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Modelling the Choices of Telecommuting (On-line Learning) of Post-Secondary Students:

Learning from the Revealed Behaviour to Prepare for Greater Acceptance in COVID-19 Induced Contexts

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ABSTRACT
As post-secondary institutions across the world shift to online course delivery to reduce the spread of the novel coronavirus disease-2019 (COVID-19), telecommuting has become essential for the students. However, little is known about what factors should be targeted through policies so that there is greater and easier acceptance of such mandatory telecommuting among the students. This paper presents an empirical investigation of the telecommuting frequency choices of post-secondary students in the Greater Toronto and Hamilton Area. It uses data from a large-scale student travel survey and a split-population ordered extreme value model to identify the factors that affect students' choice of higher weekly telecommuting frequencies. The model results reveal that age, gender, student status, living situation and personal attitudes significantly affect the choice of telecommuting among the students. In addition, stricter activity-travel scheduling constraints, transit pass ownership, car access, monthly travel cost, and poor transit accessibility lead to more frequent telecommuting, whereas heavier course load, living with roommates, owning a bike, and taking regional transit to school encourages them to telecommute less frequently. Based on these findings, it is anticipated that policies like careful redesign of the course loads, promoting positive attitudes towards telecommuting among specific student groups and provision for subsidized transit passes can lead to the greater acceptance of telecommuting among the post-secondary students and enhance their online learning experience in current and post COVID-19 situations.

Keywords: Telecommuting, Post-secondary students, COVID-19, Split-population ordered extreme value model

1. INTRODUCTION

Telecommuting provides an alternative to physical travel for work/school and is considered an effective travel demand management (TDM) strategy. By directly impacting peak period traffic, telecommuting has the potential to reduce congestion, commute-related vehicle miles travelled, and resulting greenhouse gas emission. Numerous studies in the literature have analyzed workers' telecommuting behaviour and its effect on land use and travel patterns. At the regional level, some studies have found telecommuting to encourage urban sprawl *(1-2)*, while others suggest that telecommuting is not a factor that causes different residential preferences among workers *(3)*. Mixed results are also prevalent at the network level, where studies have found both supplementary and complimentary relationships between telecommuting and travel demand in terms of workers' trip rates, commute distances, and miles travelled *(4-8)*. However, at the individual level, telecommute has been mostly found to improve work-life balance *(12)*, enable more efficient activity-travel scheduling *(9)*, and increase work productivity *(13)*.

Compared to the large amount of research has been done on workers' telecommuting pattern, telecommute[1] behaviour of post-secondary students attending universities or colleges has received much less attention *(14)*. There is a lack of understanding of how participation in virtual education (such as online lectures, tutorials during regular semesters rather than specialized online certifications) instead of travelling to school affects the overall activity participation and travel demands of the students. This has become especially critical as more and more schools shift to online course delivery to reduce the spread of the novel coronavirus disease-2019 (COVID-19). For example, post-secondary institutions across Ontario, Canada will offer majority of the courses online for the Fall 2020 semester, thereby making telecommuting essential for the students. As such, we need to identify factors that encourage students to telecommute frequently and then target those factors through policies for greater acceptance of on-line learning in current and post COVID-19 situations.

The importance of analyzing post-secondary students' telecommuting behaviour extends beyond the realm of COVID-19 response.

- First, as in the case of workers, telecommuting can entirely reshape the daily activity schedules of post-secondary students. Hence, their telecommuting frequency should be accounted for when representing their activity planning and scheduling behavior.
- Second, trips to/from schools form a good portion of peak period travel, and with the increasing rate of youth participation in post-secondary education *(15)*, telecommuting by students has the potential to enhance the TDM benefits.
- Third, telecommuting during post-secondary student life may influence their future telecommuting behaviour when they enter the workforce. It is evident that workers with post-secondary education telecommute more *(16)*. So, telecommuting habit nurtured during the student life will continue to provide long-term TDM benefits as they transition to the workforce.
- Fourth, telecommuting has the potential to offset the negative effect of long commute distance and time on active engagement in school activities. Previous studies showed that home to campus travel distance even discourages participation in post-secondary

[1] Throughout the paper, we use the term 'telecommuting' of the post-secondary students to refer to the "on-line learning of regular courses during regular semesters"

education altogether *(17)*. So, telecommuting might improve students' quality of life as well.

- Finally, a better understanding on factors that positively affect the choices of telecommuting of post-secondary students will help devising policy instruments for greater acceptance of telecommuting when this becomes the only option due to COVID-19 situations.

Given the importance of the issue, this study presents an empirical investigation of the factors that influence the telecommuting frequencies of post-secondary students in the Greater Toronto and Hamilton Area (GTHA). By using data from a recently completed survey (in Fall 2019) of students from 10 post-secondary institutions across the region, the study improves our understanding of the telecommuting behaviour of this population segment. The remainder of the paper is organized as follows. Section 2 presents an overview of the previous studies on telecommute behaviour. Section 3 describes the dataset used for empirical investigation. Section 4 presents the formulation of the split population OEV model used for modelling telecommuting frequency in this paper. Section 5 discusses the results of the empirical investigation. Finally, the paper concludes with a summary of key findings and recommendations for further research.

2. PREVIOUS STUDIES ON TELECOMMUTING

With the rapid growth of the information and communication sector since the late 1970s, the relationship between telecommuting and travel has become a popular research topic within the transportation community. Most of the previous studies on this topic follow one of two main streams *(4)*. The first stream analyzes the effects of telecommuting on travel-related decisions, network congestion measures, and urban development and regional land use patterns. The second group aims to identify the factors that affect telecommuting adoption and frequency choices.

Within the first stream of research, studies that assess the impact of telecommuting on trip rates and vehicle miles travelled (VMT) generally concur that the policy reduces commute travel *(11)*. However, there are mixed results about its overall impact on workers' travel demand *(38)*. Many studies have found that telecommuting reduces daily trip rates, travel distance, and VMT. For example, Hamer et al. *(39)* presented a before-after investigation of telecommuting effects in the Netherlands. They concluded that telecommuting reduces the total number of trips of teleworkers by 17% and the peak-hour car traffic by 26%. Based on spatial and temporal analysis of travel diaries collected during the State of California Telecommuting Pilot Project, Pendyala et al. *(9)* found that the policy reduces telecommuters' peak period trips by 60% and their total distance traveled by 75% on telecommuting days.

