An Evaluation of the Ridership Impacts of the VIVA Bus Transit System

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ABSTRACT
The Regional Municipality of York, north of the City of Toronto, introduced a new bus service known as VIVA in 2005. This distinctly branded system operates primarily in two highly-traveled corridors and features high operating speeds, offline fare payment, advanced traveler information systems, and other ITS technologies. Although this new service has been deemed a success by many, it remains to be seen to what degree transit use was affected by its introduction. To evaluate this, home-based work and post-secondary school GEV-class discrete chioce models are estimated. In the work trip model, two mode choice nests were identified: Auto (comprising auto driver and auto passenger) and Root (comprising all other modes). It was found that auto trips were more easily predictable than transit trips and that there is an appreciable difference in the heteroskedasticity of choice between occupation groups. No nesting structure for post-secondary trips was statistically identifiable. Improvements in transit service were found to have a greater impact on transit mode share than increases in congestion for both work and post-secondary school trips. It is also concluded that transit improvements played a relatively small role in the considerable shift to transit amongst post-secondary students. It is posited that VIVA attributes such as improved branding, advertising, and communications may have caused this change in preferences.

INTRODUCTION

The Regional Municipality of York, north of the City of Toronto, introduced a new, privately operated bus service known as VIVA in 2005. This distinctly branded system operates primarily in two highly-traveled corridors and features high operating speeds, offline fare payment, advanced traveler information systems, and other ITS technologies. Although this new service has been deemed a success by many, it remains to be seen to what degree transit use was affected by its introduction. Indeed, transit mode share has increased in York Region between 2001 and 2006, but it is not clear if improvements to transit levels of service are the source of this increase. In a rapidly growing suburban area like York, it is possible that increasing auto use has been exacerbated by increased traffic congestion. Using revealed preference survey data collected before and after the implementation of VIVA, this paper attempts to evaluate the extent to which the introduction of VIVA and increased traffic congestion have influenced transit mode share in York Region.

LITERATURE REVIEW

There are relatively few available examples in the literature of *ex post* (ie. after implementation) evaluations of the ridership impacts of new transit systems.

Lleras (*1*) conducted a study of the ridership impacts of the Transmilenio system in Bogota, Columbia. To assess the choice between Transmilenio and conventional bus service, a revealed preference survey was designed and performed in order to construct a discrete choice model. It was found that the value of time on Transmilenio was lower than on the traditional system; that is, users were willing to pay more to save time in the traditional system than on the Transmilenio, showing that BRT was the less “painful” alternative. It was also shown that although Transmilenio was favoured over traditional service, this advantage diminished as distance to the trunk line increased. Finally, it was shown that Transmilenio seemed to have the greatest impact on lower income groups, but that the value of travel time savings was lowered regardless of demographic group.

Another source of evaluation literature consists of a group of similar evaluative papers written as part of the United States’ Federal Transit Administration (FTA) Bus Rapid Transit Initiative (*2*) (*3*) (*4*). In general, these evaluations were fairly qualitative in nature; however, some of the evaluations employed surveys of current riders of the system. For example, the evaluation of Phase 2 of Boston’s Silver Line BRT (*5*) surveyed roughly 8000 commuters to determine their mode choice behaviour prior to the implementation of the Silver Line. Roughly 85% were previous transit users, while the remaining 15% were diverted from other modes or were “new” trip makers. Less than 2% of respondents claimed to be former single-occupancy vehicle drivers.

In another study, Chapleau, Lavigueur, and Baass (*6*), evaluated the extension of Line 1 of the Montreal Metro by conducting computer simulations of transit demand before and after the extension. It was found that although system-wide transit mode split remained constant, increases were observable near the extensions within 1.6km of the metro line. The effects of the extension were also simulated using travel demand software. Significant time savings were observed, notably in the areas to which the metro was expanded. Finally, a small savings in bus vehicle-hours was observed; however, this was largely offset by the increase in metro vehicle-hours.

To our knowledge, there is no published research that uses revealed preference data from before and after the implementation of a new transit system to assess its impact on ridership.

OVERVIEW OF YORK REGION AND VIVA

York Region is a municipality of roughly one million residents located in central Ontario, abutting the City of Toronto to the North. The municipality has experienced extremely high growth in population and commercial activity since its creation in the 1970's. This growth has manifested itself in a way typical of North American suburban development in the latter half of the 20th century; residential density is low in comparison to its neighbour to the south, Toronto, and land use is generally designed to cater to the use of the automobile. This, among other factors, has resulted in low transit use.

In an effort to increase transit use, York and its private sector partners developed the York Rapid Transit Plan (YRTP) in 2002. The first phase of this plan prescribed the introduction of a new bus system known as VIVA. Opened in 2005, VIVA consists of five colour-coded lines that run at headways of 5 to 15 minutes 20 hours a day. Four of these lines connect to Toronto's subway system, while the fifth runs an East-West path across the Region. Although the buses run in mixed traffic, several features of the system (high station spacing, transit signal priority, and queue jump lanes for example) ensure operating speeds are higher on VIVA than on local buses. Additionally, fares are completely integrated with York Region Transit's local bus network, greatly simplifying transfers between the two systems.

