

A Comparison of Online and In-Person Activity Engagement: The Case of Shopping and Eating Meals

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ABSTRACT

The virtual (online) and physical (in-person) worlds are increasingly inter-connected. Although there is considerable research into the effects of information and communication technologies (ICT) on activity-travel choices, there is little understanding of the inter-relationships between online and in-person activity participation and the extent to which the two worlds complement one another or substitute for one another. Shopping is one of the activity realms in which the virtual and physical spaces are increasingly interacting. This paper aims to unravel the relationships between online and in-person activity engagement in the shopping domain, while explicitly distinguishing between shopping for non-grocery goods, grocery products, and ready-to-eat meals. Data from the 2017 Puget Sound household travel survey is used to estimate a multivariate ordered probit model of the number of days in a week that a sample of households engages in in-person activity engagement and online activity engagement for each of these shopping activity types – leading to a model of six endogenous outcomes. Model results show that there are intricate complementary and substitution effects between in-person and online shopping activities, that these activities are considered as a single packaged bundle, and that the frequencies of these activities are significantly affected by income, built environment attributes, and household structure. The findings suggest that travel forecasting models should incorporate model components that capture the interplay between in-person and online shopping engagement and explicitly distinguish between non-grocery and grocery shopping activities. Policies that help bridge the digital divide so that households of all socio-economic strata can access goods and services in the virtual world would help improve quality of life for all. Finally, the paper highlights the need to bring passenger and freight demand modeling, at least within urban contexts, into a single integrated structure.

Keywords: physical and virtual activity engagement, shopping activities, eat-meal activities, multivariate ordered probit model, ICT effects on travel behavior, substitution and complementarity effects

1. INTRODUCTION

The widespread adoption of information and communication technologies (ICT) has greatly enabled individuals to harness the power of the internet-of-things (IoT) to conduct daily activities, access goods and amenities anywhere anytime, and fully exploit the convenience afforded by the sharing economy and delivery-based services. As the technological landscape and the types of services enabled by connectivity continue to evolve, activities that previously required, or were mostly undertaken through, in-person (face-to-face) physical travel and interaction are increasingly being accomplished online through virtual interactions of various types. A combination of the internet (media), smartphones and tablets (tools), providers (services), and Long Term Evolution (LTE) wireless communication standards (the infrastructure) is providing users with ubiquitous virtual access to work, shop, play, study, and communicate virtually. Although the effects of ICT on people’s activity-travel behavior has been studied extensively in the past (e.g., see reviews by Golob and Regan, 2001; Kenyon, 2010; Andreev et al., 2010; Aguilera et al., 2012; and Gössling, 2018), this topic area warrants constant attention in light of the rapid evolution of technology and online services in the marketplace and the significant growth in ownership and use of smartphones. The share of the population owning a smartphone in the U.S. has grown from just about 20 percent in 2010 to about 70 percent in 2017. In 2016 alone, 1.5 billion smartphones were sold worldwide (Statista, 2018).

This paper aims to study the interplay between physical (in-person) activity engagement and virtual (online) activity engagement in the *shopping* and *eat-meal* activity space (in this paper, the labels “virtual” and “online”, as well as the labels “physical” and “in-person”, are used interchangeably). Indeed, a number of previous studies have examined the relationship between in-person shopping and online shopping for goods and services (Cao et al., 2012; Zhou and Wang, 2014; Lee et al., 2017; Zhai et al., 2017).¹ Many of these studies have largely treated shopping as a single activity category without drawing a distinction between different types of shopping activities (e.g., grocery shopping versus shopping for non-grocery items); and because the actual use of online grocery shopping has not been widespread until relatively recently, past research has largely focused on shopping for goods that are not purchased very frequently – such as electronics, clothing, specialty items, and books (see Xi et al., 2018; Shi et al., 2019; Zhen et al., 2016).

Recently, a few studies have begun to explore the relationship between in-store and online shopping for groceries (e.g., Suel et al., 2015; Suel et al., 2018). Some others examine the relationship among multiple shopping dimensions and/or the interactions between multiple types of aggregate online and in-person activity purposes in which shopping is considered as a single category (either including both grocery and non-grocery purposes as one category or focusing only on one of these purposes; see, for example, Ding and Lu, 2017; Pawlak et al., 2015; Lila and Anjaneyulu, 2016; Lavieri et al., 2018). Perhaps, more importantly, as explained by Lavieri et al. (2018), most earlier studies assume online activity participation as being exogenous to in-person activity participation (that is, they examine online activity participation first, and then use online activity behavior as a determinant of in-person participation in a strictly sequential fashion; see, for example, Shi et al., 2019; Xi et al., 2018; and Lee et al., 2017). A recent literature review (Yousefi and Dadasahpoor, 2020) of the effects of ICT use on urban spatial structure that reviewed

¹ Of course, earlier studies have also focused on non-shop online activities, such as work, personal errands (e.g., banking), and social-recreation (online gaming, streaming movies, and social media), and their effects on in-person activity-travel behavior (for example, see Kwan et al., 2007; Schwanen and Kwan, 2008; Sasaki and Nishii, 2010; Mokhtarian and Tal, 2013; van den Berg et al., 2013; Ben-Elia et al., 2014; Rashidi et al., 2017; Ettema, 2018).

130 articles published between 2000 and 2018 also makes clear the implicit assumption in most earlier studies that online activity is an exogenous precursor to in-person activity participation. However, it is possible that online and in-person activity participation choices are considered as a multi-dimensional whole (that is, as a joint package), with unobserved individual factors (e.g., tech-savviness and green lifestyle) jointly impacting online as well as in-person participation in multiple activity types.

This study aims to take a deep dive into the pursuit of shopping and eat-meal activities, in both the virtual and physical realms simultaneously. In particular, the paper strives to fill a critical gap in understanding the interactions between in-person and online shopping engagement while explicitly distinguishing between different types of shopping activities. Traditional in-person shopping (for all types of goods) at brick-and-mortar stores continues to be possible today (although it may be argued that the options are decreasing as brick-and-mortar stores fold and go out of business). In the virtual space, a variety of options have emerged. People may purchase goods and services through online shopping sites (such as Amazon or virtual portals of retailers) and have them delivered directly to the home or to the nearest brick-and-mortar store location (where people can pick-up the goods when notified to do so). More recently, grocery stores have introduced and expanded their *online* grocery shopping ecosystems, providing people the ability to purchase groceries online and either pick them up at the store or have them delivered within short time-windows to the home. The ability to purchase perishables online and pick them up or have them delivered just-in-time has greatly expanded the online grocery shopping business.

In addition to shopping for grocery and non-grocery items in these different ways, another major development is in the purchase and delivery of fully cooked meals. While this was previously largely limited to the pizza delivery business, the options have now greatly expanded with the emergence of crowd-shipping services. Many restaurants have partnered with services such as Uber Eats, Grubhub, DoorDash, and Postmates enabling people to order fresh cooked meals online (through a smartphone app) and have the fully prepared ready-to-eat meals delivered to the home. Because these delivery services rely on the participation of the *crowd*, they do not have to own and maintain fleets or pay employees. Moreover, the geographic reach is extensive as the services rely on private citizens to perform deliveries using their own vehicles (similar to ride-hailing services).

