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# Factors Affecting Home Deliveries Before and During COVID-19 Lockdown: Accessibility, Environmental Justice, Equity, and Policy Implications

Miguel Figliozi

*Portland State University, [figliozi@pdx.edu](mailto:figliozi@pdx.edu)*

Avinash Unnikrishnan

*Portland State University, [uavinash@pdx.edu](mailto:uavinash@pdx.edu)*

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# **Factors Affecting Home Deliveries Before and During COVID-19 Lockdown: Accessibility, Environmental Justice, Equity, and Policy Implications**

**Miguel A. Figliozi (corresponding author)**

Professor, Department of Civil and Environmental Engineering  
Portland State University, Portland, OR, 97201  
Email: [figliozi@pdx.edu](mailto:figliozi@pdx.edu)

**Avinash Unnikrishnan**

Associate Professor Department of Civil and Environmental Engineering  
Portland State University, Portland, OR 97201  
Email: [uavinash@pdx.edu](mailto:uavinash@pdx.edu)

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1 **Factors Affecting Home Deliveries Before and During COVID-19**  
2 **Lockdown: Accessibility, Environmental Justice, Equity, and Policy**  
3 **Implications**  
4

5  
6 **ABSTRACT**  
7

8 During the COVID-19 lockdowns, home deliveries have changed from being a desirable luxury or  
9 comfortable solution to a health-supporting and essential service for many COVID-19 at-risk  
10 populations. However, not all households are equal in terms of access to home deliveries. The onset of  
11 COVID-19 has brought to light access inequalities that preceded the pandemic and that the COVID-19  
12 lockdown has exacerbated and made visible. The concept of home-based accessibility (HBA) is  
13 introduced, and novel research questions are addressed: (i) What type of households had zero home  
14 deliveries before COVID-19 lockdown? (ii) How the COVID-19 lockdown affected the type of  
15 households that receive home deliveries? and (iii) What are the implications of no access to home  
16 delivery services in terms of equity and environmental justice? To answer the first two questions,  
17 exploratory and confirmatory models are estimated utilizing data collected from an online survey  
18 representative of the population in the Portland metropolitan region. Policy and environmental equity  
19 implications are discussed using the concept of home-based accessibility (HBA). The results indicate  
20 that traditionally underserved populations, especially low-income populations, are less likely to benefit  
21 from home-based delivery services and that COVID-19 may have worsened home delivery inequalities.

22  
23 **KEYWORDS:** home deliveries, e-commerce, COVID-19, environmental justice, equity, accessibility

1 **1. Introduction**

2 In 2020 the COVID-19 pandemic and consequent lockdowns isolated households in an effort to slow  
3 down the spread of the disease. Mobility was discouraged, and citizens were urged or forced in some  
4 countries to stay at home. These changes significantly altered social interactions, work, education, and  
5 entertainment activities. During lockdowns, home deliveries changed from being a desirable luxury or  
6 comfortable solution to a health-supporting and essential service for many COVID-19 at-risk  
7 populations. However, not all households were equals in terms of access to home deliveries. The onset  
8 of COVID-19 brought to surface access inequalities that preceded the pandemic and that the COVID-  
9 19 lockdown has exacerbated and made visible.

10 Although some researchers have studied the transportation and logistics impacts of home deliveries in  
11 terms of congestion, curb demand, and parking, e.g. (Chen, Conway and Cheng, 2017), to the best of  
12 the authors' knowledge, there has been no research effort focusing on home deliveries, environmental  
13 justice, and equity. Therefore, this research explores socio-demographic factors associated with home  
14 delivery access before and during COVID-19 lockdown as well as implications of the results in terms  
15 of environmental justice and equity.

16 More specifically, this research focuses on answering these novel research questions: (i) What type of  
17 households had zero home deliveries before COVID-19 lockdown? (ii) How the COVID-19 lockdown  
18 affected the type of households that receive home deliveries? and (iii) What are the implications of no  
19 access to home delivery services in terms of equity and environmental justice? The first two questions  
20 are answered by estimating logistic models utilizing data collected from an online survey in the greater  
21 Portland metropolitan region. Policy and environmental equity implications are discussed using the  
22 concept of home-based accessibility (HBA).

23 This research defines HBA as the ease of accessing essential services and home deliveries of products  
24 such as groceries, meals, and medicines without leaving home. HBA is particularly relevant when  
25 mobility has been restricted (e.g., during COVID-19 lockdowns) or for individuals that, even in normal  
26 times, cannot easily access essential products due to physical disabilities or other mobility barriers.  
27 During a lockdown, for example, many individuals are not able to use any form of transportation to

1 access shopping simply because brick and mortar destinations are closed, or options are severely limited.  
2 At a personal or individual level, an individual or household may have the capacity to travel and access  
3 shopping destinations (using one or more modes), but in practice, this option is severely restricted  
4 because of the risk of falling ill or spreading the disease are high.

5 This research is organized as follows: Section 2 presents a literature review and an overview of relevant  
6 trends related to e-commerce and home deliveries. Section 3 describes the data collection effort and  
7 general data statistics. Section 4 analyzes the relationship between traditional equity indicators and home  
8 delivery rates. Section 5 explores factors affecting pre-lockdown access to home deliveries, access to  
9 home deliveries during the lockdown, and access to delivery subscription services. Section 6 presents a  
10 confirmatory model that takes into account potential endogeneity and correlations among variables.  
11 Section 7 expands the concept of transportation accessibility and presents a definition of home-based  
12 accessibility or HBA. Section 8 discusses environmental justice and equity implications. Section 9  
13 proposes a set of policies to reduce HBA inequalities. Section 10 ends with conclusions.

## 14 **2. Literature Review**

15 The average number of deliveries per household per month has more than doubled from 2009 to 2017  
16 in the US, according to the National Household Travel Survey (NHTS) data (FHWA, 2018). This  
17 increase is linked to e-commerce growth. According to the United States Census Bureau, e-commerce  
18 sales in the US have been steadily increasing for the past two decades, but after the onset of the COVID-  
19 19 lockdown, the rate of growth has accelerated substantially. US retail e-commerce sales for the second  
20 quarter of 2020 increased by 31.8% from the first quarter of 2020 and 44.5% from the second quarter of  
21 2019 (USDC, 2020). Some sectors grew even faster, food delivery apps double their revenue  
22 (Sumagaysay, 2020), and grocery sales increased threefold during the early days of the pandemic (FMI,  
23 2020).

24 According to results from the 2017 NHTS, there are some key variables that affect home delivery  
25 frequency. Income is a key variable; households above the poverty line are twice as likely to make online  
26 purchases than households below the poverty line. In addition, online shopping increases with the  
27 frequency of Internet usage (FHWA, 2018). Income is a variable that is linked to other household

1 characteristics such as internet access, credit card access, education levels, and the number of household  
2 workers (Cao, Xu and Douma, 2012). According to some studies, income and age are the most important  
3 predictors of online shopping (Lee, Sener and Handy, 2015).

4 There is a long line of research efforts focusing on the impact of the transportation system on  
5 accessibility and disadvantaged populations. For example, access to employment and health care  
6 opportunities in Los Angeles, CA., was studied by Wachs and Kamugai in the early seventies (1973).  
7 Environmental equity should be an essential ingredient of transportation planning, and transportation  
8 policies should be compared by analyzing their impacts on the distribution of negative externalities  
9 across populations (Feitelson, 2002).

10 The concepts of transportation justice and equity can be analyzed utilizing political philosophies such  
11 as utilitarianism, libertarianism, intuitionism, Rawls' egalitarianism, and Capability Approaches  
12 (Pereira, Schwanen and Banister, 2017). These authors argue that a combination of Rawlsian and  
13 Capability Approaches can be used to frame transportation distributive justice concerns utilizing the  
14 concept of accessibility as a human capability. Accessibility is framed as the interactions of two key  
15 components: (i) the individual capability to access different mobility technologies (modes, vehicles) and  
16 (ii) the capability to reach key destinations (based on users' needs) utilizing the existing transport system.  
17 Component (i) includes factors such as physical and/or mental fitness and financial resources, as well  
18 as external factors, such as the design of the vehicles and availability of travel information (Pereira,  
19 Schwanen and Banister, 2017).

20 In the US, transportation equity or justice analysis focuses on populations that are specified in the Title  
21 VI of the Civil Rights Act of 1964 and Executive Orders 12898 and 13166 (Aimen and Morris, 2012).  
22 According to this legislation, for environmental justice analysis, underserved populations comprise low-  
23 income populations, minorities, populations with limited English, low-literacy populations, seniors,  
24 persons with disabilities, and transit-dependent populations. There are many terms with similar or close  
25 meanings used in the literature, such as: "historically underrepresented," "socially disadvantaged,"  
26 "vulnerable," "at-risk," "in-need," and "communities of concern." Following Aimen and Morris (2012),

1 this research utilizes hereon the term “traditionally underserved populations” or simply “underserved  
2 populations.”

3 There is a large body of literature focusing on transportation and equity, and the focus has been on  
4 accessibility to key activities. Indicators can be broken down into levels of accessibility by place (e.g.,  
5 isochrones, affordability, etc. from different locations) and people-based accessibility measures that  
6 recognize individual differences, for example, in terms of physical disabilities, time scarcity, household  
7 composition, and trip chaining constraints (Di Ciommo and Shiftan, 2017). Despite decades of research  
8 and development of accessibility measures, actual use and application in transportation planning have  
9 progressed at a slow pace, perhaps due to politics, lack of consensus on accessibility metrics, and  
10 transportation planning goals that focus on reducing congestion and/or improving well-established  
11 mobility metrics (Handy, 2020).

12 There have been research efforts discussing equity and accessibility for different modes such as transit  
13 (El-Geneidy *et al.*, 2016), active transportation (Wu *et al.*, 2019), and even from a green transportation  
14 perspective (Chen and Wang, 2020). The review of the literature indicates that there is no discussion of  
15 the role of home deliveries on accessibility, equity, and environmental justice. Nonetheless, home  
16 deliveries can play an important role in providing access to basic goods to underserved populations. For  
17 example, an analysis of grocery home delivery services coverage in the Portland metropolitan region  
18 shows that 94% of residents are in areas eligible for grocery home delivery and 91% of residents of a  
19 USDA-identified, low-income, low-access census tracts are in areas eligible for home deliveries  
20 (Keeling and Figliozzi, 2019). It is also argued in this research that home deliveries are particularly  
21 valuable to some populations like non-driver populations and people with mobility impediments or  
22 visual impairments.

23 The literature review indicates that there has been steady progress and a large body of publications  
24 focusing on transportation equity and environmental justice issues, but it also indicates the lack of work  
25 related to home delivery services and the impact of COVID-19 on environmental justice and equity.

1 **3. Data Collection**

2 The focus of the study is on a single geographic region to reduce variability and uncertainty regarding  
3 lockdown enforcement rules and timing. The online survey for this research was administered in the last  
4 week of May and the first week of June 2020. Oregon Governor Brown issued a “stay at home” executive  
5 order on March 23, and the stay of emergency was extended until July 6, 2020. During this time, traffic  
6 levels on the main Portland freeways dropped significantly (ODOT, 2020).

7 The data was collected utilizing an online survey targeting households in the greater Portland  
8 metropolitan area that includes several counties and cities and is also called the Portland-Vancouver-  
9 Hillsboro Oregon-Washington Metro Area. This metro area has a total population of approximately 2.5  
10 million people spread over nearly 7,000 square miles (Census Reporter, 2020). To obtain a  
11 representative sample of the population, the following demographic quotas were imposed: (a) at least  
12 40% representation of males or females in the sample, (b) a minimum quota of 20% was imposed for  
13 each of these household annual income categories: 0-\$50,000, \$50,000-\$100,000, and greater than  
14 \$100,000, and finally (c) an age-related quota mandating at least a 20% representation in the following  
15 categories 18-29, 30-44, and 45-64 and at least 8% in 65 and above. The data collection was limited to  
16 respondents above 18 years old.

