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Exploring The Impact Of Socio-Demographic Characteristics, Health Concerns, And Product Type On Home Delivery Rates And Expenditures During A Strict Covid-19 Lockdown Period: A Case Study From Portland, Or

Miguel Figliozzi
Portland State University, figliozzi@pdx.edu

Avinash Unnikrishnan
Portland State University, uavinash@pdx.edu

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Miguel Figliozzi **(corresponding author)**
Professor, Department of Civil and Environmental Engineering,
Transportation Technology and People Lab,
Portland State University,
P.O. Box 751-CEE,
Portland, OR 97207, USA
Email: figliozzi@pdx.edu
Ph: 503 725 2836

Avinash Unnikrishnan
Associate Professor, Department of Civil and Environmental Engineering,
Transportation Technology and People Lab,
Portland State University,
P.O. Box 751-CEE,
Portland, OR 97207, USA

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ABSTRACT

E-commerce volumes and home deliveries have experienced steady growth in the last two decades. Strict COVID-19 lockdowns made home delivery an essential service and a lifeline for many households that, for travel restrictions or health concerns, were not able to utilize traditional shopping methods. This research studies the impact of socio-demographic variables and e-commerce attitudes on household deliveries for seven product categories (groceries, meals, electronics, household and office goods, recreational items, and fashion, beauty and personal care products, and medicine/health-related products) during the lockdown period in the greater Portland metropolitan region. To understand these impacts, exploratory factor analysis and choice models with latent variables are estimated utilizing data collected from an online survey representing the population in the greater Portland metropolitan region. The results indicate that each factor has a unique profile in terms of significant socio-demographic variables. A novel contribution of this research is to study the impact on home deliveries of non-traditional variables like health and safety concerns and the presence of household members with disabilities during a pandemic. The results show that health concerns are very influential and that there are substantial differences across factors on delivery rate and expenditure levels. Key findings and perspectives regarding future delivery rates and implications for transportation agencies and logistics companies are discussed.

KEYWORDS: home deliveries, product type, health and safety concerns, COVID-19, delivery rate, expenditures

1. Introduction

The sudden onset of the COVID-19 pandemic and consequent lockdowns have significantly altered the way people work, educate themselves or their children, feed their families, and seek recreation. The government-imposed lockdowns and restrictions have changed traditional business patterns and activities. As a result, many businesses have been forced to shut down or impose strict social distancing guidelines. Many consumers have found that home deliveries are a solution to some of the lockdown challenges, leading to a surge in online shopping sales during the COVID-19 pandemic. According to the Adobe index of the digital economy, US e-commerce sales jumped approximately 49% in April 2020 and 60% in May 2020 with respect to expected pre-COVID figures (Adobe, 2020). The highest growth is likely to have taken place in the online food, beverages, and grocery market, where companies like Instacart have experienced 500% year-over-year increases during the lockdown (CNBC, 2020). In this research, the term *home* delivery refers to deliveries to households, places where people reside, in contrast to commercial building-related deliveries.

In the US, there has been a steady growth in e-commerce sales in the last two decades, but there is a lack of disaggregated data that can be utilized to understand home delivery attitudes and product preferences across different populations. The 2017 National Household Travel Survey (NHTS) collected a wide array of responses related to household travel patterns, land use, and socio-demographic variables. However, only one question in the latest NHTS focused on home deliveries, and it was limited to the number of deliveries in a 30-day period (FHWA, 2018).

In the US, early studies have shown that consumers are less to shop at grocery stores when COVID-19 infections are surging (Grashuis et al., 2020). In other countries, researchers have also documented dramatic changes in travel and car utilization patterns in Australia (Beck and Hensher, 2020) and in Turkey (Shakibaei et al., 2020), for example. Though the literature in this area is evolving fast, to the best of the authors' knowledge, there is no published research study that has focused on how socio-demographic factors, health attitudes, and product type have impacted home delivery rates during the lockdown in the US.

Seven different products are studied in this research: groceries, meals, electronics, household and office goods, recreational items, and fashion, beauty and personal care products, and medicine and health products. This research explores answers for three novel research questions: (i) What is the impact of health concerns on home deliveries during the lockdown? (ii) What is the impact of socio-demographic variables on products and attitudes? and (iii) How home delivery rates do change with different levels of home delivery expenditures? To answer these questions, exploratory factor analysis and choice models with latent variables are estimated utilizing data collected from an online survey collected during a strict lockdown period.

This research is organized as follows: Section 2 presents an overview of relevant trends related to home product deliveries and a literature review. Section 3 describes the data collection effort. Section 4 utilizes exploratory factor analysis to group products and attitudes. Section 5 details the choice models with latent variables used to estimate the delivery rate and expenditure models. Section 6 presents the results of a model to explore the factors behind the changes in home delivery rates during the lockdown. Section 7 focuses on the results of models for and different levels of delivery rates and expenditures. Section 8 discusses implications of the results regarding future data collection efforts, modeling, and travel and logistic trends. Section 9 ends with a summary of key findings and conclusions.

2. Literature Review

E-commerce sales in the US have increased at double-digit rates for the past two decades and have significantly outpaced brick-and-mortar retail growth (USDC, 2020). Amazon is the largest player in market share, and Amazon Prime subscriptions have been steadily growing. An important draw to membership is the offer of free, fast shipping for many types of orders. Amazon Prime membership in the US has grown from 50 million members in late 2015 to 112 million in December 2019 (Fortune, 2020). Since Amazon is the leader in online sales in the US, trends related to its sales per category are relevant background information for this research (see Table 1). Electronic and appliances lead in expenditures, followed by sporting goods and entertainment, personal use items such as clothing and apparel, furniture, and home decorations.

Table 1: Amazon's US sales product category (in $ billions), 2014-2018.

Category	2014	2015	2016	2017	2018
Auto parts	2.5	3.6	4.6	6.0	7.7
Furniture and home decorations	5.7	8.8	12.1	16.8	23.2
Electronics and appliances	25.3	34.6	43.0	53.6	65.8
Food and beverages	1.2	1.8	2.5	3.4	4.6
Health and personal care	3.8	5.9	8.3	11.6	16.0
Clothing and apparel	9.5	14.7	20.6	28.8	39.8
Sporting goods and entertainment	18.8	25.6	31.6	39.2	48.0
Other retails	16.4	23.6	30.7	40.6	52.9
Subscriptions and other	2.9	4.8	7.1	10.9	16.9

Source: PYMNTS (2018)

Academic and government literature and consumer surveys have studied the effect of socio-demographics, product characteristics, and shopping experience on e-commerce adoption and home deliveries. Consumer surveys find that 43% of American consumers cite convenience as their strongest motivator for shopping online, and pricing is a distant second at 19% (eMarketer, 2018a). Age is also an important factor. Different age groups vary in their means of internet access and types of products purchased (eMarketer, 2018b; Schmid and Axhausen, 2019). In general, older people are less likely to adopt e-commerce compared to their younger counterparts (Farag et al. 2005, 2006a, 2007; Krizek et al., 2005; De Blasio 2008; Cao et al. 2012; Crocco et al., 2013; Zhou and Wang 2014; Clemes et al., 2014; Irawan and Wirza, 2015; Lee et al. 2015; Ding and Lu 2017). According to NHTS 2017 data, households above the poverty line are "almost twice as likely to make online purchases compared to respondents in households below the poverty level (i.e., 61% versus 33%)" (FHWA, 2018). Income is a variable that is linked to other household characteristics such as internet access, credit card access, education levels, and the number of household workers (Cao et al., 2012). Higher-income households are more likely to make purchases online (Farag et al. 2005, 2006a, 2007; De Blasio 2008; Cao et al. 2012; Crocco et al., 2013; Zhou and Wang 2014; Lee et al. 2015; Schmid and Axhausen, 2019). The 2017 NHTS results indicate online shopping is directly proportional to the frequency of Internet usage (FHWA, 2018). Other studies have confirmed this result. Utilization of smartphones, access to the internet, computers increases the likelihood of online shopping (Farag et al. 2005, 2006a, 2007; Krizek et al., 2005; Cao et al. 2012; Crocco et al., 2013; Zhou and Wang 2014; Irawan and Wirza, 2015; Lee et al. 2015; Ding and Lu 2017; Schmid and Axhausen, 2019; Alemi, et al., 2019). Variables associated with a household structure such as the number of members with driver licenses (Irawan and Wirza 2015), vehicle ownership (Dias et al. 2020), presence of workers (Farag et al. 2006a, 2006b; Zhou and Wang 2014; Irawan and Mirza 2015), etc. affect the propensity to shop online. Outside of demographic characteristics, product type plays a vital role in e-commerce adoption (Girard et al. 2003; Dias et al. 2020; Zhen et al. 2016, 2018; Zhai et al. 2017; Maat and Konings, 2018; Schmid and Axhausen, 2019). A novel contribution of this research is studying the impact of product types and groups on home delivery rates and expenditures in a pandemic setting.

