressive process of order \( i \) (\( \text{AR}(i) \)), and
\( \gamma_i \) is the innovation in the disturbance.

Note that natural logarithm transformation was not performed on the independent variable “unemployment rate” in Eq. (2). The semi-elasticity of unemployment rate with respect to toll volume indicates the percentage change in the dependent variable with respect to the increase of one absolute unit of the independent variable. The use of semi-elasticity is more straightforward to indicate the impact of one unit change in unemployment rate (e.g. 6% to 7%) on toll road usage, rather than using the percent change in unemployment rate (e.g. 6% to 6.06%) to indicate its influence on toll road usage.

The objective was to fit the above model with monthly data. However, some adjustments to the raw data were required. Personal income data of Texas were only available in quarterly format and the latest available data was Quarter 3, 2012. We converted the quarterly personal income data (for the period Quarter 3, 2008–Quarter 3, 2011) into monthly data using a simple interpolation – the resulting monthly data ranging from September 2008 to October 2011. Both population estimates and GDP data were available in a monthly format from 2007 to 2012.

The results of the regression analysis of data from September 2008 to October 2011 indicated that personal income and population did not significantly affect the use of SH 130 by 5-axle axle vehicles during that time. Additionally, population was highly correlated with unemployment. Therefore, the personal income and population variables were excluded from further models. F tests on combined toll transaction data of 5- and 6-axle vehicles indicated that the monthly dummies are jointly significant at a 5% level; however, \( t \) statistics for each individual dummy variable were not all statistically significant. The monthly fixed effects illustrate the evident seasonality effects in the demand of truck travel on SH 130, and signs were generally consistent with the expectation that truck travel demand is lower in winter (January and February) and high in other months (March–October). The winter effect was somewhat smaller than that of the other seasons. This might be due to the fact that winter months are generally short in Texas, and inclement weather usually occurs in January and February. To obtain more efficient coefficient estimates for variables of interest in this study, insignificant dummy variables were dropped from the specification using a stepwise test drop procedure based on Akaike information criterion (AIC). Therefore, Eq. (2) (excluding the Income, Population variables, and insignificant monthly dummy variables) was used to estimate the impact of the toll change on SH130 truck traffic (see Table 3).

The results were generally as expected: the elasticities of demand with respect to toll cost were negative for 5-axle vehicles. None of the demand elasticities estimates with respect to diesel prices were statistically significant. The elasticity estimate with respect to toll costs for 5-axle vehicles was –0.43; but the elasticity estimate for 6-plus axle vehicles was not statistically significant. Note that elasticity estimates with respect to toll cost for 5-axle MLT customers was –1.49 at a 1% significance level, and the elasticity estimates for 5-axle ETC customers was –0.39 at a 10% significance level. This may indicate that MLT paying customers were more sensitive to the change in toll cost. However, since this was the case of toll reduction, it is more likely that the increase in MLT customers consisted of infrequent or new users of SH 130. This drop in price convinced them to use SH 130. But since they rarely or never used the route before, they had no ETC transponder which led them to use the MLT collection system. The one unexpected result was an increase in unemployment was linked to an increase in truck traffic. This is counterintuitive and there is no logical explanation for this result. However, the unemployment coefficient was considerably smaller, and thus had a smaller impact, than any other coefficient.

5. Conclusions

In this research the effect of a March 1, 2011 toll reduction for truck traffic using SH 130 was investigated. Toll transaction data from 2007 to October 2011 were examined to find:

- Five-plus axle vehicles were a very small portion of traffic on SH 130 – just over 2%. Of this, approximately 94% have 5-axles and 6% have 6-plus axles. 94% of 5-plus axle vehicles paid by ETC.
- Since 5-axle vehicles paying by ETC made up the majority of customers receiving the discount, their elasticities are the most important and the most reliable. Time series analysis estimated the elasticity to be –0.43. This was in the same range as the elasticities for trucks when toll prices were increased.
- The elasticities for the vehicles paying manually (MLT) were considerably larger than those for vehicles paying electronically (ETC). Therefore, the change in toll rate had a larger impact on MLT paying vehicles than those that pay by ETC. This seems reasonable as (i) the physical exchange of money for the toll may impact the customers more than paying electronically when the bill is not seen until later and (ii) it is likely that those paying by MLT are infrequent users and they more readily switch from an alternate route.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Axe type (transaction type)</th>
<th>5-axle (ETC)</th>
<th>5-axle (MLT)</th>
<th>5-axle (MLT+ETC)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \ln(\text{TollTransaction}_t) )</td>
<td>6.68 (10.23)</td>
<td>15.65 (14.25)</td>
<td>6.36 (10.13)</td>
<td></td>
</tr>
<tr>
<td>( \ln(\text{TollTransaction}_{t-1}) )</td>
<td>0.27 (0.16)</td>
<td>0.11 (0.15)</td>
<td>0.26 (0.16)</td>
<td></td>
</tr>
<tr>
<td>( \ln(\text{Diesel})_t )</td>
<td>0.23 (0.19)</td>
<td>–0.04 (0.23)</td>
<td>0.22 (0.19)</td>
<td></td>
</tr>
<tr>
<td>( \ln(\text{Toll}_t) )</td>
<td>–0.39 (0.21)</td>
<td>–1.49** (0.33)</td>
<td>–0.43 (0.22)</td>
<td></td>
</tr>
<tr>
<td>( \text{UEMP} )</td>
<td>0.08* (0.03)</td>
<td>0.02 (0.03)</td>
<td>0.08* (0.03)</td>
<td></td>
</tr>
<tr>
<td>( \ln(GDP_t) )</td>
<td>0.21 (0.88)</td>
<td>0.01 (1.18)</td>
<td>0.21 (0.88)</td>
<td></td>
</tr>
<tr>
<td>( \ln(\text{Income})_t )</td>
<td>–0.16** (0.05)</td>
<td>–0.05** (0.05)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \ln(\text{Pop})_t )</td>
<td>–0.12 (0.06)</td>
<td>–0.15*** (0.05)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \ln(GDP) )</td>
<td>–0.28** (0.07)</td>
<td>0.13* (0.05)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \ln(\text{Income})_t )</td>
<td>–0.08 (0.05)</td>
<td>–</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \ln(\text{Pop})_t )</td>
<td>0.11** (0.02)</td>
<td>–</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \ln(GDP) )</td>
<td>0.09* (0.04)</td>
<td>–</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Adjusted \( R^2 \) 0.75 0.75 0.85

Numbers in the parenthesis are standard errors.

Only significant dummy variables are included in each model.

* 10% significance level.

** 5% significance level.

*** 1% significance level.

In general, the toll reduction was effective in attracting additional trucks on SH 130. However, there was a net decrease in revenue as the increase in truck traffic was not enough to make up for the reduction in the toll price.

Acknowledgements

The authors would like to thank TxDOT and their consultant, Atkins Global, for access to traffic data from the SH 130 plazas. The data for the logit model was based on research sponsored by the Federal Highway Administration through their Value Pricing Pilot Program and the Texas Department of Transportation. We thank those organizations for sponsorship of, and help with, the research on which that survey was conducted as well as two anonymous reviewers who helped to improve and focus this paper. The contents of this paper reflect the views of the authors, who are responsible for the facts and the accuracy of the data presented herein. The contents do not necessarily reflect the official views or policies of the Federal Highway Administration or the Texas Department of Transportation.

References


