ABSTRACT

Title of Dissertation:	WILLINGNESS TO PAY FOR EXPRESS LANES, HETEROGENEITY EFFECTS, RELIABILITY MEASURES, AND OPTIMAL CONTROL STRATEGIES FROM PASSIVELY COLLECTED DATA
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In March 2020, governments worldwide implemented various social restriction measures, including lockdowns, to mitigate the spread of the COVID-19 virus. This led to a profound shift in travel behavior, accompanied by a notable reduction in congestion. This dissertation investigates travel demand on Express Lanes (ELs) during two time periods: before the pandemic (from January 2020 to mid-March 2020) and during the pandemic (from mid-March 2020 to the end of May 2020). A large data set of trips observed on Express Lanes derived from transponders is combined with vehicle probe measures of travel times and used to estimate the willingness to pay (WTP) for travel time savings and reliability. This dissertation also addresses system-wide performance optimization by integrating multiple control strategies.

This dissertation is structured into four main chapters. The first chapter explores the change in travel behavior on Express Lanes and assesses changes in WTP before and during the pandemic across different temporal phases. The second chapter investigates the heterogeneity of among Express Lane users' WTP under the impact of lockdown policy. The third chapter provides a comprehensive analysis of users' value of travel time (VOT) and reliability (VOR) on the Express Lane before and during the pandemic. The fourth chapter extends the focus to system-wide optimization, presenting an integrated traffic management system that combines real-time ramp metering with dynamic toll pricing strategies to alleviate congestion and enhance freeway performance.

WILLINGNESS TO PAY FOR EXPRESS LANES, HETEROGENEITY EFFECTS, RELIABILITY MEASURES, AND OPTIMAL CONTROL STRATEGIES FROM PASSIVELY COLLECTED DATA

by

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Dissertation submitted to the Faculty of the Graduate School of the
University of Maryland, College Park, in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
2025

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Dedication

To my family,

Who inspired my life with science and art.

Acknowledgements

I would like to express my deepest gratitude to my advisor, Professor Cinzia Cirillo, for being the kindest and most supportive advisor I could have hoped for. She is talented, patient, open to new ideas, and staying calm to all difficulties. She took care of all my concerns that allowed me to focus on my research without worry. She taught me to be confident, and for that, I am deeply grateful.

I am truly thankful to my manager at Transurban, Dr. Erika Spissu, whose passion and dedication to her work have been inspiring during my internship. I deeply remembered what she said: We will figure it out. This saying encouraged me a lot. I am also grateful to my colleagues at Transurban. They let me know how to collaborate and communicate in the industry, and made my time there enjoyable.

I would also like to sincerely thank my committee members, Professor Paul Schonfeld, Professor Erich Battistin, and Professor Joshua Linn, for their time and effort on my dissertation defense. It ended in the relaxed atmosphere. Their feedback and comments from diverse fields enriched my research from multiple perspectives.

Additionally, I would like to express my gratitude to Dr. Yen-Yu Chen, for collaborating with me on the final chapter of this dissertation. His brought invaluable effort in bringing this research to completion. I am also deeply grateful to Professor Gang-Len Chang, Professor Yao T. Hsu, and Lecturer Vincent Pan. They all inspired me a lot by their knowledge and insights in transportation studies.

To my friends, both within my field of study and in my everyday life, thank you for your moments of joy. Hope that we will be together longer. Thanks to your flowers and greetings. Similarly, I hope I will not miss all of your important moments. To my bandmates in Go-Go Bang, making music with you has been a wonderful escape and a source of balance throughout this journey. I hope we can graduate together and celebrate with a performance that marks this incredible chapter of our lives.

Finally, again, thanks to my family: my parents, my grandparents, my aunts and my cousins for both supporting me and challenging me. Hope that you will be proud of me. And I know I deserve to be called as a genius.

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Introduction

0.1 Research background

0.1.1 Traffic congestion: A national and regional challenge

Traffic congestion is a widespread issue across the United States, causing substantial economic, environmental, and social impact. According to the 2019 Urban Mobility Report by the Texas A&M Transportation Institute (TTI), urban commuters lose an average of 54 hours annually due to traffic delays, leading to billions of dollars in economic losses and increased greenhouse gas emissions; the amount of fuel wasted in stalled traffic is up to 3.3 billion gallons a year.

The DC-Maryland-Virginia (DMV) region is considered a hazardous traffic zone due to its high population density, urban sprawl, and heavy reliance on private vehicles, leading to severe congestion. Aggressive driving behaviors, distracted driving, and frequent traffic violations further increase accident risks. Additionally, aging infrastructure, inadequate signage, and insufficient lighting contribute to unsafe driving conditions, especially at night (Rowe, 2023) Commuters in the Washington, D.C. area experience significant traffic delays, particularly along critical corridors like I-495 and I-95, losing approximately 86 hours annually to rush-hour congestion. This positions the nation's capital as the second most congested U.S. city, with an average of five minutes and thirty-seven seconds lost due to traffic for a six-mile trip (Mphofe, 2024)

Addressing congestion in this region has become a priority for policymakers and transportation planners, necessitating innovative solutions to improve mobility and reliability. Traditional congestion management strategies includes such as the use of alternative transportation modes (public transport, carpooling, and bicycling/walking), altering trip patterns (land-use policies, telecommuting, and pricing), roadway expansions, and improving traffic flow (route guidance systems, traffic signal management, and incident management) (FHA, 1995). While these approaches have provided partial relief, persistent congestion and evolving travel patterns highlight the need for more adaptive and data-driven strategies to effectively manage demand and optimize network performance.

0.1.2 Rise of dynamic pricing and Express Lanes

Traditional fixed tolling systems have struggled to address congestion issues effectively, particularly during peak hours. As traffic demand continues to grow, these static tolling approaches often fail to manage variability in real-time traffic volumes, leading to inefficient utilization of freeway capacity. In response, the United States has witnessed the emergence of various road pricing strategies over the past decades, particularly focusing on dynamic pricing aimed at improving congestion management.

Dynamic toll pricing has gain popularity over fixed tolls and time-of-day pricing as a more responsive and effective strategy for controlling congestion. Unlike static systems, dynamic pricing algorithms use real-time traffic data such as speeds and volumes to continuously adjust toll rates (Alshayeb et al., 2021). One of the applications of dynamic toll pricing system is the implementation of High-Occupancy Toll (HOT) lanes, also known as Express Lanes (ELs). These lanes have emerged as innovative solutions to manage demand and improve traffic flow. Revenues generated from Express Lanes can contribute to the upkeep of existing infrastructure, address aging facilities, and enhance overall mobility on congested corridors.

In DMV area, Express Lanes (ELs) are integral to several distinct projects, including those on the Capital Beltway (I-495), I-95, I-66, and a segment of I-395 in the State of Virginia. Distinct from traditional toll lanes, ELs offer a travel alternative for vehicles traversing major highway corridors. Specifically, in our case study, ELs are tolled lanes running parallel to general-purpose (free) lanes, featuring dynamically varying toll rates every five minutes based on traffic conditions on both the General-purpose (GP) lanes and ELs. Carpool vehicles, High Occupancy Vehicles (HOV), buses, motorcycles, and emergency vehicles enjoy unrestricted access to the ELs. Single Occupancy Vehicles (SOV) can utilize the ELs by paying a toll. Revenues generated from the operation of ELs serve as funding to offset the costs of constructing, maintaining, and enhancing transportation infrastructure.

0.1.3 Impact of COVID-19 pandemic on Express Lanes

In early 2020, the global presence of COVID-19 was already evident in numerous countries. In the United States, the Center for Disease Control and Prevention (CDC) took decisive measures to promote social distancing in mid-March 2020. Governors declared states of emergency, issued statewide stay-at-home orders and implemented unprecedented lockdown strategies, significantly restricting nonessential mobility. Individuals were mandated to stay at home except for work, essential shopping, and medical care (Hansen, 2020). Employees were encouraged to work remotely whenever possible, leading to many experiencing teleworking for the first time. The travel restrictions imposed by the lockdown, coupled with the increased flexibility in activity schedules afforded by remote work, resulted in reduced traffic volumes and less pronounced peak hours. According to data released by TomTom, among the 416 cities monitored globally, 387 witnessed a decline in traffic compared to 2019. In the USA, all 80 tracked cities experienced reduced congestion, with Washington DC notably seeing a 12 % reduction in traffic (Tomtom, 2020).

It comes as no surprise that the use of Express Lanes (ELs) witnessed a significant and dramatic decline during the pandemic, accompanied by a sharp decrease in generated revenue. In 2020, on the Capital Beltway and Interstate 95 in Virginia, revenue plunged by nearly 90 % compared to the preceding year, reflecting the implementation of restrictive policies and stay-at-home orders (Moore, 2020). Before the pandemic, ELs operated on the premise that users paid for reduced travel time and increased reliability, particularly during rush hours. However, the pandemic severely restricted travelers' ability to move while simultaneously providing them with a heightened level of spatial and temporal flexibility.

The pandemic has become a shared experience, potentially instigating substantial behavioral changes. For instance, there is a growing perception that increased flexibility enhances individual productivity and system efficiency, a sentiment that has become ingrained in daily routines (Choudhury et al., 2021; Hunter, 2019; Rahman and Arif, 2020). Some of the changes in travel behavior that manifested during the pandemic continue to persist today, evident in more flexible travel schedules and the emergence of flatter and different peak hours (Li et al., 2021). The ongoing debate revolves around whether these changes have resulted in a more efficient transportation network and whether they are enduring shifts or transient adjustments. Despite the COVID-19 pandemic that caused a significant decrease in traffic in 2020, congestion has largely recovered to pre-pandemic levels (Xie et al., 2024).

0.2 Research motivation and innovation

0.2.1 Understanding change in willingness to pay by EL users

Even though the pandemic ushered in unprecedented changes in traffic patterns and travel behavior, its impact on the operational performance of the transportation network is not fully understood. Additionally, the ways in which users responded to the crisis and how their reactions influenced the operational performance of Express Lanes remain unclear (Kodi et al., 2023). Due to the substantial loss of traffic volume, the traffic network undoubtedly became less congested, especially during peak hours. Given the varying congestion levels on General-purpose (GP) Lanes, users may now receive less benefit from choosing Express Lanes (ELs) compared to pre-lockdown conditions. In other words, travelers might find it unnecessary to opt for toll lanes to avoid congestion, save travel time and reduce variability. Therefore, I hypothesize that the pandemic and the associated lockdown policies had a significant impact on EL users' willingness to pay for time-saving benefits and reliability. In essence, the value of travel time (VOT) and the value of travel time reliability (VOR) may have undergone changes due to the unprecedented circumstances.

0.2.2 Limitations of traditional data in travel behavior analysis

Most analyses of willingness to pay for travel time savings and reliability have traditionally relied on stated preference (SP) surveys or revealed preference (RP) data collected from stationary detectors. Furthermore, the estimation of travel time reliability (TTR) has primarily been based on data from stationary sensors with high penetration rates (Steinmaßl et al., 2021). In recent years, advancements in data collection, such as GPS-based data and probe vehicle data (PVD), have provided more detailed and dynamic insights into travel time variability (Carrion and Levinson, 2013; Olszewski et al., 2018; Chen et al. 2018; Chen and Fan 2020). Building on these advancements, this study analyzes travel behavior on Express Lanes (ELs) using a combination of transponder data collected from EL users and probe vehicle data (PVD) obtained from the Regional Integrated Transportation Information System (RITIS). This integrated approach enables the analysis of individual differences in travel behavior and provides insights into dynamic traffic conditions.

0.2.3 Expanding system-wide optimization

The previous analysis, based on transponder data, focuses on estimating travel behavior and evaluating benefits for Express Lane (ELs) users. However, this approach is limited to EL performance and does not account for the overall system dynamics, particularly the interactions between EL and General-Purpose (GP) lanes. To improve system-wide efficiency, it is essential to extend the focus beyond EL users and consider strategies that optimize the entire network.

Setting control strategies, primarily toll pricing, for Express Lanes (ELs) is not a simple task. ELs are often constructed and operated through concessions between private operators and transportation authorities or regulators. This structure introduces not only in traffic management under uncertainty but also in balancing competing interests from: the operator (maximizing revenue), the travelers (minimizing travel time and cost), and the regulator (maximizing welfare, utilization and equity, minimizing energy expenditure and emissions). The tolling algorithm affects not just total benefits to society as a whole, but also how these benefits are distributed between the operator and the travelers, as well as among travelers (Xie et al., 2024). Given these complexities, the optimization of ELs control strategies should be considered as a multi-component objective, which incorporates the interests of different stakeholders.

0.3 Research framework

This dissertation is organized into four chapters, each addressing different aspects of travel behavior analysis and transportation system optimization.

The first chapter initially explored the change of travel behavior on Express Lanes (ELs) by analyzing data obtained from transponders equipped on vehicles traveling on two ELs in Virginia. The results indicate that the impact of lockdown policy was not uniform across to ELs. Within a day, rush hours exhibited poorer performance in various behavioral indicators. Moreover, ELs users who traveled only in toll mode before the pandemic are less likely to transfer to other modes in the lockdown period. Secondly, this chapter assessed changes in willingness to pay (WTP) before and during the lockdown across ELs by utilizing a generic ordered logit model (OL). According to the obtained results, WTP values are remarkably similar for two ELs, standing at $26 and $28 per hour before the pandemic. During the pandemic, WTP values increased to $36 and $34 per hour for respective ELs. Off-peak periods demonstrated higher WTPs than peak-periods and workdays, suggesting ELs users are willing to pay more to save time outside of rush hours.

The second chapter initially described the observed heterogeneity in WTP change before and during the pandemic across various temporal phases. The impact of lockdown measures is more pronounced on workdays compared to weekends. Furthermore, the pandemic leads to a shift in peak periods for ELs usage. Then advanced discrete choice modeling approaches were proposed to investigate the unobserved heterogeneity of ELs users' WTP on the basis of the OL model, including generalized ordered logit model (GOL), heteroskedastic ordered logit model (HOL) and latent class ordered logit model (LCOL). HOL estimates of WTP are significantly higher than those obtained using OL models with fixed coefficients. The GOL model reveals substantial heterogeneity among different categories of trip frequency, distinguishing between infrequent, occasional, and frequent users. While the pandemic accentuates preference heterogeneity between latent classes of users, this distinction remains relatively minor compared to the variability observed among trip frequency categories in GOL models. This underscores the belief that the unobserved preference heterogeneity in travel behavior is more aptly reflected by trip frequency rather than other trip attributes.

The third chapter presents a comprehensive modeling framework and empirical analysis of the Value of Travel Time (VOT) and the Value of Travel Time Reliability (VOR) on Express Lanes (ELs). The variability of travel time was explored across different dimensions: day-to-day, inter-day, and inter-period. The results indicate that ELs users are more willing to pay for reduced travel time variability than for actual time savings. Additionally, both the VOT and the VOR increased during the pandemic, with VOR experiencing a particularly sharp rise. Furthermore, the results suggest that ELs users would show an even greater willingness to pay to reduce travel time variability if they were aware of the true value of the reliability. The proposed methods and resulting analysis can assist toll operators and agencies in managing infrastructure effectively, without the need for survey data collection.

The fourth chapter presents an integrated traffic management system combining real-time ramp metering and dynamic toll pricing strategies to alleviate congestion and optimize corridor performance. The proposed system employs a weighted binomial logit model to capture users' lane choice behavior and the METANET framework to predict traffic flow evolution.

Evaluation on the I-495 corridor demonstrates that the integrated approach significantly reduces system-wide delays and enhances throughput while increasing revenue generation, with Express Lanes (ELs) showing substantial performance improvements. Despite these benefits, the system highlights trade-offs in lane performance and underscores the importance of balancing equity considerations in toll pricing. The findings support the potential for proactive, data-driven strategies to redefine urban transportation systems for enhanced efficiency and sustainability.

Chapter 1: Travel behavior and willingness to pay

1.1 Introduction

Willingness to Pay (WTP) for saving travel time is an important behavioral indicator especially in the context of mode (Cirillo and Axhausen, 2006; Cherry et al., 2023; Brownstone et al., 2003), route and lane choice (Lam and Small, 2001; Brownstone and Small, 2005; Figueroa-Medina et al., 2022; Cherry et al., 2023; Brownstone et al., 2003; Cirillo et al., 2010), and departure time choice (Ozbay et al., 2006; Cirillo et al., 2010) and it is fundamental for the evaluation and forecasting of current and future revenues (Cherry, et al., 2023; Hetrakul and Cirillo, 2013; Hetrakul and Cirillo, 2014). Monitoring traffic levels, speeds, and estimating WTP on ELs is essential for evaluating the proper functioning of toll-financed infrastructures. Additionally, it helps assess the effectiveness of these infrastructures as tools for transportation demand management in alleviating traffic congestion. Understanding how WTP evolves during unusual circumstances, such as a pandemic, provides valuable insights into the dynamic nature of traveler preferences and behavior, offering crucial information for effective transportation planning and management.

Hence, the focus of this chapter is on the turnpike operations before (from January 2020 to mid-March 2020) and during (from mid-March 2020 to May 2020) the COVID-19 pandemic on two ELs in the Greater Washington Area. Specifically, the main objectives of this chapter are 1) Examining changes in Express Lane utilization resulting from an unprecedented event that impacted travel conditions; 2) Developing an econometric framework using ordered logit, grounded in the frequency of Express Lane usage, to address data gaps associated with the absence of data relative to the General Purpose (GP) lanes; 3) Assessing willingness to pay (WTP) for various assets, accounting for diverse user types and time periods.

This analysis relies on real data collected from transponders that have traversed Express Lanes during specific time periods. This dataset is enriched with travel time information obtained from probe vehicles on both ELs and GP lanes. It is essential to note that the data is anonymized, devoid of any socio-demographic characteristics of the users. A thorough data analysis is undertaken to quantify changes in travel behavior across various temporal and spatial dimensions. This includes distinctions by ELs, time of day, day of the week, HOV and/or toll mode, toll payment details, as well as both vertical directions.

The remaining part of this chapter is articulated as follows. Section 1.2 presents a literature review centered around the estimation of WTP on ELs. Section 1.3 describes the data used for the analysis, while Section 1.4 provides the methodological framework for model estimation. Section 5 offers the analysis of travel behavior before and during pandemic. Results from the econometric models and WTPs are described in Section 1.6. Conclusions from this chapter together with following research directions are in Section 1.7.

1.2 Literature review

In this section, I delve into a substantial body of literature centered on Express Lanes (ELs), focusing on three primary themes: 1) the implementation of managed lanes in the USA and specifically in our study area; 2) methods to estimate WTP on ELs and results from previous studies; 3) evidence from the use of ELs and estimates of WTP during the COVID-19 pandemic.

1.2.1 Managed lanes and their implementation in the USA

The term "Managed Lanes" (ML) was introduced in the late 1990s to define special-usage highway lanes referred to High Occupancy Vehicle lanes (HOV), High Occupancy Toll lanes (HOT), Single Occupancy Vehicles (SOV); Express Lanes (ELs), and Truck-Only Toll lanes (TOT) lanes (Collier and Goodin, 2002). HOV lanes are open to motor vehicles carrying two or more people, which is intended to encourage ridesharing, reduce congestion on general-purpose lanes, and improve the overall traffic operations. In order to increase capacity on HOV lanes, HOT lanes have been implemented, which can be used by single-occupancy vehicles (SOV) for a fee (USDOT, 2015). HOT lane projects, which aim to reduce congestion, are operated by reducing travel time and increasing speed and the number of vehicles using the lane (GAO, 2012). The HOT concept uses price and access restrictions to control the number of vehicles traveling on them, and to maintain free-flow traffic conditions. HOT lanes achieve complementary regional transportation goals to optimize highway capacity, generate new revenues to support other transportation needs, provide new options to travelers in congested situations, and enhance transit service by excess revenues. The capacity to generate revenues has attracted the interest of Federal and State agencies struggling with shrinking budgets and in need to find solutions to alleviate (USDOT-FHWA, 2020). What transportation experts and economists envisioned as a demand management tools is now being viewed as a way to address funding shortfalls (USDOT-FHWA, 2022).

In the US, HOT lane facilities were introduced and are regulated by Section 166 of Title 23 United States Code (U.S.C.) laws and by its more recent amendments. Since the first implementation in California in 1995, several other States have adopted and are successfully managing HOT lanes: Florida, Texas, New York, Oklahoma, California, Pennsylvania, Illinois, and New Jersey, have more than 2,000 lane-miles of specialty facilities and toll roads each. On

Interstate 495 and 95, more than 45 miles of toll lanes have opened within the past six years, including six different projects over less than a decade. In 2007, before the economic crisis, the Virginia legislature approved the third project to construct a 14-mile HOT lane, that is the 495 ELs, to alleviate heavy traffic on the Capital Beltway around Washington DC (Daito, et al., 2013). In 2012, HOT lanes were added to the Capital Beltway; in 2014, on I-95 and part of I-395 existing lanes and reversible HOV lanes were converted to HOT lanes. The 95 ELs include the operation of HOT lanes on a 29-mile portion of the existing reversible HOV-3 facility on I-95 and I-395 in northern Virginia, with a 9-mile extension of the reversible lanes from their previous southern terminus near Virginia State Route 234 to Garrisonville Road in Stafford County. The 395 ELs project is the fifth project completed in November 2019, extending the I-95/I-395 HOT lanes approximately eight miles to north from "Turkeycock" ramp complex north of Edsall Road to the District of Columbia line, converting the existing reversible HOV lanes on I-395 to HOT lanes from near Alexandria to Washington DC. In 2019, the same project was further expanded North, significantly increasing the number of HOT miles offered in the region. In the same area, expansions towards I-270 on the Maryland side of the Capital Beltway are under development. Lastly, the Virginia Department of Transportation (VDOT) announced on November 2022 that the full 66 ELs corridor from Route 29 to Gainesville to I-495 Capital Beltway was open.

1.2.2 The impacts of pandemic on toll lane use

The COVID-19 pandemic and the consequent government responses have had enormous impacts on transportation related activities, which have been observed and measured using a variety of travel and behavioral data.

By observing behavior during pandemic, WSP (2020) predicted that the work-from-home policy would flatten the commuting peak levels in urban areas and that some employees will migrate out of major cities. During the period of pandemic, they also found a 12% increase in home-based trips, although home-based work trips decreased by 7% only; another 15% increase in trips which had other destinations rather than home or workplace was observed. The authors also concluded that no traffic jams during the pandemic “Stay at home” order might have reflected the fact that drivers were not seeing reason to use Northern Virginia’s toll lanes (Smith, 2020).

Obviously, the COVID-19 pandemic slowdown has had a greatest negative impact on congestion-priced ELs. If general-purpose lanes were no longer congested, ELs offer little to sell at premium toll price (WSP, 2020). On 495EL the number of trips reduced by approximately 72%, to 14,000 trips per day in Spring 2020, and during the same period the year before 49,000 trips were counted on the same toll lanes. Similar trends were observed on the 95EL (Moore, 2020). Moreover, traffic volume on the 495, 95, and 395 ELs hit a low in April when it was down by 80%. Through mid-June, the average daily traffic was at about 60% of pre-pandemic levels, according to toll operator Transurban’s most recent trading update (Lazo, 2020). As of July, the average daily trip frequency on 495EL was down 51% compared to July 2019, and on 95EL decreased by 36% compared to the same time a year earlier with more drivers returned (Moore, 2020). Compared to 2020, traffic improved on 495EL and 95EL in the first quarter of 2021, while the volumes were still below the level before the outbreak of the pandemic. The number of users of 95EL dropped 37.2% from 55,000 to 35,000 per day compared to 2020. Also, the traffic of 495EL went down 37.5%, from 39,000 per day to 24,000 (Shenk, 2021).

Managed Lanes on I-495 and I-95 are operated under a dynamic pricing strategy, which means that when traffic reduces on the GP lanes, tolls become cheaper, which also contributes to the loss in revenues. This was of course the direct consequence of a decline in the number of tolled lane users. For example on the 495 ELs, the average toll went down from $5.40 in early March to $2.50 in mid-June (Lazo, 2020). Toll prices paid by EL users reduced more than 50% on the facilities around the DC area. Typically, during the AM peak, the ELs to go all the way from the Beltway to the Potomac River on the busiest day in the middle of the week dropped from $35 before the pandemic to $2. The average toll price on the 95EL dropped by 15.9% to $6.95 in the first quarter of 2021. On 495EL, the average toll dropped 33.4% to $3.49 compared to the same period last year (Shenk, 2021). After the plunge period registered in late March, April, and May 2020, small positive signs of recovery were registered starting from June and the average prices on the ELs started to increase together with the number of users.

In Spring 2020 during the COVID-19 pandemic revenue from toll lanes on I-495 and I-95 drastically reduced due to the restrictions introduced in the attempt to contrast the spreading of the coronavirus. Official statistics released by Transurban reported that the toll revenue from 495 ELs in April, May, and June 2020 fell from $22 million to $3 million, which is a 88% decrease compared to the same period last year. There was also a 89.5% revenue decrease on 95 ELs (395 ELs included), from $31 million last spring to $3 million this spring 2020 on the Capital Beltway (Moore, 2020).

1.2.3 Willingness to pay for Express Lanes

A seminal paper about values of time and value of reliability on ELs was published by Lam and Small in 2001. The study is based on real data relative to commuters traveling on State Route 91, Orange County, California in 1998. Travel time on both free and tolled routes was measured using loop detectors. It was found that “value of time was $22.87 per hour, while value of reliability was $15.12 per hour respectively for men and $31.91 for women.” These rates were compared to wages in the sample and found realistic.

Revealed preference data collected in San Diego during a demonstration congestion pricing project in 1996 were used by Brownstone et al., (2003) to estimate willingness to pay to reduce travel time. It was found that for the population of regular drivers the median willingness to pay was roughly $30 per hour; which is higher compared to previous values obtained with Stated Preference data. Brownstone and Small (2005) compared values of times on two different toll facilities in California: I-15 and SR91. After weighing one of the samples to match income on the other, the value of time was found to be approximately $20, which is consistent with what found by Lam and Small (2001). The other major finding of the study is that the value of time estimated on Revealed Preference data is at least twice as large as the value calculated using Stated Preference data, which can undervalue tolled lane projects in appraisal. Results also suggested that reliability is valued at “at roughly 95–140% as highly as median travel time, depending on the measure”.

More recently, Devarasetty et al., (2012) studied travel behavior on Houston Katy Freeway, which at the time of the study was composed of four general purpose lanes and two Managed Lanes for each direction. On ML, Single Occupancy Vehicle pay a toll of $4.00, $2.00, and $1.00 for the 12 miles managed facility during peak, shoulder, and off-peak hour, respectively. They found that VOT was $51/h; this included also the value that travelers place on travel time reliability. The combined VOT and VOR value was found to be close to the estimate obtained using data relative to real usage.

Burris et al., (2012) examined the willingness to pay for travel time savings on the I-394 MnPASS ELs in Minneapolis, Minnesota, and the I-15 ELs in San Diego, California. The findings, based on Revealed Preference data, indicate that values of time for the I-394 toll lane users was on average $73/h in the morning and $116/h in the afternoon. Travelers on the I-15 ELs had a lower willingness to pay; the values of time averaged $49/h in the morning and $54/h in the afternoon. The authors concluded that the difference in the values found across the two facilities are due to the willingness to pay for reliability. This finding means that these lanes likely have added value to travelers beyond time savings.

