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

ABSTRACT

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

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

1. Introduction

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

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

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

This research defines HBA as the ease of accessing essential services and home deliveries of products such as groceries, meals, and medicines without leaving home. HBA is particularly relevant when mobility has been restricted (e.g., during COVID-19 lockdowns) or for individuals that, even in normal times, cannot easily access essential products due to physical disabilities or other mobility barriers. During a lockdown, for example, many individuals are not able to use any form of transportation to access shopping simply because brick and mortar destinations are closed, or options are severely limited. At a personal or individual level, an individual or household may have the capacity to travel and access shopping destinations (using one or more modes), but in practice, this option is severely restricted because of the risk of falling ill or spreading the disease are high.

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

2. Literature Review

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

According to results from the 2017 NHTS, there are some key variables that affect home delivery frequency. Income is a key variable; households above the poverty line are twice as likely to make online purchases than households below the poverty line. In addition, online shopping increases with the frequency of Internet usage (FHWA, 2018). Income is a variable that is linked to other household characteristics such as internet access, credit card access, education levels, and the number of household workers (Cao, Xu and Douma, 2012). According to some studies, income and age are the most important predictors of online shopping (Lee, Sener and Handy, 2015).

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

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

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

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

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

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

3. Data Collection

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

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

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

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

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

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

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

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		

4. Equity Indicators

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

Table 2 shows how income levels are related to race, education level, vehicles per household, and utilization of electronic devices. Respondents that declared themselves White or Asian are more likely to belong to higher income levels than respondents that declared themselves African American, Hispanic-Latino, or Native American.

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

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

Finally, there is also a clear trend indicating that respondents with low utilization of electronic devices tend to belong to - low income level. In contrast, respondents that utilize electronic devices more than 25 hours per week tend to belong to high-income levels. Since most computers and smartphones are connected to the internet, this variable is also a good proxy for potential access to online shopping.

There is a clear trend linking access to a delivery subscription and household income levels, as shown in **Table 3**. Nearly 60% of the households *without* a delivery subscription have annual incomes below $50,000, whereas nearly 60% of the households *with* a delivery subscription have annual incomes greater than $50,000.

Pre-COVID-19, nearly 59% of the households with delivery rates over 10 per month have annual incomes greater than $100,000, whereas nearly 65% of the households with zero deliveries have annual incomes below $50,000. This difference was accentuated during the COVID-19 lockdown, nearly 68 % of the households with delivery rates over 10 per month have annual incomes greater than $50,000, whereas nearly 70% of the households with zero deliveries have annual incomes below $50,000. Unfortunately, there was no follow-up question inquiring about the reasons behind the lack of home deliveries.

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

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

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

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**
Range	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	

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

5. Exploratory Analysis of Access to Home Deliveries

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

5.1. Exploratory Analysis Methodology

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

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

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

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

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

5.2. Access to Home Deliveries Before the Lockdown

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

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

(a) Having Deliveries Before COVID-19 Lockdown				
Variables	**Coef.**	**Std. Error**	**z value**	**Pr(>|z|)**
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) More than 2 Home Deliveries per month Before COVID-19 Lockdown				
Variables	**Coef.**	**Std. Error**	**z value**	**Pr(>|z|)**
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

SDND = Same Day/Next Day

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

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

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

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

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

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

Survey respondents had to answer this question: “In the last 30 days, AFTER COVID-19 lockdown started, how many times did you or members of your household purchase something online and have it delivered to your home?" To compare pre- and during-COVID-19 lockdown models, this section presents the results of a logistic model where the dependent variable is zero for no deliveries and one for deliveries greater than zero (see **Table 6**, upper section) and the results of a logistic model where the dependent variable is whether households had more than two deliveries per month during the lockdown (see **Table 6**, lower section**).**

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

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

Table 6: Deliveries During COVID-19 Lockdown

(a) Having Deliveries During COVID-19 Lockdown				
Variables	**Coef.**	**Std. Error**	**z value**	**Pr(>|z|)**
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) **More than 2 Home Deliveries per month During COVID-19 Lockdown**				
Variables	**Coef.**	**Std. Error**	**z value**	**Pr(>|z|)**
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

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

- The extremes of household income are significant variables, households with an annual income level below $10,000 are less likely to receive home deliveries, and households with an annual income level over $100,000 are more likely to receive home deliveries
- During the COVID-19 lockdown, personal health and safety concerns are now a significant variable. Being concerned about personal health increases the propensity to have home deliveries during the lockdown.
- Cost at a nearby store is still a significant factor, as well as an easy online experience (same sign as before). In addition, home delivery time became a significant variable during the lockdown.

