ANALYSIS OF THE POTENTIAL REVENUE AND EQUITY IMPACTS OF AN E-COMMERCE HOUSEHOLD DELIVERY FEE IN OREGON

SPR 875

Oregon Department of Transportation

ANALYSIS OF THE POTENTIAL REVENUE AND EQUITY IMPACTS OF AN E-COMMERCE HOUSEHOLD DELIVERY FEE IN OREGON

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by

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March 2026

Technical Report Documentation Page

1. Report No. FHWA-OR-RD-26-09	2. Government Accession No.	3. Recipient's Catalog No.
4. Title and Subtitle Analysis of the Potential Revenue and Equity Impacts of an E-commerce Household Delivery Fee in Oregon		5. Report Date March 2026 6. Performing Organization Code
7. Author(s) Miguel Figliozzi PI, ORCID: 0000-0003-2120-4929		8. Performing Organization Report No.
9. Performing Organization Name and Address Oregon Department of Transportation Research Section 555 13th Street NE Salem, OR 97301		10. Work Unit No. (TRAIS) 11. Contract or Grant No.
12. Sponsoring Agency Name and Address Oregon Dept. of Transportation Research Section 555 13th Street NE, Suite 1 Salem, OR 97301 Federal Highway Admin. 1200 New Jersey Avenue SE Washington, DC 20590		13. Type of Report and Period Covered _____ Report 14. Sponsoring Agency Code
15. Supplementary Notes		
16. Abstract The research goal of this project is to better understand the potential implications of a household e-commerce delivery fee. A survey was developed to study the factors that impact potential revenue and its equity implications.		
17. Key Words commerce, home deliveries, delivery fees	18. Distribution Statement Copies available from NTIS, and online at www.oregon.gov/ODOT/TD/TP_RES/	

19. Security Classification (of this report) Unclassified	20. Security Classification (of this page) Unclassified	21. No. of Pages 209	22. Price

Technical Report Form DOT F 1700.7 (8-72) Reproduction of completed page authorized Printed on recycled paper

SI* (Modern Metric) Conversion Factors
Approximate Conversions to SI Units

Physical Quantity	Symbol	When You Know	Multiply By	To Find	Symbol
Length	n	inches	25.4	millimeters	mm
Length	ft	feet	0.305	meters	m
Length	yd	yards	0.914	meters	m
Length	mi	miles	1.61	kilometers	km
Area	in2	square inches	645.2	square millimeters	mm2
Area	ft2	square feet	0.093	square meters	m2
Area	yd2	square yard	0.836	square meters	m2
Area	ac	acres	0.405	hectares	ha
Area	mi2	square miles	2.59	square kilometers	km2
Volume	fl oz	fluid ounces	29.57	milliliters	mL
Volume	gal	gallons	3.785	liters **	L
Volume	ft3	cubic feet	0.028	cubic meters	m3
Volume	yd3	cubic yards	0.765	cubic meters	m3
Mass	oz	ounces	28.35	grams	g
Mass	lb	pounds	0.454	kilograms	kg
Mass	T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
Temperature (exact degrees)	oF	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	oC
Illumination	fc	foot-candles	10.76	lux	lx
Illumination	fl	foot-Lamberts	3.426	candela/m2	cd/m2
Force and Pressure or Stress	lbf	poundforce	4.45	newtons	N
Force and Pressure or Stress	lbf/in2	poundforce per square inch	6.89	kilopascals	kPa

*SI is the symbol for the International System of Measurement
** Volumes greater than 1000 L shall be shown in m^3

SI* (Modern Metric) Conversion Factors
Approximate Conversions from SI Units

Physical Quantity	Symbol	When You Know	Multiply By	To Find	Symbol
Length	mm	millimeters	0.039	inches	in
Length	m	meters	3.28	feet	ft
Length	m	meters	1.09	yards	yd
Length	km	kilometers	0.621	miles	mi
Area	mm2	square millimeters	0.0016	square inches	in2
Area	m2	square meters	10.764	square feet	ft2
Area	m2	square meters	1.195	square yards	yd2
Area	ha	hectares	2.47	acres	ac
Area	km2	square kilometers	0.386	square miles	mi2
Volume	mL	milliliters	0.034	fluid ounces	fl oz
Volume	L	liters	0.264	gallons	gal
Volume	m3	cubic meters	35.314	cubic feet	ft3
Volume	m3	cubic meters	1.307	cubic yards	yd3
Mass	g	grams	0.035	ounces	oz
Mass	kg	kilograms	2.202	pounds	lb
Mass	Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2000 lb)	T
Temperature (exact degrees)	oC	Celsius	1.8C+32	Fahrenheit	oF
Illumination	lx	lux	0.0929	foot-candles	fc
Illumination	cd/m2	candela/m2	0.2919	foot-Lamberts	fl
Force and Pressure or Stress	N	newtons	0.225	poundforce	lbf
Force and Pressure or Stress	kPa	kilopascals	0.145	poundforce per square inch	lbf/in2

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ACKNOWLEDGEMENTS

The authors would like to thank the Research Coordinator Matt TAC Bagwell and members of the Technical Advisory Committee (Alexander Bettinardi, John Boren, Joe Broach, Sylvan Hoover, Ray Jackson, Christopher Melson, Thor Morris, Allen Molina, Daniel Porter, and Evan Rogers for their guidance and valuable comments.

DISCLAIMER

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1.0 INTRODUCTION

Fuel taxes have been traditionally the main source of revenue for state transportation agencies. ODOT faces in the near future declining revenues in real terms from fuel taxes due to a combination of factors: static fuel tax rates, more fuel-efficient internal combustion engine (ICE) vehicles, electric vehicle (EV) adoption, and potential changes in travel patterns that may reduce vehicle-miles-travelled (VMT) growth. In addition, future maintenance and operation costs may see large increases due to inflationary pressures or commodity price fluctuations. In this context, ODOT needs to innovate its revenue models to ensure the long-term sustainability of the transportation system.

A potential innovation to tackle declining revenues is the introduction of an e-commerce delivery fee. This type of fee could be a sustainable long-term source of revenue because:

- The last two decades have seen a rapid growth of e-commerce sales, both in the US and Oregon. This trend gained further momentum during the global COVID-19 pandemic. According to e-commerce sales reports released by the US Department of Commerce, e-commerce sales accounted for approximately 7% of total retail sales in 2015 and 16% of total retail sales in 2024 according to the US Department of Commerce (USCB, 2024).

- Long-term growth is expected to remain strong due to demographic changes. New generations are more used to online-shopping and tend to shop more online than past generations.

- Retail innovation involving new delivery models are also growing. Retailers are continuously innovating, and a new trend is the growth of delivery subscription models which are linked to higher delivery rates.

This interim report reviews and summarizes e-commerce and home delivery trends. The focus is on existing home delivery fee programs at the state level and major trends related to e-commerce and home deliveries.

1.1 ODOT CONTEXT

Oregon Department of Transportation (ODOT) revenues, like those of many transportation agencies, are primarily derived from fuel taxes, vehicle registration fees, and other road usage charges. As new vehicle types and travel patterns change ODOT's revenues are likely to be negatively impacted.

According to Porter (2024), there are a few sources of revenue for ODOT: motor fuels, commerce vehicles, driver and vehicle registrations, and other sources. ODOT revenues are likely to flatten, and the motor fuel share is going to steadily shrink – especially after adjusting for inflation – beyond 2024. For this research, it is important to note the contrast between the steady growth of e-commerce and the projected flattening of ODOT revenues after 2024.

1.2 GOAL AND OBJECTIVES

E-commerce is currently a topic of great interest and of particular importance to Oregon as a potential transportation revenue source in a context of aging transportation infrastructure and uncertain revenue streams.

Although an e-commerce delivery fee may seem appealing there is no study or data available that can assess the financial impact for households and potential equity implications.

The ultimate research goal of this project is to better understand the potential implications of a household e-commerce delivery fee. To achieve this goal the project has the following objectives:

1. Data Collection: develop a survey to gather a dataset that allows the study of the potential implications of a household e-commerce delivery fee.

2. Analysis: use the survey data to understand the factors affecting the magnitude and relative size of the household e-commerce delivery fee in Oregon its equity implications.

3. Data Evaluation: evaluate how different datasets can be utilized in the future to identify and report key delivery fee patterns related to geographic location and household attributes. In addition, it will be valuable to make recommendations to improve future e-commerce delivery fee data collection efforts.

1.3 RESEARCH QUESTIONS

The lack of data and studies in this area prompts several questions, including:

What type of households across the state are likely to pay more e-commerce delivery fees?

For households, how significant will the fees be in relation to the value of the products being delivered or other transportation related fees?

How would this fee impact households across the state, i.e. in rural vs urban areas?

What is the potential equity impact of this fee for lower income households?

This project is a necessary first step that will provide valuable insights to understand the impacts of an e-commerce delivery fee in terms of equity and potential revenue at the household level.

1.4 DEFINITIONS

The following classification and definitions are typically used for the words “taxes” and “fees”.

- Taxes

Taxes are compulsory payments imposed by governments to fund public services and infrastructure and they are typically based on income, property, or consumption. Tax benefits are usually indirect.

- Fees

Fees are payments made for specific services or benefits, there is a direct or clear benefit to the individual or entity paying the fee. Examples in the transportation sector includes toll fees, parking fees, and permit fees.

An e-commerce delivery charge or levy can be considered a “fee” if the charge is intended to cover costs directly associated with delivery infrastructure like road maintenance due to increased delivery traffic. For example, Colorado’s retail delivery fee is appropriately labeled as a fee because it supports transportation improvements related to specific transportation needs. Some jurisdictions, however, may label similar charges as “taxes” if they are broadly applied without a designated purpose.

Following the previous definitions, throughout the report we will either use “fee” or “tax” based on how the funds are appropriated or utilized. Additionally, sometimes the more general word “levy” is utilized in the literature. Summarizing, the definitions for these three words as used in this report are the following:

- Levy: a general term for imposing a charge or tax. It can refer to a tax, fee, fine, or other compulsory payment.

- Tax: a compulsory financial charge or some other type of levy imposed upon a taxpayer by a state or by a taxing authority in order to finance general government spending and various public services.

- Fee: a charge for a specific service or privilege. In this report, the e-commerce delivery fee funds specifically dedicated to improving specific projects or elements of transportation infrastructure.

1.5 ORGANIZATION OF REPORT

This report is organized into sixteen sections. After the introduction, Section 2 summarizes the literature review. An exploratory analysis of the survey data, shopping variables, and product variables is presented in sections 3, 4, and 5 respectively. Logistic models to analyze the sensitivity to delivery fees for each product type are presented in section 6. Sections 7 and 8 present the results of negative binomial models for delivery rates. Fairness concepts, characterization of high-impact households, and potential regressive impacts of a household

delivery fee for rural and low-income groups are discussed in sections 9 to 12. Section 13 considers justifications for a delivery fee regarding roadway maintenance impacts of e-commerce and section 14 contains recommendations for future data collection efforts. Finally, Section 15 concludes with a summary of key findings, insights, and recommendations.

2.0 LITERATURE REVIEW

2.1 E-COMMERCE GROWTH AND TRENDS

This section documents the rapid growth of e-commerce since the early 2000s and presents a discussion of potential growth factors that support the hypothesis of steady long-term e-commerce growth in the next decade.

2.1.1 US Census Data

According to the U.S. Department of Commerce, there are notable differences between brick-and-mortar and e-commerce retail sales in terms of growth rates and their contributions to total retail sales. The U.S. Department of Commerce distinguishes between brick-and-mortar and e-commerce retail data based on the primary method of sale:

- Brick-and-Mortar Retail: refers to traditional retail sales conducted in physical stores. This includes sales made at physical locations such as department stores, grocery stores, and specialty shops.

- E-commerce Retail: refers to retail sales conducted over the internet where the buyer places an order and/or the price and terms of sale are conducted over the internet. This includes online sales made through websites, mobile apps, and other digital platforms.

In the third quarter of 2024, U.S. retail e-commerce sales were estimated at $300.1 billion, marking a 2.6% increase from the second quarter of 2024 and a 7.4% rise compared to the same period in 2023. E-commerce accounted for 16.2% of total retail sales in 2024 third quarter, up from 15.6% in 2023 third quarter (USCB, 2024).

The growth of e-commerce sales between 2020-24 using seasonally adjusted data is shown in Figure 2.1. The data used to produce this chart comes from the U.S. Census Bureau, the Quarterly Retail E-commerce Sales Report (US Department of Commerce, 2024). This is the longest and most consistent time-series of official sales data that allows the comparison of total retail sales and e-commerce.

The lines in Figure 2.1. indicate periods of severe recessions. The dot.com recession of the early 2000s and especially the recession caused by the 2008-10 financial crisis had a negative impact on e-commerce sales. However, the relatively short COVID-19 recession caused a major increase in e-commerce sales. This increase is even more dramatic when observing the growth of e-commerce sales as a percentage of total retail sales between 2020-24 as shown in Figure 2.2. After the COVID-19 surge the e-commerce percentage dropped but it has regained its long-term upward trend.

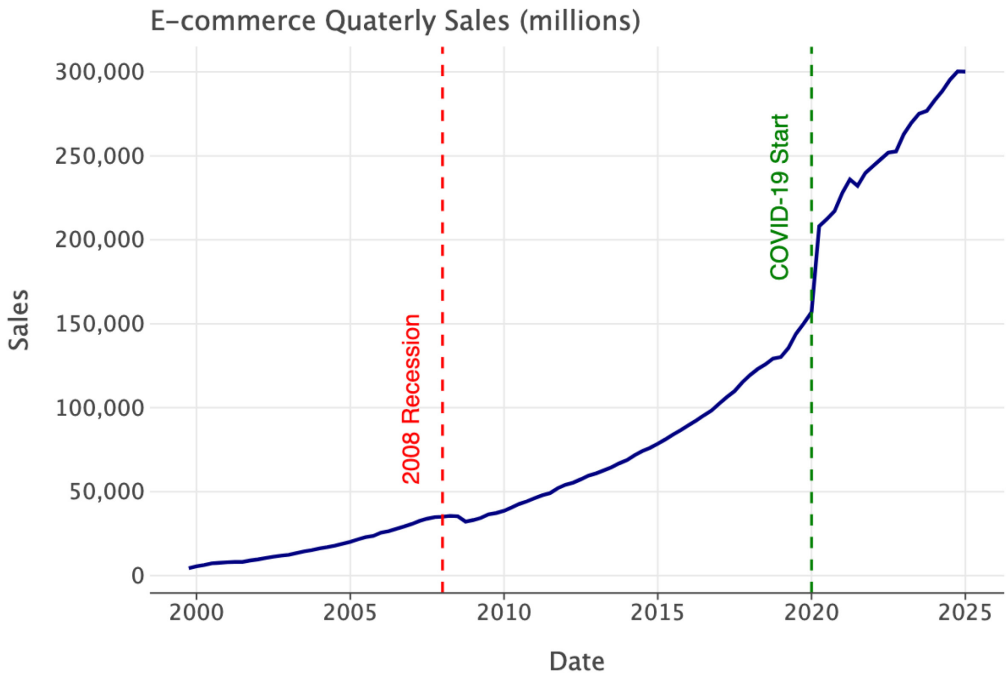

Figure 2.1: E-Commerce Retail Sales Seasonally Adjusted

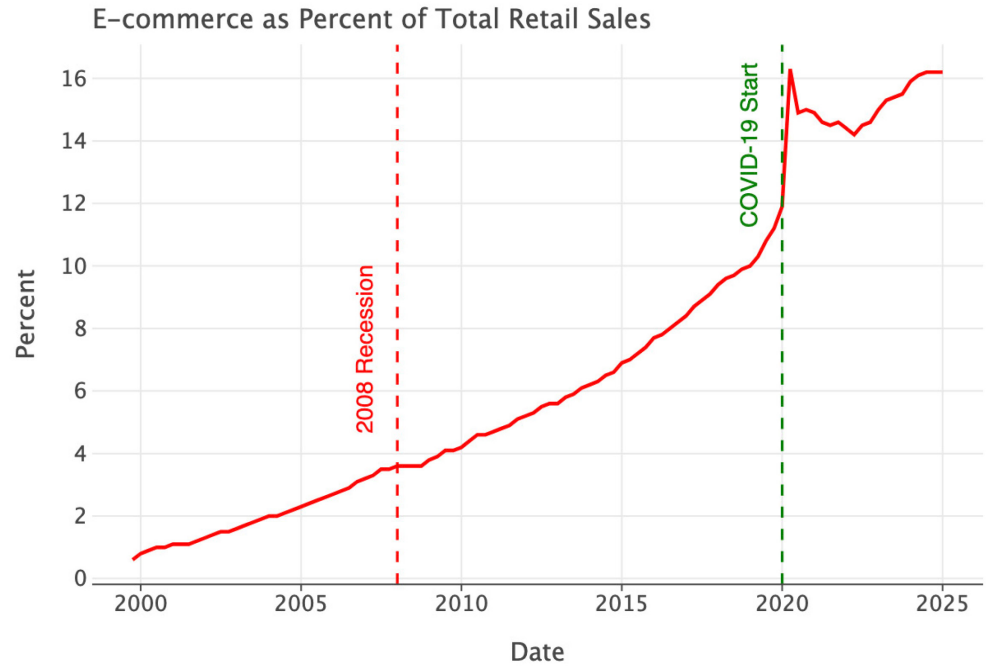

Figure 2.2: E-Commerce Retail Sales as a Percent of Total Sales

2.1.2 E-commerce Forecasts

There are many forecasts regarding e-commerce growth but the consensus among analysts and economists is that US e-commerce sales growth is projected to continue, although returning to the growth rates seen before the COVID-19 pandemic. Even this "more moderate" pace of growth is a double-digit rate of annual growth which is likely to be sustained in the next five to ten years.

Perhaps it is more important to focus on the factors that may underpin a high or double-digit growth rate. Sociodemographic population trends are likely to play a significant role in supporting double-digit U.S. e-commerce sales growth. Internet usage have been steadily growing since the 2000's (Statista, 2023). But high-speed internet is crucial to allow consumers' seamless navigation of online stores, explore product catalogs and compare options, and speeds facilitate a smoother checkout process. Government subsidies may increase internet penetration and result also in improved access to high-speed internet in rural and underserved areas, which will enable more people to engage in online shopping. Simultaneously, technology to access e-commerce is becoming more affordable due to the widespread availability of inexpensive smartphones and devices. These trends will increase access to e-commerce, it is likely that it will be easier for more people in the future to engage more frequently in e-commerce activities.

Younger generations, particularly Millennials and Gen Z, are highly familiar with digital platforms and seem prefer more the convenience of online shopping. The disposal income of tech savvy younger generations is likely to grow as these generations reach their top income years. As disposable incomes rise, consumers have more money to spend on discretionary purchases, including online shopping.

Other trends related to household size may also impact home deliveries. An increase in single-person households or smaller family units drives demand for more frequent, smaller purchases, which e-commerce caters to efficiently. Smaller households with more dual-income households may rely more on e-commerce for its ability to deliver products directly to their homes, saving time and effort.

Another element that may affect e-commerce and package delivery growth is the fact that e-commerce home delivery subscription services are experiencing significant growth. This growth is driven by factors such as increasing internet penetration, the proliferation of smartphones, and changing consumer habits that favor convenience and personalization. The global subscription e-commerce market is expected to grow at a compound annual growth rate (CAGR) of approximately 37% to 71% over the next few years, with projections reaching as high as USD 6,396.96 billion by 2030 (MMR, 2024).

A few companies that exemplify this growing trend include Nuuly, IPSY, and Barkbox. Nuuly is a clothing subscription service. The user chooses six pieces of clothing, uses them for a month and after this period the subscriber can keep or return any of the items. The process is repeated every month (Nuuly, 2024). IPSY is a beauty subscription service that delivers a set of personalized beauty products monthly, though the frequency can also be customized (IPSY, 2024). For pets, BarkBox offers a subscription for monthly deliveries of dog toys and food-treats (BarkBox, 2024). These are just a few examples of the numerous delivery and subscription services that are available to consumers in the U.S.

Other forecasts focus on package delivery growth. Package deliveries are also expected to steadily increase over the next few years, driven by factors such as increased internet penetration, the convenience of online shopping, and the growing number of online retailers. Pitney-Bowes (Pitney-Bowes, 2024) forecasts that U.S. parcel volume will reach between 23 billion and 35 billion by 2029 and the most likely scenario is that it will reach more than 28 billion with a 5% compound annual growth rate (CAGR) between 2024 and 2029.

2.2 E-COMMERCE DELIVERY FEES IN THE U.S.

In recent years, some U.S. states have introduced retail delivery fees specifically targeting e-commerce deliveries to address transportation infrastructure needs. This trend was spearheaded by Colorado, which enacted a retail delivery fee of 27 cents per order in July 2022. The Colorado fee is intended to support infrastructure funding in response to increased e-commerce and last-mile delivery demands.

Several states have considered delivery fees in the last 10 years, but in only a few cases has legislation passed and been implemented. This section describes and summarizes legislative successes and failures regarding delivery fees.

2.2.1 Successful Legislation

Colorado's retail delivery fee, implemented on July 1, 2022, was the first of its kind in the U.S., designed to generate transportation funding as part of a broader $5.4 billion package. The fee initially was $0.27 per retail delivery, later adjusted to $0.28 and $0.29 to account for inflation and with revisions scheduled annually in July.

There is an official website dedicated to Colorado's retail delivery fee that is hosted by the Department of Revenue, Taxation Division (Colorado, 2024).

The fee generated approximately $75.9 million in its first fiscal year, closely matching revenue projections (Brown, 2024). The fee applies to all motor vehicle deliveries of retail purchases containing at least one taxable item. Retailers, including large and small businesses, are required to collect and remit the fee to the Colorado Department of Revenue.

A unique feature of Colorado's system is the breakdown of the delivery fee into six sub-categories, each supporting different state initiatives, such as multimodal transportation projects, clean fleet transitions, and air pollution mitigation.

Exemptions were later introduced in 2023 (Colorado Retail Delivery Fees, 2023), after receiving feedback from small businesses. These exemptions allowed businesses with less than $500,000 in annual sales to avoid collecting the fee which eased administrative burdens for both small businesses and the State of Colorado. Retailers also have now the option to either itemize the fee on receipts or embed it within product pricing, offering flexibility in how the fee is collected.

Following Colorado, Minnesota's retail delivery fee (MN Legislature, 2024), started to be applied on July 1, 2024. The delivery fee is also part of a larger transportation funding package aimed at generating revenue for road improvements and transportation infrastructure.

There is also an official website dedicated to Minnesota's retail delivery fee that is hosted by the Department of Revenue (Minnesota, 2024). The fee imposes a $0.50 charge on retail deliveries where the total transaction exceeds $100. Unlike Colorado, where the fee applies to all deliveries regardless of order value, Minnesota's fee targets higher-value purchases, exempting smaller transactions and businesses with annual sales under $1 million. Additionally, Minnesota's law has specific exemptions for food, medical supplies, and baby products.

A key feature of Minnesota's system is its flexibility for businesses. Retailers can choose whether to itemize the fee on receipts or incorporate it into the total price, similar to the current Colorado's approach. This flexibility helps businesses manage administrative costs, especially for smaller operations. Minnesota's law also includes an exemption for marketplace providers that facilitated less than $100,000 in sales the previous year.

Revenue from the fee is projected to generate $59 million in its first fiscal year, with funds to be distributed to metropolitan counties, small cities, large cities, and town roads based on population and transportation needs (Brown, 2024). A unique aspect of Minnesota's program is the allocation of 1% of the revenue to food assistance programs, supporting transportation for individuals who struggle with food security due to mobility or financial issues.

To highlight the complexity of coverage and exemptions, the following cases are discussed in the Minnesota's retail delivery fee website (MN Department of Revenue, 2024):

- Free Shipping: the retail delivery fee still applies if the shipping is free.

- Recurrent deliveries: if a customer signs up for recurring deliveries and is charged each time the items are delivered, the fee applies to each delivery. If the customer is only charged once but the items are delivered in multiple shipments, the fee applies once.

- Sales of alcoholic beverages such as liquor, beer, and wine: the fee does not apply to sales of alcoholic beverages that are delivered by a food and beverage service establishment, whether made by a third-party delivery service or the actual establishment.

Minnesota's fee reflects some lessons learned from Colorado, with a focus on equitable implementation and minimizing the burden on small businesses, but with a significantly higher fee per delivery. A comparison of Colorado and Minnesota retail delivery fees is provided in **Table 2.1**.

Table 2.1: Summary comparison of Colorado and Minnesota Retail Delivery Fees

	Colorado	Minnesota
Implementation	July 1, 2022	July 1, 2024
Applicability	All retail sales delivered by motor vehicle. Applies to all deliveries regardless of order value.	In-state and out-of-state sellers, marketplace facilitators, only on transactions over $100
Fee Amount	$0.29 per delivery (initially $0.27, adjusted for inflation)	$0.50 per delivery
Business Exemption Threshold	Businesses with less than $500,000 in annual sales	Businesses with less than $1,000,000 in annual sales
Itemization Flexibility	Retailers can itemize the fee on receipts or embed it into the final product price	Retailers can itemize the fee on receipts or embed it into the final product price
Revenue Use	Distributed across various transportation and environmental funds, including clean fleet and air pollution mitigation	Primarily allocated to local governments, including cities, towns, and counties, with 1% for food assistance programs
Adjustments for Inflation	Yes, adjusted annually based on inflation	Not specified
Tax Treatment	Fee is not considered a tax	Fee is not considered a tax
Policy Focus	Clear and specific allocation to designated initiatives: clean transportation initiatives, reducing transportation-related emissions, etc.	Targeted at higher-value transactions, supporting transportation infrastructure and food assistance programs

2.2.2 Justification of the delivery fee

Minnesota legislation does not provide any justification to establish a delivery fee. But in Colorado the legal text is longer and more detailed because the Colorado retail delivery fee was part of a much larger Senate Bill SB21-260, entitled “Sustainability of the Transportation System”. As explained in the bill, SB21-260 aims to create a more sustainable transportation system in Colorado by:

1. Implementing new fees and taxes that besides the “retail delivery fee” include road usage fees (for gasoline and diesel vehicles), electric vehicle fees (registration fees and new road usage fees), bridge and tunnel fees and per-ride fees for transportation network companies.

2. Promoting electric vehicle adoption and the use of electric vehicles in fleets, supporting clean public transit, mitigating air pollution in specific areas, and promoting environmental sustainability by reducing greenhouse gas emissions and requiring more comprehensive planning for transportation projects.

3. Ensuring equity and accessibility by identifying and addressing barriers for disadvantaged communities and promoting equitable access.

Two main reasons are given to justify Colorado retail delivery fee in the legislation (Colorado Retail Delivery Fees, 2023):

1. Demand for retail deliveries has increased and is projected to remain a significant form of commerce, which will increase both traffic and associated motor vehicle emissions that create adverse environmental and health impacts and additional costs to the state; and

2. Imposing a reasonably calculated retail delivery fee on each delivery, made to a consumer, accounts for the use of the transportation system associated with that delivery, generates the revenue needed to mitigate the impact of retail deliveries on transportation system infrastructure, and remediates and mitigates retail-delivery-related environmental and health impacts.

Section 35 of SB21-260 also imposes road usage fees on gasoline and diesel purchases that are phased in from state FYs 2022-23 through 2031-32 and thereafter indexed to National Highway Construction Cost Index (NHCCI) inflation, with the road usage fees also being adjusted beginning in state FY 2032-33 in a manner calculated to generate the same amount of additional revenue as would be generated by indexing the existing state excise taxes imposed on gasoline and diesel to construction cost inflation. The fee revenue is credited to the Highway Users Tax Fund (HUTF) for allocation to the state, counties, and municipalities.

2.2.3 Legislation Under discussion

At least two states are currently considering a delivery fee. In nearby Washington State, cities and counties have asked state lawmakers to consider a retail delivery fee or to authorize cities to collect one. State lawmakers commissioned an analysis (CDM Smith, 2024), looking at the potential for such a program. In terms of revenue, Washington's estimates predict the fee could generate between $45 and $112 million in 2026, depending on exemptions, with projections reaching up to $160 million by 2030. These numbers align closely with Colorado's revenue experience, which generated $75.9 million in its first fiscal year with a $0.27 fee. Minnesota, starting in 2024 with a $0.50 fee on orders over $100, anticipates $59 million in its first year (Johnson, 2024).

Washington's proposed retail delivery fee, under consideration for 2026, takes inspiration from both Colorado and Minnesota but it also seems tailored to local needs. Like Colorado, Washington's proposal suggests a flat fee per delivery—likely around $0.30—applied to all taxable retail items delivered by motor vehicles within the state. However, Washington is evaluating multiple exemption scenarios, including exclusions for orders below $75 and small

businesses with annual revenues under $1 million, drawing from Minnesota's approach. Colorado, in contrast, uses a broader exemption threshold of $500,000 in annual sales.

In Maryland there is a proposed HB1215 delivery fee of 50-cent fee to be added to the cost of retail orders that are home delivered and also adding the same fee on transportation network companies like UBER and LYFT (Maryland, 2024). The delivery fee would be assessed on taxable items like clothing, but it would not apply to the delivery of groceries that are tax-exempt in Maryland.

2.2.4 Failed Delivery Fee Legislation

At least three states that have considered e-commerce delivery fees, but the legislation was not yet adopted. A 2023 analysis evaluated a potential retail delivery fee, scaling data from Colorado's implementation. Ohio projected that a $0.50 fee could generate $306 million by 2025 and $512 million by 2040. Despite the favorable revenue projections, no concrete legislation has been passed (Ohio DOT, 2023). In Nebraska, in 2024, bills LB19 and LB26 proposed new online delivery taxes for goods purchased online including food delivery, the bills are currently indefinitely (Blood, 2024) postponed.

Finally, in 2023, the New York State Assembly proposed a retail delivery fee of $0.25 on each delivery transaction as part of the state budget new funding sources (Gounardes, 2024). The Senate bill focused specifically on New York City, aiming to use the revenue for infrastructure projects, including rehabilitating the Brooklyn Queens Expressway. However, this proposal was not included in the final state budget and is currently in a senate committee.

2.3 SALES TAXES AND E-COMMERCE

While state sales taxes and home delivery fees are distinct, there is a connection in terms of how they impact consumers and the revenue they generate for states. In some states, a delivery fee itself can be subject to sales tax.

Sales taxes are governed at the state level. Each state can decide whether to have a sales tax, and forty-five states and Washington, D.C. have a sales tax. Only four states —Delaware, Montana, New Hampshire, and Oregon – do not have a sales tax. The Alaska state sales tax rate is currently 0% but individual municipalities can set their own taxation rates that can be as high as 7.5%. Sales tax is a percentage – usually between 4 and 8% of a retail sale. Most states that have a sales tax also allow local areas (e.g. cities and counties) to have a sales tax too. E-commerce has led to increased sales tax revenue for states after 2018, as online retailers are able to collect sales tax based on the customer's shipping address.

States put new legal tax requirements for e-sellers, following a Supreme Court decision in 2018, a.k.a. the Wayfair ruling. This ruling affirmed that states could require out-of-state businesses, referred to as remote sellers, to collect and remit sales taxes even in the absence of a physical presence, such as a store or warehouse in the state. Most states have adopted requirements shifting primary tax collection obligations from sellers in an online marketplace to the company facilitating the sale, such as Amazon or eBay. The consequences for remote sellers have been mostly higher costs to comply with new remote sales tax requirements, mainly software, reporting, legal, and audit costs (GAO, 2022).

Large differences in terms of taxes along state borders can result in some distortions as later seen in the literature review. Oregon currently has neither sales nor delivery taxes or fees as detailed in Table 2.2. A delivery fee that is less that 0.50 % of the sales amount like in Colorado or Minnesota are at least one order of magnitude smaller than median sales tax among the states that discussed or implemented a delivery fee, see Table 2.2.

Table 2.2: Comparison of State Income and Sales Taxes

State	Income Tax	Sales Tax
Oregon	Progressive: 4.75% to 9.9%	None
Colorado	Flat: 4.4%	2.90%
Minnesota	Progressive: 5.35% to 9.85%	6.88%
Washington	None	6.50%
Maryland	Progressive: 2% to 5.75%	6%
Nevada	None	6.85%
New York	Progressive: 4% to 10.9%	4%
Ohio	Progressive: 2.765% to 3.99%	5.75%

Regarding fuel taxes in the states that discussed or implemented a delivery fee, in Table 2.3 it is possible to see that Oregon fuel taxes per gallon are slightly above the table median fuel tax of $0.36 and $0.37 for gasoline and diesel respectively. Vehicle registration fees are more difficult to summarize because they depend on multiple vehicle types, weight brackets, and local fees.

Table 2.3: Comparison of 2024 Road Fuel Taxes

State	Gasoline Tax (per gallon)	Diesel Tax (per gallon)
Oregon	$0.400	$0.400
Colorado	$0.220	$0.205
Minnesota*	$0.318	$0.318
Washington	$0.494	$0.494
Maryland	$0.427	$0.427
Nevada	$0.235	$0.270
New York	$0.338	$0.338
Ohio	$0.385	$0.470

*In Minnesota gas taxes increase to this level on January 1, 2025, from the current $0.285 level.

2.4 SHIPPING AND DELIVERY FEES AND TAXES

There is academic research related to the impact of shipping fees and delivery attributes. But there is a lack of academic studies in the U.S. regarding e-commerce, retail, or home delivery fees or taxes. The only published academic study that has direct relation to these topics focused on an ecommerce delivery fee in Barcelona, Spain and was published in 2021. There have been other studies focusing on ancillary tax issues that are later discussed in a later section.

2.4.1 Shipping Fees and Delivery Attributes

E-commerce shipping fees are the costs associated with transporting products from a seller to a customer. These fees can significantly impact consumer behavior and e-commerce demand and have been studied in the academic literature.

The paper of Chen & Ngwe (2018) examines the impact of shipping fees on online orders. A key finding identifies shipping fees as a significant barrier to online shopping, often leading to cart abandonment. Customers tend to be more sensitive to shipping costs compared to product prices, meaning even a small increase in shipping fees can negatively affect purchase decisions. Also, free shipping conditions (e.g., on orders above a certain amount) encourage customers to complete their purchases and may lead to an increase in average order value.

