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Exploratory analysis of factors affecting levels of home deliveries before, during, and post- COVID-19

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A R T I C L E I N F O

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A B S T R A C T

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 that affect home delivery levels before, during, and post-COVID-19. There was a significant increase in home deliveries during the COVID-19 lockdown relative to the before COVID-19 period. A high proportion of the households that made less than three deliveries per month before the pandemic stated they would order more online post-pandemic. A majority of the households that ordered more than three deliveries per month before COVID-19 are expected to revert to their original levels post-pandemic. The two variables most positively affecting the likelihood of online shopping were 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 post-pandemic. 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. Households with disabled members, single workers, and respondents concerned about online experience and health are more likely to be first-time online shoppers during the pandemic.

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 (Abdullah et al., 2020; Beck and Hensher, 2020a, 2020b; De Vos, 2020; Grida et al., 2020; Jenelius and Cebecauer, 2020; Katrakazas et al., 2020; Loske, 2020; Mogaji, 2020; Monmousseau et al., 2020; Parady et al., 2020; Shamshiripour et al., 2020; Sobieralski, 2020). Specifically, the pandemic has had a significant impact on the way we shop, with a movement towards e-commerce. 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 and the environment (Figliozzi, 2020; Mokhtarian, 2004).

Several studies have explored the impact of socio-economic, personal, and technology-related factors on e-commerce adoption with conflicting insights at times. Crocco et al. (2013) and Farag et al. (2007, 2006a,b) found males are more likely to shop online whereas, Clemes et al. (2014), Ding and Lu (2017), Ren and Kwan (2009), Shi et al. (2019) had the opposite finding. A majority of the literature (Cao et al., 2012; Clemes et al., 2014; Crocco et al., 2013; DE BLASIO, 2008; Ding and Lu, 2017; Farag et al., 2007, 2006a, 2005; Irawan and Wirza, 2015; Krizek et al., 2005; Lee et al., 2015; Zhou and Wang, 2014) 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 (Cao et al., 2013, 2012; Crocco et al., 2013; DE BLASIO, 2008; Dias et al., 2020; Farag et al., 2007, 2006a, 2005; Lee et al., 2015; Schmid and Axhausen, 2019; Zhou and Wang, 2014) 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 (Cao et al., 2013, 2012; Clemes et al., 2014; DE BLASIO, 2008; Farag et al., 2007,

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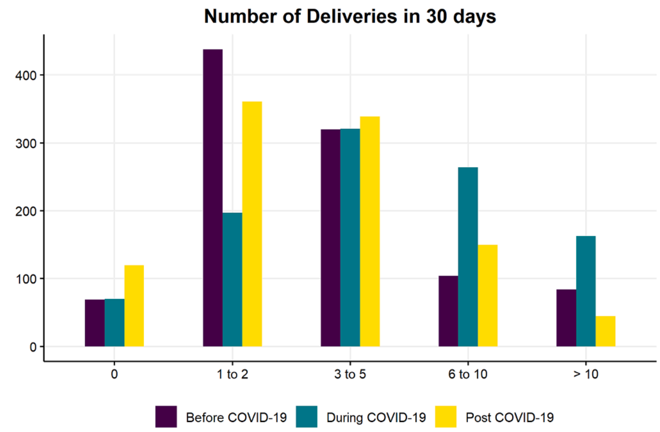

Fig. 1. Number of home deliveries in 30 days.

2006a; Krizek et al., 2005; Rotem-Mindali, 2010; Schmid and Axhausen, 2019; Zhou and Wang, 2014) and with experience with internet usage, internet access, and being more tech-savvy (Cao et al., 2013, 2012; Ding and Lu, 2017; Farag et al., 2007, 2006b, 2005; Irawan and Wirza, 2015; Krizek et al., 2005; Lee et al., 2015; Ren and Kwan, 2009; Rotem-Mindali, 2010). Some of these effects are corelated. 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; Irawan and Wirza, 2015; Zhou and Wang, 2014), and children (Dias et al., 2020; Farag et al., 2006a). Household location - urban vs. suburban vs. rural- was also found to affect the likelihood of adopting e-commerce with studies showing conflicting results (Cao et al., 2013; DE BLASIO, 2008; Dias et al., 2020; Farag et al., 2007, 2005; Krizek et al., 2005; Shi et al., 2019; Zhou and Wang, 2014). Other factors that were found to affect e-commerce adoption include product type (Dias et al., 2020; Girard et al., 2003; Maat and Konings, 2018; Schmid and Axhausen, 2019; Zhai et al., 2017; Zhen et al., 2018, 2016) and online shopping experience and convenience (Clemes et al., 2014; Lee et al., 2015; Ramanathan, 2010). 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 COVID-19. Similar insights were obtained for food delivery. And the pandemic has highlighted preexisting inequities regarding access to home deliveries (Figliozzi and Unnikrishnan, 2021).

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 home deliveries, with a 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. This research also looks at factors that increase the likelihood of a household shopping online for the first time during the pandemic. To the best of the authors' knowledge, after an extensive literature review, the focus and contribution of this paper are novel.

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. In May and June 2020, the unemployment rate in the Metro region was 14.0% and 11.8%, respectively. In comparison, the unemployment rate in May and June 2019 was 3.4% and 3.8%, respectively (Bureau of Labor Statistics (BLS), 2020). Before the pandemic, the metro region's economy experienced significant growth with a Gross Domestic Product (GDP) output of US \$ 158.8 billion in 2018 (The Brookings Institute, 2019) and US \$ 164.4 billion in 2019 (Portland Business Alliance, 2020). The Portland Metro region also experienced the third-highest median household income growth in the United States since 2010. There were seven industries employing more than 100,000 workers in the Metro region in 2019 – Education (186,350), Professional and Business Services (185,983), Healthcare and Social Assistance (155,550), Government (152,183), Manufacturing (131,517), Leisure and Hospitality (127,325), and Retail Trade (118,367) (Portland Business Alliance, 2020). Since 2010, Manufacturing job growth in Portland was higher than that of the US's manufacturing job growth, with 60% of the manufacturing spread across diverse sectors such as Aerospace, Metals, Machinery, and Semiconductors. Industries that produce tradable commodities that are exported and sold all over the world are responsible for approximately 45% of the regional GDP output (The Brookings Institute, 2019). These economic developments have resulted in interesting trends concerning traffic. In 2018 in Oregon, per capita truck vehicle miles traveled (VMT) was 2% higher than 2007 (pre-recession 2009) levels. However, while heavy truck VMT per capita is 9% lower, medium truck VMT per capita is 20% higher than the 2007 levels which is potentially the result of a higher growth in e-commerce and parcel deliveries (Dunn and Knudson, 2020).

