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Exploratory Analysis of Factors Affecting Levels of Home Deliveries Before, During, and Post COVID-19

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Abstract

The COVID-19 pandemic has significantly affected shopping behavior and has accelerated the adoption of online shopping and home deliveries. We administered an online survey among the population in the Portland-Vancouver-Hillsboro Metropolitan area on household and demographic characteristics, e-commerce preferences and factors, number of deliveries made before and during the COVID-19 lockdown, and number of deliveries expected to make post-pandemic. In this research, we conduct an exploratory analysis of the factors which affect levels of home deliveries before, during, and post COVID-19. There was a significant increase in home deliveries during the COVID-19 lockdown relative to before the COVID-19 period. Households that made less than three deliveries per month before the pandemic will order more online post-pandemic. A majority of the homes that ordered more than three deliveries per month before COVID-19 are expected to revert back to their original levels post-pandemic. The two most variables positively affecting the likelihood of online shopping were found to be access to delivery subscriptions and income. Tech-savvy individuals are expected to make more home delivery orders post-pandemic compared to before and during COVID-19. Health concerns positively increase the likelihood of ordering online during the pandemic and does not have a significant impact post-pandemic. Households with more number of workers are more likely to make more home deliveries. Older and retired individuals are less likely to use online deliveries. However, the likelihood of older and retired individuals ordering more home deliveries increased during the pandemic lockdown.

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

1. Introduction

The COVID-19 pandemic has had a significant impact on our day-to-day lives. The associated lockdowns have affected traffic patterns, with a reasonable percentage of the population working remotely if viable (Beck et al. 2020a, 2020b; De Vos 2020; Loske, 2020; Sobieralski, 2020; Mogaji, 2020;Katrakazas et al., 2020; Shamshiripour et al., 2020). Specifically, the pandemic has had a significant impact on the way we shop, with a movement away from brick-and-mortar shops to e-commerce. While the share of e-commerce has been growing and outpacing brick-and-mortar retail growth over the last two decades, the pandemic has further accelerated the adoption of online deliveries. Instacart, a popular grocery delivery service in the United States, experienced a 500% growth in April 2020 (CNBC, 2020). May 2020 saw a 78% increase in online shopping compared to May 2019 (eMarketer, 2020). The e-commerce explosion has significant implications for the transportation sector as well as the environment (Mokhtarian, 2004; Figliozzi, 2020).

Several studies have explored the impact of socio-economic, personal, and technology-related factors on e-commerce adoption with conflicting insights at times. Farag et al. (2005, 2006a, 2006b, 2007), Crocco et al. (2013) found males are more likely to shop online whereas, Ren and Kwan (2009), Ding and Lu (2017), Clemes et al. (2014), Shi et al. (2019) had the opposite insight. A majority of the literature (Farag et al. 2005, 2006a, 2007; Krizek et al., 2005; De Blasio 2008; Cao et al. 2012; Crocco et al., 2013; Zhou and Wang 2014; Clemes et al., 2014; Irawan and Wirza, 2015; Lee et al. 2015; Ding and Lu 2017) found that older people are less likely to adopt e-commerce with only one conflicting study (Shi et al. 2019). Higher-income households are generally found to be more likely to shop online (Farag et al. 2005, 2006a, 2007; De Blasio 2008; Cao et al. 2012, 2013; Crocco et al., 2013; Zhou and Wang 2014; Lee et al. 2015; Lee et al. 2017; Schmid and Axhausen, 2019; Dias et al. 2020) with contrasting results obtained by Farag et al. (2006b), Irawan and Wirza (2015), and Shi et al. (2019). The likelihood of shopping online was found to increase with education levels (Krizek et al. 2005; Farag et al. 2006a, 2007; De Blasio 2008; Rotem-Mindali 2010; Cao et al. 2012, 2013; Zhou and Wang 2014; Clemes et al. 2014; Schmid and Axhausen, 2019) and with experience with internet usage, internet access, and being more tech-savvy (Farag et al. 2005, 2006b, 2007; Krizek et al., 2005; Ren and Kwan 2009; Rotem-Mindali 2010; Cao et al. 2012, 2013; Irawan and Wirza 2015; Lee et al., 2015, 2017; Ding and Lu 2017). Some of these effects are related. For example, households with higher levels of education often have better access to computers, smartphones, and internet (Schmid and Axhausen, 2019). Surprisingly, Irawan and Wirza (2015) found an increase in education levels to decrease the propensity to shop online.