When shipping fees are low or free, customers are more likely to purchase a broader range of items, including low-cost or bulky products, which they might avoid if they had to pay a high shipping fee. But there is also a psychological impact, often perceiving a shipping fee as an

additional "penalty" rather than a necessary cost. This perception can deter potential buyers, making pricing transparency and shipping cost reduction important for customer satisfaction.

It is likely that some businesses in Colorado and Minnesota asked for the option to hide the delivery fee within the total cost of the transaction or order to decrease the “shipping penalty” perception and the likelihood of e-shopping cart abandonments.

The paper, "What Is the Right Delivery Option for You? Consumer Preferences for Delivery Attributes in Online Retailing" by Nguyen et al. (2019) investigates how consumers evaluate various delivery attributes in online retail settings in the U.K. The study applies mental accounting theory and uses conjoint and cluster analyses to understand consumer preferences for delivery attributes and identifies consumer segments with distinct preference. The main findings of the paper indicate that the delivery fee is the most critical attribute across all product categories (convenience goods, shopping goods, and specialty goods). Delivery speed is the second most important attribute and, obviously, consumers prefer faster delivery times. Shorter/specific time slots is third, customers specific time slots (e.g., 2-hour slots) rather than unspecified delivery times. Delivery date is the fourth ranked attribute. Consumers prefer delivery options that include weekdays and Saturdays, but extending this to Sunday does not significantly increase preference. The final, and least important, attribute is daytime/evening delivery, though some consumers favor evening delivery due to work schedules.

Three consumer segments were identified: (a) Price-Oriented consumers are highly sensitive to delivery fees and prioritize low-cost options over other attributes; (b) Time- and Convenience-Oriented consumers value faster delivery and specific time slots, willing to pay a premium for these services; and finally (c) Value-for-Money-Oriented consumers seek a balance between cost and non-monetary benefits, such as convenience and speed.

Regarding demographic characteristics, this paper found that: (a) men value time slots and evening delivery more, while women emphasize lower delivery fees; (b) low-income consumers prioritize lower delivery fees, whereas higher-income groups value time slots more, and (c) frequency of online purchases has minimal influence on delivery preferences.

2.4.2 The last-mile hidden costs

Last-mile delivery is the final phase of the delivery process. In a product’s journey, it is moved from the warehouse shelf, which is often at a distribution center, to the back of a truck, to the customer’s doorstep—the final step of this process, known as the last-mile of delivery. High shipping costs are often associated with last-mile delivery, though the actual percentage depends on product and logistical factors (Vanelslander et al., 2013).

While last-mile delivery may be the most expensive part of the shipping process, it is key to overall customer satisfaction. Hence, last-mile delivery costs are often hidden for consumers due to various strategies and market dynamics designed to create a seamless and appealing shopping experience. Retailers frequently advertise "free shipping" to attract customers, but the cost of last-mile delivery is incorporated into the product price or subsidized by the retailer. Consumers do not see the breakdown of this cost. Services like Amazon Prime include delivery costs bundled within subscription fees and multiple fringe benefits, effectively spreading the cost across numerous transactions and costumer activities. Consumers perceive deliveries as "free" after

paying the subscription fee, even though they are indirectly covering the cost. Furthermore, platforms like Amazon generate substantial revenue from advertising, allowing them to offset delivery costs and keep them hidden from consumers.

Concluding, it is likely that businesses prefer to hide actual delivery fees or taxes, and this is related to consumer psychology and preferences: consumers are happier if it looks like they are not paying for shipping even if the shipping fees are partially or fully included the online price. One of the main changes made to Colorado's legislations was to give businesses the option to either itemize the fee on receipts or embed it within product pricing.

2.5 DELIVERY TAXES

The only academic study that has addressed the topic of an e-commerce tax is the work of Majoral et al. (2021) for the city of Barcelona in Spain. The motivation of the study was the rapid growth of E-commerce deliveries in Barcelona and its contribution to local pollution and traffic issues. According to the authors, the high percentage of trucks and vans in the city exacerbates pollution levels, which often exceed World Health Organization recommendations, posing health risks to residents (Majoral et al., 2021).

The work of Majoral et al. (2021) calculate a Pigouvian tax aims to internalize externalities by imposing a tax that reflects the social costs of economic activities, thereby adjusting market equilibrium. Data on e-commerce vehicle kilometers (veh-km) is derived from the Barcelona metropolitan area, where e-commerce related milage is estimated to be five percent of the light commercial vehicle usage. The study models delivery routes, assuming express deliveries double the number of stops compared to standard deliveries, impacting overall veh-km. The average Pigouvian tax calculated for e-commerce purchases in Barcelona is €1.36 but differentiating by delivery type there would be specific taxes for standard (€1.28) and express (€1.92) deliveries with shorter delivery window. The study estimates a price-demand elasticity of -0.79 for e-commerce, indicating a modest reduction in demand (2.86%) following the implementation of the tax. The cost-benefit analysis (CBA) indicates that the proposed €1.36 tax could yield a net present value (NPV) between €12.74 million and €15.96 million over five years.

The paper concludes that an e-commerce delivery tax can incentivize the use of electric vehicles and sustainable practices in last-mile delivery, aiming to curb externalities associated with traditional delivery methods. Though, switching to electric delivery vehicles will not reduce congestion or road infrastructure and maintenance.

The focus of this paper is on a delivery tax with the general purpose of reducing emissions and traffic congestions which is different from the focus home delivery fees in the U.S. where the main purpose of delivery fees is generating transportation funding.

2.5.1 Ancillary Tax issues

Several researchers have studied ancillary issues related to e-commerce and taxes and e-commerce economic impacts.

E-commerce has created taxation issues that are seen internationally. In the U.S., sales tax liability was confirmed by the Wayfair ruling, while in the European Union (EU), value-added-

tax (VAT) obligations apply even if an EU customer purchases a product from a non-EU supplier (Scoromtsova et al., 2023). Additionally, this research highlights the importance of determining the place of delivery, as it determines where services are taxed.

Dolfen et al. (2023), investigates the consumer benefits resulting from the expansion of e-commerce in the U.S. Using a large dataset of Visa credit and debit card transactions from 2007 to 2017, the study assesses two primary types of consumer gains convenience gains and variety/quality gains. The former takes place when consumers save travel costs by shopping online instead of visiting physical stores. This is quantified by analyzing consumer behavior relative to the distance from physical stores. The convenience gain for consumers by 2017 was estimated to be about 0.4% of spending. The latter, variety gains, result from access to a broader selection of merchants and products online than is typically available locally. The study found that these gains, arising from greater product diversity and accessibility, accounted for an additional 1.1% of consumer spending.

There are equity implications too, higher-income households and consumers in urban areas benefited the most from e-commerce. These groups experienced greater access to a wide array of products and derived more value from the convenience and variety offered by online shopping.

Nexus is a legal term that refers to the connection between a business and a state or local government that triggers the requirement to collect and remit sales tax in that state. Historically, businesses were required to have a physical presence (like a warehouse, office, or employee) in a state to be obligated to collect and remit sales tax. This was known as the physical presence nexus standard. In 2018, the U.S. Supreme Court's ruling in *South Dakota v. Wayfair, Inc.* significantly changed the landscape of sales tax. The Court overturned the physical presence standard, introducing the concept of economic nexus. Economic nexus means that a business can be required to collect and remit sales tax in a state even if it does not have a physical presence there. This is typically triggered when a business exceeds certain sales thresholds or transaction thresholds within a state.

The paper by Houde et al. (2023) examines the impact of nexus tax laws on Amazon's distribution network decisions, specifically its fulfillment and sortation centers. Initially Nexus tax laws required e-commerce companies to collect sales tax only if they had a physical presence in a state. These laws created incentives for Amazon to strategically delay opening fulfillment centers in high-tax states to avoid triggering tax obligations for as long as possible. Over time, after the Wayfair ruling and as Amazon expanded, Amazon’s distribution network became denser, the company increasingly had to comply with state tax collection, leading to significant shifts in its distribution strategy.

Using data from 1999 to 2018, the authors analyze how these tax policies influence Amazon’s geographic expansion, facility density, and economies of scale. Amazon’s network densification—opening multiple facilities close together—helped reduce shipping costs through "economies of density." By having a greater presence in high-demand areas, Amazon minimized average shipping distances and reduced dependence on third-party logistics providers. The study finds that in-house sortation centers, introduced in 2014, lowered shipping costs by 40% in 2018. Despite higher fixed costs in urban areas, these scale economies allowed Amazon to achieve lower per-order fulfillment costs.

In addition, the study models a hypothetical shift to a non-discriminatory tax policy, where all states uniformly require sales tax collection without nexus rules. The analysis suggests that such a policy would lead Amazon to adopt a less centralized network, lowering shipping distances and costs further. However, tax-inclusive prices would slightly reduce Amazon's profit and consumer demand, despite yielding higher overall tax revenue and benefiting Amazon's competitors. It is a complex issue, but with some simplifying assumptions the authors estimate that abolishing nexus laws could increase total welfare by about $5 billion due to gains in shipping efficiency and higher tax revenue. This welfare increase, however, depends on Amazon's ability to maintain economies of scale within a decentralized network configuration, as well as the fiscal multiplier from increased tax revenue.

More research on the Nexus law suggests that the Wayfair court decision improved states' ability to enforce destination-based sales tax collection, reducing tax competition with untaxed internet sales. It shifted some sales from online purchases, which often had no tax, to local sales, thereby increasing tax revenues for states. However, it also revived cross-border shopping as consumers may seek lower tax rates, maintaining some level of tax competition (Bruce et al., 2023).

For Oregon, it may be relevant the observation that state border areas have experienced increased cross-border shopping as consumers seek to evade higher sales taxes, leading to a competitive dynamic between neighboring states. The tax rate differentials, as observed in Tennessee and neighboring states, can result in faster sales tax revenue growth on the lower tax side, while higher tax states may see slower growth. Over time, the effects of cross-border shopping and tax rate changes could become more pronounced, influencing local tax policies and business location decisions.

Another study analyzes the effects of fulfillment centers (FCs) on retail workers' income and employment (Chava et al., 2024). Utilizing data from 2.6 million workers across 57 retail firms in the period 2010-2016 the authors find that there is a negative income impact primarily on hourly and part-time workers, especially in general merchandise and home improvement sectors.

The establishment of fulfillment centers increases demand for e-commerce, leading to reduced sales for nearby traditional retailers, which results in a 2.4% average decrease in retail workers' labor income (Chava et al., 2024). Hourly workers, particularly part-time employees, experience a significant income decline, averaging $825 annually, primarily due to reduced hours worked. The negative effects are geographically concentrated, diminishing beyond 100 miles from FCs, and financially vulnerable workers face increased credit card delinquency as a result of these changes. No significant gender differences were detected.

But the literature has also used the term "retail job apocalypse" to highlight the potential job losses in brick-and-mortar retail caused by the rapid growth of e-commerce (Chun et al., 2023) and the excess of store space per capita in the U.S. (Berman, 2019). It is hard to disentangle the impacts, but it is likely that the impacts may be different in urban vs non-metropolitan areas and by the type of business that are downsizing its brick-and-mortar presence.

2.6 U.S. DELIVERY RATES

Estimating household e-commerce delivery rates is crucial for not only for potential revenue collection but also for effective transportation planning and to make informed decisions that

contribute to efficient, sustainable, and equitable transportation infrastructure development and access to home delivery goods and services.

The largest somewhat consistent dataset that can be used to estimate delivery rates in the U.S. is the National Household Travel Survey (NHTS) that has asked e-commerce related questions in the 2009, 2017, and 2022 editions.

2.6.1 NHTS 2009 results

The 2009 National Household Travel Survey included for the first-time questions related to the monthly households' web use pattern, online shopping frequency, and home delivery frequency. The survey interviewed 150,147 households that included 308,901 individuals across the U.S.

Using the 2009 NHTS data researchers used a binary choice model to identify households likely to make online purchases, followed by a negative binomial model to estimate delivery frequency.

to identify the impacts of person-related, household-related, and regional-specific variables on home delivery frequency (Wang & Zhou, 2015). The main findings of this research include the statistical significance of the following variables, here divided by type or level to ease presentation and later comparison with other papers:

Personal variables:

- Internet use frequency: this is a strong predictor; more frequent web use correlates with higher delivery rates.
- Education level: higher education levels are associated with more frequent deliveries.
- Age, Gender, and Self-employment: younger individuals, females, and the self-employed have higher delivery rates.

Household variables:

- Income: higher income households tend to receive more deliveries.
- Size and vehicle ownership: larger households and those with more vehicles have more deliveries.
- Children: households with children receive more deliveries than those with only adults.
- Regional Variables:
- Population and housing density: higher densities lead to more deliveries, but the effect is relatively minor.
- Urban vs. Rural location: rural areas have slightly higher delivery rates, potentially due to fewer local shopping options.

2.6.2 NHTS 2017 results

Approximately 103,000 households participated in the 2017 NHTS survey. The 2017 sample size was smaller than the 2009 survey, due to budget constraints and a shift in data collection priorities and technologies. For example, the 2017 survey was expanded to include questions related to emerging trends, such as ride-hailing services (e.g., Uber, Lyft) and the use of technology in travel planning.

A research paper used NHTS 2017 data but focused on a county of the state of Florida (Fabusuyi et al., 2020). This study develops methods to estimate demand for online deliveries at a granular level (Micro Analysis Zones or MAZs) in Miami-Dade County, using publicly available data sources like the 2017 National Household Travel Survey (NHTS) and synthetic data from the Southeast Florida Regional Planning Model (SERPM).

Two approaches were tested to estimate delivery demand: (a) a Negative Binomial Regression Model (NBRM) enhanced by an empirical Bayes (EB) method and (b) a Multiple Imputation by Chained Equations (MICE) method for missing data imputation. The MICE approach produced better accuracy compared to the NBRM-EB method.

The dependent variable is a count variable that represents the number of times items were purchased online for delivery in the past month. Data analysis is limited to those who provided responses that are either zero or positive. Three of the most important variables are having at least a university degree; being in the working age population, defined as those aged 18 to 64, and belonging to a household that makes more than $100,000 income per year.

The key variables for estimating deliveries are divided into three types:

Household variables:

- Income: households with annual incomes above $100,000 tend to have more deliveries.
- Household size: larger household size correlates with fewer online purchases, potentially due to shared shopping trips.
- Vehicle ownership: higher vehicle ownership has a slight positive effect on delivery demand, reflecting increased purchasing power.

Individual variables:

- Education level: individuals with at least a bachelor's degree show higher delivery demand.
- Age: working-age individuals (18-64) have higher rates of online deliveries.
- Gender: female respondents tend to generate more deliveries.
- Employment status: employed individuals are more likely to make online purchases.

Regional Variables:

- Population Density: Areas with higher population densities are associated with higher online delivery demands.

The only variable that had a counterintuitive sign is household size, but the authors are unable to provide an explanation.

The work of Saphores and Xu (2024) analyze household travel data from the 2017 US National Household Travel Survey to study the links between e-shopping and travel. The analysis is done at the household level because the authors consider that overall travel and shopping decisions within a household are correlated. Another distinct element of this work is that a propensity score matching is used to try to control for self-selection and check whether observed differences in household travel were caused by different e-shopping frequencies.

Household are classified into three groups based on how many orders per person per month they placed online: low (up to one), medium (more than once but less than four), and high (over four). Some of the key findings include:

- More e-shopping is linked to more household travel (number of trips, miles, and VMT), but this effect depends on e-shopping frequency and population density.

- The link between e-shopping and household travel is more important for weekdays than weekends.

- The impacts of e-shopping are higher on low density areas and weekdays. Mid-frequency e-shoppers take on average 8 more monthly trips and travel ~104 extra miles (including 31 miles for shopping) when compared to similar low frequency e-shoppers on weekdays.

- Some groups do not travel more, for example high frequency e-shoppers in dense areas do not travel more on weekends than similar low e-shopping frequency households.

The authors conclude that the topic is complex, and that more data is needed. For example, travel and shopping attitudes are likely a confounding variable in the relationship between e-shopping and travel, therefore, ignoring attitudes is likely to produce biased results. The authors also highlight a limitation of the data related to shopping data aggregation. For example, purchases of groceries, clothing, appliances, and vehicle fuel are all lumped together in the NHTS data, some of these goods can be purchased online and others not.

2.6.3 Comparing NHTS 2009-17 Data

The two surveys were not identical in terms of sample size, questions, or data collection technologies. However, researchers found ways to compare trends regarding e-shopping using different modeling tools.

The paper by Barua et al. (2021) investigates online shopping demand using household-level data. This study uses U.S. National Household Travel Survey data from 2009 and 2017. Unlike previous studies these authors employ machine learning models, particularly gradient boosting machine (GBM) and recursive feature elimination is used to select input variables. GBM is

chosen among various Machine Learning (ML) models because it shows the best prediction accuracy. This research also quantifies input variable importance in online shopping demand.

The authors first cleaned the datasets and if the online purchase record for a member in a household is missing, then the household was not included. Also, a household is not included if any member in the household skipped, refused to answer, or answered "don't know" for any input variable in the GBM model. The data for household online purchases have 27,026 observations for 2009 and 95,519 observations for 2017.

The key variables for estimating the number of household deliveries divided by type are the following:

- Socioeconomic characteristics: variables such as household income, household size, and adult percentage play a crucial role in estimating the number of deliveries.
- Trip characteristics: factors like the number of trips per day and travel time per day also impact the delivery frequency.
- Land use characteristics: population density and whether the area is classified as urban or rural are key variables that influence the number of deliveries.
- Internet use: daily Internet use can also be a significant variable in estimating the number of deliveries, especially in the context of online shopping demand.

The researchers found that household income contributes the most to predicting online shopping demand. In addition, over time, the importance of internet use and gender diminishes but household member age and household size become more important. Total travel time of a household has an overall positive relationship with online purchases but not number of trips. The relationship between population density of the living neighborhood and online purchases seems to follow a "V" shape.

A more recent Kim and Wang (2024) explores the changes in shopping behaviors and delivery patterns from 2009 to 2017. This research uses path analysis to analyze whether the relationships among home deliveries, non-motorized shopping trips, and motorized shopping trips have shifted during an eight-year period. It specifically examines how these changes vary by urban size, income level and other sociodemographic variables, highlighting the complexity of trying to untangle these relationships.

In this paper there are three models with three endogenous variables that represent each part of the problem under study:

- - Number of monthly deliveries, representing the dependent variable for the delivery model.
- - Frequency of in-store shopping trips using non-motorized modes (walking, biking).
- - Frequency of in-store shopping trips using motorized modes.

The main findings and key model variables for the delivery model are the following:

- Age of individuals, with younger individuals linked to more delivery use.
- Income groups (low, mid, high), influencing delivery frequency and substitution or complementarity with in-store shopping. As usual, it is found that more income is linked to more deliveries.
- Urbanization level of the area (non-urban, small/mid, large), impacting access to deliveries and shopping trip modes.
- Education level: Higher education correlated with more delivery use.
- Number of vehicles indicates reliance on non-motorized trips for low-vehicle households.
- Household size impacts shopping and delivery preferences, with larger households engaging in more in-store trips.

The variables which influence in-store shopping trip frequency and mode, include:

- Income: low, mid, and high, income level affects the frequency of in-store shopping trips and choice of motorized vs. non-motorized modes.
- Urban Size: categorized into non-urban, small/mid-urban, and large urban areas. urban size impacts accessibility to stores and travel mode preference, with larger urban areas having more non-motorized trips due to greater accessibility and infrastructure supporting walking and biking.
- Age: younger individuals tend to use non-motorized modes more frequently for in-store shopping trips.
- Household size: larger households may require more frequent in-store shopping trips, with household size influencing the choice between motorized and non-motorized travel modes.
- Number of vehicles: households with fewer vehicles are more likely to rely on non-motorized modes for shopping trips.
- Education level: lower education levels are associated with fewer shopping trips overall, while higher education may correlate with a preference for in-store shopping via motorized modes.
- Gender: gender influences shopping trip mode choice, with males often associated with more non-motorized shopping trips.
- Worker Status: working individuals often have fewer in-store shopping trips, perhaps due to time constraints and prefer deliveries over in-store shopping.

Overall, this research confirms previous findings regarding the importance of a few key sociodemographic variables but also shed light into the complex interrelationships between online shopping, in store shopping, and mode used for shopping trips.

2.6.4 NHTS 2022 "NextGen" results

The latest NHTS survey took place in 2022, and it was renamed as "NextGen" NHTS. In 2022, the NHTS survey was conducted entirely online and abandoned the use of a trip diary. There was a significant reduction in sample size in the 2022 NextGen NHTS with only 7,894 households participating in the study but plan is to have more frequent surveys and current plans call for implementing the same design and a similar sample size in 2024 and 2026.

There are no publications related to e-commerce using the 2022 NHTS data yet, but according to the NextGen NHTS Summer 2024 newsletter from 2017 to 2022 the mean number of e-commerce home deliveries increased 117% from 2.5 deliveries per person to 5.4 deliveries per person per month or 30-day period (NHTS, 2024). This increase in online deliveries is correlated to the increase in WFH, respondents who WFH has 3.08 more deliveries on average.

2.7 ANCILLARY E-COMMERCE LITERATURE

This section provides an overview of e-commerce delivery factors, mostly from U.S. based studies, that are not based on NHTS data. There are many factors that affect e-commerce adoption and delivery rates and researchers have been publishing related literature since the early 2000s. However, given the impact of the COVID-19 pandemic, the technological changes that took place and the rapid growth of e-commerce in the last 25 years this review will focus mostly on recent academic articles. This is because some early articles are somewhat outdated, for example in the early 2000s internet access was a key factor that affected e-commerce household activity. Nowadays with internet penetration rates in 90+ percent this factor (internet access) is far less relevant. The focus of this section is on: (1) the impact of product type on delivery rates, (2) the relationship between home deliveries and equity, (3) the relationship between home deliveries and emissions, (4) the impact of working from home on e-shopping, and (5) some international results.

2.7.1 Product Impacts

The demand for passenger transportation is generally considered a derived demand because it is not typically desired for its own sake but rather stems from the need to fulfill other purposes or goals. People travel to reach destinations where they engage in activities that meet their primary needs, such as work, education, leisure, shopping, or visiting family and friends. Thus, the demand for transportation services arises only as a means to achieve these primary objectives, rather than from an inherent demand for the act of traveling itself.

Similarly, the demand for e-commerce home deliveries is also a derived demand because it originates from the primary need or desire for goods rather than from an inherent demand for the delivery service itself. People order products online because they want or need the goods, and the delivery service is simply a means of fulfilling that need by bringing the items to them. Consumers place orders to obtain products, such as clothing, electronics, or groceries. The delivery component only becomes necessary because of the demand for these goods, not due to any inherent desire for delivery services.

Despite the derived-demand nature of e-commerce most research efforts focus on one product like groceries or an overall delivery rate grouping all products. There is limited research that has

analyzed the impacts of products on delivery rates and expenditures. In a study of impacts of products on delivery rates and expenditures, Figliozzi and Unnikrishnan (2021a) used exploratory factor analysis and choice models with latent variables. This research has shown that the factors driving household delivery expenditure levels are not necessarily the same as those driving household delivery frequencies. For example, electronic products affect more expenditures than deliveries and the opposite can be said about meals. The paper concludes that there has been scant or no research regarding the type of products and household characteristics that trigger high levels of deliveries and expenditures, and that more and better data are needed.

However, it is not trivial to study the impact of product type on household deliveries. One barrier is the high number of products that could be ordered online. An online surveys (Statista, 2024) shows that over 18 product categories could be included in a survey. When U.S. consumers are asked about the categories that were purchased at least once, the two most popular categories for online purchases are Clothing and Shoes 43 percent and 33 percent of consumers respectively. These results come from an online survey with 10,109 respondents in the U.S. in 2024 (Statista, 2024). However, the results are not frequency weighted though they provide a reasonable basis to prioritize survey categories given the lack of frequency-weighted data.

Finally, it is also important to notice that while e-commerce has expanded significantly, certain products are still challenging to purchase via home deliveries due to factors such as perishability, immediacy of need, logistical constraints, or regulations. Due to regulatory constrains some products cannot be home delivered like vehicle fuel, firearms, ammunition, or hazardous materials such as chemical products, e.g. industrial solvents. Regulatory restrictions or local laws may limit the delivery of alcohol and tobacco in some regions or cities.

2.7.2 Home Deliveries and Equity

Equity issues are increasingly visible and now significantly influence transportation programs and funding decisions. Research indicates that the benefits of home deliveries disproportionately favor higher-income and more educated populations. For instance, Figliozzi and Unnikrishnan (2021b), observed that low-income households benefited less from these services during the COVID-19 lockdown. They suggest policymakers explore options to enhance access to e-commerce and home deliveries, introducing the concept of Home-Based Accessibility (HBA). This research uses an online survey, representative of the Portland metropolitan region, to estimate exploratory and confirmatory structural models addressing two key questions: (a) What type of households had zero home deliveries before COVID-19 lockdown? and (b) How the COVID-19 lockdown affected the type of households that receive home deliveries?

The results of 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 also showed that the COVID-19 pandemic worsened home delivery inequalities within the population. During the pandemic, higher-income households substantially increased home delivery rates. Pre-COVID-19, nearly 59% of the households with delivery rates over 10 per month had annual incomes greater than $100,000, whereas nearly 65% of the households with zero deliveries had 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 had annual incomes greater than $50,000, whereas nearly 70% of the households with zero deliveries had annual incomes below $50,000. These numbers are compounded by the fact that data and 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.

Other researchers have proposed a method to quantify access to online home delivery services (Sanchez-Diaz et al., 2021) utilizing data from the Västra Götaland Region in the West coast of Sweden. The results of this research show significant inequalities in access to home deliveries. Other researchers evaluate urban freight using an equity lens (Fried et al., 2024). This study adapts empirical methodologies from activity-based modeling, transport equity evaluation, and residential freight trip generation to estimate person- and household-level delivery demand and cargo van traffic exposure in 41 U.S. Metropolitan Statistical Areas (MSAs). There is evidence for racial and socio-economic inequities in last-mile delivery for low-income and populations of color that are exposed to more cargo van traffic than white populations, on average, despite ordering less packages.

2.7.3 Home Deliveries and Emissions or trips

According to the review of Aziz et al. (2022) there are several factors affecting grocery delivery emissions. Vehicle type is a key variable. In addition, other less obvious variables also affect grocery delivery emissions: if there is additional or demand substitution, the type of products delivered (frozen, refrigerated or dry products), shopping frequency and subscriptions, and other logistical factors such as delivery time windows.

This problem is complex, most research efforts use streamlined assumptions to arrive to meaningful results. Electric vehicles (EV) can dramatically reduce emission and the reductions are even higher if fleets of ground or air autonomous vehicles are utilized as shown by Figliozzi (2020). These results are significant because there are billions of annual grocery shopping trips in the U.S. according to NHTS 2017 data. However, in terms of energy and emissions efficiency there is no vehicle type that dominates across the board. The analysis of the carbon footprint of grocery in-store shopping and store delivery showed that many factors must be considered: delivery vehicle type, customer vehicle type, depot-service area distance, in-store order size, and delivery order size. With the advent of passenger EVs, it is no longer true that store deliveries are always more efficient. Delivery density and logistics sprawl, passenger and delivery vehicle type, and the location of the delivery depot are also key factors.

In all research efforts, simplifying assumptions are needed and therefore there are no models that fully replicates the complexity of real-world scenarios. However, cleaner electric vehicles are reducing emissions unless there are major increases in the number of trips caused by e-commerce.

2.7.4 The impact of WFH on Online Shopping

The post-COVID-19 world has seen a major increase in the number of people working from home (WFH) and this may impact e-commerce expenditures, type of products purchased, and delivery rates.

The pandemic caused a rapid transition to work from home over extended periods, but not all workers were able to telework. Research indicates that younger and older aged individuals had lower benefits and higher barriers to teleworking compared to middle aged individuals and the same can be said regarding Hispanic or Black individuals (Tahlyan et al., 2022). Barriers to telework are higher for essential workers compared to workers in remote friendly industries (Tahlyan et al., 2022).

Some researchers have recently studied how the rise of WFH influences online shopping behaviors (Mohammadi et al., 2024). Focusing on non-grocery items, this study found that WFH positively impacts online shopping, i.e. individuals who work from home tend to shop online more often.

According to Tahlyan et al. (2022) the key household and personal variables that affect WFH and online shopping frequency are:

- Income: high-income households are more likely to shop online.

- Age: older individuals (age 60+) are less likely to shop online frequently.

- Race and Physical Disability: Black/African American individuals and those with physical disabilities tend to shop online more frequently, possibly due to convenience and accessibility.

- Employer Flexibility: which affects WFH frequency, indirectly influencing online shopping behaviors.

The study also found latent variables that affect both WFH and online shopping. Results from NHTS 2022 Next Gen also validate this results (NHTS, 2024). The relationships between WFH, shopping trips, and home deliveries is a complex topic that was affected by the COVID-19 pandemic, and it is perhaps still evolving. It is likely that more research is needed to confirm early results and trends.

2.7.5 International research

So far, the review has focused almost exclusive in the U.S. e-commerce sector. This subsection summarizes a few relevant international studies, but it is limited to studies that have sample sizes of 250 respondents or more. For example Choi et al. (2019) concludes that the factors affecting customer satisfaction in the online shopping industry are quality of order, quality of information, quality of delivery, price of delivery, and customer service. Factor analysis is used though the sample size is quite small, only 150 respondents. Given the differences in e-commerce development across countries it is unlikely that international research efforts are going to provide meaningful insights unless the economies and sociodemographic characteristics are somewhat comparable, and the studies are performed utilizing good survey designs and adequate sample sizes.

According to a UK based research, gender, age, and socioeconomic status are the key determinants of home delivery rates for grocery e-commerce within the UK (Hood et al., 2020). Higher income groups demonstrate more regular use of home delivery, with lower usage rates observed in lower income or social grades, particularly among semi-skilled and unskilled manual workers. Also, females are more likely to use home delivery services compared to males and adults aged 25–44 are the primary users of home delivery services which aligns with previous research suggesting that younger to middle-aged adults are more inclined to use e-commerce for groceries.

Researchers in Singapore evaluated the influence of locational and household characteristics on e-commerce home delivery demand (Cheng et al., 2021). Unlike previous studies that have mostly used individual or household survey data to understand delivery rates, these researchers used data from an e-commerce carrier and estimated a linear regression model. The following variables tend to increase home deliveries: population density, household size, household income, and household vehicle ownership. The following variables tend to decrease delivery rates: building age and accessibility measures to shopping malls.

Although the data and the approach used in Singapore are clearly different than typical survey-based studies, the results are mostly similar regarding household variables such as income, size, and vehicle ownership which is reassuring.

2.8 SUMMARY

The US has witnessed a rapid surge in e-commerce, driven by various factors including: (a) increased internet penetration, (b), the convenience of online shopping, (c) the proliferation of smartphones, and (d) the rise of subscription services. Forecasts predict continued robust growth in the e-commerce sector, making it a potentially stable and substantial source of revenue for transportation funding. This projection is supported by sociodemographic trends, such as the increasing disposable income of tech-savvy younger generations and the growth of single-person households or smaller family units, which are well-suited for e-commerce's efficient handling of frequent, smaller purchases.

To address the challenges posed by declining fuel tax revenues and growing transportation infrastructure needs, several US states have explored or implemented retail delivery fees specifically targeting e-commerce deliveries. Colorado and Minnesota are the frontrunners, having successfully implemented e-commerce delivery fees. Colorado's fee, launched in July 2022, charges $0.29 per retail delivery (adjusted for inflation), while Minnesota's fee, effective July 2024, is $0.50 per delivery on transactions exceeding $100. Both states have incorporated features designed to mitigate potential drawbacks, such as allowing retailers flexibility in itemizing the fee or embedding it within product pricing to minimize administrative burdens and potential consumer resistance. These states also offer exemptions for small businesses to alleviate the impact on smaller retailers. Maryland and Washington state are currently considering imposing delivery fees. Other states have considered similar fees, but legislative efforts have faced challenges and have not been yet enacted in Ohio, Nebraska, and New York.

Academic research on the direct impact of e-commerce delivery fees is limited, but studies on shipping fees and delivery attributes offer valuable insights. Research has consistently shown that consumers are highly sensitive to shipping costs, often leading to cart abandonment when fees are perceived as excessive. This underscores the importance of carefully considering fee structures and consumer perceptions when designing e-commerce delivery fees. Studies also emphasize the significance of delivery attributes like speed, time slots, and delivery date in shaping consumer preferences, with delivery fees being the most critical factor influencing purchase decisions.

The National Household Travel Survey (NHTS) provides valuable data for understanding delivery rates and their potential equity implications. Several studies using NHTS data have identified consistent trends: higher-income households, larger households, and households with more vehicles generally have higher delivery rates. Other factors like education level, age, employment status, and urbanization level also influence delivery frequency, and many variables are highly correlated.

Beyond the NHTS data, research has explored various aspects of e-commerce, such as the impact of product type on delivery rates and expenditures, the relationship between home deliveries and emissions, and the influence of work-from-home trends on online shopping behavior. Studies highlight the need to consider product-specific factors when analyzing delivery patterns, as the demand for different goods can significantly influence delivery frequency and associated costs. Research on equity suggests that home deliveries may disproportionately benefit higher-income and more educated populations, potentially exacerbating existing inequalities. This raises

concerns about the potential regressive nature of e-commerce delivery fees if not carefully designed. Research also underscores the importance of addressing the environmental impacts of e-commerce, particularly the potential for increased emissions and traffic congestion associated with deliveries. The shift towards work-from-home arrangements has further accelerated the growth of e-commerce, underscoring the evolving nature of consumer behavior and the need for transportation policies to adapt accordingly.

3.0 EXPLORATORY ANALYSIS OF SURVEY DATA

This section presents a survey description and an exploratory analysis of key sociodemographic factors like age, income, household size. A key goal for this section is to analyze whether the trends observed are congruent with findings from the literature review.

3.1 SURVEY DESCRIPTION

A survey was submitted for TAC review and during the November 2024 TAC meeting there was a presentation summarizing key literature review findings and a discussion of the survey design and structure. Also, in November some TAC members provided specific survey feedback and suggestions, and the PSU team shortly afterwards submitted a document responding to the comments and indicating how the suggestions could be incorporated. The survey was successfully deployed in November and the survey data delivered in December 2024.