We eliminated respondents with inconsistent responses for the household sizes, number of workers, number of children, and elderly members. We also removed respondents who took less than three 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
  - o made in 30 days before COVID-19 lockdown,
  - o made in 30 days during the COVID-19 lockdown,
  - o expected to make in 30 days once the pandemic is over.

In three separate questions, we asked the respondents information on the number of times they purchased goods online and had them delivered to home. The questions are shown below:

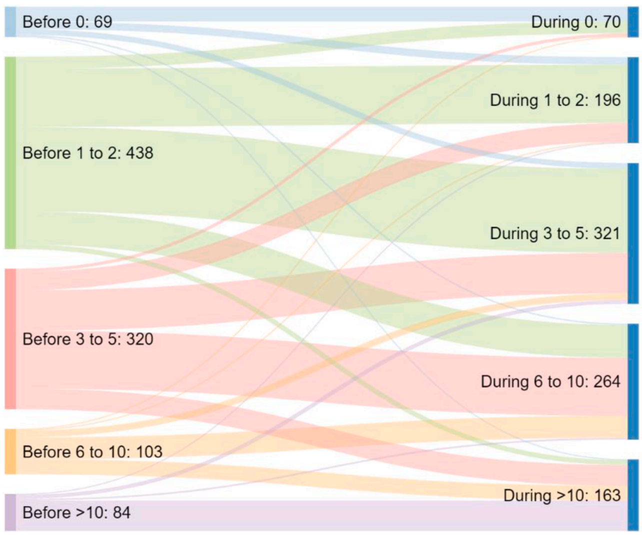

Fig. 2. Sankey plot of before COVID-19 home deliveries and during COVID-19 home deliveries.

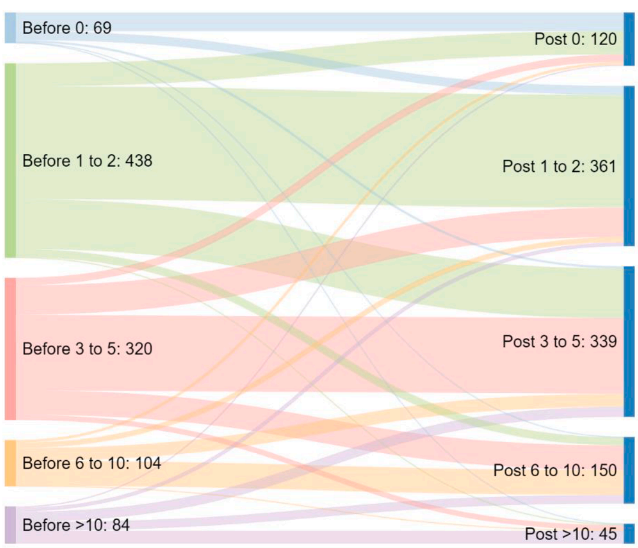

Fig. 3. Sankey plot of before COVID-19 and post-COVID-19 home deliveries.

"In a typical month BEFORE COVID-19, how many times did you or members of your household purchase something online and have it delivered to your home?"

"In the last 30 days, AFTER COVID-19 lockdown started, how many times did you or members of your household purchase something online and have it delivered to your home?"

"Once the COVID-19 pandemic is over and commercial business restrictions are lifted, how many purchases with home delivery you or members of your household are expected to do in a typical month?"

The respondents had to select between (i) 0, (ii) 1 to 2, (iii) 3 to 5, (iv) 6 to 10, (v) More than 10. Fig. 1 shows the frequencies.

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. During COVID-19 and post-COVID-19 home deliveries are cross-tabulated with the before COVID-19 delivery levels. Fig. 2 and Fig. 3 provide the Sankey plots, and Tables 1 and 2 in Appendix B provide the cross-tabulation tables. 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.

The cross-tabulations also reveal strong positive correlations between the before 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.

Descriptive statistics of relevant demographic and household variables

Appendix A Presents the questions used to elicit the relevant demographic and household variables whose descriptive statistics are described in this section. Table 3 in Appendix B provide the descriptive statistics in tabular form. 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 $ 50,000 annually (see Fig. 4). The age and income distribution are consistent with the median age of the metro at 38.4 and the median annual household income of $ 76,000 (Census Reporter, 2020).

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 children in the household. Nearly 18% of the households indicate the presence of a member with a disability. This number is higher as only around 8% of the population in Portland City below the age of 65 identified as disabled (United States Census Bureau, 2020) but the higher percentage is expected given that the responces are at the household level and the average household size is greater than two. Almost two-thirds of the respondents are from homes with 1 or 2 vehicles (see Fig. 4).

The respondents are reasonably tech-savvy (see Fig. 5). Nearly 80% of the respondents spend more than 10 h per week on desktop, laptop, tablet, or smartphone and almost 70% of them subscribe to delivery services such as Amazon Prime or Instacart Express. In Oregon, 88% of the households have broadband access compared to the national average of 84%. In the Portland Metro region, the broadband access percentage is higher than 89% (Lehner, 2020). In Beaverton and Hillsboro city in the Portland Metro Region, over 96% of households had access to a computer at home (United States Census Bureau, 2020). We believe the computer savviness of the respondents is reflective of the population.

A majority (nearly 55%) of the respondents are employed for pay or profit, with slightly more than 40% of the respondents employed full-time. Almost one-fifth of the respondents are retired, with a small percentage of students. Around 20% of the respondents have a work from home option (see Fig. 5). Before the pandemic, Oregon was ranked second in the nation in the percentage of employed who are working from home, with approximately 15% of employers offering telecommuting options (Lehner, 2020). The survey percentage is consistent with this statistic.