Choo et al. *(5)* investigated the impact of telecommuting on VMT using an aggregate time-series model and reported that this policy could reduce annual VMT up to 0.8%. Similarly, Helminen and Ristimäki *(6)* found that home-based telecommuting in Finland reduces the total commute distance by 0.7%, and Lachapelle et al. *(7)* found that this policy can reduce daily travel time by an average of 13 minutes in Canada. In contrast to these studies, Zhu *(2, 10)* and Zhu and Mason *(8)* found that telecommuting has complementary effects on individual and household level daily travel demands of workers. The authors developed regression models using data from 2001 and 2009 US National Household Travel Surveys to reach a conclusion. Similarly, using a censored regression model and 2006 Household Travel Survey data from Korea, Kim *(11)* found that when household heads telecommute, it results in increased person-kilometers travelled per household member.

Studies that fall under the second stream of research analyzes the relationship between individual's telecommuting decisions and various types of personal, household, job-related, and built-environment attributes. These studies mostly rely on econometric modelling techniques to quantify the relationship. Some of the earliest attempts in this regard include the works of Bernardino et al. *(18)* and Sullivan et al. *(19)*. They modelled the decision to adopt telecommuting using an ordered probit model and a multinomial logit model, respectively. Both studies used stated preference survey data in their empirical investigation. On the other hand, Mokhtarian and Salomon *(20)* estimated a binary logit model of the preference/desire to telecommute using revealed preference data.

In terms of telecommuting frequency, Mannering and Mokhtarian *(21)* used the multinomial logit model to predict the likelihood of a worker choosing a particular rate (never, infrequently, and frequently). Drucker and Khattak *(22)* estimated three models to investigate telecommuting frequency: ordered logit, ordered probit, and multinomial logit models, using a probit sample selection regression process. They found that ordered regression and unordered discrete choice models gave very similar results. Zhou et al. *(23)* applied a generalized ordered logit model to estimate the impacts of various work-related factors on telecommuting frequency choices. More recently, Paleti *(24)* modelled workers' monthly telecommuting frequency choices using a Generalized Extreme Value model for count data that combines the properties of a count variable regression with the Random Utility Maximization (RUM) framework.

Several studies modelled the decisions of adoption and frequency of telecommuting simultaneously to account for the correlation between them. For example, Popuri and Bhat *(25)* jointly estimated a binary choice model for the choice of telecommuting and an ordered regression model for the frequency of telecommuting. Sener and Bhat *(26)* presented a copula-based joint model that incorporates a binary choice model for adoption, and an ordered-response model for frequency. In another study, Singh et al. *(27)* presented a joint trivariate model to estimate the option, choice, and frequency of telecommuting. They modelled the count of telecommuting days per month using a generalized ordered-response model. Asgari et al. *(28)* used a series of probit models to investigate the choice, frequency, and engagement of telecommuting. Shabanpour et al. *(4)* used a zero-inflated hierarchical ordered probit model for telecommuting participation and frequency in their integrated framework for evaluating the impact of telecommuting on travel demand and the environment.

In terms of factors affecting telecommuting frequency, most studies highlight the importance of workers' individual demographics like age, gender, education level, and possession of driver's license *(4, 24, 25, 28)*. Although there is a consensus in the studies about the positive association of age and education level with telecommuting choice and frequency, there are mixed findings of the effect of gender. Among the household factors, the number of children is found to positively affect telecommuting behaviour *(27, 28)* whereas the number of vehicles, household size, and income can have both positive and negative effects. In terms of job-related attributes, flexible work schedule increases the choice and frequency of telecommuting *(4, 24, 26-28)*, whereas occupation types that require physical interaction/activity (e.g., professional, managerial, manufacturing, construction, health care, and social services) decreases telecommuting propensity. Employees with longer commute distance and time telecommute more frequently compared to employees with shorter commutes *(4, 24, 27)*. Other factors associated with telecommuting frequency include built-environment attributes like population density of home census tract, employment density of work census tract etc. *(4, 27)* and attitudinal variables *(20, 24)*.

From the above review, it is understood that telecommuting behaviour is highly dependent on an individual's socio-economic and work-related factors. Given that post-secondary students represent a specific socio-economic group and they have somewhat unique travel needs and challenges *(29)*, it is anticipated that their telecommuting behaviour is quite different from the workers. Moreover, in the current context of the coronavirus pandemic and mandatory online learning, it has become even more important to identify the factors that positively affect students' telecommuting behaviour. However, there is hardly any study in the literature that focuses explicitly on post-secondary students' telecommuting propensity. To contribute to this gap in the literature, this study presents an empirical investigation of the factors that influence the telecommuting frequencies of post-secondary students in the GTHA. The findings of the study can be used to develop targeted policy instruments for greater acceptance of telecommuting among the students when this becomes the only option due to COVID-19 situations.

3. DESCRIPTION OF SURVEY AND DATA FOR EMPIRICAL INVESTIGATION

Data for the empirical investigation came from a large-scale post-secondary student travel survey that was conducted in the GTHA in Fall 2019. The survey represents around 0.6 million university and college students from 10 post-secondary institutions across the study area. It is the second phase of the StudentMoveTO program, which aims to promote evidence-based research on post-secondary students' travel behaviour in the region. The first phase of the survey was conducted in Fall 2015 among four major universities in Toronto *(30)*, namely University of Toronto, OCAD (Ontario College of Art and Design) University, Ryerson University, and York University. The second, expanded phase of the study includes six new partner institutions, including Ontario Tech University, McMaster University, Mohawk College, Sheridan College, Centennial College, and Durham College. Together, these 10 institutions have 28 campuses located across the GTHA (see Figure 1).