17 Regarding race, nearly 78% of the respondents were White, with Asians being the second-highest  
18 respondents at approximately 8%. Hispanic- Latinos reach a 5 % representation and African Americans  
19 3.3 %. Other races account for 5.4 % of the respondents. This representation is realistic according to US  
20 census data given that in the Portland region, this is the population distribution by race: White 73%,  
21 Asian 7%, Hispanic-Latino 12%, Black 3%, other races (Two+, Native, Islander) account for  
22 approximately 5% of the population (Census Reporter, 2020).

23 A majority of the respondents are females, and the minimum, median, average, and maximum age in  
24 the dataset are 18, 40, 43.2, and 86, respectively. The median sample age is close to the median age of  
25 the metro region, being 38.4 (Census Reporter, 2020). There is a proper distribution of respondents  
26 among various age categories, with nearly 15% of the respondents being at or close to retirement age.



1 There is a good representation of respondents among the income levels, with more than half of the  
2 respondents having a household annual income of greater than \$50,000. This is consistent with the  
3 income distribution of the Portland metro region, which has a median household income of nearly  
4 \$76,000 (Census Reporter, 2020). Regarding occupation, this is the breakdown of the responses 41%  
5 full time workers, 14% part-time workers, 18% retirees, 8% homemakers, 7% students, 5% unemployed  
6 before COVID-19, and 8% temporarily unemployed or furloughed after COVID-19. As a reference, the  
7 unemployment rate before COVID-19 was close to 4% (June 2019) and surged during the lockdown to  
8 11.4 (June 2020) in the Portland region according to the Bureau of Labor Statistics (BLS, 2020).

9 Slightly more than one-third of the respondents belong to households with two members. Nearly 80%  
10 of the households have at least one worker. More than half of the respondents spent more than 25 hours  
11 per week on desktop, laptop, tablets, or smartphones. The survey also collected information on  
12 employment type, the number of elderly members in the household. Almost 20% of the respondents  
13 worked in professional, managerial, or technical jobs. Nearly one-fourth of the respondents have at least  
14 one member of the household aged over 65 years. A summary of the key socio-demographic variables  
15 is presented in **Table 1**. All tables herein are produced using the collected survey data.

16 Logical checks were applied to the data by comparing the household size with the number of workers,  
17 number of children, number of elderly and inconsistent responses were removed. After data cleaning,  
18 the dataset has 1,015 fully complete and clean responses that are utilized in the estimation of all the  
19 models presented in this research. In addition, Likert-type attitudinal questions related to products that  
20 are delivered utilizing same day or next day (SDND) delivery are summarized in **Table A.1** in the  
21 Appendix. **Table A.2** in the Appendix summarizes Likert type responses regarding attitudes towards  
22 brick and mortar and online/home delivery attributes.

1 **Table 1: Distribution of relevant demographic and household variables (1,015 observations)**

Variable	Relative Frequency as %	Variable	Relative Frequency as %
Age		Education	
18-29	26	Less than high school	4
30-44	31	High School/GED	17
45-64	28	College or Associates	34
>= 65	15	Bachelors	30
		Graduate degree	15
Annual Income		Household Size	
Less than \$ 10,000	10	1	20
\$10,000 to \$ 29,999	15	2	35
\$30,000 to \$ 49,999	20	3	17
\$ 50,000 to \$ 99,999	27	4	17
Greater than \$ 100,000	28	5 or higher	11
Number of Workers		Number of children	
0	21	0	76
1	35	1	13
2	34	2	8
3	7	3	2
4 or higher	3	4 or higher	1
Number of Vehicles		Weekly hrs on desktop, laptop, smartphone	
0	9	0 to 3 hrs	5
1	34	3 to 10 hrs	15
2	37	10 to 25 hrs	27
3	14	25 to 40 hrs	27
4 or higher	6	More than 40 hrs	26
Occupation		Gender	
Full-time employed	41	Female	60
Part-time employed	14	Male	39
Retired	17	Other	1
Homemaker	8	Subscription Service	
Student	7	No	30
Unemployed before COVID	5	Yes	70
Unemployed after COVID	8		

2

3 **4. Equity Indicators**

4 This section describes the relationship among several key equity and transportation accessibility  
5 indicators, such as income level, race, education level, vehicle ownership, and technological access (Di  
6 Ciommo and Shiftan, 2017). In addition, the relationships between income levels and delivery rates and  
7 access to a delivery subscription and delivery rates are also explored. Income level distribution is utilized  
8 in all the tables to facilitate comparisons.

9 **Table 2** shows how income levels are related to race, education level, vehicles per household, and  
10 utilization of electronic devices. Respondents that declared themselves White or Asian are more likely

1 to belong to higher income levels than respondents that declared themselves African American,  
 2 Hispanic-Latino, or Native American.

3 **Table 2: Equity Indicators and Annual Household Income Distribution (%)**

Variable	Level	Less than \$10,000	\$10,000 to \$30,000	\$30,000 to \$50,000	\$50,000 to \$100,000	Greater than \$100,000	Total (row sum)
Race	African American	24.2	18.2	27.3	18.2	12.1	100
	Asian	3.9	14.3	20.8	33.8	27.3	100
	Hispanic-Latino	15.7	11.8	33.3	15.7	23.5	100
	Native American	9.1	36.4	36.4	18.2	0.0	100
	White	9.5	15.2	18.3	27.3	29.6	100
	Other	8.5	19.1	21.3	27.7	23.4	100
Educat. Level	Less than HS	71.4	5.7	11.4	8.6	2.9	100
	HS - GED	21.3	26.4	23.0	18.0	11.2	100
	College Associate	7.5	23.2	25.5	24.6	19.1	100
	Bachelor	2.6	6.6	16.8	36.0	38.0	100
	Graduate	1.9	5.2	11.7	27.9	53.2	100
Vehicles per Househ.	0	41.9	29.0	19.4	5.4	4.3	100
	1	6.9	23.1	27.1	28.8	14.1	100
	2	6.4	8.5	15.7	30.4	38.9	100
	3	6.5	9.4	18.1	28.3	37.7	100
	4+	6.5	8.1	9.7	22.6	53.2	100
Hours Using Electron. Devices	0 to 3	29.8	29.8	25.5	10.6	4.3	100
	3 to 10	14.1	20.8	24.8	23.5	16.8	100
	10 to 25	10.3	13.1	21.6	28.7	26.2	100
	25 to 40	5.9	15.8	19.4	26.4	32.6	100
	More than 40	7.6	12.1	14.8	29.9	35.6	100

4  
5

6 Respondents that achieved Bachelor or Graduate levels of education are likely to belong to higher  
 7 income levels, whereas respondents with less than High School education are highly likely to belong to  
 8 the lowest income level. Automobile or vehicle ownership is an important input to trip planning models  
 9 and can also be used as an equity/accessibility indicator. There is a clear correlation between vehicles  
 10 per household and income levels, and this finding is consistent with commuter travel trends regarding  
 11 household size, the number of workers per household, and mode choice in the Portland region (METRO,  
 12 2015). Travel mode is also a function of the number of vehicles per household. Households with zero  
 13 vehicles show a higher transit and walk mode share (>30%). For modes bicycle, transit, and walk 69%,  
 14 61%, and 67% of the observations, respectively, take place in households with zero or one vehicle. For  
 15 mode “auto” and working from home, 64% and 58% of the observations occur in households with two  
 16 or more vehicles. Details are shown in **Table A.3** in the Appendix.

1 Finally, there is also a clear trend indicating that respondents with low utilization of electronic devices  
 2 tend to belong to - low income level. In contrast, respondents that utilize electronic devices more than  
 3 25 hours per week tend to belong to high-income levels. Since most computers and smartphones are  
 4 connected to the internet, this variable is also a good proxy for potential access to online shopping.  
 5 There is a clear trend linking access to a delivery subscription and household income levels, as shown  
 6 in **Table 3**. Nearly 60% of the households *without* a delivery subscription have annual incomes below  
 7 \$50,000, whereas nearly 60% of the households *with* a delivery subscription have annual incomes  
 8 greater than \$50,000.  
 9 Pre-COVID-19, nearly 59% of the households with delivery rates over 10 per month have annual  
 10 incomes greater than \$100,000, whereas nearly 65% of the households with zero deliveries have annual  
 11 incomes below \$50,000. This difference was accentuated during the COVID-19 lockdown, nearly 68 %  
 12 of the households with delivery rates over 10 per month have annual incomes greater than \$50,000,  
 13 whereas nearly 70% of the households with zero deliveries have annual incomes below \$50,000.  
 14 Unfortunately, there was no follow-up question inquiring about the reasons behind the lack of home  
 15 deliveries.

16 **Table 3: Annual Household Income Distribution by Access to Deliveries (%)**

Variable	Level	Less than \$10,000	\$10,000 to \$30,000	\$30,000 to \$50,000	\$50,000 to \$100,000	Greater than \$100,000	Total (row sum)
Delivery Subscription	No	18.4	21.1	21.0	25.6	13.9	100
	Yes	6.1	13.0	19.4	27.4	34.1	100
Pre-COVID Monthly Delivery Rate	0	18.8	27.5	20.3	23.2	10.1	100
	1 to 2	9.6	18.0	20.1	28.1	24.2	100
	3 to 5	9.7	12.8	20.3	27.8	29.4	100
	6 to 10	6.7	7.7	17.3	26.9	41.3	100
	More than 10	8.3	11.9	20.2	19.0	40.5	100
COVID Monthly Delivery Rate	0	27.1	24.3	18.6	20.0	10.0	100
	1 to 2	13.7	19.8	21.3	27.9	17.3	100
	3 to 5	8.4	19.0	20.9	26.2	25.5	100
	6 to 10	6.8	9.1	20.1	29.9	34.1	100
	More than 10	5.5	9.8	16.6	24.5	43.6	100

17  
 18 Comparing before and during answers it is possible to observe that the overall number of households  
 19 that received “0” (zero) or “3 to 5” deliveries barely changed. However, there was a large decrease in  
 20 the “1 to 2” category and large increases in the “6 to 10” and “More than 10” categories, as seen in

1 **Table 4.** The null hypothesis stating equality of proportions before and during the lockdown is rejected.  
 2 As mentioned previously, the lockdown coincided with a dramatic increase in unemployment rates and  
 3 changes in the labor market are additional barriers to access home deliveries when they may be needed  
 4 the most. These changes may explain why the zero delivery rate remained almost unchanged.

5 **Table 4: Number of home deliveries in 30 days before and during COVID-19 lockdown**

Number of Deliveries in 30 days	Before COVID-19 Lockdown		During COVID-19 lockdown		Difference During minus Before
	Frequency	%	Frequency	%	
0	69	6.8	70	6.9	1.4
1 to 2	438	43.2	197	19.4	-55.0
3 to 5	320	31.5	321	31.6	0.3
6 to 10	104	10.2	264	26.0	153.8
More than 10	84	8.3	163	16.1	94.0
Total	1015	100.0	1015	100.0	

6  
 7 The next section presents the results of exploratory models that link sociodemographic variables to  
 8 home deliveries before and during the lockdown.

9 **5. Exploratory Analysis of Access to Home Deliveries**

10 Given the lack of research and background in the area of home deliveries and equity (in general) and  
 11 during a lockdown (in particular), the research methodology is divided into two approaches: a)  
 12 exploratory analysis and b) confirmatory analysis. The goal of the former (this Section) is to get a sense  
 13 of the key variables and relationships; the goal of the latter (next Section) is to provide a joint and more  
 14 efficient estimation of a model with structural relationships that takes into account correlation among  
 15 variables and leverage the results of the exploratory analysis.

16 **5.1. Exploratory Analysis Methodology**

17 In the exploratory analysis logistic regressions are utilized. Logistic regressions are useful to model the  
 18 probability of binary events, such as whether a household receives home deliveries. In the logistic model,  
 19 the log-odds for the dependent variable with the value “one” is a linear combination of one or  
 20 more independent variables that can be of different types such as categorical, interval, or ratio variables.

