Analysing Estimation Methods for the Value of Travel Time from Stated-preference Surveys

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ABSTRACT

The value of travel time (VOTT) is one of the key components for the transportation benefit evaluations. It is an imperative element in appraising the time saving benefits from transportation improvement projects and an essential input for travel demand forecast models. Furthermore, the welfare evaluation of transport pricing schemes is directly determined by VOTT estimates. After decades of research, the VOTT estimation is still a complicated task, and a research gap exists in terms of the development of an effective approach to estimate VOTT accurately. Our knowledge is limited in terms of a detailed comparison among different approaches to estimate VOTTs.

This study examines two common methods to derive VOTTs from a stated-preference survey: contingent valuation (CV) and discrete choice modeling (DCM). To explore the impacts of using these two methods on VOTT estimates, the same data samples are employed from an online survey conducted in the Dallas-Fort Worth metroplex. For the CV method, the ordinal logistic regression is performed to estimate the expected willingness to pay given hypothetical time saving levels. For the DCM method, multinomial logistic regression models are developed to estimate the utility functions that determine the relative importance of travel time and travel cost and thus estimate VOTT. Furthermore, this thesis examines the traveler characteristics that affect VOTT by incorporating gender, age, income, and trip lengths in regression models.

The results suggest that even if the data source (respondents) is the same, the two methods could result in different and even conflicting estimates. The CV method estimates an average VOTT of \$6.10 per hour, substantially lower than the average estimate of \$22.65 per hour using the DCM method. Generally, the DCM VOTT estimates are closer to calculated practical VOTTs (based on revealed preference data) and seem more reliable. The reason is that when asking respondents directly (CV), they generally hide their true willingness to pay, which results in lower VOTT estimates than those of DCM (with hypothetical scenarios). Furthermore, the two methods provide conflicting estimates when the effects of socio-demographics and travel characteristics are considered. This study sheds light on such discrepancies among methodologies to estimate VOTT.

Finally, this study provides evidence that current project evaluation practices using a single method to estimate VOTT are biased/inaccurate, considering the potential inconsistencies among the estimation methods.

Key words: *value of travel time, cotingent valuation, discrete choice modelling, willingness to pay, stated-preference surveys.*

RÉSUMÉ

La valeur du temps de parcours est l'une des composantes clé pour l'évaluation des avantages du transport. Il s'agit d'un élément impératif dans l'évaluation des gains de temps des projets d'amélioration de transports et une contribution essentielle aux modèles de prévision de la demande de transport. En outre, l'évaluation du bien-être des systèmes de tarification des transports est directement déterminée par les estimations de la valeur du temps de parcours. Après des décennies de recherche, l'estimation de la valeur du temps de parcours est encore une tâche compliquée, et un écart de recherche existe pour ce qui est du développement d'une approche efficace pour estimer la valeur du temps de déplacement avec précision. Nos connaissances sont limitées en ce qui concerne la comparaison détaillée entre différentes approches pour estimer les valeurs du temps de parcours.

Cette étude examine deux méthodes courantes pour calculer les valeurs du temps de parcours â partir d'une enquête sur les préférences déclarées: l'évaluation contingente et la modélisation des choix discrets. Pour explorer les impacts de l'utilisation de ces deux méthodes sur les estimations de la valeur du temps de parcours, les mêmes échantillons de données sont utilisés à partir d'un sondage en ligne mené dans le Dallas-Fort Worth metroplex. Pour la méthode de l'évaluation contingente, la régression logistique ordinale est effectuée pour estimer la volonté de paiement attendue, compte tenu des niveaux hypothétiques d'économie de temps. Pour la méthode de la modélisation des choix discrets, des modèles de régression logistique multinomiale sont développés pour estimer les fonctions d'utilité qui déterminent

l'importance relative du temps de déplacement et du coût du voyagement et donc estimer la valeur du temps de parcours. En outre, cette thèse examine les caractéristiques des voyageurs qui affectent la valeur du temps de parcours en intégrant le sexe, l'âge, le revenu et la durée des voyages dans les modèles de régression.

Les résultats suggèrent que même si la source de données (répondants) est la même, les deux méthodes pourraient aboutir à des estimations différentes et même contradictoires. La méthode de l'évaluation contingente estime la valeur du temps de parcours moyen à 6,10 $ l'heure, ce qui est nettement inférieur à l'estimation moyenne de 22,65 $ l'heure selon la méthode de la modélisation des choix discrets. Gnralement, les estimations de la modlisation des choix discrets sont plus proches des pratiques calcules (bases sur les donnes de prfrence rvles) et semblent plus fiables. La raison en est qu'en demandant directement aux rpondants (l'valuation contingente), ils cachent gnralement leur volont relle de payer, ce qui se traduit par des estimations infrieures celles de la modlisation des choix discrets (avec des scnarios hypothtiques). De plus, les deux méthodes fournissent des estimations contradictoires lorsque l'on considère les effets de la socio-démographie et des caractéristiques de voyage. Cette étude met en lumière de telles divergences entre les deux méthodologies pour estimer la valeur du temps de parcours

Enfin, cette étude fournit la preuve que les pratiques actuelles d'évaluation de projet utilisant une seule méthode pour estimer la valeur du temps de parcours sont biaisées / inexactes, compte tenu des incohérences observées entre les méthodes et même les spécifications d'un même modèle.

Mots clés: *la valeur du temps de parcours, l'évaluation contingente, la modélisation des choix discrets, les sondages sur les préférences déclarées*

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INTRODUCTION

1.1 BACKGROUND

Traffic congestion, fiscal constraints to construct new road infrastructure, right-of-way restrictions, and substantial environmental and social footprints pose significant challenges to the transport sector worldwide [1]. Transport Canada estimates the annual traffic congestion costs in Canada in a range from \$3.1 billion to \$4.6 billion [2]. The increasing growth in travel demand outpaces roadway capacity expansions mainly because of our limited public funding sources. As a result, public transport agencies are incited to explore other alternatives, including managed lanes (MLs), to mitigate congestion while optimizing the use of limited public funding [3].

MLs are highway facilities or a set of lanes where operational strategies are proactively implemented and managed in response to various congestion conditions [4]. They are designed to enhance operational performance through the effective use of existing or new infrastructure. A comprehensive review on various ML strategies can be found in Appendix A. Numerous ML facilities exist in Canada. In Montreal, noteworthy examples are two tolled bridges on highways Autoroute 25 and Autoroute 30. In Toronto, high-occupancy-vehicle (HOV) lanes are present on highways 403, 404, and 417. As another example in Toronto, the Queen Elizabeth Way, was opened to traffic in September 2016, as the first high-occupancy-toll (HOT) lanes in Canada.

Implementing ML strategies complicates the welfare analysis of transportation stakeholders. This is because MLs provide a high degree of operational flexibility and offer a wider range of travel options available to road users [3] [4]. From users' perspective, a substantial part of welfare gains from transport improvements is in the form of travel time savings [5]. Therefore, transport experts should carefully evaluate the welfare (monetary) value associated with time savings.

Travellers' valuation of their travel time (savings) plays a critical role in the evaluation. For highway administrators, it is critical to understand the travel behavior changes and the underlying causalities in users' responses to the implementation of MLs. The travel behavior information will be used to evaluate the transport programs'/projects' impacts and effectiveness [6]. To examine the key factor in the welfare analysis of the ML implementation, this thesis studies two common methods to estimate the value of travel time (VOTT).

1.2 RESEARCH OBJECTIVES

VOTT is an important indicator of willingness-to-pay (WTP), a commonly used factor for appraising costs and benefits of transport improvement projects [7]. It is also an essential input in travel demand models and is used for the welfare evaluation of transport pricing schemes [8] [9].

Research on VOTT has been developed over past decades with a well-established theoretical background supported by numerous empirical studies [10]. However, after decades of research, the VOTT estimation is still a complicated task, and a full consensus on many issues has not been achieved [11] [12] [13]. The key research questions surrounding VOTT studies are:

- What are the impacts of using different estimation approaches?
- What is an effective approach to estimating an individual's VOTT?
- What factors could influence an individual's VOTT? and
- How can transport agencies utilize the results of VOTT studies?

This thesis aims to answer these questions. The focus would be the first question: *the impacts of using different estimation approaches*. Based on the results of a case study in which two commonly-used methods of VOTT estimation are applied, the rest of the aforementioned research questions are examined.

1.3 VALUE OF TRAVEL TIME (VOTT)

1.3.1 Definition

In the context of transportation economics, VOTT is defined as the opportunity cost of the time that a traveller spends on his/her journey [14]. The opportunity cost is quantified by a traveller's marginal rate of substitution (MRS) of travel time for travel cost. MRS is the slope of an indifference curve, which connects points at which different quantities of travel time and travel cost render the same level of utility for an individual (Figure 1–1). In other words, VOTT is the amount of money that a traveller is willing to pay in order to save time or the amount of compensation that the traveller would accept in exchange for his/her travel time loss.

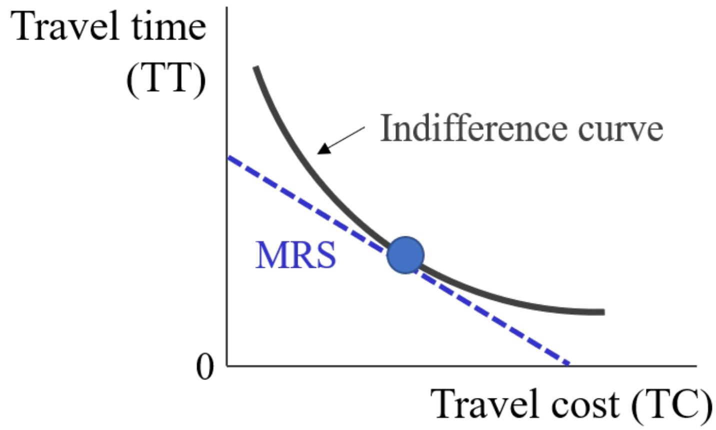

Figure 1–1: Marginal rate of substitution of travel time for travel cost

1.3.2 Applications of the VOTT Analysis

VOTT offers important information for three major transportation applications.

First, VOTT has been extensively used in social cost-benefit analysis (CBA) and the economic appraisal of transportation projects. Decisions about transportation investments are often made based on CBA, where the direct economic impacts of a transportation project are measured and evaluated. CBA is a useful tool for decision-making in planning and evaluation of projects and it can be used to determine whether and when a project should be implemented and to rank and prioritize various projects. According to Mackie et al. [15], travel time savings capture a large share (around 80%) of the quantified benefits of major road projects. By its definition, VOTT is a factor that should be multiplied by travel time savings to quantify the change in consumer surplus in monetary terms. It is therefore imperative for the validity of CBA to estimate VOTT accurately and to reflect the preferences of individuals in those estimates.

Second, VOTT is a piece of required information for travel demand forecasting (TDF). The forecasts are fundamentally important inputs in developing transport infrastructure - from establishing the overall transportation policy, to planning and engineering design of a specific project [16]. When forecasting travel demand for various types of transport models, travel time is assumed to be a very valuable resource; one which individuals would be happy to consume less (save time) [17]. Therefore, the time saving valuation is paramount in travel demand forecasting in order to model transport users' decision processes and their travel patterns.

Third, in relation to the previous application, VOTT elucidates broader questions about travel behavior. The travel decision process, or the travel activity choices more broadly, involves complex psychological reasoning unique to each individual. It is a daunting challenge to model how people arrange their activity schedules in the modern world facing new and constantly changing technologies, lifestyle, values and service provisions [18]. Nonetheless, most transport researchers agree that VOTT can shed light on the research analysing travellers' behavioural patterns by studying variations in VOTTs across individuals and incorporating the variations into travel choice modelling [18].

1.3.3 VOTT Theory

The theoretical definition of VOTT was originally explained using the time allocation theory. Becker [19] developed the theory in the context of the consumption choice. Based on utility maximization, each individual chooses the amount of goods/services to consume subject to constraints on income and the minimum amount of time required by each activity. Becker's model assumes that travel time savings could be transferred to work hours. Thus, VOTT could be approximated by a traveller's wage rate. In the 1960s and early 1970s, the time allocation theory was the mainstream approach to estimate VOTT, for example see [20]. To date, the wage rate is still used to approximate VOTT, and some transportation projects use the minimum wage rate in the region to provide a conservative estimate of the travel time savings' benefits.

In the 1970s, a breakthrough methodological advancement was developed with the introduction of discrete choice modelling (DCM) based on the random utility theory [21]. DCM matches well with the travel demand forecasting models, especially in terms of travel mode choices and route choices. DCM was applied to transportation studies and led to the development of disaggregate travel demand models [22]. In the disaggregate DCM models, the marginal rate of substitution (MRS) of travel time (TT) for travel costs (TC) determines VOTT. With the commonly used linear utility functions, MRS can be simply expressed as the ratio of the travel time parameter (util/time) over the travel cost parameter (util/money). With the increasing application of disaggregate choice models in transportation, an increasing number of studies have been conducted to investigate the variations of MRS across individuals, e.g., see [7] and [23].

The most recent development is related to the activity-based models (ABM). The basic proposition of ABM is that people travel to participate in various out-of-home activities. ABM identifies the sequence and the tour structure among all activities and trips taken by an individual over a time period [24]. Duann and Show

[25] presents theoretical derivation of VOTT using the ABM framework. In their analysis, VOTT consists of two elements: the shadow price of the time associated with each activity and the travel time disutility associated with travel. Their results indicate that VOTT is estimated at 482NT$ per hour, which is equivalent to US$16 per hour when data on traveller's actual behaviour (revealed-preferences) are used and ranges from 331NT$ to 466NT$ per hour, which is around US$11 to US$15 per hour when stated-preference data are used (1US $\approx$ 31NT$).

1.3.4 Key Factors in VOTT Analysis

The VOTT of a particular driver largely dictates his or her travel decisions, with factors such as the availability of travel alternatives and the ability to pay for services also influencing those decisions [26]. VOTT for a particular person varies based on a number of factors, such as [26]:

- The purpose and type of trip (e.g., commuting, recreational, or business related);
- The characteristics of the traveler (e.g., income or age);
- The transportation mode (e.g., bus, personal car, or walk);
- Travel conditions (e.g., the weather conditions or the congestion level);
- The time of year, week, or day (e.g., going home at the end of the day versus going to work in the morning); and
- The location (intercity/interstate versus local trips).

Hereinafter, the focus is on the first two points: the purpose and type of trips and the characteristics of the traveler because the case study of this thesis, discussed in Chapter 2 and Chapter 3, mainly examines those two points.

(1) Trip Characteristics

The principal distinction in trip purpose is between business and private trips. Business trips include a trip between one business location to another. Personal trips are made without business purpose such as leisure trips and commuting (commuting from home to a work place is also counted as a personal trip). VOTT for business trips differs in nature from VOTT for personal trips because for a business trip, the willingness to pay for time reduction derives from the benefits realized by the company, on behalf of which a traveller makes his/her journey [18]. On the other hand, the VOTT for personal trips is often derived from empirical studies, according to the traveller's personal characteristics.

In contrast to VOTT for personal trips, VOTT for business trips are elicited from traveller's wage rate [27]. With this approach, as the employers control their employees' decisions, the travel time incurred by an employee is directly translated into the company's cost. Therefore, VOTT is equal to the marginal labour cost of the traveller. A number of assumptions are made within this approach, resulting in a valid criticism about the use of the marginal labour cost. Prominent assumptions are that travel time reduction is transferred to work hours and that during travel time, a traveller is only dedicated to non-labour activities, both of which may not always be realistic.

For the VOTT analysis of personal trips, commuting is often treated as a separate category. Studies have investigated the impacts of the trip purpose on personal trips and found that the nature of commuting significantly differs from other trip purposes, e.g., see [28]. As a long commuting time is becoming very common in modern industrialized societies, the VOTT analysis for commuting is becoming increasingly important to study traffic-related problems.

(2) Socio-demographics

Socio-demographic variables such as income, employment status, age, educational background, gender, housing location are extensively examined in VOTT studies. Several recent studies have reported the impacts of such variables on the VOTT of each individual [29] [30] [31].

As early VOTT studies (based on time allocation theory) assumed travel time is directly transferable to work hours, income has been considered as the primal cause of variations in VOTT. Empirical studies also supported the hypothesis that the income level affects VOTT as presented in [32] [33].

Studies argue that socio-demographic variables other than an individuals' income may as well play a significant role in explaining the variations of VOTT among individuals [34] [35] [36]. However, after decades of research, there is no consensus on the effects of these variables and the extent they affect an individual's VOTT. The key reason is that results of empirical studies are usually unique and their generalization is not plausible. Demographics vary among locations, and the results from one study area cannot be extended to other areas/studies. In addition, the transportation services available to citizens are different from one region to another; e.g., for people living in a heavily-motorized environment, the VOTT estimates derived from a public-transit-oriented region may not be well suited.

The interpretation of the VOTT analysis is another challenge, making it difficult to draw policy implications from such analysis. Some studies have found that, although controversial, gender can affect an individual's VOTT [12] [37]. However, if a VOTT study claims that either gender has a higher VOTT than the other, the transportation policy implication is to enhance welfare gains by providing the gender group with higher VOTT with a faster transportation service. Nonetheless, such inequity in transportation decision making is against our values of gender equality. Gender might be the most obvious example, but any transportation policy driven by socio-demographic studies on VOTT would most likely be challenged by equality and ethics.