The number of deliveries per household has not been widely studied. Based on a study of a large apartment building near New York City in 2016 and 2017, the average apartment received about 1.5 packages per week (Rodrigue, 2017). This study showed that package deliveries peaked in December, which correlates with holiday spending trends. In South Korea, a country that has widely adopted e-commerce, the estimated annual package deliveries per person was 39.6. (Seo and Lee, 2017).

Before COVID-19, there have been growing concerns about increasing home package deliveries and their associated externalities. Some researchers have studied different ways to minimize the impact of household deliveries utilizing newer and greener delivery modes (Perboli and Rosano, 2019). Cherrett et al. (2017) analyzed the externalities brought about by parcel deliveries, using a survey of residence halls and university students in Southampton (UK). This research found that there are significant opportunities to increase delivery efficiency by consolidating trips. The magnitude of home deliveries is likely to be significant. A modeling effort and case study utilizing 2009 NHTS data estimated that the volume of freight trips destined for residences may be on par with the magnitude of freight trips to businesses (Zhou and Wang, 2014).

Several research efforts have focused on how perceptions of online risk may be associated with consumers' purchasing decisions (Potoglou et al., 2015). This research shows that privacy and online shopping concerns reduce the likelihood of online shopping. Schmid et al. (2016) studied tradeoffs between online and in-store shopping for groceries and electronic appliances. They found that socio-economic characteristics significantly impact shopping cost sensitivity and highlight the potential of online shopping services for some products depending on the relation between the value of time and delivery time savings. Both research efforts utilized integrated choice and latent variable (ICLV) models.

Despite the significant amount of work on e-commerce adoption, to the best of the authors' knowledge, no published work has focused on the impact of socio-demographic variables, products, and health concerns on home delivery rate and expenditures during COVID-19 lockdowns or in a pandemic setting.

3. Data Collection

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 state of emergency was extended until July 6, 2020. During this time, the lockdown was widely accepted by the general population, and traffic levels on the main Portland freeways dropped between 40 and 60% (ODOT, 2020). The focus of the study is on a single geographic region to reduce variability and uncertainty regarding lockdown enforcement rules and timing.

The data was collected utilizing an online survey targeting residents 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 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.

The survey focused on questions related to (a) demographic and household-level information regarding age, income, household size, and presence of members with a disability who require assistance and (b) the number of home deliveries made 30 days before and during the lockdown, and lockdown delivery levels for the products analyzed in this research.

Table 2 provides the descriptive statistics of the relevant socio-demographic variables found to be significant in the model. Slightly more than 40% of the respondents are male. All age and income groups are well represented, with nearly one-third of the respondents between the ages of 31 and 45 and more than half of the respondents having an annual household 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 and a median age of 38.4 for the Metro region (Census Reporter, 2020). One-fifth of the respondents live alone. Two people households are the most common group and compose nearly one-third of the samples.

Unlike previous research efforts regarding e-commerce, this effort includes a question about "the presence of members with a disability who require assistance". Home deliveries may be an important lifeline for populations with disabilities and/or health concerns. This question was included to gauge the impact of disabilities or special needs on home delivery rates during the lockdown period. Nearly one-fifth of the households have at least one member with a disability.

Table 2: Descriptive Statistics of Relevant Demographic Variables

Variable	Frequency	Sample %	Region %
Gender			
Female plus others	605	59.6	50.5
Male	410	40.4	49.5
Age			
18-30	268	26.4	21.8
31-45	315	31.0	28.6
46-65	284	28.0	31.5
66 and higher	148	14.2	18.2
Income			
Less than $ 10,000	100	9.85	4.7
$10,000 to $ 29,999	157	15.5	11.6
$ 30,000 to $ 49,999	202	19.9	14.1
$ 50,000 to $ 99,999	272	26.8	31.4
Greater than $ 100,000	284	28.0	38.3
Household Size			
1	205	20.2	27.7
2	351	34.6	35.1
3	173	17.0	15.2
4	170	16.7	13.3
5 or higher	116	11.4	8.7
Presence of Household Members with Disability			
Yes	178	17.5	See text
No	837	82.5	
Household with a Delivery Subscription			
Yes	706	69.6	See text
No	309	30.4	

The numbers provided in Table 2, right column, for gender, age, and household income and size were obtained from ACS (American Community Survey) data for the region surveyed (USCB, 2021). The age distribution follows the regional data, and there are some differences at the top and bottom ends of the income and household size distributions. Males are underrepresented and show the largest percental deviation in absolute terms. Regarding disabilities and the number of subscriptions, it was not possible to get regional data. The number of adults with any disability in large urban areas is approximately 23% (Zhao et al., 2019). Regarding subscriptions, precise numbers are difficult to obtain, but Amazon (the e-commerce leader in the US but not the only company offering subscriptions) in mid-2020 had 128 million subscribers, roughly 38% of the US population (DC360, 2021). Also, the number of subscriptions in the US has been growing at double-digit rates and the COVID pandemic has accelerated this trend (SUBTA, 2021). It was not possible to obtain figures for the period under study for other e-commerce and home delivery services.

The main reference used for the design of socio-demographic questions was the 2017 NHTS (FHWA, 2018). However, due to the unprecedented nature of the data collection during the pandemic COVID-19 additional attitudinal questions related to health concerns and products (e.g., medicines, meal deliveries) were also included. After data cleaning, the dataset has 1,015 fully complete and clean responses that are utilized to estimate all the models presented in this research.

In the survey, the questions related to home delivery rates are the following: “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?” and “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?”. In these two questions, respondents had to choose one of the five categories shown in Table 3. Comparing before and during answers, it is possible to observe that the 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 to10” and “More than 10” categories. In aggregate, there is a clear increase in delivery rates, but a more in-depth view shows that roughly 10% of the households decrease a category, 37% of the households kept the same level, 37% of the households increased one level, and 15% of the households increased two or more levels during the lockdown. The shift towards higher categories can be better observed in Table 4; for categories “1 to 2, “3 to 5”, and “6 to 10” the category with the highest percentage is the next level up.

Table 3: 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	

Table 4: Crosstabulation (row percentages) of home deliveries in 30 days before COVID-19 lockdown and after COVID-19 lockdown.

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

Table 5 presents the frequency and relative frequency of response to “In the last 30 days, how much money you or members of your household have spent on items that have been delivered to your household?”. More than 40% of households spent between $ 100 and $ 499 on household deliveries in 30 days. Slightly more than 10% of the respondents had household delivery expenditures exceeding $ 1000 per month. The right side of Table 5 presents the distribution of expenditures by the number of deliveries. For low levels of expenditure, the frequency of deliveries is also low. However, as the level of expenditure increases, the values are more evenly spread, and this is likely the result of factors such as household attitudes and products.

Table 5: Descriptive Statistics of household delivery expenditures in 30 days and crosstabulation with home deliveries during COVID

				During COVID-19 Deliveries					
Household Delivery Expenditures in 30 days During COVID	**Frequency**	**%**		**0**	**1 to 2**	**3 to 5**	**6 to 10**	**10+**	**Row Sum (%)**
Less than $ 100	250	24.6		87.1	10.0	1.4	0.0	1.4	100
$ 100 to $ 499	434	42.8		49.7	40.1	9.1	1.0	0.0	100
$ 500 to $ 999	202	19.9		21.2	57.0	14.6	5.3	1.9	100
$ 1000 to $ 2000	89	8.7		6.1	45.1	32.6	12.5	3.8	100
More than $ 2,000	40	3.9		4.3	28.2	30.7	22.7	14.1	100
Column Sum	1015	100		NA	NA	NA	NA	NA	NA

NA: not applicable

4. Exploratory Factor Analysis

A key goal of the survey was to gather data about attitudes regarding safety and home delivery features as well the type of products purchased online and with home delivery. The survey asked, "If you have made online purchases with home delivery in the last 30 days, which of the following categories did you purchase most often? For each category, assign a number ranging from 0 to 5, assign 0 if a category is never ordered, and 5 for the most frequently ordered category." The seven categories included were: 1) groceries, 2) meals home-delivered, 3) electronics and related products, 4) fashion, beauty, or personal care (FBPC) products, 5) recreational/entertainment items, 6) household or office goods, and 7) medicines/medical or health-related goods. The last category was included to gauge the relative importance of health-related items during the pandemic. Table 6 shows the distribution of delivery frequency by product. Given the sample size of 1015, the smallest number of observations per bin in Table 6 is 18, i.e., electronics, column 5 "most frequent" with 1.8%. In this and similar questions, the goal was to obtain an ordering frequency for each category being possible to have two categories with the same category or score. Herein, a shortened description of the categories is included in tables and text to improve readability and table format.

