ESSAYS ON TRAVEL DEMAND FOR TOLL ROADS

by

Jeong Yun Kweun
A Dissertation
Submitted to the
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of
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in Partial Fulfillment of
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of
Doctor of Philosophy
Public Policy

Committee:

______________________________	Roger R. Stough, Chair
______________________________	Kenneth J. Button
______________________________	Shanjiang Zhu
	Stephen G. Ison, External Reader
______________________________	Sita N. Slavov, Program Director
______________________________	Mark J. Rozell, Dean
Date: ________________________	Spring Semester 2017 George Mason University Fairfax, VA

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Jeong Yun Kweun
Master of International Studies
Ewha Womans University, 2009
Bachelor of Art
Ewha Womans University, 2007

Director: Roger R. Stough, University Professor
Department of Public Policy

Spring Semester 2017
George Mason University
Fairfax, VA

DEDICATION

Oh Yeong Kweun & Jeong Eui Kim

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I have always been interested in how people make decisions and how relevant information enters their decision-making processes. If you look at my resume, you will quickly find that I have jumped from one field to another, with no relevancy between subject areas. In fact, I have always been searching for mechanism through which information enters the decision-making process. Turning this curiosity into a solid dissertation research topic was more challenging than I thought it would be. After spending nearly four years in the doctoral program, I did not have a research topic and I could not find an advisor who could walk with me through the muddy process of finding one. That is when I met Professor Roger R. Stough, my dissertation chair, who came back to then School of Public Policy after finishing his post at the Office of the Provost as Vice President for Research & Economic Development. I am still not sure why he said he would accept me as his student, but it was one of the best things that happened during my doctoral program.

The question of how people respond to changes in road pricing came from my experience using the newly opened express lanes near my house. Price sends signals to people about road conditions, and people decide whether or not to take express lanes. Well, isn’t this some sort of decision-making process? I convinced myself that this might be a topic for a small grant. When I talked about this with Roger, he suggested that I write about this for my dissertation. He recommended that I go talk to two professors, Kenneth Button, who is a renowned transportation economist at the Schar School of Policy and Government, and Shanjiang Zhu, who is a rising young scholar at the Volgenau School of Engineering. Meeting them was another good thing that happened during the program. Ken inspired me to be a scholar, not just a researcher. I have always been grateful for Shanjiang’s patience with me and the confidence he taught me. I was introduced to Professor Stephen Ison at the School of Civil and Building Engineering at Loughborough University in the United Kingdom. My one-hour conversation with him at the 2016 Transportation Research Board was one of the most delightful events that happened that winter.

I cannot thank Professor Jonathan Gifford, who funded me during the late years of my doctoral research and helped me get connected to transportation communities, enough. I was fortunate to meet Ronald Davis, who helped me access the toll road dataset from CDM Smith Inc., at the TRB meeting. Without Ron, my empirical studies could not have begun. Ricardo Sanches from Cintra helped me realize the value of my research from a practical perspective. Juan Gomez Sanchez at Universidad Politécnica de Madrid in Spain provided detailed comments on an earlier version of the second essay. Dr. Allison Frendak funded my first four years of the program and convinced me to finish my doctoral program when I was thinking of quitting. Ambassador Robert W. Farrand would listen to my stories and tell me that I was perky; he really helped me fight the most depressing moments during the program. Beth Eck and Shannon Williams helped me with administration at every step of the program. I thank Judith A. vanBever-Green at the Office of International Programs and Services for her administrative and emotional support. Byung-il Choi, my advisor at Ewha Womans University, has always encouraged me to pursue my dreams and helped me start the doctoral program. I especially thank Timothy Maeng, Kyung Min Lee, Lisardo Bolaños, Nobuhiko Daito, Misong Yoo, Chongon Kim, Sooyeong Lee, Hana Kim, and Hyun Kyung Kim for their love and support throughout the program. I thank the Schar School of Policy and Government, the Center for Transportation Public-Private Partnership Policy, and the Office of the Provost at George Mason University for funding my dissertation research. I also thank the Transportation Informatics Tier I University Transportation Center for its financial support of my presentations. I thank anonymous reviewers of the Transportation Research Board and *Transportation Research Part A: Policy and Practice* for their critical comments and feedback. Lastly, I would like to thank my parents, Oh Yeong Kweun and Jeong Eui Kim, and my brother, Hyeok Jin Kweun, all of whom made me who I am today.

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ABSTRACT

Essays on Travel Demand for Toll Roads

Jeong Yun Kweun, Ph.D.

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Dissertation Director: Dr. Roger R. Stough

Road pricing, a fee related to using a road, is one of the main instruments used in transport regulation to manage both externalities such as congestion and revenue for infrastructure investment. As road pricing attracts ongoing interest from policymakers, there is a gap in the literature examining road pricing and its impacts on traveler behavior and demand for priced limited access roads (or toll roads). This dissertation examines policy-related empirical questions regarding the relationship between road pricing and travel demand in a three-essay format and aims to provide empirical evidence regarding two main areas of ongoing road pricing experiments in the United States: the road pricing of interstate highways and the conversion of existing high-occupancy vehicle (HOV) lanes to high-occupancy toll (HOT) lanes.

The first essay, *Road Pricing Elasticity of Demand – A Survey*, centers around one of the main parameters of demand, namely price elasticity of demand, and examines the sources of variation in road pricing elasticity of demand through an in-depth survey of

24 studies published between 1981 and 2015 on travel demand for toll roads. The results show that potential sources of variation include the method of estimating road pricing elasticity of demand, characteristics of facilities, types of facilities, vehicle types examined, payment methods, types of data analyzed, such as stated or revealed preference, and importantly, the level of road pricing implemented in place.

The second essay, *Road Pricing Elasticity of Demand for U.S. Toll Roads – a Dynamic Panel Data Analysis*, examines both the traveler's responsiveness to road pricing and whether functional class and geographic coverage of the toll facility explains the variation in estimates of road pricing elasticity of demand. The analysis of travel demand data for 64 U.S. toll roads in 15 states from 2004 to 2013 shows that the short-run price elasticity is smaller for urban toll roads than intercity roads and smaller for interstate than non-interstate toll roads. One explanation is that despite the availability of free alternative routes in urban areas, free routes are not practical to use due to higher travel cost and reduced travel time savings because of congestion in urban areas.

The third essay, *Impact of HOV-to-HOT Conversion on Drivers*, focuses on the impact of converting high-occupancy vehicle (HOV) lanes to high-occupancy toll (HOT) lanes on carpoolers. Taking the I-85 HOV-to-HOT conversion project in Atlanta, Georgia as an empirical case, the analysis used a publically available dataset called the I-85 Corridor Household Travel Survey, which took place before and after the conversion of the facility. The binary logit estimators show that drivers in medium- to high-income groups, younger age cohorts, being white, having smaller household size, and taking trips for child care purposes were more likely to drive in the express lanes. Females driving to take care of their children were less likely to use the express lanes, but the result was not statistically significant.

CHAPTER ONE: INTRODUCTION TO THREE ESSAYS

Road pricing, a fee related to using a road, is one of the main instruments used in transport regulation to manage both externalities such as congestion and revenue for infrastructure investment. Road pricing was proposed in the 1920s by Pigou (1920) and Knight (1924), and the idea has continuously received interest from both academic scholars and policymakers. The practice, however, followed slowly over a period of one hundred years. In the United States, public toll authorities were established from the 1920s to 1950s to manage user fees for constructing limited access roads and bridges, resulting in more than 3,000 miles of tolled roads by the end of 1950s (Garrison and Levinson 2006; Dyble 2010). As the paradigm of infrastructure development shifted toward more federal funding and no user charges during the construction of the interstate highway system throughout the nation from 1956 to 1991, only 1,000 miles of new toll roads opened and the collection of user fees was prohibited on federally funded roads (Gómez-Ibáñez and Meyer 1993). Transport regulations have seen significant changes at all levels of government since 1991, as the interstate highway construction was near completion and public authorities began to consider road pricing as an instrument for both supplementing funding sources and managing travel demand effectively. In 2017, the United States is in the middle of experimenting with various road pricing schemes, including dynamic pricing, in which the rate varies with current traffic level. Many other road pricing projects are still in the pipeline.

As road pricing continues to attract ongoing interest from policymakers, there is a gap in the literature examining road pricing and its impact on traveler behavior and demand for priced limited access roads (or toll roads). This dissertation examines policy-related empirical questions regarding the relationship between road pricing and travel demand in a three-essay format. The overarching aim of the dissertation is to provide empirical evidence regarding two main areas of ongoing road pricing experiments in the United States: the road pricing of interstate highways and the conversion of existing high-occupancy vehicle (HOV) lanes to high-occupancy toll (HOT) lanes.

The first essay, *Road Pricing Elasticity of Demand – A Survey*, centers around one of the main parameters of demand, namely price elasticity of demand, and examines the sources of variation in road pricing elasticity of demand through an in-depth survey of literature on travel demand for toll roads. Although empirical studies on travel demand for toll facilities have increased over time, there is no clear consensus on how road pricing elasticity of demand may vary by context and the method of collecting tolls and by owner. The importance of road pricing elasticity of demand is that it is a key parameter in planning and forecasting for toll facility projects and influencing investment decisions. This survey provides evidence on the sources of variation in 349 observations of road price elasticities collected from 24 studies published between 1981 and 2015.

The second essay, *Road Pricing Elasticity of Demand for U.S. Toll Roads – a Dynamic Panel Data Analysis*, examines both the traveler's responsiveness to road pricing and whether functional class and geographic coverage of the toll facility explains the variation in estimates of road pricing elasticity of demand. This essay empirically estimates a dynamic panel data model using an unbalanced panel data of 64 U.S. toll roads in 15 states from 2004 to 2013. The sample was further segmented by functional class and geographic coverage to examine variation in elasticity estimates among different groups of toll facilities. The toll facilities examined in this research are characterized by roads only and traditional types of tolling schemes in which tolls are not adjusted by the congestion level on tolled lanes.

The third essay, *Impact of HOV-to-HOT Conversion on Drivers*, focuses on the impact of converting high-occupancy vehicle (HOV) lanes to high-occupancy toll (HOT) lanes on carpoolers. Recent federal regulatory changes have opened opportunities for policymakers to impose tolls on existing HOV lanes. The research uses panel survey data of I-85 corridor users in Atlanta, Georgia, called the I-85 Corridor Household Travel Survey, which took place before and after the conversion of the facility. The binary logit model was estimated to examine characteristics of drivers choosing to drive on express lanes. Special attention was given to the effect of trip purpose on demand for express lanes.

The structure of each essay is similar, in that each begins with an introduction describing the relevant policy background and proposes the main research question of interest. A review of relevant literature follows each introduction section. All essays are empirical studies; therefore, data and methods used to examine the questions are described in detail. Each result section describes the main findings of the empirical analysis of the data and their policy implications. The last sections conclude each essay. The main findings of each essay and their relationships to each other will be once again summarized in *Chapter Five: Policy Implications and Conclusion*, along with a description of the implications for academics, policymakers, and stakeholders who are trying to understand, expand, and implement road pricing in the operational environment.

In this dissertation, the term "road pricing" is broadly defined as a fee associated with using roadways. In the academic literature, as well as in practice, the term is often used interchangeably with other phrases, such as "congestion pricing," "congestion charges," "value pricing," and "road user charge." In practice, road pricing is simply referred as "tolls," "toll rates," and "toll charges." Phrases such as "variable pricing," "peak-period pricing," "market-based pricing," and "dynamic pricing" are used to characterize the type of road pricing implemented in place. Phrases including "cordon," "area charging," and "distance-based charging" are used to characterize the geographical coverage of the road pricing scheme. The difficulty of coming up with a single term to illustrate Pigou's idea is not new. For example, when experts in road pricing from around the world were gathered at the International Symposium on Road Pricing in 2003, the conference committee had to come to consensus on the definition of road pricing, as variety of terms were used by researchers and practitioners. They determined that, "Under a road pricing strategy, road users are charged a fee that reflects the cost of their use of the road more fully than do existing fees and taxes, and thus pricing can serve as a public policy tool to help manage demand for a limited resource— road space" (International Symposium on Road Pricing, 2005). Among listed terms, this dissertation mainly uses the term "road pricing," and the author's usage of the term is in line with the understanding of the conference committee members of the International Symposium on Road Pricing in 2003.

CHAPTER TWO: ROAD PRICING ELASTICITY OF DEMAND – A SURVEY

Introduction

This essay examines sources contributing to the variability of road pricing elasticity of demand estimates reported in studies by employing a comprehensive survey of the relevant literature. The road pricing elasticity of demand is a key parameter for planning, evaluating, managing, and forecasting the revenue of toll facility projects. Road pricing elasticity, a measure of the relative sensitivity of a change in the travel volume to a change in price continuously, sparks interest in researchers, policymakers, and practitioners in transportation because it is a critical parameter for the level of service and revenue prediction and thus significantly influences transportation policy, operation strategies, and investment decisions. Existing evidence, however, shows that variation in road pricing elasticities across toll facilities, from time to time, and from place to place is large, and there is no consensus on the size of toll elasticity that should be used in the analysis of tolling.

A price elasticity of demand is a percentage change in demand that is associated with a percentage change in price. A change in demand due to change in price may be calculated as a simple derivative, however, economists often measure the relationship between demand and price by elasticities rather than derivatives because measurement scales are normalized (i.e. elasticity is a unitless measure) (Train 2009, 57-60). This attribute allows elasticity estimates transferable from one context to another, which is important when evaluating policy such as road pricing *ex ante*.

As policy environment becomes more acceptable for operationalizing road pricing as a tool for managing congestion and funding for infrastructure investment, it becomes more important to evaluate how travel demand will change according to price. Parameters such as road pricing elasticity of demand from similar context can feed into the early stage of *ex ante* project appraisal process as well as in *ex post* evaluation of project to forecast future demand, revenue, and welfare effect.

For similar reasons, influential review studies on travel demand published in the 1990s and early 2000s were motivated by government programs requiring more accurate information of demand elasticity to reappraise traffic models in place. For example, Goodwin et al. (2004) and Graham and Glaister (2004) were commissioned by the U.K. Department of Environment, Transport and the Regions to inform the agency of factors explaining variation in price elasticities of various demand measures such as car travel, car ownership, freight traffic, and fuel consumption. De Jong and Gunn (2001) examined car cost and time elasticities of travel demand as part of the TRACE project in 1998 and 1999 commissioned by the European Commission. Oum et al. (1992) originated from a project on Pricing, Cost Recovery and Efficient Resource Use in Transport at the World Bank surveying empirical evidence on magnitudes of price elasticities of transport demand including automobile usage, urban transit, air passenger travel, and intercity rail travel. Researchers continue to synthesize empirical evidence on price elasticities in gray literature such as Lee and Burris (2005) to establish values for the Highway Economic

Requirements System (HERS) model used by the U.S. Department of Transportation. Still there are many surveys of road traffic demand (Goodwin 1992; Oum, Waters, and Yong 1992; Jong and Gunn 2001; Cervero and Hansen 2002; Goodwin, Dargay, and Hanly 2004; Graham and Glaister 2004; Oum, Waters, and Fu 2008; Wardman 2014; Kremers, Nijkamp, and Rietveld 2002) and, more broadly, surveys on public transportation demand (Nijkamp and Pepping 1998; Kremers, Nijkamp, and Rietveld 2002; Holmgren 2007; Hensher 2008).

What is currently missing in the travel demand literature is a systematic review of road pricing elasticity of demand. Until the 1990s, there were few empirical studies of road pricing elasticity of demand, and previous review studies seldom included discussions on road pricing elasticities. The number of empirical studies started to grow in the 2000s with the growing acceptance of road pricing as a policy tool for managing congestion, opening the opportunity to understand patterns, if any, in the size and variation of road pricing elasticities. Findings of this essay, therefore, complement the stream of review studies on travel demand elasticities by presenting evidence on the relationship between road pricing and travel demand. This essay also contributes to the literature by acknowledging the importance of considering the relationship between the level of price and estimated elasticities (Button 2015). Lastly, as opposed to a recent trend of employing meta-regression for synthesizing parameter of interest in transport literature, this essay collects and collates elasticity estimates from empirical studies and factors that may explain variation in estimates, following the spirit of more traditional and revealing surveys such as Oum et al. (1992), Goodwin (1992), Goodwin et al. (2004), and Graham and Glaister (2004).

This survey collects information on road pricing elasticities and potential sources of variation from an in-depth reading of 24 studies published between 1981 and 2015. The total number of toll elasticity estimates examined in this survey is 349 observations. The data used in selected studies cover the years 1950 to 2011, which is 61 years of data. The selected studies analyze toll facilities in eight different countries: Canada, Chile, Hong Kong, Norway, Singapore, Spain, Taiwan, and the U.S. In addition to toll elasticity of demand, data on facility characteristics, travel attributes, and methods used were collected.

The remainder of this essay is organized as follows. The introduction is followed by a discussion of the data collection process, including literature identification and the dataset building process. The method of analysis employment in this survey is discussed, followed by an overview of various models of travel demand used for estimating toll elasticities in the literature. The survey results are presented as variations in the toll elasticity of demand estimates by the methods used in estimation. The last section concludes the essay.

Data

The first step of this survey was to identify studies analyzing the travel demand on toll roads to collect information on road price elasticities, the main variable of interest in this survey, and factors affecting the variation of estimates. A keyword search of road pricing elasticity, congestion pricing, and toll elasticity on the Transportation Research

Information and International Transport Research Document (TRID) was conducted to identify relevant studies. Once the initial set of studies was identified, the author used the Web of Science to identify cited references, using the so-called snowball sampling method. The author conducted an in-depth reading of each study to identify any relevant references cited in each article. Both peer-reviewed papers and reports published by transportation agencies were identified and included in this survey. Because the purpose of this essay is to examine factors explaining variation in toll elasticity of demand across studies, collecting information on variables of interest other than the toll elasticity estimates was also important. To avoid making inferences based on information from secondary sources, studies were considered in the survey only if the full report was available. Studies that use the activity-based approach, as in Arentze, Hofman, and Timmermans (2004), or experiments, as in Janson and Levinson (2014), are not included in the analysis to avoid over-generalization of their unique approaches to analyzing travel demand on toll roads. Any repeated publication in different forms or updated versions are not included, following the practice of Goodwin et al. (2004).

After the sampling of studies was completed, the author read through each study thoroughly to identify point estimates of toll elasticities and potential sources of variation: characteristics of the study; vehicle types; facility characteristics including countries, geographic coverage, facility type, pricing type, and travel attributes such as vehicle type, day of week, hours of day, trip purpose, and decision-making context; data and the methods including the data type, type of dependent variable, model, estimation method, and the time horizon (short-run vs. long-run). When available, the data on other price elasticities like fuel, income, and alternative model were also collected. A list of potential sources of variation was established based on factors analyzed in published review articles (Cervero and Hansen 2002; Goodwin 1992; Goodwin, Dargay, and Hanly 2004; Graham and Glaister 2004; Jong and Gunn 2001; Kremers, Nijkamp, and Rietveld 2002; Oum, Waters, and Yong 1992; Oum, Waters, and Fu 2008; Wardman 2014). Also, the author organized meetings with practitioners in the toll industry to verify potential factors affecting price elasticity estimates on toll roads. Once values or descriptions of listed variables were identified in each study, they were coded in a spreadsheet. For example, to code a facility type as a road, bridge, or tunnel, three separate columns were created called "fc_road," fc_bridge," and "fc_tunnel." For example, to code the Turner Turnpike in Oklahoma as road, "fc_road" was coded as 1, "fc_birdge" as 0, and "fc_tunnel" as 0.

In sum, a total of 349 toll elasticity of demand estimates was compiled from 24 studies published between 1981 and 2015. The studies cover different periods over the 61 years from 1950 to 2011. The data is drawn from sources in 8 countries (Canada, Chile, Hong Kong, Norway, Singapore, Spain, Taiwan, and the U.S.). Each study analyzes 1 to 30 different facilities/groups of facilities/contexts, resulting in the total of 89 facilities/groups of facilities/contexts covered in this survey. Four methods are mainly used for deriving toll elasticities: before-and-after comparison, static model, dynamic panel data model, and discrete choice model. Various measures of dependent variables were used in the study, such as traffic volume, transaction, vehicle-miles traveled, the number of journeys, average daily traffic, and average daily toll transactions. The discrete choice model examined choice sets including mode choice and route choice. The complete list of studies is available in Appendix A. (The full dataset is available upon request.)

Before moving to the next section on the approach taken to analyze collected toll elasticities, it is worth discussing how vehicle types are categorized in the dataset and some of the challenges the author faced during the data collection process. Because type of vehicle infers a trip purpose, it is important to understand what type of vehicle is under consideration in the analysis. The initial review of sampled studies revealed that six types of vehicles were analyzed in the studies: all vehicles, passenger cars, light vehicles, heavy vehicles, 2-axles, and 5-axles. During the review process, it was found that studies use different terminologies to refer to vehicles types. Although, for example, passenger cars and 2-axle vehicles seem to refer to the same category of vehicles, additional procedures were needed in order to determine whether or not to group elasticity estimates of passenger cars and 2-axle vehicles into the same category. Another decision was needed on whether or not to include findings on light vehicles in the survey due to a small number of observations on light vehicle road pricing elasticities of demand found in the literature.

The following two procedures were employed to determine whether six categories of vehicles could be reduced to a smaller number. First, the author examined the sample mean difference of toll elasticity estimates for passenger cars versus 2-axles and heavy vehicles versus 5-axles. The test results showed that the sample mean is not statistically different between heavy vehicles and 5-axles. For passenger cars and 2-axle vehicles, the sample mean was different with statistical significance. However, considering that 2-axle vehicles are cars, trucks, SUVs, and motorcycles that carry passengers, the trip purpose of passenger cars and 2-axle vehicles could broadly be viewed similarly. Based on this assumption, passenger cars and 2-axle vehicles were grouped together, and likewise heavy trucks and 5-axle vehicles were grouped together. Second, two of the analyzed studies examined toll elasticities for light vehicles: Hirschman et al. (1995) looked at light trucks using Triborough Bridge and Tunnel Authority (now called MTA Tunnels and Bridges) crossings in New York City, and Olszewski and Xie (2005) calculated arc elasticity of Light Goods Vehicles with MLW of 3,500 kg or less. Due to the very different characteristics of light vehicles and passenger cars and heavy trucks, and due to a small number of observations, the author decided not to include findings on light vehicles and instead focus on the passenger cars and heavy trucks that dominate trips. Based on the two procedures discussed, the vehicle types were narrowed down to three categories: all vehicles, passenger cars (including 2-axle vehicles), and heavy trucks (including 5-axle vehicles).

Method of Analysis

It is not uncommon to find cases in which the meta-analysis approach is applied to transportation studies for analyzing transportation-related price elasticities, such as Hensher (2008) on public transit fare elasticity, Wardman (2014) on price elasticities of surface travel demand, and Holmgren (2007). On the other hand, Goodwin et al. (2004) decided not to report their meta-analysis results on fuel demand because, from the authors' point of view, the approach "fail(s) to show a systematic pattern" and is "not very revealing" in producing sensible hypotheses to examine.

The earlier version of this essay carried out a meta-analysis to systematically summarize factors that influence the variations in point estimates of toll elasticity across studies (Van den Bergh and others 1997). In this version of the essay, however, the author chose to conduct a detailed survey of the literature instead of employing a meta-analysis. One of the reasons why a survey of variation in road pricing elasticity of demand estimates is needed is to draw implications for future road pricing policy initiatives from the existing body of knowledge and to predict changes in travel demand in various contexts. To compare elasticities across studies, it is critical to take into account the price level of tolls, the price level of alternative goods (i.e., the price level of public transit), and the income level. Economic theory suggests that these are key parameters explaining movements along the travel demand curve and the shift of the travel demand curve. Without information on these three key economic variables, other attributes found in studies, such as data type, functional form, vehicle type, facility type, and the country, would not be sufficient for understanding the variation in toll elasticities (Button 2015). The author found that the price level of tolls, the price level of alternative goods, and the income level from each study was too limited to perform a meta-analysis and instead chose to conduct a detailed survey of the literature.

Estimating Road Price Elasticities from Travel Demand Models

Road price elasticities can be derived from various travel demand models. In this survey, four types of travel demand models are predominantly used for deriving toll elasticities: before-and-after comparison, static model, dynamic panel data model, and discrete choice model (Table 1).

The elasticities estimated from each method are interpreted differently, and the unique features of each method provide various aspects of evidence on changes in traffic volume on toll facilities with respect to changes in tolls. This section discusses the features of each demand model identified from 24 studies selected for the survey as discussed in the Data Section (see Table A1 in Appendix A for the full list of studies), the interpretation of elasticities by model, and the variation in toll elasticities across methods used.