1.3.5 Data for VOTT Estimation

There are two types of data available for VOTT analysis in general: revealed-preference (RP) data and stated-preference (SP) data [38]. RP data represent observed data on actual choices made by travellers. They can be either observed directly or self-reported, such as via a survey. SP data are collected via a survey on what travelers, consumers, or decision makers state they would do under given, hypothetical choice scenarios or experiments.

In general, RP data are preferred because they reflect real-world choices of travellers [39]. In addition, RP data could be usually collected in large samples via monitoring devices. On the other hand, there are disadvantages and limitations associated with using RP data, such as:

- The chosen alternative is known with certainty, but often little is known about the alternatives the traveller considered but did not choose;
- There are typically interdependences between variables in the data, e.g., travel time, average speed, chosen transportation mode, etc.; and
- The data reflect the existing market only, not a newly designed/introduced market.

In the context of the VOTT analysis, the major limitation of RP data is that they are incapable of capturing socio-economic and demographic data if the observed data are acquired by conventional monitoring tools such as traffic counts.

For new changes in a transportation network or for travellers' characteristics that are not observed by RP data, we need to conduct SP surveys. In SP surveys, potential users of the transport system are targeted and asked to state their preferences/choices based on predesigned sets of scenarios. Advantages of SP over RP data can be summarized as follows [40]:

- Enables testing new products or attribute levels that do not currently exist in the market;

- Using carefully-developed experimental designs, allow for statistically-efficient estimations of effects;
- Ensures that choices are made with complete knowledge of the alternatives;
- Allows a robust understanding of how individuals make choices by observing multiple choices from one individual; and
- Enriches DCM by providing the data on the relationships between choice behavior and socio-economic and demographics data.

Even though SP surveys could be the only approach to study new non-existing conditions/markets, they could be discredited because respondents simply answer imaginary questions, and the validity of their answers is arguable [41].

The two most-widely-used methodologies to estimate VOTT from SP surveys are (i) contingent valuation (CV) [42] and (ii) discrete choice modelling (DCM) [43]. CV asks respondents directly about how much they are willing to pay to reduce their travel time [42]. DCM is another approach to estimate VOTT from SP surveys. Based on the utility theory developed by economists (discussed in Section 1.3.3), DCM constructs travel utility functions consisting of a travel time variable and a monetary cost variable [43].

1.3.6 Empirical Studies

Early work on VOTT reports estimates ranging from 30 to 50 percent of the average wage [19] [32] [44]. For instance, Beesley [32] estimates VOTTs of civil servants working for the Ministry of Transport in London. With 1,465 survey responses, the study examined ″Accepted Maxima″ and ″Rejected Maxima″ of extra costs to save time on their travel. By elucidating the trade-off between travel time and monetary costs of travel, the study found that highly-paid people (executive officers) showed higher VOTT spent in a car travel than their counterparts (clerical officers). The estimates are 37 percent of wage rate for the executive officers and 31 percent for clerical officers. The study also found that the trade-off became blurry for non-commuting trips. In addition, the study argued that while the hypothesis that trips made in working time should be valued at a rate near an hourly wage rate, the hypothesis that the level of comfort of the journeys affects valuation on time should be taken into account, e.g., irritating trips on congested roads could lead to higher VOTT valuations.

With the aid of DCM, the literature initiated empirical studies to estimate VOTTs from developing route choice/mode choice models from the 1980s, and these studies typically report estimates equivalent to 20 to 100 percent of the wage rate [8] [45] [46]. In particular, using a SP approach, Calfee and Winston [8] found that long-distance automobile commuters' willingness to pay to reduce their travel time on average ranges from 14 to 26 percent of the gross wage in major U.S. metropolitan areas. They also found that commuter's willingness to pay rises with income. For example, while commuters annually earning between $7,500-$12,500 value automobile travel time at $3.06 per hour, commuters earning between $125,000-$175,000 annually value automobile travel time at $7.11 per hour. In addition, the study argued that VOTT might be insensitive to travel conditions, e.g., congestion level.

They explain the lower estimates may come from the fact that commuters are able to adjust to congestion through their modal and departure time choices as well as the choice of residential and work place location.

U.S. Department of Transportation suggests various VOTTs to be used for evaluating transportation projects [47]. These values range from 50 to 120 percent of the wage rate, depending on the length of travel (local or inter-city) and the type of travel (personal or business). U.S. Department of Transportation recommends the following VOTTs for the economic analysis studies of surface transportation (except for high-speed rail) in year 2015 dollars: $13.60 per hour for personal local travel, $25.40 per hour for business local travel and $14.10 per hour for all purposes, calculated by the weighted averages using the distributions of travel by trip purpose.

Some notable examples of the empirical estimates of VOTT found in the literature, including those discussed above, are summarized in Table 1–1.

1.4 SCOPE AND OVERVIEW

The second and the third chapters of this thesis examine and compare the VOTT estimates when employing the CV and the DCM methods. The data for both methods are collected via an online questionnaire survey in the Dallas-Fort Worth metropolitan region as a case study. In addition, since VOTT is affected by each individual's socio-economic characteristics and trip characteristics, the results from the two methods are examined considering the impacts of various socio-economic and trip characteristics.

Table 1–1: Empirical VOTT estimates from literature

Study	Location	Data	VOTT Estimate
Beesley (1965)	London, U.K.	Survey of government officials	31 to 37 percent of wage rate (plausible range of 31 to 50 percent).
Lisco (1967)	Chicago, Illinois	Household interview data collected as part of the Chicago Skokie Swift Mass Transportation Demonstration project.	20 to 51 percent of wage rate.
Calfee and Winston (1998)	U.S. (Nationwide)	National Family Opinion survey.	14 to 26 percent of gross wage.
Miller (1989)	Survey of route choice questions.	60 percent of gross wage.	
Small (1982)	San Francisco, California	Values derived from multiple mode choice transportation models.	20 to 100 percent of the gross wage.
Small, Winston and Yan (2005)	Greater Los Angeles metropolitan area, California	Multiple surveys of travellers on SR-91	Median VOTT $21.46 per hour or 93 percent of average wage rate
Tilahun and Levinson (2007)	Minneapolis, Minnesota	Survey of travellers on I-394	$10.62 per hour for MnPass (ETC system) subscribers that were early/on-time $25.42 per hour for MnPass subscribers that were late.
Fezzi et al. (2014)	Riviera romagnola, Italy	Face-to-face interviews of travellers to three resort beaches in Italy.	75 percent of the wage rate
Burris et al. (2016)	Houston, Texas	Revealed preference data on the Katy Freeway managed lane facilities.	$0 to $26 per hour for travellers with transponders.
USDOT (2016)	U.S. (Nationwide)	Updated 1997 Value of Travel Time Guidance using 2015 income statistics.	50 percent of wage rate for personal local travel. 100 percent of wage rate for commercial local travel.

CHAPTER 2
ORDINAL LOGIT MODEL FOR THE CONTINGENT VALUATION (CV) METHOD

2.1 BACKGROUND

Stated-preference (SP) surveys provide a source of data for the VOTT estimations, where hypothetical situations are presented to the respondents. The respondents choose among finite travel alternatives, according to the set of hypothetical scenarios (designs). The SP experiment designs are often utilized for examining people's attitude towards improvements in transportation services. The CV method is then used to quantify the impacts (VOTTs). In general, the CV method is an approach to estimate a value of good or service by asking people directly about their willingness to pays (WTP) for specified improvements of the good or service. Therefore, it could elucidate people's WTP for specified travel time savings.

To derive VOTTs from the CV method, one can divide the stated WTP by the hypothetical travel time savings, resulting in a $ per hour ($ per min) measure. One limitation of this approach is that the trade-off between the travel time and cost provides a point estimate of the individual MRS. Therefore, descriptive statistics such as mean, median, mode and standard deviation of VOTT estimates are considerably affected by the distribution of respondents' time savings. On the other hand, the general relationship between WTP and time savings can be modelled by regression analysis. In fact, this approach could estimate the MRS continuously, for various individuals through the time savings domains. Moreover, using the regression analysis, the statistical significance of explanatory variables (e.g., age, income, and gender) for VOTT estimations can be examined.

The data samples of hypothetical WTPs in questionnaires are often obtained as category data (ranges). Ideally, the dollar amount of WTP for specified time savings should be obtained as continuous variables. However, this is not practical because asking respondents exact WTP values increases the survey complexity, which could lower the survey response rate and its validity. As a result, survey questions are usually designed to provide ranges of WTP rather than exact values.

When a response variable is measured on an ordinal scale, the responses represent a rough measurement of an underlying interval scale. For such response variables, the ordinal logit regression can be used to describe the variable relationship(s) with other variables. In view of that, this study develops a set of ordinal logit models which consider WTP as a response variable and the specified travel time savings as one of the explanatory variables. Identical to the WTP responses, time savings are obtained as grouped data representing ranges of reduced travel time by using a hypothetical faster transportation service. Next, the Monte Carlo simulation method is employed to transform discrete time savings to a continuous variable by randomly generating data samples according the selected ranges. Finally, by incorporating socio-demographics variables as explanatory variables, the models are capable of explaining the influence of socio-demographic characteristics on an individual's VOTT.

2.2 PREVIOUS STUDIES

This section introduces two studies which have demonstrated the applicability of the ordinal logit models to analyze data from the CV method. Although there are only a handful applications of VOTT estimations, the ordinal logit model has been utilized in many other fields of study.

Xia and Zeng [48] developed an ordinal logit model describing WTP for the green-labeled food in Beijing. Their model incorporates socio-demographic variables such as age and gender. They found that the WTP is significantly influenced by respondents' age; the youth reports high WTP, while gender does not statistically influence the WTP.

An example of the ordinal logit model application in transportation is studied by Mackenzie et al. [49]. The study analyses the demand for various non-market attributes of waterfowl hunting trips, modelled as a composite recreation good, using the CV method approach. Incorporating attributes (e.g., travel costs and travel times) presented in scenarios into a regression model, they found that the value of recreational travel time is in fact endogenous to the choices of recreation activity and site, and is significantly higher than the hourly wage-equivalent rate, approximately twice the rate. The waterfowl hunters were willing to incur an average of $37.07 in additional travel expenses in order to reduce their travel time by one hour.

2.3 METHODOLOGY

2.3.1 Ordinal Response Variable

Suppose y is an unobserved continuous variable, representing a respondent's true value of WTP for a given scenario, and c_0, c_1, $\cdots$, and c_I denote cut-points (end points of ranges/categories) of the distribution. In most surveys, WTP is observed as an ordinal variable y^* representing the range (category) i ($i = 1, \cdots, I$) within which the unobserved variable y falls, which is:

$$c_{i-1} \leq y < c_i \qquad if \quad y^* = i \tag{2.1}$$

Suppose y follows a probability distribution with the probability density function of $f(y)$. The probability π_i that y^* falls within the range i is:

$$P(y^* = i) = \pi_i = \int_{c_{i-1}}^{c_i} f(y)dy \tag{2.2}$$

The cumulative probability for y^*, $F(y^*)$, is the probability that y^* falls below a particular level. For the response category i the cumulative probability (π^i) is:

$$P(y^* \leq i) = \pi^i = \pi_1 + \pi_2 + \cdots + \pi_i \tag{2.3}$$

where $\pi_1 = P(y^* \leq 1) \leq \pi_2 = P(y^* \leq 2) \leq \cdots \leq \pi_I = P(y^* \leq I) = 1$ The logit form of the cumulative probabilities is:

$$Logit P(y^* \leq 1) = \ln\left[\frac{P(y^* \leq 1)}{1 - P(y^* \leq 1)}\right] = \ln\left[\frac{\pi^i}{1 - \pi^i}\right] \tag{2.4}$$

2.3.2 Proportional Odds Assumption

Given the measurement of the response and explanatory variables, we could model the effects of independent variables with an ordinal dependent variable. Let x_j $(j = 1, \cdots, J)$ be an observed independent variable vector, and β_{ij} be an unknown parameter vector to be estimated. There are two general formulations for the ordinal logit model. First, the model can assume proportional odds, or what is called the proportional odds model, where the fitted models make use of a common (same) set of coefficients for the explanatory variables, across all categories of the ordinal response variable ($\beta_{i,j} = \beta_{i+1,j}$, for $i = 1, \cdots, I-1$). For the data record n $(n = 1, \cdots, N)$, the i^{th} category's proportional odds model is defined as:

$$\ln\left[\frac{\pi^{i,n}}{1-\pi^{i,n}}\right] = \alpha_i + \beta_1 x_{n,1} + \beta_2 x_{n,2} + \cdots + \beta_J x_{n,J} \tag{2.5}$$

For the above proportional odds model, the only parameter that can vary across the response categories is the intercept α_i. For example, if the outcome response (WTP) has four possible ranges, the intercept is estimated for three response categories, and one category is set as the reference category. Parameters for the explanatory variables are the same across all categories, and all parameters including intercepts are estimated simultaneously.

The other formulation is to relax this constraint and allow variations of coefficients across categories, what is called the mixed-effect model. The model is a general form of the proportional odds model, where Equation (2.5) can be rewritten as:

$$\ln\left[\frac{\pi^{i,n}}{1-\pi^{i,n}}\right] = \alpha_i + \beta_{i,1}x_{n,1} + \beta_{i,2}x_{n,2} + \cdots + \beta_{i,J}x_{n,J} \tag{2.6}$$

For the mixed-effect model, if the outcome variable has four possible values, for instance, the model will have three sets of coefficients for various categories; coefficients will be omitted for one value as a reference category. Then, the three equations will be estimated simultaneously.

The hypothesis (assumption) that parameters are proportional for the ordinal response or not must be tested. The validity of the proportional odds assumption can be checked by a log-likelihood ratio test using χ^2 (chi squared) statistic. The χ^2 test examines the null hypothesis that all regression coefficients in the model except the intercepts are equal to zero (compared to the reference category). In other words, the test determines the probability of obtaining the chi-squared statistic if there is in fact no effect of the explanatory variables. Let L_p denote the likelihood function given by the proportional odds model. L_p is defined as follows:

$$\mathcal{L}(\alpha_i, \beta_j) = \prod_{n=1}^{N}\prod_{i=1}^{I}\pi_i^n = \prod_{n=1}^{N}\prod_{i=2}^{I}(\pi^{i,n} - \pi^{i-1,n}) \tag{2.7}$$

Similarly, the likelihood function L_m given by the mixed-effect model is defined as follows:

$$\mathcal{L}(\alpha_i, \beta_{i,j}) = \prod_{n=1}^{N}\prod_{i=1}^{I}\pi_i^n = \prod_{n=1}^{N}\prod_{i=2}^{I}(\pi^{i,n} - \pi^{i-1,n}) \tag{2.8}$$

The chi squared statistic can be calculated using the log-form of the likelihood functions:

$$\chi^2 = -2 \left[\log L_p - \log L_m\right] \tag{2.9}$$

It should be noted that other methods to check the assumption exist, and the χ^2 test has been criticized for ineffectively testing the relative goodness-of-fit of the models [50]. Nonetheless, since this method is the most commonly-used approach in the literature, this study employs the χ^2 test for examining the null hypothesis.

2.3.3 Formulation of the Value of Travel Time

VOTT is quantified by the MRS of travel time for travel cost. In this study the MRS for each individual is expressed as the trade-off between time savings and WTP to reduce their travel time. Let $U_{n,i}$ denotes the utility that person n obtains from choosing a transport alternative i. The $U_{n,i}$ could be written as:

$$U_{n,i} = V_{n,i} + \epsilon_{n,i} \tag{2.10}$$

where $V_{n,i}$ denotes the deterministic term of the utility and $\epsilon_{n,i}$ denotes the error term. The deterministic part $V_{n,i}$ of the utilities could be simplified by including only two travel attributes: travel-time (TT) and a travel cost attribute (TC). Then, VOTT is computed as:

$$VOTT_n = \frac{\partial V_n / \partial TT_n}{\partial V_n / \partial TT_n} \tag{2.11}$$

While calculating the travel time attribute is clear, the travel cost attribute needs to be clarified. In this study, the travel cost attribute is approximated by the WTP for specified travel time reductions. The ordinal logit model determines the probability of WTP falling within a range given the specified values of explanatory variables. Therefore, the expected WTP is calculated by:

$$E[WTP] = \sum_{i=1}^{I} k_i \cdot P(WTP = i) \tag{2.12}$$

where k_i the representative (average) value of WTP for the range i. By reformulating Equation 2.11, VOTT could be estimated as:

$$VOTT_n = \frac{\partial E_n[WTP]}{\partial TT_n} \tag{2.13}$$

This VOTT estimation approach is based on a few assumptions. The key assumption is that the full travel cost is represented by the WTP for using a faster transportation service. However, transport services often include other monetary costs (e.g., fuel costs), and a faster service could result in benefits other than merely time savings, such as more reliable travel time, energy savings, environmentally-friendly driving, and the improved utility by avoiding congestion. These benefits are not considered in this study although they may affect individual's WTP.

2.4 CASE STUDY

2.4.1 Overview

This study uses the SP survey data collected from a sample of the Dallas County and Tarrant County residents in Texas, USA. A market research firm conducted the

SP survey in June and July 2017. The respondents were first contacted via email contacts registered in the firm's proprietary panel. Then, the online survey link was sent out for those who agreed to participate in the survey. The survey aims at:

1. identifying users of higher-quality transportation services, e.g., express lanes, and their socio-demographic characteristics;
2. forecasting the changes in travel demand if new transportation facilities and/or management strategies are implemented; and
3. elucidating transportation alternatives available to residents and analyze their travel choice behavior.

