Interaction Between Information and Communication Technologies and Travel Behavior: Using Behavioral Data to Explore Correlates of the COVID-19 Pandemic

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Abstract
The COVID-19 pandemic has highlighted the importance of information and communication technologies (ICTs) in providing virtual engagement. Planners and engineers must determine whether cities will see reductions in travel demand, given the increasing use of ICTs. Notably, ICTs facilitate online shopping and working from home (WFH). Generally, online shopping may lead to fewer shopping trips; similarly, WFH may reduce work-related trips. However, more WFH has the potential to generate other non-work trips, including shopping trips. To find answers and explore interdependencies, this study integrates pre-pandemic behavioral data with during-pandemic travel data. In our framework, WFH and online shopping are considered together. By harnessing the pre-pandemic 2017 National Household Travel Survey data, this study jointly analyzes the relationships between shopping trips, online shopping, and WFH with a conditional mixed process model that can address unobserved endogeneity and selection bias. The results suggest that, before the pandemic, online shopping was associated with fewer in-person shopping trips while WFH was associated with more shopping trips. The role of socio-demographic, locational, and travel-related factors is also explored. The during-pandemic data and analysis capture how COVID-19 affected travel behavior. Results show that the relationships among the key variables found in the pre-pandemic data are similar but differ in magnitude from during the pandemic. WFH increased from 12% to 61% during COVID-19, admittedly an unusual situation. In the next “new normal,” planners may improve travel demand models by treating WFH explicitly as an alternative to traveling to work in the trip generation and time of day models.

Keywords
planning and analysis, applications, communications/communications technology, e-shopping/e-shopping, ICT, technology, telecommuting

The world is changing through the advancement of information and communication technologies (ICTs). With affordable ICT appliances and widely available internet, many activities that needed a fixed location and time are no longer bounded as before (1). Therefore, partial decoupling of virtual and physical activity spaces is expected (2). These changes challenge the traditional belief that an individual’s daily activity is limited to fixed spaces and times (3). Virtual communication behaviors could substitute for activities that previously required physical travel, as well as stimulating more virtual communication (4). This can be in the form of e-commerce (e.g., online shopping) and teleworking (e.g., working from home), among others.

The COVID-19 pandemic and the ever-changing ICT landscape have further prompted changes in daily activity travel. During the pandemic, ICTs have played a crucial role in fulfilling the daily necessities through enabling...
working from home (WFH) and online shopping. The e-commerce surge sees more and more individuals buying from online stores. In the United States, e-commerce sales grew by 17.3% in 2019, and escalated by 36.7% in the third quarter of 2020; e-commerce comprised up to 14.3% of total retail sales, and this growth is expected to continue in the coming years (5). This surge in online shopping has the potential to affect travel behavior. Moreover, ICTs have given people the option to work virtually, leading to change in the workforce and economy. It enables companies to permit workers to work from remote locations, which can bring significant changes in workers' travel behavior. It is estimated that in 2017, 5.2% of people surveyed were engaged in full-time remote working (6); however, this number increased to 51% in April 2020 and 33% in September 2020 (7). These new routines and alternate activities are also expected to be continued in the post-COVID-19 period.

WFH is presumed to generate numerous benefits, including reduced traffic congestion and emissions, saving office space costs, and offering greater flexibility (8). Moreover, policymakers are promoting WFH to substitute for the commute to work (9). They stand on the traditional belief that WFH and online shopping might reduce physical shopping trips. However, the relationships among these activities do not provide any clear results, as expected. Do ICTs substitute for travel, especially in conditions of uncertainty like COVID-19, or can they incite new opportunities for people to engage in other activities involving travel? For example, Cao et al. (10) found that online shopping could increase shopping trips as opposed to reducing them. Besides, WFH can intervene in this relationship, as it has the potential to generate other non-work trips, like shopping trips. Moreover, WFH and online shopping can also be influenced by socio-demographic behavior, location, and travel-specific factors. However, lack of empirical evidence indicates there have been no significant prior works on the integration of these activities. It is warranted to discover the potential relationships among the mentioned ICT uses together and their overall policy-driven implications, as understanding these relationships is important for considering and planning for future travel behavior patterns.

Therefore, this study aims to analyze WFH and online shopping together to find their impacts on shopping trip generation. It further explores whether the relationships are similar or not before and during the COVID-19 pandemic. The study also aims to discover the exogenous factors that may encourage people to work from home, shop online, and make shopping trips. The structure of this paper is as follows: a literature review, which includes the previous works based on which the objectives were formulated, a conceptual framework, the methodology used, the results, and a discussion of the limitations of the study and the final conclusion.

**Literature Review**

ICTs can interact with travel in four different ways: substitution, modification, neutrality, and complementarity (11). In general, ICT use can reduce travel costs and time (substitution). Nevertheless, these savings may be used to participate in other activities where travel might be needed (complementarity). This rebound eventually offsets the initial gains in travel reduction (11–13). A major share of research has focused on online shopping and WFH among all the ICT uses (14). Online shopping (also known as e-shopping or e-commerce) has experienced substantial growth over recent years, but online sales soared amid the COVID-19 pandemic. This surge certainly can affect the generation of shopping trips, which accounted for nearly 20% of all trips in the United States in 2017 (15). Therefore, online shopping is of interest to many engineers and planners. A lasting debate is going on: whether the relationship between online shopping and shopping trips is substitutive or complementary. Several studies have explored this relationship and found a complementary effect, implying the increase in overall trips is caused by increased frequency of online shopping (10, 16). Wilson et al. (17) surveyed people in three cities in the United States and found that e-shopping for the last purchase replaced 79% of shopping trips. They also found that 55.5% of the shoppers made new trips after obtaining information online. Other studies found the relationship to be one of substitution (18–20). People substitute online shopping time for travel time, which leads the online shoppers to take fewer trips and also to travel to nearby places for shopping purposes. Moreover, online shopping has the potential to reduce longer shopping trips (19). Some studies found both substitution and complementary effects on travel. For example, Weltevreden and Rietbergen (21) found that more than 20% of online buyers made fewer trips to city center stores in the long run, whereas they also found a complementary effect in the short run. In addition, Tonn and Hemrick (22) in a study of residents of Knoxville, Tennessee, found that certain internet users reduced their trips to stores, with a minor percentage of them making new trips.