Respondents were asked to indicate whether the cost of delivery, time of delivery, online experience, and health concerns are factors that impact online purchases (see Question 6 of Appendix A). 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 (see Fig. 6).

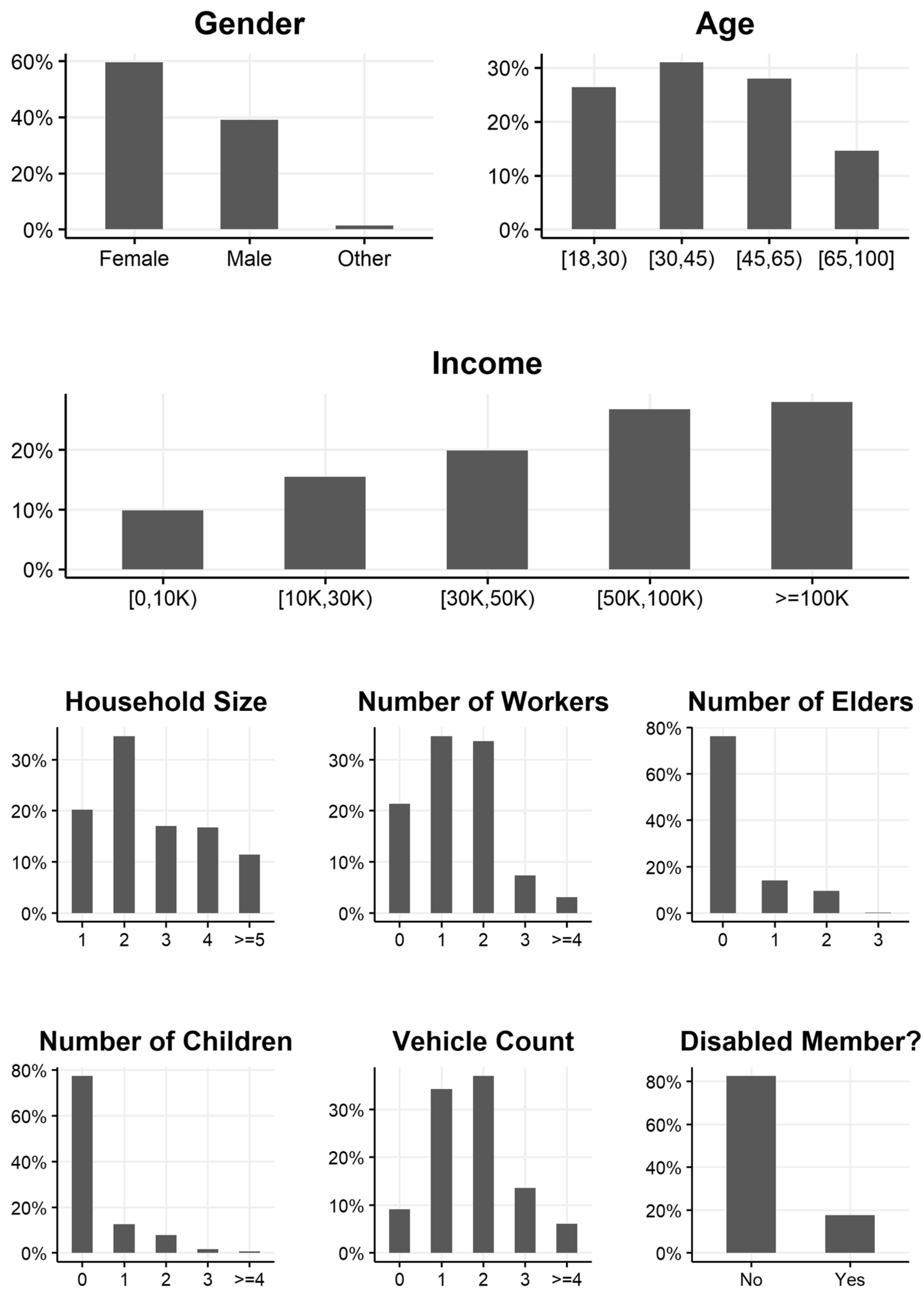

Fig. 4. Relative frequencies of personal and household characteristics.

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 (Agresti, 2012; Greene, 2018). We used the polr function from the MASS package in R (Ripley et al., 2020) to fit the ordered logit model. The dependent variable chosen is: (i) the number of home deliveries in 30 days before COVID-19, (ii) the number of home deliveries made in 30 days during COVID-19 lockdown, (iii) the number of home deliveries expected to make in 30 days post-COVID-19 lockdown. The dependent variable was categorized into three levels (i) 0 to 2, (ii) 3 to 5, (ii) 6 or higher. We test the independent variables one by one. This study aims to do an exploratory analysis to get an overall picture of key trends and variables. More especifically, the focus is on comparing the individual effects of the household, demographic, and technology access related variables on the number of home deliveries made before, during, and post-COVID-19 period. Table 4 of Appendix B provides the detailed table of the ordered logit model. Figs. 7 and 8 shows the ordered logit model's coefficients for significant variables at 5% significance level.