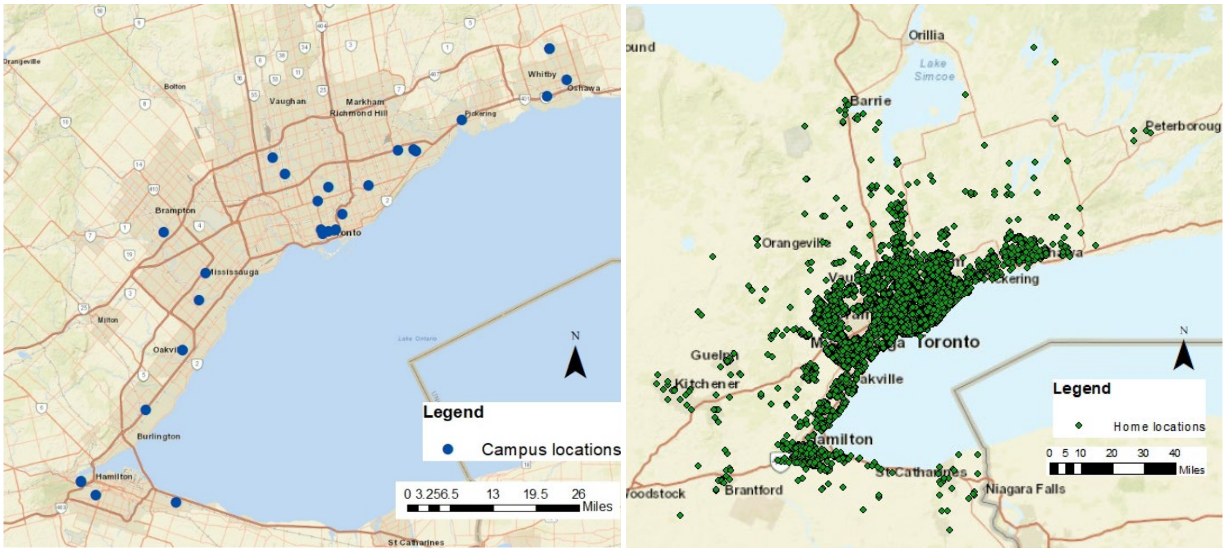

Figure 1: Campus locations and home locations the students

The survey question that forms the basis for constructing the frequency of telecommuting dependent variable in this study is: "How many days per week do you typically participate in virtual education (such as online lectures, tutorials) instead of travelling to school?" The final sample size after cleaning for missing information is 7,593. The data shows that about 27% of the student population telecommutes at least 1 day/week. Table 1 summarizes some of the key sample attributes. The home locations of the students are well dispersed across the 6 major regions in the GTHA (see Figure 1). Measures of the built environment and transit accessibility around the place of residence are considered in the model estimation. These measures were calculated at the Traffic Analysis Zone (TAZ) level using the 2016 Canadian census database, the DMTI spatial database *(31)*, and the GTFS data of the transit agencies in the region for a typical day in October 2019.

Table 1: Descriptive statistics of the sample

Variables	**Mean**	**Std. dev.**
Individual demographics		
Age	22.91	5.99
Female	65.80%	
Male	31.60%	
Student status		
College	16.50%	
University	83.50%	
Full-time	93.70%	
Part-time	4.40%	
Other	1.90%	
Household characteristics		
Number of household vehicles	1.29	1.23
Household living situation		
Live with family/parents	54.90%	

Live with roommates	24.00%	
Live with partner	10.30%	
Live alone	8.90%	
Live with host family or at friend's house	1.90%	
Mobility tool ownership		
Driving license owner	63.70%	
Age of acquiring driving license	18.57	3.29
Automobile available for personal use	32.70%	
Transit pass owner	38.30%	
Bike owner	40.60%	
Installed ridesourcing app	62.00%	
Weekly telecommuting frequency		
0 days	73.32%	
1 day	14.22%	
2 days	6.02%	
3 days	2.63%	
4 days	1.16%	
5 days	1.30%	
6+ days	1.34%	

Figure 2 shows the distribution of weekly telecommuting frequencies among different student sub-populations. Overall, telecommuting seems to be practiced at varying degrees by students of all the sub-groups. Specifically, college students tend to telecommute more frequently than university students. Graduate students are less likely to telecommute than undergraduate students, whereas part-time students are more likely to telecommute than full-time students. Telecommuting is prevalent among all mode users, although students who drives alone or share rides to school tend to telecommute more frequently than those who take transit to school. Bike riders telecommute least frequently. These descriptive analysis reveals the presence of considerable heterogeneity among the students in terms of weekly telecommuting frequency distribution, and the empirical model should take this into account.

The survey asked the students to respond to 26 attitudinal statements that measure their attitudes and preferences towards campus life, travel motivations, transportation safety, travel satisfaction based on their latest commute experience, and overall subjective wellbeing. Among them, the 6 statements related to campus life had binary agree/disagree response options, while the rest had 5-point Likert-type scale options ranging from "Strongly disagree" to "Strongly agree." In this empirical investigation, we estimated two models of weekly telecommuting frequency choices. The first model includes socio-demographic variables, mobility tool ownership information, typical commute characteristics, and built environment and transit accessibility variables. The second model is an extended version of the first one with the inclusion of individual attitudes.

After data cleaning and preprocessing, we performed a principal axis factor analysis with oblique rotation to identify the main factors behind the attitudinal constructs. We incorporated these factors in the second model via their standardized Bartlett factor scores. Figure 3 provides details on the three-factor scores that were included in the final model and the attitudinal statements loading on each of them.

