UNIVERSITY OF MARYLAND

National Transportation Center

Project ID: NTC2015-SU-R-09

UNDERSTANDING CHANGES IN TRAVEL BEHAVIOR DUE TO MANAGED LANES

Final Report

by

Javier Bas Vicente
Department of Civil and Environmental Engineering, University of Maryland
3109 Kim Bldg., College Park, MD 20742
Tel: +1 301-405-6864 Fax: +1 301-405-2585; Email: jbas@umd.edu

Cinzia Cirillo
Department of Civil and Environmental Engineering, University of Maryland
3109 Kim Bldg., College Park, MD 20742
Tel: +1 301-405-6864 Fax: +1 301-405-2585; Email: ccirillo@umd.edu

for

National Transportation Center at Maryland (NTC@Maryland)
1124 Glenn Martin Hall
University of Maryland
College Park, MD 20742

November, 2017

ACKNOWLEDGEMENTS

This project was funded by the National Transportation Center @ Maryland (NTC@Maryland), one of the five National Centers that were selected in this nationwide competition, by the Office of the Assistant Secretary for Research and Technology (OST-R), U.S. Department of Transportation (US DOT).

DISCLAIMER

The contents of this report reflect the views of the authors, who are solely responsible for the facts and the accuracy of the material and information presented herein. This document is disseminated under the sponsorship of the U.S. Department of Transportation University Transportation Centers Program in the interest of information exchange. The U.S. Government assumes no liability for the contents or use thereof. The contents do not necessarily reflect the official views of the U.S. Government. This report does not constitute a standard, specification, or regulation.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

EXCUTIVE SUMMARY

Along with Rule of a Half (RoH), Log-sum (LS) is probably the most used welfare measure, to assess policy impact on consumer's welfare. However, they both rely on the assumption of an absence of income effect, this is, fixed marginal utility of income, invariant along the population. Such a strong presumption facilitates calculations due to the correspondence between LS and Compensating Variation (CV), the exact measure to evaluate changes in consumer surplus. That approach has been usually grounded in two ideas: i) that the household's transportation expenditure is negligible and; ii) that changes in policies that affect that expenditure are also minor. We can even find this rationalization in the authors that set the microeconomic foundations for the current mode choice models. In McFadden's (1981) formulation, alternative choice 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 are questionable. The fact is that transportation expenditure may represent an important share of the total, especially in the case of low-earning households. Furthermore, aggressive pricing policies or a global rise in energy prices might decisively affect income in real terms. Hence, the calculation of benefit measures based on demand models that do not account for income effect may produce inaccurate results. In this regard, the empirical evidence of the consequences of ignoring it is scarce, and the question of whether LS or RoH are good approximations to the true CV remains open. The results of Willig (1976) suggest that the percentage error of approximating Compensating Variation by consumer surplus 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, Karsltröm (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 (2004) have investigated to which extent the commonly used consumer benefit measures are close to CV (yet using synthetic data). 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.

Although some authors have explored the gap between CV and other benefit measures, very little research has been done with non-synthetic recent data, especially 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, but they didn't compare them with the true CV. Gupta et al. (2004) explored impacts in welfare of road pricing in Austin, Texas, but focusing only on LS variation. In turn, Gulipalli and Kockelman (2008) expand Gupta et al.'s (2004) work, incorporating environmental impact but, unfortunately, setting aside welfare changes. Now then, although these works may not comprise all aspects of deep welfare analysis, the general pith of the research is that in presence of income effect, LS and RoH are not correct approximations to CV.

The practical importance of toll policies and the recurrent discussion about the improvement of social welfare by such strategies, make the matter at hand particularly relevant. However, to the best of our knowledge, there is an apparent absence of substantial welfare analysis supported by real data in the field. In order to shed light on the issue, the present study closely follows the work of Cherchi and Polak (2004) with the aim of testing whether or not LS and RoH are good approximations to the true CV under nonlinear effect in the marginal utility of income, but using real data instead of synthetic. This is the first contribution of our work, the use of information gathered through a dedicated Stated Preferences survey to evaluate the gap between true CV and both LS and RoH. The second is the inclusion of heterogeneity in Travel Time, one of the fundamental elements that impact travelers' decisions. This effect of taste is considered through a Multinomial Mixed Logit (MML) model with random parameters, from which the measures will be computed and compare to the case of a Multinomial Logit (MNL).

This report is organized as follows: in section 1 the relevant welfare economics concepts and the approaches followed in the computation of benefit measures are reviewed. How income effect is contemplated in this study is described in the second section. Section 3 describes the data set and models used. The fourth section presents the analysis of the results obtained. Finally, the last section summarizes the conclusions.