In short, at least three different types of in-person and online shopping and meal consumption activities are possible. Non-grocery items can be purchased at the store or online; grocery items can be purchased at the store or online; and prepared meals can be purchased and eaten at a restaurant or ordered online and delivered to the home. This paper considers these six types of online/in-person shopping and eat-meal activities as a package decision and explores the inter-relationships among them. The effort is motivated by the desire to seek answers to the following questions. To what extent are there common unobserved factors that impact these activities, thus calling for a joint model system? Do these activities complement one another or substitute for one another? Are there both direct and cross-effects among these different types of shopping and eat-meal activities? An exploration of such inter-relationships between in-person and online activity engagement would help advance an understanding of how the emergence of online shopping and delivery-based services are influencing activity-travel patterns and choices. These insights are critically needed for forecasting activity-travel behaviors in an increasingly connected and internet-enabled world.

In summary, the current paper may be distinguished from earlier examinations of online and physical activities in three important ways. First, the paper explicitly considers three

potentially inter-related shopping/meals activity purposes, and models both the online as well as in-person participation variants of these three activity purposes. Doing so is important as online providers such as Amazon today allow online grocery, non-grocery shopping, as well as the ability to order meals, all under a single online platform. Similarly stores such as Walmart and Costco allow the physical shopping of both grocery and non-grocery shopping, as well as having a meal, all under one roof. Thus, it is of interest to understand the rich interplay in the interrelationships in the activity types, both online and offline, and to examine if and how these activities are reshaping urban activity-travel patterns and time-use patterns. For example, it is possible that an individual from a household who goes in-person shopping at Walmart for groceries happens to come across an electronic item that is prominently advertised, then returns home and undertakes research online for the electronic item, and then makes another trip to purchase the advertised item in person because of a sale available only at the store. This is a case where in-person grocery shopping impacts in-person non-grocery shopping. Or perhaps this individual, after pursuing in-person grocery shopping, comes home to undertake additional research and then purchases the electronic item online. This is a case where in-person grocery shopping impacts online non-grocery shopping. In both of these (and other possible) cases, there may be substitutions and complementarities between the in-person and online platforms *across* activity purposes, not just within a *single* activity purpose. Second, the combinations of online versus in-person activity participations are modeled *jointly* in our study, rather than assuming *a priori* that there are no unobserved factors that impact these alternatives. The latter approach can underestimate or overestimate substitution/complementarity effects. For example, consider households that are pre-disposed to both online and in-person grocery shopping (due to factors not observed in the data, such as a generic penchant for grocery shopping and eating). If a methodology that ignores such unobserved correlations is applied, and online grocery shopping is used as an exogenous variable in predicting in-person grocery shopping, there would be an exaggeration of any complementary effect of online grocery shopping on in-person shopping, and a resulting overestimation of grocery shopping trips due to the increasing penetrations of broadband internet in households. On the other hand, if such unobserved effects are controlled for, one can estimate the “uncorrupted” complementary/substitution effects of one platform-activity purpose combination on another. Third, the model in this paper does not impose a structure *a priori* wherein online activities are determined first and then exogenously influence in-person activity participation. In fact, a significant amount of earlier empirical work in this space is based on the typology developed by Salomon (1986) (and used by many later empirical studies, such as those discussed earlier) that proposes six main impacts of virtual activities on personal physical activities and travel: substitution (replacement of a location-based activity by a tele-activity, thus eliminating travel), complementarity (a virtual activity leads to new location-based activities), modification (virtual activity changes the timing, duration or place of a location-based activity), neutrality (there is no observed effect of the virtual activity on location-based activities), activity fragmentation (splitting of a certain activity into several smaller pieces that can be performed at different times and locations, because ICT allows remote and continuous access to files, information, and people), and multitasking (the simultaneous realization of two or more activities during the same time period, such as teleworking or shopping online while traveling as a passenger or even physically shopping at the same time). Such an *a priori* framework can be seriously limiting, in the sense that it assumes that online decisions are determined first and exogenously affect in-person decisions. Our viewpoint, on the other hand, models virtual and physical activity participations as a joint package

decision, thus alleviating endogeneity bias issues in the interactions between virtual activities and physical activity engagement.

This paper utilizes data from the 2017 Puget Sound Regional Household Travel Survey to conduct an analysis of the relationships between in-person and online shopping and meal activities. The data includes a week's worth of activity-travel patterns together with information about deliveries of various types of goods and services to the home (based on online purchases). Thus, the data is ideally suited for exploring the types of relationships of interest in this study. A multivariate ordered probit modeling methodology is employed to capture correlated unobserved attributes that may simultaneously affect the pursuit of multiple types of in-person and/or online shopping and meal activities. The model system is structured in a way to tease out relationships among endogenous variables (i.e., in-person and online activity engagement) while explicitly accounting for the influence of exogenous variables such as socio-demographic characteristics and built environment attributes. Relationships among the endogenous variables constitute the complementary and substitution effects of interest in this paper.

The remainder of this paper is organized as follows. The next section provides a description of the data. The third section presents the modeling methodology while the fourth section offers details on model estimation results. Concluding remarks and a discussion of the implications of the findings are presented in the fifth and final section.

2. DATA DESCRIPTION

The data for this study is derived from the 2017 Puget Sound Regional Household Travel Survey, which collected detailed household- and person-level socio-economic, demographic, and activity-travel pattern information from residents throughout the Puget Sound (Greater Seattle) region (PSRC, 2018). The survey is a rather typical comprehensive household travel survey, except for a few distinctive features. The survey offered multiple modes for households to furnish activity-travel information. Based on responses in a recruitment phase of the survey (that gathered standard socio-economic and demographic information), some households were provided the option to furnish activity-travel diary information in the reporting phase of the survey through the use of a smartphone app. If all household members owned relatively new smartphones (less than four years old) and the household fell within a certain quota (number of households that the app could handle in each travel diary week), then that household was given a choice of reporting activity-travel diary information using the *rMove* smartphone app. Otherwise, households furnished activity-travel diary information using a standard web-based online survey. Whereas households who responded using *rMove* furnished activity-travel and related information for an entire week, households responding via the web survey furnished activity-travel information only for one day (similar to many other household travel surveys).

In addition to collecting revealed preference data about activity-travel behavior, the survey gathered information about home-deliveries of goods, groceries, and meals purchased online over a one-week period. Because the online activity-driven home-deliveries data is based on a time-window of a week, the physical activity-travel participation data should also be based on a week so that the online and in-person activity engagement can be compared for equivalent time periods. For this reason, only the sample of respondents that provided seven-day activity-travel data using the *rMove* app is extracted for use in this study.

A description of the data is furnished in Table 1. The table also shows corresponding demographic information for the Puget Sound Region (PSR) as a whole, with a view to provide insights on the extent to which the analysis sample differs from the general population. The

subsample of households furnishing data through the *rMove* app has to meet certain criteria to be eligible to do so, and then self-selects into the smartphone-app based mode of data collection. As such, this subsample of households is likely to differ from the general population with respect to various socio-economic, demographic, residential, and activity-travel characteristics. As these households furnished one week of activity-travel information through a smartphone-app, it is plausible to expect that these households will be smaller in size, younger, urban, and educated, who are comfortable with using technology for a variety of applications (tech-savvy) (Astroza et al., 2017; Lavieri et al., 2017). However, given that the objective of the paper is to study interactions between in-person and online activity engagement, this type of skew in the make-up of the sample is warranted and desirable to ensure that there are sufficient records with home-deliveries over the course of a week for various shopping and meal purposes.

