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The future of telecommuting post COVID-19 pandemic

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ABSTRACT

COVID-19 caused unprecedented changes in the daily lives of many people worldwide, with many working from home for the first time. This shift in working arrangement has the potential to have a lasting impact in future. This paper investigates longer-term impacts of COVID-19 on work-arrangements, specifically, individuals’ preferences towards work-from-home post COVID-19. This study utilizes data from a stated preference component of a travel survey conducted in the Central Okanagan region of British Columbia. A random parameter ordered logit model is developed to accommodate the ordinal nature of the preference variable and capture unobserved heterogeneity. One of the key features of the study is to confirm the effects of residential choice in terms of location characteristics and dwelling attributes on work-from-home preferences after the pandemic. For example, individuals’ dwelling attributes such as larger sized dwelling, larger sized apartments are likely to have positive effect on frequent work-from-home. The model confirms significant heterogeneity, in relation to location characteristics such as commute distance and distance to urban center. For instance, initially, females were less likely to work-from-home. However, they showed significant heterogeneity with large standard deviation, specifically their preference was found to vary by residential location. For instance, females residing farther from urban centers prefer a higher frequency of work-from-home. Elasticity analysis suggests that part-time female workers, mid-age individuals, full-time workers with children, and full-time workers with longer commutes have a significantly higher probability to work-from-home every day after the pandemic. The findings of the study provide important insights which will assist in developing effective work-from-home strategies post-the-pandemic.

Introduction

Work-from-home has emerged as a feasible alternative way to work for many sectors in many parts of the world due to government restrictions on travel, and business and office closures during COVID-19 (Shamshiripour et al., 2020). Statistics Canada reported that 32% of Canadian employees worked from home at the beginning of 2021, a sizeable increase from 4% in 2016 (Statistics Canada, 2021). Telecommuting has the potential to reduce daily trips and traffic congestion, improve air quality, increase productivity and efficiency, offer flexibility in schedule, and work-life balance, among other benefits (Harpaz, 2002). Although work-from-home has been a topic of interest to transportation researcher for many years (Mokhtarian, 2009; Mokhtarian et al., 2004); it is during COVID-19, when the benefits of work-from-home were realized by employers, employees and government agencies. As a result, policies and strategies to promote work-from-home or some form of telecommute are likely to occur as we begin to re-open businesses and offices after the pandemic (Shamshiripour et al., 2020). For effective policymaking, it is critical to understand the factors influencing the choice. However, the decision to work-from-home is a complex choice which is often influenced by many factors such as location of residence, space in the house, household composition, employment type and built environment attributes (Caulfield, 2015; Ettema, 2010; Fu et al., 2012). For example, individuals who are working from home spend more daytime hours in the home, indicating the importance of understanding the residential location and housing attributes of individuals who prefer to telecommunicate regularly. Previous studies have made tremendous efforts in providing insights on the predictors of work-from-home; however, most of this research was conducted for the pre-pandemic context. COVID-19 is likely to have a long-lasting impact on individuals’ travel behavior. Although there is likely to be greater interest from the employees towards a flexible work...
arrangement, limited research exists on this likely phenomenon. Therefore, the research question is: how will individuals’ preferences towards work-from-home evolve after the pandemic?

This paper investigates individuals’ preferences towards work-from-home after the pandemic. Data comes from a web-based survey conducted in the Central Okanagan region of British Columbia, Canada from November 2020, to January 2021. The use of this data collected from the latter half of 2020 enables this study to offer better insights towards the post-pandemic period. Since individuals have spent more than 6 months in the pandemic by the time this data was collected, they have experienced the pros and cons of working from home for a reasonably extended period and have a better understanding on how their behavior might evolve in the post-pandemic period. A random parameters ordered logit (RPOL) modeling technique is adopted to accommodate the ordered nature of the preference and capture unobserved heterogeneity among individuals by assuming a continuous distribution of parameters. One of the key features of this study is it examines how residential choice effects work-from-home. The effects of residential choice are accommodated in terms of location characteristic of the residence such as distance to work and distance to urban center, and the characteristics of the dwelling such as number of bedrooms and tenure type. In addition, this study tests the effects of socio-demographics such as gender and income, dwelling characteristics such as number of bedrooms, and built environment such as transportation infrastructure, land use and neighborhood attributes.