1.0 COMPENSATING VARIATION AND APPROXIMATIONS

Compensating Variation, defined by Hicks (1939), is the amount subtracted from the income of an individual that faces a price reduction, in order to make him to stay on its initial level of utility. Following McFadden (2000), CV is the quantity such that:

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

where $U(\cdot)$ is the 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 η is a vector of unobserved both attributes and characteristics of the alternative and the individual. The single and double apostrophes only indicate the before-after states. Since η is unobserved and randomly distributed, CV is also random. Thus, CV will be:

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

Equation (*2*) may be difficult to compute since it usually 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, is to assume absence of income effect. From an analytical perspective, that means that the marginal utility of income is a fixed value (λ). In other words, the effect of income is the same for all individuals over the population. If we make this assumption, we can reformulate equation (1) as:

$$\lambda CV_q = Emax_{j\in C}\left\{f\left(x^{"}_{jq}; s_q, \eta_{qj}\right) - \lambda c^{"}_{jq}\right\} - Emax_{j\in C}\left\{f\left(x^{'}_{jq}; s_q, \eta_{qj}\right) - \lambda c^{'}_{jq}\right\} \tag{3}$$

In addition, under the common supposition in discrete choice modelling of additive disturbances with GEV joint cumulative distribution function:

$$Emax_{j\in C}\left\{f\left(I_q - c^{'}_{jq}, x^{'}_{jq}; \beta_{jq}\right) + \varepsilon_{jq}\right\} = \log H\left(e^{f_1}, \ldots, e^{f_j}\right) + 0.57721 \tag{4}$$

In particular, if H is linear, which leads to the Multinomial Logit model, the well-known log-sum expression is obtained:

$$CV_q = \frac{1}{\lambda}\left\{\log\sum_{j=1}^{J}\left[\exp\left(-\lambda c^{"}_{jq} + f\left(x^{"}_{jq}; \beta_{jq}\right)\right)\right] - \log\sum_{j=1}^{J}\left[\exp\left(-\lambda c^{'}_{jq} + f\left(x^{'}_{jq}; \beta_{jq}\right)\right)\right]\right\} \tag{5}$$

Therefore, log-sum is equivalent to CV under GEV distribution of disturbances and absence of income effect.

Rule of a Half (RoH) is another welfare measure widely used as an approximation to the area under the Marshallian demand curve. To serve to that purpose, 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. The use of Marshallian demands implies, as in the case of Logit and log-sum, the absence of income effect. The general expression of RoH is:

$$RoH = -0.5\sum_{od}\sum_{j}\Delta GC_{od,j}\overline{T}_{od,j} \tag{6}$$

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

$$\Delta GC_{od,j} = \left(c_{od,j}\left(after\right) - c_{od,j}\left(before\right)\right) - \frac{1}{\lambda}\sum_{h}\beta_{hj}\left(x_{od,hj}\left(after\right) - x_{od,hj}\left(before\right)\right) \tag{7}$$

2.0 INCOME EFFECT AND SICRETE 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 it relies in microeconomic foundations. The general approach in a transportation context is as follows:

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 this direct utility function satisfies, the solution of the maximization program leads to the following conditional indirect utility function:

$$V(p, I - c_j, x_j) = V_j \tag{8}$$

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. 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 consider income effect, it has to be explicitly incorporated in the utility function nonlinearly. In this work, the Jara-Díaz and Videla (1989) approach is followed:

$$V_j = \beta_1(I - c_j) - \beta_2(I - c_j)^2 + \sum \beta_k x_{kj} \tag{9}$$

where x_{kj} is a vector of modal characteristics of alternative j.

For the sake of a complete satisfaction of relevant microeconomic conditions, the marginal utility of income should be positive and decreasing, while the marginal utility of cost should be negative and increasing:

$$\frac{\partial V_{jq}}{\partial I_q} \geq 0, \frac{\partial V_{jq}}{\partial c_{jq}} \leq 0 \text{ and } \frac{\partial^2 V_{jq}}{\partial^2 I_q} \leq 0, \frac{\partial^2 V_{jq}}{\partial^2 c_{jq}} \leq 0 \tag{10}$$

On the other hand, Roy's identity should also be satisfied.

$$-\frac{\partial V_{jq}}{\partial c_{jq}} \Bigg/ \frac{\partial V_{jq}}{\partial I_q} = 1 \tag{11}$$

Both conditions are clearly satisfied by equation (*9*).

3.0 DATA, MODEL SPECIFICATION AND METHODOLOGY

3.1 DATA DESCRIPTION

The data sample used in this study gathers 1,211 responses of drivers traveling during weekday extended peak periods (8:00 AM–11:00 AM and 3:30 PM– 6:00 PM), on 21–25 March and 23–27 May 2011, in the Maryland side of Capital Beltway. After cleaning up the data, that figure was reduced to 766. 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	21-25 March 2011 and 23-27 May 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

In this case, different scenarios where presented to motorists, who chose among three alternatives (General Purpose lane, High Occupancy lane and High Occupancy Toll lane) with different costs and travel times. Modal attributes where calculated based on the information entered in a pre-questionnaire in which individuals detailed information regarding their last trip. The main characteristics of respondents in the sample can be summarized as follows:

- Gender: 54% of the sample was male.
- Age: The average age is 43 and the median age is 45. Youngest respondent was 19 and 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 government and less than 1% were unemployed.
- Income: 9.8% of households had an income lower than $50K, 24.4% between $50K and $75K, 25.7% between $75K and $125K. 40% of households had income higher than $125K. A comparison between the survey's and state of Maryland's income distributions yields a slight bias towards high income.
- 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 refers exclusively to salary. For consistency with the reference base of the Level-of-Service (LOS) variables, it has been transformed to income per trip, assuming 2.88 trips per day and 260 working days.