WFH (also known as teleworking or telecommuting) helps to achieve travel reduction (substitution) and urban sustainability goals based on policy implementation (23, 24), while it is also found that the impact might be smaller than expected or complementary (25, 26). WFH exerts complex travel substitution effects, rather than the common assumption that it enables reduction in overall
travel demand. It can promote more dispersed, decentralized, and car-dependent patterns of working while reducing congestion (27). Importantly, WFH provides workplace and work-time flexibility that may ease peak-hour congestion (28). There also might be an overall increase in mobility with regard to personal travel attributes. For example, it is observed that people with higher education levels are more likely to work from home and take fewer commuting trips but also to take more insignificant trips (20). Silva et al. (29) suggested that WFH is an approach used to avoid long and costly travel, especially for workers living in remote areas. Overall, while the benefits of WFH for sustainability, flexibility, or reducing commute trips have been explored, the potential for WFH to promote alternate activities, like more online shopping or making shopping trips, is less explored in previous studies. Furthermore, the COVID-19 pandemic may intervene in these relationships, as suggested by the recent literature on COVID-19 and ICT uses (30–33). Therefore, it is necessary to investigate the effects of COVID-19 as well.

Online shopping and WFH are strongly influenced by socio-demographic characteristics, regional features, and travel attributes (10, 16, 18, 21, 34). Higher education and urban location tend to increase online shopping frequency. Internet use and e-shopping are largely urban phenomena (10). People living in urban areas buy online more frequently than those in rural areas, which reveals a complementary effect between traveling and buying online (34). Higher household income, shopping attitude, and full-time employment (FTE) have both positive and negative effects on online shopping. For example, Zhou and Wang (16) and Cao (35) found household income had a positive impact on online shopping, whereas Farag et al. (34) found a negative result. A summary of the impacts of some key variables is presented in Table 1.

This research contributes to the literature in two ways while filling the gaps. First, we investigate the ICT uses (i.e., WFH and online shopping) for their association with shopping trip generation while controlling for other exogenous factors using pre-pandemic data in a joint estimation framework. Second, using the same framework, we examine whether the relationships between WFH, online shopping, and shopping trip generation are similar or not during the pandemic.

### Conceptual Framework and Hypothesis

The interaction between online shopping and shopping trip generation is not straightforward. Previous studies suggest that this relationship can be either complementary or substitutive. WFH can also intervene in this relationship since WFH itself can be influenced by the same exogenous features (e.g., socio-demographics) that define

| Table 1. Summary of Relevant Literature | Some exogenous variables and their impacts on online shopping/telework | Findings | Study approach | Analysis method | Location and data | Overall effects on travel |
|----------------------------------------|-------------------------------------------------|----------|----------------|-----------------|-------------------|-------------------------|
| Zhou and Wang (16)                     | Household income, Education                      | Complementary | Structural equation modeling (SEM) | USA, N = 85,663, National Household Travel Survey, 2009 | ++ + + + + + + + + + + | ++ + + + + + + + + + + |
| Farrell (18)                           | Household income, Education                      | Substitution | Two-stage least squares regression | San Francisco, N = 14,563, Area travel survey for the year 2000 | ++ + + + + + + + + + + | ++ + + + + + + + + + + |
| Cao et al. (10)                        | Household income, Education, FTE                 | Complementary | SEM               | Minneapolis, N = 539, online survey | ++ + + + + + + + + + + | ++ + + + + + + + + + + |
| Farag et al. (34)                      | Household income                                 | Complementary | SEM               | Netherlands, N = 2,190, online survey | ++ + + + + + + + + + + | ++ + + + + + + + + + + |
| Weltvreden and Rietbergen (21)         | Household income                                 | Substitution  | Multinomial logit | Netherlands, N = 3,200, online survey | ++ + + + + + + + + + + | ++ + + + + + + + + + + |
| Tonn and Hemrick (22)                  | Household income                                 | Substitution  | Trip generation model (regression) | Knoxville, TN, N = 118, web survey | ++ + + + + + + + + + + | ++ + + + + + + + + + + |
| Loo and Wang (20)                      | Household income, FTE                            | Substitution  | Household Survey  | China, N = 608, FTE employees | ++ + + + + + + + + + + | ++ + + + + + + + + + + |

Note: FTE = full-time employment. ‘‘+’’ and ‘‘−’’ denote positive and negative impacts, respectively.
online shopping and shopping trip association. On the other hand, recent developments in e-commerce suggest that online shopping can take many new and different forms, for example, online shopping for durable goods or groceries. These components of online shopping can be interconnected with each other and also with physical shopping trips (36). However, such nuances could not be explored because of data limitations, that is, these components were aggregated in a broad category of online shopping. To analyze the overall potential impacts, we identify the number of shopping trips, online shopping, and WFH as the outcome variables, which may be influenced by some specific person, household, location, and travel-related variables (Figure 1).