Table 1 Summary of toll elasticities by model characteristics

	Before-and-After [a]	Static Model [b]	Dynamic Model [c]	Discrete Choice [d]
Average Toll Elasticity of Demand	Arc: -0.373 Shrinkage: -0.434	-0.157	-0.338 SR: -0.267 LR: -0.783	-0.452
Number of Studies	6	7	7	7
Number of Toll Elasticities	177	43	65	64
Data Type	Before-and-after	Panel	Panel	Survey (SP, RP, or SP/RP)
Data Interval	Half-hourly 4 months 6 months	Hourly Monthly Quarterly Annual	Monthly Quarterly Annual	Cross-section
Data Period (range)	1975 to 2001	1950 to 2011	1973 to 2011	1999 to 2004
Demand Measure	Traffic volume Transaction	Traffic volume Transaction Average daily traffic Number of journeys	Traffic volume AADT ADTT VKT	Mode choice Route choice Multiple choices
Estimation		OLS	OLS GMM-DIFF GMM-SYS WLS	ML MSLE WESMLE
Model	Arc elasticity Shrinkage ratio	Fixed effects	AR ARCH	Logit, joint logit, mixed logit, nested logit, conditional logit, and generalized nested logit

Notes: SR = short-run. LR = long-run. SP = stated preference survey. RP = revealed preference survey. AADT = annual average daily traffic. ADTT = average daily toll transaction. VKT = vehicle-km traveled. WLS = weighted least squares. ML = maximum likelihood estimation. MSLE = maximum simulated likelihood estimation. WESMLE = weighted exogenous sample maximum-likelihood estimator. GMM-DIFF = difference generalized method of moments. GMM-system = system generalized method of moments. AR = autoregressive model. ARCH = autoregressive conditional heteroskedasticity.

Sources: [a] Before-and-after comparison (Hirschman et al. 1995; Holguín-Veras, Ozbay, and de Cerreño 2005; Luk 1999; Odeck and Bråthen 2008; Olszewski and Xie 2005; Wuestefeld and Regan 1981); [b] Static (Álvarez, Cantos, and García 2007; Cervero 2012; De Grange, González, and Troncoso 2015; Finkelstein 2009; Gifford and Talkington 1996; Hirschman et al. 1995; Loo 2003); [c] Dynamic (Bari, Burris, and Huang 2015; Gomez, Vassallo, and Herraiz 2015; Gomez and Vassallo 2015; Huang and Burris 2013; Matas and Raymond 2003; Odeck and Bråthen 2008, 77-94; Zhang and Marshment 2012); [d] Discrete choice (Álvarez, Cantos, and García 2007; Dehghani et al. 2003; Holguín-Veras and Allen 2013; Small, Winston, and Yan 2005; Washbrook, Haider, and Jaccard 2006; Wen and Tsai 2005; Yan, Small, and Sullivan 2002)

First, the before-and-after comparison uses the definition of price elasticity of demand to calculate elasticity based on the elasticity formula. The two main methods to calculate before-and-after type elasticities are the arc elasticity method (Luk 1999; Odeck and Bråthen 2008; Olszewski and Xie 2005) and the point elasticity method, also referred to as the shrinkage ratio in travel demand studies (Hirschman et al. 1995; Holguín-Veras, Ozbay, and de Cerreño 2005; Wuestefeld and Regan 1981). The arc elasticity formula is a percent change in traffic volume over a percent change in price

Equation 1

$$E_x = \frac{\Delta Q_d \,/ Q_d}{\Delta P \,/ P}$$

where the elasticities are assumed constant along the demand curve, and P may vary depending on whether Laspeyres, Paasch, Fisher Idea or other index is used in the estimation (Button 2005). The point elasticity, or shrinkage ratio in the literature, is

Equation 2

$$E_x = \frac{\partial Q_d \,/\, Q_d}{\partial P \,/\, \mathrm{P}}$$

where the elasticities are assumed to vary along the demand curves.

It is important to note that the arc elasticity calculates the average elasticity between two points on the demand curve, whereas the point elasticity calculates the marginal change in elasticity for a certain point on the demand curve. These non-econometric approaches to calculating elasticity were used in early studies on toll road demand, which cover the years 1975 to 2001 in the data. Odeck and Bråthen (2008), for example, used arc elasticity because the changes in tolls are large in the real world and the travel demand function is assumed to be convex. Hirschman et al. (1995) calculated the shrinkage ratio for each of the Triborough Bridge and Tunnel Authority facilities as a reference point for the static model results. The average toll elasticity from the shrinkage ratio is -0.434, ranging from -1.973 to 0.75 (Figure 1(1a)); the average toll elasticity from the arc elasticity method is -0.373, ranging from -2.26 to -0.007 (Figure 1(1b)).

The second approach is to use what the current research calls a static regression model to explain toll road demand as a function of toll rate and other factors affecting demand using panel data (Álvarez, Cantos, and García 2007; De Grange, González, and Troncoso 2015; Cervero 2012; Finkelstein 2009; Loo 2003; Hirschman et al. 1995; Gifford and Talkington 1996). The static model examines the contemporaneous relationship between traffic volume and explanatory variables. When the log-log functional form is used, coefficient estimates are interpreted as direct point elasticity. In this survey, 43 observations of toll elasticities from 7 studies are estimated from the static model, with a wide coverage of data from 1950 to 2011. All studies use the log-log functional form with the exception of Cervero (2012), which uses linear, log-linear, and log-log functions. The direct demand model specification is similar as well as studies that try to explain changes in traffic level (measured in traffic volume, transactions, average daily traffic, and number of journeys) as a function of fuel price, income, alternative modes and services, and dummies explaining any shocks in the system (see Appendix A). The average toll elasticity of demand estimated from the static model studies is -0.157, ranging from -0.6 and 0.2 with a standard deviation 0.190 (Figure 1(2)).

The third approach is to use a dynamic panel data model and take into account both the short- and long-run adjustments of demand to changes in toll rates (Bari, Burris, and Huang 2015; Gomez, Vassallo, and Herraiz 2015; Gomez and Vassallo 2015; Matas and Raymond 2003; Odeck and Bråthen 2008; Zhang and Marshment 2012). The feature that differentiates the dynamic panel data model from the static model is its econometrics equation, in which the lag of a dependent variable is specified as an explanatory variable in the equation (Baltagi 2013). There are variants of dynamic regression models, but the version most often found among the 7 studies that use a dynamic regression model in the current survey is the autoregressive model specified with one period lag. There was one instance with an explanatory variable and an autoregressive conditional heteroskedasticity (ARCH) model. One of the benefits of using the dynamic panel data model is the explicit estimation of both the short- and long-run elasticities. The 65 toll elasticity samples are estimates from dynamic panel data models, and the average toll elasticity is -0.267 in the short-run, ranging from -1.49 to 0.52 (Figure 1(3a)), and -0.783 in the long-run, ranging from -1.307 to -0.33 (Figure 1(3b)).

Lastly, the discrete choice approach is often used in travel demand analyses based on the recognition that travel decisions are made by individuals trying to optimize their behavior, and therefore their travel demands can be analyzed as a utility maximization problem subject to the attributes of travel alternatives and individual characteristics (Ben-Akiva and Lerman 1985; Quandt 1976). The family of logit models (i.e. logit, joint logit, mixed logit, nested logit, conditional logit, and generalized nested logit) is estimated using the maximum likelihood estimation method (with one instance of a weighted exogenous sample maximum-likelihood estimation method used in Yan et al. (2002)) to evaluate traveler choices (Álvarez, Cantos, and García 2007; Dehghani et al. 2003; Holguín-Veras and Allen 2013; Small, Winston, and Yan 2005; Washbrook, Haider, and Jaccard 2006; Wen and Tsai 2005; Yan, Small, and Sullivan 2002). The context of discrete choice analysis includes the choices between modes (drive alone, carpool, and transit), routes (tolled route and alternative route), and the combination of multiple choices (mode, route, departure time, time of day, and transponder choice). For data, studies conducted between 1999 and 2004 used stated preference data, revealed preference data, or both. It is important to note that elasticity estimates from discrete choice models are interpreted as changes in the probability of choosing an alternative over others in the choice set with respect to the percentage change in the attribute of the chosen alternative (Louviere, Hensher, and Swait 2000, 58). Overall, the average road price elasticity estimate from discrete choice models is -0.452, ranging from -1.588 to -0.054 (Figure 1(4)).

Figure 1 illustrates the distribution of road price elasticities by methods. First, the distribution of road price elasticity estimates is the widest when calculated using the shrinkage ratio with a range from -1.973 to 0.75 (Figure 1(1a)). The estimates from the static model are narrowly concentrated around the mean -0.157, ranging from -0.6 and 0.2 with a standard deviation 0.190 (Figure 1(2)).

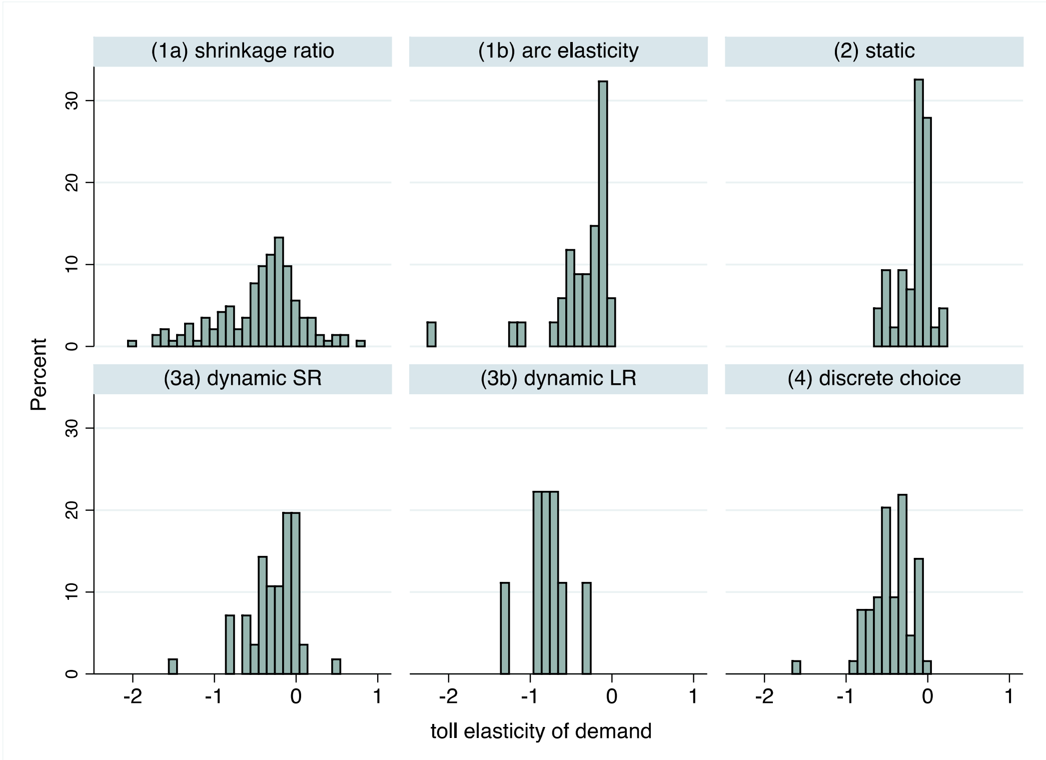

Figure 1 Distribution of road price elasticity of demand by the methods
Notes: The mean toll elasticity of demand in each panel is as follows: (1a) shrinkage ratio, -0.434 (0.508, 143); (1b) arc elasticity, -0.373 (0.435, 34); (2) static model, -0.157 (0.19, 43); (3a) dynamic short-run, -0.267 (0.312, 56); (3b) dynamic long-run, -0.783 (0.262, 9); (4) discrete choice, -0.452 (0.267, 65). The width of each bin/bar is 0.1. All toll elasticities are direct point estimates except in panel (1b) arc elasticity.

To examine the variations between and within methods, the road price elasticities are summarized by method, vehicle type, and facility type in Table 2. First, in general, estimates from all four methods confirm that passenger cars are more sensitive to toll increases than heavy trucks in all facility types except for tunnel toll facility users based on the static model. Second, long-run toll elasticities from dynamic panel data models are about 1.6 times larger than short-run elasticities, which will be discussed in more detail in the results section. Third, the road price elasticity by vehicle type and facility type across methods varies widely. Likewise, estimates from before-and-after studies show passenger cars and heavy trucks are more responsive to tunnel tolls than road or bridge tolls, but estimates from the other three regression models do not present such a pattern. Overall, when road price elasticity estimates from the four methods are disaggregated by vehicle type and facility type, no distinctive patterns emerge other than confirming the differences between elasticities of passenger cars and heavy trucks and the short-run and long-run elasticities.

Table 2 Road price elasticities by model, vehicle type, and facility type

Facility Type	Before-and-After Comparison				Discrete
	Shrinkage ratio	Arc elasticity	Static	Dynamic	Choice
Passenger Cars					
Road	-0.224 (9)	-0.230 (10)	-0.537 (1)	-0.238 (21) SR	-0.455 (63)
Bridge	-0.857 (38)		-0.110 (6)	-0.035 (2) SR	
Tunnel	-1.300 (12)		-0.157 (7)		
Heavy Trucks					
Road	-0.148 (9)	-0.058 (2)	-0.395 (1)	-0.215 (22) SR	-0.247 (1)
Bridge	-0.290 (19)		-0.008 (5)	-0.21 (1) SR	
Tunnel	-0.333 (6)		-0.600 (2)		
All Vehicles					
Road	-0.185 (4)	-0.456 (22)	-0.180 (8)	-0.486 (9) SR -0.770 (8) LR	
Bridge	-0.015 (34)		-0.149 (7)		
Tunnel	-0.152 (12)			-0.550 (1) SR -0.880 (1) LR	
All			-0.058 (6)		

Notes: The number of observations is in parentheses. SR = short-run. LR = long-run.
Sources: See the list of sources in Table 1.

Results

Among the four methods of examining travel demand discussed in the previous section, elasticity estimates are focused on those findings from studies utilizing regression techniques, namely static models, dynamic panel data models, and discrete choice models. The impact of changes in fuel price, income level, and alternative modes and services are discussed. Lastly, the relationship between the level of toll price and elasticity is discussed.

Static model results

Table 1 shows that the average road price elasticity from static demand models (-0.157) is the smallest compared to estimates from other methods, with a smallest standard deviation 0.19. The graph shows that the 43 observations of road price elasticities are closely clustered in the range of -0.6 and 0.2. The context examined in static demand models partly explains the small size of road price elasticity estimates. Table 3 shows that the sample of observations from static models comprises 32 urban facilities (-0.155) and bridges (-0.097). The observed road price elasticities are similar across countries as well.

Table 3 Road price elasticity of demand from static models by attributes

	Passenger Cars	Heavy Trucks	All Vehicle Types	All Samples
Toll Elasticity by Vehicle	-0.164 (14)	-0.204 (8)	-0.135 (21)	-0.157 (43)
Facility Type				
Road	-0.537 (1)	-0.395 (1)	-0.180 (8)	-0.237 (10)
Bridge	-0.110 (6)	-0.008 (5)	-0.149 (7)	-0.097 (18)
Tunnel	-0.157 (7)	-0.600 (2)		-0.256 (9)
All			-0.058 (6)	-0.058 (6)
Geographic Coverage				
Urban	-0.123 (10)	-0.177 (7)	-0.165 (15)	-0.155 (32)
Intercity	-0.268 (4)	-0.395 (1)		-0.293 (5)
Countries				
Chile			-0.180 (8)	-0.180 (8)
Hong Kong	-0.154 (5)			-0.154 (5)
Spain	-0.537 (1)	-0.395 (1)		-0.466 (2)
US	-0.124 (8)	-0.177 (7)	-0.107 (13)	-0.129 (28)

Notes: The presented toll elasticities are the average values. The number of observations are in parentheses. "All Vehicles" refers to samples in which vehicles are not distinguished by type (i.e,. passenger cars, heavy trucks, etc).
Sources: Alvarez et al. (2007), Cervero (2012), De Grange et al. (2005), Finkelstein (2009), Gifford and Talkington (1996), Hirschman et al. (1995), Loo (2003)

Among static demand studies, the magnitude of road price elasticities from Álvarez et al. (2007) is larger (-0.537 for passenger cars and -0.395 for heavy trucks) compared to estimates in other studies (Appendix A). The authors estimated travel demand for 9 aggregated toll routes in the Mediterranean coastal trips in Spain using quarterly data from 1989 to 2000. The number of journeys is explained as a function of the toll, fuel price, the gross national product, and time dummies to control shocks. One potential explanation is that renegotiations with private concessionaires and the growing interest in toll road constructions led to policy changes in the 1980s and 1990s that caused toll rates to vary a great deal from one segment to the other, from 0.037 euros to 0.22 euros per kilometer (Matas and Raymond 2003). Traffic in the coastal area is dependent on seasonal activities such as tourism (Gomez, Vassallo, and Herraiz 2015) as opposed to commuter traffic in urban toll facilities.

Short-run and long-run road price elasticities from dynamic panel data model

One of the ongoing debates in the travel demand literature is the difference between short-run and long-run price elasticity estimates. The reviews on travel demand (Oum, Waters, and Yong 1992; Goodwin 1992; Goodwin, Dargay, and Hanly 2004) emphasize the distinction between short-run and long-run elasticities of demand because, in the long run, drivers are better able to adjust behavior and assets in response to changes in price. Unfortunately, as was observed by Oum et al. in 1992 (Oum, Waters, and Yong 1992), few studies are explicit about whether estimated elasticities are short-run or long-run. Following suit in Oum et al. (1992) and Goodwin et al. (2004), coefficients were coded short-run or long-run only if they were estimated from dynamic panel data models (Bari, Burris, and Huang 2015; Gomez, Vassallo, and Herraiz 2015; Gomez and Vassallo 2015; Burris and Huang 2011; Matas and Raymond 2003; Odeck and Bråthen 2008; Zhang and Marshment 2012). For long-run elasticities, those explicitly calculated by the authors of the studies were included in the dataset even though the calculation of long-run elasticity is only possible when the coefficients of short-run elasticity and lag term are available (i.e., given a dynamic equation of the form $y_t = \alpha + \beta x_t + \gamma y_{t-1}$ in log-log functional form, the long-run elasticity is $\beta/(1-\gamma)$ (Greene 2012, 462-463)).

Table 4 shows that the long-run toll elasticity (-0.783) from 56 observations is about three times larger than the short-run toll elasticity (-0.267) from 9 observations. Table 5 compares short-run and long-run toll elasticities at the facility level from two studies, Matas and Raymond (2003) and Odeck and Bråthen (2008). At the facility level, long-run toll elasticity is about 1 to 1.6 times larger than short-run toll elasticity. Early evidence on transport price elasticity in a review by Goodwin (1992) suggested that the long-run price elasticities are 0.5 to three times greater than short-run elasticities. The current evidence suggests that toll elasticities in the long-run behave similarly to other price elasticities.

Table 4 Short-run vs. long-run toll elasticity of demand from studies using dynamic panel data model

	Avg Toll Elasticity	Std Dev	Min	Max	Observations
Short-run	-0.267	0.312	-1.490	0.520	56
Long-run	-0.783	0.262	-1.307	-0.330	9

Table 5 Short-run and long-run toll elasticities by dynamic panel data study

Author	Facility Name		Toll Elasticity All Vehicles	Note
Odeck and Bråthen (2008)	Ålesund tunnels	SR	-0.55	10-year data; Norway
		LR	-0.88	
	Askøy (Bergen)	SR	-0.62	
		LR	-0.75	
	Helgeland	SR	-0.76	
		LR	-0.80	
	Kristiansund	SR	-0.59	
		LR	-0.79	
	Molde	SR	-0.57	
		LR	-0.90	
Matas and Raymond (2003)	Low toll elasticity motorways	SR	-0.21	1981-1998; WLS; motorways grouped into 4 groups from 72 segments of toll roads in Spain
		LR	-0.33	
	Low-medium toll elasticity motorways	SR	-0.37	
		LR	-0.59	
	Medium-high toll elasticity motorways	SR	-0.45	
		LR	-0.70	
	High toll elasticity motorways	SR	-0.83	
		LR	-1.31	

Notes: The listed toll elasticities for all vehicle types are point estimates and are not the average of multiple toll elasticity estimates. All studies in this table use dynamic panel data model with a lag of dependent variable, usually one period lag, specified as an explanatory variable. SR is short-run, LR is long-run, and WLS is the weighted least squares estimator. The dependent variables are traffic volume (Odeck and Bråthen, 2008) and annual average daily traffic volume (AADT) (Matas and Raymond, 2003). The data interval is annual in Matas and Raymond (2003) and unknown in Odeck and Bråthen (2008).

Figure 2 suggests that one source of variation across short-run elasticities is the geographic coverage—intercity or urban—of a facility. The graph shows that drivers using urban toll facilities (-0.112) are less sensitive to toll changes than those using intercity toll facilities (-0.396). This result may be counterintuitive because trips are shorter and alternative routes are almost always available in the urban context, giving drivers a better chance to avoid toll increases. However, when considering the context of a trip in an urban setting, toll road users may not have much flexibility in changing routes because of time constraints and work schedules. The dataset indicates that intercity travel is associated with commercial trips, and commercial vehicles may be more flexible in switching to toll-free routes if time constraints are not severe in the short run.

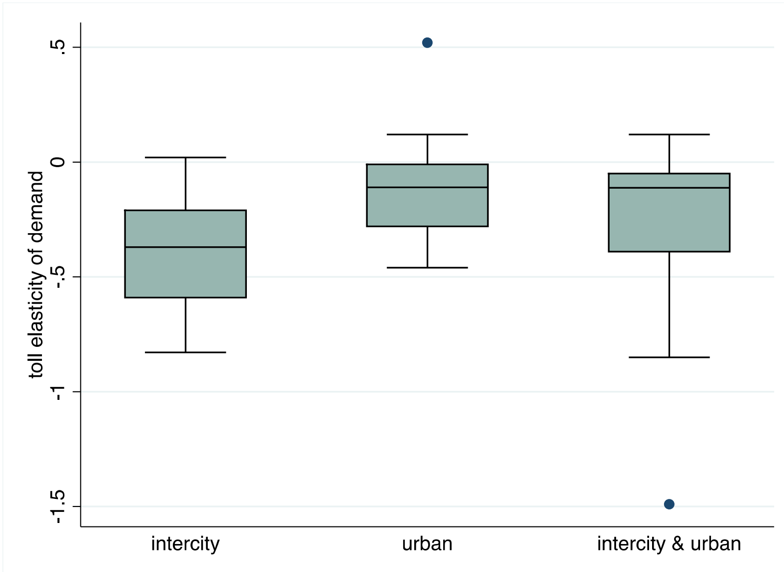

Figure 2 Short-run toll elasticities by geographic coverage of facilities
Notes: The average short-run toll elasticity estimates are -0.396 (21 observations) for intercity toll facilities, -0.112 (17) for urban, and -0.262 (18) for both intercity and urban toll facilities.

To further examine sources of variation in short-run road price elasticities, Table 6 summarizes short-run point estimates of road price elasticities from five studies by facility, vehicle type, geographic coverage, and data and methods. The average length of facilities is 14.5 miles for urban facilities, 41.9 miles for intercity facilities, and 79.2 miles for intercity/urban facilities. First, let's look at the variation in short-run road price elasticities by vehicle types and geographic coverage. For passenger cars, the average road price elasticity for intercity facilities (-0.422) is about three times larger than the average road price elasticity for urban facilities (-0.141). For heavy trucks, the sensitivity to toll increases at intercity facilities (-0.139) about 1.7 times higher than at urban facilities (-0.080).

Table 6 Short-run toll elasticities by facility, vehicle, and geographic coverage

Author	Facility	Toll Elasticity (point estimates) Passenger Car	Heavy Truck	Urban/Intercity	Notes
Huang and Burris (2013)	Cherokee Turnpike (US412)	-0.79	-0.22	Intercity	2000-2010
	Cimarron Turnpike (US412)	-0.27	-0.21	Intercity	2000-2010
	Indian Nation Turnpike	-0.64	-0.02	Intercity	2000-2010
	Muskogee Turnpike	-0.33	0.02	Intercity	2000-2010
	Creek Turnpike	-0.36	-0.11	Urban	2003-2010
	East-West (Dolphin) Expressway	-0.24	-0.31	Urban	2004-2010, cash
	Gratigny Expressway (SR924)	-0.2	-0.31	Urban	2004-2010, cash
	Harbor Tunnel Thruway (I-895)	-0.02	-0.01	Urban	2003-2010
	Kilpatrick Turnpike	-0.14	-0.08	Urban	2003-2010
	Miami Airport Expressway	0.01	0.12	Urban	2004-2010, ETC
	Miami Airport Expressway	-0.28	-0.46	Urban	2004-2010, cash
	SR241(Foothill)/SR261(Eastern)	-0.01	0.52	Urban	2005-2009
	H.E. Bailey Turnpike (I-44)	-0.11	-0.12	Intercity & Urban	2000-2010
	Kansas Turnpike	-0.08	-0.01	Intercity & Urban	2000-2010
	San Francisco Bay Area 7 bridges	-0.02	0.12	Intercity & Urban	2006-2008
	San Francisco Bay Area 7 bridges	-0.05	-0.21	Intercity & Urban	2000-2009
	Turner Turnpike	-0.41	-0.85	Intercity & Urban	2000-2010
	Will Rogers Turnpike	-0.38	-0.09	Intercity & Urban	2003-2010
Zhang and Marshment (2012)	Turner Turnpike	-0.114		Intercity & Urban	1973-2010
	Will Rogers Turnpike	-0.098		Intercity & Urban	1973-2010
Bari et al. (2015)	SH130(segment 1-4)/SH45SE		-0.39	Intercity & Urban	2008-2011, ETC
	SH130(segment 1-4)/SH45SE		-1.49	Intercity & Urban	2008-2011, cash
	SH130(segment 1-4)/SH45SE		-0.43	Intercity & Urban	2008-2011, ETC & cash
Gomez et al. (2015)	14 toll roads	-0.103		Intercity	1990-2010, GMM-SYS
		-0.400		Intercity	1990-2010, GMM-DIFF
Gomez and Vassallo (2015)	14 toll roads		-0.069	Intercity	1990-2007, GMM-SYS
			-0.333	Intercity	1990-2007, GMM-DIF

Notes: The listed toll elasticities for passenger cars and heavy trucks are point estimates and are not the average of multiple toll elasticity estimates. All studies in this table use dynamic panel data model with a lag of dependent variable, usually one period lag, specified as an explanatory variable. GMM-SYS is the system generalized method of moments estimator, and GMM-DIFF is the difference generalized method of moments estimator. The dependent variables are traffic volume (Huang and Burris, 2013; and Zhang and Marshment, 2012), annual average daily traffic volume (AADT) (Gomez et al., 2015), average daily toll transactions (ADTT) (Bari et al., 2015), and vehicle-km travelled (VKT) (Gomez and Vassallo, 2015). The data interval is annual (Gomez et al., 2015; Gomez and Vassallo, 2015), quarterly (Zhang and Marshment, 2012), and monthly (Huang and Burris, 2013; Bari et al., 2015).

