



## Final Report

### **EVALUATING EQUITY ISSUES FOR MANAGED LANES: METHODS FOR ANALYSIS AND EMPIRICAL RESULTS**

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<b>16. Abstract</b>  <p>Transportation planning decisions can have significant and diverse equity impacts (Litman, 2002). In particular, congestion and road pricing have raised equity concerns. Notably, the toll imposed on Managed Lanes on US highways affects drivers' income. This is especially true for low-earning individuals, who devote a large portion of their available budget to transportation. Therefore, any policy or project assessment should take into consideration the so-called Income Effect. This concept refers to the fact that the impact of a change in driving cost – for instance, a toll increase – is not constant for all individuals but depends on their own income level. Unfortunately, the two measures most commonly used in project evaluation practice, Rule of a Half (RoH) and Log-sum (LS), rely on the assumption of absence of Income Effect. Since microeconomic theory does not support these grounds, not to account for income effect in policy evaluation may produce inaccurate results. Applying a policy for which the economic impact is not well-assessed may lead to severe equity issues. This project proposes a methodology that accounts for income effect in the appraisal of Managed Lanes and calculates the errors due to the use of approximated methods. In particular, the analysis is based on three pillars: i) the use of real data, ii) the use of more realistic assumptions about drivers' behavior, considering different income levels and correlations between the alternatives, and iii) comparison of the LS and RoH and LS to the Compensating Variation (CV), the true benefit measure derived from microeconomic theory. These improvements provide a refined tool for the appraisal of the social, economic and equity aspects of transportation policy in the context of Managed Lanes. The tool will benefit private entities involved in road pricing projects, and transportation public agencies in need of ameliorating their evaluation of equity issues.</p>			
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## 1.0 EXECUTIVE SUMMARY

The concept of Managed Lanes is gaining importance among policy makers as a strategy to alleviate traffic congestion due to its potential to improve network efficiency and generate revenue to be reinvested in infrastructure (Safirova et al, 2003). One approach is to convert underused High Occupancy Vehicle (HOV) lanes into High Occupancy Toll (HOT) lanes. HOT is a pricing policy that lets vehicles that do not meet the HOV requirements to transit these lanes upon payment of a toll. However, one key question is the impact of these policies on the consumer surplus (CS), especially in the case of low-earning individuals. This matter is closely related to an economic concept known as Income Effect (IE), which refers to the fact that the decrease in income caused by a rise in transportation costs is not constant for all persons, but may be more intense for those with low incomes. Despite this, the two measures mainly used to evaluate CS in project appraisal practice, the Rule of a Half (RoH) and the Log-sum (LS), rely on the absence of income effect. Since the grounds for that are not really justified by the microeconomic theory, both measures can make a significant error in quantifying the loss or gain of consumer surplus. This error may be determined by comparing LS and RoH with the Compensating Variation (CV), the true measure of the consumer surplus.

We propose a methodology that provides a reliable quantification of the error made by LS and RoH when approximating the Compensating Variation (CV), the true measure of the consumer surplus. To do so, we estimate, using real data, an advanced discrete choice model. Based on its output, we calculate the aggregated LS, representative LS, RoH, and CV, for different levels of toll policy. Then we compute the gap among these measures. Our results show that the LS and RoH are inaccurate for any level of policy, evincing that they both are equally inappropriate as proxies for CV. This is especially the case for the aggregated LS, whose percentage of error is substantial. The non-aggregated measures show a slightly better performance. However, they still deviate significantly and overestimate the CV in the case of cost reductions, while underestimating it in the opposite situation. In addition, these measures become more inefficient as the policy intensifies. Such divergence would cloud any assessment of a pricing policy interested in social and economic impact. Therefore, the commonly used methodologies should be reconsidered because, without an accurate appraisal, the impact of projects will never be fully evaluated, especially on equity matters.

## 2.0 INTRODUCTION AND LITERATURE REVIEW

Transportation planning decisions can have significant and diverse equity impacts (Litman, 2002). Notably, road pricing has raised equity concerns since the toll imposed on Managed Lanes on US highways may affect drivers' income significantly. The concept of Managed Lanes is gaining importance among policy makers as a strategy to alleviate traffic congestion due to its potential to improve network efficiency and generate revenue to be reinvested in infrastructure (Safirova et al, 2003). One approach is to convert underused High Occupancy Vehicle (HOV) lanes into High Occupancy Toll (HOT) lanes. HOT is a pricing policy that lets vehicles that do not meet the HOV requirements transit these lanes upon payment of a toll. Since HOV lanes are less congested and offer more reliable travel times, drivers may be inclined to pay to access them. Some examples of US cities that have implemented HOT lanes are Miami, Seattle, Denver, San Diego and Atlanta, among others. However, one of the key questions arising from these pricing policies is their impact on the consumer surplus, especially in the case of low-earning individuals, who allocate a significant fraction of their available budget to transportation. This is closely related to an economic concept known as Income Effect (IE). It refers to the fact that the decrease in income caused by a rise in transport costs – such as a more burdensome toll policy – is not constant for all persons, but dependent on their income level. In other words, the impact on the well-being of each household is not homogeneous but may be more intense for those with low incomes.

Although very intuitive – and fully supported by microeconomic theory – this reality is usually ignored in the quantification of the impact on well-being. As a matter of fact, the two measures most commonly used for that purpose in project evaluation practice, the Rule of a Half (RoH) and the Log-sum (LS), rely on the assumption of absence of income effect. The main reason for that is twofold; in theory, a household's transportation expenditure is negligible and the effect of policies on this expenditure is minor. Surprisingly, we can even find this rationalization in the authors who set the microeconomic foundations for the current mode choice models. In McFadden's (1981) formulation, the choice of an alternative is only made upon modal costs and attributes, since income is cancelled out when utility functions are compared to find a maximum. Small and Rosen (1981) approximate compensated demands through their market counterparts and Roy's identity, explicitly neglecting income effect (for a synthesis of both cases, see Jara-Diaz and Videla, (1987)). However, these justifications have been questioned since transportation expenditure may actually represent an important share of the total

available income, especially in the case of low-earning individuals. Therefore, not accounting for income effect in policy evaluation may produce inaccurate results, leading to severe equity issues.