Literature review

Telecommuting increased during the pandemic, keeping businesses, schools, and governments virtually operational while the physical space was closed. For example, in March of 2020, the number of workers primarily working from home increased from 6 % to 39 % in the Netherlands (de Haas et al., 2020). They also found that 27 % of those working from home will expect to work-from-home more in the future than they did before the pandemic Conway et al. (2020) revealed that 6 % of the residents of Chicago, USA reported working from home full-time before the pandemic; while in the spring of 2020, 90 % of full-time workers were working from home at least four days a week. Furthermore, they reported that 62 % of respondents would like to work-from-home at least a few times a month in the future. Hambly et al. (2019) similarly found that 7 % of Canadians worked from home in 2017, additionally they argued that working from home can have significant financial benefits which could increase its appeal post-pandemic.

Work-from-home is a complex decision as it is affected by several factors which include but are not limited to commute travel time (de Vos et al., 2018), one-way commute trips (Zhu, 2013), and residential location choice (Ettema, 2010; Zhu, 2013). Among the many, location of residence and dwelling characteristics are critical indicators for work-from-home. For example, Zhu et al. (2018) adopted a two-stage least square model using National Household Travel Survey data collected from 2001 to 2009 in many American cities in 2018. They identified that telecommuters live farther from their workplace and travel farther for non-work trips, increasing their distance travelled and trips taken, making working from home less sustainable than expected. This same study found that trip distance grew faster in larger Metropolitan Statistical Areas (MSAs), indicating that telecommuters might be moving farther from shops, schools, and other routine destinations in bigger cities when telecommuting is available. Delventhal et al. (2021) used a quantitative model to investigate the way Los Angeles would change with increased work-from-home using origin-destination employment statistics data collected from 2012 to 2016. They found that jobs moved to the city centre while residents moved away from the CBD. Melo and Silva (Melo and de Abreu e Silva, 2017) considered binary and ordered measure of telecommuting for examining weekly commuting distance travelled for Great Britain using data from the National Travel Survey. They argued that work-from-home is more likely to increase weekly commuting distances travelled. Kim (2016) used 2006 data from Seoul, South Korea, to conduct path analysis on telecommuting households. They found that rather than residential location being decided due to telecommuting, telecommuting was adopted due to long commutes. This may have been altered due to work-from-home requirements during the pandemic. Ettema (2010) confirmed the effects of work-from-home on residential location using the 2002 housing demand survey from the Netherlands. This study reported that there is a higher likelihood for telecommuters of choosing outer city or rural areas having less amenities and facilities. However, residential location attributes might have influence on the preference of work-from-home. For example, distance to work from the residence might influence the decision of work-from-home (Zhu, 2013). Therefore, it is important to investigate how residential location characteristics impacts work-from-home for a better understanding of how daily travel is impacted. Furthermore, Ettema (2010) used latent class modelling to investigate heterogeneity among the telecommuters, and confirmed heterogeneity exists within individuals’ sensitivity to commute distance. This indicates that there could be heterogeneity within the telecommuter group which need to be investigated further considering the post-pandemic period.

Socio-demographics and built environment characteristics also influence work-from-home preference. For instance, Zhu (2013) used National Household Travel Surveys conducted in 2001 to 2009 in American cities to discover that telecommuters having higher income, children living in the household, and owning vehicles have a longer commute distance and duration. This same study found that in a two-worker household, one worker telecommuting has no impact on the other worker’s commute distance. Bhuian et al. (2020) used data from 185 communities in Calgary, Canada in 2011 and formulated a multiple regression model using neighbourhood design and social characteristics to examine work-from-home adoption. They found that the irregular street patterns often found in older suburban communities increased work-from-home. They also found that individuals dwelling in highly residential areas are more likely to telecommute. In addition to the built environment attributes, they found that larger household size decreased telecommuting with three person households yielding the least work-from-home. Additionally, female lone parents are less likely to work-from-home when compared to their male counterparts. However, households with young children (6 to 14 years old) revealed increased work-from-home. Fu et al. (2012) used a binary logit model considering whether an individual chose to work-from-home or not. They examined the effects of socio-demographics, land use, and transportation infrastructure on the rate of work-from-home using a case study in Ireland. Their results suggested that there is a higher likelihood of increased rate of work-from-home with an increased railway coverage. Results further reveal that increased scattering of residential, commercial, and industrial land use might motivate higher rates of work-from-home. Additionally, Caulfield (2015) developed a multinomial logit model to examine the factors that influence work-from-home preference. They investigated the effect of transit access, commercial grouping, vehicle ownership, household type, and density of residential land use on work-from-home. Results revealed a positive association of excellent internet connection, transit availability, and job/occupation with the likelihood of work-from-home.