Information about mode choice in York Region was gathered from before and after VIVA's introduction by performing various queries of the Greater Toronto and Hamilton Area's (GTHA) Transportation Tomorrow Survey (TTS). The TTS is a revealed preference survey that randomly samples 5% of the GTHA every 5 years; the last two surveys occurred before (2001) and after (2006) the introduction of VIVA. This exercise showed that a large majority (roughly 75%) of the increase in transit trips could be attributed to home-based work and post-secondary school trips. Post-secondary school trips were particularly important, accounting for 35% of the transit trip increase despite making up less than 4% of the total number of trips. Figure 1 and Figure 2 present the 24-hour mode split amongst York Region residents for home-based work and home-based post-secondary school trips, respectively.

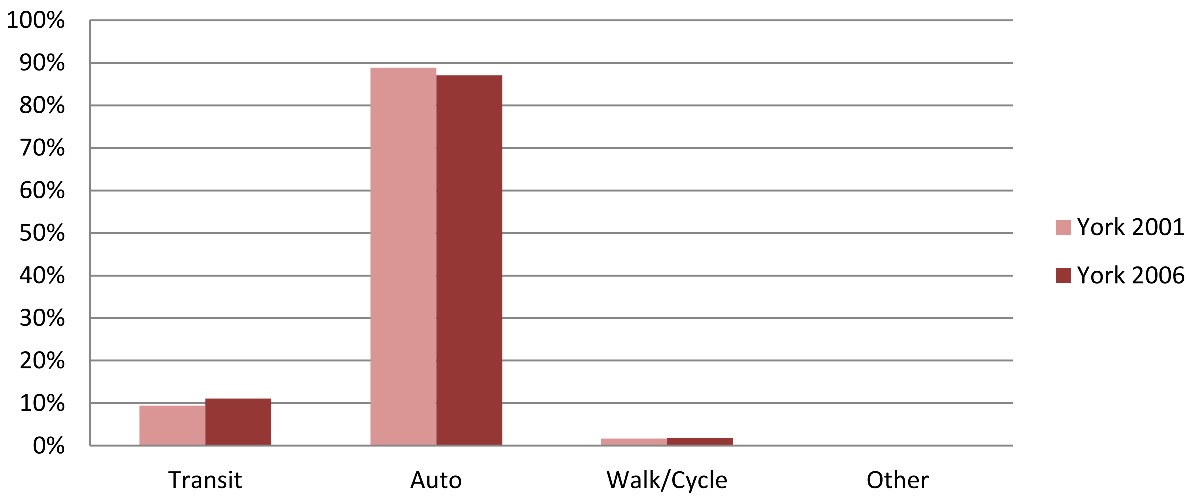

FIGURE 1 Mode Split – York Region Home-Based Work Trips.

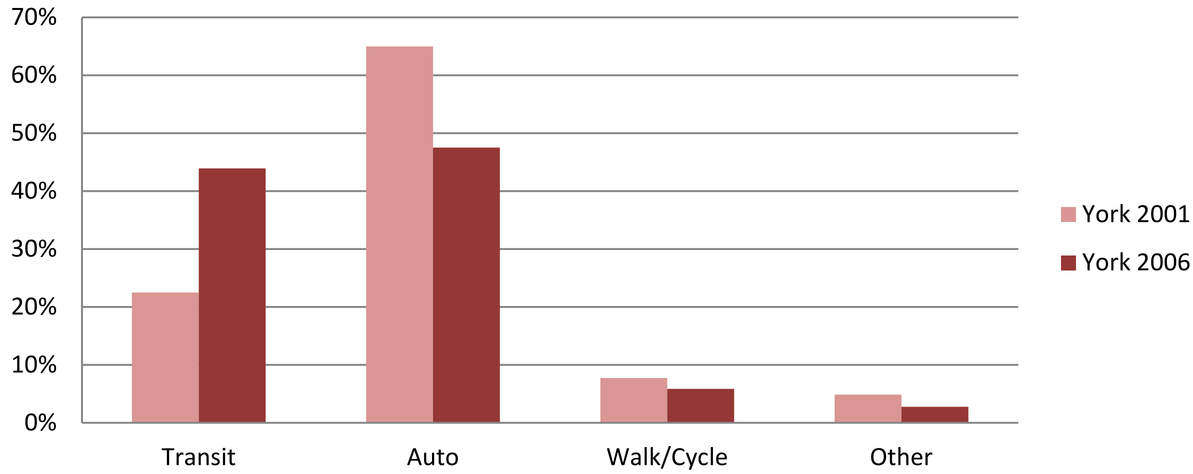

FIGURE 2 Mode Split – York Region Home-Based Post-Secondary School Trips.