Table 6: Distribution of Delivery Frequency by Product (rows sum to 100%)

Product Type	(0) Never	1	2	3	4	(5) Most Frequent
Grocery	55.6	10.7	7.4	8.5	5.6	12.2
Meals	55.9	9.6	9.7	10.2	6.6	8.1
Electronics	47.6	25.3	14.5	7.4	3.5	1.8
FBPC	33.9	19.1	18.1	14.7	8.3	5.9
Rec. Items	48.6	18.2	12.5	11.6	5.1	3.9
Household/Office	35.5	18.8	18.4	14.2	7.6	5.5
Medicines/Health	49.3	16.4	13.2	10.1	5.5	5.5

In addition, four questions regarding the importance of delivery cost, delivery time, overall online experience, and health concerns to gauge attitudes in these areas during the lockdown. The wording of the question was the following: "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) home delivery cost, (b) home delivery time, (c) easy overall online experience, and (d) personal health and safety concerns. The relative distribution frequencies for each of the factors are displayed in Table 7.

Table 7: Distribution of Attitudinal Questions (rows sum to 100%)

Attitudes	(0) Not relevant	1	2	3	4	(5) Most Important
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

Since the product frequency and attitudinal variables are correlated, it is necessary to find groups of variables or factors that can allow the estimation of the models. Exploratory factor analysis (EFA) was performed to group the products into four factors. The Kaiser-Meyer-Olkin (KMO) test was applied to measure the adequacy of the data for EFA (Fabrigar and Wegener, 2011). The overall score is 0.75, and for each variable, the scores are shown in Table 8. As a general guideline, KMO values between 0.8 and 1 are usually considered very good and below 0.6 is considered inadequate for EFA. The values of the product data are between 0.67 and 0.8, mostly in the 0.7-0.8 range, which indicates that the data is acceptable for EFA.

The eigenvalue and parallel analysis suggested that four factors would be adequate, and the results are shown in Table 8. The EFA was performed using the Psych package in R version 2.1.5 (Revelle and Revelle, 2015) and the "Varimax" rotation at its default parameters. The factor loadings are shown in Table 8, with a standard cutoff value of 0.3 to ease interpretation.

Table 8: Rotated factor loadings

Product or Attitude	Factor 1 "food related"	Factor 2 "consumer products"	Factor 3 "home del. attributes"	Factor 4 "health and safety"	KMO
Grocery	0.99				0.72
Meals	0.30				0.72
Electronics		0.54			0.77
FBPC		0.53			0.82
Recreational Items		0.64			0.76
Household/Office		0.62			0.78
Medicine/health products		0.40			0.82
Cost of Delivery			0.74		0.69
Time of Delivery			0.79		0.72
Online Experience			0.50		0.77
Health and Safety				0.95	0.74

The first factor could be labeled "food-related" categories. The second factor can be labeled non-food "consumer products". The third and fourth factors can be labeled "home delivery attributes" and the last factor "health and safety" concerns. These factors are used to define the latent variables in the frequency and expenditure models. Factor 4 has only one indicator and Factor 1 two indicators. In many studies with more attitudinal questions, the factors are related to three or more indicators. However, it is valid to have for example two latent factors with one indicator each as shown in Vij and Walker (2016).

5. Methodology

The model utilized in this research involves the simultaneous estimation of choice models for order frequency and/or expenditures, latent variables, attitudinal/ordered responses, and socio-demographic variables. The joint estimation of the models offers insights into the contribution of each factor, the different products/attitudes, and the socio-demographic variables (Daly et al., 2012). The formulation presented herein roughly follows Daly et al. (2012) and Potoglou et al. (2015) models, but in this case, there is no panel data, and the upper-level choice model is either an ordered logit model or a binary logit instead of a multinomial logit model.

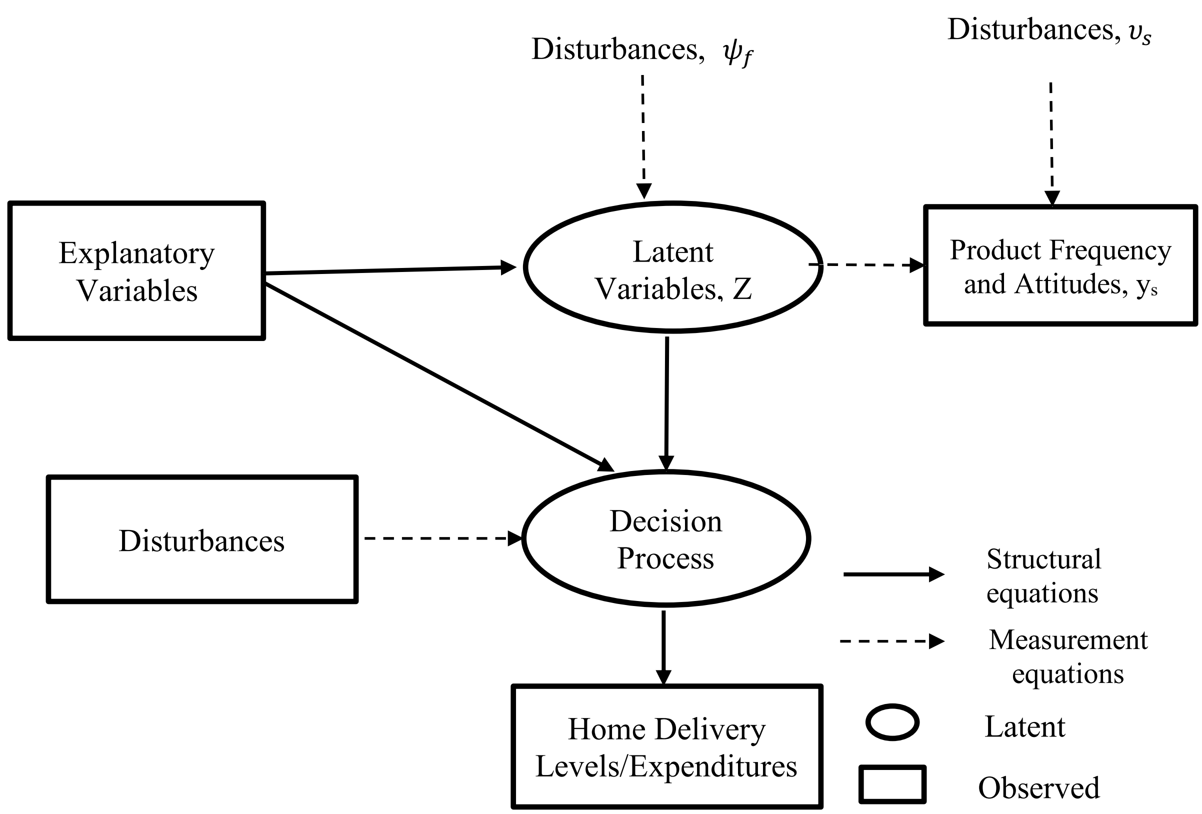
The latent variable model focuses on the four latent factors identified in the previous section. The measurement equations for each product or attitude s links the ordered response, y_s, as follows:

$$y_s = d_s Z + \upsilon_s$$

where Z is the corresponding latent variable and υ_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:

$$Z_{f,n} = b_f W_{f,n} + \sigma_f \, \psi_{f,n}$$

The vector of parameters b_f is estimated for each factor, and the term $W_{f,n}$ represents a set of socio-demographic variables (delivery subscription, gender, income, age, household size, disability). The term $\sigma_f\ \psi_{f,n}$ is a normally distributed error term with zero mean and standard deviation σ_f for each factor.



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 a product or attitude s is estimated as follows:

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

where Λ is the closed cumulative form of the logistic distribution and with constraints:

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

for each response level. The threshold parameters τ are estimated, and to set the additive scale of the ordinal model, constants are omitted. To normalize the scale of the measurement equations, one of the parameters d_p for each group of products is set to one (Ben-Akiva et al., 2002). The likelihood of the set of S ($s \in S$) ordered responses for products and attitudes for respondent n is:

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

There is a final ordered logit or binary logit model. In the ordered model, the observed utility of individual n is given by this expression:

$$V_n = \sum_f \gamma_f \ Z_{f,n}$$

The parameter γ_f is the contribution of the latent factor f and the parameter β_i is the contribution of the independent variable $x_{i,n}$. To differentiate thresholds, η is utilized to denote estimated threshold parameters in this final model. The dependent variable, u_n (change in delivery frequency) is also naturally ordered, and the probability that an individual n generates the observed response k is estimated as follows:

$$P\{u_n = k\} = \Lambda(\eta_k - V_n) - \Lambda(\eta_{k-1} - V_n)$$

In the binary logit model, the dependent variable is a given level of delivery and expenditure, the observed utility of individual n is given by this expression:

$$V_n = constant + \sum_f \gamma_{f,n} \ Z_{f,n}$$

Without alternative specific variables and normalizing to zero the γ coefficients for the first alternative, the probability of the first alternative is:

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

Following Daly et al. (2012), it is assumed that the disturbances are independent and that their covariance matrices are diagonal matrices. All the parameters $(d_s, b_f, \sigma_f, \tau_{y_{s,q}}, \beta_i, \gamma_f, \eta_k)$ are jointly estimated by maximizing the log-likelihood function utilizing the package Apollo version 0.2.1 (Hess and Palma, 2019) in the R environment version 4.0.3 (R Core Team, 2020). The coefficients of the estimated parameters are stable after approximately 100 draws, but the results presented are obtained with 500 draws per random parameter utilizing the Modified Latin Hypercube Sampling (MLHS) method (Hess et al., 2006). The results of initial exploratory models were validated against the results of the "polr" function of the MASS package in R (Ripley et al., 2013).

