Authors' Response to Reviews of

Evaluating the Impacts of Parameter Uncertainty in a Practical Transportation Demand Model

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Future Transportation, futuretransp-3339770

RC: ***Reviewers' Comment***, AR: Authors' Response, ☐ Manuscript Text

We are grateful for the reviewer's comments on this manuscript. We address each point in turn, with text added to the manuscript in blueand ~~text deleted from the manuscript in red~~.

1. Reviewer #3

1.1. General Comments

RC: ***The paper is well-structured and follows a logical progression from introduction to conclusion. The research addresses an important issue in transportation demand modeling—parameter uncertainty. It adds value to the field by analyzing its impacts using Latin Hypercube Sampling (LHS).***

AR: We appreciate that the reviewer found our paper well-structured and on an important issue.

RC: ***However, the real-world implications of the findings could be emphasized more, particularly in the "Conclusions" section.***

RC: ***[moved from end of review] Conclusion: The conclusion section needs to be strengthened. Summarize the main results clearly and discuss their implications for real-world applications. Additionally, outline potential directions for future research to provide a comprehensive closure.***

AR: We weclome the invitation to strengthen our conclusions, and have done so in a revised conclusions section.

> ~~In general, this research has shown that statistical parameter uncertainty does not appear to be a significant factor in forecasting traffic volumes using trip-based travel demand models. The result uncertainty is generally equal to or~~ The results of this research show that despite large variations in mode and destination choice parameters – and consequently large variations in accessibility, the impact of this variation on assigned highway volumes is limited. To our knowledge, this is the first systematic evaluation of parameter uncertainty in a practical travel model in the literature, with prior research being limited to toy networks (e.g., Zhao and Kockelman, 2002). The resulting uncertainty in the output forecasts was shown to be generally smaller than the input parameter variance~~. The uncertainty in parameter inputs appears to lead to variation in highway volumes that is lower than the error between the model forecast and the highway counts. Any~~ , confirming the results of Petrik et al. (2020) in a different context. In this application at least, the variation in mode and destination choice probabilities appears to be constrained by the ~~limitations~~ capacities and procedures of the highway network assignment.
>
> There are several limitations that must be mentioned in this research, however. First, we did not attempt to address the statistical uncertainty in trip production estimates; these may play a substantially larger

> role than destination and mode choice parameters, given that lower trip rates may lead to lower traffic volumes globally, which could not be "corrected" by the static user equilibrium assignment. Second, a different methodology of sampling might have produced a different result at the extremes than the results of LHS. Additionally, the relatively sparse network of the RVTPO model region — lacking parallel high-capacity highway facilities — may have meant that the static network assignment would converge to a similar solution point regardless of modest changes to the trip matrix. It may be that in a larger network with more path redundancies ~~,~~ or more alternative transit services the assignment may not have been as helpful in constraining the forecast volumes.
>
> In this research we had only the estimates of the statistical coefficients, and therefore had to assume a coefficient of variation to derive variation in the sampling procedure. It would be better if model user and development documentation more regularly provided estimates of the standard errors of model parameters. ~~Even better~~ The ideal would be variance-covariance matrices for the estimated models, enabling researchers to ensure that covariance relationships between sampled parameters are maintained. Future research might reconsider the present expermiment but allowing for correlation between parameter values.

1.2. Keywords

RC: ***Keywords: Having only two keywords is insufficient. Consider expanding the list to include more relevant terms to improve discoverability and accurately reflect the scope of the research.***

AR: Thank you for this suggestion. We have expanded with two additional keywords,

> Travel modeling; Uncertainty; Choice models; Trip-based models

1.3. Travel modeling key challenges

RC: ***Line 21: Before introducing the function in this line, provide a more comprehensive overview of the current state of transportation demand modeling and its key challenges. This will help set the context for your research.***

AR: This is a good point. We have strengthened the first paragraph of the manuscript by including references to the attention uncertainy is receiving in the travel forecasting community,

> The inherent accuracy and uncertainty in travel forecasting models is receiving increasing attention from the scholarly and practicing community. As an example of this attention, the Standing Committee on Transport Forecasting of the Transportation Research Board has made uncertainty one of its primary research agenda issues (TRB AEP50, 2025), following a major report from Federal Highway Administration on the topic (Lempert et al., 2022).

1.4. Literature Review

RC: ***Line 57: For the literature review, it may be more effective to organize the discussion by related topics or themes rather than describing each study in detail.***

AR: While we agree that the literature review could be more coherently organized, the time necessary to do this revision has not been granted by the journal's editorial staff.