In terms of household composition, the likelihood of shopping online increases with a higher number of members with driving license, vehicle ownership (Irawan and Wirza 2015), workers (Dias et al., 2020; Farag et al. 2006a, 2006b; Zhou and Wang 2014; Irawan and Mirza 2015), and children (Farag et al. 2006a, Dias et al. 2020). Household location -urban vs. suburban vs. rural- was also found to affect the likelihood of adopting e-commerce with studies showing conflicting results (Krizek et al. 2005; Farag et al. 2005, 2007; De Blasio et al. 2008; Cao et al. 2013; Zhou and Wang 2014; Shi et al. 2019; Dias et al. 2020). Other factors which were found to affect e-commerce adoption include product type (Girard et al. 2003; Dias et al. 2020; Zhen et al. 2016, 2018; Zhai et al. 2017; Maat and Konings, 2018; Schmid and Axhausen, 2019) and online shopping experience and convenience (Ramanathan 2010; Clemes et al., 2014; Lee et al. 2017). Recently Shamshiripour et al., (2020) show through a survey conducted in Chicago, that 74% of the respondents would rely on online shopping for groceries in the first few months post pandemic compared to before pandemic. Similar insights were obtained for food delivery also.

The focus of this research is to conduct an exploratory, descriptive analysis to understand the impact of household, socio-economic, and technology usage related factors on the home deliveries with particular focus on the effects of the COVID-19 pandemic. We conducted an online survey in the Portland-Vancouver-Hillsboro Oregon-Washington Metro Area. The survey asked questions on household and socio-demographic characteristics, technology usage, e-commerce factors, number of home deliveries made in 30 days before COVID-19, during COVID-19 lockdown, and the number of home deliveries expected to make post-pandemic. This study differentiates itself from past works by focusing on factors affecting the number of deliveries made in a pandemic lockdown and compares the effects to the pre-and post-pandemic setting.

2. Data Collection

The data collection was limited to the Portland-Vancouver-Hillsboro Oregon-Washington Metro Area, which has a population of around 2.5 million, with a total area of nearly 7000 square miles (Census Reporter, 2020). Since the lockdown regulations, enforcement, and compliance varied widely, we decided to focus our efforts on a single urban area. The online survey was administered through the Qualtrics survey platform. The following demographic checks were enforced: (i) 40% representation of males or females, (ii) 20% representation in the three income levels of 0- $50,000, $50,000 - $100,000, and greater than $100,000, (iii) 20% representation in ages 18-19, 30-44, 45-64 and at least 8% of the respondents must be over the age of 65. We restricted the data collection to respondents above 18 years old only.

Qualtrics administered the survey in the last week of May and the first week of June 2020, when the counties comprising the Metro area were either in Phase 1 reopening or being considered for Phase 1 reopening (Oregon, 2020). Therefore, the respondents were still under lockdown. We eliminated respondents with inconsistent responses for the household sizes, number of workers, number of children, and elderly members. We also eliminated respondents who took less than 3 minutes to complete the survey. The final dataset used for the analysis had 1015 responses. The survey focused on five types of questions:

- Demographic information
- Questions on familiarity with usage of computers, smartphone, laptops, and access to delivery subscriptions;
- Household characteristics;
- E-commerce and house delivery products and service preferences; and
- The number of home deliveries
    - made in 30 days before COVID-19 lockdown,
    - made in 30 days during the COVID-19 lockdown,
    - expected to make in 30 days once the pandemic is over.

In three separate questions, we asked the respondents the number of times they purchased goods online and had it delivered to home in thirty days before COVID-19, during the COVID-19 lockdown, and the number of times they expect to make home deliveries post COVID-19 pandemic. The respondents had to select between (i) 0, (ii) 1 to 2, (iii) 3 to 5, (iv) 6 to 10, (v) More than 10. Table 1 shows the frequencies.