When looking at within-facility variation, the payment method explains the variation in short-run toll elasticities. The road price elasticity estimates of the Miami Airport Expressway and SH130 (Table 6) indicate that drivers paying with cash are much more sensitive to tolls than those paying using electronic toll collection (ETC) systems when short-run price elasticities are explicitly estimated using the dynamic panel data model. This finding is the opposite of the evidence when the time horizon is not explicitly considered in the model that drivers paying tolls with cash were less sensitive to toll increases compared to those paying with ETC systems. The implication is that when like samples are compared, evidence confirms the findings in Finkelstein (2009) that the cash toll elasticity is larger than the ETC toll elasticity.

Another source of variation in short-run road price elasticities is estimation methods. Gomez et al. (2015) and Gomez and Vassallo (2015) use two types of generalized method of moments (GMM) estimation methods, one called the difference GMM estimator (GMM-DIFF) developed by Arellano and Bond (1991) and the other called the system GMM estimator (GMM-SYS) developed by Arellano and Bover (1995) and Blundell and Bond (1998). The main difference between the two approaches is the treatment of instrument variables in the estimation process. The results from Gomez et al. (2015) and Gomez and Vassallo (2015) show that the magnitude of toll elasticity coefficients is smaller when the system GMM estimator is used compared to when the difference GMM estimator is used.

Discrete choice models and elasticity estimation

In this survey, seven studies use the discrete choice method to examine traveler behavior when using tolled facilities. Figure 1 showed that the average toll elasticity from discrete choice studies is -0.452 from 65 observations, with a standard deviation of 0.26 ranging from -1.588 to -0.054. It is important to note that the interpretation of toll elasticities derived from discrete choice models will depend on the choice set being examined: the direct point elasticity derived from discrete choice models measures the percentage change in the probability of choosing an alternative over others in the choice set due to the percentage change in the attribute of the chosen alternative (Louviere, Hensher, and Swait 2000, 58). For example, Washbrook et al. (2006) studied commuters' mode choices between driving alone, carpooling, and nonexistent express bus services when time and cost attributes of each mode change. The derived overall toll elasticity is -0.32, which means that a 1 percent increase in tolls will lead to a 0.32 percent reduction in the *probability* of choosing the driving alone mode as a whole. The types of choice sets found in toll road demand studies can be grouped into three choices: mode choices, route choices, and multiple choices.

Table 7 summarizes toll elasticities from seven discrete choice studies by choice sets, facilities, data types, and models.

Table 7 Summary of studies using the discrete choice model

Author	Facility	Choice set [a]	Toll Elasticity (passengers)	Data	Survey Year	Notes
Dehghani et al. (2003)	Orlando I-4	Mode choice	-0.354 [-0.43, -0.3] (5)	SP	2000	Generalized nested logit (ML); nests – route choice, time of day, trip purpose; choice set – solo driving, carpool, transit
Washbrook et al. (2006)	Greater Vancouver suburb	Mode choice	-0.353 [-0.41, -0.31] (4)	SP	2001	Conditional logit (ML); choice set - solo driving, carpool, express bus
Alvarez et al. (2007)	Spain	Route choice	-0.509 (1)	SP	n/a	Logit; choice set – toll and free route
Holguín-Veras and Allen (2013)	New Jersey Turnpike	Route choice	-0.354 [-0.856, -0.054] (28)	SP	2004	Joint logit (ML); choice set – toll and alternative route due to time of day pricing
Wen and Tsai (2005)	Taiwan National Freeway	Route choice	-0.214 [-0.328, -0.135] (6)	SP	2004	Nested logit (ML); choice set – toll and free route; nests - departure time
Small et al. (2005)	SR91 Express Lanes	Route choice	-1.588	SP/RP	1999-2000	Mixed logit (MSLE); choice set – toll and free route
Yan et al. (2002)	SR91 Express Lanes	Route choice	-0.677 [-0.901, -0.5336] (18)	RP	1999	Joint logit (WESMLE) Nested logit (WESMLE); choice set – toll and free route; nests – transponder, mode, time of day

Notes: [a] The choice sets for nested logit models refer to the level 1 sets. ML = maximum likelihood estimator. MSLE = maximum simulated likelihood estimator. WESMLE = weighted exogenous sample maximum likelihood estimator

Looking at Table 7, one may question the differences in elasticity estimates from the stated preference (SP) data (-0.336), the revealed preference (RP) data (-0.677), and the combined stated and revealed data (-1.588). The revealed preference data refers to data on people’s actual choices in real world contexts; the stated preference data refers to a collection of data on people’s choices based on hypothetical situations. The benefit of RP data is that actual choices among existing alternatives are observed. The benefit of SP data, which is also a downside of RP data, is that variation within each attribute can be controlled in hypothetical situations and situations that do not exist can be formulated (Louviere, Hensher, and Swait 2000). The question arises from the fact that SP data are not calibrated for real world situations and the idea that SP data should supplement the

RP data and not be used as stand-alone data. Some literature warns against using stand-alone SP data for analysis unless it has been adjusted for bias (Hensher and Li 2010).

In the sample, the route choice of State Route 91 in California is examined using two different data, the RP data (Yan, Small, and Sullivan 2002) and the RP/SP data (Small, Winston, and Yan 2005), which open the opportunity to understand elasticity estimates of the same facility from two perspectives. The SR91 Express Lanes opened in 1995, adding 10 miles of four lanes (two lanes in each direction) to the median of the existing eight general purpose lanes on SR91. It was the first variable pricing (i.e., price changes hour-by-hour) project in the U.S. and the first full electronic toll collection (ETC) system in the world. In 1999 and 2000, surveys were conducted to evaluate the impact of both the decision to toll high-occupancy vehicles at 50 percent of the published price and the opening of the Eastern Toll Road in October 1998, which competes with SR91 Express Lanes (Sullivan et al. 2000; Small, Winston, and Yan 2005).

The differences in model specifications explain the average toll elasticity of -0.677 from the RP data in Yan et al. (2002) and -1.588 from the SP/RP data in Small et al. (2005). First, Small et al. (2005) examined the choice between SR91 Express Lanes and the SR91 general purpose lanes, whereas Yan et al. (2002) examined the choice between the SR91 Express Lanes, the Eastern Toll Road, and the SR91 general purpose lanes. The models and estimation methods are different, in that Small et al. (2005) used the mixed logit model estimated by maximizing a simulated log-likelihood function (McFadden and Train 2000), whereas Yan et al. (2002) used a joint model and the nested logit model estimated by the weighted exogenous sample maximum-likelihood estimator.

Another source of variation is the aggregation procedure in discrete choice models, which calculates the overall elasticity in the market (Oum, Waters, and Yong 1992). When the family of logit model is used, the procedure for deriving the aggregate or market elasticity begins with the calculation of direct elasticities for each individual based on estimated parameters and the predicted probability of choosing the alternative followed by the aggregation of individual elasticities (Train 2009; Louviere, Hensher, and Swait 2000). To aggregate individual elasticities, Small et al. (2005) first calculated individual probability using simulation conditional on estimated parameters and then calculated elasticity. Yan et al. (2002) used the weighted average of individual elasticities, which is called the sample enumeration method.

Now look at the characteristics of studies using stand-alone SP data to compare two studies on the SR 91 Express Lanes and examine the variations in toll elasticities within studies using SP data. Studies used the SP data to help develop express lanes for the I-4 corridor (Dehghani et al. 2003), evaluate the potential impact of tolling on commuter mode choice (Washbrook, Haider, and Jaccard 2006), evaluate the route choice between toll and free routes (Álvarez, Cantos, and García 2007), evaluate the impact of time-of-day pricing on route choice on the New Jersey Turnpike (Holguín-Veras and Allen 2013), and examine the potential impact of introducing an electronic toll collection system and time-of-day pricing on the route choice between toll and free routes (Wen and Tsai 2005).

Among studies using SP data, mode choice studies look at alternatives to solo driving, carpooling, and taking express bus/transit. Despite different models being used, the average toll elasticity value is very similar in both Orlando and the Greater Vancouver area. Dehghani et al. (2003) found that the probability of choosing solo driving will decrease by 0.35 percent on average when tolls increase by one percent for non-home based work purposes, varied by peak periods; Washbrook et al. (2006) similarly found that the probability of choosing solo driving would decrease at a similar rate as tolls increased, but the impact will vary depending on the household income level.

Route choice studies examine the impact of changes in toll policies on travelers' choices between tolled and free routes. In general, the magnitude of average toll elasticity is smaller when derived from a model with a more complex structure. In terms of policy implications, Holguín-Veras and Allen (2013) found that the probability of driving on a toll road will decrease by 0.35 percent when tolls increase by one percent. However, a traveler's response to time-of-day pricing is very wide, ranging from -0.856 to -0.054: college-educated people are the most sensitive to tolls and Middlesex County residents are the least responsive to them, compared to African Americans, part-time workers, retired workers, and Essex County residents. The implementation of all electronic tolling and time-of-day pricing will reduce the probability of driving on toll roads for current daily morning passenger car commuters by 0.21 percent on average and also divert drivers to commute before or after peaks.

Level of price and elasticity

Road pricing elasticity of demand is a function of initial price, initial quantity, and changes in price and quantity. Calculated elasticity, whether point elasticity or arc elasticity, depends on both initial price and quantity. The review of 24 studies revealed that studies rarely address the basic relationship between calculated elasticity and the initial price and quantity. This evaluation is based on the observation that not all studies that use revealed preference datasets report initial price and quantity used in the elasticity calculation.

From a policy evaluation perspective, a limited understanding of initial price especially and its impact on price elasticity prevents the evaluation of whether the level of toll rate is appropriate. This question may have received limited attention from researchers because the majority of toll rates are fixed by authorities or contracts (KPMG 2015), and therefore researchers may have felt that there is no need to address the issue.

Another factor that complicates the analysis of price elasticity and initial price/quantity is a wide variety of toll rate structures adopted by toll agencies around the world. For example, the U.S. Federal Highway Administration classifies toll rates into three categories (Federal Highway Administration 2016):

- Fixed Variable: Rate does not vary by time-of-day or traffic conditions (may vary by vehicle/weight class or distance traveled).
- Fixed Variable: Rate varies by time of day based on a preset schedule.
- Dynamic Variable: Rate varies based on current traffic conditions.

Given the wide variety of toll rate structures, the normalization of toll rates across studies becomes a challenge. In fact, the pricing structure of each facility to some extent determines the method of estimating road pricing elasticities.

Among the 24 studies surveyed, the work of Odeck and Brathen (2008), who examined the correlation between the level of tolls and the magnitude of price elasticities of 19 facilities in Norway, is noteworthy. Their results showed a correlation of 0.28 between tolls and elasticity (in absolute value), with statistical significance at the 5% level. The correlation analysis is intuitive, but the analysis assumes that all elasticity estimates from 19 different facilities lie on the same demand curve. Also, the impact of initial traffic volume was not considered in the analysis.

Mindful of the limitation of correlation analysis, a similar analysis was performed using the 143 observations of levels of tolls and the magnitudes of point elasticity available from three studies (all dollars are converted to real dollars): Hirschman et al. (1995), Holguin-Veras et al (2005), and Wuestefeld and Regan (1981). The level of toll refers to the price after the increase in toll rates. Note that elasticities are calculated using the point elasticity formula. The result, that the correlation between tolls per mile (in absolute value) and elasticity is 0.33, which is statistically significant at 1% level (Figure 3), is similar to that found in Odeck and Brathen (2008). In other words, drivers become more sensitive to tolls as the level of toll increases. This result suggest that interpretations of road pricing elasticity should consider the level of tolls in the analysis and that the magnitude of elasticity may vary from one facility to another depending on the level of tolls implemented in each place.

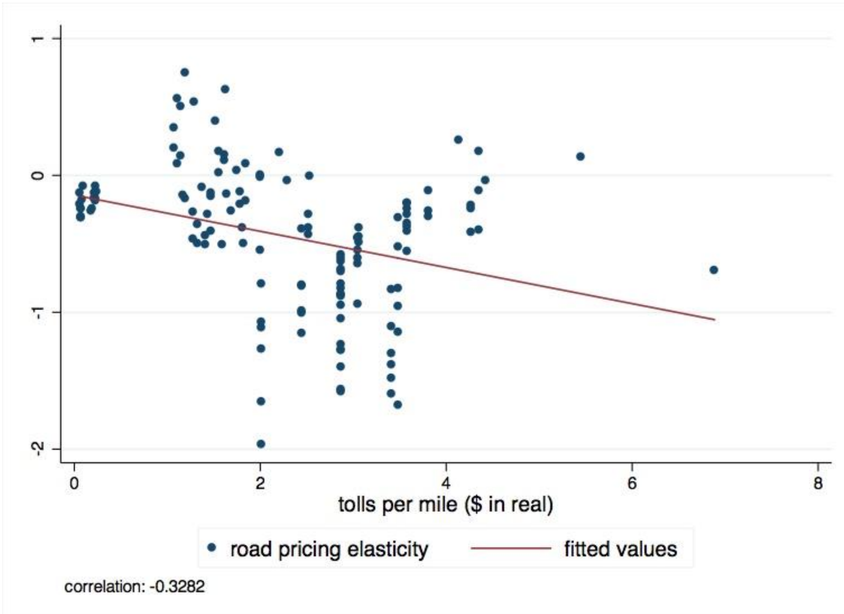

Figure 3 Correlation between tolls per mile and price elasticity of demand

Elasticities of other prices

So far, the discussion has focused on explaining variations in toll elasticities of demand. This section discusses elasticities of other prices and socioeconomic variables found in the surveyed literature. It should be noted that there are excellent surveys on transportation-related price demand elasticities, including Oum et al. (1992), Goodwin (1992), Graham and Glaister (2004), Goodwin et al. (2004), and De Jong and Gunn (2001). These surveys provide insights into various transportation price and quantity relationships, such as the impact of fuel price on fuel demand and traffic, the impact of income on fuel demand and traffic, and the impact of car operating cost and income on car ownership. The discussions, however, are limited to demand for non-tolled roadways and do not provide insights into how traffic on tolled roadways would vary with respect to prices other than the direct cost of tolls (i.e. fuel cost, income, and cost of alternative modes). This section presents a summary of price elasticity estimates such as fuel elasticity, income elasticity, and the cost of alternative mode elasticity as found among the 24 studies surveyed in the present essay (Table A1 in Appendix A).

Table 8 is a summary of fuel, income, and cost of alternative modes and toll elasticities by model type and time horizon. First, the relationship between fuel and toll road demand is negative because fuel price increase is associated with a decrease in traffic volume. Long-run fuel elasticity (-0.531) is about ten times larger than the short-run (-0.049). Results are not shown, but intercity toll facility users (-0.125) are more sensitive to gas price increases than users of either urban (-0.034) or intercity/urban (0.004) toll facilities. Looking at the average elasticities by method, the size of fuel elasticity is almost the same as toll elasticity when estimated by the static model. The dynamic model results show that toll elasticity is about 5 times larger than fuel elasticity in the short run and about 1.5 times larger in the long run. This indicates that toll road users are more sensitive to percentage changes in tolls than changes in fuel price. This finding is in line with results in Huang and Burris (2013).

Table 8 Elasticities of fuel, income, alternatives, and toll

	Fuel	Income	Alternative	Toll
Static model	-0.106	n/a	0.021	-0.157
Dynamic model	-0.084	0.467	n/a	-0.338
Short-run	-0.049	0.391	n/a	-0.267
Long-run	-0.531	0.565	n/a	-0.783

Sources: Fuel elasticity – 91 observations (Huang and Burris 2013; Bari, Burris, and Huang 2015; Cervero 2012; De Grange, González, and Troncoso 2015; Gifford and Talkington 1996; Gomez, Vassallo, and Herraiz 2015; Gomez and Vassallo 2015; Hirschman et al. 1995; Loo 2003; Matas and Raymond 2003; Zhang and Marshment 2012); Income elasticity – 10 observations (Odeck and Bråthen 2008); Alternative elasticities – 15 observations (Cervero 2012; Hirschman et al. 1995; Loo 2003); Toll elasticities – 108 observations (Odeck and Bråthen 2008; Bari, Burris, and Huang 2015; Cervero 2012; De Grange, González, and Troncoso 2015; Finkelstein 2009; Gifford and Talkington 1996; Gomez, Vassallo, and Herraiz 2015; Gomez and Vassallo 2015; Hirschman et al. 1995; Loo 2003; Matas and Raymond 2003; Zhang and Marshment 2012).

Second, the higher the income, the higher the traffic level on toll facilities. The ratio of long-run (0.565) over short-run (0.391) income elasticity is 1.4. Among the studies surveyed, only one paper by Odeck and Bråthen (2008) looked at the impact of changes in income on toll road traffic volume. In the paper, as a proxy for a household income, the authors used the aggregated net wealth for households in the area where the project is located, in which 85% of users live and commute, within the project area. The variation in income elasticity is large across five trunk road facilities (see Table 6 for the list of facilities), but that short-run income elasticity ranges from 0.11 to 0.78 and long-run from 0.15 to 0.85. Despite the variation, income elasticity estimates have statistically significant impacts on traffic volume.

In the dataset, three studies specified alternatives to the estimation model, which can be defined differently according to the relevant context. In Cervero (2012), the alternative is defined as Bay Area Rapid Transit (BART) ridership; in Hirschman et al. (1995), it is the subway fare, which is a direct alternative to driving in Manhattan; and in Loo (2003), the on-street meter parking fee is controlled as an alternative. The evidence on the impact of alternative services is mixed in the literature. Both positive and negative coefficients of alternative services were found in Hirschman et al. (1995) and Loo (2003), but many of them were not statistically significant. Cervero (2012) found that about 10% of lost peak-hour traffic is absorbed into BART ridership when the peak-hour tolls increase on the San Francisco-Oakland Bay Bridge.

Conclusion

This essay examined the sources of variation in the road pricing elasticity of demand through an extensive survey of 24 studies on travel demand for toll roads. There may be many ways to group 349 observations of elasticity estimates from 24 studies; this essay chose to group estimates based on the type of demand model employed to derive toll elasticities as interpretations of elasticity estimates depending on estimation method. The survey revealed that four methods are mainly used for elasticity estimations, namely the before-and-after comparison using point and arc elasticity formulas, the static model (not including the discrete choice model), the dynamic panel data model, and the discrete choice model. After commonly used estimation methods were identified, the sources of variation were then examined within each group of studies, paying special attention to the interpretation of toll elasticity measures from each model.

The magnitude of road pricing elasticities derived from static models was smallest among four groups of elasticities examined, which may be explained by characteristics of the facilities examined in the studies: most facilities examined were either urban or bridge facilities for which alternative free routes are often not available. The road pricing elasticities estimated from dynamic panel data models enable the comparison between short-run and long-run elasticities, and it was found that long-run road pricing elasticities are about three times larger than short-run elasticity estimates. The variation within short-run road pricing elasticity estimates was explained by vehicle types, payment methods, and estimation strategy. The discrete choice studies examined traveler responses to toll increases due to changes in toll policies. The changes in the probability of choosing toll roads and solo driving modes were explained by the data type used (i.e., stated and revealed preference), the model and estimation strategy, and the aggregation method employed.

From a policy perspective, the question of how drivers respond to road pricing is an important question, and a parameter like price elasticity of demand seems to provide a quick answer. This survey showed the complex relationship between road pricing and travel demand and that road pricing elasticity estimates could vary widely depending on methodologies and factors considered in each study. Beyond such factors, this survey discussed the importance of understanding the relationship between level of price and quantity and estimates of road pricing elasticity of demand. The analysis of a subset of data from the studies showed that the magnitude of road pricing elasticity tends to be larger when the level of toll rate is higher. In other words, drivers are more responsive to road pricing when the amount of money they pay out of pocket is larger.

CHAPTER THREE: ROAD PRICING ELASTICITY OF DEMAND FOR U.S. TOLL ROADS – A DYNAMIC PANEL DATA ANALAYSIS

Introduction

Road pricing, a fee related to using a road facility, is one of the main instruments used in transport regulation to manage externalities such as congestion and revenue for infrastructure investment. The idea of road pricing was proposed in the 1920s by Pigou (1920) and Knight (1924), but practice followed slowly over a period of one hundred years. In the United States, public toll authorities were established between the 1920s and 1950s to manage user fees for constructing limited access roads and bridges, resulting in more than 3,000 miles of tolled roads by the end of the 1950s (Garrison and Levinson 2006; Dyble 2010). As the paradigm of infrastructure development shifted toward more federal funding and no user charges during the construction of the interstate highway system throughout the nation from 1956 to 1991, only 1,000 miles of new toll roads opened and the collection of user fees was prohibited on federally funded roads (Gómez-Ibáñez and Meyer 1993).

Transport regulations have seen significant changes since 1991 at all levels of governments, and public authorities have begun to consider road pricing as an instrument both to supplement funding source and as an effective measure for travel demand management. In 1991, the Intermodal Surface Transportation Efficiency Act (ISTEA) authorized the Congestion Pricing Pilot Program to examine the effectiveness of congestion pricing in managing traffic in five selected project areas. In 1998, the federal government authorized the Interstate System Reconstruction and Rehabilitation Pilot Program (ISRRPP). The significance of this program is that it is the first to allow toll collection on segments of federally funded interstate highways for three selected states: North Carolina, Missouri, and Virginia. In 2015, the Fixing America's Surface Transportation (FAST) Act proposed by the Obama administration pushed forward the idea of charging user fees on existing interstate highways by imposing expiration timeframes on the three states selected for the ISRRPP, opening the door for other states to participate if any of three states fails to implement the program within a limited timeframe.

During the process of reauthorizing the transportation bill in 2014, the outcome of which was the FAST Act, the Obama Administration proposed the GROW AMERICA (Generating Renewal, Opportunity, and Work with Accelerated Mobility, Efficiency, and Rebuilding of Infrastructure and Communities throughout America Act) bill, which radically departed from the no tolling on federally funded highways policy. The bill proposed giving states the right to toll interstate highways, to use variable pricing to manage congestion, to expand the scope of toll revenue usage, and to use all-electronic toll collection systems. Although the GROW AMERICA bill failed to gain enough votes from Congress, the bill illustrated the extent to which policymakers are willing to adopt road pricing in the nation. Also, the bill introduced the possibility of implementing road pricing on federally funded roadways throughout the nation. Some in the toll road industry are predicting that road pricing will eventually be implemented on interstate highways nationwide as a tool to manage growing congestion and raise funds for building and maintaining transportation infrastructure (from the author's conversation with the toll industry representatives at the 2014 International Bridge, Tunnel and Turnpike Association Annual Meeting in Austin, Texas).

Having described recent policy developments on road pricing, one can contemplate the idea of nationwide adoption of road pricing in the U.S. One of the biggest challenges in implementing a nationwide road pricing policies is the wide variation of evidence on how travelers will respond to road pricing. Road pricing elasticity of demand is one of the most important parameters for understanding travel demand for toll roads and has significant implications for transportation policy and investment decisions. The price elasticity of demand measures the relative sensitivity of a change in quantity demanded to a change in price, where sensitivity could also be understood as responsiveness. The concept of price elasticity is especially relevant for the analysis of toll roads because it relates price choices to total revenue for toll authorities or operators. The theory predicts that inelastic demand will lead to higher total revenue. with a price increase compared to the scenario under elastic demand. In practice, practitioners use measures of elasticity in traffic and revenue forecasting studies and policymakers rely on the price elasticity of demand in their decision-making processes. The existing empirical studies on toll road demand provide a wide range of estimates of road pricing elasticity of demand, which provides little to no guidance on how to implement road pricing at a national level.