Sheikh et al., (2014) study focuses on the 1-85 ELs in Atlanta, Georgia. The analysis is based on data collected over a period of 9 months for drivers who traveled along the “entire length of the Express Lane corridor during the morning and afternoon peak periods”. The authors report a median value of time of $36/h in the southbound morning peak period and of $26/h in the northbound afternoon peak period. These values are found to exceed the values that would be used by just considering the average wages in the region. The authors also acknowledge that reliability effects should be estimated and taken into account to calculate benefits, but the estimation of value of reliability was not part of this study.

RSG (2019) designed a stated preference (SP) survey of drivers who used any part of the I-495 and I-270 corridors during June and July of 2019 to estimate the willingness of to pay toll on using ELs. After providing sociodemographic information and answering some basic trip characteristic questions, such as income and trip purpose, respondents were required to decide between choosing the EL or regular lane under the given travel time and toll. RSG implemented the multinomial logit model (MNL) and the mixed multinomial logit model (MMNL) to identify the heterogeneity in low VOT, high VOT, and those in between. Finally they got an average VOT of $23.62 per hour for work trips and $20.55 for non-work trips at the sample mean income.

A study proposed by Cherry et al., (2023) considered the impact of COVID-19 pandemic on travel behavior and consumer preferences on ELs and estimated both VOT and value of reliability (VOR) on Stated Preference data. The sample was divided into two groups: 'Before the pandemic' corresponded to respondents who finished the survey between December 10, 2019 and March 15, 2020; 'During the pandemic' included the survey completed after March 15, 2020. The survey administrated to residents in the National Capital Region who traveled on target sections of I-495, I-66, I-95, and I-395 corridors in the last one month. VOT and VOR before and during the pandemic were estimated using a multinomial logit model (MNL). The model showed that VOTs before the pandemic were $27 and $21 per hour for work trips and nonwork trips, and that during the pandemic these values reduced by 21% and 15% respectively.

Table 1 summarizes results obtained in previous studies by presenting the authors of the paper, year of publication, data source and type, model specification and VOT estimate, and VOT adjusted by inflation and Gross Domestic Product (GDP).

Based on the evidence available in the literature, this chapter contributes to a comprehensive analysis of the impact of the pandemic on Express Lane usage, the economic valuation of these lanes by users, and the exploration of alternative data sources for model estimation in the absence of complete information about GP lane use.

Table 1: Summary of VOT estimates from previous EL studies

Author	Data	When collected	Lane type	Data type	Model	VOT estimate	VOT adjusted by inflation and GDP
Lam and Small (2001)	Mail survey by license places on SR 91; owners' address from MDOT;	1997-1998	EL-GP	RP	Binomial logit	$22.87/h	$46.18/h

	loop detector data						
Brownstone et al. (2003)	A panel survey of travelers who use I-15 Express Lanes and other I-15 users; loop detector data	1997-1999	EL-GP	RP	Conditional logit	$30/h	$60.70/h
Liu et al. (2004)	Freeway loop data from California State Route 91	1999-2000	EL-GP	RP	Mixed logit	$12.81/h	$23.58/h
Small et al. (2005)	A telephone RP survey including commuting and other trips; and a mail SP survey obtaining hypothetical time and costs on SR 91	1999-2000	EL-GP	RP-SP	Mixed logit	$21.46 by RP $11.92 by SP	$39.50 by RP $21.74 by SP
Tilahun and Levinson (2010)	A computer-administered stated-preference survey	Not mentioned	EL-GP	SP	Binomial logit	$7.44/h - $8.07/h	
Devarasetty et al. (2012)	A stated preference survey was given to Houston's Katy Freeway travelers	2010	EL	RP-SP	Mixed logit	$51/h	$68.65/h
Burris et al. (2012)	Tolling data for I-394 HOT lanes and loop detector data; Toll payment data for each traveler of the	2008; 2009-2010	EL-GP	RP	Direct estimation	$73/h (I-394) and $49/h (I-15) in the morning; $116/h (I-394) and $54/h (I-15)	$95.48/h (I-394) and $63.28/h (I-15) in the morning; $149.81h (I-394) and $69.74/h (I-

	FasTrak lanes on I-15 and vehicle detector stations (VDS)					in the afternoon	15) in the afternoon
Carrion and Levinson (2013)	A logging Global Positioning System device and a MnPass transponder on I-394 HOT lanes in the Minneapolis	2008-2009	Arterial-EL-GP	RP	Mixed logit	$9.15/h	$11.82/h
Sheikh et al. (2014)	Travel time for the I-85 Express Lanes in Atlanta, Georgia from the vehicle detection stream; and records of vehicles from detectors	2012	EL-GP	RP	Direct estimation	$36/h in the southbound morning; $26/h in the northbound afternoon	$44.17/h in the southbound morning; $31.90/h in the northbound afternoon
RSG (2019)	A designed stated preference survey of drivers on I-495 and I-270 corridors	2019	EL-GP	SP	Multinomial logit model	$23.62/h for work trips and $20.55/h for non-work trips	$23.04/h for work trips and $20.05/h for non-work trips

1.3 Data source

The analysis relies on the integration of multiple datasets, which were consolidated before initiating the behavioral analysis and modeling tasks. However, as part of an agreement with the toll operator, specific details about the exact locations where the data was collected or the corridor under examination cannot be disclosed. In presenting findings, I will generically refer to "ELs." The analysis pertains to two assets referred to as EL1 and EL2, with a focus on preserving the confidentiality of the specific locations and corridors involved in the chapter.

The primary source of data is derived from transponders detected at one of the EL entry plaza and contains information about their frequency of use over the study period. Each record in the database refers to a particular trip registered by the transponder; it contains detailed information about transponder ID, travel date, time of day, day of week, entry plaza, exit plaza, trip distance, direction, toll payment mode, and toll paid. If the toll was waved because 3+ people were in the car, this information is used to identify high occupancy vehicles. It should be mentioned that this sample of historical travel data does not include any personal information relative to users. It is also important to note the lack of information about the origin and final destination of the trip, about the traffic on GP lanes, and the change lane behavior. Eventually, I used historical travel data for two different ELs in the same regional context from January 2020 to May 2020. The two datasets contain 4,909,017 and 3,667,359 trip observations respectively on EL1, EL2 in chronological order.

Travel times on general-purpose lanes and ELs were derived from the Regional Integrated Transportation Information System (RITIS), that is a nationwide big data platform that integrates information from the private and public sectors. For this study, I adopt the travel time on a five-minute time interval provided by RITIS for the period from January 2020 to May 2020. According to RITIS, vehicle travel time can be derived from point sensor speed data or directly measured by probe vehicles. Travel times are measured for each Traffic Message Channel (TMC) segment which is characterized by a code that is unique to each segment or link, which in turns define segments of road (INRIX, 2024). By adding up the travel times on the segment that defines the path between entry and exit plazas, I obtained the total travel time on GP lanes and their corresponding on ELs for each pair observed in the primary dataset. In order to map the TMC segments to the plaza pairs, I used the indexes as defined in the TMC inventory. GP and EL segments will have the same code, with the exception of the middle letter in the TMC code.

The transponder dataset was then merged with the RITIS travel times according to the entry and exit plazas. The level of service variables available for model estimation were the following: travel time on GP lane, the travel time on EL, and consequently the travel time saved by choosing ELs, corresponding toll paid by the owners of the transponders. Data was cleaned by removing trip observations with 1) unavailable transponder ID; 2) missing GP or EL travel time; 3) negative travel time saved[1]; 4) non-positive travel cost. After cleaning the data, for the pre-pandemic phase I obtained 2,484,426 toll trip observations generated by 524,953 users/transponders for EL1; 1,584,131 toll trips by 351,903 users/transponders for EL2. During the pandemic, I observed 590,164 toll trip observations and 168,457 users/transponders for EL1; 470,959 toll trips by 151,143 users/transponders for EL2.

1.4 Methodological approach

To estimate the willingness to pay tolls among Express Lane users, an ordered logit model is selected. This model seeks to determine the utility of toll trip frequency, with the key factors being travel time saved and toll payments for the observed trips. The analysis aims to ascertain the significance of these two factors in contributing to trip generation, providing valuable insights into the decision-making processes and preferences of EL users in response to toll-related considerations.

The dataset described in Section 1.3 was used to calculate the number of trips recorded by each transponder travelling on two ELs considered for the period before lockdown (January 1st to March 15th, 2020) and the period during lockdown (March 15th to May 31st, 2020). The

[1] This assumption is not too restrictive, on EL1 just 10,426 observations have negative travel time saved, which is about 0.27 percentage of the total observations. During pandemic, the percentage of negative travel time saved is a little bit higher, but still less than 1%.

frequency of travel Y_i represents the dependent variable of the behavioral model. A natural way to think about the decision process is that the individual has some level of utility associated with the number of trips generated in the observed time period by each transponder. In ordered logit models the utility is latent and can be decomposed into an observed and an unobserved component (Train, 2009).

$$U_i = X_j'\beta + \varepsilon_i, \text{ where } i = 1, \dots, n.$$

The utility is formulated as a function of the observed travel time and travel cost:

$$U = \beta_t(\Delta T) + \beta_c(Toll) + \varepsilon_i$$

$$\Delta T = T_{GP} - T_{EL}$$

Where ΔT is the difference in travel time between GP lanes (T_{GP}) and ELs (T_{EL}) for user *i* during the targeted time period; *Toll* is the average travel cost of each trip for user *i*. β_t and β_c are coefficients to be estimated, which define how time and cost contribute to the utility to travel on ELs. Other factors except time and cost that affect the user's trip frequency are embedded into the random error term ε_i, which is assumed to be i.i.d EV distributed (Train, 2009).

The users choose to travel on ELs a certain number of trips based on their level of utility. If the utility U_i is under a certain threshold, which I label α_1, the user is supposed to travel once during that time. Similarly for all the other values that the ordinal variables assume in the dataset.

$$Y_i = \begin{cases} 1 \text{ } if -\infty < U_i \leq \alpha_1; \\ 2 \text{ } if \text{ } \alpha_1 < U_i \leq \alpha_2; \\ \dots \\ j \text{ } if \text{ } \alpha_{j-1} < U_i \leq +\infty \end{cases}$$

The ordered logit assigns probabilities that the utility will fall below a certain threshold according to the following equation, with F being the cumulative logistic distribution function:

$$\Pr(Y_i = j) = \Pr\left(\alpha_{j-1} < U_i \leq \alpha_j\right) = F\left(\alpha_j - X_i'\beta\right) - F(\alpha_{j-1} - X_i'\beta)$$

Once the ordered logit model was estimated, the corresponding value of time or the amount of toll a user is willing to pay ($) to save one hour of travel time when using the ELs. The willingness to pay is defined follows:

$$WTP = \frac{\beta_t}{\beta_c}(60 \min per\ hour)$$

WTP was calculated for the two ELs in the study areas and compared across the two time periods considered.

1.5 Changes in travel behavior on ELs during the COVID-19 pandemic

1.5.1 Travel behavior indicators

The overall analysis about the impacts of the pandemic on Express Lane users' travel behavior is presented in this Section. Table 2 shows the general data statistics relative to EL1 and EL2 for the two time periods defined as pre-lockdown and during lockdown. The travel behavior indicators computed include the total number of trips observed, the number of devices in the database, total toll paid, total distance covered on the EL assets, total travel time, total travel time saved. I also calculate the average number of trips per device and the average number of a transponder's repeated trips records, which is the number of trips generated by the same user, on the same time of day, same day of week, and same entry and exit point on the

ELs. Average cost, distance travel time, travel time saved is also reported at the device level. All the indicators are reported for EL1 and EL2 assets.

Before the outbreak of the pandemic, the larger number of total trips was found on EL1 compared to EL2, while the corresponding average trip frequency of each transponder of EL1 is slightly less than that of EL2. Comparably, the total number of users (transponders) of EL1 is greater than that of EL2. The total travel distance and travel time on EL2 are greater than those on EL1, even more, the average trip distance and trip time on EL2 are also twice as much as the corresponding indicators relative to EL1. This confirms the fact that EL2 is much longer than that of EL1, and it is commonly used for long-distance travel. EL1 serves the function of short-distance corridor for frequent travelers, such as commuting trips. On the other hand, the average time saving of each transponder on EL2 is more than two times larger than that of EL1, which indicates that the longer per trip travel distance, the more average travel time saved by choosing ELs instead of general-purpose lanes. The analysis clearly shows that the total as well as the average number of tolls paid by users of EL2 is greater compared to that of EL1 travelers.

During the pandemic, travel statistics are shown by comparing the same indicators calculated for the during pandemic period and across two ELs. From pre to during pandemic, EL1 still presents the largest number of trips as well as unique users across both ELs. EL2 still shows the greatest value of travel cost, distance, duration, and time saving. Differently, the average number of trips per transponder of EL1 became greater than that of EL2. EL1 witnesses the higher average value of repeated trips compared to EL2.

Table 2: Summary of statistics of two ELs

	EL1		EL2	
	Before	During	Before	During

Total number of trips	3,828,559	1,080,458	2,725,595	941,764
Number of devices	642,588	226,791	426,235	196,766
Total Revenues ($)	15,134,868	1,585,891	16,073,432	2,685,968
Total travel distance (mi)	21,418,498	5,871,907	31,753,429	10,865,149
Total travel time (hr)	344,626	86,955	447,800	142,059
Travel time saved (hr)	270,269	27,531	383,789	43,657
Average number of trips per device	5.336	3.963	5.471	3.761
Number of repeated trips per device	1.626	1.482	1.574	1.384
Average cost per device ($/device)	21.871	6.341	35.753	12.750
Cost per device per trip ($/device/toll trip)	5.206	2.366	9.582	5.384
Travel distance per device (mi/device)	32.709	25.530	72.913	53.461
Average travel time per device (hr/device)	0.507	0.367	1.033	0.723
Average travel time saved per device (hr/device)	0.394	0.112	0.878	0.218

Figure 1 and Figure 2 illustrate the overall change of the behavioral indicators under the impact of the pandemic and the lockdown policies. Figure 4 to Figure 15 specifically look at the variation in behavior by time of day, day of week, HOT or HOV modality, and direction of traffic.

Figure 1 illustrates the percentage change of total trip frequency, number of users, travel distance, travel time and time saving from the pre-pandemic period to the during-pandemic period. I observe a dramatic decrease of all the parameters analyzed at the total level; in particular, the total travel time saving is the most affected parameter by the pandemic policy. The percentage decrease in total travel time saving of EL1 and EL2 are 90% and 89%

respectively. These percentage changes are close to 100%, meaning that the travel time saved by choosing the Express Lane becomes roughly zero during the pandemic. That is, for the same OD pair, the travel time of general-purpose lanes and ELs are almost the same, indicating that choosing the ELs cannot actually save travel time during the lockdown period. The second large percentage decrease is found on the total toll paid. The total toll revenues plunged 90% and 83% respectively on EL1 and EL2, respectively. Since the Express Lane revenue is used to fund other transportation projects, this amount of loss is no doubt a hard hit to the Express Lane operators, which are still bracing for a gradual recovery (Moore, 2020). Moreover, the drop in revenue comes amid a sharp decline in the number of trip observations and users on ELs under the restriction of lockdown and WFH policies. The total toll trip frequency declined 72% and 65%, and came with the corresponding decrease of users (65% and 54%). Nevertheless, the number of users is the least affected parameter overall.

Figure 2 presents the percentage change of the parameters on an average for each user (transponder). Overall, the pandemic impact on the user level is much lighter than on the total level. It can be seen that the drop of the average travel time savings and toll paid are greater than other parameters, which indicate users saw less benefit from choosing ELs compared to general-purpose lanes during the lockdown period. This can also be explained by the shrink of average trip generation and travel time spent of each user on the ELs. Differently, between two ELs, each user of EL1 was less affected except the costs.

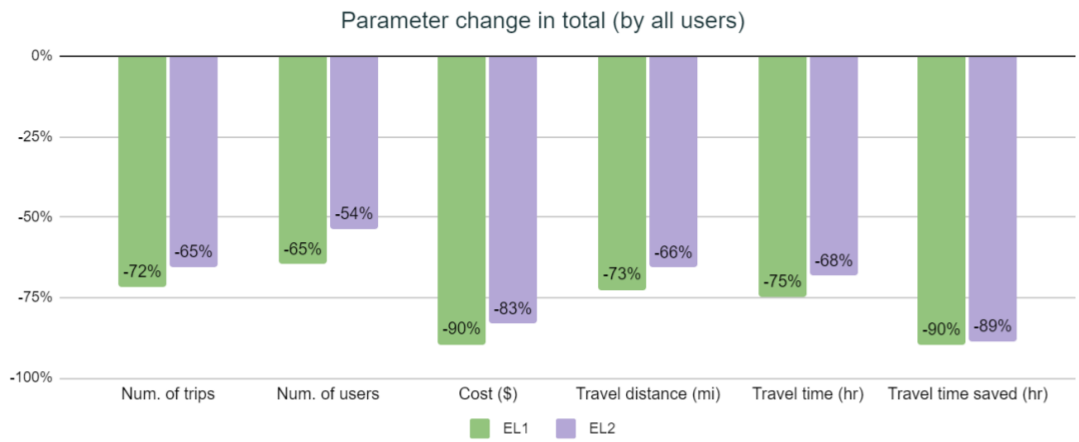


Figure 1: Parameter change in total (by all users)

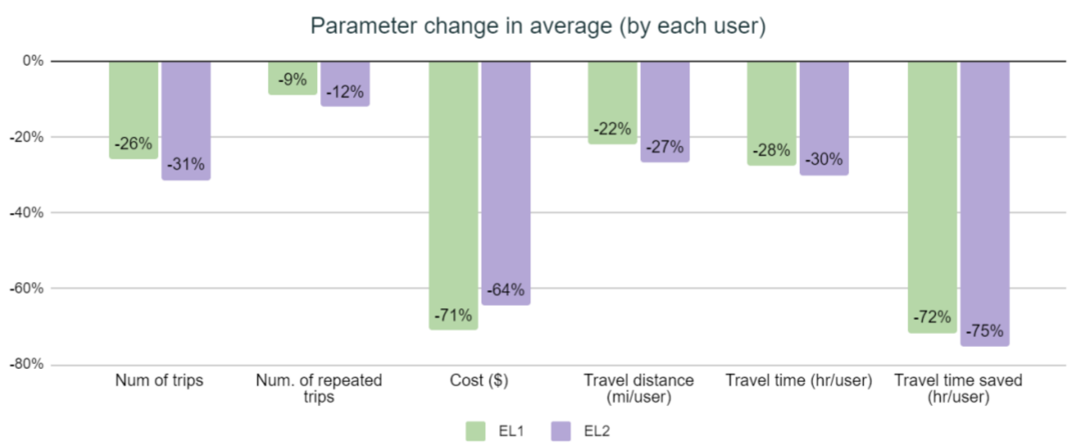


Figure 2: Parameter change in average (by each user)

I also computed the ratio between the toll paid and the travel time saved for both EL1 and EL2 pre- and during pandemic (Figure 3). Several notable observations can be made from the analysis. Firstly, there exists a distinction between EL1 and EL2. While the histograms for EL1 show minimal changes between the pre-pandemic and during-pandemic periods, the histograms for EL2 exhibit noticeable variations. This suggests that the impact of the pandemic on travel behavior and toll usage differs between the two Express Lanes. Secondly, on EL2, there is an average reduction in the toll paid by drivers for the same amount of travel time saved during the pandemic. This implies that, on average, drivers using EL2 experienced a cost saving during the pandemic period. Thirdly, it's noteworthy that although negative values are present, they constitute a small fraction of the total observations. This suggests that instances where drivers paid and did not save any travel time from the use of ELs are not the norm but rather an exception within the dataset. Finally, although there are instances of high values for the trade-offs, their occurrence represents a relatively low percentage; the majority of observations tend to align with more moderate or typical trade-off scenarios.

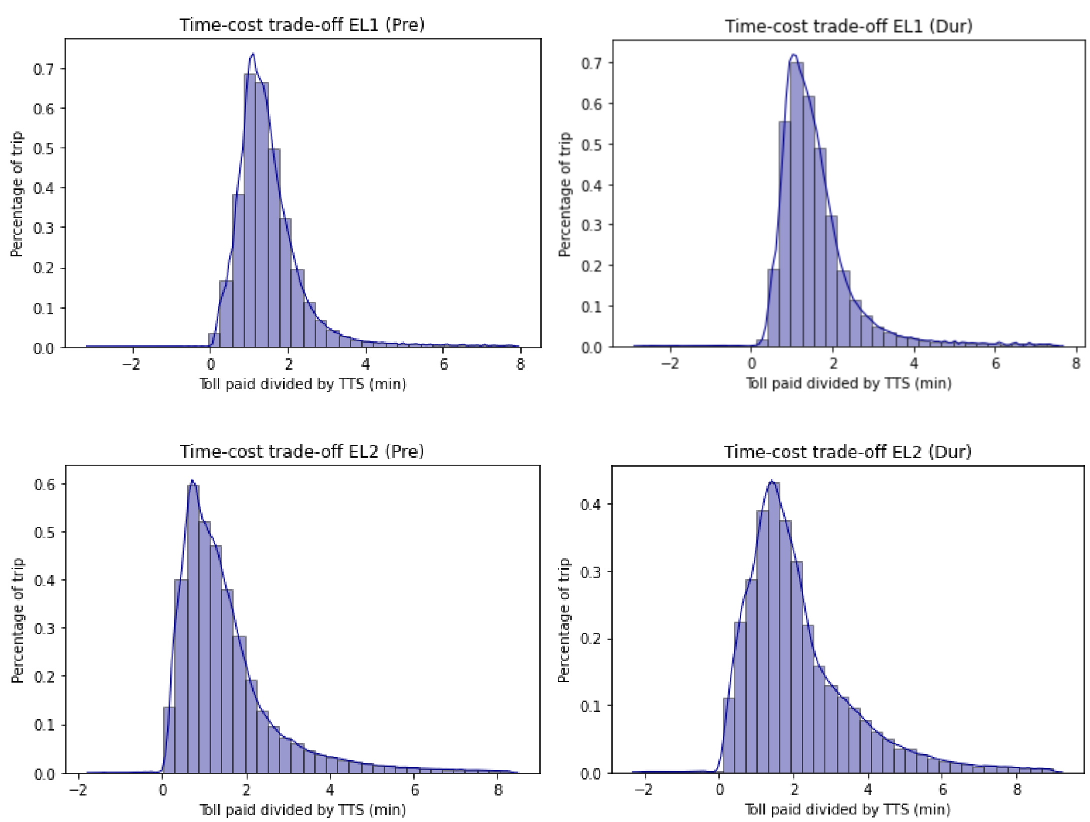


Figure 3: Trade-off between toll and travel time saved (pre and during pandemic)

1.5.2 Temporal and spatial data analysis

To comprehend the influence of the pandemic on the temporal and spatial features of traffic, I categorize all observations in the dataset based on weekday types (workdays/weekends & holidays), peak periods (AM peak/PM peak/Off-peak), toll or High Occupancy Vehicle (HOV), and directions (Northbound/Southbound). Peak periods are defined within the time frame of 7 a.m. to 8 a.m. for the morning peak (AM peak) and between 5 p.m. and 6 p.m. for the afternoon peak (PM peak). This classification scheme provides a nuanced breakdown of traffic patterns, allowing for a more detailed analysis of how different factors, such as time of day, may have been impacted during the pandemic.

Specifically, Figure 4 and Figure 8 compare the percentage change from pre-pandemic to during-pandemic and between workdays and non-workdays on EL1 and EL2 respectively. Workdays are generally impacted more than weekends/holidays by the lockdown and WFH policies, except for the number of users, which decreased more on non-workdays across the two ELs. Especially, the travel cost and travel time saved witness the largest change, followed by the number of trips between workdays and non-workdays across two ELs. The decrease in travel distance and travel time during the pandemic are similar during weekday for EL1 and EL2.

Figure 5 and Figure 9 present the percentage changes during the pandemic by different times of day. From the analysis of all ELs, it is evident that traffic declined more during rush hours, meaning that traffic during off-peak periods was less affected by the lockdown policies. However, on EL2 the reductions during the off-peak periods were similar to those observed during PM peaks. It is interesting to note that the impacts of the policy across the AM peak and the PM peak are not uniform. For example, on EL1, trip frequency, trip distance and travel time decrease by a similar degree during the AM peak and the PM peak, while on EL2 those parameters for the AM peak are much worse than for the PM peak. Besides, EL2 present the greater reduction in travel cost during the AM peak, while EL1 goes in the opposite direction. If on EL1, the decrease in travel time saved by choosing ELs during the AM peak is lower than that of the PM peak, it can be found opposite for EL2.

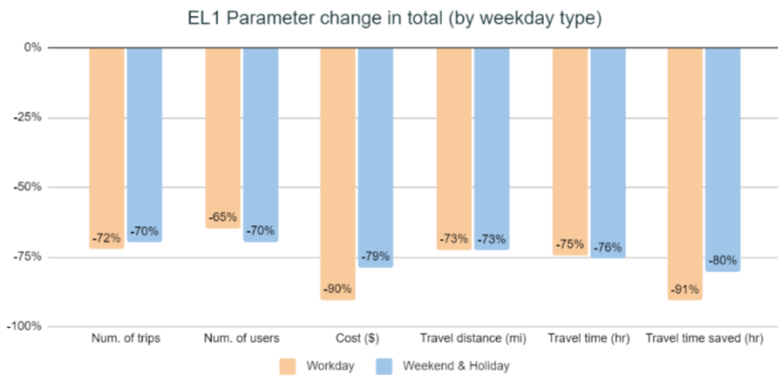
Figure 6 and Figure 10 compare the change during pandemic between toll trips and HOV trips. Interestingly, toll and HOV trips performed similarly across all the indicators. Figure 7 and Figure 11 compare the changes across the two traffic directions. The trips toward the south direction on EL1 were affected more than those leading to north under the impact of the pandemic. Besides, the northbound trips and the southbound trips were affected by a similar percentage change on EL2.

1.5.3 Users' type analysis

Now turn the attention to the Express Lane users, whose behavior is captured from a detailed exploration of the utilization of their transponders before and during pandemic. In this study, the users are classified into three categories: toll-only users, HOV-only users, and traders (i.e. those who switch from HOT to HOV and vice versa).

Figure 12 to Figure 15 represent the variation in users' trips before and during the pandemic period. Figure 12 and Figure 14 reflect the switching behavior among the three categories of users and for two ELs, while Figure 13 and Figure 15 report the corresponding generated trips. Based on the results obtained, the toll-only user is the largest proportion of user type across all the ELs, followed by the HOV-only user and traders. Before the outbreak of the pandemic, the shares of toll-only users are 71% and 64% on EL1 and EL2 respectively. The share of traders is slightly higher (7%) on EL2, than on EL1, which is about 5%. Similar findings are reported for the number of trips generated by users/transponders. EL1 and EL2 have the same share of HOV-only users (12%). During the lockdown period, EL1 lost the largest share of users (69%), followed by EL2 (62%). EL1 and EL2 also lost 65% and 54% of trips during the lockdown, respectively. It is possible to conclude that EL2 was less affected by the pandemic policy and that most of the commuting trips disappeared from EL1 under the impact of the WFH policy. Specific to the behavior of users, the share of toll-only users on EL2 (29%) is greater than that of EL1 (25%), and generated the greater value of trips during the pandemic. Similarly, the EL2 covers the most volume of HOV-only users (7%) and traders (2%) when compared to EL1.

