EVALUATING IMPACTS OF TDM POLICIES THROUGH BEFORE-AFTER TRAVEL SURVEY: APPLICATION OF DATA FUSION FOR DISCRETE CHOICE MODELLING

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Introduction

A large segment of transportation demand management (TDM) strategies aim to change people's travel patterns by encouraging a move away from single occupancy vehicle (SOV) to public transit, carpooling, walking, cycling, and telecommuting. TDM strategies not only reduce traffic congestion but also increase travel safety and reduce traffic emission (Litman, 2003, Zaman and Habib 2011, Habib et al 2011). A number of Canadian regions are attempting to implement and investigate various TDM strategies. As a part of the implementation process, various Canadian municipalities have been performing surveys before and after implementing TDM strategies. These surveys help to quantify the effect of the TDM strategies in question. The Smart-Commute data set for the Greater Toronto and Hamilton area (GTHA) is one such survey and forms the basis for the forthcoming analysis. Unfortunately, studies on the effect of TDM strategies which utilize a discrete choice modelling framework and before and after survey data are for the most part absent for Canadian regions. The limited number of studies within a Canadian context that do utilize a discrete choice framework for addressing TDM effectiveness typically utilized joint revealed and stated preference (RP-SP) survey to develop their discrete choice models. While there are numerous advantages associated with the use of joint RP-SP surveys, the data collection process can be quite cumbersome (Hasnine et. al., 2016). To the best of our knowledge, no comprehensive joint RP-SP survey exists for the GTHA, prompting the need for alternative means of analysing the impacts of TDM. Other studies in the region have investigated TDM strategies that affect only carpooling (Buliung et. al., 2008; Buliung et. al., 2010), or have examined smaller sub regions (Hasnine et. al., 2016). As such, the application of the region wide Smart Commute Dataset for the estimation of a mode choice model is an apparent gap in the region and more broadly, the country. While TDM strategies are decade old concepts in many Canadian regions, the ideal quantification process under a discrete choice modelling framework using multiple cross-sectional datasets is still missing from the Canadian TDM literature.

The aim of this paper is to investigate the impact of stated adaptation and opinion responses on individuals' mode choice before and after travel demand management (TDM) strategy implementation. This investigation makes use of econometric modelling approaches, including the scaled multinomial logit model to capture these trends. This approach allows for the interpretation of differences in the decision making process based on the parameterization of the scale. The key outcomes of this analysis provides new insights into the effectiveness of TDM policies drawn from the perceptions and attitudes of travelers. These insights will permit policy/decision makers to justify the allocation of resources to different policies based on small scale, easy to implement stated adaption surveys.

The Study Area and Descriptive Statistics and Data Limitations

Two cross-sectional datasets designed and collected by Metrolinx under its Smart-Commute program are used in this study. Smart Commute is a joint program between Metrolinx and several municipalities in the GTHA, including Hamilton, Halton, Peel, York, Durham and Toronto (Meghan et. el., 2016). The baseline and follow-up surveys comprise of 37 participating workplaces of the program from these six regions. The data was collected between 2005 to 2014. The workplaces joined the Smart Commute program at different points in time, as such, the data collection period spans over nine years. Table 1 and Table 2 present the descriptive statistics of these two cross-sectional datasets. While comparing the descriptive statistics, it is found that there are numerous inconsistencies in the sample frame. In the baseline survey, only 28.15% of the respondents were fulltime worker, while 68.64% in the follow-up survey worked fulltime. It is always preferable to have similar sample frames for pooled discrete choice modeling exercise so that the change in behaviour between individuals across datasets can be captured properly.

In the baseline survey, 59% of the respondents are female, whereas in the follow-up survey 61% are female. As an initial indication to auto-oriented mode choice behaviour within the study area, the baseline survey analysis shows 65.28% of the respondents use single occupancy vehicles for their daily commute. 23.16% of the respondents reported using public transit as a commuting mode and 5.31% reported using carpools. As expected, the carpool mode share increased significantly (11.46%) in the follow-up survey, whereas public transit use saw a reduction relative to the baseline. The average peak period travel cost and in vehicle travel time by carpool mode is significantly than the peak period travel cost and in vehicle travel time by transit in the after implementation survey. This could explain the considerable proportion of people shifted their travel mode from transit to carpool. It is also revealed from the descriptive statistics that most people work day time shifts in both surveys. The baseline and follow-up surveys include various stated adaptive questions which reveal various preferences of the commuters (Table 2). Based on these questions is found that flexible work hour and bus stop near workplaces would elicit commuters to consider taking transit. Moreover, cycling lane and segregated paths for walking influence people to think about walking and biking to work, whereas carpool and vanpool meeting places encourage commuters to contemplate carpool and vanpool as a commuting mode. It is found that commuters are only interested in telecommuting if their workplaces would provide them sufficient infrastructural facilities.