The survey included three attention questions to guarantee data quality and consistency throughout the questionnaire. In addition, respondents that chose "Prefer not to answer" in the questions related to age, gender and income did not complete the survey.

The number of responses that completed the survey and successfully answered the attention questions was 958. In terms of data quality, the results presented in this draft report indicate that data trends are congruent with the key literature findings. In areas where questions are novel and not previously studied in the literature the modeling results and derived insights do not raise any concerns.

In this report, questions will be formatted to differentiate them from surrounding text. The main question will be ***bolded*** and the options (if any) just *italicized*. The question used to disaggregate between households with and without home deliveries was the following:

How often does your household use online shopping with home deliveries? Please consider only physical products (clothing, consumer products, groceries, food, etc.)

- *Very often (more than 6 deliveries per WEEK))*
- *Often (4 or 5 deliveries per WEEK)*
- *Sometimes (2 or 3 deliveries per WEEK)*
- *Rarely (1 delivery per WEEK or less)*
- *Never (my household receives ZERO deliveries)*

The group or categorical distribution of households is used in future sections to present basic trends and judge the quality of the responses. Hence, this distribution of households by home delivery frequency group is presented with additional detail in this introductory section. The categorical distribution of home delivery both in terms of percentages and frequencies is presented in Table 3.1.

Table 3.1: Frequency and percentages of the categorical distribution of home delivery frequency

Category	Frequency	Percentage
Never	134	14.0
Rarely	357	37.3
Sometimes	275	28.7
Often	124	12.9
Very Often	68	7.1

The plot with the distribution of responses is shown in Figure 3.1.

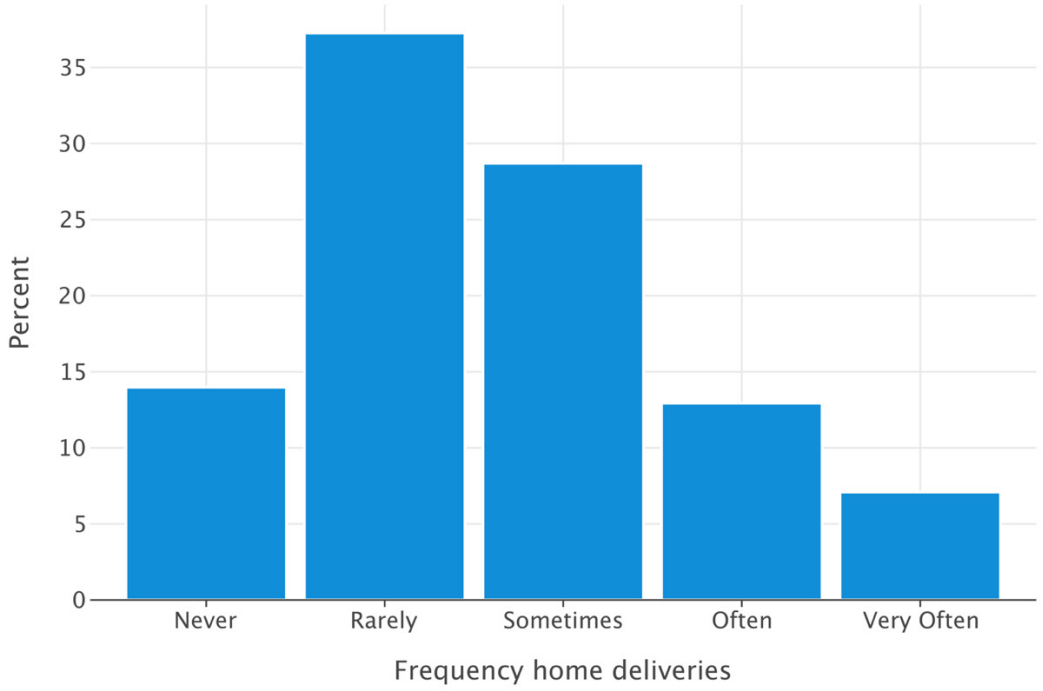

Figure 3.1: Categorical distribution of home delivery frequency

The number of households that engaged in online shopping and home deliveries was 824 out of 958 completed surveys. This implies that 134 households, approximately 14% of the observations, do not engage in e-commerce. Based on the literature review, the 14% figure seems realistic.

As a reference, it is recommended to have 30 or more observations per group or category when exploring data trends. Given the sample size, categories with at least 3.5% of the sample size meet this requirement. In later sections, there will be a note when this threshold is not met.

3.2 EXPLORATORY ANALYSIS OF SOCIODEMOGRAPHIC VARIABLES

This section documents results using key sociodemographic variables like age, income, and household size. The goals are to (a) observe the distribution of the data and potential data gaps and (b) check whether the trends observed in the survey data regarding e-commerce delivery rates match with literature review findings. For the former goal, for each variable there is a plot describing the distribution of the variable and for the later goal each variable is plotted against the home delivery frequency category. The survey question is always introduced first to facilitate the interpretation of the data.

3.3 AGE

The literature review indicated that age has been a significant factor to model the rate of adoption of e-commerce. The survey question is the following:

What is your age?

- Less than 18
- 18 to 24
- 25 to 34
- 35 to 44
- 45 to 54
- 55 to 64
- 65 to 74
- 75 or more
- Prefer not to answer

Age was a filtering question, meaning that respondents that chose “Prefer not to answer” did not complete the survey. The distribution of respondents by age group is shown below in Figure 3.2 with an adequate percentage of observations per group.

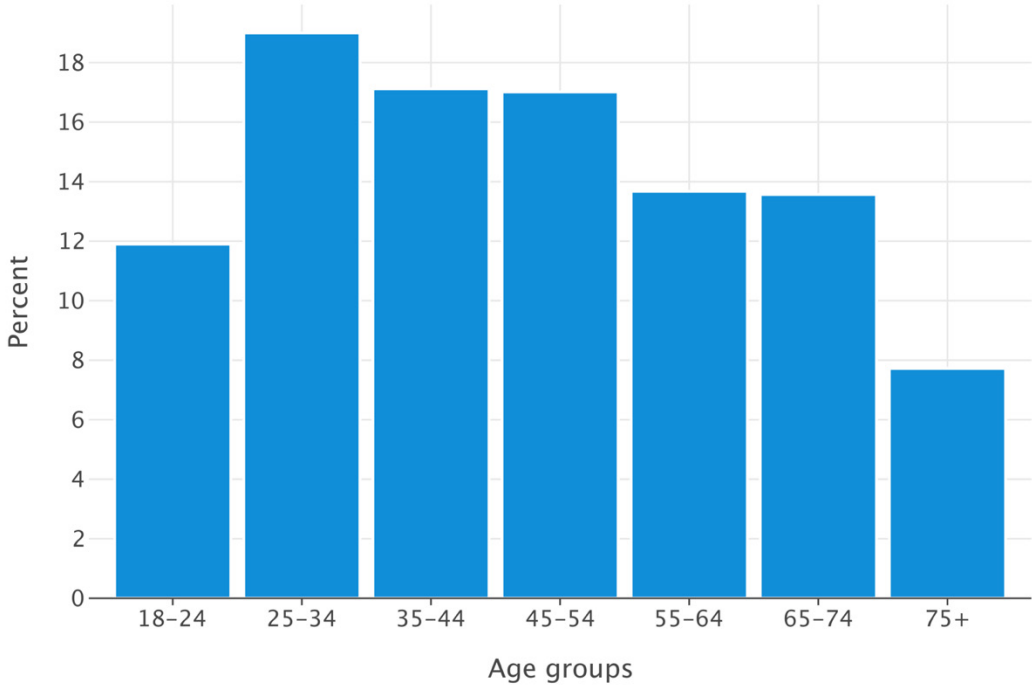

Figure 3.2: Survey age distribution

The impact of age on home delivery frequency can be seen in Figure 3.3 showing highest delivery frequencies for the 35-44 age group and lowest for the 75+ group. The trends observed in the Figure 3.3 are consistent with trends discussed in the literature review.

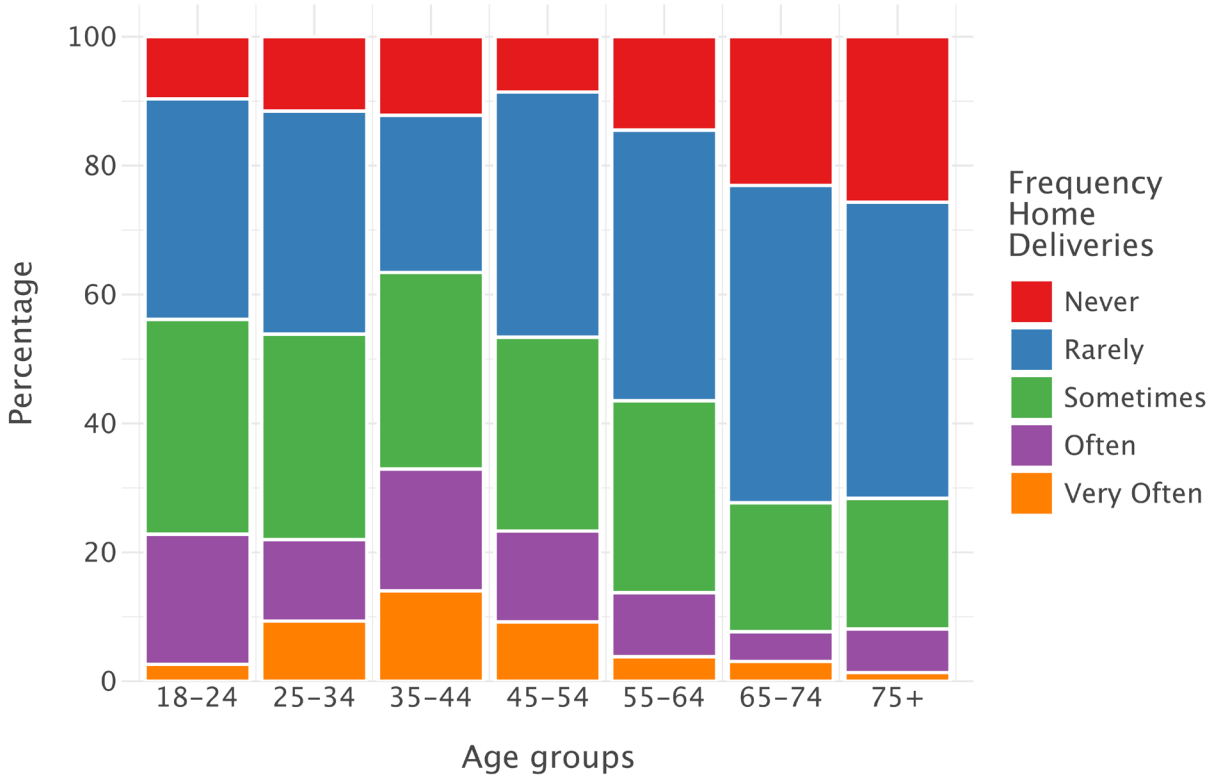

Figure 3.3: Home delivery frequency vs. age group distributions

3.4 GENDER

The literature review has shown that gender may be a factor, but it is not a strong or consistent predictor regarding e-commerce delivery rates. The survey question is the following:

What is your gender?

- Female
- Male
- Non-binary
- Prefer not to answer

Gender was a filtering question, meaning that respondents that chose "Prefer not to answer" did not complete the survey. The distribution of respondents by gender is shown below in Figure 3.4 with an adequate percentage of observations for Female and Male but insufficient observations (slightly less than 1%) for the non-binary category.

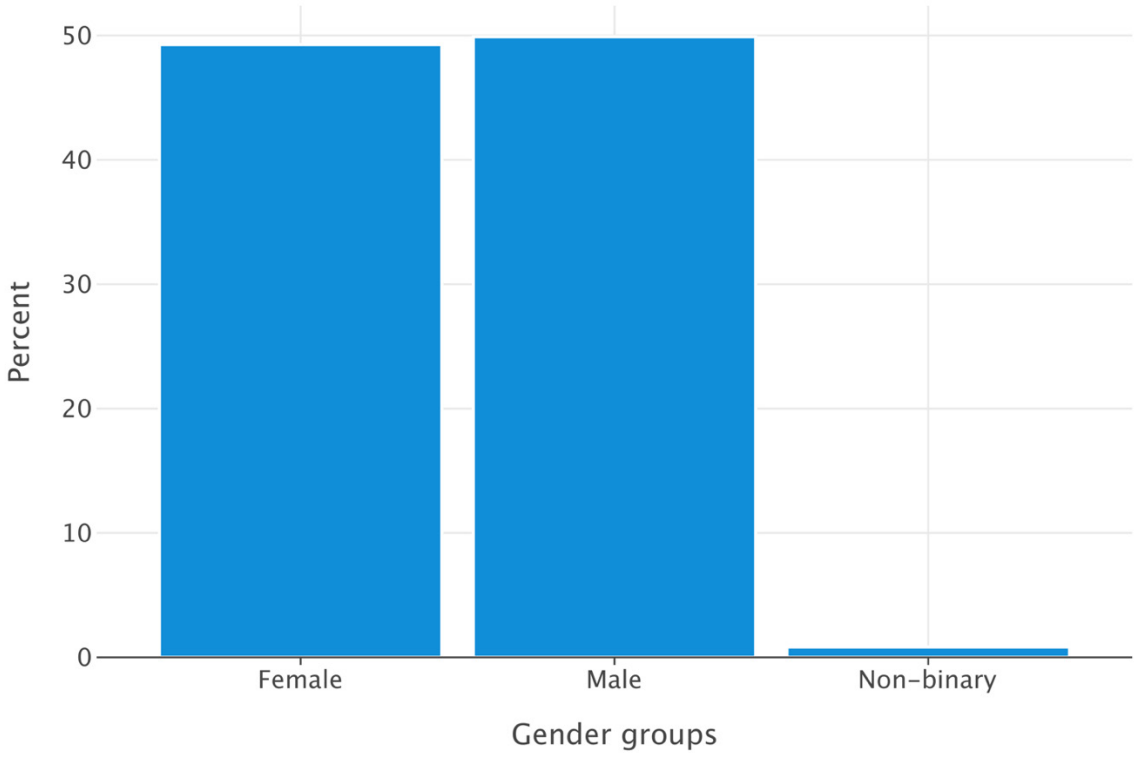

Figure 3.4: Survey gender distribution

The impact of gender on home delivery frequency can be seen in Figure 3.5. There is no clear trend besides a slightly higher deliveries for males. For non-binary the plot is meaningless given the low number of observations.

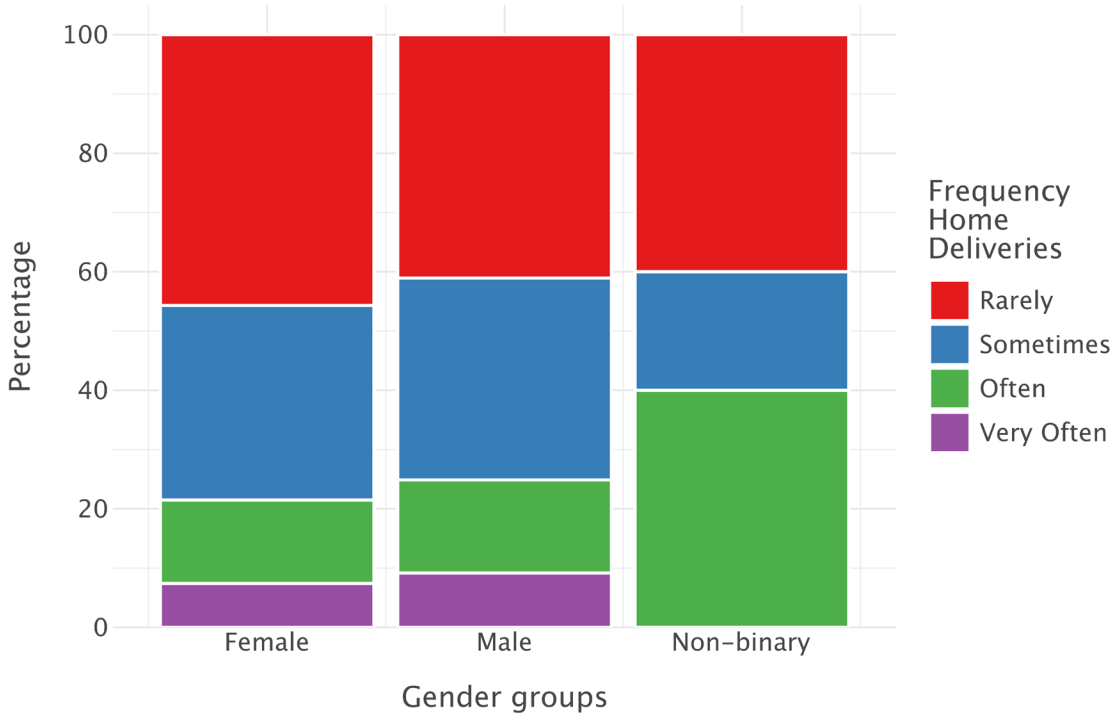

Figure 3.5: Home delivery frequency vs. gender group distributions

3.5 INCOME

The literature review indicated that income is a significant factor to model the adoption of e-commerce and home deliveries. The survey question related to income is the following:

Which category best represents last year's household income before taxes (2023 income)?

- Less than $15,000
- $15,000 to $24,999
- $25,000 to $49,999
- $50,000 to $74,999
- $75,000 to $99,999
- $100,000 to $150,000
- $150,000 to $200,000
- Greater than $200,000
- Prefer not to answer

Income was the last filtering question, meaning that respondents that chose "Prefer not to answer" did not complete the survey. The distribution of respondents by income group is shown below in Figure 3.6 with an adequate percentage of observations per group.

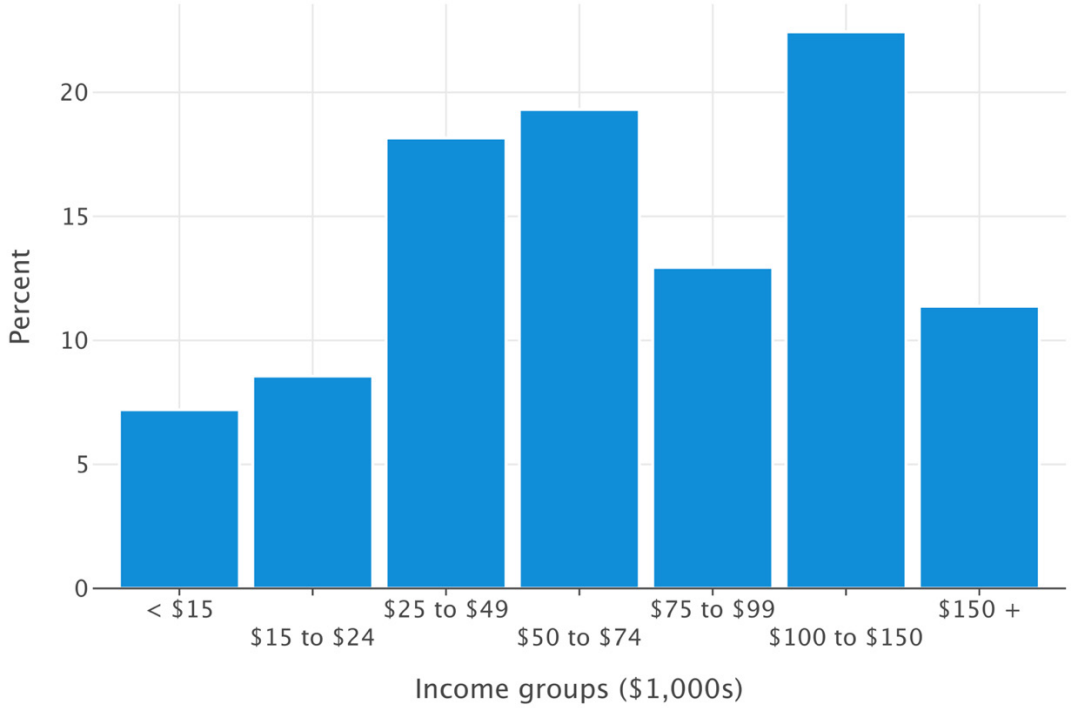

Figure 3.6: Survey income distribution

The impact of income on home deliveries frequency can be seen in Figure 3.7 showing higher income is associated with more often deliveries and less associated with "never" using home deliveries. On the other hand, lower income groups tend to have a higher percentage of "never" users. The trends observed are consistent with trends discussed in the literature review.

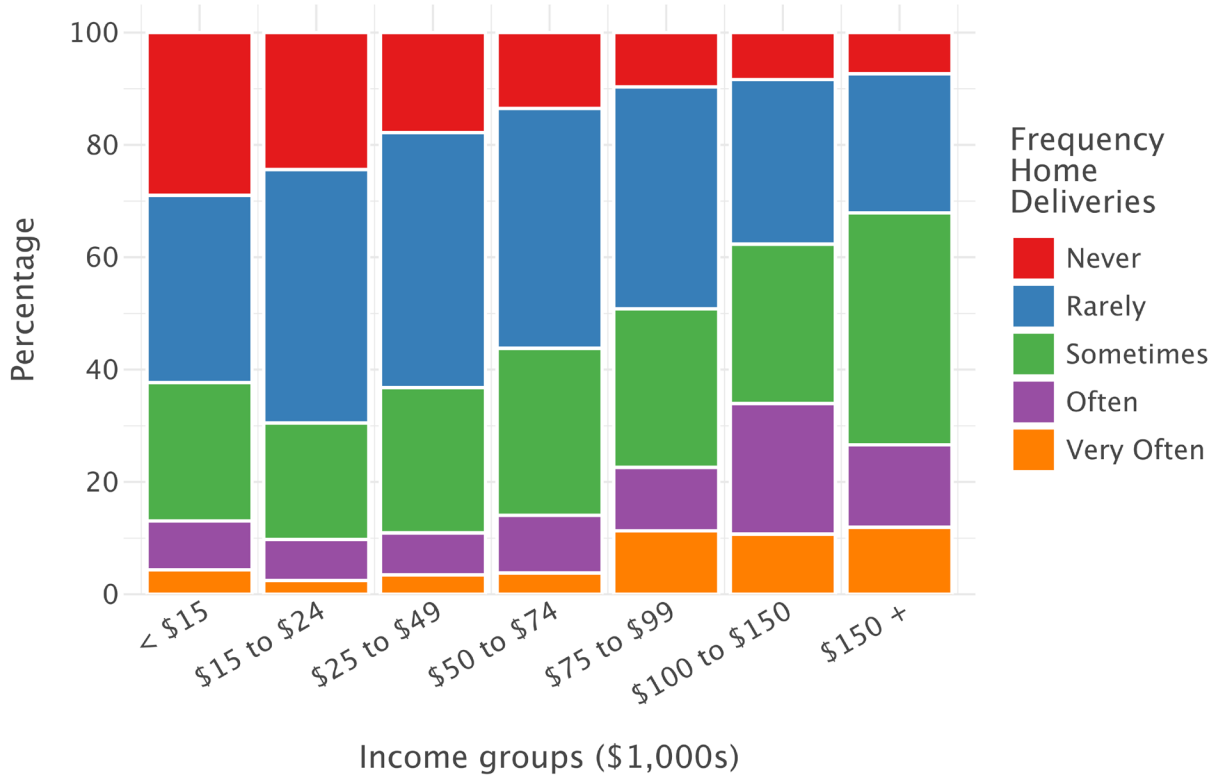

Figure 3.7: Home delivery frequency vs. income group distributions

3.6 HOUSEHOLD SIZE

The literature review indicated that household size is another significant factor to model the adoption of e-commerce. The survey question related to household size is the following:

How many people live in your household by age group? Provide a number for each group

- 0 to 17 years old
- 18 to 34 years old
- 35 to 64 years old
- 65 years old or more

This question was originally asking the total household size, but it was disaggregated by age group as suggested by TAC member Joe Broach. The distribution of respondents by household size (summing all categories) is shown below in Figure 3.8 that shows an adequate percentage of observations per size in the range 1 to 6+.

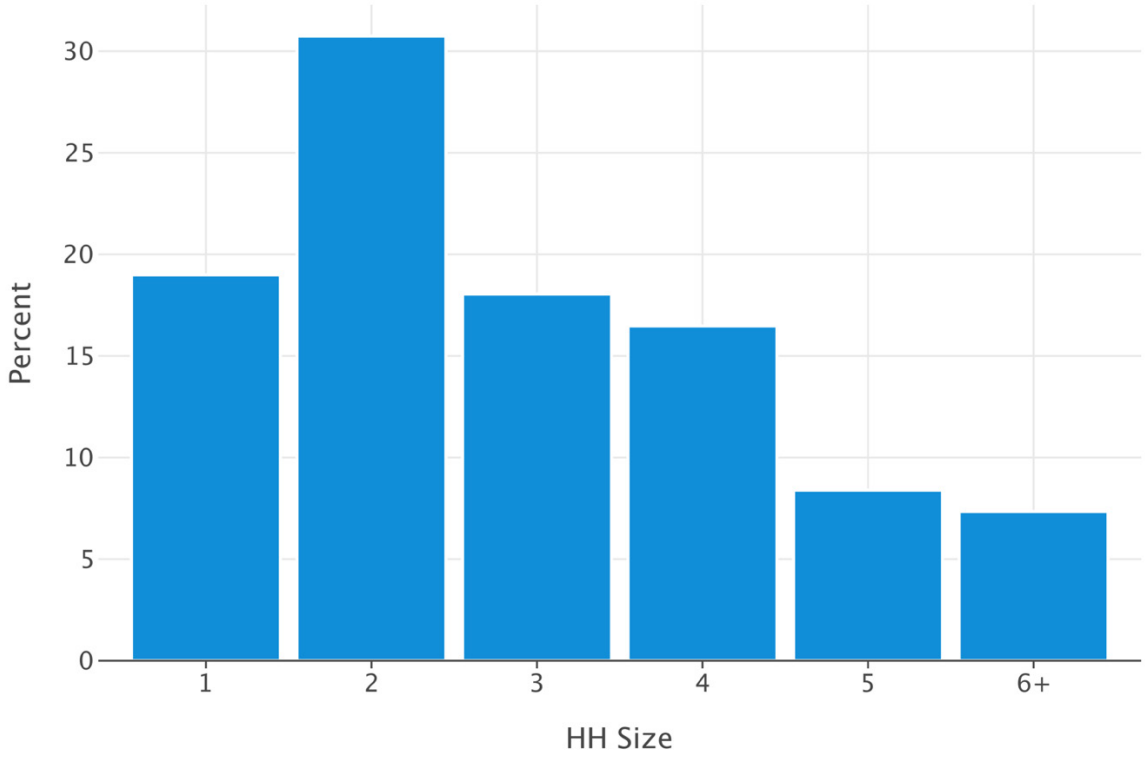

Figure 3.8: Survey household size distribution

The impact of household size on home deliveries frequency can be seen in Figure 3.9 with a trend already seen for income groups. Larger household sizes are associated with more often deliveries and less associated with "never" using home deliveries.

Figure 3.9: Home delivery frequency vs. household size

The following subsections discuss trends by household size by age group. The literature review does not provide a clear insight regarding the impact of the distribution of household ages on e-commerce adoption and deliveries beyond what was already said about respondent age. To facilitate interpretation some sizes have been consolidated to include at least 30 observations in the largest size category of the group.

3.6.1 Group 0-17

The impact of age group 0-17 size on home deliveries frequency can be seen in Figure 3.10. The trend is more deliveries with more members up to size two with a slight decrease for size three-plus.

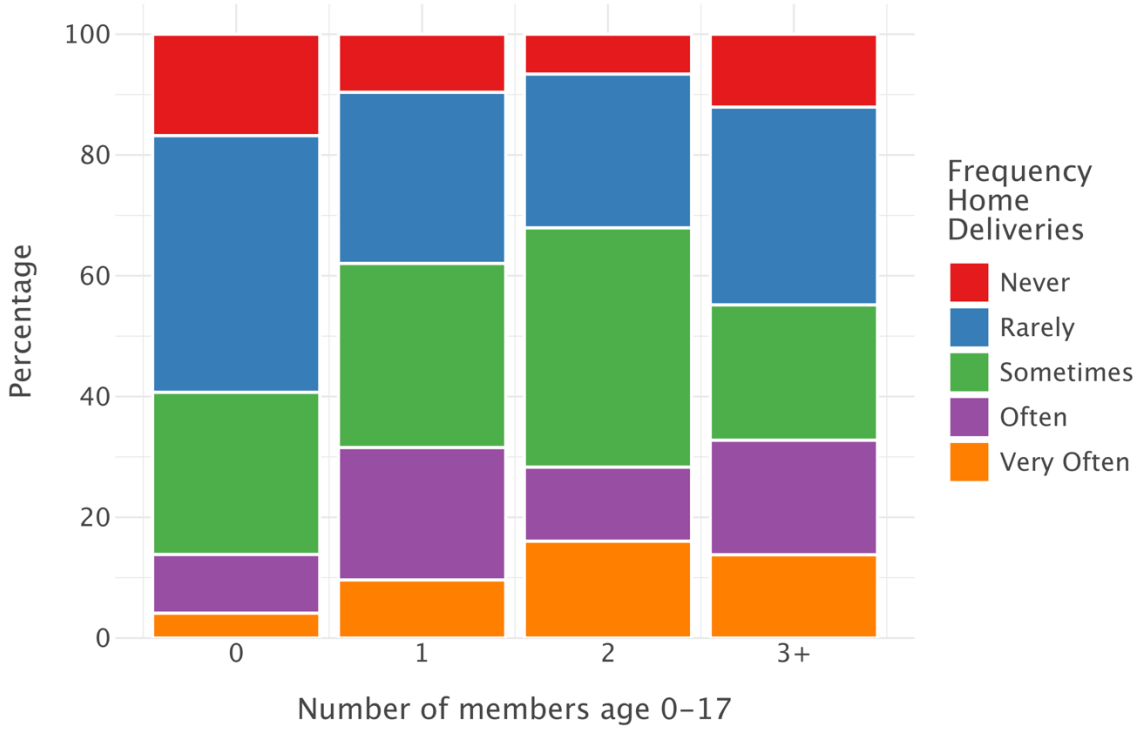

Figure 3.10: Home delivery frequency vs. members aged 0-17

3.6.2 Group 18-34

The impact of age group 18-34 size on home deliveries frequency can be seen in Figure 3.11. The trend is more deliveries with more members up to size two and stable for size three-plus.

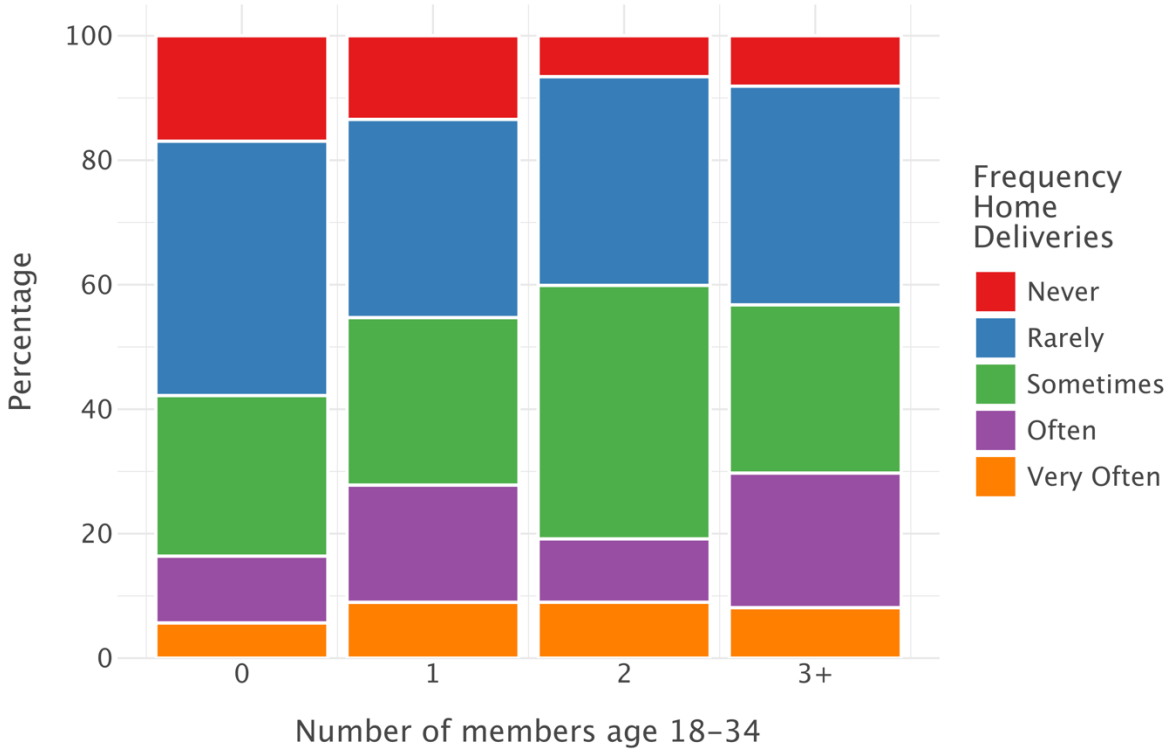

Figure 3.11: Home delivery frequency vs. members aged 18-34

3.6.3 Group 35-64

The impact of age group 35-64 size on home deliveries frequency can be seen in Figure 3.12. The distributions are similar for size zero and one, there is a clear increase for size two and a drop for size three-plus.