Figure 1 shows a slight increase in work trip transit mode share from 2001 to 2006, largely at the expense of auto trips. In contrast, Figure 2 shows that post-secondary school transit mode share doubled from 22% to 44%. This is a very considerable increase and clearly represents a fundamental change in travel behaviour amongst post-secondary students. What is not clear from these graphs, however, is the reason for these changes. The remainder of this paper attempts to determine this reason by constructing discrete choice models of home-based work and post-secondary school trips.

MODEL FORMULATION

The mode choice model used for this analysis is based on a model developed by Habib and Swait (7). Briefly stated, the goal of the formulation is to introduce choice heterogeneity into a model that allows for general dependence amongst alternatives. In most mode choice models, individuals are assumed to value the parameters of mode choice the same; however, it is fair to assume that these parameters may be a function of some attribute of the individual. Furthermore, in standard logit models, choices are assumed to be independent of each other; however, this is often not the case in reality. To address both these concerns, this analysis employs a generalized extreme value (GEV) model that parameterizes the scale parameter as a function of occupation.

Consider a GEV model with random utility component ε_{in} for individual *i* and mode *n* and a cumulative distribution function of:

$$F(\varepsilon_{i1}, \varepsilon_{i2}, \dots, \varepsilon_{i3}) = \exp(-G(e^{-\varepsilon_{in}\mu_{in}})) \tag{1}$$

The marginal distribution of any random element ε_{in} is thus:

$$F(\varepsilon_{in}) = F(\infty, \dots, \varepsilon_{in}, \dots, \infty) = \exp\left(-G(0, \dots, e^{-\varepsilon_{in}\mu_{in}}, \dots, 0)\right) = \exp(-a_m e^{-\varepsilon_{in}\mu_{in}}) \tag{2}$$

where $a_m = G(\delta_{1n,}\delta_{2n,} \dots, \delta_{Jn})$; $\delta_{1n} = 1$ if *i*=*m*, 0 otherwise. From this, we can derive the probability of individual *i* choosing mode *n* as:

$$P_{im} = e^{V_{in}\mu_{in}} G_n(e^{V_{in}\mu_{in}})/G(e^{V_{in}\mu_{in}}) \tag{3}$$

To obtain the function *G*, we need to assume a choice structure. Following the work of Habib and Swait, the choice structure for this model follows what is illustrated in Figure 3. Each choice cluster has a separate scale parameter μ, as indicated on the graph.

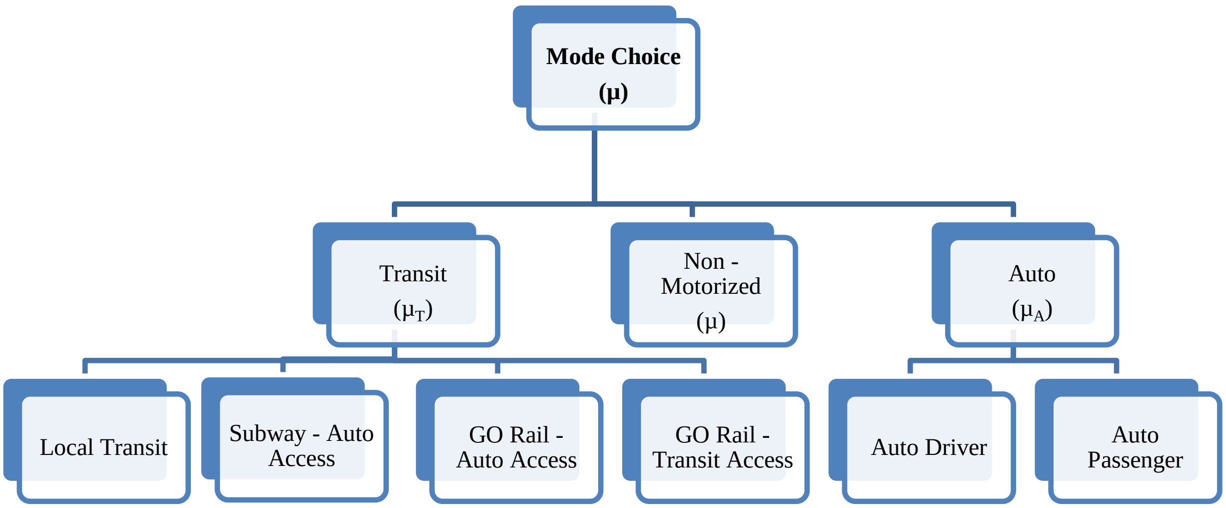

FIGURE 3 Model Mode Choice Structure

The choice structure above leads to the following generating function:

$$G_i = \left(\sum_{n=AD,AP} e^{V_{in}\mu_A}\right)^{\mu/\mu_A} + \left(\sum_{n=LT,SAA,GAA,GTA} e^{V_{in}\mu_T}\right)^{\mu/\mu_T} + e^{V_{i(NMT)}\mu} \quad (4)$$

The non-motorized cluster has same value as the root; that is, we identify the auto and transit scale parameters *relative* to the non-motorized scale parameter.