Table 1. Description of Sample (n=705) Relative to Puget Sound Region

Sample			Region	Sample			Region
<i>Household structure</i>	Count	%	%	<i>Household type</i>	Count	%	%
Single adult - No children	328	46.52	27.46	Detached house	165	23.40	59.78
Single adult - With children	20	2.84	1.84	Attached house	66	9.36	7.27
Two or more adults - No children	263	37.30	44.64	Apartments/condos	469	66.52	31.33
Two or more adults - With children	94	13.34	26.06	Other	5	0.72	1.62
<i>Employment status</i>	Count	%	%	<i>Vehicle availability</i>	Count	%	%
No workers in household	57	8.09	21.25	None	140	19.86	8.29
Single worker in household	406	57.59	39.26	< 1 per adult	154	21.84	15.89
Multiple workers in household	242	34.32	39.49	= 1 per adult	356	50.50	56.28
<i>Residential density</i>	Count	%	%	> 1 per adult	55	7.80	19.54
<2,000 hh/km ²	134	19.01	49.96	<i>Income</i>	Count	%	%
2,000-4,000 hh/km ²	151	21.42	28.23	< \$25,000	67	9.50	14.52
4,000-8,000 hh/km ²	160	22.70	12.93	\$25,000-\$49,999	115	16.31	16.49
>8,000 hh/km ²	260	36.87	8.88	\$50,000-\$74,999	121	17.16	15.85
<i>Household tenure</i>	Count	%	%	\$75,000-\$99,999	116	16.45	15.30
Rent	415	58.87	32.93	≥\$100,000	286	40.58	37.84
Own	279	39.57	60.63				
Other	11	1.56	6.44				

The total sample size is 705 households (after extensive data cleaning) and, as expected, is heavily comprised of single person households, who account for 46.5 percent of the sample (in contrast to just 27.5 percent in the general population). Households with multiple adults and one or more children comprise 13.3 percent of the sample, just about one-half of that in the general population (where the corresponding percentage is 26 percent). Compared to the general population, households that reside in higher-density areas are over-represented; in the sample, nearly 37 percent of the households reside in areas with density greater than 8000 households/km²; the corresponding percent in the population stands at just 8.9 percent. Consistent with this residential pattern, nearly 59 percent of the sample are renters; in the general population, only 33 percent of households are renters. Consistent with the household tenure distribution, the housing unit type distribution shows a similar skew relative to the general population. While nearly 60 percent of households in the general population live in single family detached houses, only 23.4 percent of sample households do so. Just about two-thirds of the households in the sample reside in apartments and condominiums.

The sample skews towards single-worker households. While 39.3 percent of households in the population have one worker, the corresponding fraction in the sample stands at 57.6 percent. While 21.3 percent of households in the general population have no workers, only 8.1 percent of households in the sample have no workers. Vehicle availability shows a similar skew as well. Nearly 20 percent of households in the sample have no vehicle, compared to just 8.3 percent in the general population. It is clear the sample has an over-representation of urban car-free households; hence their activity-travel patterns are not likely to be representative of the general population, but the data set is likely to offer rich information for analyzing relationships between in-person and online activity engagement. Income distributions are somewhat more similar between the sample and general population (when compared with other characteristics), with some differences in the lowest and highest income categories. The respondent subsample has a smaller percent of households in the lowest income category (< \$25,000 per year) and a slightly larger percentage in the highest income category (\geq \$100,000 per year).

Table 2 presents the distribution of six different activity types of specific interest in this study. These six variables constitute the endogenous variables for the subsequent multivariate modeling effort, and are as follows:

- Number of days in which there was at least one package delivered to the household
- Number of days in which there was at least one grocery delivery to the household
- Number of days in which there was at least one meal delivery to the household
- Number of days in which there was at least one episode for general shopping purposes (excluding grocery shopping)
- Number of days in which there was at least one episode of grocery shopping
- Number of days in which there was at least one episode to go to restaurant/eating establishment

Table 2. Distribution of Weekly Occurrences of Delivery and In-person Trips by Type

<i>Days in week with deliveries or episodes</i>	<i>Deliveries to house by type</i>						<i>In-person episodes by type</i>					
	<i>Packages</i>		<i>Groceries</i>		<i>Meals</i>		<i>Shopping</i>		<i>Groceries</i>		<i>Meals</i>	
	<i>Count</i>	<i>%</i>	<i>Count</i>	<i>%</i>	<i>Count</i>	<i>%</i>	<i>Count</i>	<i>%</i>	<i>Count</i>	<i>%</i>	<i>Count</i>	<i>%</i>
0	281	39.86	628	89.08	608	86.24	229	32.48	132	18.72	105	14.89
1	158	22.41	59	8.37	69	9.79	206	29.22	200	28.37	113	16.03
2	112	15.89	9	1.28	20	2.84	148	20.99	179	25.39	151	21.42
3	68	9.65	4	0.57	5	0.71	69	9.79	112	15.89	123	17.45
4	43	6.10	3	0.43	0	0.00	36	5.11	52	7.38	96	13.62
5	26	3.69	0	0.00	1	0.14	11	1.56	23	3.26	68	9.65
6	12	1.70	1	0.14	2	0.28	4	0.57	7	0.99	31	4.40
7	5	0.70	1	0.13	0	0.00	2	0.28	0	0.00	18	2.54

Overall, it can be seen that grocery and meal delivery has not yet been adopted on as wide a scale as package delivery (which may be considered as representing non-grocery online shopping). While excess of 85 percent of households report absolutely no deliveries of groceries or prepared meals, only about 40 percent of households report absolutely no package deliveries over the course of a week. Whereas the distributions for package delivery and in-person shopping (non-grocery) show some degree of similarity (from a qualitative viewpoint), the distributions for in-person grocery shopping and in-person eat-mail activity stand in stark contrast to the corresponding online activity engagement distributions. Only 18.7 percent of the households report

no grocery shopping episodes over the course of the week and only 14.9 percent report no out-of-home eat-meal activity episodes. A review of these distributions suggests that online and in-person shopping (non-grocery) appears to be occurring on a comparable scale for this subsample of households (that is clearly a self-selected subsample of the general population), but in-person grocery shopping and eat-meal activity engagement clearly dominates corresponding online activity engagement. The goal of this paper is to understand the complex inter-relationships among these six different activity participation choices.

3. STUDY METHODOLOGY

This section presents the methodological approach used in this study. The model formulation (Multivariate Ordered Probit model) is presented first; this is followed by a description of the conceptual framework used to explore inter-outcome dependencies.

3.1. Model Formulation

Let the term “activity type” encompass all outcomes of interest: regular package deliveries, grocery deliveries, meal deliveries, in-person shopping trips, in-person grocery shopping trips, and in-person meal trips.

