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A Study of the Impact of COVID-19 on Home Delivery Purchases and Expenditures

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ABSTRACT

Lockdowns caused by the COVID-19 pandemic have significantly affected shopping behavior. This study surveys people living in Portland-Vancouver-Hillsboro Metropolitan area on household and demographic characteristics, e-commerce and home delivery service and product preferences, number of deliveries made before and during the COVID-19 lockdown, and household expenditures on home deliveries. Ordered choice models are developed to understand factors that affect the number of online deliveries made before COVID-19, and the number and household expenditures on online deliveries during the COVID-19 lockdown. Results indicate that higher-income households are more likely to make more online deliveries and spend more money on home deliveries during the COVID-19 lockdown. Higher levels of technology utilization are also associated with higher levels of deliveries and expenditures. Same-day or next-day services are expected for items such as groceries or meals. Respondents who are concerned about product costs at brick and mortar stores are less likely to have high levels of house deliveries, but respondents who are worried about health issues are more likely to spend more money and have more home deliveries during COVID-19 lockdown. The results have important implications in terms of equity and access to e-commerce and house grocery deliveries.

KEYWORDS: COVID-19, home deliveries, e-commerce

1. Introduction

The onset of the COVID-19 pandemic has disrupted most aspects of life, including the way people access goods. Government-mandated lockdowns have kept consumers at home, preventing normal shopping patterns, and many brick-and-mortar businesses have closed down. Some essential businesses, such as pharmacies and grocery stores, have remained open but with altered operations. Many restaurants have closed or relied on takeout to survive. For many consumers, home delivery has been a solution to some of the challenges created by COVID-19. E-commerce and house delivery can be a convenient solution for workers forced to work remotely as well as many other groups such as parents that have to juggle both work and parenting demands or groups at risk of developing serious COVID-19 health-related complications.

E-commerce has been growing rapidly, but the advent of COVID-19 is likely to have accelerated the trend. The online food, beverages, and grocery market have seen explosive growth. For example, Instacart, a popular food and grocery delivery service, has reported a year over year increase of 500% in April 2020 (CNBC, 2020). E-commerce and home delivery changes are likely to have a great impact on the job market but also the transportation sector and the environment (Mokhtarian, 2004). For example, in the US, the number of packages delivered exceed 13 billion, and household-based grocery shopping trips exceeded 15 billion in 2018 (Figliozzi, 2020). Given the magnitude of these numbers, percentual changes that exceed single-digit numbers results in significant changes in travel and transportation-related emissions.

This research analyzes home delivery changes brought about by COVID-19. Data was collected using an online survey in the Portland-Vancouver-Hillsboro Oregon-Washington Metro Area. The survey elicited responses on household and demographic characteristics, e-commerce and house delivery service and product preferences, the number of deliveries made before and during COVID-19 lockdown, and household expenditures on home deliveries. Novel contributions include the development of models that compare the factors driving pre-COVID-19 and during-COVID-19 home deliveries. Additionally, the factors impacting household delivery expenditures during COVID-19 are analyzed.

This research is organized as follows: Section 2 presents an overview of relevant trends related to house deliveries and a literature review. Section 3 summarizes the data collection, analysis methodology, and descriptive statistics of key variables. Section 4 compares the factors affecting pre-COVID-19 deliveries with during-COVID-19 deliveries. Section 5 analyzes the variables affecting household income and the level of house delivery expenditures during COVID-19. Section 6 presents policy implications for freight and transportation. Section 7 ends with conclusions and a discussion of implications and future research opportunities.

2. Literature Review

According to the United States Quarterly E-Commerce Report, e-commerce sales in the United States (US) have increased at double-digit rates for the past two decades. During this time, e-commerce growth has greatly outpaced brick-and-mortar retail growth (US Department of Commerce, 2020). Amazon is often mentioned when discussing e-commerce in the US because it is the largest player in terms of market share. Amazon Prime subscriptions have been steadily growing, and an important draw to membership is the offer of free shipping for many types of orders. Amazon Prime membership in the US has grown from 50 million members in late 2015 to 112 million in December 2019 (Fortune, 2020). Online shopping sales have skyrocketed during the COVID-19 pandemic. May 2020 saw a 78% increase over May 2019, and sales in April and May were 7% higher than in November and December 2019, the standard peak shopping period (eMarketer, 2020). The highest growth is likely to have taken place in the online food, beverages, and grocery market where companies like Instacart have experienced 500% year over year increases during the lockdown (CNBC, 2020).

According to the 2017 National Household Travel Survey (NHTS), in the US, urban dwellers are more likely to purchase online for home delivery than their rural counterparts (FHWA, 2018). Approximately 56% of urban households purchased online at least monthly, compared to 51% of rural residents, and this may be attributed to the relatively limited availability of broadband networks in rural areas.

According to the 2017 NHTS results, online shopping is directly proportional to the frequency of Internet usage. In addition, "online shopping was highest for those households with young children (63%) or with no children (60%). Reports of online shopping among households with children decreased as the age of the children increased" (FHWA, 2018).