To meet these objectives effectively, the sampling population was limited to the survey participants residing in the two counties who were 18 years old or older and have a driver's license. The respondents' age and gender were also controlled to represent the general population in the area. The invitation to participate in the survey was terminated when the number of responses reached 609 complete samples.

The first few questions asked the respondents about their socio-demographic characteristics, including gender, age and income (questions and their raw responses are shown in Appendix B). The respondents' socio-demographic distributions are shown in Table 2–1. The table also reports comparative data obtained from the U.S. census bureau about the general population characteristics. Since the respondent selection process was controlled, the demographics of the sample are quite similar to those of the general population.

Table 2–1: Socio-demographic distributions

Data source	Survey	Responses	U.S. census	Population
Gender	Male	41.1%	Male	49.0%
(census 2010 estimates)	Female	58.9%	Female	51.0%
Age groups	-	-	Under 18 years	28.0%
(census: 2010 estimates)	18-24	16.5%	18-24	9.6%
	25-34	31.6%	25-34	14.7%
	35-44	22.7%	35-44	14.6%
	45-54	12.2%	45-54	14.3%
	55 or older	17.0%	55 or older	18.8%
Income	Less than $30,000	30.6%	Less than $35,000	36.3%
	$30,000 to $50,000	26.0%	$35,000 to $49,999	19.2%
	$50,001 to $75,000	19.4%	$50,000 to $74,999	22.7%
	$75,001 to $100,000	10.6%	$75,000 to $99,000	9.2%
	$100,001 to $200,000	10.8%	$100,000 or more	12.7%
	$200,001 to $500,000	2.1%	-	-
	$500,001 or more	0.5%	-	-

Note: Income distribution from the U.S. census is based on earnings (Full-time, year-round workers with earnings).

After the socio-demographic questions, a contingent valuation experiment was designed to directly elicit people's WTP for hypothetical time savings. First, the survey asks respondents their average travel times during AM peak hours (6 am to 9 am) and PM peak hours (4 pm to 7 pm). Then, the respondents are asked how much they were willing to pay to shorten the reported average travel times by 25% and 50%.

Table 2–2 reports the average travel time distributions among the respondents for a weekday one-way trip during AM and PM peak hours. Noticeably, around half of the respondents who answered these questions stated their average travel times are less than 20 minutes for both AM and PM peak hours. More than 90% of the respondents reported the average travel time of less than 45 minutes. When

Table 2–2: Distribution of average travel time for one-way trip on weekdays

	AM (6 am to 9 am)	PM (4 pm to 7 pm)
No travel	16.7%	10.5%
1-10 minutes	24.5%	21.7%
11-20 minutes	28.5%	27.2%
21-30 minutes	13.5%	18.9%
31-45 minutes	10.9%	12.2%
46-60 minutes	3.5%	6.5%
61-90 minutes	1.3%	1.7%
91 minutes or more	1.0%	1.3%

responses "No travel" are removed and uniform distributions within the travel time ranges are assumed, overall average travel time is around 19 minutes for AM peak hours and 22 minutes for PM peak hours. Travel times are slightly longer for PM peak hours. The respondents who chose No travel and 1-10 minutes are notably fewer for PM peak hours, resulting in relatively longer trips during the PM peak period.

Table 2–3 reports the percentage of WTP responses for each category. For each of the two travel time reduction scenarios (25% and 50%), 10 choices (categories) were presented, including Not applicable meaning that the respondents do not travel in those hours. The survey was designed such that those respondents who answered No travel for both AM and PM peak hours automatically skipped the WTP questions. It is noteworthy that more than one-third of the respondents answered Nothing for their WTP. Around 90% of the respondents stated that they would pay less than $4 for both 25% and 50% reduction scenarios and for both peak hours. WTP seems to be slightly higher for PM peak hours. While the percentages for Nothing and Less than $1 remain almost the same for AM and PM peak hours, other higher WTP

Table 2–3: WTP for two hypothetical scenarios (by category)

Scenario	Category	Number of responses (percentage)	
		AM (6 am to 9 am)	PM (4 pm to 7 pm)
WTP for a 25% travel time reduction	Not applicable - no travel	17.9%	13.5%
	Nothing	34.0%	33.5%
	Less than $1	12.0%	12.6%
	$1-$2	16.9%	18.2%
	$3-$4	9.7%	11.0%
	$5-$7	4.6%	5.9%
	$8-$10	2.1%	2.1%
	$11-$15	2.3%	2.1%
	$16-$20	0.0%	1.0%
	$21 or more	0.5%	0.0%

categories have more responses for the PM peak period, representing a relatively higher VOTT for the period. Interestingly, the stated WTPs are not substantially higher for the 50% time reduction, relative to the 25% reduction scenario.

2.4.2 Data Preparation for Ordinal Logit models

Performing regression analysis, one can set the ordinal responses to the WTP questions as the response variable and average travel times as the explanatory variables. Counting each response of WTP by two travel reduction scenarios (25% and 50%) and two time periods of peak hours (6 am to 9 am and 4 pm to 7 pm) as one record, 2436 (609 multiplied by 4) records are originally obtained. For the estimation, the records are restricted those which have no missing data, i.e., with complete socio-demographic, travel time, and WTP information. During this process, respondents who chose Prefer not to disclose for their socio-demographic information are removed. Furthermore, the records without proper travel time and cost trade-offs are eliminated, i.e., WTP for 50% reduction scenario must be greater than or equal to that of 25% reduction scenario. At the end of the process, 985 records (from 530 individuals) are obtained.

Consider converting grouped data into continuous variables. First variable to convert is the travel time data. It needs to be treated as a continuous variable to elicit the general relationship between travel time and WTP. Secondly, presented ranged of the WTP responses are different for the 25% and 50% reduction scenarios. In order to include them in the same measurement, WTP responses from the 50% reduction scenario are converted to the WTP ranges defined by the 25% reduction scenario. For both cases (travel time and WTP for the 50% reduction scenario), continuous variables are generated using uniform probability distributions, defined by two parameters (a and b) with the following probability density function:

$$X \sim uniform(a, b) \quad where\ f(X) = \begin{cases} \frac{1}{b-a} & \text{for} \quad a \leq X \leq b \\ 0 & \text{otherwise} \end{cases} \tag{2.14}$$

The a and b parameters are set to represent both lower and upper limits of each range, as shown in Table 2–4.

2.4.3 Regression Analysis

In general, the ordinal logit models take one of the two following model specifications: (i) the proportional odds models and (ii) the mixed-effect models. For each specification, a regression analysis is performed using 10,000 iterations (using

Table 2–4: Parameters of uniform distributions $\sim$ *uniform* $(a, b \mid a < b)$

		a	b
Travel Time	1-10 minutes	1	10
	11-20 minutes	11	20
	21-30 minutes	21	30
	31-45 minutes	31	45
	46-60 minutes	46	60
	61-90 minutes	61	90
	91 minutes or more	91	120
WTP for 50% reduction scenario	Less than $1	0	1
	$1-$4	1	4
	$5-$8	5	8
	$9-$14	9	14
	$15-$20	15	20
	$21-$30	21	30
	$31-$40	31	40
	$41 or more	41	50

Monte Carlo simulation), and parameters are estimated by taking the average of all the iterations for the corresponding parameters in order to avoid overfitting to a particular data set, some of whose variables are randomly generated.

Socio-demographic variables are incorporated as explanatory variables in the regression models. Gender is treated as a dummy variable taking either male or female. Age is divided into three subgroups: (i) 35 years or younger, (ii) 36 to 54 years, and (iii) 55 years or older. Annual income is also divided into three subgroups: (a) less than $30,000, (b) $30,000 to $75,000, and (c) more than $75,000. These socio-demographic variables are incorporated by dummy coding, as shown in Table 2.4.2. In contrast, time savings variable is a continuous variable calculated from multiplying the travel time variable generated from the uniform distributions

Table 2–5: The data sample means for the CV method

Explanatory Variables	Subgroups	Mean
Gender (dummy-male=0, female=1)		0.55
Age (dummy coding)	35 or younger	0.56
	36 - 54	0.33
	55 or older	(Reference category)
Annual income (dummy coding)	Less than $30,000	0.28
	$30,000 to $75,000	0.42
	More than $75,000	(Reference category)
Time savings (minutes)		9.54

Note: In contrast to Table 2–1 to 2–3 which show the sample distributions, this table shows the record distribution. A record is the smallest unit representing each response for survey questions in the data; a respondent (sample) can provide multiple (up tp 4) records.

according to the ranges shown in Table 2–4 by 25% and 50%.

2.4.4 Estimation Results

Regression models are developed and fitted to the data set using the maximum likelihood estimation. To avoid overfitting to a particular data set, some of whose variables are randomly generated, parameters are estimated by taking the average of the regression analyses applied to 10,000 randomly generated data sets, following the procedure discussed in Section 2.4.2. The estimated parameters of the proportional odds model and the mixed-effect model are shown in Table 2–6 and Table 2–7, respectively. For the proportional odds model, the absolute t-values of all explanatory variables are greater than 1.96, meaning that the model describes WTP better by incorporating all socio-demographic variables. For the mixed-effect model, a stepwise regression procedure is performed. The procedure begins with an initial model and then compares the explanatory power of incrementally larger and smaller models. If

Table 2–6: Estimated parameters of the proportional odds model

Intercept	Nothing	Less than $1	$1-$2	$3-$4
($21 or more	-0.445	0.216	1.141	2.088
is the reference)	(-2.876)	(1.397)	(7.307)	(12.913)
	$5-$7	$8-$10	$11-$15	$16-$20
	2.929	3.389	4.083	4.828
	(16.973)	(18.571)	(19.856)	(19.554)
Explanatory	Gender	Age (55 or older is the reference)		
variables	male=0, female=1	35 or younger	36-54	
	0.358	-1.093	-0.461	
	(4.137)	(-8.117)	(-3.271)	
	Time savings	Annual Income (More than $75,000 is the reference)		
		Less than $30,000	$30,000 to $75,000	
	1.088	-0.066	0.938	
	(10.075)	(11.579)	(7.803)	

Note: The parameters of the explanatory variables (β_j) are common for all ranges of WTP. Numbers in the parentheses are t-stats.

a term is not currently in the model, the null hypothesis is that the term would have a zero coefficient if added to the model. If there is sufficient evidence to reject the null hypothesis, the term is added to the model. Conversely, if a term is currently in the model, the null hypothesis is that the term has a zero coefficient. If there is insufficient evidence to reject the null hypothesis, the term is removed from the model. The confidence level to determine whether the terms are included in the model is set at 90%. This means that the procedure removes the variables whose absolute t-values are smaller than 1.65, which corresponds to the t-value at the 90% confidence level when the degree of freedom is large.

Table 2–7: Estimated parameters of the mixed-effect model

WTP range	Intercept	Gender	Age (55 or older is the reference)		Annual Income (More than $75,000 is the reference)		Time savings
		(male=0, female=1)	(35 or younger)	(36-54)	(Less than $30,000)	($30,000 to $75,000)	
Nothing	-0.33	0.230	-0.817	-0.300	0.787	0.860	-0.074
	(-1.829)	(2.172)	(-5.319)	(-1.852)	(5.041)	(6.199)	(-7.977)
Less than $1	-0.630	-	-0.795	-0.554	0.430	0.707	-0.060
	(-2.420)		(-3.697)	(-2.438)	(1.962)	(3.786)	(-4.877)
$1-$2	-0.518	-	-0.516	-	0.608	0.901	-0.036
	(-1.883)		(-2.153)		(3.059)	(5.065)	(-3.770)
$3-$4	0.539	0.544	-	-0.932	0.498	0.718	-0.021
	(1.488)	(2.989)		(-2.528)	(2.170)	(3.351)	(-2.248)
$5-$7	0.542	0.575	-	-	0.967	1.442	-0.045
	(0.708)	(2.090)			(3.079)	(4.306)	(-2.855)
$8-$10	0.112	-	-	-	-	1.568	-0.064
	(0.064)				(2.977)	(-2.650)	
$11-$15	0.816	-	-	-	-	-	-0.072
	(0.433)						(-2.558)
$16-$20	-79.763	-	-	-	-	-	-0.015
	(0.000)						(-2.376)
$21 or more	Reference	-	-	-	-	-	-

Note: Numbers in the parentheses are t-stat values.

Table 2–8: Chi-squared test

	Log-likelihood	Chi-square Statistic	Sig. (def=6)
Proportional Odds Model	-3076.09		
Mixed-effect Model	-3009.34	133.5	> 0.999

Table 2–9: Representative values of WTP categories

WTP category	k_i
Less than $1	0.5
$1-$2	1.5
$3-$4	3.5
$5-$7	6
$8-$10	9
$11-$15	13
$16-$20	18
$21 or more	25

Table 2–8 shows the result of Chi-squared test (χ^2). The Chi-square statistic is very large, and the null hypothesis is rejected at significance greater than 99.9%. This result indicates that the null hypothesis that the proportional odds assumption holds is rejected. In other words, the model should use different parameters among WTP ranges ($\beta_{i,j}$) for explanatory variables. As a result, the mixed-effect model provides the better fit. The remainder of the chapter discusses the results of the mixed-effect model.

The mixed-effect model describes the probability of WTP falling within a range given specified values of explanatory variables. The expected value of WTP is calculated using Equation 2.12. k_i, the representative value of WTP range i is specified as shown in Table 2–9.

VOTT is calculated as the ratio of marginal increase of expected WTP to marginal increase of time savings (Equation 2.13). The derivative, however, cannot be analytically calculated. Instead, by considering a small interval of time savings, the VOTT can be numerically computed and approximated. Figure 2–1 illustrates the baseline VOTT curve where input values of the explanatory variables except the time savings variable are set to sample means shown in Table 2–5. Moreover, Figure 2–1 illustrates that VOTT generally increases with time savings. When time savings are close to 0 minute, the average baseline VOTT estimate is $4.64 per hour. The VOTT monotonically increases with time savings, and for the time savings of 9.54 minutes, which is the sample mean, the VOTT estimate increases to $6.10 per hour. This value represents the average VOTT for all the respondents. For 40 minutes of time savings, VOTT reaches $12.38 per hour. This finding is supported by the past studies [36], which found that VOTT increases with the trip length. However, it should be noted that although time savings and trip length are closely related measurements, they could be different depending on the congestion level and road characteristics.

Figure 2–2 depicts the average VOTT curves by gender. The average VOTT estimates are generally higher for males than for females. For instance, with the time saving of 9.54 minutes, which is the sample mean, the average VOTT estimate for male respondents is $7.00 per hour while the estimate is $5.54 per hour for females. It is also noteworthy that the difference between the VOTT estimates for males and females is a function of time savings. The difference is small when time savings are also small; the smallest difference is found when time savings are close to zero ($5.13

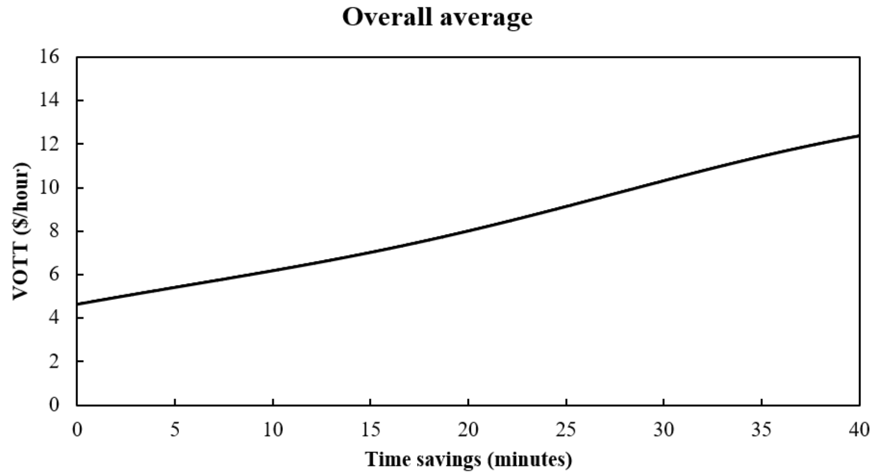

Figure 2–1: Overall average VOTT curve

per hour for males and $4.32 per hour for females). This difference becomes larger with time savings; the largest difference is seen when time savings are 30 minutes ($13.67 per hour for males and $9.65 per hour for females).

Figure 2–3 illustrates the effect of age on VOTT. Overall, age group is seen less influential than other socio-demographic variables' impacts. Using the average time savings of 9.54 minutes, the estimated average VOTTs for the young (35 years or younger), middle (35 to 55 years), and old (55 years or older) subgroups are $5.72, $6.69, and $5.06 per hour, respectively. In fact, the middle-age group has the highest VOTT. This result could be due to the fact that the majority of respondents in this age group are full-time workers with relatively higher wage rates. In addition, they travel during peak hours to perform work-related activities and are bound to arrive at work within a specific timeframe [51] [52]; thus, they might value their travel time relatively higher than the other two age groups. As mentioned before, this shows that

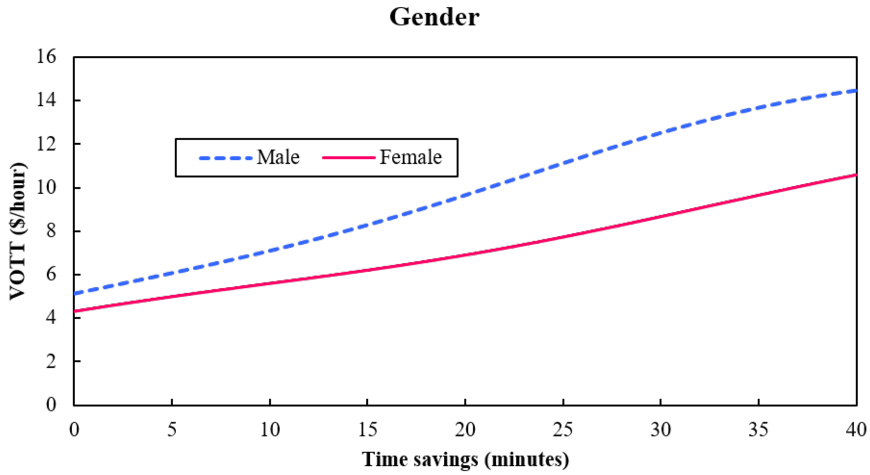

Figure 2–2: Average VOTT curves by gender

the interactions (age and income) could better describe VOTT. The lowest estimated VOTT is for the 55 years or older group. Most respondents in this subgroup might be retired from their jobs and they do not need to travel in peak hours. Nonetheless, the differences in the average VOTT estimates due to age are not as large as other socio-demographic variables.