In order to isolate the effects of heterogeneity, this model parameterizes the scale parameter as a function of occupation category. We express the scale for mode cluster *c* and individual *i* as:

$$\mu_{ic} = \exp(\boldsymbol{\theta_k}\boldsymbol{\varphi_k})\ all\ i, c \quad (5)$$

where $\boldsymbol{\varphi_k}$ is a vector of zeroes except element *k*, which is equal to 1 if individual *i* has job occupation category *k*. $\boldsymbol{\theta_k}$ is the vector of estimation parameters for all *k* job categories. By parameterizing scale in this way, it is possible to assess which professions are more likely to have a high degree of variance in their choice preferences. Since the scale parameter is inversely proportional to the standard error of the random utility components, we can conclude that higher values of scale indicate a lower degree of choice variability. Note that the exponentiation of the scale parameter guarantees a positive value, which is an assumption of GEV-class models.

We can now express the model using the following conditional probability equations. Here, the commuter subscript *i* is omitted for clarity.

Construct Nodes:

$$Q_{NMT} = \frac{\exp(\mu I_{NMT})}{\exp(\mu I_{NMT}) + \exp(\mu I_A) + \exp(\mu I_T)} \tag{6}$$

$$Q_A = \frac{\exp(\mu I_A)}{\exp(\mu I_{NMT}) + \exp(\mu I_A) + \exp(\mu I_T)} \tag{7}$$

$$Q_T = \frac{\exp(\mu I_T)}{\exp(\mu I_{NMT}) + \exp(\mu I_A) + \exp(\mu I_T)} \tag{8}$$

Inclusive Values:

$$I_{NMT} = \frac{1}{\mu}\ln(\exp(\mu V_{NMT})) = V_{NMT} \tag{9}$$

$$I_A = \frac{1}{\mu_A}\ln(\exp(\mu_A V_{AD}) + \exp(\mu_A V_{AP})) \tag{10}$$

$$I_T = \frac{1}{\mu_T}\ln(\exp(\mu_T V_{LT}) + \exp(\mu_T V_{SAA}) + \exp(\mu_T V_{GAA}) + \exp(\mu_T V_{GTA})) \tag{11}$$

Elemental Alternatives:

$$P_{NMT|NMT} = 1 \tag{12}$$

$$P_{AD|A} = \frac{\exp(\mu_A V_{AD})}{\exp(\mu_A V_{AD}) + \exp(\mu_A V_{AP})} \tag{13}$$

$$P_{AP|A} = \frac{\exp(\mu_A V_{AP})}{\exp(\mu_A V_{AD}) + \exp(\mu_A V_{AP})} \tag{14}$$

$$P_{LT|T} = \frac{\exp(\mu_T V_{LT})}{\exp(\mu_T V_{LT}) + \exp(\mu_T V_{SAA}) + \exp(\mu_T V_{GAA}) + \exp(\mu_T V_{GTA})} \tag{15}$$

$$P_{SAA|T} = \frac{\exp(\mu_T V_{SAA})}{\exp(\mu_T V_{LT}) + \exp(\mu_T V_{SAA}) + \exp(\mu_T V_{GAA}) + \exp(\mu_T V_{GTA})} \tag{16}$$

$$P_{GAA|T} = \frac{\exp(\mu_T V_{GAA})}{\exp(\mu_T V_{LT}) + \exp(\mu_T V_{SAA}) + \exp(\mu_T V_{GAA}) + \exp(\mu_T V_{GTA})} \tag{17}$$

$$P_{GTA|T} = \frac{\exp(\mu_T V_{GTA})}{\exp(\mu_T V_{LT}) + \exp(\mu_T V_{SAA}) + \exp(\mu_T V_{GAA}) + \exp(\mu_T V_{GTA})} \tag{18}$$

Unconditional Mode Choice Probabilities:

$$P_{NMT} = P_{NMT|NMT} \cdot Q_{NMT} = Q_{NMT} \tag{19}$$

$$P_{AD} = P_{AD|A} \cdot Q_A \tag{20}$$

$$P_{AP} = P_{AP|A} \cdot Q_A \tag{21}$$

$$P_{LT} = P_{LT|T} \cdot Q_T \tag{22}$$

$$P_{SAA} = P_{SAA|T} \cdot Q_T \tag{23}$$

$$P_{GAA} = P_{GAA|T} \cdot Q_T \tag{24}$$

$$P_{GTA} = P_{GTA|T} \cdot Q_T \tag{25}$$

In the preceding expressions, the systematic utilities are linear-in-the-parameters:

$$V_n = \boldsymbol{\beta}'\boldsymbol{X_n} \tag{26}$$

RESULTS

As previously described, the increase in transit trips observed in York Region was largely due to increases in the number of post-secondary school and work trips being made by transit. ned in the model formulation.