The propensity to make a higher number of home deliveries decreases with age. This result is consistent with several studies (Cao et al., 2012; Clemes et al., 2014; Crocco et al., 2013; DE BLASIO, 2008; Ding and Lu, 2017; Farag et al., 2007, 2006a, 2005; Irawan and Wirza, 2015; Krizek et al., 2005; Lee et al., 2015; Zhou and Wang, 2014). 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

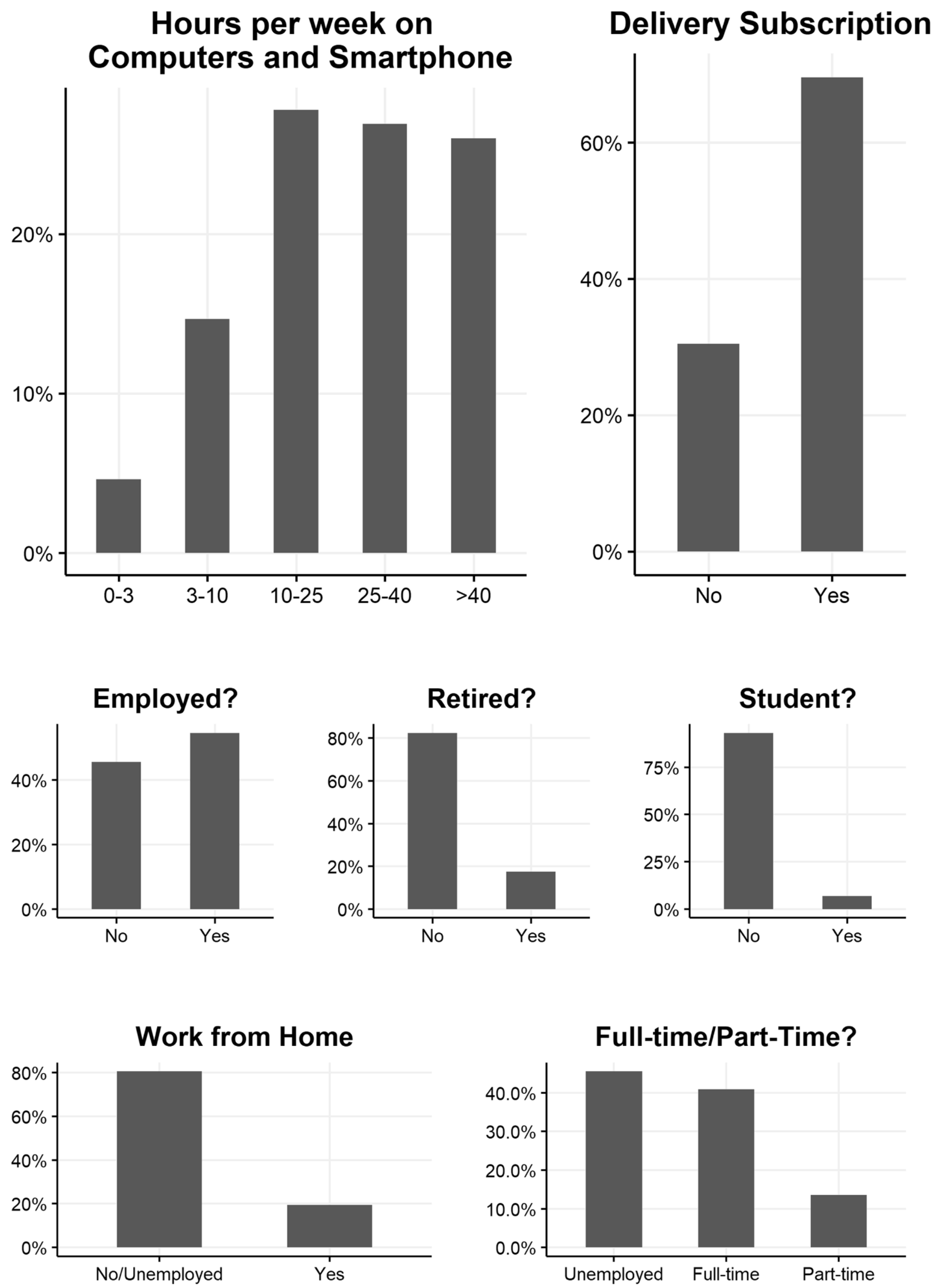

Fig. 5. Relative frequencies of responses to technology-related questions and work related variables.

increases with income. Higher-income respondents are more likely to make a greater 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 (see Fig. 7).

Tech-savvy respondents are more likely to make a higher number of home deliveries. This result is consistent with the findings of past studies (Cao et al., 2013, 2012; Ding and Lu, 2017; Farag et al., 2007, 2006b, 2005; Irawan and Wirza, 2015; Krizek et al., 2005; Lee et al., 2015; Ren and Kwan, 2009; Rotem-Mindali, 2010). Individuals who spent more time on desktops, 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 (see Fig. 7).

Time of delivery, cost of delivery, online experience, and health concern – all affect the propensity to make a higher number of home deliveries (see Fig. 7). Several studies have found good website design, customer service, and overall online experience to increase the propensity to shop online (Clemes et al., 2014; Lee et al., 2015; Ramanathan, 2010). 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.

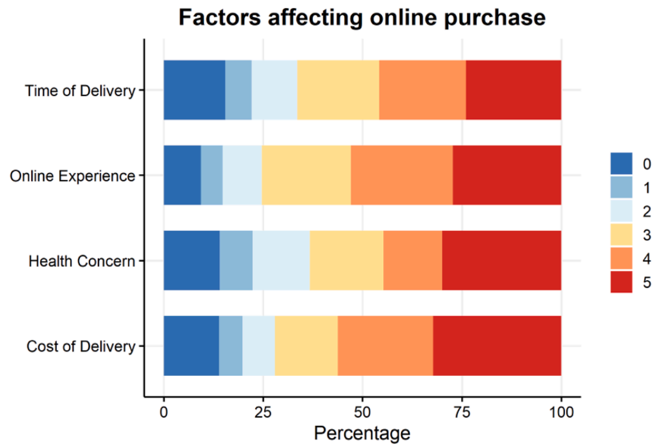

Fig. 6. Likelihood of concerns affecting the choice to purchase online.

Respondents who are employed and work full-time 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 (see Fig. 7).

The propensity to make more 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,b), Irawan and Wirza (2015), and Zhou and Wang (2014) also had similar insights. This likelihood increases in the COVID-19 period compared to the before COVID-19 period and then decreases marginally (see Fig. 8).

The likelihood of making home deliveries increases with the number of children in the household. Surprisingly, the likelihood of households with two or more children making more home deliveries during COVID-19 was lower than before COVID-19 or post-COVID-19 period. One possible reason could be related to trip chaining related to school, work, and shopping that was not possible during the lockdown (see Fig. 8). 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.