An interesting result is observed for the impact of the annual income variable shown in Figure 2–4. The average VOTT estimates for low-income, middle-income, and high-income groups are $6.08, $4.75, and $9.41 per hour, respectively. In fact, the high-income subgroup has the highest VOTT. The differences in VOTT estimates are the largest for various income groups, compared to all other socio-demographic variables considered in this study. The fact that the estimated VOTT is the highest for the high-income group is consistent with the time-allocation theory developed by early VOTT studies. The theory assumes that travel time is transferable to working

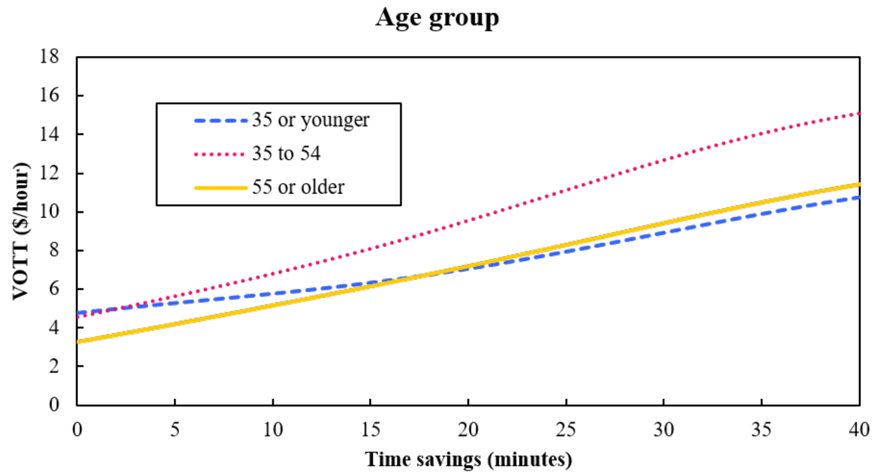

Figure 2–3: Average VOTT curves by age group

hours. However, the effect of income is not the same across all income levels. The middle-income group is estimated to have the lowest VOTT even lower than those of the low-income subgroup. This result is not consistent with the results reported in the literature. The inconsistency could be due to the proposed model specification.

For the high-income group in Figure 2–4, the associated curve peaks at time savings of around 30 minutes. However, as shown in Table 2–7, all socio-demographic variables are not statistically significant for higher WTP ranges and are removed from the models, which could explain why the curve have the peak. Two possible reasons could explain why those variables are not significant. First, the variables might not indeed influence VOTT when WTP is high. Second, the linear model specification or the selected WTP categories should be examined further to better explain VOTT. Also, as Table 2–3 shows, the majority of respondents stated substantially low WTPs. Thus, the sample size for high WTP ranges might have been

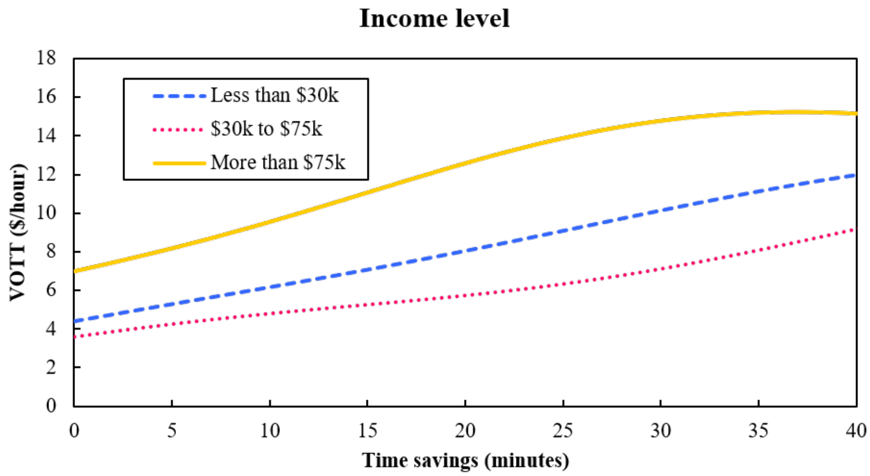

Figure 2–4: Average VOTT curves by income level

small, and the small sample size could not describe important explanatory variables. Rather, the VOTT baseline curve (Figure 2–1) monotonically increasing with time savings seems reasonable.

Although this study does not extend the discussion to the results of the proportional odds model, they are presented in Appendix C for interested readers to compare them with those of the mixed-effect model.

CHAPTER 3
MULTINOMIAL LOGIT MODEL USING THE DISCRETE CHOICE MODELLING METHOD

3.1 Introduction

VOTT could be considered as a latent measure that could be estimated from travel choices instead of calculating it directly [51]. To estimate VOTT from choices, one can develop discrete choice models, derived from the random utility maximization theory and then calculate VOTT using the estimated coefficients in the utility function. Through DCM experiments, VOTT is derived by developing utility functions associated with travel mode/route choices. The DCM experiments are designed for eliciting preferences in the absence of real (revealed) preference data. The method provides individuals with hypothetical alternative scenarios and asks for their preferred travel choices. Each travel choice is described by several attributes. The preferred choices are used to determine the statistical significance of the attributes and their relative importance.

The multinomial logit (MNL) formulation [21] [53] [54] has been widely used in transportation for discrete choice models. The key reasons for the popularity are its simple mathematical form, the ease of estimation and interpretation, and the ability to add/remove choice alternatives [55]. The MNL formulation is based on three basic underlying assumptions. The first assumption is that the random components of different alternatives' utility functions are independent and identically distributed with a Type I extreme-value distribution. This assumption implies that there are no common unobserved factors affecting various utility functions. The second assumption is the homogeneity across individuals in responsiveness to the attributes of alternatives. More specifically, the basic MNL model does not allow variations in the parameters of travel attributes (for example, travel cost or travel time in a mode choice model) due to unobserved individual characteristics. The third assumption of the MNL model is that the error variance-covariance structure of alternatives is identical across individuals. Error variance-covariance homogeneity implies the same attractiveness structure among alternatives for all individuals. Essentially, all DCM applications focus on relaxing one of these three MNL formulation assumptions [56].

This study aims to address two research questions surrounding the VOTT estimation from the DCM method. First, there is a gap in our knowledge about the impacts of various MNL model specifications. For a particular set of data, the parameter estimates could be very sensitive to how the model is specified [57]. For the case study, the MNL model is developed with 17 model specifications, and their VOTT estimates are compared against each other. Second, related to the first point, the impact of the individual characteristics on VOTT has not been examined in the literature, especially in comparison with other approaches. This study analyzes the impacts of individuals' socio-demographic and trip characteristics on VOTT. The seventeen model specifications incorporate different sets of the socio-demographic and trip characteristic variables.

The structure of this chapter is as follows. Section 3.2, provides a literature review on the MNL model focusing on its application to VOTT estimations. Section

4.3 explains the MNL concept and mathematical formulation. Section 4.4 presents the overview and analysis results of the case study. Section 4.5 discusses findings and concludes this chapter.

3.2 Literature Review

The very first attempt to quantify VOTT dates back to the 1960's. Beesley [32] proposes a framework for the economic appraisal of transportation projects. The framework is utilized to analyze people's valuation of travel time by presenting a binary choice between two public transportation modes. The choices are modeled through the evaluation of two attributes travel time and travel cost. Changing travel time and travel cost levels for the two alternatives, four options are offered to the travellers more expensive and quicker alternative, more expensive and slower alternative, less expensive and quicker alternative, and less expensive and slower alternative. Finally based on a graphical representation of the survey data, the study identifies travelers into two categories traders, who choose the alternative that is better on one attribute (either travel time or travel cost) but worse on another attribute, and non-traders who choose the alternative which both attributes are better. The study does not apply a statistical regression modelling and does not estimate a definitive VOTT; rather, it shows the extent of trade-offs between travel time and travel cost by plotting willingness to pay and willingness to accept for different time savings.

In 1970s, researchers started applying discrete choice modeling techniques [21] [22] [58] to estimating VOTT. In DCM, travelers choose their preferred alternative travel route(s), mode(s), or departure time choice(s), considering a trade-off between higher monetary costs and lower travel time costs or lower monetary costs and higher travel time costs. The choice preference provides a direct indication of how much the travel time savings are worth to travelers.

Lam and Small [12] proposed a novel approach to develop random utility models from combining stated-preference and revealed-preference data. They measured VOTTs using survey data on commuters of State Route 91 in Orange County, California where they chose between a free route and a variably-tolled route. Although the data source remained the same, they estimated VOTTs differently using data on (i) the route choice only, (ii) the route and time-of-day choice, (iii) the route and mode choice, and (iv) the transponder choice. They examined various model specifications and found that VOTT estimates vary from \$4.74 to \$24.52 per hour. They concluded that their best model, accounting for both transponder and mode choices explicitly, estimates VOTT of \$22.87 per hour. In addition, they found that women value the reliability of travel time more than men.

Tseng and Verhoef [59] presented the empirical results of how model formulations could affect VOTT estimates, focusing on variations among VOTTs depending time of day. Their model formulation represented time preferences as the excess time-varying willingness to pay for being in one location, over being elsewhere. They applied their modeling framework to SP data representing the respondents' departure time choices for the morning commute. They developed a multinomial logit model and a mixed logit model. The results showed that the willingness to pay is clearly affected by the model formulation. Their outcomes are related to one of this thesis's objective. However, Tseng and Verhoef [59] investigated the impact of model formulations. In contrast, the objective of this thesis is to analyze the impact of model specifications considering the same model formulation (multinomial logit model).

Another research thread is travellers' characteristics and their impacts on VOTT. The most frequent research theme is related to the effect of one's income level on VOTT. As early VOTT studies [19] [20] developed theoretical models based on the time-allocation theory, VOTT has been explained and measured in relation to wage rate. Gronau [60] argued that wage rate could approximates VOTT although the estimation based on wage rate could suffer from substantial variations . Cherlow [61] examined a number of studies and found that VOTT estimates varies from 9% to 140% of the traveler's wage rate. Shaw [62] concluded that VOTT can range from the wage rage level at maximum to zero at minimum. On the other hand, Jara-Diaz [63] asserted that VOTT could be significantly higher or lower than the wage rate depending on the importance of activities. For instance, the VOTT estimates by Sheikh et al. [64] exceeds Atlanta's average wage rate. In a recent study, Devarasetty et al. [65] found that VOTT equals 63% of the average wage rate in Houston, Texas.

Only a few studies analyze the impacts of socio-demographic characteristics other than income on VOTT. A noteworthy study is Swärdh [66] who used stated-preference data to derive VOTT estimates for commuting in Sweden. Mixed logit models were estimated using both a specification with separate wage and commuting time variables and the approach to estimate the VOTT directly on the offer price. The study found that VOTT for commuting does not differ significantly between men and women. However, when the decisions affecting commuting time and wage of both spouses were analyzed, both men and women tended to value the commuting time of the wives higher, indicating different responsibilities and cultural norms affecting VOTT.

3.3 METHODOLOGY

3.3.1 Discrete Choice Experiment

A careful design and implementation of a discrete choice experiment is an important requirement for a proper survey design. Designing an experiment is a cyclical process involving four steps: (i) select alternatives; (ii) determine possible measures/values for each attribute; (iii) decide the number of levels for each attribute; and (iv) develop scenarios. Feedbacks from different steps are sequentially incorporated in the final design of the discrete choice experiment.

Trip attributes and their provided levels in each scenario are critical aspects of any discrete choice experiment, given that the only information indicated by respondents is their preferred choice. Attributes can be quantitative or qualitative and can be generic (the same level for all alternatives) or alternative-specific (may differ across alternatives). While some respondents may consider a different set of attributes in their choices from what is provided to them, it is important that the discrete choice experiment includes the main attributes for the majority of respondents so that concerns about omitted attributes are avoided.

3.3.2 Multinomial Logit Model

A widely used functional form for discrete choice probabilities is the MNL model formulation:

$$P(\ i \mid , C, \beta\ ) = \exp^{z_i \beta} / \sum_{j \in C} \exp^{z_i \beta} \tag{3.1}$$

where

C $(1, \cdots, J)$ is a finite choice set.

i, j are choice alternatives in C.

z_j is a K-vector of explanatory variables describing the attributes (characteristics) of alternatives j which affect the desirability of an alternative j.

$z = (z_1, \cdots, z_j)$ are the sets of the attributes of C.

β is a K-vector of explanatory parameters (coefficients).

$P(\ i \mid z, C, \beta\ )$ is the probability of choosing an alternative i from the choice set C with attributes z.

The MNL model requires a necessary and sufficient condition, termed independence from irrelevant alternatives (IIA), that the ratio of the probabilities of choosing any two alternatives is independent of the availability of a third alternative or,

$$P(\ i \mid z, C, \beta\ ) \equiv P(\ i \mid z, A, \beta\ )\ P(\ A \mid z, C, \beta\ ) \tag{3.2}$$

where $i \in A \subseteq C$ and

$$P(\ A \mid z, C, \beta\ ) = \sum_{j \in A}\ P(\ j \mid z, C, \beta\ ) \tag{3.3}$$

This property greatly facilitates estimation and forecasting of parameters β because it implies the model can be estimated from data on binomial choices, or by restricting choices within a limited subset of the full choice set. On the other hand, this property severely restricts the flexibility of the functional form, forcing equal cross-elasticities of the probabilities of choosing various alternatives with respect to an attribute of another alternative.

Consider a random sample with observations n ($n = 1, \cdots, N$). Let z_n be the attributes of C for individual (case) n, and define S_{in} as a binary variable which equals 1 if individual n chooses i and $S_{in} = 0$ otherwise. The log-likelihood of the sample is

$$\mathcal{L}_C(\beta) = \frac{1}{N} \sum_{n=1}^{N} \sum_{i \in C} S_{in} \ln P(\, i \mid z^n, C, \beta\,) \tag{3.4}$$

Parameters in the MNL model can be estimated using maximum likelihood estimation (MLE). For the MLE method, three assumptions must be made;

1. The vector of attributes z has a distribution μ in the population which has a bounded support.
2. The MNL specification with a parameter vector β^* is the true model.
3. The parameter vector β^* is asymptotically identified, i.e., if $\beta \neq \beta^*$, there exists a set Z of z values and an alternative i such that;

$$\int_Z P(i|z, C, \beta^*) du(z) \neq \int_Z P(i|z, C, \beta) du(z) \tag{3.5}$$

$\mathcal{L}_C(\beta)$ has a unique maximum at $\beta = \beta^*$. Then, the maximum likelihood estimator, β_C, is consistent, and $\sqrt{N}(\beta_C - \beta^*)$ converges in distribution to a normal random distribution vector with zero mean and covariance matrix: $\lim_{N\to\infty}(-\partial^2\mathcal{L}_C(\beta^*))/(\partial\beta\partial\beta')$.

3.3.3 Formulation of Value of Travel Time

VOTT is the MRS of travel times for travel costs. Let U_{ni} denotes the utility person n obtains from choosing a transport alternative i. The specification of the utility U_{ni} is written as:

$$U_{ni} = V_{ni} + \epsilon_{ni} \tag{3.6}$$

where V_{ni} denotes the deterministic term of the utilities and ϵ_{ni} denotes the error term. If the deterministic part V_{ni} of the utilities contains a travel-time attribute TT and a travel cost attribute TC, the VOTT is computed as:

$$VOTT_n = \frac{\partial V/\partial TT}{\partial V/\partial TT} \tag{3.7}$$

For instance, if the deterministic part V_{ni} involves only terms, TT and TC, that is:

$$V_{ni} = \alpha_i + \beta_{i,TT}x_{n,TT} + \beta_{i,TC}x_{n,TC} \tag{3.8}$$

where α_i is a constant, VOTT could be computed as:

$$VOTT_n = \frac{\beta_{TT}}{\beta_{TC}} \tag{3.9}$$

This approach comes with some assumptions. First, this functional form implicitly assumes constant marginal utilities which yield to a single average value of travel time savings. With other specifications, one can estimate variations in VOTT. Second, the full travel cost is represented by out-of-pocket money paid for using a faster transportation service. However, using such service often results in benefits other than merely time savings, such as reliable travel time, fuel consumption savings, environmentally-friendly driving, and improved comfortableness by avoiding traffic congestion. Countermeasures for these assumptions are out of scope of this study.