Unfortunately, the dataset was not ideal for the development of a discrete choice model for a number of reasons. The first reasons is due to key missing information. Missing data included household vehicle ownership and individual drivers licence ownership data, which is essential for determining modal availability. Also missing were key socio-demographic information, such as income, age, transit pass ownership, and the presence of free parking at their workplace. Finally, little to no information regarding which specific polices were implemented at a given workplace is present in the dataset. This severely limits the ability of any mode choice model to predict the cause of a behavioural shift. The second issue relates to a fundamental concern associated with before and after surveys. Even if information regarding specific TDM policies was present, the behavioural shift that occurs between the baseline and after implementation datasets may be attributed to other system changes. These changes may have nothing to do with the specific TDM policy in question (i.e. bus service increased between the commuter's home and work). To capture commuter's behaviour in response to a given set of TDM policies, it is desirable to carry out stated preference surveys rather than using stated adaptive questions. Stated preference surveys developed through an experimental design technique can more accurately capture the human behaviours in a hypothetical context without the interference of external factors. The third drawback relates to the difference in sample frame between the before and after surveys. Because there is no way to track respondents between the two surveys, any discrete choice model estimated from this data will have limited capacity to capture the impact of a specific TDM policy on an individual. As a result, there is no choice but to consider the baseline and after implementation datasets as a single cross-section. Finally, the dataset was generated by pooling a number of workplace specific surveys together. The lack of consistency between these individual work place surveys made data preparation a significant challenge. Despite these concerns, a number of workarounds aimed to maximize the information that can be gained from the dataset within a discrete choice context are presented and performed in subsequent sections.

Table 1. Descriptive Statistics of Variables

	BASELINE SURVEY				FOLLOW-UP SURVEY			
VARIABLE	Mean	Std.Dev.	Minimum	Maximum	Mean	Std.Dev.	Minimum	Maximum
GENDER (FEMALE=1, MALE=0)	0.59	0.49	0	1	0.61	0.49	0	1
EMPLOYMENT STATUS								
FULL-TIME PERMANENT	28.15%	0.45	0	1	68.64%	0.46	0	1
FULL-TIME TEMPORARY/CONTRACT	2.14%	0.14	0	1	17.44%	0.38	0	1
PART-TIME PERMANENT	2.18%	0.15	0	1	3.42%	0.18	0	1
PART-TIME TEMPORARY/CONTRACT	3.05%	0.17	0	1	0.84%	0.09	0	1
OTHER	64.48%	0.48	0	1	9.66%	0.42	0	1
NUMBER OF WORK DAYS PER WEEK								
1	0.35%	0.06	0	1	1.09%	0.10	0	1
2	0.69%	0.08	0	1	1.53%	0.12	0	1
3	1.37%	0.12	0	1	2.98%	0.17	0	1
4	3.45%	0.18	0	1	5.58%	0.23	0	1
5	63.46%	0.48	0	1	79.71%	0.40	0	1
6	0.74%	0.09	0	1	1.53%	0.12	0	1
7	0.15%	0.04	0	1	0.80%	0.09	0	1
OTHER	28.52%	0.45	0	1	6.79%	0.25	0	1
WHAT SHIFT DO YOU USUALLY WORK?								
DAY	36.56%	0.48	0	1	64.11%	0.48	0	1
AFTERNOON	2.11%	0.14	0	1	4.90%	0.22	0	1
EVENING	4.59%	0.21	0	1	3.35%	0.18	0	1
NIGHT	1.22%	0.11	0	1	1.28%	0.11	0	1
ROTATING SHIFTS	1.59%	0.13	0	1	5.56%	0.23	0	1
OTHER	53.93%				30.70%	0.46	0	1
PEAK PERIOD AUTO-DRIVE COST ($)	3.69	3.53	0	29.38	3.51	3.51	0	31.43
PEAK PERIOD AUTO-DRIVE IVTT (MIN)	25.65	18.31	0	135.82	23.67	18.29	0	170.75
AUTO PASSENGER COST ($)	1.85	1.77	0	14.69	1.75	1.75	0	15.71
AUTO PASSENGER IVTT (MIN)	25.65	18.31	0	135.82	23.67	18.29	0	170.75
TRANSIT FARE ($)	3.91	2.95	0	17.12	3.86	2.95	0	19.05
PEAK PERIOD TRANSIT IVTT (MIN)	61.14	38.71	0	250.62	53.45	38.85	0	239.47
PEAK PERIOD TRANSIT WALK TIME (MIN)	27.49	29.55	0	300.41	28.23	33.70	0	601.29
PEAK PERIOD TRANSIT WAIT TIME (MIN)	10.40	6.77	0	46.92	10.34	7.53	0	62.30
TRANSIT OVTT (MIN)	37.89	31.89	0	322.57	92.02	60.89	0	886.56
TOTAL TRANSIT TRAVEL TIME (MIN)	99.03	53.17	0	408.13	38.57	37.37	0	663.58
PEAK PERIOD CARPOOL COST ($)	1.85	1.77	0	14.69	1.75	1.75	0	15.71
PEAK PERIOD CARPOOL IVTT (MIN)	25.65	18.31	0	135.82	23.67	18.29	0	170.75
DISTANCE (ONE WAY) (KM)	16.53	14.22	0	317.29	15.88	15.21	0	325.24