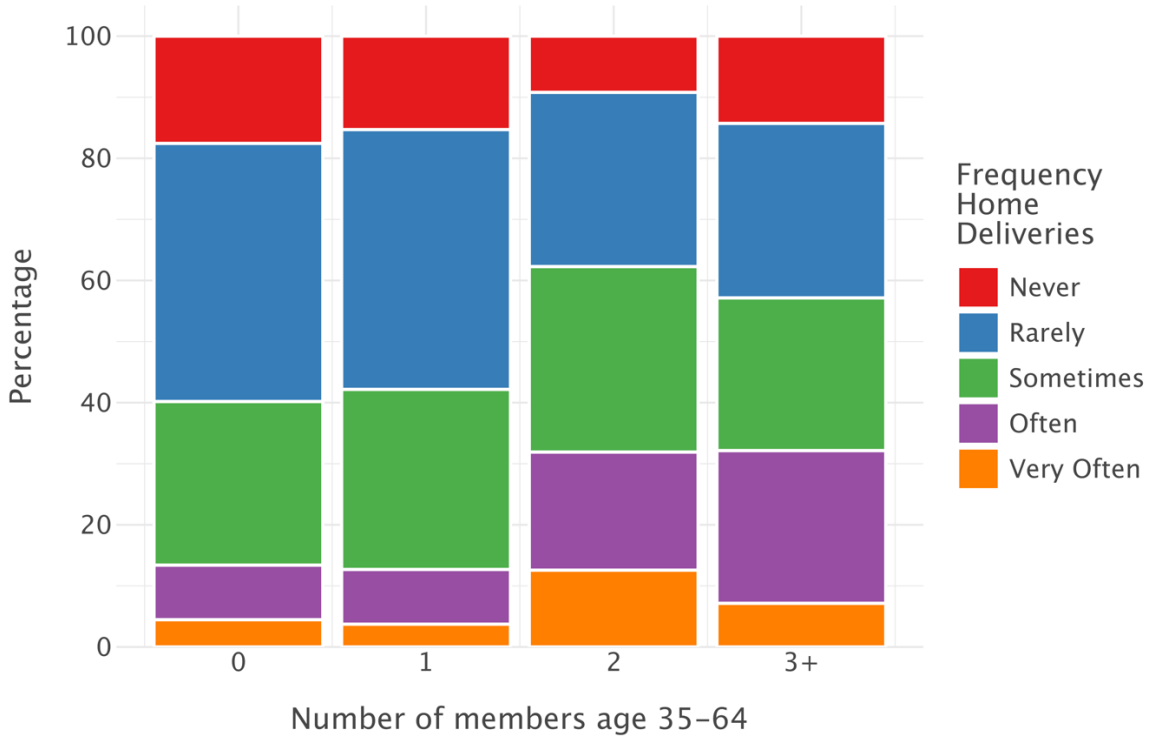

Figure 3.12: Home delivery frequency vs. members aged 35-64

3.6.4 Group 65+

The impact of age group 65+ size on home deliveries frequency can be seen in Figure 3.13. There is no clear trend in this plot. Households with two members age 65+ seem to be on the side of more deliveries when compared to households with one member. And households with zero members age 65+ seem to have more deliveries than households with one member age 65+ which confirms the impact of age on deliveries that was previously seen when analyzing age groups.

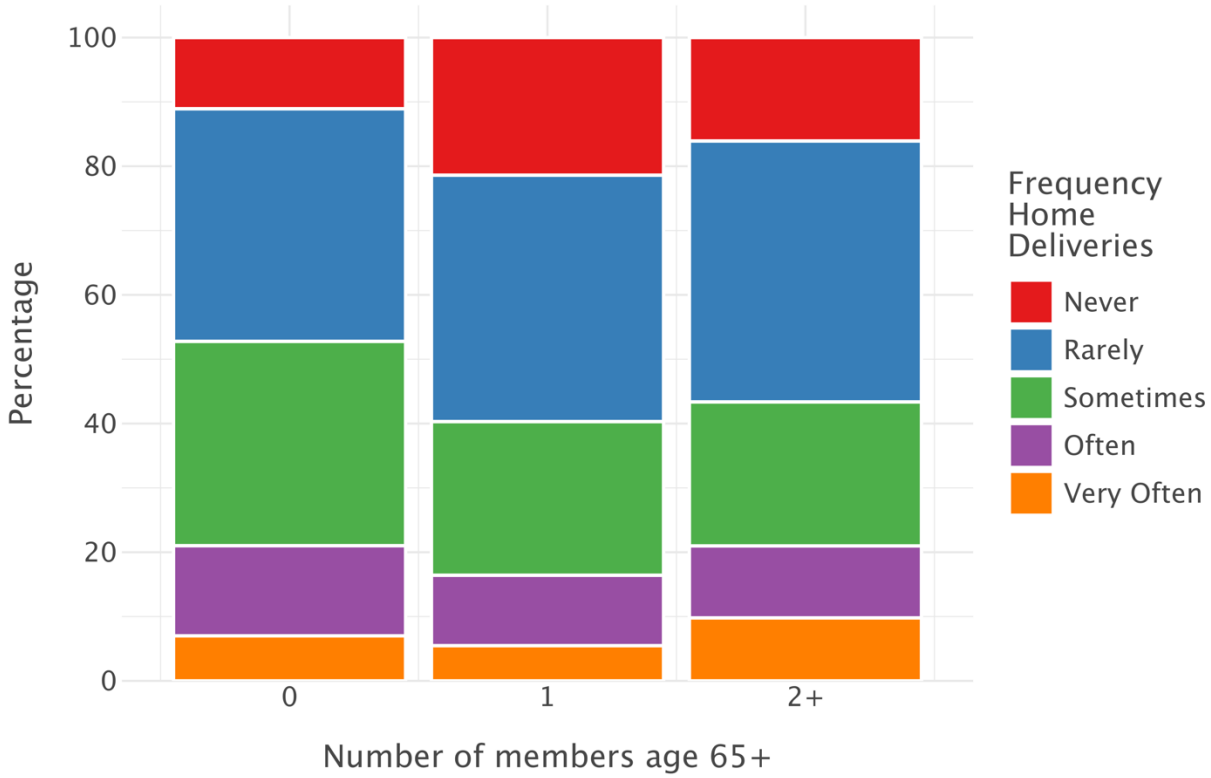

Figure 3.13: Home delivery frequency vs. members aged 65+

3.7 RACE

The literature review has shown that race may be a factor, but it is not a strong or consistent predictor regarding e-commerce delivery frequency. The survey question for race is the following:

Which of the following options best describe the race or ethnicity of members of your household? *Select one or more options.*

- American Indian or Alaska Native
- Asian
- Black or African American
- Hispanic or Latino
- Native Hawaiian or Pacific Islander
- White
- Other

Only five race groups have more than 30 observations and they are listed in order from highest to lowest percentage: White (87.3%), Hispanic (7.9%), Asian (4.9%), Black (4.7%), and Native Hawaiian or Pacific Islander (4.3%). The sum of the percentages is greater than 100% because was possible to mark one or more options as an acceptable response.

3.7.1 White

For White households the distribution of home deliveries frequency can be seen in Figure 3.14. When comparing to the all the other groups combined the differences are small except perhaps for the very often category.

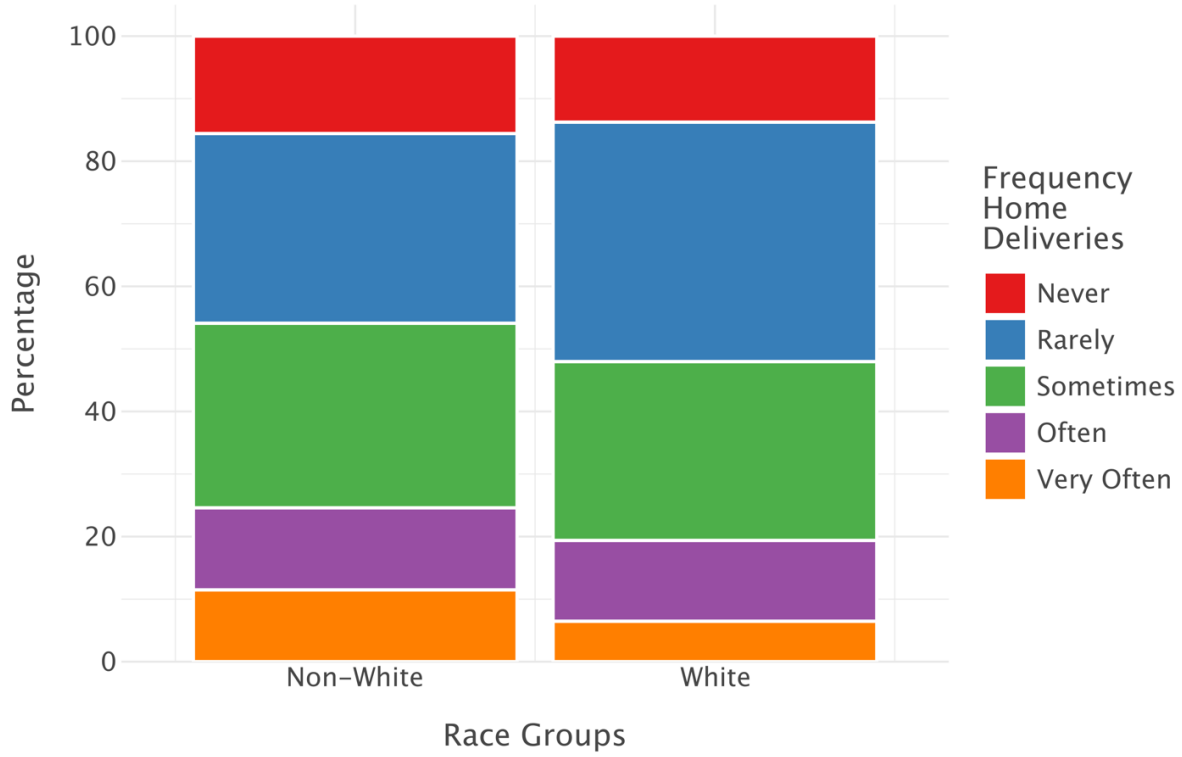

Figure 3.14: Home delivery frequency for White households

3.7.2 Hispanic

For Hispanic households the distribution of home deliveries frequency can be seen in Figure 3.15. When comparing to the all the other groups combined the differences are small except perhaps for a small difference in the often and “never” categories.

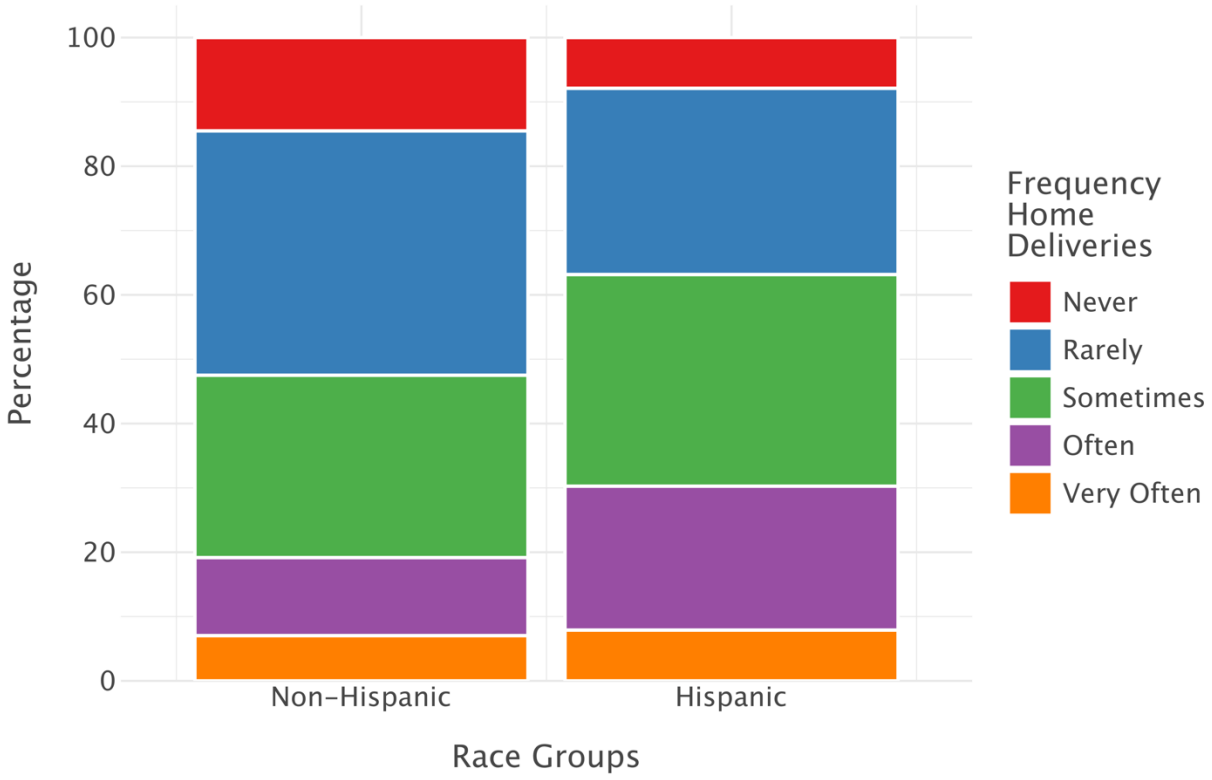

Figure 3.15: Home delivery frequency for Hispanic households

3.7.3 Asian

For Asian households the distribution of home deliveries frequency can be seen in Figure 3.16. When comparing to the all the other groups combined the differences seem contradictory, with higher percentages for the “very often” and the “never” categories.

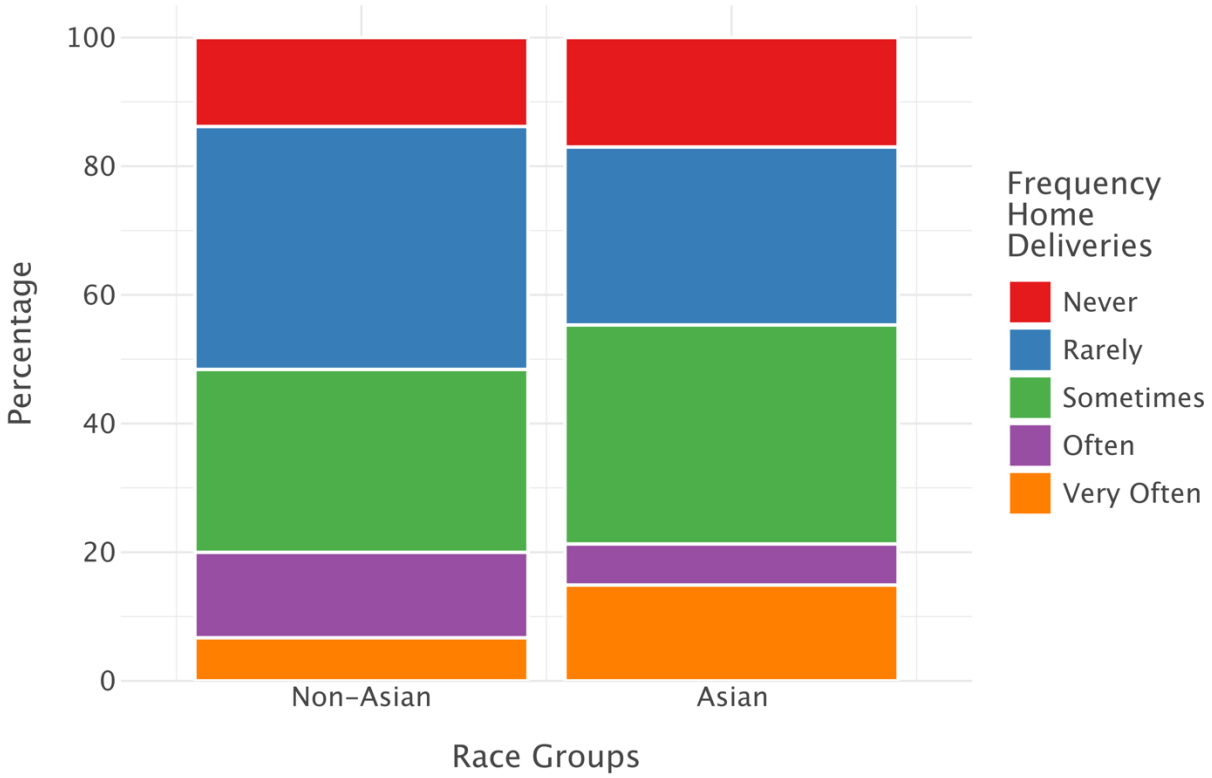

Figure 3.16: Home delivery frequency for Asian households

3.7.4 Black

For Black households the distribution of home deliveries frequency can be seen in Figure 3.17. When comparing to the all the other groups combined the differences are more consistent, lower percentage of “very often” and higher percentage of “never” for Black households.

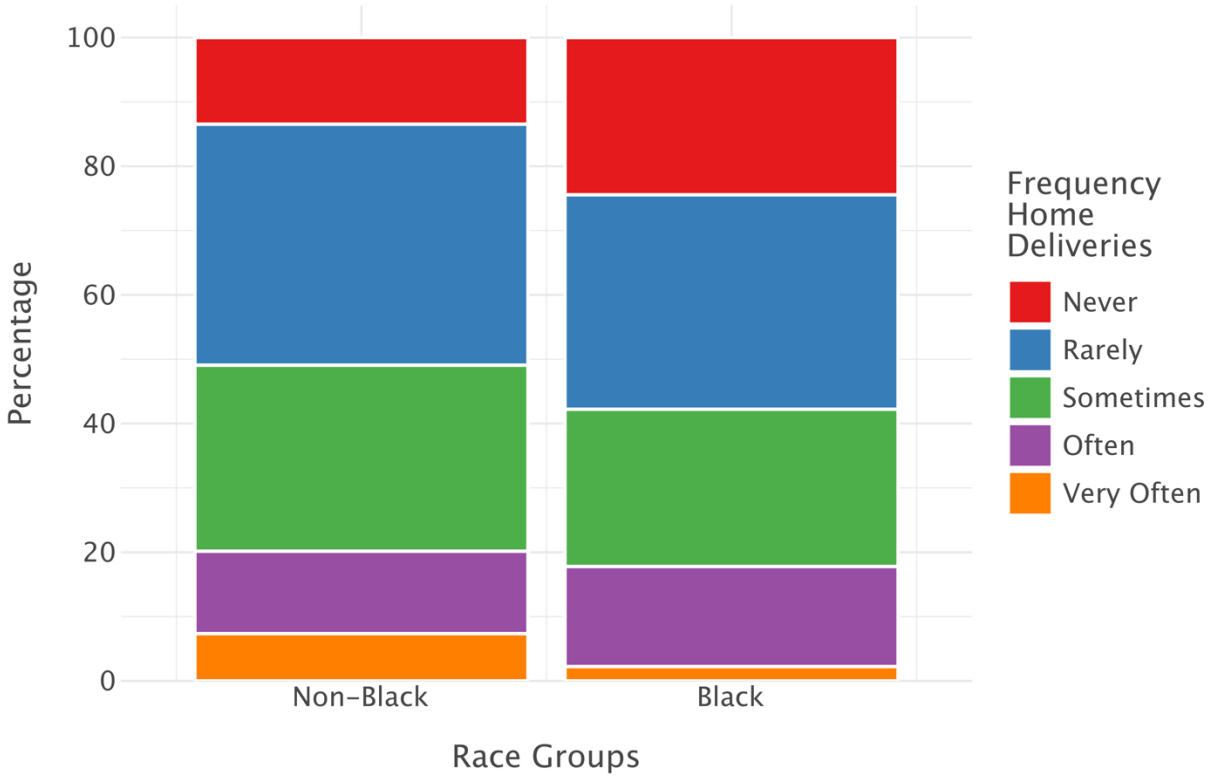

Figure 3.17: Home delivery frequency for Black households

3.7.5 Native Hawaiian or Pacific Islander

For Native Hawaiian or Pacific Islander (NHPI) households the distribution of home deliveries frequency can be seen in Figure 3.18. When comparing to the all the other groups combined the differences are small at the extremes ("never" or "very often") with a noticeable difference for the "often" category.

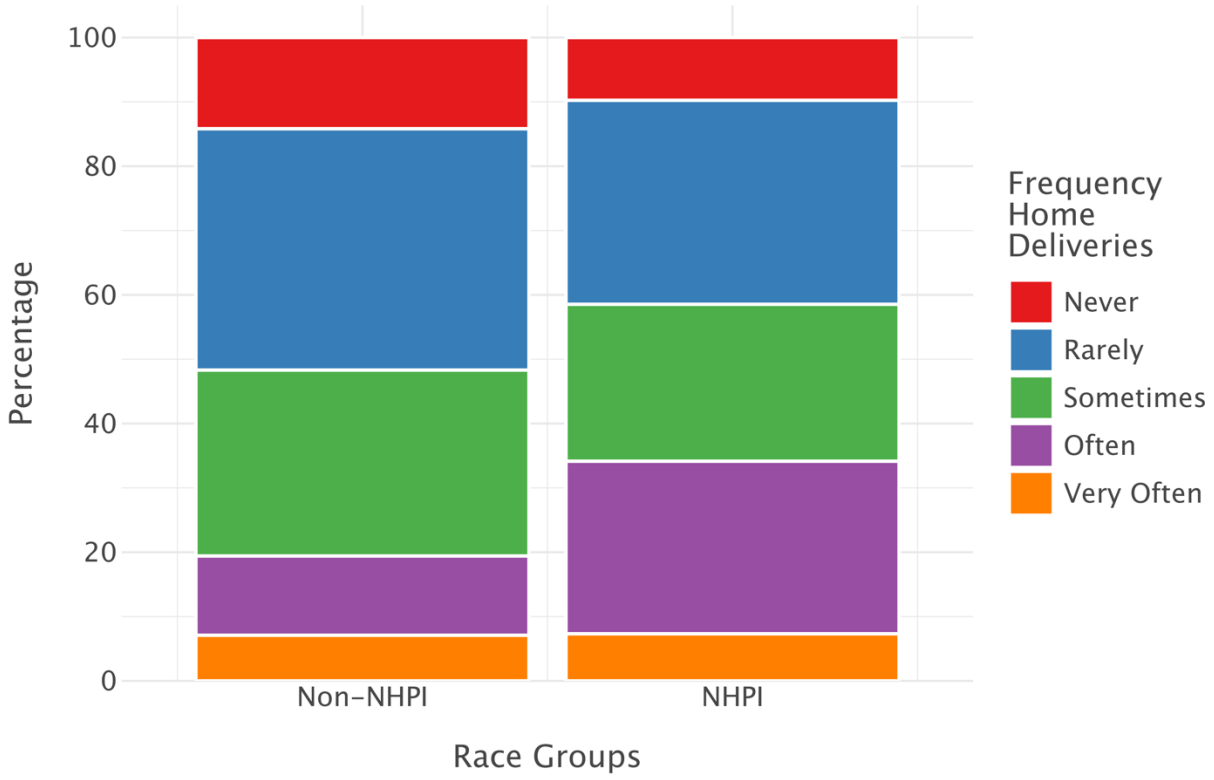

Figure 3.18: Home delivery frequency for NHPI households

3.8 AREA TYPE

The literature review seems to indicate that less dense areas tend to have less deliveries though not all the surveys include questions related to this type of variable. The survey question for area type is the following:

Which of the following best describes the area where you live?

- Large city
- Small town or city
- Suburban area
- Rural area

The distribution of respondents by income group is shown below in Figure 3.6 with an adequate percentage of observations per group.

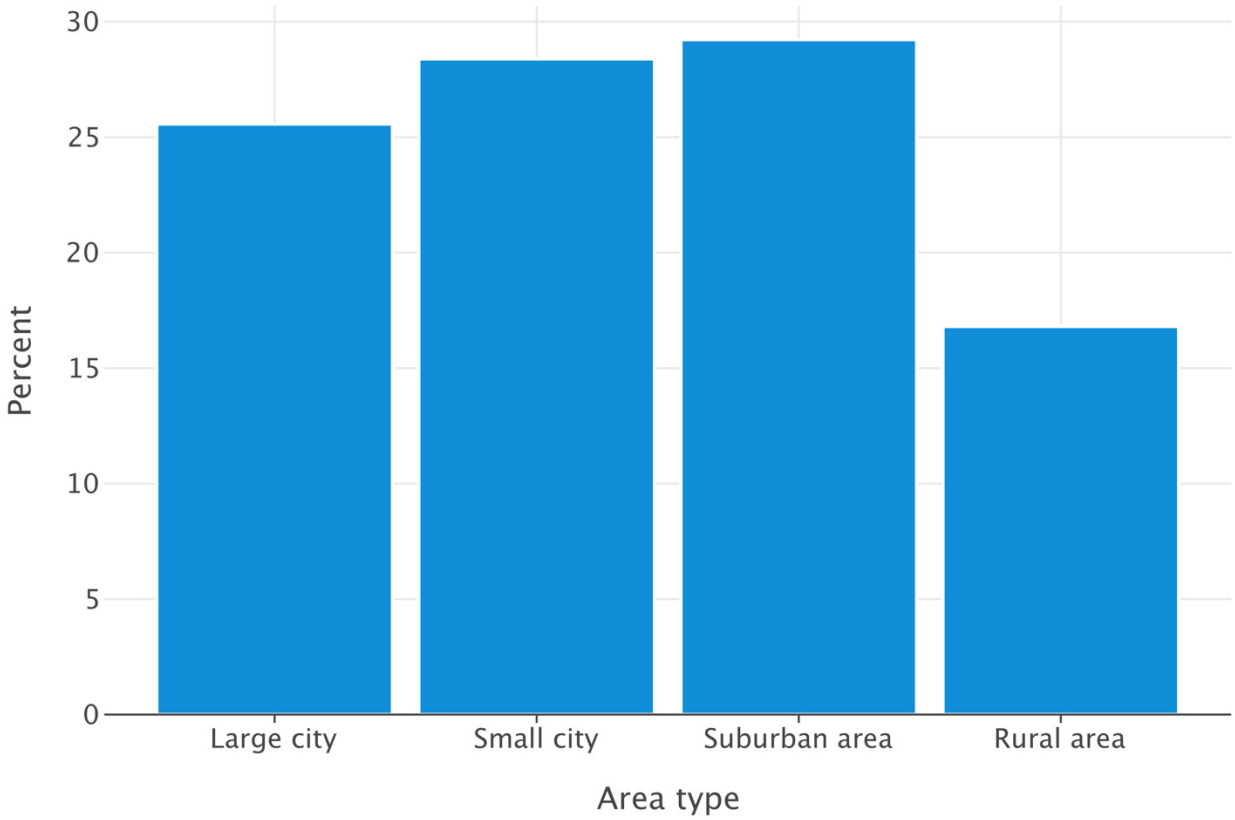

Figure 3.19: Area type distribution

The impact of area type on home deliveries frequency can be seen in Figure 3.20. When comparing to the all the other area types “Large city” a higher percentage of “very often” and lower percentage of “never”.

Figure 3.20: Home delivery frequency vs. area type distribution

3.9 DISTANCE TO STORES

The literature review has shown that distance to stores is not a commonly used variable to model e-commerce activity. The survey question used to capture distance is the following:

Approximately, how far from home (in miles) are the stores where you would get some of the following products/services? *(range 0-15+)*

- Grocery store/ supermarket
- Prepared food/restaurants
- Pharmacy
- Clothing/apparel
- Post office

The distribution of distances (25th percentile, median, mean, and 75th percentile) by store type and delivery frequency is shown in Table 3.2. A few observations can be made:

- The distance distribution is in all cases right skewed.

- Data has been presented is ascending order, meaning that food stores are usually closer to respondents than clothing stores.

- In some instances, it is possible to see that longer distances are associated with higher delivery frequency but not always.

Table 3.2: Frequency and percentages of the categorical distribution of home delivery frequency

Store Type	Frequency	P.25th	Median	Mean	P.75th
Food	Never	1.0	2.0	3.7	5.0
Food	Rarely	1.0	3.0	4.4	5.0
Food	Sometimes	1.0	3.0	4.3	5.0
Food	Often	2.0	3.0	4.3	6.0
Food	Very Often	2.0	4.5	5.7	8.5
Pharmacy	Never	1.0	3.0	4.7	7.0
Pharmacy	Rarely	1.0	2.0	4.2	5.0
Pharmacy	Sometimes	2.0	3.0	4.7	5.0
Pharmacy	Often	1.0	4.0	4.8	6.2
Pharmacy	Very Often	2.0	4.5	5.1	7.2
Grocery	Never	1.0	2.5	4.0	5.0
Grocery	Rarely	2.0	3.0	4.5	5.0
Grocery	Sometimes	2.0	3.0	4.6	6.0
Grocery	Often	2.0	4.0	4.7	7.0
Grocery	Very Often	1.8	5.0	5.6	9.0
Post Office	Never	2.0	3.0	4.3	5.0
Post Office	Rarely	2.0	3.0	4.1	5.0
Post Office	Sometimes	2.0	3.0	3.9	5.0
Post Office	Often	2.0	4.0	4.5	6.0
Post Office	Very Often	2.0	4.0	4.7	7.0
Clothing	Never	2.0	5.0	6.3	10.0
Clothing	Rarely	3.0	5.0	6.6	10.0
Clothing	Sometimes	3.0	5.0	7.0	10.0
Clothing	Often	3.0	5.0	6.5	10.0
Clothing	Very Often	3.0	5.5	6.8	10.0

3.10 HH MEMBERS WITH DISABILITIES

The literature review has shown that disabilities is not a variable typically found in e-commerce surveys. The survey question is the following:

Disabilities can affect the way people travel and buy. How many household members have difficulty walking, climbing stairs, reaching, lifting, or carrying? *(range 0-3+)*

The distribution of members with disabilities is shown below in Figure 3.21 with an adequate percentage of observations per group.

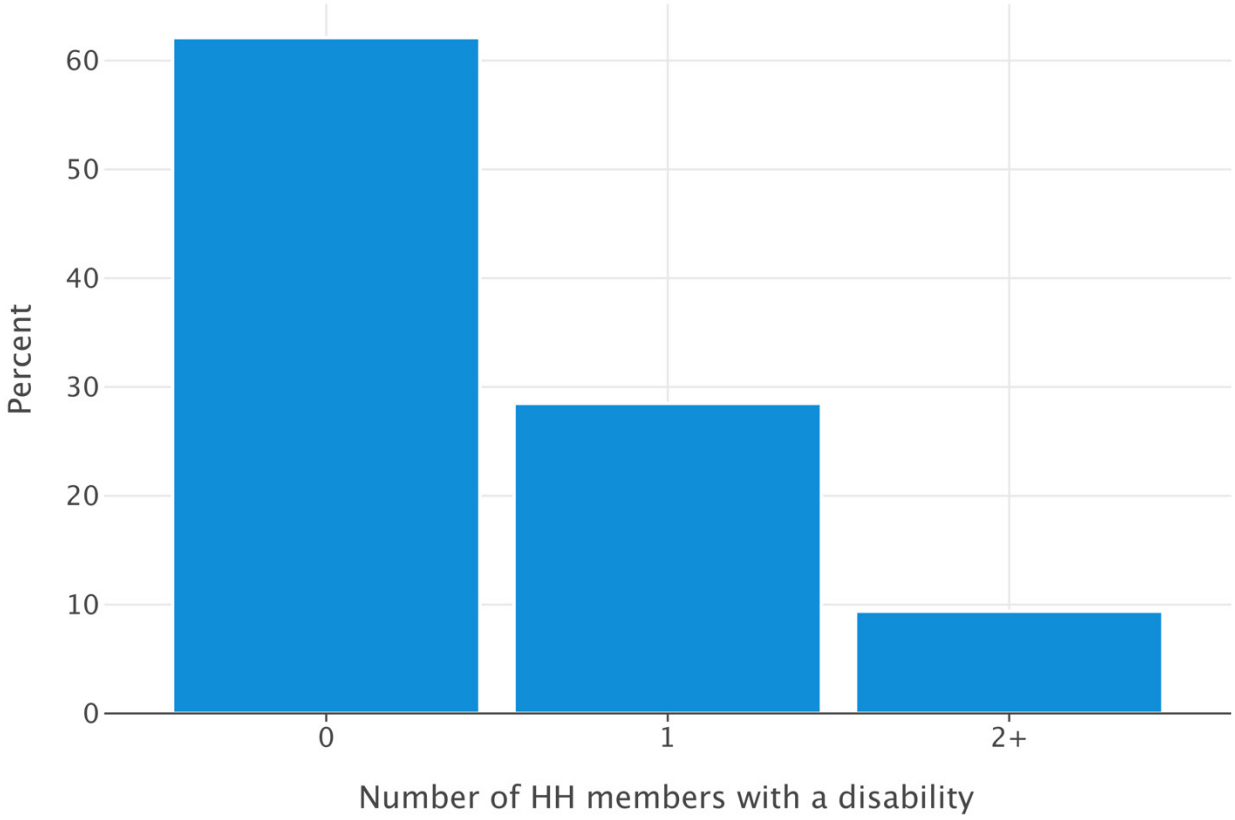

Figure 3.21: HH members with disabilities distribution

The impact of HH members with disability on delivery frequency can be seen Figure 3.22. There is no clear trend for zero and one distributions, but more frequencies are seen for two+ households.

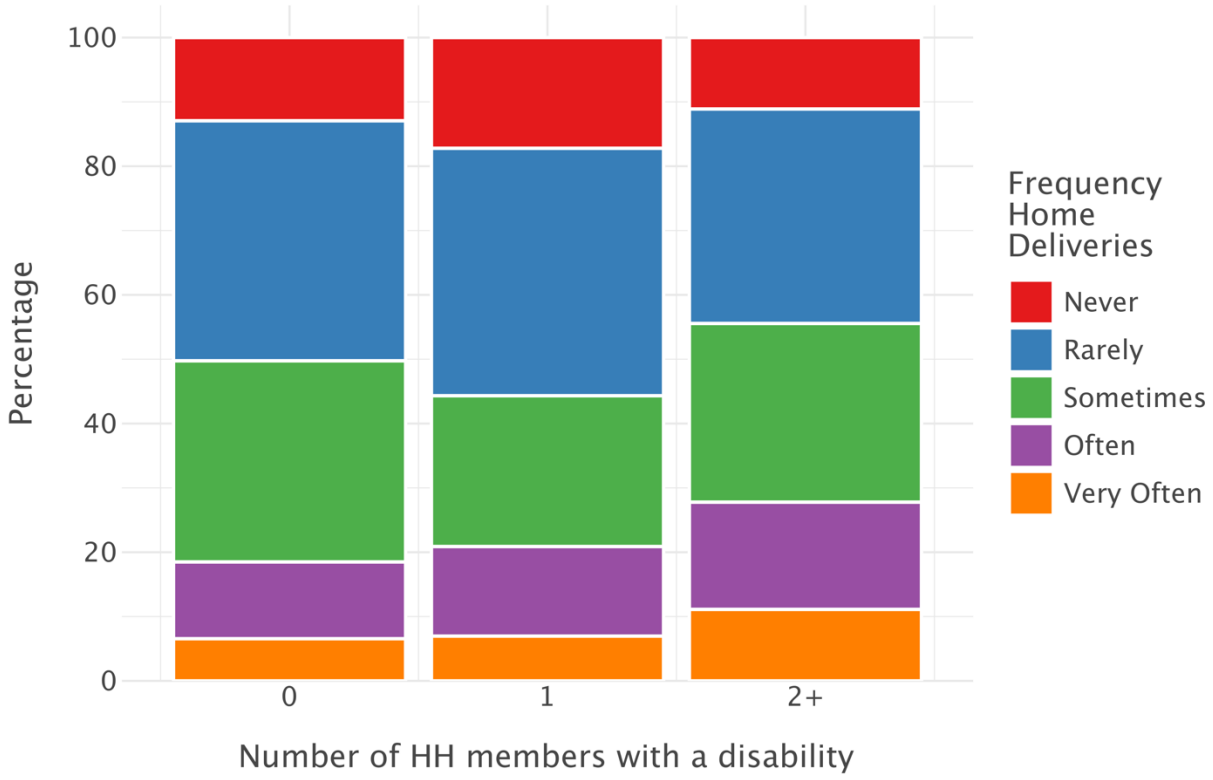

Figure 3.22: Home delivery frequency vs. HH. Members with a disability

3.11 SUMMARY

The results presented in this section utilizing sociodemographic variables seem congruent with findings from the literature review. The variables that seem to have a larger impact on home delivery frequency are household income, household size, and age. Identifying as part of large urban area seems associated with more frequent deliveries. The impact of other variables like gender, disabilities, or race is not as clear or consistent. Modeling results presented in later sections will confirm these initial findings.