However, the majority of the above studies have investigated work-from-home in a pre-pandemic context. The work-from-home behavior post-pandemic may not be the same as pre-pandemic, since many people were forced to switch to work-from-home during the pandemic. Recently, some studies have explored work-from-home frequency during the pandemic. For example, Nayak and Pandit (2021) used data from March of 2020 collected in India to investigate telecommuting before, during, and after the pandemic. They found that middle-ages males and those living in households of 2 to 3 people are likely to telecommute post-pandemic. However, possibly due to the novelty of the circumstances, investigation regarding work-from-home preferences after

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COVID-19 is limited. Furthermore, the majority of the existing studies analyzing work-from-home preferences post-pandemic used data that were collected immediately after the COVID-19 lockdown. To better understand the long-lasting effects of COVID-19 on work-from-home, it is critical that individuals have spent a reasonably extended period working from home which is expected to enable them to have a better realization of their preferences. It is also important as many of the workers experienced it for the first time during the pandemic. As a result, the influential factors for work-from-home might vary in the future.

Contributions of the current study

This study contributes to the literature by investigating the longer-term effects of COVID-19 on individuals’ travel behaviour. Specifically, this paper models individuals’ preferences towards work-from-home - after the pandemic. Data comes from a web-based survey conducted in the Central Okanagan region of British Columbia, Canada from November 2020 to January 2021. A random parameters ordered logit (RPOL) modeling technique is adopted for two major purposes: 1) to accommodate the ordinal nature of the preference response towards the future work-from-home scenario, and 2) to capture unobserved heterogeneity by allowing a continuous distribution of random parameters. One of the key features of this study is to extensively test the effects of residential choice such as location and dwelling attributes, socio-demographics, dwelling characteristics, transportation infrastructure attributes, land use, and neighbourhood characteristics, among others. Furthermore, the role of residential location on the preference of frequency of work-from-home is evaluated by measures representing access to work such as distance to workplace and access to different destinations such as distance to urban centre. Several hypotheses related to how work-from-home behaviour might evolve after the pandemic are tested in this study, which includes: Do residential location and dwelling attributes have influence on work-from-home preferences? Do employment types such as full-time and part-time work have influence on work-from-home preferences? Do males prefer to work-from-home more than females? Does built environment, such as transportation infrastructure attributes, affect work-from-home frequency? Is there any heterogeneity in work-from-home preference? Is the heterogeneity related to where individuals live?

Data

Data sources

This paper uses data from a web-based survey conducted in the Central Okanagan region of British Columbia, Canada. They surveyed were distributed via social media advertisements from November 2020, to January 2021. The survey had the following sections: location information, socio-demographics, work/school-related information, shopping trips and online purchases, daily travel, and residential location and vehicle ownership. The work/school component collected information related to the work and school arrangements for the following four periods: before the pandemic, March of 2020, the week prior to the survey, and long after the pandemic. The question for the long after the pandemic period was a stated preference question, which collected the preferred frequency of work-from-home post COVID-19 in a 5-point scale of: everyday (17.3 %), few times a week (27.1 %), few times a month (7.1 %), few times a year (1.3 %), and never (34.6 %). The location collected information related to the home and work locations, in addition to questions about the individual and the household they reside in. The data was validated using an iterative proportional fitting technique comparing it to the Census Canada 2016 data (Lomax and Norman, 2016). Gender and occupation were used as the calibration variables while the other socio-demographics were used as validation variables. The final sample size is 226, with 77 % of characteristics falling within 5 % variability from the census values, for example occupation fell within 3.4 % of the Census distribution. The sample slightly over-represents higher income and higher education while underrepresenting lower education individuals.

This study uses secondary data from various sources. For example, parcel-level dwelling unit data (e.g., number of bedrooms, property value) is collected from BC Assessment. Neighborhood attributes (e.g., percentage of single-detached, percentage owners) are collected from Statistics Canada. Land use attributes (e.g., percentage of residential land use, percentage of commercial land use) are collected from the City’s Open Data portal. Location of urban centers and activity points - such as bus stops are also extracted from the City’s Open Data portal and Desktop Mapping Technologies Inc. (DMTI).

Descriptive analysis

The COVID-19 pandemic impacted the way many people worked, with a large portion of the labor force telecommuting for the first time. Fig. 1 shows the percentage of workers working from home before COVID-19, during March of 2020, and after COVID-19. The data analysis suggests that only 16.3 % of respondents in the labor force worked from home a few times a week before the pandemic. This share increased to 66.1 % during March of 2020. 57 % of respondents working full or part time would prefer to work-from-home at least a few days a week after the pandemic is over. Additionally, 62.2 % of worker had never telecommuted before the pandemic and only 34.6 % prefer not to work-from-home in the future. Among the workers who prefer not to work-from-home in the future, 41 % would like to go back to in-person work as they do not have adequate technology available at home and 31.5 % do not have a job that allows them to work-from-home after the pandemic, such as teachers or retail employees. Other barriers included distractions and less effective communication. This figure shows a drastic increase in the frequency of work-from-home in future compared to before the pandemic.