It is anticipated that the number of shopping trips will decrease with more online shopping. As the products are delivered to the door, there is less need for physical travel for shopping (18). On the other hand, WFH may stimulate shopping trips. While people work from home, it is expected that they will desire to make other non-work trips, for example, shopping trips, as opposed to shopping online. Nonetheless, they can also be encouraged to buy online, as they are gaining more free time by not commuting to workplaces. We can expect that an older individual with higher level of education is likely to make more physical shopping trips (35). However, they may also be more comfortable with WFH (8). Whereas young people and females may spend more time online, searching for discounts or deals and will, therefore, prefer online shopping to shopping in person.

People with higher incomes are expected to shop more in-store and online than lower-income people (16, 20, 34). People living in urban areas have greater accessibility to newer technologies. Therefore, they may shop more online instead of in stores. However, they may be less interested in WFH, as most workplaces are in urban areas, so travel time should be lower for those in urban areas as compared with people living in rural areas (16, 34). Longer travel time may also play a role in more online shopping, fewer shopping trips, and WFH. Higher gas prices may also be linked to this association (16). Day of travel may also influence shopping trip generation. If people go out on weekends, it is generally anticipated that they may go shopping as well (16).

**Methodology**

**Data**

Pre-pandemic data for this study is collected from the 2017 U.S. National Household Travel Survey (NHTS) (15). The survey covered 129,696 households, including 264,234 individuals over all the U.S. states and the District of Columbia (DC). The survey produces four data files, on household, person, vehicle, and trips. These files are merged, summarized, and averaged to generate person-specific variables. First, samples are sorted out based on the person-specific shopping trips on each travel day. Individuals who are less than 18 years of age are dropped. Observations with missing values are also discarded. A total of 108,297 observations (N) finally remain after dropping the invalid observations. The cleaned dataset contains three endogenous variables and four types of exogenous variables: person, household,
location, and travel pattern. Overall, the NHTS data is carefully collected, and error checking is performed using descriptive analysis (Tables 2 and 3).

Shopping trips, online shopping, and WFH are the endogenous variables. It can be observed from the descriptive statistics that 59% of the sample do not make any shopping trips, whereas 34% make one or two trips, 6% make three or four trips, and 1% make more than four trips on a travel day. A travel day is specified in the NHTS user guide as a day that starts from 4:00 a.m. of one day and ends at 3.59 a.m. of the next day (15). In the sample, 79% of travel days are on weekdays. It is seen that 83% of the sample shop online from zero to five times in a month; 12% of the respondents in the sample work from home. It is understood from the NHTS survey that hybrid workers (i.e., workers who work both from the office and home) fall into the “Yes” response category of WFH for working a few days a week from home. Of the sample, 51% are male, 25% have a graduate or professional degree, and 80% are FTE. Most of the individuals reside in urban areas and in affluent households (i.e., 74% of households have income greater than $50,000). It is not surprising that 96% of the people sampled use the internet daily.

During-pandemic data is collected from the U.S. Census Bureau, which introduced an experimental household pulse survey to collect data to quickly and effectively capture how the ongoing COVID-19 pandemic is changing people’s travel behavior (37). The survey collects weekly data from all over the USA. This study uses person-level data of week 23 (i.e., January 20–February 1, 2021) from the survey. The data are cleaned and checked for errors. The final dataset has a sample size of 69,905. In the sample, 60% are male, 30% have bachelor’s degrees, and 60% are from households having an income of more than $50,000 (Tables 2 and 3). The data shows that 61% of people aged 18 or older live in households where at least one person teleworks to substitute for work trips during COVID-19, while, before COVID-19, only 12% of people worked from home. However, a total of 70% of people took fewer trips to the store, and 53% of people made more online purchases in the last seven days in the data collection period because of COVID-19. Notably, the recent developments during COVID-19 highlight online grocery shopping being as crucial as online shopping for other household and personal items. In the pre-COVID-19 and during-COVID-19 databases, online shopping is identified as a broad category, including online grocery shopping and online shopping for other personal or household items. The substitution versus complementarity framework is flexible enough to incorporate these new developments.

Model

In this paper, for the pre-pandemic data, we define shopping trips as a categorical variable, where the frequency of the trips is ordered, ranging from “no trips” to “>4 trips.” Online shopping is also defined as a categorical ordered variable, including making an online purchase “0 to 5 times” per month as the lowest category and “>15 times” as the highest category. WFH is a binary variable. On the other hand, WFH, online shopping, and shopping trips are all binary variables for the during-pandemic data. If we denote online shopping as $OS_i$, and shopping trips as $ST_i$, the following empirical models can be estimated:

$$WFH_i = \alpha_0 + \alpha_1 X_i + \mu_{1i} \quad (1)$$
$$OS_i = \beta_0 + \beta_1 X_i + \delta WFH_i + \mu_{2i} \quad (2)$$
$$ST_i = \gamma_0 + \gamma_1 X_i + \varphi OS_i + \tau WFH_i + \mu_{3i} \quad (3)$$

where $X_i$ signifies a vector of the explanatory variables associated with the individual which are hypothesized to influence WFH, online shopping, and making shopping trips; $\mu_{1i}$, $\mu_{2i}$, and $\mu_{3i}$ are the corresponding random error terms; and $\alpha$, $\beta$, $\gamma$, $\delta$, $\tau$, and $\varphi$ are the parameters to be estimated. The parameters $\delta$, $\varphi$, and $\tau$ are the estimate of WFH on online shopping, the estimate of online shopping on shopping trips, and the estimate of WFH on shopping trips, respectively.

The estimation of the above Equations 1–3 can be performed using conventional path analysis or structural equation modeling. The individual models may produce biased and unreliable estimates because of a potential issue of selection and unobserved endogeneity. To overcome these concerns, we can propose a framework that can jointly estimate the equations. Conventional models become inapplicable if mixed equations are used (38). The mentioned three equations are mixed for the pre-pandemic data; Equations 2 and 3 are ordered probit models, and Equation 1 is a binary model, whereas these three equations are binary models for the during-pandemic data. The conditional mixed process (CMP) model developed by Roodman (39) provides a unique opportunity to employ this sort of mixed structural model with different types of equations while correcting bias and unobserved endogeneity. CMP jointly estimates two or more equations with associations among their error processes. These are individual equations with correlated errors. CMP can handle all types of dependent variables, for example, binary, ordered (39).