Table 2. Descriptive Statistics of Stated Adaptive Questions and Mode Choice

	VARIABLE	MEAN	STD.DEV.	MIN	MAX	MEAN	STD.DEV.	MIN	MAX
DO YOU WORK COMPRESSED WORK WEEKS?	Yes	3.00%	0.17	0	1	17.17%	0.37	0	1
	No	26.49%	0.44	0	1	34.09%	0.47	0	1
	No, but I am interested in trying	11.51%	0.32	0	1	18.79%	0.39	0	1
	Not Applicable	59.00%	0.49	0	1	29.95%	0.46	0	1
HOW DO YOU USUALLY COMMUTE TO WORK?	Vanpool (employee subsidized vehicle)	0.07%	0.025	0	1	0.18%	0.042	0	1
	Drive alone (including motorcycle)	65.28%	0.48	0	1	64.11%	0.47	0	1
	Carpool	5.31%	0.22	0	1	11.46%	0.31	0	1
	Public transit	23.16%	0.42	0	1	15.99%	0.36	0	1
	Bicycle	1.12%	0.11	0	1	1.41%	0.11	0	1
	Walk	2.48%	0.16	0	1	3.83%	0.19	0	1
	Get dropped off	2.58%	0.16	0	1	3.03%	0.17	0	1
IF AND WHEN YOU TAKE TRANSIT TO WORK, WHICH TRANSIT SYSTEM(S) DO YOU USE? (CHECK ALL THAT APPLY.)	GO Transit bus	0.04	0.19	0	1	0.03	0.16	0	1
	GO Transit train	0.03	0.16	0	1	0.03	0.16	0	1
	TTC Subway (Toronto Transit Commission)	0.11	0.31	0	1	0.08	0.27	0	1
	TTC Bus/Streetcar (TTC)	0.10	0.31	0	1	0.06	0.24	0	1
	YRT/VIVA (York Region Transit)	0.03	0.17	0	1	0.03	0.16	0	1
	DRT (Durham Region Transit)	0.00	0.04	0	1	0.01	0.08	0	1
	Mississauga Transit	0.02	0.14	0	1	0.04	0.20	0	1
	Brampton Transit / Züm	0.01	0.09	0	1	0.02	0.13	0	1
	Oakville Transit	0.00	0.04	0	1	0.01	0.07	0	1
	Burlington Transit	0.00	0.06	0	1	0.00	0.07	0	1
	HSR (Hamilton Street Railway Company)	0.02	0.15	0	1	0.01	0.11	0	1
	VIA Rail	0.00	0.03	0	1	0.00	0.02	0	1
	Don't know / Other	0.00	0.00	0	0	0.01	0.10	0	1
WHICH OF THE FOLLOWING WOULD ENCOURAGE YOU TO USE PUBLIC TRANSIT? (CHOOSE UP TO THREE)	Discounted transit pass	0.13	0.34	0	1	0.20	0.40	0	1
	Eliminating double fares	0.18	0.38	0	1	0.18	0.38	0	1
	Incentive in monthly passes	0.14	0.35	0	1	0.21	0.40	0	1
	Transit info and advice at my workplace	0.08	0.28	0	1	0.08	0.28	0	1
	Bus stop at work	0.18	0.39	0	1	0.23	0.42	0	1
	More flexible working arrangements	0.21	0.41	0	1	0.22	0.41	0	1
	A free ride home in case of emergency	0.19	0.39	0	1	0.22	0.41	0	1
	If I no longer need my car for work	0.16	0.37	0	1	0.21	0.41	0	1
	I already take transit	0.17	0.37	0	1	0.15	0.36	0	1