The drastic increase in work-from-home during the pandemic has altered the way many jobs and workers view the effectiveness of working from home. Individuals who are telecommuting are finding it to be a productive alternative to working in-person - 63.9 % of telecommuters found work-from-home somewhat or extremely productive with 33.7 % finding it somewhat unproductive and only 2.4 % finding it extremely unproductive. These initial findings indicate that work-from-home is a viable alternative to in-person work. Further investigation is needed to understand the factors effecting the preferences towards work-from-home.

Methodology

This study develops a random parameter ordered logit (RPOL) model to assess the preferences towards work-from-home long after COVID-19. RPOL model accommodates the ordered nature of the dependent variable (i.e., preferred frequency of work-from-home) and captures unobserved heterogeneity by allowing parameter values to vary across the population. RPOL model adopts a latent regression modeling approach where the dependent variable is in ordered characteristics, at the same time parameter values vary across the observations. Let, $Z_i$ represents the latent continuous function which assesses the frequency of work-from-home outcome. The logit formulation can be expressed as:

$$ Z_i = \beta X + \epsilon_i $$

Here,

- $Z_i$ = latent continuous function for frequency of work-from-home outcome $i$
- $\beta$ = vector of parameters corresponding to the explanatory variables.
- $X$ = vector of explanatory variables.
\( \varepsilon_i = \text{random error term that follows standard logistic distribution.} \)

The ordered scale \( k (0, 1, 2, \ldots, k-1) \) denotes the discrete frequency of work-from-home categories by using certain threshold values \( \lambda_k \). For example, frequency of work-from-home responses are recorded as the work-from-home categories by using certain threshold values.

\[
Z_i = \begin{cases} 
0: & \text{if } \lambda_2 \leq Z_i \leq \lambda_1 (\text{never}) \\
1: & \text{if } \lambda_3 \leq Z_i \leq \lambda_2 (\text{few times a year}) \\
2: & \text{if } \lambda_4 \leq Z_i \leq \lambda_3 (\text{few times a month}) \\
3: & \text{if } \lambda_5 \leq Z_i \leq \lambda_4 (\text{few times a week}) \\
4: & \text{if } Z_i < \lambda_5 (\text{everyday}) 
\end{cases}
\]  

Now, the unobserved heterogeneity is accommodated by allowing a continuous variation of random parameters. Random parameters follow a normal distribution across the observations. This study further allows interactions of random parameters with explanatory variables (i.e., heterogeneity in means of random parameter). This study considers accessibility measures such as distance to urban center and distance to home location. Among the neighborhood infrastructure and land use attributes are extracted within a 500-meter buffer from the respondent’s home location. Among the neighborhood characteristics variables representing individuals such as age, gender, income, job status (part-time or full-time), education, occupation, transit pass ownership, driving license among others are tested. In the case of household-level attributes, number of persons, number of children, and vehicle ownership are tested. Land use attributes include percentage of residential area, percentage of commercial area, and land use index (LUI). Transportation infrastructure characteristics include length of bicycle lane, length of sidewalk, and number of bus stops among others. Transportation infrastructure and land use attributes are extracted within a 500-meter buffer from the respondent’s home location.

The outcome probability of frequency of work-from-home outcome \( i \) can be formulated as:

\[ P_i(X|\beta_i, \Delta_i) = \frac{\exp(\beta_i X)}{\sum_{j=0}^{m-1} \exp(\beta_j X)} \]  

Here, \( \Delta_i = \text{vector of uncorrelated random variables.} \)

Considering the identically and independently distributed error term, probability of frequency of work-from-home outcome \( i \) unconditional on \( \Delta_i \) can be expressed as:

\[ P_i(X|\beta_i) = \frac{\exp(\beta_i X)}{\sum_{j=0}^{m-1} \exp(\beta_j X)} f(\Delta_i, k) d \Delta_i \]  

Here, \( f(\Delta_i, k) = \text{joint density function of } \Delta_i. \)

The model is estimated by maximizing the simulated log-likelihood function. The simulated log-likelihood (SL) can be formulated as:

\[
SL = \sum_{m=1}^{M} \sum_{k=1}^{k-1} \ln \frac{1}{R} \sum_{r=1}^{R} P_i(X|\beta_i) 
\]  

Here, \( M = \text{number of observations.} \)

\( \alpha_m = \text{dummy; if respondent } m \text{ has experienced } k \text{ frequency of work-from-home} = 1, \text{ else } 0. \)

\( R = \text{number of random draws} = 200 \text{ Halton draws.} \)

The probabilities are approximated by drawing values of \( \Delta_i \) from density function \( f(\Delta_i, k) \). The model estimates the probabilities for several draws of \( \Delta_i \). After that, the approximate probability is estimated by determining the average of the probabilities from \( R \) random draws. This average is the simulated probability which is maximized to estimate the parameters.