3.2 MODEL ESTIMATION

In addition to the already mentioned treatment of the Income variable, cost and travel time are also included, yielding the following utility function, which is in accordance with equation (9) as defined by Jara-Díaz and Videla (1989):

$$V_j = \beta_0 + \beta_1 (I - c_j) + \beta_2 (I - c_j)^2 + \beta_3 TT_j \tag{1}$$

In this case, c_j represents total cost, which includes toll and fuel costs. Obviously, toll only applies to the HOT alternative presented to drivers. On the other hand, TT_j represents travel time of each alternative for the trip proposed. It is worth noting that other modal attributes related to time have also been considered (congestion time and time due to uncertainty, specifically), without resulting significant or improving the fit of the model.

In order to analyze the impact on welfare of variations in both tolls and travel times, two models have been estimated, Multinomial Logit and Mixed Logit. Although MNL have well-known limitations (no taste heterogeneity, IIA…), they are usually computed due to its simplicity and, as in this case, as a starting reference for comparison. On the other hand, to use MML one needs to first define which of the parameters are considered random, and then which distributions they will follow. We tested all combinations of random parameters, distributed Lognormal since it seemed the most coherent choice according to behavioral theory and prior experience. Nevertheless, the best results were obtained when considering Time Travel as the only random element. All other cases fitted worse the sample or showed incoherent parameters.

	Dependent variable:	
	CHOICE	
	MNL	MXL (TT ln)
	(1)	(2)
GP-ASC	0.070 (0.180)	-0.192^{**} (0.081)
HOV-ASC	-2.054^{***} (0.194)	-2.434^{***} (0.142)
TT	-0.013^{***} (0.004)	-4.818^{***} (0.011)
(I-C)	0.402^{***} (0.055)	0.525^{***} (0.001)
$(\text{I-C})^2$	-0.001^{***} (0.0002)	-0.001^{***} (0.00001)
sd.TT		7.671^{***} (0.012)
Observations	766	766
R^2	0.067	0.171
Log Likelihood	−643.469	−571.268
LR Test	91.993^{***} (df = 5)	236.395^{***} (df = 6)
Note:		*p<0.1; **p<0.05; ***p<0.01

Figure 1: Model Estimation Results

The mixed logit specification shows a better fit, and the significance of the standard deviation of the travel time parameter confirms the heterogeneity of this variable's effect. The rest of the parameters are also highly significant and their signs are coherent. In this respect, it is a great finding that in both models the parameters of the available income and squared available income are positive and negative, respectively. This confirms the existence of income effect; while the first derivative is positive, the second is negative, verifying diminishing returns as indicated in eq.10. In other words, the effect of income in the utility (and, therefore, in choice), is in fact dependent on the income level, as the economic theory suggests. This corroboration provides a solid foundation on which move forward.

3.3 METHODOLOGY

Based on the discussion on section 1, the two sets parameters obtained above are used to compute the following welfare measures:

- Compensating variation by resampling (CV). This method consists in computing, for each individual and each alternative, the corresponding random utility, searching for the maximum over alternatives and then calculating the CVs that equate the two maxima.
- Log-sum. This measure is calculated in two different ways. *Agg. lsum* is the log-sum calculated for each individual and then aggregated over the population. *Rep. lsum* is the log-sum calculated for an average representative individual considering as if all individuals behave the same way.
- Rule-of-a-half (RoH). As shown by Jara-Díaz (1990), rearranging the terms in equations (6) and (11), it is possible to express the RoH in terms of the SVT, as follows:

$$CV = -\sum_i \Delta c_i \overline{T_\iota} + \sum_i \sum_h SVh_i \Delta X_{hi} \overline{\overline{T_\iota}} \tag{13}$$

where all the terms have the meaning explained above.
In the following section, all these measures are computed after applying improvements/deteriorations of the travel time and the toll cost of the alternatives (only for HOT in the toll case). The gap between log-sum and RoH compared to CV hints at the error made by estimating them instead of using CV when income effect exists. The computations will be done using the parameters of the MNL model and, afterwards, using those from the MML. Finally, comparisons in the results will be carried out in order to draw conclusions about the contribution of taste heterogeneity to the matter.

4.0 INFLUENCE OF NONLINEAR EFFECT OF MARGINAL UTILITY OF INCOME ON BENEFIT MEASURES

Two types of policies are explored: variations in travel time and variations in toll cost, with the latter only affecting, obviously, the HOT alternative. The range of the policies goes from a -20% improvement to a +20% deterioration, in 5% increments. Table 2 illustrates, for a policy applied to the travel time of the GP lane, the values of the benefit measures, as well as the error made by log-sums and RoH with respect to the exact Compensating Variation. In this case, the measures increase as long as the policy becomes more "harmful", as one may expect. On the other hand, the aggregated log-sum yields negligible error in approximating the true CV, while the representative log-sum and RoH performs much worse. It is also worth noting noteworthy that they systematically overestimate CV.