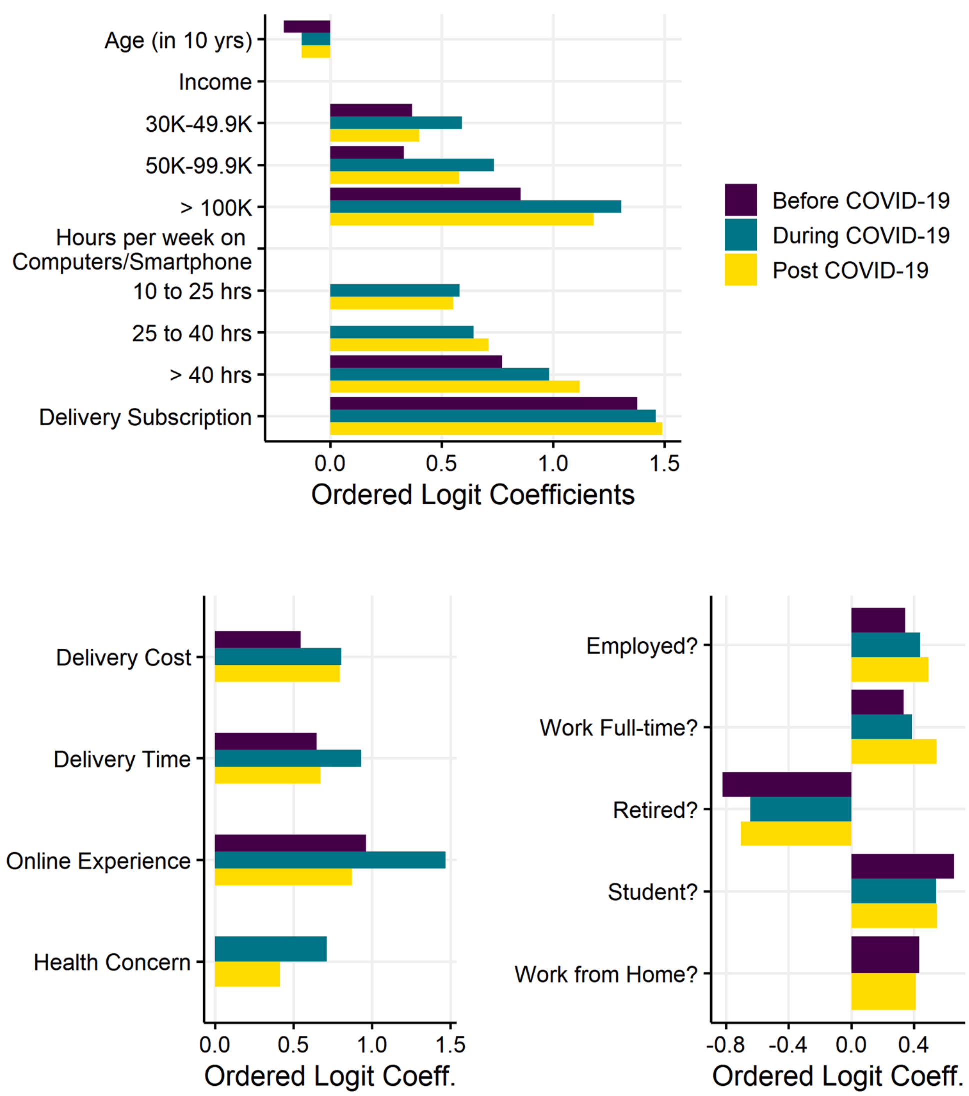

Fig. 7. Effect of demographic, technology, e-commerce, and work related variables.

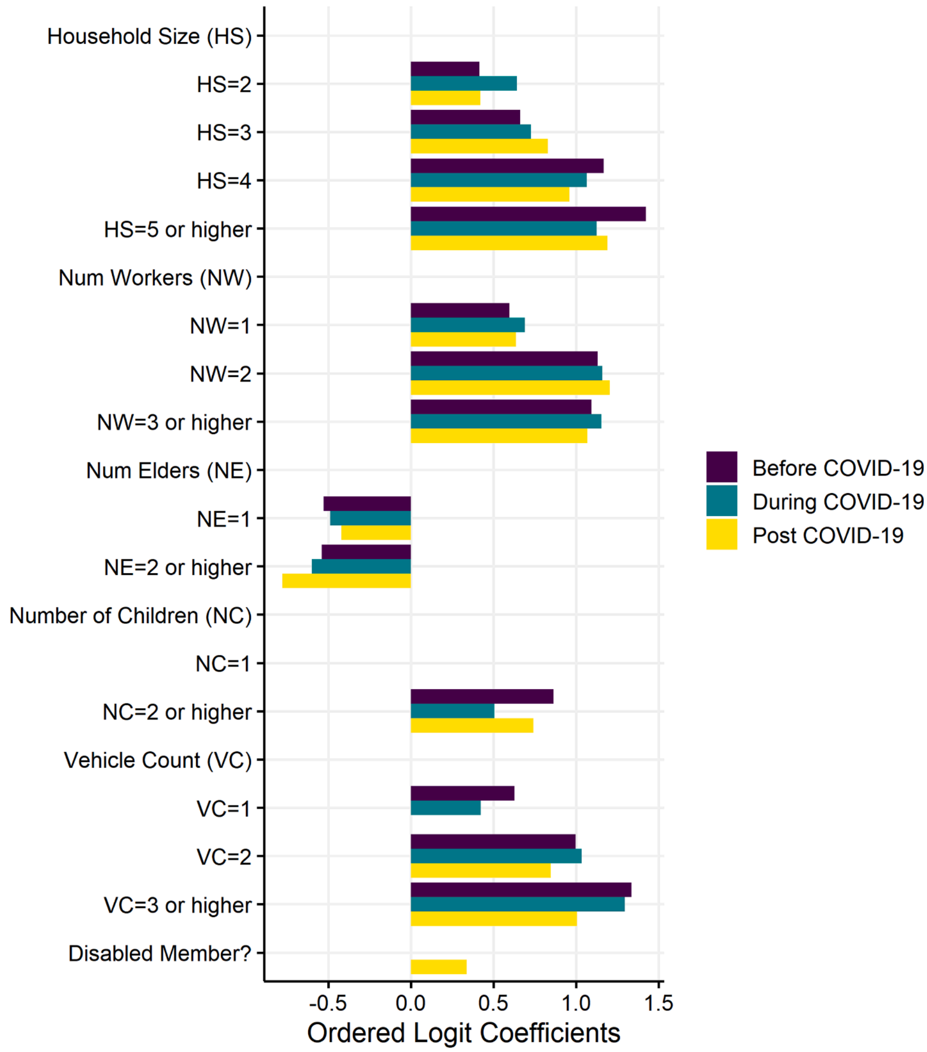

Fig. 8. Effect of Household Related Variables.