6. Change in Delivery Frequency Results

This section presents the latent variable model results when applied to the increase in delivery rates per month. In all tables henceforth, t-ratios are shown, and to guide the reader, variable coefficients with t-ratios $\geq$ 1.96 (0.05 significant level) in absolute value are **bold** to facilitate the interpretation of the results. In addition, * and ** symbols have been added to indicate significant levels of 0.01. and 0.001 with t-ratios 2.58 and 3.30 respectively.

For the delivery rate model, a difference model is estimated, i.e., the dependent variable is the difference between COVID and pre-COVID delivery rates. The difference in delivery rates produces a dependent variable with four levels: decreased, the same level, increased by one, or increased by more than one category. This difference between ordered variables is not ideal, but it reduces biases in the estimated parameters because the error distributions of COVID and pre-COVID delivery rates are likely correlated (i.e., not independent over time). There are four levels; comparing before and during COVID-19 rates roughly 10% of the households decreased a category, 37% of the households kept the same level, 37% of the households increased one level, and 15% of the households increased two or more levels during the lockdown.

Regarding socio-demographic variables, mid-income comprises incomes in the range of $30,000 to $100,000 and high income above $100,000. According to the literature review, age is likely to be negative, and mid/high-income groups are expected to be positive. Except for "Age", all the socio-demographic variables are treated as binary variables, which means that no ordering or structure is imposed on them. For example, income level has a natural order, but each income level is estimated in relation to the baseline, which is low household annual income (less than $30,000). In all the results, high income has a higher coefficient than mid-income, but this is not the result of imposing a constraint. The whole model LL, AIC, and BIC is -17647, 35496, and 36244 respectively.

Latent Model Results

The results are compared side by side in Table 9. Factors 1, 2, and 4 are significant and positive, and Factor 3 (related to delivery time and cost and online experience) is not significant. Health and safety concerns had the largest contribution in terms of coefficient value followed by food products.

Table 9: Ordered Logit Model Results

Variable	**Delivery Rate Difference Model**	
	Coef.	**t-ratio**
γ_1 (food products)	**0.199**	2.27
γ_2 (non-food products)	**0.152**	2.55
γ_3 (delivery/purch. attributes)	0.016	0.49
γ_4 (health/safety concerns)	****0.681**	3.57
Thresholds η		
Level 1	****-1.773**	-8.61
Level 2	0.375	1.93
Level 3	****2.311**	10.92

Bold p<.05, * p<.01, ** p<.001

Socio-demographic Variables

Table 10 presents the effect of socio-demographic variables on the four latent factors. Table 10 shows that for Factor 1 (food products), only delivery subscription, age, and households with a disability are positive and statistically significant factors. Same results are observed for Factor 2, but in addition, income variables and household size are positive and statistically significant variables. For Factor 3, only subscription, income, and age are significant. An important change is observed in Factor 4 (health and safety), age is no longer negative but positive, indicating a major reversal in trend regarding age. In addition, the variable male is significant and with a negative sign. These results seem to indicate that younger and/or males are less concerned about health and safety than other groups.

The variable disability has a significant and positive coefficient for Factors 1, 2, and 4, whereas income variables are positive and significant for Factors 2, 3, and 4. In all cases, a delivery subscription is a significant variable, but the results are stronger in terms of coefficients and t-ratios for Factors 1, 2 and 3. Household size is positive and significant only for Factor 2 non-food products. Overall, the results confirm some previous expectations based on the literature review, but there are novel results regarding age and disability. A graph showing significant variables for the delivery frequency model is presented in Figure 1.

Table 10. Socio-demographic Variables

Group	Variable	Delivery Rate Difference Model	
		Coef.	t-ratio
Factor 1 (food)	Subscription	****0.720**	4.61
	Male	-0.066	-0.57
	Mid Income	0.259	1.82
	High Income	0.293	1.75
	Age	****-0.023**	-6.15
	HH Size	-0.040	-0.89
	Disability	***0.380**	2.62
	σ_1	****1.010**	6.64
Factor 2 (non-food)	Subscription	****0.942**	7.31
	Male	0.106	1.10
	Mid Income	****0.726**	5.66
	High Income	****0.872**	5.95
	Age	****-0.021**	-6.19
	HH Size	****0.155**	3.89
	Disability	**0.310**	2.43
	σ_2	****1.234**	11.98
Factor 3 (purchase attributes)	Subscription	****0.732**	4.19
	Male	0.054	0.35
	Mid Income	****0.737**	3.71
	High Income	****0.979**	4.23
	Age	***-0.013**	-2.59
	HH Size	0.070	1.07
	Disability	0.286	1.29
	σ_3	****2.189**	13.30
Factor 4 (health/safety)	Subscription	**0.289**	2.08
	Male	****-0.526**	-4.22
	Mid Income	***0.497**	3.13
	High Income	****0.648**	3.53
	Age	**0.008**	2.26
	HH Size	-0.085	-1.82
	Disability	**0.342**	2.05
	σ_4	***-0.449**	-2.70

Bold p<.05, * p<.01, ** p<.001

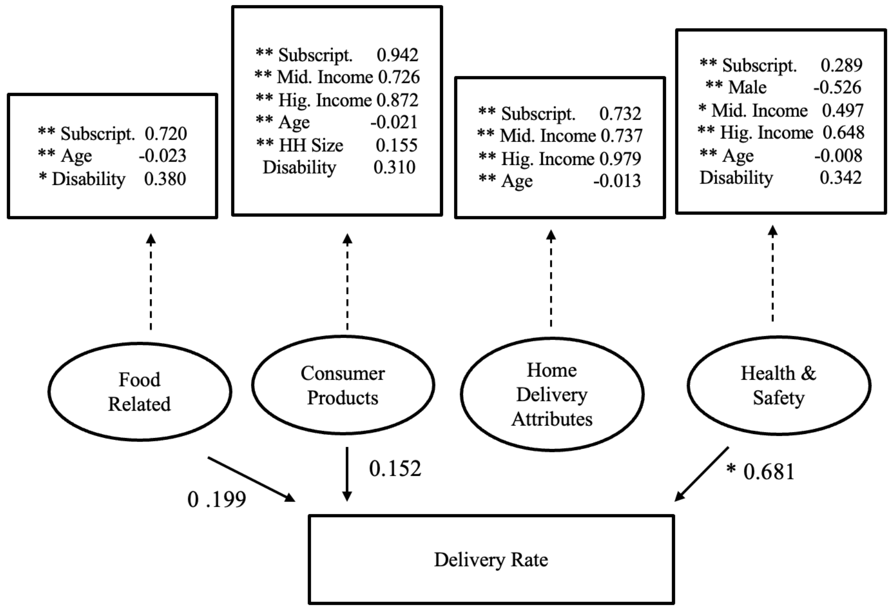


Figure 1. Delivery Rate Model
Note: only significant variables p<0.05 are included with symbols * for p<0.01 and ** for p<0s.001

Latent Variable Results

Table 11 shows the impact of latent factors on product frequency. When comparing results in terms of d_s parameters it is possible to see the sign and relative standing of each product. Groceries, electronic products, delivery cost, and online experience are set to 1 as required to have an efficient estimation process. All the estimated parameters are significant. The value of medicine/health products is significantly lower than household products and recreational items. Online experience is significantly lower than delivery time.

Table 11: Latent Variable Results

Factor	**Variable d_p**	**Delivery Rate Difference Model**	
		Coef.	**t-ratio**
1	Grocery	1.000	-
	Meals	****1.391**	6.10
2	Electronics	1.000	-
	Rec. Items	****1.454**	9.45
	Household/Off.	****1.320**	8.91
	Medicine/Heath	****0.728**	8.11
	FBPC	****0.992**	8.83
3	Delivery Cost	1.000	-
	Delivery Time	****1.473**	7.57
	Online Experience	****0.622**	9.94
4	Health/safety Concerns	1.000	-

Bold p<.05, * p<.01, ** p<.001

Finally, Tables A1 and A2 in appendix A show the threshold parameters for product and attitude models.