It is worth exploring the changes in trip production caused by the lockdown and travel restriction policies (Figure 16 to Figure 19). During the pandemic, it is remarkable that EL1 lost a larger number of toll-only users (57.4%) than EL2 (51.2%). On EL1, 49.1% of trips generated by toll-only users disappeared; this percentage reduces to 38.2% on EL2. The EL1 retained the largest share of toll-only users (12.7%) from the pre-pandemic stage, and presented 11.1% of new users. Very few (no more than 0.4%) of the pre-pandemic toll-only users transitioned into other user types across two ELs. Concerning the HOV-only users, EL2 kept the greater percentage of HOV-only users (3.1%). No more than 0.3% of previous HOV-only users traveled in other modalities on the ELs across two ELs during lockdown. Lastly, on EL2 more traders transferred into toll-only users (1.4%) and HOV-only users (1.3%) during the lockdown period compared to EL1. Overall, traders are more likely to transfer into toll-only or HOV-only users, compared to other user types.



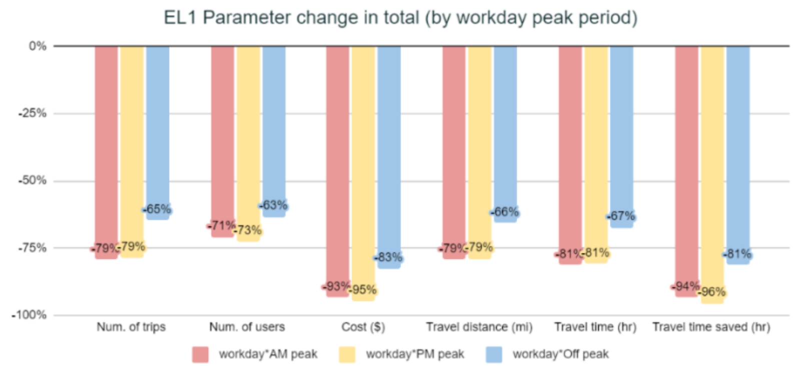
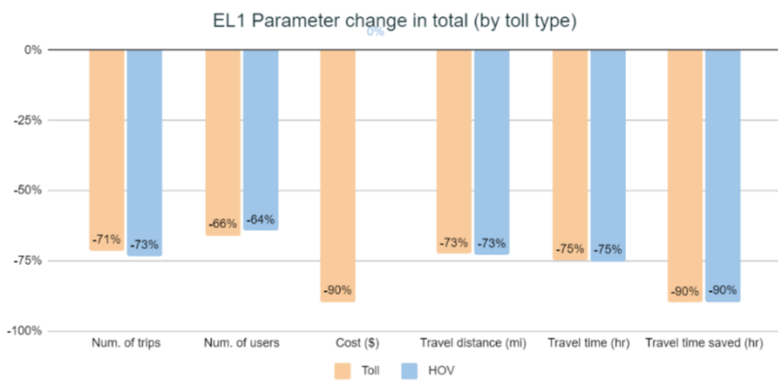


Figure 4: EL1 parameter change in total (by weekday type)

Figure 5: EL1 parameter change in total (by workday peak period)



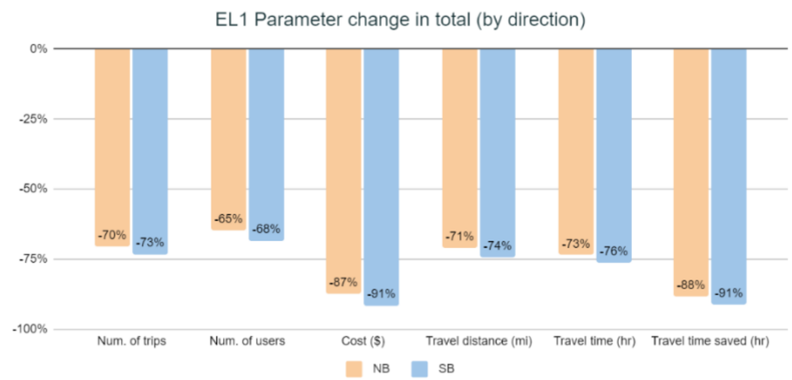


Figure 6: EL1 parameter change in total (by toll type)

Figure 7: EL1 parameter change in total (by direction)

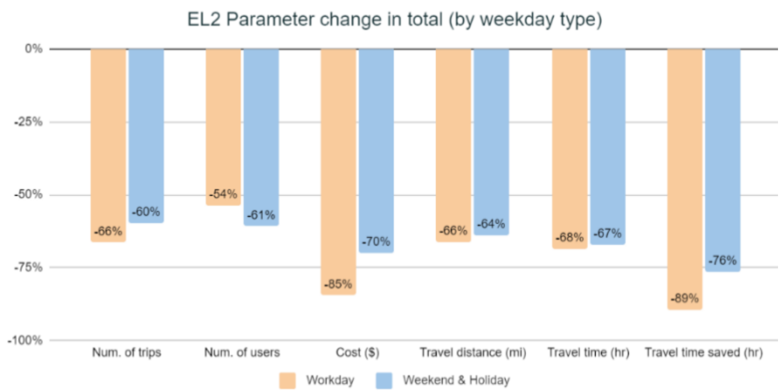


Figure 8: EL2 parameter change in total (by weekday type)

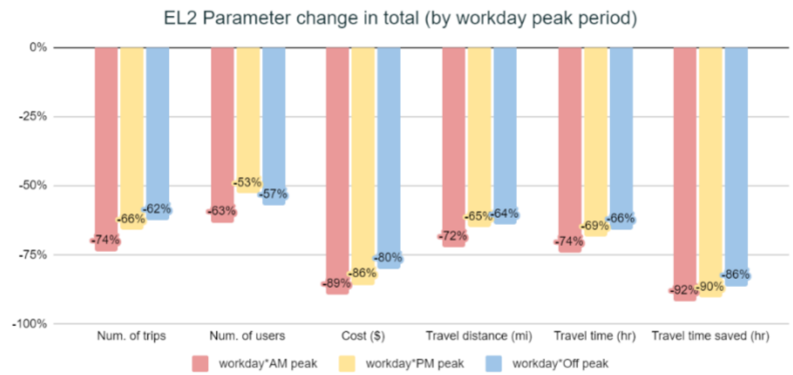


Figure 9: EL2 parameter change in total (by workday peak period)

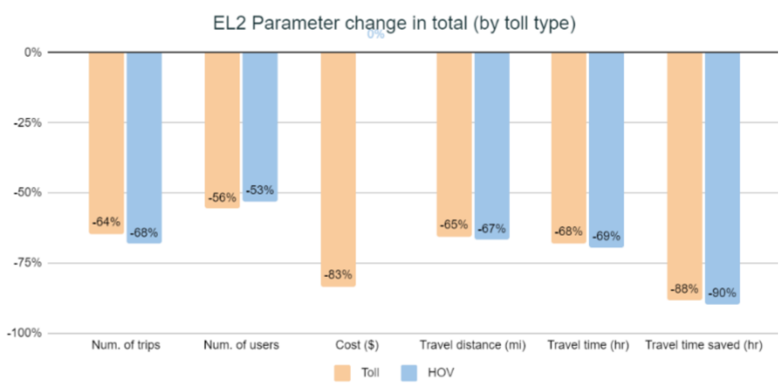


Figure 10: EL2 parameter change in total (by toll type)

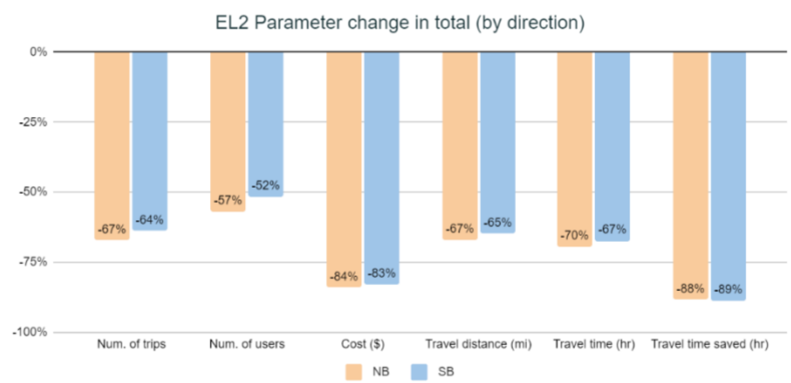


Figure 11: EL2 parameter change in total (by direction)

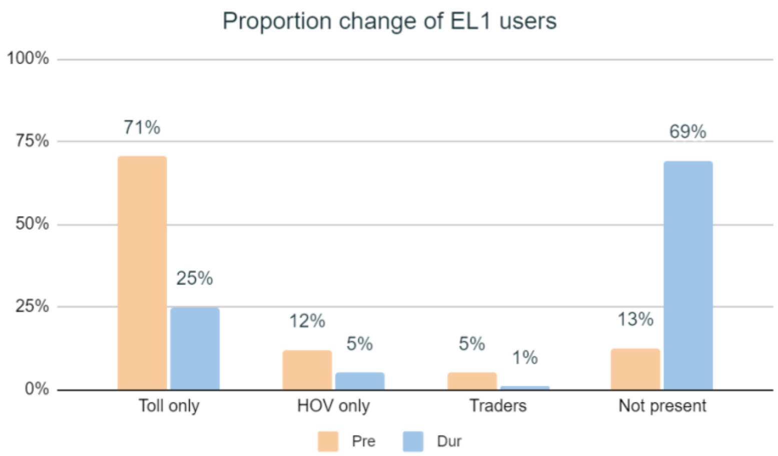


Figure 12: Proportional change of EL1 users

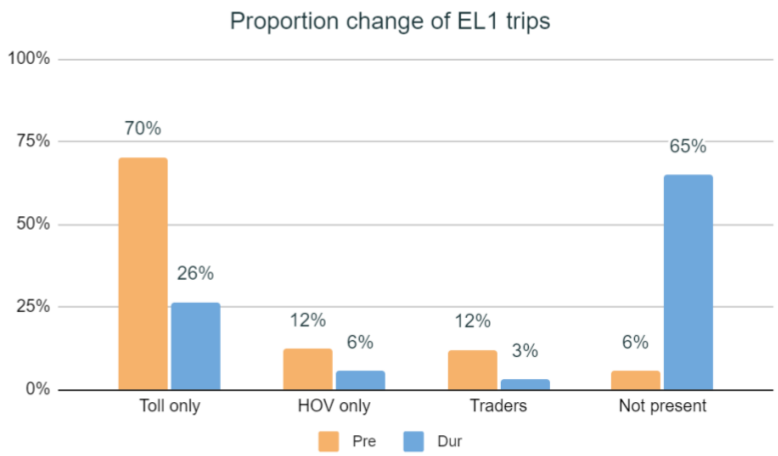


Figure 13: Proportional change of EL1 trips

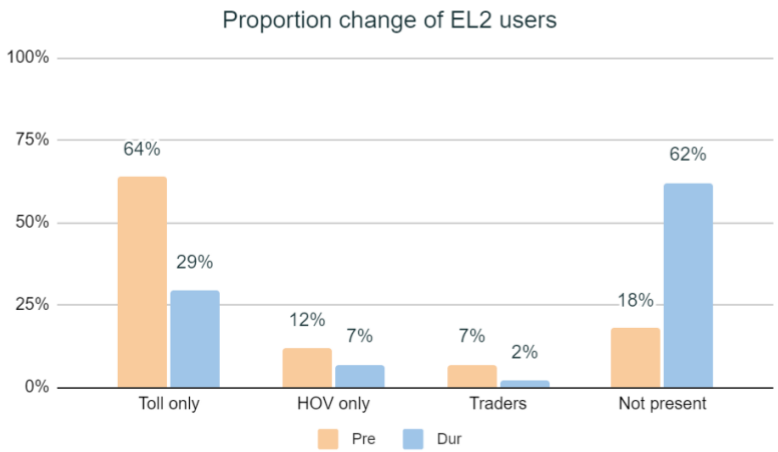


Figure 14: Proportional change of EL2 users

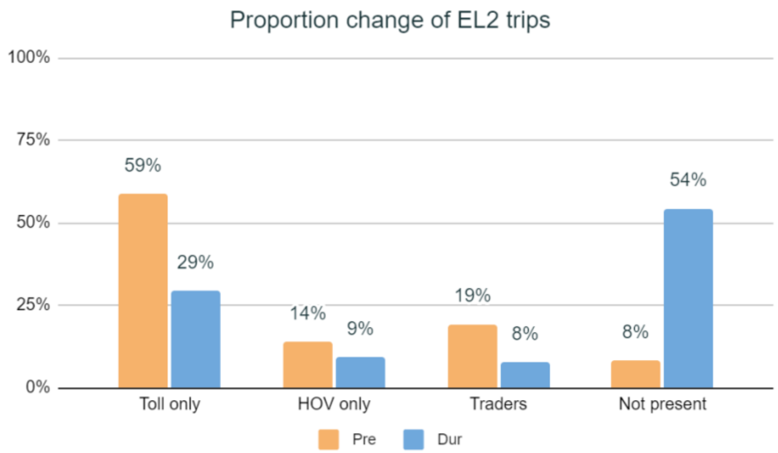


Figure 15: Proportional change of EL2 trips

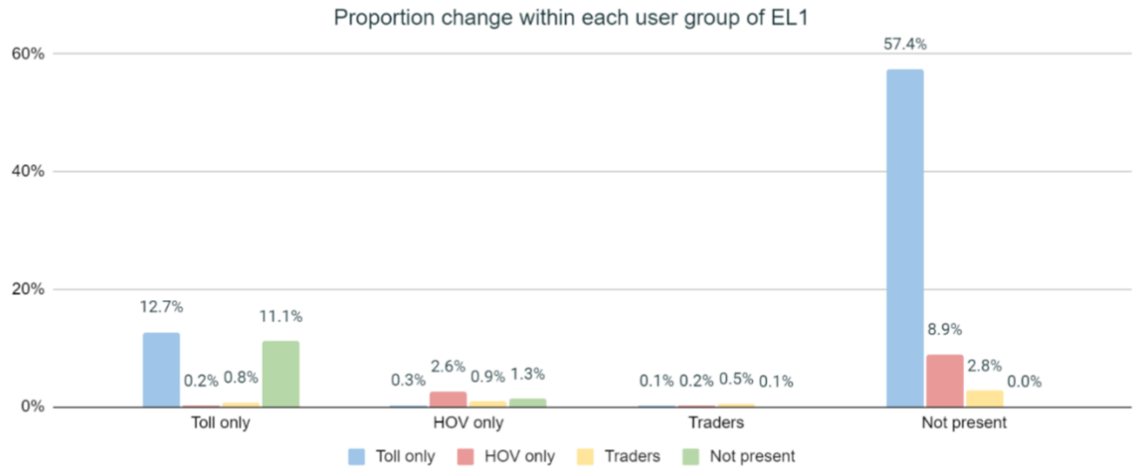


Figure 16: Proportional change within user group of EL1

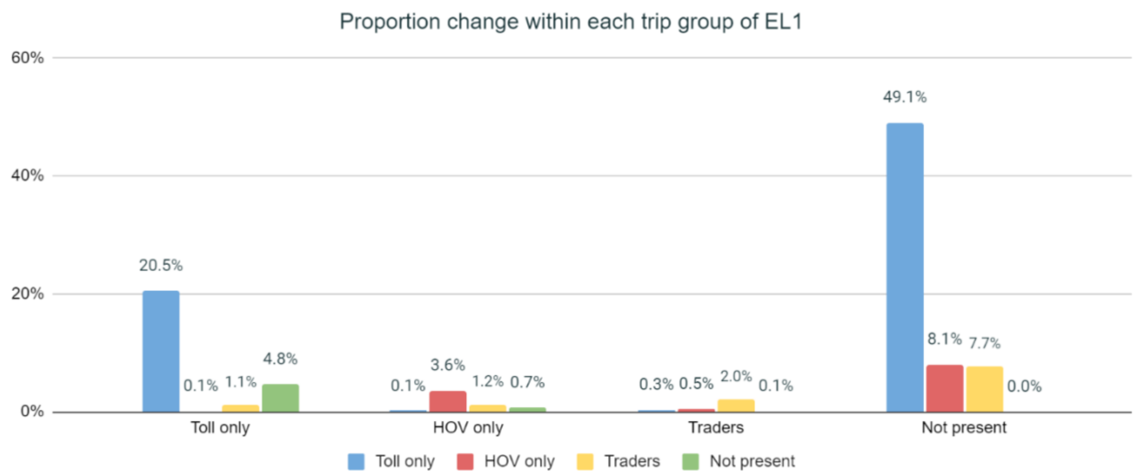


Figure 17: Proportional change within each trip group of EL1

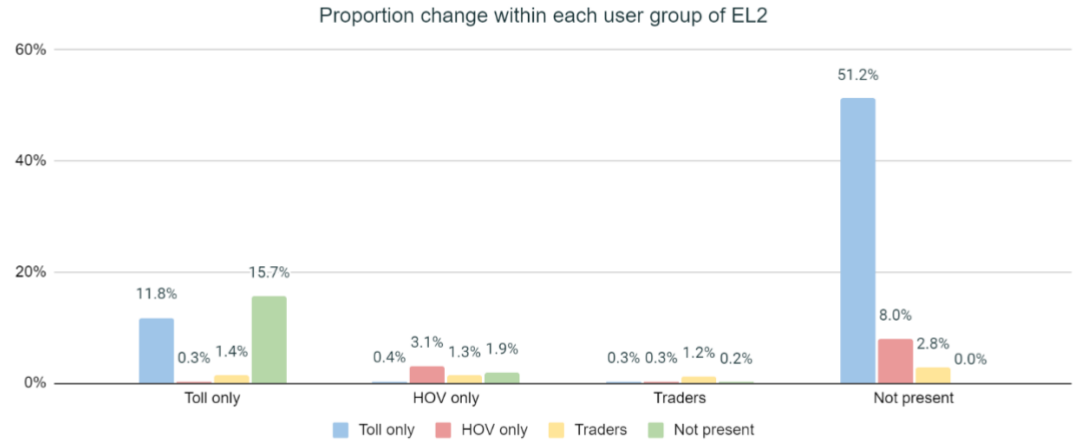


Figure 18: Proportional change within each user group of EL2

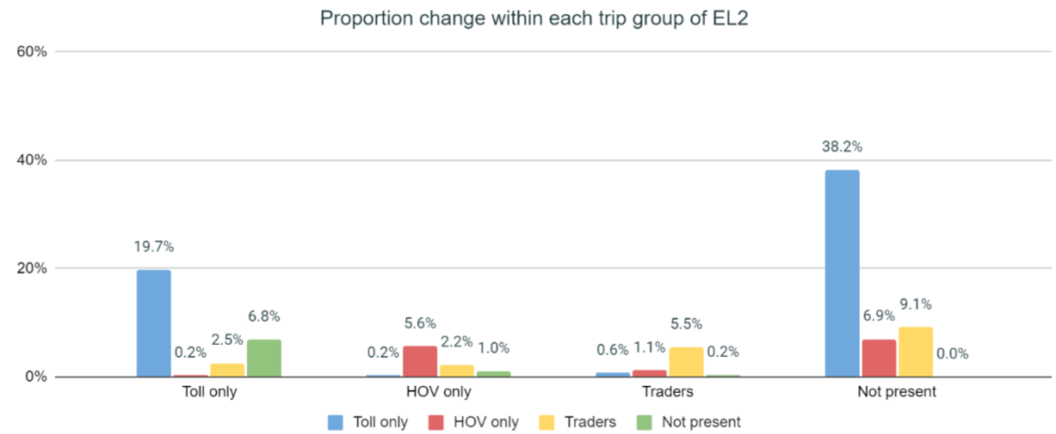


Figure 19: Proportional change within each trip group of EL2

1.6 Willingness to pay estimation

In this Section, willingness to pay was estimated on the two EL assets before and during pandemic. As described in the data Section, I first merged observations about frequency of ELs use from transponders with RITIS dynamic travel time on both ELs and GP lanes, the key parameters being the entry and exit points and the time of day when the trip occurred. The model is formulated as an ordered logit, where the dependent variable is the trip frequency registered on each transponder while the independent variables are the total travel time saved on ELs and the average toll paid for each trip. The coefficient estimates are then used to calculate the average willingness to pay for an additional trip on the ELs during the time period observed.

Table 3 presents the modeling results obtained from the datasets relative to EL1 and EL2 respectively. The signs of cost per trip coefficients are found to be negative in both the pre-lockdown and the during-lockdown periods across all the models estimated. This is consistent with the economic consumer theory; intuitively, an increase in the posted toll decreases the likelihood that users will choose ELs. On the other hand, the coefficients of time savings show a positive sign for each time period considered and on the two assets, meaning that more time saved by traveling on ELs will induce drivers to choose ELs over GP lanes. Similarly, Brownstone et al., (2003) considered the median time savings from EL and estimated a logit model obtaining a positive sign for this coefficient. Mitrovic et al., (2020) also considered the travel time savings on ELs in model specification and obtained a positive coefficient. The willingness to pay calculated on the data observed before the outbreak for EL1 and EL2 are \$26/h and \$28/h respectively. After the shock of the pandemic and the adoption of lockdown policies starting in mid-March 2020, the willingness to pay on EL1 and EL2 changed to \$36/h and $34/h, respectively. It is noted that the results do not differ much between the two ELs. The values obtained are higher than estimates recently published by RSG on data collected in 2019, obtained on SP data relative to both EL and GP lanes, but significantly lower than the values estimated on data relative to the late 90's (Lam and Small, (2001); Brownstone et al., (2003)) and adjusted by inflation and GDP (see Table 1 literature review). The USDOT recommended hourly Values of Travel Time Savings for all purpose in 2020 was $17.80/h (USDOT, 2022).

The obtained results can be effectively explained through the lens of the adopted econometric model specification. As outlined in the data description, a substantial reduction in overall traffic volume occurred across both EL assets post-lockdown. With fewer drivers and vehicles, the potential time difference saved between the GP lanes and the ELs diminished, contributing to a decrease in travel time savings. In this context, to maintain the same level of individual utility, the coefficient of travel time should logically increase. Consequently, the Willingness to Pay (WTP) also increased. The observed increase in WTP further justifies the smaller group of users, or market share, on ELs during lockdown. The elevated price per unit time saved led to a situation where a much smaller percentage of the driving population was willing to pay for the use of ELs, reflecting the economic dynamics of demand and pricing elasticity in the context of changed travel conditions during the lockdown.

To get a specific estimation of the WTP change during the pandemic period, the full data is divided into subgroups by considering the type of user and the time of day. In particular, the specific segments modeled include all toll-only users and traders; workday AM peak, workday PM peak, and workday off peak. All models are estimated according to an ordered logit specification. Table 4 presents the estimated WTP values as well as the percentage changes during lockdown among different groups.

Panel A compares the group that combines toll-only users and traders, to toll-only users for a given time period. Before the pandemic, WTP for toll-only users were \$27/h and \$31/h on EL1 and EL2 respectively, which are slightly higher than the values estimated for the general population (\$26 and \$28). During the pandemic, WTPs for the two user groups of EL1 became \$37 on EL1 and \$34 on EL2. Greater increase (40% and 21%) in WTP are calculated for the group that includes toll-only users and traders across corridors, compared to toll-only users (37% and 16%), indicating that traders' travel behavior are more sensitive to the introduction of the lockdown policy. When comparing the two assets, it can be found that EL1 users were impacted more than twice as much than EL2 users by the pandemic.

Panel B compares the variations in WTP across different time periods. In the pre-pandemic period, the WTPs were similar on the two assets during the peak periods, which ranged from \$20 to \$23 per hour in the morning peak, and roughly \$25 per hour during the afternoon peak. WTP estimations on off-peak periods are slightly higher than those calculated for peak periods on both ELs in the study area. Overall, before pandemic EL1 witnessed slightly higher WTP during each time period of the day compared to EL2. During the pandemic, the difference in WTP between EL1 and EL2 becomes more evident especially during peak hours. In general, it is possible to conclude that EL1 was affected more by the pandemic than EL2. The WTP during the AM peak on EL1 became more than twice as much as that of the pre-pandemic period (\$47/h), while off peak WTP did not change much (\$38/h). EL2 users present a slightly higher WTP during off-peak hours. Besides, the WTP increase for workday AM peak on EL1 is much higher than the percentage change of PM peak, while EL2 presents a different pattern with a greater WTP increase on PM peak. Differently, the travel behavior variations across ELs of the off-peak periods are less sensitive to the adoption of the pandemic related policies, with only 8% and 9% of increase of WTP respectively across the ELs. These amounts are roughly consistent across EL1 and EL2. Overall, these results can be attributed to the same factors previously discussed to justify the higher Value of Time (VOT) estimated during the pandemic. In pre-COVID conditions, the disparity between peak and off-peak hours was more pronounced. However, during the pandemic, the increased flexibility acquired by users has led to a attenuation of these differences, a phenomenon that persists to date (as reported by the Washington Post in 2023).

Table 3: Overall results of ordered logit model

Pre lockdown					During Lockdown				
EL1									
	Estimate	s.e.	z value	Pr(>|z|)		Estimate	s.e.	z value	Pr(>|z|)
cost/trip	-0.108	0.001	-147.30	<2e-16 ***	cost/trip	-0.504	0.005	-95.56	<2e-16 ***
timesaving	0.047	0.000	360.80	<2e-16 ***	timesaving	0.307	0.001	232.32	<2e-16 ***
No. of observations				524953	No. of observations				168457
Initial log-likelihood				-1037988.74	Initial log-likelihood				-280444.14
Final log-likelihood				-899249.22	Final log-likelihood				-218346.77
Pseudo R squared				0.133	Pseudo R squared				0.221
WTP = 26.174					WTP = 36.600				
EL2									
	Estimate	s.e.	z value	Pr(>|z|)		Estimate	s.e.	z value	Pr(>|z|)
cost/trip	-0.065	0.001	-114.40	<2e-16 ***	cost/trip	-0.203	0.002	-84.50	<2e-16 ***
timesaving	0.030	0.000	325.70	<2e-16 ***	timesaving	0.115	0.001	213.40	<2e-16 ***
No. of observations				351903	No. of observations				151143
Initial log-likelihood				-641766.23	Initial log-likelihood				-227016.33
Final log-likelihood				-521749.39	Final log-likelihood				-181115.93
Pseudo R squared				0.187	Pseudo R squared				0.202
WTP = 28.030					WTP = 34.016				

Table 4: WTP change comparison in groups

Panel A: User type

	Toll-only users & Traders			Toll-only users		
	Pre	During	Change	Pre	During	Change
EL1	$26/hr	$37/hr	+40%	$27/hr	$37/hr	+37%
EL2	$28/hr	$34/hr	+21%	$31/hr	$35/hr	+16%

Panel B: Peak period

	Workday AM peak			Workday PM peak			Workday Off peak		
	Pre	During	Change	Pre	During	Change	Pre	During	Change
EL1	$23/hr	$47/hr	+102%	$26/hr	$43/hr	+63%	$35/hr	$38/hr	+8%
EL2	$20/hr	$24/hr	+19%	$24/hr	$34/hr	+45%	$33/hr	$36/hr	+9%

1.7 Conclusions

This chapter examined travel behavior on Express Lanes (ELs) by analyzing data obtained from vehicles equipped with transponders on two ELs in Virginia. The study covered the period from January to mid-March 2020 (pre-pandemic) and from mid-March to the end of May 2020 (pandemic or lockdown period). The research includes a comprehensive analysis of the willingness to pay for EL usage during these defined time frames.