Ever since the seminal work of Manski and Solomon (1987), who applied discrete choice analysis to study teleshopping demand, there has been a lot of interest in understanding non-traditional shopping behavior away from regular stores. Since the explosion of e-commerce, several researchers have focused on understanding socio-economic, personal, attitudinal, alternative shopping service, and product-related factors that affect the propensity to shop online (Farag et al., 2006; Cao, 2009; Chocaro et al., 2013; Clems et al., 2014; Scarpi et al.,2014; Faqih and Jaradat, 2015; Zhai et al. 2017; Schmid and Axhausen, 2019). Hsiao (2009) focused on the impact of the value of travel time and delivery time estimates on the choice of in-store vs. online shopping. Ramanathan (2010) showed that favorable customer attitudes towards website operational factors such as refunds, prices, customer service, etc. result in increased loyalty. Rutner et al. (2003), Barenji et al. (2019), Shao et al., (2019), Ponce et al. (2020), Ren et al. (2020), Yang et al. (2020) focus on optimizing the operational aspect of e-commerce supply chain systems and Lafkihi et al. (2019) provide a detailed review of various procurement mechanism.

There is also limited research on impact of COVID-19 on supply chain. Ivanov (202) focus on simulation based modeling of short term and long term impacts of supply chain disruptions due to epidemics. Choi (2020) analyze logistics inspired new paradigm of mobile service operations which along with government subsidies can help business operations to survive in this new era.

This study differentiates itself from previous research in several aspects. We focus on factors affecting the number of deliveries made and household expenditures on online shopping. A key contribution of this work is trying to understand the online shopping behavior in a pandemic lockdown setting and compare it to the pre-pandemic situation. To the best of our knowledge, there is no other work that studies the demand for online shopping in a COVID-19 pandemic lockdown.

3. Data Collection and Methodology

The data was collected through an online survey. The data collection was limited to the Portland-Vancouver-Hillsboro Oregon-Washington Metro Area. We decided to focus on a single urban area, as lockdown related regulations and compliance vary from location to location. The metro area has a total population of approximately 2.5 million spread over nearly 7000 square miles (Census Reporter, 2020).

To get a good representative sample, we enforced the following demographic quota checks:

- There should be at least 40% representation of males or females in the sample.
- In terms of household annual income, at least 20% representation in each of the following categories: 0-$50,000, $50,000-$100,000, and greater than $100,000.
- In terms of age, at least 20% representation in the following categories 18-29, 30-44, and 45-64 and at least 8 % in 65 and above. The data collection was limited to respondents above 18 years old.

The online survey was administered in the last week of May and the first week of June 2020. During the data collection period, the counties under study were either in the first week of Phase 1 of reopening or were being considered for Phase 1 reopening (Oregon, 2020). Therefore, the data was collected when the respondents were either experiencing or had fresh memories of the lockdown. Logical checks were applied to the data by comparing the household size with the number of workers, number of children, number of elderly and inconsistent responses were removed. Respondents who took less than 3 minutes to complete the survey were also eliminated. After data cleaning, the dataset had 1018 complete responses.

The survey focused on five types of questions:

- Demographic information like age, race, education, and employment;

- Individual characteristics such as hours spent on desktop, laptop, tablets or smartphones, and delivery service subscriptions;
- Household characteristics such as income, size, number of workers, children, adults, and presence of members with a disability who require assistance;
- E-commerce and house delivery products and service preferences; and
- The number of home deliveries made in 30 days before and during the COVID-19 lockdown.

Except for age, all questions were in the form of multiple choices. In this study, we considered the following dependent variables; (i) number of deliveries made in 30 days before COVID-19 lockdown, (ii) number of deliveries made in 30 days during the COVID-19 lockdown, (iii) income levels and (iv) household expenditures on home deliveries during the COVID-19 lockdown. For the questions associated with the dependent variable, respondents had to pick one from a list of ranked or ordered choices. Therefore, we used the ordered logit regression framework in this research (Agresti, 2012; Greene, 2018).

3.1 Methodology

In the ordinal logit regression framework, the discrete response variable can be described by an underlying unobserved continuous latent variable with cutoff points (Agresti, 2012). Let $k = 1, \dots, K$ represent the set of ordered discrete outcomes. Let y_i and U_i^* represent the response and underlying unobserved latent variable for each individual i. In the ordered logit framework, the underlying latent variable is assumed to be a linear function of the explanatory variables and the error term, as shown below:

$$U_i^* = X_i\beta + \epsilon_i$$

where β is a $p \times 1$ vector denoting the set of coefficients, X_i is the $1 \times p$ vector of explanatory variables for individual i and ϵ_i is the error term which follows a standard logistic distribution. The response variable takes specific values depending on whether U_i^* crosses estimated thresholds, as shown below.

$$y_i = k \text{ if } \eta_{k-1} \leq U_i \leq \eta_k \quad \forall k = 1, .., K$$