4.0 EXPLORATORY ANALYSIS OF SHOPPING VARIABLES

This section focuses on the analysis of shopping characteristics for households that engage in e-commerce. The variables analyzed are related to the number of household members that have online activities, type of household subscriptions, type of brick-and-mortar stores visited, and e-commerce attitudes. The goals are to (a) observe the distribution of the data and potential data gaps and (b) check the trends observed in the data with respect to delivery frequency. For the former goal, for each variable there is a plot describing the distribution of the variable and for the later goal each variable is plotted against the home delivery frequency category. The survey question is first introduced to facilitate the interpretation of the plots.

4.1 HH MEMBERS WITH ONLINE ACTIVITIES

The literature review indicated that online/internet exposure could be a key variable to explain delivery frequency. The survey question in this area is the following:

How many household members usually spend time ONLINE doing these activities *(range 0-3+):*

- Shopping
- Working

4.1.1 HH members that shop online

The distribution of respondents by number of household members that usually shop online is shown in Figure 4.1 with an adequate percentage of observations per group. Italics are used for the word *usually* because it is already known that the household engages in e-commerce and at least one household member makes online orders.

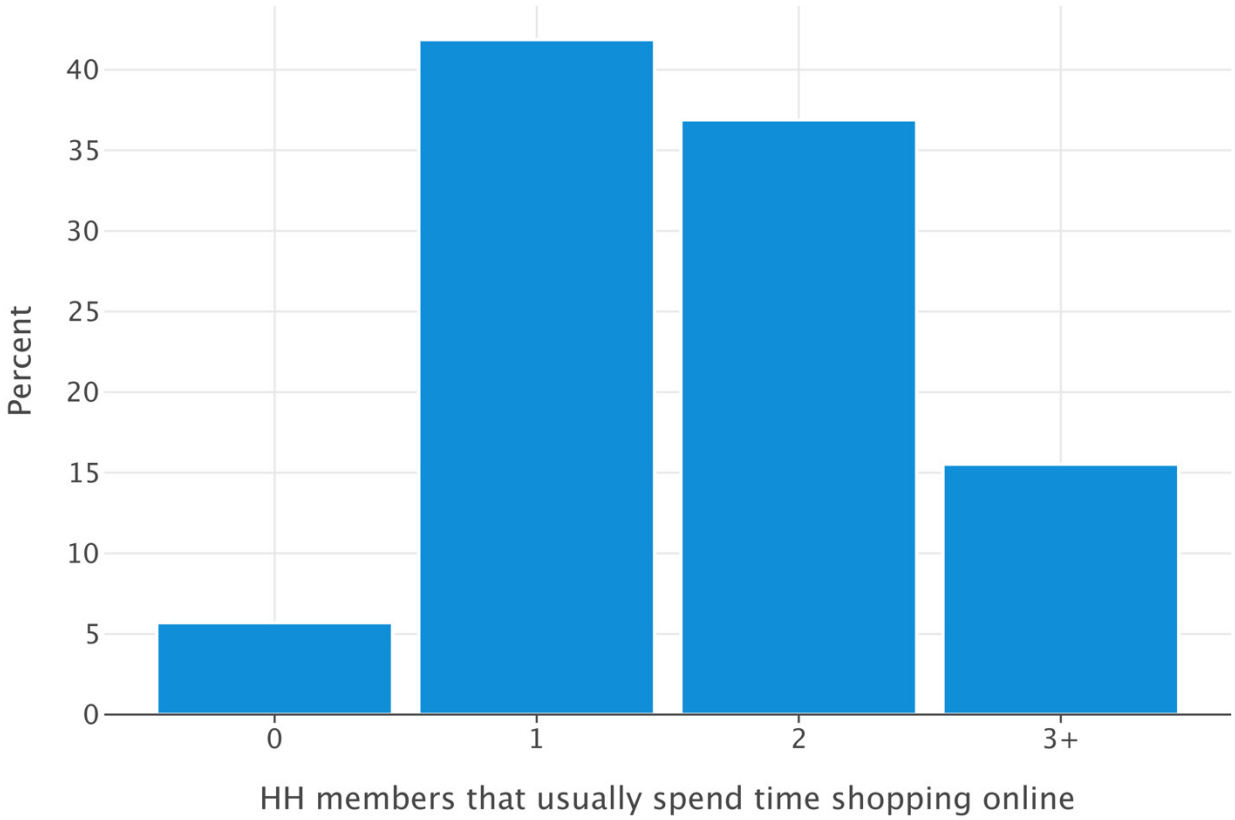

Figure 4.1: Distribution of HH members that usually spend time shopping online

The impact of the number of household members that usually shop online on home deliveries frequency can be seen in Figure 4.2 showing that there is a clear impact as expected. The distribution for 3+ has the highest percentage of "very often" and the lowest percentage of "rarely".

Figure 4.2: Home delivery frequency vs. usual online shoppers

4.1.2 HH members that work online

Being online due to work activities also facilitates access to e-commerce. The distribution of the number of household members that usually work online is shown below in Figure 4.3 with an adequate percentage of observations per group. The distribution seems reasonable with the highest frequency for zero and a decreasing frequency for higher numbers.

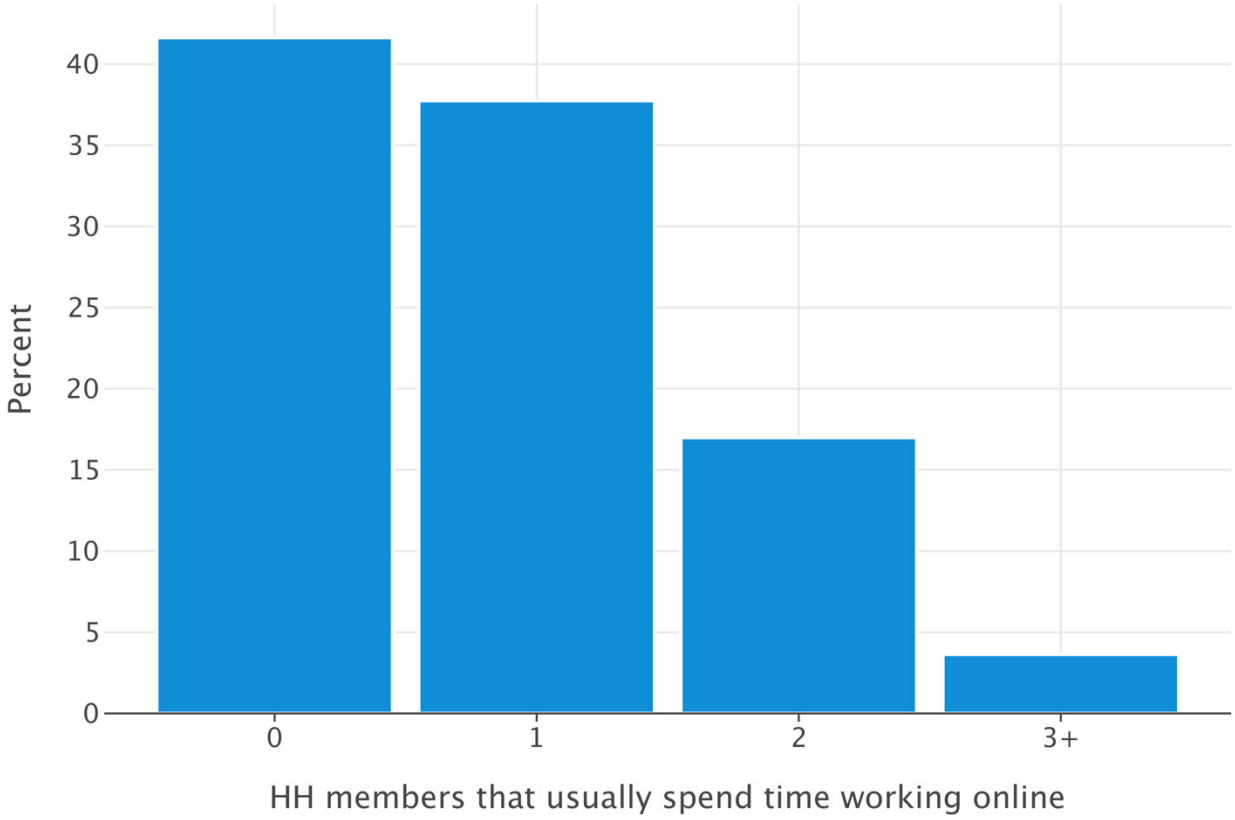

Figure 4.3: Distribution of HH members that usually spend time working online

The impact of the number of household members that usually work online on home deliveries frequency can be seen in Figure 4.4 clearly showing that more members that work online correlates positively with more frequent deliveries (up to two members) and negatively for low frequency of deliveries.

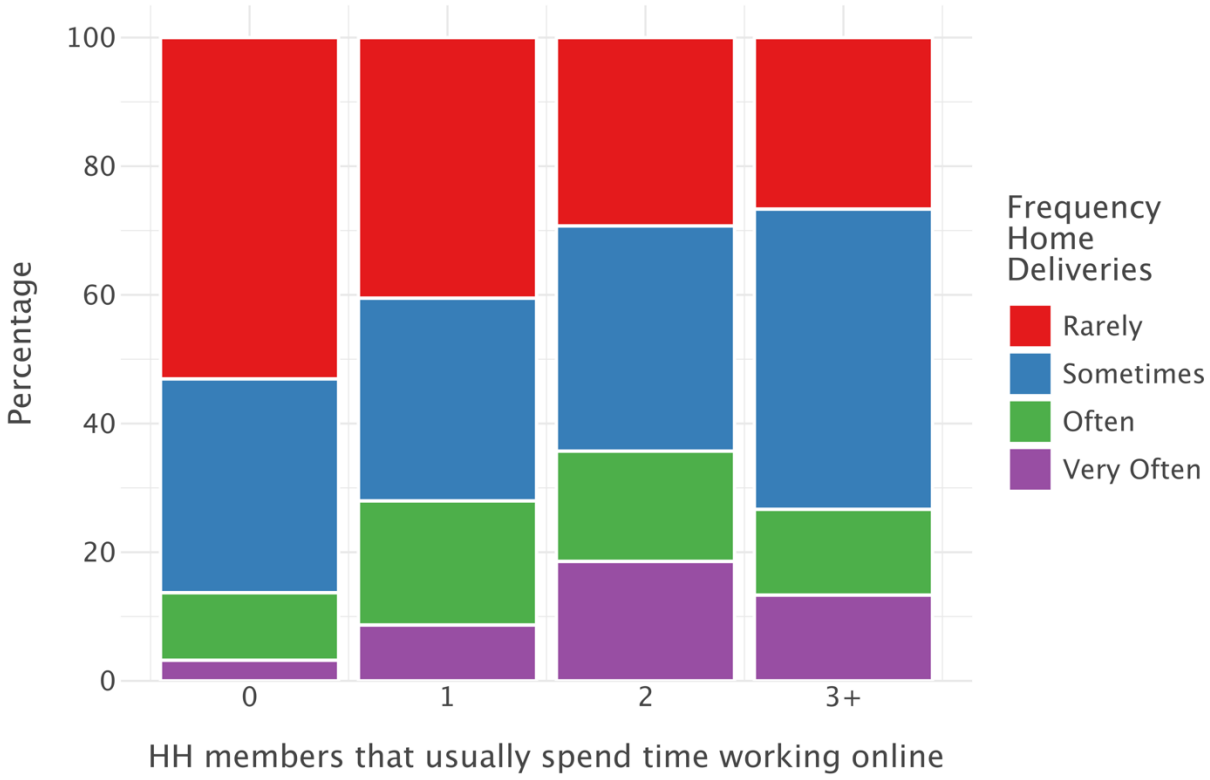

Figure 4.4: Home delivery frequency vs. usual online workers

4.2 SUBSCRIPTIONS

The literature review has indicated that e-commerce subscriptions can be an important factor for e-commerce deliveries. The survey question for subscriptions is the following:

Does your household have any the following shopping membership or subscriptions for home deliveries? *Please mark ALL that apply.*

- Amazon Prime
- Walmart+, Sam's Club, Target or Costco
- Grocery Loyalty Program (e.g., Kroger, Safeway)
- Medical, pharmaceutical, or vitamin subscriptions
- Clothing or personal products subscriptions
- Other (not listed) membership or subscription
- NO shopping memberships or subscriptions

Amazon is clearly ahead in terms of number of subscriptions closely followed by grocery and big-box stores (Walmart, Target, etc.). For the other types of subscriptions, the numbers are significantly lower and relatively few households have zero subscriptions. The sum of the percentages is greater than 100% because it is possible to mark one or more options as an acceptable response.

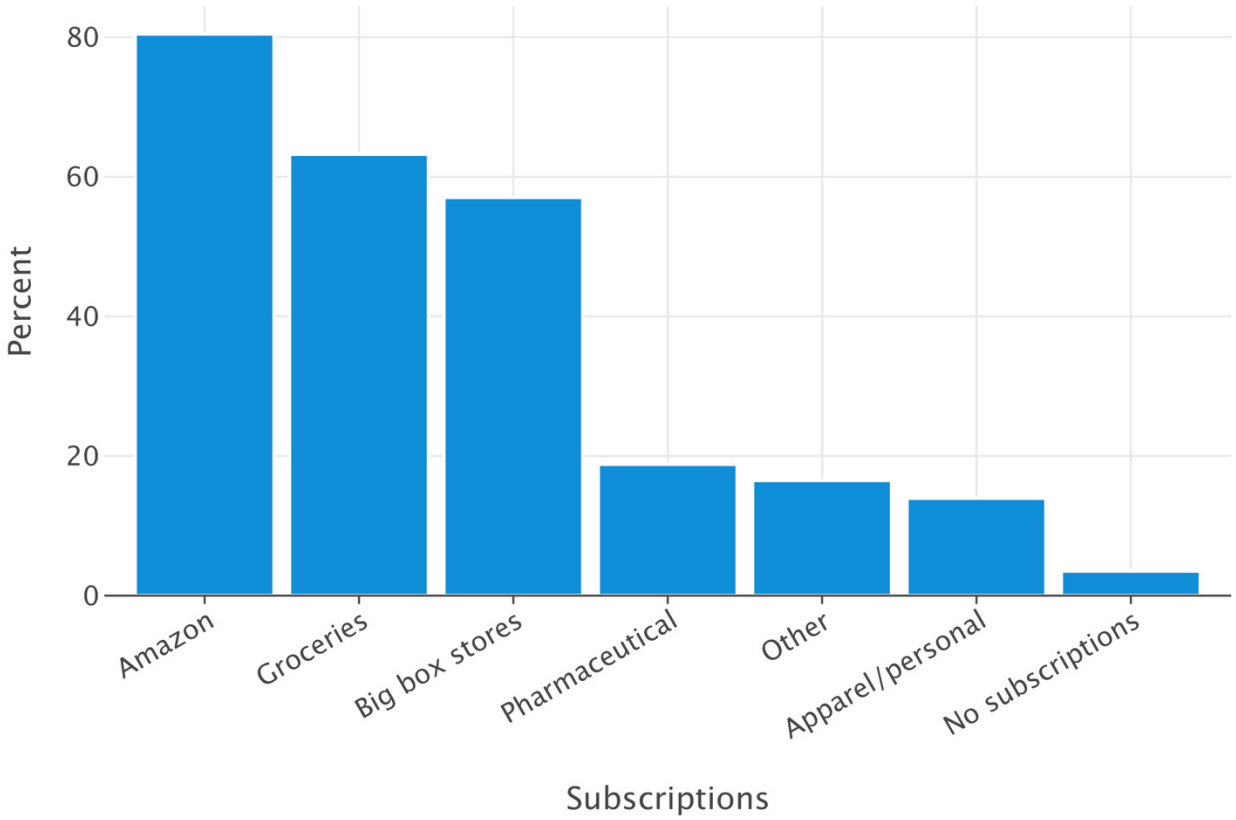

Figure 4.5: Percentage of subscription penetration by type

The influence of each type of subscription on home delivery frequency will be presented in decreasing order of subscription frequency.

4.2.1 Amazon

Households with Amazon subscriptions tend not to be in the "Rarely" category as shown in Figure 4.6. The other categories (sometimes, often, very often) account for over 60% of the households with an Amazon subscription.

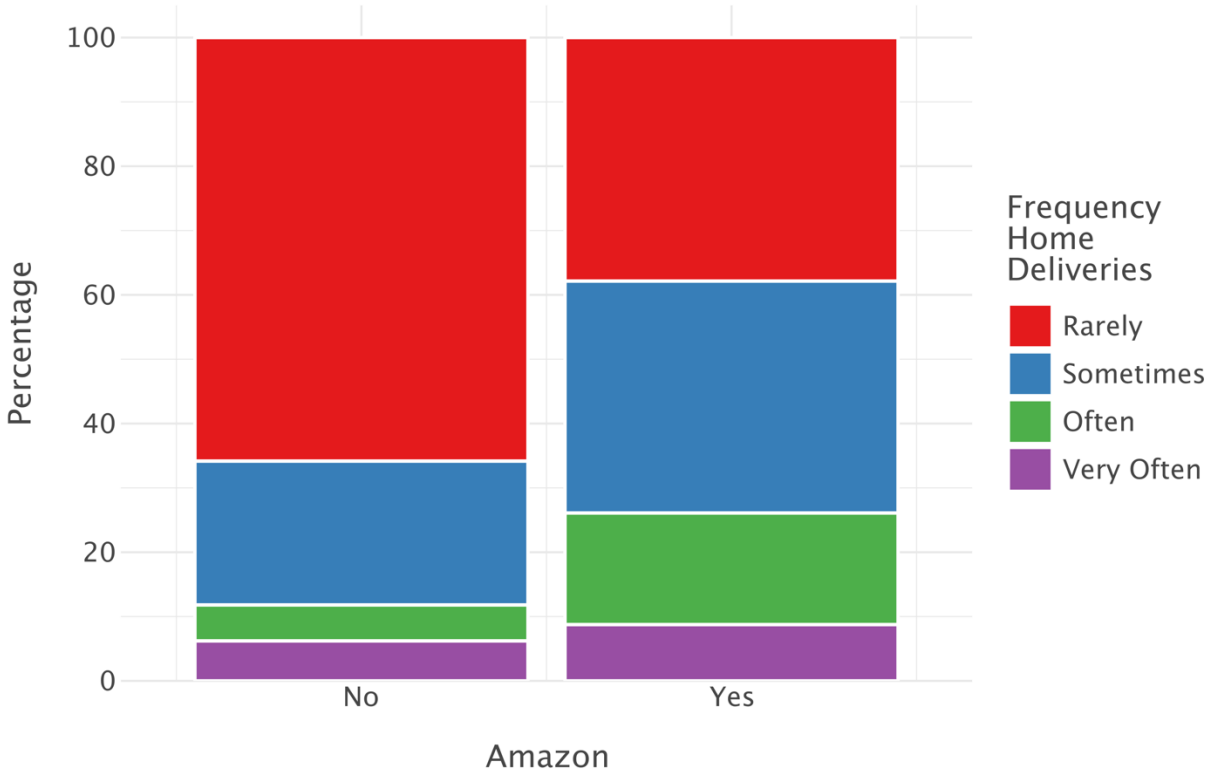

Figure 4.6: Home delivery frequency for households with Amazon subscription

4.2.2 Groceries

Households with grocery subscriptions do not present stark differences as shown in Figure 4.7.

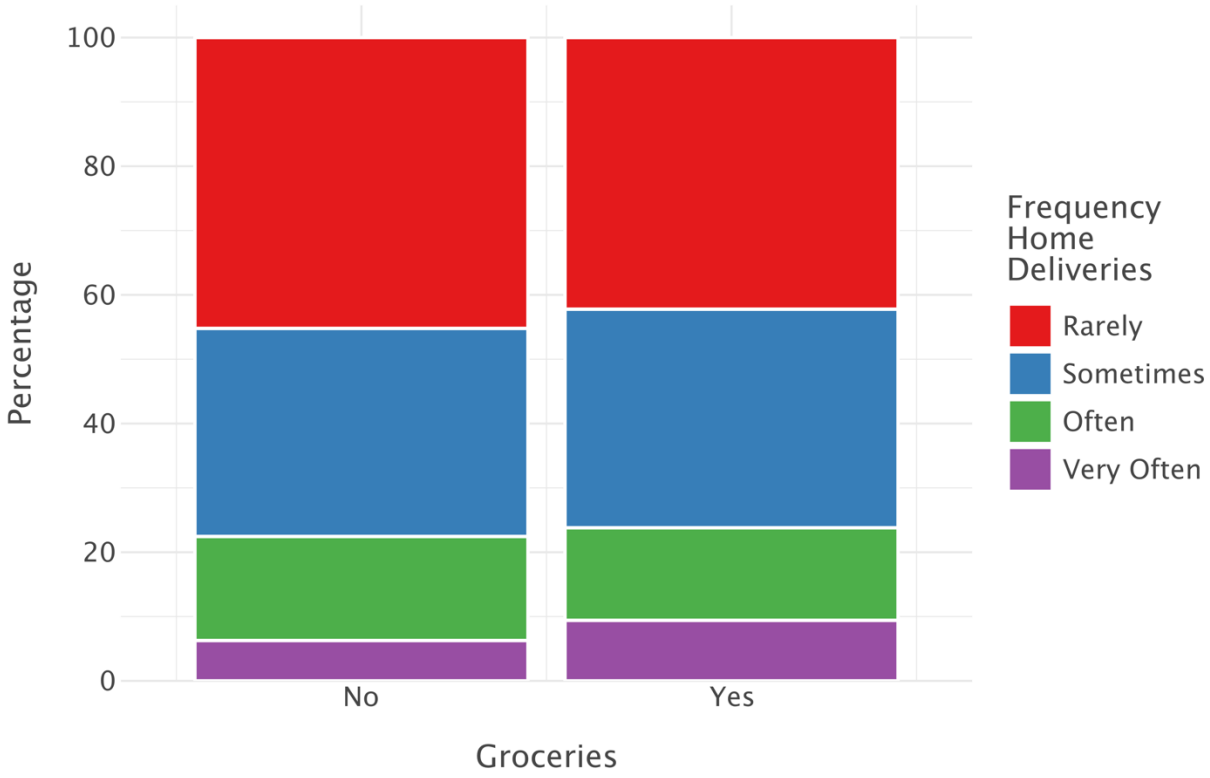

Figure 4.7: Home delivery frequency for households with a grocery subscription

4.2.3 Big-box stores

Households with big-box store subscriptions show an increase in deliveries but not as much as households with an Amazon subscription.

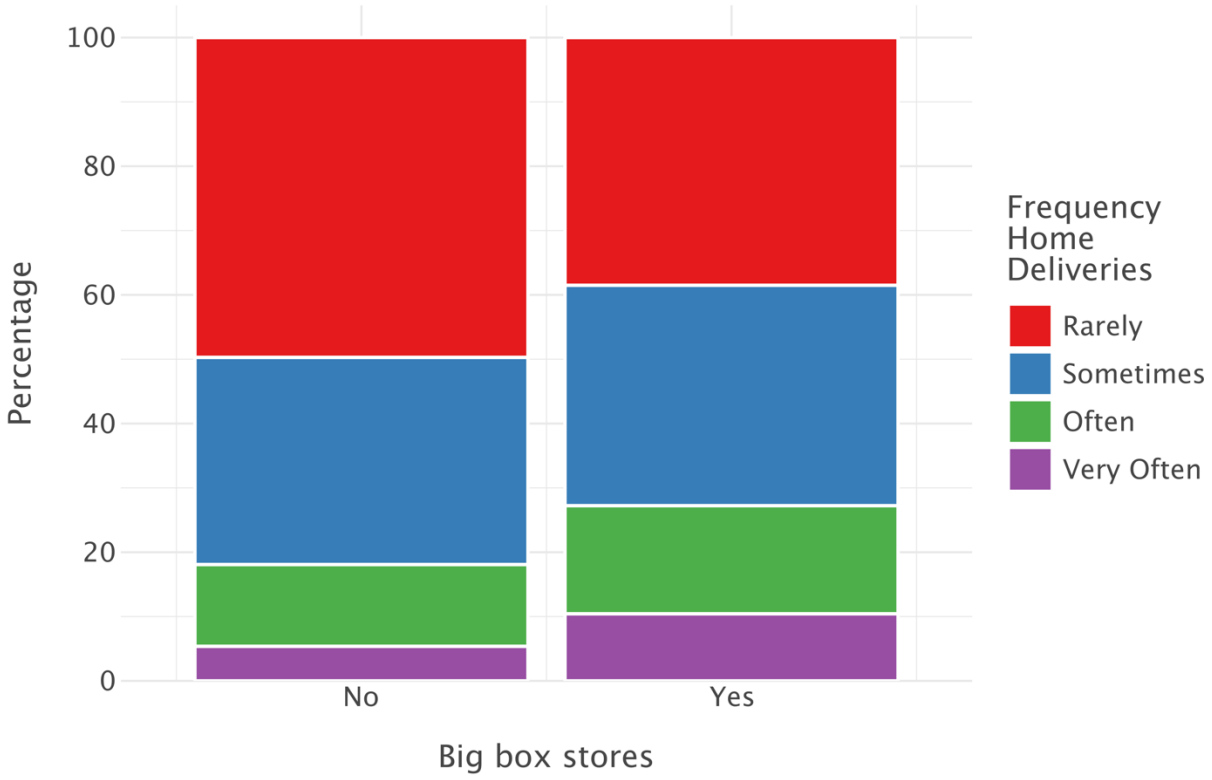

Figure 4.8: Home delivery frequency for households with a big-box store subscription

4.2.4 Pharmaceutical

Households with pharmaceutical or medicine related subscriptions show a clear increase in the "very often" category.

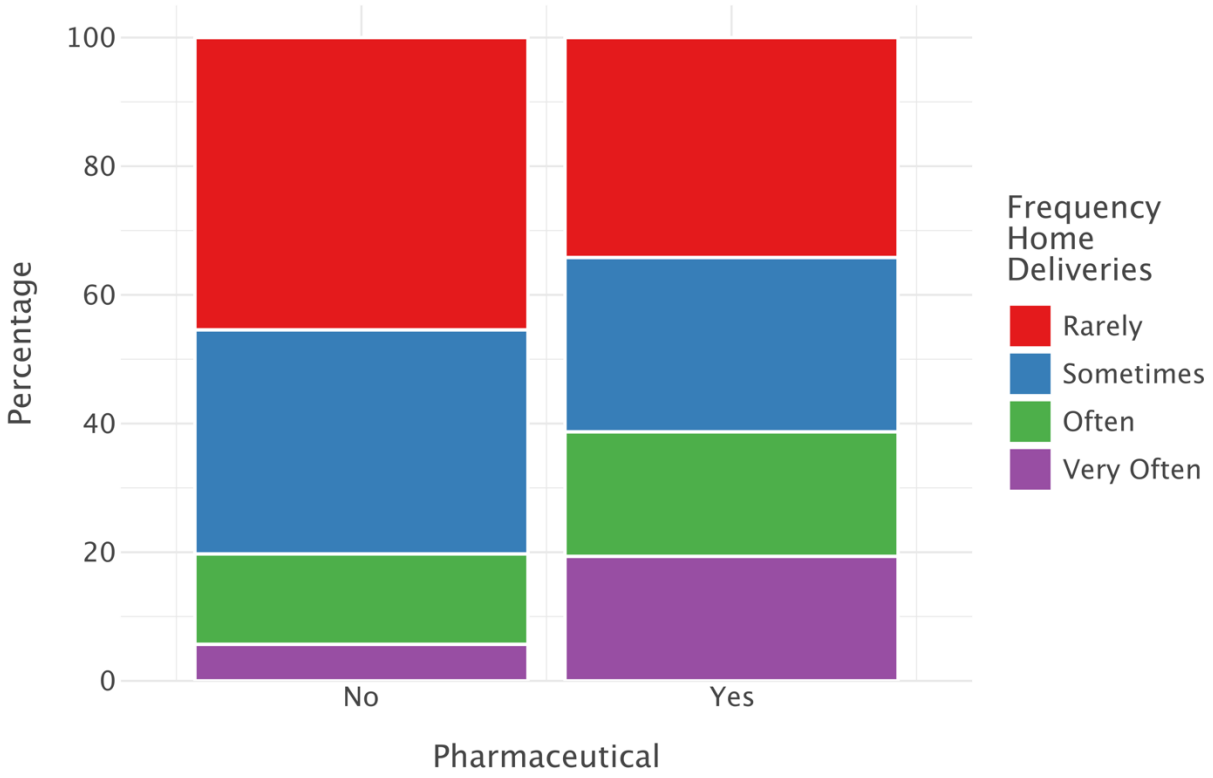

Figure 4.9: Home delivery frequency for households with pharmaceutical subscriptions

4.2.5 Other

Similarly to households with grocery subscriptions, households with "other" subscriptions do not present stark differences between the yes/no answers.

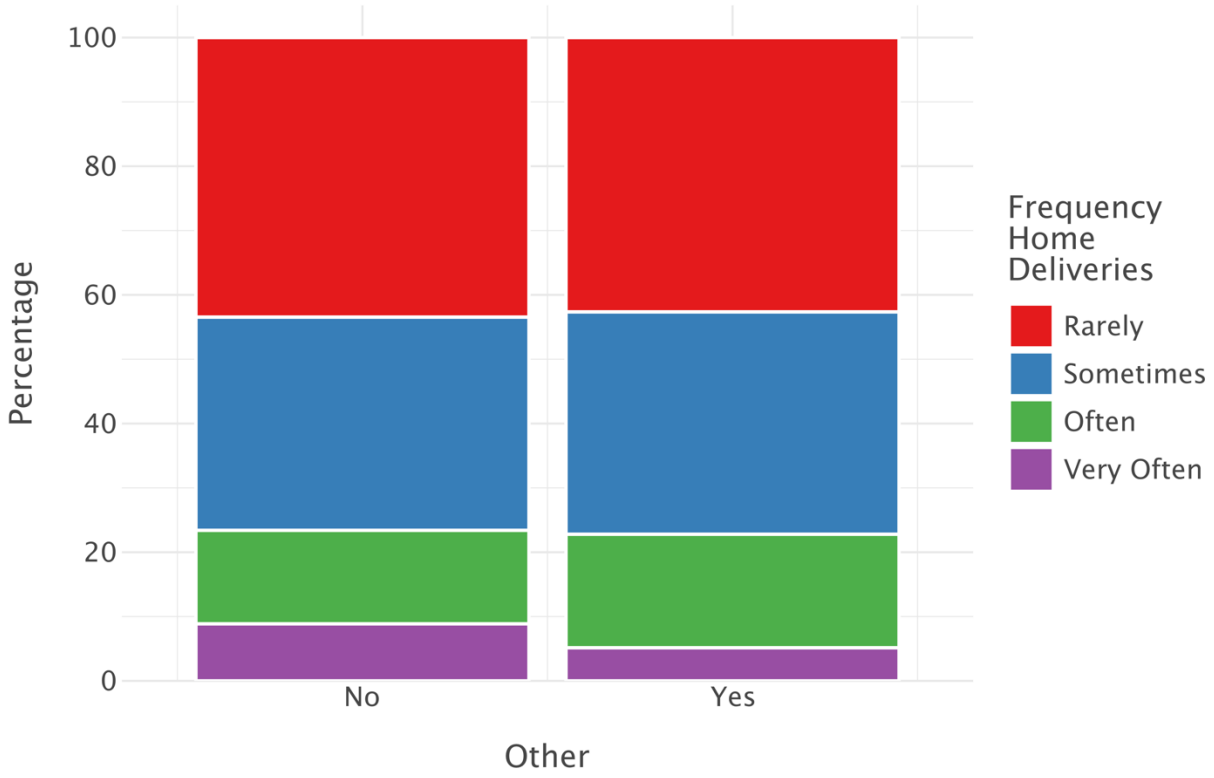

Figure 4.10: Home delivery frequency for households with other types of subscriptions

4.2.6 Apparel/personal products

Households with apparel or personal product subscriptions show a clear increase in the “very often” category and a significant decrease in the “rarely” category.