The modeling framework used is the Multivariate Ordered Probit model, which is presented in detail in Ferdous et al. (2010). Let q be an index for individuals ($q = 1, 2, \dots, Q$), and let i be the index for activity type ($i = 1, 2, \dots, I$), where I denotes the total number of activity types for each individual. In the current study, $I = 6$. Let the number of weekly frequency categories for activity i be $K_i + 1$ (i.e., the weekly frequency categories of activity type i are indexed by k and belong in $\{0, 1, 2, \dots, K_i\}$). Following the usual ordered response framework notation, it is possible to write the latent propensity (y_{qi}^*) for activity type i as a function of relevant covariates and relate this latent propensity to the observed weekly frequency outcome (y_{qi}) through threshold bounds (see McKelvey and Zavoina, 1975):

$$y_{qi}^* = \beta_i' x_{qi} + \varepsilon_{qi}, y_{qi} = k \text{ if } \theta_i^k < y_{qi}^* < \theta_i^{k+1} \quad (1)$$

where x_{qi} is a $(L \times 1)$ vector of exogenous variables (not including a constant), β_i is a corresponding $(L \times 1)$ vector of coefficients to be estimated, ε_{qi} is a standard normal error term, and θ_i^k is the lower bound threshold for weekly frequency category k of activity type i ($\theta_i^0 < \theta_i^1 < \theta_i^2 \dots < \theta_i^{K_i+1}$; $\theta_i^0 = -\infty$, $\theta_i^{K_i+1} = +\infty$ for each activity type i). The ε_{qi} terms are assumed independent and identical across individuals (for each and all i). Due to the need for identification restrictions, the variance of each ε_{qi} term is normalized to 1. However, correlations are allowed in the ε_{qi} terms across activity types i for each individual q . Specifically, define $\varepsilon_q = (\varepsilon_{q1}, \varepsilon_{q2}, \varepsilon_{q3}, \dots, \varepsilon_{qI})'$. Then, ε_q is multivariate normal distributed with a mean vector of zeros and a correlation matrix as follows:

$$\varepsilon_q \sim N \left[\begin{pmatrix} 0 \\ 0 \\ \vdots \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho_{12} & \rho_{13} & \cdots & \rho_{1I} \\ \rho_{21} & 1 & \rho_{23} & \cdots & \rho_{2I} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \rho_{I1} & \rho_{I2} & \rho_{I3} & \cdots & 1 \end{pmatrix} \right], \text{ or } \varepsilon_q \sim N[\mathbf{0}, \mathbf{\Sigma}] \quad (2)$$

The off-diagonal terms of Σ capture the error covariance across the underlying latent continuous variables of the different destination purposes; that is, they capture the effect of common unobserved factors influencing the propensity of weekly engagement in each activity type. Thus, if ρ_{12} is positive, it implies that individuals with a higher than average propensity to engage in the first activity type more frequently are also likely to have a higher than average propensity to engage in the second activity type more frequently. If all correlation parameters (i.e., off-diagonal elements of Σ), which can be stacked into a vertical vector Ω , are identically zero, the model system in Equation (1) collapses to independent ordered response probit models for each activity type.

The parameter vector of the multivariate ordered probit model is $\delta = (\beta'_1, \beta'_2, \dots, \beta'_I; \theta'_1, \theta'_2, \dots, \theta'_I; \Omega')$, where $\theta_i = (\theta_i^1, \theta_i^2, \dots, \theta_i^{K_i})'$ for $i = 1, 2, \dots, I$. Let the actual observed weekly frequency category for individual q and activity i be m_{qi} . In that case, the likelihood function for individual q can be written as follows:

$$L_q(\delta) = \Pr(y_{q1} = m_{q1}, y_{q2} = m_{q2}, \dots, y_{qI} = m_{qI})$$

$$L_q(\delta) = \int_{v_1 = \theta_1^{m_{q1}} - \beta'_1 x_{q1}}^{\theta_1^{m_{q1}+1} - \beta'_1 x_{q1}} \int_{v_2 = \theta_2^{m_{q2}} - \beta'_2 x_{q2}}^{\theta_2^{m_{q2}+1} - \beta'_2 x_{q2}} \cdots \int_{v_I = \theta_I^{m_{qI}} - \beta'_I x_{qI}}^{\theta_I^{m_{qI}+1} - \beta'_I x_{qI}} \phi_I(v_1, v_2, \dots, v_I | \Sigma) dv_1 dv_2 \dots dv_I, \quad (3)$$

where $\phi_I(v_1, v_2, \dots, v_I | \Sigma)$ represents the multivariate normal density of dimension I with correlation matrix Σ , evaluated at the abscissae (v_1, v_2, \dots, v_I) . Calculating the high-order I -dimensional rectangular integral above can prove to be computationally challenging. In order to overcome the computational complexity, this study employs a composite marginal likelihood computation approach, which involves approximating the higher-order integral through the computation of a series of bivariate marginal distributions (see Ferdous et al., 2010 and Bhat, 2015 for details).

3.2. Conceptual Framework

The multivariate ordered probit modeling methodology is used to analyze the influence of exogenous variables on the weekly frequencies of six different activity types and explore the nature of the inter-relationships among them. As noted earlier, the six endogenous variables represent the number of days of pursuing at least one episode of the following six activity types:

- Online shopping (inferred by deliveries of non-grocery and non-food/meal packages), labeled as “OL Shop”
- Online grocery shopping, labeled as “OL Groc”
- Online food/meal shopping, labeled as “OL Meal”
- In-person trips for shopping (excluding groceries and meals), labeled as “IP Shop”
- In person trips for grocery shopping, labeled as “IP Groc”
- In-person trips for meals (restaurants), labeled as “IP Meal”.

The presence of six endogenous variables gives rise to many possible specifications of relationships among them. Independent ordered probit models were estimated to help identify significant exogenous variables that influenced weekly frequency of engagement in each of the six activity types. This process helped in developing an appropriate initial specification for the joint model system, H0, where all exogenous variable effects were incorporated and all error

correlations were free to be estimated, but all endogenous variable effects were suppressed (i.e., set to zero). The specification was continuously modified to reach a balance between statistical significance and behavioral intuitiveness of the coefficient magnitudes and signs. With respect to the myriad relationships among the endogenous variables, four model structures were considered. These are depicted in Figure 1 (as H1 through H4).