Table 1 Number of home deliveries in 30 days

	Before COVID-19	During COVID-19	Post COVID-19
0	69	70	120
1 to 2	438	197	361
3 to 5	320	321	339
6 to 10	104	264	150
More than 10	84	163	45

The proportion of households making more than six deliveries increases significantly during COVID-19 lockdown and is expected to move back to before COVID-19 levels once the pandemic is over. To get a better comparison, during COVID-19 and post COVID-19 home deliveries are cross-tabulated with the before COVID-19 delivery levels (see Table 2 and Table 3). Nearly two-thirds (63.4%) of the respondents who made 1 to 2 home deliveries and more than half of the respondents (55.9%) who completed 3 to 5 home deliveries before COVID-19 made more home deliveries during COVID-19. In comparison, once the pandemic is over, it appears a good majority of respondents plan to go back to pre-pandemic levels with increases observed at a lower number of delivery levels. Nearly 60% of the respondents who made 1 to 2 home deliveries before COVID-19 will make the same level of home deliveries once the pandemic is over. Around 30% of respondents who made 1 to 2 home deliveries before COVID-19 will make more home deliveries once the pandemic is over. Similarly, nearly 60% of the respondents who made no home deliveries before the COVID-19 pandemic will go back to making no home deliveries. Slightly more than 40% of those homes which made no home deliveries before COVID-19 will use online purchases and deliveries in the post-pandemic world.

Table 2 Cross-tabulation of before COVID-19 home deliveries and during COVID-19 home deliveries

	During COVID-19				
Before COVID-19	0	1 to 2	3 to 5	6 to 10	More than 10
0	34	17	13	3	2
1 to 2	27	133	192	75	11
3 to 5	7	42	92	132	47
6 to 10	2	2	15	50	34
More than 10	0	2	9	4	69

Table 3 Cross-tabulation of before COVID-19 home deliveries and post COVID-19 home deliveries

	During COVID-19				
Before COVID-19	0	1 to 2	3 to 5	6 to 10	More than 10
0	42	20	5	1	1
1 to 2	52	254	112	18	2
3 to 5	17	66	170	55	12
6 to 10	6	12	29	56	1
More than 10	3	9	23	20	29

The cross-tabulations also reveal strong positive correlations between the pre-pandemic and during pandemic, and pre-pandemic and post-pandemic home delivery numbers. To ensure adequate samples, we recoded the number of home deliveries made into three levels: (i) 0 to 2, (ii) 3 to 5, (ii) 6 and higher.

Ordered logit regression models were run with the number of home deliveries made during COVID-19 and post-pandemic as the dependent variable and the number of deliveries made 30 days before COVID-19 as the independent variable (Agresti, 2012; Greene, 2018) (see Table 4). We used the polr function from the MASS package in R (Ripley et al., 2020) to fit the ordered logit model. As expected, there are strong correlations between the number of home deliveries made in the three time periods. Households making more home deliveries before COVID-19 make a higher number of home deliveries during and post-pandemic. The deviance compares the loglikelihood of the ordered logit model with before COVID-19 home deliveries as the independent variable with the loglikelihood of the constant only ordered logit model. The deviance and the coefficient signs and magnitude indicate a stronger correlation between post-COVID-19 home deliveries and before COVID-19 home deliveries relative to during COVID-19 home deliveries and before COVID-19 home deliveries. This is consistent with the cross-tabulation results (Table 2 and Table 3).

Table 4 Ordered Logit regression of the number of home deliveries during COVID-19 and post COVID-19 versus the number of home deliveries before COVID-19

	During COVID-19		Post COVID-19	
	Coefficient	P-value	Coefficient	P-value
Before COVID-19 deliveries				
3 to 5	1.611	0.000	1.891	0.000
More than 6	3.041	0.000	3.186	0.000
Deviance	310.754		359.50	

3. Descriptive Statistics of Relevant Demographic and Household Variables

Table 5 presents the descriptive statistics of relevant demographic, household, and technology access variables. There is a good representation of all age and income categories. Nearly one-third of the respondents are between the ages of 30 and 44, and we have close to 150 respondents above the age of 65. More than half of the respondents are from households making more than $ 50000 annually. The age and income distribution are consistent with the median age of the metro at 38.4 and median annual household income of $ 76,000 (Census Reporter, 2020).