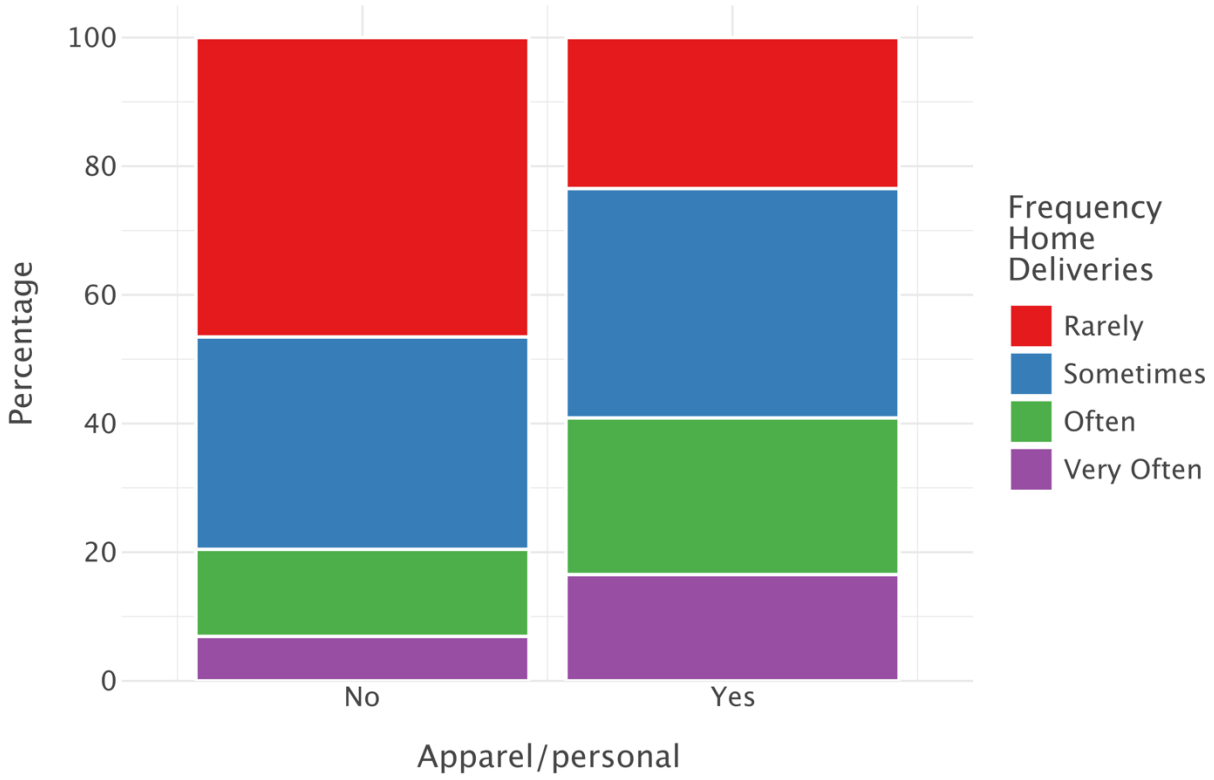

Figure 4.11: Home delivery frequency for households with apparel/personal products subscription

4.2.7 No subscriptions

As expected, no subscriptions are clearly associated with "rarely" and an overall lower number of deliveries.

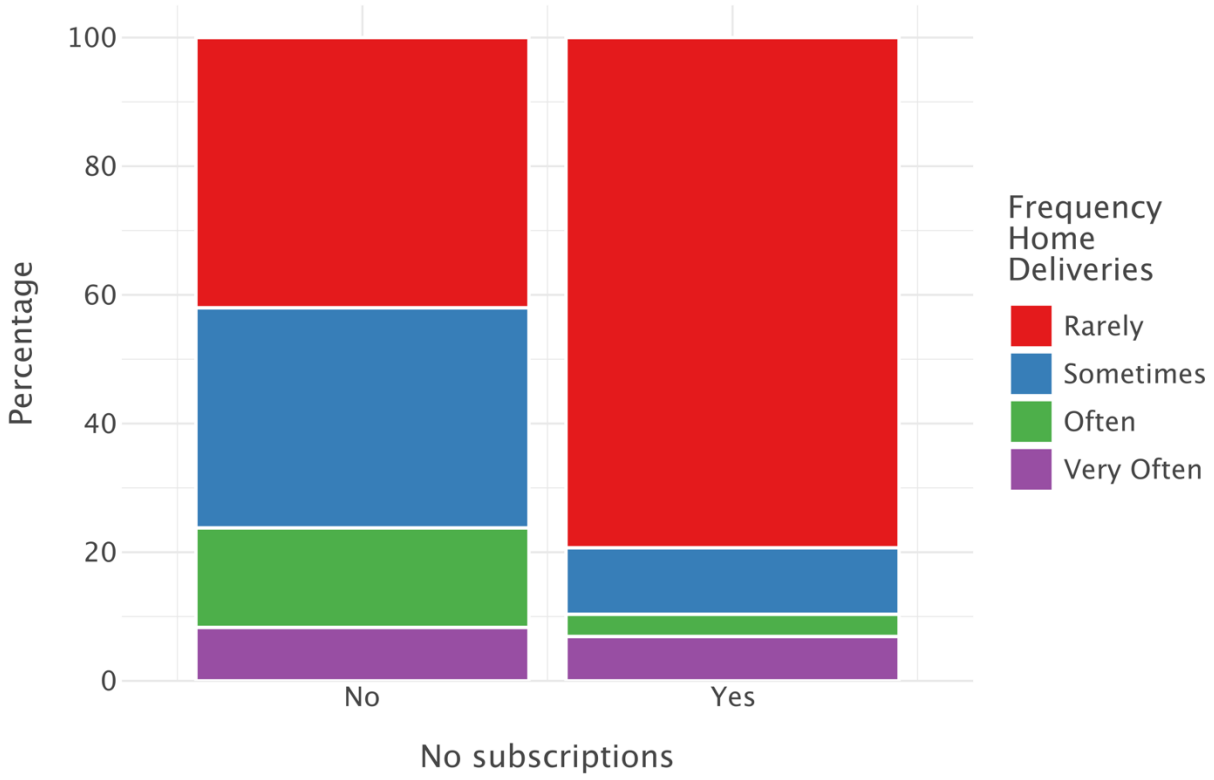

Figure 4.12: Home delivery frequency for households with NO subscriptions

4.3 TYPE OF STORES VISITED

The transportation e-commerce literature has not studied the impact of brick-and-mortar shopping stores on e-commerce deliveries though this may be an important factor to understand e-commerce deliveries. A small pilot showed that there was time to add a short question related to types of stores visited and e-commerce attitudes.

The survey question for type of brick-and-mortar stores visited is the following:

Which types of stores do members of your household typically visit? *Mark ALL that apply.*

- Supermarkets/Grocery stores
- Convenience Stores
- Discount Stores (e.g., Dollar Store)
- Walmart, Target, Costco, or Sam's Club
- Small Local/Independent Stores
- Other not listed

Supermarket and big-box retailers dominate in terms of frequency. Convenience, small/local/independent and discount are near 50%.

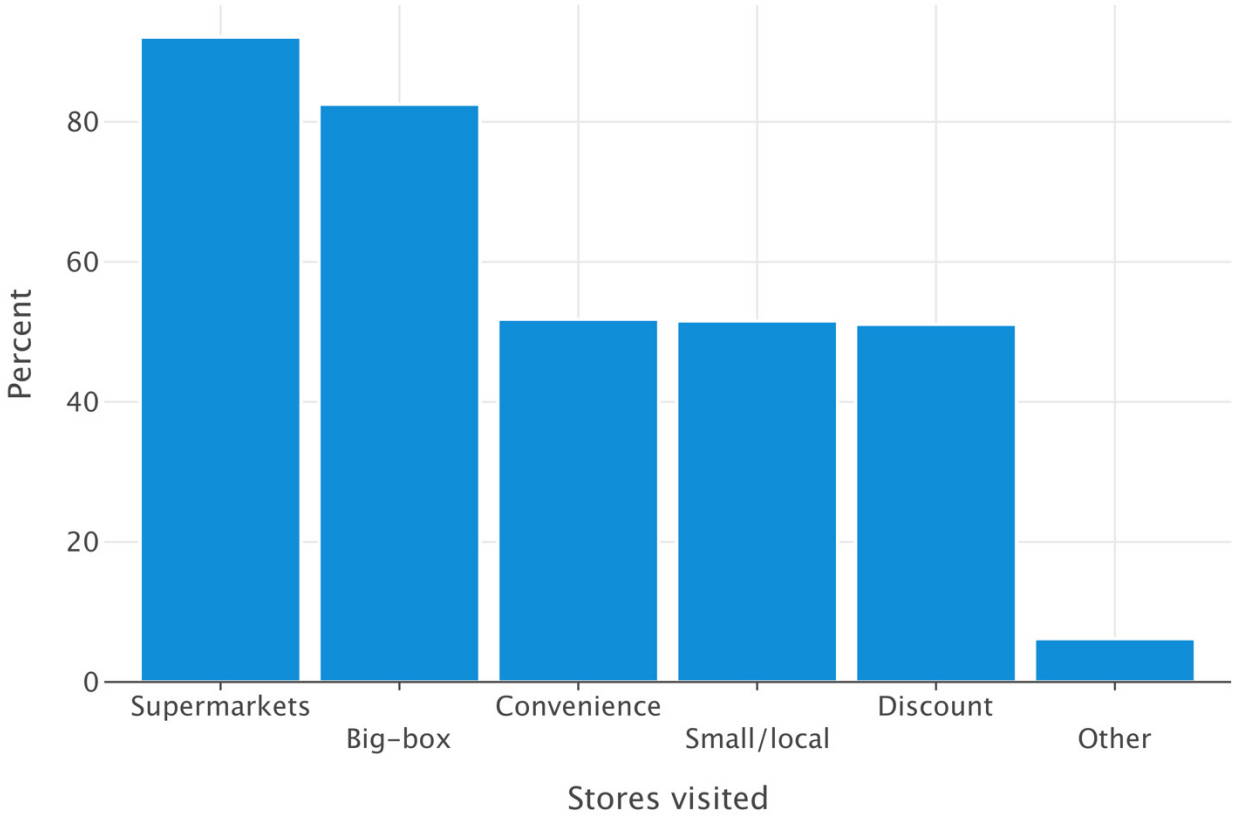

Figure 4.13: Distribution of types of stores visited

4.3.1 Supermarkets

For households that visit supermarkets there is a clear increase in the "rarely" category and a clear decrease in the "very often" category. The frequency of supermarket visits and the trend shown in Figure 4.14 indicates that this is potentially strong variable to predict e-commerce deliveries.

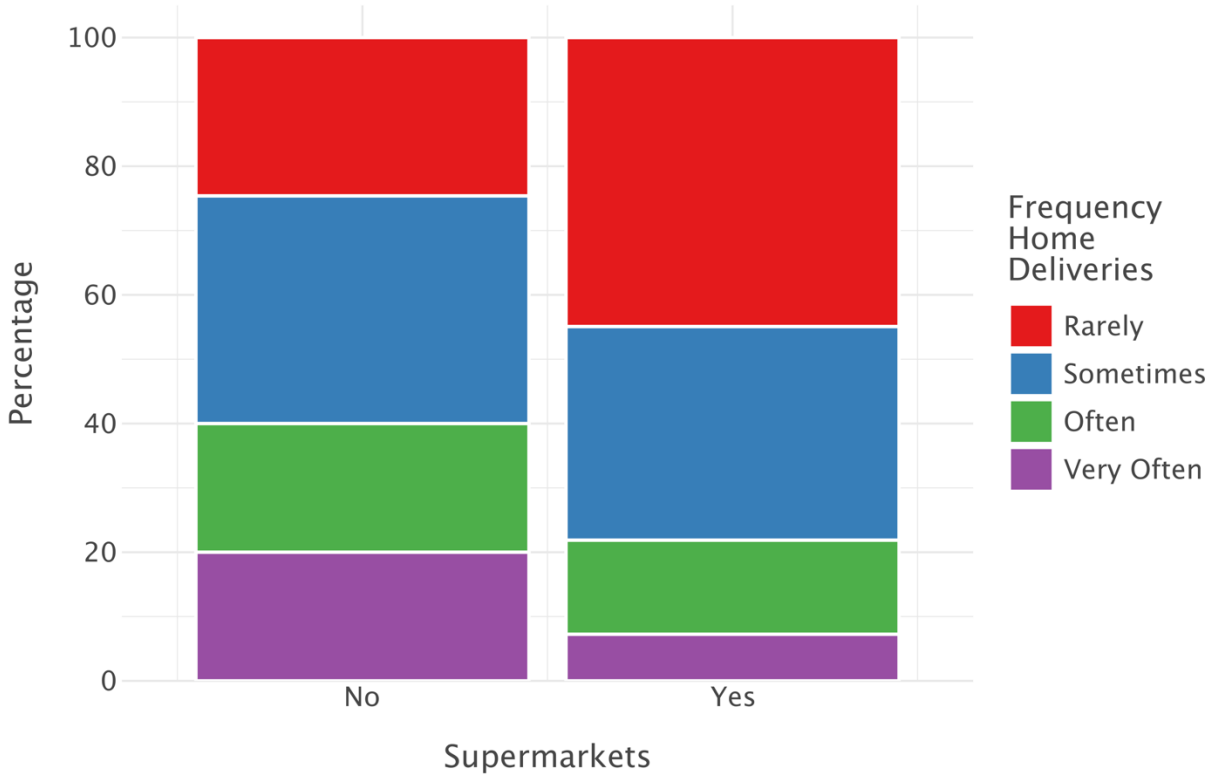

Figure 4.14: Home delivery frequency for households that visit supermarkets

4.3.2 Big-box stores

We see the opposite trend for households that visit big-box stores. there is a decrease in the "rarely" category and an increase in the "very often" category.

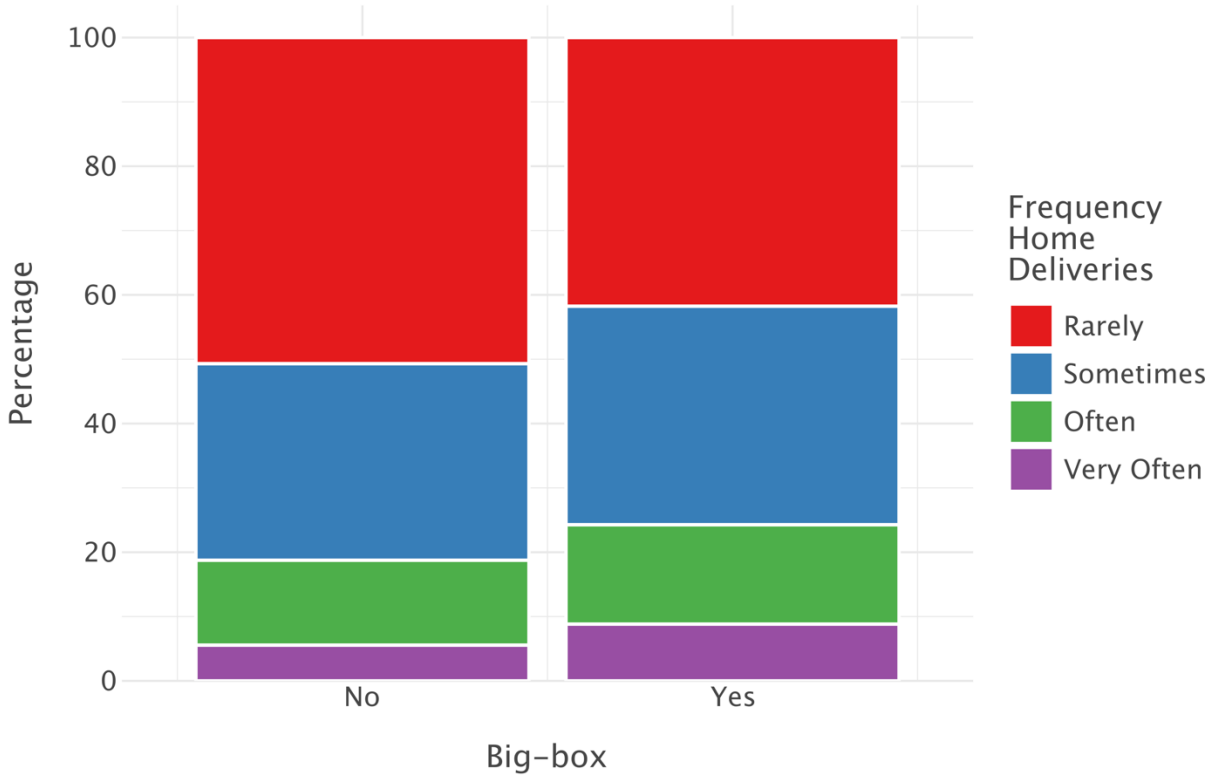

Figure 4.15: Home delivery frequency for households that visit big-box stores

4.3.3 Convenience

Convenience and big-box stores show similar trends.

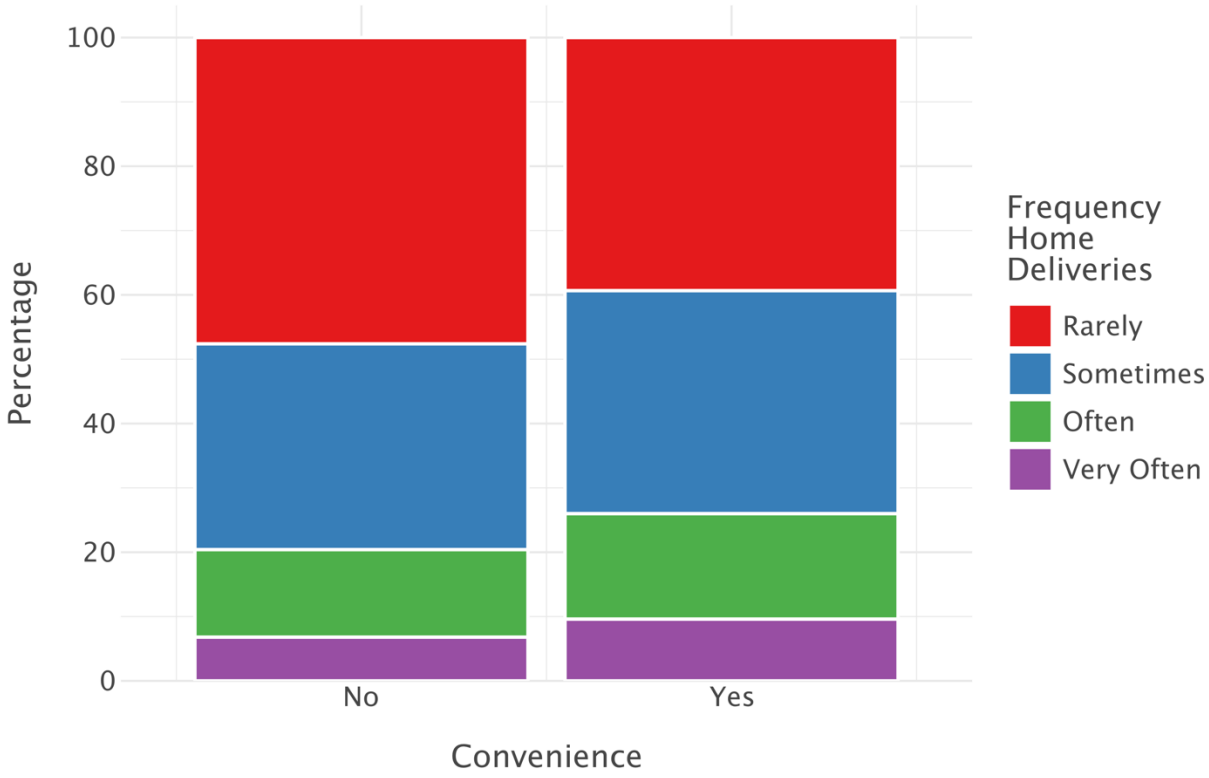

Figure 4.16: Home delivery frequency for households that visit convenience stores

4.3.4 Small/local stores

Visiting small/local stores does not seem to impact household delivery frequency.

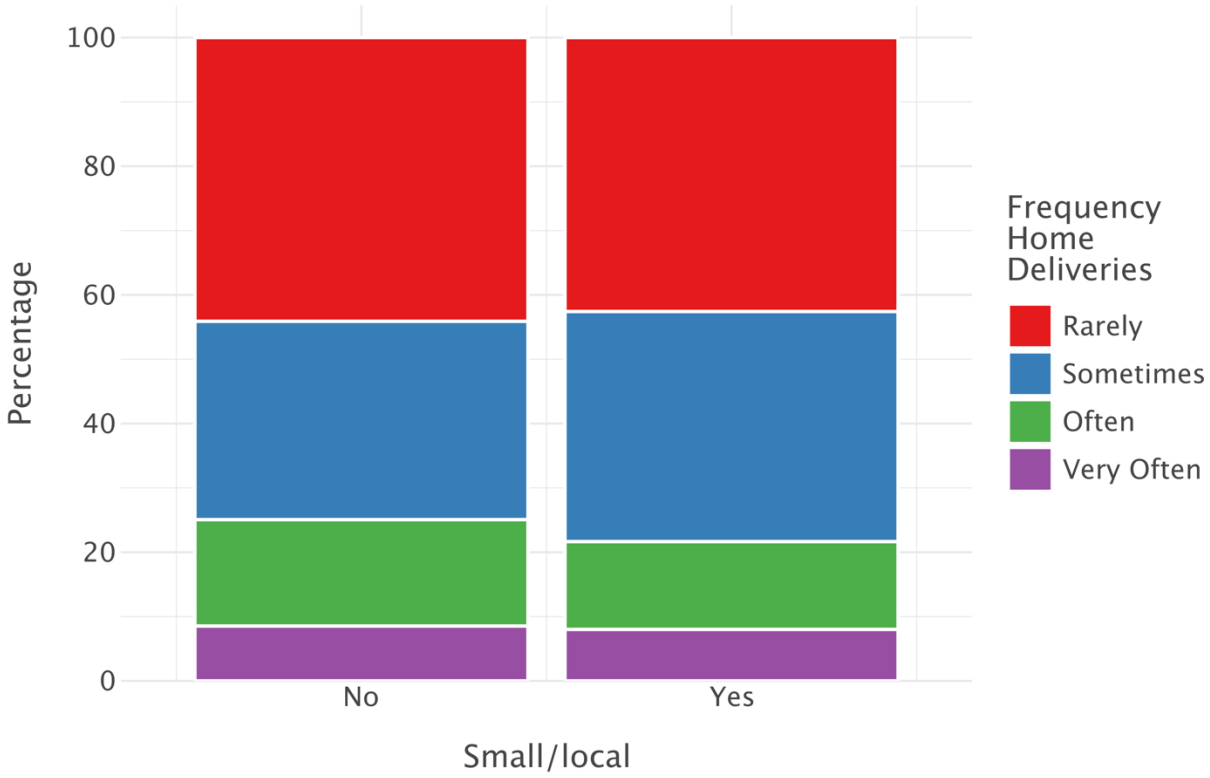

Figure 4.17: Home delivery frequency for households that visit small/local stores

4.3.5 Discount

Visiting discount stores does not seem to impact household delivery frequency.

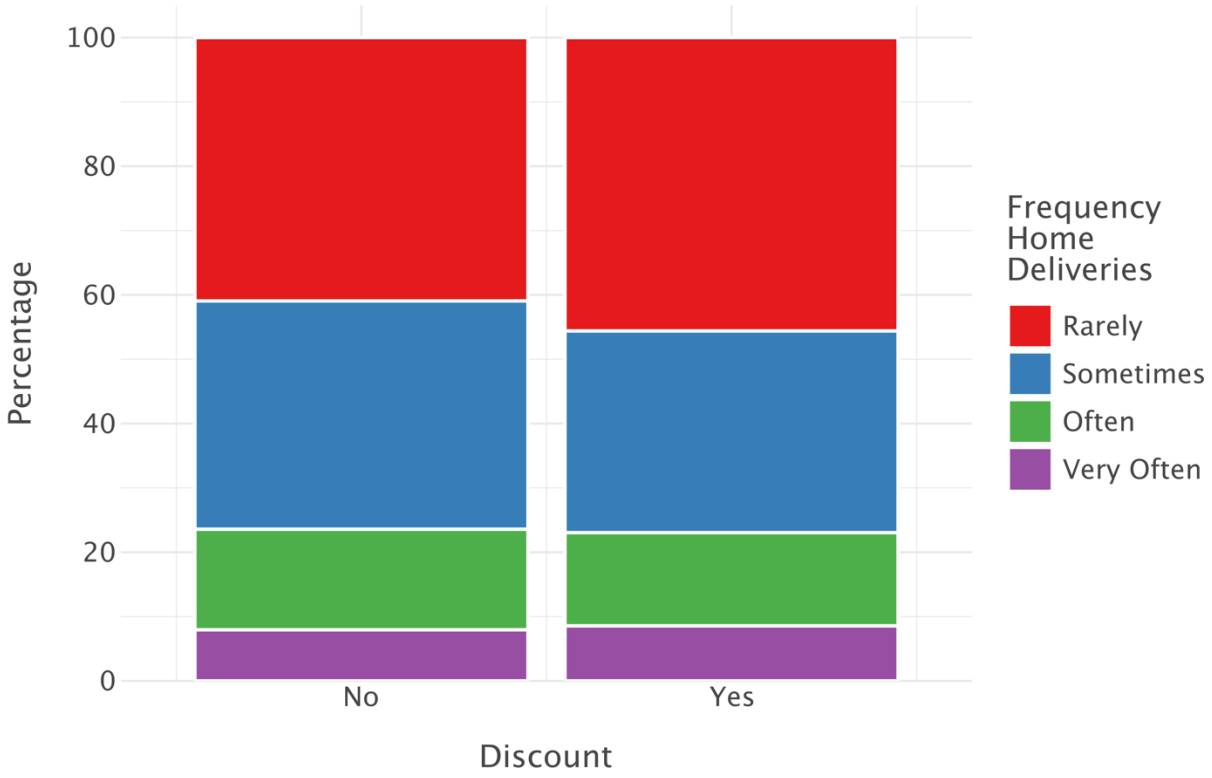

Figure 4.18: Home delivery frequency for households that visit discount stores

4.3.6 Other

Households that visit other types of stores seem to have a delivery distribution that is squeezed in the middle, more “rarely” and more “very often”.

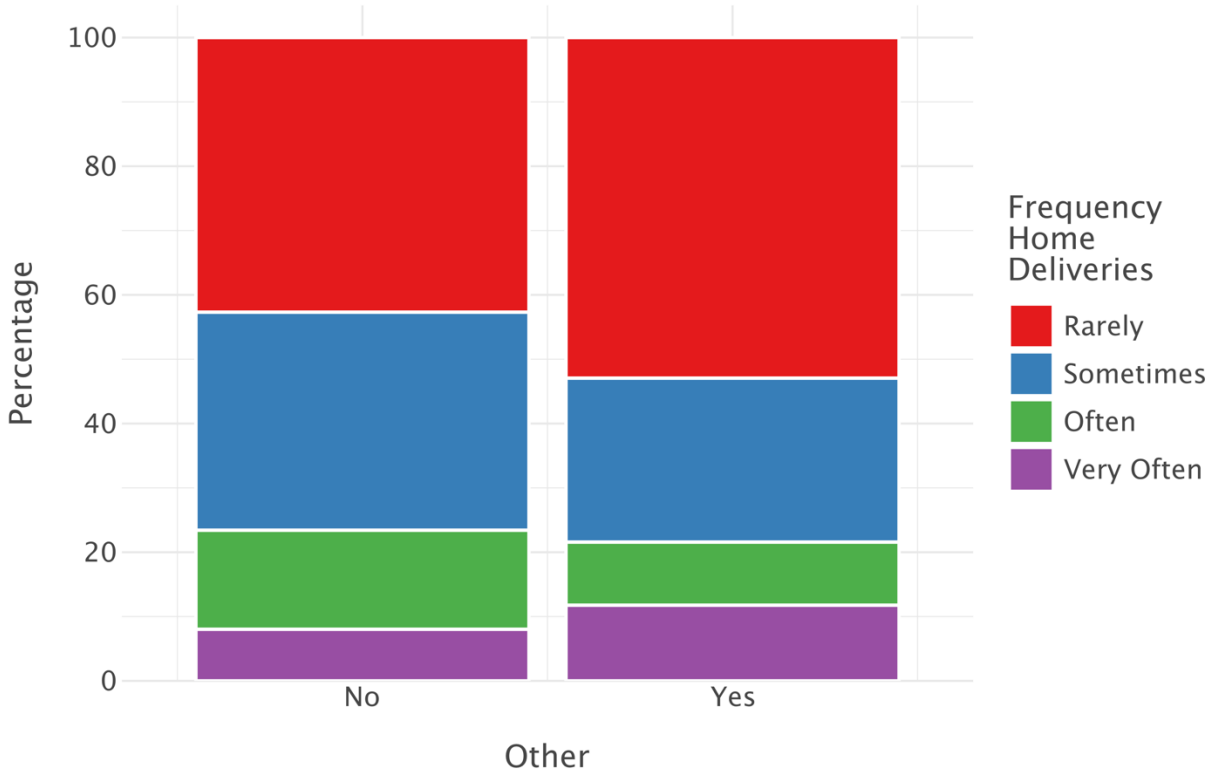

Figure 4.19: Home delivery frequency for households that other type of stores

4.4 E-COMMERCE ATTITUDES

The literature review indicated that attitudes can be important elements to explain household shopping decisions. The survey question for attitude is the following:

The following statements are about your online shopping preferences. For each statement choose the best option *(options: Important, Neutral, NOT important)*

It is better to shop online or have home deliveries because:

- delivery subscriptions are convenient
- it saves time
- it is safer
- I have more options
- it is hard to travel to stores
- shipping is free

- it is easier to compare
- it is cheaper

The overall distribution of altitudes is shown in Figure 4.20 that shows that some attitudes like "it saves time", "I can compare", or "I have more options" seem to be more important for most respondents.

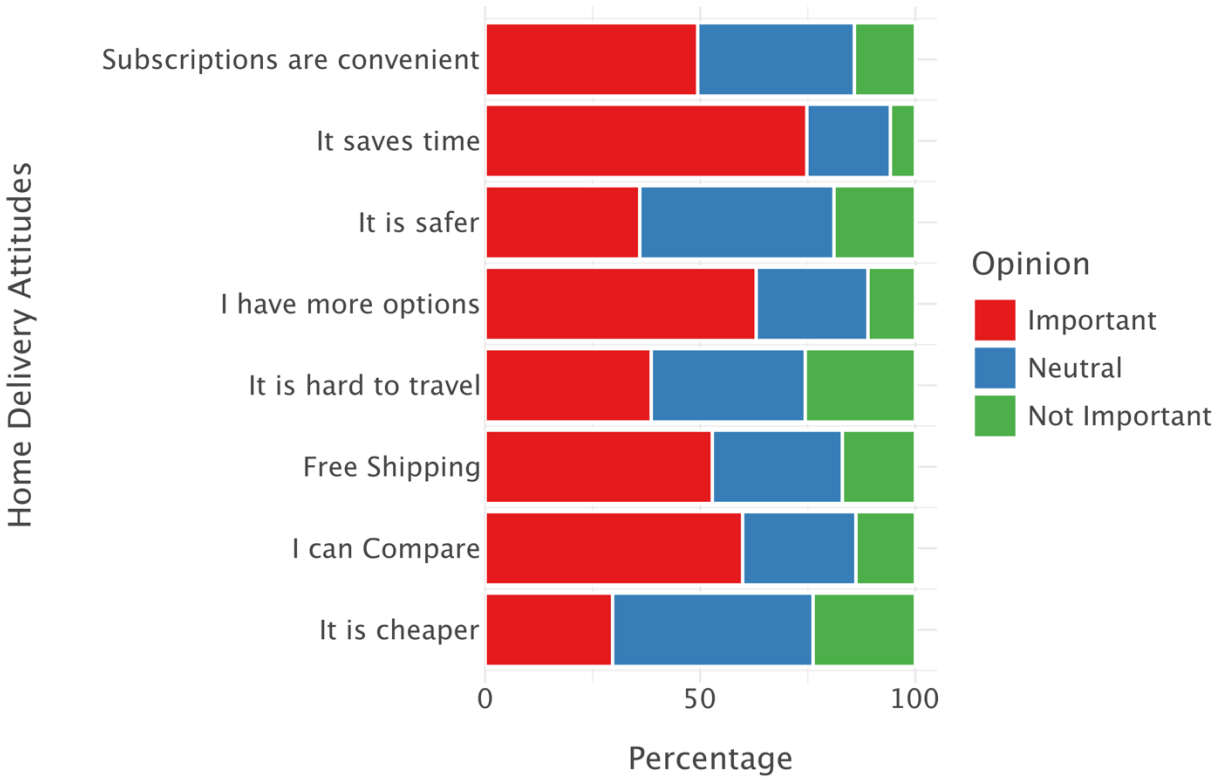

Figure 4.20: Distribution of attitudinal categories

To quantify the relative importance of attitudes, values one, zero, or minus one were assigned to the important, neutral and not important categories respectively and then the mean score was calculated. The plot shown in Figure 4.21 provides the mean scores sorted in decreasing order. The intuition provided by Figure 4.20 is confirmed with "saves time" topping the plot of mean scores. On the other hand, "it is cheaper" has almost the same number of important and not important responses.