Findings indicate that the impact of the work-from-home order was not uniform, with the shorter corridor (EL1) experiencing a greater loss in ridership when compared to EL2. The EL1 corridor notably serves white collars workers from high-income families, who could easily switch to telework during the initial phases of the pandemic. Also, EL2 is serving longer trips, which might have offered perceivable travel time savings to users even when congestion was not at its height. Within a day, rush hours exhibited poorer performance in revenue collected compared to other times, and the frequencies of tolled and high-occupancy vehicle trips were similarly affected. I argue that the gain in flexibility due to greater telework participation allowed more flexible trip schedules or generated other types of trips.

To gain a deeper understanding of the shifts in Express Lane (EL) usage amid the pandemic, I categorized users/transponders into three segments: toll-only users, high-occupancy vehicle (HOV)-only users, and traders. Toll-only users represent the users who only traveled in the toll mode on the Express Lane, while HOV-only users are those who only traveled in HOV mode on the ELs before or during lockdown. Traders are the users who generated both toll trips and HOV trips on the ELs before or during the period of lockdown. It is interesting to note that before the outbreak of the pandemic the share of toll-only users on EL1 was greater than on EL2. During lockdown, EL1 lost the higher share of toll-only users compared to EL2, which also attracted the greater share of new toll-only users during the pandemic. Very few of the pre-pandemic toll-only users and HOV-only users transferred into other mode types across both two ELs. In contrast, traders were more likely to switch to other mode types, especially on EL2.

This chapter also includes an econometric analysis utilizing an ordered logit model to assess changes in willingness to pay (WTP) before and after the lockdown across Express Lanes (ELs). The dependent variable is defined as the number of trips observed for each transponder during the two time periods under examination. According to the obtained results, WTP values are remarkably similar for the two ELs considered, standing at \$26 and \$28 per hour before the pandemic. During the lockdown, WTP values increase, reaching \$36 and \$34 per hour for the respective ELs. The higher WTPs are associated with smaller population segments, indicating lower market shares than usual on ELs.

From the analysis results, not all assets are equal; EL2 was less impacted by mobility restrictions compared to EL1 and exhibited a faster recovery. Generally, the willingness to pay (WTP) of toll-only users consistently surpassed that of traders, indicating high sensitivity among traders to the pandemic's effects. Off-peak periods demonstrated higher WTPs than peak periods and workdays, suggesting that EL users are willing to pay more to save time outside of rush hours. I posit that this effect could be attributed to a shift in daily activities, facilitated by the flexibility afforded by the work-from-home order.

The COVID-19 pandemic has significantly altered travel and activity patterns, with an increased prevalence of remote work. According to a survey by Parker et al. (2020), over half of the surveyed employees (54%) believe their job can be done from home and express a desire to continue teleworking post-pandemic if allowed. Scholars argue that travel behavior will continue evolving even after the pandemic (Currie et al., 2021; Costa et al., 2022). Metrics such as the percentage of telecommuting workers, public transportation market shares, and congestion levels, especially during peak hours, should be continually monitored as crucial indicators of emerging travel trends. These indicators are vital for EL operators who may need to adapt their business and adjust revenue management strategies in response to this unprecedented situation.

In concluding this chapter, it is important to acknowledge certain limitations and propose avenues for future research. Firstly, results are based on historical data from January to May 2020, capturing travel behavior only before and during the initial phases of the pandemic. Changes that occurred as the pandemic evolved are not reflected in this analysis. Secondly, the dataset lacks information about transponder owners' socio-demographic characteristics. Access to users' profiles through the local Department of Transportation (DOT), while respecting privacy, would provide valuable insights. Thirdly, this analysis does not consider behavior related to non-chosen alternatives, such as the choice of traveling on general-purpose lanes. Availability of a secondary dataset on general-purpose lane users would enable the study of lane-changing behavior before and during the pandemic. Lastly, this chapter does not account for heterogeneity in the value of time or estimate the value of reliability, which is part of my ongoing research.

Chapter 2: Preference heterogeneity in willingness to pay

2.1 Introduction

Preference heterogeneity plays a pivotal role in assessing the impact of transport economic policies (Koster and Koster, 2015). Highly cited research underscores the significance of such heterogeneity in shaping road pricing schemes, making differentiated pricing on Express Lanes (ELs) more appealing (Brownstone and Small, 2005). Empirical studies analyzing the VOT across drivers, such as those by Greene et al. (2006), Liu et al. (2004), and Jin et al. (2015), consistently reveal substantial variations in VOT among users. Relying solely on average VOT values may lead to biased welfare estimates and imprecise policy recommendations (Koster and Koster, 2015). Therefore, understanding unobserved preference heterogeneity among EL users becomes crucial. Such insights can offer valuable information for enhancing transportation systems, addressing the impacts of evolving travel behavior, and ultimately informing policy and planning decisions. The overarching objective being to enhance the overall experience for EL users.

This chapter addresses three primary research questions: 1) Isolating heterogeneity in VOT from passively collected data, devoid of socio-demographic variables. 2) Investigating variations in travel behavior and VOT from the pre-pandemic period to the initial and dramatic phases of the Stay-at-Home Order. 3) Comparing behavior and VOT on two distinct assets serving the same region but exhibiting inherent differences in network characteristics and user types.

The remainder of this chapter is structured as follows. In Section 2.2, a comprehensive literature review is presented, focusing on key aspects: VOT estimation and heterogeneity in VOT. Section 2.3 provides an overview of data quantitative statistics. Section 2.4 delves into methodological approaches designed to account for heterogeneity in travel behavior. Various econometric models are detailed, presenting distinct methods proposed for estimating heterogeneity in VOT. The results obtained from model estimation are presented in Section 2.5. Finally, Section 2.6 concludes the chapter, offering insights and recommendations for future research directions.

2.2 Literature review

The VOT is a monetary measure of the value that people place on travel time saving, or the amount of money they are willing to pay to reduce their travel time (Ojeda-Cabral et al., 2016). Econometric models based on random utility theory have been proposed to estimate the ratio between travel time and travel cost coefficients (i.e. VOT), based on revealed or stated choices. Multinomial Logit Models (MNL) are widely used to evaluate VOTs, but they are notoriously limited by the inability to account for random heterogeneity (Train, 2009). This limitation is particularly relevant in the context of data that do not contain any information about the socio-economic status of the respondents. As noted by Small (2012), VOT is strongly connected to economic factors, individual and household characteristics, but also to daily activity schedule, time of day, and travel time reliability. Moreover, if the restrictive assumption of monotonic impact of contributing factors across different alternatives and individuals (Washington et al., 2020, Savolainen and Mannering, 2007) is not released, the estimated coefficients may be biased, inconsistent, and inefficient. (King and Zeng, 2001; Greene and Hensher, 2003). Advances in computing power and simulation methods for estimating nonlinear models have heightened interest in the sources of heterogeneity in behavioral parameters including VOT. Thus, it seems natural to try to isolate the sources of heterogeneity, especially in the context of passively collected data with no socio-demographic characteristics.

2.2.1 Heterogeneity in VOT

The literature distinguishes between two types of heterogeneity in random utility-based models: observed and unobserved heterogeneity (Carrion and Levinson, 2012). Early studies on Value of Time (VOT) often incorporate observed heterogeneity by allowing model coefficients to vary based on socio-demographic characteristics such as income, age, gender, race, and other relevant factors (Small and Winston, 1999). The estimation of observed heterogeneity in Value of Time (VOT) typically involves introducing interaction terms between travelers' attributes and variables related to travel time and cost (Carrion and Levinson, 2012).

Small et al. (2005) highlighted that a major limitation in Value of Time (VOT) studies has been the failure to account for heterogeneity in travel time and cost elasticities stemming from unobserved sources. The issue of heterogeneity in VOT measures has been extensively explored in transportation literature, as evidenced by studies such as Algers et al. (1998), Hensher and Greene (2003), Fosgerau and Bierlaire (2007), Hess et al. (2005, 2008), Cirillo and Axhausen (2006), and others. Unobserved heterogeneity is typically addressed using mixed logit models with random parameters specification. The distribution of these random coefficients can be analytical and take various specified forms, including normal, lognormal, triangular (Train, 2009), or non-parametric (Fosgerau and Bierlaire, 2007, Bastin and Cirillo, 2010). While most distributions are unconstrained across positive and negative domains, additional assumptions can impose constraints (Greene et al., 2006).

An example of a study addressing both observed and unobserved heterogeneity can be found in Amador et al. (2005). They suggested that individuals may have varying Values of Time (VOTs) based on their unique preferences and circumstances. Initially, they estimated systematic preference variations between two gender groups using a multinomial logit model. Subsequently, they demonstrated that this heterogeneity was underestimated by identifying significant differences (up to a 40% increase in VOT) estimated by the mixed logit model. Small (2012) also found that the unobserved heterogeneity assumed from the stochastic distribution of parameters is much larger than the observed heterogeneity.

Further behavioral insights associated with the random parameter distribution can be gained by parameterizing variance heterogeneity or heteroskedasticity. Variance heterogeneity is often conditioned on individual-specific variables. Greene et al. (2006) expanded the mixed logit framework to accommodate this heterogeneity and demonstrated its implications on the valuation of travel time savings, particularly in commuter mode choice contexts. However, their estimates using mixed logit models sometimes yielded problematic results, such as negative Values of Time (VOTs). Nevertheless, their findings suggested that incorporating heterogeneity in the variance of unobserved effects tends to significantly reduce the mean VOT.

An alternative to mixed logit models is latent class models, which Greene and Hensher (2003) describe as a semi-parametric variant of the multinomial logit model. They note that the latent class model is somewhat less flexible than mixed logit because it approximates the underlying continuous distribution with a discrete one, yet it does not require specific assumptions about parameter distributions across individuals. Koster and Koster (2015) proposed semi-parametric panel latent class models to address both observed and unobserved heterogeneity in Value of Time (VOT) estimation using panel data from stated choice experiments. They posited that individuals with similar characteristics, such as income and age, would likely have more similar VOTs, with class membership probabilities depending on these individual characteristics. When accounting for unobserved heterogeneity with two latent classes, their estimated average VOT was slightly lower compared to the baseline binary logit model estimate. They concluded that unobserved heterogeneity outweighs heterogeneity related to observable individual characteristics based on model fitting parameters. Additionally, beyond average estimates, they identified significant heterogeneity in semi-parametric VOT distributions, ranging from €20 to €80.

2.2.2 Heterogeneity in VOT on EL

Liu et al. (2004) employed the mixed logit model to estimate travelers' route choices and measure Value of Time (VOT) using data from a real pricing project on California State Route 91 (SR91), a major commuting highway. They found that the median VOT was estimated to be $12.81, with a measure of travelers' heterogeneity, represented by the difference between the 75th and 25th quantiles, at 8.72. This indicates that there is significant heterogeneity in VOT, with values varying by more than 60% around the median. This variation underscores the diverse preferences commuters have regarding travel speed and reliability.

Small et al. (2005) estimated the distribution of Value of Time (VOT), accounting for both observed and unobserved heterogeneity among motorists participating in a value-pricing experiment on SR91. They collected data through telephone revealed preference (RP) trips, stated preference (SP) surveys with eight route choice scenarios, and socio-demographic information. Observed heterogeneity in behavior was captured through recorded data, while unobserved heterogeneity was modeled using random variables in a mixed logit framework.

Their results revealed a wide range of preferences for fast and reliable highway travel. Total heterogeneity in VOT ranged from approximately 50% to over 100% of the corresponding median value, with unobserved sources contributing significantly. This underscores the importance of incorporating random parameters to capture variations in motorists' preferences.

Lee et al. (2016) also addressed observed and unobserved heterogeneity in willingness to pay for travel time and reliability using a mixed logit model framework. They analyzed stated preference data concerning drivers' route choices between a tolled highway and a free national road in South Korea. The sample was categorized into groups based on observed trip purposes: "non-business trip", "non-business trip + high-income group", "business trip", and "business trip + high-income group". When considering only observed heterogeneity, mean VOT values ranged from $7.81 to $12.19 per hour across different groups. However, incorporating both observed and unobserved heterogeneity expanded this range to $3.21 to $64.56 per hour among the groups. They found that VOT values for business trips were 1.3 to 2.3 times higher than those for non-business trips, and those in the high-income group exhibited VOT values 1.1 to 2.4 times greater than those in the lower income group. These findings underscored that ignoring observed and unobserved individual heterogeneity effects could lead to underestimating VOT values.

Hossan et al. (2016) conducted an empirical study using mixed logit modeling to investigate user heterogeneity in Value of Time (VOT). They analyzed combined Revealed Preference (RP) and Stated Preference (SP) data to understand the travel behavior choices of automobile drivers on I-75, I-95, or SR826 corridors in South Florida. The study highlighted that few previous studies had adequately addressed heterogeneity in estimating VOT, despite recognizing significant unobserved heterogeneity indicated by the standard deviations of random parameters. Hossan et al. aimed to fill this gap by conducting a detailed investigation to identify and quantify the sources of user heterogeneity in VOT. They considered three main variables as random parameters: travel time, travel time reliability, and travel cost. Interaction terms between these parameters, individual characteristics, and trip attributes were tested to explore user heterogeneity. Their findings revealed several key insights: 1) High-income individuals, employed individuals, older travelers, and those traveling on weekdays tend to have higher VOT. 2) Trips perceived as urgent, of median distance, and taken by younger individuals also exhibit higher VOT. 3) Users of Sunpass (electronic toll payment), solo drivers, and drivers with only one passenger tend to have lower VOT. 4) Travelers who experience delays show lower VOT. These results highlight the complexity and diversity of factors influencing VOT among different segments of drivers, providing valuable insights for transportation planning and policy making.

2.3 Data sources

This analysis about travel behavior on tolled laned is based on real data collected from transponders that traversed Express Lanes (ELs) in the study area both before the COVID-19 pandemic (January 1st to mid-March 2020) and during the lockdown (mid-March to May 31st, 2020). This dataset is augmented with travel time data from probe vehicles observed on both ELs and GP lanes.

The main data source provides insights into the usage patterns of Express Lanes (EL) on the considered asset. The dataset comprises 6,542,984 trip observations arranged in chronological order. Each record in the database corresponds to a specific trip, offering detailed information such as travel date, time of day, day of the week, transponder ID, entry plaza, exit plaza, trip distance, direction, toll payment mode, and toll paid. It is important to note that the data is anonymized, ensuring the absence of any personal information related to the users.

The travel times on both ELs and GP lanes are sourced from the Regional Integrated Transportation Information System (RITIS). This nationwide big data platform integrates information from various sources, including private operators and public agencies[2]. For our study, I utilize the travel time data on a five-minute interval provided by RITIS, covering the period from January 2020 to May 2020. According to RITIS, vehicle travel times are derived either from point sensor speed data or directly measured by probe vehicles. These travel times are measured for each Traffic Message Channel (TMC) segment, each characterized by a unique code that defines specific segments or links on the road[3].

To calculate the total travel time on GP lanes and their corresponding ELs between entry and exit plazas, I summed the travel times on the segments defining the path. This process was applied for each pair of entry and exit plazas observed in the primary dataset. To map Traffic Message Channel (TMC) segments to Origin-Destination (OD) pairs, I utilized the indexes defined in the TMC inventory. For instance, decomposing the TMC code '110P01456' reveals three parts: '110' as the area code, 'P' indicating road-specific information such as direction or lane type, and the last 5 numbers defining the road (Young et al., 2015). Both GP and EL segments share the same code, except for the middle letter in the TMC code. Subsequently, the transponder dataset was merged with the RITIS travel times based on the entry and exit plazas observed during each trip.

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[2] General-purpose lane data were derived from the Regional Integrated Transportation Information System (RITIS), that is a nationwide big data platform that integrates information from the private and public sectors (https://ritis.org/intro)

[3] Reference: INRIX Segments (https://docs.inrix.com/reference/getsegments/)

The level of service variables utilized for model estimation included travel time on GP lanes, travel time on ELs, and, consequently, the travel time saved by opting for ELs, along with the corresponding toll paid by transponder owners.

An empirical data analysis is undertaken to investigate travel behavior on the asset before and during the pandemic. Specifically, I examine various aspects, including time of day, days of the week, revenues, and travel time saved through the use of Express Lanes (ELs). I categorize the day into six time windows: (1) early morning (0:00 AM - 7:00 AM); (2) AM peak (7:00 AM - 10:00 AM); (3) AM off-peak (10:00 AM - 13:00 PM); (4) PM off-peak (13:00 PM - 16:00 PM); (5) PM peak (16:00 PM - 19:00 PM); and (6) evening (19:00 PM - 00:00 AM). The analysis covers all days of the week, from Monday to Sunday. Computed travel behavior indicators include trip frequency (Figure 20, Figure 22, and Figure 26), total toll revenue (Figure 22, Figure 23, and Figure 27), and total travel time saved by choosing ELs (Figure 24, Figure 25, and Figure 28).

Figure 20, Figure 22, and Figure 24 illustrate behavioral indicators before the pandemic, while Figure 21, Figure 23, and Figure 25 depict the same indicators during the lockdown. Prior to the pandemic, users exhibited a notable trend of more frequent travel on the asset during workdays compared to weekends, and during rush hours (AM peak and PM peak) as opposed to off-peak hours on workdays. This trend is evident in the generated revenue (Figure 22) and the travel time difference between ELs and GP lanes (Figure 24). Commuters were evidently willing to pay tolls during peak hours on workdays to save travel time and reach their destinations faster by choosing ELs. The implementation of travel restrictions in March 2020 resulted in a leveling of peaks, and the discrepancy in ELs utilization between workdays and weekends significantly diminished, as reflected in all the considered behavioral indicators. Surprisingly, during the pandemic, people traveled on ELs more during the PM off-peak hours than at other times of the day. Similar findings have been reported by Bomey, 2021 and Muller, 2022, indicating a greater flexibility acquired by commuters, particularly in avoiding rush hours through work-from-home arrangements. Traffic experts suggest that the increasing flexibility in work schedules is likely to reshape the traditional style of commuting (Bomey, 2021). Many companies have reconsidered their return-to-office plans due to uncertainties and embraced the concept of hybrid work (Muller, 2022). This shift makes predicting future traffic patterns more difficult.

Table 5: Proportion of categorical dependent variable

Pre-pandemic (Jan-Mid Mar)				**During-pandemic (Mid Mar-May)**			
Category	Trip frequency	Num. of users	Proportion	Category	Trip frequency	Num. of users	Proportion
1	1	268538	51.15%	1	1	98921	58.72%
2	2-9	201834	38.45%	2	2-9	57791	34.31%
3	10-19	26941	5.13%	3	10-19	6492	3.85%
4	20-29	10327	1.97%	4	20-29	2228	1.32%
5	30-39	6059	1.15%	5	30-39	1133	0.67%
6	40-49	4089	0.78%	6	40-49	704	0.42%
7	50-59	2402	0.46%	7	50-59	418	0.25%
8	60+	4763	0.91%	8	60+	770	0.46%
Total		524953	100%	Total		168457	100%

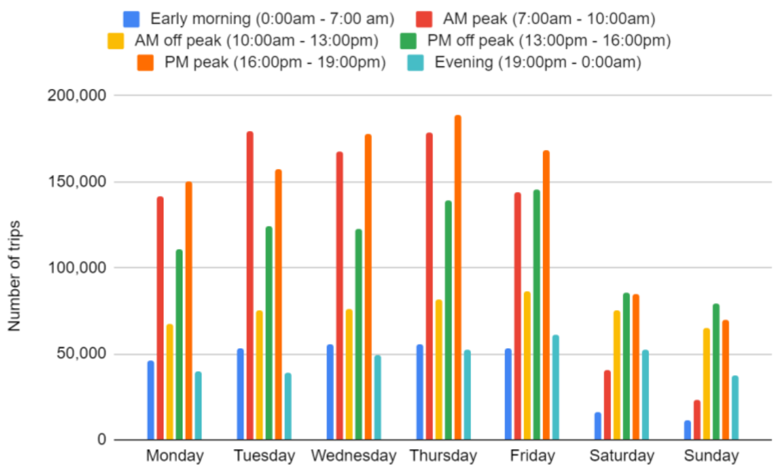

Figure 20: Trip frequency before pandemic

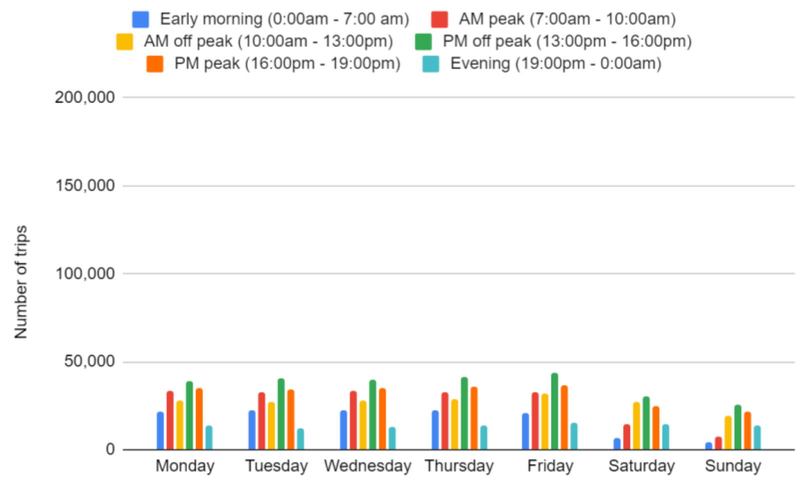

Figure 21: Trip frequency during pandemic

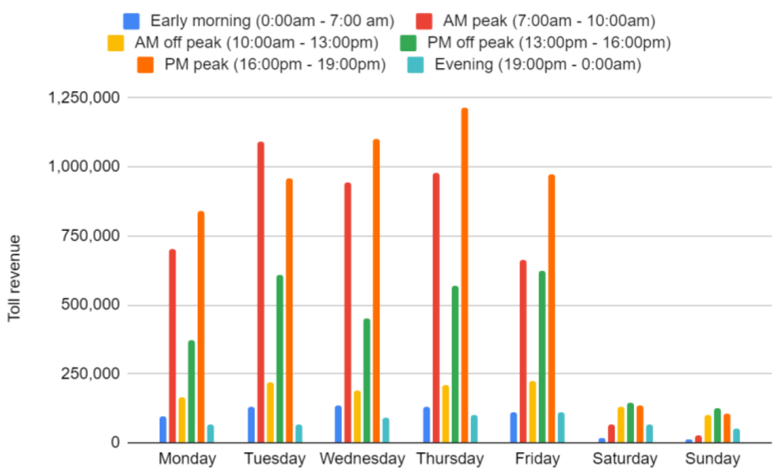

Figure 22: Toll revenue before pandemic

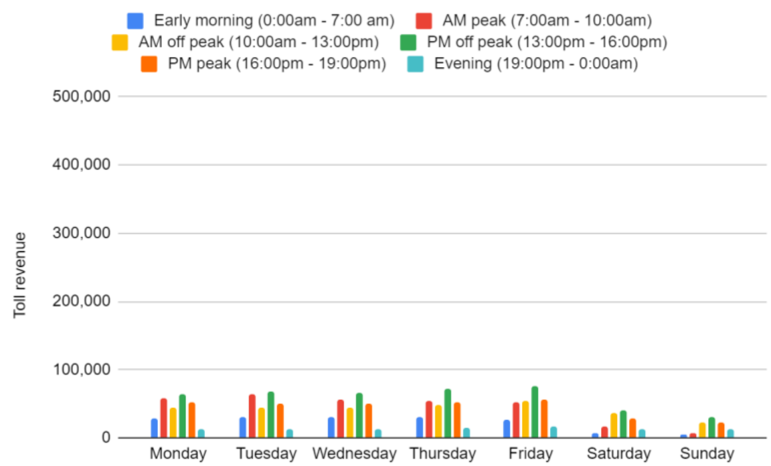

Figure 23: Toll revenue during pandemic

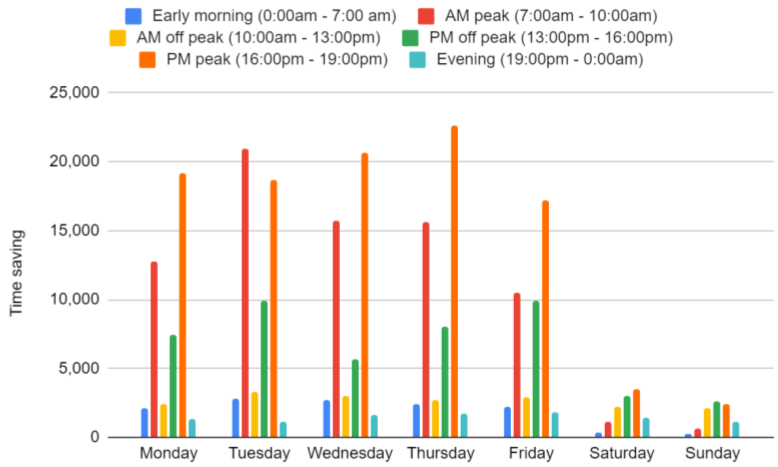

Figure 24: Time saving before pandemic

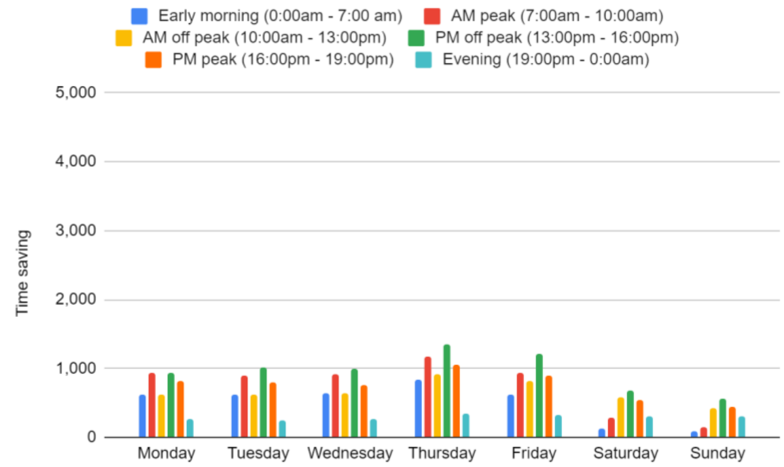

Figure 25: Time saving during pandemic

2.4 Methodological approach

In this chapter, I use econometric models based on random utility theory to estimate VOT for EL users. The observed dependent variable is the number of trips recorded by each transponder observed on the EL before and during lockdown. The base model formulation is an Ordered logit model (OL). A natural way to think about the decision process is that the individual has some level of utility associated with the number of trips traveled on the ELs in the observed time period and recorded by each transponder. The utility function is latent and is decomposed into an observed and an unobserved component (Train, 2009).

$$U_i = X_j'\beta + \varepsilon_i, \text{ where } i = 1, \dots, n.$$

I model the utility as a function of the observed travel time and travel cost:

$$U = \beta_t(\Delta T) + \beta_c(Toll) + \varepsilon_i$$

$$\Delta T = T_{GP} - T_{EL}$$

Where ΔT is the difference in travel time between GP (T_{GP}) and EL (T_{EL}) for user i during the targeted time period; *Toll* is the average travel cost of each trip for user i, β_t and β_c are coefficients to be estimated, which define how time and cost contribute to the utility to travel on ELs. Of course, other factors affect the utility associated to the user's trip frequency choice, but these are not observed and are therefore embedded into the random error term, which is assumed to be i.i.d EV distributed (Train, 2009).