In the above equation, η_{k-1} and η_k represent estimated thresholds for the latent unobserved continuous variable. Note that $\eta_0 = -\infty$ and $\eta_K = \infty$. Let $G(z)$ represent the standard logistic distribution cumulative distribution function. The probability of the response variable taking value k, $P[y_i = k]$ is given as

$$P[y_i = k] = G(\eta_k - X_i\beta) - G(\eta_{k-1} - X_i\beta)$$

Estimates of the coefficients β are obtained by maximizing the following log-likelihood function

$$LL = \sum_{i=1}^{I}\sum_{k=1}^{K} \delta_{ik} \ln[G(\eta_k - X_i\beta) - G(\eta_{k-1} - X_i\beta)]$$

In the above equation, δ_{ik} is an indicator variable taking value 1 when $y_i = k$, and 0 otherwise. The ordered logit model was fitted using the polr function from the MASS package in R (Ripley et al., 2020). Variables were selected using the backward selection procedure accounting for correlations and significance. The Brant test was used to test for the proportional odds assumption (Brant, 1990). Marginal effects were obtained using the ocME function from the erer package in R (Sun, 2020). After identifying the final model, the significance or importance of each variable was assessed by determining the changes in log-likelihood when one variable at the time was removed from the final model.

3.2 Descriptive Statistics of Independent Variables.

Table 1 provides the frequency and relative frequencies for key household and demographic variables, which were found to be significant in our models. The minimum, median, average, and maximum age in the dataset are 18, 40, 43.2, and 86, respectively. The median sample age is close to the median age of the metro region being 38.4 (Census Reporter, 2020). There is a proper distribution of respondents among various age categories, with nearly 15% of the respondents being at or close to retirement age. A majority of the respondents are females. There is a good representation of respondents among the income levels, with more than half of the respondents having a household annual income of greater than $50,000. This is consistent with the income distribution of the Portland metro region, which has a median household income of nearly $76,000 (Census Reporter, 2020). More than 40% of the respondents are employed full-time with an additional 14% employed part-time. Slightly more than one-third of the respondents belong to households with two members. Nearly 80% of the households have at least one worker. A majority of the households have no children. More than half of the respondents spent more than 25 hours per week on desktop, laptop, tablets, or smartphones.

Slightly more than 5% of the respondents strictly worked from home. 17.5% of the respondents indicated the presence of household members with disabilities or chronic health conditions that require assistance. The median household income of each ZIP Code ranged from $10,338 to $105,969. The survey also collected information on race, employment type, number of elderly members in the household (which are not shown in the table as they were not found to be significant in any of the models). Nearly 80% of the respondents where white, with Asians being the second-highest respondents at 7.5%. Almost 20% of the respondents worked in professional, managerial, or technical jobs. Nearly one-fourth of the respondents have at least one member of the household aged over 65 years.

Table 1: Descriptive statistics of relevant demographic and household variables

Variable	**Frequency (Relative Frequency as %)**	**Variable**	**Frequency (Relative Frequency as %)**
Age		Education	
18-29	268 (26.4)	Less than high school	35 (3.45)
30-44	315 (31)	High School/GED	178 (17.5)
45-64	284 (28)	College or Associates	345 (34.0)
>= 65	148 (14.6)	Bachelors	303 (29.9)
		Graduate degree	154 (15.2)
Gender		Employment	
Female	605 (59.6)	Unemployed	462 (45.52)
Male	396 (39.0)	Full-time	415 (40.89)
Other	14 (1.4)	Part-time	138 (13.60)
Annual Income		Household Size	
Less than $ 10,000	100 (9.85)	1	205 (20.2)
$10,000 to $ 29,999	157 (15.5)	2	351 (34.6)
$30,000 to $ 49,999	202 (19.9)	3	173 (17.0)
$ 50,000 to $ 99,999	272 (26.8)	4	170 (16.7)
Greater than $ 100,000	284 (28.0)	5 or higher	116 (11.4)
Number of Workers		Number of children	
0	217 (21.4)	0	785 (77.3)
1	351 (34.6)	1	127 (12.5)
2	341 (33.6)	2	79 (7.78)
3	75 (7.39)	3	17 (1.67)
4 or higher	31 (3.05)	4 or higher	7 (0.69)
Number of Vehicles		Weekly hrs on desktop, laptop, smartphone	
0	93 (9.16)	0 to 3 hrs	47 (4.63)
1	347 (34.2)	3 to 10 hrs	149 (14.7)
2	375 (36.9)	10 to 25 hrs	282 (27.8)
3	138 (13.6)	25 to 40 hrs	273 (26.9)
4 or higher	62 (6.11)	More than 40 hrs	264 (26.0)

Respondents were asked to rate in a 0 (not important) to 5 (most important) scale factors affecting the adoption of e-commerce and household deliveries. Based on the average rating, the online experience is the most critical factor affecting the choice of purchasing from store vs. online, followed by the cost of delivery and availability (see Table 2). Looking at the frequency of factors chosen at level 5 (most important), the cost of delivery comes first, followed by availability and health concerns. In the ordered choice models, we assumed that if a respondent rated a factor as 5, then that factor is critical, three or higher means the factor is important, any rating other than 0 (>0) implies the factor affects decision making.