1 Following Feitelson (2002), the goal of estimating these models is to understand HBA across different  
2 populations.

3 In the exploratory analysis, the binary logit regression models were estimated utilizing the “glm”  
4 function from the MASS package in R (Ripley *et al.*, 2013). Variables were selected using a backward  
5 and forward selection procedure accounting for meaning, correlations, and significance, as well as  
6 changes in log-likelihood (LL) and Akaike Information Criteria (AIC) values. A p-value threshold of  
7 0.05 or less was used to determine significance. Insignificant variables were removed one at the time.

8 The dependent variables utilized to answer the research questions were initially whether a household  
9 received home deliveries *before* the COVID-19 lockdown and whether a household received home  
10 deliveries *during* the COVID-19 lockdown. In addition, a second set of logistic regression models were  
11 estimated, focusing on whether a household received home deliveries below or above the median pre-  
12 lockdown delivery rate. Finally, because having a delivery subscription is a key variable in all the  
13 estimated models, a model was estimated utilizing delivery subscription as the binary dependent variable.

14 In this exploratory section with exploratory results, the Likert type responses shown in **Tables A.2** and  
15 **A.3** are treated as numerical variables (treated as ordinal variables in the confirmatory model though).  
16 If there is a “>” sign, then Likert type responses are treated as categorical variables. For example, “Easy  
17 Online Experience” is a numerical variable from 0 to 5, whereas “Easy Online Experience >3” is a  
18 categorical (binary) variable with a zero assigned to responses 0 to 3 and a one assigned to responses 4  
19 to 5.

20 **5.2. Access to Home Deliveries Before the Lockdown**

21 Survey respondents had to answer this question: “In a typical month BEFORE COVID-19, how many  
22 times did you or members of your household purchase something online and have it delivered to your  
23 home?” The focus of this research is on households with zero deliveries. The results of the logistics  
24 regression where the dependent variable is zero for no deliveries and one for deliveries greater than zero  
25 are shown in **Table 5** (upper section). Zero or no delivery is the reference used in the estimation of the  
26 models.

Henceforward, in the analysis and discussion of the statistically significant variables, it is implicit that the sign and magnitude of the coefficients are discussed *ceteris paribus*. The results indicate that larger households (more workers and/or the number of children 12-year-old or younger) are more likely to receive home deliveries before COVID-19. Travel to work by transit reduces the likelihood of receiving home deliveries. It is important to note that the pandemic reduces transit ridership significantly but mostly in zones with higher percentages of white, educated, and high-income individuals and that ridership had lower decline in areas with “essential” jobs (Hu and Chen, 2021).. Finally, having a delivery subscription and indicating that a good online experience is a relevant factor is associated with receiving home deliveries.

10

11 **Table 5: Results of Delivery Models Before COVID-19 Lockdown**

<b>(a) Having Deliveries Before COVID-19 Lockdown</b>				
<b>Variables</b>	<b>Coef.</b>	<b>Std. Error</b>	<b>z value</b>	<b>Pr(&gt; z )</b>
Intercept	0.246	0.261	0.943	0.346
Delivery Subscription	1.975	0.318	6.221	0.000
Number of Household Workers	0.384	0.171	2.237	0.025
Number of Household Members Age $\leq$ 12	0.900	0.397	2.267	0.023
Travel to Work (pre-COVID) by Transit	-1.219	0.499	-2.445	0.014
Easy online experience	0.343	0.077	4.455	0.000
<b>(b) More than 2 Home Deliveries per month Before COVID-19 Lockdown</b>				
<b>Variables</b>	<b>Coef.</b>	<b>Std. Error</b>	<b>z value</b>	<b>Pr(&gt; z )</b>
Intercept	-2.679	0.494	-5.420	0.000
Age (years)	-0.011	0.005	-2.320	0.020
Delivery Subscription	1.016	0.160	6.370	0.000
Electronic device use > 3 hrs per week	0.971	0.370	2.620	0.009
Number of Household Members (size)	0.185	0.060	3.090	0.002
At least one Vehicle per Household	0.539	0.269	2.010	0.045
Working from Home (pre-COVID)	0.650	0.317	2.050	0.040
Easy online experience (> 4)	0.525	0.160	3.270	0.001
Cost at a nearby store (> 3)	-0.293	0.142	-2.070	0.039
Meals Same/Next Day Delivery	0.096	0.034	2.800	0.005
FBPC Products SDND Delivery (> 2)	0.501	0.176	2.840	0.005
Recreational Items SDND Delivery (> 0)	0.394	0.154	2.560	0.010

12 SDND = Same Day/Next Day

13

14 In the survey, almost 50% of the respondents declared that their households received two or less  
 15 deliveries per month pre-COVID-19. Another logistic model was estimated to understand what are the  
 16 factors that separate households below and above the median (two or less deliveries is the reference, see

1 **Table 5** lower section). Two variables (Delivery Subscription and Easy Online Experience) are present  
2 in both models. There are several new variables in the above-median model:

- 3 - Age is a significant variable with a negative sign indicating less propensity for home deliveries for  
4 older consumers
- 5 - Utilizing electronic devices three or more hours per week is also a significant variable and, like  
6 Delivery Subscription and Easy Online Experience, indicates that internet access and a minimum  
7 level tech-savviness is necessary to be above the median.
- 8 - Household size is significant, as well as having at least one vehicle per household. This can be  
9 contrasted with the access model (**Table 3**), where commuting by transit is a negative variable.  
10 Working from home pre-COVID lockdown also increases the likelihood of receiving deliveries  
11 above the median.
- 12 - Cost at a nearby store is deemed a significant factor and associated with more deliveries, indicating  
13 that households are aware of potential price differences between e-commerce and brick and mortar  
14 retailers.
- 15 - Finally, a higher number of deliveries is likely when the same day or next delivery is considered  
16 important for meals, fashion, beauty and personal care (FBPC) products, and recreational items.

17 To estimate the relative contribution of each significant variable to the model, the AIC absolute change  
18 between the full model and the model when one variable at the time is removed (*ceteris paribus*) is  
19 shown in Appendix **Table A.4**. Delivery Subscription and Easy online experience are the top variables  
20 in both models though access to a delivery subscription is clearly the critical variable in both models.

### 21 **5.3. Access to Home Deliveries During the COVID-19 Lockdown**

22 The sudden onset of the COVID-19 pandemic and consequent lockdowns have significantly altered the  
23 way people work, educate themselves or their children, and seek recreation. It is important to understand  
24 how home deliveries have changed during the lockdown and from an equity perspective to understand  
25 what populations may be underserved or without access to home deliveries during the pandemic.

26 Survey respondents had to answer this question: “In the last 30 days, AFTER COVID-19 lockdown  
27 started, how many times did you or members of your household purchase something online and have it



1 delivered to your home?” To compare pre- and during-COVID-19 lockdown models, this section  
2 presents the results of a logistic model where the dependent variable is zero for no deliveries and one  
3 for deliveries greater than zero (see **Table 6**, upper section) and the results of a logistic model where the  
4 dependent variable is whether households had more than two deliveries per month during the lockdown  
5 (see **Table 6**, lower section).

6 The number of deliveries pre-COVID-19 was included as an independent variable, as expected, this is  
7 a significant variable in both models, though with different coefficients and specification. Pre-COVID  
8 deliveries is a lagged variable and correlated with the dependent variable, these issues are addressed in  
9 the next section with a more advanced confirmatory model. The results of the first model (see **Table 6**,  
10 upper section) indicate that not receiving home deliveries pre-lockdown is significant, as well as access  
11 to a delivery subscription. However, several independent variables that are meaningful from an equity  
12 perspective are now significant. Hispanic-Latino households are less likely to receive home deliveries.  
13 Education levels below college associate, i.e., high school or less, are also less likely to receive home  
14 deliveries during the lockdown. The pandemic has affected Hispanic families in the US  
15 disproportionately in terms of health impacts and unemployment, in particular the labor market has  
16 worsened significantly for Hispanic women (Fernandez *et al.*, 2020; Gonzalez *et al.*, 2020).

17 As previously seen in the data description, there are clear links among income level, race, and  
18 educational achievement. In addition, respondents that deem important cost at a nearby store are less  
19 likely to receive home deliveries, but respondents that deem important delivery costs are more likely to  
20 receive home deliveries *ceteris paribus*. The significant variables in **Table 5** (having deliveries pre-  
21 lockdown) are related to household size and transit usage instead of race and education attainment.

1 **Table 6: Deliveries During COVID-19 Lockdown**

<b>(a) Having Deliveries During COVID-19 Lockdown</b>				
<b>Variables</b>	<b>Coef.</b>	<b>Std. Error</b>	<b>z value</b>	<b>Pr(&gt; z )</b>
Intercept	2.156	0.358	6.03	0.000
No home deliveries (pre-COVID)	-2.478	0.34	-7.28	0.000
Delivery Subscription	2.024	0.356	5.68	0.000
Hispanic-Latino	-1.218	0.531	-2.29	0.022
Education less than College Associate	-0.749	0.315	-2.38	0.017
Home delivery cost (> 1) *	1.113	0.333	3.34	0.001
Cost at a nearby store (> 3) *	-0.793	0.327	-2.43	0.015
<b>(b) More than 2 Home Deliveries per month During COVID-19 Lockdown</b>				
<b>Variables</b>	<b>Coef.</b>	<b>Std. Error</b>	<b>z value</b>	<b>Pr(&gt; z )</b>
Intercept	0.328	0.343	0.955	0.340
No Home deliveries (pre-COVID)	-2.130	0.343	-6.201	0.000
1 to 2 Home Deliveries (pre-COVID)	-1.029	0.194	-5.307	0.000
> 5 Home Deliveries (pre-COVID)	1.457	0.424	3.439	0.001
Delivery Subscription	0.767	0.174	4.403	0.000
Household Income less than \$10,000	-0.585	0.262	-2.238	0.025
Household Income greater than \$100,000	0.413	0.211	1.951	0.050
Personal health and safety concerns (num.) *	0.121	0.051	2.370	0.018
Easy online experience (> 0) *	0.849	0.290	2.925	0.003
Cost at a nearby store (> 1) *	-0.603	0.238	-2.535	0.011
Home delivery time (> 3) *	0.372	0.178	2.097	0.036

2

3

4 Another logistic model was estimated to understand the factors that separate households below and  
 5 above the median during the lockdown (**Table 6**, lower section). Delivery subscription and number of  
 6 deliveries pre-COVID are significant variables as expected. In addition, there are several new variables  
 7 in the median model:

8 - The extremes of household income are significant variables, households with an annual income  
 9 level below \$10,000 are less likely to receive home deliveries, and households with an annual  
 10 income level over \$100,000 are more likely to receive home deliveries

11 - During the COVID-19 lockdown, personal health and safety concerns are now a significant variable.  
 12 Being concerned about personal health increases the propensity to have home deliveries during the  
 13 lockdown.

14 - Cost at a nearby store is still a significant factor, as well as an easy online experience (same sign as  
 15 before). In addition, home delivery time became a significant variable during the lockdown.

1 Comparing the results of **Table 6**, three variables (pre-lockdown delivery rate, Delivery Subscription,  
2 and cost at a nearby store) are present in both models. To estimate the relative contribution of each  
3 significant variable to the model, the AIC absolute change between the full model and the model when  
4 one variable at the time is removed (*ceteris paribus*) is shown in **Table A.5** (in the Appendix) for during-  
5 Lockdown deliveries. Pre-lockdown delivery rates (lagged variables) are ranked highest, closely  
6 followed by Delivery Subscription.