The choice probability can be expressed as follows:

$$P(Y_i > j \mid X) = \frac{\exp\,(X_i\beta' - \emptyset_j)}{1 + [\exp(X_i\beta' - \emptyset_j)]}, j = 1, 2, \dots, M - 1,$$

Where j is a trip frequency category, X_i is the vector of observed explanatory variables, β is the vector of parameters to be estimated, $\emptyset_j$ are cut points for the thresholds, M is the number of categories of the ordered-response variable.

Once the ordered logit model is estimated, the corresponding value of time or the amount of toll a user is willing to pay ($) for saving one hour of travel time when using the Express Lane is calculated as follows:

$$VOT = \frac{\beta_t}{\beta_c}(60\,\mathrm{min}\;per\;hour)$$

VOT was calculated for the ELs in study areas and compared across in the two conditions before and during lockdown.

2.4.1 Heteroskedastic ordered logit model (HOL)

One of the primary assumptions of the standard ordered logit model is homoscedasticity of the error term variance. To overcome this issue, a heteroskedastic ordered logit model (HOL) is proposed as the following:

$$\mathrm{P}(Y_i > j \mid X) = g\left(\frac{X_i\beta'}{\sigma_i}\right) = \frac{\exp\,(\frac{X_i\beta'}{\sigma_i} - \emptyset_j)}{1 + \exp\,(\frac{X_i\beta'}{\sigma_i} - \emptyset_j)}, j = 1, 2, \dots, M - 1$$

in which $ln\sigma_i = Z_i\theta'$, where Z_i denotes vector of explanatory variables that effect the error variance σ_i and Z_i could be either a subset of X_i or a subset of new variables not included in X_i (Quddus et al., 2010; Williams, 2010).

2.4.2 Latent class ordered logit model (LCOL)

Latent class ordered logit model is based on a discrete segmentation of the population which assumes that heterogeneity in users' travel behavior is likely to be driven by specific segments. The approach generally groups observations into classes with similar needs, constraints, and preferences with a class membership model (Hetrakul and Cirillo, 2014). The class membership model is combined with the choice model, which enables the model to account for heterogeneous choice behavior between different segments of the market (Carrier, 2008).

The structure of the latent class choice model can be written as follows:

$$P_i(j|X_M, X_C) = \sum_{s=1}^{S} P(S|\, X_M)P(j|X_C, S) \quad \forall j \in C$$

Where s is class index; {1, …, S}; X_M is class membership emplantatory variable, X_C is class specific choice model explanatory variable.

The class specific choice probability of alternative j can be expressed as:

$$P\left(j\middle|X_{Cj}, S\right) = \frac{\exp\,(X_{Cj,s}\beta_{C,s} - \emptyset_j)}{1 + [\exp\left(X_{Cj,s}\beta_{C,s} - \emptyset_j\right)]}, \quad \forall s \in S, \forall j \in C$$

Where $\beta_{C,s}$ are the unknown parameters of the class-specific choice model. The utility function of user i belonging to class s can be written as:

$$U_{is} = X_{M,s}\beta_M + \varepsilon_{is}$$

The probability of belonging to the latent class s can be written as:

$$P(s|X_M) = \frac{\exp\,(X_{M,s}\beta_M)}{\sum_{s=1}^{S} \exp\,(X_{M,s}\beta_M)}$$

Where β_M are the unknown parameters for class membership model.

2.4.3 Generalized ordered logit model (GOL)/ Partial proportional odds model (PPO)

Parallel lines assumption is another crucial assumption of the standard ordered logit model. Williams (2016) explained why the ordered logit model often fails, showed how and why GOL can often provide a superior alternative to it, and discussed the ways in which the parameters of the GOL model can be interpreted to gain insights that are often overlooked. Williams emphasized that if the parallel lines assumption holds, all of the corresponding coefficients (except the intercepts) of the ordered logit model should be the same across different logistic regressions. Similarly, the proportional odds assumption restricts the odd ratios staying the same regardless of which of the collapsed logistic regressions is estimated. These two assumptions of the ordered logit model are easily violated for each of the ordered dichotomization of the outcome variable when there are multiple explanatory variables. Consequently, there is a pursuit of a more flexible model capable of addressing these complexities and providing nuanced insights not achievable through the conventional ordered logit model. This leads to the exploration of the Generalized Ordered Logit (GOL) model, chosen for its ability to handle situations where the assumptions of the ordered logit model are easily violated.

The GOL model can be written as:

$$P(Y_i > j \mid X) = g(X_i\beta_j') = \frac{\exp\,(X_i\beta_j' - \emptyset_j)}{1 + [\exp\left(X_i\beta_j' - \emptyset_j\right)]}, j = 1, 2, \dots, M-1,$$

For the ordinal outcome variable with M categories, the GOL model will generate M-1 sets of coefficients, with equations estimated simultaneously. When M equals 2, the GOL model is equivalent to the ordered logit model. The unconstrained GOL model goes beyond the proportional odds/parallel lines assumption by relaxing this constraint for all variables, generating alternative-specific parameters for each category, denoted as j. A notable variant of the GOL model is the partial proportional odds model (PPO), where certain coefficients can remain constant for all values of j, while others may differ.

2.5 Results from model estimation

In this Section, I present model estimates and willingness to pay for ELs before and during pandemic (Table 6 and 7). The models are formulated according to the Ordered logit (OL), Heteroscedastic ordered logit, Latent class ordered logit (LCOL), Generalized ordered logit (GOL) and Partial proportional odds (PPO) models. The dependent variable is assumed to be the trip frequency observed from each transponder on the ELs, while the independent variables include the total travel time saved by choosing the EL and the average toll paid for each trip.

After data cleaning, I obtained 2,484,426 observations from 524,953 transponders/users on all the assets for the pre-pandemic period, and 590,164 toll trip observations from 168,457 transponders/users during pandemic. OL, GOL, PPO and HOL models were fitted using Stata[4] while the LCOL models were estimated using Biogeme[5].

I coded the trip frequency of the user within such a time period in categories from the least to the most frequent: 1 trip = 1; 2-9 trips = 2; 10-19 trips = 3; 20-29 trips = 4; 30-39 trips = 5; 40-49 trips = 6, 50-50 trips = 7; 60+ trips = 8. Table 5 provides the proportion of each category of the dependent variable. The trip characteristics (e.g. time of day, day of week and direction) are added to the latent class membership modeling. The estimated coefficients are then applied to calculate alternative-specific VOTs by GOL and PPO models, average individual-specific VOT by HOL models, and group-specific VOT by LCOL on the Express Lane during each time period observed.

In general, the coefficient signs of cost per trip are found to be negative in both pre-pandemic and during-pandemic phases across all the models estimated. This is consistent with the economic consumer theory: an increase in the posted toll decreases the likelihood that users choose toll lanes. The positive signs of time saving for each time period considered by all four models show that an increase in travel time saved on EL will encourage drivers to choose EL over GP lanes. Mitrovic et al., (2020) and Brownstone et al., (2003) also considered travel time saved in their model specification and obtained a positive coefficient. The time saving and cost coefficients are statistically significant on all model specifications considered.

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[4] Stata is a full-featured statistical programming language for Window, Max OS X, Unix and Linux. **Introduction to Stata** (PDF), Christopher F. Baum, Boston College, USA. A 67-page description of Stata, its key features and benefits, and other useful information.

[5] Biogeme is an open source Python package designed for the maximum likelihood estimation of parametric models in general, with a special emphasis on discrete choice models.

2.5.1 Ordered logit model (OL)

The baseline specification is an OL model defined according to the ascending categories described in the previous Section. I found that the VOT is $26/h before the pandemic and $34/h during the pandemic, which results in an increase of about 30%. A more comprehensive analysis of OL based VOT estimates and how they compare with values reported in the literature can be found in the previous chapter.

2.5.2 Heteroskedastic ordered logit model (HOL)

It's reasonable to assume that some individuals may highly value their time savings and be willing to pay more for faster travel, while others may place less value on time savings and be less inclined to use Express Lanes (ELs) even if they offer substantial time savings. However, since the database lacks socio-demographic information or trip purpose, deterministic heterogeneity cannot be estimated. Therefore, I utilize the HOL model to estimate heterogeneity in the population and allow the variance of the error terms to vary across the ranges of the independent variables.

I tested two model specifications: HOL1, where only heterogeneity in travel time saving is accounted for, and HOL2, which assumes that both travel time and travel cost vary in the population. According to the results in Tables 2 (pre-pandemic) and 3 (during pandemic), the estimated standard deviation for both travel time and travel cost is significant. The value of time (VOT) estimated by HOL1 and HOL2 is $50/h before the pandemic. During the pandemic, the VOT increased to $68/h and $61/h according to HOL1 and HOL2, respectively, representing a slightly greater percentage increase in VOT estimated by HOL1 (36%) compared to the value estimated by HOL2 (25%), influenced by the lockdown measures.

2.5.3 Generalized ordered logit model (GOL)/ Partial proportional odds model (PPO)

The GOL formulation is employed to relax the parallel constraint for time and cost and allowed for heterogeneity between each category of the dependent variable. The variables labeled by "1" compare the first panel contrast category 1 with categories 2 to 8, while the second panel contrasts categories 1 and 2 with categories 3 to 8. The GOL model provides specific estimates for each category of the dependent variable. The first category, representing users with only one trip generated in the observed time period, was chosen as the base category of the dependent variable. The explanatory variables, such as time saved by choosing the Express Lane and the corresponding toll paid, encompass factors affecting the utility of each category.

Results show that the first group of users' willingness to pay for saving travel time was $56/h before the lockdown, which closely aligns with the estimate from the HOL model. However, it increased to $71/h during the lockdown. From the second category onwards, I observed a dramatic decrease in VOT estimates both before and during the pandemic period.

The significant heterogeneity in traveling behavior on the Express Lane between categories, especially between the base category (infrequent users) and others (regular users), was explored. It appears that less frequent Express Lane users, who traveled only once during the observed time period, have a higher willingness to pay for saving travel time by choosing the toll lane compared to regular Express Lane users or commuters. This may be attributed to the fact that infrequent travelers are not heavily reliant on the Express Lane and may place a higher value on saving time when they do use it.

On the other hand, the percentage change of VOT during the pandemic estimated by GOL ranges from 17% to 25%. Such differences between categories are comparatively slight compared to the heterogeneity in VOT estimates varied among categories of trip frequency. The percentage change of VOT estimated by GOL is generally lower than the estimate (36%) by the HOL model.

For completeness, I also present results obtained with the PPO model, which relaxes the parallel constraint only for travel time, while maintaining that the cost still adheres to the parallel assumption in the setting. The findings from the PPO formulation align closely with those observed by GOL before and during the pandemic. This confirms the relative stability of the cost factor across the analyzed categories.

2.5.4 Latent class ordered logit model (LCOL)

In the latent class model, my aim is to address the absence of individual-specific variables by segmenting travel behavior based on trip characteristics. I hypothesize that drivers traveling during specific time periods and/or directions share relatively homogeneous characteristics. To define the latent classes, I consider the following variables:

Travel day of the week: I utilize dummy variables to indicate whether a user has taken trips on a particular day of the week. This results in six dummy variables for the class membership model, with one variable for each day of the week (excluding Sunday).

Time of Day: Dummy variables are employed to signify whether the user has undertaken trips during specific times of the. For the class membership model, I utilize five departure times of day (excluding evening).

Direction: Dummy variables are utilized to indicate whether the user has taken trips in either the northbound or southbound direction. This results in one dummy variable (northbound) for the class membership model.

Repeated Trip: A dummy variable is utilized to indicate whether the user has previously taken trips at the same specific time of day, day of the week, and distance. This results in one dummy variable for the class membership model.

For this study, I initially assumed two latent classes (LCOL-2), segmented by the class membership model. I hypothesized that users would exhibit varying preferences in travel decision-making on the Express Lane, leading to heterogeneous Value of Time (VOT) estimates across different classes. Before the lockdown, both class 1 and class 2 had the same VOT value ($26/h), which also aligned with the estimate from the baseline OL model. Class 2 users constituted 60% of the market, a proportion that remained relatively stable during the pandemic. During the lockdown, the willingness to pay for time savings for class 1 users increased to $37/h, surpassing that of class 2 users ($31/h).

In the subsequent step, I segmented travelers into three latent classes (LCOL-3), with respective proportions of 24%, 36%, and 40%. This segmentation remained consistent even during the pandemic. The estimated values of travel time (VOTs) before the pandemic were $26/h, identical across the three classes. However, during the lockdown, the VOT estimates varied: $35/h, $38/h, and $37/h for the three latent classes, respectively. While this reflected a slight increase in VOT heterogeneity compared to pre-pandemic levels, the differences were still subtle. I also explored a model with four latent classes (LCOL-4), but found that the parameters remained identical to those of the LCOL-3 model before the pandemic. During the pandemic, transitioning from two to three classes increased the final log-likelihood and adjusted rho square, but these metrics remained unchanged when moving from three to four classes. This suggests that adding more latent classes did not notably enhance the model's performance. Therefore, it can be concluded that preference heterogeneity in travel behavior is more effectively reflected by trip frequency rather than other trip attributes.

2.5.5 Comparison on model performance

Table 8 presents the estimates of Value of Time (VOT) and the corresponding percentage changes attributed to the lockdown and Work From Home (WFH) policies. This analysis, consistent with Lin et al., (2024), confirms an increase in VOT during the pandemic, ranging from 17% to 36%. These elevated VOTs suggest that, on average, drivers were willing to expend more resources to achieve the same amount of travel time savings during the pandemic period. The significant reduction in overall traffic volume following the lockdown resulted in fewer drivers/vehicles on the roads. Consequently, the time difference between the general-purpose lanes and the Express Lanes became negligible, leading to a decrease in travel time savings. All else being equal, an increase in the coefficient of travel time is necessary to maintain the same level of individual utility, hence the observed rise in VOT. Furthermore, the heightened VOT values justify the smaller user groups, or market share, observed on the Express Lanes during the lockdown. Smaller cohorts of drivers, willing to expend more for equivalent travel time savings, naturally translate to lower market shares on the Express Lanes.

In Table 9, I examine goodness-of-fit statistics across different models. Both pre-pandemic and during-pandemic periods show that the GOL and PPO models exhibit the lowest log-likelihood values at convergence and the highest adjusted rho squared values. Regarding the impact of heterogeneity on VOT estimates, I observe that estimates from the HOL model are substantially higher compared to those obtained with fixed coefficients. This indicates that neglecting heterogeneity in travel time and travel cost leads to an underestimation of VOTs.

GOL and PPO undercover the high VOT for users that travel on the ELs just once; VOTs decrease significantly with increased EL usage frequency. Lastly, the LOC model demonstrates limited ability to distinguish differences among the latent classes in the population. VOT estimates remain very similar across latent classes, and little variation in the classes' sizes is observed.

2.6 Conclusion

In this chapter, I propose advanced discrete choice modeling approaches to investigate the unobserved heterogeneity of Express Lane users' travel behavior. I consider modeling formulations such as the heteroskedastic ordered logit (HOL) model, generalized ordered logit (GOL) model, and latent class ordered logit (LCOL) model. I segment the historical traffic dataset of the Express Lane into two phases: before and during the implementation of lockdown and work-from-home policies, which began in mid-March 2020.

Initially, I describe the observed heterogeneity in travel behavior changes during the pandemic across various temporal phases based on time of day and day of the week. I find a substantial reduction in travel demand and toll revenue for the Express Lane throughout all temporal phases following the lockdown. The impact of the lockdown measures is more pronounced on workdays (Monday to Friday) compared to weekends. Additionally, rush hours experience greater declines than other times of the day. Notably, the disparity in Express Lane usage between workdays and weekends diminishes significantly under the pandemic's influence. Furthermore, the Covid-19 pandemic leads to a shift in peak periods for Express Lane usage.

Findings from model estimation indicate a notable increase in Value of Time (VOT) across all advanced ordered logit models following the onset of the Covid-19 pandemic and the implementation of lockdown policies from mid-March 2020 onwards. This surge in VOT helps explain the reduced user base, or market share, on Express Lanes during the lockdown period. In line with HOL results, travel time and travel cost are characterized by significant standard deviations in both pre-pandemic and pandemic periods, demonstrating the presence of taste heterogeneity. HOL estimates of VOT are significantly higher than those obtained using OL models with fixed coefficients. The GOL model also reveals substantial heterogeneity among different categories of trip frequency, distinguishing between infrequent, occasional, and frequent users. Particularly noteworthy is that infrequent Express Lane users demonstrate a higher willingness to pay a premium for time-saving convenience compared to regular commuters who utilize the Express Lane more frequently.

While the pandemic accentuates preference heterogeneity between latent classes of users, this distinction remains relatively minor compared to the variability observed among trip frequency categories in the GOL and PPO models. This underscores my belief that preference heterogeneity in travel behavior is more aptly reflected by trip frequency rather than other trip attributes. Overall, the GOL and PPO models demonstrated superior goodness of fit compared to the HOL and LCOL models in this analysis.

Each model offers distinct advantages and limitations. The GOL provides a more intuitive explanation of heterogeneity in willingness to pay for different frequency of use. On the other hand, the HOL model allows for different variances across response categories, addressing issues of unequal dispersion in the data. The LCOL model permits modeling unobserved heterogeneity in the response, identifying latent classes of users with varying travel patterns despite the absence of socio-demographic information.

The richness of the model proposed might help tailoring the Express Lane service to the preferences of different user types while ensuring its financial sustainability and attractiveness to a diverse range of users. For example, results about the willingness to pay among infrequent Express Lane travelers can inform decision-makers and toll lane operators in establishing pricing structures and optimizing investment in Express Lane services.

However, this chapter has certain limitations that warrant consideration for future research. Firstly, the LCOL model's effectiveness in capturing heterogeneity in user travel behavior may be limited by the lack of socio-demographic information about transponders/users. Socio-demographic factors such as age, income, education, and employment status can provide valuable contextual information to explain behavioral differences among different segments of Express Lane users. Without this information, the LCOL model may not fully capture heterogeneity, potentially compromising the accuracy and reliability of the model. Secondly, this analysis may be limited by the use of data from a restricted time period, potentially failing to capture the long-term effects of lockdown and work-from-home policies. The COVID-19 pandemic might have caused long-term effects on travel behavior and willingness to pay for Express which are not captured in this study. Therefore, future research should consider longitudinal data to better understand the enduring impact of the pandemic on travel behavior and preferences.

Table 6: Modeling results (Before pandemic)

	OL		HOL1	HOL2		GOL	PPO	LCOL-2			LCOL-3		
								Choice model	**Class1**	**Class2**	**Class1**	**Class2**	**Class3**
		Explanatory variable			cost/trip1	-0.638 (0.003)	-0.811 (0.002)	cost/trip	-0.121 (0.001)	-0.121 (0.001)	-0.121 (0.001)	-0.121 (0.001)	-0.121 (0.001)
cost/trip	-0.121 (0.001)	cost/trip	-0.434 (0.002)	-0.350 (0.002)	cost/trip2	-1.282 (0.008)		time saving	0.053 (0.000)	0.053 (0.000)	0.053 (0.000)	0.053 (0.000)	0.053 (0.000)
time saving	0.053 (0.000)	time saving	0.347 (0.001)	0.292 (0.001)	cost/trip3	-1.364 (0.011)		Class model	**Class1**	**Class2**	**Class1**	**Class2**	**Class3**
		Heteroskedastic variable			cost/trip4	-1.308 (0.011)		Class size	39.9%	60.1%	24.2%	36.0%	39.8%
		cost/trip	-	-0.028 (0.001)	cost/trip5	-1.201 (0.013)		*Time of day*					
		time saving	0.018 (0.000)	0.018 (0.000)	cost/trip6	-1.232 (0.017)		early morning	-0.194 (3.725)	1.410 (2.859)	-1.061 (3.468)	0.379 (3.804)	0.274 (6.214)
cut1	0.059 (0.005)	cut1	0.642 (0.006)	0.607 (0.006)	cost/trip7	-1.395 (0.023)		AM peak	-1.605 (4.771)	2.163 (2.888)	-3.236 (7.028)	0.950 (3.388)	0.883 (5.627)
cut2	3.214 (0.008)	cut2	10.737 (0.044)	9.496 (0.029)	time saving1	0.560 (0.002)	0.716 (0.002)	AM off-peak	-2.145 (4.414)	2.601 (2.433)	-4.243 (7.218)	1.214 (2.994)	1.186 (5.058)
cut3	5.396 (0.016)	cut3	21.158 (0.088)	18.587 (0.062)	time saving2	0.203 (0.001)	0.150 (0.000)	PM off-peak	-2.748 (5.154)	2.995 (2.647)	-5.178 (10.58)	1.504 (3.009)	1.534 (5.174)
cut4	7.522 (0.025)	cut4	29.822 (0.124)	26.384 (0.098)	time saving3	0.102 (0.001)	0.072 (0.000)	PM peak	-2.658 (5.092)	2.934 (2.718)	-5.068 (11.10)	1.456 (2.991)	1.476 (5.113)
cut5	9.707 (0.035)	cut5	41.209 (0.166)	37.033 (0.166)	time saving4	0.065 (0.000)	0.046 (0.000)	*Day of week*					
cut6	11.802 (0.043)	cut6	59.591 (0.341)	54.953 (0.352)	time saving5	0.044 (0.000)	0.034 (0.000)	Monday	-1.271 (4.727)	1.971 (2.888)	-2.682 (5.589)	0.802 (3.514)	0.700 (5.862)
cut7	13.158 (0.048)	cut7	80.419 (0.606)	75.955 (0.621)	time saving6	0.034 (0.000)	0.027 (0.000)	Tuesday	-1.404 (5.009)	2.038 (3.048)	-2.879 (6.521)	0.858 (3.532)	0.771 (5.909)
					time saving7	0.032 (0.000)	0.023 (0.000)	Wednesday	-1.551 (4.895)	2.147 (2.852)	-3.137 (6.326)	0.929 (3.413)	0.854 (5.749)

Thursday	-1.725 (4.807)	2.271 (2.701)	-3.435 (6.359)	1.011 (3.308)	0.950 (5.603)
Friday	-1.959 (4.533)	2.476 (2.461)	-3.883 (6.211)	1.130 (3.137)	1.085 (5.355)
Saturday	-1.501 (4.089)	2.258 (2.548)	-3.279 (5.488)	0.949 (3.146)	0.854 (5.284)
Trip attribute					
Northbound	-4.386 (12.22)	3.876 (5.070)	-7.587 (51.82)	2.270 (3.385)	2.482 (6.204)
repeat trip	-0.548 (15.07)	1.407 (12.25)	-1.259 (19.21)	0.460 (8.637)	0.303 (13.64)

Table 7: Modeling results (During pandemic)

	OL		**HOL1**	**HOL2**		**GOL**	**PPO**	**LCOL-2**			**LCOL-3**		
								Choice model	**Class1**	**Class2**	**Class1**	**Class2**	**Class3**
		Explanatory variable			cost/trip1	-1.552 (0.012)	-1.698 (0.012)	cost/trip	-0.372 (0.005)	-0.459 (0.005)	-0.395 (0.005)	-0.348 (0.005)	-0.366 (0.005)
cost/trip	-0.406 (0.005)	cost/trip	-1.336 (0.000)	-0.633 (0.001)	cost/trip2	-2.388 (0.039)		time saving	0.230 (0.001)	0.235 (0.001)	0.230 (0.001)	0.225 (0.001)	0.227 (0.001)
time saving	0.233 (0.001)	time saving	1.470 (0.000)	0.811 (-)	cost/trip3	-2.509 (0.054)		Class model	**Class1**	**Class2**	**Class1**	**Class2**	**Class3**
		Heteroskedastic variable			cost/trip4	-2.322 (0.063)		Class size	40.7%	59.3%	24.8%	35.7%	39.5%
		cost/trip	-	0.212 (0.000)	cost/trip5	-2.109 (0.071)		*Time of day*					
		time saving	0.056 (0.000)	0.056 (-)	cost/trip6	-2.066 (0.094)		early morning	-0.308 (0.471)	0.469 (0.477)	-0.569 (0.251)	0.319 (0.721)	0.318 (0.722)
cut1	0.348 (0.013)	cut1	1.518 (0.008)	1.115 (0.009)	cost/trip7	-2.105 (0.121)		AM peak	-0.876 (0.435)	0.990 (0.432)	-1.408 (0.259)	0.642 (0.598)	0.639 (0.598)
cut2	4.388 (0.024)	cut2	19.103 (0.063)	11.406 (0.038)	time saving1	1.838 (0.010)	1.924 (0.010)	AM off-peak	-1.374 (0.416)	1.446 (0.407)	-2.112 (0.264)	0.921 (0.543)	0.918 (0.544)
cut3	7.650 (0.048)	cut3	38.927 (0.161)	23.074 (0.104)	time saving2	0.462 (0.004)	0.407 (0.003)	PM off-peak	-1.571 (0.422)	1.627 (0.411)	-2.370 (0.276)	1.025 (0.536)	1.021 (0.536)
cut4	10.659 (0.073)	cut4	56.085 (-)	34.636 (0.220)	time saving3	0.221 (0.003)	0.191 (0.002)	PM peak	-1.198 (0.412)	1.292 (0.406)	-1.885 (0.257)	0.829 (0.551)	0.827 (0.552)
cut5	13.440 (0.096)	cut5	77.130 (-)	51.789 (-)	time saving4	0.138 (0.002)	0.124 (0.001)	*Day of week*					
cut6	16.157 (0.121)	cut6	115.85 (-)	83.764 (0.036)	time saving5	0.093 (0.002)	0.090 (0.001)	Monday	-0.882 (0.462)	0.981 (0.456)	-1.395 (0.281)	0.638 (0.600)	0.635 (0.600)
cut7	18.271 (0.144)	cut7	181.90 (3.447)	131.92 (2.547)	time saving6	0.069 (0.002)	0.072 (0.001)	Tuesday	-0.821 (0.465)	0.921 (0.459)	-1.305 (0.279)	0.601 (0.609)	0.598 (0.609)
					time saving7	0.060 (0.002)	0.060 (0.001)	Wednesday	-0.830 (0.468)	0.929 (0.462)	-1.316 (0.282)	0.606 (0.611)	0.603 (0.611)

Thursday	-0.924 (0.453)	1.014 (0.445)	-1.453 (0.275)	0.659 (0.588)	0.656 (0.589)
Friday	-1.073 (0.434)	1.157 (0.424)	-1.679 (0.265)	0.747 (0.560)	0.744 (0.560)
Saturday	-0.827 (0.431)	0.998 (0.433)	-1.391 (0.262)	0.641 (0.582)	0.640 (0.583)
Trip attribute					
Northbound	-2.660 (0.501)	2.593 (0.482)	-3.767 (0.496)	1.635 (0.459)	1.650 (0.461)
repeat trip	-0.339 (1.355)	0.431 (1.415)	-0.534 (1.062)	0.310 (1.381)	0.306 (1.382)

Table 8: Summary of VOT estimates

	OL				**GOL**				**LCOL-2**	
VOT (before)	VOT (during)	VOT (change)		VOT (before)	VOT (during)	VOT (change)		VOT (before)	VOT (during)	VOT (change)
26.38	34.40	+30.38%	category1	56.43	71.04	+25.90%	class1	26.39	37.05	-
			category2	9.49	11.60	+22.20%	class2	26.38	30.66	-
			category3	4.51	5.28	+17.16%				
	HOL1		category4	2.97	3.57	+20.26%		Class size (before)	Class size (during)	
VOT (before)	VOT (during)	VOT (change)	category5	2.19	2.64	+20.67%	class1	39.90%	40.70%	
50.41	68.56	+36.00%	category6	1.67	1.99	+19.31%	class2	60.10%	59.30%	
			category7	1.40	1.70	+21.86%				
	HOL2				**PPO**				**LCOL-3**	
VOT (before)	VOT (during)	VOT (change)		VOT (before)	VOT (during)	VOT (change)		VOT (before)	VOT (during)	VOT (change)
49.20	61.68	+25.37%	category1	52.95	68.03	+28.48%	class1	26.39	35.05	-
			category2	11.12	14.40	+29.43%	class2	26.39	38.88	-
			category3	5.31	6.76	+27.19%	class3	26.38	37.13	-
			category4	3.42	4.39	+28.19%		Class size (before)	Class size (during)	
			category5	2.52	3.17	+25.69%	class1	24.20%	24.76%	
			category6	2.00	2.54	+26.73%	class2	36.00%	35.74%	
			category7	1.72	2.13	+24.28%	class3	39.80%	39.50%	

Table 9: Summary of modeling parameters

	OL	HOL1	HOL2	GOL	PPO	LCOL-2	LCOL-3	LCOC-4
Pre-pandemic								
Num. of observations	524953							
Final log likelihood	-435211.5	-339945.2	-339238.27	-247500.64	-254584.82	-435211.6	-435211.6	-435211.6
Likelihood ratio test	281037.02	471140.35	472554.01	656029.47	642290.38	405219.5	405219.5	405219.5
Rho-square	0.2441	0.4093	0.4105	0.5699	0.5578	0.318	0.318	0.318
During-pandemic								
Num. of observations	168457							
Final log likelihood	-107609.56	-75255.202	-76196.915	-63529.418	-63950.245	-136346	-108659.1	-108659.1
Likelihood ratio test	107670.41	172234.35	170350.93	195685.92	194989.04	148686.3	132074.9	132074.9
Adjusted Rho-square	0.3335	0.5337	0.5278	0.6063	0.6039	0.353	0.378	0.378

Chapter 3: Value of travel time reliability

3.1 Introduction

The concept of value of time (VOT) on Express Lanes (ELs) has been widely used by analysts to understand how drivers decide whether to use these lanes and avoid congestion by paying a fee (Carrion and Levinson, 2012). Beyond VOT, travel time reliability has become increasingly important in evaluating transportation infrastructure performance. The value of travel time reliability (VOR), which measures the benefits of more predictable travel times, has garnered growing attention, with methodologies for quantifying it being a subject of ongoing debate (Cherry et al., 2023, Fosgerau, 2010).