Table 2: Factors affecting the choice of purchasing from store vs. online (0: Not Relevant, 5: Most Important)

	Ratings						
Factors	**0**	**1**	**2**	**3**	**4**	**5**	**Average**
Availability	126	53	104	188	239	305	3.25
Cost at store	110	69	100	201	271	264	3.22
Cost of delivery	141	60	83	160	244	327	3.26
Time of delivery	157	67	117	209	222	243	2.98
Online Experience	95	55	100	228	260	277	3.31
Health	143	84	146	188	150	304	3.01

The respondents were asked about the type of products that are purchased utilizing same-day or next-day delivery. Meals and groceries are most frequently ordered to be delivered the same or the next day (see Table 3). Electronics are least likely to be ordered with the same- or next-day delivery. In the ordered choice models, if a respondent rated a product as 5, then the respondent always wants the product same or next day, three or higher implies that product is frequently wanted same or next day, and any number other than 0 (>0) means the respondent prefers the product to be delivered same or next day.

Table 3: Products requested same or next day (0: Never ordered and 5: Most frequently ordered)

	Rating						
	0	**1**	**2**	**3**	**4**	**5**	**Average**
Grocery	549	81	62	72	74	177	1.58
Meals	523	62	61	71	57	241	1.8
Electronics	496	182	146	119	39	33	1.12
Fashion	446	182	146	144	63	34	1.31
Recreational items	519	152	131	121	53	39	1.16
Household and office	456	183	145	138	64	29	1.27
Medicines	530	113	104	105	92	71	1.33

4. Comparing Pre-COVID-19 and During COVID-19 Deliveries

One of the main goals of this research is to compare the factors that are driving house deliveries before and during COVID-19. We considered the following two dependent variables: (i) number of home deliveries made in 30 days before COVID-19 lockdown, and (ii) number of deliveries made in 30 days during COVID-19 lockdown. In general, the number of home deliveries increased during COVID-19 lockdown with the number of people making more than six deliveries every 30 days more than doubled (see Table 5).

The cross-tabulation reveals that a majority of the respondents went up a category level in the number of purchases or remained at the highest level (see Table 6). For example, among respondents who made

3 to 5 home delivery purchases before COVID-19 lockdown, nearly 55% ordered more home deliveries during the COVID-19 lockdown.

Table 5: Number of home deliveries in 30 days before and during COVID-19 lockdown

Number of Deliveries in 30 days	**Before COVID-19 Lockdown Frequency (Relative Frequency as a percentage)**	**During COVID-19 lockdown Frequency (Relative Frequency as a percentage)**
0	69 (6.8)	70 (6.9)
1 to 2	438 (43.2)	197 (19.4)
3 to 5	320 (31.5)	321 (31.6)
6 to 10	104 (10.2)	263 (26)
More than 10	84 (8.28)	163 (16.1)

Table 6: Crosstabulation (row percentages) of home deliveries in 30 days before COVID-19 lockdown and after COVID-19 lockdown.

		During COVID-19					
		0	**1 to 2**	**3 to 5**	**6 to 10**	**More than 10**	**Row Sum (%)**
Before COVID-19	**0**	49.28	24.64	18.84	4.35	2.9	100
	1 to 2	6.16	30.37	43.84	17.12	2.51	100
	3 to 5	2.19	13.12	28.75	41.25	14.69	100
	6 to 10	1.92	2.88	14.42	48.08	32.69	100
	More than 10	0	2.38	10.71	4.76	82.14	100

Table 7 summarizes the ordered logit model results for the number of home deliveries in 30 days before and during the COVID-19 lockdown. For the ordered logit models, to ensure adequate samples in each level of the dependent variable, we consider the following categories: (i) less than 3 deliveries, (ii) 3 to 5 deliveries, and (iii) more than 5 deliveries per month.

Older respondents are less likely to order a higher number of deliveries pre-COVID-19. For higher-income households earning more than $100,000 per annum, the odds of making a higher number of home deliveries pre-COVID-19 is 1.374 times higher than households earning less than $100,000 per annum. During the COVID-19 lockdown, this odds increases to 1.426. Households with at least four workers and one vehicle are more likely to order online pre-COVID-19. The likelihood of ordering online pre-COVID-19 also increases with the number of children in the household. Respondents who have work from home options are more likely to make a higher number of home deliveries before COVID-19. The odds are more than twice the respondents who do not have work from home option.

As expected, tech-savvy respondents are more likely to order online. The odds of respondents who spent more than 40 hrs per week on desktop, laptop, or smartphones of ordering more home deliveries pre-COVID-19 is nearly 1.5 times higher than the rest of the respondents. The odds of households with delivery subscriptions making a higher number of home deliveries pre-COVID-19 is 2.7 times that of households without delivery subscriptions. During the COVID-19 lockdown, the odds decrease to 1.81. This result is expected as during COVID-19, more households are ordering online, including those without subscriptions such as Amazon Prime.