The equations are restructured into the following in the CMP format:

$$y_{1i}^* = \sigma_1 + \mu_1 \quad (4)$$
Table 2. Descriptive Statistics of Categorical Variables

| Variable                        | Description                                                                 | Frequency | %  |
|---------------------------------|-----------------------------------------------------------------------------|-----------|----|
| **Pre-pandemic data (N = 108,297)** |                                                                             |           |    |
| Shopping trips*                 | Number of shopping trips on travel day                                       |           |    |
|                                 | No trips                                                                     | 60,737    | 59 |
|                                 | 1–2 trips                                                                    | 34,888    | 34 |
|                                 | 3–4 trips                                                                    | 5,871     | 6  |
|                                 | >4 trips                                                                     | 1,198     | 1  |
| Online shopping*                | Number of online purchases in past month                                     |           |    |
|                                 | 0–5 times                                                                    | 90,240    | 83 |
|                                 | 6–10 times                                                                   | 12,454    | 11 |
|                                 | 11–15 times                                                                  | 4,815     | 4  |
|                                 | >15 times                                                                    | 788       | 1  |
| Working from home*              |                                                                             |           |    |
|                                 | Yes                                                                          | 13,197    | 12 |
|                                 | No                                                                           | 95,100    | 88 |
| Person specific                 |                                                                             |           |    |
| Age                             |                                                                             |           |    |
|                                 | 1 = "18–30"                                                                  | 17,893    | 17 |
|                                 | 0 = "> 30"                                                                   | 90,404    | 83 |
| Gender                          |                                                                             |           |    |
|                                 | 1 = male                                                                      | 55,210    | 51 |
|                                 | 0 = female                                                                    | 53,087    | 49 |
| Education                       |                                                                             |           |    |
|                                 | 1 = graduate or professional degree                                          | 27,174    | 25 |
|                                 | 2 = bachelor's degree                                                        | 30,928    | 29 |
|                                 | 3 = some college or less                                                     | 50,195    | 46 |
| Work status                     |                                                                             |           |    |
|                                 | 1 = full time                                                                | 86,243    | 80 |
|                                 | 0 = part time                                                                | 22,054    | 20 |
| Household specific              |                                                                             |           |    |
| Household income                |                                                                             |           |    |
|                                 | 1 = household income ≥ 50,000                                                | 80,646    | 74 |
|                                 | 0 = household income < 50,000                                                 | 24,651    | 26 |
| Internet use                    |                                                                             |           |    |
|                                 | 1 = once a week or less                                                      | 2,283     | 2  |
|                                 | 2 = several times a week                                                     | 2,524     | 2  |
|                                 | 3 = daily                                                                    | 103,490   | 96 |
| Location specific               |                                                                             |           |    |
| Urban                           |                                                                             |           |    |
|                                 | 1 = urban                                                                    | 86,025    | 79 |
|                                 | 0 = rural                                                                    | 22,272    | 21 |
| Travel pattern specific         |                                                                             |           |    |
| Travel day                      |                                                                             |           |    |
|                                 | 1 = weekend                                                                  | 22,303    | 21 |
|                                 | 0 = weekdays                                                                 | 85,994    | 79 |
| Household income                |                                                                             |           |    |
|                                 | 1 = household income ≥ 50,000                                                | 42,612    | 61 |
|                                 | 0 = household income < 50,000                                                 | 27,293    | 39 |
| **During-pandemic data (N = 69,905)** |                                                                             |           |    |
| Shopping trips*                 | Whether took fewer trips to the store in the last seven days during COVID-19|           |    |
|                                 | Yes                                                                          | 49,214    | 70 |
|                                 | No                                                                           | 20,691    | 30 |
| Online shopping*                | Whether made more purchases online in the last seven days during COVID-19   |           |    |
|                                 | Yes                                                                          | 37,196    | 53 |
|                                 | No                                                                           | 32,709    | 47 |
| Working from home*              | Whether at least one person in a household teleworking during COVID-19      |           |    |
|                                 | Yes                                                                          | 42,589    | 61 |
|                                 | No                                                                           | 27,316    | 39 |
| Age                             |                                                                             |           |    |
|                                 | 1 = "18–30"                                                                  | 6,479     | 10 |
|                                 | 0 = "> 30"                                                                   | 63,426    | 90 |
| Gender                          |                                                                             |           |    |
|                                 | 1 = male                                                                      | 41,895    | 60 |
|                                 | 0 = female                                                                    | 28,010    | 40 |
| Education                       |                                                                             |           |    |
|                                 | 1 = graduate or professional degree                                          | 18,299    | 26 |
|                                 | 2 = bachelor's degree                                                        | 20,803    | 30 |
|                                 | 3 = some college or less                                                     | 30,803    | 44 |
| Household income                |                                                                             |           |    |
|                                 | 1 = household income ≥ 50,000                                                | 42,612    | 61 |
|                                 | 0 = household income < 50,000                                                 | 27,293    | 39 |

Note: *Endogenous variable. Sources: NHTS, 2017; Census, 2021.
Table 3. Descriptive Statistics of Continuous Variables

| Variable               | Description                  | Min | Mean | Max  | SD  |
|------------------------|------------------------------|-----|------|------|-----|
| Pre-pandemic data (N = 108,297) |                              |     |      |      |     |
| Household size         | Count of household members   | 1   | 2.65 | 13   | 1.29|
| Travel time            | Avg. travel time (minute) per trip | 0.5 | 26.26| 1,200| 34.59|
| Gas price              | USD per gallon               | 2.01| 2.4  | 2.96 | 0.23|
| During-pandemic data (N = 69,905) |                            |     |      |      |     |
| Household Size         | Count of household members   | 1   | 2.74 | 10   | 1.46|