Table 2: Percentage variation in benefit measures (fixed parameters) for different variations in the travel time of the general purpose lane

	% Change	CV_res	Agg. lsum	Rep. lsum	RoH	(Agg.lsum-CV)/CV	(Rep. lsum-CV)/CV	(RoH-CV)/CV
Policy-1	-20	-149.51	-150.43	-178.54	-178.51	0.61%	19.41%	19.39%
Policy-2	-15	-114.11	-112.07	-133.23	-133.22	-1.78%	16.76%	16.75%
Policy-3	-10	-74.70	-74.21	-88.37	-88.37	-0.65%	18.30%	18.30%
Policy-4	-5	-38.49	-36.86	-43.96	-43.96	-4.23%	14.21%	14.21%
Policy-5	0	0.00	0.00	0.00	0.00			
Policy-6	+5	35.15	36.36	43.50	43.50	3.44%	23.76%	23.76%
Policy-7	+10	76.40	72.20	86.53	86.53	-5.50%	13.26%	13.25%
Policy-8	+15	110.94	107.56	129.09	129.08	-3.05%	16.36%	16.35%
Policy-9	+20	141.27	142.39	171.18	171.15	0.79%	21.17%	21.15%

For the sake of clarity, the results for each scenario will be provided in a chart instead of a table, like in Figure 2, which is presenting the same information of Table 2, only more visually appealing.

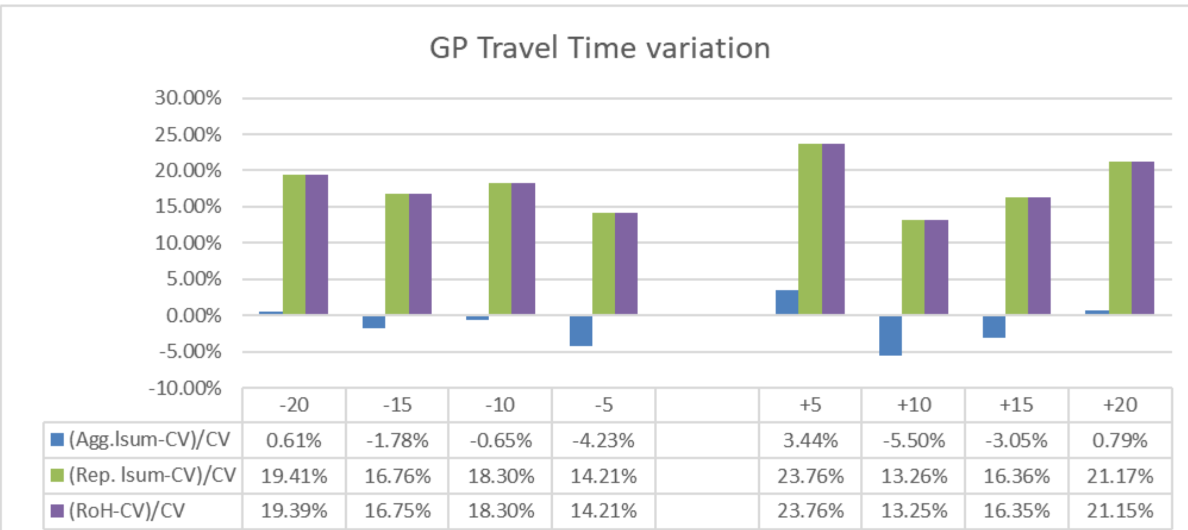


Figure 2: **Percentage variation in benefit measures (fixed parameters) for different variations in the Travel Time of the General Purpose lane.**

Figure 3 shows the impact on welfare of the time policies that affect the tolled case. It must be brought to our attention that, although the error made by the aggregated log-sum is far from small, between 30.4% and 51.88%, this measure performs better than the representative log-sum and RoH. It is also notable that in the case of a travel time improvement (better infrastructure, less traffic congestion…), there is a significant leap at the -10% level of improvement, meaning that the used measures better render the effect on social welfare of a -15% and -5% change. On the other side of the spectrum, when travel time worsen, the errors are generally inferior and, except for a steep increase in the measures accuracy when the policy increases to a 10%, it stays around 37.8% - 41.6%. This volatility may be due to the fact that, although HOT is not the most demanded alternative in our data set, it is chosen by the 27.15% of the respondents. The proposed variations in the travel time data may have caused some displacement in some of their choices. However, it is difficult to know how many drivers would actually switch to another alternative, and that incorporates an additional source of uncertainty that affects the accuracy of the measures.