Table 1, Table 2, Table 3 and Table 4 present the results of the model estimation process for these two trip types. In all tables, the number in parentheses below the parameter denotes the t-statistic. Bold type denotes parameters not significant at a 95% level of confidence.

Validation

Home-Based Work Model

We first note the high value of the rho-squared statistic; this indicates that a good degree of choice information is explained by the model. Furthermore, by calculating the difference between the rho-squared statistic for this model and the market share model, we note that the model explains roughly 17% more information that the market share model. Finally, the likelihood ratio statistics show that the model is a statistically better model than both the null and market share models to a very high level of confidence.

With respect to the structure of the model, the scale parameter function parameters in Table 2 indicate that only two mode clusters were found to be statistically different in their choice behaviour: an “Auto” nest—consisting of the auto driver and passenger modes—and the “Root” nest—consisting of all transit modes and the non-motorized mode. In other words, it was not possible to isolate a “transit nest” as defined in the model formulation.

TABLE 1 2006 HBW Model Estimation – Systematic Utility Functions

	Auto Driver	Auto Passenger	Local Transit Walk Access	Subway P&R	GO Rail Transit Access	GO Rail P&R	Non-motorized
ASC	8.4613 (108.400)	5.8076 (74.847)	8.3820 (93.830)	7.7358 (74.168)	9.4636 (91.563)	-	1.9208 (21.266)
IVTT	-0.0209 (-27.280)	-0.0209 (-27.280)	-0.0209 (-27.280)	-0.0209 (-27.280)	-0.0209 (-27.280)	-0.0209 (-27.280)	-
Travel Cost	-0.1504 (-33.189)	-0.1504 (-33.189)	-0.1504 (-33.189)	-0.1504 (-33.189)	-0.1504 (-33.189)	-0.1504 (-33.189)	-
Walk Time	-	-	-0.0435 (-27.640)	-0.0435 (-27.640)	-0.0435 (-27.640)	-0.0435 (-27.640)	-
Wait Time	-	-	-0.0902 (-32.241)	-0.0902 (-32.241)	-0.0902 (-32.241)	-0.0902 (-32.241)	-
nveh=1	-	1.5797 (31.557)	-	-	-	-	-
nveh=2	1.8429 (72.054)	-	-	-	-	-	-
nveh>2	2.2771 (80.727)	-	-	-	-	-	-
nveh>=2	-	2.2801 (40.215)	-	-	-	-	-
nveh	-	-	-	1.3170 (36.152)	-	4.6722 (94.490)	-
tripdist<1	-	-	-	-	-	-	7.8621 (75.213)
1<=tripdist<2	-	-	-	-	-	-	5.7669 (64.771)
2<=tripdist<3	-	-	-	-	-	-	3.5914 (37.472)
Male Dummy	-	-0.8191 (-67.393)	-0.6062 (-24.498)	-0.3549 (-6.713)	-	1.7990 (22.356)	-0.4084 (8.866)
Age<=25 Dummy	-	1.4732 (77.034)	1.3880 (37.998)	-	1.3880 (37.998)	-	1.6017 (23.995)
25<Age<=30 Dummy	-	0.1956 (9.583)	0.5170 (13.592)	-0.4949 (-6.591)	0.5170 (13.592)	-0.4949 (-6.591)	-0.1671 (-1.779)
Age>55 Dummy	-	-	-	-0.3749 (-4.733)	-	-0.3749 (-4.733)	0.1762 (2.781)
Metropass Dummy	-	-	3.2658 (75.260)	3.2658 (75.260)	-	-	-
Other Pass Dummy	-	-	4.0214 (58.932)	4.0214 (58.932)	-	-	-
GO Pass Dummy	-	-	-	-	2.5120 (33.731)	2.5120 (33.731)	-

TABLE 2 2006 HBW Model Estimation – Scale Parameter Functions

	Auto		Root	
	θ	μ	θ	μ
Retail, Sales and Service Dummy	0.0918 (11.190)	1.09614557	-0.1757 (-18.829)	0.8388696
General Office/Clerical Dummy	0.1265 (13.374)	1.13484945	-0.2507 (-26.157)	0.7782558
Professional Dummy	0.2775 (35.260)	1.31982612	-0.1674 (-19.376)	0.8458612