Households that made more home deliveries before COVID-19 have a higher chance of ordering more deliveries during COVID-19 lockdown. This is an intuitive result. The odds of a household which made 1 to 2 home deliveries before COVID-19 lockdown of making higher home deliveries during COVID-19 lockdown is 2.63 times that of households that made no home deliveries before COVID-19 lockdown. These odds increases to 9.5, 30.1, and 44 for households, which made 3 to 5, 6 to 10, and more than ten home deliveries before COVID-19 lockdown. Respondents who rated the online experience as a critical factor in choosing between online and store-based purchases are increasingly likely to make a higher number of home deliveries before COVID-19. The odds are nearly 1.75 times higher. The odds of respondents who rated the time of delivery as an important factor in making a higher number of home deliveries during COVID-19 is 1.46 times higher. Similarly, the odds of respondents for whom health is an important factor in making a higher number of home deliveries during COVID-19 is 1.59 times that of respondents for whom health is not an important factor. Respondents for whom cost at the store is a factor are less likely to make a higher number of home deliveries during COVID-19.

Table 7: Ordered logit model for the number of deliveries made in 30 days before COVID-19 lockdown and during COVID-19 lockdown

	Pre-COVID-19		**During COVID-19**	
Variables	**Coeff. (p-value)**	**Odds Ratio**	**Coeff. (p-value)**	**Odds Ratio**
Age	-0.012 (0.001)	0.987		
Income				
Greater than $100,000	0.317 (0.024)	1.374	0.354 (0.024)	1.426
Desktop, Laptop, Smartphone Usage > 40 hrs	0.405 (0.005)	1.499		
Delivery Subscription	1.017 (0.000)	2.765	0.598 (0.000)	1.818
Number of deliveries in 30 days pre COVID-19 Lockdown				
1 to 2			0.968 (0.001)	2.634
3 to 5			2.260 (0.000)	9.590
6 to 10			3.407 (0.000)	30.177
More than 10			3.786 (0.000)	44.095
Factors affecting online vs. at home purchase				
Online experience rated as critical (5)	0.559 (0.000)	1.749		
Time of delivery rated as important (> 2)			0.380 (0.008)	1.462
Cost at store is a factor (> 0)			-0.638 (0.004)	0.527
Health rated as important (> 2)			0.466 (0.000)	1.593
Products Requested for same-day or next-day delivery				
Grocery (>0)	0.297 (0.022)	1.347	0.532 (0.000)	1.702
Fashion (Frequently) (>2)	0.594 (0.000)	1.811		
Meals (Always) (5)			0.647 (0.000)	1.910
Household Office (>0)			0.413 (0.003)	1.512
Work from Home	0.698 (0.010)	2.011		
Number of Workers atleast 4	0.937 (0.008)	2.554		
Number of Children	0.164 (0.048)	1.178		
Owns at least one vehicle	0.688 (0.005)	1.991		
Number of vehicles			0.231 (0.001)	1.260
Less than 3| 3 to 5	**1.533 (0.000)**		**1.755 (0.000)**	
3 to 5| More than 5	**3.277 (0.000)**		**3.750 (0.000)**	
AIC	**1890**		**1725**	
Log-Likelihood	**-932.18**		**-847.6**	
McFadden Pseudo R^2	**0.1022**		**0.2265**	

Table 8 shows the importance of each significant variable for the two ordered logit models. The importance of each variable was determined by the change in log-likelihood when that variable was removed from the full model. It is clear that the number of deliveries in the pre-COVID-19 periods is a key variable. Without considering pre-COVID delivery levels, having a delivery subscription appears as the most important variable in both models.

Table 8: Importance of each variable in the ordered logit model

Pre-COVID-19		During COVID-19	
Variable	**Change in LL**	**Variable**	**Change in LL**
Delivery Subscription	22.28	Number of deliveries in 30 days pre COVID-19 Lockdown	103.57
Products Requested for same-day or next-day delivery Fashion (>2)	8.21	Delivery Subscription	7.86
Online experience rated as critical (5)	8.04	Products Requested for same-day or next-day delivery: Meals (5)	7.69
Age	4.91	Products Requested for same-day or next-day delivery: Grocery (>0)	6.95
Owns at least one vehicle	4.01	Health rated as important (>2)	5.42
Desktop, Laptop, Smartphone Usage > 40 hrs	3.90	Number of vehicles	5.37
Number of Workers atleast 4	3.53	Products Requested for same-day or next-day delivery: Household Office (>0)	4.21
Work from Home	3.27	Cost at store is a factor (> 0)	4.18
Products Requested for same-day or next-day delivery: Grocery (>0)	2.61	Time of delivery rated as important (> 2)	3.44
Income greater than $100,000	2.50	Income greater than $100,000	2.55
Number of Children	1.94		

5. COVID-19 Expenditures

In this section, we focus on household expenditures on home deliveries during COVID-19 lockdown. Since income is a key variable affecting purchase levels and e-commerce adoption, this section starts with an analysis of factors related to household income before developing a household expenditure model.