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

5.4. Access to a Delivery Subscription

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

The results of the logistic regression for access to a delivery subscription are shown in **Table 7**. Not having access to a delivery subscription is the reference. The results have important implications in terms of equity and access to home deliveries. The extreme income levels are again significant variables as well as the median household income of the zip code where the respondent resides. The results are consistent, higher income is positively associated with having a delivery subscription.

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

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

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

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

* In a $10,000-dollar unit

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

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

6. Confirmatory Analysis of Access to Home Deliveries

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

6.1. Confirmatory Analysis Methodology

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

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

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

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

$$y = Z + \upsilon$$

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

$$Z_{,} = \sum_{i} \zeta_i x_{i,n} + \sigma_i \, \psi_{i,n}$$

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

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

$$P\{Z_n = q\} = \Lambda\left(\tau_{y_{i,q}} - Z_n\right) - \Lambda\left(\tau_{y_{i,q-1}} - d_i Z_n\right)$$

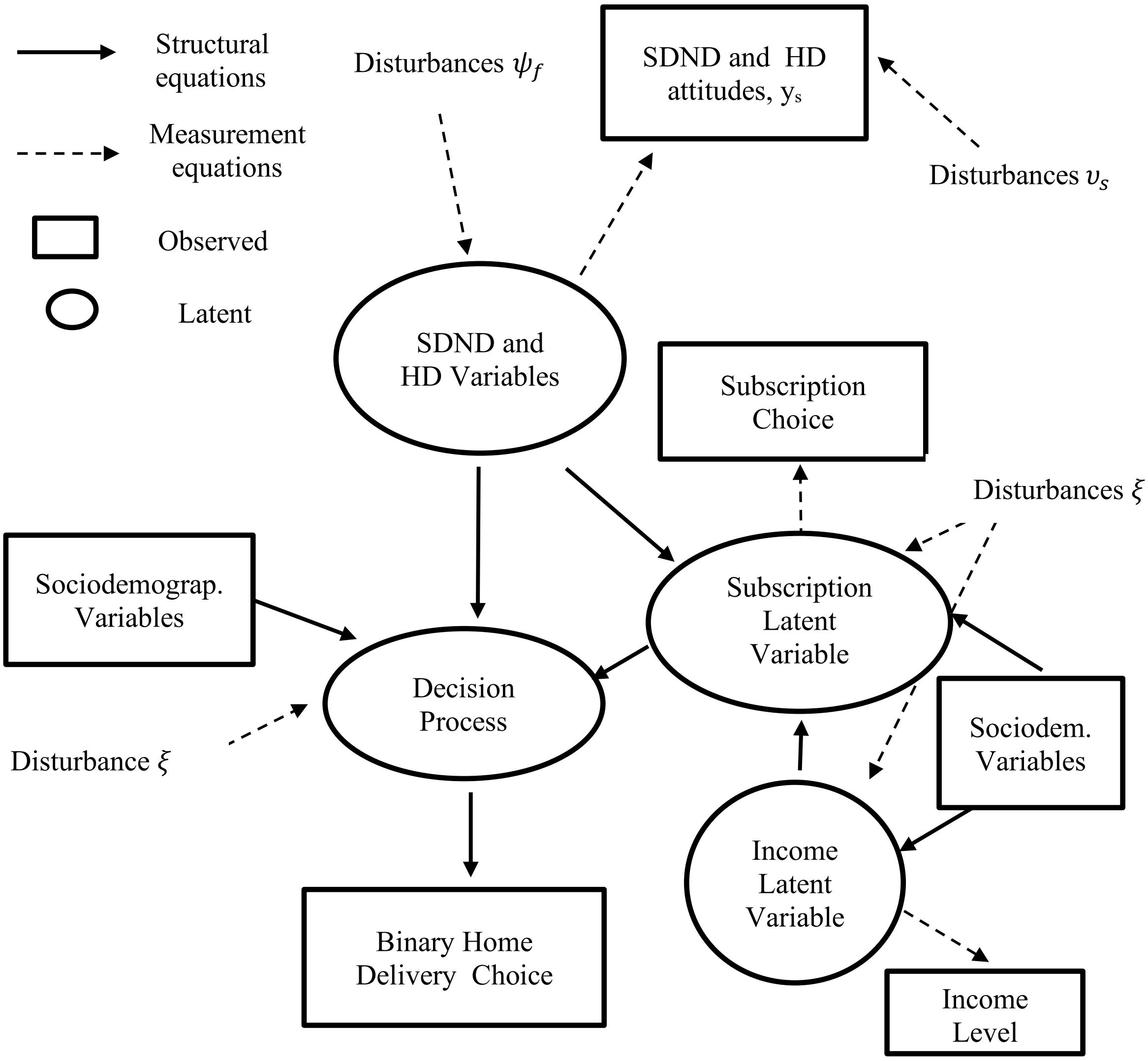

Figure 1. Confirmatory Model – adapted from Ben-Akiva et al. (2002)