7. Exploring Factors Affecting High/Low Delivery Rates and Expenditures

Binary logit models with latent variables are estimated to further explore the factors that result in different levels of deliveries and expenditures. This section presents the results of the latent variable models when applied to customers with (a) low delivery rates and high level of expenditures – herein denoted "LD-HE" model – (b) high delivery rates and low level of expenditures – herein denoted "HD-LE" model – and (c) high delivery rates and high level of expenditures – herein denoted "HD-HE" model.

As shown in Table 3 and Table 5, approximately 36% of the households reported expenditures larger than $500 per month, and 42% of the households reported more than six deliveries per month. These are the thresholds used to create binary variables with low and high levels of deliveries and expenditures. Approximately 9% of the households (92 observations) belong to the LD-HE case, 19% of the households (188 observations) belong to the HD-LE case, and 24% of the households (239 observations) belong to the HD-HE case. For the HD-LE model, the whole model LL is -16691, AIC 33579 and BIC 34313; for the LD-HE model, the whole model LL is -16862, AIC 33923 and BIC 34656; and for the HD-HE model, the whole model LL is -16843, AIC 33884 and BIC 34617.

Latent Model Results

The results are compared side by side in Table 12. There are major differences among model results. In the LD-HE model, Factor 2 (non-food products) is the only significant latent factor that contributes to low delivery rates but high level of expenditures. High level of deliveries but low expenditures (HD-LE) has positive and significant contributions from safety/health followed by non-food products and delivery/purchase attributes. Finally, high levels of deliveries and expenditures (HD-HE) also has positive and significant contributions from safety/health but followed by non-food products and food-products. The results confirm that high delivery rates took place in households with higher levels of health and safety concerns, health and safety concerns is not a significant factor in households with low delivery rates.

Table 12: Ordered Logit Model Results

Variable	LD-HE model		HD-LE model		HD-HE model	
	Coef.	**t-ratio**	**Coef.**	**t-ratio**	**Coef.**	**t-ratio**
Constant	**-2.182	-6.81	**-2.266	-8.30	**-3.993	-7.44
γ_1 (food products)	0.284	1.50	0.053	0.38	**0.658	3.72
γ_2 (non-food products)	**0.388	3.50	**0.216**	2.55	**0.763	6.03
γ_3 (delivery/purch. attributes)	-0.029	-0.46	**0.109**	2.30	0.055	0.98
γ_4 (health/safety concerns)	**-0.665**	-1.98	*0.800	2.61	*2.066	2.81

Bold p<.05, * p<.01, ** p<.001

Socio-demographic Variables

Table 13 shows the results regarding socio-demographic variables. In most cases, the same variables are significant (using as a reference a t-ratio > 2) and with the same sign when comparing with the results in Table 10. For Factor 1 (food products), only delivery subscription, age, and households with a disability are positive and statistically significant factors with the sole addition of mid-income in the LD-HE model. Same significant variables are observed for Factors 2 and 3 in Table 13 (also similar to significant variables in Table 10).

Major changes are observed in Factor 4 (health and safety); the variable "age" is positive and significant only for the HD-HE model, indicating that only in households with more deliveries and expenditures there is a reversal in the sign of the variable "age". In addition, the variable "male" is significant and with a negative sign only for models LD-HE and HD-LE. These results indicate that younger and/or males are less concerned about health and safety mostly in LD-HE and HD-LE households. The variable "high income" is only positive and significant in the models with high levels of expenditures. The variable "disability" has a significant and positive coefficient only in the LD-HE model.

Graphs showing significant variables for the three models are presented in Figure 2.

Table 13. Socio-demographic Variables

Group	Variable	LD-HE model		HD-LE model		HD-HE model	
		Coef.	t-ratio	Coef.	t-ratio	Coef.	t-ratio
Factor 1 (food)	Subscription	**0.695	**4.64**	**0.688	**4.60**	**0.717	**4.58**
	Male	-0.032	-0.30	-0.058	-0.54	-0.023	-0.20
	Mid Income	0.269	**2.01**	0.248	1.85	0.224	1.56
	High Income	0.281	1.79	0.260	1.64	0.291	1.71
	Age	**-0.023	**-6.31**	**-0.023	**-6.28**	**-0.023	**-6.09**
	HH Size	-0.042	-0.98	-0.036	-0.85	-0.033	-0.70
	Disability	*0.401	**2.91**	*0.381	**2.78**	*0.383	**2.60**
	σ_1	**0.881	**6.07**	**0.897	**6.30**	**1.036	**7.14**
Factor 2 (non-food)	Subscription	**0.943	**7.26**	**0.936	**7.26**	**0.899	**6.99**
	Male	0.112	1.13	0.097	0.99	0.134	1.36
	Mid Income	**0.755	**5.77**	**0.722	**5.61**	**0.689	**5.33**
	High Income	**0.920	**6.11**	**0.864	**5.85**	**0.878	**5.91**
	Age	**-0.023	**-6.37**	**-0.022	**-6.28**	**-0.022	**-6.21**
	HH Size	**0.151	**3.73**	**0.155	**3.88**	**0.154	**3.84**
	Disability	*0.335	**2.60**	0.317	**2.49**	*0.333	**2.62**
	σ_2	**1.250	**4.18**	**1.242	**4.16**	**0.729	**4.21**
Factor 3 (purchase attributes)	Subscription	**0.735	**4.18**	**0.731	**4.16**	**0.729	**4.21**
	Male	0.059	0.38	0.049	0.32	0.045	0.30
	Mid Income	**0.741	**3.65**	**0.762	**3.78**	**0.732	**3.71**
	High Income	**1.021	**4.36**	**1.002	**4.29**	**0.995	**4.33**
	Age	*-0.013	**-2.67**	*-0.013	**-2.69**	*-0.013	**-2.63**
	HH Size	0.059	0.90	0.062	0.93	0.067	1.03
	Disability	0.243	1.06	0.284	1.28	0.242	1.10
	σ_3	0.243	1.06	0.284	1.28	0.242	1.10
Factor 4 (health/safety)	Subscription	*0.408	**2.83**	*0.398	**2.88**	0.209	1.68
	Male	**-0.591	**-4.64**	**-0.576	**-4.58**	-0.136	-1.25
	Mid Income	0.437	**2.39**	*0.489	**2.94**	0.266	1.91
	High Income	0.514	**2.42**	0.350	1.66	*0.628	**3.28**
	Age	0.006	1.49	0.003	0.88	*0.009	**2.96**
	HH Size	-0.008	-0.14	-0.026	-0.54	0.026	0.82
	Disability	0.454	**2.53**	0.341	**1.96**	0.171	1.34
	σ_4	-0.202	-0.90	-0.329	**-2.03**	-0.097	-0.62