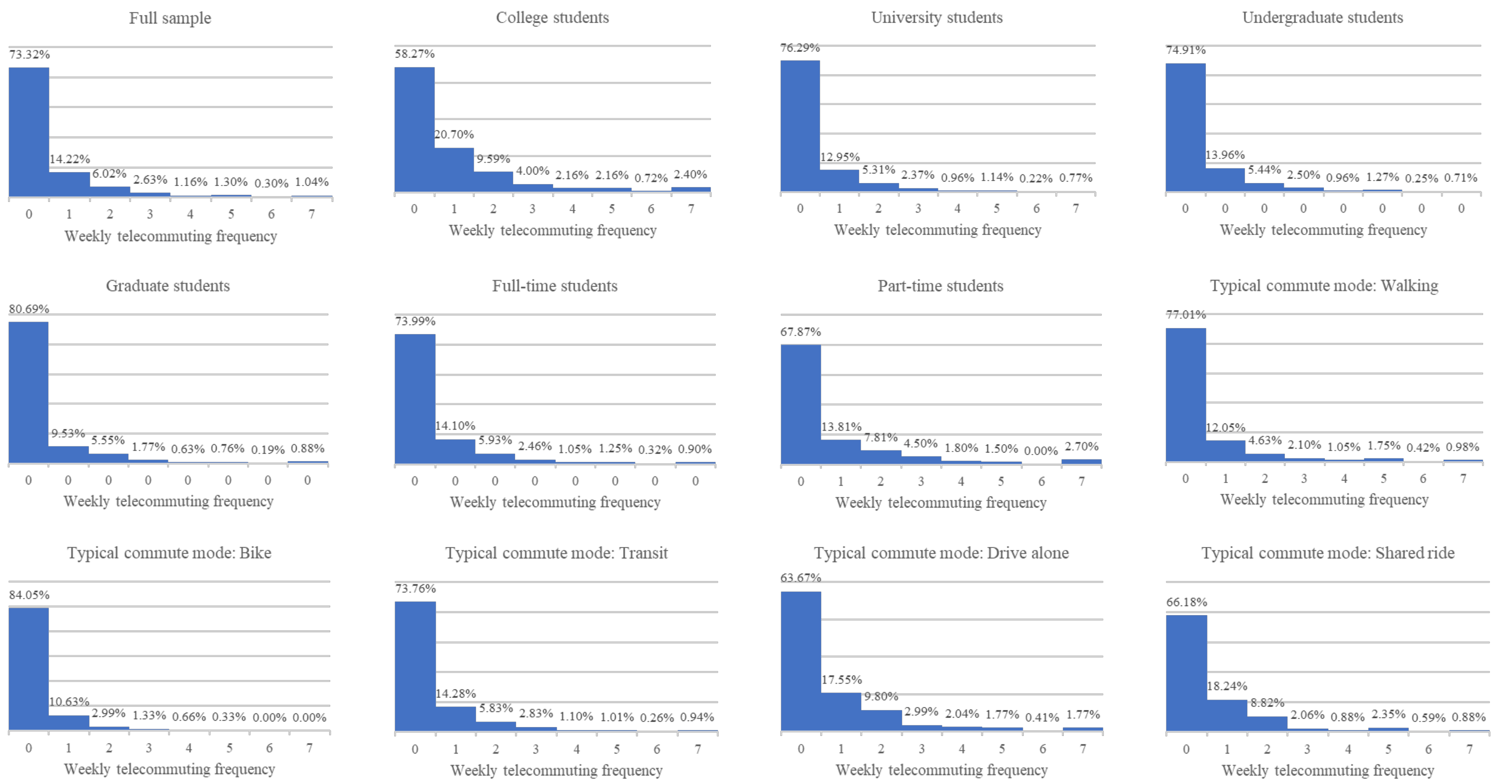

Figure 2: Weekly telecommuting frequency distribution among different sub-samples

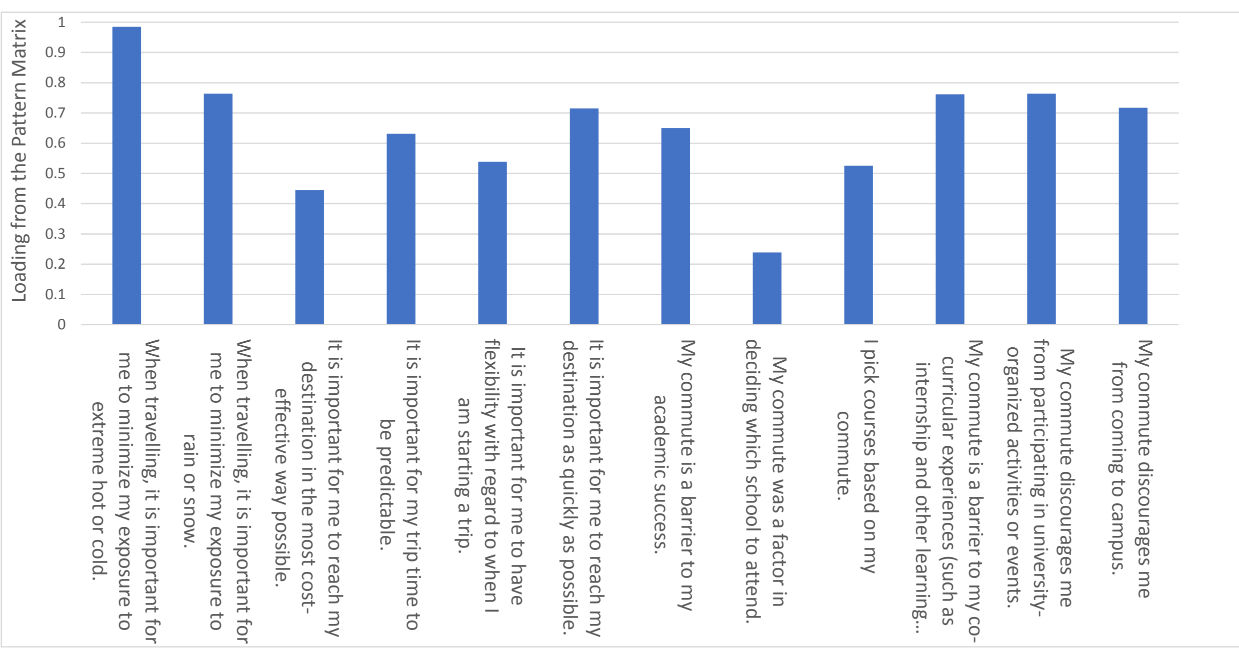

Figure 3: Relevant factors and their associated attitudinal statements

4. ECONOMETRIC MODEL

We propose to use a RUM based approach of the ordinal discrete choice model here. An Ordered Extreme Value (OEV) choice model has the potential of accommodating the heterogeneity (over-dispersion of telecommuting frequency data) observed data while capturing the effects of various covariates in influencing the ordinal choice outcomes of telecommuting frequencies. Further, to accommodate the large proportion of the choice of zero-frequency (no telecommuting), we extension of the OEV model to a zero-inflation OEV model.

The OEV approach assumes an underlying continuous function of telecommuting frequency:

$$F_i = U_i + \varepsilon_i \tag{1}$$

Here, the observed frequency id is f_i. U_i is the underlying continuous function counterpart if f_i is F_i, and ε_i is a random error component. The probability of an observed frequency, $f_i = k$ can be written as:

$$Pr(f_i = k) = G(\delta_k - \sum \beta x_i) - G(\delta_{k-1} - \sum \beta x_i) \tag{2}$$

Here, δ_{k-1} and δ_k are the nonparametric baseline frequency thresholds for observed frequencies (k-1) and k respectively. $G(.)$ represents the cumulative distribution function of the distribution of ε_i. β is the parameter vector and x_i is a vector of observed variables relating to the underlying continuous function. Assuming an extreme value distribution for the random term ε_i, the probability of observed frequency becomes:

$$Pr(f_i = k) = \left(1 - e^{\left(-e^{(\delta_k - \sum \beta x_i)}\right)}\right) - \left(1 - e^{\left(-e^{(\delta_{k-1} - \sum \beta x_i)}\right)}\right) \tag{3}$$

However, this assumption does not consider any dispersion or heterogeneity. A common practice in the literature for inducing a parametric dispersion/heterogeneity is to mix a positive distribution *(32, 33)*. In this study, we consider mixing a Gamma distribution of unit mean and σ^2 variance, so that the probability equation becomes:

$$Pr(f_i > k) = \left(1 + \frac{1}{\sigma^2}\Delta_k e^{(-\sum \beta x_i)}\right)^{-\sigma^2} \tag{4}$$

$$Pr(f_i < k) = 1 - \left(1 + \frac{1}{\sigma^2}\Delta_k e^{(-\sum \beta x_i)}\right)^{-\sigma^2} \tag{5}$$

$$Pr(f_i = k) = \left(1 + \frac{1}{\sigma^2}\Delta_{k-1} e^{(-\sum \beta x_i)}\right)^{-\sigma^2} - \left(1 + \frac{1}{\sigma^2}\Delta_k e^{(-\sum \beta x_i)}\right)^{-\sigma^2} \tag{6}$$