5.1 Household income and related variables

According to NHTS 2017 data households above the poverty line are “almost twice as likely to make online purchases compared to respondents in households below the poverty level (i.e., 61% versus 33%)” (FHWA, 2018). Income and age are the most important predictors of online shopping (Lee et al., 2015). Also, income is a variable that is linked to other household characteristics such as internet access, credit card access, education levels, and the number of household workers (Cao et al., 2012).

To evaluate the relationships between income and the other socioeconomic variables, an initial ordered model was estimated utilizing as a dependent variable four levels of household income. The levels are the following: less than $30,000, between $30,000 and $50,000, between $50,000 and $100,000, and greater than $100,000 per household per year. As a reference, the median household income in Oregon is $69,165 in 2018, and in the greater Portland region, the median household income is $75,599 (Census Reporter, 2020).

The results shown in Table 9 below are an indication that the data is consistent with findings previously reported in the literature. Education level is the main predictor of household income, and there is ample evidence that supports this finding, not only concerning income but also regarding unemployment levels (BLS, 2018). The odds of a respondent with Bachelors having a higher household annual income are at least nine times that of a respondent who did not complete high school. These odds increase to 17 times for a respondent with a graduate degree. As expected from previous studies, age, number of vehicles per household, gender, full-time work, and the number of workers per household is strongly and positively correlated with income levels. The odds of households with a single-vehicle having higher income levels are more than twice that of households with no vehicles. These odds increase with the number of vehicles. On the flip side, households with a member that is disabled and requires attention are 57% less likely to have higher income levels.

In terms of e-commerce related variables, households with more internet utilization/access, and with a delivery subscription (like Amazon Prime) are more likely to be higher household incomes. It is also worth noting that higher-income households judge fashion, beauty, and personal care items as worthy of the same-day or next-day delivery. It is particularly relevant for this COVID-19 related study that there is a strong and direct link between health and safety concerns and income levels.

Table 9: Ordered logit model for income

Variables	Coeff. (p-value)	Odds Ratio	Change in LL (Rank)
Age	0.030 (0.000)	1.030	22.04 (3)
Male	0.483 (0.000)	1.622	6.75 (8)
Desktop, Laptop, Smartphone Usage			11.57 (6)
3 to 10 hrs	0.872 (0.015)	2.392	
10 to 25 hrs	1.159 (0.000)	3.187	
25 to 40 hrs	1.331 (0.000)	3.788	
More than 40 hrs	1.442 (0.000)	4.229	
Delivery Subscription	0.471 (0.001)	1.602	5.22 (10)
Education			61.06 (1)
High School/GED	0.878 (0.073)	2.406	
College or Associates	1.195 (0.013)	3.306	
Bachelors	2.251 (0.000)	9.504	
Graduate degree	2.836 (0.000)	17.047	
Employment- Full time	0.510 (0.000)	1.666	5.77 (9)
Number of Workers			20.03 (4)
1	0.709 (0.000)	2.033	
2	1.439 (0.000)	4.218	
3	0.993 (0.002)	2.701	
4 or higher	0.942 (0.040)	2.565	
Presence of Household Members with Disability	-0.841 (0.000)	0.431	11.83 (5)
Vehicle Ownership			40.51 (2)
1	0.818 (0.003)	2.266	
2	1.737 (0.000)	5.680	
3	1.802 (0.000)	6.065	
4 or higher	2.753 (0.000)	15.693	
Median Household Income of ZIP Code	0.098 (0.027)	1.000	2.43 (12)
Factors affecting online vs. at home purchase			11.53 (7)
Health (>0)	0.897 (0.000)	2.452	
Products Requested for the same-day or next-day delivery			
Fashion (>0)	0.362 (0.007)	1.436	3.60 (11)
Less than \$30,000|\$30,000 to \$49,999	6.821 (0.000)		
\$30,000 to \$49,999|\$50,000 to \$99,999	8.265 (0.000)		
\$50,000 to \$99,999|Greater than \$100,000	10.040 (0.000)		
AIC	**2206**		
Log-Likelihood	**-1076.21**		
McFadden Pseudo R^2	**0.2307**		

5.2 Household expenditures model

Close to 60% of the respondents spent between \$100 and \$1,000 on home deliveries. A small but sizeable percentage of nearly 13% spent more than \$1000 on home deliveries during the COVID-19 lockdown (see Table 10).

Table 10: Expenditures on home deliveries in 30 days during COVID-19 lockdown

Money spent on home deliveries in 30 days	Frequency (Relative frequency)
Less than \$ 100	250 (24.6)
\$ 100 to \$ 499	434 (42.8)
\$ 500 to \$ 999	202 (19.9)
\$ 1,000 to \$ 2,000	89 (8.77)
Greater than \$ 2,000	40 (3.94)

The results of the ordered choice model are shown in Table 11. Respondents who are older than 45 years are less likely to spend more money on home deliveries compared to younger respondents. The odds of male respondents spending more money on deliveries during COVID-19 lockdown is nearly one and half times that of female respondents. The likelihood of spending more money on home deliveries increases with household income. For households whose annual income is between \$30,000 and \$49,999 per year, the odds of spending more money on deliveries during COVID-19 is twice that of households whose annual income is lower than \$ 30,000 per year. Household expenditures on home deliveries during COVID-19 also increase with the number of workers.