The respondents are reasonably tech-savvy. Nearly 80% of the respondents spend more than 10 hours per week on desktop, laptop, tablet, or smartphone and almost 70% of them subscribe to delivery services such as Amazon Prime or Instacart Express.

A majority (nearly 55%) of the respondents are employed, with slightly more than 40% of the respondents being employed full-time. Almost one-fifth of the respondents are retired, with a small percentage of students. A majority of the respondents (slightly more than 80%) do not have a work from home option.

There is a fair distribution of respondents across various household sizes and the number of workers categories. Slightly more than three-fourths of the respondents do not have elders or kids in the household. Nearly 18% of the households indicate the presence of a member with a disability. Almost two-thirds of the respondents are from homes with 1 or 2 vehicles.

Table 5 Descriptive Statistics of Relevant Demographic and Household Variables

Variable	Frequency	Relative Frequency	Variable	Frequency	Relative Frequency
Age			**Income**		
18-29	268	26.4	Less than 30K	257	25.3
30-44	315	31	30K to 49,999	202	19.9
45-64	284	28	50K to 99,999	272	26.8
>= 65	148	14.6	Greater than 100K	284	28.0
Hours per week utilizing desktop, laptop, tablet or smartphone?			**Access to Delivery Subscription Service?**		
0 to 10 hours	196	19.3	No	309	30.4
10 to 25 hours	282	27.8	Yes	706	69.6
25 to 40 hours	273	26.9			
More than 40 hours	264	25.0			
Employed for pay or profit?			**Do you work full-time?**		
No	462	45.5	No	600	59.11
Yes	553	54.5	Yes	415	40.89
Are you Retired?			**Are you a Student?**		
No	837	82.47	No	945	93.11
Yes	178	17.53	Yes	70	6.89
Can you work from home?			**Presence of household member with disability?**		
No	817	80.49	No	837	82.5
Yes	198	19.51	Yes	178	17.5
Household Size			**Number of workers in household**		
1	205	20.2	0	217	21.4
2	351	34.6	1	351	34.6
3	173	17.0	2	346	33.6
4	170	16.7	3 or higher	106	10.4
5 or higher	116	11.4			
Number of elders			**Number of kids**		
0	774	76.3	0	785	77.3
1	143	14.1	1	127	12.5
2 or higher	98	9.66	2 or higher	103	10.1
Vehicle Count					
0	93	9.16			
1	347	34.2			
2	375	36.9			
3 or higher	200	19.7			

Respondents were asked to indicate whether the cost of delivery, time of delivery, online experience, and health concerns is a factor in choosing to make purchases online (see Table 6). A significant majority of the respondents indicated that these four factors affected their choice of purchasing online. For example, slightly more than 85% of the respondents stated health is a concern.

Table 6 Factors affecting the choice of online purchase

	Frequency	**Relative Frequency**
Cost of Delivery is a factor?		
No	141	13.9
Yes	874	86.1
Time of Delivery is a factor?		
No	157	15.5
Yes	858	84.5
Online experience is a factor?		
No	95	9.36
Yes	920	90.6
Health concern is a factor?		
No	143	14.1
Yes	872	85.9

4. Impact of Household, Demographic, and Technology Access Variables on Number of Home Deliveries

This section uses ordered logit regression to test the impact of individual variables on the number of home deliveries made. The dependent variable chosen is: (i) number of home deliveries in 30 days before COVID-19, (ii) number of home deliveries made in 30 days during COVID-19 lockdown, (iii) number of home deliveries expected to make in 30 days post COVID-19 lockdown (see Table 7). The dependent variable was categorized into three levels (i) 0 to 2, (ii) 3 to 5, (ii) 6 or higher.