The ability to reliably predict travel time and arrive on time is critical for various reasons, such as enhancing productivity, meeting personal and business commitments, and improving quality of life. VOR reflects the advantages individuals and businesses gain from more dependable travel times, including time and cost savings, heightened economic activity in specific regions, and improved traveler satisfaction.

As a result, VOR has become a key consideration for transportation planners and policymakers when determining the most effective investments in transportation infrastructure. Incorporating both VOT and VOR in the planning process helps ensure that Express Lanes and other infrastructure investments offer real value to commuters and the broader economy.

This chapter introduces new measures of travel time reliability for Express Lane (EL) users, based on real travel times linked to the frequency of ELs use. The analysis leverages passively collected data to capture how often drivers choose to use ELs, as well as the variability in travel times across different times of the day, departure times, and days of the week. Given the richness of the data, these measures are rooted in the personal experiences of transponder users and real-time travel metrics from probe vehicle data.

These measures provide valuable insights into the value of travel time reliability (VOR), enabling transportation planners to better understand the trade-offs commuters make between cost, time savings, and reliability when opting for Express Lanes. Additionally, the study underscores the importance of integrating both VOR and VOT when assessing the overall performance and user satisfaction with Express Lane systems.

The analysis still covers two distinct periods: pre-pandemic (January 2020 to mid-March 2020) and during the pandemic (mid-March 2020 to May 2020), offering a unique perspective on how travel behavior and reliability perceptions evolved during these times.

The remainder of this chapter is structured as follows: first, I discuss the concept of travel time variability; second, I provide a summary of research related to the estimation of the value of travel time reliability (VOR); third, details regarding the data utilized in this analysis are presented; fourth, I outline the methodology employed in the study; and finally, I present the results and conclusions drawn from the analysis.

3.2 Concept of travel time variability and reliability

In road networks, travel time is often broken down into two key components: free-flow travel time and additional travel time. Free-flow travel time represents the duration required for a driver to reach their destination under optimal traffic conditions with minimal delays. In contrast, additional travel time refers to the extra time incurred due to traffic congestion or other disruptions. These variations in travel time can stem from predictable sources, such as peak-hour traffic, or unpredictable ones, like accidents or road closures (Carrion and Levinson 2012).

Variability in travel time is caused by several factors, including different vehicle types sharing the road, varying driver behavior, intersection delays, and random events (Liu et al., 2004). Such variability introduces uncertainty, which challenges travelers who must plan for potentially longer journeys with uncertain arrival times. When variations are predictable, travelers can adjust by changing their departure times. However, under unpredictable conditions, such as accidents or sudden congestion, travelers may find it difficult to accurately estimate their travel times in advance (Li et al., 2009).

The advent of crowdsourced traffic data and real-time navigation apps, such as Waze and Google Maps, has dramatically transformed the concept of travel time reliability. By providing real-time updates on traffic conditions and route recommendations, these technologies help drivers make more informed decisions (Gao et al., 2011). They shift the emphasis from static, long-term averages of travel time reliability to moment-by-moment accuracy. This real-time adaptability allows drivers to avoid delays by dynamically adjusting routes, including switching to Express Lanes (ELs) under unforeseen traffic conditions (Liu et al., 2004).

From a statistical perspective, travel time reliability is linked to the variability and predictability of travel times (Liu et al., 2004). The more consistent the travel time for repeated trips, the more reliable the journey is considered. When faced with high variability and uncertainty, travelers may opt to pay tolls for Express Lanes to ensure greater travel time reliability. Ghosh (2001) pointed out that users of toll lanes often pay not just for shorter travel times but also for reduced uncertainty. In essence, the value of reliability quantifies how much commuters are willing to pay to reduce the unpredictability of their journey. When uncertainty exceeds a certain threshold, drivers are willing to pay significantly more for reliable travel, making Express Lanes an attractive option during unpredictable traffic conditions.

Thus, the use of toll lanes like Express Lanes reflects a broader shift in how travelers value both time savings and the reduction in uncertainty, particularly when real-time traffic data can inform those decisions.

3.3 Literature review

3.3.1 Theoretical frameworks

3.3.1.1 Mean-variance (Centrality-dispersion)

The mean-variance approach, primarily known from risk-return models in finance, has been effectively applied to transportation research to measure travel time reliability. In finance, decision-makers aim to maximize returns while minimizing risk, with returns represented by expected values and risk by variance (Markowitz, 1999). This framework translates well to transportation, where both travel time and its variability contribute to disutility for travelers (Carrion and Levinson, 2012). In transportation, the framework considers that travelers aim to minimize the sum of two components: the expected travel time and the variability of travel time. The expected travel time serves as a certainty measure (mean or centrality) of the travel time distribution, while travel time variability acts as a dispersion measure (e.g., variance or standard deviation) of the travel time distribution. This dual consideration acknowledges that not only the average travel time but also its unpredictability can affect travelers' route choices and satisfaction. Several studies have employed standard deviation as a measure of travel time variability (Yan, 2002; Liu et al., 2004; Liu et al., 2007; Peer et al., 2012; Carrion and Levinson

2013; Cherry et al., 2023). This approach highlights how much travel times deviate from the mean, offering a straightforward measure of reliability.

Other studies have used percentile-based measures to capture travel time variability, such as the difference between specific percentiles within a travel time distribution (Lam and Small 2001; Ghosh 2001; Yan 2002; Liu et al., 2004; Small et al., 2005; Liu et al., 2007; Carrion and Levinson 2013; Abir et al., 2017):

- Buffer Time Index: Difference between the 95th and 50th percentiles.
- Shorten Right Range: Difference between the 90th and 50th percentiles.
- Inter-Quartile Range: Difference between the 75th and 25th percentiles

These percentile-based measures provide insights into the extreme values and the spread of travel time distributions, capturing the tail behavior and overall variability experienced by travelers. By integrating these measures, researchers and policymakers can better understand and mitigate the impact of travel time unreliability on commuters' daily experiences and decision-making processes. Moreover, variation of travel time can be categorized spatially (i.e., link, corridor, system), spatially (i.e., peak and off-peak), or by different level of aggregation (Tufuor and Rilett, 2022). In this chapter I consider:

- Inter-day Variability: Caused by seasonal and day-to-day variations such as demand fluctuations, accidents, road construction, and weather changes.
- Inter-period Variability: Reflects the impact of differences in departure times and the resultant changes in congestion.
- Inter-vehicle Variability: Mainly due to individual driving styles and traffic signals.
- Over Repeated Trips: Variations experienced by a single traveler making the same trip repeatedly.

3.3.1.2 Scheduling delays

Peer et al. (2012) suggested that the valuation of travel time unreliability often correlates more with the valuation of implied schedule delays rather than direct dispersion indicators. This perspective aligns with the scheduling delay approach, which accounts for travelers' most common response to variable travel times: adjusting their departure times. The scheduling delay model considers the disutility travelers incur when they do not arrive at their preferred arrival time, either arriving early or late (Jin et al., 2015). Delay, in this context, is defined as the difference between the preferred arrival time and the actual arrival time.

Several empirical studies have applied the scheduling delays approach to measure travel time reliability (Fosgerau and Karlström 2010; Peer et al., 2012; Kroes et al., 2018). This method reflects travelers' real-world experiences and decision-making processes more accurately than simple measures of variance or standard deviation. The approach focuses on the disutility or inconvenience caused by deviations from preferred schedules. Some key measures used in this approach include:

- Actual Late Arrival - Usual Travel Time: The difference between the time of actual late arrival and the typical travel time.
- Early Arrival Time - Preferred Arrival Time: The difference between the time of early arrival and the preferred arrival time.
- Late Arrival Time - Preferred Arrival Time: The difference between the time of late arrival and the preferred arrival time.

3.3.1.3 Mean-lateness

The mean-lateness approach for measuring travel time reliability focuses on two main elements: scheduled journey time and mean lateness at the destination. The scheduled journey time is the expected travel time based on the timetable, while the mean lateness at the destination is the average delay experienced by travelers. This approach differs from the scheduling delays model in that it primarily considers lateness, focusing on the delays both at the start and end of the journey relative to the scheduled timetable. In contrast, the scheduling model accounts for both early and late arrivals with respect to the preferred arrival time (Jin et al., 2015).

3.3.1.4 Other approaches

Additionally, Tilahun and Levinson (2010) explored innovative measures beyond traditional approaches. They introduced the mode-variance model, which considers the mode (the most frequent travel time observed) and the mode-right range (the difference between the 100th percentile and the 50th percentile of travel times). They also proposed a measure involving two moments: one representing earliness and the other representing lateness. This approach aims to capture a more nuanced view of travel time reliability by distinguishing between early and late arrivals. Kodi et al., (2023) and Tufuor and Rilett (2022) assessed travel time variability using statistical measures such as the coefficient of variation (CV) and index-based measures like the planning time index (PTI) and travel time index (TTI). The CV is a normalized measure of dispersion, calculated as the ratio of the standard deviation to the mean travel time. PTI represents the total time that should be planned for a trip to arrive on time 95% of the time, while TTI measures the ratio of travel time in traffic to the travel time under free-flow conditions. These studies contribute to a broader understanding of travel time variability by incorporating various statistical and index-based measures that capture different aspects of travel time reliability.

3.3.2 Data type

In the realm of valuing travel time reliability (VOR), researchers primarily rely on two types of data sources: revealed preference (RP) and stated preference (SP) data, each offering distinct advantages and challenges. RP data are derived from observed choices made by travelers in real-world scenarios. These choices can be directly observed through travel behavior or self-reported via surveys that reflect past experiences. RP data provide insights into actual decision-making without relying on hypothetical scenarios. However, reported travel time is often unreliable, and the variation in travel time experienced by travelers over extended periods is typically not available from surveys. SP data, on the other hand, are gathered through surveys where respondents are presented with hypothetical scenarios and asked to make choices under those conditions. SP surveys allow researchers to control variables, minimize correlation effects, and obtain detailed information about preferences that might not be observable through RP data alone. However, SP results can be influenced by survey design, including question framing and the level of information provided to respondents. Concerns about the validity of SP data arise because responses may not align with actual behaviors and could be subject to hypothetical bias, where individuals overstate the importance of factors presented in the survey (Liu et al., 2004). Researchers employ either RP or SP data, or a combination of both to estimate VOT and VOR. Studies using RP data (Lam and Small, 2001; Ghosh, 2001; Liu et al., 2004, 2007; Carrion and Levinson, 2013) focus on actual travel behaviors and decisions made under real conditions. Conversely, SP surveys (Li et al., 2009; Tilahun and Levinson, 2010; Devarasetty et al., 2012; Cherry et al., 2023) are designed to capture stated preferences in hypothetical scenarios. Some studies leverage both RP and SP data (Small et al., 2005; Brownstone and Small, 2005; Hossan et al., 2016) to combine the strengths of both methodologies.

Indirect methods (Jackson and Jucker, 1982) might also be used to evaluate travel time and travel time reliability. They involve analyzing observed data on traffic flows across alternative routes, providing insights into how travel time variability influences route selection. Advancements in traffic surveillance and monitoring technologies have significantly enhanced the ability to collect and analyze real-time data, providing valuable insights into travel behavior and traffic patterns. Inductive loop detectors, for instance, are extensively used to monitor traffic flow, vehicle density, and travel times. These technologies offer aggregated information derived from individual travel choices, which can be crucial for understanding route, mode, and departure time decisions in real-time. Liu et al., (2004) proposed an indirect method to estimate choice probabilities using real-time loop detector data. This method involves analyzing aggregated data to infer the disaggregated individual travel choices, thus eliminating the need for direct surveys.

Travel time reliability has traditionally been explored using data from stationary sensors with high penetration rates, but research utilizing mobile sensors, which typically have lower penetration rates, remains limited (Steinmaßl et al., 2021). Equipping vehicles with Global Positioning Systems (GPS) overcomes challenges in gathering detailed trip-level data, such as travel time, distance, and origin-destination pairs, along with link-by-link trajectory information (Carrion and Levinson, 2013). Li et al. (2004) leveraged travelers' GPS data to estimate travel time variability in commute trips and investigated how this variability impacts departure time and route choice decisions.

Recently, probe vehicle data (PVD), also known as floating car data, has emerged as a valuable resource for analyzing travel time reliability along road corridors. Probe vehicles, equipped with GPS receivers, provide real-time positioning, enabling the determination of travel times from the collected data (Olszewski et al., 2018). Olszewski et al. (2018) utilized historical probe vehicle data to evaluate highway travel time reliability. Similarly, Chen et al., (2018) explored travel time distribution and variability patterns using a substantial amount of probe vehicle data collected in Beijing, China. Chen and Fan (2020) extended this work by using probe vehicle data from the Regional Integrated Transportation Information System (RITIS) to examine travel time reliability patterns, identifying significant variations based on day-of-week and weather conditions.

3.3.3 Choice alternatives

In transportation studies, understanding how travelers make decisions regarding route choice, mode choice, departure time, and their combinations is crucial for evaluating the impact of infrastructure like Express Lanes (ELs) on travel behavior. Here's an exploration of these concepts and their implications based on relevant literature:

3.3.3.1 Route choice

Route choice refers to the decision-making process where travelers select between toll routes (Express Lanes) and toll-free routes (general-purpose lanes). The perceived disutility for travelers is influenced by factors such as travel time, travel time variability, monetary cost, and personal attitudes towards these variables. Studies (Lam and Small, 2001; Yan, 2002; Liu et al., 2004; Small et al., 2005; Carrion and Levinson, 2013; Hossan et al., 2016; Abir et al., 2017) consistently show that travel time reliability significantly impacts route choice decisions. Moreover, Carrion and Levinson (2012) highlight that travelers often prioritize predictability in travel time over shorter but less reliable routes. This preference suggests that travelers may opt for routes with longer average travel times if they provide greater certainty of arrival times, especially when reliability is critical.

3.3.3.2 Mode choice

Mode choice involves decisions about the means of travel, influenced by factors such as time, cost, and now increasingly, travel time reliability. The availability of Express Lanes, which offer free access to carpoolers, can sway individuals towards shared modes of transport (Jin et al., 2015). In addition to traditional factors, travel time reliability has emerged as a significant consideration in mode choice models (Bhat and Sardesai, 2006). Various studies (Ghosh, 2001; Bhat and Sardesai, 2006; Devarasetty et al., 2012; Cherry et al., 2023) have explored how commuters weigh reliability alongside other factors when choosing between transportation modes. Reliability can influence decisions to use private vehicles versus public transit, particularly in environments where Express Lanes provide reliable, congestion-free travel for carpoolers.

3.3.3.3 Departure time choice

Departure time choice refers to the decision to travel at specific times of day, influenced by variable toll pricing on Express Lanes. Typically, lower tolls towards peak shoulders incentivize travelers to adjust their departure times to minimize costs and potentially avoid congestion (Kroes et al., 2018). This variability in toll pricing impacts commuter behavior and traffic flow dynamics, particularly in urban areas.

3.3.3.4 Combination of choices

The presence of Express Lanes introduces complexities where travelers may simultaneously consider route, mode, and departure time choices (Jin et al., 2015). Integrated studies (Lam and Small, 2001; Small et al., 2005) have examined how these decisions interrelate and influence overall travel behavior. For instance, travelers may select Express Lanes not only based on route preferences but also in combination with preferred departure times or chosen modes of transportation. Liu et al. (2007) challenge the assumption that departure time is exogenous to route choice, suggesting instead a time-dependent approach that accounts for how departure time influences route decisions. This approach acknowledges the dynamic nature of travel behavior and the continuous evaluation of travel time reliability across different times of day.

3.3.4 Findings related to VOR

The relationship between VOR and VOT is not straightforward. Devarasetty et al. (2012) noted that there is no inherent reason to assume equality between the two values, as individuals may prioritize time savings differently from reliability. Liu et al. (2004) observed that VOR tends to be higher than VOT in route choice decisions, implying that travelers may place a higher premium on consistent travel times over simply reducing travel time. Conversely, Tilahun and Levinson (2010) found that VOR can be quite close to VOT, suggesting variability based on context and individual preferences. Jin et al. (2015) highlighted how VOR varies under different circumstances, including travel purpose, time of day, day of the week, and socioeconomic status. Key findings include:

- Gender Differences: Females generally exhibit a higher VOR than males, a conclusion also supported by Carrion and Levinson (2012).
- Commuters vs. Non-Commuters: Commuters tend to show higher VOR than non-commuters.
- Time of Day: Morning trips often have the highest VOR compared to other times of the day.
- Trip Urgency: Urgent trips present a higher VOR than regular trips.
- Day of the Week: Fridays typically experience the highest VOR among weekdays.
- Trip Purpose: Cherry et al. (2023) found that non-work trips have greater VOR compared to work trips.

Table 10 summarizes VOR estimates from previous studies. As it can be seen the range of VOR estimates varies significantly, often spanning from 0.55 to 3.22 times the VOT estimates. This wide range indicates that the importance of travel time reliability can differ greatly depending on the specific context and individual preferences.

Table 10: Summary of VOR estimates from previous studies

Author	Data	Study site	When collected	Lane type	Data type	Measurement	Model	VOR estimate
Lam and Small (2001)	Mail survey; Loop detector data	SR91	1997-1998	EL-GP	RP	Difference in 90th-50th percentiles	Route choice etc; Binomial logit model	$15.12/h for men; $31.91/h for women
Ghosh (2001)	Panel survey; Network data	I-95 HOT lanes	1998-1999	EL-GP	RP	Difference in 90th-50th percentiles	Mode choice; Conditional logit model	Median $34.43/h; Mean $49.88/h
Yan (2002)	Telephone RP survey; Two-stage RP-SP survey; Floating-car data	SR91	1999-2000	EL-GP	RP-SP	Standard deviation; Difference in 90th-50th and 80th-50th percentile	Route choice; Binomial logit model	Median between $19-$30/h by RP; Median roughly $5/h by SP
Liu et al., (2004)	Field measurements (floating car); Loop detector	SR91	1999-2000	EL-GP	RP	Standard deviation; Difference in 90th-50th or 80th-50th percentiles etc.	Route choice; Mixed logit model	Median $20.63/h
Small et al., (2005)	Telephone RP survey; Mail SP survey; Field measurements	SR91	1999-2000	EL-GP	RP-SP	Difference in 80th-50th percentiles	Route choice etc; Mixed logit model	Median $19.56/h by RP; Median 5.40/h by SP
Bhat and Sardesai (2006)	Web-based survey of Austin, Texas area commuters; zonal network skims	-	-	-	RP-SP	Additional travel time to reach to destination in SP design	Mode choice; Mixed logit model; joint RP/SP multinomial logit model	$7/h for flexible work; $14/h for inflexible work
Liu et al., (2007)	Loop detector	SR91	2001	GP	RP	Standard deviation; difference in 80th-50th, 90th-50th	Route choice; Mixed logit model	Ranged from $17.49/h to $39.24/h from

						percentile		5am to 10am
Tilahun and Levinson (2010)	Computer-administered stated-preference survey	-	-	EL-GP	SP	Mode-variance; mode-right range; earliness, lateness	Route choice; Binomial logit model	$7.11/h by model 1; $2.31/h by model 2; $6.93/h by model 3
Devarasetty et al. (2012)	Internet-based survey; Traffic volume and travel time from sensors	Katy Freeway	2009-2010	EL-GP	SP	Percentage of travel time variation away from a mean travel time	Mode choice; Mixed logit model	$50/h (VOT+VOR)
Carrion and Levinson (2013)	Global positioning system (GPS) tracking data; information about toll data	I-394 MnPass lanes	2008-2009	EL-GP	RP	Standard deviation; shortened right range; difference in 75th-25th percentile	Route choice; Mixed logit model	Mean $5.99/h; Men $1.96/h and women $8.6/h
Hossan et al., (2016)	South Florida Expressway Stated Preference Survey; Detector data from RITIS[6]	I-75, I-95, SR826	2011-2012	EL-GP	RP-SP	Semi-standard deviation	Route choice (five choices); Mixed logit	$16.13/h
Abir et al., (2017)	Data generated from AVI sensors	Katy Freeway	2012-2014	EL-GP	RP	Standard deviation; percentile 10th, 25th, 50th, 75th, 80th, 85th, 90th, and 95th.	Route choice; Binomial logit model	Ranged from $-39.56/h to $6.6/h; and from $-7.19/h to $21.97/h
Cherry et al., (2021)	Online SP survey; GIS data	Dulles toll road; Dulles Greenwa	2019-2020	EL-GP	SP	Standard deviation	Mode choice; Multinomial logit model	Before pandemic: $16.53/h for work trip; $20.21/h for non-

[6] The Regional Integrated Transportation Information Systems (RITIS) CATT Lab, 2015

	y; 66, 495, 95, 395 Express Lanes		work trip. During pandemic: \$10.14/h for work trip; \$16.93 for non-work trip.

3.4 Data sources

This chapter still relies on the integration of multiple datasets relative to Express Lanes in Virginia, similar to what described in previous chapters. These datasets were consolidated before initiating the behavioral analysis and modeling tasks.

In summary, the transponder dataset was merged with the RITIS travel times according to the entry and exit plazas. Data was cleaned by removing trip observations with unavailable transponder ID, missing GP or EL travel time, negative travel time saved, and non-positive travel cost. After cleaning the data, for the pre-pandemic phase, I obtained 2,484,426 toll trip observations generated by 524,953 users/transponders. During the pandemic, I observed 590,164 toll trip observations and 168,457 users/transponders.

3.5 Methodological approach

The proposed model establishes a relationship between travel time, travel cost, and travel time variability as significant factors influencing the frequency of use of Express Lanes (ELs). To estimate travelers' willingness to pay for reducing travel time unreliability, an ordered logit model is selected. This model seeks to determine the utility of toll trip frequency, with the key factors being travel time saved by choosing Express Lanes, the variability of travel time saved, and the toll payment for the observed trip. The utility function is based on the concept that travelers want to minimize their disutility from travel time, travel time unreliability, and travel cost. The analysis aims to ascertain the significance of these three factors in contributing to toll trip generation and provide valuable insights into the Express Lane travelers' decision-making processes and responses to toll-related considerations.

In the ordered logit model, the latent utility is formulated as follows:

$$U_i = \beta_{TTS}(TTS_i) + \beta_{TTR}(TTR_i) + \beta_C(Toll_i) + \varepsilon_i$$

Where

U_i = The individual's utility associated with the number of trips generated in the observed time period by each transponder;

TTS_i = The difference in travel time between GP lanes and EL lanes for user i during the targeted time period;

TTR_i = The reliability of travel time difference between GP lanes and EL lanes for user i during the targeted time period;

$Toll_i$ = The average travel cost of each trip for user i;

ε_i = Other factors expect the travel time, cost and reliability that affect the user's trip frequency are embedded into the random error term. It is assumed to be i.i.d EV distributed (Train, 2009).

β_{TTS}, β_{TTR}, and β_C are coefficients to be estimated, which define how time, cost and reliability contribute to travel on ELs.

Once the ordered logit model was estimated, I calculated the corresponding value of travel time, value of travel time reliability (or user's willingness to pay for saving one hour travel time and reducing the travel time unreliability when using ELs), and the reliability ratio (RR). The VOT, VOR and RR are defined as follows:

$$VOT = \frac{\beta_{TTS}}{\beta_C}(60 minperhour)$$

$$VOR = \frac{\beta_{TTR}}{\beta_C}(60 minperhour)$$

$$RR = \frac{VOR}{VOT}$$

VOT and VOR were calculated for the EL users in the study area and compared across the two time periods considered.