Bold p<.05, * p<.01, ** p<.001

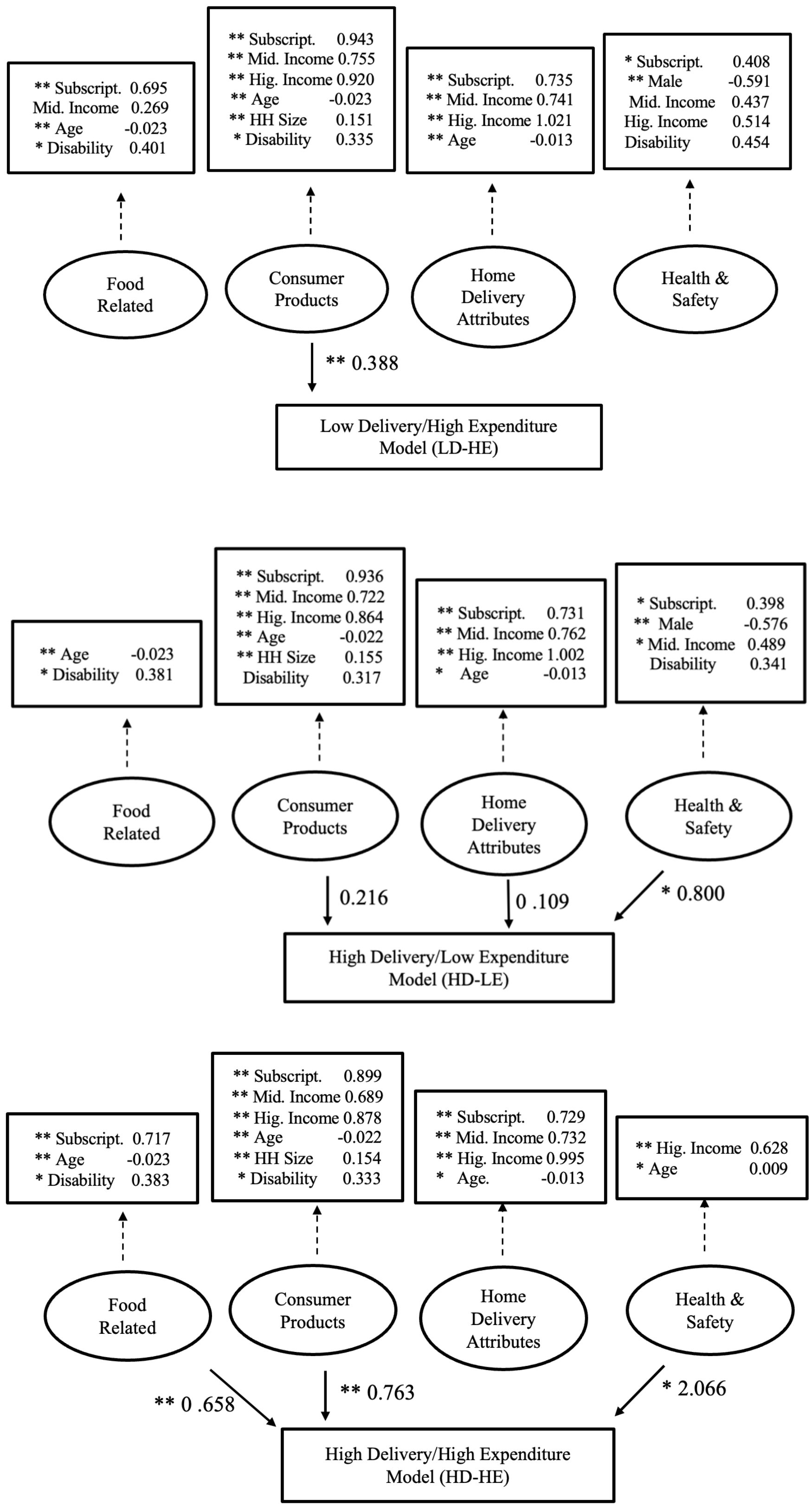


Figure 2. Frequency and Expenditure Models
Note: only significant variables $p<0.05$ are included with symbols * for $p<0.01$ and ** for $p<0.001$

Latent Variable Results

Latent variable results are displayed in Table 14. All the estimated parameters are again positive and significant. In all cases, the values of the coefficients do not show a large variation.

Table 14. Latent Variable Results

Factor	Variable d_p	LD-HE model		HD-LE model		HD-HE model	
		Coef.	t-ratio	Coef.	t-ratio		
1	Grocery	1.000	-	1.000	-	1.000	-
	Meals	****1.391**	6.10	****1.411**	6.06	****1.289**	6.05
2	Electronics	1.000	-	1.000	-	1.000	-
	Rec. Items	****1.454**	9.45	****1.484**	9.37	****1.437**	9.56
	Household/Off.	****1.320**	8.91	****1.312**	8.89	****1.361**	8.87
	Medicine/Heath	****0.728**	8.11	****0.733**	8.07	****0.748**	8.15
	FBPC	****0.992**	8.83	****1.015**	8.78	****1.013**	8.87
3	Delivery Cost	1.000	-	1.000	-	1.000	-
	Delivery Time	****1.473**	7.57	****1.451**	7.61	****1.480**	7.62
	Online Experience	****0.622**	9.94	****0.622**	9.89	****0.632**	9.81
4	Health Concerns	1.000	-	1.000	-	1.000	-

Bold p<.05, * p<.01, ** p<.001

Finally, Tables B1 and B2 in Appendix B show the threshold parameters for product and attitude models.

8. Discussion

The unprecedented scope and speed of changes brought about by the COVID-19 lockdown on household activities, travel, and consumption patterns are still ongoing and likely to leave an indelible mark on attitudes towards online shopping and household deliveries. The extent and severity of the COVID-19 pandemic and its associated lockdown were mostly unexpected, and its speed was a shock to traditional ways of commerce and work for most businesses and workers. The lockdowns have accelerated a trend towards teleworking, remote schooling, and remote delivery of many services and activities that used to be only (or mostly) offered at brick-and-mortar locations.

A high degree of uncertainty has characterized the evolution of the COVID-19 pandemic and its ongoing and future impacts on transportation systems and, more specifically, on household shopping patterns. It is possible to conjecture that the post-COVID-19 world will strengthen trends clearly visible before the pandemics, such as teleworking and online shopping with home deliveries. Lessons learned from the early days of teleworking may provide an insight into future trends for home deliveries. The impacts of remote working have been studied since the late nineties, e.g., Varma et al. (1998) analyzing the adoption of telecommuting and telecenters and Mokhtarian and Meenakshisundaram (1999) showing that there was an early and "stable" segment of adopters of telecommuting but with a spectrum regarding long-term commitments. It is possible that a similar trend will be observed in terms of home deliveries but with sharp differences across product types and households. For example, home deliveries of electronic products may have a steadier growth. In contrast, home deliveries of products like groceries or meals may depend more on the evolution of the pandemic and population concerns about health and safety while shopping at a physical location (as well as costs and other factors found significant).

This section discusses insights related to home deliveries and speculates about different aspects of home deliveries that have implications for policy analysis and future research efforts. The discussion is divided into the following subsections: data collection, future demand trends, freight and logistics impacts, integration of freight and travel demand modeling, equity, and study limitations.

Data Collection

There has been scant or no research regarding the type of products and household characteristics that trigger high levels of deliveries and expenditures. There are sources of e-commerce data at the government level (USDC, 2020) and at the private level (Adobe, 2020) that provide relatively fast and highly accurate information regarding e-commerce sales and online price inflation. However, there is little data about actual household delivery rates, at least in the US. The NHTS is conducted typically every eight years; the most recent surveys are dated 2009 and 2017, and the next release of data is years away.

This research has also shown that the factors driving household delivery expenditure levels are not necessarily the same as those driving household delivery frequencies. Expenditures are a useful proxy, but actual travel impacts regarding miles traveled, emissions, and crashes are related to actual delivery rates per household and the type of product. From a logistics perspective, the efficiency of household delivery systems is not affected directly by expenditure levels but instead by the overall number of deliveries, the number of deliveries per vehicle or route, and delivery constraints such as time windows and delivery time.

Home deliveries can be a substitution for in-person travel to stores. Hence, home deliveries are at the intersection of personal travel and commercial vehicle (last mile) travel. However, there are no datasets that can provide a joint comprehensive view of these two complementary travel modes. There is also a lack of long-term longitudinal data to track detailed consumer behavior regarding shopping trips, home deliveries, and e-commerce.

Data collection is now becoming even more complex with different ways to receive products shopped online. Alternatives to traditional home delivery include now ordering online (e-commerce) with in-store pickup or pickup at locker facilities. New acronyms like BOPAC (buy online pick-up at curbside) and BOPIS (buy online and pick up in-store) became mainstream in logistic circles during the pandemic. In addition, it is possible to add BOPL (buy online pick up at locker) which is more common in Europe but that Amazon is also introducing in the US. In some countries like Poland, with a high locker density, there are even more advanced alternatives regarding lockers. It is possible for companies (and consumers) to ship products from locker to locker and to request delivery of products from locker to locker.

Home Delivery Demand Trends

The results of the latent models show clear variation across factors and socio-demographic variables. Unlike previous research efforts, there is a clear reversal regarding the sign of the variable age and the factor health and safety concerns (age is significant and positive). If older respondents are more likely to engage in home deliveries due to health and safety concerns, this has large future implications in terms of demographic changes and future home delivery demand.

Previous research efforts have alerted about long known demographics trends such as population aging and more specifically, the impact of the baby boomer generation on travel demand (Goulias et al., 2007; Metz, 2012; Siren and Haustein, 2013). The potential impacts of population aging are not clear yet, and the travel propensity of baby boomers and future retirees is likely to depend on many factors. The COVID-19 pandemic has likely added another layer of complexity in terms of long-term household decisions such as housing location and vehicle ownership or level of comfort utilizing public transportation options. Future research should explicitly include health and safety (Factor 4 in this research) as well as disabilities as factors that impact transportation-related decisions in future research efforts.

Population aging is also likely to increase trips related to health and assistance services as total percentage of trips. However, telehealth or telemedicine received a boost during the pandemic; in the future, in-person visits could be reduced, but it is likely that this is going to trigger the demand for home deliveries related to ancillary services such as medicines, home tests, as well as devices to remotely monitor health indicators. Robotization of care may also impact the number or health care worker trips.

Recent studies have indicated that public transportation is perceived to be associated with higher levels of risk and that risk perception might depend on characteristics of residential location (Rahimi et al., 2021). A future research topic is the investigation of risk perception regarding transportation modes and their relationship with the adoption of home deliveries and e-commerce. A recent review of travel demand studies indicates that the literature has not yet reached a consensus on the dominant effect of online shopping (Le et al., 2021). Although there is more evidence indicating that online shopping substitutes for shopping travel demand, there is also a lot of heterogeneity, and this research effort now indicates that the heterogeneity may be related to product types, home delivery attributes, and health/safety factors.

The long-term impact of the 'urban exodus' seen at the start of the COVID-19 pandemic is not clear. It is likely that a sizable percentage of people that moved out of cities had second homes and therefore higher incomes. It is also likely that another percentage of movers were teleworkers "escaping" from expensive urban areas and looking for cheaper and larger housing units in suburban and rural areas.