The propensity to make a higher number of home deliveries decreases with age. This result is consistent with several studies (Farag et al. 2005, 2006a, 2007; Krizek et al., 2005; De Blasio 2008; Cao et al. 2012; Crocco et al., 2013; Zhou and Wang 2014; Clemes et al., 2014; Irawan and Wirza, 2015; Lee et al. 2015; Ding and Lu 2017). However, elderly respondents are more likely to make more home deliveries during COVID-19 and post COVID-19 compared to before COVID-19. The likelihood of making a higher number of home deliveries increases with income. Higher-income respondents are more likely to make a higher number of home deliveries during COVID-19 compared to before COVID-19 and post COVID-19. However, the likelihood of higher-income individuals making more home deliveries post COVID-19 is higher than before COVID-19.

Tech-savvy respondents are more likely to make a higher number of home deliveries. This result is consistent with the findings of past studies (Farag et al. 2005, 2006b, 2007; Krizek et al., 2005; Ren and Kwan 2009; Rotem-Mindali 2010; Cao et al. 2012, 2013; Irawan and Wirza 2015; Lee et al., 2015, 2017; Ding and Lu 2017). Individuals who spent more time on desktop, laptops, tablets, or smartphones and individuals with a subscription to Amazon Prime or Instacart Express are more likely to purchase more online. Surprisingly, the propensity of tech-savvy individuals to make a higher number of home deliveries is higher during the post-COVID-19 period compared to the COVID-19 period, which in turn is higher than the before COVID-19 period. Therefore, people who spent more time on computers and have delivery company subscriptions are getting more comfortable shopping online.

Time of delivery, cost of delivery, online experience, and health concern – all affect the propensity to make a higher number of home deliveries. Several studies have found good website design, customer service, and overall online experience to increase the propensity to shop online (Ramanathan 2010; Clemes et al., 2014; Lee et al. 2017).The health concern is not significant for the before COVID-19 period but strongly significant in the COVID-19 period, which is expected. In the post-COVID-19 period, respondents with health concerns are more likely to make a higher number of home deliveries. However, the likelihood of making a higher number of home deliveries post COVID-19 is lower compared to the COVID-19 lockdown period.

Respondents who are employed, work full-time, and can work from home are more likely to make a higher number of home deliveries. The likelihood increases from before COVID-19 to during COVID-19 to post COVID-19 period. Retired respondents are less likely to make a higher number of home deliveries.

The propensity to make more number of home deliveries increases with household size. Large household sizes were more likely to make a higher number of home deliveries in the before COVID-19 period. One possible reason could be that larger households had more people unemployed or reduced work, which meant they could use the time to shop at stores. The likelihood of making more home deliveries increases with the number of workers in the household. Farag et al. (2006a, 2006b), Zhou and Wang (2014), and Irawan and Mirza (2015) also had similar insights. This likelihood increases in the COVID-19 period compared to the before COVID-19 period and then decreases marginally.

The likelihood of making home deliveries increases with the number of kids in the household. Surprisingly, the likelihood of households with two or more kids making more home deliveries during COVID-19 was lower than before COVID-19 or post-COVID-19 period. One possible reason could be that parents could be viewing the shopping trip as one way to get kids out of the house.

The propensity for making more home deliveries increases with the number of vehicles owned by the household. This could be because vehicle count could be a proxy for income, and higher-income families are more likely to make more home delivery purchases. The likelihood increased during the COVID-19 period compared to before COVID-19. In the post-COVID-19 period, the possibility of households with more number of vehicles making more home deliveries decreased compared to the before COVID-19 period. One possible reason is that members of such households enjoy driving, and they are more eager to get back to a “normal” way of conducting daily activities like shopping once the pandemic is over.