3.5.1 Centrality measures, and dispersion of travel time saving

In this study, the measurement of travel time reliability is based on centrality and dispersion measures. For the centrality measure, both the mean and median are considered. For the dispersion measure, distinct metrics have been theorized and developed to establish a more direct connection between travel time variability (i.e., dispersion or spread of a travel time distribution) and travel time unreliability, and consequently measure the latter accurately (Carrion and Levinson, 2012). The following measures have been explored:

- Standard Deviation (SD)
- Shortened Right Range of the Travel Time Distribution (90th-50th Percentile)
- 80th-50th Percentile of Travel Time Distribution
- Inter-Quartile Range of Travel Time Distribution (75th-25th Percentile)

Different formulations offer insight into how each unreliability variable is traded off in decision-making with travel time and travel cost. These measures allow us to understand better the relationship between travel time variability and travelers' preferences, providing a nuanced view of how travelers value reliability in their travel. By integrating these measures into the model, the study aims to capture the multifaceted nature of travel time reliability and its impact on travelers' choices.

3.5.2 Variation across time of day, day of week

In this chapter, I also considered that the distribution of travel time savings varies across different times of day (peak periods) and days of the week due to fluctuations in travel demand. In other words, the different underlying variations in travel time savings are categorized as follows:

- Day-to-Day Variation (with Fixed Departure Time): This category captures the variability in travel time savings on a daily basis, assuming a fixed departure time. It reflects how travel time savings fluctuate from one day to another.
- Inter-Day Variation (During the Travel Day): This category addresses the variability in travel time savings within a single day. It reflects how travel time savings fluctuate throughout the day.
- Inter-Period Variation (During the Peak Period of the Travel Day): This category considers the variability in travel time savings during peak periods within a single day. It captures the differences in travel time savings during high-demand times.

By categorizing the variations in travel time savings in this manner, the study aims to provide a more detailed understanding of how travel time reliability affects travelers' choices throughout different times and conditions.

3.6 Results from model estimation

3.6.1 Travel time variability across EL observations

In this section, I estimate value of travel time saving and reliability on the Express Lane users before and during the pandemic. Initially, I merged the EL trip observations from transponders with the RITIS dynamic travel time on both EL and GP lanes, using the entry and exit point and the exact time of day when the trip occurred as the key parameters. Following the process of data merging, I calculated the travel time saving by choosing EL, as well as variability of travel time saving, for each toll trip observation. In the ordered logit modeling, the dependent variable is the frequency of toll trips registered on each transponder during the observed time periods. The independent variables include: the total travel time saved on EL (TTS), the average unreliability of travel time saved of each trip on EL (TTR), and the average toll paid for each trip (Cost/trip). The variable of travel time variability was measured using standard deviation, differences in the 90th-50th, 80th-50th, and 75th-25th percentiles (although not all results are shown). I also considered the day-to-day, inter-day, and inter-period variations for the time segments before and during the pandemic. Coefficient estimates from the ordered logit model are then used to calculate the average willingness to pay for an additional trip on the Express Lane during the observed time periods.

The modeling results presented in Tables 11 and 12 reveal important insights into the cost per trip, travel time savings (TTS), and variability factors for both pre-pandemic and pandemic periods. Across all models, the cost per trip coefficient is negative, reflecting that as toll prices increase, the likelihood of travelers choosing Express Lanes (ELs) decreases. This aligns with the basic principles of economic consumer theory—higher costs deter usage (Lin et al., 2024).

For the TTS coefficient, it consistently shows a positive sign, meaning that as drivers save more travel time by using ELs, they are more likely to choose them over general-purpose (GP) lanes. This finding is consistent with previous studies (Brownstone et al., 2003; Mitrovic et al., 2020; Lin et al., 2024).

The analysis also finds negative coefficients for travel time variability, particularly for factors like the standard deviation and differences in percentiles (except for inter-day variations in the pre-lockdown period). This negative relationship suggests that as travel time variability increases between ELs and GP lanes, users are less inclined to use ELs, confirming earlier findings (Small et al., 2005; Yan et al., 2002; Carrion and Levinson, 2013; Cherry et al., 2023).

Table 15 summarizes the value of time (VOT), value of reliability (VOR), and reliability ratio (RR) estimates for both periods, with percentage changes influenced by the pandemic. Before the pandemic, the VOT was approximately $30 per hour, rising to $40 per hour during the pandemic. These estimates are higher than those reported by RSG (Cherry et al., 2023) in 2019. For reference, the USDOT's 2020 recommendation for travel time savings was $17.8 per hour (USDOT, 2022).

The VOR estimates based on standard deviation were $48/h and $38/h for day-to-day and inter-period variation before the pandemic, rising to $57/h and $69/h during the pandemic. When measured by the 90th-50th percentile difference, pre-pandemic VOR was $16/h and $12/h, increasing to $69/h and $32/h during the pandemic. The VOR estimates based on percentiles tend to be lower but exhibit a higher percentage increase than those based on standard deviation, likely due to the exclusion of extreme values.

The results indicate that both VOT and VOR increased during the pandemic, which can be explained by reduced traffic volumes on ELs. With fewer vehicles, the time saved by using ELs decreased, as did travel time variability. However, to maintain individual utility as per the econometric model (Lin et al., 2024), the coefficients for time savings and variability increased, reflecting that travelers were willing to pay more for these benefits during the pandemic.

Interestingly, the increase in VOR outpaced that of VOT, suggesting that travelers became more sensitive to reducing variability than saving time under pandemic conditions. This finding aligns with Cherry et al., (2023), who observed a greater change in VOR than VOT during the pandemic.

Overall, the study shows that VOT and VOR are not equal, confirming the idea that travelers value time savings and reliability differently (Devarasetty et al., 2012). Furthermore, the reliability ratio (RR)—the ratio of VOR to VOT—was greater than one when measured by standard deviation, indicating that VOR was consistently higher than VOT. However, the percentile-based measure showed RR values less than 1, with Carrion and Levinson (2012) reporting an average of 0.58. The observed increase in RR during the pandemic, except for inter-day variation by standard deviation, suggests that the rise in VOR outpaced the rise in VOT during the lockdown.

3.6.2 Travel time variability across RITIS Sensor data

In contrast to the previous section, where the variability of travel time saved was calculated solely based on observed toll trip data, Tables 13 and 14 utilize RITIS (Regional Integrated Transportation Information System) data to calculate Travel Time Reliability (TTR) before merging it with EL trip observations. This approach seeks to capture the ‘real’ variability that users cannot directly experience during their trips but reflects broader network variability.

In Table 16, the VOR estimates derived from this method are notably higher than those calculated in the previous section using the same variability measures. For example, in day-to-day variation by standard deviation, VOR values are \$98/h pre-lockdown and \$88/h during-lockdown, approximately twice the estimates from Table 15, where VOR was \$48/h pre-lockdown and \$57/h during-lockdown. This substantial increase in VOR leads to a corresponding rise in Reliability Ratios (RRs).

The doubled VOR values suggest that Express Lane (EL) travelers may demonstrate a higher willingness to pay for reducing travel time variability, especially when they have an accurate perception of unreliability in travel conditions. The finding points to the importance of realistic perceptions of variability in influencing users' decisions about EL usage.

Interestingly, in the case of day-to-day variation by standard deviation, the VOR decreases from $98/h before the pandemic to $88/h during the pandemic. This reduction indicates that, under less congested conditions, such as those observed during the pandemic, travelers' willingness to pay for reduced travel time variability diminishes. This makes sense, as less congestion leads to a more predictable travel experience, reducing the need for users to invest in variability reduction.

Table 11: TTR by Standard deviation (based on EL observations)

	Pre Lockdown					During Lockdown			
Day-to-day variation across the same departure time									
	Estimate	s.e.	z value	Pr(>|z|)		Estimate	s.e.	z value	Pr(>|z|)
Cost/trip	-0.090	0.001	-98.64	0.000***	Cost/trip	-0.441	0.006	-75.69	0.000***
TTS	0.047	0.000	360.90	0.000***	TTS	0.309	0.001	232.66	0.000***
TTR	-0.072	0.002	-32.26	0.000***	TTR	-0.422	0.017	-24.14	0.000***
No. of observations		524953			No. of observations		168457		
Initial log-likelihood		-1037988.74			Initial log-likelihood		-280444.14		
Final log-likelihood		-898723.8			Final log-likelihood		-218000.29		
Pseudo R squared		0.134			Pseudo R squared		0.223		
VOT		31.391			VOT		42.062		
VOR		48.254			VOR		57.294		
RR		1.537			RR		1.362		
Inter-day variation within the travel day									
	Estimate	s.e.	z value	Pr(>|z|)		Estimate	s.e.	z value	Pr(>|z|)
Cost/trip	-0.116	0.001	-136.71	0.000***	Cost/trip	-0.458	0.006	-82.63	0.000***
TTS	0.047	0.000	359.85	0.000***	TTS	0.310	0.001	232.36	0.000***
TTR	0.030	0.002	19.09	0.000***	TTR	-0.403	0.016	-24.73	0.000***
No. of observations		524953			No. of observations		168457		
Initial log-likelihood		-1037988.74			Initial log-likelihood		-280444.14		
Final log-likelihood		-899067.99			Final log-likelihood		-217982.74		
Pseudo R squared		0.134			Pseudo R squared		0.223		
VOT		24.286			VOT		40.588		
VOR		-			VOR		52.810		
RR		-			RR		1.301		
Inter-period variation within the peak/off peak period of the travel day									
	Estimate	s.e.	z value	Pr(>|z|)		Estimate	s.e.	z value	Pr(>|z|)
Cost/trip	-0.097	0.001	-110.40	0.000***	Cost/trip	-0.456	0.005	-83.18	0.000***
TTS	0.047	0.000	359.52	0.000***	TTS	0.310	0.001	232.34	0.000***
TTR	-0.062	0.003	-22.84	0.000***	TTR	-0.526	0.019	-27.36	0.000***
No. of observations		524953			No. of observations		168457		
Initial log-likelihood		-1037988.74			Initial log-likelihood		-280444.14		
Final log-likelihood		-898983.11			Final log-likelihood		-217858.56		
Pseudo R squared		0.134			Pseudo R squared		0.223		
VOT		29.397			VOT		40.872		
VOR		38.398			VOR		69.186		
RR		1.306			RR		1.693		

Notes: The empty fields denote omitted unreasonable results, either due to incorrect signs or estimates falling far outside reasonable ranges.

Table 12: TTR by difference in 90th-50th percentile (based on EL observations)

Pre Lockdown					During Lockdown				
Day-to-day variation across the same departure time									
	Estimate	s.e.	z value	Pr(>|z|)		Estimate	s.e.	z value	Pr(>|z|)
Cost/trip	-0.102	0.001	-129.30	0.000***	Cost/trip	-0.441	0.006	-72.21	0.000***
TTS	0.047	0.000	360.77	0.000***	TTS	0.309	0.001	232.54	0.000***
TTR	-0.027	0.001	-19.06	0.000***	TTR	-0.509	0.026	-19.76	0.000***
No. of observations		524953			No. of observations		168457		
Initial log-likelihood		-1037988.74			Initial log-likelihood		-280444.14		
Final log-likelihood		-899066.53			Final log-likelihood		-218123.7		
Pseudo R squared		0.134			Pseudo R squared		0.222		
VOT		27.682			VOT		42.105		
VOR		15.566			VOR		69.388		
RR		0.562			RR		1.648		
Inter-day variation within the travel day									
	Estimate	s.e.	z value	Pr(>|z|)		Estimate	s.e.	z value	Pr(>|z|)
Cost/trip	-0.113	0.001	-139.78	0.000***	Cost/trip	-0.474	0.006	-85.51	0.000***
TTS	0.047	0.000	360.73	0.000***	TTS	0.309	0.001	232.27	0.000***
TTR	0.011	0.001	15.49	0.000***	TTR	-0.255	0.015	-16.67	0.000***
No. of observations		524953			No. of observations		168457		
Initial log-likelihood		-1037988.74			Initial log-likelihood		-280444.14		
Final log-likelihood		-899129.39			Final log-likelihood		-218190.26		
Pseudo R squared		0.134			Pseudo R squared		0.222		
VOT		24.940			VOT		39.093		
VOR		-			VOR		32.271		
RR		-			RR		0.825		
Inter-period variation within the peak/off peak period of the travel day									
	Estimate	s.e.	z value	Pr(>|z|)		Estimate	s.e.	z value	Pr(>|z|)
Cost/trip	-0.104	0.001	-130.96	0.000***	Cost/trip	-0.474	0.005	-88.09	0.000***
TTS	0.047	0.000	360.06	0.000***	TTS	0.310	0.001	232.38	0.000***
TTR	-0.021	0.002	-13.89	0.000***	TTR	-0.252	0.010	-24.15	0.000***
No. of observations		524953			No. of observations		168457		
Initial log-likelihood		-1037988.74			Initial log-likelihood		-280444.14		
Final log-likelihood		-899151.46			Final log-likelihood		-217971.58		
Pseudo R squared		0.134			Pseudo R squared		0.223		
VOT		27.328			VOT		39.220		
VOR		12.163			VOR		31.895		
RR		0.445			RR		0.813		

Notes: The empty fields denote omitted unreasonable results, either due to incorrect signs or estimates falling far outside reasonable ranges.

Table 13: TTR by Standard deviation (based on RITIS sensor data)

Pre Lockdown					During Lockdown				
Day-to-day variation across the same departure time									
	Estimate	s.e.	z value	Pr(>|z|)		Estimate	s.e.	z value	Pr(>|z|)
Cost/trip	-0.073	0.001	-72.17	0.000***	Cost/trip	-0.421	0.006	-71.13	0.000***
TTS	0.047	0.000	361.62	0.000***	TTS	0.310	0.001	232.74	0.000***
TTR	-0.119	0.002	-49.98	0.000***	TTR	-0.617	0.021	-29.44	0.000***
No. of observations		524953			No. of observations		168457		
Initial log-likelihood		-1037988.74			Initial log-likelihood		-280444.14		
Final log-likelihood		-897875.19			Final log-likelihood		-217817.5		
Pseudo R squared		0.135			Pseudo R squared		0.223		
VOT		38.999			VOT		44.241		
VOR		97.782			VOR		87.886		
RR		2.507			RR		1.987		
Inter-day variation within the travel day									
	Estimate	s.e.	z value	Pr(>|z|)		Estimate	s.e.	z value	Pr(>|z|)
Cost/trip	-0.111	0.001	-131.45	0.000***	Cost/trip	-0.435	0.006	-76.72	0.000***
TTS	0.047	0.000	360.41	0.000***	TTS	0.311	0.001	232.54	0.000***
TTR	0.014	0.002	6.86	0.000***	TTR	-0.491	0.016	-30.16	0.000***
No. of observations		524953			No. of observations		168457		
Initial log-likelihood		-1037988.74			Initial log-likelihood		-280444.14		
Final log-likelihood		-898882.1			Final log-likelihood		-217837.26		
Pseudo R squared		0.134			Pseudo R squared		0.223		
VOT		25.483			VOT		42.915		
VOR		-			VOR		67.779		
RR		-			RR		1.579		
Inter-period variation within the peak/off peak period of the travel day									
	Estimate	s.e.	z value	Pr(>|z|)		Estimate	s.e.	z value	Pr(>|z|)
Cost/trip	-0.094	0.001	-106.05	0.000***	Cost/trip	-0.462	0.005	-84.81	0.000***
TTS	0.047	0.000	359.59	0.000***	TTS	0.310	0.001	232.40	0.000***
TTR	-0.072	0.003	-26.75	0.000***	TTR	-0.459	0.017	-26.61	0.000***
No. of observations		524953			No. of observations		168457		
Initial log-likelihood		-1037988.74			Initial log-likelihood		-280444.14		
Final log-likelihood		-898882.1			Final log-likelihood		-217894.5		
Pseudo R squared		0.134			Pseudo R squared		0.223		
VOT		30.226			VOT		40.357		
VOR		45.753			VOR		59.583		
RR		1.514			RR		1.476		

Notes: The empty fields denote omitted unreasonable results, either due to incorrect signs or estimates falling far outside reasonable ranges.

Table 14: TTR by difference in 90^{th}-50^{th} percentile (based on RITIS sensor data)

Pre Lockdown					During Lockdown				
Day-to-day variation across the same departure time									
	Estimate	s.e.	z value	Pr(>|z|)		Estimate	s.e.	z value	Pr(>|z|)
Cost/trip	-0.096	0.001	-113.9	0.000***	Cost/trip	-0.315	0.008	-41.27	0.000***
TTS	0.047	0.000	361.0	0.000***	TTS	0.310	0.001	233.14	0.000***
TTR	-0.046	0.002	-28.0	0.000***	TTR	-1.734	0.052	-33.07	0.000***
No. of observations		524953			No. of observations		168457		
Initial log-likelihood		-1037988.74			Initial log-likelihood		-280444.14		
Final log-likelihood		-898854.93			Final log-likelihood		-217789.9		
Pseudo R squared		0.134			Pseudo R squared		0.223		
VOT		29.476			VOT		59.179		
VOR		28.840			VOR		-		
RR		0.978			RR		-		
Inter-day variation within the travel day									
	Estimate	s.e.	z value	Pr(>|z|)		Estimate	s.e.	z value	Pr(>|z|)
Cost/trip	-0.110	0.001	-131.4	0.000***	Cost/trip	-0.270	0.007	-36.97	0.000***
TTS	0.047	0.000	361.51	0.000***	TTS	0.315	0.001	233.09	0.000***
TTR	0.005	0.001	5.21	0.000***	TTR	-2.128	0.049	-43.85	0.000***
No. of observations		524953			No. of observations		168457		
Initial log-likelihood		-1037988.74			Initial log-likelihood		-280444.14		
Final log-likelihood		-899235.61			Final log-likelihood		-217343.32		
Pseudo R squared		0.134			Pseudo R squared		0.225		
VOT		25.660			VOT		70.148		
VOR		-			VOR		-		
RR		-			RR		-		
Inter-period variation within the peak/off peak period of the travel day									
	Estimate	s.e.	z value	Pr(>|z|)		Estimate	s.e.	z value	Pr(>|z|)
Cost/trip	-0.102	0.001	-129.8	0.000***	Cost/trip	-0.471	0.005	-86.91	0.000***
TTS	0.047	0.000	360.10	0.000***	TTS	0.310	0.001	232.22	0.000***
TTR	-0.025	0.001	-18.04	0.000***	TTR	-0.282	0.012	-22.93	0.000***
No. of observations		524953			No. of observations		168457		
Initial log-likelihood		-1037988.74			Initial log-likelihood		-280444.14		
Final log-likelihood		-899083.02			Final log-likelihood		-217988.48		
Pseudo R squared		0.134			Pseudo R squared		0.223		
VOT		27.672			VOT		39.532		
VOR		14.679			VOR		54.600		
RR		0.530			RR		1.381		

Notes: The empty fields denote omitted unreasonable results, either due to incorrect signs or estimates falling far outside reasonable ranges.

Table 15: Summary of VOT/VOR change (EL observations)

	Standard deviation				Difference in 90th-50th percentile			
		Pre	During	Change		Pre	During	Change
Day-to-day	VOT	$31/h	$42/h	+34%	VOT	$28/h	$42/h	+52%
	VOR	$48/h	$57/h	+19%	VOR	$16/h	$69/h	+346%
	RR	1.53	1.36	-11%	RR	0.56	1.65	+193%
Inter-period	VOT	$29/h	$41/h	+39%	VOT	$27/h	$39/h	+44%
	VOR	$38/h	$69/h	+80%	VOR	$12/h	$32/h	+162%
	RR	1.31	1.69	+30%	RR	0.45	0.81	+83%

Table 16: Summary of VOT/VOR change (RITIS sensor data)

	Standard deviation				Difference in 90th-50th percentile			
		Pre	During	Change		Pre	During	Change
Day-to-day	VOT	$39/h	$44/h	+13%	VOT	$29/h	$59/h	+101%
	VOR	$98/h	$88/h	-10%	VOR	$29/h	-	-
	RR	2.51	1.99	-21%	RR	0.98	-	-
Inter-period	VOT	$30/h	$40/h	+34%	VOT	$28/h	$40/h	+43%
	VOR	$46/h	$60/h	+30%	VOR	$15/h	$55/h	+272%
	RR	1.51	1.47	-2%	RR	0.53	1.38	+160%

Notes: The empty fields denote omitted unreasonable results, identified as estimates significantly diverging from reasonable ranges.

3.7 Conclusion

This chapter presents a comprehensive analysis of users' willingness to pay for saving travel time and reducing travel time unreliability on Express Lanes (ELs). The study spans two distinct periods: January to mid-March 2020 (pre-pandemic) and mid-March to the end of May 2020 (during the pandemic).

The analysis draws on nearly 5 million EZ Pass transaction records, complemented by real-time travel measurements from probe vehicle data. This integration enables the calculation of various travel time reliability metrics and allows for analyses that were previously unattainable due to data scarcity. The comprehensive dataset offers unprecedented insights into travel time variability and reliability across different conditions and time periods.

Several key contributions emerge from this study. The methodology, which relies solely on E-ZPass observations and uses ordered logit models to estimate both the Value of Travel Time (VOT) and the Value of Travel Time Reliability (VOR), is innovative. It leverages readily available usage frequency data, eliminating the need for additional survey collection or observations from general-purpose lanes. This allows toll operators to continuously monitor travelers' willingness to pay for time savings and reliability, enabling them to optimize both revenue generation and overall traffic operations on their infrastructure.

From a quantitative perspective, I conclude that when reliability is measured using the standard deviation and travel time variability is calculated based on users' actual experiences, the Value of Reliability (VOR) consistently surpasses the Value of Time (VOT) by a factor ranging from 1.3 to 1.6. Notably, there is little difference observed between day-to-day variability and inter-period variability. This suggests that the overall preference for travel time reliability remains consistent regardless of the specific timeframes within which the variability occurs. Both the Value of Time (VOT) and Value of Reliability (VOR) increased during the pandemic, which can be attributed to the lower number of vehicles on Express Lanes (ELs) and reduced congestion as a result of lockdown measures (Lin et al., 2024). The only instance where the Value of Reliability (VOR) is lower than the Value of Time (VOT) occurs when VOR is measured as the difference between the 90th and 50th percentiles, especially during pre-pandemic conditions.

Remarkably, when the Value of Reliability (VOR) is assessed using actual travel time variations derived from INRIX data, the VOR significantly increases, ranging from 1.5 to 2.5 times the Value of Time (VOT). This suggests that Express Lane users receive greater value for their investment when it comes to stable travel conditions on the tolled lanes.

While the data utilized in this analysis offers several advantages over traditional survey data, it is limited by the absence of socio-demographic variables. This lack of information restricts the ability to estimate taste heterogeneity, particularly in relation to income. Furthermore, travel behavior has continued to evolve post-pandemic, and both the Value of Reliability (VOR) and the Value of Time (VOT) may have shifted as a result of the increased flexibility experienced by commuters in the study area. Despite the aforementioned limitations, the methodology remains valid and can be applied across different time periods and geographic locations.

Chapter 4: Integrated control strategies and optimization

4.1 Introduction

Addressing persistent traffic congestion along major freeway corridors remains a paramount concern within the transportation sector. The latest Urban Mobility Report, published by the Texas A&M Transportation Institute in 2021, underscores the profound impact of this issue. In 2019, traffic congestion led urban Americans to spend an additional 9.4 billion hours on the road and consume an extra 3.9 billion gallons of fuel, resulting in a staggering financial cost of $166 billion. More than 50% of this congestion burden is squarely placed upon freeways.

What is particularly concerning is the upward trajectory of freeway congestion over the past decade, despite significant investments in traffic controls and management by various highway agencies. Startling statistics from the Bureau of Transportation Statistics, a division of the U.S. Department of Transportation, reveal a disconcerting trend: the annual cost of highway congestion in the Washington DC area surged by a remarkable 20.12% between 2006 and 2017, and by 8.79% between 2009 and 2019. These statistics underscore the urgency of finding innovative solutions to the ongoing traffic challenges.

Within the extensive body of literature addressing freeway interchange control, on-ramp metering stands out as the most extensively studied strategy. The primary objective of this control approach is to effectively manage the influx of vehicles from on-ramps, thereby preventing the creation of bottlenecks on the freeway's weaving segment, which can result from extensive merging and lane-changing maneuvers.

Over the past few decades, the traffic management community has proposed a diverse range of ramp metering control strategies. These strategies encompass local metering control (Papageorgiou et al., 1991; Zhang and Ritchie, 1997; Smaragdis et al., 2004; Gomes and Horowitz, 2006; Wang and Papageorgiou, 2006), coordinated ramp metering control (Kotsialos et al., 2002; Papamichail et al., 2010a; Papamichail et al., 2010b; Ghods et al., 2010; Geroliminis et al., 2011; Zhao et al., 2011; Chow and Li, 2014; Agarwal et al., 2015), integrated ramp metering and variable speed limit controls (Hegyi et al., 2005; Carlson et al., 2010a; Carlson et al., 2010b; Frejo and Camacho, 2012; Carlson et al., 2014; Li et al., 2017), cooperated ramp metering and local traffic controls (Head and Mirchandani, 1997; Tian et al., 2005; Tian, 2007; Cheng and Chang, 2021; Cheng et al., 2022; Chen and Cheng, 2023) and collaborative ramp metering control and route guidance strategy (Kotsialos et al., 2002; Karimi et al., 2004; Liu et al., 2011; Pasquale et al., 2017).

In addition to ramp metering, toll lanes are also implemented to manage congestion. Arnott et al., (1993) introduced a structural model for bottleneck congestion, including the critical concept of elastic demand. This seminal work laid the foundation for subsequent research in congestion pricing. Later, Verhoef and Rouwendal (2004) emphasize the importance of dynamic pricing as a powerful tool to manage congestion in bottleneck scenarios effectively. It sets the stage by highlighting the necessity of adaptive pricing strategies to optimize traffic flow. Building on this foundation, Levinson and Kanchi (2002) delve into the integration of toll lanes into mixed networks, addressing the fundamental question of whether these lanes should be segregated from or integrated with general-purpose lanes. Their work underscores the complexity of toll lane design and its implications for congestion management.

In recent years, Yang et al. (2021) have presented contemporary research on dynamic pricing, emphasizing the real-time adjustments necessary to balance demand and capacity in managed lanes. This work underscores the need for responsive toll pricing strategies that can dynamically adapt to varying traffic conditions. Additionally, Lam and Shao (2019) explore the implications of dynamic toll pricing in a future dominated by autonomous vehicles. Their research highlights the potential of dynamic pricing not only for congestion management but also for accommodating emerging transportation technologies.

Moreover, equity and social considerations are central to the discourse on toll lane implementation. Litman (2021) offers a comprehensive examination of the social equity impacts of road and congestion pricing, advocating for equitable toll lane systems accessible to all income groups. His work underscores the importance of ensuring that toll lanes do not disproportionately burden vulnerable populations. Complementing this perspective, Brownstone and Small (2005) provide insights into travelers' valuation of time and reliability, which are essential for assessing the social impacts of pricing strategies. These considerations are critical for ensuring that toll lanes are not only efficient but also fair.