In this respect, the empirical evidence of the consequences of ignoring IE is scarce. The results of Willig (1976) suggest that the percentage error of approximating Compensating Variation is reduced in most applications and likely to be dominated by the errors involved in estimating the demand curve. Jara-Díaz and Videla (1990) showed that in a simple transport choice context the error in benefit assessment caused by ignoring income effects was approximately 12%. In line with the work of Willig, Herriges and Kling (1999) found that benefit estimates were more strongly influenced by assumptions about the error distribution than by the introduction of nonlinear income effect. On the other hand, Karslström (2000), using an exact formula for the Compensating Variation, found that the error introduced by using consumer surplus largely depends on the context and may under some circumstances be quite substantial. Only Cherchi and Polak (2005) have investigated to what extent LS and RoH are close to CV. They found that, under different model specifications, the results were seriously biased from the correct value, questioning the reliability of these measures as a basis for decision-making.

On the other hand, there is an additional source of error in the evaluation of inequalities due to transportation cost-increasing policies. The use of functional forms such as the MNL is widespread because LS and RoH can be calculated easily from the output of the model. However, MNL and other similar specifications suffer from rigidities that prevent adequate representation of drivers' behavior. Applying more flexible structures would lead to more accurate results, to the detriment, however, of the ease of calculation. The evidence on this topic is even more limited than for IE. Cherchi and Polak (2005), as well as Cherchi et al. (2009), dove deeper into this question, exploring the use of Mixed Logit (ML) models with random parameters. They found that failing to account for the correct distribution of tastes may have unpredictable effects on benefit estimations. For our part, we have found that a ML with Error Components better captures the behavior of individuals, as detailed in the corresponding section of this report.

Finally, to the best of our knowledge, there is in the field an apparent absence of substantial welfare analysis supported by real data. Although some authors have explored the gap between CV and other benefit measures, very little research has been done with non-synthetic recent data in the context of Managed Lanes. Odeck et al. (2003) centered their research on both LS and RoH for the case of converting an existent cordon toll into a congestion-pricing scheme. However, they didn't compare them with the true CV. Gupta et al. (2006) explored impacts in welfare of road pricing in Austin, Texas,



but focused only on LS variations. In turn, Gulipalli and Kockelman (2008) expanded Gupta et al.'s (2006) work, incorporating environmental impact; unfortunately, they set aside welfare changes. On their part, Zao et al. (2008) examined the effect of error term correlations in policy analysis, finding that results vary substantially across synthetic populations. In another study, Zao and Huang (2018) provide conditions for the determination of the direction of the bias of welfare measures.

In short, while it is fundamental to properly evaluate transport projects in all cases, when there is a special interest in inequality, crucial aspects must be taken into account, so a different approach is required. This work presents a solidly grounded methodology that explicitly considers all of them. It aims at providing reliable measures for benefit evaluation and assessing their validity in the presence of income effect, which is relevant for Managed Lanes project appraisal. To do so, we gather the behavior of drivers in a better way than is usually done thanks to an advanced discrete choice model. Based on the output of such specification, we calculate the CV, LS and RoH, and the magnitude of the error made by RoH and LS in comparison to CV. Therefore, the three pillars of this methodology are:

- i. Use of real data.
- ii. Use of more realistic assumptions about drivers' behavior, considering different income levels and correlations between the alternatives.
- iii. Comparison of the LS and RoH and LS to the CV, the true benefit measure derived from microeconomic theory.

These improvements should refine the appraisal of the social, economic and equity aspects of transportation policy in the context of Managed Lanes, and become a useful tool for private agents involved in road pricing projects and transportation public agencies in need of ameliorating their evaluation of equity issues.

This report is organized as follows: Section 1 reviews the economic concepts needed to understand the impact of the income effect on the subject at hand. It explains what the Compensating Variation is and how to obtain it mathematically, as well the relation among CV, LS and RoH. In Section 2, the microeconomic foundations of income effect are explained in detail. The mathematical conditions to be fulfilled by the utility functions are enumerated, offering a first approximation to the expected results. Section 3 describes the data used for model estimation. In addition to a brief overview of the socioeconomic

variables, it details the treatment given to the income information, due to its importance. The fourth section presents the results, providing an analysis of the gap among the benefit measures for each applied policy. Finally, the last section summarizes the conclusions.

### 3.0 COMPENSATING VARIATION AND APPROXIMATIONS

As mentioned in the previous Section, three benefit measures can be used for project appraisal: Compensation Variation (CV), Log-sum (LS) and Rule of a Half (RoH). This section provides the mathematical formulation for each of these measures and discusses their properties and the relation existing among them.

The CV, defined by Hicks (1939), is the amount subtracted from the income of an individual, after a price reduction, that makes that individual reach its initial level of utility. More intuitively, when a price is reduced, the consumer reaches a higher level of utility. The amount of income to be subtracted from the consumer's budget in order to leave him or her no better off than before, considering the price reduction, is the CV. We can express it more formally in equation 1, following McFadden (2000):

$$\max_{j \in C} U(I_q - c'_{jq}, x'_{jq}; s_q, \eta_{qj}) = \max_{j \in C} U(I_q - CV_q - c''_{jq}, x''_{jq}; s_q, \eta_{qj}) \quad (1)$$

where  $U(\cdot)$  is the indirect utility obtained by an individual  $q$  choosing alternative  $j$ ,  $I$  is income,  $c_j$  is the cost of consuming alternative (mode)  $j$ ,  $x_j$  is a vector of observed attributes of the alternative,  $s$  is a vector of observed characteristics of the individual and  $\eta$  is a vector of unobserved both attributes and characteristics of the alternative and the individual. The single and double apostrophes indicate the before-after states. Therefore, the CV is a function of all the variables in the utility, before and after the change, including the unobserved  $\eta$ , which induces a distribution of CVs. Thus, for a given policy, the CV (in equation 2) will be the mean of that distribution:

$$CV_q = E \left[ CV(I_q, c'_{jq}, c'_{jq}, x'_{jq}, x''_{jq}; s_q, \eta_q) \right] \quad (2)$$