For the maximum K frequencies, a total of (K-1) nonparametric baseline thresholds can be identified. So,

$$Pr(f_i = 0) = 1 - \left(1 + \frac{1}{\sigma^2}\Delta_k e^{(-\sum \beta x_i)}\right)^{-\sigma^2} \tag{7}$$

$$Pr(f_i = k) = \left(1 + \frac{1}{\sigma^2}\Delta_{k-1} e^{(-\sum \beta x_i)}\right)^{-\sigma^2} - \left(1 + \frac{1}{\sigma^2}\Delta_k e^{(-\sum \beta x_i)}\right)^{-\sigma^2} \tag{8}$$

$$Pr(f_i = K) = \left(1 + \frac{1}{\sigma^2}\Delta_k e^{(-\sum \beta x_i)}\right)^{-\sigma^2} \tag{9}$$

Considering all possible non-negative values, the likelihood function of any observation is:

$$L_i = \begin{cases} \left[1 - \left(1 + \frac{1}{\sigma^2}\Delta_1 e^{(-\sum \beta x_i)}\right)^{-\sigma^2}\right] & if\ f_i = 0, no\ telecommuting \\ \left[\left(1 + \frac{1}{\sigma^2}\Delta_{k-1} e^{(-\sum \beta x_i)}\right)^{-\sigma^2}\right] - \left[\left(1 + \frac{1}{\sigma^2}\Delta_k e^{(-\sum \beta x_i)}\right)^{-\sigma^2}\right] & if\ f_i = k, any\ intermediate\ frequency \\ \left[\left(1 + \frac{1}{\sigma^2}\Delta_K e^{(-\sum \beta x_i)}\right)^{-\sigma^2}\right] & if\ f_i = K, the\ maximum\ frequency \end{cases} \quad (10)$$

Given that we want to treat the zero frequency separately from the positive frequencies, the resulting model should essentially split the student population into two latent regimes and consider that their decision outcomes relate to potentially two different sets of explanatory variables. Under this consideration, the choice of zero frequency versus all other positive frequencies takes the form of a binary logit model, and the choice of positive frequencies follow the OEV structure described above. Thus, the final structure is a latent frequency model with zero-inflation.

Let, γ be the parameter vector, z_i be a vector of explanatory variables and $F(.)$ be the logit probability for the zero-frequency alternative. Then the final likelihood function can be written as:

$$L_i = \left(\left(1 - F\left(\sum \gamma z_i\right)\right) L_i\right)^{1-C} \times \left(F\left(\sum \gamma z_i\right)\left[1 - \left(1 + \frac{1}{\sigma^2}\Delta_k e^{(-\sum \beta x_i)}\right)^{-\sigma^2}\right]\right)^{C} \quad (11)$$

Where C is an indicator that takes the value of 1 if the individual reports zero telecommute frequency, and 1 for all positive frequencies.

For this split-population OEV model, the marginal effect of the variable (z) on the probability of not telecommuting is given by:

$$ME_z = \left(F\left(\sum \gamma z\right)\left(1 - F\left(\sum \gamma z\right)\right)\right)\gamma \quad (12)$$

Whereas the marginal effect of the variable (x) on the probability of non-zero telecommuting frequencies is given by:

$$ME_x = \begin{cases} -(1 - F(\gamma z))\left[1 - \left(1 + \frac{1}{\sigma^2}\Delta_1 e^{(-\sum \beta x_i)}\right)^{-\sigma^2 - 1}\right]\beta\, \Delta_1 e^{(-\sum \beta x_i)} & if\ f_i = 1 \\ (1 - F(\gamma z))\left[\left(1 + \frac{1}{\sigma^2}\Delta_{k-1} e^{(-\sum \beta x_i)}\right)^{-\sigma^2 - 1}\right]\beta\, \Delta_{k-1} e^{(-\sum \beta x_i)} - (1 - F(\gamma z))\left[\left(1 + \frac{1}{\sigma^2}\Delta_k e^{(-\sum \beta x_i)}\right)^{-\sigma^2 - 1}\right]\beta\, \Delta_k e^{(-\sum \beta x_i)} & if\ f_i = k, any\ intermediate\ frequency \\ (1 - F(\gamma z))\left[\left(1 + \frac{1}{\sigma^2}\Delta_K e^{(-\sum \beta x_i)}\right)^{-\sigma^2 - 1}\right]\beta\, \Delta_K e^{(-\sum \beta x_i)} & if\ f_i = K, the\ maximum\ frequency \end{cases} \quad (13)$$

In the empirical model, we incorporated the attitudinal factors via their standardized Bartlett scores. We acknowledge that the inclusion of attitudinal variables into the split-population OEV model in the form of separately estimated factor scores may introduce measurement bias *(34)*.

Nonetheless, this approach provides useful indications of the effect of various attitudinal factors on telecommuting frequency choice and future research should focus on a joint modelling technique that can use attitudinal indicators as outcomes of latent explanatory variables in the model, similar to a hybrid choice model *(35)*.

The final model has a closed-form formulation and is estimated by a program written in GAUSS *(36)* using its classical maximum likelihood estimation routine.

5. RESULTS AND DISCUSSION

Table 2 presents the final models of weekly telecommuting frequencies of post-secondary students without and with personal attitudes.