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

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

Table 8. Rotated factor loadings

Product SDND and Home Delivery Attitude	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

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

$$y_s = d_s Z + v_s$$

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

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

The term $\sigma_f \, \psi_{f,n}$ is a normally distributed error term with zero mean and standard deviation σ_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:

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

where Λ 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:

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

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 δ_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 σ_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 ξ_n. In the observed part, the parameter θ_f is the contribution of the latent factor f and the parameter δ_i (for variable i) is the contribution of a socio-demographic independent variables $x_{i,n}$. The unobserved component ξ_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 β and γ 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:

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

the observed component V_n and the unobserved component ξ_n. In the observed part, the parameter γ_f is the contribution of the latent factor f and the parameter β_i is the contribution of the sociodemographic independent variables $x_{i,n}$. Without alternative specific variables and normalizing to zero the β and γ 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.

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

6.2. Confirmatory Analysis Results

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

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

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

Table 9 Results for Income Submodel

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

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

Table 10 Results for Factor Variables: d_p and σ

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	**0.000**	1.37	9.76	**0.000**
d Medicine/Heath	0.49	11.04	**0.000**	0.52	10.89	**0.000**
σ_1	2.21	13.47	**0.000**	2.10	12.68	**0.000**
d Electronics	1.00	-	-	-	-	-
d FBPC	1.15	22.10	**0.000**	1.13	20.64	**0.000**
d Rec. Items	1.16	22.13	**0.000**	1.16	21.15	**0.000**
d Household/Off.	1.13	20.28	**0.000**	1.11	19.34	**0.000**
σ_2	2.80	16.38	**0.000**	2.86	15.87	**0.000**
d Product Availability Brick&Mortar	1.00	-	-	-	-	-
d Cost Brick&Mortar Store	0.92	23.13	**0.000**	0.92	22.63	**0.000**
σ_3	2.92	13.67	**0.000**	2.90	11.77	**0.000**
d Delivery Cost	1.00	-	-	-	-	-
d Delivery Time	0.96	17.94	**0.000**	1.01	19.26	**0.000**
d Online Experience	0.61	12.03	**0.000**	0.64	12.52	**0.000**
σ_4	2.50	14.95	**0.000**	2.46	17.69	**0.000**

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

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

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

For the final model where the dependent variable is whether there is a delivery (see **Table 12**), the results are also mostly consistent with previous findings in the exploratory results section. Travel by transit has a negative sign (not significant though) and working from home has a positive sign and is significant, which indicates that those able to work from home (even a few hours or days) before the pandemic engaged more in-home deliveries. Among the race variables, "White" is the only positive and significant variable, which indicates that ceteris paribus white households engage more on home deliveries than households from other races. Regarding latent variables, the contribution of the latent variable Subscription to the delivery model is significant and positive, $\gamma = 1.22$, with the largest coefficient which is consistent with the results of the exploratory models. The other three positive and significant attributes (in decreasing order of coefficient) are: non-essential products $(\gamma = 0.31)$, delivery/online attributes $(\gamma = 0.28)$, and essential products $(\gamma = 0.20)$. The factor associated with concerns about costs and availability of home deliveries had negative value $(\gamma = -0.07)$ but it was not significant.

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

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

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

7. Implications for Home-based Accessibility (HBA)

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

Home-based accessibility (HBA) was earlier defined as the ease of accessing essential home deliveries of products such as groceries and medicines without leaving home. The concept of HBA *reverses* the traditional direction of access. Instead of thinking about individuals accessing locations or services, HBA posits that it is equally important that essential services and products can easily arrive or be delivered at home, especially during pandemics or even during normal times for certain populations. HBA is also a reversal of ideas because it focuses on a *stationary* individual or household, and the movement or transportation is carried out by logistics companies, the postal service, transit agencies, or other entities. The challenge is to ensure that these services reach traditionally underserved populations.

Given the potential negative impacts of mobility on exposure during a pandemic, HBA is particularly relevant during COVID-19 lockdowns or even in normal times for individuals and households that cannot easily access essential products due to physical disabilities or other mobility barriers. During pandemic, transportation services are altered. For example, some transit agencies stopped services. In addition, many households are not able to use any form of transportation to access shopping simply because brick and mortar destinations are closed, or options are severely limited.