Evaluating equation (2) requires simulation methods, like the one proposed by McFadden (2000). Thus, some simplifications are normally assumed for the sake of a more tractable expression. The first, and stronger assumption, is to assume the absence of income effect. From an analytical perspective, this means that the marginal utility of income is a fixed value ( $\lambda$ ). In other words, the effect of income is the same for all individuals over the population. Making this assumption allows us to reformulate equation (1) as equation 3:

$$\lambda CV_q = Emax_{j \in C} \left\{ f(x_{jq}''; s_q, \eta_{qj}) - \lambda c_{jq}'' \right\} - Emax_{j \in C} \left\{ f(x_{jq}' ; s_q, \eta_{qj}) - \lambda c_{jq}' \right\} \quad (3)$$

In addition, assume that the disturbances have a joint cumulative distribution function of generalized extreme value (GEV) form (equation 4):

$$F(\eta_1, \dots, \eta_j) = \exp(-H(e^{-\eta_1}, \dots, e^{-\eta_j})) \quad (4)$$

where  $H(w_1, \dots, w_j)$  is a non-negative linear homogeneous function. Then, the random utility satisfies equation 5:

$$Emax_{j \in C} \left\{ f(I_q - c_{jq}', x_{jq}'; \beta_{jq}) + \varepsilon_{jq} \right\} = \log H(e^{f_1}, \dots, e^{f_j}) + E \quad (5)$$

where  $E = 0.57721$  is Euler's constant.

McFadden (1996) proves that  $H$  is a GEV generating function which yields the multinomial logit (MNL) model. He also provides evidence on the calculation of CV in the target population when the

disturbances follow GEV and the indirect utility is linear in income. Combining equations (3) and (4) we obtain equation 6:

$$CV_q = \frac{1}{\lambda} \left\{ \log H(e^{V_i^*}, \dots, e^{V_j^*}) - \log \log H(e^{V_i}, \dots, e^{V_j}) \right\} \quad (6)$$

That can be re-formulated in equation 7 as:

$$CV_q = \frac{1}{\lambda} \left\{ \log \sum_{j=1}^J \left[ \exp \left( -\lambda c_{jq}'' + f(x_{jq}''; \beta_{jq}) \right) \right] - \log \sum_{j=1}^J \left[ \exp \left( -\lambda c_{jq}' + f(x_{jq}'; \beta_{jq}) \right) \right] \right\} \quad (7)$$

Which is the Log-sum for the multinomial logit model. Therefore, under these two assumptions, GEV disturbances and linearity in income, the interpretation of the Log-sum is equivalent to that of the CV.

The Rule of a Half (RoH) is another welfare measure widely used as an approximation to the CV. However, additional assumptions need to be made, specifically, linearity of the uncompensated demand between initial and future situation, uniqueness of the path of integration and small variation of prices. Again, the use of Marshallian demands implies, as in the case of Logit and the LS, the absence of income effect. The general expression of RoH is given in equation 8:

$$RoH = -0.5 \sum_{od} \sum_j \Delta GC_{od,j} \bar{T}_{od,j} \quad (8)$$

where  $\bar{T}_{od,j} = N \left( \pi_j(after) + \pi_j(before) \right)$  is the number of trips between origin and destination using mode  $j$ .  $\pi_j$  is the probability of choosing mode  $j$ , averaged among the population,  $GC_{od,j}$  (equation 9) is the generalized cost between origin and destination calculated as:

$$\Delta GC_{od,j} = (c_{od,j}(after) - c_{od,j}(before)) - \frac{1}{\lambda} \sum_h \beta_{hj} (x_{od,hj}(after) - x_{od,hj}(before)) \quad (9)$$

In this particular study, a package has been coded in the programming language *R*, which calculates the following benefit measures and compares them.

1. Compensating variation by resampling: For each individual and alternative, the utility is computed, searching for the maximum over the alternatives. Then, the CVs that equate the two maxima for each individual are calculated.
2. Aggregated Log-Sum: It is the measure formulated above computed for each individual and then aggregated over the sample.
3. Representative Log-Sum: It is the measure formulated above computed for an average representative individual, considering as if all the individuals behave the same way.
4. Rule of a Half: The probability of choosing each alternative is calculated using the aggregation method, and the generalized cost using average attributes and parameters values.

## 4.0 INCOME EFFECT AND DISCRETE CHOICE MODELS

How to correctly account for the effect of income in demand models is not a straightforward task. The most appropriate specification of the utility function is unknown, although its theoretical formulation relies on microeconomic foundations. The general approach adopted in economics and related disciplines including transportation is the following. Given a utility function  $U(x)$ , where  $x = (x_1, \dots, x_j)$  is a vector of goods quantities, the consumer maximization program is set as that of maximizing  $U(x)$  subject to a budget constraint  $px \leq y$  where  $p = (p_1, \dots, p_j)$  is a vector of goods prices and  $y > 0$  is consumer expenditure on the  $N$  goods. Besides the properties that the direct utility function satisfies, the solution of the maximization program leads to the following conditional indirect utility function (equation 10):

$$V(p, I - c_j, x_j) = V_j \quad (10)$$

In transportation, income is commonly included in the utility function linearly, which inherently assumes that its effect is constant and not dependent on any other variable, like cost. However, this approach considers income as any other socioeconomic variable, leading to the conclusion that the individual earnings are not influenced by the cost of the alternative, neither in the initial situation nor ex-post. Therefore, this approximation to the problem disregards any income effect. Another usual procedure, especially in market research, is to segment the sample by income, allowing to account for differences in its marginal utility among the different groups. However, inside each group, the utility is still independent from earnings and any potential effect is not pondered (see Ortúzar and Gonzales, 2002).