Tech-savvy respondents spend more money on household deliveries, which is expected. The odds of respondents who spent between 10 and 25 hours per week on desktop, laptop, or smartphone spending more money on deliveries during COVID-19 lockdown is nearly twice that of respondents who spent less than 10 hours. These odds increase to almost 2.5 times for respondents who spent more than 25 hours per week on desktop, laptop, or smartphones.

As expected, households which make more deliveries spend more money on deliveries. Respondents for whom cost at the store is a factor are almost 50% less likely to spend more money on home deliveries. This makes sense as often purchasing at the store is cheaper than making home deliveries. The odds of respondents for whom health is an important factor is 1.33 times that of respondents who do not worry about health.

Respondents who want groceries, electronics, and recreational items deliveries the same or next day are more likely to spend more money on home deliveries during COVID-19. The odds are 1.67, 1.64, and 1.46 times those who do not require these items delivered within a day. The importance of each variable was calculated by ascertaining its contribution to the log-likelihood. As expected, the number of deliveries made during COVID-19 is the most critical variable. Without considering delivery levels, household income is the most important variable. As shown in the previous model, income is strongly linked to education level.

Table 11: Ordered logit model for household expenditures on home deliveries in 30 days during COVID-19 lockdown

Variables	**Coeff. (p-value)**	**Odds Ratio**	**Change in LL (Rank)**
Age >= 45 years	-0.397 (0.004)	0.671	4.02 (8)
Male	0.393 (0.003)	1.482	4.37 (7)
Income			30.27 (2)
$30,000 to $50,000	0.729 (0.000)	2.073	
$50,000 to $99,999	0.832 (0.000)	2.299	
Greater than $100,000	1.523 (0.000)	4.59	
Desktop, Laptop, Smartphone Usage			12.57 (3)
10 to 25 hours	0.643 (0.001)	1.902	
More than 25 hours	0.905 (0.000)	2.472	
Number of deliveries in 30 days during COVID-19 Lockdown			116.74 (1)
1 to 2	1.794 (0.000)	6.014	
3 to 5	2.977 (0.000)	19.629	
6 to 10	3.806 (0.000)	44.974	
More than 10	4.472 (0.000)	87.572	
Factors affecting online vs. at home purchase			
Cost at store is a factor (> 0)	-0.660 (0.001)	0.5166	5.18 (6)
Health is rated as important (> 2)	0.288 (0.033)	1.333	2.27 (11)
Products Requested for same-day or next-day delivery			
Grocery (>0)	0.515 (0.000)	1.674	7.34 (4)
Electronics (>0)	0.499 (0.000)	1.647	5.48 (5)
Recreational items (>0)	0.384 (0.010)	1.469	3.28 (9)
Number of Workers	0.176 (0.014)	1.193	2.96 (10)
Less than $100 | $100 to $499	**3.230 (0.000)**		
$100 to $499 | $500 to $999	**6.197 (0.000)**		
$500 to $999 | $1000 to $2000	**7.875 (0.000)**		
$1000 to $2000 | More than $2000	**9.416 (0.000)**		
AIC	**2176.85**		
Log-Likelihood	**-1067.42**		
McFadden Pseudo R^2	**0.2327**		

6. Discussion of Implications for Logistics and Transportation

Table 12 shows the marginal effects of the number of deliveries made in 30 days before and during the COVID-19 lockdown. The increase in the probability of higher-income households making more than five deliveries more than doubled during the COVID-19 lockdown. Similarly, the increase in the probability of households with subscriptions to free delivery services such as Instacart express and Amazon prime making more than five deliveries also increased during COVID-19.

A key insight is that households that had more deliveries pre-COVID-19 had a higher likelihood of requesting more deliveries during the COVID-19 lockdown. For example, the probability of households with 1 to 2 deliveries before COVID-19 making more than five deliveries during COVID-19 increased by 0.230. Therefore, neighborhoods with higher-income households, with tech-savvy residents who spend quite a bit of time on computers and smartphones and are used to making online purchases, will see an increase in freight traffic during the COVID-19 lockdown. From an optimization perspective, there is scope for companies such as Amazon, Instacart, UPS, and FedEx to use this information of expected higher demand to further optimize their routes and service offerings in higher-income areas.

In terms of e-commerce and products, same- or next-day services is critical for groceries and meals, which is expected. For groceries, the increases in the chances of households expecting the same- or next-day services making five or higher deliveries almost quadruples during COVID-19. This a large change that would look suspicious in normal circumstances. However, it is reasonable given the increase in business activity in delivery companies like Instacart that have experienced a fivefold increase in activity during the lockdown. Since a lot of people are working from home, there is an increase in the chance of respondents expecting the same- or next-day services for household goods making five or more deliveries.