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 as households that made more online purchases before this pandemic are more likely to continue using home deliveries at the same or higher level during and after the 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, and household-related characteristics are correlated with the number of deliveries made in 30 days in all three time frames. This section aims to study the additional impact of household, socio-demographic, and technology-related variables considered in the previous section individually after controlling for the home delivery levels pre-pandemic.

To do that, we run ordered logit regressions of (i) dependent variable: number of deliveries made in 30 days during COVID-19 and independent variable: number of deliveries made in 30 days before COVID-19, (ii) dependent variable: number of deliveries made in 30 days during COVID-19 and independent variables: number of deliveries made in 30 days before COVID-19 plus each of the household, socio-demographic, and technology-related variables introduced individually, (iii) dependent variable: number of deliveries made in 30 days post-COVID-19 and independent variable: number of deliveries made in 30 days before COVID-19, (iv) dependent variable: number of deliveries made in 30 days post-COVID-19 and independent variables: number of deliveries made in 30 days before COVID-19 plus each of the household, socio-demographic, and technology-related variables introduced individually. Note that discrete regression models that account for collinearity, endogeneity, and latent variables is outside the scope of this paper. This analysis aims to be a purely exploratory study that provides insights on the individual variable effects across the three time periods.

We introduce the variables found significant in the previous section 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 (ii, iv) 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 (i, iii).

In general, the deviances for all variables in the post-COVID-19 model is lower than the deviances for all variables in the COVID-19 model (see Fig. 9). 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 Tables 1 and 2. For both 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.

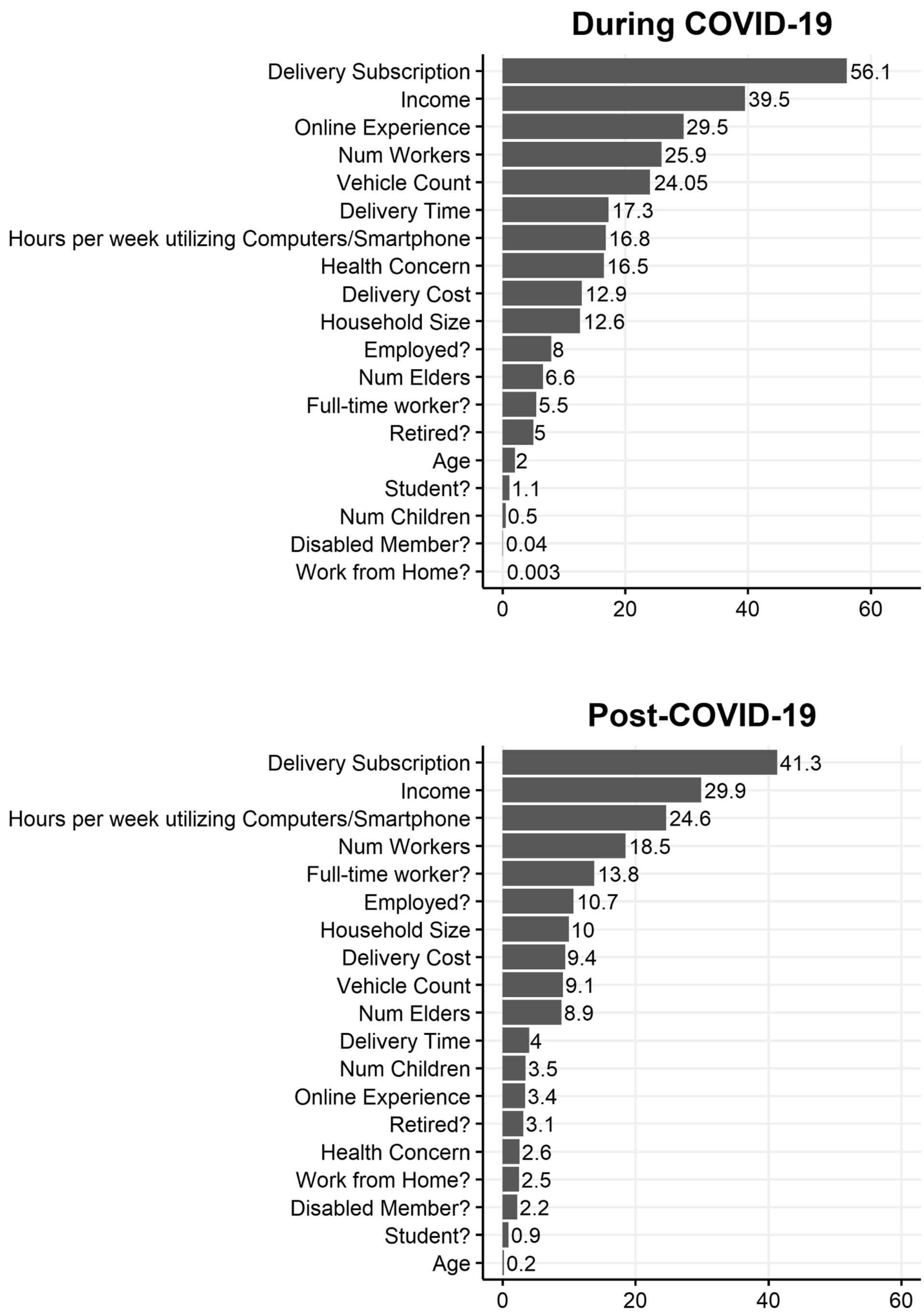

Fig. 9. Additional effect of household, socio-demographic, and technology access related variables.