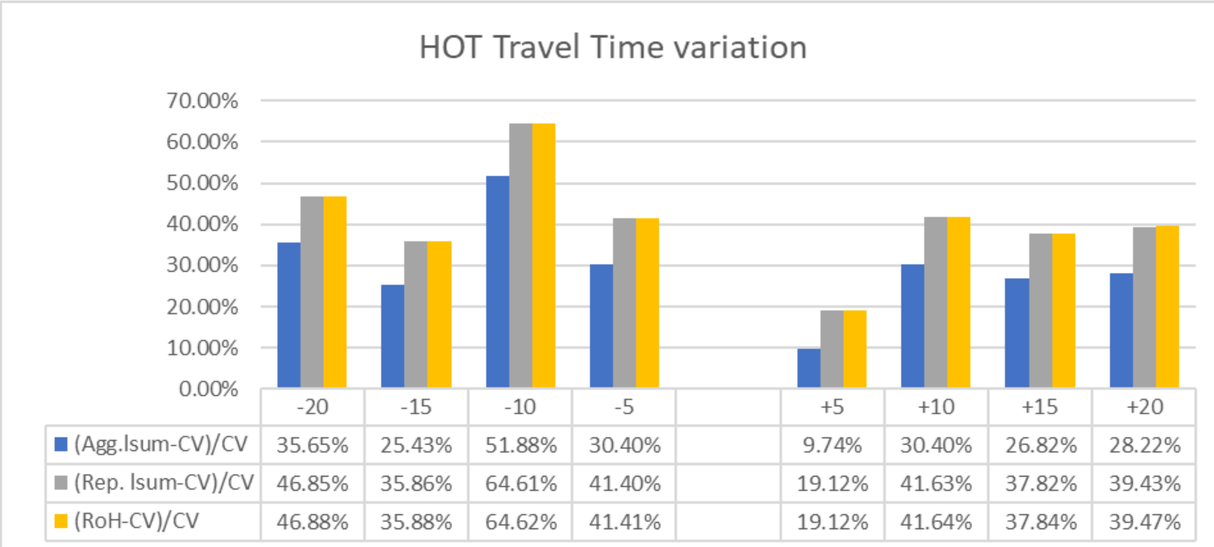
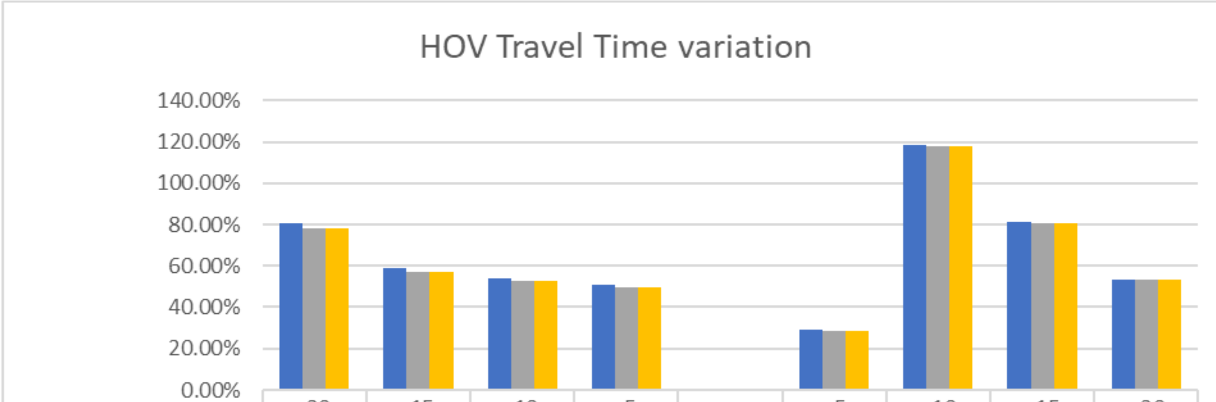


Figure 3: Percentage variation in benefit measures (fixed parameters) for different variations in the Travel Time of the High Occupancy Toll lane.

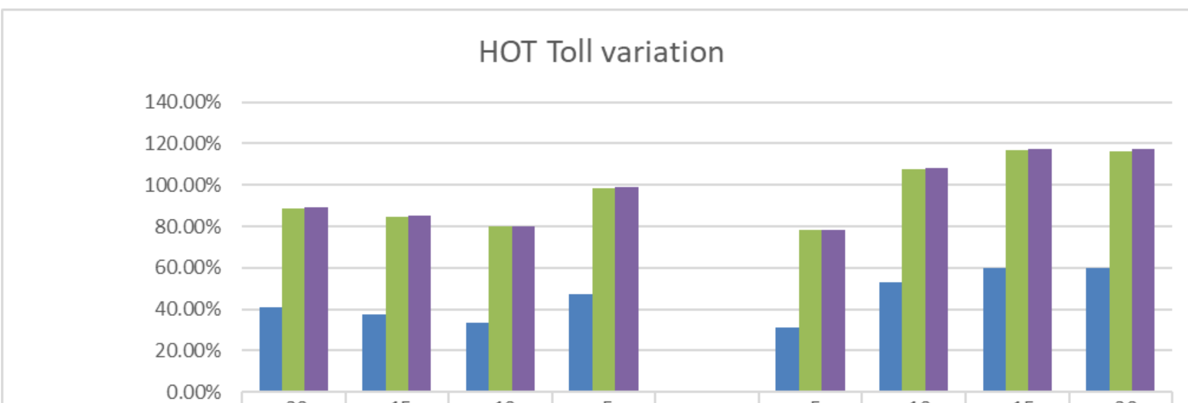
This reasoning is supported by Figure 4, which shows the HOV case, the less demanded alternative, since it requires 3+ car occupants to be used. Since only a 11.35% of drivers chose this alternative, the impact of an decrease/increase in its travel time is more certain. Consequently, all measures evolve together, following a decreasing trend while the travel time variation is less intense. Nevertheless, for a 10% increase in travel time, the error remarkably boosts up again, up to 118%. The authors believe that, when individuals face a policy limited in magnitude they alter their decisions ever so slightly, in which case log-sum and RoH are closer to CV since the model can capture that behavior better. However, when changes are larger, the model fails in estimating the choices accurately, and these measures fail for a larger margin. The results of the mixed logit sustain this statement, as describe in the following section.