Note: Source: NHTS, 2017; Census, 2021.

\[
y_2^* = \sigma_2 + \mu_2 \tag{5}
\]

\[
y_3^* = \sigma_3 + \mu_3 \tag{6}
\]

where,

\[
\sigma_1 = \alpha_1 X, \quad \sigma_2 = \beta_1 X + \delta y_1, \quad \sigma_3 = \gamma_1 X + \varphi y_2 + \tau y_1
\]

\[
y = g(y^*) = (1\{y_1^* > 0\}, y_2^*, 1\{y_3^* > 0\}) \tag{7}
\]

\[
\mu = (\mu_1, \mu_2, \mu_3)^T \sim N(0, \sum) \quad \text{and} \quad \sum = \begin{bmatrix}
1 & \rho_{12} & \rho_{13} \\
\rho_{12} & 1 & \rho_{23} \\
\rho_{13} & \rho_{23} & 1
\end{bmatrix}
\]

Here, \(y_1^*, y_2^*, \text{ and } y_3^*\) are latent factors for WFH, online shopping, and shopping trips, respectively. The terms \(\rho_{12}, \rho_{13}, \text{ and } \rho_{23}\), respectively, are the correlation between the error terms of WFH and online shopping, WFH and shopping trips, and online shopping and shopping trips. Presuming that \(y_z = (0, y_{12}, 0)^T\) is observed, a consequent likelihood function can be denoted as follows:

\[
L_i(\alpha_1, \beta_1, \gamma_1, \delta, \varphi, \tau, \sum; y_i|x_i) = \\
\int_{-\infty}^{-\sigma_1}\int_{-\sigma_2}^{-\sigma_3} \int_{-\infty}^{-\infty} \theta_1(\mu_{12}, y_{12} - \sigma_{12}, \mu_3^1; \sum) d\mu_{12} d\mu_3 d\mu_3 \tag{8}
\]

This modeling framework is applied to produce results for both pre-pandemic and during-pandemic data. Survey estimation design is employed in the CMP modeling. The analysis is performed using the statistical software STATA version 17. STATA’s sampling weight option (pweight) is adopted to generate justifiable population-level estimates for the survey data. Besides, direct marginal effects are produced in the CMP post-estimation.

Results and Discussion

Pre-Pandemic Data

The results of the CMP modeling approach are reported in Table 4. Columns 1, 2, and 3 show the estimates for WFH, online shopping, and shopping trips, respectively. The model significance test indicates that the model fits the data well. We first discuss the results to explore the relationships among the endogenous variables (i.e., bold entries in Table 4). We then expound on the effect of exogenous variables on each of the endogenous variables in the model. The signs of expected and observed findings are summarized in Table 5.

The results indicate that, structurally, WFH positively affects online shopping. Specifically, compared with not WFH, WFH is associated with being 18.5% less likely to shop online from zero to five times, but 9.1% more likely to shop online 6 to 10 times, 7.2% more likely to shop online 11 to 15 times, and 2.1% more likely to shop online >15 times. Online shopping is negatively associated with shopping trips (from the lower category “no trips” to the higher category “>4 trips”). The direct marginal effect of online shopping in the shopping trips model is negative for making shopping trips. For example, compared with the base of online shopping (0 to 5 times), online shopping 6 to 10 times is associated with being 8.5% less likely to make one or two trips, 2.9% less likely to make three or four trips, and 1% less likely to make more than four trips. Similarly, the effects are increased for the remaining categories of online shopping. WFH is positively associated with shopping trips (i.e., from making “no trips” to “>4 trips”). People who work from home are 13.3% more likely to make one or two trips, 9% to make three or four trips, and 4% to make more than four trips. The overall findings suggest that online shopping reduces shopping trips, which is consistent with our earlier assumption. This finding is, however, in contrast with Cao (35), who found a positive association between online purchase frequency and physical shopping trips. Mostly, people prefer online shopping instead of making shopping trips because of the convenience of online shopping—the products are delivered to the doorstep. Online shopping has many benefits, for example, people can shop any time they want and compare prices from different online stores. Thus, in comparison with previous studies on whether
### Table 4. Conditional Mixed Process Joint Estimation Results for Before COVID-19 Data (N = 108,297)