Hence, in order to explicitly consider income effect, it must be explicitly incorporated in the utility function nonlinearly, as in Jara-Díaz and Videla (1989), who proposed the following formulation (equation 11):

$$V_j = \beta_1(I_q - c_{qj}) - \beta_2(I_q - c_{qj})^2 + \sum \beta_k x_{qkj} + \sum (\delta_k x_{qkj}^2 + \xi_k x_{qkj} (I_q - c_{qj})) \quad (11)$$

where  $x_{kj}$  is a vector of modal characteristics of alternative  $j$ ,  $\beta_1$  and  $\beta_k$  are the derivatives of the indirect utility function in equation (8) with respect to income minus cost and to the  $k$ -th characteristic of the alternative, and  $\beta_2$ ,  $\delta_k$  and  $\xi_k$  are the second derivatives.

Other approaches to include income in the indirect utility function have also been considered, but they pertain more to the domain of economics, and are used in particular cases in which the nature of two goods is special. This is the case of the Leontief function, which is appropriate for representing complementary goods, or the CES, suitable for substitutive ones. In any case, care must be taken to ensure that the utility function still satisfies all relevant microeconomic conditions. Specially, the marginal utility of income should vary with the income of each individual and with the cost of each

alternative. Actually, the marginal utility of income should be positive and decreasing, while the marginal utility of cost should be negative and increasing (see equations 12):

$$\frac{\partial V_{jq}}{\partial I_q} \geq 0, \frac{\partial V_{jq}}{\partial c_{jq}} \leq 0 \text{ and } \frac{\partial^2 V_{jq}}{\partial^2 I_q} \leq 0, \frac{\partial^2 V_{jq}}{\partial^2 c_{jq}} \leq 0 \quad (12)$$

These conditions imply that in equation (9), one should obtain  $\beta_1 \geq 0$  and  $\beta_2 \leq 0$  after estimation, as well as  $(I_q - c_{qi}) \leq -\beta_1 / 2\beta_2$ . On the other hand, Roy's identity (in equation 13), which relates the Marshallian demand function to the derivatives of the utility function, should also be satisfied.

$$-\frac{\partial V_{jq}}{\partial c_{jq}} \bigg/ \frac{\partial V_{jq}}{\partial I_q} = 1 \quad (13)$$

Both conditions are clearly satisfied in equation (9).

There is an additional consideration with respect to the policies that can be applied. In the situation before a policy is put into practice an individual must have  $(I_q - c_{qi}) \geq 0$ , whereas  $(I_q - CV_q - c_{qi}) \geq 0$  after. However, it might be the case that the CV needed to make the individual stay at his or her initial level of utility is greater than the individual income minus the cost after the change. Namely (equation 14),

$$CV_q \geq (I_q - c_{qi}) \quad (14)$$

In these cases, the lower the income or the higher the cost, the less probable is the existence of a value of CV that satisfies equations (1) and (12). These effects cannot be accounted for if the specification is all linear in attributes and includes income but not income minus cost as an explicit term.

## 5.0 DATA, MODEL SPECIFICATION AND METHODOLOGY

### 5.1 DATA DESCRIPTION

The data sample used in this study gathers 1,211 responses from drivers traveling during weekday extended peak periods (8:00 AM–11:00 AM and 3:30 PM– 6:00 PM), on March 21–25 and May 23–27, 2011, on the Maryland side of the Capital Beltway. After cleaning the data, that figure was reduced to 766. The survey was conducted to capture the behavior of regional drivers in response to the possibility of converting one lane of the Capital Beltway into an HOT lane. The questionnaire consisted of three parts: socioeconomic and vehicle ownership, recent trip, and stated preference (SP) questions. The SP part presented to motorists seven scenarios with different travel conditions on three lane alternatives: General Purpose (GP), HOV and HOT lanes. The attributes proposed in each scenario (calculated based on the recent trip information) were average travel time, travel time due to congestion, travel time due to uncertainty, fuel cost, and toll cost. Table 1 summarizes the characteristics and methodology of the survey (for further information, see Cirillo et al., 2014).

**Table 1: Survey details**

Characteristics	Methodology
Time frame	March 21-25, 2011 and May 23-27, 2011
Target population	Potential High Occupancy Toll (HOT) users
Sampling frame	Current I-495 users with internet
Sample design	Flyers distributed at randomly selected exits of I-495



Mode of administration	Self-administered
Computer assistance	Computer-assisted self-interview (CASI) and web-based survey
Reporting unit	1 person age 18 or older per household reports for the entire household
Time dimension	Cross-sectional survey with hypothetical stated preference (SP) experiments
Frequency	Two 4-day phases of flyers distribution
Levels of observation	Household, vehicle and person

The main characteristics of respondents in the sample can be summarized as follows. Not all the categories of variables are included in this description, as certain variables have a large set of them and represent meager shares in some cases:

- Gender: 54% of the sample was male.
- Age: The average age is 43 and the median age is 45. The youngest respondent was 19 and the oldest 76.
- Education: 54% were at a graduate or professional level, 38% had a bachelor's degree and 6% some college education.
- Occupation: 49% of respondents worked for a private company, 31% for the government and less than 1% were unemployed.
- Number of workers: 29.63% of households had 1 worker, 61.9% had 2 workers and 8.5% more than 2 workers.
- Number of vehicles in the household: 23% of households had 2 cars, while 54% had 3 cars and 24% more than 3.
- Income: 9.8% of households had an income lower than \$50K, 24.4% between \$50K and \$75K, 25.7% between \$75K and \$125K. Some 40% of households had an income higher than \$125K. A comparison between the survey's and state of Maryland's income distributions yields a slight bias toward high income.