Table 2: Estimation results for the split-population OEV models

	Model without attitudinal variables		Model with attitudinal variables	
Total number of observations	7593		7593	
Adjusted rho-squared value	0.5580		0.5594	
AIC Value	13958		13913	
BIC Value	14256		14246	
Variable	**Parameter of**		**Parameter of**	
	Binary Logit	**Covariate function**	**Binary Logit**	**Covariate function**
Constant	1.592***		1.084*	
Personal demographics				
Female	-0.188***		-0.159***	
Log of Age	-0.445***	0.488***	-0.345**	0.408**
Works part time (< 30 hours/week)	-0.133**		-0.117**	
Works full time (>=30 hours/week)	-0.378***	0.254**	-0.352***	0.251**
Student status				
University student	0.556***		0.605***	
Graduate student	0.586***		0.545***	
Full time student	0.348***	-0.238*	0.369***	-0.261*
International student	-0.407***		-0.390***	
Log of years in school	0.091**	-0.168***	0.087*	-0.162***
Household characteristics and living situation				
Lives with family/parents in house	0.171**		0.241***	
Lives with roommates		-0.136		-0.132
Lives in detached, semi-detached or town house		-0.245***		-0.241***
Number of household vehicles	-0.043		-0.037	
Mobility tools ownership				
Age of acquiring driving license	-0.050**	-0.052*	-0.0607***	-0.054*
Auto available for personal use		0.159*		0.161*
Transit pass owner		0.168**	-0.077	0.174**
Bike owner		-0.090		-0.094

Uses ridesourcing frequently (at least once per week)	-0.321***		-0.273***	
Commute characteristics				
Log of home to campus distance for Toronto residents (km)	-0.006		-0.002	
Monthly travel cost (CAD)		0.059*		0.062**
Main commute mode: Driving alone	-0.215**		-0.221**	
Main commute mode: Ride sharing	-0.260**		-0.254**	
Main commute mode: Regional transit		-0.217*		-0.202*
Main commute mode: Walk		0.222**		0.200*
Same commute modes in Fall and Winter	-0.199*		-0.151	
Built environment attributes of residential TAZ				
Living in Downtown Toronto	0.395***		0.324***	
Population in home TAZ	0.047*		0.059**	
Distance from home to nearest rail stop (km)		-0.125*		-0.127*
Distance from home to nearest subway stop (km)	-0.083	0.080**	-0.097*	0.077**
Personal attitudes (Factor scores)				
Commute adversity			-0.132***	
Sensitivity to trip characteristics			0.127***	-0.053*
Sensitivity to weather			-0.107***	
Gamma Variance		1.783**		1.756**
Ordered Pair Correlation Coefficients				
Threshold Parameter for frequency: 0				
Threshold Parameter for frequency: 1		1.238*		0.989
Threshold Parameter for frequency: 2		2.090***		1.846***
Threshold Parameter for frequency: 3		2.593***		2.352***
Threshold Parameter for frequency: 4		2.895***		2.655***
Threshold Parameter for frequency: 5		3.404***		3.165***
Threshold Parameter for frequency: 6+		3.584***		3.345***

****, **, * Significant at 99%, 95%, 90% levels of confidence*

Variables in the final specifications are selected based on the expected sign, and statistical significance (90% confidence interval) of corresponding parameters. Some parameters with lower than 90% confidence are still retained in the model because it is perceived that these variables provide essential insights when comparing the two models. For comparing the relative performance of the models, Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC) measures are used. In contrast, the goodness-of-fit of the models are compared by estimating Rho-square values.

5.1 Model of weekly telecommuting frequency – without attitudes

In the split-population approach, modelling choice of no telecommuting separately from the positive frequencies is synonymous with a zero-inflation model. The estimated model indicates that the choice of not telecommuting at all has a different underlying behavioural process than the choice of the non-zero frequency of telecommuting. The effects of different categories of explanatory variables as found in the model are discussed in the following subsections.

5.1.1 Role of personal and household attributes on telecommuting frequencies

Age and gender of the students are the most influential personal attributes in explaining their weekly telecommuting frequency choices. The negative parameter of the age variable in the zero-frequency component of the model and the corresponding positive parameter in the covariate function reveals that not only are older students more likely to telecommute but also, they would telecommute more frequently than younger students. In terms of the effect of gender, female students are more likely to telecommute than males. These findings are consistent with previous studies like *(24, 27, 28)*. Students who work off-campus either full-time or part-time telecommute more frequently than students who don't work. This is intuitive given that students working off-campus have more complex activity-travel scheduling, which might make telecommuting more lucrative to them. Interestingly, the model captures the trend that full-time work has a higher negative effect on zero telecommuting frequency than part-time work.

In terms of the household attributes, type of housing, and living situation affect the weekly telecommuting frequency of the students. Specifically, students living in detached, semi-detached or townhouses telecommute less frequently than students living in other housing types (like apartments/condominiums off-campus, on-campus residences, etc.). Students living with family/parents in houses have a higher probability of not telecommuting at all, whereas students living with roommates telecommute less frequently. The latter might be a manifestation of the fact that students who share the living space with non-family members of the same generation don’t have the proper environment at their residences to concentrate on studies, and as such, they prefer to commute to the school. When these students will be forced to regularly participate in online learning as a response to COVID-19, the lack of a proper study environment might hamper their overall telecommuting experience. To tackle this issue, they should be encouraged to create a dedicated study corner at home for the upcoming online semester.

5.1.2 Role of student status on telecommuting frequencies

University students have a higher zero telecommuting frequency than college students. As such, their propensity of telecommuting is less than the college students. International students telecommute less than domestic students (interestingly, Paleti *(24)* reported a similar trend for immigrant employees). Based on the level of education, graduate students are less likely to telecommute than undergraduate students (after controlling for age); whereas, full-time students are found to telecommute less frequently than part-time students. The longer a student is enrolled in a school, the more likely it is for them to have lower propensity and frequency for telecommuting. Overall, these findings indicate that course load is a deciding factor in students’ telecommuting frequency choice; hence institutional policy that leads to balanced course load might encourage students to accept telecommuting effectively when forced online semesters happen in Fall 2020 and beyond.

5.1.3 Role of mobility tool ownership and commute characteristics on telecommuting frequencies

Mobility tool ownership, in terms of ownership of driver's license, transit pass, bicycle, and availability of a car for personal use affects the telecommuting choices of post-secondary

students. The model reveals that students who received their driver's license later than others are more likely to telecommute, but their weekly telecommuting frequency would be less than those got their license earlier. This finding is significant as it indicates that delaying the process of obtaining a driver's license might reduce the overall travel demand of the students and grow the habit of telecommuting among them. The pattern of lower telecommuting frequency is also observed for bicycle ownership. However, students who own transit pass or has a car available for personal use telecommute more frequently than those who don't have these mobility tools. It is interesting to note that the relative impact of transit pass ownership on telecommuting frequency choices is higher than that of either bicycle ownership or car availability. As such, subsidized transit passes for the students might act as an effective policy tool to make their telecommuting experience more enjoyable.
The model also shows that students living farther from campus are less likely to have zero telecommuting frequency, i.e. they have higher telecommuting propensity than those who live closer to campus. However, as Paleti noted, this result does not imply causation because it is possible that students reside at farther locations from school because they are inclined to exercise telecommuting more frequently or they telecommute more frequently because they reside farther from their schools. Higher monthly travel costs induce more frequent telecommuting among the students.