| Variables | (1) Working from home (WFH) | (2) Online shopping | (3) Shopping trips |
|-----------|-----------------------------|---------------------|-------------------|
|           | Coef. | Marginal effect | Coef. | Marginal effect | Coef. | Marginal effect |
|           |       | 0–5 times | 6–10 times | 11–15 times | >15 times | No trips | 1–2 trips | 3–4 trips | >4 Trips |
| WFH (base: no), Yes | na | na | 0.656*** | −0.186 | 0.092 | 0.073 | 0.021 | 0.814*** | −0.296 | 0.145 | 0.100 | 0.051 |
| Online shopping (base: 0–5 times) | na | na | na | na | na | na | na | −0.362*** | 0.124 | −0.085 | −0.029 | −0.010 |
| 6–10 times | na | na | na | na | na | na | na | −0.592*** | 0.193 | −0.138 | −0.041 | −0.014 |
| 11–15 times | na | na | na | na | na | na | na | −1.027*** | 0.294 | −0.223 | −0.054 | −0.017 |
| >15 times | na | na | na | na | na | na | na | −0.246*** | 0.086 | −0.057 | −0.021 | −0.008 |
| Person specific | −0.493*** | −0.073 | 0.108*** | −0.025 | 0.014 | 0.009 | 0.002 | −0.171*** | 0.061 | −0.039 | −0.016 | −0.006 |
| Age (base: >30, “18–30”) | 0.047** | 0.008 | −0.181*** | 0.042 | −0.023 | −0.015 | −0.004 | na | na | na | na | na |
| Gender (base: female, male) | −0.029*** | −0.005 | na | na | na | na | na | na | na | na | na | na |
| Education (base: graduate or professional degree) | 0.071** | 0.015 | −0.013*** | 0.034 | −0.018 | −0.013 | −0.003 | 0.003 | 0.002 | −0.001 | 0.000 |
| Bachelor’s | −0.247*** | −0.042 | −0.334*** | 0.079 | −0.045 | −0.028 | −0.007 | 0.032 | 0.021 | −0.008 | −0.003 |
| Some college or less | −0.589*** | −0.125 | −0.185*** | −0.040 | 0.023 | 0.014 | 0.003 | 0.003 | 0.002 | −0.001 | 0.000 |
| Work status (base: part time), full time | na | na | na | na | na | na | na | na | na | na | na | na |
| Household specific | −0.029*** | −0.005 | na | na | na | na | na | na | na | na | na | na |
| Household size | 0.013 | 0.002 | 0.368*** | −0.079 | 0.046 | 0.026 | 0.006 | 0.038 | −0.024 | −0.010 | −0.004 |
| Household income (base: ≤50,000), ≥50,000 | 0.002 | 0.000 | 0.930*** | −0.133 | 0.086 | 0.040 | 0.007 | 0.015 | −0.009 | −0.004 | −0.002 |
| Internet use (base: once a week or less) | 0.258** | 0.039 | 0.279** | −0.024 | 0.017 | 0.006 | 0.001 | 0.009 | 0.006 | −0.002 | −0.001 |
| Daily | −0.160*** | −0.005 | −0.069** | −0.015 | 0.009 | 0.005 | 0.001 | 0.003 | 0.001 | 0.000 | 0.000 |
| Several times a week | na | na | na | na | na | na | na | na | na | na | na | na |
| Location specific | 0.001*** | 0.000 | na | na | na | na | na | na | na | na | na | na |
| Urban (base: no), yes | −0.029*** | −0.005 | −0.069** | −0.015 | 0.009 | 0.005 | 0.001 | 0.003 | 0.001 | 0.000 | 0.000 |
| Travel pattern specific | na | na | na | na | na | na | na | na | na | na | na | na |
| Travel day (base: weekdays), weekend | na | na | na | na | na | na | na | na | na | na | na | na |
| Avg. travel time | 0.032*** | 0.041 | 0.194*** | −0.045 | 0.025 | 0.016 | 0.004 | 0.037 | −0.024 | −0.009 | −0.004 |
| Gas price | na | na | na | na | na | na | na | na | na | na | na | na |
| Constant | −0.091*** | −0.005 | −0.069** | −0.015 | 0.009 | 0.005 | 0.001 | 0.003 | 0.001 | 0.000 | 0.000 |

Note:
- *p < .1
- **p < .05
- ***p < .01
- "na" = not applicable.
the association between online shopping and shopping trips is a complementary or substitution effect, our study suggests that the relationship is one of substitution. However, we should acknowledge that shopping is usually comprised of several stages that may be completely or partially completed online. In-store purchases can be associated with online searches. For example, people can make trips to stores to compare or experience the actual goods they browse online. In addition, shopping trips are influenced by WFH, as we found that WFH stimulates shopping trips. While people are working from home, they may desire to make other non-work and/or insignificant trips, and shopping trips are one of them.

We shift our discussion to other factors that influence people to work from home, shop online, and make shopping trips. It is observed that the probability of young people of age 18 to 30 buying online zero to five times is 2.5% lower than for the older people; however, this age group has a higher probability of buying online for other higher purchase categories (“6 to 10,” “11 to 15,” and “> 15” categories). They are also 8.6% more inclined to make no shopping trips than the older population. As we expected, older-aged people prefer buying online less and they make shopping trips more than younger people. These findings are aligned with Zhou and Wang (16) and Cao (35). However, older people are 7% more likely to work from home than younger people. It is also observed that males are more likely to work from home than females. Males are less likely to shop online (fewer males in the “6 to 10,” “11 to 15,” and “>15” categories) than females, whereas males are more likely to purchase for online zero to five times. As we assumed earlier, males prefer both less online shopping as well as fewer shopping trips than females, which is also consistent with the results of Ferrell (18). Young people and females may spend more time online searching for discounts or deals; accordingly, they prefer to shop online rather than in person.

Our results further suggest that people with bachelor’s degrees are 1.5% more likely, and people with some college degrees are 4.3% less likely, to work from home than people with graduate or professional degrees. As we anticipated, higher educational attainment motivates some people to work from home. Drucker and Khattak (8), among others, discovered similar findings (29). Higher educational attainment is also associated with more online shopping. Higher household income (> $50,000) is also associated with more online purchases for “6 to 10,” “11 to 15,” and “>15” categories, whereas lower household income is more associated only with the “0 to 5 times” online purchase category. This finding is supported by Farag et al. (34). Compared with those who use the internet once a week or less, using the internet daily increases the probability of buying online for “6 to 10,” “11 to 15,” and “>15” categories. Increases in travel time and in gas price increase the probability of WFH. An increase in gas price is associated with more online shopping for “6 to 10,” “11 to 15,” and “>15” times