	-20	-15	-10	-5		+5	+10	+15	+20
(Agg.lsum-CV)/CV	80.83%	58.83%	54.08%	51.11%		28.98%	118.61%	81.15%	53.23%
(Rep. lsum-CV)/CV	78.32%	56.91%	52.46%	49.76%		28.23%	117.67%	80.65%	53.06%
(RoH-CV)/CV	78.37%	56.94%	52.47%	49.76%		28.23%	117.69%	80.68%	53.10%

Figure 4: Percentage variation in benefit measures (fixed parameters) for different variations in the Travel Time of the High Occupancy Vehicle lane.

The case of price change pulls a different string in the behavior of travelers, one that is more interesting for the purpose of this project. Since cost influences available income per trip, and we have also proved that there is income effect in this sample, it is quite interesting to analyze how much LS and RoH are deviated from CV.

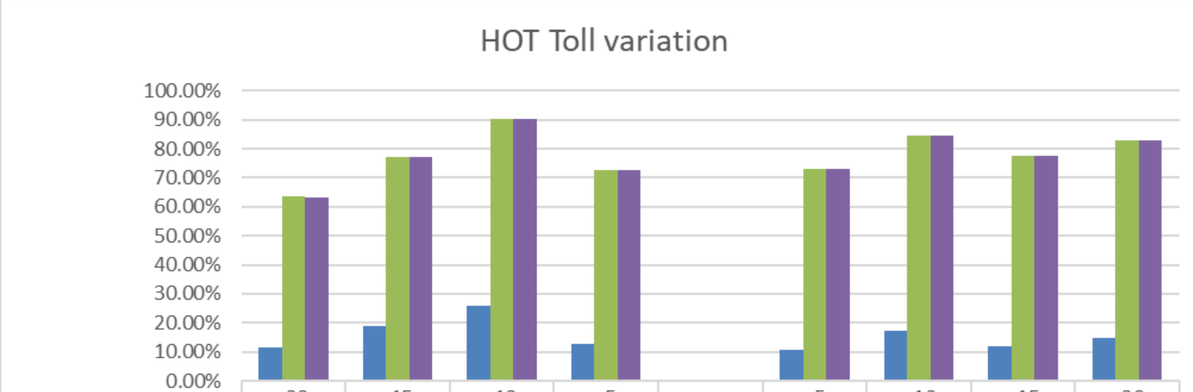


	-20	-15	-10	-5		+5	+10	+15	+20
(Agg.lsum-CV)/CV	41.14%	37.67%	33.65%	47.02%		31.37%	53.22%	59.89%	59.64%
(Rep. lsum-CV)/CV	88.49%	84.74%	80.02%	98.62%		78.06%	107.79%	116.79%	116.23%
(RoH-CV)/CV	89.32%	85.21%	80.24%	98.68%		78.12%	108.06%	117.45%	117.42%

Figure 5: Percentage variation in benefit measures (fixed parameters) for different variations in the toll of the High Occupancy Toll lane.

It is clear that the aggregated log-sum is closer to the true benefit measure, the Compensating Variation. This is common to all cases; we can conclude that the representative measures perform poorly. This should not surprise us if we realize that both Representative log-sum and RoH consider all individuals as if they behave as the representative. However, if most of the respondents are not actually affected by the policy, then the error hikes, as is the case.

Two general conclusions may be derived from the results based on Logit estimations. First, errors are significant in all cases and, second, representative measures perform worse than the aggregated one. Now, for the sake of brevity, and since the main purpose of this project is to exhibit the error of the benefit measures in presence of income effect, we will focus on the pricing policy, which directly impacts income per trip.
Looking at the results of Figure 6, we can conclude that adding taste heterogeneity improves significantly the performance of LS and RoH. Although the errors are still significant for the representative measures, they are smaller than in the logit case. Even the aggregated log-sum presents noticeable decrease on its bias. That implies, and this is the second key finding of this work, that under the existence of income effect, less error is made approximating CV through LS and RoH if taste heterogeneity is considered. Although it may be expected theoretically that a better identification of user's behavior (i.e., better parameters) leads to more precise measures, to prove it numerically, with real data, is definitely of great value.



	-20	-15	-10	-5		+5	+10	+15	+20
(Agg.lsum-CV)/CV	11.56%	18.90%	25.89%	12.70%	0.00%	10.68%	17.03%	11.81%	14.71%
(Rep. lsum-CV)/CV	63.61%	77.17%	90.30%	72.54%	0.00%	73.05%	84.52%	77.48%	83.05%
(RoH-CV)/CV	63.38%	77.05%	90.25%	72.53%	0.00%	73.05%	84.50%	77.46%	83.06%

Figure 6: Percentage variation in benefit measures (random parameters) for different variations in the toll of High Occupancy Toll lane.