3.4 CASE STUDY

3.4.1 Overview

This thesis uses the SP survey data collected from a sample of the Dallas County and Tarrant County residents in Texas, USA. The survey is the same with the one described in Chapter 3 of this thesis.

As discussed in Section 2.4.1, the survey collected 609 complete samples that are used for VOTT estimation (totaling 800 samples including incomplete ones). The survey participants are targeted people residing in the two counties who were 18 years old or older and have a driver's license. The respondents' age and gender were also controlled to represent the general population in the area.

First few questions of the survey are related to respondents' socio-demographics and information on their average trip. The responses to these questions are summarized in Table 2–1 and 2–2. Then, the SP experiment to elicit respondents' WTP to save their travel time is designed. The responses are summarized in Table 2–3. VOTT estimation using these responses can be found in Section 2.4.4. Other questions that are included in the survey can also be found in Appendix B.

Drive alone- toll-free lanes	Drive alone on express lanes	Carpool on express lanes
Travel time: (*a*) minutes	Travel time: (*b*) minutes	Time for pickup carpoolers: (*d*) minutes
Toll free	Tolls: $(*c*)	Total travel time: *(b + d) minutes*
		Tolls: *$(e)*
		People in car: 2 or more

Figure 3–1: Format of the discrete choice experiment

After designing socio-demographic questions and average travel times questions, the discrete choice experiment is designed providing several hypothetical choice scenarios to understand travel choice behavior of transport users in the region during peak hours.

Three travel alternatives are selected: (1) drive alone-toll-free-lanes, (2) drive alone on express lanes, and (3) carpool on express lanes.) These alternatives are selected according to available travel options in the region., Each travel alternative has its own travel attributes in terms of travel time (for all alternatives), cost (i.e., tolls for Alternatives 2 and 3), and time to pick up carpoolers (for the last alternative only). The alternatives are described by five attributes (a-Travel time on the drive-alone lanes, b-Travel time on the express lanes, c-Tolls paid on the express lanes, d-Time for pick-up carpoolers, and e-(discounted) Tolls paid as a carpooler), as shown in Figure 3–1. The discrete attribute levels assumed for this empirical study are: $a = \{30, 35, \text{and } 50 \text{ minutes}\}$, $b = \{25, 28, \text{and } 45 \text{ minutes}\}$, $c = \{\$2, \$3, \text{and } \$6\}$ and $d = \{5 \text{ and}, 10 \text{ minutes}\}$ and $e = \{\$1, \$1.5, \text{and } \$3\}$.

A full factorial design (which includes all different combinations) of five attributes with their given attribute levels would result in 162 possible choice combinations (3*3*3*2*3, the multiplication of all possible levels). To reduce the number of scenarios presented to respondents, an orthogonal design is utilized. An orthogonal design is a common fractional factorial design [67]. The smallest orthogonal design requires 16 scenarios (much smaller than 162) in order to provide enough statistical variations. Table 3–1 shows these 16 scenarios divided into four subsets (each set consists of four scenarios). In order to increase the response rate and decrease the survey time, each respondent is randomly provided with only one of these subsets (four scenarios). For each scenario, the respondent chooses one of the travel alternatives. Therefore, the discrete choice experiment with 800 respondents produces a total of 3,200 observations (travel choices) for the discrete choice model estimations. However, to make the analysis consistent with the contingent method results, those respondents who do not drive are excluded from the analysis. After data refinement, a total of 2,120 observations are considered for the discrete choice model estimations.

With the 2120 observations, the MNL models are estimated for the three travel alternatives (drive alone-toll-free-lanes, drive alone on express lanes, and carpool on express lanes). This study focuses only on the two travel-related attributes (travel time, and cost in terms of tolls). Some of the MNL models also include socio-demographic attributes (age, gender, income) interacting with the two travel-related attributes. All MNL models are estimated using the Biogeme software [68]. Different utility specifications are experimented and estimated as reported in Table 3–2, titled *Base Model, Interaction Model 1, Interaction Model 2, Interaction Model 3,* and *Interaction Model 4.* The utility functions in multinomial logit model are assumed linear-in-parameters. As a result, the average VOTT for the Base model is estimated simply by dividing the coefficient of the travel time attribute, and the coefficient of the travel cost attribute (Equation 3.7). Table 4.3 also shows the corresponding value

Table 3–1: 16 scenarios in the discrete choice experiment

Set of Scenarios		Parameters (a) minutes	(b) minutes	(c) dollars	(d) minutes	(e) dollars
ENTRY1	i	50	25	6	10	3
	ii	35	45	2	10	1
	iii	30	25	2	10	1
	iv	35	25	3	5	1.5
ENTRY2	i	30	45	6	5	1.5
	ii	50	25	3	5	1
	iii	30	25	2	10	1.5
	iv	30	28	3	10	1
ENTRY3	i	30	25	2	5	1
	ii	30	45	3	10	3
	iii	35	28	2	5	3
	iv	50	45	2	5	1
ENTRY4	i	30	28	6	5	1
	ii	30	25	2	5	3
	iii	35	25	6	10	1
	iv	50	28	2	10	1.5

of travel time calculations required for different utility function specifications for the interaction models as well.

Table 3–2: Different utility function specifications and their corresponding value of time calculations

Types of Specification	Model ID	Deterministic portion of the utility specification (Multinomial logit models)	VOTT calculation
Base model	1-13	$V_{in} = \beta_{TT} traveltime_{in} + \beta_{TC} toll_{in}$	β_{TT}/β_{TC}
Interaction 1	14	$V_{in} = \beta_{TT} traveltime_{in} + \beta_{TT,fem} traveltime_{in} Fem_{in}$ $+\beta_{TC} toll_{in} + beta_{TC,fem} toll_{in} Fem_{in}$	For males, β_{TT}/β_{TC} For females, $\frac{\beta_{TT}+\beta_{TT,fem}}{\beta_{TC}+\beta_{TC,fem}}$
Interaction 2	15	$V_{in} = \beta_{TT} traveltime_{in}$ $+\beta_{TollInc} \frac{toll_{in}}{Income_n}$	$\frac{\beta_{TT}}{\beta_{TollInc}/Income_n}$
Interaction 3	16	$V_{in} = \beta_{TT} traveltime_{in}$ $+\beta_{TollInc} \frac{toll_{in}}{\ln[Income_n]}$	$\frac{\beta_{TT}}{\beta_{TollInc}/\ln[Income_n]}$
Interaction 4	17	$V_{in} = \beta_{TT} \frac{traveltime_{in}}{Age_n}$ $+\beta_{TollInc} \frac{toll_{in}}{\ln[Income_n]}$	$\frac{\beta_{TT}/Age_n}{\beta_{TollInc}/\ln[Income_n]}$

Note: V_{in} denotes the deterministic portion of utility of individual n for alternative i: (1) drive alone-toll-free-lanes, (2) drive alone on express lanes, and (3) carpool on express lanes.

Table 3–3: VOTT estimations for all respondents and subgroups (Models 1 - 13)

Groups		Model ID	Number of observations	Travel time coefficient (t-stat)	Cost (toll) coefficient (t-stat)	VOTT ($/hour)
All respondents		1	2120	-0.0642 (-13.48)*	-0.170 (-4.85)*	23
Groups by socio-demographic characteristics						
Gender	Male	2	856	-0.0520 (-7.41)*	-0.112 (2.16)*	28
	Female	3	1264	-0.0743 (-11.38)*	-0.220 (-4.61)*	20
Age groups	Less than 35 yrs old	4	1056	-0.0548 (-8.85)*	-0.152 (-3.34)*	22
	35-54 yrs old	5	728	-0.0761 (-8.68)*	-0.202 (-3.17)*	23
	55 yrs old or older	6	336	-0.0937 (-5.82)*	-0.250 (-2.15)*	22
Income	Less than $30,000	7	628	-0.0641 (-7.26)*	-0.194 (-2.94)*	20
	$30,000 to $75,000	8	988	-0.0775 (-10.20)*	-0.163 (-2.97)*	29
	More than $75,000	9	504	-0.0482 (-5.53)*	-0.162 (-2.54)*	18
Groups by travel characteristics						
Average travel time (peak hours)	10 minutes and less	10	584	-0.0751 (-7.57)*	-0.226 (-3.03)*	20
	11-20 minutes	11	720	-0.0649 (-8.01)*	-0.0908 (-1.58)	43
	21-30 minutes	12	348	-0.0605 (-5.30)*	-0.201 (-2.45)*	18
	More than 30 minutes	13	468	-0.0574 (-5.88)*	-0.214 (-2.79)*	16

*indicates statistical significance at the 95% confidence level.

Using the *Base model* specification for various sample groups, Table 3–3 reports the estimated coefficients for travel time and cost, and the estimated average VOTTs during peak hours. All travel time and toll coefficients in the models are statistically significant at the 95% confidence level with one exception (toll coefficient for the respondents who their travel time is 11-20 minutes, which is significant for 90% but not 95%). However, this attribute is still included in the model so that the average VOTT for the respective group can be computed. Consistent with priori expectations, travel time and toll coefficients in all models are negative which implies that an increase in travel time or travel cost attribute decrease the utility of (preference towards) travel alternatives.

The last column of Table 3–3 shows the VOTT estimates for various sociodemographic groups. Note that all the estimations are for peak hours, as the time period was clearly mentioned in the scenarios. The estimated average VOTT for all respondents (the whole sample) is $23 per hour. The estimated average VOTT is higher for males ($28 per hour) than for females ($20 per hour). This implies that male are willing to pay more to shorten their travel times during peak hours, this finding is consistent with what was found in the previous literature [69]. However, a slight variation is observed between the estimated average VOTTs for different age groups. The estimated average VOTT is $22 per hour for both the younger (less than 35 years old) and the older (55 years old or older) subgroups, however, it is slightly higher ($23 per hour) for the middle-aged respondents (between 35 - 54 years old). The higher VOTT could be due to the fact that the majority of middle-aged respondents work outside and are full-time workers with relatively higher wage rates. In addition, the key assumption is that these users travel during peak hours to perform work-related activities and bound to arrive at work within a specific time-frame [51] [52]; thus, they might value their travel time relatively higher than the other two age groups . For the first two income groups, the average VOTT increases with the income level; the estimated average VOTTs for the respondents with an income level less than $30,000 and between $30,000 and $75,000 are $20 and $29 per hour, respectively. This is consistent with the literature as the higher income groups are generally willing to pay more to reduce their travel time during peak hours. However, surprisingly this assumption does not hold for the highest income group; the estimated average VOTT is the lowest ($18 per hour) for this group. An important note is that some of these contradictions could result from the simple separation between these groups (the *Base model* specification) without considering the interactions that are assumed in the model specifications discussed later.

The VOTTs are also estimated based on the average travel time (trip length) subgroups. The results are mixed. The estimated average VOTT for the respondents, who travel shorter (10 minutes and less) is \$20 per hour; whereas the estimated average VOTT increases first and then decreases with the increase of travel time. The estimated average VOTT is surprisingly much higher (\$43 per hour) for the second group (the respondents with travel time between 11 - 20 minutes) than the subgroups with a longer travel time \$18 and \$16 for the respondents with travel time of 21-30 and more than 30 minutes, respectively.

Along with the *Base Model* (Model 1), some interaction models are also experimented - *Interaction Model 1, Interaction Model 2, Interaction Model 3, and Interaction Model 4* (See Table 3–2 for the model specifications). Table 3–4 presents the estimated coefficients of various models, using all observations from the survey. All estimated coefficients are statistically significant at the 95% confidence interval. In the last rows, Table 3–4 also presents the goodness of fit measures (the log-likelihood and the rho-square values) of the MNL models.

Models 2 and 3 are developed to estimate separate VOTTs for male and female respondents. The models' VOTT estimates are \$28 per hour for males and \$20 for females as shown in Table 3–3. Model 14, however, employs another model specification for analyzing the gender effect on VOTTs. Eventually, VOTT estimates of Model 14 are \$27 and \$20 per hour for males and females, quite similar to the results of Model 2 and 3 (Figure 3–2).

Table 3–4: Model estimation results using different utility function specifications

	Model 1 Base model	Model 14 Interaction model 1	Model 15 Interaction model2	Model 16 Interaction model3	Model 17 Interaction model4
Variables					
Travel time (minute)	-0.0642 (-13.48)*	-0.0510 (-7.46)*	-0.0632 (-13.50)*	-0.0646 (-13.53)*	—-
Additional utility of travel time for female (minute)	—-	-0.0239 (-2.59)*	—-	—-	—-
Travel time (minute) by age	—-	—-	—-	—-	-1.99 (-13.12)*
Toll ($)	-0.170 (-4.85)*	-0.112(-2.80)*	—-	—-	—-
Additional utility of toll for female ($)	—-	-0.109 (-2.82)*	—-	—-	—-
Toll ($) by incomen Ln[income]	—-	—-	By income -2.49 (-4.14)*	By Ln[income] -0.621 (-5.36)*	By Ln[income] -0.640 (-5.48)*
Choice constants					
Drive alone-toll-free lanes	—-	—-	—-	—-	—-
Drive alone on express lanes	-1.04 (-8.77)*	-1.04 (-8.72)*	-1.32 (-15.70)*	-1.04 (-9.30)*	-0.987 (-8.91)*
Carpool on express lanes	-1.52 (-16.91)*	-1.52 (-16.86)*	-1.66 (-21.15)*	-1.52 (-17.27)*	-1.51 (-17.20)*
Log-likelihood at zero coefficient	-2329.058	-2329.058	-2329.058	-2329.058	-2329.058
Log-likelihood at sample shares	-1775.621	-1775.621	-1775.621	-1775.621	-1775.621
Log-likelihood at convergence	-1659.675	-1654.845	-1662.917	-1656.570	-1661.568
Rho-square	0.287	0.289	0.286	0.289	0.287
Number of observations	2120	2120	2120	2120	2120

*indicates statistical significance at the 95% confidence level.

Models 15 and 16 describe the relationship between VOTT estimates and annual income levels. Model 15 treats the income variable in its current format (the net income level) while Model 16 uses the logarithm of the income variable (Ln income). The VOTT estimates of both models are illustrated in Figure 3–3. Note that these models estimate the VOTT as a function of income. For Model 15, its average VOTT estimate starts with $15 per hour with an individual annual income of $10,000 and skyrockets to $228 per hour with an individual annual income of $150,000. In contrast, VOTT estimates of Model 16, incorporating the logarithmic effect of annual income levels, plateau at around $30 per hour. Considering our revealed preference (real data) VOTT estimations, Model 15 provides more realistic estimates. However, the key observation is that these two model specifications result in very different

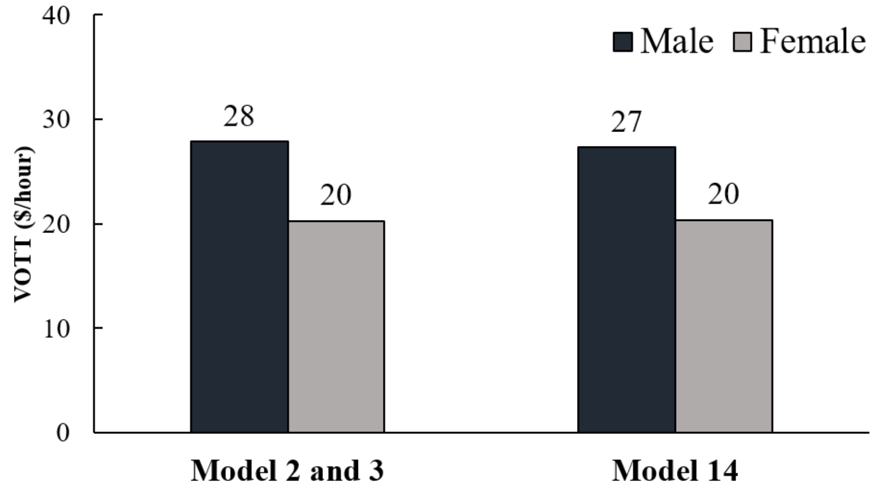

Figure 3–2: Comparison of between Models 2 and 3 and Model 14 (gender effects)

estimates, which emphasizes the importance of the model specification choice on the results.

Model 17 is the final model. This model specification includes two interaction attributes (travel time interacted with average age, and toll interacted with average income) as explanatory variables/attributes. The model provides the VOTT estimations for various age and income groups, as presented in Figure 3–4. Considering the interactions, the impacts of age and income are more reasonable; VOTT estimates increase slightly with income and decrease significantly with age.