A movement of population towards urban or suburban areas is likely to put pressure on local services (Gallent, 2020) in the short-term. But for home deliveries, a movement towards less dense and populated areas is likely to result in more home deliveries, i.e., more store trip substitutions since higher-income households buy more and more often online and because former city dwellers are more familiar with e-commerce and home deliveries. Changes in teleworking rates are also likely to have direct impacts on home delivery frequency but also potential indirect effects such as the need to continue improving homes that are also work environments. The term "home nesting" became popular during the pandemic as many consumers (and companies in some cases) invested in home furniture and equipment. Home nesting may result in redirecting deliveries that traditionally were shipped to office or company buildings in dense urban cores.

Impacts on Freight and logistics Operations

The type of product is likely to play a key role regarding home delivery frequency by type of household and by location. Some types of home deliveries like food or certain groceries (refrigerated or vegetables) may not be available in low-density areas. However, durable consumer products are likely to dominate home deliveries in rural and suburban areas with low density.

Type of product is also key in terms of logistics efficiency. Meals and food products for immediate or same-day consumption are not typically delivered by the same vehicles and/or companies. Furthermore, there are significant differences in supply/service chains and distribution networks for food-related (Factor 1 in this research) and non-food-related products (Factor 2 in this research). Hence, commercial trips and flows cannot be captured solely by focusing on traditional heavy-duty commercial vehicles. Data collection efforts such as the NHTS should include variables that better reflect the evolution of home deliveries and the attitudes and non-traditional products and services (like food delivery) that impact home delivery rates.

Demographic and spending habit changes and the growth of home delivery will trigger changes in the logistics networks needed to meet spatial changes of home deliveries demand (for example reshoring sourcing and the addition of warehouses and distribution centers) as well as changes in freight patterns. In addition, as a result of the pandemic and other disruptions (like electronic chips), supply chains will likely increase safety stocks or change sourcing locations to meet changing consumer expectations in terms of delivery time and reliability.

It is expected that the last mile of home deliveries will have to evolve to meet the growth of customer demands but also growing expectations regarding accessibility, affordability, and convenience. Logistics and shipping capacity in the last mile will have to increase to meet surges that are not limited to Black Friday events or the holiday season.

The growth of home delivery and new delivery modalities like BOPIS will require that many stores in urban areas will have to be redesigned to serve in-person customers as well as a growing demand at the curb (access by auto/transit/peds) and docks to facilitate delivery fleet access. For cities, especially where roadside space is scarce, it may be challenging to allocate space for growing logistical access. Road, parking, and sidewalk space reallocations may be needed, especially at locations where parking and access to automobiles were reduced during the pandemic to allow for on-street/sidewalk outdoor restaurant seating and other uses.

The aftermath of COVID-19 may not only change the geography of work and urban centers but also the geography of freight and logistics at regional, urban, and even at the block level.

Integrating Freight and Travel Demand Modeling

The previous discussion highlights the need for greater integration between freight and passenger demand modeling. E-commerce not only may reduce or change in-store shopping frequency (complementary or substitution effects), but it also impacts flows at the regional level (warehousing, freight flows), urban level (fulfillment centers and more delivery traffic), and even at the block or street level when considering parking and access for last-mile delivery vehicles and fulfillment utilizing BOPIS systems.

There is also a need for more freight and specifically last-mile models within urban areas. A paper analyzing best practices for urban freight management, an international survey, indicates that there are many opportunities for freight research, starting with the question of how many vehicles are engaged in freight activities (Dablanc et al., 2013). Freight models are more undeveloped than passenger models, and there is no model that can integrate and forecast trips disaggregating by vehicle types such as heavy truck, light-duty truck, van, car, rideshare, and even less by modality type including parcel delivery, BOPIS, BOPAC, and BOPL. Traditional freight models have focused on heavy and medium trucks and business-to-business flows, neglecting home deliveries and the impacts of e-commerce at different geographic scales. The emergence of new vehicle types such as electric cargo bicycles or trikes, autonomous delivery robots, and drones may also play a significant role in future home delivery operations.

The connections and interactions among home deliveries, passenger trips, and commercial trips are growing stronger due to the COVID-19 pandemic. Still, current modeling approaches are rather elementary at best when representing these interactions. Part of the problem stems from the lack of suitable datasets, as mentioned earlier.

Home Delivery and Equity

Income is another key socio-demographic variable. Equity is becoming more relevant and increasingly affecting transportation programs and funding decisions. Home deliveries disproportionally benefit higher-income more educated sectors of the population (Figliozzi and Unnikrishnan, 2021). In this regard policymakers may consider policy options that facilitate access to e-commerce and home deliveries. More specifically, measures to reduce the digital divide will increase e-commerce adoption among disadvantaged groups. In addition, the installation of common carrier lockers can reduce delivery costs and facilitate access to consumers that due to work constraints or residential locations do not feel comfortable with unattended home deliveries (Keeling et al., 2021). The integration of transit services, that usually cater to disadvantaged populations or groups with low or no auto ownership, with common carrier lockers or other methods that reduce cost or facilitate access could also be beneficial to reduce home delivery inequality in urban and rural areas.

Equity can also be impacted from the supply and labor side of home deliveries. Higher delivery volumes and pressures to cut costs and become more competitive are likely to foster last-mile delivery innovations that increase productivity and reliability. At the same time, the logistics delivery system has shown some signs of fragility related to labor unrest. Protests motivated by low wages, equity issues, and workers' health at distribution centers have been a challenge for many companies that had to ramp up operations and swiftly hire an unprecedented number of new workers. Automatization and contact-free delivery systems may provide long-term advantages both in terms of delivery costs but also on the resiliency and sustainability of delivery systems. Research has found that the market penetration of autonomous trucks would, in part, depend on autonomous delivery technology (Jennings Figliozzi, 2019; 2020) and public opinion (Pani et al., 2020); higher income households are more likely to order home deliveries utilizing autonomous delivery vehicles. COVID-19 may accelerate the necessary public opinion changes to support autonomous home deliveries but this may also bring equity concerns regarding access to this type of service.

Limitations

The data used in this paper is one snapshot at a specific point in time. It is likely an important point in time though, COVID-19 may have created an inflection point and triggered many long-term changes in societal behavior and norms, passenger travel, freight and supply chains, and home deliveries. Research efforts that include longitudinal panel data would be key to complement the presented findings and analyze the evolution of attitudinal changes regarding travel and home deliveries. It would have been desirable to collect data at other locations with a different sociodemographic profile to compare results and derive more complex insights.

The findings regarding products and factors such as health and safety are very likely to be robust, especially the ones supported by variables with a stringent significant level. However, with the caveat that the results are robust but limited to a specific yet important point in time. It is difficult to speculate about the "new normal" and long-term "stickiness" of the changes brought up by the COVID-19 pandemic as other researchers have already discussed (Salon et al., 2021).

9. Conclusions

This research is a first towards understanding how the lockdown has changed home delivery patterns by trying to disaggregate the impacts of a set of products and consumer attitudes utilizing latent variable models. The data used in this research effort was collected during the period of a strict lockdown in Oregon, when traffic levels on main freeways were 40 to 60% lower than usual.

An important finding of this research is that the factors that increase or decrease the adoption of home deliveries during a lockdown can vary widely across factors related to products and attitudes. Each factor has a unique profile regarding household characteristics.

Unlike previous research efforts related to e-commerce and home deliveries, this effort analyzed the impacts of health and safety concerns and the impact of household members with disabilities or special needs on home delivery rates and expenditures. Nearly one-fifth of the households surveyed have at least one member with a disability or a special need. Health and safety concerns is the latent factor with the largest contribution to home deliveries rates and in households with high levels of deliveries and expenditures.

Gender also plays a role in attitudes during the lockdown, the variable "male" only has a significant and negative sign in the health and safety concerns factor. Households with a member with a disability or special need are more likely to order food-products (meals and groceries), non-food products, and are also likely to be more concerned in terms of health and safety.

The results of the latent models show clear variation across factors and socio-demographic variables. Age is a significant and negative variable for factors related to products or home delivery attributes, i.e. younger respondents are more likely to engage in home deliveries related to food or non-food products as previously shown by many research efforts. However, there is clear reversal regarding health and safety concerns where age is significant and positive, indicating that older respondents are more likely to engage in home deliveries due to health and safety concerns.

Based on the modeling results, the number and type of deliveries are expected to vary widely across one urban area. Consumers and households evaluate tradeoffs regarding costs, convenience, and health concerns; these tradeoffs are affected by household and personal characteristics such as household size, age, income, and the presence of members with disabilities. The adoption of subscription services and the cost of deliveries (flat monthly fee or per purchase) is also likely to play an important role in the evolution of home delivery rates. If the home delivery sector continues to grow rapidly, this will also have implications for cities and planning organizations that will have to adapt and react to the changes and their broader implications in terms of accessibility, safety, and equity. The results of this research provide new insights into the adoption and utilization of home deliveries and may help inform future data collection and planning endeavors.