#### 7 **5.4. Access to a Delivery Subscription**

8 Having a delivery subscription is a key variable for receiving home deliveries and exceeding the median  
9 delivery rate, as shown in the previous exploratory models. Before analyzing the results of this section,  
10 it is important to recognize that delivery subscriptions are not only utilized for home deliveries. For  
11 example, Amazon, which is the largest online retailer in the US offers many additional benefits and  
12 services linked to its subscription service called “Amazon Prime” (Amazon, 2020). Some of these  
13 additional benefits include free access to online streaming of movies and TV series, online books and  
14 reading material, online games, online music, photo storage and printing, credit card services, and  
15 monetary rewards. The *bundling* of services is a strategy that has been widely used by e-commerce  
16 marketplaces and intermediaries to attract and retain customers (Anderson and Anderson, 2002).  
17 Unfortunately, the strategy of bundling content, financial, and complementary goods/services with home  
18 delivery means that the importance of the delivery aspect cannot be easily isolated from the other  
19 elements of the bundle. This may explain why a small percentage of households with an annual  
20 subscription did not have home deliveries in a 30-day period. Amazon Prime currently has 126 million  
21 members in the US, and the number of subscriptions grew 13% between the last quarter of 2019 and the  
22 third quarter of 2020 (DigitalCommerce, 2020). The population of the US is approximately 323 million,  
23 which indicates that there is approximately 1 Amazon Prime subscription for 2.61 inhabitants on average.  
24 The results of the logistic regression for access to a delivery subscription are shown in **Table 7**. Not  
25 having access to a delivery subscription is the reference. The results have important implications in  
26 terms of equity and access to home deliveries. The extreme income levels are again significant variables

1 as well as the median household income of the zip code where the respondent resides. The results are  
 2 consistent, higher income is positively associated with having a delivery subscription.

3 Age is also significant, and the results are consistent with previous results and research; younger  
 4 respondents (between 18 and 30) have a higher likelihood of having a delivery subscription, and  
 5 households with at least one member over 65 are less likely to have a delivery subscription. High  
 6 utilization of electronic devices (over 40 hours per week) is positively associated with a delivery  
 7 subscription as well as the number of workers per household and household size.

8 Travel to work by automobile has a positive sign, whereas travel by bicycle a negative sign. In **Table 3**,  
 9 commuting by transit had a negative sign. Residing in an exurban area increases the likelihood of having  
 10 a delivery subscription. Urban, suburban, exurban, and rural areas (from high to low in terms of  
 11 population density) are classified based on the population and area of the zip code of the respondent.

12 Respondents that consider that medicines, groceries, and household/office products should be delivered  
 13 same day or next day are more likely to have a delivery subscription. Finally, respondents that value an  
 14 easy online experience are more likely to have a subscription.

15 **Table 7: Having a Delivery Subscription**

Variables	Coef.	Std. Error	z value	Pr(> z )
Intercept	-1.206	0.419	-2.87	0.004
Household Income less than \$10,000	-1.002	0.262	-3.82	0.000
Household Income greater than \$100,000	0.693	0.211	3.29	0.001
Median household income (at Zip code level) *	0.097	0.043	2.25	0.025
Age between 18 and 30	0.539	0.203	2.66	0.008
At least one household member age 65 or older	-0.493	0.188	-2.62	0.009
Electronic device use > 40 hrs. per week	0.580	0.194	2.99	0.003
More than one worker per household	0.457	0.195	2.35	0.019
Household size greater than 3	0.465	0.201	2.31	0.021
Travel to work (pre-COVID) by Automobile	0.439	0.183	2.40	0.017
Travel to work (pre- COVID) by Bicycle	-1.279	0.568	-2.25	0.024
Exurban Area	0.744	0.337	2.21	0.027
Easy online experience (>0)	0.761	0.264	2.89	0.004
Availability at a nearby store (>1)	-0.688	0.219	-3.15	0.002
Groceries Same/Next Day Delivery (>4)	0.771	0.251	3.08	0.002
Household/Office Goods Same/Next Day Delivery (>0)	0.597	0.175	3.42	0.001
Medicines Same/Next Day Delivery (>1)	0.556	0.192	2.90	0.004

16 \* In a \$10,000-dollar unit  
 17

1 To estimate the relative contribution of each significant variable to the model, the AIC absolute change  
2 between the full model and the model when one variable at the time is removed (*ceteris paribus*) is  
3 shown in **Table A.6** (in the Appendix) for the delivery subscription model. Income levels are ranked  
4 highest, but the differences are less pronounced than in the models seen in previous sections.

5 The results of the delivery subscription model indicate that several variables that are relevant from an  
6 equity perspective (income level, travel mode, access to electronic devices, number of workers) are also  
7 key variables to explain who has access to a delivery subscription.

## 8 **6. Confirmatory Analysis of Access to Home Deliveries**

9 Leveraging the results of the exploratory analysis, this section presents a confirmatory choice model  
10 with latent variables that simultaneously estimates all the parameters. To account for potential  
11 correlations among sociodemographic variables, models for income and subscription are proposed and  
12 they are linked to the binary model for deliveries utilizing latent variables and random components.  
13 Similarly, attitudinal variables are jointly estimated utilizing ordered logistic models based on the  
14 groupings that resulted from exploratory factor analysis as detailed in this section.

### 15 **6.1. Confirmatory Analysis Methodology**

16 The model utilized in this section jointly (simultaneously) estimates all the parameters for the before  
17 and during lockdown delivery data (panel choice data for before and after). Socio-demographic variables  
18 impact the binary logit delivery model, the subscription model, and the income level model as shown in  
19 **Figure 1**.

20 Based on the exploratory analysis, different sets of variables are utilized in each model. In particular,  
21 income is highly correlated with three household related variables: size, number of workers, and number  
22 of vehicles. In the income model, of these three potential variables, only the variable number of  
23 household workers is included because it is assumed that as the number of workers increases, then  
24 income and number of vehicles also increase (i.e. this direction of causality is more likely this way than  
25 in the opposite direction). In addition, the presence of a member with a disability or special need  
26 decreases household income. Other variables that are correlated with income such as age (correlation

1 0.13) and male (correlation 0.18) were also added to the income model. The highest correlations with  
2 the variable income are shown in **Table A.7** in the appendix.

3 Income is an ordered variable with five levels and sociodemographic variables (e.g. education level) are  
4 utilized in the measurement equations. The equation for the ordered variable income level  $y$  is as  
5 follows:

$$6 \quad y = Z + v$$

7  
8 where  $Z$  is the corresponding latent variable and  $v$  is the random (normal) component of the response  
9 for product or attitude. The measurement equations for the income level  $y_i$  includes the impact of socio-  
10 demographic variables as follows:

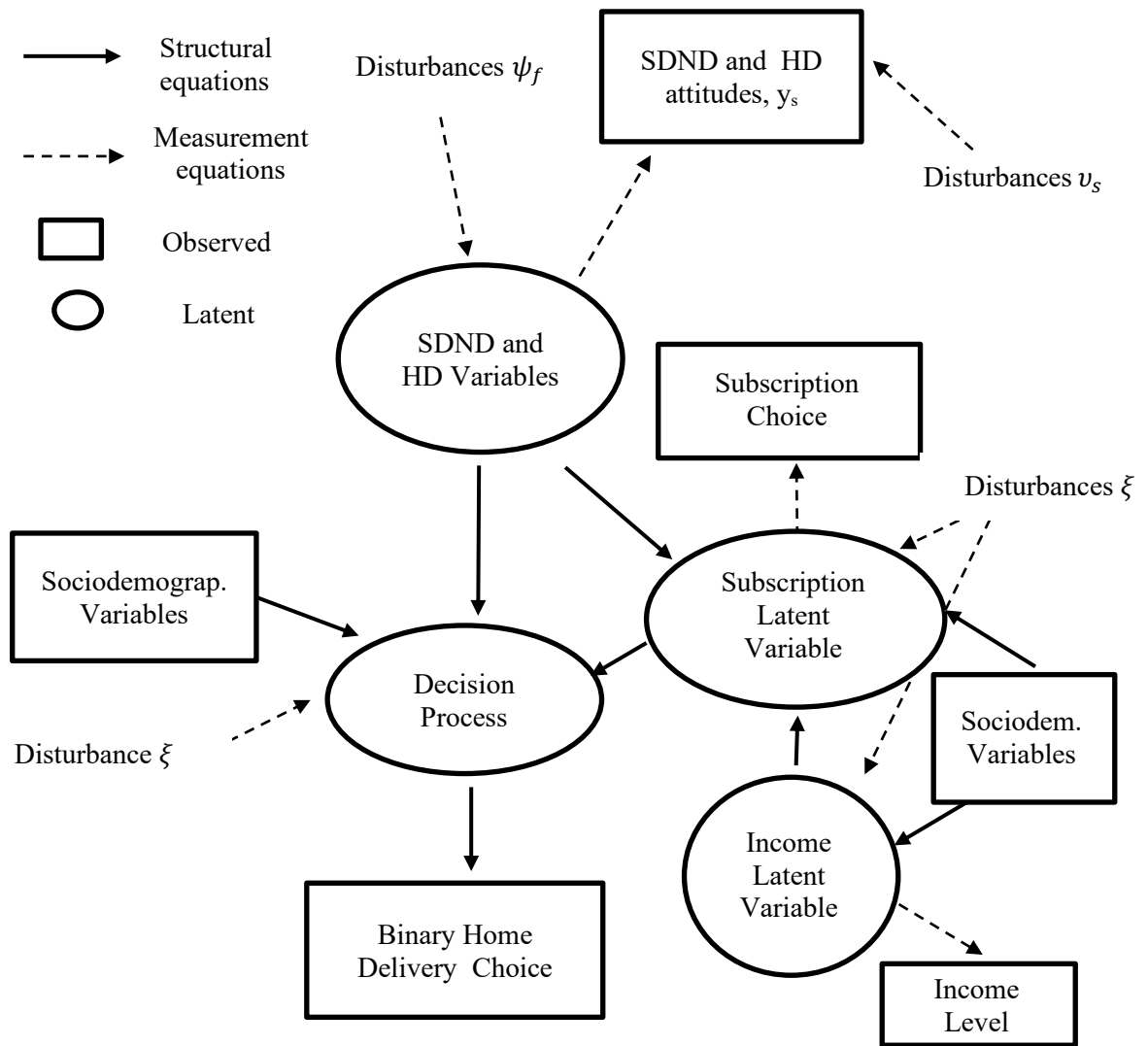
$$11 \quad Z_i = \sum_i \zeta_i x_{i,n} + \sigma_i \psi_{i,n}$$

12  
13  
14 The vector of parameters  $\zeta_i$  is estimated and each  $x_{i,n}$  is a socio-demographic variable (e.g. education  
15 level). The term  $\sigma_i \psi_{i,n}$  is a normally distributed error term with zero mean and standard deviation  $\sigma_i$ .

16 The probability that an individual  $n$  generates the observed income level  $q$  is estimated as follows:

$$17 \quad P\{Z_n = q\} = \Lambda(\tau_{y_i,q} - Z_n) - \Lambda(\tau_{y_i,q-1} - d_i Z_n)$$

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**Figure 1.** Confirmatory Model – adapted from Ben-Akiva et al. (2002)

The attitudinal variables are modeled utilizing ordered logit models that take into account the Likert type structure of the data and also impact both the binary logit delivery model and the subscription model. Some attitudinal factors are strongly correlated, and for an efficient estimation process, factors are determined after performing exploratory factor analysis (EFA) for the attitudinal questions (products ordered with same/next day (SDND) delivery and home delivery attitudes described in Appendix **Tables A.2** and **A.3**). The Kaiser-Meyer-Olkin (KMO) test was applied to measure the adequacy of the data for EFA (Fabrigar and Wegener, 2011). The overall KMO score is 0.80, and as a general guideline, KMO values between 0.8 and 1 are usually considered very good, between 0.8 and 0.6 are considered adequate, and below 0.6 considered inadequate for EFA. The values of each individual attitude range

1 between 0.60 and 0.88, which also indicates that the data is acceptable for EFA (details in **Table 8**, last  
 2 column). The EFA was performed using the Psych package in R (Revelle and Revelle, 2015) using the  
 3 oblique “Oblimin” rotation at its default parameters. The eigenvalue and parallel analysis suggested that  
 4 four factors would be adequate to capture the correlations between attitudes.