**Independent variables**

The study extensively examines the influence of residential choice, socio-demographic characteristics, accessibility, land use, transportation, and neighborhood characteristics. The effects of residential choice are accommodated in terms of location characteristic of the residence such as distance to work and distance to urban center, and the characteristics of the dwelling such as number of bedrooms, tenure type, dwelling type, presence of basement, and property value among others. In the case of socio-demographic characteristics variables representing individuals such as age, gender, income, job status (part-time or full-time), education, occupation, transit pass ownership, driving license among others are tested. In the case of the household-level attributes, number of persons, number of children, and vehicle ownership are tested. Land use attributes include percentage of residential area, percentage of commercial area, and land use index (LUI). Transportation infrastructure characteristics include length of bicycle lane, length of sidewalk, and number of bus stops among others. Transportation infrastructure and land use attributes are extracted within a 500-meter buffer from the respondent’s home location. Among the neighborhood attributes, variables including percentage single-detached house, ratio of apartment to single-detached, percentage of owners, and employment rates among others are tested.
Results

The summary statistics of the variables retained in the final model are presented in Table 1.

Table 1

| Variables                              | Description                                      | % or Mean | Std. dev. |
|----------------------------------------|--------------------------------------------------|-----------|-----------|
| **Socio-demographic characteristics**  |                                                  |           |           |
| Age 18 to 24                           | Dummy; If respondent is 18 to 24 years old       | 12.38     | n/a       |
| Age 25 to 49                           | Dummy; If respondent is 25 to 49 years old       | 41.15     | n/a       |
| Age 30 to 54                           | Dummy; If respondent is 30 to 54 years old       | 52.65     | n/a       |
| Female                                 | Dummy; If respondent is female                   | 50.44     | n/a       |
| Child                                  | Dummy; If respondent’s household has child       | 19.47     | n/a       |
| Income > 150                          | Dummy; If respondent’s annual gross household income is greater than 150,000 CAD | 20.35     | n/a       |
| Vehicle                               | Dummy; If respondent’s household owns vehicle   | 62.39     | n/a       |
| Full-time worker                      | Dummy; If respondent’s current employment status is full-time worker | 52.21     | n/a       |
| Part-time worker                      | Dummy; If respondent’s current employment status is part-time worker | 16.81     | n/a       |
| **Dwelling characteristics**          |                                                  |           |           |
| Owned                                 | Dummy; If respondent owns the dwelling            | 70.79     | n/a       |
| Number of bedrooms                    | Number of bedrooms in the dwelling               | 3.25      | 0.887     |
| Bedroom > one                         | Dummy; If number of bedrooms in the dwelling      | 99.11     | n/a       |
| **Accessibility characteristics**      |                                                  |           |           |
| Distance to work                      | Distance to workplace from the home in km        | 16.33     | 13.61     |
| Distance to urban center              | Distance to nearest urban center from the home in km | 8.44      | 17.13     |
| Distance to urban center < three km   | Dummy; If distance to nearest urban center from the home is less than 3 km | 45.13     | n/a       |
| Distance to urban center three to five km | Dummy; If distance to nearest urban center from the home is less than 5 km and greater than equal 3 km | 10.18     | n/a       |
| Distance to urban center three to ten km | Dummy; If distance to nearest urban center from the home is less than 10 km and greater than equal 3 km | 37.17     | n/a       |
| **Transportation Infrastructure Attributes** |                                              |           |           |
| Length of sidewalk                    | Length of sidewalk in 500 m buffer of the home in km | 5.53      | 4.36      |
| Length of bicycle lane                | Length of bicycle lane in 500 m buffer of the home in km | 4.42      | 4.20      |
| **Land use and neighborhood characteristics** |                                            |           |           |
| Percentage residential area           | Percentage of residential land use within the household dissemination area | 58.31     | 22.10     |
| Percentage single-detached            | Percentage of single-detached houses within the household dissemination area | 45.38     | 22.25     |
| Ratio of percentage of apartment to single-detached | Ratio of percentage of apartment to single-detached houses within the household dissemination area | 2.75      | 12.69     |

Goodness-of-fit measures of the models

For comparison purposes, in addition to the Random Parameters Ordered Logit (RPOL) model, Ordered Logit (OL) model is developed. The performance of RPOL model is compared on the basis of AIC, BIC, and adjusted pseudo r-squared values. The results reveal that the adjusted pseudo r-squared value is higher for RPOL (i.e., 0.437) model than that of the OL (i.e., 0.204) model. Furthermore, BIC value for the RPOL and OL models are 427.7 and 497.7 respectively. Since the model with lower BIC value fits the data best, the RPOL model outperforms other models and is considered for further result discussions.