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

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

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

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

Regarding COVID-19 health impacts, medical research shows that the pandemic has affected underserved populations disproportionately. Higher in-hospital mortality is strongly influenced by the age of COVID-19 patients and comorbidities. The odds of hospital admission increase with age, black race, and residence in a low-income area (Price-Haywood et al., 2020). Other studies indicate that non-white and low-income households tend to have conditions that increase COVID-19 illness risks relative to populations that live in high-income households or are white (Raifman and Raifman, 2020) (van Dorn, Cooney and Sabin, 2020). Higher rates of hospitalization and death take place in areas with a higher proportion of non-white population, higher poverty rates, and lower levels of educational attainment (Wadhera et al., 2020).

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

8. Environmental Justice and Home-based Accessibility

E-commerce and home deliveries have increased substantially during the lockdown. According to the Adobe index of the digital economy, US e-commerce sales increased 76 % in June 2020 compared to the expected pre-COVID figures in June 2019 (Adobe, 2020). The Adobe estimations are based on more than one trillion online transactions from 80 of the top 100 US online retailers. The results of the survey also show an increase in home deliveries in the Portland Vancouver Hillsboro Metropolitan region. However, the results of our analysis demonstrate potential inequities in home delivery access. Results in previous sections show that households with higher income levels are engaging in higher levels of online shopping activities than low-income households and some specific populations (older, less computer literate, non-auto mode users). The growth of deliveries and delivery vehicles generates traffic, safety issues, and air pollution. Although lower income communities are less likely to benefit from home delivery services they are more likely to suffer the externalities generated by e-commerce. This is a clear case where environmental justice (EJ) and transportation justice (TJ) concepts apply. Studies of population and traffic distribution indicate that non-white and lower-income communities are more likely to be exposed to poor ambient air quality (Rowangould, 2013). Exposure inequity and the emission levels per individual are positively associated with income levels, vehicle ownership, and employment status (Shekarrizfard et al., 2016), and these variables are strongly linked to home delivery access as the logistic regression models have shown. Therefore, lower-income communities are less likely to benefit from home delivery services, though they are more likely to suffer the externalities generated by e-commerce.

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

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

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

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

9. Policy Implications

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

9.1. Transit Policies

Transit is essential to provide access for jobs, shopping, and opportunities for essential workers that staff hospitals, grocery stores, and delivery warehouses. Research results suggest that during the pandemic, transit is utilized by a greater percentage of essential workers, non-white riders, and lower-income households that are less likely to stay home during the pandemic (Sy et al., 2020). These socio-demographic and economic population segments are also less likely to use home deliveries. Transit agencies have innovated and provided home delivery services to vulnerable members of the communities in non-traditional ways. For example, after COVID-19 pandemic started, TriMet, the transit agency in the Portland region has offered grocery home delivery services to paratransit users at a reduced cost (TriMet, 2020). Other transit agencies all across the US have delivered food and other essential commodities to the elderly and disabled (SUMC, 2020). One potential way to increase HBA of lower-income and underserved communities is to leverage and optimize the design of transit operations for home delivery services at lower costs, particularly during lower ridership times. This will require a rethinking of existing transit policies and funding mechanisms to ensure that the mobility as well shopping needs of underserved population are appropriately met.

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

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

9.2. Leveraging Socially Responsible Logistics and Existing Delivery Networks

During a pandemic, it may be useful to partner or seek cooperation from businesses and logistics service providers (LSP). The concept of socially responsible companies is relevant in this context. Murphy and Poist (2002) indicate that the decision making of socially responsible logistics managers pursues both socially beneficial results as well as positive economic results. Logistics social responsibility can be extended to include the impacts of company actions in terms of safety, diversity, human rights, philanthropy, and the environment (Carter and Jennings, 2002). As part of LSP social responsibility efforts, cooperation with the government and non-profit organizations to provide home delivery services during a pandemic must be encouraged.

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

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

Another possibility is to leverage the existing delivery network and capabilities of the US Postal Service (USPS) to introduce economic and reliable delivery services for underserved, low-income communities with low digital penetration. USPS by law has the universal service obligation (USO) and already delivers e-commerce packages and products. USO ensures that all US citizens in urban and rural areas receive postal service several days a week (Fortunato *et al.*, 2013). It is expensive to provide USO (Cremer, Laffont and Grimaud, 2000), the existing USPS infrastructure and reach can be leveraged to reach lower income communities and underserved populations with low digital literacy or other barriers. Longer-term policy initiatives may involve fostering the development of autonomous and contactless delivery services (Jennings and Figliozzi, 2019, 2020) for grocery deliveries and other products and services (Figliozzi, 2020).