Typical commute mode choice has an important effect on the choice of weekly telecommuting frequencies. Students who typically drive alone to school or share a ride to school are more likely to telecommute than those who take transit or active modes to school. In terms of frequency, students who walk to school would telecommute more frequently compared to others; whereas those who take regional transit would telecommute less frequently. Students who use regional transit might pick their courses so as to reduce commute, and consequently their frequency of telecommuting would also be less. Students who use the same travel mode in winter and non-winter seasons are more likely to telecommute.

5.1.4 Role of built environment attributes of residential TAZ and transit accessibility measures
Places of residence of the post-secondary students have a strong influence on their telecommuting behaviour. Students living in downtown Toronto are more likely to not telecommute at all than those living outside the area. Downtown Toronto usually has good transit accessibility. Perhaps the improved transit accessibility makes the commute to school less troublesome for the students, which in turn increases their likelihood of not telecommuting. The importance of home zone transit accessibility on telecommute behaviour is also revealed by the distance between home and nearest subway stop variable. Poor subway network accessibility increases the probability of telecommuting and it also encourages students to telecommute more frequently. However, the opposite effect is found for rail network, which indicates that students living farther away from the rail network are less likely to telecommute. Also, students living in more densely populated zones are found to more likely to telecommute.

Apart from these major groups of variables, increased use of ride-sourcing services improves the probability of telecommuting among post-secondary students. This variable can be thought of an indirect measure of the technology savviness of the students, which seems to be positively associated with the propensity to telecommute. A variety of other built environment variables of the home zone, including land use mix (calculated using the entropy formula introduced by *(37)*), and density of different business types, were also tested, but none showed any significant contribution to the model.

5.2 Model of weekly telecommuting frequency – with attitudes

To test the impact of individual attitudes and preferences on the weekly telecommuting frequencies of post-secondary students, we incorporate factor scores as explanatory variables in the model. We find that telecommuting is more prevalent among students who believes that commute has a negative impact on their overall campus life experience, have negative attitudes towards commuting in general (as reflected by the 'commute adversity' factor) and are more sensitive to weather conditions. On the contrary, students who have positive factor scores for sensitivity towards trip characteristics like travel time, cost, the flexibility of departure time, and predictability of trips telecommute less.

As shown in Table 3, the inclusion of the attitudinal variables improves the goodness of fit of the model but has only a small impact on the coefficients and statistical significance of the variables included. This indicates that the attitudinal variables mostly add independent explanatory power not captured by other variables in the model, thereby highlighting the importance of considering attitudes when modelling telecommuting frequency choices of post-secondary students. In fact, promoting positive attitudes towards telecommuting might encourage greater acceptance of the mandatory online learning adopted by the schools as a response to minimize the spread of COVID-19. The inclusion of the attitudinal variables significantly reduces the magnitude of two variables: commute distance and using the same mode for fall and winter. Thus, the apparent impacts of these two variables are more properly explained by the personal attitudes of the individuals, and the true impact of commute adversity and weather sensitivity is attributed to commute distance and seasonal mode choice when we do not control for the students' attitudes.

5.3 Marginal effects

The marginal effects are presented in Figure 3. The marginal effects further highlight the relative influences of different variables on weekly telecommuting frequency choice of students and can be used to inform policies and instruments targeted towards increasing the telecommuting frequency of this population segment. Similar telecommuting frequency trend is observed for older students and students who work full-time. Both groups are less likely to telecommute 0-1 day/week and are more likely to telecommute 2 or more days. This trend is reflective of the stricter activity-travel scheduling constraints of the two groups who must make time for work and other family/household-related duties besides studies. The opposite trend is observed for full-time students and students who are enrolled in schools for many years (and as such, are more likely to graduate soon). These groups have considerably higher course loads and prefer telecommuting less frequently (0-1 day/week). These findings indicate that telecommuting frequency choices of post-secondary students are dependent to a large extent on their activity-travel scheduling constraints.