5 The first group is labeled “essential products” (groceries, meals, and medicine/health products). The  
 6 second group is labeled “non-essential products” and include electronics, fashion/beauty/personal care  
 7 products, recreational items, and household/office products. The third group is labeled “brick and mortar”  
 8 attributes (cost and availability), and the fourth factor, “home delivery” attributes (delivery cost and time  
 9 and online ordering experience).

10

11 **Table 8. Rotated factor loadings**

<b>Product SDND and Home Delivery Attitude</b>	Factor 1	Factor 2	Factor 3	Factor 4	KMO
Grocery SDND	0.72				0.79
Meals SDND	0.55				0.82
Medicine/health products SDND	0.38				0.88
Electronics SDND		0.76			0.87
FBPC SDND		0.73			0.88
Recreational Items SDND		0.83			0.84
Household/Office SDND		0.73			0.86
Availability at nearby story			0.62		0.60
Cost at nearby story			1.00		0.63
Cost of Delivery				0.70	0.72
Time of Delivery				0.83	0.77
Online Experience				0.54	0.81

12

13 The four factors identified are modeled utilizing measurement equations for each product or attitude  $s$   
 14 links the ordered response,  $y_s$ , as follows:

$$15 \quad y_s = d_s Z + v_s$$

16

17 where  $Z$  is the corresponding latent variable and  $v_s$  is the random (normal) component of the response  
 18 for product or attitude. The four latent factors are assumed to be determined by linear structural  
 19 relationships for each factor  $f$  and individual  $n$  as follows:

20



$$Z_{f,n} = \sigma_f \psi_{f,n}$$

The term  $\sigma_f \psi_{f,n}$  is a normally distributed error term with zero mean and standard deviation  $\sigma_f$  for each factor. To normalize the scale of the measurement equations, one of the parameters  $d_s$  for each group of products is set to one (Ben-Akiva *et al.*, 2002). Following Daly *et al.* (2012) an ordered logit model is utilized to account for the ordinal character of the product purchased frequency response. The probability that an individual  $n$  generates the observed response  $q$  for product or attitude  $s$  is estimated as follows:

$$P\{Z_n = q\} = \Lambda(\tau_{y_{s,q}} - d_s Z_n) - \Lambda(\tau_{y_{s,q-1}} - d_s Z_n)$$

where  $\Lambda$  is the closed cumulative form of the logistic distribution and with constraints:

$$\tau_{y_{s,q}} > \tau_{y_{s,q-1}}$$

To set the additive scale of the ordinal model, constants are omitted. The likelihood of the set of  $r$  ( $r \in R$ ) ordered responses for products and attitudes for respondent  $n$  is:

$$P\{Z_n\} = \prod_R \left( \Lambda(\tau_{y_{s,q}} - d_s Z_n) - \Lambda(\tau_{y_{s,q-1}} - d_s Z_n) \right)$$

The third latent variable model is the delivery subscription model. The measurement equations for the binary delivery subscription choice,  $y_c$  includes the impact of socio-demographic variables as follows:

$$Z_{c,n} = \delta_c W_{c,n} + \sigma_c \psi_{c,n}$$

The vector of parameters  $\delta_c$  is estimated and the term  $W_{c,n}$  represents a matrix of socio-demographic variables found in the exploratory analysis (income, age, household size, etc.). As before, the term  $\sigma_c \psi_{c,n}$  is a normally distributed error term with zero mean and standard deviation  $\sigma_c$ .

In the subscription binary logit model, the utility of individual  $n$  is given by this expression with two terms:

$$U_n = V_n + \xi_n = \sum_i \delta_i x_{i,n} + \sum_f \theta_f Z_{f,n} + \sigma_c \psi_{c,n} + \xi_n$$

the observed component  $V_n$  and the unobserved component  $\xi_n$ . In the observed part, the parameter  $\theta_f$  is the contribution of the latent factor  $f$  and the parameter  $\delta_i$  (for variable  $i$ ) is the contribution of a socio-demographic independent variables  $x_{i,n}$ . The unobserved component  $\xi_n$  is the sum of i.i.d. type I extreme value (Gumbel) and a random (normal) distributions. Without alternative specific variables and normalizing to zero the  $\beta$  and  $\gamma$  coefficients for the first alternative, the probability of the first alternative (not having a subscription) is:

$$P_{1,n} = 1/(1 + e^{V_n})$$

In the final binary logit model, there is panel data (before and during COVID) and the index  $t$  is utilized to denote each instance. The utility for an individual  $n$  in instance  $t$  is given by this expression that sums the observed and unobserved terms:

$$U_{t,n} = V_{t,n} + \xi_{t,n} = \sum_i \beta_i x_{i,n} + \sum_f \gamma_f Z_{f,n} + \xi_{t,n}$$

the observed component  $V_n$  and the unobserved component  $\xi_n$ . In the observed part, the parameter  $\gamma_f$  is the contribution of the latent factor  $f$  and the parameter  $\beta_i$  is the contribution of the sociodemographic independent variables  $x_{i,n}$ . Without alternative specific variables and normalizing to zero the  $\beta$  and  $\gamma$  coefficients for the first alternative, the probability of the sequence of two choices for the first alternative  $k = 0$  (not having home deliveries) conditional on  $Z$  is the product:

$$P_{1,n}(k|Z) = \prod_{t \in T} 1/(1 + e^{V_{t,n}})$$

Following Daly et al. (2012) it is assumed that all the disturbances are independent and that their covariance matrices are diagonal matrices. The normal random disturbances are included to account for correlations in error terms before and during the lockdown as well as correlations with the subscription model, latent variables, and attitudinal responses.

1 All the parameters are jointly estimated by maximizing the log-likelihood function utilizing the package  
2 Apollo (Hess and Palma, 2019) in the R environment (R Core Team, 2020). The coefficients of the  
3 estimated parameters are stable after approximately 100 draws, but the results presented are obtained  
4 with 1000 draws per random parameter utilizing the Modified Latin Hypercube Sampling (MLHS)  
5 method (Hess, Train and Polak, 2006).

## 6 **6.2. Confirmatory Analysis Results**

7 Unlike previous tables obtained after stepwise regression and containing only statistically significant  
8 variables, the results in this section contains both significant and non-significant variables. To facilitate  
9 the interpretation of the results, bold values highlight estimates with  $p \leq 0.01$  and italics highlight  
10 estimated with the expected sign based on the preliminary analysis and  $p$  value between  $0.01 < p \leq$   
11  $0.10$ . All the parameters are jointly estimated, though to facilitate interpretation and presentation, each  
12 submodel is presented in a different table. Herein the interpretation is again done *ceteris paribus*,  
13 assuming that the coefficient sign represents the impact of the variable after accounting for the effect of  
14 other variables.

15 Results are presented following the structure of the model (**Figure 1**): income, attitudes, delivery  
16 subscription, and finally deliveries before/during the lockdown. On the left side of the following tables  
17 (9 to 12) the results for deliveries greater than zero are on the left and the results for deliveries greater  
18 than the median are on the right.

19 **Table 9** shows the results of the income submodel. All the sociodemographic variables are statistically  
20 significant. Income levels increase with educational levels and number of household workers (similar  
21 coefficients and large t-ratios). Income also increases with “Age” and when the variable is “Male” (in  
22 the latter the reference or base is females and others). Having a household member with special needs  
23 or a disability has a negative sign and therefore decreases household income on average. Race related  
24 binary variables were not included in the income model because they are not significant after including  
25 educational level, number of workers, age, male, and disability. The results for deliveries greater than  
26 zero and greater than the median are very similar.

1 **Table 9 Results for Income Submodel**

Variables	Delivery > 0			Delivery > median		
	Coef.	t-value	Pr(> t )	Coef.	t-value	Pr(> t )
$\zeta$ Education Level	1.06	12.72	<b>0.000</b>	1.04	12.69	<b>0.000</b>
$\zeta$ Age	0.03	5.79	<b>0.000</b>	0.03	5.87	<b>0.000</b>
$\zeta$ Male	0.50	3.35	<b>0.000</b>	0.47	3.14	<b>0.001</b>
$\zeta$ Number of household workers	0.99	10.59	<b>0.000</b>	0.98	10.32	<b>0.000</b>
$\zeta$ Disability or special need presence	-0.69	-3.91	<b>0.000</b>	-0.72	-3.98	<b>0.000</b>
$\sigma_{income}$	-0.07	-0.27	0.393	0.31	1.01	0.155

2

3 Factor variables and variances are in all cases significant (see **Table 10**). It is possible to observe the  
 4 relatively large values for meals and delivery cost (in relative terms) within their groups. The  
 5 interpretation of these values must be done together with the sign and significant of each parameter  $\delta$   
 6 and  $\beta$  in **Tables 11** and **12** respectively. Since all the  $d_p$  coefficients are positive, an increase in the  
 7 Likert scale results in an increase in the impact of the latent variable on the likelihood of have a delivery  
 8 subscription or receiving home deliveries. Thresholds for ordered models (attitudes, products, and  
 9 income) are not shown for the sake of conciseness but they are increasing and consistent as expected.

10 **Table 10 Results for Factor Variables:  $d_p$  and  $\sigma$**

Product SDND or Attitudinal Variables	Delivery > 0			Delivery > median		
	Coef.	t-value	Pr(> t )	Coef.	t-value	Pr(> t )
$d$ Grocery	1.00	-	-	-	-	-
$d$ Meals	1.29	10.15	<b>0.000</b>	1.37	9.76	<b>0.000</b>
$d$ Medicine/Heath	0.49	11.04	<b>0.000</b>	0.52	10.89	<b>0.000</b>
$\sigma_1$	2.21	13.47	<b>0.000</b>	2.10	12.68	<b>0.000</b>
$d$ Electronics	1.00	-	-	-	-	-
$d$ FBPC	1.15	22.10	<b>0.000</b>	1.13	20.64	<b>0.000</b>
$d$ Rec. Items	1.16	22.13	<b>0.000</b>	1.16	21.15	<b>0.000</b>
$d$ Household/Off.	1.13	20.28	<b>0.000</b>	1.11	19.34	<b>0.000</b>
$\sigma_2$	2.80	16.38	<b>0.000</b>	2.86	15.87	<b>0.000</b>
$d$ Product Availability Brick&Mortar	1.00	-	-	-	-	-
$d$ Cost Brick&Mortar Store	0.92	23.13	<b>0.000</b>	0.92	22.63	<b>0.000</b>
$\sigma_3$	2.92	13.67	<b>0.000</b>	2.90	11.77	<b>0.000</b>
$d$ Delivery Cost	1.00	-	-	-	-	-
$d$ Delivery Time	0.96	17.94	<b>0.000</b>	1.01	19.26	<b>0.000</b>
$d$ Online Experience	0.61	12.03	<b>0.000</b>	0.64	12.52	<b>0.000</b>
$\sigma_4$	2.50	14.95	<b>0.000</b>	2.46	17.69	<b>0.000</b>

11

12 Again, the results for deliveries greater than zero and greater than the median are very similar.

1 The results of the subscription model (see **Table 11**) are also consistent with previous findings in the  
2 exploratory results section. Age has a negative sign, indicating that older households are less likely to  
3 have a subscription even though age is positively correlated with household income (see **Table 9**).  
4 Travel by auto to work (before the lockdown) is significant and has a positive sign. Larger households  
5 are more likely to have a subscription. High access to electronic devices is also positive and significant.  
6 As expected, the effect of the latent variable income is also positive and significant. For the latent  
7 variables, the four positive and significant attributes (in decreasing order of coefficient value) are income  
8 ( $\theta = 0.23$ ), non-essential products ( $\theta = 0.22$ ), essential products ( $\theta = 0.18$ ), and delivery/online  
9 attributes ( $\theta = 0.13$ ). The factor associated with concerns about costs and availability of home  
10 deliveries has a negative value ( $\theta = -0.07$ ). Hence, an increase in the Likert-scale related to brick and  
11 mortar costs and availability reduces the likelihood of a subscription. It is possible that households that  
12 are more cost conscious engage less in-home deliveries and subscriptions, i.e. a tradeoff between cost  
13 and convenience. Again, the results for deliveries greater than zero and greater than the median are very  
14 similar.