Table 7 Logit Regression with Individual Variables

	Before COVID-19		During COVID-19		Post COVID-19	
Variable	**Coefficient**	**P-value**	**Coefficient**	**P-value**	**Coefficient**	**P-value**
Age						
	-0.021	0.000	-0.013	0.000	-0.013	0.000
Deviance	37.094		16.003		14.209	
Income						
30K to 49,999	0.367	0.042	0.590	0.000	0.400	0.027
50K to 99,999	0.329	0.050	0.734	0.000	0.577	0.000
Greater than 100K	0.854	0.000	1.306	0.000	1.182	0.000
Deviance	27.778		65.60		53.569	
Hours per week utilizing desktop, laptop, tablet or smartphone?						
10 to 25 hours	0.283	0.112	0.580	0.000	0.552	0.002
25 to 40 hours	0.343	0.056	0.642	0.000	0.710	0.000
More than 40 hours	0.771	0.000	0.981	0.000	1.118	0.000
Deviance	19.443		32.235		39.607	
Access to Delivery Subscription Service?						
Yes	1.377	0.000	1.461	0.000	1.491	0.000
Deviance	99.632		125.948		115.872	
Cost of Delivery is a factor?						
Yes	0.544	0.002	0.804	0.000	0.796	0.000
Deviance	9.422		23.131		19.746	
Time of Delivery is a factor?						
Yes	0.646	0.000	0.932	0.000	0.670	0.000
Deviance	14.480		34.004		15.240	
Online experience is a factor?						
Yes	0.961	0.000	1.467	0.000	0.873	0.000
Deviance	19.168		50.068		16.246	
Health concern is a factor?						
Yes	0.240	0.178	0.713	0.000	0.413	0.021
Deviance	1.834		18.012		5.370	
Employed for pay or profit?						
Yes	0.344	0.004	0.441	0.000	0.492	0.000
Deviance	8.284		14.231		17.042	
Do you work full-time?						
	0.336	0.005	0.388	0.001	0.544	0.000
Deviance	7.788		10.693		20.634	
Are you Retired?						
	-0.823	0.000	-0.647	0.000	-0.704	0.000
Deviance	25.621		18.346		18.972	
Are you a Student?						
	0.655	0.004	0.541	0.022	0.547	0.015
Deviance	8.047		5.37		5.853	

Can you Work from Home?						
	0.434	0.003	0.191	0.196	0.411	0.005
Deviance	8.427		1.67		7.774	
Household Size						
2	0.415	0.018	0.6410	0.000	0.421	0.015
3	0.661	0.001	0.726	0.000	0.830	0.000
4	1.166	0.000	1.066	0.000	0.960	0.000
5 or higher	1.424	0.000	1.126	0.000	1.189	0.000
Deviance	59.174		40.90		42.422	
Number of workers in household						
1	0.595	0.000	0.691	0.000	0.636	0.000
2	1.131	0.000	1.159	0.000	1.203	0.000
3 or higher	1.093	0.000	1.154	0.000	1.068	0.000
Deviance	49.688		57.21		54.695	
Number of elders						
1	-0.528	0.002	-0.488	0.003	-0.420	0.016
2 or higher	-0.540	0.012	-0.599	0.002	-0.780	0.003
Deviance	13.912		15.837		17.358	
Number of Kids						
1	0.347	0.053	0.088	0.621	0.144	0.416
2 or higher	0.862	0.000	0.506	0.01	0.741	0.000
Deviance	21.846		6.675		14.392	
Vehicle Count						
1	0.627	0.01	0.423	0.048	0.311	0.181
2	0.998	0.000	1.035	0.000	0.846	0.000
3 or higher	1.335	0.000	1.294	0.000	1.006	0.000
Deviance	35.924		50.861		32.229	
Presence of household member with disability?						
	0.228	0.136	0.158	0.303	0.339	0.026
	2.202		1.062		4.893	

5. The additional effect of household, socio-demographic, and technology access variables

The number of home deliveries made before COVID-19 is the strongest predictor for the number of home deliveries made in 30 days during COVID-19 and post-pandemic. This is expected in the sense that households that made more electronic purchases before this pandemic are more likely to continue using home deliveries at the same or higher level during and post pandemic. The results also reveal that variables such as income, hours per week utilizing a desktop, laptop, tablet, or smartphone, access to delivery services, health concern, household related variables are correlated with the number of deliveries made in 30 days in all three time frames.

Next, we study the additional impact of including the variables considered in Table 7 in the ordered logit regression of (i) number of deliveries made in 30 days during COVID-19 with the number of deliveries made in 30 days before COVID-19 as the independent variable, and (ii) number of deliveries expect to make in 30 days post COVID-19 with the number of deliveries made in 30 days before COVID-19 as the independent variable (see Table 8). We introduce the variable one by one and calculate the deviance. The deviance is twice the difference in the loglikelihood of the regression model with the number of deliveries made in 30 days before COVID-19 and the new variable as the independent variables from the loglikelihood of the regression model, which contains the number of deliveries made in 30 days before COVID-19 as the only independent variable.