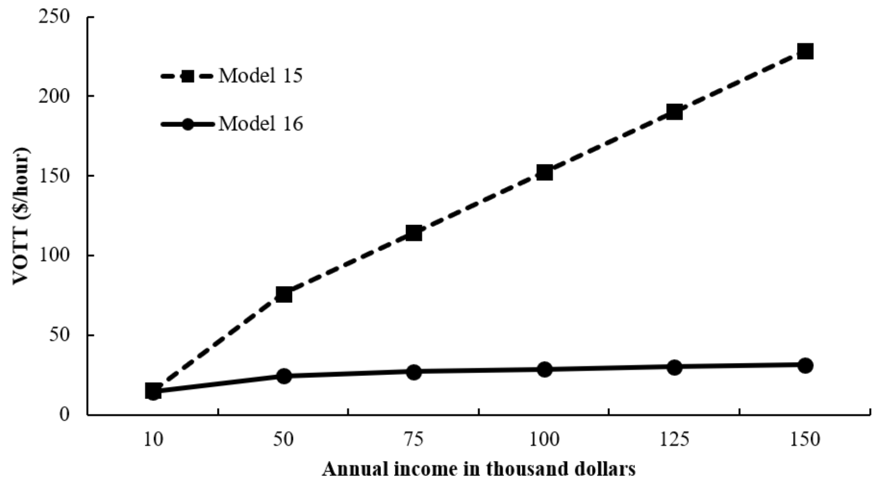

Figure 3–3: Comparison between Model 15 and Model 16 (income effects)

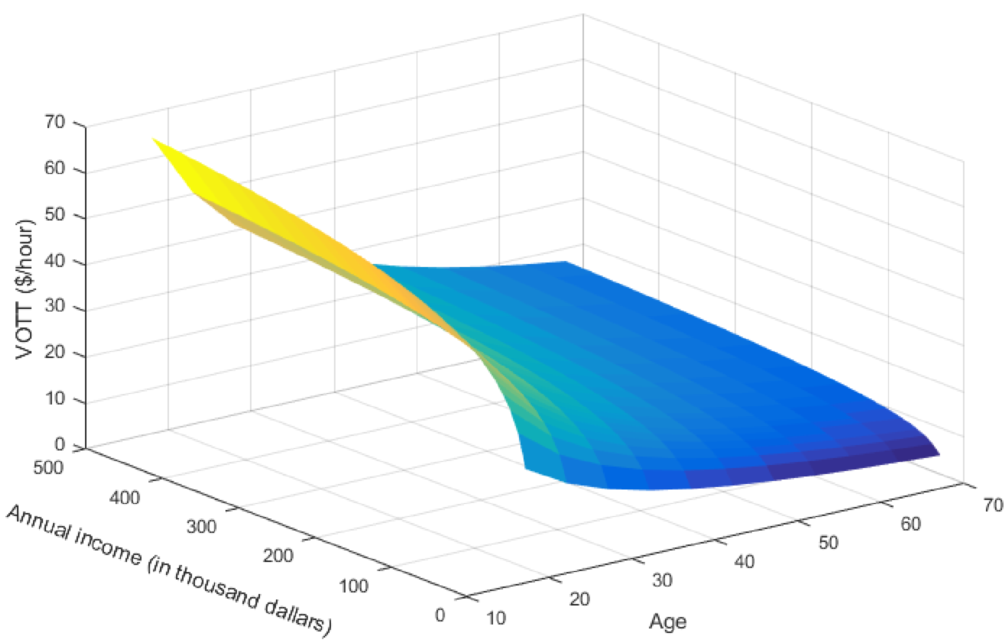

Figure 3–4: Value of travel time (VOTT) estimation using Model 17

CHAPTER 4
DISCUSSION

4.1 CONTINGENT VALUATION SUMMARY

A SP survey is conducted targeting the residents of Dallas County and Tarrant County, in Texas, USA. The results suggest that the average VOTT estimate for all respondents is \$6.10 per hour. In general, the VOTT estimate increases with time savings; VOTT estimates change from \$4.64 to \$12.28 per hour when the travel time savings are at close to 0 minutes to 40 minutes, respectively. It is also found that socio-demographic variables affect one's VOTT. First, male respondents are found to have higher VOTTs than their female counterparts (Figure 2–2). Second, the middle-age subgroup has the highest VOTT estimate, more than their younger and older counterparts (Figure 2–3). These findings are consistent with what were found in the previous studies. Third, an interesting result is observed for the annual income variable (Figure 2–4). Annual income provides a mixed effect. The high-income subgroup has the highest VOTT, which is consistent with both theoretical and empirical models' findings. However, the low-income subgroup seems to have a higher VOTT than the middle-income subgroup. This result is questionable, and further research is needed to investigate the validity of the result. However, this can be due to the linear model specification and to the mixed effect model's limitation. A possible solution to this problem is to develop models that explicitly account for correlation among socio-demographic variables.

The CV method implemented in this study has several limitations. First, many data records are removed to avoid inconsistent responses. For instance, the responses from individuals which do not make trade-offs between WTP and time savings are removed following the steps explained in 2.4.2 in detail. Second, this study incorporates only three socio-demographic variables (age, income, gender) due in part to the survey design's limitations. Although these variables are most commonly used in the VOTT and travel behaviour research, other socio-demographic variables (e.g., ethnicity, education level and employment status) can contribute to each individual's VOTT. Especially for travel behaviour research, it is important to analyze what other characteristics could derive VOTT. Finally, to the best of the author's knowledge, this study is one of the few, if not the first, example of analyzing VOTTs by developing ordinal logit models. Because of the ordinal logit models' robust applicability to the SP survey data with directly-inquiring questions, like those in the CV method, the proposed models have potentials for further application to other empirical VOTT studies.

4.2 DISCRETE CHOICE MODELLING SUMMARY

With the same data sample used for the CV method, targeting residents of Dallas County and Tarrant County, Texas, MNL models are developed and VOTTs are estimated. The results suggest that average VOTT estimate for all survey respondents is \$23 per hour. The results also show that socio-demographics of travellers affect their VOTTs. The average VOTT estimate for male respondents is \$28 per hour, higher than their female counterparts, \$20 per hour. Age seems to be less influential than other socio-demographic characteristics. When the base case model (separating the samples according to socio-demographic categories) is used, The highest estimate is given found for middle-age respondents, $23 per hour, slightly higher than their young and old counterparts, $22 per hour for both groups. The interaction models (using continuous explanatory variables) estimate VOTT decreasing with age. Investigating the impact of annual income level reveals mixed results. When the base case model is used, The assumption that people with high income are willing to pay more to reduce their travel time holds when comparing low-income and middle-income groups, $20 and $29 per hour of VOTT, respectively, and . However, the model estimates the lowest VOTT for the high-income group ($18 per hour). On the other hand, when the interaction models are used, the VOTT is estimated to increase with income. Analyzing the effects of average travel time (trip length) on VOTT reveals non-liner relationships between average travel time and VOTT. Starting with $20 per hour for the respondents with the average travel time of 10 minutes or less, the VOTT estimate increases to $43 per hour when for the average travel time of 11 to 20 minutes. However, the VOTT decreases to $18 and $16 per hour for the average travel times of 21 to 30 minutes and 31 minutes or more, respectively.

The results of the case study demonstrate that model specifications can considerably affect VOTT for some cases. A noteworthy finding is observed when two model specifications for the annual income variable are considered. While a model taking logarithm of the income variable estimates VOTT plateauing with one's annual income levels at around $30 per hour, skyrocketing VOTT estimates with one's annual income levels are observed for the other model specification taking the income variable in its current format. In contrast, the two model specifications experimented for analyzing the gender effects provide similar VOTT estimates, and a discrepancy is hardly observed.

The applied DCM methodology has several limitations which a future study could address. First, the MNL model requires several assumptions that have been criticized in the literature. Future research could compare the VOTT estimates using different random utility model formulations. Second, similar to the CV method, this part of the study incorporates three socio-demographic variables only (age, income and gender) due in part to survey design and limited data availability. Last but not least, more case studies are needed where the methodology developed in this study is utilized. This paper mainly presents the results of one case study of applying the random utility model with the MNL formulation, and it is hard to generalize the results to other case studies with other underlying conditions. Growing popularity of priced road infrastructure provides increasing opportunities and motivation for researchers to establish an effective and systematic approach to estimate VOTT.

4.3 DISCUSSION ON THE COMPARISON OF THE TWO MODELS' EMPIRICAL RESULTS

The previous sections of this thesis examine two common methods to derive VOTTs from a stated-preference survey: contingent valuation (CV) and discrete choice modeling (DCM). Table 4–1 provides a summary of the VOTT estimates using the CV method (discussed in Chapter 2) and the DCM method estimates (discussed in Chapter 3).

Table 4–1: Summary of VOTT estimates in the case study

Average VOTT estimates ($ per hour)		Contingent Valuation	Discrete Choice Modelling (Base Case)	Discrete Choice Modelling (Interaction Model)
All respondents		6	23	-
Gender	Male	7	28	27
	Female	6	20	20
Age	Young (≤ 35)	6	22	VOTT decreases with respondent's age.
	Middle (35-54)	7	23	
	Old (≥ 55)	5	22	
Annual income	Low (≤ $30k)	6	20	VOTT increases with respondent's income level.
	Middle ($30-75k)	5	29	
	High (≥ $75k)	9	18	

In general, VOTT estimates are substantially lower for the CV method than for the DCM method; the overall average estimates for all respondents are $6.10 per hour (for CV) and $22.65 per hour (for DCM). This result suggests that the design of survey questions, i.e., the CV method (asking survey respondents to directly state their WTP) and the DCM method (asking survey respondents to select their preferred choices in scenarios), could have substantial impacts on deriving VOTT. Facing direct questions (using CV), respondents might hide their true WTP, which leads to lower VOTTs. On the other hand, when presented a fixed set of choices (DCM), survey respondents are more prone to select more costly travel choices (or state higher willingness to pay). Furthermore, the CV method questions are designed such that the respondents state their WTP to improve the current transportation service. This could lead to the situation where respondents exhibit their tenacious intent to preserve the status quo (no additional payments for a better service). Many respondents state their WTP very small by choosing the Nothing ($0) and Less than $1 options. A large share (around the half) of respondents choose these WTP categories for both 25% and 50% travel time reduction scenarios. The CV-method VOTT estimates are largely influenced by these respondents stating very small WTP.

Another possible explanation for the difference in VOTT estimates is that although the attributes in a discrete choice experiment do not reflect respondents actual travel choice behavior completely, the experiment represents more realistic decision making process than what used in the CV method. Studies have found that the trade-offs between travel time and travel cost revealed by the actual behavior of users are much higher than what they would state in surveys, resulting in lower VOTT estimates from surveys [70]. A possible explanation for this is the difference between WTP and willingness to accept (WTA). Travellers would make decision depending on whether incurred travel costs for taking a faster transport service is below or above the amount they would accept (WTA) while their WTP remains close to $0. Accordingly, the key to improve the CV method approach is to take this into account in the survey design. For instance, surveyors can provide only a few choices for the CV method questions and design the question so that it would elucidate both WTP and WTA.

The two methods predict similar effects of gender and age on individuals' VOTT; however, the results are mixed when the effects of income levels and travel time length are analyzed. It is observed that depending on the estimation method, the impact of socio-demographics and travel characteristics differs. Although this finding is particularly important for travel behavior research, this thesis does not draw a conclusion of the impact from the results of the case study for several reasons. First, according to the models' formulation, neither of the two models are capable of describing multicollinearity in the regression models. To account for correlations between explanatory variables, terms that specifically denote the correlations must be added to the regression model. Interested readers can refer to (1) for the methodology and empirical results in detail. Second, due to limited data availability, this study does not explore other important socio-demographics and travel characteristics which could explain VOTT better (e.g., employment status and trip purpose) and could have been incorporated in modeling processes. Finally, logistic regression models require making several simplifying assumptions [71].

CHAPTER 5
CONCLUSION

The key objective of this thesis is to present the empirical VOTT estimations using two different methods. The key to the comparison is that the data sample (the individuals who take the survey) is the same for the both analysis. To the best of author's knowledge, previous studies do not examine and compare different VOTT estimation methodologies. Empirical studies to investigate the impact are very limited, if existing, due in part to constraints imposed by the case studies settings. This study, however, fills this gap by including two sets of questions (for CV and DCM) and applies the two different methods on the same data sample.

Chapter 1 discusses the definition and basic concepts of VOTT and then explains applications of VOTT, previous studies to estimate VOTT in the literature, required/recommended data inputs for the VOTT estimation and several empirical results of VOTT estimations in the literature.

Chapter 2 examines the VOTT estimation using the CV method (direct questions). As is often the case with data acquired thorough the CV method, the survey responses are obtained as grouped (categorical) data. To analyze the relationship between the WTP and time savings, the ordinal logit models are developed and the information on the time savings as well as socio-demographic variables are incorporated as explanatory variables. To the best of authors knowledge, this methodology is a novel approach to estimate VOTTs. The overall average VOTT estimate is $6.10

per hour. This result is a relatively smaller estimate than the ones that are usually reported in the literature. However, considering the survey design, which allowed the respondents to state very small WTP, the estimate itself seems plausible.

Chapter 3 discusses and reports the VOTT estimation using the DCM method. This thesis develops multinomial logit models to determine the utility functions for the choice of three transportation alternatives presented in the survey. Overall, the average VOTT estimate is $22.65 per hour. In addition, two important aspects are examined in this chapter. One is to analyze the impact of model specifications. The results of the case study show that the specifications have large impact when the form of the income term varies by specification (an identity/normal term or a logarithmic term). But when alternative terms for representing the gender variable are analyzed, the results suggest that this type of model specification does not considerably affect VOTT estimates. The other aspect is the impact of socio-demographics and trip characteristics of respondents. Large impacts are observed for gender, income levels and trip length while a small impact is found for age groups with the base case model specification. However, these results are also sensitive to the specifications, interactive models, which incorporate multivariate terms in utility functions, show that age groups might indeed affect VOTT estimates; VOTT decreases with age..

In conclusion, this thesis shows a clear example of the cases in which different methodologies could result in substantially different VOTT estimates. Transport policies must be based on assessments that address the impacts of applied methodologies and the possible bias of derived VOTT estimates. Further research is needed to compare the impacts of different estimation methods by using data from different case studies.

Appendix A. Delivery Options of Highway Expansion Projects

Highway lanes are classified into four major categories: (1) General purpose lanes, (2) High-Occupancy-Vehicle (HOV) lanes, (3) High-Occupancy-Toll (HOT) lanes, and (4) Fully-tolled lanes. Figure A1 illustrates their relationships in terms of their management strategies and the complexity in their implementation, employed by Federal Highway Administration, U.S. In this section, we investigate their characteristics and economic impacts of managed lanes in terms of social welfare through recent studies and reports. In April 2016, Kentucky became the 34th state in the U.S. to authorize the use of P3s for the development of transportation infrastructure [72].

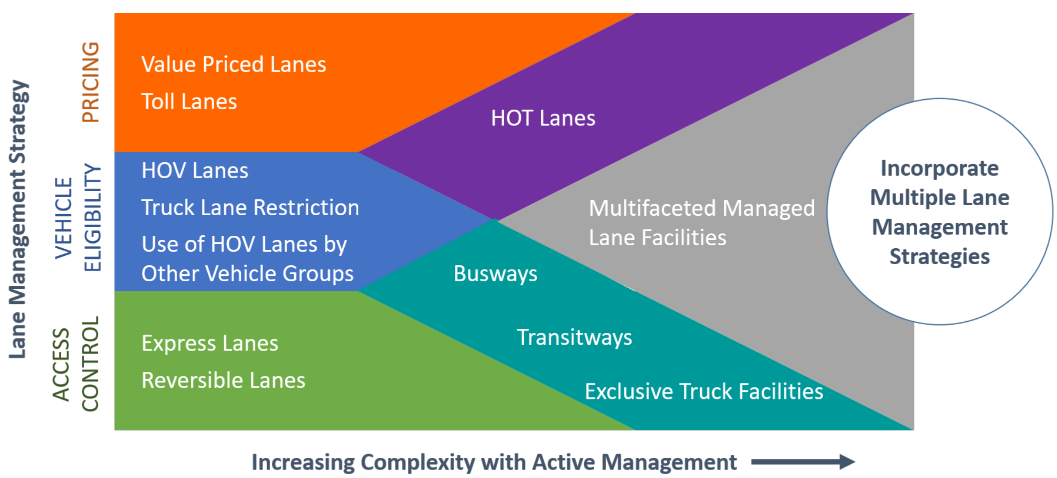

Figure A1: Managed lanes definition.

(1) Free new capacity

- Some claim that adding free new capacity will not resolve the ever-growing traffic demand problems. Downs [73] introduced the concept of triple convergence when new capacity is added to an existing highway and answered the question of why adding free new capacity usually fails to effectively mitigate traffic congestion. Triple convergence is a collective idea of: (i) spatial convergence: users of alternative routes switch to the new lane; (ii) time convergence: users of non-peak hours start travelling during peak hours; and (iii) modal convergence: public transit users switch to private automobiles. The literature emphasize the principle of triple convergence when analyzing the effects of any proposed remedies.
- Gordon et al. [74] proposed an approach to determine local economic impacts in spatial details. Studying the capacity expansion of I-5 (a major freeway in Los Angeles) case study, they found that the most likely scenario would result in a loss of 7,746 jobs with 10-lane and 12,693 with 12 lanes in seven corridor cities in Los Angeles due in part to business relocations.

(2) High-occupancy-vehicle (HOV) Lanes

- The term "High-Occupancy Vehicle (HOV)" is defined as a motor vehicle with at least two or more persons, including carpools, vanpools, and buses [75]. The primary concept behind priority facilities is to implement HOVs with both goals of travel time savings and more reliable travel accommodations. These two goals encourage individuals to choose a higher-occupancy vehicle mode over driving alone. HOV lanes increase the passenger-flow capacity of a roadway by carrying more passengers in fewer vehicles. The intent of implementing HOV facilities is not to force individuals to change their behavior against their will. Rather, the objective is to provide a cost-effective travel alternative that a significant volume of commuters will find attractive enough to change from driving alone to use a high-occupancy mode [75].

- Studies on HOV lanes are typically limited in: (a) their focus on performance metrics without examining general welfare or environmental consequences, (b) assumptions about how carpools form, (c) unrealistic assumptions about inelastic demand (thus ignoring induced demand), or (d) results specific only to a particular HOV case study [76].
- Whether HOV enhances social welfare is unclear. Konishi and Mun [77] investigated the question of under what conditions, introducing HOV lanes is socially beneficial. They argued that introducing HOV policy improves the social welfare under some conditions. For instance, when many commuters switch to carpool by small monetary incentives, HOV lanes could lead to a Pareto improvement. However, HOV lanes could aggravate the business as usual situation under other conditions like heavy congestion levels.