1.5. Number of draws

RC: ***Line 293: The rationale for selecting 100 and 600 draws needs to be explained more clearly. Why were these specific numbers chosen? Discuss how they are sufficient for capturing the parameter variability in this study.***

AR: We agree that this could have used more explanation. We have revised this section extensively to improve clarity.

> ith the trip-based model described above, MC and LHS methods were used to develop alternative parameter sets to evaluate uncertainty. To identify a standard deviation for each parameter, we asserted a coefficient of variation ~~was used. A set coefficient of variation of 0.10 was used for~~ $c_v = 0.10$ the four mode choice coefficients and the destination choice parameters~~. The~~ ; the mode choice constants ~~were kept the same~~ remained fixed across all iterations. Literature had identified a coefficient of variation of 0.30, but for this analysis that caused an unrealistic value of time, and thus it was changed to be 0.10 (Zhao and Kockelman, 2002). Value of time is a ratio in units of money per time that should be compared to the regional wage rate. ~~Using a~~ A c_v of 0.30 ~~the~~ implied a value of time ~~range was~~ extending from \$2 to \$32 ~~/hr, whereas using~~ per hour, whereas a c_v of 0.10 ~~the range was~~ implied values between \$6 to \$14 /hr~~. The latter seemed more rational because it is related to wage rates and thus a c_v of 0.10 was used for our analysis~~, which we assess as more reasonable for this context. The standard deviation ~~was~~ for sampling the parameters was therefore equal to 0.10 multiplied by the mean, where the mean values in this situation are the base scenario parameters (as identified in Table 2).
>
> The MC random sampling uses the R function of `rnorm`. LHS uses the `lhs` package in R. ~~Since this package only chooses variables on a zero to one scale, the values given use a function to put the random sampling on the right scale needed for the given parameter.~~ The full code for both methods can be found in a public GitHub repository. ~~One hundred and~~ We wish to ensure in our simulations first, that we explore the full parameter uncertainty space of the model, and second that we run a sufficient number of simulations that outlying and extreme draws do not overly influence our analysis. We therefore designed and present a short experiment to evaluate the average mode choice logsum in the model determined by 100 and 600 ~~draws of random samples for both methods are generated. With these generated parameters, the mode choice modelstep was run for every set of input parameters for each purpose. The average MCLS value for each run was determined to compare each continuous draw. This allowed us to see how many iterations of which sampling type would be sufficient to show a full range of possible outcomes.~~ draws of parameters via both MC and LHS.
>
> ~~The parameters generated were compared for both sampling methods.~~ Figure 1 shows the distributions ~~for~~ of the HBW parameters when using 100 and 600 draws, including the distribution of implied value of time, which is an indirect number based on two separate draws. These distributions show in general that LHS gives normally distributed parameters with fewer draws than MC sampling~~: at 100 draws LHS shows a nearly perfect normal distribution, where there are some discrepancies for the MC generated parameters. These Figures show that LHS is likely to estimate the full variance of the results with fewer draws.~~ , as expected by theory (Helton and Davis, 2003).
>
> To determine if LHS is effective at a reasonable amount of iterations, the cumulative mean and the cumulative standard deviation of the ~~average~~ mean MCLS value for ~~every zone~~ all zones (see Equation 2) was calculated for each additional draw for both sampling methods. MCLS is an impedance term which is an important value for destination choice and region routing. The ~~average~~ mean MCLS, x, was used as a measure of outcome possibilities to simplify a complex term as a single value to compare

by across all iterations. The cumulative mean is calculated as:

$$\mu_i = \frac{x_1 + ... + x_i}{n} \tag{5}$$

and the cumulative standard deviation is calculated as:

$$SD_i = \sqrt{\frac{\sum(x_i - \mu_i)^2}{n-1}}. \tag{6}$$

~~The cumulative mean shows~~ Figure 2 illustrates how the average MCLS stabilizes ~~across each iteration~~as the number of draws increases, and the cumulative standard deviation is used to show the 95% confidence interval of that mean. ~~When the cumulative mean for the draws stabilizes, that shows that the amount of generated parameters has captured the possible variance of the results. This is shown for two of the three trip purposes in Figure 2.~~

1.6. Figure placement

RC: ***Figures 5 and 6: These figures should be placed before the conclusion section to ensure that all supporting visualizations are discussed prior to summarizing the findings.***

AR: We are using the LaTeX formatting engine, which may move floating objects forward or backward depending on available page space; we leave this to editorial choice.