Recent developments in empirical methods for analyzing toll road demand also fall short of providing satisfying policy guides. Two major paradigms of empirical approaches are employed to analyze toll road demand and estimate road pricing elasticity of demand: aggregate and disaggregate analysis. Disaggregate discrete choice models have become more popular for toll road demand analysis because they have a sounder behavioral foundation based on utility maximization theory (Ben-Akiva and Lerman, 1985). Disaggregate demand models are useful when the objective of analysis is to derive measures of willingness to pay, such as the value of travel time savings and value of travel reliability (Hensher et al., 2015). However, most discrete choice analysis of travel demand on toll roads is based on stated preference survey data that is often designed to predict customer choices on a specific roadway rather than to predict a system-wide demand elasticity. In cases where revealed preference data are used, most, if not all, empirical studies rely on cross-section data due to the high cost of repeatedly collecting individual-level data. When road pricing elasticity is estimated using cross-section data in the discrete choice model, the estimates are long-run elasticities. Short-run elasticities cannot be easily obtained.

Aggregate demand models, on the other hand, are useful for analyzing panel data and can provide estimation of both short- and long-run elasticities. Aggregate demand models provide intuitive preliminary results that can be used as a benchmark for studies using disaggregate data (Oum, 1989). While a few studies use aggregate panel data analysis to estimate toll elasticity of demand for multiple toll facilities in other countries, studies published in the U.S. context often focus on one or only a small number of toll facilities, with the exception of Finkelstein (2009). This lack of comprehensive analysis is partially attributed to the difficulty of accessing panel data of toll roads in the U.S.

This essay examines the sensitivity of toll road usage to changes in tolls using a panel dataset of U.S. toll roads with the most comprehensive coverage of toll facilities in the U.S., to the author's knowledge, paying special attention to the estimation of both short- and long-run elasticities and differences in estimates by functional classification of roads. A dynamic panel data model is employed to study the relationship using the system generalized method of moments (GMM) method for analyzing the unbalanced panel data of 64 U.S. toll roads in 15 states from 2004 to 2013. Some features of tolled facilities in the panel data distinguish the current analysis of toll road demand from other similar studies in the literature. First, all facilities in the dataset are road facilities; no bridges or tunnels are included in the analysis. Traveler behavior on road facilities is different from those on bridge or tunnel facilities due to the availability of multiple entry and exit points as well as alternative toll-free routes. Second, the dataset consists of traditional toll roads with fixed toll rates. Although many new toll facilities have begun to adopt dynamic pricing schemes, they are not included in the analysis due to a lack of history and the difficulty of acquiring dynamic toll and demand data. Moreover, accurate demand elasticity estimated from fixed toll facilities also provides an important reference for designing dynamic toll schemes.

The contribution of this research to the literature and policy is manifold. To the author's knowledge, the current research is the first to analyze a unique panel data of U.S. toll roads with similar characteristics. The panel data of toll roads in the United States does not exist in the public domain due to regulatory and institutional reasons, which has posed challenges for researchers and policymakers trying to evaluate toll road performances. On the institutional side, toll roads are regulated and managed by public agencies that are authorized by state legislation. Due to this institutional set-up, not all toll authorities are required to report information of operations (U.S. Department of Transportation 2014). The Federal Highway Administration publishes the *Highway Statistics* every year, but toll road data are only published every two years. The data limitation has been a significant challenge for researchers analyzing U.S. toll roads, and the current essay overcomes this data limitation by accessing a panel data initially established by a private firm and expanded by the author. The details of the data source are further discussed in the data section.

The current research also contributes to the literature by expanding the pool of empirical methods analyzing U.S. toll roads. The availability of panel data has enabled authors to examine the dynamic of travel demand adjustment in a large number of toll roads in the United States. The dynamic panel data model has been implemented in other country settings such as Spain (Matas and Raymond 2003; Gomez, Vassallo, and Herraiz 2015) and Norway (Odeck and Bråthen 2008). In the U.S. context, the model has only been used for examining individual facilities (Zhang and Marshment 2012; Burris and Huang 2011), not a multiple number of toll facilities at the same time. Moreover, among the dynamic panel data models available (Baltagi 2013), this research provides the first application of the system of GMM estimators (Arellano and Bover 1995; Blundell and Bond 1998) for analyzing demand for toll roads in the United States. Despite the advisability of distinguishing between short- and long-run adjustments of travel (Goodwin 1992; Goodwin, Dargay, and Hanly 2004; Oum, Waters, and Yong 1992), only a few studies provide insights on short- versus long-run road pricing elasticity. The current research pays particular attention to travel demand adjustment, providing a derivation of long-run price elasticity based on short-run elasticity estimates and examining differences between short-run and long-run price elasticities.

Lastly, this research contributes to the policy discussion on imposing road pricing on interstate highways by examining the variation of road pricing elasticity of demand by functional classification of toll roads. The primary purpose of roadway functional classification is to identify the role of a particular road in moving vehicles in the system (U.S. Department of Transportation 2013). Beyond its primary role, functional classification represents many things, including the design of a physical infrastructure, accessibility, relationship to surrounding geography and land use, level of investment, and intensity of usage. In this research, toll roads were divided into four subgroups—urban interstate, intercity interstate, urban non-interstate, and intercity non-interstate—to examine whether drivers respond to road pricing schemes differently at each functional class of road. The findings will provide evidence on the potential differentiation of pricing schemes based on the functional classification of toll roads.

This essay is organized as follows: the introduction is followed by a review of relevant literature. The data and methodology used is discussed and then results are presented, followed by the concluding section.

Literature Review

The proportion of toll roads in the road network system is still limited around the world. Not surprisingly, the number of empirical studies that systematically analyze road pricing elasticity of demand across regions are very limited. Although there are many studies on discrete choice analysis in the literature approaching this problem based on stated preference data, it is unclear whether these findings, which are based on hypothetical scenarios and a limited sample size, can be applied to guide price elasticity estimation for the long term and for a wide range of facilities. A comparison of these two types of studies is an interesting topic but is beyond the scope of this study. Instead, this section reviews selected aggregate travel demand studies of interurban toll roads in Spain, Norway, and the United States. The review also focuses on studies using econometrics approaches to analyzing aggregate data, while studies using the basic elasticity formula or discrete choice models for estimating toll elasticity of demand are excluded.

Gomez et al. (2015) used data from 14 interurban toll roads in Spain collected from 1990 to 2011. The demand equation is specified as the annual average daily traffic volume (AADT) for light vehicles in relation to toll, a weighted average of gasoline and diesel prices, GDP at a provincial level, and lagged AADT. The resulting estimate for the short-run toll elasticity of demand is -0.40. When the time period was varied from 1990-2000 to 1990-2010, the estimate of toll elasticity varied from -0.20 to -0.41. The reason for the increased magnitude of toll elasticity was attributed to users who became more price-sensitive after an economic crisis. The authors lastly found a smaller magnitude of toll elasticity estimate in coastal roads than in interior roads.

Another study of Spanish toll roads is by Matas and Raymond (2003), who analyzed a national tolled network from 1981 to 1998. The authors estimated the demand model of AADT specified as toll, gasoline price, GDP as a proxy for the level of economic activity, and the lag of AADT. Using the weighted least squares method, estimated toll elasticity of demand ranges from -0.828 to -0.209 in the short-run and from -1.307 to -0.330 in the long-run. Factors affecting the sensitivity of toll elasticities, including the quality of alternative free roads, the length of each road section, and the location of each road section, suggested that demand is more elastic in leisure districts.

Odeck and Bråthen (2008) analyzed five trunk roads in Norway using an autoregressive model. The demand as traffic volume is expressed as a function of toll, household income, quality changes, and the lagged dependent variable. The estimates for short-run toll elasticity of demand ranges from -0.76 to -0.55 and long-run elasticity ranges from -0.90 to -0.75. The authors acknowledged that the magnitude of short-run toll elasticity estimates is larger than those found in the literature, but they suggested that the size is not too large to raise particular concerns.

Travel demand studies of tolled bridges, tunnels, and urban roads in the U.S. are not difficult to find, but two studies in particular analyze interurban toll roads. First, Zhang and Marshment (2012) employed quarterly data from 1973 to 2010 for two interstate turnpikes in Oklahoma to estimate an autoregressive demand model. Demand was passenger car traffic volume as a function of passenger toll rates, gasoline price, and non-agriculture employment. The estimated short-run toll elasticity is -0.098 for Will Rogers Turnpike and -0.114 for Turner Turnpike in Oklahoma. The authors explained that the highly inelastic estimates are likely based on the observation that long-distance travelers and irregular users comprise most of the passenger car population on both turnpikes.

Another study of interurban toll roads in the U.S. is by Burris and Huang (2013), who used the autoregressive model and estimated the toll elasticity of demand for toll facilities operated by 13 agencies. Using a monthly data between 2000 and 2010, the authors ran a separate regression for each facility by vehicle type. They estimated the toll traffic volume as a function of toll rate, gas price in the metropolitan region, unemployment rate, the population of the metropolitan region, and the lagged traffic volume. The statistically significant estimates of toll elasticity range from -0.79 to -0.02 with a mean of -0.30 for 2-axle vehicles and from -0.85 to -0.09 with a mean of -0.35 for 5-axle vehicles. When the authors estimated the toll elasticity using data in which traffic volume is not available for vehicle type, the toll elasticity of demand ranges from -0.31 to -0.05 with a mean of -0.18. The result shows that the magnitude of average toll elasticity estimate is larger when using traffic volume data disaggregated by vehicle type. The authors also found that the magnitudes of toll elasticity estimates are generally larger than that of gasoline price elasticity of demand.

As part of their analysis, Burris and Huang (2013) estimated toll elasticity of demand on Will Rogers Turnpike and Turner Turnpike in Oklahoma using the ADL model, the same model specification described in the previous paragraph. Based on monthly data from 2000 to 2009, the estimated short-run toll elasticity for 2-axle cars is -0.38 for Will Rogers Turnpike and -0.41 for Turner Turnpike. Compared to results in

Zhang and Marshment (2012), the magnitude of toll elasticity estimates in Burris and Huang (2013) is nearly four times larger. Although further research is needed to identify reasons, it could be inferred that the difference is due to the different time periods covered in the two studies, estimation approach, the level of data, and variables controlled in the demand model.

Table 9 summarizes the main findings on the toll elasticity of demand from the reviewed studies. Overall, previous studies on travel demand for toll facilities show that the toll elasticity of demand on interurban toll roads is inelastic in the short-run. The current research is in line with the reviewed studies, in that the research employs long panel data of toll roads in the U.S. to estimate toll elasticity of demand using the dynamic panel data model. Special attention is given to estimation strategy and policy implications of the findings.

Table 9 Road pricing elasticities from previous studies

Author	Facility/Location	Panel Period	Type of Vehicle	Toll Elasticity
Gomez et al (2015, 1-27)	14 toll roads in Spain	1990-2011	Light vehicles	SR: -0.4 (GMM-DIFF) SR: -0.103 (GMM-SYS)
Matas and Raymond (2003, 91-108)	72 toll road sections in Spain	1981-1998	All vehicles	SR: -0.828 to -0.209 LR: -1.307 to -0.330
Odeck and Bråthen (2008)	5 trunk toll roads in Norway	n/a	All vehicles	SR: -0.76 to -0.55 LR: -0.90 to -0.75
Zhang and Marshment (2012)	Will Rogers Turnpike and Turner Turnpike in Oklahoma, USA	1973-2010	Passenger cars	SR: -0.098 for Will Rogers Turnpike; -0.114 for Turner Turnpike
Burris and Huang (2013)	19 toll facilities in USA	2000-2010	2-axle and 5-axle vehicles	SR: -0.79 to -0.02 for 2-axle vehicles; -0.85 to -0.09 for 5 axle vehicles

Notes: SR = short-run elasticity. LR = long-run elasticity. GMM-DIFF = difference general methods of moment estimator. GMM-SYS = system general methods of moment estimator.

Methodology

Data

The main dataset used in this research is toll-road-level panel data collected by CDM Smith Inc. (Davis 2014). In the U.S., there is no central authority collecting data such as toll rates, traffic level, and revenue from toll road authorities because the information of revenue-generating agencies is regarded as proprietary; this has been a big challenge for researchers analyzing the impact of road pricing. The Federal Highway Administration of the U.S. Department of Transportation releases a biennial publication titled *Toll Facilities in the United States*, but data are voluntarily reported by willing authorities and only provide limited statistics such as location, length, authority, toll rates by vehicle type, and pricing type on toll roads. The International Bridge, Tunnel and Turnpike Associations used to publish another such dataset, titled *Toll Rate Survey*, but its publication discontinued in 1990s. To overcome gaps in the data, CDM Smith developed a toll-road-level dataset from historically published sources, including reports, books, toll authority pamphlets, news articles, agency websites, and agency information requests. This toll-road-level dataset identifies each facility with a unique identification number and provides information on location, facility type (i.e., urban or intercity), facility name, governing agency name, public or private, length, toll rate for passenger cars and 5-axle vehicles, payment system type (i.e., cash or electronic), traffic measured in the annual number of transactions, and revenue.

A considerable effort was put into preparing the dataset for analysis. The current research employs two main variables from the dataset: the total number of transactions as a dependent variable and toll rates as the main independent variable. The primary motivation for CDM Smith to compile this dataset was to collect information on toll rates for a population of toll roads in the U.S.; because of this, the dataset contains no missing data points for toll rates but much missing data on total transactions for facilities that were not sufficient to conduct analysis. The dataset, therefore, was supplemented by collecting additional data points on total transactions from official statements published on the Electronic Municipal Market Access (EMMA) website operated by the Municipal Securities Rulemaking Board (MSRB).

Furthermore, the original dataset that the author obtained from CDM Smith contained information on tolls and total transaction and other facility characteristics of 125 toll roads in 25 states from 1980 to 2014. Despite the availability of a long panel, the author decided to analyze the 10-year data from 2004 to 2013 for several reasons. First, despite a best effort to fill the missing data, the total transaction data were not available for over 40 facilities; even if available, many data points were missing, especially in the earlier periods in the dataset. Second, the decision was also driven by methodological challenges of using the GMM approach for panel data with large T, which will be discussed in the following section. There is no clear consensus on asymptotic properties of the GMM approach in the literature. After removing opening year data to account for the ramp-up period, the final sample data consists of unbalanced panel data with no gaps for 64 U.S. toll roads in 15 states from 2004 to 2013; the list of 64 toll roads can be found in Appendix B.

In the analysis, the travel demand measured as the annual number of transactions is modeled as a function of a lag of transactions, tolls, gasoline prices, household incomes, unemployment rates, and population. The dependent variable is the annual number of transactions at each toll road from the CDM Smith data. Studies use various measures of travel demand when estimating aggregate road pricing elasticity of demand, such as annual average daily traffic (AADT) volume, traffic volume, toll transactions, vehicle miles traveled (VMT), and traffic count data using a loop detector. The choice of demand measure affects the interpretation of the elasticity estimates; for example, this research employs the number of transactions as a proxy for travel demand, which could also be viewed as the usage of the toll road. The challenge is that there is no clear guidance in the literature on what measure should represent the demand on toll roads. Practitioners in recent years have leaned towards using VMT as a measure of travel demand, but elasticity estimates would be the same whether VMT or AADT is used because the only difference between the two is constant. The literature implies that the choice of demand measure is largely driven by the availability of data at the time of research. Further research is needed to understand whether the choice of travel demand measure results in different empirical estimates for the toll elasticity of demand.

The main independent variable of interest is the per mile cash toll for passenger cars from CDM Smith, calculated as the end-to-end cash toll for each passenger car divided by the total length of the toll road. A negative relationship is expected between toll and the number of transactions.

Gasoline price data is from the U.S. Energy Information Administration's State Energy Data System (U.S. Energy Information Administration). The state-level motor gasoline price in the transportation sector that includes motor gasoline used for privately owned vehicles (dollars per million Btu) was employed. The price is defined as the retail price, which includes federal and state motor fuel taxes but excludes state general sales taxes and local fuel and sales taxes. When gasoline price increases, people tend to use their vehicles less and reduce the distance traveled to mitigate the price increase. A survey study by Graham and Glaister (2002) shows that the travel demand with respect to gasoline price is -0.15 in the short-run and -0.31 in the long-run. Based on these measures, a negative relationship between gasoline price and demand is expected.

Median household income by state represents the well-being of travelers using toll roads. The data is from the Annual Social and Economic Supplement (ASCE) to the Current Population Survey (CPS) from the U.S. Census Bureau (U.S. Census Bureau a). The relationship between income and travel demand is not a direct relationship. What changes together with income growth are the value of travel time (Graham and Glaister 2004; Hensher and Goodwin 2004) and toll roads, which may benefit drivers by reducing travel time on less congested roads. Based on this, a positive relationship is expected between income and travel demand in the analysis.

Population data is collected from the U.S. Census Bureau (U.S. Census Bureau b). The estimated annual population for each state as of July 1st of each year was used in the analysis. Since population growth is related to general traffic growth in the region, a positive sign is expected on the population coefficient.

One challenge in interpreting coefficients on economic variables—gasoline price, household income, and population—is that the data are aggregated at the state level, but road pricing elasticity of demand may be very local. One way of overcoming this challenge is to identify counties through which toll roads pass and construct economic data within a selected geographic scope. However, because there is no origin-destination information for travelers on toll roads, imposing a geographic restriction on the data at a county level may fail to capture economic conditions of some travelers, not to mention being too subjective in data use. Readers are advised to be mindful of the fact that the economic variables in the analysis are state-level data instead of toll-road-level data when interpreting economic variables in the analysis. In addition, a number of potential explanatory variables were explored for inclusion in the demand model, such as the unemployment rate and the gross domestic product (GDP). After performing statistical tests on multicollinearity, these variables were not included in the analysis due to potential multicollinearity issues.

Table 10 shows the summary statistics of variables. In the analysis, the results are further compared between roads segmented by their functional classifications. The summary statistics of variables by functional classification of roads are available in Appendix B. All dollar figures are adjusted for inflation by using the CPI (year 2000=100).

Table 10 Summary statistics of variables

	Observation	Mean	Std. Dev.	Min	Max
All Samples - 64 facilities					
Total Transaction (million)	539	58.54	83.40	0.34	610.09
Toll per Mile ($)	539	0.11	0.07	0.02	0.38
Gas Price (million Btu)	539	22.72	3.61	15.68	30.61
Household Income ($)	539	50,115	6,890	37,667	73,614
Population (million)	539	12.51	8.10	0.83	38.33
Miles	539	42.13	38.41	3.00	173.00

Dynamic panel data model

The advantage of working with long panel data is that it helps explain the dynamic of travel demand adjustment (Baltagi 2013). From a policy perspective, it answers how travel demand changes over time. Autoregressive models characterized by a lagged dependent variable as an explanatory variable are especially useful for measuring adjustment of travel demand by allowing explicit estimation of both short- and long-run elasticities. For example, consider the following model:

Equation 3

$$\begin{aligned}\ln transaction_{it} &= \beta_0 + \rho \ln transaction_{i,t-1} + \beta_1 \ln toll_{it} + \beta_2 \ln gas_{it} \\ &\quad + \beta_3 \ln income_{it} + \beta_4 \ln population_{it} + a_i + \theta_t + u_{it}\end{aligned}$$

for $i = 1, \dots, N$ and $t = 1, \dots, T$, where $transaction_{i,t-1}$ is a lag of dependent variable, which is the number of transactions, $toll_{it}$ is passenger car toll, gas_{it} is gasoline price, $income_{it}$ is household median income, $population_{it}$ is state population, a_i is unobserved facility specific fixed effects that are time-invariant, θ_t is a year intercept and u_{it} is the error term.

Introducing an endogenous lagged dependent variable in a model creates challenges for the estimation strategy. Assuming the error term u_{it} is not serially correlated, the lagged dependent variable is correlated with the facility fixed effects since ln $transaction_{it}$ is a function of a_i, which implies ln $transaction_{i,t-1}$ is also a function of a_i. The within transformation of the fixed effects estimator would remove the facility fixed effects, but transformed regressors and transformed errors would still be correlated. Even if the random effects generalized least squares (GLS) estimator is used, the problem would still be similar, giving inconsistent estimates of the model.

If error terms are indeed serially correlated, meaning error terms in different time periods are correlated, the ordinary least squares (OLS) estimation assumption of zero correlation in u_{it} (i.e. $Cov[u_{it}u_{is}|X_{i,}\ \alpha_i] = 0$) is violated, requiring another strategy to produce consistent parameter estimates. After running Eq. 1, the procedure proposed by Wooldridge (2010) was employed to test for the presence of serial correlation (see Appendix C for the test procedure). The test result shows that errors are correlated within cross-section units, suggesting the use of an estimation strategy other than OLS.

To estimate consistent and efficient estimators in the presence of serial correlation and to better understand the dynamics of demand adjustments, the generalized method of moments (GMM) estimator has been suggested as a possible solution (Arellano and Bond 1991; Arellano and Bover 1995; Blundell and Bond 1998). The GMM estimator uses exogenous instrumental variables that are correlated with the regressors but not with errors to define and solve moment conditions. In the context of panel data, additional instruments are obtained based on the fact that lagged values of the dependent variable and the error terms u_{it} are orthogonal.

The model begins by first differencing Eq. 3 to eliminate unobserved facility fixed effects:

Equation 4

$$\Delta\ln transaction_{it} = \beta_0 + \rho\,\Delta\ln transaction_{i,t-1} + \beta_1\,\Delta\ln toll_{it} + \beta_2\,\Delta\ln gas_{it} + \beta_3\,\Delta\ln income_{it} + \beta_4\,\Delta\ln population_{it} + \eta_t + \Delta u_{it},$$

where η_t is the first differenced year intercept and $\rho \in [0, 1]$. Eq. 2 is then estimated using the Arellano and Bond (1991) GMM procedure, called the difference GMM estimator to handle the serial correlation problem. Here, for example, $\ln transaction_{it-2}$ can be used as a valid instrument since it is correlated with $\Delta\ln transaction_{i,t-1}$ but not with Δu_{it-1} as long as u_{it} is not serially correlated. In this fashion, one can continue and get a set of valid instruments as (y_{i1}, y_{i2}, …, y_{it-2}). For more information on the instrumental variable approach, see Baltagi (2013).

The difference GMM approach improves efficiency by giving more weight to moment conditions that can be estimated with low variance. It also enables the use of endogenous regressors in the model (Graham, Crotte, and Anderson 2009). It is known, however, that instruments used in the difference GMM approach are less informative when the value of ρ gets close to unity and the variance of fixed effects a_i increases (Blundell and Bond 1998). The weak instrument problem results in bias and poor precision of the difference GMM estimators.

To reduce the finite sample bias and improve the precision, and therefore overcome the weak instrument problem, studies propose using additional moment conditions (Arellano and Bover 1995; Blundell and Bond 1998). This approach, called the system GMM estimator, uses lagged differences of y_{it} as instruments in addition to lagged levels of y_{it}, as used in the difference GMM estimator.

The validity of GMM estimators relies on the assumption of the serial correlation of the error terms. After the estimation, a test proposed by Arellano and Bond (1991) was performed to examine the hypothesis of no second-order serial correlation in the first-differenced errors. The validity of instruments used in the model was further examined by performing a Sargan test of overidentifying restrictions (Hansen 1982; Sargan 1958).

One advantage of the autoregressive model is the explicit estimation of both short- and long-run elasticities: β coefficients are interpreted as a short-run elasticity, and a long-run elasticity can be calculated as $\beta/(1-\rho)$, where the denominator measures the speed of adjustment. For the derivation of a long-run elasticity equation from a structural demand model, see Appendix D. Based on the annual data structure and AR model used, a short-run elasticity indicates any adjustments made within a one-year period and a long-run elasticity indicates the total adjustment to a toll increase over time. In general, empirical studies show that long-run elasticities are 50 percent to three times higher than short-run elasticities, and a similar result is expected in the analysis (Goodwin 1992).

In the following section, estimation results using a system GMM model are presented. To our best knowledge, this essay is the first implementation of a system GMM method for analyzing a large panel data of U.S. toll roads. Empirical studies employing system GMM models often present estimation results in comparison to those using OLS, Fixed Effects, and Difference GMM models. The purpose is to show the consistency of the system GMM model estimates by comparing ρ estimates from each model. For readers interested in model comparison, see Appendix E. Another empirical challenge raised in the literature when using a system GMM model is the "too many instruments" issue (Roodman 2009). Because the purpose of this essay is to present empirical estimations of the toll elasticity of demand for different types of toll roads, the discussion on methodological challenges of too many instruments is deferred to Appendix F.

Results

Table 11 shows the estimation results of the system GMM estimator. The coefficient parameters are interpreted as short-run elasticities. Column 1 presents estimation results based on all samples of 539 observations and 64 toll roads in the data. Columns 2 to 5 correspond to estimation results for mutually exclusive sub-samples in the data: 33 urban non-interstate facilities in Column 2; 14 intercity (or non-urban) non-interstate facilities in Column 3; 4 urban interstate facilities in Column 4; and 13 intercity interstate facilities in Column 5. See Appendix B for the list of toll roads corresponding to each sub-sample (Table B1) and the summary statistics of variables (Table B2).

The estimated short-run toll elasticity of demand from the entire sample in Column 1 is -0.038 based on data from 64 toll roads from 2004 and 2013. The magnitude of the toll elasticity is small compared to those reported in the literature. As noted in the previous section, data points in the opening year of each facility have been excluded so that the estimated elasticity represents the sensitivity of toll road usage to tolls when the traffic level has reached its normal conditions after the ramp-up period is over. The estimate infers that a 100% increase in tolls is associated with a 3.8% reduction in the number of transactions. For example, you would expect to see a 3.8% reduction in transactions if tolls for passenger cars increased from $1 to $2.