As expected, during COVID-19 fashion goods, which are more of a luxury item, are not seen as necessary. Therefore, in terms of products, the supply chain should be optimizing grocery and food deliveries during pandemics. Note that in the initial phases of the lockdown, this was an issue as getting delivery slots was difficult through Instacart and other delivery services. The chances of households concerned about delivery times, making five or more deliveries during a pandemic, also increased. Therefore, having an efficient delivery system is critical.

Table 12: Marginal effects of number of deliveries made

	Pre-COVID-19		During COVID-19	
Variables	**Less than 3**	**More than 5**	**Less than 3**	**More than 5**
Age	0.003	-0.002		
Income				
Greater than $100,000	-0.079	0.042	-0.048	0.086
Desktop, Laptop, Smartphone Usage > 40 hrs	-0.101	0.055		
Delivery Subscription	-0.247	0.113	-0.093	0.138
Number of deliveries in 30 days pre COVID-19 Lockdown				
1 to 2			-0.134	0.230
3 to 5			-0.258	0.512
6 to 10			-0.220	0.619
More than 10			-0.217	0.633
Factors affecting online vs. at home purchase				
Online experience rated as critical (5)	-0.138	0.078		
Time of delivery rated as important (> 2)			-0.057	0.089
Cost at store is a factor (> 0)			0.078	-0.157
Health rated as important (> 2)			-0.070	0.109
Products Requested for same-day or next-day delivery				
Grocery (>0)	-.074	0.038	-0.076	0.127
Fashion (Frequently) (>2)	-0.147	0.084		
Meals (Always) (5)			-0.083	0.158
Household Office (>0)			-0.060	0.098
Work from Home	-0.169	0.109		
Number of Workers atleast 4	-0.220	0.158		
Number of Children	-0.041	0.021		
Owns at least one vehicle	-0.167	0.072		
Number of vehicles			-0.033	0.055

Cost at a store is a crucial factor in decreasing the likelihood of home deliveries even during a pandemic. For people concerned about cost at a store, the chances of making five or more deliveries reduce by 0.15. Often product costs for online purchases, particularly for items such as groceries and foods, are higher, especially when delivery charges, tips, and other service fees are added. If delivery services want to attract more customers, they should consider providing aggressive incentives and discounts which can attract more customers. Chances of customers who are more concerned about health making five or higher number of deliveries also increased by 0.10. Therefore, there is scope for delivery businesses increasing their profit margins by specifically targeting such customers.

Older customers are less likely to use online delivery services. The online experience is also rated as a critical factor in the likelihood of making a higher number of deliveries. Therefore, there is scope for delivery companies to improve their customer base, especially among the elderly population by designing, intuitive, and easy-to-use interfaces.

From an equity perspective, it appears that lower-income households are less likely to use online delivery systems. Since COVID-19 is disproportionately affecting lower-income communities (Wadhera et al., 2020), governments should provide subsidies and incentives to grocery stores and restaurants located in more impoverished neighborhoods to offer economical grocery and meal deliveries.

7. Conclusions

The sudden onset of the COVID-19 crisis has surprised consumers, companies, and government agencies. With federal, state, and/or local governments around the world imposing lockdowns of varying degrees of strictness, there has been a substantial increase in e-commerce and house deliveries.

This study compares factors affecting the number of online deliveries made before and during COVID-19 lockdown and household expenditures during COVID-19 lockdown. Using results from a survey conducted in the Portland-Vancouver-Hillsboro Metropolitan area, ordered choice models were estimated. The number of house deliveries had a significant increase during the COVID-19 lockdown. More than 60% of the households which made 1 to 2 deliveries in 30 days before COVID-19 ordered more deliveries post COVID-19. Among households that made 3 to 5 home delivery purchases before COVID-19 lockdown, nearly 55% ordered more home deliveries during the COVID-19 lockdown.

Household income is a key variable to understand changes during the lockdown. Based on marginal effects, higher-income households and households with delivery subscriptions have a higher likelihood of receiving more than five house deliveries in 30 day period during the COVID-19 lockdown. Higher-income households also spend more money on home deliveries. Same-day or next-day services are expected for items such as groceries or meals. During the COVID-19 lockdown, the propensity of families which expect the same- or next-day service for groceries towards ordering five or more deliveries almost quadruples.

Cost at the store is a crucial factor which reduces the likelihood of more deliveries as well as the expenditures. People who are concerned about health are also more likely to spend more money and make more home deliveries during COVID-19 lockdown, and health concerns are also linked to higher income levels. From an equity perspective, the results indicate that lower-income households are less likely to use online delivery systems, but the COVID-19 pandemic is disproportionately affecting lower-income communities. This suggests that government policies may be necessary to improve the access of low-income households to e-commerce and grocery deliveries.

This research can be extended in multiple directions. It will be interesting to conduct this survey six to eight months post COVID-19 lockdown and once after the threat of COVID-19 threat has been eliminated. Another potential direction of future research is to focus on lower income neighborhoods, elderly population and understand factors which can help with adoption of home deliveries as an option for such communities.

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