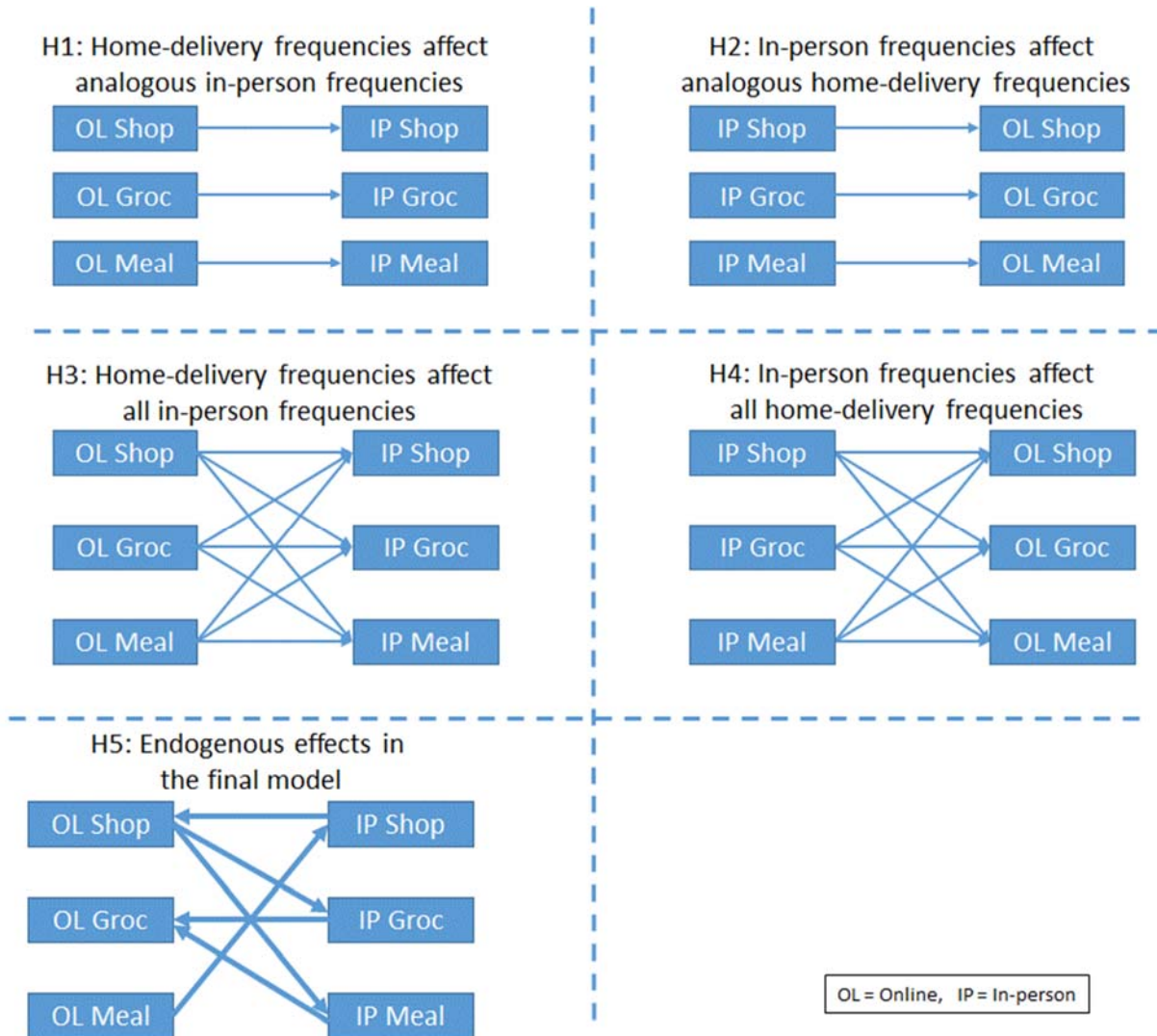


Figure 1. Hypotheses Regarding Relationships Among Endogenous Variables

They include:

- H1: Online activity engagement frequency affects corresponding in-person activity engagement.
- H2: In-person activity engagement frequency affects corresponding online behavior.
- H3: All online activity engagement frequencies affect all in-person activity engagement frequencies.
- H4: All in-person activity engagement frequencies affect all online activity engagement frequencies.

In all of the above specifications, an error correlation structure is incorporated to accommodate the bundled nature of the many choices. Thus, the directionality of relationship of an observed endogenous variable on the propensity underlying another endogenous variable can only be in one direction. That is, only recursive effects are allowed in cases of multivariate ordinal model systems, due to logical consistency considerations (see Bhat, 2015 for a detailed discussion). After estimating model specifications corresponding to H1 through H4, the analysis involved using goodness-of-fit measures, behavioral intuitiveness, and statistical significance of coefficients to arrive at a final model structure that was both intuitive and supported by the data. The final model structure is shown as H5 in the figure, and all model estimation results in this paper are presented for this model structure. Through an examination of the endogenous variable effects, it is possible to identify complementarity and substitution in the relationships among online and in-person activity engagement (in the context of shopping and meal activities).

4. MODEL ESTIMATION RESULTS

Model estimation results in the form of exogenous and endogenous variable effects are depicted in Tables 3 and 4 respectively and discussed in detail in this section. Also, average treatment effects are computed and presented in this section; these effects serve as a measure of change in online and in-person activity engagement in response to changes in exogenous variables.

4.1. Exogenous Variable Effects

Table 3 presents estimation results depicting the influence of exogenous variables on the propensity to engage in online and in-person shopping and eat-meal activities. While in-person activity engagement is directly observed in the data set (in the form of trips to engage in these activities), online activities are not directly observed because individuals do not report their online activities. Rather, information about the frequency of deliveries of packages, groceries, and prepared meals is available in the data set, and this information is used as a proxy for the frequency of online shopping for goods, groceries, and meals. In reality, the frequency of online activity may not be exactly identical to the number of deliveries; however, in the absence of data about online activity, the number of deliveries is a useful proxy.

Income is found to significantly affect online and in-person activity engagement for shopping and meals. The propensity to engage in online shopping for goods, groceries, and meals increases with household income, a result consistent with that reported in the literature (e.g., Cao et al., 2012; Zhou and Wang, 2014; Lee et al., 2015). Higher income households are also more likely to engage in eating out (presumably at restaurants) in person, consistent with their greater purchasing power and ability to afford discretionary eat-out activities. In-person shopping frequency tends to be higher for the middle-income households; they have the income to shop for goods and groceries more often, but have not quite transitioned to utilizing virtual means to do so (whereas the highest income group may have made that transition to some degree). One-worker households are more likely to shop online for non-grocery goods. Households with multiple workers show the lowest propensity for grocery shopping – both online and in-person. This may be reflective of the time constraints faced by multi-worker households, who may opt to engage in fewer consolidated shopping episodes for gaining efficiencies. These households show a propensity to eat out (in-person) more often, presumably because they can afford to do so and gain some efficiencies in the process (Daniels et al., 2012).

Table 3. Estimation Results for Selected Model (H5): Exogenous Variable Effects

Variables	Online Shop		Online Grocery		Online Meals		In-person Shop		In-person Grocery		In-person Meals	
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
Exogenous Variables												
<i>Household income (base: ≥\$100,000)</i>												
< \$25,000	-0.262	-10.062	-0.197	-5.290	-0.277	-7.657			0.061	2.516	-0.277	-14.676
\$25,000-\$49,999	-0.262	-10.062	-0.197	-5.290	-0.277	-7.657			0.061	2.516	-0.277	-14.676
\$50,000-\$74,999	-0.313	-12.243			-0.127	-4.000	0.113	4.911	0.178	8.241	-0.277	-14.676
\$75,000-\$99,999	-0.104	-3.782			-0.127	-4.000			0.178	8.241	-0.277	-14.676
<i>Employment status (base: Single worker)</i>												
No workers	-0.264	-6.852			0.188	3.981	0.250	6.416				
Multiple workers	-0.270	-9.784	-0.229	-5.906			-0.098	-3.468	-0.388	-13.934	0.269	10.138
<i>Household structure (base: Single adult with or without children)</i>												
Two or more adults without children	0.698	22.787	0.538	10.878			0.751	24.652	0.998	31.573	0.250	8.921
Two or more adults with children	0.646	18.626	0.823	14.892	0.376	9.535	0.713	19.870	0.984	28.079	0.174	5.176
<i>Residential density (base: >4,000 hh/km²)</i>												
<2,000 hh/km ²	-0.178	-6.788	-0.407	-8.907	-0.251	-8.853	0.165	8.502	0.111	4.698	-0.109	-5.970
2,000-4,000 hh/km ²	-0.152	-6.001	-0.337	-8.783	-0.251	-8.853	0.165	8.502			-0.109	-5.970
<i>Household tenure (base: Rent and other)</i>												
Own	-0.083	-3.383	-0.278	-8.036	-0.212	-6.884	0.102	4.537			-0.085	-3.856
<i>Household type (base: Detached house, attached house, other)</i>												
Building with apartments and condos	-0.313	-11.910	-0.136	-3.712			-0.076	-3.117	0.066	3.042	0.142	6.016
<i>Vehicle availability (base: ≥ 1 per adult)</i>												
None	0.128	4.898	-0.224	-4.105	-0.087	-2.232	-0.211	-8.209	-0.291	-11.867	-0.126	-5.550
< 1 per adult	0.153	5.522	0.242	6.196	0.102	3.114	-0.323	-12.232	-0.154	-5.698	-0.059	-2.253