15 **Table 11 Results Subscription Submodel**

Variables	Delivery > 0			Delivery > median		
	Coef.	t-value	Pr(> t )	Coef.	t-value	Pr(> t )
Constant	-0.61	-1.25	0.106	-0.83	-1.86	0.031
$\delta$ Age	-0.01	-1.80	0.036	-0.01	-2.46	<b>0.007</b>
$\delta$ Hours with electronic devices 25-40	0.24	1.07	0.142	0.20	1.05	0.146
$\delta$ Hours with electronic devices > 40	0.54	1.87	0.031	0.72	3.10	<b>0.001</b>
$\delta$ Auto travel to work	0.65	3.05	<b>0.001</b>	0.42	2.31	0.011
$\delta$ Bicycle travel to work	-0.76	-1.54	0.062	-0.95	-1.60	0.055
$\delta$ Household Size	0.18	2.31	<b>0.010</b>	0.23	3.33	<b>0.000</b>
$\theta$ Income latent variable	0.23	3.40	<b>0.000</b>	0.28	4.07	<b>0.000</b>
$\theta$ Factor 1 (essential products)	0.18	3.04	<b>0.001</b>	0.23	3.63	<b>0.000</b>
$\theta$ Factor 2 (non-essential products)	0.22	4.44	<b>0.000</b>	0.17	4.04	<b>0.000</b>
$\theta$ Factor 3 (brick and mortar attributes)	-0.07	-1.59	0.056	-0.07	-1.60	0.055
$\theta$ Factor 4 (online/delivery attributes)	0.13	2.16	0.016	0.12	2.23	0.013
$\sigma_{subscription}$	-1.31	-6.00	<b>0.000</b>	0.98	3.61	<b>0.000</b>

16  
17 For the final model where the dependent variable is whether there is a delivery (see **Table 12**), the results  
18 are also mostly consistent with previous findings in the exploratory results section. Travel by transit has  
19 a negative sign (not significant though) and working from home has a positive sign and is significant,  
20 which indicates that those able to work from home (even a few hours or days) before the pandemic

1 engaged more in-home deliveries. Among the race variables, “White” is the only positive and  
 2 significant variable, which indicates that ceteris paribus white households engage more on home  
 3 deliveries than households from other races. Regarding latent variables, the contribution of the latent  
 4 variable Subscription to the delivery model is significant and positive,  $\gamma = 1.22$ , with the largest  
 5 coefficient which is consistent with the results of the exploratory models. The other three positive and  
 6 significant attributes (in decreasing order of coefficient) are: non-essential products ( $\gamma = 0.31$ ),  
 7 delivery/online attributes ( $\gamma = 0.28$ ), and essential products ( $\gamma = 0.20$ ). The factor associated with  
 8 concerns about costs and availability of home deliveries had negative value ( $\gamma = -0.07$ ) but it was  
 9 not significant.

10 **Table 12 Results Delivery Model**

Variables	Delivery > 0			Delivery > median		
	Coef.	t-value	Pr(> t )	Coef.	t-value	Pr(> t )
Constant	4.04	5.65	0.000	0.95	2.41	<b>0.008</b>
$\beta$ Transit travel to work	-0.47	-0.86	0.194	-0.30	-1.03	0.152
$\beta$ Working from home	1.67	1.81	0.035	0.50	1.62	0.053
$\beta$ African American	-0.22	-0.25	0.401	-0.29	-0.63	0.265
$\beta$ Asian American	0.24	0.34	0.367	0.02	0.05	0.481
$\beta$ Hispanic-Latino	-0.59	-0.90	0.184	-0.09	-0.21	0.416
$\beta$ White	0.88	1.74	0.041	0.14	0.44	0.329
$\beta$ Hours with electronic devices < 3	0.26	0.39	0.347	-0.88	-2.81	<b>0.003</b>
$\gamma$ Subscription	1.22	4.14	<b>0.000</b>	0.62	5.26	<b>0.000</b>
$\gamma$ Factor 1 (essential products)	0.20	1.99	0.023	0.26	4.93	<b>0.000</b>
$\gamma$ Factor 2 (non-essential products)	0.31	3.18	<b>0.001</b>	0.14	4.26	<b>0.000</b>
$\gamma$ Factor 3 (brick and mortar attributes)	-0.07	-1.06	0.145	-0.06	-1.90	0.029
$\gamma$ Factor 4 (online/delivery attributes)	0.28	2.53	<b>0.006</b>	0.13	3.59	<b>0.000</b>

11 The results for deliveries greater than zero and greater than the median are similar, but the variable  
 12 “Hours with electronic devices < 3” is significant for the greater than median model. In addition, the  
 13 coefficient value of subscription has decreased and Factor 1 (essential products) has now more relative  
 14 weight than the other factors. Factor 3 (brick and mortar attributes) is now significant and still negative.

15 Overall, there is considerable stability in the results of the submodels for income, attitudes, and  
 16 subscription as expected. Some differences are observed in the delivery model, where the factor for  
 17 essential products has more weight in the greater than median model and the variables for race are not  
 18 significant.

## 1 **7. Implications for Home-based Accessibility (HBA)**

2 This section discusses the importance of home deliveries and access barriers based on the modeling  
3 results. It is argued in this section that during lockdowns, home deliveries have become a health-  
4 supporting, and essential service for many COVID-19 at-risk populations. The results of the models  
5 indicate that the onset of COVID-19 may have impacted incomes and worsened home-based access for  
6 underserved populations.

7 Home-based accessibility (HBA) was earlier defined as the ease of accessing essential home deliveries  
8 of products such as groceries and medicines without leaving home. The concept of HBA *reverses* the  
9 traditional direction of access. Instead of thinking about individuals accessing locations or services,  
10 HBA posits that it is equally important that essential services and products can easily arrive or be  
11 delivered at home, especially during pandemics or even during normal times for certain populations.  
12 HBA is also a reversal of ideas because it focuses on a *stationary* individual or household, and the  
13 movement or transportation is carried out by logistics companies, the postal service, transit agencies, or  
14 other entities. The challenge is to ensure that these services reach traditionally underserved populations.  
15 Given the potential negative impacts of mobility on exposure during a pandemic, HBA is particularly  
16 relevant during COVID-19 lockdowns or even in normal times for individuals and households that  
17 cannot easily access essential products due to physical disabilities or other mobility barriers. During  
18 pandemic, transportation services are altered. For example, some transit agencies stopped services. In  
19 addition, many households are not able to use any form of transportation to access shopping simply  
20 because brick and mortar destinations are closed, or options are severely limited.

21 At a personal or household level, an individual or household may have the capacity to travel and access  
22 shopping destinations (using one or more modes) though, in practice, this option is severely restricted  
23 because the risk of falling ill or spreading the disease are high. In addition to concrete physical design  
24 or geographic variables that are commonly discussed in the literature, there could also be intangible and  
25 physiological barriers (like fear) that arise during a pandemic. HBA is also relevant during a pandemic  
26 if the risk of spreading the disease is reduced when delivery services follow strict safety protocols (CDC,  
27 2020a) because the disease is mainly airborne and spreads mainly by droplets and close contact with

1 infected people. In relation to airborne contaminated droplets, packages and mail are significantly less  
2 likely to spread the disease (CDC, 2020b).

3 Home deliveries can have a positive impact on reducing exposure to COVID-19, for example, home  
4 deliveries facilitate a reduction of shopping trips, and therefore, a reduction of contact with workers and  
5 consumers at brick and mortar stores. However, based on the results of the models, the following groups  
6 are less likely to access the benefits of home deliveries during a pandemic:

- 7 - Low income households
- 8 - Households with lower educational levels
- 9 - Small size and/or single member households
- 10 - Households with less access to electronic devices and internet
- 11 - Households that do not usually commute by automobile or work from home
- 12 - Non-white households

13 The results of the models closely match the definition of underserved populations stated in Executive  
14 Order 12898 on Environmental Justice (Aimen and Morris, 2012). In addition, lower income levels are  
15 observed in households with members with a disabilities or special need and non-male respondents.  
16 These findings are significant taking into account that COVID-19 has impacted especially hard the  
17 labor market for low income households. New-hiring cuts and downskilling have been most pronounced  
18 in areas with low-income workers and greater income inequality. In addition, more job cuts took place  
19 in industries with higher levels of unionization that tends to attract minorities and low-income  
20 households (Campello, Kankanhalli and Muthukrishnan, 2020). The pandemic has also affected women,  
21 in particular working mothers with school-age children that have to juggle employment with the  
22 education of children. As a result of the complications more working mothers than working fathers have  
23 left the labor force which is likely to have long-term impacts in terms of future income growth and career  
24 opportunities. (Heggeness, 2020). Home deliveries also provide relief in households with time poverty,  
25 where women spend more time on household tasks (Turner and Grieco, 2000).

26 Regarding COVID-19 health impacts, medical research shows that the pandemic has affected  
27 underserved populations disproportionately. Higher in-hospital mortality is strongly influenced by the



1 age of COVID-19 patients and comorbidities. The odds of hospital admission increase with age, black  
2 race, and residence in a low-income area (Price-Haywood et al., 2020). Other studies indicate that non-  
3 white and low-income households tend to have conditions that increase COVID-19 illness risks relative  
4 to populations that live in high-income households or are white (Raifman and Raifman, 2020) (van Dorn,  
5 Cooney and Sabin, 2020). Higher rates of hospitalization and death take place in areas with a higher  
6 proportion of non-white population, higher poverty rates, and lower levels of educational attainment  
7 (Wadhera et al., 2020).

8 The findings of the models and previous research findings in terms of health, time poverty, and labor  
9 participation, indicate that underserved and at risk populations are likely to benefit from greater access  
10 to home deliveries, especially when income and digital literacy are then main barriers to access online  
11 services.

12 **8. Environmental Justice and Home-based Accessibility**

13 E-commerce and home deliveries have increased substantially during the lockdown. According to the  
14 Adobe index of the digital economy, US e-commerce sales increased 76 % in June 2020 compared to  
15 the expected pre-COVID figures in June 2019 (Adobe, 2020). The Adobe estimations are based on more  
16 than one trillion online transactions from 80 of the top 100 US online retailers. The results of the survey  
17 also show an increase in home deliveries in the Portland Vancouver Hillsboro Metropolitan region.  
18 However, the results of our analysis demonstrate potential inequities in home delivery access. Results  
19 in previous sections show that households with higher income levels are engaging in higher levels of  
20 online shopping activities than low-income households and some specific populations (older, less  
21 computer literate, non-auto mode users). The growth of deliveries and delivery vehicles generates traffic,  
22 safety issues, and air pollution. Although lower income communities are less likely to benefit from home  
23 delivery services they are more likely to suffer the externalities generated by e-commerce. This is a clear  
24 case where environmental justice (EJ) and transportation justice (TJ) concepts apply. Studies of  
25 population and traffic distribution indicate that non-white and lower-income communities are more  
26 likely to be exposed to poor ambient air quality (Rowangould, 2013). Exposure inequity and the  
27 emission levels per individual are positively associated with income levels, vehicle ownership, and

1 employment status (Shekarrizfard et al., 2016), and these variables are strongly linked to home delivery  
2 access as the logistic regression models have shown. Therefore, lower-income communities are less  
3 likely to benefit from home delivery services, though they are more likely to suffer the externalities  
4 generated by e-commerce.