Table 5. Expected and Observed Signs of the Exogenous Variables

| Exogenous variables                  | Working from home | Online shopping | Shopping trips |
|--------------------------------------|-------------------|----------------|---------------|
|                                      | Expected | Observed | Expected | Observed | Expected | Observed |
| Person specific                      |          |          |          |          |          |          |
| Higher age                           | ++       |          |          |          |          |          |
| Gender (male)                        | ++       |          |          |          |          |          |
| Education (bachelors)                | ++       |          |          |          |          |          |
| Full time                            |          | ++       |          |          |          |          |
| Household specific                   |          |          |          |          |          |          |
| Household size                       | +        | –        | na       | na       | na       | na       |
| Household income                     | +        | NS       | +        | +        | +        | –         |
| Daily internet use                   | +        | NS       | +        | +        | –         | –         |
| Location specific                    |          |          |          |          |          |          |
| Urban                                | –        | –        | +        | –        | –         | NS        |
| Travel pattern specific              |          |          |          |          |          |          |
| Average travel time per trip         | +        | +        | na       | na       | –         | –         |
| Weekend travel day                   | na       | na       | na       | na       | +         | +         |
| Gas price                            | +        | +        | +        | +        | –         | –         |
| Others                               |          |          |          |          |          |          |
| Online shopping                      | na       | na       | na       | na       | –         | –         |
| WFH                                  | na       | na       | + /−     | + /−     | +         | +         |

Note: NS = not statistically significant; na = not applicable.
categories and less for the “0 to 5 times” category. As we anticipated earlier, longer travel times and higher gas prices discourage people from making shopping trips; instead, they prefer to shop online and work from home. Daily internet use contributes to this association. This is also supported by Zhou and Wang (16).

People residing in urban areas are 3% less likely to telework than those in rural areas. In urban areas, people are less likely to shop online just zero to five times per month than people in rural areas, whereas they are more likely to shop online for other higher purchase categories (“6 to 10”, “11 to 15”, and “>15” categories). As we expected, people living in urban areas are more reluctant to work from home than people in rural areas. However, they shop online more frequently than people from rural areas, which aligns with our earlier assumptions. Farag et al. (34) discovered similar findings in their study. This may be because both shopping accessibility and internet use in rural areas are limited. People from rural areas are thus less encouraged to buy online than those in urban areas.

**During-Pandemic Data**

The study attempts to shed light on the relationships among the key variables during the COVID-19 pandemic. As COVID-19 is affecting the world economy, including the transportation sector, travel behavior has changed substantially. Commuting to work is a vital element of local travel, and it is related to many other aspects of local transportation. COVID-19 pushes people to telework in substitution for physical travel for work. Activities like trips to stores, which are a vital element of local travel, are also being substituted by online shopping.

The CMP joint estimation results for the during-pandemic data are presented in Table 6. The model significance test suggests that the model fits the data well. The results are examined to explore the relationships between WFH, shopping trips, and online shopping during COVID-19 (i.e., bold entries in Table 6) and compare them with the pre-COVID-19 results. First, the results reveal that WFH is negatively associated with purchasing more online, which is consistent with online shopping zero to five times in a month but contradicts the higher categories of purchases (more than five times in a month) in pre-COVID-19 findings. However, this relationship is not statistically significant for the during-COVID-19 data. Second, the findings suggest that WFH is negatively associated with the making of fewer shopping trips, which indicates that, compared with not WFH, WFH is likely to increase the probability of making shopping trips by 14.2% during COVID-19. This finding is consistent with the pre-pandemic periods (29.6%).
Although the magnitude is 52% lower during COVID-19. Third, online shopping is positively associated with fewer shopping trips, that is, it is more likely to reduce shopping trips. More specifically, online shopping lowers the probability of making shopping trips by 20.7% during COVID-19. This relationship is also aligned with the pre-pandemic findings. During the pandemic and its associated stay-at-home orders, more people are working from home, and many of them buy online rather than making other non-essential trips, such as shopping trips. However, during COVID-19, online shopping also introduced several travel components that need to be acknowledged. COVID-19 saw the frequent use of the curbside pickup of goods ordered online, which warrants making physical trips. Moreover, the trips could be made to the courier office, locker facility, or other designated locations where orders are fulfilled through goods delivery.

The factors that influence WFH, online shopping, and shopping trips are also explored during COVID-19. CMP modeling results indicate that younger age people are 10.2% more likely than older people to work from home during COVID-19, whereas they were 7.3% less likely to work from home before COVID-19. This may be because younger people are forced to work at home, as some schools or companies are encouraging WFH during COVID-19. The findings are similar to Tahlyan et al. (31), who indicated that older people have lower satisfaction and higher obstacles to WFH than the younger middle-aged people during COVID-19. Unlike the pre-pandemic period, our findings suggest that younger people are 2.9% more likely to make shopping trips. However, they are also more likely to shop online, like in the pre-COVID-19 period, which is supported by recent research on COVID-19 and shopping behavior (32). Our results further indicate that males are 1.4% more likely than females to work from home but 4.6% less likely to shop online during COVID-19—similar to the pre-COVID-19 findings. On the other hand, males are 4.9% more likely to make shopping trips, which contradicts the findings from the pre-pandemic period when males were less likely to buy in person than females. Compared with people with graduate or professional degrees, people with bachelor’s degrees are less likely to work from home or shop online, and more likely to make shopping trips. The pre-pandemic findings on online shopping and shopping trips are consistent with the during-pandemic findings; however, they contradict the probability of WFH. An increase in household size increased the probability of WFH by 0.7% during COVID-19, whereas it decreased by 0.5% before COVID-19. In addition, higher-income households’ probability of making more shopping trips increased during COVID-19, compared with before COVID-19. It has been observed that workers in higher-income households are 12.3% more likely to work from home during COVID-19. They are also more likely to shop online, and the relationship is similar to the pre-COVID-19 period. These results are consistent with Wang et al. (32), who found the association between higher-income households and online shopping during COVID-19 to be positive, and similar to the previous studies based on “normal” conditions before COVID-19.