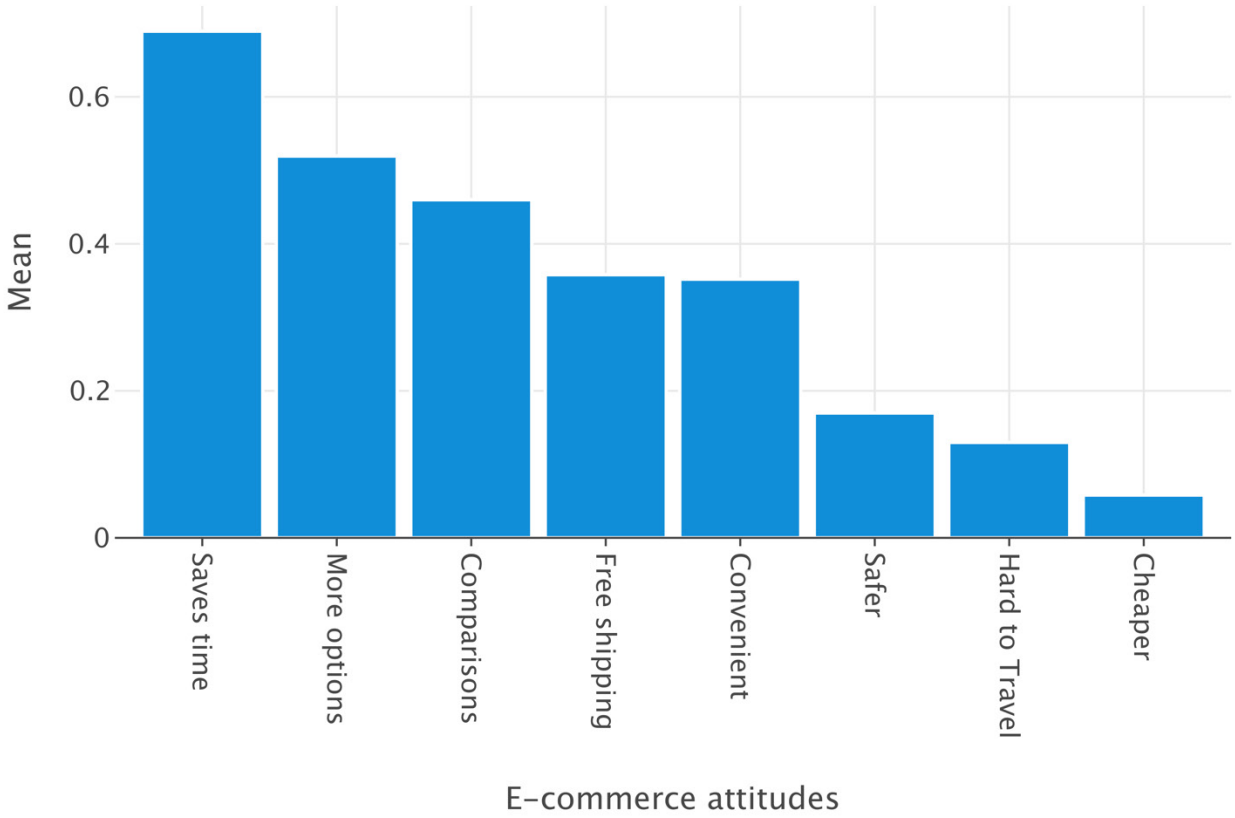

Figure 4.21: Mean score for attitudinal categories

4.4.1 It saves time

For respondents that consider that "it saves time" is important there is a clear decrease in the "rarely" category and a clear increase in the "very often" category, especially when comparing the two extremes of the scale.

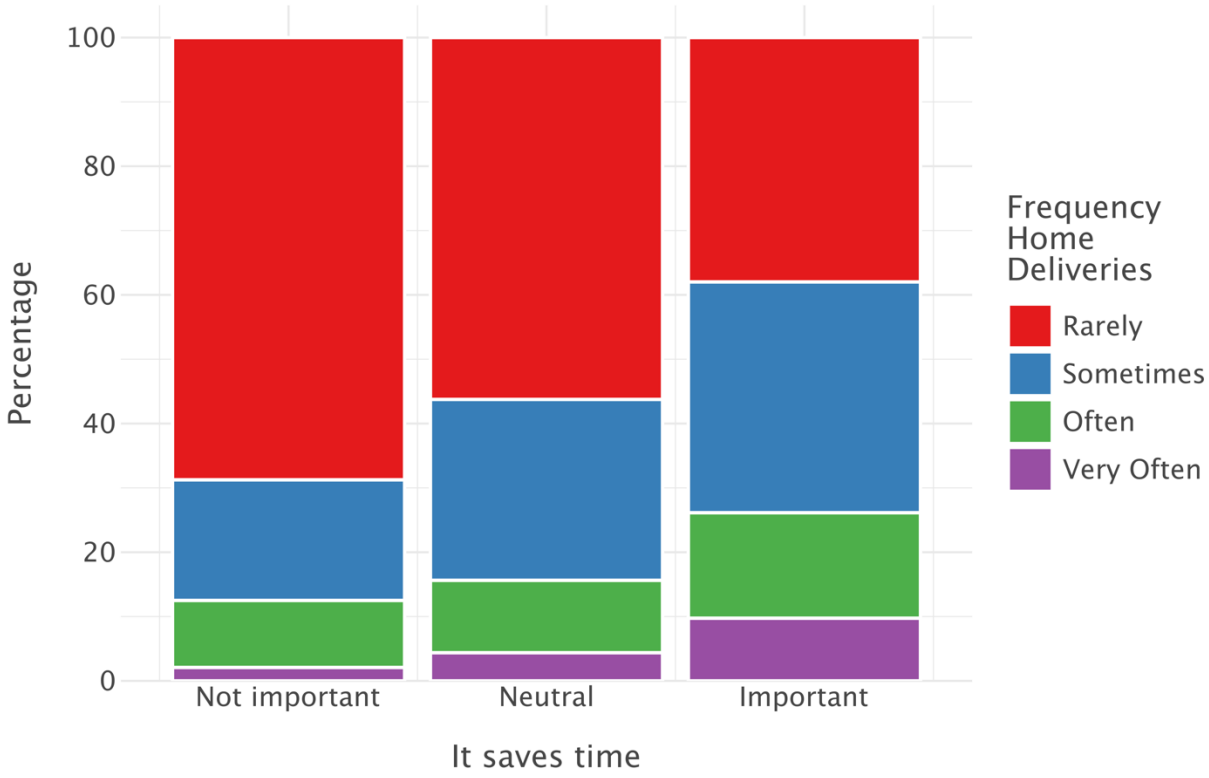

Figure 4.22: Home delivery frequency for "it saves time"

4.4.2 More Options

For respondents that consider that "more options" is important the trend is similar to "it saves time" bus less strong. There is a decrease in the "rarely" category and an increase in the "very often" category, especially when comparing the two extremes of the scale.

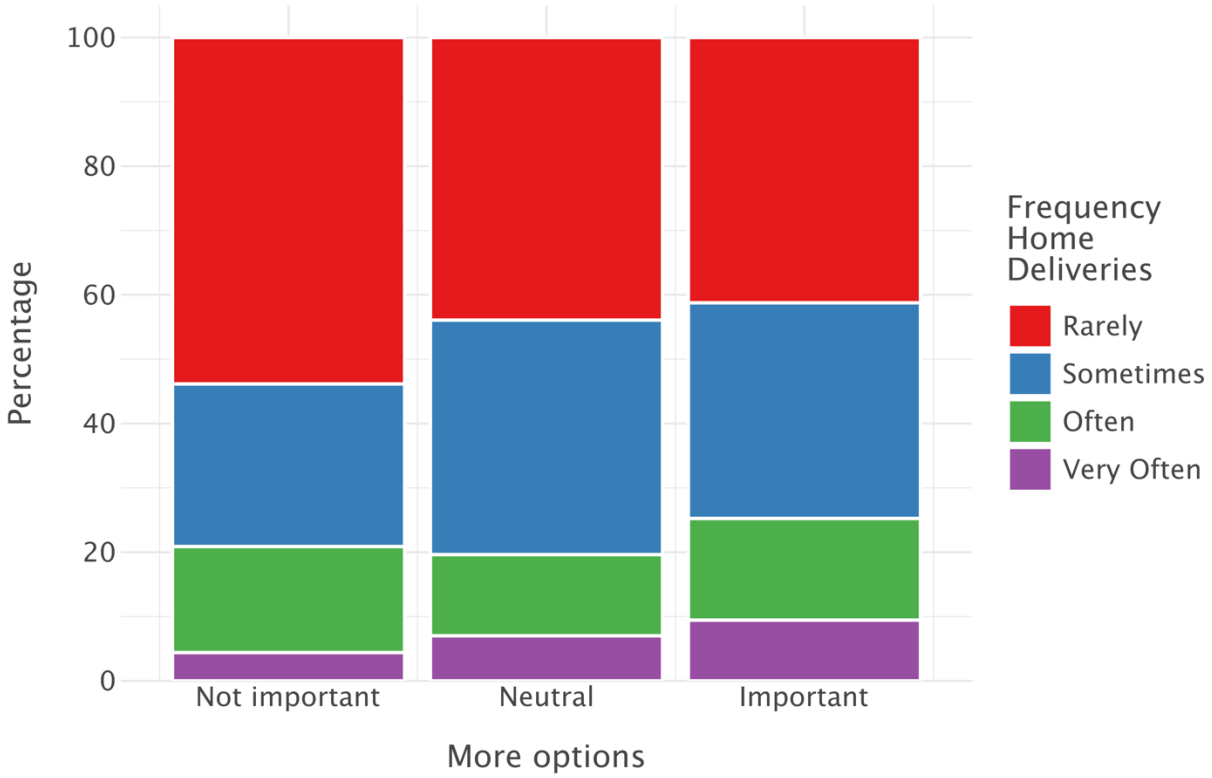

Figure 4.23: Home delivery frequency for "more options"

4.4.3 More Comparisons

For respondents that consider that "more comparisons" is important the trend is also similar to "it saves time" and "more options".

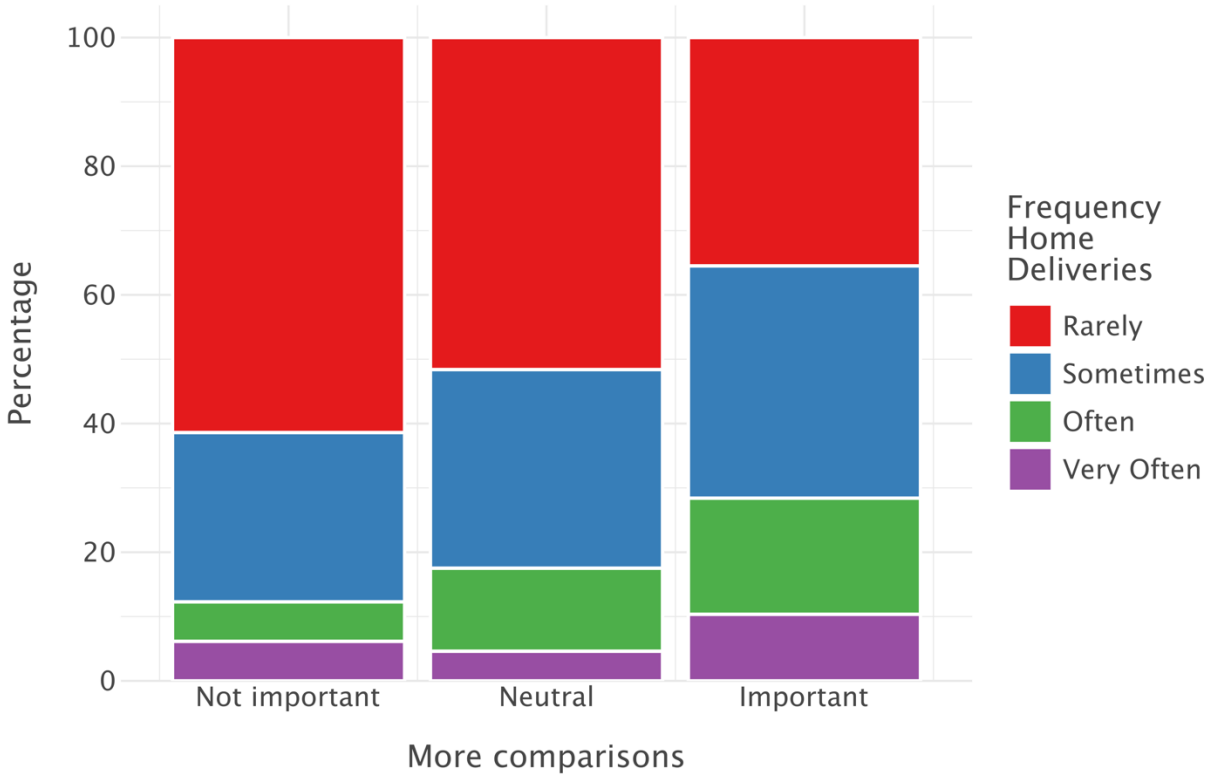

Figure 4.24: Home delivery frequency for "more comparisons"

4.4.4 Free Shipping

For respondents that consider that "free shipping" is important the trend is also similar to the previous ones.

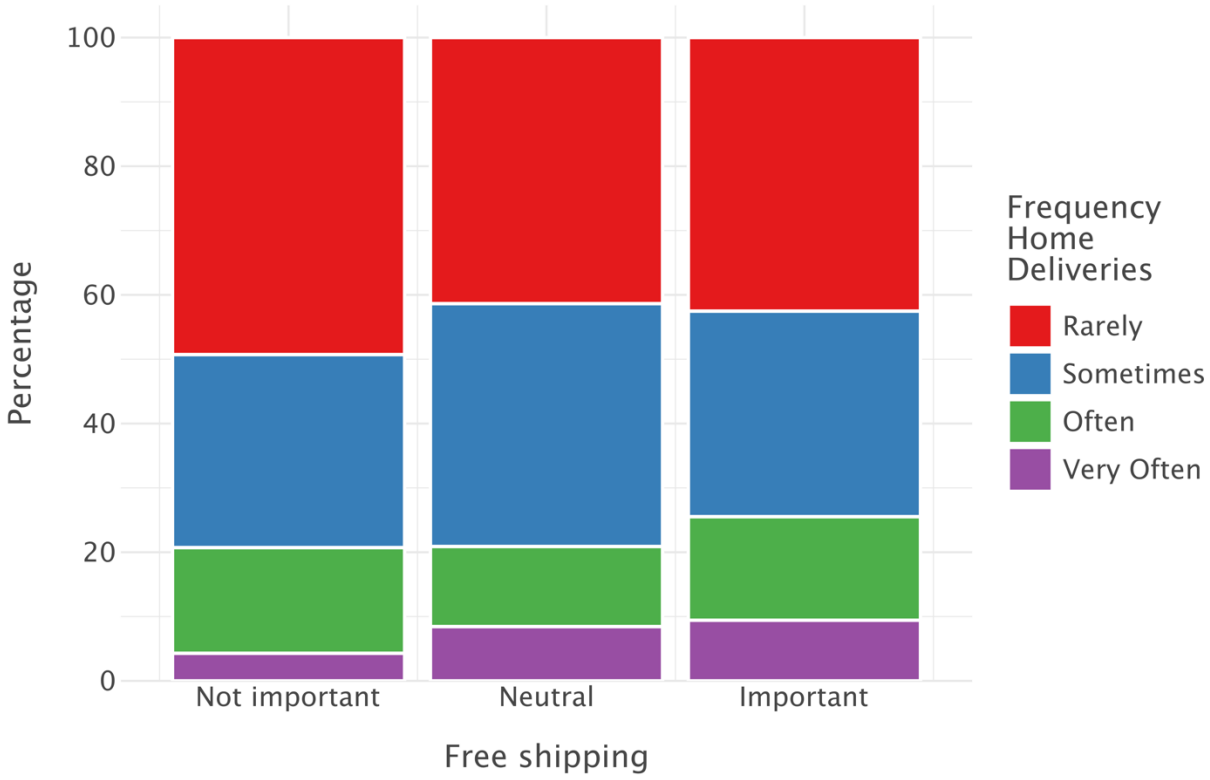

Figure 4.25: Home delivery frequency for "free shipping"

4.4.5 Subscriptions are convenient

For respondents that consider that "subscriptions are convenient" is important the trend is also similar to the previous ones.

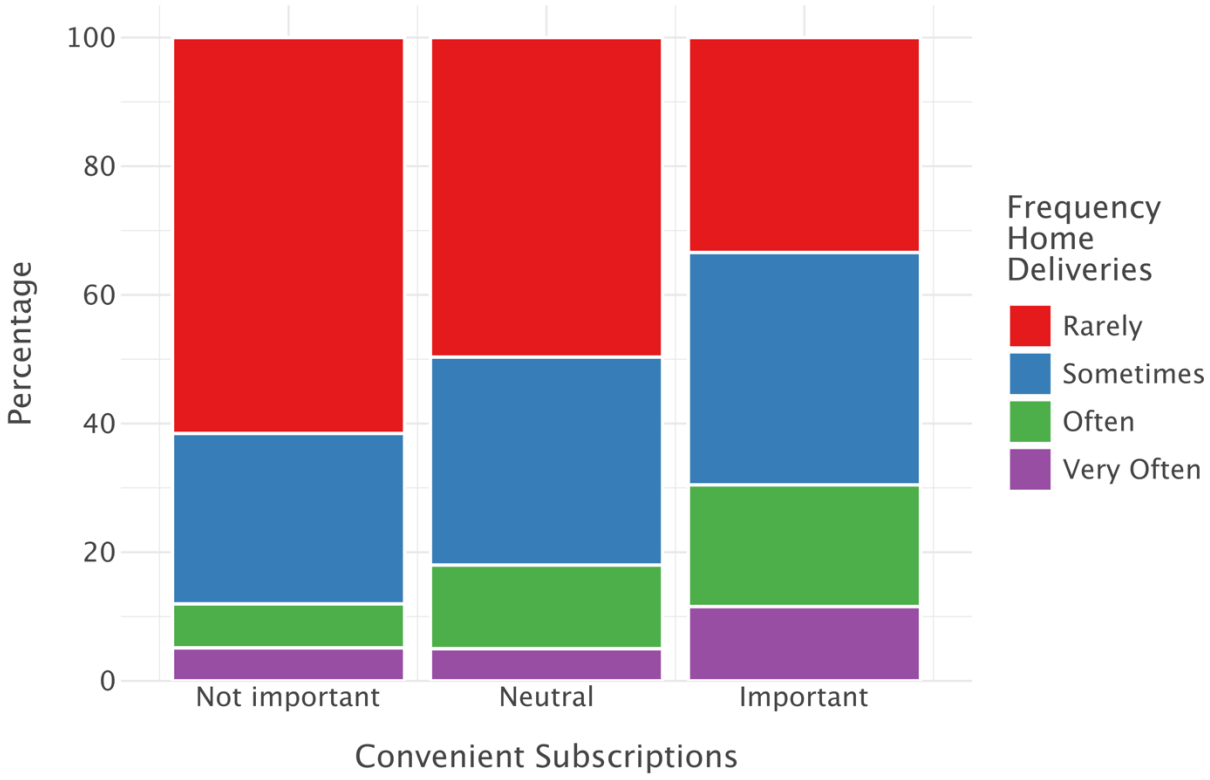

Figure 4.26: Home delivery frequency for "subscriptions are convenient"

4.4.6 It is safer

For respondents that consider that "it is safer" is important the trend is also similar to the previous ones.

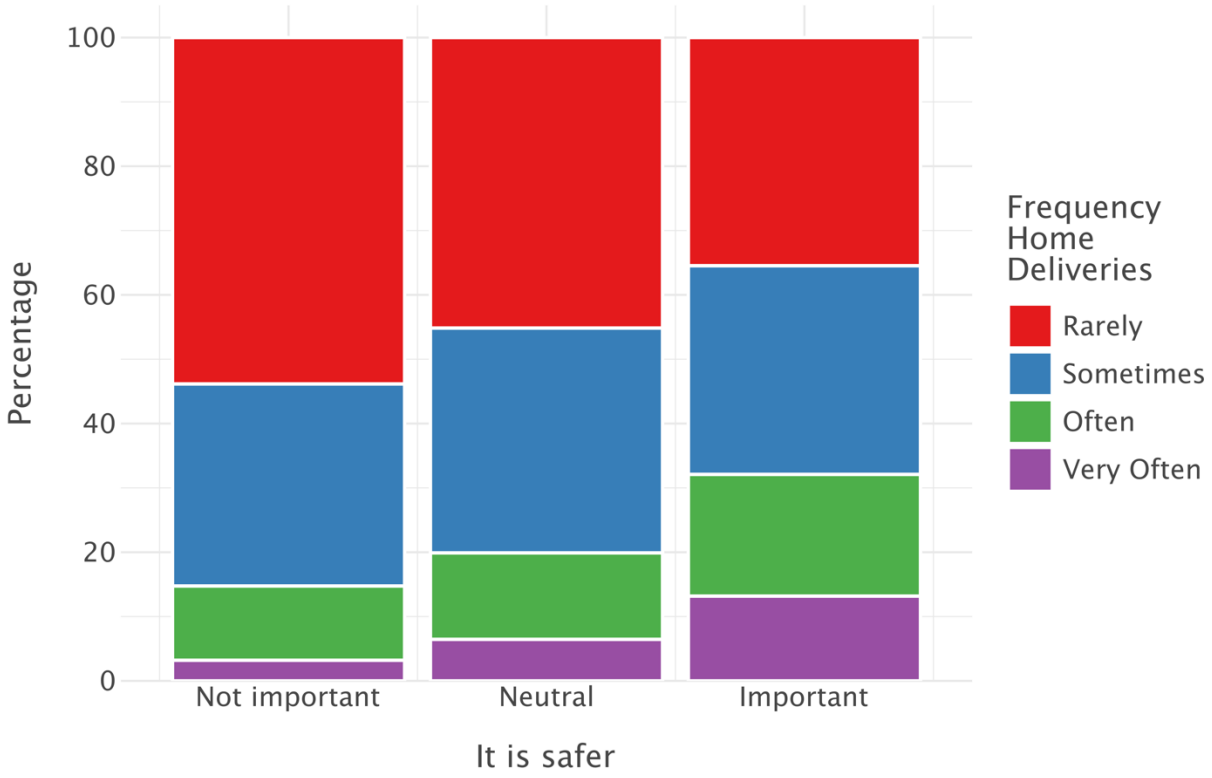

Figure 4.27: Home delivery frequency for "it is safer"

4.4.7 It is hard to travel

For respondents that consider that "it is hard to travel" is important the trend is also similar to the previous ones.

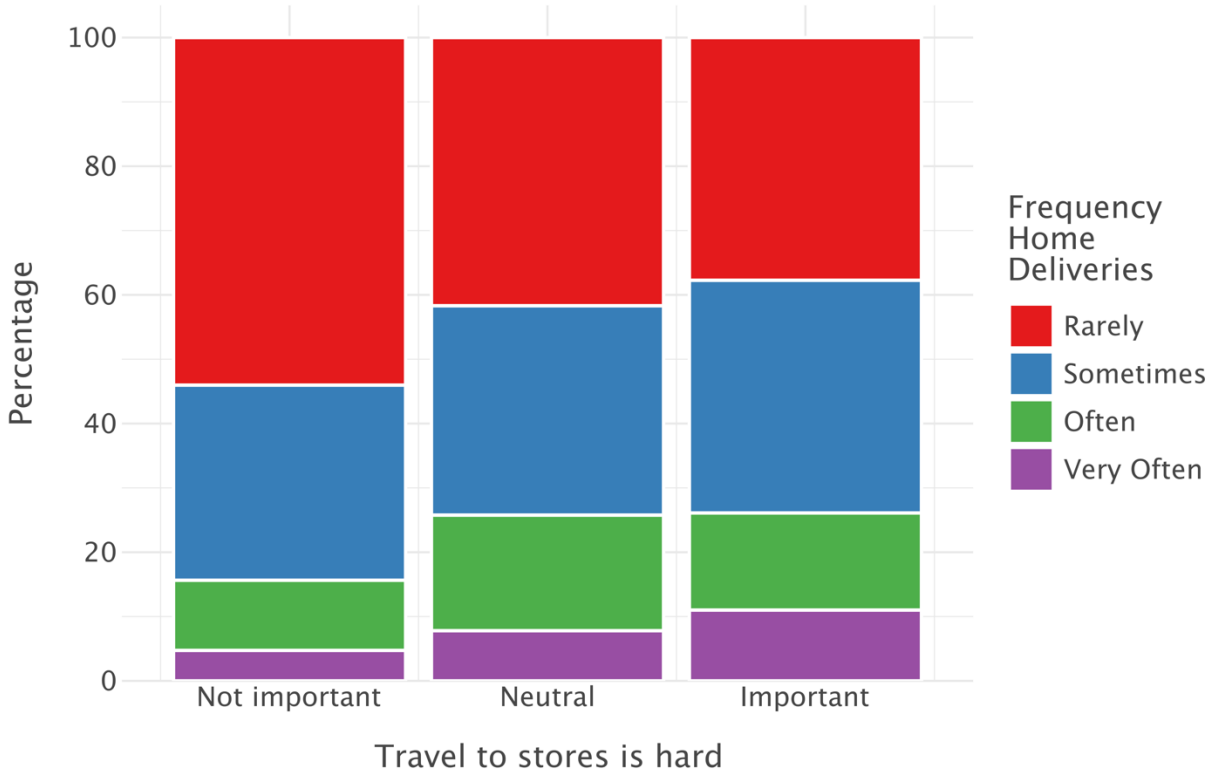

Figure 4.28: Home delivery frequency for "travel to stores is hard"

4.4.8 It is cheaper

For respondents that consider that "it is cheaper" is important the trend is also similar to previous ones.

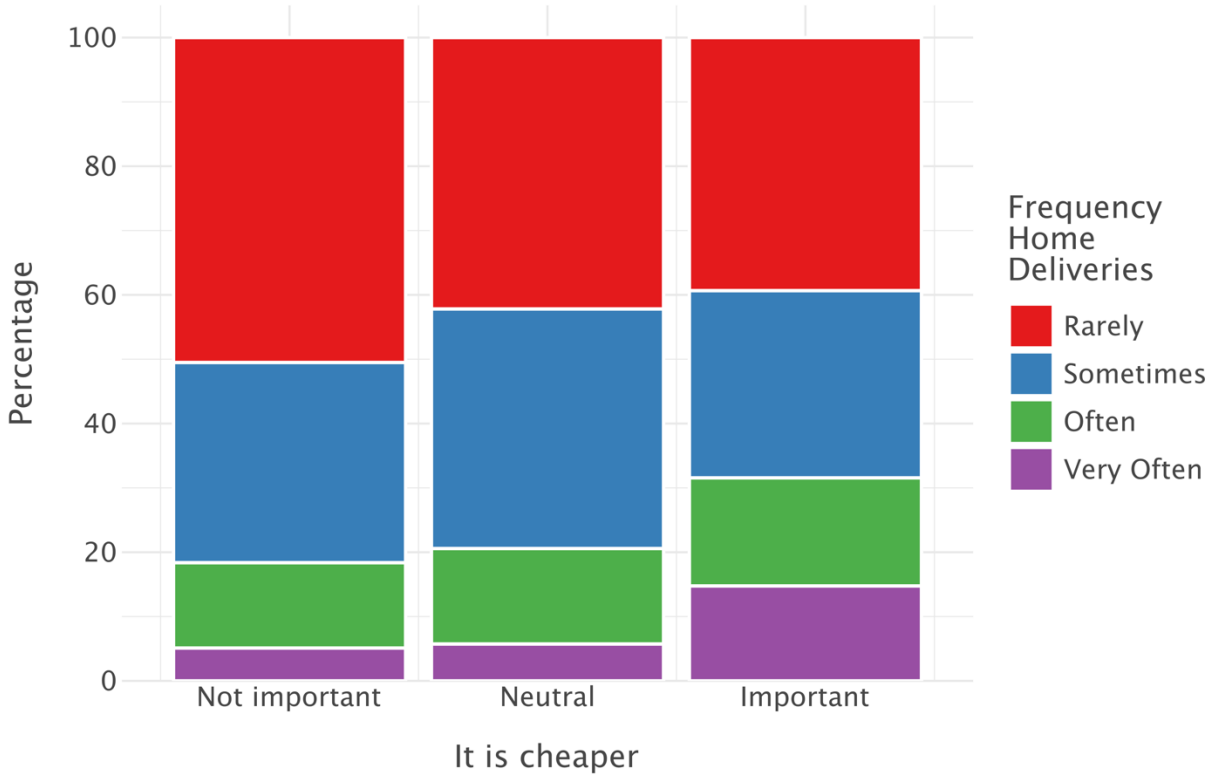

Figure 4.29: Home delivery frequency for "it is cheaper"

4.5 SUMMARY

Unlike the basic sociodemographic variables analyzed in the previous section, many of the variables studied in this section are novel or have not been yet sufficiently studied in the literature.

Overall, it is clear that the number of household members that usually spend time shopping or working online is a strong predictor of home deliveries. The attitudes show a consistent trend which indicates that for some households each of the attributes is important though the distribution of the number of households in each category show large differences across attitudes. The attitudinal results show that many households engage in e-commerce and home deliveries for many reasons that are not just related to cost related attitudes like "cheaper" or "free shipping". Finally, the type of store visited seems to have an impact on the frequency of deliveries, for example, visiting supermarkets seem to decrease home delivery frequency.

5.0 EXPLORATORY ANALYSIS OF PRODUCT DELIVERIES AND FEES

This section focuses on the analysis of deliveries and potential fees but at the product level. In the first subsection the delivery rates across products are compared and analyzed. Int the second subsection the focus is on understanding how many households may be affected by delivery fees. For each product there is a plot describing the distribution home delivery frequency conditional a fee affecting delivery frequency. As in previous sections, the survey question is first introduced to facilitate the interpretation of the plots and results.

5.1 PRODUCTS

The literature review indicates that accounting for type of product is a key factor to model the adoption of e-commerce. The survey question related to product delivery frequency is the following:

For each of the following categories, approximately how many home deliveries took place LAST week? *(range 0-8)*

- Groceries
- Prepared food, restaurant deliveries
- Clothing/shoes
- Personal care, beauty products
- Miscellaneous supplies
- Home products/appliances/décor
- Electronic products/accessories
- Pet products
- Pharmacy products
- Other (sports equipment, hobbies, toys, etc.)

The distribution of the mean deliveries per product is shown below in Figure 5.1. As expected from the literature review products related to food, groceries, and clothing are at the top. It is not surprising that miscellaneous is at the top as well because the literature review highlighted that

there are too many product categories that can be fit into the eight or ten options that are usually feasible in a standard survey length.

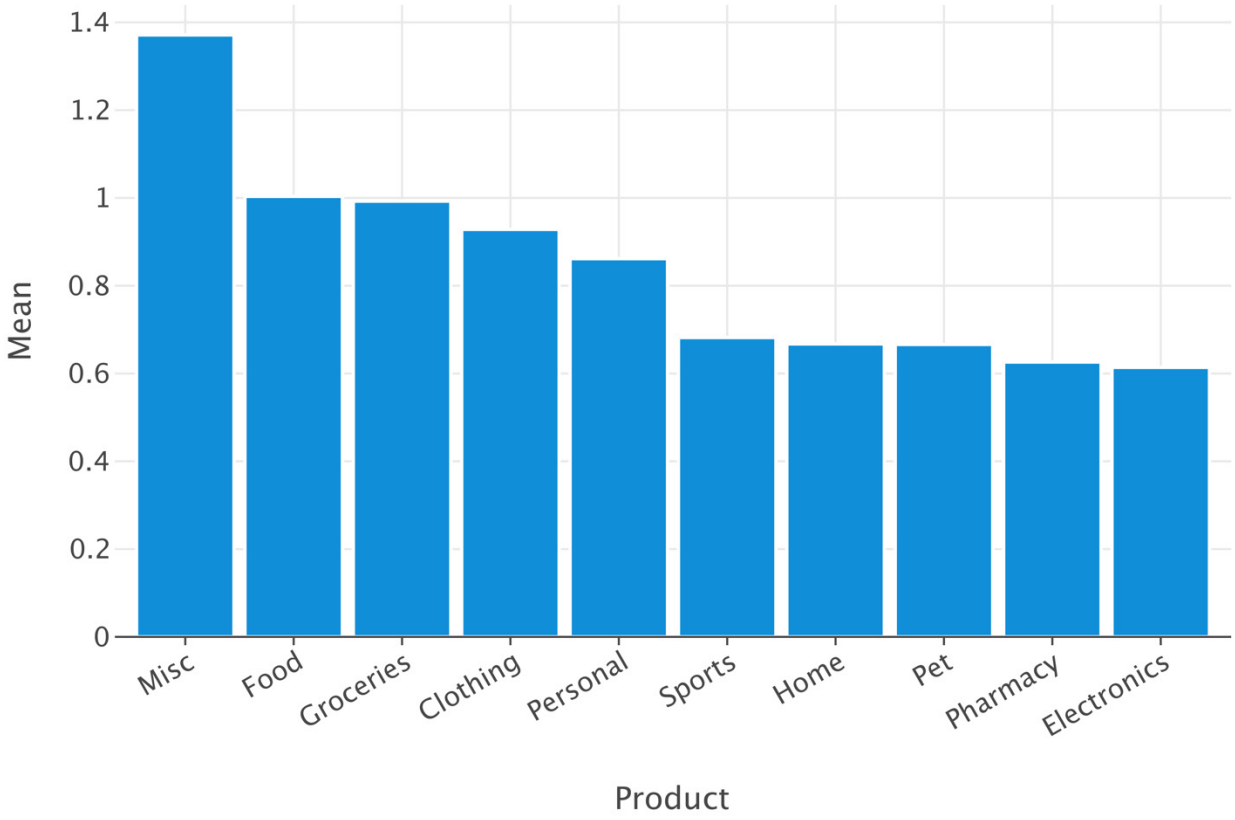

Figure 5.1: Mean deliveries by product (last week)

The correlations among product frequency are shown in Figure 5.2. Highest correlations are among food and groceries (0.58) and clothing and personal (0.51) which seem reasonable results. The lowest correlations are among miscellaneous and groceries (0.19).