WHICH OF THE FOLLOWING WOULD ENCOURAGE YOU TO CHOOSE WALKING OR CYCLING? (CHOOSE UP TO THREE)	Shower and locker facilities at work	0.19	0.39	0	1	0.19	0.39	0	1
	Secure or sheltered bicycle parking at work	0.19	0.39	0	1	0.15	0.36	0	1
	Cycling lanes and pedestrian paths	0.24	0.43	0	1	0.22	0.42	0	1
	Relaxed dress code at work	0.14	0.35	0	1	0.14	0.35	0	1
	Route advice and maps	0.08	0.27	0	1	0.05	0.21	0	1
	Financial incentives	0.07	0.25	0	1	0.14	0.35	0	1
	Training on how to ride a bike safely	0.04	0.20	0	1	0.04	0.21	0	1
	More flexible working arrangements	0.11	0.31	0	1	0.11	0.31	0	1
	A free ride home in case of emergency	0.11	0.32	0	1	0.14	0.35	0	1
	If I no longer need my car for work	0.08	0.28	0	1	0.11	0.31	0	1
	Distance is too great to walk or cycle	0.32	0.47	0	1	0.39	0.49	0	1
	I already cycle	0.09	0.29	0	1	0.04	0.21	0	1
	I already walk	0.05	0.21	0	1	0.05	0.23	0	1
WHICH OF THE FOLLOWING WOULD ENCOURAGE YOU TO CARPOOL OR VANPOOL? (CHOOSE UP TO THREE)	A vanpool meeting place near my home	0.47	0.50	0	1	0.34	0.48	0	1
	Regulations set in place prior to vanpooling	0.17	0.38	0	1	0.13	0.34	0	1
	More matches for carpooling train station	0.21	0.41	0	1	0.28	0.45	0	1
	Having a car available for meetings	0.32	0.47	0	1	0.13	0.34	0	1
	Employer organized vanpools matching	0.26	0.44	0	1	0.31	0.46	0	1
	I will never carpool	0.23	0.42	0	1	0.21	0.41	0	1
	Other	0.15	0.35	0	1	0.23	0.42	0	1
	Need more information please	0.10	0.30	0	1	0.15	0.36	0	1
	Already registered	0.11	0.31	0	1	0.12	0.33	0	1
WHICH OF THE FOLLOWING WOULD ENCOURAGE YOU TO TELEWORK? (CHOOSE UP TO THREE)	Access to email from home	0.09	0.28	0	1	0.37	0.48	0	1
	Access to voicemail from home	0.13	0.34	0	1	0.19	0.39	0	1
	Satellite offices	0.22	0.41	0	1	0.29	0.46	0	1
	Within 2-5 years	0.04	0.20	0	1	0.11	0.31	0	1
	My job is not suitable for telework	0.19	0.39	0	1	0.52	0.50	0	1
	I will never telework	0.10	0.30	0	1	0.10	0.25	0	1

Model Formulation

In order to address the limitations associated with this dataset, this paper presents two novel approaches. The first approach addresses the missing data regarding modal availability and the second provides a link between the baseline and follow-up datasets.