Due to its importance, the income data obtained from the survey have been treated for an adequate incorporation to the utility function. In the first place, in this survey the respondent was asked about the gross salary income of the household. This amount was adjusted by the number of workers in the household to obtain the individual gross income of the respondent. Then, a tax rate was applied making some assumptions about marital status (most favorable) in order to get the net individual income. Secondly, in order to obtain the disposable income allocated to transportation, the major components of expenditure were consulted in official sources (Federal Highway Administration 2017; US Department of Labor Statistics, 2018). Finally, for consistency with the reference base of the cost variables, the disposable net income per individual was calculated per trip, assuming 2.88 trips per day and 260 working days. This final variable is the one included in the utility in conjunction with the cost, in the manner indicated in the next section.

Since one of the main interests of this work is to incorporate in the calculation of the benefit measures the effect of different categories of income, this variable has been split in three levels: low, medium and high. There is no official source to know what is considered low, medium or high income in the region in which the data were collected; thus different amplitudes have been tested for these intervals. In the end, we found that the division low-medium / high provided the best results.

Moreover, in this study we also explored the existence of *time effect*. The nature of the time effect is analogous to the income effect. Therefore, the time variable requires a treatment, in terms of disposability, similar to that of the income variable. In this case, the disposable leisure time (DLT) is needed. This is the fraction of time available for the individual after working and traveling. We rely here on the findings of Cherchi and Ortúzar (2006), who found an average disposable leisure time of 76.33 minutes.

## **5.2 MODEL ESTIMATION**

The first step in calculating the welfare measures is to obtain from the discrete choice model the coefficient of each variable present in the utility. In this stage, the definition of both, the utility and the model, is crucial, since an incorrect specification of any of them may lead to inaccurate coefficients that would distort the CV. In this regard, we wanted to explore more advanced forms than those present in

the literature. Following the discussion in Section 2 and based on equations (8) and (9), we define the utility (equation 15) as:

$$U = \beta_0 + \beta_1 fc + \beta_2 income\_toll + \beta_3 income\_toll^2 + \beta_4 EC + \varepsilon \quad (15)$$

where income effect is explicitly considered in contrast to the most common, linear on income, formulation (equation 16):

$$U = \beta_0 + \beta_1 fc + \beta_2 income\_toll + \beta_4 EC + \varepsilon \quad (16)$$

where *fc* represents fuel cost of the alternative, and *income\_toll* the income (treated as detailed in the previous section) minus the cost of driving. *EC* represents the error component element, corresponding to the specification described in the next section.

Finally, we define a third specification in which two effects are examined. Firstly, the interaction of the toll cost and the two levels of income in which we segmented the sample — low-medium and high — is studied, to identify the impact of that cost in each group. Along with that, due to the population characteristics, we presumed the existence of time effect. Secondly, we incorporate time in a similar manner to how we incorporate income (equation 17).

$$U = \beta_0 + \beta_1 carpool + \beta_2 fc + \beta_3 (toll * income\_lome) + \beta_4 (toll * income\_hi) + \beta_5 income\_toll^2 + \beta_6 t\_tt^2 + \beta_7 EC + \varepsilon \quad (17)$$

where *carpool* is a binary variable that is only present in the utility of the HOV alternative. This seemed relevant to this alternative, since there must be a minimum of passengers in the vehicle to be allowed to drive in the HOV lane. *income\_lome* and *income\_hi* are also binary variables, representing which

segment the individual pertains to. In order to consider time effect,  $t_{tt}$  is also present, calculated as DLT minus the travel time of the alternative. Finally, the Error Component element is also present in the utility.

Following the microeconomic foundations described in Section 2, we could expect  $\beta_2 \geq 0$  and  $\beta_3 \leq 0$  in equation (13). That is, positive but decreasing marginal utility of income, in accordance with equation (10). In addition to that, we could expect  $\beta_3 \leq \beta_4$  in the specification shown in equation (17), meaning a more negative effect of the toll in the low and medium segments.  $\beta_5$  and, analogously,  $\beta_6$  should be negative to comply with the microeconomic conditions, indicating the existence of income and time effect, respectively.

The estimated discrete choice model is an Error Component Mixed Logit. We estimated first several specifications based on random parameters, in order to identify taste heterogeneity. However, some incoherent results guided us to the Error Component (EC) formula. Random parameters and EC are formally equivalent (see Train, 2009). However, EC is appropriate when the objective is to represent substitution patterns, which we think is appropriate for this case. The three types of lanes are clearly substitutes for each other, at least to some extent. Table 1 shows the results for ML1, ML2, and ML3, which correspond, respectively, to equations (16), (15) and (17).

**Table 2: Model Estimation Results**

	<i>ML1</i>		<i>ML2</i>		<i>ML3</i>	
	<i>(no income effect)</i>		<i>(income effect)</i>		<i>(income and time effect)</i>	
<b>Attribute</b>	<b>Value</b>	<b>Robust t-test</b>	<b>Value</b>	<b>Robust t-test</b>	<b>Value</b>	<b>Robust t-test</b>
ASC_HOT	0.744	1.78	0.769	0.08	-0.035	-0.06
ASC_HOV	-11.9	-5.42	-13.5	-4.02	-11.3	-3.68
Carpool					-1.58	-1.08
Fuel Cost	-0.234	-2.04	-0.234	-2.05	-0.274	-2.33
Toll*Income low-medium					-0.857	-4.55
Toll*Income high					-0.869	-3.25
(Income – Toll)	0.67	6.41	0.847	4.84		
(Income – Toll) <sup>2</sup>			-0.00381	-1.57	-0.003	-1.08
(DLT – Travel Time) <sup>2</sup>					0.003	2.99
<b>Error Component</b>						
EC_HOT	-2.15	-7.35	-2.72	-7.37	0.257	0.16
EC_HOV	-9.53	-5.89	-10.9	-4.22	-7.83	-4.65
EC_NORM	2.08	6.46	-0.833	-4.22	-3.25	-6.49
<b>Loglikelihood</b>	-387		-386		-376.07	