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

9.3. Ancillary Services to Support HBA

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

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

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

9.4. Broader Policies to Support HBA

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

10. Conclusions

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

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

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

The COVID-19 pandemic is forcing a redefinition of transportation equity and accessibility. This research proposes an extension of traditional measures of transportation accessibility to include also home-based deliveries. Extending Pereira et al. (2017) ideas, accessibility as a human capability should also include access to home deliveries (at least during a pandemic or similarly disruptive event). Home-based accessibility or HBA *reverses* the traditional direction of access. In HBA, the individual is *stationary,* and the transportation service originates outside the home and ends in the household. It is important to consider that zero or no home deliveries may be the result of lack of interest or negative attitudes towards online shopping and home deliveries. The equity aspect is meaningful only for households that would like to enjoy the benefits of home deliveries but are unable to do it due to income barriers, internet literacy, or other barriers. The lockdown coincided with a dramatic increase in unemployment rates and changes in the labor market are additional barriers to access home deliveries when they may be needed the most.

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

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

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

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

References

Adobe (2020) *Adobe Digital Economy Index | Adobe Analytics*, *Adobe*. Available at: https://www.adobe.com/experience-cloud/digital-insights/digital-economy-index.html (Accessed: 4 September 2020).

Aimen, D. and Morris, A. (2012) *Practical approaches for involving traditionally underserved populations in transportation decisionmaking*. Washington, DC: National Cooperative Highway Research Program (NCHRP Report, 710).

Amazon (2020) *Prime Member Benefits - Prime Insider*, *Amazon.com*. Available at: https://www.amazon.com/primeinsider/about/index.html (Accessed: 2 September 2020).

Anderson, P. and Anderson, E. (2002) 'The new e-commerce intermediaries', *MIT Sloan Management Review*, 43(4), p. 53.

Bauerly, B. C. *et al.* (2019) 'Broadband Access as a Public Health Issue: The Role of Law in Expanding Broadband Access and Connecting Underserved Communities for Better Health Outcomes', *Journal of Law, Medicine & Ethics*, 47(S2), pp. 39–42. doi: 10.1177/1073110519857314.

Beaunoyer, E., Dupéré, S. and Guitton, M. J. (2020) 'COVID-19 and digital inequalities: Reciprocal impacts and mitigation strategies', *Computers in Human Behavior*, p. 106424.

Beck, M. J. and Hensher, D. A. (2020) 'Insights into the impact of COVID-19 on household travel and activities in Australia–The early days of easing restrictions', *Transport Policy*.

Beiler, M. O. and Mohammed, M. (2016) 'Exploring transportation equity: Development and application of a transportation justice framework', *Transportation research part D: transport and environment*, 47, pp. 285–298.

Ben-Akiva, M. *et al.* (2002) 'Integration of choice and latent variable models', *Perpetual motion: Travel behaviour research opportunities and application challenges*, pp. 431–470.

BLS (2020) *Unemployment in the Portland Area by County, June 2020 : Western Information Office : U.S. Bureau of Labor Statistics*. Available at: https://www.bls.gov/regions/west/news-release/unemployment_portland.htm (Accessed: 30 December 2020).

Business Insider (2020) *Amazon's physical growth shows it sees e-shopping surge as permanent - Business Insider*. Available at: https://www.businessinsider.com/amazon-fulfillment-center-growth-reveals-pandemic-online-ordering-surge-2020-7 (Accessed: 30 December 2020).

Campello, M., Kankanhalli, G. and Muthukrishnan, P. (2020) *Corporate hiring under covid-19: Labor market concentration, downskilling, and income inequality*. 0898–2937. National Bureau of Economic Research.

Cao, X. J., Xu, Z. and Douma, F. (2012) 'The interactions between e-shopping and traditional in-store shopping: an application of structural equations model', *Transportation*, 39(5), pp. 957–974.

Carter, C. R. and Jennings, M. M. (2002) 'Logistics social responsibility: an integrative framework', *Journal of business logistics*, 23(1), pp. 145–180.

CDC (2020a) *Communities, Schools, Workplaces, & Events*, *Centers for Disease Control and Prevention*. Available at: https://www.cdc.gov/coronavirus/2019-ncov/community/organizations/mail-parcel-drivers.html (Accessed: 9 September 2020).

CDC (2020b) *Coronavirus Disease 2019 (COVID-19)*, *Centers for Disease Control and Prevention*. Available at: https://www.cdc.gov/coronavirus/2019-ncov/faq.html (Accessed: 9 September 2020).

Chakraborty, J. (2006) ‘Evaluating the environmental justice impacts of transportation improvement projects in the US’, *Transportation Research Part D: Transport and Environment*, 11(5), pp. 315–323.