(3) High-occupancy-toll (HOT) Lanes

- Both HOV and HOT lanes have been criticized for their enforcement costs. The issue is that some drivers try to camouflage with placing fake pictures/dolls on the passenger seats. Xu et al. [78] argues that without an effective enforcement and high violation fines, HOT pricing becomes ineffective in congestion reduction. Enforcement is seen as the main barrier to further the expansion of HOT lanes. Xu et al.[78] also proposed a system that uses two cameras to capture images of the front seat and rear seat of vehicles traveling in HOV lanes and identifies violators by processing the captured images. Their reported their proposed system showed a 90 percent accuracy as an HOV2+ system under a variety of noisy conditions, e.g., weather, day/night, site-to-site variations from multiple test sites.

- Janson and Levinson [79] summarizes HOT lane operations in the U.S. (see Table A1 below). With a specific focus on Minneapolis, MN, they outlined four HOT lane-pricing strategies that could serve as alternatives to the current MnPASS pricing system. The proposed alternatives determine the toll based on a simple function relating the HOT lane density (and GP density) to the toll rate.
- Some criticize HOV operations for the so-called empty-lane syndrome, where almost no one is using HOV lanes. Chang et al. [80] discussed this issue and argued that because of HOV being underutilized, transportation agencies are switching to HOT lanes. The authors report the policy implementation success factors, including favorable geometrics and access locations, public acceptance, a political champion, clear roles and responsibilities between agencies, and strong interests shown by transit operators.
- Some argue that HOT brings about equity issues. Weinstein and Sciara [81] introduced three types of equity issues related to HOT implementation: (i)

Table A1: HOT Lane Tolling Strategies.

City	Highway System	Open Date	Length (miles)	Toll Dependency
Atlanta	I-85	2011	16	HOT Density
Denver	I-25	2006	7	Time of Day
Houston	I-10	2009	12	Time of Day
Miami	I-95	2008, 2014	8, 13 (total)	HOT Density
Minneapolis	I-394	2005	11	HOT Density
Orange County	SR 91	2003	10	Time of Day
San Diego	I-15	1998	12	HOT Density
Seattle	SR 167	2008	9	HOT Speed
Washington, D.C.	I-495	2012	14	HOT Density

Adapted from "Alternative High Occupancy/Toll Lane Pricing Strategies and their Effect on Market Share" by Janson and Levinson, 2014

environmental justice low-income and minority communities host a disproportionate share of these transportation facilities and the associated negative human health and environmental impacts; (ii) adequate and equitable access to jobs, social services, and other essential activities that require driving one particular related issue is spatial mismatch, or the claim that low-income workers residing in the inner city are unable to access low-skilled job opportunities growing in suburban locales; and (iii) the relative burden of the transportation finance system on different social groups.

(4) Fully Tolled

- Research studies argue that dynamic tolling systems outperform discrete tolling schemes in most cases (e.g., Rouhani and Niemeier, 2014 [82]). Fan [83] states the optimal toll locations and toll levels with elastic demand (OTLTLED) problem under continuous tolling schemes are always better than the discrete tolling solutions, due to the inherent constraints involved with discrete tolling.

He also found that as the value of time (VOT) increases, the optimal solution tends to recommend to toll wider neighbor segments of road networks in order to produce higher total social welfare.

- Rouhani et al. [84] developed a general social welfare analysis framework that considers the major stakeholders (residents, users, government, and the private sector) for the assessment of the alternative investment publicprivate partnership (IP3) schemes that stimulate public support for road pricing. Their case study of the urban transportation network of Fresno, CA suggest that the system-optimal tolling favors average users, but that governmentand consequently taxpayers should pay for costly tolling systems while in contrast, unlimited profit-maximizing tolls raise substantial profits for the government (or the private operators) and for the infrastructure's citizen-owners, but the average user is worse off. The study recommends a hybrid-tolling scheme that considers both profitability and traffic flow (system) operations.
- Guzman et al. [85] argue that transport decision makers need to maximize the city's welfare; what is missing in currently-implemented pricing schemes. This requires considering long-term changes in land-use and transport dynamics. Their results show that a pricing policy for car users may generates significant net gains and the optimal toll ring rate estimated was significantly lower than the rate in other toll schemes.
- Zhang et al. [86] develop a general framework for evaluating the long-term lease of toll roads, comparing the economic efficiency trade-offs between in-house management and privatization and promoting the public interest during

and after the privatization process. They conducted a case study of the Indiana Toll Road lease (I-90 highway) and conclude that a public agency (with an in-house public toll road management) could not provide as much benefit as the private sector did (the up-front payment received from the private concessionaire).

(5)Road capacity expansion and its impacts on businesses

Whether road network improvements induce growth in economies and business profits is an extremely important question. However, there are many uncertainties regarding the impacts. Hodge et al. [87] states The problem is that most transportation-based analysis tools, such as travel network and user benefit models, are not designed to answer the question of the potential for a highway investment to lead to business attraction (which is inherently speculative).

- Regional economic impacts are easier to estimate compared to nation/state-wide analysis. Yet, whether the improvements have positive impacts on regional business growth is uncertain and while some studies found strong positive impacts from road facility improvements, others found non-significant results. Hodge et al. [87] conducted an economic development analysis on rural and isolated regions of northern New York. Their analysis show that transportation improvements could lead to the attraction of businesses, providing 750 new jobs to 4,000. In contrast, Rogers and Marshment [88] found no significant impacts of transportation improvements on employment in their analysis for Stonewall, Oklahoma, a town of approximately 530 people. However, their results was limited to regions with already declining population.

- Forecasting impacts of road network improvements on economy or businesses is another important research area. Juri and Kockelman [89] applied a random-utility-based multiregional inputoutput model to evaluate the Trans-Texas Corridor projects. The authors assessed their impacts on trade, production, and worker locations. The study predicted a slight redistribution of economic activities, improving the economies of counties located closer to export zones, and an 8% reduction in the traffic volumes on existing highways. The study also suggested a greater diversification of economic activity or production: Positive and negative percentage changes in production levels are predicted across Texas, and the greatest impacts can be noted in counties nearest the new corridorsparticularly in those that originally had lower production levels and poorer access to the Texas network. It was also suggested that moderate changes in the distribution of wages (most are around $\pm$ 10%), floor space rents and population (range from a 50% decrease to increases of more than ten times the base case), following the production trends.

Appendix B. Survey Questions and Results

	Question	Label	Count	%
Q1	Please select your gender:	Male	326	40.8
		Female	472	59.0
		Prefer not to disclose	2	0.3
		SUM	800	100
Q2	Please select your age from one of the following groups:	18-24	116	14.5
		25-34	232	29
		35-44	179	22.4
		45-54	110	13.8
		55 or older	160	20
		Prefer not to disclose	3	0.4
		SUM	800	100
Q3	Do you have a driver's license?	Yes	800	100
		No	0	0
		SUM	800	100
Q4	What is your current employment status? Choose the best option that applies:	Work at home	59	7.4
		Work outside home and full-time worker	417	52.1
		Work outside home and part-time worker	63	7.9

		Student and unemployed	25	3.1
		Student and part-time worker	33	4.1
		Student and full-time worker	20	2.5
		Retired	76	9.5
		Homemaker	54	6.8
		Unemployed	47	5.9
		Prefer not to disclose	6	0.8
		SUM	800	100
Q5	What is your total (personal) annual income?	Less than $30,000	238	29.8
		$30,000 to $50,000	187	23.4
		$50,001 to $75,000	143	17.9
		$75,001 to $100,000	92	11.5
		$100,001 to $200,000	79	9.9
		$200,001 to $500,000	13	1.6
		$500,001 or more	3	0.4
		Prefer not to disclose	45	5.6
		SUM	800	100
Q6	What is the zip code of your home location?	Collin	0	0
		Dallas	459	57.4
		Denton	0	0
		Tarrant	341	42.6
		The other counties	0	0
		SUM	800	100

Q7A	Please choose the average daily mileage you travel for the following trip purposes in each time period (using any travel mode):Work/School - AM-peak - 6:00AM-9:00AM	No travel	69	12.4
		1-5 mile(s)	130	23.3
		6-10 miles	124	22.2
		11-20 miles	125	22.4
		21-30 miles	68	12.2
		31-40 miles	28	5
		41-60 miles	5	0.9
		61 miles or more	9	1.6
		SUM	558	100
Q7B	Please choose the average daily mileage you travel for the following trip purposes in each time period (using any travel mode):Work/School - PM-peak - 4:00PM-7:00PM	No travel	70	12.5
		1-5 mile(s)	126	22.6
		6-10 miles	116	20.8
		11-20 miles	130	23.3
		21-30 miles	71	12.7
		31-40 miles	28	5
		41-60 miles	10	1.8
		61 miles or more	7	1.3
		SUM	558	100
Q7C	Please choose the average daily mileage you travel for the following trip purposes in each time period (using any travel mode):Work/School - Other times	No travel	165	29.6
		1-5 mile(s)	99	17.7
		6-10 miles	91	16.3
		11-20 miles	88	15.8

		21-30 miles	58	10.4
		31-40 miles	28	5
		41-60 miles	11	2
		61 miles or more	18	3.2
		SUM	558	100
Q8A	Please choose the average daily mileage you travel for the following trip purposes in each time period (using any travel mode):Other - AM-peak - 6:00AM-9:00AM	No travel	318	39.8
		1-5 mile(s)	197	24.6
		6-10 miles	148	18.5
		11-20 miles	66	8.3
		21-30 miles	38	4.8
		31-40 miles	19	2.4
		41-60 miles	7	0.9
		61 miles or more	7	0.9
		SUM	800	100
Q8B	Please choose the average daily mileage you travel for the following trip purposes in each time period (using any travel mode):Other - PM-peak - 4:00PM-7:00PM	No travel	171	21.4
		1-5 mile(s)	173	21.6
		6-10 miles	225	28.1
		11-20 miles	107	13.4
		21-30 miles	71	8.9
		31-40 miles	28	3.5
		41-60 miles	12	1.5
		61 miles or more	13	1.6
		SUM	800	100

Q8C	Please choose the average daily mileage you travel for the following trip purposes in each time period (using any travel mode):Other - Other times	No travel	209	26.1
		1-5 mile(s)	181	22.6
		6-10 miles	158	19.8
		11-20 miles	108	13.5
		21-30 miles	72	9
		31-40 miles	36	4.5
		41-60 miles	15	1.9
		61 miles or more	21	2.6
		SUM	800	100
Q9A	What is the average travel time of your most frequent trip (one-way direction)? - AM-peak	No travel	137	17.8
		1-10 minutes	193	25
		11-20 minutes	214	27.8
		21-30 minutes	106	13.7
		31-45 minutes	79	10.2
		46-60 minutes	25	3.2
		61-90 minutes	8	1
		91 minutes or more	9	1.2
		SUM	771	100
Q9B	What is the average travel time of your most frequent trip (one-way direction)? - PM-peak	No travel	91	11.8
		1-10 minutes	161	20.9
		11-20 minutes	220	28.5
		21-30 minutes	139	18

		31-45 minutes	93	12.1
		46-60 minutes	45	5.8
		61-90 minutes	11	1.4
		91 minutes or more	11	1.4
		SUM	771	100
Q9C	What is the average travel time of your most frequent trip (one-way direction)? - Other times	No travel	171	22.2
		1-10 minutes	164	21.3
		11-20 minutes	186	24.1
		21-30 minutes	128	16.6
		31-45 minutes	61	7.9
		46-60 minutes	31	4
		61-90 minutes	17	2.2
		91 minutes or more	13	1.7
		SUM	771	100
Q10A	How much in tolls are you willing to pay (per trip) to get a 25% travel time reduction in your most frequent trip? AM peak	Not applicable - no travel	109	17.9
		Nothing	207	34
		Less than $1	73	12
		$1-$2	103	16.9
		$3-$4	59	9.7
		$5-$7	28	4.6
		$8-$10	13	2.1
		$11-$15	14	2.3
		$16-$20	0	0

		$21 or more	3	0.5
		SUM	609	100
Q10B	How much in tolls are you willing to pay (per trip) to get a 25% travel time reduction in your most frequent trip? PM peak	Not applicable - no travel	82	13.5
		Nothing	204	33.5
		Less than $1	77	12.6
		$1-$2	111	18.2
		$3-$4	67	11
		$5-$7	36	5.9
		$8-$10	13	2.1
		$11-$15	13	2.1
		$16-$20	6	1
		$21 or more	0	0
		SUM	609	100
Q10C	How much in tolls are you willing to pay (per trip) to get a 25% travel time reduction in your most frequent trip? off peak	Not applicable - no travel	111	18.2
		Nothing	255	41.9
		Less than $1	72	11.8
		$1-$2	72	11.8
		$3-$4	44	7.2
		$5-$7	29	4.8
		$8-$10	5	0.8
		$11-$15	9	1.5
		$16-$20	5	0.8
		$21 or more	7	1.1

		SUM	609	100
Q11A	How much in tolls are you willing to pay (per trip) to get a 50% travel time reduction in your most frequent trip? AM peak	Not applicable - no travel	89	14.6
		Nothing	187	30.7
		Less than $1	77	12.6
		$1-$4	161	26.4
		$5-$8	58	9.5
		$9-$14	15	2.5
		$15-$20	8	1.3
		$21-$30	9	1.5
		$31-$40	4	0.7
		$41 or more	1	0.2
		SUM	609	100
Q11B	How much in tolls are you willing to pay (per trip) to get a 50% travel time reduction in your most frequent trip? PM peak	Not applicable - no travel	89	14.6
		Nothing	187	30.7
		Less than $1	77	12.6
		$1-$4	161	26.4
		$5-$8	58	9.5
		$9-$14	15	2.5
		$15-$20	8	1.3
		$21-$30	9	1.5
		$31-$40	4	0.7
		$41 or more	1	0.2
		SUM	609	100

Q11C	How much in tolls are you willing to pay (per trip) to get a 50% travel time reduction in your most frequent trip? off peak	Not applicable - no travel	61	10
		Nothing	179	29.4
		Less than $1	86	14.1
		$1-$4	178	29.2
		$5-$8	51	8.4
		$9-$14	26	4.3
		$15-$20	16	2.6
		$21-$30	3	0.5
		$31-$40	6	1
		$41 or more	3	0.5
		SUM	609	100

Appendix C. Results of the VOTT Estimation Using the Proportional Odds Model

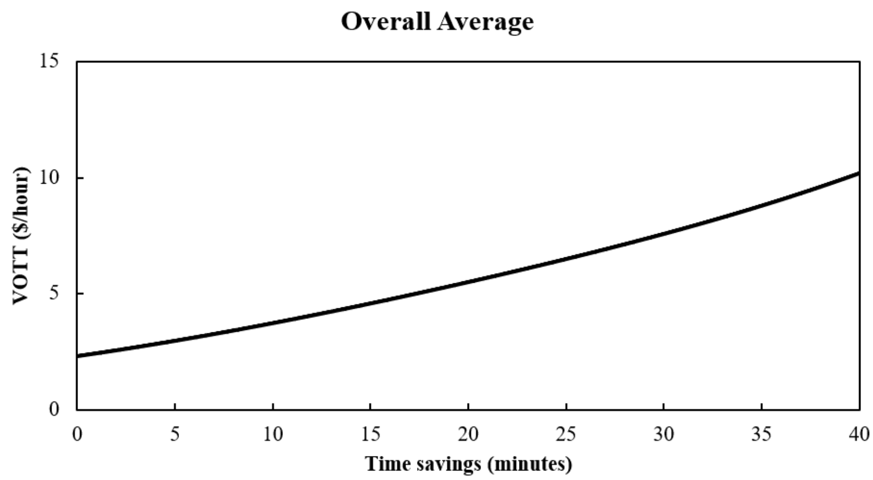

Figure C1: Overall average VOTT curve (proportional odds model)

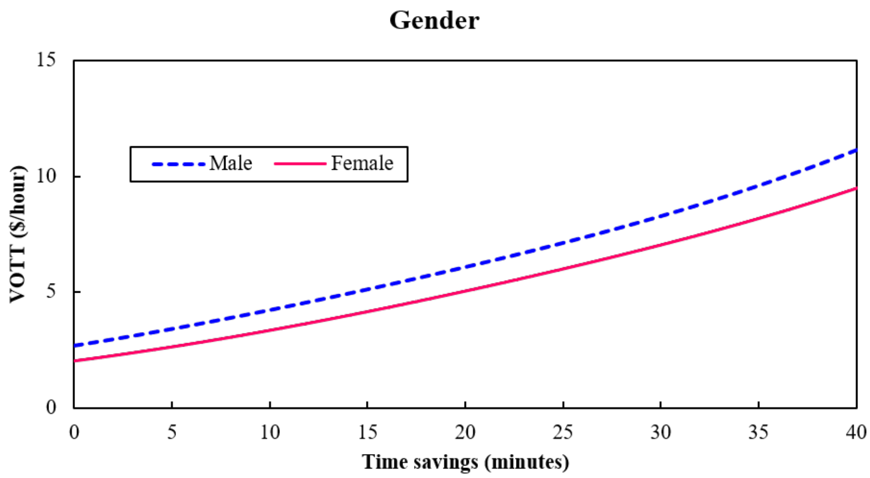

Figure C2: by gender (proportional odds model)