TABLE 3 2006 HB Post-Secondary School Model Estimation

	Drive Alone	Auto Passenger	Local Transit Walk Access	Subway P&R	GO Rail Transit Access	GO Rail P&R	Non-motorized
ASC	5.5587 (32.883)	**-5.1531 (-1.313)**	6.0051 (31.686)	5.3497 (22.630)	-	-	3.2361 (15.815)
IVTT	-0.0088 (-7.371)	-0.0088 (-7.371)	-0.0088 (-7.371)	-0.0088 (-7.371)	-0.0088 (-7.371)	-0.0088 (-7.371)	-
Travel Cost	-0.1776 (-22.012)	-0.1776 (-22.012)	-0.1776 (-22.012)	-0.1776 (-22.012)	-0.1776 (-22.012)	-0.1776 (-22.012)	-
Walk Time	-	-	-0.0217 (-8.228)	-0.0217 (-8.228)	-0.0217 (-8.228)	-0.0217 (-8.228)	-
Wait Time	-	-	-	-	-	-	-
nveh=1	-	8.2641 (2.109)	-	-	-	-	-
nveh=2	1.8698 (25.054)	-	-	-	-	-	-
nveh>2	3.3541 (42.730)	-	-	-	-	-	-
nveh>=2	-	9.0002 (2.297)	-	-	-	-	-
nveh	-	-	-	0.9509 (21.155)	-	0.7351 (9.131)	-
tripdist<1	-	-	-	-	-	-	6.2799 (35.816)
1<=tripdist<2	-	-	-	-	-	-	3.9107 (33.544)
2<=tripdist<3	-	-	-	-	-	-	2.5304 (20.064)
Male Dummy	-	**-0.0737 (-1.587)**	-0.1746 (-3.561)	**-0.1376 (-1.632)**	-0.6669 (-3.783)	**0.3479 (1.614)**	0.3112 (3.760)
Age<=23 Dummy	-	3.6754 (27.400)	2.5816 (28.418)	1.8628 (11.307)	10.9768 (49.172)	7.1798 (22.829)	0.6371 (4.700)
23<Age<=28 Dummy	-	2.4755 (16.430)	1.5741 (14.415)	0.6329 (3.138)	11.0483 (29.342)	7.6201 (15.677)	-1.5920 (-3.626)

TABLE 4 Goodness of Fit Statistics

	Home-Based Work	Home-Based Post-Secondary School
No. of Observations	19862	1046
No. of Cases	384564	20548
L(Null)	-429635	-23298
L(Share)	-216614	-23012
L(β)	-144451	-16957
ρ^2	0.663781	0.272171
ρ^2_{Share}	0.495819	0.012268
No. of parameters	42	35
Adj. ρ^2	0.663744	0.270929
Likelihood Ratio (Null)	570367.064	12682.267
Likelihood Ratio (Share)	144325.064	12110.621

The parameters estimated for the work model are, for the most part, logical in their magnitude and sign. Starting with the alternative specific constants (labelled ASC), we note that they are fairly large in magnitude, but not so much that the model should be rejected. Rather, their magnitude is likely an indication that there is a determinant of mode choice that is absent from the model. It could be hypothesized that the inclusion of an income parameter might have a sizeable effect on the magnitude of the constants, but this data is not available to be modelled. The ASC parameter values for GO transit local and auto access are not listed; the former is the reference mode and cannot be identified while the latter returned an insignificant t-statistic. We observe that individuals find in-vehicle travel time (labelled IVTT) to be the least burdensome component of travel time, while wait time is found to be the most burdensome. This is consistent with past models of mode choice in the GTA (*8*). Variables relating to the number of household vehicles are specific to modes that require an automobile. For the Auto Driver mode, the dummy variable nveh=1 is the reference case (since nveh=0 is impossible for this mode); for Auto Passenger, nveh=0 is the reference case. For both modes, we observed that as the number of household vehicles increases, the utility of the mode increases. For the auto access to transit modes, the number of vehicles is entered as a standard alternative specific variable; it is interesting to note that the number of vehicles has a larger impact on the utility of GO Rail Park and Ride than on Subway Park and Ride. The trip distance variables (labelled tripdist) are specific to the Non-Motorized mode. The transformation of this quantity into dummy variables can be justified by noting its non-linear nature. We do not expect there to be a linear relationship between trip distance and the utility of walking or cycling; rather, we expect the utility to drop for trips longer than a comfortable walking/cycling distance. This is shown by the parameter values in the model. The male dummy variable parameters are measured relative to the Auto Driver mode. Although this explains the negativity of the Auto Passenger parameter, it is not entirely clear why it is more negative than the local transit parameter value. For the age dummy variables, the general trend is one of decreasing utility with increasing age for transit and non-motorized modes. This is intuitive given the general upward trend in income as age increases. Although this trend is not always present, any deviation from it can likely be explained by instances of a low number of observations. Finally, the transit pass dummy variables proved to be highly significant components of the utilities of transit modes. It could be argued that the inclusion of this variable is somewhat redundant since it seems likely that if an individual possesses a transit pass, they will take transit. However, not every individual with a transit pass will use it for a work trip and therefore these variables were left in the model.