All the coefficients resulting from ML1 and ML2 have the expected sign and significance at the 95% level. The negative effect of the propulsion costs as well as its significance is the same in both cases. The positive coefficient of the disposable income as well as its high significance varies slightly between models, too. Along with the negative sign of  $(Income - Toll)^2$ , both confirm the positive but decreasing marginal utility that the theory suggests. Regarding ML3, we expected *Carpool* to be significantly different from zero. However, it seems not to be a determining factor in drivers' choice, at least at a 95% level. In the case of the error component associated to the HOT alternative, the lack of significance does not represent a problem since it is a random term not to be used in forecasting yet one that improves the estimation. With respect to  $(Income - Toll)^2$ , we expected a significance similar to ML2. We cannot

confirm with certainty the reason for this unexpected result, but it could be due to a confounding effect in the other variables, or to just a non-optimum model specification. Unfortunately, the sign of  $(DLT - Travel\ Time)^2$  doesn't point to the presence of time effect, which encourages us to investigate in this direction in the future. Even though the results of ML3 could serve as a starting point for future studies, they prevent a rigorous welfare analysis. Therefore, the use of this model was rejected and ML2 was chosen instead. It is an important finding that  $(Income - Toll)$  and  $(Income - Toll)^2$  are significant, as well as positive and negative, respectively, in accordance with equation (10), thus demonstrating the existence of an income effect. Namely, the effect of income in choice is in fact dependent on the income level, as the microeconomic theory suggests.

### 5.3 METHODOLOGY

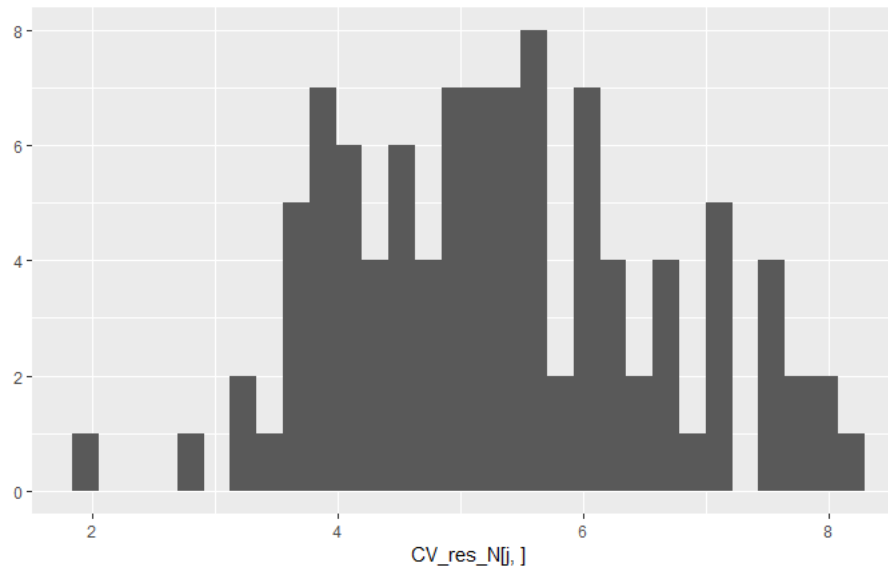
In order to calculate the benefit measures when a policy is applied, we need to recreate the before and after situations. To do so, we first compute the value of the utility functions for each alternative using the coefficients of the estimated model and the existing data. Then, we apply a policy derived from the variation in travel time or cost and we generate new data for the *ex-post* situation. By combining the new data and the coefficients we re-calculate the value of the utilities and obtain the benefit measures described in Section 1. Finally, we quantify and plot the extent to which LS and RoH differ from the true CV.

Time policies are related to changes in infrastructure that lead to a variation in travel time, while cost policies are related to variations in the elements that change the expense of travelling. We focus on the latter, especially on the effect of variation in toll and not on variation in fuel price. Toll pricing is subject to greater interest, as it is directly influenced by state regulations and not by macroeconomic factors such as energy prices. It is worth recalling at this point that, although toll price only directly affects the HOT lane, changes in it may lead to variations in the utility that, ultimately, might motivate individuals to switch to another alternative.

For the sake of completeness, we evaluate the measures and the gap among them for policies of different intensity. We define a range of variation from a 20% toll reduction to a 20% increase, in 5% increments. For each of these levels the benefit measures are calculated and compared. It is worth noting that the resampling method proposed in Section 1 requires the calculation of  $n$  CVs, as equation (2) suggests. We found no significant differences in the calculation of the CV for a number of draws superior to 100. Therefore, in this work  $n = 100$  and the CV ultimately computed is the average of those

hundred. For illustration purposes, Figure 1 depicts the distribution of the one hundred CVs calculated for the 20% increase policy. Its mean is 5.45 (value that can be found in Table 3) while its standard deviation is 1.31.

**Figure 1 Distribution of CV for a + 20% toll policy.**



## **6.0 INFLUENCE OF NONLINEAR EFFECT OF MARGINAL UTILITY OF INCOME ON BENEFIT MEASURES**

In this section we present the value of the welfare measures as well as the gap among them, for each of the policies under investigation. As stated in the previous section, the variation in toll covers a range from -20% to +20%, in 5% increments, providing 8 different reference points. We consider that, in addition to being realistic, this span allows for easy identification of possible trends, such as a decreasing value in a measure as the policy becomes less intense. Table 3 illustrates the calculations derived from the results of ML2.