Results of random parameters ordered logit (RPOL) model

The model confirms the effects of socio-demographics, dwelling, accessibility, land use, neighborhood, and transportation attributes (Table 2). The majority of the factors retained in the final model are statistically significant at least at 1% level.

In the case of socio-demographic, the variable representing age 25 to 49 reveals a positive relationship. This indicates that the individuals aged 25 to 49 years are more likely to frequently work-from-home post COVID-19. This finding is consistent with earlier studies that the likelihood of work-from-home increases with the age (Fu et al., 2012). Full-
time workers were found to show a positive relationship; particularly, those who reside farther from their workplace. This is an interesting finding as full-time workers are typically required to make daily trips to work. A higher frequency of work-from-home is likely to save a significant amount of travel time for those who have a longer commute distance. They can then use that time for other activities such as spending time with their children. In this line of investigation, the model results confirm that full-time workers with children prefer to frequently work-from-home after the pandemic. During COVID-19, when both parents and children were at home, they could spend more time together after work/school as they had more time savings from eliminating their commute. This saving is particularly significant for full-time workers due to their typical daily commute trips. This likely positive experience during the pandemic might have triggered a longer-term behavioral change towards more frequent work-from-home among full-time workers after the pandemic. For the variable representing female, a negative relationship (i.e., mean value of $-6.02$) is confirmed, implying that women might not prefer to telecommunicate frequently post COVID-19. A previous study also argued that males are more motivated to work-from-home than their female counterpart (Fu et al., 2012).

However, the model confirms significant heterogeneity across the female individuals as indicated by the statistically significant standard deviation (i.e., 9.32). This suggests that considering a normal distribution, 26% of the observations for female is positive (i.e., increased likelihood of frequent work-from-home post COVID-19); whereas 74% is negative (i.e., decreased likelihood of frequent work-from-home post COVID-19). Interestingly, this variable shows significant heterogeneity in means for the variable represented by distance to urban center. This result suggests that females residing in suburban areas who are likely to have longer commute to work, prefer more frequent work-from-home opportunities after COVID-19. Results further reveal that if females are part-time workers, they are likely to prefer more frequent work-from-home opportunities after COVID-19. When female is interacted with age 30 to 54, a negative relationship is confirmed. However, this variable exhibits a statistically significant heterogeneity in mean in reference to the variable representing higher distance to urban center. This implies a higher likelihood for frequent work-from-home after COVID-19 by middle-aged females who have longer commute. They could use the travel time saving to engage in other activities such as personal care and/or spending time with children/friends/family.

In the case of dwelling characteristics, the variable representing number of bedrooms shows a positive relationship. This suggests a higher likelihood of frequent work-from-home by those who live in bigger dwelling units with many beds. This is expected because increased number of bedrooms enhances the flexibility to work in a separate space without any interference. For the variable representing owned dwelling interacted with vehicle ownership, a negative relationship (i.e., $-21.84$) was revealed. This implies that individuals dwelling in owned house and having vehicles in the household are less likely to consider frequently working from home. Vehicle ownership might make it convenient to travel to work, hence discouraging individuals to work-from-home. However, a previous study reported positive association of work-from-home with vehicle ownership (Fu et al., 2012). Interestingly, model results reveal that variable representing home ownership interacted with vehicle ownership shows significant standard deviation (i.e., 25.25). This implies a lower likelihood of frequent work-from-home for 81% observations, in contrast, a higher likelihood of frequent work-from-home for 19% observations. Furthermore, this interacted variable shows significant heterogeneity in mean for the variable representing distance to urban center. Those who reside closer to urban center are less likely to frequently work-from-home. However, those who reside farther away from an urban center are more likely to frequently work-from-home.

Among the land use and neighborhood attributes, the variable representing percentage of residential area interacted with income greater than $CS150,000 shows a positive relationship. This indicates that higher income individuals residing in higher percentage of residential neighborhoods are more likely to work-from-home frequently after the lifting of COVID-19 measures. Similarly, percentage of single-detached shows a positive sign. Since, higher percentage of single-detached houses in a neighborhood indicates a suburban setting (Giner et al., 2013), this finding is consistent with previous studies which found that individuals dwelling in suburban areas consider work-from-home more (Mummad et al., 2007). Interestingly, this variable revealed a significant heterogeneity in mean for distance to work. This result suggests that individuals residing in suburban neighborhoods with a higher percentage of single-detached houses might consider frequent work-from-home even if the workplace is closer to home. This is an interesting finding. Mandatory work-from-home during the lockdown phase might have influenced individuals to continue working from home even after the lifting of COVID-19 measures. Furthermore, suburban neighborhoods are identified by larger household sizes (De Vos and Alemi, 2020) and higher percentage of single-detached houses. Often families with children prefer such neighborhoods. Such larger dwelling with space for work and opportunity to interact with children more might motivate individuals to work-from-home even if their workplace is close by. For the variable representing the ratio of percentage of apartment to single-detached dwellings interacted with number of bedrooms greater than one shows a positive sign, implying a higher likelihood of frequent work-from-home preference for individuals residing in larger dwelling in neighborhoods with higher ratio of apartments than single-detached houses. This might further illustrate that the availability of space at home is a significant factor for the work-from-home.