The scale parameters listed in Table 2 can be compared across two dimensions. We can first compare them amongst occupation categories, thus illustrating choice heterogeneity across different population segments. There are 4 categories defined by the TTS: Retail/Sales/Service, General Office/Clerical, Professional, and Manufacturing/Trades/Construction (the reference case). All scale parameter values are measured relative to the reference case, which has an assumed value of 1. This defines a simple multinomial logit model for that occupation category. We observe that, in the “Auto” nest, the scale parameter values are all greater than one. Therefore, for this nest, we can conclude that the occupation categories listed are more predictable than the reference case. However, in the transit nest, the listed occupations have a lower scale and therefore lower variability than the reference case. The general trend observed among occupation categories is that choice predictability tends to increase with the “regularity” or “stability” of the occupation. For example, the Professional category has a consistently high scale parameter relative to the other occupations. Professionals tend to work at predictable locations at predictable hours, making their mode choices more predictable. By contrast, the Retail/Sales/Servicess category is more prone to shift work and therefore volatility in shift time and duration; the mode choice behaviour resulting from this lifestyle is inherently more difficult to predict.

The second dimension of comparison is between mode clusters; this captures heteroskedasticity in the mode choice process. Table 2 shows that the scales in the “Root” nest are consistently lower than in the “Auto” nest, implying that trips by auto are consistently more predictable than modes in the “Root” nest. There may be several reasons for this. Firstly, the choice to travel by transit may be a result of factors that are difficult to capture in a model. For example, transit may be chosen for environmental reasons or because the prospect of heavy traffic may be stressful for some. Furthermore, network and mode choice models often have issues capturing the capital costs associated with auto ownership. There may be certain situations in which the choice of auto is economically superior on the basis of time and out-of-pocket costs, but in reality the capital costs outweigh those short term cost savings. If individuals are cognizant of these scenarios, they may make the choice to take transit which, in the logic of the model, would not be easily predictable.

Home-Base Post-Secondary School Model

Unlike the work trip model, the rho-squared statistic for the post-secondary school model is fairly low; the model explains only 27% of mode choice information. This can be at least partially attributed to the smaller number of observations for this model. However, the post-secondary school model is better than the market share model by a greater margin than the work trip model. Whereas the work model outperformed the market share model by 17%, this model was better by 26%. As with the work model, the likelihood ratio statistics show that the school model is statistically better than both the null and market share models at a high level of confidence. Unfortunately, no statistically significant nesting was observed in the post-secondary model. As such, all scale parameters are set to 1 and the model simplifies to a multinomial logit model.

The parameter values resulting from the estimation of the post-secondary school model were not all as intuitive as those in the work model. The first notable difference is the negative alternative specific constant for the Auto Passenger mode. This may be due to the dearth of observations for the reference alternative (GO Rail Transit Access), which may have led to a scenario in which difference between the two parameters resulted in a negative value. Although this parameter is not statistically significant at a 95% confidence level, it was deemed close enough to be included in the model. The time and cost terms for this model are specified in the same manner as in the work model; however, it was not possible to estimate a parameter for wait time that had a negative sign. The parameter values for the number of household vehicles are similar to those estimated for the work model. However, there are two differences of note. Firstly, the increase in utility between 2 and greater than 2 household vehicles for the Auto Driver mode is greater for the post-secondary school model. Assuming an average of 2 workers per household, having more than 2 vehicles would greatly facilitate the Auto Driver mode for a post-secondary student. Secondly, the parameter values for the Auto Passenger mode are considerably higher than in the work model, likely a result of the negative alternative specific constant of the post-secondary model. With respect to the trip distance variables, we observe a greater drop in utility from trips between 0 and 1km to trips between 1 and 2 kms than from 1-2kms to 2-3kms. For the work trip model, the opposite is true. This suggests that the "threshold" distance for post-secondary walking trips is lower than for work trips. The estimation of the Male Dummy parameters returned some statistically insignificant results; however, they were left in the model because they were either very close to a 95% level of confidence or they amounted to a minimal impact on overall utility. Generally, the magnitude and sign of the parameters are logical. For example, the modes that involve some auto component are all more positive than the transit-only modes; this is consistent with the higher likelihood of females taking transit. Finally, the dataset was split into 3 age categories: younger than 23, between 23 and 28, and older than 28 (the reference case). We observe a predictable decrease in the utility of transit and non-motorized modes as age increases. This is generally consistent with the home-based work trip model.

Estimation of Travel Time Impacts

In this subsection, the impact of travel time changes on mode choice is calculated using the preceding models. Several model runs were performed to assess two different impacts on transit mode share: congestion and transit improvements. The 2001 and 2006 auto and transit levels of service are available from an EMME network model of the GTHA (*8*); by substituting 2001 travel time data into the 2006 data file, it is possible to isolate both of these effects. Congestion impacts can be isolated by comparing modeled 2006 transit mode split with the mode split of a model run with 2001 auto travel time substituted for 2006 times. Similarly, the impact of transit improvements can be calculated by comparing the transit mode share of the 2006 model with a model run with 2001 transit times substituted for 2006 times.

First, the impacts of congestion and transit improvements on home-based work trips are examined. Table 5 presents the calculated impact of both congestion and improved transit service along with the actual changes observed in the TTS between 2001 and 2006. The results are presented as the difference in percentage points of mode share.