As discussed above, the dataset is missing crucial socio-demographic values at the individual and household level; namely if the commuter has a driver's license and automobile ownership at the household. These values are crucial in traditional mode choice models for determining the availability of the auto drive alone mode (individuals must have both a driver's license and a vehicle at their home to be able to drive). In order to avoid the incorrect results that would result from estimating a model which assumes the drive alone mode is available for all commuters, a work around is presented and applied. This work around utilizes the vehicle availability rules present in a much larger and more complete dataset, the transportation tomorrow survey to gain the aggregate availability statistics across the population (Data Management Group, 2011). Next, two separate probabilities for each feasible mode are calculated; one assuming the auto driver mode is available, and one assuming it is not available. It should be noted that these probabilities are calculated using the same utilities and the probability of selecting the auto drive alone mode if it is not available is obviously zero. Finally, the probability of any given mode being selected is equal to the product of the probability of selecting a mode given auto driver is available times the aggregate probability that it is available plus the probability of selecting that same mode given that auto driver is not available times the aggregate probability that auto driver is not available. An outline of this discussion is presented in Figure 1. Also worth noting:

- The carpool and the auto passenger modes were considered available across the dataset.
- Two 15 and 5 kilometer straight line distance thresholds between home and work were considered for biking and walking availability respectively.
- A 3-hour transit travel time threshold was used for transit availability.

While a novel approach for addressing the issue of missing information in a dataset, the authors strongly caution against using this approach as a substitute for using appropriate data when and where available. While certainly an improvement over simply assuming all commuters have this mode available, the results will still produce incorrect estimates at an individual level. Specifically, an individual without the auto drive alternative in their choice set will still have a non-zero probability of selecting the auto driver mode, which is fundamentally incorrect.

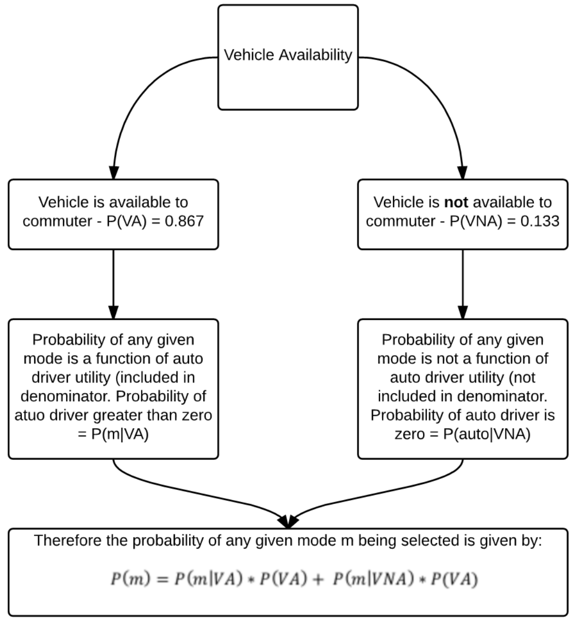

Figure 1. Integrating vehicle availability into a MNL framework

The second main novelty of the work presented herein relates to the use of a scale to account for the differences between the baseline and follow-up datasets used in the analysis. As discussed in chapter 3.2 of Kenneth Train's seminal work (Train, 2009), it can be expected that the variance of unobserved factors/error term to be different across different segments of the population or different populations. This difference can be accounted for by normalizing the variance of the error term to one for one segment/group and then estimating the "scale parameter" for the second portion. In the case of the model presented below the before dataset had the variance normalized to one and the after implementation dataset had its scale as a function of a parameter to be estimated. As a result of taking this pooled modelling approach, it is possible to estimate a single metric, such as value of travel time savings, across both samples, while still recognizing the implicit differences between the two datasets. Furthermore, it is possible to further parameterize the scale using the stated adaptation questions present in the dataset, further capturing difference in variance in the dataset.