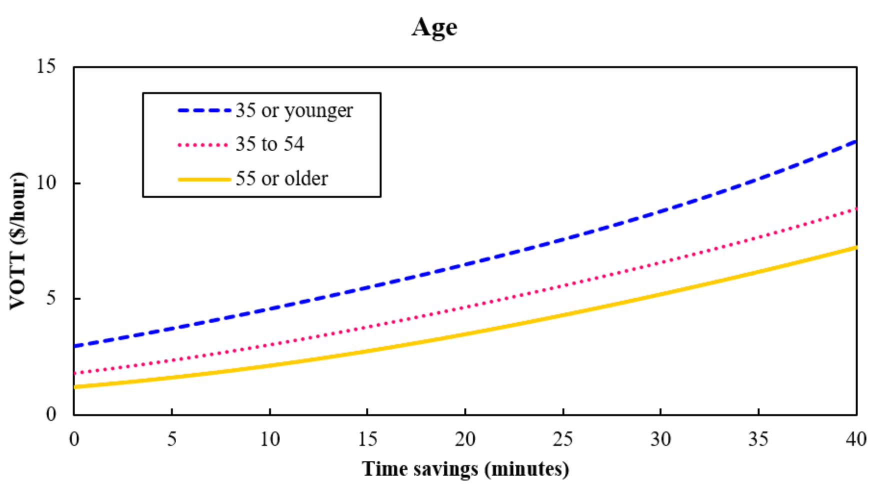

Figure C3: Average VOTT curves by age (proportional odds model)

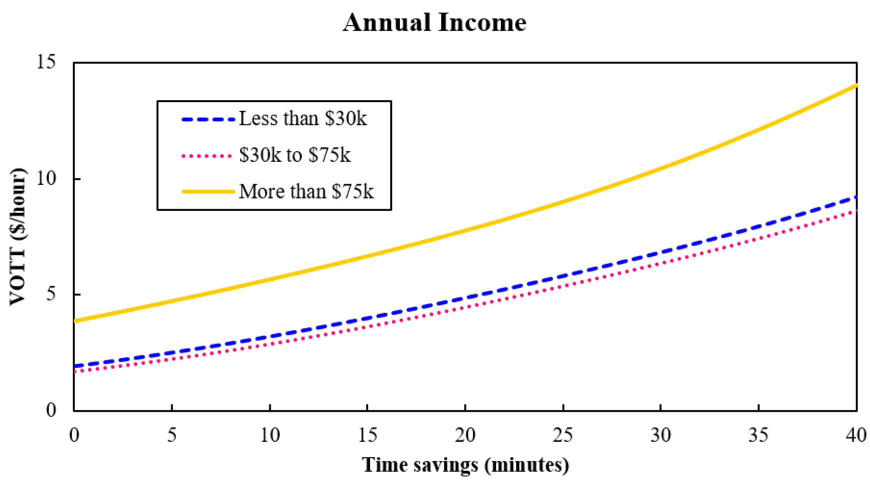

Figure C4: Average VOTT curves by annual income (proportional odds model)

References

[1] U.S. Department of Transportation Federal Highway Administration. Use of freeway shoulders for travel. Technical report, February 2016.

[2] Transports Canada Affaires environnementales. Le coût de la congestion urbaine au canada. Technical report, March 2006.

[3] Jon Obenberger. Managed lanes. *Public Roads*, 68(3), 2004.

[4] U.S. Department of Transportation Federal Highway Administration. A primer. *Publication Number FHWA-HOP-05-031, US Department of Transportation, Washington, DC*, 2008.

[5] Department for Transport. Transport, wider economic benefits, and impacts on gdp. Technical report, July 2005.

[6] Xia Jin, Md Sakoat Hossan, Hamidreza Asgari, et al. *Investigating the Value of Time and Value of Reliability for Managed Lanes*. Florida Department of Transportation, 2015.

[7] Stephane Hess, Michel Bierlaire, and John W Polak. Estimation of value of travel-time savings using mixed logit models. *Transportation Research Part A: Policy and Practice*, 39(2-3):221–236, 2005.

[8] John Calfee and Clifford Winston. The value of automobile travel time: implications for congestion policy. *Journal of Public Economics*, 69(1):83–102, 1998.

[9] Bruno De Borger and Stef Proost. *Reforming transport pricing in the European Union: A modelling approach*. Edward Elgar Publishing, 2001.

[10] Carlos Carrion and David Levinson. Value of travel time reliability: A review of current evidence. *Transportation research part A: policy and practice*, 46(4):720–741, 2012.

[11] Mark Wardman. The value of travel time: a review of british evidence. *Journal of transport economics and policy*, pages 285–316, 1998.

[12] Terence C Lam and Kenneth A Small. The value of time and reliability: measurement from a value pricing experiment. *Transportation Research Part E: Logistics and Transportation Review*, 37(2-3):231–251, 2001.

[13] Kenneth Small. *Urban transportation economics*, volume 4. Taylor & Francis, 2013.

[14] Edgar K Browning and Mark A Zupan. *Microeconomics: theory and applications*. John Wiley distributor, 2009.

[15] PJ Mackie, S Jara-Dıaz, and AS Fowkes. The value of travel time savings in evaluation. *Transportation Research Part E: Logistics and Transportation Review*, 37(2):91–106, 2001.

[16] Wisconsin Department of Transportation. Transportation planning manual: Chapter 9 traffic forecasting, travel demand models and planning data. Technical report, August 2016.

[17] Sergio Jara-Daz. *Microeconomics: theory and applications*. Transport Economic Theory, 2007.

[18] Kenneth A Small. Valuation of travel time. *Economics of transportation*, 1(1-2):2–14, 2012.

[19] Gary S Becker. A theory of the allocation of time. *The economic journal*, pages 493–517, 1965.

[20] Allan C DeSerpa. A theory of the economics of time. *The Economic Journal*, 81(324):828–846, 1971.

[21] Daniel McFadden et al. Conditional logit analysis of qualitative choice behavior. 1973.

[22] Martin Gomm Richards and Moshe E Ben-Akiva. A disaggregate travel demand model. 1975.

[23] Cinzia Cirillo and Kay W Axhausen. Evidence on the distribution of values of travel time savings from a six-week diary. *Transportation Research Part A: policy and practice*, 40(5):444–457, 2006.

[24] EJ MILLER, J Vaughan, D King, and M Austin. Implementation of a next generation activity-based travel demand model: The toronto case. *2015 Conference of the Transportation Association of Canada Charlottetown, PEI*, 2015.

[25] Liang-Shyong Duann and Ming-Shong Shiaw. Value of travel time: An activity-based analysis with combined rp and sp data. *Journal of advanced transportation*, 35(1):15–31, 2001.

[26] Mark Burris, Cliff Spiegelman, AKM Abir, Sunghoon Lee, et al. Value of travel time. 2016.

[27] AS Fowkes, P Marks, and CA Nash. The value of business travel time savings. 1986.

[28] Kay W Axhausen, Arnd Knig, Gyrgy Abay, John J Bates, and Michel Bierlaire. The value of business travel time savings. *Arbeitsbericht Verkehrs-und Raumplanung*, 253, 2006.

[29] Mark Burris, Margie Byers, and Chris Swenson. Results of driver survey investigating intersection queue jumps. *Transportation Research Record: Journal of the Transportation Research Board*, (1839):25–33, 2003.

[30] Jan-Erik Swärdh and Staffan Algers. Willingness to accept commuting time within the household: stated preference evidence. *Transportation*, 43(2):219–241, 2016.

[31] Mogens Fosgerau. Investigating the distribution of the value of travel time savings. *Transportation Research Part B: Methodological*, 40(8):688–707, 2006.

[32] Michael E Beesley. The value of time spent in travelling: some new evidence. *Economica*, 32(126):174–185, 1965.

[33] Thomas C Thomas and Gordon I Thompson. The value of time for commuting motorists as a function of their income level and amount of time saved. *Highway Research Record*, (314), 1970.

[34] Alex Anas. The estimation of multinomial logit models of joint location and travel mode choice from aggregated data. *Journal of regional science*, 21(2):223–242, 1981.

[35] David A Hensher. The valuation of commuter travel time savings for car drivers: evaluating alternative model specifications. *Transportation*, 28(2):101–118, 2001.

[36] IC Athira, CP Muneera, K Krishnamurthy, and MVLR Anjaneyulu. Estimation of value of travel time for work trips. *Transportation Research Procedia*, 17:116–123, 2016.

[37] Ioannis Tikoudis. Value of travel time savings. a study in the cross mode variations of mixed logit estimates. Master's thesis, 2008.

[38] Juan de Dios OrtÃozar and Luis G Willumsen. *Modelling transport*. John Wiley & Sons, 2011.

[39] Samer Madanat and Nitin K Jain. Modeling driver's route choice behavior under the influence of advanced traveler information systems. Technical report, March 1997.

[40] Jeffrey Dumont and Stacey Falzarano. The complementary benefits of stated preference and revealed preference for choice modeling: Theory and practice. http://garrowlab.ce.gatech.edu/sites/default/files/files/rsg.pdf, 2012. Online; accessed 6 March 2018.

[41] Peter Kroes. *Technical Artefacts: Creations of Mind and Matter*. Springer Netherlands, 2012.

[42] Robert Cameron Mitchell and Richard T Carson. *Using surveys to value public goods: the contingent valuation method*. Resources for the Future, 1989.

[43] Moshe E Ben-Akiva and Steven R Lerman. *Discrete choice analysis: theory and application to travel demand*, volume 9. MIT press, 1985.

[44] Thomas E Lisco. Value of commuters travel time-a study in urban transportation. Technical report, 1968.

[45] Ted R Miller. *The value of time and the benefit of time saving*. Urban Institute, 1989.

[46] Kenneth A Small. Urban transportation economics, vol. 51 of fundamentals of pure and applied economics series, 1992.

[47] Vinn White. Revised departmental guidance on valuation of travel time in economic analysis. Technical report, September 2016.

[48] Wei Xia and Yinchu Zeng. Consumer's attitudes and willingness-to-pay for green food in beijing. 2006.

[49] John Mackenzie. Evaluating recreation trip attributes and travel time via conjoint analysis. *Journal of Leisure Research*, 24(2):171–184, 1992.

[50] Hyun Yung Lee. Goodness-of-fit tests for a proportional odds model. *Journal of the Korean Data and Information Science Society*, 24(6):1465–1475, 2013.

[51] Constantinos Antoniou, Evangelos Matsoukis, and Penelope Roussi. A methodology for the estimation of value-of-time using state-of-the-art econometric models. *Journal of public transportation*, 10(3):1, 2007.

[52] Farhana Yasmin, Catherine Morency, and Matthew J Roorda. Trend analysis of activity generation attributes over time. *Transportation*, 44(1):69–89, 2017.

[53] Jacob Marschak et al. Binary choice constraints on random utility indicators. Technical report, Cowles Foundation for Research in Economics, Yale University, 1959.

[54] R Duncan Luce. *Individual choice behavior: A theoretical analysis*. Courier Corporation, 2005.

[55] Frank S Koppelman and Chandra Bhat. A self instructing course in mode choice modeling: multinomial and nested logit models. 2006.

[56] Chandra R Bhat. Random utility-based discrete choice models for travel demand analysis. *Transportation Systems Planning: Methods and Applications*, 10:1–30, 2003.

[57] Staffan Algers, Pål Bergström, Matz Dahlberg, and Johanna Lindqvist Dillén. Mixed logit estimation of the value of travel time. Technical report, Working Paper, Department of Economics, Uppsala University, 1998.

[58] Kenneth Train and Daniel McFadden. The goods/leisure tradeoff and disaggregate work trip mode choice models. *Transportation research*, 12(5):349–353, 1978.

[59] Yin-Yen Tseng and Erik T Verhoef. Value of time by time of day: A stated-preference study. *Transportation Research Part B: Methodological*, 42(7-8):607–618, 2008.

[60] Reuben Gronau. Economic approach to value of time and transportation choice. *Transportation Research Record*, (587), 1976.

[61] Jay R Cherlow. Measuring values of travel time savings. *Journal of Consumer Research*, 7(4):360–371, 1981.

[62] W Douglass Shaw. Searching for the opportunity cost of an individual's time. *Land Economics*, pages 107–115, 1992.

[63] S Jara-Diaz. The goods/activities framework for discrete travel choices: indirect utility and value of time. *In Perpetual Motion-Travel Behaviour Research Opportunities And Application Challenges. Elsevier, Netherlands*, 2002.

[64] Adnan Sheikh, Angshuman Guin, and Randall Guensler. Value of travel time savings: Evidence from atlantas i-85 express lanes. In *Transportation Research Board 93rd Annual Meeting*, 2014.

[65] Prem Devarasetty, Mark Burris, and W Shaw. Do travelers pay for managed-lane travel as they claimed they would? before-and-after study of travelers on katy freeway, houston, texas. *Transportation Research Record: Journal of the Transportation Research Board*, (2297):56–65, 2012.

[66] Jan-Erik Swärdh. *Commuting time choice and the value of travel time*. PhD thesis, Örebro universitet, 2009.

[67] John M Rose and Michiel CJ Bliemer. Constructing efficient stated choice experimental designs. *Transport Reviews*, 29(5):587–617, 2009.

[68] Michel Bierlaire. Biogeme: a free package for the estimation of discrete choice models, 2003.

[69] A Veeraragavan and NRN SIMHA. Value of travel time and comfort by willingness to pay approach. *Highway Research Bulletin,(New Delhi)*, 37, 1989.

[70] C. J. Bliemer, Corinne Mulley, and Claudine J. Moutou. *Urban transportation economics*. Edward Elgar Pub, 2016.

[71] Scott Menard. *Applied logistic regression analysis*, volume 106. SAGE publications, 2002.

[72] FitchRatings. U.s. managed lanes: Empirical data steers credit analysis. Technical report, FitchRatings, 2013.

[73] Anthony Downs. *Still stuck in traffic: coping with peak-hour traffic congestion*. Brookings Institution Press, 2005.

[74] Peter Gordon, James E Moore, Qisheng Pan, Harry W Richardson, Sunbin Cho, and Christopher Williamson. The economic impacts of sr-91 and i-5 corridor improvements. In *Regional Economic Impacts of Terrorist Attacks, Natural Disasters and Metropolitan Policies*, pages 175–194. Springer, 2015.

[75] Louis G Neudorff, Jeffrey E Randall, Robert Reiss, and Robert Gordon. Freeway management and operations handbook. Technical report, 2003.

[76] Sharon Shewmake. Can carpooling clear the road and clean the air? evidence from the literature on the impact of hov lanes on vmt and air pollution. *Journal of Planning Literature*, 27(4):363–374, 2012.

[77] Hideo Konishi and Se-il Mun. Carpooling and congestion pricing: Hov and hot lanes. *Regional Science and Urban Economics*, 40(4):173–186, 2010.

[78] Beilei Xu, Orhan Bulan, Jayant Kumar, Safwan Wshah, Vladimir Kozitsky, and Peter Paul. Comparison of early and late information fusion for multi-camera hov lane enforcement. In *Intelligent Transportation Systems (ITSC), 2015 IEEE 18th International Conference on*, pages 913–918. IEEE, 2015.

[79] Michael Janson, David Levinson, et al. Alternative high occupancy/toll lane pricing strategies and their effect on market share. Technical report, 2014.

[80] Mark Chang, John Wiegmann, Andrew Smith, Claudia Bilotto, et al. A review of hov lane performance and policy options in the united states. Technical report, United States. Federal Highway Administration, 2008.

[81] Asha Weinstein and Gian-Claudia Sciara. Unraveling equity in hot lane planning: A view from practice. *Journal of Planning Education and Research*, 26(2):174–184, 2006.

[82] Omid M Rouhani and Debbie Niemeier. Flat versus spatially variable tolling: A case study in fresno, california. *Journal of Transport Geography*, 37:10–18, 2014.

[83] Wei Fan. Social welfare maximization by optimal toll design for congestion management: models and comprehensive numerical results. *Transportation Letters*, 9(2):81–89, 2017.

[84] Omid M Rouhani, R Richard Geddes, H Oliver Gao, and Germà Bel. Social welfare analysis of investment public–private partnership approaches for transportation projects. *Transportation Research Part A: Policy and Practice*, 88:86–103, 2016.

[85] Luis A Guzman, Daniel de la Hoz, and Andrés Monzón. Optimal and long-term dynamic transport policy design: Seeking maximum social welfare through a pricing scheme. *International Journal of Sustainable Transportation*, 8(4):297–316, 2014.

[86] Zhibo Zhang, Qiang Bai, Samuel Labi, and Kumares Sinha. General framework for evaluating long-term leasing of toll roads: Case study of indiana i-90 highway. *Transportation Research Record: Journal of the Transportation Research Board*, (2345):83–91, 2013.

[87] Daniel Hodge, Glen Weisbrod, and Arno Hart. Do new highways attract businesses?: Case study for north country, new york. *Transportation Research Record: Journal of the Transportation Research Board*, (1839):150–158, 2003.

[88] Cynthia L Rogers and Richard Marshment. Measuring highway bypass impacts on small town business districts. *Review of Urban & Regional Development Studies*, 12(3):250–265, 2000.

[89] Natalia Ruiz Juri and Kara M Kockelman. Evaluation of the trans-texas corridor proposal: application and enhancements of the random-utility-based multiregional input–output model. *Journal of Transportation Engineering*, 132(7):531–539, 2006.