5 But the last mile is not the only source of negative externalities for underserved populations, the last  
6 mile is just the last link of supply chains that use multiple modes and facilities. For example, intermodal  
7 freight facilities and long-haul trucks can be major sources of pollution. Hence, freight and truck  
8 volumes should be monitored and compared across areas with different populations (Beiler and  
9 Mohammed, 2016). Industrial and logistics facilities should be monitored as well as the rate of hazmat  
10 spills during transport that may disproportionately affect non-white neighborhoods (Schweitzer, 2006).  
11 The utilization of standardized performance measures is needed to evaluate the negative impacts of the  
12 transportation system changes on lower-income populations (Chakraborty, 2006), and these ideas can  
13 be extended to HBA.

14 E-commerce has boomed during the coronavirus pandemic, and companies are responding by adding  
15 warehouse capacity and rethinking supply chains to allow for faster deliveries by being closer to their  
16 customers. The largest increases in warehouse capacity and distribution centers are seen in food, fast-  
17 moving consumer goods, health and pharmaceutical products (JLL, 2020). During the pandemic there  
18 has been a rapid increase in warehousing and distribution center footage. For example, Amazon in 2019  
19 increased network square footage by approximately 15% and in 2020 it is expected as 50% growth in a  
20 year-over-year basis (Business Insider, 2020). However, from an EJ perspective, warehousing activities  
21 increase road traffic, truck volumes, and warehouses are usually located in low-income and/or minority  
22 neighborhoods (Yuan, 2018), in the outskirts of metropolitan areas where land values are cheaper but  
23 close enough to deliver to Amazon Prime customers within a day. Logistics sprawl is also a problem  
24 when commercial vehicles must travel from distribution centers located in low-income areas to deliver  
25 in higher-income areas, and there is a significant increase in truck traffic and emissions for the same day  
26 or shorter time deliveries (Figliozi, 2011). Lower-income neighborhoods most likely will bear the brunt  
27 of congestion related negative externalities.

1 Alternative delivery systems like crowdsourcing have increased during the pandemic in part due to a  
2 reduction in ridesharing demand. Crowdsourcing can reduce costs and facilitate same-day delivery  
3 services, but the trend towards same day and even next hour delivery may also increase traffic, fuel  
4 consumption, and emissions (Lin, Zhou and Du, 2018). In addition, commercial vehicle crashes and  
5 safety issues in urban areas are likely increasing due to the growth of e-commerce (McDonald, Yuan  
6 and Naumann, 2019).

7 Summarizing, e-commerce and home deliveries have many positive aspects, but its impressive growth  
8 should be monitored to avoid unfairness regarding transportation emissions, safety problems, noise, and  
9 other negative externalities in low-income neighborhoods. Underserved communities tend to generate  
10 fewer transportation emissions but face higher exposure to pollution (Sider et al., 2015). To ensure that  
11 EJ and TJ concepts are considered during the freight and transportation planning process, government  
12 agencies should monitor how e-commerce volumes and trends affect the HBA and exposure of  
13 underserved populations.

## 14 **9. Policy Implications**

15 The future is unpredictable; hence, it is not possible to forecast accurately the next pandemic or event  
16 that will upend lifestyles, transportation services, or individuals' access to essential deliveries. However,  
17 it is possible to prepare now for a response that results in a more efficient and equitable outcome  
18 regarding HBA. Income is a key variable, and access to delivery subscriptions is likely out of the reach  
19 of low-income households. A 2019 survey of households by the Federal Reserve shows the financial  
20 fragility of many households. When households were asked about paying for a hypothetical unexpected  
21 expense of \$400, almost 27 percent said that they would have to borrow or sell something, and 12 percent  
22 indicated that they would not be able to cover it (Federal Reserve, 2019). This section discusses policies  
23 that can increase HBA among underserved and vulnerable populations.

### 24 **9.1. Transit Policies**

25 Transit is essential to provide access for jobs, shopping, and opportunities for essential workers that staff  
26 hospitals, grocery stores, and delivery warehouses. Research results suggest that during the pandemic,  
27 transit is utilized by a greater percentage of essential workers, non-white riders, and lower-income

1 households that are less likely to stay home during the pandemic (Sy et al., 2020). These socio-  
2 demographic and economic population segments are also less likely to use home deliveries. Transit  
3 agencies have innovated and provided home delivery services to vulnerable members of the  
4 communities in non-traditional ways. For example, after COVID-19 pandemic started, TriMet, the  
5 transit agency in the Portland region has offered grocery home delivery services to paratransit users at  
6 a reduced cost (TriMet, 2020). Other transit agencies all across the US have delivered food and other  
7 essential commodities to the elderly and disabled (SUMC, 2020). One potential way to increase HBA  
8 of lower-income and underserved communities is to leverage and optimize the design of transit  
9 operations for home delivery services at lower costs, particularly during lower ridership times. This will  
10 require a rethinking of existing transit policies and funding mechanisms to ensure that the mobility as  
11 well shopping needs of underserved population are appropriately met.

12 During a pandemic, this type of service could be extended to other populations at risk and with low  
13 access to home deliveries. Given the higher COVID-19 mortality and risk for low-income households,  
14 an appropriate transportation policy response is to address the needs of captive riders by maximizing  
15 transit service coverage taking into account the design routes and schedules as well as socio-economic,  
16 demographic and spatial activity patterns (Welch and Mishra, 2013). Increases in transit frequency  
17 throughout the day disproportionate help underserved populations (Ferguson et al., 2012) but also  
18 facilitates appropriate social distancing in transit vehicles.

19 For paratransit users that tend to be lower-income and older, it is important to maintain access to  
20 shopping but minimizing exposure. Overall, current transit services and funding have not evolved at  
21 the same pace as the technological and societal changes brought about by technology (home deliveries,  
22 ride sourcing) and the ongoing COVID pandemic. This could be an opportunity to redesign transit and  
23 paratransit services and funding taking into account the needs of underserved populations.

## 24 **9.2. Leveraging Socially Responsible Logistics and Existing Delivery Networks**

25 During a pandemic, it may be useful to partner or seek cooperation from businesses and logistics service  
26 providers (LSP). The concept of socially responsible companies is relevant in this context. Murphy and  
27 Poist (2002) indicate that the decision making of socially responsible logistics managers pursues both  
28 socially beneficial results as well as positive economic results. Logistics social responsibility can be

1 extended to include the impacts of company actions in terms of safety, diversity, human rights,  
2 philanthropy, and the environment (Carter and Jennings, 2002). As part of LSP social responsibility  
3 efforts, cooperation with the government and non-profit organizations to provide home delivery services  
4 during a pandemic must be encouraged.

5 It is also possible to think about potential subsidies for populations underserved or at risk that do not  
6 have access to home deliveries before the pandemic. A *proactive* policy action is to work with logistic  
7 service providers to identify mechanisms for subsidies or areas of metropolitan regions or the state that  
8 have both populations at risk and low or zero home delivery rates. In the case of a pandemic, *reactive*  
9 policy action is to implement pre-accorded LSP delivery subsidies or extend services like the ones  
10 provided by TriMet (2020) to more users (in addition to paratransit users). The nature of the most  
11 appropriate subsidy mechanism is beyond the scope of this paper, but it may take different forms, such  
12 as fixed cost subsidy per delivery, operations cost subsidy, or technological support (Choi, 2020).

13 Home delivery services may favor larger companies or chains with more resources to respond to major  
14 service disruptions during a pandemic. It is important to involve also smaller and local retail businesses  
15 that may not have the resources to implement delivery services. Proactive coordination with LSP may  
16 be beneficial as well as coordinating with local governments to determine the most effective utilization  
17 of roadway space to facilitate services that reduce exposure during a pandemic. For example, some  
18 solutions that have been implemented during the COVID-19 pandemic include the facilitation of  
19 online/phone ordering and curb space for outside store pick up and separate hours of operation for  
20 vulnerable populations.

21 Another possibility is to leverage the existing delivery network and capabilities of the US Postal  
22 Service (USPS) to introduce economic and reliable delivery services for underserved, low-income  
23 communities with low digital penetration. USPS by law has the universal service obligation (USO) and  
24 already delivers e-commerce packages and products. USO ensures that all US citizens in urban and rural  
25 areas receive postal service several days a week (Fortunato *et al.*, 2013). It is expensive to provide USO  
26 (Cremer, Laffont and Grimaud, 2000), the existing USPS infrastructure and reach can be leveraged to  
27 reach lower income communities and underserved populations with low digital literacy or other barriers.  
28 Longer-term policy initiatives may involve fostering the development of autonomous and contactless

1 delivery services (Jennings and Figliozi, 2019, 2020) for grocery deliveries and other products and  
2 services (Figliozi, 2020).

3 A new type of accessibility problems requires innovative thinking and fostering novel non-traditional  
4 partnerships. The government can have a major supporting role in terms of transportation planning and  
5 financing home delivery for underserved populations, but it is likely that successful delivery and  
6 practical implementation of solutions requires partnering with non-governmental institutions and private  
7 companies. Keeping a role for the state but moving beyond strategies that only involve the state is within  
8 the realm of new ideas in the field of equity and environmental justice (Karner et al., 2020).

### 9 **9.3. Ancillary Services to Support HBA**

10 Home deliveries require the support of ancillary services such as access to banking and internet access  
11 to provide contactless payment systems. According to the Federal Deposit Insurance Corporation  
12 (FDIC), in 2017, unbanked and underbanked rates were higher among households with the following  
13 characteristics: lower-income, less-educated, black and Hispanic-Latino, with disabled working-age  
14 member, and with volatile income (FDIC, 2017). Based on the results of our analysis, these socio-  
15 demographics have lower HBA. The pandemic has accelerated adoption of internet banking services all  
16 over the world (IMF, 2020). Providing access to digital finance has shown to increase consumption and  
17 beneficial for poorer households (Ozili, 2018). Therefore, government policies which promote increased  
18 electronic and digital payment adoption will help improve HBA.

19 To access home deliveries, a shopper must have reliable internet service and a device (computer/tablet,  
20 or smartphone). Moreover, digital literacy is also necessary to effectively search and navigate retailer  
21 websites/apps. Low-income households have less access to equipment (devices) and quality of internet  
22 access (both in terms of speed and data limits). Racial disparities have also been found in access to  
23 broadband internet (Prieger, 2015). These common resources (equipment, internet) are in high demand  
24 during a lockdown since multiple household members utilize the same equipment and internet  
25 connection for remote working, schooling, entertaining, and/or shopping (Beaunoyer, Dupéré and  
26 Guitton, 2020). Policies that promote economic broadband internet access and help reduce the digital  
27 divide will aid in improving the HBA of rural and underserved populations (Bauerly *et al.*, 2019).

1 Providing these ancillary services are also likely to reduce future inequalities. As the share of “intangible”  
2 capital like software and data (in contrast to machines, factories, buildings, etc.) continues to grow in  
3 the economy (Haskel and Westlake, 2018), besides access to groceries and essential products, it is  
4 important to provide home-based work and education access opportunities to rural as well as  
5 underserved populations.

#### 6 **9.4. Broader Policies to Support HBA**

7 As telecommuting and remote education progresses, it is also important to consider the wider  
8 implications of these changes on transportation infrastructure funding and how to provide resources to  
9 support HBA. Each physical trip that is replaced by an electronic communication reduces physical  
10 infrastructure wear and tear as well as transportation emissions. Research will need to be conducted on  
11 how whether online shopping complements or substitutes physical shopping trips in low-income and  
12 underserved communities. Investment in HBA could be seen as a way to offset other costs and  
13 externalities and therefore having a justification in terms of broader tax policy incentives.  
14 Transportation researchers and discussion groups are also advocating for considering home-based work  
15 as a transportation investment that should be encouraged via tax breaks and a unique opportunity to  
16 increase the sustainability of the transportation system (Beck and Hensher, 2020). There are other  
17 opportunities related to new technologies such as deliveries utilizing autonomous robots that would  
18 eventually lower the cost of deliveries utilizing a contactless solution (Pani *et al.*, 2020).