Table 4. Estimation Results for Selected Model (H5): Endogenous Variable Effects, Correlation Effects, and Goodness-of-Fit

Variables	Online Shop		Online Grocery		Online Meals		In-person Shop		In-person Grocery		In-person Meals	
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
Endogenous Variables												
<i>Online meals (base: 0 days per week)</i>												
1-7 days per week							-0.103	-3.784				
<i>In-person shopping (base: 0 days per week)</i>												
1 day per week	0.092	3.802										
2-7 days per week	0.138	5.996										
<i>Online shopping (base: 0-2 days per week)</i>												
3-7 days per week									0.123	5.365	0.126	5.990
<i>In-person groceries (base: 0-2 days per week)</i>												
3-7 days per week			-0.357	-10.082								
<i>In-person meals (base: 0 days per week)</i>												
1-7 days per week			0.389	6.709								
Thresholds												
Threshold 1	-0.354	-9.492	1.409	20.423	0.885	28.510	-0.183	-6.138	-0.518	-20.817	-1.041	-31.347
Threshold 2	0.763	20.545					0.620	20.660	0.361	14.460	-0.474	-14.882
Threshold 3							1.322	41.962	1.093	42.287	0.112	3.500
Threshold 4											0.595	18.590
Threshold 5											1.067	32.636
Correlation Terms												
Online Groceries	0.225	2.724										
Online Meals			0.510	5.866								
In-person Shopping												
In-person Groceries							0.275	6.193				
In-person Meals							0.188	4.056	0.192	4.182		
<i>Goodness-of-Fit Measures:</i>												
Free Parameters: 88; Composite Marginal, LL: -21274.3920; Predicted, LL: -4278.3787; Rho-squared: 0.0555												
Adjusted rho-squared: 0.0394; Likelihood Ratio vs. Null: 502.7996 (p=0.00)												
Likelihood Ratio vs. Independent Model: 143.7270 (p=0.00); Likelihood Ratio vs. H0: 50.7350 (p=0.00)												

Households with no workers depict a higher propensity to engage in online meal delivery; these are households with retirees who are likely to enjoy the convenience of having prepared meals delivered to the home. Because it is possible to order meals from many establishments over the phone, technology may not necessarily be a barrier for virtual meal engagement for these households (Pearce and Rice, 2013). Additionally, these no-worker households are able to pursue a greater frequency of in-person shopping episodes, presumably because they do not have the same time constraints as households with workers do (Zhou and Wang, 2014).

Households with greater number of adults and children show a propensity to engage in a higher frequency of both online and in-person shopping episodes for goods, groceries, and meals. This is consistent with expectations as larger households are likely to consume (and hence shop) more across all commodity categories considered in this paper. The presence of children appears to enhance the propensity to pursue online grocery and meal purchases; this finding is similar to that in prior research (e.g., Lavieri et al., 2018). Households with children may find the convenience afforded by online grocery and meal delivery appealing, in light of their busy schedules. Households in higher density areas (presumably more urban core areas) have a higher propensity to engage in online shopping for goods, groceries, and meals. On the other hand, those in lower density areas (such as suburban and rural environments) have a higher propensity to engage in in-person shopping for goods and groceries. Those residing in urban areas are likely to be more technology-savvy and participating in the sharing/delivery-based economy, thereby leading to this finding; similar findings have been reported by others (e.g., Cao et al., 2012; Zhou and Wang, 2014). Households in dense urban areas have a higher propensity to eat out; the greater access to eating establishments in urban core areas likely contribute to this finding.

Household tenure and housing unit type are found to significantly impact propensity to pursue in-person and online shopping for various types of commodities. Homeowners display a lower propensity to engage in online shopping for goods, groceries, and meals; but exhibit a higher propensity to engage in in-person shopping episodes for non-grocery items. Their propensity to participate in in-person eat-out activities is also low. All of these findings are consistent with homeowners being more stabilized in their lifecycles and preferring a traditional lifestyle wherein shopping at the neighborhood store and eating cooked meals inside the home constitute the norm (Lallukka et al., 2007). Those residing in apartments and condos are found to engage in less online activity and higher in-person activities for groceries and eating out. The higher propensity to eat out among those who live in apartments and condos may be a reflection of relatively transient populations who are open to exploring a variety of types of cuisines.

Finally, vehicle availability is found to significantly impact the propensity of online and in-person shopping activities. Across all in-person activity categories, higher car ownership is associated with a greater propensity of episodes. This is consistent with expectations as auto availability facilitates in-person engagement in activities. Conversely, zero-vehicle and vehicle-deficient households depict a higher propensity to engage in online activities; these households may find it convenient to use online services to access goods and services. Households with zero cars depict a lower propensity for online grocery and meal deliveries.

4.2. Endogenous Variable Effects, Correlation Effects, and Goodness-of-Fit

A key objective of this study is to unravel the complex interplay of relationships among the six endogenous variables with a view to better understand the complementarity and substitution effects that may be present. Table 4 offers estimates of the endogenous variable effects together with error correlations and goodness-of-fit measures. A graphical depiction of the significant endogenous variable effects retained in the final model specification is shown in Figure 1

(specification H5). Note that these effects are “true” causal effects because the jointness among the six endogenous variables has been captured through the error correlations (discussed later in this section).

The chain of recursive effects starts with online meals (see H5 in Figure 1). There is a negative effect of the number of days of online meals ordered (and delivered to the home) on in-person shopping propensity. Indeed, order meals to the home may be indicative of an individual who spends more time at home and enjoys the convenience of having things delivered to the home. Such a person is likely to engage in fewer in-person shopping activities. A higher level of in-person shopping itself then has a positive effect on the propensity for online shopping (though there is no statistically significant difference in this latter effect between 2-7 days of in-person shopping). The complementarity between online and in-person shopping for goods has been observed in a number of previous studies (e.g., Cao et al., 2012; Ding and Lu, 2017; Lee et al., 2017). However, the results here suggest that the primary element of complementarity originates from individuals employing in-person shopping episodes as a means to “scout” for goods and then using online platforms to undertake additional research, comparison-shop, and ultimately buy goods (technically, it is also possible that in-person shopping leads to placing orders that are then shipped to homes; unfortunately, the Puget Sound survey is not able to distinguish between store purchases followed by a delivery home and an online purchase followed by a delivery home). Overall, based on the results, it is not that online shopping activity for goods engenders more frequent in-person visits to stores, but that in-person visits to stores leads to online shopping activity.

While shopping for non-grocery appears to depict a complementary effect between in-person and online activity, shopping for grocery items depicts a substitution effect. As expected, a higher frequency of in-person grocery shopping is associated with a lower propensity for online grocery shopping activity, which is a finding also reported by Suel et al. (2018). A higher frequency of in-person eat-meal activities is associated with a higher propensity for online grocery shopping. It is possible that those who eat out often find something appealing and decide to try it at home, thus potentially leading to more online grocery shopping in the process of obtaining the specialty dish or ingredients.