In the case of transportation characteristics, length of sidewalk interacted with age 18 to 24 shows a negative sign. This indicates that younger adults residing in neighborhoods with good facility of alternative transportation such as walking, are less likely to work-from-home frequently when COVID-19 measures are lifted. This is expected because improvement of transportation facilities might negatively influence the likelihood of telecommuting (Fu et al., 2012). Similarly, a negative relationship is retained for the variable representing the length of bicycle lane.

**Elasticity results**

The parameter estimates of explanatory variables do not directly represent the magnitude of the impacts of the variables on the frequency of work-from-home. This study estimates the elasticities to evaluate the magnitude of impact of the independent variables on the probability of frequency of work-from-home. Elasticity values are averaged over the sample individuals and show the effect of unit increase in an explanatory variable on the frequency of work-from-home outcome probabilities. In the case of dummy variables, the change in the probability of the frequency of work-from-home is estimated when an explanatory variable’s value changes from 0 to 1 (Wang et al., 2019; Yasmin et al., 2014).

Elasticity effects can be expressed as:

$$Elasticity = \left\{ \begin{array}{ll}
\frac{\delta P_{m}(X_{mn})}{\delta X_{mn}} & \text{if continuous variable} \\
\frac{P_{m}(X_{mn} = 1) - P_{m}(X_{mn} = 0)}{P_{m}(X_{mn} = 0)} & \text{if dummy variable}
\end{array} \right.$$  

(7)

Here, $Elasticity_{X_{mn}}$ is elasticity, and $X_{mn}$ with indicator variable for observation m.

Elasticity results in Table 3 illustrate the percentage change in the probability of the frequency of work-from-home post COVID-19 due to the change in specific explanatory variables.

Results suggest that the variable representing age 25 to 49, female part-time worker, full-time worker with children, full-time worker residing farther from work, number of bedrooms, percentage of single-detached dwelling, percentage residential area with more high-income groups show significant positive impact on work-from-home every day.
after COVID-19. For instance, the likelihood of work-from-home everyday increases by 7.31 % for mid-age individuals (i.e., age 25 to 49). For female part-time workers, the probability of work-from-home everyday increases by 24.34 %. Furthermore, probability of work-from-home everyday and few times a week increases by 7.79 % and 4.04 % respectively for unit increase of number of bedrooms.

In the case of variables that revealed a significant impact towards never working from home, mid-age female and owned dwelling with vehicle are the most significant. For example, middle-aged females showed a 4.5 % increase in the likelihood of never working from home after COVID-19. The probability of work-from-home never and few times a year will increase by 4.19 % and 0.5 % for owned household with vehicle.

### Conclusion

This paper presents findings on the longer-term impact of COVID-19 on individuals’ work-from-home behavior. Specifically, a random parameter ordered logit (RPOL) modeling technique is adopted to examine preference towards work-from-home after COVID-19. The model accommodates the ordered nature of the preference variable on a five-point scale of never to everyday, and captures unobserved heterogeneity. The model results suggest that residential location and dwelling attributes, socio-demographics, land use, transportation, and neighborhood attributes significantly influence the frequency of work-from-home post COVID-19. For instance, full-time workers, specifically, if they reside farther away from workplace and/or have children, revealed a positive association for higher frequency of work-from-home. Variables representing higher income individuals residing in areas with higher share of residential buildings are more likely to frequently work-from-home. Dwelling attributes such as dwellings with more bedrooms were found to have a significant positive effect. Interestingly, areas with larger sized apartments also showed a positive relationship, indicating the strong influence of space availability at home for work-from-home. Individuals residing in neighborhoods with alternative transportation infrastructure such as length of bike lane and length of sidewalk revealed a lower likelihood for frequent work-from-home. The model confirms significant heterogeneity among the sample individuals. The preference is found to vary by residential location characteristics represented by commute distance, and distance between home and urban center. For example, initially, females are found to be less interested in work-from-home. However, they show significant heterogeneity with a large standard deviation. Further investigation in respect to heterogeneity in mean reveals that females residing farther from urban centers prefer a higher frequency of work-from-home. Females who are part-time also suggested a higher probability for frequent work-from-home after the pandemic. Individuals residing in areas with a higher percentage of single-detached dwellings are more likely to frequently work-from-home. This variable showed heterogeneity in mean for distance to work, indicating that suburban dwellers are likely to prefer to work-from-home even if their workplace was closer to home. The elasticity results suggest that part-time female workers, mid-age individuals, full-time workers with children, full-time workers with longer commutes and individuals residing in larger size dwellings have a higher likelihood to work-from-home every day after the pandemic. For example, the likelihood of work-from-home everyday increases by 24.34 % if the individual is a female part-time worker. On the other hand, mid-age females, and individuals’ owning vehicles and residing in owned dwelling have a significantly higher likelihood to never work-from-home. For instance, the probability of never working from home increases by 4.19 % if individuals own a vehicle and reside in owned dwellings.