Table 11 System GMM model results by functional classification and geographic coverage of toll roads, 2004-2013

		Interstate		Non-Interstate	
	All Samples	Urban	Intercity	Urban	Intercity
	(1)	(2)	(3)	(4)	(5)
ln (toll rate)	-0.038***	-0.028	-0.052***	-0.076***	-0.123
	(0.004)	(0.068)	(0.013)	(0.018)	(0.090)
ln (gasoline price)	-0.050***	-0.160	-0.076***	-0.039	-0.056
	(0.006)	(0.196)	(0.029)	(0.034)	(0.154)
ln (household income)	0.201***	0.080	0.020	0.153***	0.117*
	(0.002)	(0.078)	(0.019)	(0.059)	(0.070)
ln (population)	0.087***	0.149	-0.027**	0.140	0.114
	(0.006)	(0.186)	(0.011)	(0.150)	(0.074)
ln (transaction) L1.	0.866***	0.956***	0.995***	0.884***	0.904***
	(0.002)	(0.051)	(0.009)	(0.031)	(0.034)
Observations	539	37	120	259	123
# facilities	64	4	13	33	14
Arellano-Bond Test for AR(1)	-1.914 (P>z: 0.056)	.	.	-1.687 (P>z: 0.092)	.
Arellano-Bond Test for AR(2)	0.822 (P>z: 0.411)	.	.	-0.160 (P>z: 0.873)	.
Sargan Test of overid. restriction	Chi2(59)=62.61 (P>chi2: 0.35)	Chi2(33)=23.99 (P>chi2: 0.87)	Chi2(117)=115.0 (P>chi2: 0.54)	Chi2(59)=27.12 (P>chi2: 1.00)	Chi2(119)=109.4 (P>chi2: 0.72)

Notes: Standard errors are in parentheses. The significance levels are marked as *** for p<0.01, ** for p<0.05, and * for p<0.1. All estimates are based on system-GMM model. The coefficients of year dummy (2006-2013) in each column are suppressed. Columns 1 and 2 use two-step estimator and maximum lags of dependent variable for use as instruments are capped to 5 lags. Columns 3, 4 and 5 use one-step estimator and no restriction on the number of lags of dependent variable for use as instruments. Arellano-Bond test for AR(1) and AR(2) is not available for one-step estimators.

Columns 2 to 5 further show the estimated parameters by functional class (interstate and non-interstate) and geographical coverage (urban and intercity). The signs of the short-run toll elasticity of demand estimates are negative as expected, with variation across different sample segments. The first general observation from Table 11 is that at the functional classification level, drivers using interstate highways are less sensitive to toll increases than those using non-interstate toll roads. In the sample, the average number of transactions is about two times greater on interstate toll roads than on non-interstate toll roads. The second observation is that when comparing toll elasticities by geographic coverage, the magnitude of short-run toll elasticity for urban toll facilities is about half the size of intercity (i.e., non-urban) toll facilities for both interstate and non-interstate toll roads. One may argue that toll elasticities in urban facilities should be larger than in intercity facilities because alternative routes are more readily available. However, the evidence in Table 11 shows that urban travelers are less sensitive to toll increases compared to intercity travelers. This observation is attributable not to the availability of alternative routes but to the different characteristics of users driving on urban versus non-urban toll facilities. It could be the case that urban toll road users drive on urban facilities on regular basis for commuting purposes, whereas users of non-urban facilities do not use toll roads on regular basis.

The empirical evidence on the differences in toll elasticities between intercity and urban facilities is found in Huang and Burris (2013). As a comparison, toll elasticities of road facilities in California, Florida, Kansas, Maryland, and Oklahoma were synthesized and toll elasticities were estimated for the entire length of each road. This exercise showed that the magnitude of average toll elasticity is larger for intercity toll roads than urban toll roads. The exercise also showed that the magnitude of toll elasticity is smaller on interstate facilities than non-interstate facilities. Based on the synthesis, the average toll elasticity of interstate urban roads in Huang and Burris (2013) was -0.02, similar to the evidence presented in Column 2 in Table 11, which is -0.028. The comparison of evidence on non-interstate toll facilities shows that the toll elasticity estimates reported in Huang and Burris (2013) were about two to three times greater than those reported in Columns 4 and 5. Overall, the findings on toll elasticity of demand by functional classification and geographic coverage are similar to those reported in the literature.

As discussed earlier, the advantage of the AR model is the explicit calculation of both short- and long-run elasticities. The long-run elasticity is $\beta/(1-\rho)$, where β is short-run parameter estimates for toll, gas price, income, and population and ρ is the estimate of the lagged dependent variable coefficient. Table 12 shows that the calculated long-run toll elasticity of demand is -0.284, inferring that a 10% increase in tolls is associated with a 2.8% reduction in toll transactions in the long run. The long-run toll elasticity of -0.284 is 7.5 times larger than the short-run elasticity. The ratio between the long-run and short-run toll elasticities varies widely between types of road, which can be explained by differences in the speed of adjustment. The speed of adjustment $(1-\rho)$ for all samples is 0.134, which implies that the demand on toll roads does not change quickly in response to toll increases. The speed of adjustment is slow on non-interstate toll roads (0.116 for urban and 0.096 for intercity) and even slower on interstate toll roads (0.044 for urban and 0.005 for intercity).

Table 12 Short-run and long-run elasticities

			Interstate		Non-Interstate	
		All Samples	Urban	Intercity	Urban	Intercity
		(1)	(4)	(5)	(2)	(3)
ln (toll rate)	SR	-0.038***	-0.028	-0.052***	-0.076***	-0.123
	LR	-0.284	-0.636	-10.400	-0.655	-1.281
ln (gasoline price)	SR	-0.050***	-0.160	-0.076***	-0.039	-0.056
	LR	-0.373	-3.636	-15.200	-0.336	-0.583
ln (household income)	SR	0.201***	0.080	0.020	0.153***	0.117*
	LR	1.500	1.818	4.000	1.319	1.219
ln (population)	SR	0.087***	0.149	-0.027**	0.140	0.114
	LR	0.649	3.386	-5.400	1.207	1.188

The impacts of gasoline price on the demand for toll roads are negative for all types of road. The gasoline price elasticity of toll road demand is -0.050 in the short-run with statistical significance and -0.373 in the long run based on all samples. Although the signs of gasoline price elasticities are negative as expected for all road types, the parameter is only statistically significant for the non-interstate intercity toll road sample. Among the empirical studies reviewed earlier, Huang and Burris (2013) and Zhang and Marshment (2012) examined the impact of gasoline price on the travel demands of U.S. toll roads in their analyses. Huang and Burris (2013) found that the average fuel price elasticity is -0.06 for 2-axle vehicles and -0.03 for 5-axle vehicles in the short-run. Zhang and Marshment (2012) showed that the short-run gasoline price elasticity is -0.055 on the Turner Turnpike and -0.057 on the Will Rogers Turnpike, both facilities in Oklahoma. Overall, the evidence of short-run gasoline price elasticity is consistent with the literature. Also, the evidence presented here and in the literature shows that the short-run toll road demand with respect to gasoline price ranges from -0.03 to -0.06. When this range is compared to the gasoline price elasticity of non-tolled roads, which is -0.15 in Graham and Glaister (2002) and -0.16 in Goodwin (1992), the toll road users are much less responsive to gasoline price increases than the users of non-tolled roads in the short-run.

The rise of household income is associated with an increase in toll road usage across functional classes of toll roads: a 10% percent increase in household income is associated with about a 2% increase in toll road transactions. The impact of household income is statistically significant for interstate urban and intercity toll roads. The relationship between population and toll road demand is positive in general except in the non-interstate intercity toll road sample.

Conclusion

This essay examined variation in the toll elasticity of demand by analyzing unbalanced panel data of 64 U.S. toll roads in 15 states from 2004 to 2013. To derive the toll elasticity of demand, the travel demand measured by the number of transactions was modeled as a function of a lag of transactions, tolls, gasoline prices, household incomes, and population. The autoregressive model was estimated using a system GMM method, which to our best knowledge is the first implementation of a system GMM method to analyze a large panel data of U.S. toll roads. The estimated toll elasticity of demand was -0.038 in the short-run and -0.284 in the long-run. The sample was further segmented into four groups by functional class (i.e., interstate or non-interstate) and geographic coverage (i.e., urban or intercity). When the toll elasticity of demand was estimated by sample segments, the magnitude of toll elasticity was smaller on interstate facilities than non-interstate facilities. Also, the magnitude was smaller on urban toll roads than intercity toll roads. The comparison of estimated toll elasticities with studies using similar demand model specifications showed that the evidence presented in this essay is consistent with the previous findings. In addition, the findings showed that the impact of gasoline price on toll road demand is negative. In the short-run, the gasoline price elasticity is -0.050. It was shown that the estimated gasoline price elasticity of toll road demand is within the range of findings in the literature, and the size is smaller than gasoline elasticity of non-tolled road demand. The impact of household income and population on toll road demand was positive, as expected.

This essay provided new empirical evidence of toll elasticities on U.S. toll roads that are currently under operation and are not dynamically tolled, which contributes to recent policy discussion on tolling interstate highways and expanding the pool of infrastructure revenue sources. The findings of this essay should be used in conjunction with discussions presented throughout the essay, including the type of toll roads under analysis, the use of state-level data for economic variables of gasoline prices, household incomes, and population, and methodological discussion on using the GMM approach given a lagged dependent variable as an explanatory variable.

CHAPTER FOUR: IMPACT OF HOV-TO-HOT CONVERSION ON DRIVERS

Introduction

Economists have suggested road pricing as a tool for increasing the efficiency of using limited road space and optimizing traffic conditions since the inception of the idea by Pigou (1920) and Knight (1924). The implementation of road pricing in the real-world has followed slowly for practical reasons, such as technology and political barriers (Button 1998). Instead, alternatives to road pricing have been adopted by policymakers to manage problems associated with congestions, such as parking charges, public transportation subsidies, road expansion, staggered business hours, vehicle license fees, and high-occupancy vehicle (HOV) lanes (Button 1998; Mohring 1998). Of these alternative approaches to managing congestion, the current research focuses on the relationship between high-occupancy toll (HOT) lanes converted from existing HOV lanes and road pricing.

Since the opening of the first HOV lanes in Virginia on I-395 between Washington, D.C. and the Capital Beltway in 1969, nearly 350 HOV lanes are operating throughout over 3,300 miles in the United States (U.S. Department of Transportation 2008; Federal Highway Administration 2015). HOV lanes refer to limited access roads designated for use by vehicles with two or more occupants to manage congestion and increase person throughput by incentivizing carpoolers with travel time savings and travel time reliability (U.S. Department of Transportation 2016). Despite their popularity among policymakers, HOV lanes have been criticized for not achieving intended optimal congestion levels and wasting valuable road space. Consequently, many HOV lanes are either underutilized or degraded, causing congestion in general purpose lanes.

In recent years, several regulatory changes at the federal level have opened opportunities to add a road pricing component to the operation of existing HOV facilities, namely a high-occupancy vehicle (HOV) to high-occupancy toll (HOT) conversion. First, the successful implementation of road pricing pilot programs convinced the federal government to be supportive of converting existing HOV facilities to tolled facilities (see Appendix G for the full list of programs). The Value Pricing Pilot Program in 1998—initially started as the Congestion Pricing Pilot Program authorized by the Intermodal Surface Transportation Efficiency Act (ISTEA) of 1991—funded the conversion of HOV lanes in locations such as I-15 near San Diego, CA (the first HOV-to-HOT conversion project); I-25 near Denver, CO; I-394 and I-35W in Minnesota; I-10/U.S. 290 in Houston, TX; and SR167 in Seattle, WA (Bhatt et al. 2008). These projects have achieved their intended goals of managing congestion and providing reliable travel time by using road pricing. Another example of such a pilot program is the Urban Partnership Agreement and Congestion Reduction Demonstration Program of 2006, which converted HOV lanes in the following locations: I-85 in Atlanta, GA; I-95 near Miami, FL; and highways in Minneapolis and St. Paul, MN. These changes enable and promote tolling on federally funded roads with HOV facilities, which makes it important to evaluate possible ramifications of HOV-to-HOT conversion projects for policymakers considering imposing road pricing on existing HOV facilities.

Second, following the success of a series of pilot programs, Section 166 of Title 23, United States Code (U.S.C.), provides opportunities for states operating federally funded HOV lanes to use road pricing as a tool for fixing degraded facilities amended by the Fixing America's Surface Transportation Act (FAST Act) on December 4, 2015 (U.S. Department of Transportation 2016). Degraded facilities refer to facilities "failing to maintain a minimum average operating speed (i.e., 45 miles per hour) 90 percent of the time over a consecutive 180-day period during morning or evening weekday peak hour periods (or both) (23 US Code §166(d)(2)(B))." The operating authority may combine road pricing with any other tools authorized in the statute for dealing with a degraded facility.

The goal of this essay is to understand changes in traveler behavior caused by HOV-to-HOT conversion projects. This research is particularly interested in learning the traveler behavior of drivers who choose to drive in express lanes. The case area of interest is the I-85 Express Lanes located northeast of Atlanta, Georgia, which converted the existing one-lane HOV facility to a HOT lane without involving new roadway construction. From the analysis using a binary logit model, this research tries to understand the impact of driver attributes on their decisions. The results are then compared to the findings from previous works on traveler choices on express lanes.

From a broader perspective, the contributions of the current research to the literature are many. First, using a revealed preference survey data, this essay incorporates the impact of trip purpose—one of the major factors to account for when examining traveler behavior—into the driver's route choice between express lanes and general purpose lanes. Trip purpose infers why people travel. A traveler would not begin his or her trip, in most cases, without a predetermined purpose, activities, and/or destination in mind. When a road is priced, it could be thought that travelers would choose to pay road pricing if the trip purpose is worthy of paying tolls (Santos and Verhoef 2011, 575). This is how trip purpose links travelers to heterogeneity in value of trip, value of travel time, value of travel reliabilities, and their trip choices in the end. Trip purpose is therefore an important factor to consider when analyzing a traveler's route choice between express lanes and other lanes.

Second, HOV-to-HOT conversion projects have attracted attention from policymakers because such projects utilize already existing infrastructure and free policymakers from considering complex problems such as right-of-ways. Analysis of the I-85 Express Lanes project provides a representative example for potential HOV-to-HOT conversion projects, and findings are expected to uncover policy implications for future conversion projects. The I-85 Express Lanes are characterized by one lane in each direction and an increased HOV occupancy requirement from two occupants to three occupants to be eligible to use the express lanes for free. These characteristics are representative of the majority of HOV lanes in the United States.

This research is organized as follows: the introduction is followed by a review of literature on HOV-to-HOT conversion projects and their impacts on carpoolers. The general overview of the HOV-to-HOT conversion project on I-85 in Atlanta is introduced, then the I-85 Corridor Household Travel Survey Data is discussed in detail.

The empirical framework section describes the econometric approaches used in the analysis. The estimation results are then discussed, followed by the conclusion section.

Literature Review

The impact of road pricing on traveler behavior has been extensively studied, especially in those facilities with dynamic tolling schemes where tolls are adjusted at given time intervals based on levels of traffic and travel speed, but focused research on the impact of HOV-to-HOT conversions on carpoolers is less common. One possible explanation is that among facilities that went through HOV-to-HOT conversions, only a few experienced an implementation of road pricing and an increase in the vehicle occupancy requirement at the same time (Appendix H). The facilities that have maintained the same vehicle occupancy requirements as before an HOT conversion experienced growing congestion in HOT lanes due to high-occupancy vehicles (Poole 2016), which shows the importance of incorporating changes in occupancy requirements into an HOV-to-HOT conversion project and developing policy dialogue on carpoolers who would be dis-incentivized by road pricing (Fuhs and others 1993, 41).

The evaluation of early HOV-to-HOT conversion projects federally funded via the Value Pricing Pilot Program shows that the volume of HOV2+ in express lanes increased substantially after the conversion, with very little change in the volume of HOV3+ vehicles on Katy Freeway on I-10 in Houston (Bhatt et al. 2008). On U.S. 290 HOT lanes, which is the first conversion project to increase the vehicle occupancy requirements from HOV2+ to HOV3+, there was an increase in two-occupants vehicles in tolled lanes that shifted from the general purpose lanes (Bhatt et al. 2008). The results, however, did not evaluate the impact of tolling on those who did not previously have to pay tolls for using HOV lanes.

Goel and Burris (2012) examined carpooler behavior in six HOV-to-HOT conversion projects by comparing carpooler data before and after each conversion based on survey data results. Among the six projects under examination, only one increased the occupancy requirements from HOV2+ to HOV3+, which is I-95 Express Lanes in Miami. The simple interpolation of data before and after this conversion shows that there was a decrease in the number of two-occupant vehicles in tolled lanes. However, the data did not provide information on whether there had been shifts in the number of occupants. Similarly, HOV3+ users indicated that 81% of them had experience using HOV lanes before the conversion, but it is not clear whether they were driving as two-occupants or continuing as three-occupants. Another evaluation of the I-95 Express Lanes in Miami by Pessaro and Nostrand (2011) found that the reduced number of two-occupant vehicles on tolled lanes were due to their shifts to general purpose lanes. Once again, the analysis does not show how much of the route shift is caused by the implementation of tolling and does not explain the shifts in the number of occupants among drivers who benefited from free rides in HOV lanes before the conversion.

Empirical Context: HOV-to-HOT Conversion Project on I-85 in Atlanta

The I-85 Express Lanes project in Atlanta is one of six projects funded by the Urban Partnership Agreement and Congestion Reduction Demonstration program that is part of the *National Strategy to Reduce Congestion on America's Transportation Network* launched by the U.S. Department of Transportation (USDOT) in 2006 (Federal

Highway Administration 2017).[1] The Transportation Equity Act for the 21st Century (TEA-21) authorized a $110 million grant, which covers about 60 percent of the total $182 million project investment. The federal grant supports the long-run regional goal of implementing integrated congestion-priced lanes, enhanced transit services, and innovative technology (Federal Highway Administration 2008).

The I-85 Express Lanes opened on September 30, 2011. The project converted the existing 15.5-mile single-lane high occupancy vehicle (HOV) lane in each direction to a high occupancy toll (HOT) lane—an HOV-to-HOT conversion project—without adding an additional lane. This single-lane toll road has no physical barrier, with two solid lines separating the managed lane from the general purpose lanes (Feigenbaum 2013). The facility is located between I-285 in DeKalb County and Old Peachtree Road in Gwinnett County (see Figure 4). The pricing is dynamically adjusted every 5 minutes from $0.01 to $0.90 per mile depending on the traffic level and the travel speed in the express lanes (State Road and Tolling Authority 2015b). Under this pricing scheme, the maximum possible toll rate is $14.40 (i.e., the full length of the facility is considered 16 miles in the toll calculation). The State Road and Tolling Authority (SRTA) of Georgia sets tolls based on factors including the number of vehicles in both the express lanes and the general purpose lanes, the speed of traffic in both the express lanes and the general purpose lanes, driver behavior, travel distance on the express lanes, and the capacity of all the lanes (Shrestha 2013). All users of the express lanes must use an electronic toll collection (ETC) device called a Peach Pass. The usage is free to registered transit,

[1] Other recipient cities include Los Angeles, Miami, Minnesota, San Francisco, and Seattle.

vanpools, carpools with three or more occupants, and other toll-exempt vehicles. The key feature of this conversion program is the changes in the number of occupants allowed for toll-exempt vehicles, which is decided by the State Transportation Board (Goodin et al. 2011). Prior to the conversion, vehicles with more than two occupants could use the HOV lanes. After the conversion, both single- and double-occupancy vehicles pay tolls, with vehicles with more than three occupants exempted from paying them.

Figure 4 Map of I-85 Corridor in Atlanta, Georgia (State Road and Tolling Authority 2017a)

In January 2016, the average weekday traffic count on both northbound and southbound I-85 was 255,212. Out of that, the traffic on the I-85 Express Lanes consisted of 10.1% of average weekday trips on I-85 (Figure 5). The percentage of traffic volume on the I-85 Express Lanes has more than doubled since January 2012, when usage was about 4.5% of the average weekday trips on the entire I-85 section. See Appendix I for details on the calculation.

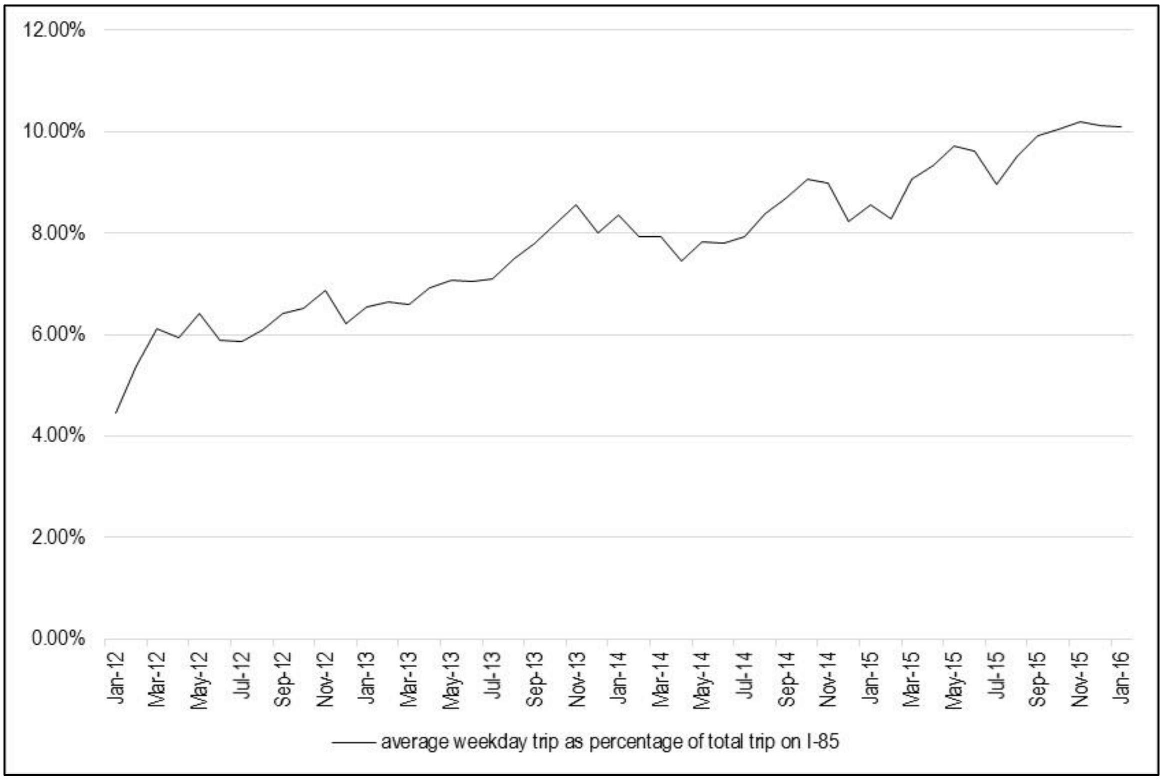

Figure 5 I-85 Express Lanes average weekday trips as percentage of total trips on I-85, January 2012 – January 2016 (Georgia Department of Transportation 2017)

Figure 6 shows the monthly changes in the average weekday trips in a solid line and the average daily fare in a dotted line. During the first month after opening, the weekday trips averaged 7,273, which quickly doubled in just a five-month period. The number of weekday trips reached its height of 29,548 in October 2016. The average tolls paid by travelers steadily increased as the number of trips increased, from $1.19 in October 2011, to $3.13 in August 2016 at the highest, to $2.05 in December 2016. The total revenue from I-85 Express Lanes increased nearly four times, from $2.35 million in FY2012 to $10.32 million in FY2015 (State Road and Tolling Authority 2016). The number of non-tolled trips in the managed lanes has steadily increased since the opening, reaching its highest point of 118,776 trips in October 2016.