Chen, N. and Wang, C.-H. (2020) ‘Does green transportation promote accessibility for equity in medium-size US cites?’, *Transportation Research Part D: Transport and Environment*, 84, p. 102365.

Chen, Q., Conway, A. and Cheng, J. (2017) ‘Parking for residential delivery in New York City: Regulations and behavior’, *Transport Policy*, 54, pp. 53–60.

Choi, T.-M. (2020) ‘Innovative “bring-service-near-your-home” operations under Corona-virus (COVID-19/SARS-CoV-2) outbreak: Can logistics become the messiah?’, *Transportation Research Part E: Logistics and Transportation Review*, 140, p. 101961.

Cremer, H., Laffont, J.-J. and Grimaud, A. (2000) ‘The Cost of Universal Service in the Postal Sector’, in Crew, M. A. and Kleindorfer, P. R. (eds) *Current Directions in Postal Reform*. Boston, MA: Springer US, pp. 47–68. doi: 10.1007/978-1-4615-4481-4_3.

Daly, A. *et al.* (2012) ‘Using ordered attitudinal indicators in a latent variable choice model: a study of the impact of security on rail travel behaviour’, *Transportation*, 39(2), pp. 267–297. doi: 10.1007/s11116-011-9351-z.

Di Ciommo, F. and Shiftan, Y. (2017) ‘Transport equity analysis’, *Transport Reviews*, 37(2), pp. 139–151.

DigitalCommerce (2020) *Amazon Prime has 126 million members in the US*, *Digital Commerce 360*. Available at: https://www.digitalcommerce360.com/article/amazon-prime-membership/ (Accessed: 31 December 2020).

van Dorn, A., Cooney, R. E. and Sabin, M. L. (2020) ‘COVID-19 exacerbating inequalities in the US’, *Lancet (London, England)*, 395(10232), p. 1243.

El-Geneidy, A. *et al.* (2016) ‘The cost of equity: Assessing transit accessibility and social disparity using total travel cost’, *Transportation Research Part A: Policy and Practice*, 91, pp. 302–316.

Fabrigar, L. R. and Wegener, D. T. (2011) *Exploratory factor analysis*. Oxford University Press.

FDIC (2017) *National Survey of Unbanked and Underbanked Households*. FEDERAL DEPOSIT INSURANCE CORPORATION. Available at: https://www.fdic.gov/householdsurvey/2017/2017report.pdf (Accessed: 14 July 2020).

Federal Reserve (2019) *Federal Reserve Board issues Report on the Economic Well-Being of U.S. Households*, *Board of Governors of the Federal Reserve System*. Available at: https://www.federalreserve.gov/newsevents/pressreleases/other20190523b.htm (Accessed: 31 December 2020).

Feitelson, E. (2002) ‘Introducing environmental equity dimensions into the sustainable transport discourse: issues and pitfalls’, *Transportation Research Part D: Transport and Environment*, 7(2), pp. 99–118.

Ferguson, E. M. *et al.* (2012) ‘Incorporating equity into the transit frequency-setting problem’, *Transportation Research Part A: Policy and Practice*, 46(1), pp. 190–199.

Fernandez, J. *et al.* (2020) 'Hispanic Economic Outlook'.

FHWA (2018) *NHTS Brief: Changes in Online Shopping Trends*. Federal Highway Administration FHWA. Available at: https://nhts.ornl.gov/assets/NHTSBriefOnlineShopping081018.pdf (Accessed: 28 June 2020).

Figliozzi, M. A. (2011) 'The impacts of congestion on time-definitive urban freight distribution networks CO2 emission levels: Results from a case study in Portland, Oregon', *Transportation Research Part C: Emerging Technologies*, 19(5), pp. 766–778.

Figliozzi, M. A. (2020) 'Carbon emissions reductions in last mile and grocery deliveries utilizing air and ground autonomous vehicles', *Transportation Research Part D: Transport and Environment*, 85, p. 102443.

FMI (2020) *FMI: Online grocery sales jumped 300% early in pandemic*, *Supermarket News*. Available at: https://www.supermarketnews.com/issues-trends/fmi-online-grocery-sales-jumped-300-early-pandemic (Accessed: 31 December 2020).

Fortunato, M. W.-P. *et al.* (2013) 'Weighing the universal service obligation: introducing rural well-being as a consideration in the viability of the United States Postal Service', *Community Development*, 44(2), pp. 200–221. doi: 10.1080/15575330.2012.705871.

Gonzalez, D. *et al.* (2020) 'Hispanic adults in families with noncitizens disproportionately feel the economic fallout from COVID-19', *Washington, DC: Urban Institute*.