In general, the deviances for all variables in the post-COVID-19 model is lower than the deviances for all variables in the during COVID-19 model. This indicates that the number of home deliveries made before COVID-19 is a stronger predictor for the post-COVID-19 period than for the home deliveries made during the COVID-19 period. We observed this in the cross-tabulations in Table 2 and Table 3. For both time periods, the most important variable is access to delivery subscription services. This makes sense as subscribers to Amazon Prime, Instacart Express, etc., are more likely to use the services. The second most important variable is income in both the models.

Interestingly, online experience is the third most important variable for the during COVID-19 model but not that important for the post-COVID-19 model. One possible reason could be that respondents expect to be comfortable using smartphone delivery apps and delivery company websites in the post-pandemic world because of the experience they gain ordering online during COVID-19 lockdown.

The number of workers in the household is the fourth most important variable in both models. Households with a higher number of workers are more likely to make more deliveries during COVID-19 and post COVID-19 periods. The number of workers is more important than other household related variables, including household size, number of elders, and kids.

The hours per week spent on desktop, laptop, tablet, and smartphone is the third most important variable for the post-COVID-19 period. The significance of this variable is higher for the post-COVID-19 model than during COVID-19 model. One possible reason could be that in the post-COVID-19 world, only the more tech-savvy respondents intend to continue with online deliveries. Whereas during COVID-19 lockdown, more people, irrespective of their comfort level in the use of computers and smartphones, are making an effort to order online. Health concerns and delivery time are important factors during the COVID-19 model but not that important in post-COVID-19.

Being employed and working full time is more critical for post-COVID-19 model compared to during the COVID-19 model. One potential reason could be full-time working people are financially more secure and willing to pay more extra for home deliveries. They may also be busier and prefer to shop online so that the time saved can be used for work or other recreational activities.

Table 8 Additional effect of household, socio-demographic, and technology access related variables

	During COVID-19	**Post COVID-19**
	Deviance	**Deviance (Rank)**
Access to Delivery Subscription Service?	56.124	41.265 (1)
Income	39.477	29.861 (2)
Online experience is a factor?	29.447	3.378
Number of workers in household	25.941	18.533 (4)
Vehicle Count	24.046	9.063 (9)
Hours per week utilizing desktop, laptop, tablet or smartphone?	16.831	24.548 (3)
Time of delivery is a factor?	17.332	3.990
Health concern is a factor?	16.503	2.545
Cost of Delivery is a factor?	12.848	9.391 (8)
Household Size	12.638	9.945 (7)
Employed for pay or profit?	7.973	10.733 (6)
Number of elders	6.609	8.860 (10)
Do you work full-time?	5.538	13.833 (5)
Are you Retired?	5.035	3.10
Age	1.987	0.1555
Are you a Student?	1.069	0.899
Number of Kids	0.504	3.519
Presence of household member with disability?	0.035	2.233
Work from Home?	0.003	2.494

While selecting key important, one also needs to recognize correlations among these variables. For example, one would expect strong positive correlations between access to delivery subscription services and income (see Table 9, p-value=1.7×10^{-14}), access to delivery subscription services and hours per week utilizing computers and communication devices (see Table 10, p-value=3.388×10^{-6}), income and vehicle ownership (see Table 11, p-value = 2.2×10^{-16}), household size and the number of workers (see Table 12, p-value = 2.2×10^{-16}), etc.