#### 19 **10. Conclusions**

20 COVID-19 lockdowns have increased teleworking, remote schooling, and remote delivery of many  
21 services and activities that used to be only (or mostly) offered at brick and mortar locations. During  
22 lockdowns, home deliveries have changed from being a desirable luxury or comfortable solution to a  
23 health-supporting and essential service for many COVID-19 at-risk and underserved populations.  
24 However, not all households are equals in terms of access to home deliveries. The onset of COVID-19  
25 has brought to surface access inequalities that preceded the pandemic and that the COVID-19 lockdown  
26 seems to have exacerbated and made visible.

1 The results of survey and logistics models indicate that the following populations are less likely to access  
2 the benefits of home deliveries during a pandemic: low-income households, small size and/or single-  
3 member households, households with less access to electronic devices, households with older members,  
4 households with lower educational levels, household that do not commute by automobile or work from  
5 home, and non-white households. The results of this research show that COVID-19 has worsened home  
6 delivery inequalities within the population. During the pandemic, higher-income households have  
7 substantially increased home delivery rates, whereas low-income underserved populations have not been  
8 able to benefit from this type of service that reduces exposure to the virus itself and the risk of illness  
9 and mortality.

10 Pre-COVID-19, nearly 59% of the households with delivery rates over 10 per month have annual  
11 incomes greater than \$100,000, whereas nearly 65% of the households with zero deliveries have annual  
12 incomes below \$50,000. This difference was accentuated during the COVID-19 lockdown, nearly 68 %  
13 of the households with delivery rates over 10 per month have annual incomes greater than \$50,000,  
14 whereas nearly 70% of the households with zero deliveries have annual incomes below \$50,000. These  
15 numbers are compounded by the fact that model results indicate that households with vulnerable  
16 populations, e.g. households with at least one member with special needs or a disability, have lower  
17 incomes. There is also a clear relationship between income levels, educational attainment, and race  
18 (lower incomes for non-white households).

19 The COVID-19 pandemic is forcing a redefinition of transportation equity and accessibility. This  
20 research proposes an extension of traditional measures of transportation accessibility to include also  
21 home-based deliveries. Extending Pereira et al. (2017) ideas, accessibility as a human capability should  
22 also include access to home deliveries (at least during a pandemic or similarly disruptive event). Home-  
23 based accessibility or HBA *reverses* the traditional direction of access. In HBA, the individual is  
24 *stationary*, and the transportation service originates outside the home and ends in the household. It is  
25 important to consider that zero or no home deliveries may be the result of lack of interest or negative  
26 attitudes towards online shopping and home deliveries. The equity aspect is meaningful only for  
27 households that would like to enjoy the benefits of home deliveries but are unable to do it due to income



1 barriers, internet literacy, or other barriers. The lockdown coincided with a dramatic increase in  
2 unemployment rates and changes in the labor market are additional barriers to access home deliveries  
3 when they may be needed the most.

4 The COVID-19 pandemic has also shown that during lockdowns, traditional measures of mobility based  
5 on level-of-service and congestion are not relevant since demand is reduced significantly. For example,  
6 in the Portland region, traffic levels on the main Portland freeways dropped between 40 to 60% during  
7 the lockdown (ODOT, 2020). However, accessibility from the safety of a home becomes key to provide  
8 harmless access to essential products. HBA becomes relevant to slow the spread of the disease, for  
9 example by reducing trips that can spread the infection among transit service operators or essential  
10 workers at grocery stores. A silver lining of these unprecedented times is the opportunity to put more  
11 emphasis on *safe* accessibility than mobility (Handy, 2020).

12 Lessons from the current pandemic indicate that a faster support system to provide HBA for shopping  
13 essentials (groceries, medicines, etc.) for the underserved population (e.g., low-income, elderly, and/or  
14 disabled populations) requires both proactive and reactive measures. This research discusses potential  
15 proactive and reactive policies and strategies to increase home-based accessibility (HBA) such as  
16 rethinking and expanding non-traditional transit services that deliver food and essentials to paratransit  
17 users, the utilization of existing delivery systems and infrastructure based on the concept of socially  
18 responsible logistics, and the provision of ancillary services that facilitate the adoption of online services  
19 and home deliveries in low income or digitally illiterate households.

20 It is also argued that underserved populations benefit less from home deliveries but are likely to suffer  
21 more exposure to transportation emissions, traffic volumes, and crashes generated by home-delivery  
22 activities. Transportation policies should take into account externalities brought about by the increase  
23 in home delivery traffic as well as the growth of intermodal facilities and distribution centers in low-  
24 income areas. However, it is also important to point out that home delivery services do have some  
25 positive aspects for groups that have historically experienced barriers to shopping essentials in brick and  
26 mortar stores such as individuals with disabilities, households experiencing time poverty, or the non-  
27 driver/carless population.

1 This is an initial exploratory study, and future research can analyze how e-commerce and package  
2 delivery trends continue after the worst effects of the COVID-19 pandemic are over. Estimated models  
3 and results discussed in this research are likely to shift over time, and these changes should be evaluated  
4 in terms of HBA inequalities and environmental justice. It is also important to replicate this type of  
5 research in other cities or regions with a different sociodemographic composition and to analyze what  
6 are the minimum standards of HBA that are required as a function of individual and household  
7 characteristics. The development of a HBA index is another future research opportunity. Based on the  
8 findings of this research it would be important to include accessibility in terms of cost relative to income  
9 as well as other barriers such as internet literacy and access.

10  
11  
12

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- 3



1 **Appendix**

2

3 **Table A.1 Travel Mode Choice Distribution and Vehicles per Household**

4

<b>Mode</b>	<b>Vehicles per Household</b>			
	<b>0</b>	<b>1</b>	<b>2</b>	<b>≥3</b>
Automobile	1.2	35.0	39.1	24.7
Bicycle	6.2	62.5	25.0	6.2
Transit (Bus, rail)	32.2	28.8	28.8	10.2
Walk	33.3	33.3	25.0	8.3
Worked from home	3.5	38.6	40.4	17.5

5

6

1 **Table A.2 Distribution of Delivery Frequency by Product (rows sum to 100%)**

<b>Product Type</b>	<b>(0) Never ordered SDND</b>	<b>1</b>	<b>2</b>	<b>3</b>	<b>4</b>	<b>(5) Most Frequently ordered SDND</b>
Grocery	54.1	8.0	6.1	7.1	7.3	17.4
Meals	51.5	6.1	6.0	7.0	5.6	23.7
Electronics	48.9	17.9	14.4	11.7	3.8	3.3
FBPC	43.9	17.9	14.4	14.2	6.2	3.4
Rec.Items	51.1	15.0	12.9	11.9	5.2	3.8
Household/Office	44.9	18.0	14.3	13.6	6.3	2.9
Medicines/Health	52.2	11.1	10.2	10.3	9.1	7.0

2

3 **Table A2** shows the distribution of responses to the question: “For what category of products do you  
 4 request same day or next day delivery? For each category assign a number ranging from 0 to 5, assign  
 5 zero if a category is never ordered same/next day (SDND) and 5 for the most frequently ordered category  
 6 using same/next day delivery”

7

1 **Table A.3 Distribution of Attitudinal Questions (rows sum to 100%)**

Attitudes	(0) Not relevant	1	2	3	4	(5) Most Important
Availability at a nearby store	12.4	5.2	10.2	18.5	23.6	30.1
Cost at a nearby store	10.8	6.8	9.9	19.8	26.7	26.0
Cost of Delivery	13.9	5.9	8.2	15.8	24.0	32.2
Time of Delivery	15.5	6.6	11.5	20.6	21.9	23.9
Online Experience	9.4	5.4	9.9	22.5	25.6	27.3
Health/Safety	14.1	8.3	14.4	18.5	14.8	30.0

2

3 **Table A3** shows the distribution of responses to the questions: “When deciding between purchasing at  
 4 a physical store or ordering online for a home delivered product, what factors are most important? For  
 5 each factor assign a number ranging from 0 to 5, assign 0 if a factor is not relevant and 5 for the most  
 6 important factor(s). Factors: (a) availability at a nearby store, (b) cost at a nearby store, (c) home delivery  
 7 cost, (d) home delivery time, (e) easy overall online experience, and (f) personal health and safety  
 8 concerns.

9

10

1 **Table A.4 AIC Change by Removing Each Variable in the pre-Lockdown Models**

<b>Having Deliveries</b>		<b>Deliveries More than the Median HH</b>	
<b>Variable</b>	<b>AIC Change</b>	<b>Variable</b>	<b>AIC Change</b>
Delivery Subscription	44.7	Delivery Subscription	40.0
Easy online experience	18.2	Easy online experience	8.8
Nun. HH Members Age $\leq$ 12	5.7	Number of Household Members	7.6
Number of Household Workers	3.4	FBPC products S/ND delivery	6.2
Travel to Work by Transit	3.0	Meals S/ND delivery	5.9
		Electronic device use > 3 hrs. per week	5.5
		Recreational Items S/ND delivery	4.5
		Age	3.4
		Working from Home (pre-COVID)	2.4
		Cost at a nearby store	2.3
		At least one Vehicle per Household	2.2

2 Notes: S/ND stands for “Same/Next Day” and FBPC stands for “Fashion, Beauty, or Personal Care”

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4

1 **Table A.5 AIC Change by Removing Each Variable in the during-Lockdown Models**

<b>Having Deliveries</b>		<b>Deliveries More than the Median HH *</b>	
<b>Variable</b>	<b>LL Change</b>	<b>Variable</b>	<b>LL Change</b>
No Home deliveries (pre-COVID)	51.1	No Home deliveries (pre-COVID)	40.1
Delivery Subscription	36.1	1 to 2 Home Deliveries (pre-COVID)	28.3
Home delivery cost	8.8	Delivery Subscription	17.1
Cost at a nearby store	4.2	> 5 Home Deliveries (pre-COVID)	13.5
Education less than Coll. Associate	3.5	Easy online experience	6.6
Hispanic-Latino	2.6	Cost at a nearby store	4.8
		Personal health and safety concerns	3.6
		Household Income less than \$10,000	3.0
		Home delivery time	2.4
		Household Income greater than \$100,000	1.9

2 \* More than pre-COVID median household deliveries per month

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4

1 **Table A.6 AIC Change by Removing Each Variable in the Delivery Subscription Model**

<b>Variable</b>	<b>AIC Change</b>
Household Income less than \$10,000	13.0
Household/Office Goods Same/Next Day Delivery	9.8
Household Income greater than \$100,000	9.4
Availability at a nearby store	8.5
Groceries Same/Next Day Delivery	8.3
Electronic device use > 40 hrs. per week	7.3
Medicines Same/Next Day Delivery	6.5
Easy online experience	6.4
Age between 18 and 30	5.3
At least one household member age 65 or older	4.8
Travel to work (pre-COVID) by Automobile	3.8
More than one worker per household	3.5
Household size greater than 3	3.5
Exurban Area	3.3
Median household income (at Zip code level)	3.1
Travel to work (pre-COVID) by Bicycle	2.9

2

1 **Table A.7 Highest Correlations with Variable Income**

	<b>Income</b>	<b>Disability</b>	<b>HH Size</b>	<b>HH Workers</b>	<b>HH Vehicles</b>	<b>Subscription</b>
<b>Income</b>	1	-0.20	0.20	0.33	0.38	0.26
<b>Disability</b>	-0.20	1	0.11	-0.07	-0.03	-0.01
<b>HH Size</b>	0.20	0.11	1	0.54	0.49	0.17
<b>HH Workers</b>	0.33	-0.07	0.54	1	0.46	0.28
<b>HH Vehicles</b>	0.38	-0.03	0.49	0.46	1	0.19
<b>Subscription</b>	0.26	-0.01	0.17	0.28	0.19	1

2