Handy, S. (2020) 'Is accessibility an idea whose time has finally come?', *Transportation Research Part D: Transport and Environment*, 83, p. 102319.

Haskel, J. and Westlake, S. (2018) *Capitalism without capital: The rise of the intangible economy*. Princeton University Press.

Heggeness, M. L. (2020) 'Estimating the immediate impact of the COVID-19 shock on parental attachment to the labor market and the double bind of mothers', *Review of Economics of the Household*, 18(4), pp. 1053–1078. doi: 10.1007/s11150-020-09514-x.

Hess, S. and Palma, D. (2019) 'Apollo: A flexible, powerful and customisable freeware package for choice model estimation and application', *Journal of choice modelling*, 32, p. 100170.

Hess, S., Train, K. E. and Polak, J. W. (2006) 'On the use of a Modified Latin Hypercube Sampling (MLHS) method in the estimation of a Mixed Logit Model for vehicle choice', *Transportation Research Part B: Methodological*, 40(2), pp. 147–163. doi: 10.1016/j.trb.2004.10.005.

Hu, S. and Chen, P. (2021) 'Who left riding transit? Examining socioeconomic disparities in the impact of COVID-19 on ridership', *Transportation Research Part D: Transport and Environment*, 90, p. 102654. doi: 10.1016/j.trd.2020.102654.

IMF (2020) 'Digital Financial Inclusion in the Times of COVID-19', *IMF Blog*. Available at: https://blogs.imf.org/2020/07/01/digital-financial-inclusion-in-the-times-of-covid-19/ (Accessed: 5 January 2021).

Jennings, D. and Figliozzi, M. (2019) 'Study of sidewalk autonomous delivery robots and their potential impacts on freight efficiency and travel', *Transportation Research Record*, 2673(6), pp. 317–326.

Jennings, D. and Figliozzi, M. A. (2020) 'A Study of Road Autonomous Delivery Robots and Their Potential Impacts on Freight Efficiency and Travel', *Transportation Research Record*.

JLL (2020) *How the e-commerce boom during COVID-19 is changing industrial real estate*, *trends-and-insights*. Available at: https://www.us.jll.com/en/trends-and-insights/investor/how-the-e-commerce-boom-during-covid-19-is-changing-industrial-real-estate (Accessed: 4 September 2020).

Karner, A. *et al.* (2020) 'From Transportation Equity to Transportation Justice: Within, Through, and Beyond the State', *Journal of Planning Literature*, p. 0885412220927691.

Keeling, K. and Figliozzi, M. (2019) 'E-Grocery Home Delivery Impacts on Food Distribution, Access and Equity: a Portland Case Study', *PDX Scholar*. Available at: https://pdxscholar.library.pdx.edu/cengin_fac/544/.

Lee, R. J., Sener, I. N. and Handy, S. L. (2015) 'Picture of online shoppers: Specific focus on Davis, California', *Transportation Research Record*, 2496(1), pp. 55–63.

Lin, J., Zhou, W. and Du, L. (2018) 'Is on-demand same day package delivery service green?', *Transportation Research Part D: Transport and Environment*, 61, pp. 118–139.

McDonald, N., Yuan, Q. and Naumann, R. (2019) 'Urban freight and road safety in the era of e-commerce', *Traffic injury prevention*, 20(7), pp. 764–770.

METRO (2015) '2015 Trip-Based Travel Demand Model Methodology Report'. Available at: https://www.oregonmetro.gov/sites/default/files/2015/04/16/trip-based_travel_demand_model_methodology.pdf (Accessed: 15 July 2020).

Murphy, P. R. and Poist, R. F. (2002) 'Socially responsible logistics: an exploratory study', *Transportation Journal*, pp. 23–35.

ODOT (2020) *Impact of Covid-19 on Traffic: March 16 to May 6 and May 4 to June 24 2020 Reports.* Oregon Department of Transportation.

Ozili, P. K. (2018) 'Impact of digital finance on financial inclusion and stability', *Borsa Istanbul Review*, 18(4), pp. 329–340. doi: 10.1016/j.bir.2017.12.003.

Pani, A. *et al.* (2020) 'Evaluating Public Acceptance of Autonomous Delivery Robots During COVID-19 Pandemic', *Transportation Research Part D: Transport and Environment*, p. 102600.

Pereira, R. H., Schwanen, T. and Banister, D. (2017) 'Distributive justice and equity in transportation', *Transport reviews*, 37(2), pp. 170–191.

Price-Haywood, E. G. *et al.* (2020) 'Hospitalization and mortality among black patients and white patients with Covid-19', *New England Journal of Medicine*.