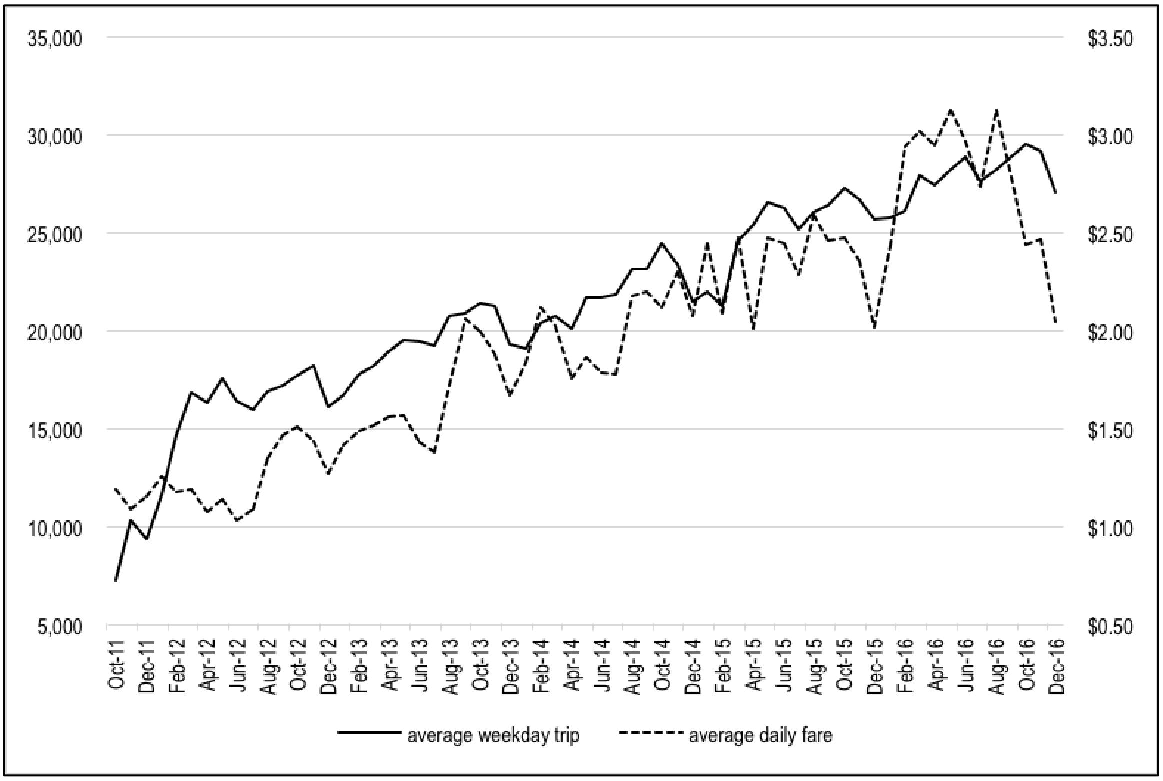

Figure 6 I-85 Express Lanes average weekday trips and fare, Oct 2011 – December 2016 (State Road and Tolling Authority 2017b)

Figure 7 compares changes in the monthly average tolls and the maximum tolls paid during each month from October 2011 to December 2016. Under the current road pricing scheme, drivers could pay up to $14.40 to travel the full length of the I-85 Express Lanes during peak-of-peak hours. After five years of operation, the price ceiling has nearly been reached; starting in August 2016, drivers have paid \$13.95 during the busiest hours. The trend line of the maximum toll each month marked in solid line infers some of pricing policies implemented by the toll authority over time. For example, the maximum toll dropped by 40% from \$5.55 to \$3.35 during the second month after opening the facility in October 2011 despite a 42% increase in the average weekday trips. Until mid-2013, the trend line of the maximum toll each month does not show any particular pattern, but afterwards the graph shows step-shaped increases in maximum tolls. The graph illustrates the possibility that the toll authority closely controlled the price level.

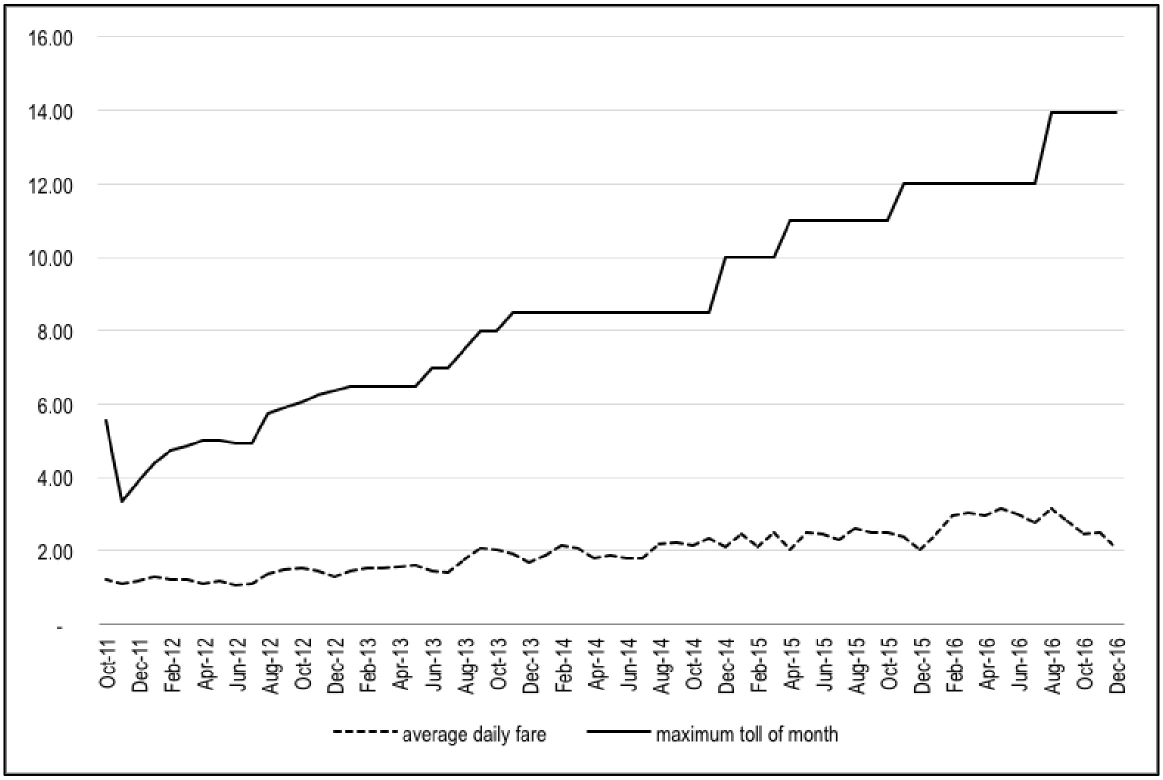

Figure 7 I-85 Express Lanes average daily fare and maximum toll of month, October 2011 – December 2016 (State Road and Tolling Authority 2017b)

Figure 8 shows the total number of trips per month and the number of toll-exempted vehicles from October 2011 to August 2016. While the total number of trips in the managed lanes exponentially increased over time, the number of toll-exempt HOV vehicles increased slowly. In terms of the percentage of the total number of trips, the percentage of HOV vehicles steadily increased from 13% to 15.5% during the same period.

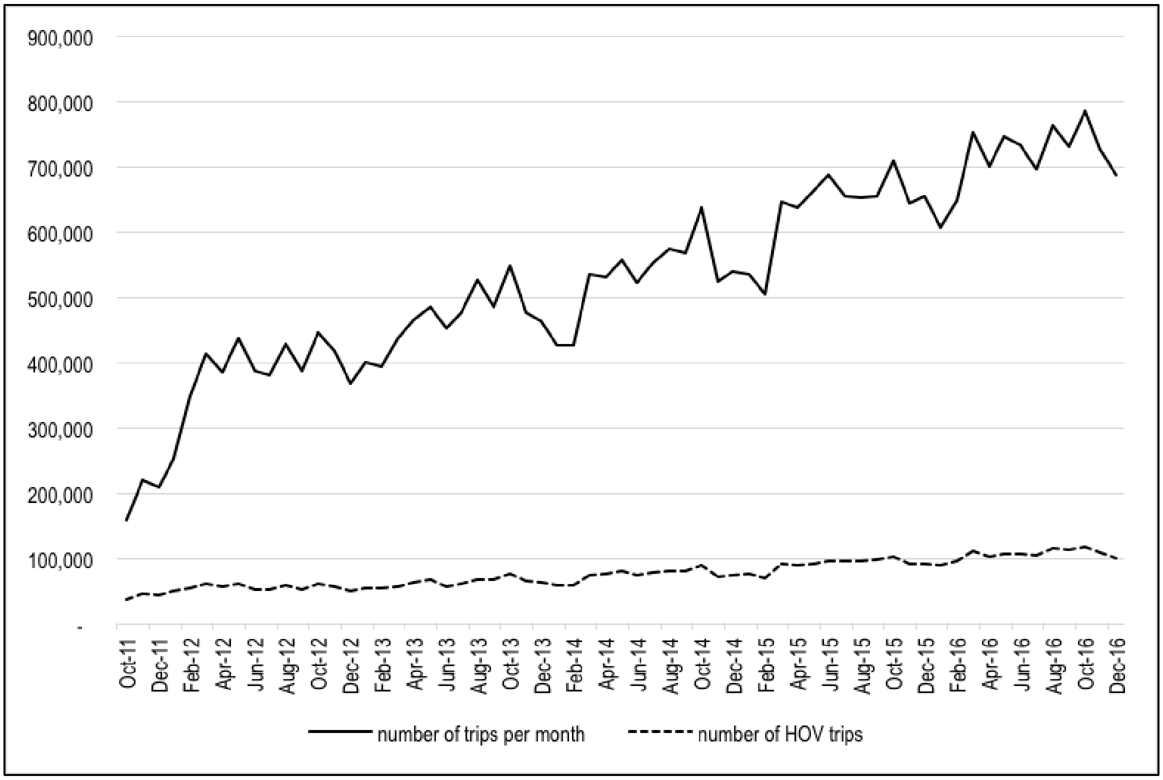

Figure 8 I-85 Express Lanes the total number of trips per month and the number of HOV trips, Oct 2011 – December 2016 (State Road and Tolling Authority 2017b)

The conversion project had a significant impact on travel time and speeds for both the managed lanes and the general purpose lanes. Before the opening of the managed lanes, the southbound trip from I-285 to Old Peachtree during the morning peak period took about 25 minutes in 2005/2006 and 20 minutes in 2009 (State Road and Tolling Authority 2010). After the opening of the HOT lanes, the southbound weekday travel time reduced to 14.8 minutes in the managed lanes and 17.5 minutes in the general purpose lanes during peak hours (6-10 a.m.) between September 2012 and May 2013 (Sheikh, Guin, and Guensler 2014). During the same period, the northbound weekday travel time during the peak hours (3-7 p.m.) reduced to 13.3 minutes in the managed lanes and 16.3 minutes in the general purpose lanes. The forecast model predicted the average travel time would be 18 minutes at a travel speed of 50 miles per hour in 2015 during the morning peak hours (State Road and Tolling Authority 2010). The actual data showed that it took 24 minutes on average to travel the entire 15.5-mile southbound trip at a speed of 42 miles per hour on average during the FY2015 (State Road and Tolling Authority 2015a). As the number of trips increased and the travel time and speeds reduced in the managed lanes, the SRTA made an adjustment to the toll pricing algorithm in FY2015 to maintain reliability during the morning rush hour as requested by the Federal Highway Administration (Department of Audits and Accounts of state of Georgia 2015).

Data: I-85 Corridor Household Travel Survey

To examine the impact of the I-85 HOV-to-HOT conversion on driver behavior, this research employs the I-85 Corridor Household Travel Survey as a main data source. The survey was funded by the Federal Highway Administration (FHWA) to assess changes in route and mode choice, trip timing, trip purpose, and impact of pricing. The survey was conducted by the John A. Volpe National Transportation Systems Center at the U.S. Department of Transportation (Petrella et al. 2014). The dataset is publically available on the Transportation Secure Data Center website hosted within the National Renewable Energy Laboratory website (2017). The household travel survey took place before and after the opening of the I-85 Express Lanes in 2011 (Wave 1) and 2012 (Wave 2): Wave 1 took place in April-May 2011, which is before the opening of the managed lanes, and Wave 2 took place in April-May 2012, after the opening of the managed lanes.[2] The components of the household survey consist of demographic information, a 48-hour-period travel diary, and follow-up questions on travel patterns and attitudes.

The target population of this revealed preference survey[3] was households using the I-85 corridor northeast of Atlanta living in Georgia who had no plans to move during the survey period. Three groups of users were recruited for the survey: peak hour drivers,

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[2] Wave 1 survey schedules in 2011 were April 18-19, April 19-20, April 26-27, April 27-28, and May 11-12 (8 weekdays). Wave 2 survey schedules in 2012 were April 24-25, April 25-26, April 30-May 1, and May 1-2 (5 weekdays).

[3] Revealed preference survey data refers to data recording travelers' actual decisions, which is a big advantage of revealed preference data. Revealed preference data suffers from problems such as multicollinearity among independent variables and endogeneity issues (Whitehead , Haab, and Huang 2011, 2). In revealed preference data there is information on chosen alternatives but little to no information on non-chosen alternatives. This also means that revealed preference data is only collectable on existing conditions and not on non-existing conditions. Researchers may find insufficient variation within variables in revealed preference data (Train 2011, 152). In the case of surveys, revealed preference data are inefficient to collect, and often such data is only collected for one period of time. The I-85 Corridor Household Travel Survey data analyzed in Chapter Four is a rare exception among many existing revealed travel surveys because the same group of households responded to the survey for two time periods, before and after the conversion of the HOV lanes to HOT lanes. From a survey methodology perspective, revealed preference data is not free of measurement error issues because respondents may consciously or unconsciously make mistakes in responding to questionnaires. For example, the survey on electronic toll collection (ETC) in Finkelstein (2009) showed that drivers remembered the amount of tolls paid almost correctly when they paid in cash, but the team found errors in responses from those who paid using ETC.

Stated preference data, on the other hand, are data collected from experimental surveys in which people are asked what they would do in hypothetical situations. These types of surveys are appropriate when evaluating situations that does not yet exist. Also, research could design hypothetical situations so as to avoid problems of multicollinearity and endogeneity, which are problems of revealed preferences data. The biggest challenge with stated preference data is that people's choices made in hypothetical situations may not necessarily reflect their actual choices in real life. Since revealed and stated preference data could complement each other, methods have been developed for combining these two types of datasets. See Train (2011) for further details.

transit riders, and users of organized vanpools. Incentives were provided to respondents as a $15 Amazon gift card for completing the Wave 1 survey and an additional $30 gift card for completing the Wave 2 survey. All members of the household aged above 18 were asked to participate in the survey regardless of their I-85 corridor usage in order to capture how congestion pricing affects travel behavior within a household. In total, 2,412 households completed the Wave 1 survey. After the opening of the I-85 Express Lanes, the Wave 2 survey was sent out to households who had completed the travel survey in Wave 1. The retention rate was 69%, and 1,655 households or 3,126 individuals participated in the Wave 2 survey. About 36% of the households earned more than $100,000 in a year.

Because the survey was targeted to the users of the I-85 corridor, it is important to understand how the I-85 corridor was defined in the survey. The corridor first refers to the 15-mile portion of I-85 north of I-285 and south of Old Peachtree Road as highlighted on the map in Figure 1 (i.e., I-85 Exit 94 to Exit 109). The corridor also includes roads and highways close to I-85, including Buford Highway (State Route 13/U.S. Route 23), Peachtree Parkway Northwest (Peachtree Industrial Blvd/State Route 141), and Lawrenceville Highway (U.S. Route 29). Local and secondary roads running parallel to I-85 are also considered part of the corridor.

The advantages of the I-85 survey are many. First, compared to existing congestion pricing studies, the sample size of the household survey from I-85 Corridor users supersedes other surveys found in the literature. A large sample size provides opportunities to explore variations of route choice explained by exploratory variables in the analysis. Second, because the survey data is publically available—a very rare case in transportation literature—the validity of results in this essay may be checked through replications.

For the purpose of analysis, the sample is restricted to trips made by primary household members who drove on I-85, either in express lanes or general purpose lanes. Due to the design of the survey, this sampling process leaves users with following characteristics. First, only those who drove on I-85 are left in the sample. Any traveler who used mixed modes was restricted from the sample. Second, all respondents in the sample are now 18 years or older. Third, only one member of each household (i.e., the primary respondent in the household who filled out the survey) is now included in the sample, which means no two respondents in the sample belong to the same household. After the sampling restrictions, the number of households is 816 with 3,431 trip records.

Table 13 shows the attributes of trips in the sample that occurred between April and May of 2012. The percentage of trips using the I-85 Express Lanes is 15% in the sample. The calculation based on a traffic count in April 2012 shows that the percentage of trips using I-85 Express Lanes on average weekdays is about 6% of the total trips (Figure 5). The mode share among solo drivers, double occupants, and more than three occupants on all lanes is 66%, 10%, and 24%, respectively. The proportion of mode share is similar when only looking at the 517 trips that used express lanes. Figure 8 showed that the actual proportion of HOV3+ vehicles is about 14%, whereas in the survey it is about 24%. The comparison between the survey data and the actual data shows that the usage of the express lanes is upward biased in the sample.

Table 13 Descriptive statistics: trip attributes

	Survey Sample
Route share	
I-85 Express Lanes	0.15
I-85 General Purpose Lanes	0.85
Mode share	
Solo	0.66
HOT2	0.10
HOV3	0.24
Travel time	
Mean	50 minutes (SD 36 min)
Tolls	
Mean	$2.26 (SD $1.54)
Trip distance on I-85 (miles)	
Mean	10.2 miles (SD 4.2 miles)
Percent of trips by time period	
Peak hours (6-10 a.m. & 3-7 p.m.)	0.84
Non-peak hours (other hours)	0.16
Purpose of trip	
Go home	0.37
Go to primary workplace	0.42
Others	0.21
Number of respondents	816
Number of trips	3,431

The average toll paid by trips using the I-85 Express Lanes is $2.26 or $0.22 per mile in the sample, which is about two times greater than the average toll of $1.31 paid by all users of the I-85 Express Lanes during the five days the survey took place in April and May. In the dataset, of the 517 trips that used express lanes, 95% occurred during peak hours. Also, trips involving express lanes are longer distance trips (12.3 miles) than those using general purpose lanes (9.8 miles), which are significantly different. The average trip distance in the survey is similar to the finding in Nelson et al (2010), with the users of I-85 Express Lanes corridor traveling 10 miles on average. Among 3,431 trips, 84% of trips took place during peak hours (6-10 am and 3-7 pm), whereas the actual traffic count on I-85 shows that about 46% of trips took place during the same hours. The high number of peak hour trips is explained by characteristics of respondents in the sample. Among 816 households, 89% are full-time employees, and respondents made 85.5% of their trips during peak hours for the purpose of going home or going to their primary workplaces. Overall, the trips in the sample represent long-distance commutes that involve express lanes more often than what the public data shows.

In terms of individual household characteristics in the sample, Table 14 shows some differences between respondents and the actual demographic characteristics found in Gwinnett County. Eight hundred sixteen households in the sample are compared to those living in Gwinnett County, since the majority of the households (76.10%) live in Gwinnett County, followed by 6.62% in Fulton County, and 17.28% in 21 other counties. In the data, 55% of households are aged between 35 and 55, whereas only 32% of those in Gwinnett County belong to that age group.

Table 14 Descriptive statistics: individual characteristics

	Survey Sample	Gwinnett County
Age of respondents		
18 – 35	0.22	0.23
35 – 55	0.55	0.32
>55	0.23	0.16
Gender		
Female	0.47	0.51
Male	0.53	0.49
Household income		
<$50,000	0.12	0.27
$50,000 - $75,000	0.19	0.19
$75,000 - $100,000	0.23	0.13
$100,000 - $150,000	0.21	0.16
>$150,000	0.25	0.11
Median ($)	87,500	60,329
Race		
White	0.75	0.56
Black	0.14	0.25
Asian	0.08	0.12
Others	0.03	0.10
Education		
Bachelor's degree or higher	0.72	0.34
Number of people in household		
Mean	2.65	2.98
Number of respondents	816	-
Number of trips	3,431	-

Source: Age, gender, race, the number of people in household are from 2010 Census. The household income is from 2010-2014 American Community Survey 5-Year Estimates.

The median household income in the data is $87,500, which is higher than the median household income of the county at $60,329. Looking at the distribution of household income, 46% of respondents have a household income greater than $100,000, whereas only 17% of households in Gwinnett County belong to the same income group. The income gap between I-85 users and the population from the census block was also observed is Nelson et al. (2010) in their sociodemographic analysis of I-85 peak period commuters passing through the I-85 Express Lanes corridor. Nelson and coauthors found that the interstate highway users on I-85 had median household incomes 10.3% greater than the reported income in the region. They also found that I-85 users of both general-purpose lanes and HOV lanes had a higher representation in the $50,000 to $200,000 range than residents in the region. The current survey data provides some explanations of why there might be group differences between the users of I-85 and the general population in Gwinnett County. One explanation is education level, with 72% of the sample having a bachelor's degree or higher, whereas just over 34% have such a degree in Gwinnett County. Another explanation is the employment status; as mentioned before, 89.1% of the 816 households in the sample are full-time employees. Race and household size also explain income differences, as respondents in the sample are predominantly white and have significantly smaller numbers of household members.

Overall, the survey data shows that the users of I-85 Express Lanes have different socio-demographic characteristics than the general public. One should, therefore, be mindful of individual characteristics and trip attributes distinct to the dataset when interpreting results in this research. Also, the users of findings in this research should be aware of possible bias in the estimates.

Econometric Framework

Binary logit

To examine characteristics of drivers using I-85 Express Lanes, he model in this research specifies a binary dependent variable, where one represents driving on I-85 Express Lanes and zero represents driving on the adjacent general purpose lane as a function of trip attributes and individual characteristics. The binary logit model was estimated using maximum likelihood. Before commencing with the analysis, the author considered various binary outcome models (also called binary response models) such as tobit, probit, and logit models. Tobit model is relevant when the dependent variable is censored. Probit model is relevant when the residual is assumed to be normally distributed. Logit model is relevant when the residual is assumed to be logistic distributed. Among these three models, the current analysis chose to use the logit model following its wide acceptance and usage among transportation studies.[4] It is known that the marginal effects estimated from logit and probit models are not very different from each other, and empirical researchers often compare logit and probit estimates as a robustness check (Cameron and Trivedi 2010, 405-406). Following suit, the marginal effects from the logit model were compared to that of the probit model with the same model specifications to check the robustness of estimates after conducting a logit regression. The marginal effects from logit and probit models were found to be similar.

Results

This section discusses the binary logit model results estimated by maximum likelihood, examining the characteristics of the I-85 Express Lanes users. Between two waves of survey data, only the second wave data was used to evaluate user choices between express lanes and general purpose lanes after the tolling was implemented. The unit of analysis is individual trips, with the number of trips totaling 3,270. The binary

[4] Cramer says, "There is no direct intuitive justification for the use of logistic function," but he finds justifications from approximation arguments, consideration of random process, and models of individual behavior (Cramer 2003, 12). The wide usage of families of logit model in transportation may be due to the ability to model human behavior, the main justification of McFadden's model of random utility maximization, and his early analysis of traveler choice among multiple travel modes.

choice between express lanes and general purpose lanes is modeled as a function of trip attributes, such as cost per mile, the total cost interacted with income groups, and the interaction between travel time and three powers of trip distance. Individual characteristics are also included in the model, including age, gender, education level, household size, work hour flexibility, and trip purposes.

Table 15 shows that the cost per mile is not statistically significant and the magnitude is very small. This may be attributable to the very low level of tolls paid by users. On average, survey respondents traveled 10.2 miles and paid $2.26, which is $0.22 per mile (see Table 13). The actual data from the State Road and Tollway Authority shows that during the same period drivers paid $1.08, which is even lower than the amount paid by survey respondents. Such low tolls may be attributable to the surge of paid trips on express lanes in May 2012, as shown in Figure 6. It is known that the I-85 Express Lanes had been suffering from excess demand, but the toll authority was neither able to raise the toll rate nor to expand the toll lanes (Poole 2016).

Table 15 Binary logit model results
(DV: 1 if choose I-85 Express Lanes, 0 if choose general purpose lanes)

	(1) Coefficient	(2) Standard Error
Travel cost per mile	-0.006	(0.144)
Travel cost * medium household income	0.379***	(0.045)
Travel cost * high household income	0.279***	(0.041)
Travel time * distance	-0.009***	(0.002)
Travel time * distance^2	0.001***	(0.000)
Travel time * distance^3	-0.000***	(0.000)
Age 25-34	1.441*	(0.750)
Age 35-44	1.195	(0.749)
Age 45-54	1.092	(0.749)
Age 55-64	0.879	(0.755)
Age 65-74	1.213	(0.807)
Female	0.168	(0.108)
Some college or more	0.037	(0.266)
White	0.317**	(0.131)
Number of household members	-0.025**	(0.012)
Flexibility to change work schedule	0.030	(0.120)
Trip purpose: going home	0.222	(0.151)
Trip purpose: going to work	-0.197	(0.154)
Trip purpose: child care	1.534**	(0.687)
Female * child care	-1.001	(0.757)
Price Elasticity	-0.0003	
Observations	3,270	
Pseudo R-squared	0.112	
log likelihood	-1262	
chi2	317.2	

Notes: Standard errors are in parentheses. The significance levels are marked as *** for p<0.01, ** for p<0.05, and * for p<0.1. Constants are suppressed.

The “cost per mile” includes tolls and parking fee, the only two types of transportation costs available in the dataset. Some of components of the generalized cost of travel (Button 2010, 142-147), such as monetary costs (i.e., cost of gasoline, insurance cost, other operating cost, and vehicle depreciation rate), time costs (i.e., value of travel time), and inconvenience costs (i.e., value of travel reliability) were not available in the dataset and so were not included in the travel cost. Because such costs are not included in the cost structure, the estimates of travel cost coefficients are expected to be underestimated. In Chapter 2, the survey of toll road demand studies showed that the travelers using toll roads do respond to changes in fuel price, with fuel elasticity among toll road users -0.049 in the short-run and -0.531 in the long-run. In April 2012, when the second wave of the I-85 Household Travel Survey was taken, the average price of gasoline hit $3.83 per gallon, the highest since the financial crisis in 2008, and started to decline until the mid-year (Bureau of Labor Statistics, U.S. Department of Labor 2017). Travel cost also does not account for the frequency of a traveler using the I-85 Express Lanes. For example, the cost of travel for a driver using the express lanes five days per week during peak hours is exponentially higher than for a driver using the lanes one or two times per week at random hours. The cost coefficient may be severely underestimated for the frequent user, whereas downward bias is smaller for other types of users.