The error correlation matrix at the bottom of Table 4 shows that a few error covariances are statistically significant in this data set. This is to be expected, as unobserved lifestyle preferences and attitudinal variables are likely to simultaneously affect frequency of in-person and online shopping and meal activities. The positive error correlation between online groceries and online shopping suggests that unobserved attributes (e.g., tech-savviness) that contribute to increasing online grocery episodes also contribute to increasing online shopping episodes. A similar positive error correlation is found for online meal activity and online grocery shopping (people comfortable with ordering perishable items are likely to increase both online meal and online grocery activity) and between in-person grocery shopping and in-person goods shopping (households with intrinsically higher consumption lifestyles and a proclivity for out-of-home activity engagement are likely to engage in higher levels of both of these shopping types). A positive error correlation exists between in-personal meals and in-person grocery shopping, presumably due to the same reasons. Overall, it can be seen that a multivariate ordered probit modeling methodology is warranted because there are significant error correlations that capture the effects of correlated unobserved attributes simultaneously affecting multiple activity engagement outcomes. It is imperative that these error correlations be estimated so that consistent estimates of exogenous and endogenous variable effects can be obtained, and accurate forecasts of combinations of the six endogenous variables may be made.

The goodness-of-fit measures at the bottom of Table 4 are in line with expectations for a multivariate ordered probit model of the type presented in this paper. The likelihood ratio χ^2 statistic is computed against the null model (all parameters set to zero), the independent model (all error covariances set to zero), and the base model (called H0). In all cases, the χ^2 statistic is statistically significant suggesting that the model H5 is providing a significant improvement over the base, null, and independent models. The ρ^2 and adjusted ρ^2 values appear low but are consistent with values generally obtained for relatively high-dimensional multivariate ordered probit models where the probability of any high-dimensional combination (six-dimensional in this setting) is bound to be low. In addition to assessing these goodness-of-fit measures, additional evaluations of goodness-of-fit were conducted by computing probability of correct predictions offered by the model and by comparing model-predicted market shares against observed (true) shares of households choosing various combinations of endogenous variable outcomes. These results are suppressed in the interest of brevity, but the findings suggest that the model H5 offers significantly better data fit relative to the more restrictive models. Essentially, the result is that both jointness (due to error correlations) as well as recursive effects need to be accommodated. More broadly, the model results offer strong support for the notion that online and in-person activities of multiple purposes constitute a lifestyle package and need to be considered as such.

4.3. Average Treatment Effects

To assess the magnitude of the impact of exogenous variables on online and in-person shopping and meal activity engagement, average treatment effects (ATEs) are computed and presented in this section. While it is possible to obtain ATEs for any combination of the six activity purposes, for simplicity, only the marginal ATEs for each univariate activity purpose are considered here. For all six outcomes of interest, cardinal values are assigned to each of the ordinal levels, and then the ATEs of the determinant variables are computed on the expected number days in which each activity takes place. For presentation ease, only the two extreme categories are considered in the case of variables with multiple categories (for example, only the effect on each endogenous variable of a change from the lowest income level of “<25,000” to the highest income level of “≥100,000” is presented).

In more general terms, the ATE of the determinant variable that is changed from category k to category i is computed as follows:

$$\hat{ATE}_{ik} = \frac{1}{Q} \sum_{q=1}^Q \left(\sum_{h=1}^5 c_h \cdot \left[P(Freq_Act_q = h | a_{qi} = 1) - P(Freq_Act_q = h | a_{qk} = 1) \right] \right) \quad (4)$$

where c_h is the cardinal value assignment corresponding to the ordinal level h , and $Freq_Act_q$ corresponds to the ordinal category of frequency of online or in-person activity engagement of household q in one day. To compute this effect, the value of the base category is first assigned to all households in the sample (that is, assign the value of $a_{qk} = 1$ to the determinant variable for all households to compute $P(y_q = j | a_{qk} = 1)$ and then change the value of the variable to $a_{qi} = 1$ and compute $P(y_q = j | a_{qi} = 1)$). Results of ATE computations are presented in Table 5. The base category varies for each exogenous variable analyzed. To calculate the ATE values, a realization of random draws is constructed by appropriately drawing from the sampling distribution of all relevant parameters. The ATE values are then computed for 1000 different draws (for each household) so that standard errors are obtained.

Table 5. Average Treatment Effects of Exogenous Variables

Exogenous variable	Categories compared	Online Shop		Online Grocery		Online Meals		In-person Shop		In-person Grocery		In-person Meals	
		Value	t-stat	Value	t-stat	Value	t-stat	Value	t-stat	Value	t-stat	Value	t-stat
Income	From "< \$25,000" to "≥\$100,000"	0.161	69.931	0.034	34.944	0.056	39.466			-0.054	-81.696	0.372	91.414
Worker Status	From "Single worker" to "Multiple workers"	-0.163	-67.321	-0.040	-35.685			-0.085	-71.142	-0.335	-77.093	0.362	92.617
Household Structure	From "Single adult w/ or w/o children" to "Multiple adults with children"	0.400	70.965	0.157	39.590	0.083	43.702	0.627	76.643	0.877	90.811	0.234	90.820
Density	From "<2,000 hh/km2" to ">4,000 hh/km2"	0.198	65.890	0.115	32.324	0.051	39.544	-0.145	-74.114	-0.098	-82.517	0.145	88.697
Tenure	From "Rent or other" to "Own"	-0.050	-68.152	-0.049	-35.461	-0.043	-39.412	0.089	73.313			-0.113	-88.686
Household Type	From "Attached, detached or other" to "Building"	-0.194	-71.524	-0.025	-36.484			-0.067	-73.348	0.058	81.790	0.189	88.759
Vehicle Avail (veh/adult)	From "≥1" to "0"	0.079	69.038	-0.037	-33.530	-0.018	-38.785	-0.184	-73.765	-0.257	-81.890	-0.168	-88.537

The results in Table 5 are, of course, consistent with the earlier estimation results. However, unlike the estimation results, Table 5 provides a clear sense of the magnitude of effects of variables. For example, a random household that “moves” from the lowest to the highest income category is estimated to increase the number of days of in-person meal activity by approximately 0.372 days per week (the largest change associated with income) and a decrease in the amount of in-person grocery trips by approximately 0.054 days per week (see the last two columns of Table 5 in the first row). This income change also increases the number of days of online shopping by 0.161 days per week, the number of days of online grocery shopping by 0.034 days, and the number of days of online meals by 0.056 days per week. Other results may be similarly interpreted.

Among the many exogenous variables, household structure appears to be the most impactful variable. The results suggest that the trend away from the nuclear family (in the U.S. and many other western countries) and toward single adult families may actually result in fewer in-person episodes for shopping as well as in-person meals activity. Of course, this could also be viewed as a sign of inequity and social exclusion (especially for single mothers) arising from the design of land use and transportation systems. At the same time, single adult families also undertake more online shopping and meal activities, which may itself lead to more delivery trips to homes. While the effects in Table 5 suggest that there would be a significant reduction in trips overall even assuming that a delivery vehicle would simply replace a sojourn from home of the individual (note that the magnitudes of the ATEs are higher for the in-person categories than for the online categories), there are additional complications and efficiencies brought about by delivery chaining (for delivery trips) and activity chaining (for in-person participations). The net result of the combination is unknown at this time and calls for more investigations into not only activity generation (as in this paper), but also scheduling considerations.