Econometric Investigation on the Pooled Data

After numerous trials with various variables the final model was estimated and tabulated in Table 3. The log-likelihood value for the pooled model is -9830.21, which is compared to the log-likelihood value of the null-model. The rho-square value against the null is 0.411, which is a reasonable fit against the null-model. All travel time, cost and distance variables are statistically significant at 95 percent confidence interval (1.96) and showing intuitive sign. The value of time (VOT) for Auto-Drive mode is 5.68$/hour, which is fairly reasonable and matches with other similar studies (Habib, 2014; Hasnine et. al., 2016). VOT for transit is 3.82$/hour, which means that the transit travel time is less sensitive than auto-drive travel time. This result also implies that individual will derive a net benefit of 1.86$/hour by switching from auto-drive to transit (Truong & Hensher, 1985).

Table 3. Mode Choice Model Using Pooled Data

Log Likelihood of Full Model	-9830.21		
Log Likelihood of Null Model	-16680.79		
Rho-square value against Null Model	0.411		
Number of Observations	10335		
Coefficient Description	**Parameter Estimate**	**Standard Error**	**T-Statistic**
Alternative Specific Constant Drive	3.2434	0.0785	41.296
Alternative Specific Constant Car/Van pool	0.1672	0.0905	1.847
Alternative Specific Constant Transit	2.2448	0.0973	23.068
Alternative Specific Constant Bike	0.4349	0.1792	2.427
Alternative Specific Constant Walk	4.2894	0.1542	27.824
Travel Cost	-0.1774	0.012	-14.76
Drive Travel Time	-0.0168	0.0027	-6.177
Transit Time (includes Walk, Wait and in Vehicle Times)	-0.0113	0.0013	-8.788
Straight Line Distance (Bike Mode)	-0.2571	0.0265	-9.697
Straight Line Distance (Walk Mode)	-1.4422	0.0767	-18.791
After Implementation Scale parameter*	-0.0951	0.0254	-3.74
Scale Dummy for unwillingness to carpool or vanpool (after implementation Data only)	0.8079	0.1325	6.099

**Scale* = exp(0) *for before and* exp(-0.0951 + 0.8079*if(unwilling to carpool)) *for after*

The fact that the scale for the after implementation case results in lower parameter values relative to the baseline suggests that unobserved factors, such as the TDM strategies that were implemented between the two data collection projects have a much more significant impact on individuals' travel preference than the time and cost variables which were included in the model. This is a highly intuitive and encouraging result. Ideally, a more robust data collection exercise, which captures the specific policies implemented between the two data collection projects should be undertaken in order to understand the source of this variance. Furthermore, the unwillingness to carpool dummy variable included in the scale for the after case has a positive value, suggesting lower heteroskedasticity relative to those who are willing to consider carpooling. This is again intuitive, as individuals who are unwilling to consider TDM strategies such as carpooling are likely more concerned about travel time and cost in their commute and are not swayed by the unobserved TDM policies that individuals open to carpooling may consider. In light of this finding, other dummies for unwillingness to engage in alternative modes were tested, however the dummy for unwillingness to carpool was the only one to be significant.

Conclusions

This paper presents a framework and the application of a two cross-sectional datasets for the evaluation of TDM strategies. The paper mainly introduces two novel approaches. First, this paper suggests an alternative approach of tackling missing information regarding vehicle availability which provides modest improvements over the naïve approach of assuming vehicles are available for all individuals. Second, the paper uses a scale to account for the differences between the baseline and follow-up datasets used in the analysis which captures heteroskedasticity. Through the use of scale to capture heteroskedasticity, the proposed model formulation provides insight into the hidden effectiveness of the TDM strategies, without having explicit information regarding the specific policies that were implemented. The results of the pooled mode choice models provide valuable insights into how commuters can incentivise to use active modes of travel and discourage single occupancy vehicle commuting trips. All the variables in the pooled model show correct signs and are statistically significant. The VOT of taking transit is lower than the VOT of driving which is an intuitive and expected result.

The major limitation of this study is the lack of adequate data for the given modelling exercise. The data inconsistency is a challenge and an opportunity for estimating advanced models such as the generalized extreme value model and more interestingly, the mixed random parameter logit models. The lack of information regarding socio demographic variables within the data may be accounted for using a mixed random parameter logit to capture preference variation across the population normally captured using socio demographics. Furthermore, the lack of adequate TDM strategy sensitive variables is a hindrance to quantifying the specific effect of various TDM strategies. Finally, the datasets only contain commuter based TDM strategies, but the model could be expanded to test home-based strategies, if home based TDM variables available.

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