TABLE 5 Change in Mode Share – Home-Based Work Trips

	Auto	**Transit - Local Access**	**Transit - Auto Access**	**NMT**
Congestion Impact	0.15%	0.10%	-0.24%	-0.01%
Transit Impact	-0.91%	0.89%	0.06%	-0.04%
Actual Change	-1.06%	0.65%	0.46%	-0.05%

Beginning with the impact of congestion, we observe that auto access to transit modes lost share at the expense of local access to transit and auto modes. The increase in auto mode share is not intuitive. On average, auto times increased roughly 5%; one would expect that as auto times increase auto mode share would decrease. However, average and median transit in-vehicle times also increased by 6% and 4%, respectively. The only component of transit time to decrease was wait time, which dropped 6% on average. Furthermore, since auto access to transit was the only mode group whose share declined, it is reasonable to assume that the increase in auto trips comes at the expense of auto access to transit trips. It is possible that links leading to P&R stations became more congested (in the network model or otherwise) or that subway parking lots reached capacity, making the total travel time by auto more competitive. Moreover, there may have been road improvements made that benefited a certain segment of the population enough to change their choice in mode, even if the average and median travel times increased. Regardless of the explanation, the impact of the increase equates to only 30 additional home-based work trips.

The impact of transit improvements is easier to explain. Table 5 shows that the gains in transit mode share as a result of improvements to transit service came almost entirely at the expense of auto mode share. These impacts are greater in magnitude than the congestion impacts; this suggests that improved transit service has been more successful at changing the travel behaviour of individuals than increased congestion. Interestingly, since both in-vehicle and walk times actually increased between 2001 and 2006, the observed impact on transit mode share must be a result of the improvement in wait time. This is a reasonable result since the mode choice model has shown that wait time is the most onerous component of transit travel time. Finally, it is worth noting that the observed local transit improvement impact is greater than the actual increase in local transit mode share. It is likely that issues estimating auto access to transit trips contributed to this result; if auto-access and local-access to transit modes are summed, the total transit improvement impact is less than the observed increase in transit mode share.

The impacts of congestion and transit improvements on home-based post-secondary school transit mode share are presented in Table 6. As before, the results are presented as the difference in percentage points of mode share.

TABLE 6 Change in Mode Share – Home-Based Post-Secondary School Trips

	Auto	**Transit - Local Access**	**Transit - Auto Access**	**NMT**
Congestion Impact	0.90%	1.05%	-1.96%	0.00%
Transit Impact	-2.90%	3.83%	0.11%	-1.04%
Actual Change	-19.62%	17.07%	3.10%	-0.55%

Table 6 shows that the calculated impacts on post-secondary school trips are considerably larger than the impacts on work trips. With respect to congestion impacts, we can observe a similar—although scaled-up—pattern of the impact on auto and transit mode shares. Once again, auto access to transit was the only mode group to lose share; the benefactors of this loss were the auto and local access to transit modes. The explanatory reasons behind this phenomenon described for home-based work trips apply here. Again, the unintuitive increase in auto mode share works out to a very small number of trips.

Transit improvement impacts on post-secondary trips also follow a similar pattern to work trips. The improvement in transit times resulted in an increase in transit mode share roughly offset by auto mode share. It is interesting to note that among post-secondary students, both wait and walk times decreased from 2001; transit in-vehicle travel time also increased by a smaller margin than for work trips. This is indicative of a concerted effort on the part of York Region to target post-secondary trip makers. VIVA was clearly an important part of that strategy given that two of the five VIVA routes serve York University.

One interesting characteristic of the post-secondary school trip impacts is that they are considerably less than the actual change in mode share that was observed. This suggests that the reason behind the change in behaviour was motivated by something other than travel time. To test this hypothesis, the 2006 model was run using exclusively 2001 data (both level of service and demographic). The result of this exercise was a very large overestimation of transit ridership. This may be an indication of a change in tastes and preferences between 2001 and 2006 that is unexplained by the mode choice model. It is possible that factors such as improved branding, advertising, and communications to post-secondary students may have caused this change in preferences.

CONCLUSIONS

This paper has evaluated the ridership impacts of the VIVA bus transit system. The impacts on both home-based work and home-based post-secondary school were tested using GEV-class discrete choice models. In the work trip model, two mode choice nests were identified: Auto (comprising auto driver and auto passenger) and Root (comprising all other modes). It was found that auto trips were more easily predictable than transit trips and that there is an appreciable difference in the heteroskedasticity of choice between occupation groups. No nesting structure for post-secondary trips was statistically identifiable.

Improvements in transit service were found to have a greater impact on transit mode share than increases in congestion for both work and post-secondary school trips. The reason for this was largely because of reductions in waiting time between 2001 and 2006. It is also concluded that transit improvements played a relatively small role in the considerable shift to transit amongst post-secondary students. It is posited that VIVA attributes such as improved branding, advertising, and communications may have caused this change in preferences.

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