Figure 7 compares graphically the evolution of the absolute benefit measures in the case of variations in toll policy, for both model specifications. Dashed lines correspond to MML and solid ones to MNL. The reference, CV, is illustrated by the blue lines.

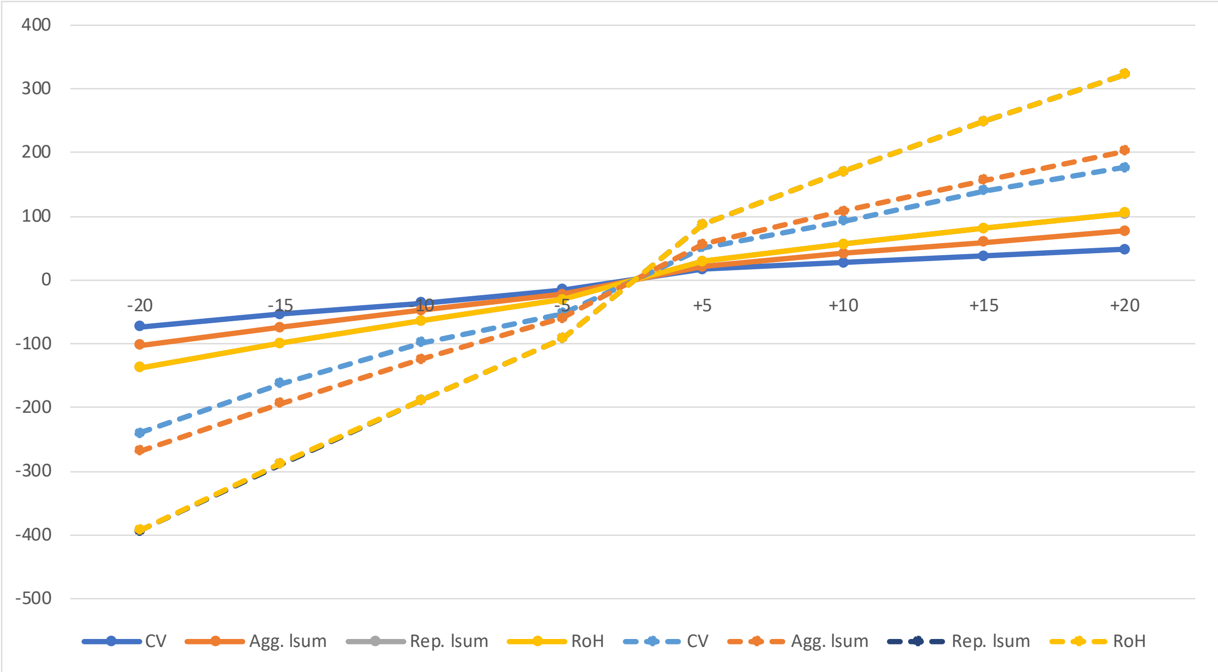


Figure 7: Evolution of the absolute benefit measures. MNL and MML, toll policy.

Log-sums and RoH are negative for toll reductions and positive for toll increments, as they should, according to the Compensating Variation theory developed in Section 1. However, they systematically underestimate CV in the former case, and overestimate it in the latter. Namely, when it is negative, they are more negative; when they are positive, they are even more positive.
The chart shows, as well, more intense effects when the MML parameters are used. This is an interesting conclusion if one assumes that MML gathers better driver's choices. The social and economic effect of measures may be more profound than assumed if welfare is obtained through a simple logit estimation, as is common practice. It is worth noting noteworthy that representative log-sum is actually in the chart, but it is so close to RoH that both lines are overlapping.
It may be more interesting to take a look, in Figure 8, at the evolution of the relative gap between log-sum and RoH with respect to CV. As it has been shown before, in general terms, aggregated log-sum always underestimate CV whereas representative log-sum and RoH consistently overestimate it. However, the magnitude of the error is not consistent. In MNL specification, all measures seem to perform worse at the -5% policy and when it is over +5%. Curiously enough, the tendency in the MML is almost the opposite. When the gap increases for one specification, it decreases for the other, and vice versa.