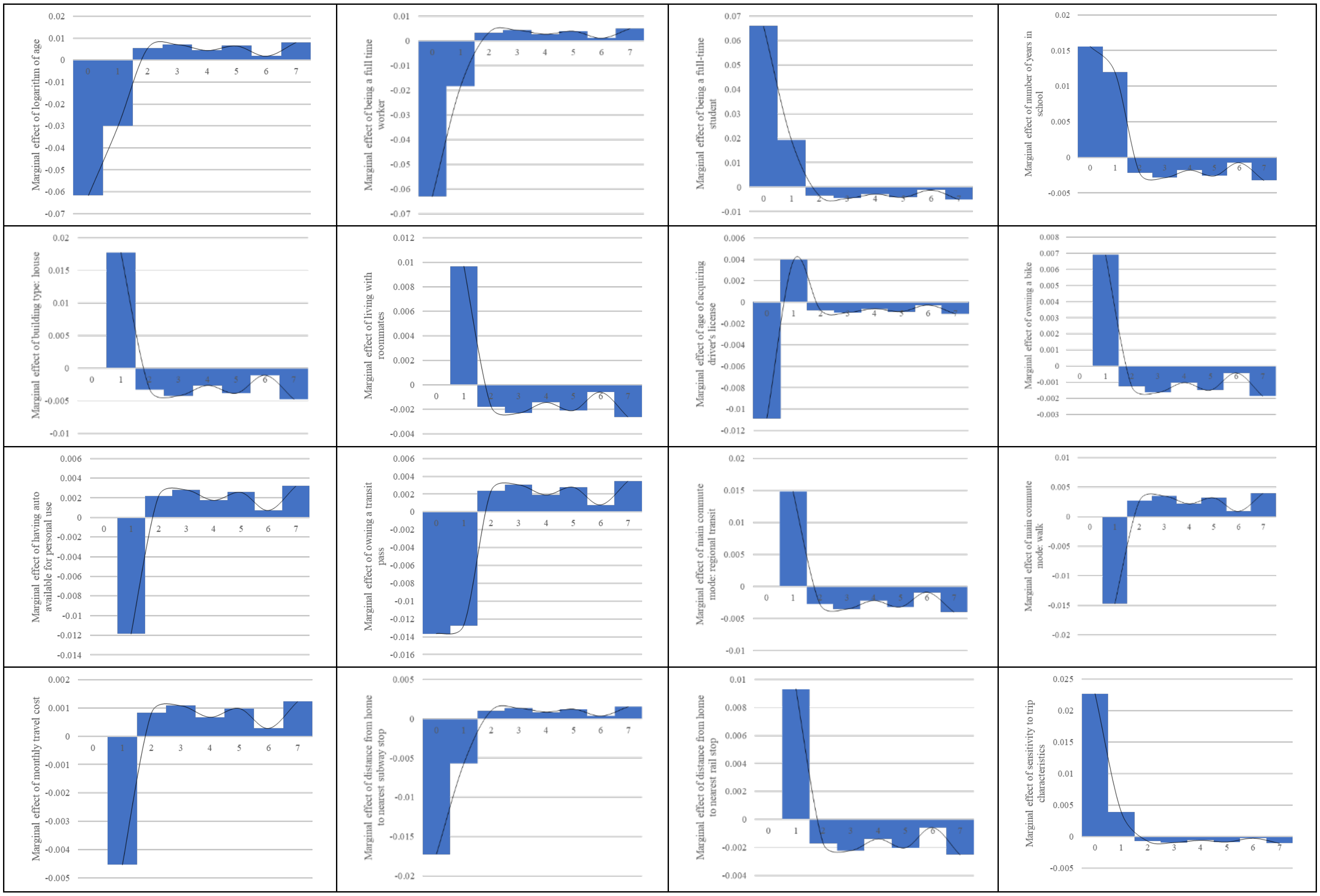

Figure 3: Marginal effects of covariates of the model with attitudinal variables

Interestingly, students who obtained their driver's license relatively later are most likely to telecommute once a week. A similar trend is observed for students who own a bike. On the contrary, students who possess a transit pass and have car available for personal use telecommute more frequently (2 or more days per week). Hence, transit pass and auto availability seem to encourage more frequent telecommuting than driver's license or bike ownership. In terms of commute characteristics, using regional transit for school trips encourages students to telecommute once per week, but they are less likely to telecommute more frequently. On the contrary, students who walk to school telecommute twice or more per week. Increased monthly travel expenditure also induces students to telecommute twice or more per week. From transit accessibility perspective, longer access distance to nearest subway stop pushes students to telecommute two or more days per week, whereas longer access distance to nearest rail stop encourages them to telecommute once per week.

The findings of the study are instrumental in predicting the extent of telecommuting in the future, especially as post-secondary institutions opt to online course delivery in Fall 2020 (or beyond) in response to COVID-19. They also have important policy implications. First, given the negative association of telecommuting frequency with course load, the schools should give special attention to redesigning their curriculum for the upcoming online semesters. The redesign should involve a healthy balance between academic studies and co/extra curricular activities (offered virtually) so that the students can effectively adapt to the enforced telecommuting experience. Second, the model indicates that personal attitudes play an important role in students' telecommuting choices. As such, training programs should be devised for promoting positive attitudes towards telecommuting among the students. Especially, younger students (may be undergrads) and students who are in the early years of their academic journey should be targeted for this, given that they tend to telecommute less frequently under normal circumstances. Third, a policy for providing subsidized transit passes to the students during the online semesters might contribute towards enhancing their telecommuting experience, given that transit pass ownership is positively associated with telecommuting propensity under normal circumstances. However, this policy should be backed up by proper practice of health and safety guidelines for COVID-19 on the transit vehicles and stations.

6. CONCLUSION AND FUTURE WORKS

The paper presents an empirical investigation of the factors influencing the weekly telecommuting frequencies of post-secondary students in the GTHA. Using a large-scale travel survey data of students attending 10 post-secondary institutions across the region, this study estimates a split-population OEV model of telecommuting frequency choices. The model accounts for the zero-inflation and the heterogeneity observed in the frequency data. It accommodates separate explanatory variables for the zero frequency and for the positive frequencies thereby acknowledging the fact that the choice of not telecommuting at all has a different underlying behavioural process than the choice of non-zero frequency of telecommuting.

The model identifies several important factors related to telecommuting frequency choice of the students. In terms of personal demographics, age, gender (being a female) and full-time off-campus work are found to be positively associated with telecommuting behaviour. Students living with roommates telecommute less frequently, perhaps because they don't have the proper environment at their residences to concentrate on studies, and as such they prefer to commute to the school. Also, the number of vehicles in the household is negatively associated with zero telecommuting frequency. In terms of the student status, university students and international students tend to telecommute less than college students and local students respectively. Heavier course load (as manifested by full-time student status) tend to discourage students from telecommuting frequently.

In terms of travel related characteristics, mobility tool ownership, typical commute mode choice, commute distance and travel cost affect the telecommuting frequency of post-secondary students. Among the mobility tools, transit pass and auto availability encourage more frequent telecommuting than driver's license or bike ownership. Longer commute distance and higher monthly travel cost also encourage students to telecommute. Students who drives or shares ride to school are more likely to telecommute than those who takes transit or active modes. From the frequency perspective, students who walk to school telecommute more frequently compared to others; whereas those who take regional transit would telecommute less frequently. Built environment attributes and transit accessibility of residential zone also have significant impact on telecommuting frequency. Poor subway network accessibility and higher population density increase the probability of telecommuting and they also encourage students to telecommute more frequently.

The overall impacts of telecommuting on post-secondary students' productivity, lifestyles, and travel are quite complex. However, there is a general interest in understanding which group of students are the likely telecommuters, and on exploring the influence of the land-use and transportation systems on their telecommuting decisions. The findings of this study not only improve our understanding of the factors affecting telecommuting frequencies, but also play instrumental role in predicting the extent of telecommuting in the future and assessing its impact on overall travel demand. Future extensions of the study should explore the effects of telecommuting on post-secondary students' activity-travel scheduling and on their study productivity. It will also be interesting to develop a joint model of telecommuting frequency that can accommodate attitudinal indicators as outcomes of latent explanatory variables. Future studies that will investigate this topic might also consider including a separate survey question to assess which individuals consider the telecommuting option and then do an integrated analysis of the option, choice and frequency of telecommuting by post-secondary students.

The study also provides important insights for policy analysis related to post-secondary students' telecommuting frequency and to develop specialized targeted programs that can make the telecommuting experience better, especially in the coming semesters when most courses will be offered online in response to the pandemic. It is anticipated that policies like careful redesign of the course loads, promoting positive attitudes towards telecommuting among specific student groups and provision for subsidized transit passes can lead to the greater acceptance of telecommuting among the post-secondary students and enhance their online learning experience in current and post COVID-19 situations.

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AUTHOR CONTRIBUTIONS

Study conception and design: K.N. Habib; Data preparation: S. Hossain, K. Wang; Analysis and interpretation of results: S. Hossain, K.N. Habib; Manuscript preparation: S. Hossain, K. Wang, K.N. Habib. All authors reviewed the results and approved the final version of the manuscript.

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