Prieger, J. E. (2015) 'The broadband digital divide and the benefits of mobile broadband for minorities', *The Journal of Economic Inequality*, 13(3), pp. 373–400. doi: 10.1007/s10888-015-9296-0.

R Core Team (2020) *R: A language and environment for statistical computing*. R Foundation for Statistical Computing, Vienna, Austria. https://www.R-project.org/. Available at: https://www.R-project.org/.

Raifman, M. A. and Raifman, J. R. (2020) 'Disparities in the population at risk of severe illness from covid-19 by race/ethnicity and income', *American journal of preventive medicine*.

Revelle, W. and Revelle, M. W. (2015) ‘Package “psych”’, *The comprehensive R archive network*.

Ripley, B. *et al.* (2013) ‘Package “mass”’, *Cran R*, 538. Available at: https://cran.r-project.org/web/packages/MASS/MASS.pdf (Accessed: 10 June 2020).

Rowangould, G. M. (2013) ‘A census of the US near-roadway population: Public health and environmental justice considerations’, *Transportation Research Part D: Transport and Environment*, 25, pp. 59–67.

Schweitzer, L. (2006) ‘Environmental justice and hazmat transport: A spatial analysis in southern California’, *Transportation Research Part D: Transport and Environment*, 11(6), pp. 408–421.

Shekarrizfard, M. *et al.* (2016) ‘Individual exposure to traffic related air pollution across land-use clusters’, *Transportation Research Part D: Transport and Environment*, 46, pp. 339–350.

Sider, T. *et al.* (2015) ‘Smog and socioeconomics: an evaluation of equity in traffic-related air pollution generation and exposure’, *Environment and Planning B: Planning and Design*, 42(5), pp. 870–887.

Sumagaysay, L. (2020) *The pandemic has more than doubled food-delivery apps’ business. Now what? - MarketWatch*. Available at: https://www.marketwatch.com/story/the-pandemic-has-more-than-doubled-americans-use-of-food-delivery-apps-but-that-doesnt-mean-the-companies-are-making-money-11606340169 (Accessed: 31 December 2020).

SUMC (2020) ‘National Review of Public Transit COVID-19 Delivery Programs’, *MOD Learning Center*. Available at: https://learn.sharedusemobilitycenter.org/casestudy/covid-19-national-review-of-public-transit-food-delivery-programs/ (Accessed: 6 January 2021).

Sy, K. T. L. *et al.* (2020) ‘Socioeconomic disparities in subway use and COVID-19 outcomes in New York City’, *medRxiv*.

TriMet (2020) *TriMet LIFT Grocery and Goods Delivery*. Available at: https://trimet.org/lift/delivery.htm (Accessed: 3 September 2020).

Turner, J. and Grieco, M. (2000) ‘Gender and Time Poverty: The Neglected Social Policy Implications of Gendered Time, Transport and Travel’, *Time & Society*, 9(1), pp. 129–136. doi: 10.1177/0961463X00009001007.

USDC (2020) *U.S. Department of Commerce Quarterly retail e-commerce sales: 2nd quarter 2020 (online).* Available at: https://www.census.gov/retail/index.html#ecommerce (Accessed: 24 August 2020).

Wachs, M. and Kumagai, T. G. (1973) ‘Physical accessibility as a social indicator’, *Socio-Economic Planning Sciences*, 7(5), pp. 437–456.

Wadhera, R. K. *et al.* (2020) ‘Variation in COVID-19 hospitalizations and deaths across New York City boroughs’, *Jama*.

Welch, T. F. and Mishra, S. (2013) ‘A measure of equity for public transit connectivity’, *Journal of Transport Geography*, 33, pp. 29–41.

Wu, Y. *et al.* (2019) ‘Modeling health equity in active transportation planning’, *Transportation research part D: transport and environment*, 67, pp. 528–540.

Yuan, Q. (2018) ‘Location of warehouses and environmental justice’, *Journal of Planning Education and Research*, p. 0739456X18786392.

Appendix

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

Mode	Vehicles per Household			
	0	1	2	≥3
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

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

Product Type	(0) Never ordered SDND	1	2	3	4	(5) Most Frequently ordered SDND
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

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

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

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

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

Having Deliveries		Deliveries More than the Median HH	
Variable	**AIC Change**	**Variable**	**AIC Change**
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

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

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

Having Deliveries		Deliveries More than the Median HH *	
Variable	**LL Change**	**Variable**	**LL Change**
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

* More than pre-COVID median household deliveries per month

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

Variable	AIC Change
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

Table A.7 Highest Correlations with Variable Income

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