Interactions between cost and income show that medium- and high-income groups are less responsive to tolls. This evidence implies that toll rates on the I-85 Express Lanes have no influence on driver behavior of choosing express lanes over general purpose lanes.

The coefficient of travel time varies with distance, showing an inverse U-shape pattern. Following Small, Winston, and Yan (2005) and Calfee and Winston (1998), the result may infer reduced leisure time, as commutes take a longer time and people who have a lower value of travel time choose to live farther away from major destinations.

Turning to demographic characteristics of drivers choosing to drive in the I-85 Express Lanes, medium- to higher-income groups, younger age cohorts, being white, smaller household sizes, and trips for child care purposes have significant impacts on choosing the express lanes. The results show that female drivers are likely to choose express lanes, but female drivers with child care responsibilities are less likely to choose them. This finding is contrary to the conventional explanation provided in the literature about higher female usage of express lanes.[5] It has been thought that female drivers are more likely to use express lanes because they are more often responsible for taking care of the children in their house than their counterparts, which often involve trips with no time flexibility, such as afternoon school activities. The analysis here provides evidence that the higher probability of choosing express lanes by female drivers is not necessarily explained by their child care responsibilities. When route choice is examined by each household income group, as in Table 16—low-income (less than $50,000), medium income ($50,000 to $100,000), and high-income (greater than $100,000)—the log odds

[5] One of the common findings in a wide range of studies on demand for express lanes is that female drivers are more likely to use express lanes than male drivers. To explain why that is so, researchers and practitioners alike have hypothesized that child care responsibility makes female users more prone to use express lanes to save time and travel reliably. The author has attended numerous toll road industry events and heard from industry leaders how express lanes help so called “soccer moms” to get to their childrens’ soccer practice on time. This stereotype may have resulted in a witty advertisement released by the LBJ TEXpress Lanes in which a soccer mom poses fashionably and proudly in front of a soccer-practicing child (check out the advertisement at http://www.lbjtexpress.com/news-and-resources/newsroom/news-stories/%E2%80%98tongue-cheek-over-top%E2%80%99-ad-campaign-meant-get-drivers-new). What has been missing in the literature is actual evidence on whether female drivers use express lanes for the purpose of caring their children. The current research provides evidence that child care responsibility does not explain female drivers’ higher likelihood of using express lanes.

of choosing express lanes is significantly higher for female drivers from high-income households and for child care purposes, similar to the main results in Table 15. However, for female drivers with child care purposes, the log odds of choosing express lanes significantly reduces.

It is known that middle-aged groups are more likely to use express lanes (Small, Winston, and Yan 2005; Yan, Small, and Sullivan 2002). The users of the I-85 Express Lanes in the Atlanta region show a slightly different pattern, with drivers in older age groups less likely to choose express lanes, similar to results found in Sheikh, Misra, and Guensler (2015). When coefficients are estimated for each age group as in Figure 9, the pattern shows that, compared to the youngest cohort aged 18 to 24, drivers are less likely to choose express lanes as they move up the age cohort. This could be explained by the fact that the value of travel time decreases as age increases.

Table 16 Binary logit model result by income
(DV: 1 if choose I-85 Express Lanes, 0 if choose general purpose lanes)

	(1) Low Income	(2) Medium Income	(3) High Income
Travel cost per mile	1.713***	-2.108**	-1.873**
	(0.507)	(0.925)	(0.933)
Travel cost * medium household income		0.680***	
		(0.109)	
Travel cost * high household income			0.464***
			(0.102)
Travel time * distance	-0.035***	-0.006**	-0.007**
	(0.010)	(0.003)	(0.003)
Travel time * distance^2	0.006***	0.001**	0.001*
	(0.002)	(0.000)	(0.001)
Travel time * distance^3	-0.000***	-0.000**	-0.000*
	(0.000)	(0.000)	(0.000)
Age 25-34	-0.411	4.950*	-0.253
	(0.964)	(2.736)	(0.530)
Age 35-44	-2.609**	4.333	-0.457
	(1.284)	(2.739)	(0.501)
Age 45-54	-0.595	4.176	-0.532
	(0.975)	(2.742)	(0.486)
Age 55-64	0.163	4.189	-0.873*
	(0.988)	(2.744)	(0.523)
Age 65-74	-0.360	4.302	
	(1.535)	(2.777)	
Female	-0.421	0.066	0.479***
	(0.425)	(0.179)	(0.185)
Some college or more	0.043	-0.348	-0.201
	(0.777)	(0.369)	(0.592)
White	-0.289	0.500**	0.187
	(0.433)	(0.234)	(0.227)
Number of household members	-0.071	-0.032	0.000
	(0.050)	(0.023)	(0.018)
Flexibility to change work schedule	0.426	-0.075	-0.166
	(0.419)	(0.196)	(0.215)
Trip purpose: going home	0.195	0.158	0.312
	(0.605)	(0.253)	(0.248)
Trip purpose: going to work	0.488	-0.563**	-0.241
	(0.568)	(0.265)	(0.254)
Trip purpose: child care		15.371	2.370*
		(915.958)	(1.272)
Female * child care		-15.449	-2.557*
		(915.958)	(1.381)
Observations	442	1,308	1,081
Pseudo R-squared	0.237	0.189	0.120
log likelihood	-95.19	-452.3	-464.7
chi2	59.17	210.9	126.5

Notes: Standard errors are in parentheses. The significance levels are marked as *** for p<0.01, ** for p<0.05, and * for p<0.1. Constants are suppressed.

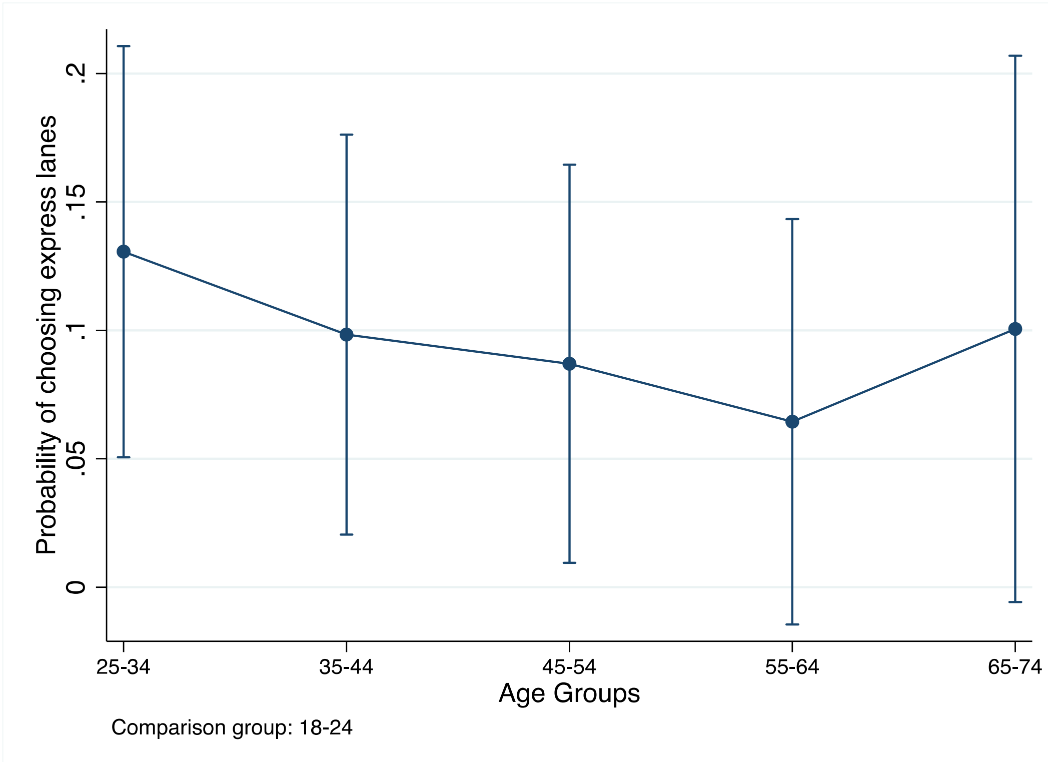

Figure 9 Probability of choosing express lanes by age groups and 95% confidence interval

Conclusion

This essay examined the characteristics of drivers choosing to use express lanes. The analysis used a publically available dataset called the I-85 Corridor Household Travel Survey, which took place before and after the conversion of the facility. The binary logit estimators show that drivers in medium- to high-income groups, younger age cohorts, being white, having smaller household size, and taking trips for child care purposes were more likely to drive in the express lanes. Females driving to take care of their children were less likely to use the express lanes, but the result was not statistically significant.

In the policy world, it is import to anticipate what is going to happen after policy changes. HOV-to-HOT conversion projects entail multiple policy changes at the same time, including changes in vehicle occupancy rate requirements that ultimately determines the beneficiaries of free rides on limited access roads, decisions on how to implement road pricing in a region as a tool to manage travel demand, and whether or not to increase existing road capacity. Because the outcomes of combining multiple policies are truly unknown, HOV-to-HOT conversion projects that are unique to the United States are truly experimental in nature for the jurisdictions implementing them. Evidence from descriptive statistics and econometrics analyses show that the road pricing policy in Atlanta is not truly effective in altering traveler behavior, possibly due to the very low level of tolls—as low as $0.01 per mile and $0.16 to drive the entire length of the facility. The findings of the current research are expected to provide a list of policy considerations when implementing road pricing policy combined with converting existing HOV lanes to HOT lanes.

CHAPTER FIVE: POLICY IMPLICATIONS AND CONCLUSION

Since Pigou's work in 1920, proposals to price roads as tools for managing congestion and externalities associated with increasing traffic have continuously attracted interest from scholars and policymakers. The theory of road pricing states that drivers should be charged a marginal external congestion cost to optimize the level of traffic on a road. In practice, it took many decades until this idea of road pricing was adopted by policymakers and implemented to manage congestion. Although the adoption of road pricing is becoming widespread around the world, questions still arise regarding the relationship between implementing road pricing and the actual usage of the priced road infrastructure and travelers' reaction to road pricing.

In three essays, this dissertation examined various questions regarding the relationships between road pricing and traveler demand for toll roads that have not been adequately addressed in the previous literature. First, the literature showed that there is a wide variation in findings on the relationship between road pricing and travel demand for toll roads measured by the road pricing elasticity of demand estimates, but no systematic synthesis of studies is available. The first essay, *Road Pricing Elasticity of Demand – A Survey*, examines the sources of variation in road pricing elasticity of demand by analyzing a dataset compiled by the author consisting of 349 observations of road pricing elasticity estimates and relevant information on travel demand for toll roads collected from 24 studies published between 1981 and 2015. To the author's knowledge, this essay is the first attempt in the relevant literature to synthesize studies specifically on travel demand for toll roads. It contributes to the literature by complementing findings of well-established line of survey studies on road traffic demand.

The results showed that studies use various travel demand models, such as before-and-after comparison, static model, dynamic panel data model, and discrete choice model, to examine toll elasticities. Road price elasticity estimates are compared across and within groups of studies employing each model. The road price elasticity of demand for static and dynamic models is examined by time horizon (short-run and long-run), geographic location (intercity and urban), vehicle type (passenger cars and heavy trucks), payment methods, and estimation strategy. Road price elasticities are derived from discrete choice models and are examined by choice sets (mode and route choice), data type (stated and revealed preference), model and estimation strategy, and aggregation methods employed.

The essay discussed one of the main challenges of synthesizing price elasticity estimates from a number of studies, which is limited information on the actual level of tolls and traffic needed for evaluating the relationship between price elasticity and the level of tolls and traffic. The correlation analysis of price elasticity and the level of tolls show that higher tolls are associated with a larger magnitude of road pricing elasticity. Toll authorities in the United States have been experimenting with various toll schemes—namely fixed tolls, fixed variable tolls, and dynamic variable tolls—but little attention has been given to understanding the impact of various tolling schemes on driver behavior.

Also, policy process is not transparent when it comes to determining the level of tolls. Often, toll rates are determined arbitrarily by elected officials, as was the case for the Elizabeth River Tunnels, where toll authorities would increase/decrease tolls at their discretion. These policy questions are left for the future research as tolling experiments mature around the nation and data and methodologies can be accommodated to examine such questions.

One interesting finding in the first essay is the larger road pricing elasticity found among intercity drivers on toll roads compared to those among urban toll road drivers. This finding contrasts with the conventional thinking that drivers in urban areas would be more responsive to toll increases than drivers in rural areas because alternative free lanes are always available in urban areas and therefore drivers may choose to use or pay for tolls. The second essay, *Road Pricing Elasticity of Demand for U.S. Toll Roads – A Dynamic Panel Data Analysis*, examined the question of whether driver sensitivity to road pricing differs by geographic location of a facility. In the United States, studies on travel demand for toll roads mainly focus on one or few facilities at the same time, which makes it difficult to compare the variation of price elasticity across facilities. Access to a large panel dataset of U.S. toll facilities from a private firm enabled the author to examine the question by employing a dynamic panel data model. The analysis of travel demand data for 64 U.S. toll roads in 15 states from 2004 to 2013 shows that the short-run price elasticity is smaller for urban toll roads than intercity roads and smaller for interstate than non-interstate toll roads. One explanation is that despite the availability of free alternative routes in urban areas, they are not practical to use due to higher travel cost and reduced travel time savings because of congestion.

The problems of congestion have continued to grow over time. Road pricing was banned on federally funded highways from 1957 to 1991. Many alternatives to road pricing were promoted, including policymakers widely adopting high-occupancy vehicle (HOV) lanes to manage congestion while promoting carpooling. After the completion of interstate highway construction, the federal government began to test the idea of road pricing through various pilot programs. One idea was to convert existing HOV facilities to tolled lanes called high-occupancy toll (HOT) lanes.

The third essay, *Impact of HOV-to-HOT Conversion on Drivers*, evaluated the impact of the HOV-to-HOT conversion projects on traveler behavior, especially carpoolers who used to benefit from HOV policies before the conversion. This research takes the I-85 Express Lanes project in Atlanta, Georgia, as an empirical case to examine the question. The binary logit estimators show that drivers in medium- to high-income groups, younger age cohorts, being white, having smaller household size, and taking trips for child care purposes were more likely to drive in the express lanes. Females driving to take care of their children were less likely to use the express lanes, but the result was not statistically significant.

The United States has been experimenting with various forms of road pricing. The three essays in this dissertation show that the political acceptance of road pricing, the available regulatory framework, and technological development at the time of implementation affect the design and implementation of road pricing at the time of policy discussion. This dissertation research examined two main types of priced road facilities in the United States. The first type is traditional toll roads that began operations between the 1950s until the early 2000s, where drivers pay a fixed amount of tolls. The second type is the hybrid HOV-to-HOT conversion projects that began to appear early in the 1990s that utilize existing road infrastructure and implement multiple congestion management schemes at the same time, including variable/dynamic road pricing, carpooling, and transit subsidies. The findings from the analysis of traditional toll roads provide implications for the future implementation of road pricing on the entire interstate network in the United States, as proposed by the Obama Administration in the GROW AMERICA bill in 2014. The analysis of the project in Atlanta, Georgia, provides implications for policymakers considering converting existing HOV lanes to tolled lanes.

Incremental changes in road pricing policies in the United States have resulted in another type of road pricing scheme called the toll concession model, in which private investors operate publically owned road infrastructure taking risks at various levels, such as demand-risk, construction cost risk, or operation and maintenance service level risk. The concession projects in Northern Virginia (i.e., I-495, I-95, and upcoming I-66 projects) have been exceptionally successful in terms of providing the expected benefits of road pricing and partnering between public and private stakeholders. These projects often combine all existing congestion management schemes that have been proven to be successful in project evaluations, including ones discussed in this dissertation. Despite the fact that concession projects involve private entities, variation in user responses to diverse road pricing schemes are expected to be similar to findings from this dissertation.

Consequently, the dissertation results are expected to provide insights on future innovations in road pricing.

APPENDIX

Appendix A. Summary of Surveyed Studies

Table A1 Summary of studies

Author	Country	Method	Facility	Data	Toll Elasticities: Passenger Car	Toll Elasticities: Heavy Truck	Toll Elasticities: All Vehicles	Notes
Alvarez, Cantos and Garcia (2007)	Spain	static discrete choice	9 routes in the Mediterranean coastal strip	Static: 1989-2000, quarterly Discrete choice: SP survey	Static: -0.537 (1) Discrete: -0.509 (1)	Static: -0.395 (1) Discrete: -0.247 (1)		Static: DV - Number of journey; IV - toll, fuel, GNP, time dummy Discrete choice: Logit; route choice set – toll and free route
Bari, Burris and Huang (2015)	US	dynamic	SH130 (segment 1-4) / SH45SE	2008-2011, monthly		-0.77 [-1.49, -0.39] (3)		DV - average daily toll transactions (ADTT); IV – lag ADTT, toll, diesel price, unemployment rate, GDP
Cervero (2012)	US	static	San Francisco-Oakland Bay Bridge	2009-2011, monthly			-0.216 [-0.296, -0.119] (3)	DV - traffic volume; IV - toll, gasoline price, unemployment rate, BART ridership, major events dummy
De Grange et al. (2015)	Chile	static	Autopista Central, Costanera Norte, Vespucio Norte, Vespucio Sur	2009-2010, hourly			-0.18 [-0.47, -0.044] (8)	Fixed variable pricing; DV – transaction; IV - toll, fuel price, alternative road traffic flow, time dummy
Dehghani et al. (2003)	US	discrete choice	Toll roads in Orlando I-4 corridor	2000, SP survey	-0.354 [-0.43, -0.3] (5)			Generalized nested logit (ML); nests – route choice, time of day, trip purpose; mode choice sets – solo driving, carpool, transit
Finkelstein (2009)	US	static	33 to 76 US toll roads, bridges, tunnels	1950-2005, annual			-0.058 [-0.062, -0.049] (6)	DV - traffic volume; IV - toll, toll interacted with the ETC penetration rate
Gifford and Talkington (1996)	US	static	Golden Gate Bridge	1979-1983, monthly			-0.098 [-0.187, 0.021] (4)	Fixed variable pricing; DV - average daily traffic; IV - toll, gasoline price, time dummy
Gomez and Vassallo (2015)	Spain	dynamic	14 toll roads	1990-2007, annual		-0.201 [-0.333, -0.069] (2)		DV - vehicle-km travelled (VKT); IV - lag VKT, toll, fuel cost, GDP
Gomez, Vassallo, and Herraiz (2015)	Spain	dynamic	14 toll roads					DV - annual average daily traffic volume (AADT); IV - lag AADT, toll, fuel price, GDP

Author	Country	Method	Facility	Data	Toll Elasticities Passenger Car	Heavy Truck	All Vehicles	Notes
Hirschman et al. (1995)	US	before-and-after static	Triborough Bridge and Tunnel Authority 8 bridges and tunnels			1990-2010, annual	-0.252 [-0.4, -0.103] (2)	Before-and-after: shrinkage ratio Static: DV - traffic volume; IV - toll, gasoline price, employment, car registration, transit fare, transit strike dummy, time dummy
Holguín-Veras and Allen (2013)	US	discrete choice	New Jersey Turnpike	2004, SP survey	-0.354 [-0.856, -0.054] (28)	Before-and-after: 6-month interval when tolls increased in 1980, 1982, 1984, 1986, 1987, 1989 Static: 1979-1990, monthly	Static: -0.124 [-0.5, 0.19] (8)	Fixed variable pricing; Joint logit (ML); route choice set – toll and alternative route
Holguín-Veras, Ozbay and de Cerreño (2005)	US	before-and-after	Port Authority of New York and New Jersey bridge and tunnels	2000:04-08 / 2001: 04-08	-0.995 [-1.973, -0.316] (48)	-0.305 [-0.559, 0.169] (23)		Shrinkage ratio; Demand - traffic volume
Huang and Burris (2013)	US	dynamic	Toll facilities in California, Florida, Kansas, Maryland, and Oklahoma	various periods between 2000 and 2010, monthly	-0.229 [-0.79, 0.01] (19)	-0.124 [-0.85, 0.52] (18)	0.02 (1)	DV – traffic volume; IV – lag traffic volume, fuel price, unemployment rate, population
Loo (2003)	Hong Kong	static	6 tunnels in Hong Kong	1979-2000, monthly	-0.154 [-0.309, 0.054]			DV - traffic volume; IV - toll, population, income, gasoline price, parking fee, cars registered, time dummy
Luk (1999)	Singapore	before-and-after	Central Business District and Expressways	1975, 1989, 1997	-0.338 [-0.58, -0.19] (4)			Arc elasticity; Demand - traffic volume
Matas and Raymond (2003)	Spain	dynamic	72 toll road sections	1981-1998, annual	-0.597 [-1.307, -0.2092] (8)			DV - annual average daily traffic volume (AADT); IV - lag AADT, toll, gasoline price, GDP
Odeck and Bråthen (2008)	Norway	before-and-after dynamic	19 toll facilities	Before-and-after: n/a Dynamic: 10-year data			Before-and-after: -0.623 [-2.26, -0.03] (15) Dynamic: -0.721 [-0.9, -0.55] (10)	Before-and-after: arc elasticity; Demand - traffic volume Dynamic: DV - traffic volume; IV - lag traffic volume, household income, time dummy
Olszewski and Xie (2005)	Singapore	before-and-after	Central Business District and Expressways	n/a	-0.159 [-0.324, -0.082] (6)	-0.058 [-0.109, -0.007] (2)	-0.128 [-0.265, -0.069] (7)	Fixed variable pricing; arc elasticity; Demand - traffic volume
Small, Winston and Yan (2005)	US	discrete choice	SR91 Express Lanes	1999-2000, SP & RP survey	-1.588 (1)			Mixed logit (MSLE); route choice set – toll and free route

Author	Country	Method	Facility	Data	Toll Elasticities Passenger Car	 Heavy Truck	 All Vehicles	Notes
Washbrook, Haider and Jaccard (2006)	Canada	discrete choice	Greater Vancouver suburb	2001, SP survey	-0.353 [-0.41, -0.31] (4)			Conditional logit (ML); mode choice set - solo driving, carpool, express bus
Wen and Tsai (2005)	Taiwan	discrete choice	Taiwan National Freeway	2004, SP survey	-0.214 [-0.328, -0.135] (6)			Fixed variable pricing; Nested logit (ML); choice set – toll and free route; nests - departure time
Wuestefeld and Regan (1981)	US	before-and-after	13 toll roads and 3 bridges	various periods between 1978 and 1980	-0.168 [-0.26, -0.06] (11)	-0.221 [-0.31, -0.08] (11)	-0.21 [-0.31, -0.03] (5)	Shrinkage ratio; Demand - traffic volume
Yan, Small and Sullivan (2002)	US	discrete choice	SR91 Express Lanes	1999, RP survey	-0.677 [-0.901, -0.5336] (18)			Fixed variable pricing; Joint logit (WESMLE); Nested logit (WESMLE); Choice set – toll and free route; nests – transponder, mode, time of day
Zhang and Marshment (2012)	US	dynamic	Turner Turnpike and Will Rogers Turnpike in Oklahoma	1973-2010, quarterly	-0.106 [-0.114, -0.098] (2)			DV - traffic volume; IV - lag traffic volume, toll, non-agricultural employment, gasoline price,

Notes: Minimum and maximum values are in brackets. The number of observations are in parentheses. SP = stated preference. RP = revealed preference. DV = dependent variable. IV = independent variables

Appendix B. List of Toll Facilities and Summary Statistics

Table B1 List of toll facilities included in the analysis (total 64 facilities)