Interestingly, the 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 their experience 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 children.

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 using computers and smartphones, are making an effort to order online. Health concerns and delivery time are important factors for the COVID-19 model but not that important in post-COVID-19.

Working full time is more critical for the post-COVID-19 model than 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.

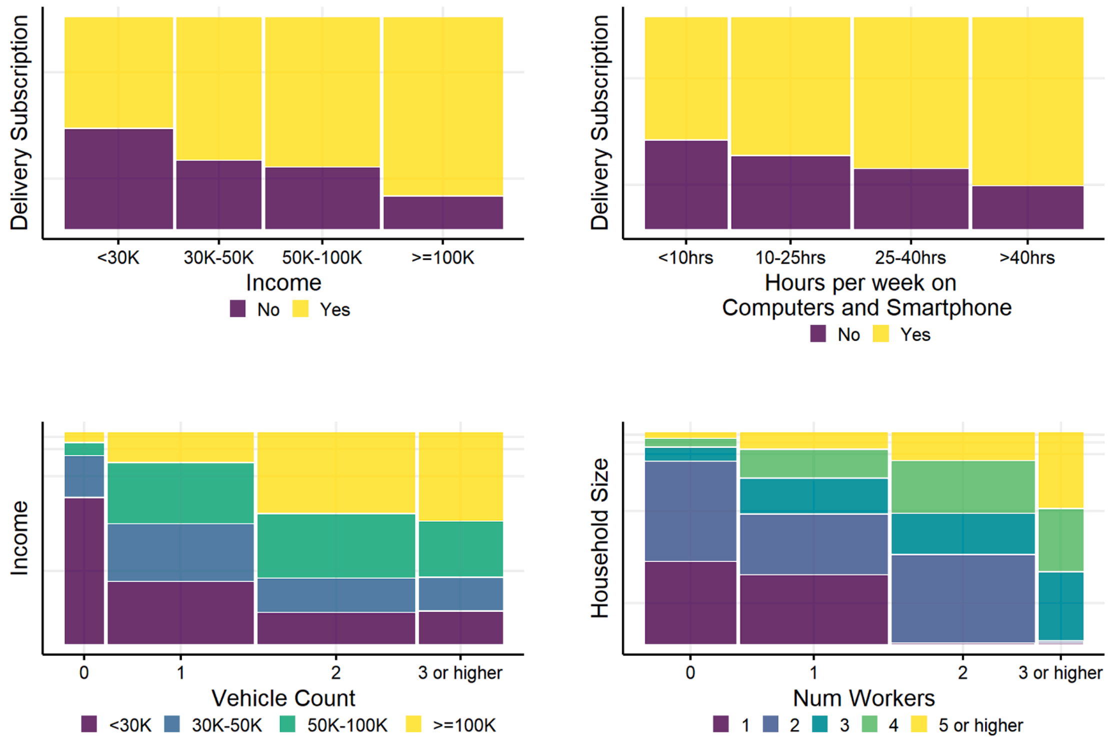

Fig. 10. Cross-tabulation between select variables.

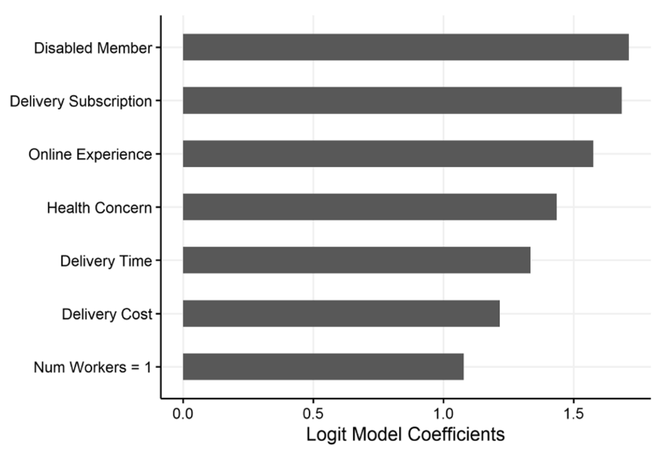

Fig. 11. Factors affecting first time online shoppers.

Table 1
Cross-tabulation of before COVID-19 home deliveries and during COVID-19 home deliveries

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

While selecting key factors, the correlations among these variables have to be recognized (see Fig. 10). For example, one would expect strong positive correlations between access to delivery subscription services and income (p-value $= 1.7 \times 10^{-14}$), access to delivery subscription services and hours per week utilizing computers and communication devices (p-value $= 3.388 \times 10^{-6}$), income and vehicle ownership (p-value $= 2.2 \times 10^{-16}$), household size and the number of workers (p-value $= 2.2 \times 10^{-16}$), etc. Therefore, while developing regression models, the correlations and endogenous effects between regressors' should be considered and modeled appropriately.

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

	Post-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

First time online shoppers

In this section, we focus on respondents who indicated that they had zero deliveries in 30 days before COVID-19 and shopped online and made home deliveries during the COVID-19 period. From Table 1, 69 respondents indicated that they made zero home deliveries in 30 days before COVID-19. Thirty five out of the 69 indicated that they ordered home deliveries during COVID-19 lockdown period. We created a new variable, which takes value 1 if a respondent who did not participate in online shopping before COVID-19 participated in online shopping during COVID-19 period. A binary logit model was run, where each of the variables studied in section 4 was introduced one by one. Due to the low sample size, a large number of these variables were found to be insignificant at 5% level. Fig. 11 shows the logit model coefficients for the variables which were found to be significant.