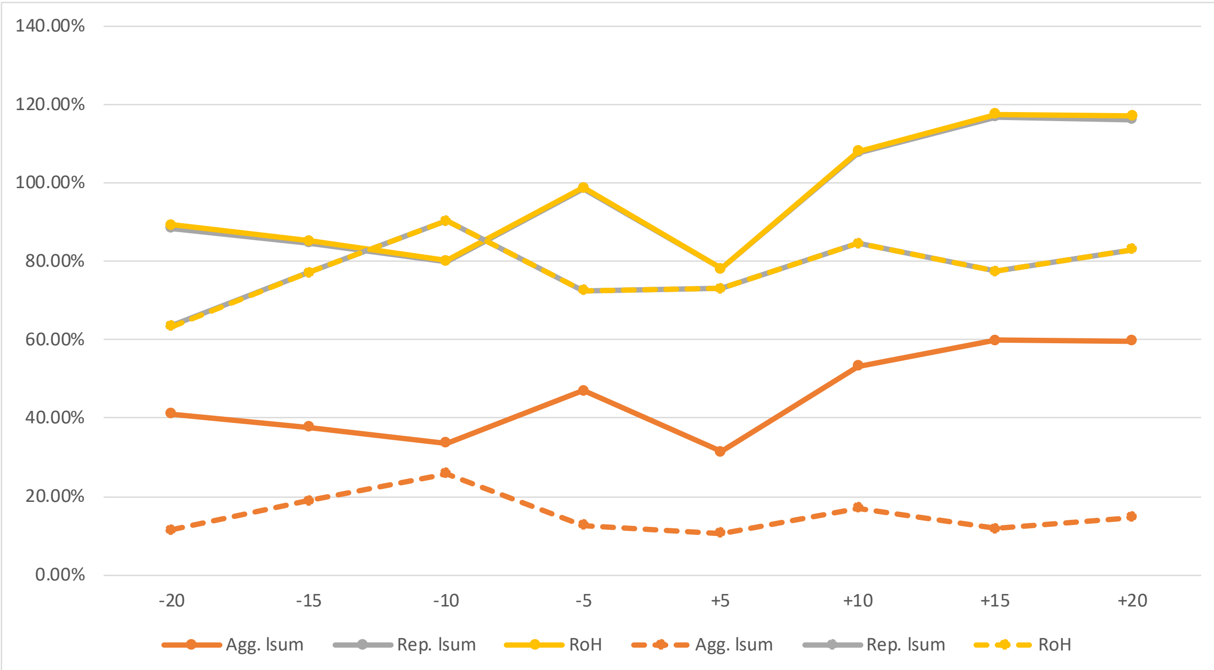


Figure 8: Evolution of the relative gap of measures in relation to CV. MNL and MML, toll policy.

5.0 CONCLUSIONS

This project has two main goals; 1) explore the implications of income effect and taste heterogeneity on the calculation of welfare measures, based on real data, and; 2) after incorporating these improvements to the methodology, analyze the gap between the most commonly used welfare measures, log-sum and RoH, and the true one, the Compensating Variation. To accomplish the first objective, 766 real observations from a Stated Preference survey has been used to prove that income effect exists, and therefore has an influence, in drivers' behavior. This finding has been made thanks to the inclusion of nonlinear income in the utility function, and it means that the influence of earnings is not constant, but depending on the level of earnings itself. Namely, the impact of income in the utility function and, hence, in the choice made, is positive, but decreasing. On the other hand, taste heterogeneity theoretically allows for better predictions since parameters reflect the influence of variables more precisely. The significance of the standard deviation of the random parameter in the Mixed Logit specification justifies its use and, as shown above, produces less deviated measures. In this respect, and focusing on pricing policies, one of the main conclusions is that LS and RoH are inaccurate for any level of policy and model specification, making clear that both measures are equally inappropriate to approximate CV. It is true that the aggregated log-sum does better, but it deviates a minimum of 10.68% in the best case. Such divergence would cloud any toll project assessment interested in social and economic impact. A common trend is that CV is systematically underestimated when users are better off, and overestimated in the opposite case.

Interestingly, although the effects of policies seem to be more intense when taste heterogeneity is considered, the percentage error approximating CV is smaller.

Although the question of whether or not Log-sum and Rule of a Half are good approximations to the exact Compensating Variation is still open, the findings of this work shed some light on the topic. The objectives pursued in this research are accomplished, demonstrating that: 1) income effect plays a role on drivers' behavior; 2) LS and RoH are not good proxies of CV and, therefore, the methodologies to evaluate welfare impact should improve in order to appraise properly social, economic and equity issues, and; 3) taste heterogeneity improves the results, reducing, at least, the margin of error. These revelations will help address 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 deteriorate individuals' welfare. Without an accurate appraisal, the impact of projects will never be evaluated correctly.

6.0 REFERENCES

Cherchi, E., J. W. Polak, and G. Hyman. (2004) The Implications of Income, Taste and Substitution Effects for the Assessment of User Benefits Using Discrete Choice Models. Presented at European Transport Conference, Strasbourg, France.

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.

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. (2004) Road pricing simulations: traffic, land use and welfare impacts for Austin, Texas. Paper Presented at the 84th Annual Meeting of the Transportation 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-Diaz S. and Videla J. (1987) On the role of income in the evaluation of users' benefits from mode choice models. *Proceedings of the 5th lnternational 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.

Karlström, A. (2000) Nonlinear value functions in random utility econometric. *Proceedings 9th IATBR Conference,* Australia.

Marshall, A. (1890) Principle of Economics. Macmillan, London.

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. (1998) Computing Willingness-to-pay In Random Utility Models. In J.Moore, R. Riezman, and J. Melvin eds., *Trade Theory and Econometrics: Essays in Honor of John S. Chipman*, Routledge.

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.

Transportation and housing costs. Federal Highway Administration, U.S Department of transportation. http://www.fhwa.dot.gov/livability/fact_sheets/transandhousing.pdf. October 2010.

Willig, R.D., (1976) Consumer's surplus without apology. *The American Economic Review*, 66(4), pp. 589-597.