The findings of this research have several implications. For instance, results reveal the frequent work-from-home for suburban people with longer commute. This has largely-two-dimensional implications. On one hand, COVID-19 forced people to work-from-home which has increased the demand for larger dwellings with additional spaces, such as office space for work-from-home arrangements, often in suburban areas as many workers do not need to commute to work everyday. However, transit services are limited in the suburban neighborhoods. Consequently, suburban people are likely to travel with car which will increase vehicle kilometer traveled (VKT). On another hand, although peak hour travel might be reduced for telecommuting people, there might be increased off-peak hour trips due to residing in suburbs away from facilities such as restaurants and shops as well as to avoid peak hour congestion. Since transit service scheduling is planned to meet peak hour demand largely, these trips might be shifted to car trips.

This indicates a need to review the transit scheduling. Results also reveal significant heterogeneity in terms of preference of work-from-home for high income and female population. This demonstrates the need to accommodate heterogeneity while developing work-from-home plans and policies. It is also observed that target group for more frequent work-from-home are female part-time workers, people with children, and people with a longer commute. Interestingly, study suggests that people owning a car has a significantly higher impact on non-frequent work-from-home. It indicates that people are likely to commute predominantly using private cars which might increase VKT and emissions in future.

This study has certain limitations. One of the limitations of the study is the over-representation of some occupations such as management, natural and applied sciences, and education-law-social-community-government services as well as under-representation of occupation such as sales and service, and trades-transport-equipment operators. This might have introduced some bias to the data. As a result, the study could not test the effects of these variables, which is critical as telecommuting is not an option for many occupations such as essential

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### Table 3

Elasticity Results.

| Variables                                      | Frequency to work-from-home |
|------------------------------------------------|-----------------------------|
|                                                  | Never                      |
|                                                  | Few times a year           |
|                                                  | Few times a month          |
|                                                  | Few times a week           |
|                                                  | Everyday                   |
| **Socio-demographic and household characteristics** |                             |
| Age 25 to 49                                    | -2.37                      |
| Female*                                         | 0.30                       |
| Female * part-time worker                       | -1.71                      |
| Female * age 30 to 54*                          | 4.50                       |
| Full-time worker *                              | -0.86                      |
| Full-time worker *                              | -3.02                      |
| Residential choice variable – distance to work  |                             |
|                                                  |                             |
| **Dwelling characteristics**                    |                             |
| Owned * vehicle*                                | 4.19                       |
| Number of bedrooms                              | -6.22                      |
| Bedroom > one * ratio                           | -0.03                      |
| of percentage of apartment to single-detached   |                             |
|                                                  |                             |
| **Land use and neighborhood characteristics**   |                             |
| Percentage residential area * income > 150     | -0.60                      |
| Percentage single-detached*                     | -0.74                      |
|                                                  |                             |
| **Transportation characteristics**              |                             |
| Length of sidewalk *                            | 0.19                       |
| age 18 to 24                                    |                             |
| Length of bicycle lane                          | 0.48                       |

# random parameter
workers. Future research should also examine whether the preferences for work-from-home vary by blue-collar and white-collar workers. Another limitation of this study is the unavailability of data related to the access to information and communication technology (ICT), which has a substantial impact on telecommuting preferences (Caulfield, 2015). Future research should also focus on extending this analysis for work-from-home to other online activities such as online shopping. A joint model can be developed to investigate how different online activities such as work-from-home, online grocery shopping and online food ordering are correlated with each other. Such findings could have important implications for both brick-and-mortar projects and transportation services such as transit. Overall, the findings of the study provide important insights into how individuals' preference to work-from-home might evolve post COVID-19. These findings are expected to assist policy-makers in developing effective policies promoting work-from-home.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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