Households with disabled members were most likely to be first time online shoppers due to COVID-19 lockdown. Respondents with delivery subscriptions were also more likely to shop online for the first time or the

Table 3
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	31.0	30K to 49,999	202	19.9
45-64	284	28.0	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	59.1
Yes	553	54.5	Yes	415	40.9
Are you Retired?			Are you a Student?		
No	837	82.5	No	945	93.1
Yes	178	17.5	Yes	70	6.9
Can you work from home?			Presence of household member with disability?		
No	817	80.5	No	837	82.5
Yes	198	19.5	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 children		
0	774	76.3	0	785	77.3
1	143	14.1	1	127	12.5
2 or higher	98	9.6	2 or higher	103	10.1
Vehicle Count					
0	93	9.2			
1	347	34.2			
2	375	36.9			
3 or higher	200	19.7			

other way around because it is not possible to determine a direction of causality from the survey data. This is a surprising result. One possible explanation is that respondents who shopped online for the first time took delivery subscriptions before shopping online. The online experience is an important factor that increases the likelihood of a person engaging in online shopping for the first time. The results also show that people who are concerned about health are more likely to move to shop online for the first time during the pandemic.

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 reasonable 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. One possibility to reduce the delivery cost is to leverage the public transit services, which are experiencing reduced ridership for making deliveries. In Spring 2020, several transit agencies across the US, launched delivery service programs for groceries and prescriptions for vulnerable members of the population (Benedict et al., 2020). This could be expanded to provide a lower-cost delivery alternative. Another possibility is for delivery companies to have specifically targeted free delivery days for customers, such as Amazon Day (Amazon, 2021). This way, the delivery services can aggregate deliveries to certain areas and offer services at reduced costs.

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. Online experience and health concerns also increase the likelihood of a person shopping online for the first time during the pandemic. Companies like Alibaba are developing e-commerce interfaces specifically customized to people over the age of 55 years (Chan, 2018). 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. Developing multilingual shopping interfaces may also help increase access to online shopping platforms among certain communities.

The propensity to order online deliveries increases for higher income, tech-savvy individuals who are comfortable using computers and smartphones. The lower-income population is less likely to shop online. However, the lower-income population is also disproportionately affected by COVID-19 from a health 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 by adopting programs found effective in other settings. In Portland, Trimet, the transit agency, has a successful reduced fares program for low-income travelers. Home delivery services companies must be encouraged and incentivized to provide reduced delivery charge options for lower-income community members to access food, grocery, and prescription delivery services. Another possibility is the distribution of vouchers for home-delivery services and other alternative payment options. For example, several bike-share agencies offer subsidized membership and cash payment options to improve access. Similar programs must be developed for home delivery services also (Biketown, 2021).

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 socio-demographic variables.

There was a significant increase in home deliveries during the COVID-19 lockdown relative to the before COVID-19 period. Nearly two-thirds (63.4%) of the households making 1 to 2 home deliveries, and

Table 4
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$\geq$65 years old						
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 children $\leq$ 12 years old						
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						

(*continued on next page*)

Table 4 (*continued*)

	Before COVID-19		During COVID-19		Post-COVID-19	
Variable	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
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	

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. A reasonable proportion of the households that made less than three deliveries per month before the pandemic will order more online post-pandemic. However, most respondents who actively participated in online shopping 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. The likelihood of tech-savvy individuals making a higher number of home deliveries is higher during the post-COVID-19 period than the COVID-19 period, which 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.

The research also looked at factors that increase the likelihood of a person shopping online for the first time during the COVID-19 pandemic. Households with disabled members and with one worker are more likely to be first-time online shoppers. People who are concerned about online experience and health issues are also more likely to be first-time online shoppers during the pandemic. It is likely that some first-time online shoppers acquire a delivery subscription since this variable was also significant.

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. This study also provides the foundation for the estimation of more complex models that can deal with correlations and endogeneity issues among the analyzed variables.

CRediT authorship contribution statement

Avinash Unnikrishnan: Conceptualization, Data curation, Formal analysis, Methodology, Software, Writing - original draft. **Miguel Figliozzi:** Conceptualization, Data curation, Formal analysis, Methodology, Writing - review & editing.

Declaration of Competing Interest

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

Appendix A Survey Questions

1. What is your age?
2. What is your gender?
   - Male
   - Female
   - Other
3. Which category represents your household income before taxes for the last year (2019 income)?
   - Less than $10,000
   - $ 10,000 to $ 29,999
   - $ 30,000 to $ 49,999
   - $ 50,000 to $ 99,999
   - Greater than $ 100,000
4. How many hours do you spend per week utilizing a desktop, laptop, tablet, or smartphone?
   - 0 to 3 hrs
   - 3 to 10 hrs
   - 10 to 25 hrs
   - 25 to 40 hrs
   - More than 40 hrs
5. Do you or members of the household have free delivery service subscription such as Amazon Prime, Instacart Express, or any other delivery service?
   - Yes
   - No
6. When deciding between purchasing at a physical store or ordering online for a home delivered product, what factors are most important? For each factor assign a number ranging from 0 to 5, assign 0 if a factor is not relevant and 5 for the most important factor(s).
   - Home delivery cost
   - Home delivery time
   - Easy online experience
   - Personal health and safety concerns
7. Do you currently work for pay or profit?
   - Yes
   - No
8. What best describes your current situation?
   - Homemaker
   - Student
   - Unemployed before COVID-19
   - Temporarily unemployed or furloughed after COVID-19
   - Retired
9. Do you work full-time or part-time at your primary job?
   - Full-time
   - Part-time
10. Before COVID-19 stay at home orders, how many days per week, did you usually work from home?
    - 0
    - 1
    - 2
    - 3
    - 4 or more

11. What is the size of your household?
    - 1
    - 2
    - 3
    - 4
    - 5 or higher
12. How many members of your household work?
    - 0
    - 1
    - 2
    - 3
    - 4 or higher
13. How many members of your household are 65 years or older?
    - 0
    - 1
    - 2
    - 3
    - 4 or higher
14. How many members of your household are 12 years or younger?
    - 0
    - 1
    - 2
    - 3
    - 4 or higher
15. Do you or any of the members of the household have any disability or chronic health conditions that require assistance?
    - Yes
    - No
16. How many vehicles does your household own or lease?
    - 0
    - 1
    - 2
    - 3
    - 4 or higher

Appendix B

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