**Table 3: Absolute values and percentage variation in benefit measures for different variations in the toll of HOT lane.**

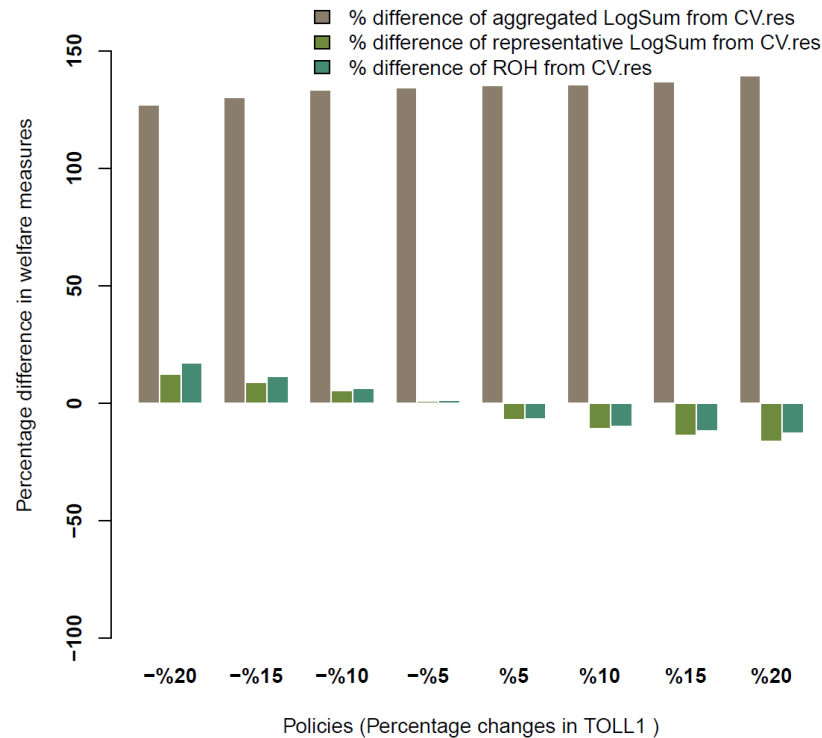
<i>% Change</i>	<i>CV_res</i>	<i>Agg. LS</i>	<i>Rep.LS</i>	<i>RoH</i>	<i>(Agg. LS - CV)/CV</i>	<i>(Rep.LS - CV)/CV</i>	<i>(RoH-CV)/CV</i>
-20	-8.26	-18.76	-9.30	-9.68	126.99%	12.51%	17.10%
-15	-5.81	-13.38	-6.33	-6.47	130.21%	8.84%	11.36%
-10	-3.64	-8.50	-3.84	-3.87	133.24%	5.27%	6.36%
-5	-1.73	-4.05	-1.75	-1.75	134.39%	1.09%	1.35%
0	0	0	0	0	-	-	-
5	1.57	3.70	1.46	1.47	135.22%	-7.07%	-6.82%
10	3.01	7.09	2.69	2.72	135.52%	-10.77%	-9.84%
15	4.31	10.21	3.71	3.80	137.05%	-13.76%	-11.74%
20	5.45	13.06	4.57	4.76	139.53%	-16.21%	-12.72%

The CV is the amount of money to be deducted from the consumer's income in order to leave him or her as well off as before a price reduction. Therefore, its value should be positive for toll decrease policies. Conversely, we should obtain positive CV values for toll increases, in order to compensate the consumer for the loss in utility. We can find this behavior in the figures in Table 3. The CV has a value of -8.26USD for a -20% policy, and progresses smoothly up to 5.45USD for a +20% policy. On the other hand, although the LS is a dimensionless measure, it presents the same trend.

Since evaluating differences by observing absolute values is difficult, the right hand of the table offers the percentage of variation of each measure with respect to the true CV. The aggregated LS makes the larger error, while the representative LS and the RoH are more precise. Figure 2 offers a visual perception of the magnitude and evolution of these percentages.



**Figure 2 Percentage variation in benefit measures for different variations in the toll of HOT lane.**



In addition to aggregated LS being the measure that diverges the most from the CV, it is noteworthy that the divergence is even greater for the positive levels of the policy. Specifically, when the policy becomes more unfavorable for the user this measure becomes even more inaccurate. Nevertheless, the difference is relevant enough that the aggregated LS is by no means a good substitute for the CV in project evaluation. The quantification of the impact of the policy would be inaccurate, especially in cases of a particularly burdensome policy, which affects fewer wealthy users most.

Although deviating significantly, representative LS and RoH have been found to be more precise. The magnitude of the aggregated LS can overshadow the fact that the representative LS and the RoH deviate as much as 17.1%. In addition, these two measures overestimate the CV for price reductions while they underestimate it for price increases, incurring in more error as the policy intensifies.

Still, the estimated values and the variables' behavior make them equally ineffective in evaluating consumer surplus. We must emphasize that the model including income effect (which results to be negative and significant) takes into accounts the fact that more aggressive pricing policies affect more low-income individuals. On the contrary, LS and RoH measures are unable to capture income effect and they result to be more inaccurate when high toll changes are tested.

## **7.0 CONCLUSIONS**

This project has provided empirical evidence on the existence of income effect in real data relative to travel behavior on managed lanes and measured the error made by LS and RoH in approximating the true Compensating Variation when IE is explicitly considered. Stated Preferences surveys were used to estimate a model that considers both the available income and its squared form. The significance and signs of the coefficients associated to those variables proved to be consistent with the microeconomic theory that suggests a positive but decreasing marginal utility of income. The effect of earnings is not constant but depending on its own level, and it highly influences drivers' behavior.

A series of discrete choice models were estimated to explain accurately the choices observed in the sample. Multinomial Logit and Mixed Logit specifications were used to explain traveler behavior. After testing different forms, we concluded that an Error Component Mixed Logit would provide the best fit, since the three alternatives clearly present some degree of substitutability. Aggregated and representative LS, RoH, and CV were calculated. The percentage difference among them was computed and plotted. We focused on toll policy since it is subject to great interest, as it is directly influenced by state regulations. The policies range from a 20% improvement to a 20% worsening, in 5% increments.