	State	Tol l Facility Name	Open Year	Urban	Intercity	Interstate
1	CA	San Joaquin Toll Road	1996	1	0	0
2	CO	E-470	1991	1	0	0
3	CO	Northwest Parkway	2003	1	0	0
4	DE	Delaware Turnpike - JFK Memorial Highway (I-95)	1963	0	1	1
5	DE	Korean War Veterans Memorial Highway (SR 1)	1957	0	1	0
6	FL	Miami Airport Expressway (SR 112)	1961	1	0	0
7	FL	Alligator Alley (I-75)	1969	0	1	1
8	FL	Martin Anderson Beachline Expressway Central (SR 528)	1967	1	0	0
9	FL	East-West (Dolphin) Expressway (SR 836)	1969	1	0	0
10	FL	Don Shula (South Dade) Expressway (SR 874)	1973	1	0	0
11	FL	Florida Turnpike Homestead Extension	1973	1	0	0
12	FL	East-West Expressway (SR 408)	1973	1	0	0
13	FL	East-West Expressway (SR 408)	1973	1	0	0
14	FL	Lee Roy Selmon Crosstown Expressway	1976	1	0	0
15	FL	Sawgrass Expressway (SR 869)	1986	1	0	0
16	FL	Seminole Expressway	1989	1	0	0
17	FL	Central Florida Greenway (SR 417)	1989	1	0	0
18	FL	Gratigny Parkway (SR 924)	1992	1	0	0
19	FL	Veterans Expressway (SR 589)	1994	1	0	0
20	FL	Southern Connector Extension (SR 417)	1996	1	0	0
21	FL	Polk Parkway (SR 570)	1998	1	0	0
22	FL	Daniel Webster Western Beltway (SR 429) - OOCEA	2000	1	0	0
23	FL	Suncoast Parkway (SR 589)	2001	1	0	0
24	FL	Daniel Webster Western Beltway (SR 429) - Turnpike	2005	1	0	0
25	IL	Jane Addams Memorial Tollway	1958	0	1	1
26	IL	Tri-State Tollway	1958	1	0	1
27	IL	Reagan Memorial Tollway	1958	0	1	1
28	IL	North-South Tollway	1989	1	0	1
29	ME	Maine Turnpike	1947	0	1	1
30	MD	JFK Memorial Highway	1963	0	1	1
31	MA	Massachusetts Turnpike	1957	0	1	1
32	MA	Boston Extension	1964	1	0	1
33	NJ	New Jersey Turnpike	1951	0	1	1
34	NJ	Garden State Parkway	1954	0	1	0
35	NJ	Atlantic City Expressway	1965	0	1	0
36	OK	Turner Turnpike	1953	0	1	1
37	OK	Will Rogers Turnpike	1957	0	1	1
38	OK	H.E. Bailey Turnpike (I-44)	1964	0	1	1
39	OK	Indian Nation Turnpike	1966	0	1	0
40	OK	Muskogee Turnpike	1969	0	1	0
41	OK	Cimarron Turnpike	1975	0	1	0
42	OK	Cherokee Turnpike	1991	0	1	0
43	OK	John Kilpatrick Turnpike	1991	0	1	0
44	OK	Chickasaw Turnpike	1991	0	1	0
45	OK	Creek Turnpike	1992	0	1	0
46	PA	Pennsylvania Turnpike Northeast Extension (I-476)	1955	0	1	1
47	PA	Mon-Fayette Expressway (Turnpike 43)	1990	0	1	0
48	PA	James E. Ross Highway (I-376)	1991	0	1	0
49	PA	Amos K. Hutchinson Highway (Toll 66)	1993	0	1	0
50	PA	Southern Beltway (Turnpike 576)	2006	1	0	0

51	SC	Greenville Southern Connector	2001	1	0	1
52	TX	Hardy Toll Road	1987	1	0	0
53	TX	Sam Houston Toll Road	1988	1	0	0
54	TX	Westpark Tollway	2004	1	0	0
55	TX	Fort Bend Parkway Toll Road	2004	1	0	0
56	TX	Fort Bend Westpark Tollway	2005	1	0	0
57	TX	SH 45 North	2007	1	0	0
58	TX	SH 130	2007	1	0	0
59	TX	Loop 1	2007	1	0	0
60	VA	Powhite Parkway	1973	1	0	0
61	VA	Downtown Expressway	1976	1	0	0
62	VA	Dulles Toll Road	1984	1	0	0
63	VA	Chesapeake Expressway	2001	0	1	0
64	WV	West Virginia Turnpike	1952	0	1	1

Table B2 Summary statistics of variables by functional class and geographic coverage

	Observation	Mean	Std. Dev.	Min	Max
All Samples - 64 facilities					
Total transaction (million)	539	58.54	83.40	0.34	610.09
Toll per mile ($)	539	0.11	0.07	0.02	0.38
Gas price (million Btu)	539	22.72	3.61	15.68	30.61
Household income ($)	539	50,115	6,890	37,667	73,614
Population (million)	539	12.51	8.10	0.83	38.33
Miles	539	42.13	38.41	3.00	173.00
Interstate Urban - 4 facilities					
Total transaction (million)	37	137.69	128.72	4.54	367.20
Toll per mile ($)	37	0.14	0.05	0.04	0.24
Gas price (million Btu)	37	22.85	3.77	16.16	28.79
Household income ($)	37	52,341	6,729	38,857	62,544
Population (million)	37	9.08	3.74	4.20	12.91
Miles	37	32.20	26.61	12.00	77.36
Interstate Intercity - 13 facilities					
Total transaction (million)	120	66.80	72.41	5.53	250.31
Toll per mile ($)	120	0.07	0.08	0.02	0.38
Gas price (million Btu)	120	22.90	3.78	15.68	29.56
Household income ($)	120	51,460	8,099	37,667	73,614
Population (million)	120	7.04	5.42	0.83	19.55
Miles	120	87.05	29.35	11.00	123.00
Non-Interstate Urban - 33 facilities					
Total transaction (million)	259	48.39	53.00	1.65	304.97
Toll per mile ($)	259	0.15	0.06	0.05	0.37
Gas price (million Btu)	259	22.85	3.49	16.11	30.61
Household income ($)	259	48,860	5,416	43,725	64,300
Population (million)	259	18.55	6.54	4.60	38.33
Miles	259	19.00	14.86	3.00	70.00
Non-Interstate Intercity – 14 facilities					
Total transaction (million)	123	48.03	111.49	0.34	610.09
Toll per mile ($)	123	0.07	0.03	0.02	0.18
Gas price (million Btu)	123	22.23	3.63	15.68	28.55
Household income ($)	123	50,775	7,932	42,008	73,614
Population (million)	123	6.17	3.83	0.83	12.74
Miles	123	50.00	42.17	13.40	173.00

Appendix C. Serial Correlation Test by Wooldridge (2010)

Suppose the fixed effect model for a panel data is

$$y_{it} = X_{it}\beta_1 + a_i + u_{it} \qquad t = 1, 2, \cdots, T$$

where X_{it} is a time-varying covariates, a_i is the intercept for cross-sectional unit i called "fixed effect" or an "unobserved effect," and u_{it} is the error term. The procedure for testing the serial correlation is as follows (Wooldridge 2010; Drukker 2003):

- To begin with, first-difference the data and run the first-difference model

$$y_{it} - y_{it-1} = (X_{it} - X_{it-1})\beta_1 + (u_{it} - u_{it-1})$$
$$\Delta y_{it} = \Delta X_{it}\beta_1 + \Delta u_{it}$$

- Obtain the residuals $\widehat{\Delta u_{it}}$;
- Regress the obtained residuals on their lags

$$\widehat{\Delta u_{it}} = \hat{\rho}_1 \widehat{\Delta u_{it-1}} + error_{it}$$

- Test the null hypothesis that the coefficient $\hat{\rho}_1$ on the first-order lagged residual is equal to -0.5.

The null hypothesis for the test is based on the following fact about the residuals $\widehat{\Delta u_{it}}$

$$corr(\Delta u_{it}, \Delta u_{it-1}) = \frac{cov(\Delta u_{it}, \Delta u_{it-1})}{\sqrt{var(\Delta u_{it})}\sqrt{var(\Delta u_{it-})}} = \frac{-\sigma_e^2}{2\sigma_e^2} = -0.5.$$

Finally, the test statistics is the t statistics.

Appendix D. Derivation of Long-Run Elasticity Estimator

This proof is adapted from Berndt (1991). Suppose a traveler desires to adjust the travel demand in the long run due to changes in factors affecting the travel demand. Let y_t be the actual travel demand in time t, y_t^* is a long-run desired or equilibrium travel, and x_{1t} to x_{kt} are K factors affecting the travel demand. Conventionally, the long-run equilibrium travel is specified as the logarithmic form equation

$$\ln y_t^* = \alpha + \lambda_1 \ln x_{1t} + \lambda_2 \ln x_{2t} + \cdots + \lambda_k \ln x_{kt} + \epsilon_t.$$

where ϵ_t is a independently and identically distributed error term. In a short-run (or one period), people may not fully adjust their travel demand to the desired level. This relationship between the actual and desired level of travel demand adjustment is conventionally specified as

$$\ln y_t - \ln y_{t-1} = \phi(\ln y_t^* - \ln y_{t-1}) + \eta_t$$

where η_t is a random error. If $\phi = 1$, then the adjustment occurs immediately whereas if $\phi = 0$ the adjustment cannot exist. It is therefore assumed $0 < \phi \leq 1$.

Solving equation (*) for $\ln y_t^*$ will yield

$$\ln y_t^* = \frac{1}{\phi}\ln y_t + \frac{\phi - 1}{\phi} \cdot \ln y_{t-1} - \frac{1}{\phi} \cdot \eta_t$$

where the unobserved and desired travel level $\ln y_t^*$ is expressed in terms of observed $\ln y_t$ and $\ln y_{t-1}$, parameter ϕ and the random error η_t.

Substitute the right side of the equation (*) into the left side of equation (*) and solve for $\ln y_t$ to yield

$$\ln y_t = \alpha\phi + \lambda_1\phi \ln x_{1t} + \lambda_2\phi \ln x_{2t} + \cdots + \lambda_k\phi \ln x_{kt} + (1-\phi)\ln y_{t-1} + (\epsilon_t\phi + \eta_t)$$

where $\lambda_i\phi$ is underlying structural parameters and $\epsilon_t\phi + \eta_t$ is a composite disturbance error term. For empirical estimation, equation (*) can be written more simply as

$$\ln y_t = \delta + \beta_1 \ln x_{1t} + \beta_2 \ln x_{2t} + \cdots + \beta_k \ln x_{kt} + \gamma \ln y_{t-1} + \upsilon_t$$

where $\delta = \alpha\phi$, $\beta_i = \lambda_i\phi$, $\gamma = 1-\phi$, and $\upsilon_t = \epsilon_t\phi + \eta_t$.

In the short-run, elasticities of demand for travel with respect to x_i is $\beta_i = \lambda_i\phi$ since over one period, change in $\ln x_{it}$ affect $\ln y_{it}$ by $\frac{\partial \ln y_{it}}{\partial \ln x_{it}}$. In the long run, as $\phi \to 1$, the total or cumulative effect of $\ln x_{it}$ on $\ln y_{it}$ is λ_i in equation (*), which can be obtained by first obtaining the value for ϕ and divide coefficients $\lambda_i\phi$ by ϕ. The same can be done with the simple econometrics model in equation (*) by first estimating γ and dividing parameter coefficients β_i by $1-\gamma$, therefore the long-run elasticity of demand is $\frac{\beta_i}{1-\gamma}$.

Appendix E. Comparison of OLS, Fixed Effects, Difference GMM and System GMM Models

In this appendix, estimation results using OLS, Fixed Effects, Difference GMM, and System GMM models are presented to check the consistency of estimated lagged dependent variable ρ in the system GMM model in Table 2 Column 1. Hsiao (1986) and Bond (2002) show that the ordinary least squares (OLS) estimator of ρ is inconsistent and biased upwards. Blundell and Bond (1998) and Bond (2002) shows that the within group (fixed effects) estimator of ρ treats the inconsistency by eliminating the individual effects in the error term but ρ is biased downwards. Arellano and Bond (1991) perform simulation and finds that a generalized methods of moments (GMM) estimator of ρ lies between that of the OLS and the within group estimator. Borrowing the words of Bond (2002), "Thus we might hope that a candidate consistent estimator will lie between the OLS and Within Groups [Fixed Effects] estimates, or at least not be significantly higher than the former or significantly lower than the latter."

Table E1 compares estimation results from OLS, Fixed Effects, Difference GMM and System GMM models using 539 observations and 64 facilities from 2004 to 2013.

Table E1 Model comparison, 2004-2013 (all samples)

	OLS	FE	GMM-DIFF	GMM-SYS
ln (toll rate)	0.007	-0.056	-0.089***	-0.038***
	(0.008)	(0.105)	(0.006)	(0.004)
ln (gasoline price)	-0.134**	-0.091	0.052***	-0.050***
	(0.058)	(0.089)	(0.013)	(0.006)
ln (household income)	-0.060**	-0.028	-0.003	0.201***
	(0.028)	(0.160)	(0.014)	(0.002)
ln (population)	0.013***	0.248	0.738***	0.087***
	(0.004)	(0.455)	(0.041)	(0.006)
ln (transaction) L1.	0.990***	0.685***	0.585***	0.866***
	(0.006)	(0.074)	(0.004)	(0.002)
Observations	539	539	522	539
Number of facility_id		64	64	64
Sargan Test of overid. restriction	.	.	Chi2(49): 57.68 (P>chi2:0.185)	Chi2(59)=62.6 (P>chi2: 0.35)
Arellano-Bond Test for AR(1)	.	.	-1.833 (P>z: 0.067)	-1.914 (P>z: 0.056)
Arellano-Bond Test for AR(2)	.	.	0.742 (P>z: 0.458)	0.822 (P>z: 0.411)

*Notes: Standard errors are in parentheses (robust standard errors in Columns 1 and 2). The significance levels are marked as *** for p<0.01, ** for p<0.05, and * for p<0.1. All estimates are based on system-GMM model. The coefficients of year dummy (2006-2013) in each column are suppressed. Columns 3 and 4 use two-step estimator and maximum lags of dependent variable for use as instruments are capped to 5 lags.*

Appendix F. Validity of Using GMM Approach for a Panel Data with Large *T*

This appendix discusses the validity of using GMM approach for panel data with large *T*. When the difference GMM approach was first introduced by Arellano and Bond (1991), and later extended to the system GMM approach (Arellano and Bover 1995; Blundell and Bond 1998), the approach was intended for situations with large *N* and small *T* panels.[6] Because the number of instruments substantially increases as *T* becomes large, usually quadratic in *T*, GMM estimator may perform poorly: instruments can overfit endogenous variables, the estimates of weighting matrix can be imprecise, standard errors may be biased, and the validity of test statistics may be weakened

[6] In addition, difference and system GMM approaches are intended to solve problems associated with endogenous regressor, fixed effects, and a limited external instruments.

(Roodman 2009). In practice, researchers restrict the number of instruments used rather than to use all available instruments (Alvarez and Arellano 2003). Another approach used is to collapse instruments to smaller sets (Roodman 2009). Using the first approach, sensitivity of estimates to the number of instruments was rigorously tested. The notes under Table 2 and Table B1 indicates the number of instruments restricted in each model if there are any.

Appendix G. Federal Programs on Road Pricing

Table G1 Federal Programs on Road Pricing, 1976 - 2016

Program	Content	Effective Fiscal Years
Road Pricing Demonstration Program	• Secretary of Transportation William T. Coleman made federal funding available for road pricing demonstration program and sent notice to mayors of cities including: Berkeley, California, Ann Arbor, Michigan; Madison, Wisconsin; Baltimore, Maryland; Atlanta, Georgia; Rochester, New York; and Honolulu, Hawaii. • Three cities expressed interest in pursuing preliminary studies: Madison, Berkeley and Honolulu. • Road pricing demonstration program was rejected in all cities during the study period.	1976
Toll Facilities Pilot Program	• Authorized by the Surface Transportation and Uniform Relocation Assistance Act • 9 states were selected as pilot states to use tolls as additional revenue to help finance federally funded roads (California, Colorado, Delaware, Florida, Georgia, Pennsylvania, South Carolina, Texas and West Virginia) • May request up to 35% of the construction cost to the federal	1987
Congestion Pricing Pilot Program	• Authorized by ISTEA • 5 pilot congestion pricing projects • Cap 3 projects on the Interstate System	1991 – 1998
Value Pricing Pilot Program	• Authorized by TEA-21 • Extension of ISTEA’s Congestion Pricing Pilot Program • 15 pilot congestion pricing projects planned • Total of $853 million of VPPP discretionary grants awarded to Urban Partnership projects in Miami, Minneapolis/St. Paul, San Francisco, and Seattle in August 2007	1998 – 2012

Program	Content	Effective Fiscal Years
	• Eliminated cap on projects on the Interstate System • Requirements on uses of revenue, performance, audit, and toll agreement • Discretionary grant component discontinued in MAP-21	
Interstate System Reconstruction and Rehabilitation Pilot Program (ISRRPP)	• First authorized by TEA-21 and reauthorized by subsequent laws (the basic structure remain the same throughout) • Allow tolls on segments of the interstate highway • Requirements on uses of revenue, audits, and toll agreement • Three projects conditionally reserved as of January 2014: I-95 in North Carolina; I-95 in Virginia; and I-70 in Missouri	1998 – 2014
Express Lanes Demonstration Program	• Authorized by SAFETEA-LU • 15 slots available; 5 projects in Texas (I-635, the North Tarrant Express, I-30, I-35E, I-595) approved in 2009 and 1 project in Georgia (I-75/I-575) conditionally approved in 2011 • This program was mainstreamed into the general toll program provisions in 23 U.S.C. 129	2005 – 2012
Interstate System Construction Toll Pilot Program	• Authorize 3 facilities on the Interstate System to toll to finance the construction of new Interstate highways • Requirements on uses of revenue, audits • All three slots reserved by states, including one in South Carolina	- Aug. 2015
GROW AMERICA Bill (proposed but not passed)	• Give the right to all states to toll interstate highways • HOVs cannot be tolled • Variable tolling • Wider range of toll revenue use • All electronic toll collection system for facilities open to traffic after October 1, 2015	2014
Fixing America's Surface Transportation (FAST) Act	• Imposed expiration timeframe on three projects selected for ISRRPP (I-95 in North Carolina; I-95 in Virginia; and I-70 in Missouri)	2015

Sources: McElroy and Timothy (2012), Federal Highway Administration (2013), Weiner (2008), and Higgins (1986)

Appendix H. HOV-to-HOT Conversion Projects in the United States

Table H1 List of HOV-to-HOT Conversion Projects in the United States

State	Name of Facility	Miles	Toll Collection Direction	Federal Authority Source	Fee Type	Notes
California	I-15 Value Pricing Project	8	Both ways	None (not a Federal-aid toll facility)		Congestion pricing & Transit Dev. Demonstration Program. HOV2+ free
California	I-680 SMART Carpool Lanes	14	S	Value Pricing Pilot Program	Dynamic Variable: Rate varies based on current traffic conditions	HOV2+ free
California	I-880 / SR 237 Express Connector	4	Both ways	Value Pricing Pilot Program	Dynamic Variable: Rate varies based on current traffic conditions	HOV2+ free
California	I-110 Express Lanes	11	Both ways	Section 166 (HOV/HOT lanes)	Dynamic Variable: Rate varies based on current traffic conditions	Congestion pricing & Transit Dev. Demonstration Program. HOV2+ free
California	I-10 Express Lanes	14	Both ways	Section 166 (HOV/HOT lanes)	Dynamic Variable: Rate varies based on current traffic conditions	Congestion pricing & Transit Dev. Demonstration Program. HOV3+ free during peak hours
Colorado	US 36 Bus Rapid Transit/HOV/Express Lanes	11	Both ways	Section 166 (HOV/HOT lanes)	Fixed Variable: Rate varies by time of day based on pre-set schedule	The first 11 miles, from I-25 to Interlocken, will open in July 2015. One express lane/HOV lane/bus rapid transit lane in each direction. It is a combined operation with I-25 HOV/ Tolled Express Lanes facility. LPT users will be assessed a surcharge for a max toll and fee of $10.00 and min of $5.00.
Colorado	I-25 HOV/Tolled Express Lanes	7	Reversible	Section 166 (HOV/HOT lanes)	Fixed Variable: Rate varies by time of day based on pre-set schedule	Facility is two lane reversible. Toll is full length. LPT users are assessed a surcharge for a max toll and fee of $6.98 and min of $1.45. HOV2+ free
Florida	I-95 Express	7	Both ways	Value Pricing Pilot Program	Dynamic Variable: Rate varies based on current traffic conditions	Trucks not allowed. HOV3+ free. Second project in the nation to increase the occupancy requirement from HOV2+ to HOV3+
Georgia	I-85 Express Lanes	15.5	Both ways		Dynamic Variable: Rate varies based on	HOV3+ free. Increased the occupancy requirement from HOV2+ to HOV3+. Urban Partnership Program

State	Name of Facility	Miles	Toll Collection Direction	Federal Authority Source	Fee Type	Notes
					current traffic conditions	
Minnesota	I-394 and I-35 W Express Lanes	11	Reversible	Value Pricing Pilot Program	Dynamic Variable: Rate varies based on current traffic conditions	HOV2+ free
Texas	US 59 (Southwest Freeway) HOV/HOT lane	14.3	Reversible	Section 166 (HOV/HOT lanes)	Fixed Variable: Rate varies by time of day based on pre-set schedule	
Texas	US 59 (Eastex Freeway) HOV/HOT lane	20.2	Reversible	Section 166 (HOV/HOT lanes)	Fixed Variable: Rate varies by time of day based on pre-set schedule	
Texas	US 290 (Northwest Freeway) HOV/HOT lane	13.5	Reversible	Section 166 (HOV/HOT lanes)	Fixed Variable: Rate varies by time of day based on pre-set schedule	HOV3+ free during peak hours. 1st project in the nation to increase the occupancy requirement to HOV3+
Texas	Katy Managed Lanes (I-10)	12	Both ways	Value Pricing Pilot Program	Fixed Variable: Rate varies by time of day based on pre-set schedule	HOV2+ free during peak hours; HOV vehicles pay tolls during non-peak hours
Texas	IH 45 North (North Freeway) HOV/HOT Lane	19.9	Reversible	Section 166 (HOV/HOT lanes)	Fixed Variable: Rate varies by time of day based on pre-set schedule	
Texas	IH 45 South (Gulf Freeway) HOV/HOT Lane	15.5	Reversible	Section 166 (HOV/HOT lanes)	Fixed Variable: Rate varies by time of day based on pre-set schedule	
Utah	Express Lanes (Salt Lake City) (I-15)	61.9	Both ways	Section 166 (HOV/HOT lanes)	Dynamic Variable: Rate varies based on current traffic conditions	HOV2+ free
Virginia	495 Express Lanes (I-495)	14	Both ways	Section 166 (HOV/HOT lanes)	Dynamic Variable: Rate varies based on current traffic conditions	Congestion management pricing does not limit the maximum toll rate.
Washington	SR 167 HOT Lanes	9	Both ways	Value Pricing Pilot Program	Dynamic Variable: Rate varies based on current traffic conditions	HOV2+ free

Sources: Bhatt et al (2008); Federal Highway Administration (2016)

Appendix I. Calculation of I-85 Express Lanes Average Weekeday Trips as Percentage of Total Trips on I-85 as in Figure 5

The traffic on I-85 Express Lanes as a percentage of total traffic on I-85 is calculated from two sources. The first source is the Georgia Department of Transportation's "Traffic Counts in Georgia" (http://trafficserver.transmetric.com/gdot-prod/tcdb.jsp?siteid=135-6287#). The author specifically compiled traffic count data from the permanent traffic count station ID 135-6287 which is located in Gwinnett County and near the City of Norcross. The traffic count station is the only permanent count station located where the I-85 Express Lanes passes. The second source is the State Road & Tollway Authority's "I-85 Express Lanes Monthly Travel Data Summaries." From these two sources, the average weekday trip count was compiled together. Based on the conversation with a staff member at the GDOT Office of Transportation Data, the author found that the station ID 135-6287 counts traffic in both general purpose lanes and the express lanes since there is no barrier between the two lanes. The author therefore subtracted the number of traffic in the I-85 Express Lanes from the total traffic count on I-85 and calculated the percentage of traffic in the I-85 Express Lanes out of the total traffic on I-85.

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BIOGRAPHY

Jeong Yun Kweun received both her Bachelor of Arts in 2007 and her Master in International Studies from in 2009 from Ewha Womans University in Seoul, South Korea. She was employed as a researcher at the Korea Institute for International Economic Policy in 2010 and a research associate at the Center for Transportation Public-Private Partnership Policy at George Mason University from May 2014 to August 2016. She also served as a transit fellow at the Northern Virginia Transportation Commission from October 2015 to May 2016. She was selected as a fellow of the International Road Federation Road Scholar Program in 2015 and received the Women's Transportation Seminar D.C. Chapter Graduate Scholarship in 2015.

EXTERNAL READER BIOGRAPHY

STEPHEN ISON
School of Civil and Building Engineering, Loughborough University,
Loughborough, Leicestershire, LE11 3TU, UK

Phone: **+44 1509 222605**
E-Mail: s.g.ison@lboro.ac.uk
URL: http://www.lboro.ac.uk/departments/cv/staff/profile/73.html

CURRENT POST

May 2007 – Professor of Transport Policy, Transport Studies Group, School of Civil and Building Engineering, Loughborough University.
August 2012 Visiting Professor Institute of Transport and Logistics Studies (ITLS), University of Sydney Business School, The University of Sydney.
August 2014 Visiting Professor Institute of Transport and Logistics Studies (ITLS), University of Sydney Business School, The University of Sydney.

OTHER POSTS HELD

Editor-in-Chief Journal of Research in Transportation Business and Management, Elsevier.
Book Series Editor Transport and Sustainability, Emerald.
Associate Editor Journal of Transportation Planning and Technology, Taylor and Francis.

QUALIFICATIONS

BA (Hons) Economics	University of Liverpool	1978
MA Transport Economics	University of Leeds	1979
Post Graduate Certificate in Educ. (Distinction)	Brunel University	1980
PhD The Policy Process and Urban Road Pricing	Loughborough University	2000

PUBLICATIONS

Ison, S.G., 2004, Road User Charging: Issues and Policies, pp. 198, Ashgate Publishing, December. ISBN 0-7546-3216-4.

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