The results in Table 5 also indicate that densification of neighborhoods as well as policies that reduce household vehicle holdings have a clear and strong negative effect on in-person activity episodes, highlighting the potential benefits (in terms of traffic congestion alleviation) of neo-urbanist designs in urban areas.

5. DISCUSSION AND CONCLUSIONS

Technology is increasingly becoming an integral part of people’s lives. Technology and connectivity, enabled by the internet of things (IoT), are leading to very different ways in which various activities are undertaken; the effects can be seen in work, education, shopping, social-recreation, eating meals, and transportation. Services that take advantage of technology and the crowd-based delivery and sharing economy are providing people access to goods and services like never before. Technology, connectivity, and crowd-based services are undoubtedly impacting activity-travel behavior, and yet travel forecasting models are woefully inadequate in reflecting the effects of these phenomena on activity-travel patterns and choices. As a consequence, transportation planning professionals are grappling with high degrees of uncertainty in their planning processes – unable to fully account for the transformative changes that technology and connectivity are bringing to their ecosystem.

To answer this knowledge gap, this study utilizes data from the 2017 Puget Sound Regional Household Travel Survey in which a subsample of 705 households reported activities and travel for a one-week period through a smartphone app. They also reported the number of home deliveries of goods, groceries, and prepared meals for the same one-week period. This data allowed an examination of the relationships between the frequency (in terms of number of days in the week) of online activity and in-person activity engagement. A multivariate ordered probit model of

frequency of online and in-person activity engagement was estimated. The model included six endogenous variables corresponding to number of days in the week that in-person or online activities were pursued for shopping (non-grocery), shopping (grocery), or meals.

Model estimation results showed that a number of exogenous variables such as income, household structure, residential density, household tenure and housing unit type, and vehicle ownership affect frequency of online and in-person activity engagement. The results were largely intuitive with higher income households engaging in more online and in-person activities, presumably due to higher consumption levels. Households in urban areas (higher density) were more frequent participants in online activities rather than in-person activities; however, they ate out (in person) more than their lower-density residential counterparts, presumably because the denser environments had more opportunities to do so.

The endogenous variable effects are of key interest in this study. The final model structure that provided the best and most intuitive results showed that there are both complementary and substitution effects at play. More in-person shopping (non-grocery) is associated with more online shopping (non-grocery), suggesting that there is a complementary effect between in-person and online activity engagement for non-grocery shopping. But a substitution effect is seen between in-person and online *grocery* shopping. These findings suggest that it is important to draw an explicit distinction between different types of shopping activities in travel demand forecasting models and planning processes. Higher frequency of online shopping (non-grocery) is associated with higher levels of in-person grocery and in-person meal consumption; higher levels of in-person eat-meal activity is associated with a higher level of online grocery shopping. All of these effects are reflective of trade-offs in activity engagement and adoption of a lifestyle package on the part of households.

A number of implications may be drawn from study findings. Results of exogenous variable effects, for example, show that households in urban (dense) areas are engaging in higher levels of online shopping activities than their observationally equivalent counterparts in lower density environments. In other words, congested urban cores may see further increases in congestion with a growth in delivery vehicles; policies need to be formulated to help manage the growth in delivery vehicle traffic to avoid unintended consequences of worsening safety, traffic congestion, and air pollution. Equity considerations also arise in the context of income. Lower income households are found to engage in less online shopping, grocery, and meal activities, presumably because of the digital divide and inability to pay the premium that often comes with the convenience of online commerce. As brick-and-mortar stores go increasingly out of business, households in lower income segments may experience greater inconvenience in accessing goods and services of various kinds. Policies that enhance digital access for lower income households need to be developed; many public assistance policies in place today (e.g., food stamps, paratransit services) have not evolved with the changing technological and service-based landscape. It is time for these policies to be updated so that lower income groups do not experience diminished access due to digital poverty (besides income poverty).

Travel demand forecasting models need to be enhanced to better reflect the relationships between online and in-person activity engagement. Despite decades of evidence (through the series of National Household Travel Surveys in the United States) that in-person shopping trip rates are dropping over time (presumably due, at least in part, to the rise of e-commerce), four-step travel demand forecasting models continue to assume constant shopping trip rates (in the trip generation step) over the forecast horizon period. No distinction is made between non-grocery and grocery shopping episodes despite the very different nature of these shopping activities. Also, it cannot be

assumed that online activity engagement strictly affects in-person activity engagement or vice-versa. The nature of the relationships is more complex; in this study, there was clear indication and strong support for the notion that online and in-person activities of multiple purposes are pursued as a lifestyle package and need to be considered as such. In addition, the direction of recursive effects (while considering jointness across all the endogenous variables) suggests complex interplays between in-person and online pursuits of different activity purposes. Given that more recent microsimulation models of activity-travel behavior can effectively simulate choices at the level of the individual agent, it would be of value to develop and integrate modeling components that explicitly simulate online activity engagement and the relationships between online and in-person activity frequencies. Data is needed to enable such model development. Activity-travel surveys should include detailed questions about home-based deliveries of various types of goods and services, frequency of online activity for different activities and purposes, and use of technology for fulfilling activities on the daily household agenda virtually. Models that span the digital and physical worlds will help reduce the uncertainty that transportation professionals have to deal with and provide a basis for more robust policy formulation that will improve accessibility to goods and services for all.

Another critical issue that this paper underscores is the need to bring passenger and freight demand modeling, at least within urban contexts, into a single integrated structure. Decisions regarding online and in-person activity engagements are made as an integrated lifestyle package, and it is absolutely imperative that travel demand models recognize the intertwined and interdependent nature of urban freight and passenger movements. As the distinction between freight and passenger movements becomes increasingly fuzzy, the days of compartmentalizing freight and passenger demand in modeling frameworks need to be behind us.

In closing, as with any research effort, many extensions of this research warrant attention. This research, and pretty much all other earlier efforts examining online and in-person activity interactions (including the empirical studies identified earlier in the paper), have used relatively small data samples (of the order of 700-900 observations) from specific cities or specific regions (mostly from China, but also from the U.S. and Europe). Part of the reason is that obtaining in-person activities as well as online activities substantially increases the respondent burden, and so such details are typically sought only for a small sample of respondents from a larger mainstream activity-travel survey data collection pool or obtained through a dedicated specialized small-scale survey. Efforts to promote the large-scale data collection of online activity and home deliveries, along with in-person activity-travel, is much needed and requires the development of new innovative data collection techniques. In doing so, it would be particularly helpful to obtain more fundamental “process” data that can be used to better trace the underlying behavioral interplay and motivations driving online activities and in-person activities. With current large scale data collection efforts, only outcome data is collected, and while such outcome data dominate (and have been the mainstay of) activity-travel modeling efforts and have formed the basis for imputing underlying behavioral processes, the collection of process data can provide substantially more behavioral insights. Further, the growth of e-retail and e-commerce has been rapid and is evolving. Though the data used in this research is from the latest available dataset from the Puget Sound Regional Council in the U.S. that collected online activity details (to the authors’ knowledge, no other metropolitan region in the U.S. collects such detail presently as part of their regional travel surveys), it is imperative that investigations of the inter-relationships between online and in-person activity participation be continually undertaken with the most recent data available.

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