The main conclusion of this comparison is that LS and RoH are inaccurate for any level of policy, evincing that both measures are equally inappropriate as proxies for CV. This is especially the case for the aggregated LS, whose percentage of error is substantial. The non-aggregated measures show a slightly better performance. However, they deviate up to 17.1% and overestimate the CV in the case of cost reductions, while underestimating it in the opposite case. In addition, these measures become more inefficient as the policy intensifies. Such divergence would cloud any toll project assessment interested in social and economic impact.

Although the question of whether LS and RoH are good approximations to the exact CV is still open, the findings of this work clearly demonstrate that IE plays a role in drivers' behavior, and that both LS and

RoH are not good proxies for CV. Therefore, the commonly used methodologies to evaluate welfare impact should be reconsidered in order to properly appraise social, economic and equity issues. We think that these results will help address the quantification of the Consumer Surplus properly, which is paramount in a context in which Managed Lanes seems to be the solution to the impossibility of increasing the capacity of transportation facilities. Pricing strategies may generate vast revenue but significantly deteriorate individuals' welfare. Without an accurate appraisal, the impact of projects will never be fully evaluated, especially when it comes to equity matters.

## 8.0 REFERENCES

- Cherchi, E. and Polak, J.W. (2005) The assessment of user benefits using discrete choice models: implications of specification errors under random taste heterogeneity. *Transportation Research Record* 1926, 61-69.
- Cherchi, E., & de Dios Ortúzar, J. (2006). Income, time effects and direct preferences in a multimodal choice context: application of mixed RP/SP models with non-linear utilities. *Networks and Spatial Economics*, 6(1), 7-23.
- Cirillo, C., M. Maness, N.U. Serulle. (2014) Measuring value of travel time in the presence of managed lanes: results from a pilot stated preference survey on the Capital Beltway. *Transportation Letters*, 6(1), pp. 23-35.
- Federal Highway Administration. (May 16, 2017) Transportation and Housing Costs. Retrieved from [https://www.fhwa.dot.gov/livability/fact\\_sheets/transandhousing.cfm](https://www.fhwa.dot.gov/livability/fact_sheets/transandhousing.cfm)
- Gulipalli P. and Kockelman K.M. (2008) Credit-Based Congestion Pricing: A Dallas-Fort Worth Application. *Transport Policy* 15 (1), pp. 23-32.
- Gupta, S., Kalmanje, S., Kockelman, K.M. (2006) Road pricing simulations: traffic, land use and welfare impacts for Austin, Texas. Paper Presented at the 84th Annual Meeting of the Transportation Research Board.
- Herriges J, Kling C (1999) Nonlinear income effects in random utility models. *Rev Econ Stat* 81, pp.62–72.
- Hicks, J.R. (1939) *Value and Capital – an inquiry into some fundamental principle of Economic Theory*. Clarendon Press, London.
- Jara-Díaz S. and Videla J. (1987) On the role of income in the evaluation of users' benefits from mode choice models. *Proceedings of the 5th International Conference on Travel Behavior*, Aix-en-Provence, France. Gower, London (in press).
- Jara-Díaz, S. R. and J. Videla (1989) Detection of income effect in mode choice: theory and application. *Transportation Research*, 23B (6), pp. 393-400.

- Jara-Díaz, S. R. and J. Videla (1990) Welfare implications of the omission of income effect in mode choice models. *Journal of Transport Economics and Policy*, 24, pp. 83-93.
- Litman, T. (2009). Transportation cost and benefit analysis. Victoria Transport Policy Institute, 31.
- McFadden, Daniel. (1996). Computing Willingness-to-Pay in Random Utility Models. University of California at Berkeley, Econometrics Laboratory Software Archive, Working Papers. doi:10.4324/9780203074206.ch15.
- McFadden D. (1981) Econometric models of probabilistic choice. In *Structural Analysis of Discrete Data with Econometric Applications*, (edited by Manski, C. H. and McFadden, D.). MIT Press, Cambridge, Massachusetts, pp. 198-272.
- McFadden, D. (2000) Disaggregate Behavioral Travel Demand's RUM Side. A 30-Year Retrospective. Prepared for the 9th IATBR. Gold Coast, Australia.
- Odeck, J., Rekdal, J., Hamre, T.N. (2003) The socio-economic benefits of moving from cordon toll to congestion pricing: the case of Oslo. Paper Presented at TRB Annual Meeting.
- Ortúzar, J.de D. and Gonzales, R.M. (2002) Inter-island travel demand response with discrete choice models: functional form, forecasts and elasticities. *Journal of Transport Economics and Policy* 36(2), pp. 115-138.
- Safirova, E., Gillingham, K., Parry, I., Nelson, P., Harrington, W., and Mason, D., 2003. Welfare and distributional effects of HOT lanes and other road pricing policies in Metropolitan Washington, DC. In: Road Pricing: Theory and Practice.
- Small, K.A. and Rosen, H.S. (1981) Applied welfare economics with discrete choice models. *Econometrica*, 49(1) 105-130.
- Train, K. E. (2009). Discrete choice methods with simulation. Cambridge University Press.
- US Department of Labor Statistics. (September 13, 2018). CONSUMER EXPENDITURES 2017. Retrieved from <https://www.bls.gov/news.release/cesan.nr0.htm>
- Willig, R.D., (1976) Consumer's surplus without apology. *The American Economic Review*, 66(4), pp. 589-597.

Zhao, M. Q., & Huang, J. C. (2018). The Representative Consumer Approximation Bias in Discrete Choice Welfare Analysis. *Environmental and Resource Economics*, 71(4), 969-984.

Zhao, Y., Kockelman, K. M., & Karlstrom, A. (2008). Welfare calculations in discrete choice settings: Role of error term correlation. In *Proceedings of the Transportation Research Board 87th Annual Meeting*.