Regarding long-term trends, demographics, and the natural aging of the population also provide support to the hypothesis of sustained growth of e-commerce and home deliveries fueled by the continuous growth of the next generation of younger and tech-savvy consumers. Currently, there are billions of annual grocery shopping trips in the US; the growth of the home delivery sector with higher route efficiency and cleaner autonomous vehicles can have a significant and positive impact in terms of safety (Sparrow and Howard, 2020) and emissions (Figliozzi, 2020). It is likely that in the post-COVID world, access for residential deliveries may still be challenging in dense urban areas (Chen et al., 2017). The extent of the pros and cons of a rapid increase in home delivery rates is likely to depend on long-term demographic, land use, and business patterns, which are particularly difficult to visualize at this point in time. Traditionally, most freight research has focused on modeling freight attraction and production rates as a function of land use and other variables, e.g., Lawson et al. (2012). This type of study will remain important for planning organizations, but it is likely that the share of trips related home deliveries will grow in importance and this should be taken into account in future data collection, research, and planning efforts.

Potential implications of the findings in terms of data collection, modeling, freight and logistics, and equity were discussed. Given that the long-term impacts of the COVID-19 pandemic are still unraveling, better and more data should be collected to let future research efforts study the connections among home deliveries, travel demand, safety and risk perceptions, and sociodemographic and location factors.

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Appendix A

Table A1. Threshold levels for products

Product	Thresholds τ	Delivery Rate Diff.	
		Coef.	t-ratio
Grocery	Level 1	-0.352	-1.17
	Level 2	0.354	1.16
	Level 3	0.886	2.86
	Level 4	1.602	5.01
	Level 5	2.201	6.64
Meals	Level 1	-0.415	-1.09
	Level 2	0.257	0.70
	Level 3	1.006	2.83
	Level 4	2.009	5.68
	Level 5	2.931	8.09
Electronics	Level 1	0.748	3.25
	Level 2	2.377	9.64
	Level 3	3.707	13.77
	Level 4	4.931	16.33
	Level 5	6.211	16.88
FBPC	Level 1	-0.089	-0.38
	Level 2	1.172	4.92
	Level 3	2.389	9.58
	Level 4	3.655	13.73
	Level 5	4.860	16.61
Recreational Items	Level 1	1.191	3.83
	Level 2	2.560	7.88
	Level 3	3.667	10.70
	Level 4	5.142	13.77
	Level 5	6.322	15.41
Household Office	Level 1	0.200	0.67
	Level 2	1.557	5.03
	Level 3	2.927	8.88
	Level 4	4.342	12.15
	Level 5	5.641	14.42
Medicine Health	Level 1	0.633	3.42
	Level 2	1.557	8.02
	Level 3	2.445	11.85
	Level 4	3.423	15.15
	Level 5	4.306	17.07

Table A2. Threshold levels for attitudes

Product	Thresholds τ	Delivery Rate Diff.	
		Coef.	t-ratio
Delivery Cost	Level 1	-3.297	-7.96
	Level 2	-2.486	-6.28
	Level 3	-1.633	-4.27
	Level 4	-0.329	-0.88
	Level 5	1.451	3.84
Delivery Time	Level 1	-3.923	-6.18
	Level 2	-2.923	-4.96
	Level 3	-1.539	-2.83
	Level 4	0.470	0.90
	Level 5	2.698	4.70
Online Experience	Level 1	-2.185	-6.80
	Level 2	-1.423	-4.48
	Level 3	-0.460	-1.42
	Level 4	1.121	3.17
	Level 5	2.800	6.98
Health Concerns	Level 1	-1.507	-4.17
	Level 2	-0.612	-1.75
	Level 3	0.551	1.58
	Level 4	1.835	5.02
	Level 5	2.895	7.41

Appendix B - Table B1. Threshold levels for products

Product	Thres-holds τ	LD-HE model (a)		HD-LE model (b)		HD-HE model (c)	
		Coef.	t-ratio	Coef.	t-ratio	Coef.	t-ratio
Grocery	Level 1	-0.037	-0.15	-0.052	-0.22	-0.08	0.38
	Level 2	0.591	2.43	0.578	2.37	2.38	1.09
	Level 3	1.067	4.31	1.055	4.26	4.16	1.06
	Level 4	1.713	6.70	1.703	6.67	6.44	1.05
	Level 5	2.255	8.53	2.247	8.51	8.19	1.04
Meals	Level 1	-0.110	-0.33	-0.136	-0.40	-0.17	0.42
	Level 2	0.513	1.54	0.493	1.45	1.72	1.18
	Level 3	1.213	3.61	1.197	3.51	3.84	1.08
	Level 4	2.133	6.18	2.123	6.08	6.49	1.05
	Level 5	2.983	8.30	2.979	8.21	8.68	1.04
Electronics	Level 1	0.600	2.56	0.594	2.55	2.36	0.94
	Level 2	2.225	8.93	2.211	8.94	8.72	0.98
	Level 3	3.537	13.08	3.518	13.10	12.91	0.99
	Level 4	4.749	15.69	4.727	15.72	15.58	0.99
	Level 5	6.033	16.31	6.011	16.33	16.24	1.00
FBPC	Level 1	-0.247	-1.08	-0.241	-1.04	-1.16	1.13
	Level 2	0.988	4.25	1.001	4.25	4.06	0.97
	Level 3	2.179	9.00	2.197	8.96	8.74	0.99
	Level 4	3.419	13.21	3.443	13.15	12.94	0.99
	Level 5	4.603	16.10	4.632	16.03	15.86	0.99
Recreational Items	Level 1	1.016	3.10	1.031	3.11	2.91	0.92
	Level 2	2.393	7.01	2.419	6.98	6.83	0.96
	Level 3	3.506	9.77	3.538	9.72	9.62	0.96
	Level 4	4.980	12.79	5.018	12.70	12.71	0.97
	Level 5	6.157	14.49	6.197	14.38	14.47	0.97
Household Office	Level 1	-0.005	-0.02	-0.010	-0.03	-0.11	3.68
	Level 2	1.335	4.38	1.320	4.37	4.18	1.00
	Level 3	2.693	8.39	2.669	8.39	8.11	1.01
	Level 4	4.097	11.88	4.068	11.89	11.57	1.01
	Level 5	5.386	14.29	5.352	14.31	14.00	1.01
Medicine Health	Level 1	0.507	2.75	0.503	2.73	2.64	1.00
	Level 2	1.429	7.45	1.424	7.42	7.25	1.00
	Level 3	2.309	11.39	2.302	11.35	11.14	1.00
	Level 4	3.275	14.83	3.267	14.77	14.57	1.01
	Level 5	4.165	16.83	4.157	16.77	16.60	1.00

Table B.2 Threshold levels for attitudes

Product	Thres-holds τ	LD-HE model (a)		HD-LE model (b)		HD-HE model (c)	
		Coef.	t-ratio	Coef.	t-ratio	Coef.	t-ratio
Delivery Cost	Level 1	-2.310	-6.12	-2.315	-6.11	-2.263	-6.08
	Level 2	-1.525	-4.13	-1.530	-4.13	-1.483	-4.07
	Level 3	-0.685	-1.88	-0.691	-1.89	-0.648	-1.80
	Level 4	0.599	1.65	0.594	1.63	0.624	1.74
	Level 5	2.346	6.27	2.347	6.27	2.355	6.37
Delivery Time	Level 1	-2.515	-4.57	-2.499	-4.61	-2.454	-4.51
	Level 2	-1.515	-2.82	-1.509	-2.85	-1.463	-2.75
	Level 3	-0.133	-0.25	-0.141	-0.27	-0.093	-0.18
	Level 4	1.853	3.39	1.826	3.37	1.882	3.46
	Level 5	4.048	6.74	4.003	6.74	4.065	6.80
Online Experience	Level 1	-2.608	-10.33	-2.610	-10.34	-2.592	-10.26
	Level 2	-1.864	-7.69	-1.867	-7.70	-1.847	-7.61
	Level 3	-0.957	-4.03	-0.960	-4.04	-0.940	-3.95
	Level 4	0.476	1.99	0.475	1.99	0.494	2.06
	Level 5	2.015	8.06	2.016	8.06	2.034	8.11
Health Concerns	Level 1	-1.444	-4.95	-1.666	-5.77	-1.249	-4.90
	Level 2	-0.786	-2.73	-1.003	-3.52	-0.600	-2.38
	Level 3	0.058	0.20	-0.154	-0.54	0.226	0.90
	Level 4	0.980	3.40	0.775	2.69	1.133	4.41
	Level 5	1.754	6.00	1.554	5.29	1.895	7.24