Further exploring equity, Srinivasan and Mahmassani (2007) conduct an income-based equity analysis of road pricing, revealing differential impacts on income groups. Their findings emphasize the need for equity-focused toll pricing policies to mitigate disparities. Broadening the equity discussion, Goodin (2019) addresses transportation racism and broader equity concerns related to toll lane projects. His work highlights the social dimensions of toll lane implementation, prompting a deeper examination of justice in transportation planning. Lastly, Watkins et al., (2011) offer a comprehensive review of the relationship between congestion pricing and social equity, summarizing existing research findings. Their collective insights underscore the nuanced challenges of achieving equity in toll lane projects.

The integration of public transit with toll lanes presents an opportunity to enhance mobility. Levinson (2013) emphasizes the importance of equity in toll lane implementation, recognizing the social implications of road pricing. His work underscores the need to ensure that the benefits of toll lanes extend to all members of the community. In the realm of transit integration, Rodier and Cirillo (2006) review U.S. high-occupancy toll (HOT) lane projects, shedding light on factors influencing their performance, including transit integration. Their research illustrates the potential synergies between transit and toll lanes in improving urban mobility.

In addition, Xie and Zhao (2018) contribute by modeling the impacts of transit in high-occupancy/toll lanes, highlighting its role in shaping traffic patterns. This modeling approach provides a quantitative perspective on the benefits of transit integration in toll lane systems. Ukkusuri and Garikapati (2009) assess managed lane strategies through a case study, illustrating the potential performance benefits of transit integration. Their work underscores the practical advantages of combining transit services with toll lanes to alleviate congestion. Lastly, Lu and Zhang (2017) evaluate the value of congestion pricing and toll rebate programs for high-occupancy toll lanes, underlining the advantages of integrating these strategies with transit. This research emphasizes the multifaceted benefits of transit integration, including improved accessibility and reduced congestion.

Xie et al., (2024) explored real-time personalized tolling strategies for managed lanes (ML) using a bi-level optimization framework. They designed a lane choice model between the ML and GP, which simultaneously optimizes toll rates at system level (displayed toll rates) and user level (personalized discounts). The proposed pricing strategy was evaluated in a traffic simulator across various scenarios.

Despite significant research progress over the past decades aimed at improving traffic conditions by toll pricing strategies, developing effective integrated real-time control strategies that can simultaneously benefit users on both toll and non-toll lanes remains an ongoing challenge in the field of traffic management. In brief, to alleviate traffic congestion on a freeway with these two types of lanes in real-time, the deployed control strategies must reliably and efficiently address several critical issues:

- How to balance the utilization of toll and non-toll lanes?
- How to maximize the benefits for both freeway users on toll and non-toll lanes simultaneously?
- How to predict traffic conditions and lane choice behaviors reliably with limited real-time information?
- How to ensure computational optimization for real-time operations?

4.2 Integrated proactive traffic management system

To address the abovementioned issues concurrently, this chapter proposes a proactive traffic management system that integrates lane choice and traffic flow models to optimize toll pricing and ramp metering rates simultaneously. The lane choice model functions to determine the proportion of drivers selecting toll lanes under different price settings, while the traffic flow model works to estimate traffic evolution based on various metering rates and demands. The operational flowchart of the proposed traffic management system is shown in Figure 26.

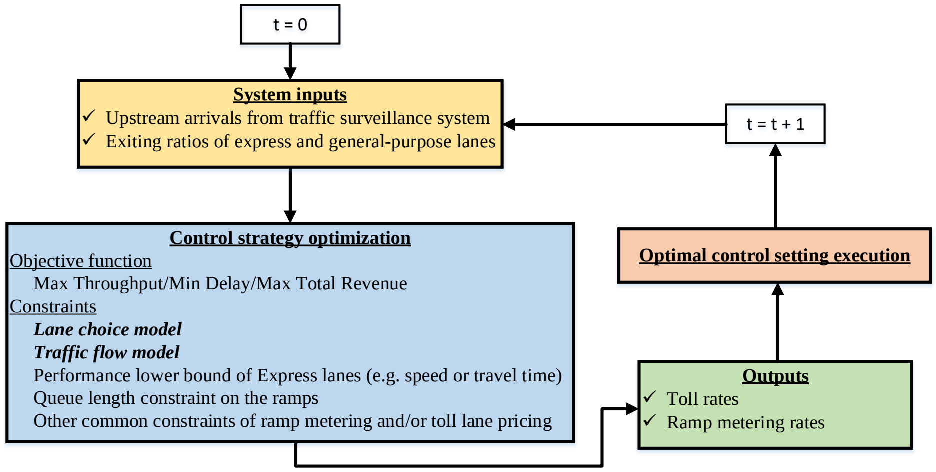


Figure 26: Operational flowchart of the proposed traffic management system

4.2.1 Lane choice model

Discrete choice models have become one of the most important tools for analyzing traffic behavior, enabling significant advancements in travel behavior research. Among these, the logit model is widely applied in road traffic analysis (Liang et al., 2019).

Several studies have employed binary logit models to analyze lane choice behavior, particularly the decision between Express Lanes (EL) and general-purpose (GP) lane (Lam and Small, 2001; Yan, 2002; Tilahun and Levinson, 2010; Abir et al., 2017). Other studies extended the analysis to mode choice models, where decisions include additional alternatives such as solo driving versus carpooling on GP or EL lanes (Ghosh, 2001; Devarasetty et al., 2012; and Cherry et al., 2021). For more complex cases, mixed logit models have been used to account for heterogeneity in preferences. Liu et al., (2004), Small et al., (2005), Liu et al., (2007), and Carrion and Levinson (2013) explored these approaches to capture variations in driver behavior that cannot be addressed by simpler models. In addition, Hossan et al., (2016) proposed five alternatives between GP and managed lanes across different time periods throughout the day.

Across most studies, monetary cost, travel time, and travel time variability emerge as the primary factors influencing lane choice decisions. These variables reflect drivers' trade-offs between the cost of using ELs and the perceived benefits, such as reduced travel time and improved reliability.

Jackson and Jucker (1981) pointed out the analysis of traveler's route choice behavior can be studied through direct and indirect method. The direct method typically involves conducting surveys with a sample of travelers in a certain population. Within this approach, the revealed preference (RP) survey capture actual behavioral responses, while the stated preference (SP) survey collects data on traveler's decisions in hypothetical scenarios. In contrast, the indirect method involves inferring the answers to these behavioral questions from observed data describing the flows on alternative routes connecting an origin-destination (OD) pair (Liu et al., 2004). Liu et al., (2004, 2007) estimated route choice based on the real-time loop detector data. Instead of surveying motorists on their choices in the direct method, their approach provide aggregated information derived from disaggregated individual travel decisions.

This study also employs the indirect method to analyze aggregated toll users' lane choice behavior, and present the share of GP/EL users in the population. While the methodology in our study is innovative in the following part:

- Segmental Analysis with Multiple Entry and Exit Points: The lane choice behavior is analyzed at the segment (leg) level, where each 'leg' represents the segment between two adjacent toll plazas for ELs, and its parallel segment for GP lanes. The model is designed to capture the lane choice considering multiple entry and exit ramps for each leg, where users can choose to enter, stay or exit the lane.
- Weighted Binomial Logit Model: Different from the traditional binomial logit choice on the individual level, our model is weighted using real-time traffic flow rates. This

weighting accounts for the aggregated choice behavior based on the observed traffic volume in the time interval, reflecting the proportion of drivers make their decisions on the lane choice at each leg.

- Dynamic Decision-Making: The model incorporates dynamic decision-making. Users make lane choices based on the displayed dynamic toll rates for each leg, which are available to them before they decide and pass the toll plaza. In addition, the model accounts for real-time travel time savings by choosing each segment of the EL. This allows the model to capture how the proportion of users on EL/GP lanes throughout the day in response to real-time traffic conditions.

4.2.1.1 Utility function

In this weighted lane choice model, I estimate the user's utility of choosing the Express Lane over general-purpose lanes based on two key factors: travel time saving (TTS) and displayed toll rate. The travel time saving represents the travel time saved by using EL compare to the parallel GP lanes. The toll rate is the cost that EL users need to pay for the amount of TTS traveling on the Express Lane. Drivers make the decision between two alternatives (using EL or not) by maximizing the individual utility.

The utility function is formatted as:

$$U_{i,t} = \beta_{time} * TTS + \beta_{cost} * Toll\ Rate + \varepsilon_{i,t}$$

Where:

$U_{i,t}$ is the utility of user to choose the Express Lane in leg *i* at time *t*;

β_{time} is the coefficient of the travel time saving by choosing the Express Lane;

β_{cost} is the coefficient of cost charged for using the Express Lane.

The utility function captures the user's trade-off between the benefit of saving the travel time and the cost for it when making their lane choice decision.

4.2.1.2 Aggregated real-time proportion of EL users

For each leg *i* at time *t*, the probability of an individual traveler choosing EL is:

$$P_{i,t} = \frac{1}{1 + e^{-U_{i,t}}}$$

where U_i is the utility based on travel time savings and displayed toll rate in leg *i*.

Each leg's probability is weighted by its corresponding travel volume $V_{i,t}$, representing the traffic volume in the each leg *i* at time *t*, to reflect the aggregate lane choice across segments and time intervals.

The weighted sum of EL users across all legs and times is given by:

$$\sum_i V_{i,t} \cdot P_{i,t}$$

Therefore, the real-time proportion of users choosing the Express Lane is:

$$Proportion\ of\ EL\ users = \frac{\sum_i V_{i,t} \cdot P_{i,t}}{\sum_i V_{i,t}}$$

4.2.2 Traffic flow model

This study adopts METANET model by Messner and Papageorgiou (1990) to predict traffic evolution under various control settings. The model views the target freeway as a series of interconnected spatial segments (as shown in Figure 27) and then employs the fundamental relations among flow rate, density, and speed within each segment to project its outgoing flow rate during each time interval, as shown in Equation 1 to Equation 3. Equation 4 and Equation 5 are additional terms that work to reflect the impacts of lane-drop and ramp merge on the traffic speed. Equation 6 functions to estimate entering flow rates when implementing ramp metering.

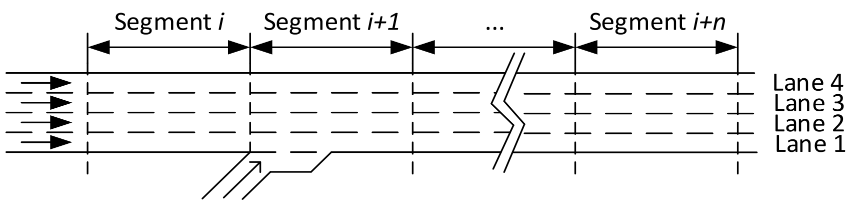


Figure 27: A macroscopic view of the freeway in the METANET model

$$\rho_i(k+1) = \rho_i(k) + \frac{T}{L_i}[q_{i-1}(k) - q_i(k)] \tag{1}$$

$$v_i(k+1) = \max\{v^m, v_i(k) + \frac{T}{\tau}\left[V_i\big(\rho_i(k)\big) - v_i(k)\right] + \frac{T}{L_i} v_i(k)[v_{i-1}(k)\text{-}v_i(k)] - \frac{\upsilon T}{\tau L_i}\frac{[\rho_{i+1,}(k) - \rho_i(k)]}{\rho_i(k)+\kappa}\} \tag{2}$$

$$q_i(k) = \rho_i(k) v_i(k) \tag{3}$$

$$-\phi v_i(k)\frac{v_i(k) T \rho_i(k) \Delta\lambda_i}{L_i \lambda_i \rho_i^C} \tag{4}$$

$$-v_i(k)\frac{\delta T r_i(k)}{L_i \lambda_i (\rho_i(k)+\kappa)} \tag{5}$$

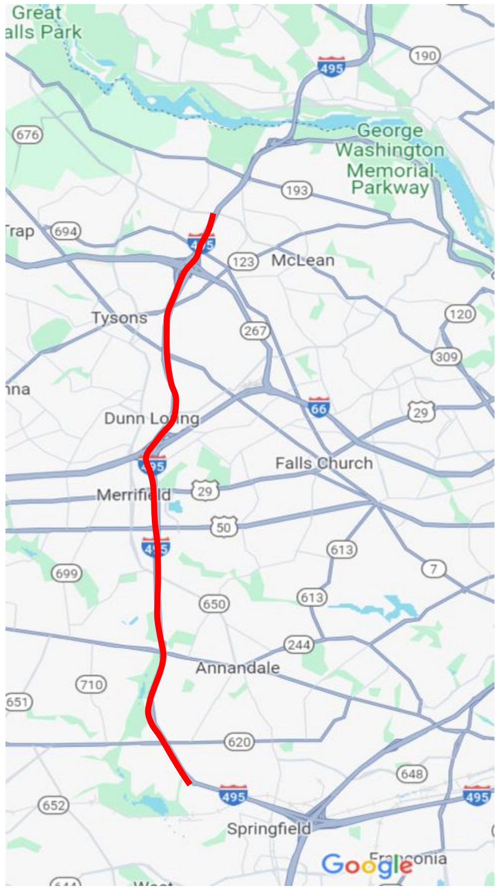
$$q_o(k) = r_o(k) \cdot \min\{d_o(k) + \frac{c_o(k)}{T}, D_o\} \tag{6}$$

where, $v_i(k)$ is the speed of segment *i* at time interval k; T is the time interval for updating the traffic state in each segment; $\rho_i(k)$ and $q_i(k)$ are the density and flow rate of segment *i* at time interval k; ρ_i^C is the critical density of segment i; $V_i(.)$ denotes the function for speed-density relation for segment *i*; L_i stands for the length of segment *i*; λ_i and $\Delta\lambda_i$ are the number of lanes and the number of dropped lanes in segment i, respectively; $r_i(k)$ indicates the on-ramp flow rate at time interval k; $q_o(k)$ denotes flow rate from ramp o at time interval k; $r_o(k)$ denotes ramp metering rate at ramp o at time interval k; $d_o(k)$ is demand from ramp o at time interval k; $c_o(k)$ is the queue on-ramp o at time interval k; D_o is the capacity of ramp o; and $\tau, \upsilon, \phi, \delta, \kappa$ are parameters to be calibrated with field data.

4.3 Integrated control system evaluation

4.3.1 Study site

The experimental site adopted in this study is the I-495 corridor in Virginia, USA, starting from the southbound 44.6 Mile section to the 54.8 Mile section (marked in red), with a total length of 10.2 miles, as shown in Figure 28. The lanes in this section are divided into general-purpose (GP) lanes and Express Lanes (ELs), with a physical separation between them. There are 11 on-ramps and 9 off-ramps for GP lanes, and 9 on-ramps and 9 off-ramps for the ELs.



[Source: google map]

Figure 28: The experimental site

4.3.2 Data description

In recent years, the availability of Revealed Preference (RP) data has grown significantly, particularly with the construction and operation of more Express Lanes. Traditionally, RP data were collected through travel surveys (Brownstone et al., 2003; Börjesson et al., 2007). While surveys provide valuable insights, they often involve substantial costs and effort, leading to limited sample sizes and potential response biases.

The advent of tolling facilities with electronic data collection capabilities has opened up opportunities for researchers by providing access to extensive RP trip records. Despite these advances, previous behavioral studies of Express Lanes based on RP data have been primarily exploratory (Burris and Brady 2018; Ben-Akiva et al., 2013), with limited applications in econometric modeling. This limitation can be attributed in part to restricted data access and the challenges posed by the absence of traveler characteristics, as well as the volume of trip records.

The study is based on several datasets that were merged before proceeding with the behavioral analysis and the modeling tasks. The historical travel data for the Express Lane from January 2020 to May 2020 contains 4,909,017 trip observations in chronological order. Each record in the database refers to a particular trip; it contains detailed information about travel date, time of day, day of week, transponder ID, origin, destination, trip distance, direction, toll payment mode, and toll paid. The transponder dataset was then merged with the Regional Integrated Transportation System (RITIS) travel times according to the trip origins and destinations. The level of service variables available for model estimation were the following: travel time on general-purpose (GP) lane, the travel time on EL, and consequently the travel time saved by choosing ELs, corresponding toll paid by the owners of the transponders.

In addition to transponder data, sensors are installed at specific mileage points along each lane of the corridor. There are 33 sensors on the GP lanes and 32 on ELs. These sensors collect data at 15-minute intervals, including information on speed, volume, and lane occupancy. Since the data from these sensors may not always be reliable enough for control purposes, a flow conservation check process is implemented to validate their performance. The process involves the following steps:

1) A flow conservation check is performed using the sensors located along the same road segment without any entrance or exit ramps.

2) Sensors before and after entrance and exit ramps are used to ensure the flow is reasonable. This includes:
    - The mainline flow downstream an entrance ramp should be equal to or greater than the flow upstream the entrance ramp.
    - The mainline flow downstream an exit ramp should be less than or equal to the flow upstream the exit ramp.

Based on the results of these checks, the usability of the sensors within the study area can be assessed. It was found that two sensors on the general-purpose lanes and one on the Express Lanes are not functioning properly.

Complementing the traffic data, the dynamic toll rate data provide real-time pricing information at 10-minute intervals. The toll rates vary by time of day and differ across toll plaza segments, enabling the study of dynamic decision making influenced by spatial and temporal variations in pricing.

4.3.3 Calibration results

In the proposed control system, both lane choice and traffic flow models have parameters to be calibrated. The calibration processes and their results are as follows.

4.3.3.1 Results of lane choice model

Table 17: Modeling results of aggregated lane choice

Parameter	Estimate	s.e.	z value	P>|z|	95% conf. interval	
Toll rate	0.115	0.000	345.03	0.000	0.114	0.115
Time saving	0.031	0.000	222.97	0.000	0.031	0.031

The results provide both travel time saving on ELs and dynamic toll rates significantly influence drivers' aggregated decision making on the lane choice. The positive coefficient of time saving implies drivers are more likely to choose the EL when they can take advantage on the greater travel time difference between EL and GP lanes.

On the other hand, the positive coefficient on the toll rate may initially seem counterintuitive, as higher tolls would typically discourage EL usage. It's important to note that this variable represents the displayed toll rate at the system level, rather than the actual toll paid by each individual driver. In this context, a higher toll rate often signals heavier congestion in the GP lanes. When traffic volume is high, the toll rate increases as a mechanism to manage demand for the EL (Burris et al., 2021), making the Express Lane a more attractive option for those seeking a reliable and faster route. This interpretation suggests that drivers are sensitive to congestion indicators, such as dynamic toll rates, and are more likely to choose the EL when they anticipate greater benefits from avoiding the congestion in GP lanes.

4.3.3.2 Results of traffic flow model

This study performed parameter calibration by minimizing the discrepancy between METANET model estimations and field data using a genetic algorithm (GA). The calibrated values of the parameters in the traffic flow model for all segments are shown in Table 18. The Mean Average Percentage Errors (MAPEs) of speeds on the Express Lanes and general-purpose lanes are 15.69% and 13.42%, respectively. The MAPEs of flow rates on ELs and general-purpose lanes are 12.56% and 13.38%, respectively.

Table 18: Parameter Settings of the Traffic Flow Model

Parameter	Segments of ELs	Segments of GPLs
v^f	66.5	67.1
τ	27.3	17.7
a_i	2.38	2.4
υ	49.8	39.6
κ	63.7	68.2

ρ_i^C	25.7	26.6 (for 1^{st} and 35^{th} segments) 32.2 (for 2^{nd} to 34^{th} segments)

4.3.4 Solution algorithm and optimal control settings for the control system

This study uses a genetic algorithm to determine the optimal toll rate and ramp metering rates for the proposed control system. The core of the solution algorithm comprises the following key steps:

Step 1: Encode decision variables, including toll rate and the metering rates. In this study, the widely used binary coding method is adopted.

Step 2: Generate a population set randomly.

Step 3: For each individual in the population set

Step 3.1: Decode it to determine the toll rate and the metering rates based on the binary coding method.

Step 3.2: Determine the value of the objective function according to the control settings.

Step 3.3: Evaluate the corresponding fitness with the objective function value.

Step 4: Implement the crossover and mutation procedure based on the fitness evaluation.

Step 5: Generate a new population set.

Step 6: Repeat steps 3 to 5 until a stop criterion is satisfied.

Step 7: Output the determined control settings.

4.3.5 Simulator for the proposed integrated traffic Management System

Figure 29 depicts the structure of the simulator used for the proposed system developed using Simulation of Urban MObility (SUMO), an open-sourced stochastic microsimulation software. The system is implemented in Python and communicates with SUMO through the Traffic Control Interface (TraCI). All the required traffic information, such as real-time speeds and flow rates, is collected periodically and transmitted to the simulator via the TraCI. All control actions generated by the system, along with their respective impacts on traffic conditions, are fed back to the simulator for continuous monitoring and assessment to ensure that necessary actions are taken to maximize the throughput or minimize total delay.

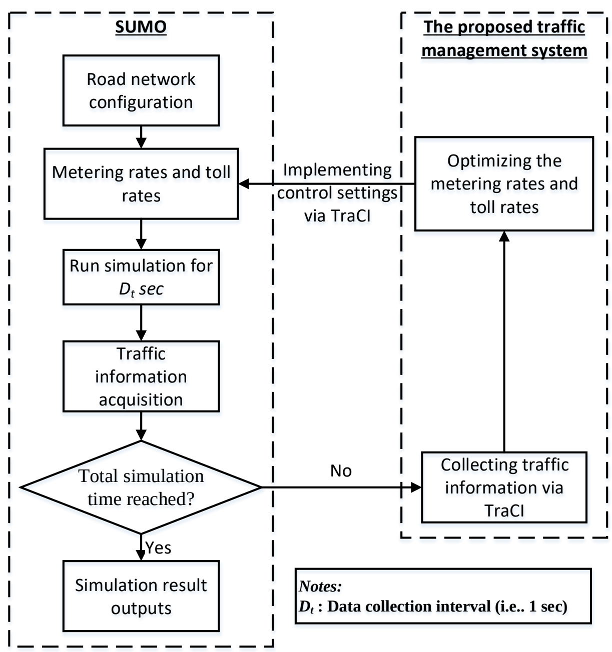


Figure 29: Structure of the simulator for the proposed traffic management system

Parameters in SUMO, which simulate driver behaviors, are calibrated through a genetic algorithm with the objective of minimizing the difference between detected and simulated traffic states. The calibrated model parameter values are outlined in Table 19. The resulting measures of effectiveness (MOEs), including delay and throughput, are obtained directly from the simulation outputs of SUMO for performance comparison. For each simulation scenario, five simulation runs with different random seeds are conducted in SUMO, and the results are averaged.

Table 19: The calibrated parameter values of the SUMO model

Parameter	Value
lcSpeedGain	2.03
lcStrategic	6.78
lcCooperative	0.54
lcSigma	0.56
Sigma	0.24
Tau	1.08
accel	3.97
decal	4.29

4.3.6 Evaluation results

Two control strategies are evaluated: Control Type 1, which applies on-ramp metering only to the GP lanes, and Control Type 2, which extends on-ramp metering to both the GP lanes and ELs. The evaluation results in Tables 20 and 21 compare the performance of the current control system against the proposed Control Types 1 and 2 under two distinct objective functions: maximizing total throughput and maximizing total revenue. These results reveal varying degrees of improvement across different lane types and performance metrics.

Under the objective of maximizing total throughput (Table 20), the proposed systems significantly reduce total system delay compared to the current control system. The current control system has a total system delay of 23,239.51 veh-hours, while Control Type 1 reduces it to 18,278.66 veh-hours (21.35% improvement) and Control Type 2 reduces it to 18,378.89 veh-hours (20.92% improvement). On general-purpose (GP) lanes, Control Type 1 achieves a

9.72% reduction in delay, and Control Type 2 achieves 8.83%. However, on Express Lanes, both proposed systems exhibit increased delays (negative improvements), with Control Type 1 and Control Type 2 resulting in -8.00% and -7.07% changes, respectively. This suggests that while the proposed systems significantly alleviated overall congestion, their effectiveness varies by lane type.

For total throughput, the overall system benefits from the proposed controls, though the impact differs between lane types. System throughput increases by 4.16% under Control Type 1 and 3.75% under Control Type 2. On GP lanes, however, throughput slightly decreases by 1.88% for Control Type 1 and 1.54% for Control Type 2. In contrast, Express Lanes show substantial increases, with throughput improvements of 64.27% for Control Type 1 and 56.42% for Control Type 2. This disparity indicates that the proposed systems prioritize Express Lane performance, potentially at the expense of GP lane throughput.

When the objective shifts to maximizing total revenue (Table 21), both proposed systems deliver remarkable improvements over the current control system. Total revenue increases by 40.26% under Control Type 1 and 27.61% under Control Type 2. Control Type 1 outperforms Control Type 2 in revenue generation, underscoring its superior ability to optimize economic outcomes. The substantial revenue growth reflects the proposed systems' ability to allocate resources more effectively and attract more users to revenue-generating Express Lanes.

Comparing the two proposed control systems, Control Type 1 consistently performs better than Control Type 2 in both delay reduction and revenue generation. Although both systems improve system-wide throughput, Control Type 1 achieves slightly higher improvements in delay and revenue while maintaining comparable throughput increases. These results highlight Control Type 1 as the more effective system overall, particularly for scenarios where revenue maximization is prioritized.

In summary, the proposed control systems offer significant advantages over the current system in reducing delays, increasing throughput, and boosting revenue. However, their impacts vary by lane type, with Express Lanes benefiting more than GP lanes. Control Type 1 emerges as the superior option, achieving greater improvements in most performance metrics, making it a more favorable choice for optimizing both traffic throughputs and economic outcomes.

Table 20: Evaluation Results with Objective Function of Maximizing Total Throughput

	Lane type	Current control	With the proposed control system		Improvement (%)	
			Control type 1	Control type 2	Control type 1	Control type 2
Total Delay (veh-hour)	GP Lanes	18820.5	16991.79806	17158.345	9.72%	8.83%
	Express Lanes	715.0	1286.859389	1220.544	-8.00%	-7.07%
	System-wide	23239.51	18278.66	18378.89	21.35%	20.92%
Total Throughput (veh/hr)	GP Lanes	43996	43169	43317	-1.88%	-1.54%
	Express Lanes	4419	7259	6912	64.27%	56.42%
	System-wide	48415	50428	50229	4.16%	3.75%

Table 21: Evaluation Results with Objective Function of Maximizing Total Revenue

	Current control	With the proposed control system		Improvement (%)	
		Control type 1	Control type 2	Control type 1	Control type 2
Total revenue	7247	10165	9248	40.26%	27.61%

4.4 Conclusion

This chapter highlights the transformative potential of integrating real-time ramp metering and dynamic toll pricing strategies to address persistent traffic congestion. By optimizing lane usage and leveraging advanced models for lane choice and traffic flow prediction, the proposed system achieves significant improvements in delay reduction, throughput, and revenue generation. Notably, Express Lanes benefit more substantially than general-purpose lanes, raising important questions about equity and the distribution of benefits among road users.

However, the adoption of such systems presents challenges, including privacy concerns, infrastructure investment, and the computational optimization required for real-time operations. Addressing these issues will necessitate collaborative efforts between researchers, policymakers, and private stakeholders to ensure sustainable implementation.

Future research should focus on refining the balance between lane performance and equity, improving system robustness, and exploring scalability for larger networks. As technology advances, integrated traffic management systems will play a pivotal role in shaping the future of urban mobility, offering a pathway toward smarter, more equitable, and more efficient transportation networks.

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