While individuals work from home during COVID-19, they make more physical shopping trips. WFH increases the desire to do more online shopping, while more online shopping reduces physical shopping trips. WFH, however, creates shopping needs for home offices and more space that may have affected typical shopping habits. The risk of contracting the virus, lockdowns, and the advancement of ICTs are some of the factors that have encouraged online shopping while people adapt to WFH. Since the pandemic has accelerated the shift to a more advanced digital era, ICT uses such as WFH and online shopping will have a lasting effect in the future with the resurgence of the economy. Moreover, WFH will continue in the form of a hybrid work system with flexible working hours and places with its positive unintended consequence for future transportation planning (30).

**Limitations**

This study ignores the bidirectional relationship among the endogenous outcome variables. Besides, this study only concentrates on national-level estimates. State-level estimation could provide different levels of estimations since travel behavior can vary across the states. In the analysis presented, online shopping is used as a broad category, which includes grocery shopping and shopping for durable goods, for example. The correlates of online grocery shopping may differ from those of online durable goods shopping, and the purchase intention may work differently for these two components. However, such correlates could not be explored because these are not included in the 2017 NHTS and 2020 household pulse survey databases. Furthermore, other variables concerning local built environment (e.g., transport accessibility, employment generation) that are not part of these databases could not be introduced in the models to measure the spatial variation of the impacts on the outcome variables.

**Conclusion**

Are the relationships between ICT uses and travel behavior similar before and during the COVID-19 pandemic? To answer this question, the paper focuses on two
different forms of ICT use: online shopping and WFH. Online shopping generally reduces the urge to make shopping trips. People who work from home may contradict this, however, by making other non-work trips such as shopping trips. Besides, these activities may also be influenced by other exogenous factors. Previous studies mainly focused on one activity (either online shopping or WFH) to investigate shopping trip generation. This study attempts to model shopping trips with online shopping and WFH together by integrating pre-pandemic data with during-pandemic data. By harnessing the pre-pandemic 2017 NHTS data, we analyze three different models for the three endogenous variables (i.e., WFH, online shopping, and shopping trips) in a joint framework with a CMP approach that can correct the unobserved endogeneity and selection bias. The during-pandemic analysis captures the impacts of COVID-19 on travel behavior by exploring the U.S. Census Bureau’s experimental household pulse survey database.

Overall results suggest that online shopping and physical shopping trips can be substitutes, suggesting that online shopping is associated with reductions in shopping trips. In contrast, WFH encouraged people to undertake more shopping trips in the pre-pandemic period. These associations are found to be similar during the pandemic but to differ in magnitude. Notably, the percentage of WFH has increased during the pandemic, as expected. People who work from home during COVID-19 are less interested in making in-person shopping trips and more interested in shopping online than in pre-pandemic periods. These key relationships are correlated with socio-demographic, location, and individual travel-related factors. The results generated for the ICT uses are thus robust. Some explanatory factors are found to be different from the pre-COVID-19 results, for example, younger people and people with larger household size are more likely to work from home during COVID-19, as opposed to the pre-COVID-19 period.

These results should be interpreted with caution because the vaccination program was still in the early stages during the data collection periods (week 23–January/February 2021). Very few people had the choice to return to work, and many people were still reluctant to make physical shopping trips. Besides, pandemic-related restrictions across blue states (i.e., Democratic-leaning) and red states (i.e., Republican-leaning) were different over time. Restrictions in red states were not as strict as in blue states. Guess et al. (40) found that blue states had significantly higher scores than red states on behavioral/mitigation efforts. These include the duration of lockdowns, mask mandates, and vaccination rates. Therefore, compared with the pre-COVID-19 period, travel behavior (e.g., shopping trips) during COVID-19 might be similar across red states but different in blue states. Nonetheless, the results have important policy implications. The findings of this study may benefit future transportation planning (e.g., trip generation forecasting) and policymaking with the progress of ICT. Currently, planners do not account fully for ICT uses (e.g., WFH and online shopping), and they do not account for uncertainty caused by large-scale events like COVID-19. Furthermore, other complications such as online shopping have a delivery component whose impacts may be large because of both the volume and the nature of the vehicles used. These types of complex relationships between ICT uses and travel behavior can inform planners and decision makers to formulate more comprehensive policy provisions on different levels of ICTs in different periods (e.g., uncertainty) that can be used as an effective travel demand management technique. For example, a reduction in commuter trips because of more people WFH needs to be integrated into the travel demand models, that is, trip generation and time of day models. In addition, the study findings show that both ICT uses have the potential to reduce the negative effects of transport (i.e., congestion, pollution, and other related external factors that may compel individuals to make unnecessary trips in the event of a global emergency). The reduction in vehicular trips following the increased ICT uses can improve the accessibility of all active transportation modes, including walking, bicycling, promoting non-motorized transport, and the local built environment (41). Overall, the behavioral changes explored in the paper have strong implications for future economic activity, safety, traffic congestion, energy consumption, emissions, and so forth.

Future research may emphasize the inclusion of variables that may effectively define the spatial variation in the parameter estimates. Future research can also conduct a bidirectional study to understand better the assumption that shopping trips, online shopping, and WFH influence each other. Newer developments in e-commerce (e.g., online grocery shopping) and the many ways in which online shopping and physical shopping trips interact should be investigated in future research with the availability of newer data. Furthermore, the changing landscape of pandemic-related restrictions both over time (i.e., different waves of the pandemic) and across space (i.e., blue versus red states) can be explored in future studies.

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Data Accessibility Statement
The data used for analysis in this study are collected from two public domain resources: National Household Travel Survey (15) and Household Pulse Survey (37).

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