Table 9 Cross-tabulation between access to delivery subscription services and income (percentage)

Access to delivery subscriptions services	Income			
	Less than 30K	30K to 49,999	50K to 99,999	Greater than 100K
No	47	32	29	15
Yes	53	68	71	85

Table 10 Cross-tabulation between access to delivery subscription services and hours spent utilizing desktop, laptop, tablet or smartphone (percentage)

Access to delivery subscriptions services	Hours per week utilizing desktop, laptop, tablet or smartphone?			
	Less than 10 hrs	10 to 25 hrs	25 to 40 hrs	More than 40 hrs
No	42	34	28	20
Yes	58	66	72	80

Table 11 Cross-tabulation between income and vehicle count (percentage)

Income	Vehicle Count			
	0	1	2	3 or higher
Less than 30K	71	30	15	16
30K to 49,999	19	27	16	16
50K to 99,999	5	29	30	26
More than 40 hrs	4	14	39	42

Table 12 Cross-tabulation between household size and number of workers (percentage)

Household Size	Number of Workers			
	0	1	2	3 or higher
1	40	34	0	0
2	48	29	43	0
3	6	17	19	33
4	3	13	25	30
5 or higher	2	8	13	37

6. Discussion and Policy Insights

Households that were more comfortable with online shopping before COVID-19 were more likely to order more home deliveries during COVID-19. In the post-COVID-19 period, a majority of the households are expected to revert to their original online shopping levels. However, a significant proportion of the households, which made less than three home deliveries per month before COVID-19 are expected to shop online at a higher rate in the post-COVID-19 period. There is scope for companies like Amazon and Instacart to target these households.

Time and cost of delivery are important factors affecting home delivery shopping decisions. Therefore, e-commerce businesses, home delivery companies should emphasize optimizing delivery routes to improve reliability and reduce cost.

Elderly and retired respondents show an increased willingness to use home deliveries during COVID-19. However, they are less likely to use online shopping compared to the general population. Online experience and health concerns are important factors that increase the likelihood of more home deliveries. There is scope for improving access to online shopping among the elderly and retired members of the population by developing intuitive and easy to use shopping and payment interfaces.

The propensity to order online deliveries increases for higher income, tech-savvy individuals who are comfortable using computers and smartphones. Lower-income population is less likely to shop online. However, the lower-income population is also disproportionately affected by COVID-19 from infection and economic perspective (Wadhera et al., 2020). Therefore, there is scope for e-commerce and online delivery platforms to adopt socially responsible policies for promoting home deliveries in lower-income neighborhoods. There is also the potential for the government to incentivize home deliveries for grocery stores, restaurants, and other businesses located in lower-income areas and zip codes.

7. Conclusions

COVID-19 and associated lockdowns have affected every aspect of our lives. From a freight and shopping perspective, there has been a shift from a traditional brick-and-mortar shopping experience to online shopping and home deliveries. We conducted an online survey targeting the population in the Portland-Vancouver-Hillsboro Oregon-Washington Metro Area. The survey elicited responses on the number of home deliveries made, household and demographic characteristics, e-commerce and product preferences, and socioeconomic variables.

There was a significant increase in home deliveries during the COVID-19 lockdown relative to before the COVID-19 period. Nearly two-thirds (63.4%) of the households making 1 to 2 home deliveries, and more than half of the households (55.9%) making 3 to 5 home deliveries before COVID-19 made more home deliveries during COVID-19. Comparing before COVID-19 home deliveries and the number of home deliveries expected to make post-pandemic, the trend is slightly different. Households that made less than three deliveries per month before the pandemic will order more online post-pandemic. However, a majority of the households ordering a healthy amount online before the pandemic, and increased their deliveries during the pandemic lockdown, are expected to revert back to the original numbers post-pandemic. In general, households that shopped online before the COVID-19 are more likely to order more during the pandemic.

Health concerns positively increase the likelihood of ordering online during the pandemic and does not have a significant impact post-pandemic. The likelihood of tech-savvy individuals to make a higher number of home deliveries is higher during post-COVID-19 period compared to the COVID-19 period, which in turn is higher than the before COVID-19 period. Respondents who work full-time and have work from home options are more likely to make a higher number of home deliveries. This likelihood increases from before COVID-19 to COVID-19 to the post-pandemic period. Households with more number of workers are more likely to make more home deliveries. This likelihood increases from before COVID-19 to during COVID-19 period and then decreases slightly during the post-pandemic.

This research can be extended in multiple ways. The survey can be extended to other regions in the US, covering rural regions. Another possible extension is conducting the study in the

Portland-Vancouver-Hillsboro Oregon-Washington Metro Area every six months and comparing responses. We are also developing multiple discrete regression models focusing on the impact of product types and equity aspects of online home deliveries.

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