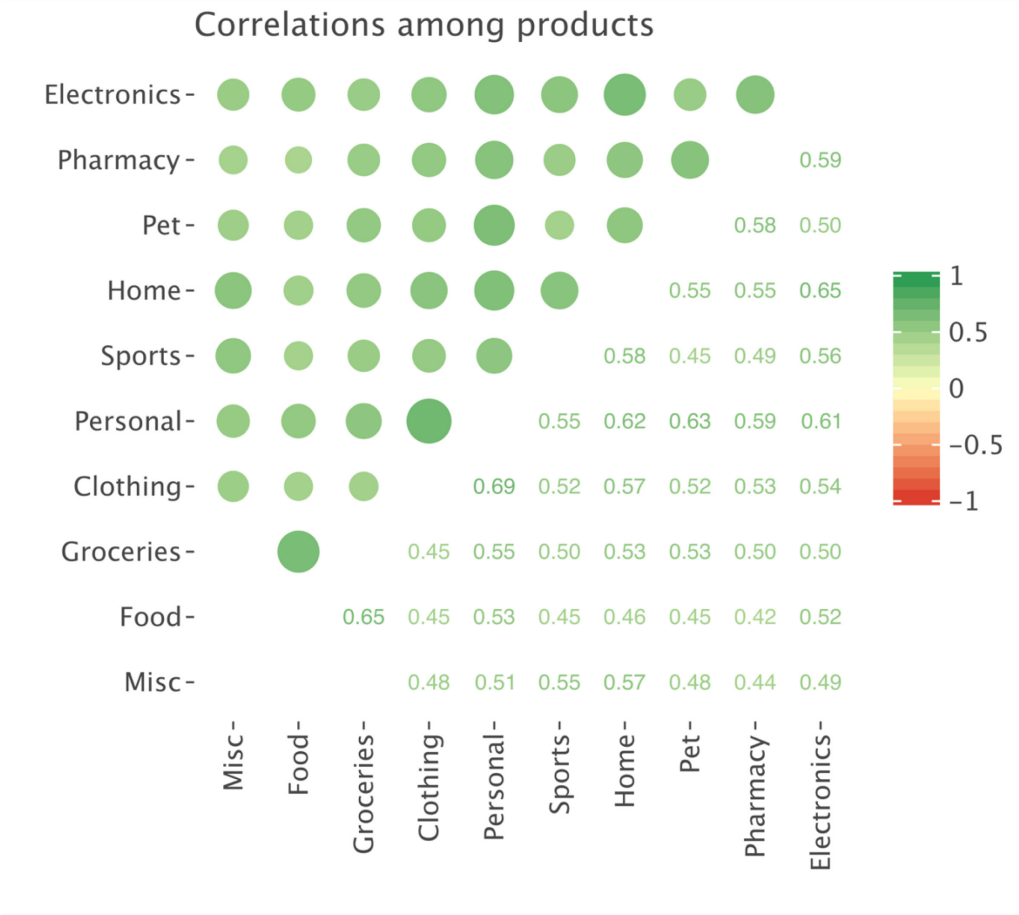

Figure 5.2: Correlations demand

5.2 DELIVERY FEE

One of the main goals of this research is to analyze the potential effects of a household e-commerce delivery fee in Oregon. The survey question used to measure if households would order less if there were a delivery fee is the following:

Some states have a delivery fee for online shopping. Please select any category where your household would order LESS OFTEN if a $0.50 delivery fee is applied to your delivery. *Mark ALL that apply.*

- Groceries
- Prepared food, restaurant deliveries
- Clothing/shoes
- Personal care, beauty products

- Miscellaneous supplies
- Home products/appliances/décor
- Electronic products/accessories
- Pet products
- Pharmacy products
- Other (sports equipment, hobbies, toys, etc.)

Feedback from TAC member Allen Molina was used to refine this question. The distribution of positive answers by product is shown below in Figure 5.3 with an adequate percentage of observations per product.

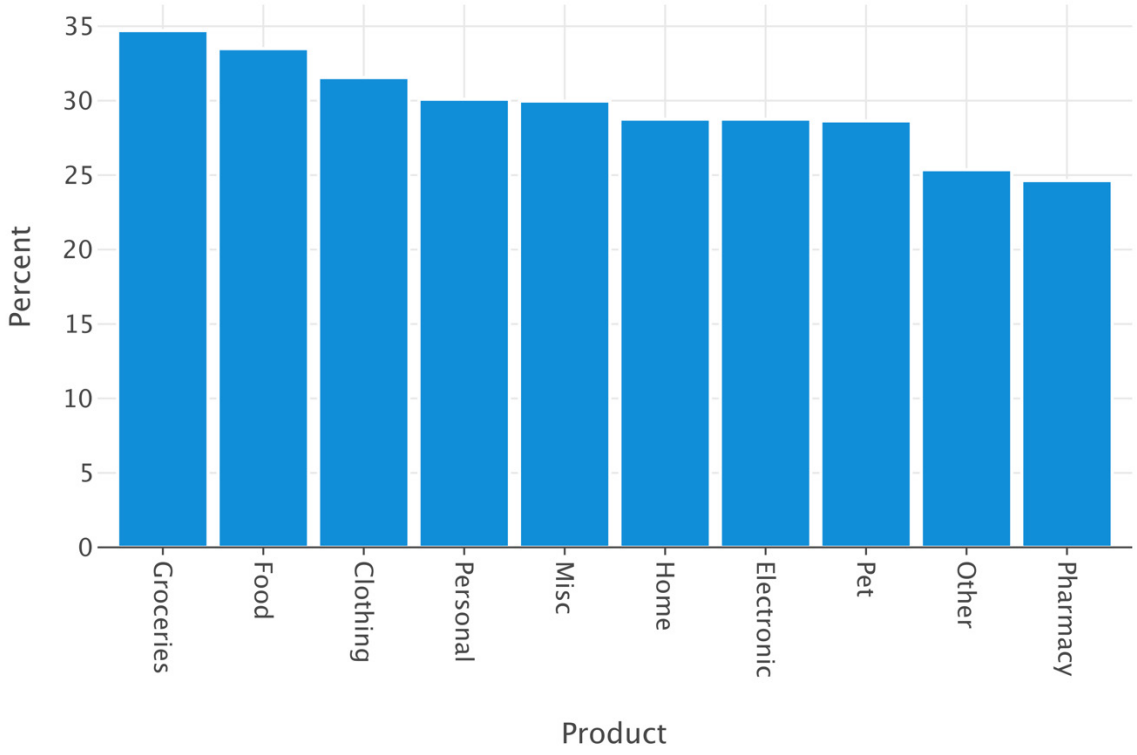

Figure 5.3: Percent of respondents that would be affected by a potential fee by product

There are significant correlations among potential fee impacts by product as shown in Figure 5.4. Highest correlations are among home and electronic products (0.82) and clothing and personal products (0.73). The lowest correlations are among other and groceries (0.47).

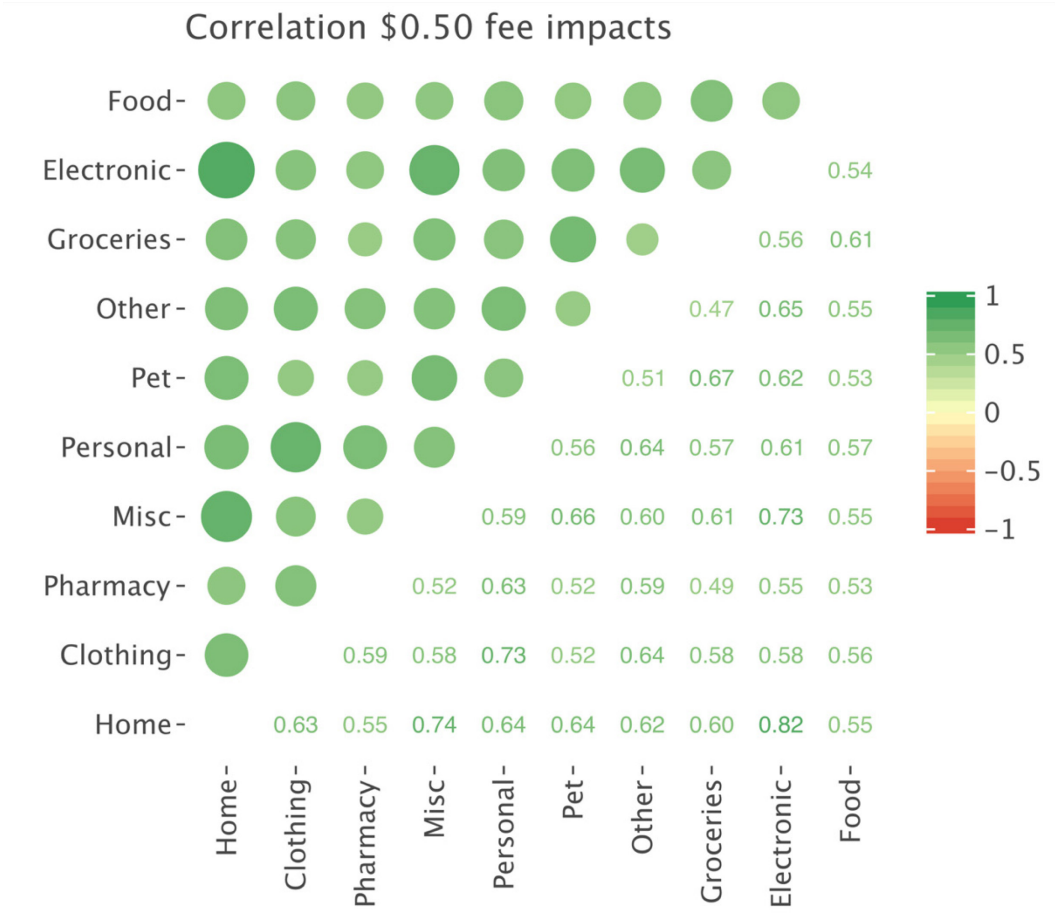

Figure 5.4: Correlations among product fee impacts

The following subsections use plots to observe if being affected by a particular delivery fee has an impact on home delivery frequency.

5.2.1 Groceries

Respondents that consider a delivery fee will reduce the number of grocery deliveries seem higher in the “very often” category.

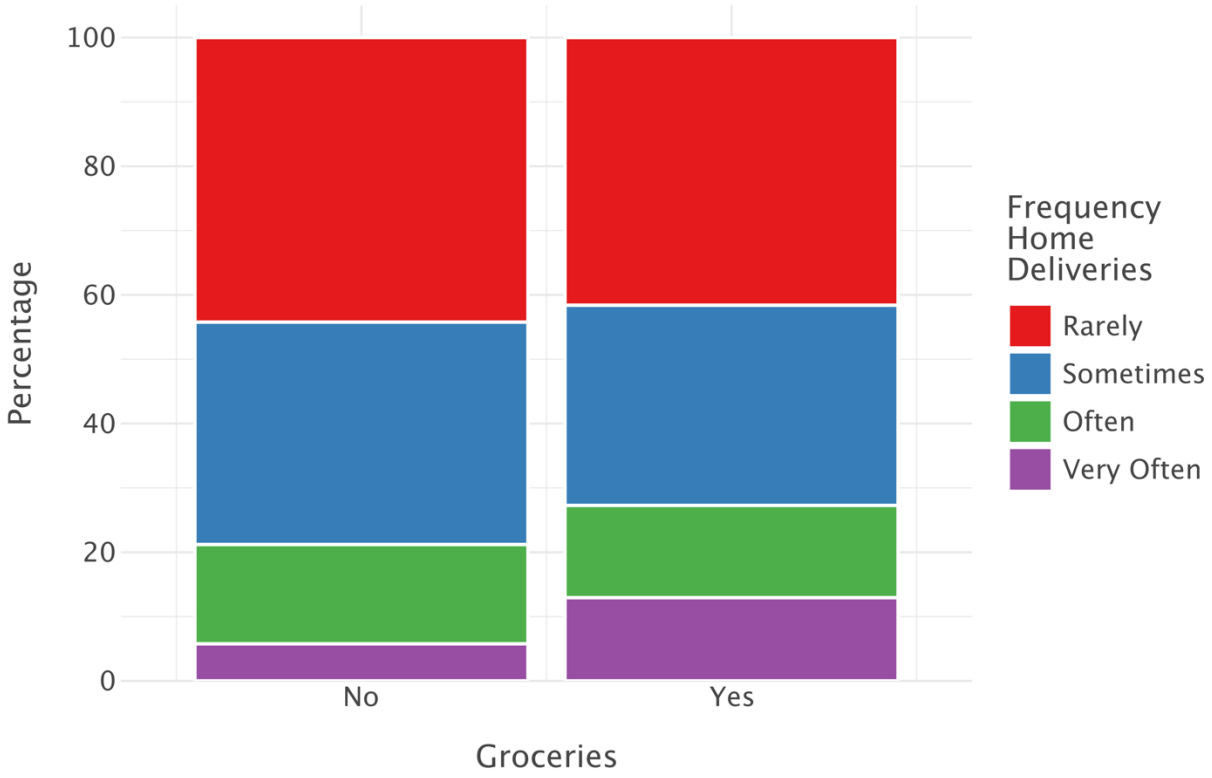

Figure 5.5: Home delivery frequency and potential fee for grocery products

5.2.2 Food (prepared food, restaurant deliveries)

Respondents that consider a delivery fee will reduce the number of prepared food deliveries also seem higher in the “very often” category.

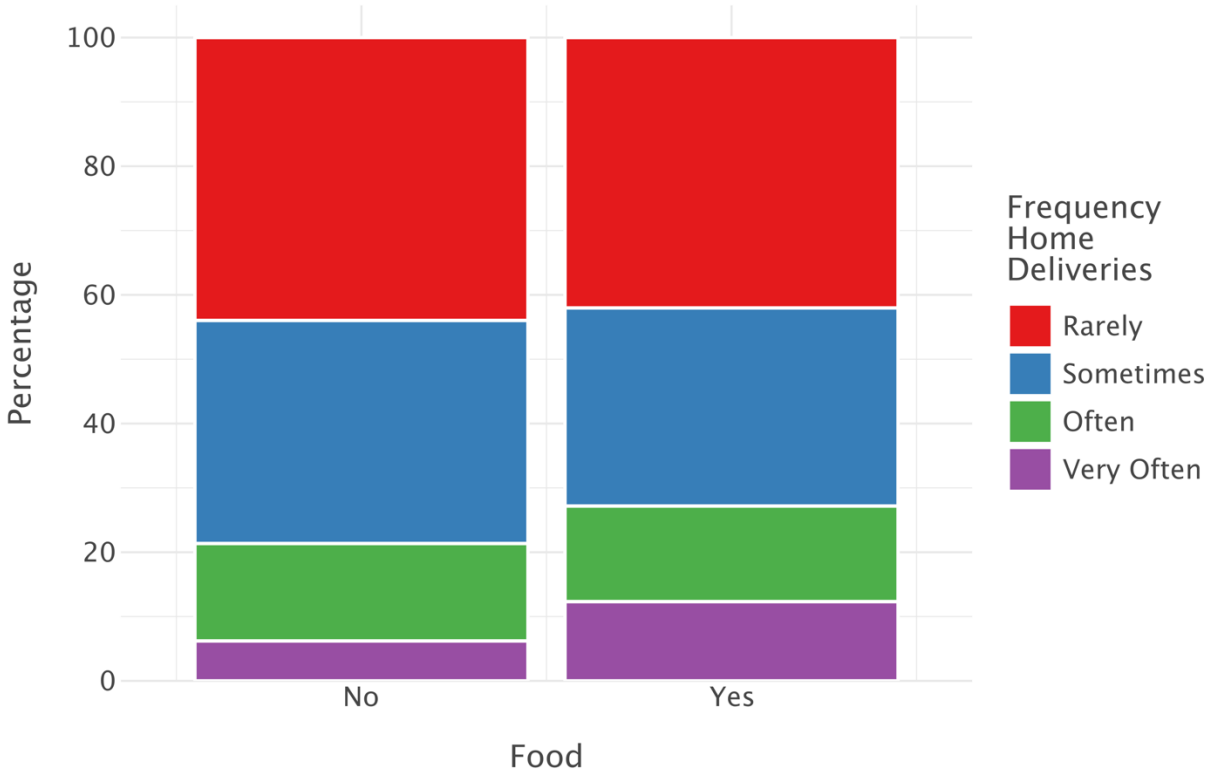

Figure 5.6: Home delivery frequency and potential fee for food deliveries

5.2.3 Clothing/shoes

Respondents that consider a delivery fee will reduce the number of clothing/shoes deliveries are clearly higher in the “very often” category.

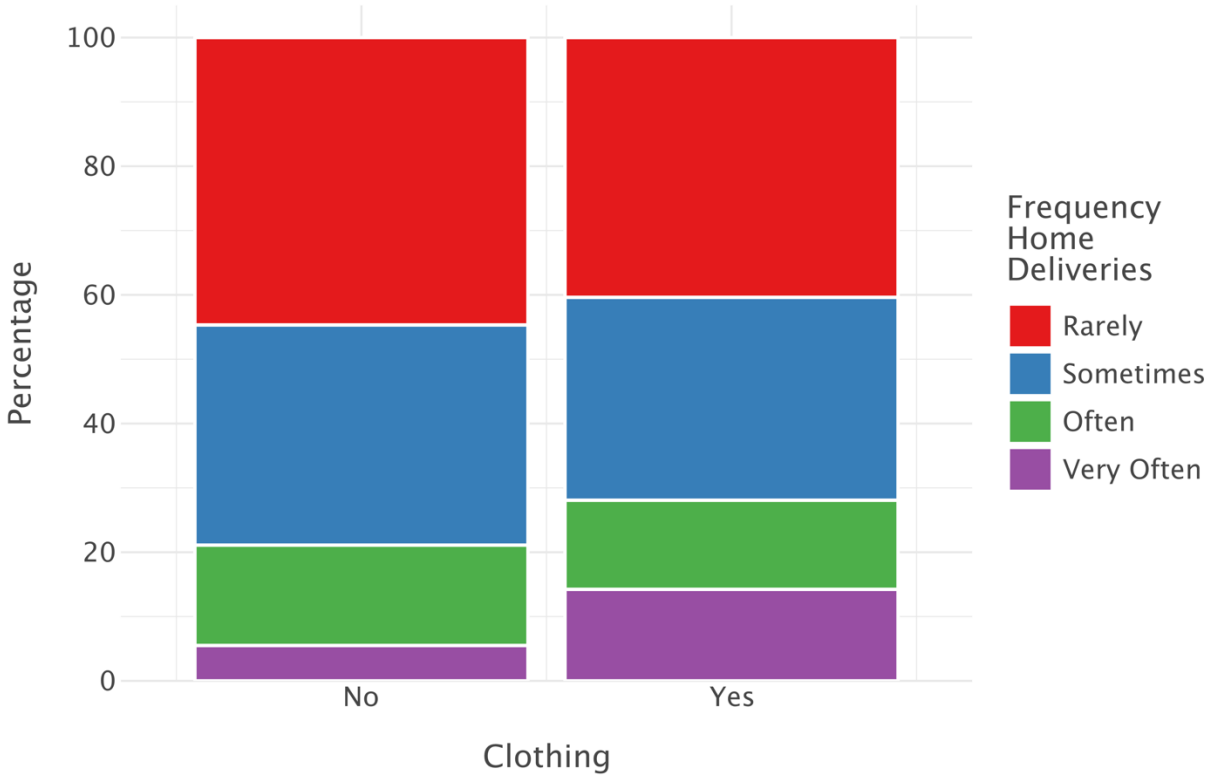

Figure 5.7: Home delivery frequency and potential fee for clothing products

5.2.4 Personal care, beauty products

Respondents that consider a delivery fee will reduce the number of personal care/beauty product deliveries are also clearly higher in the “very often” category.

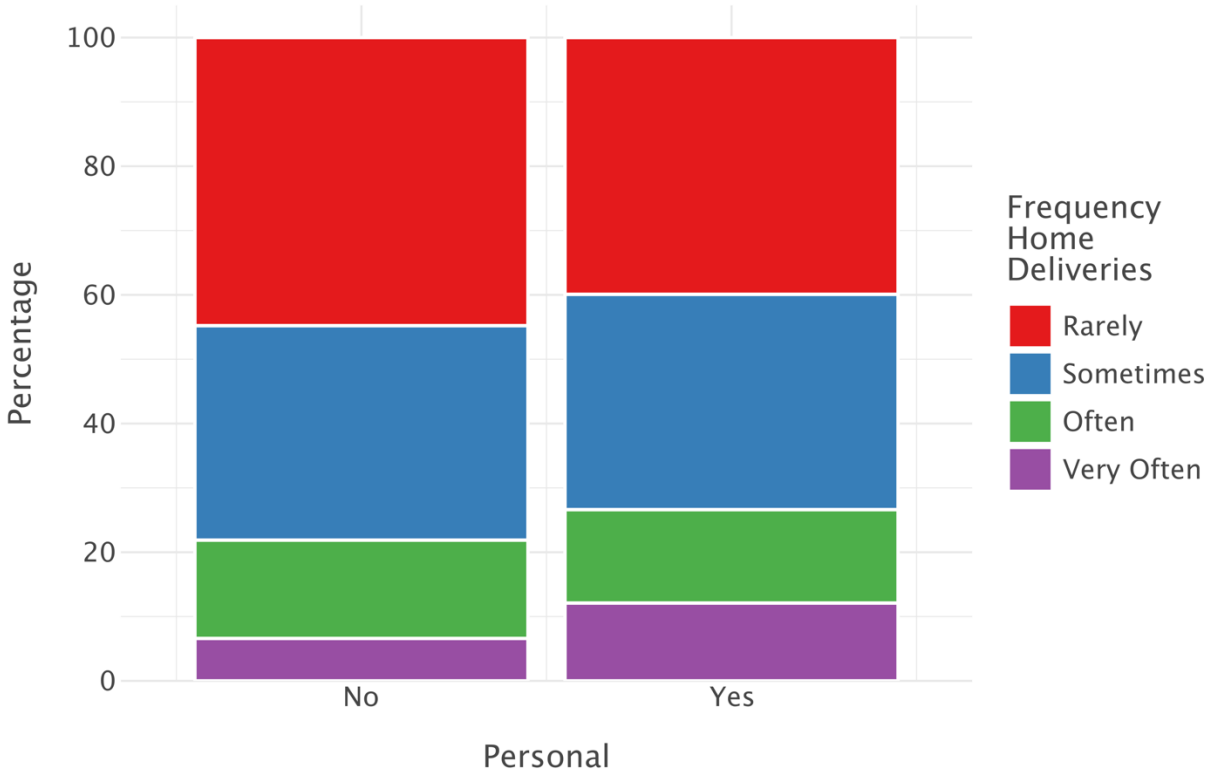

Figure 5.8: Home delivery frequency and potential fee for personal products

5.2.5 Miscellaneous products

No major trend or difference is observed for miscellaneous products which seems intuitive given the broadness of the category.

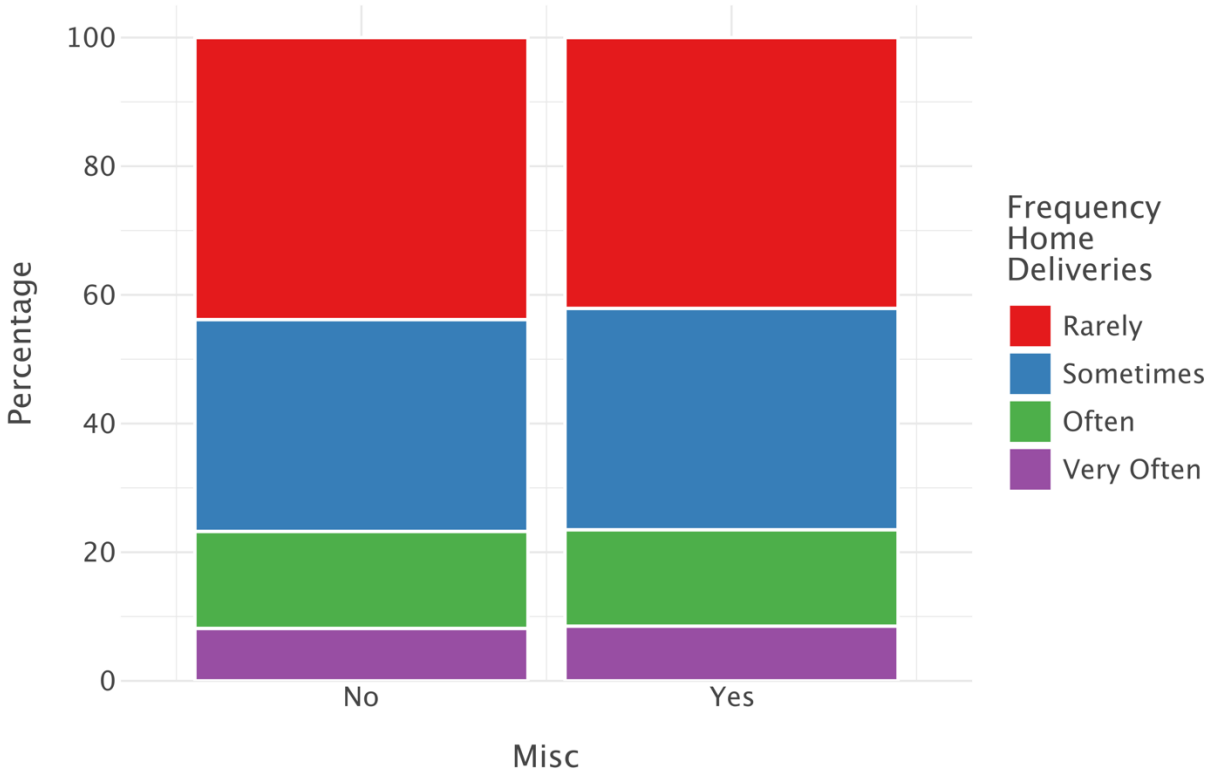

Figure 5.9: Home delivery frequency and potential fee for miscellaneous products

5.2.6 Home products/appliances/décor

Respondents that consider a delivery fee will reduce the number of home products deliveries seem slightly higher in the “very often” category.

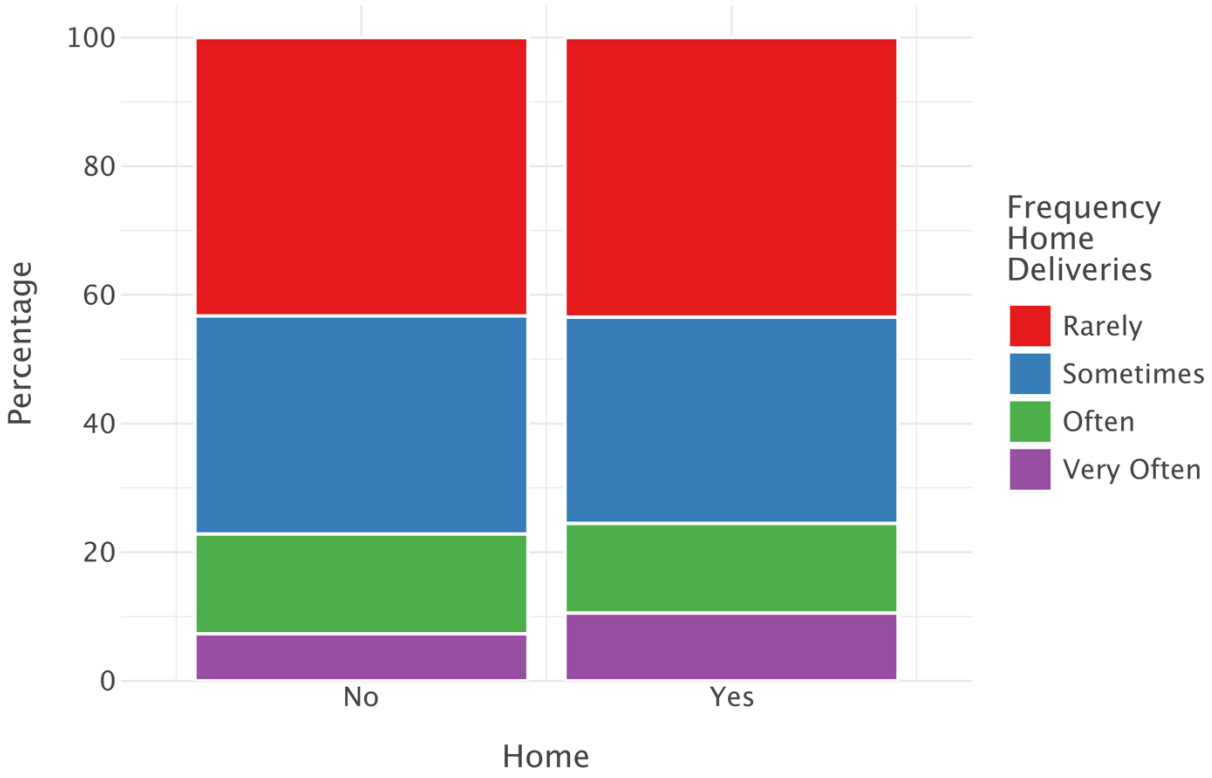

Figure 5.10: Home delivery frequency and potential fee for home/decor products

5.2.7 Electronic products/accessories

No major trends or differences are observed for electronics products, perhaps a reflection of the importance of comparison, the lower ordering frequency, or the higher value of electronic products.

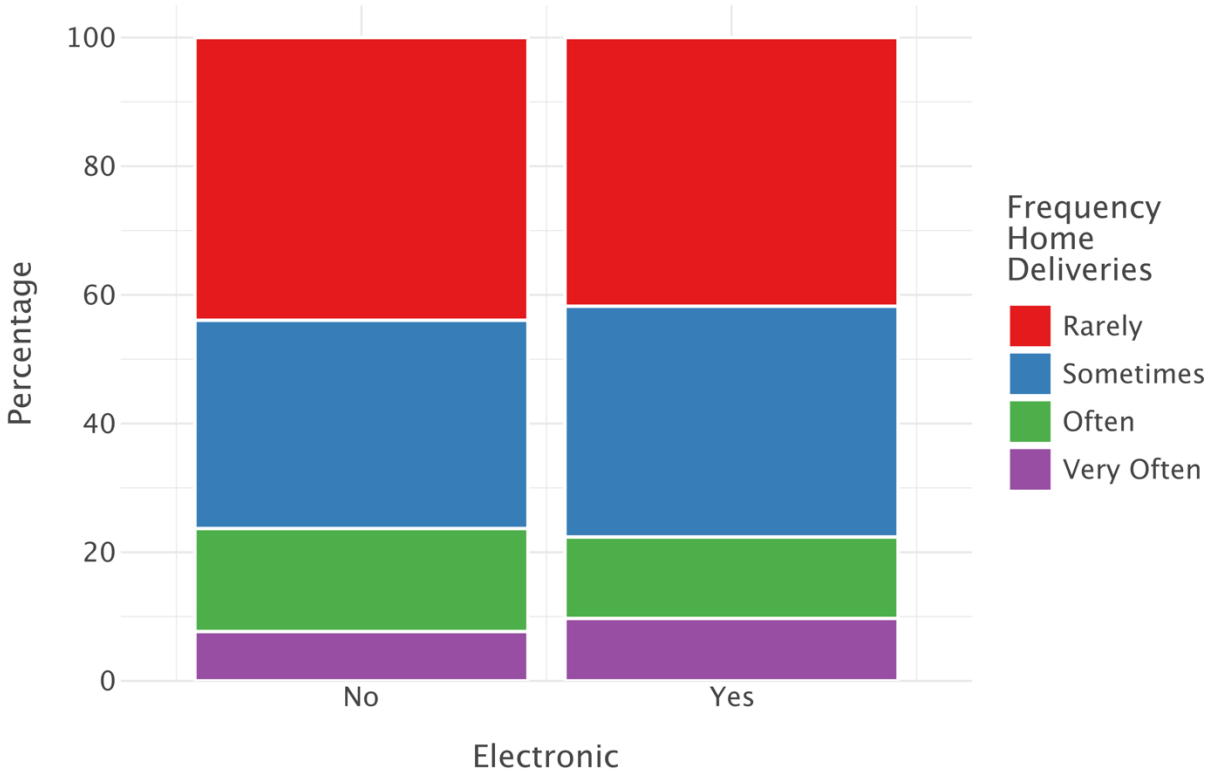

Figure 5.11: Home delivery frequency and potential fee for electronic products

5.2.8 Pharmacy products

Respondents that consider a delivery fee will reduce the number of pharmaceutical product deliveries seem higher in the “very often” category.

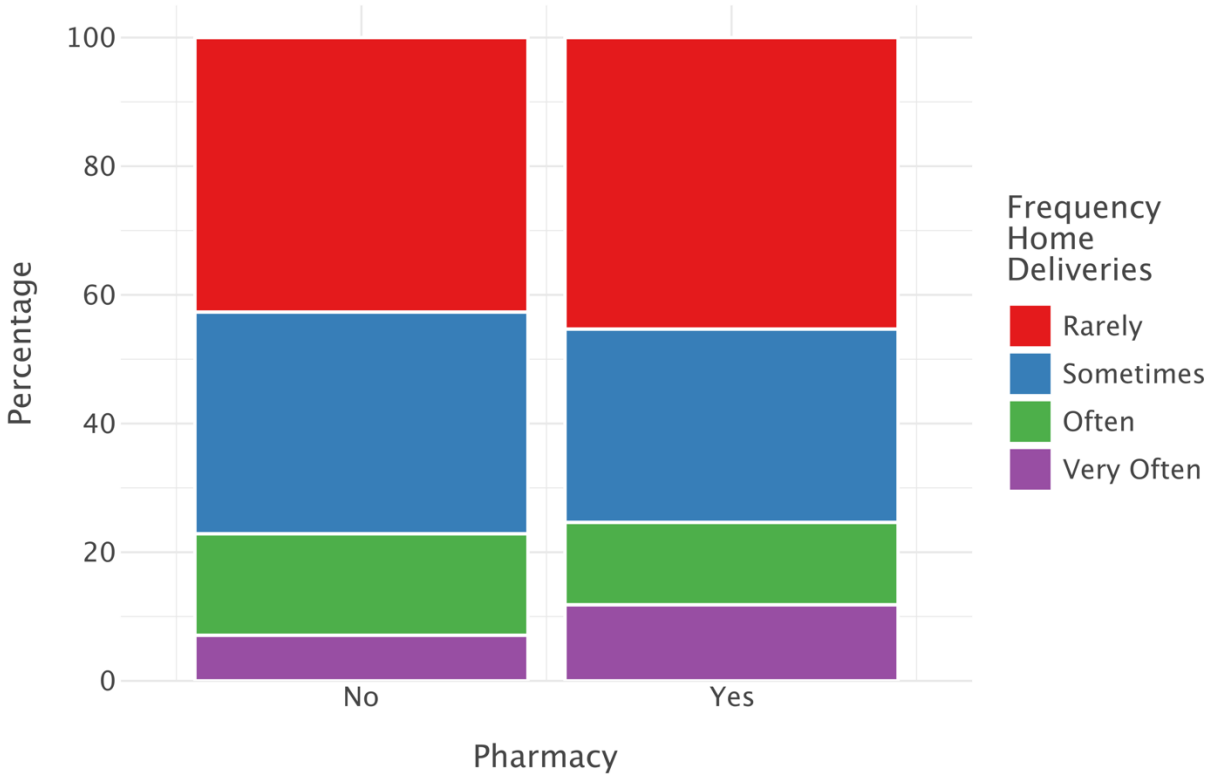

Figure 5.12: Home delivery frequency and potential fee for pharmaceutical products

5.2.9 Pet products

Respondents that consider a delivery fee will reduce the number of pet products deliveries are clearly higher in the “very often” category.

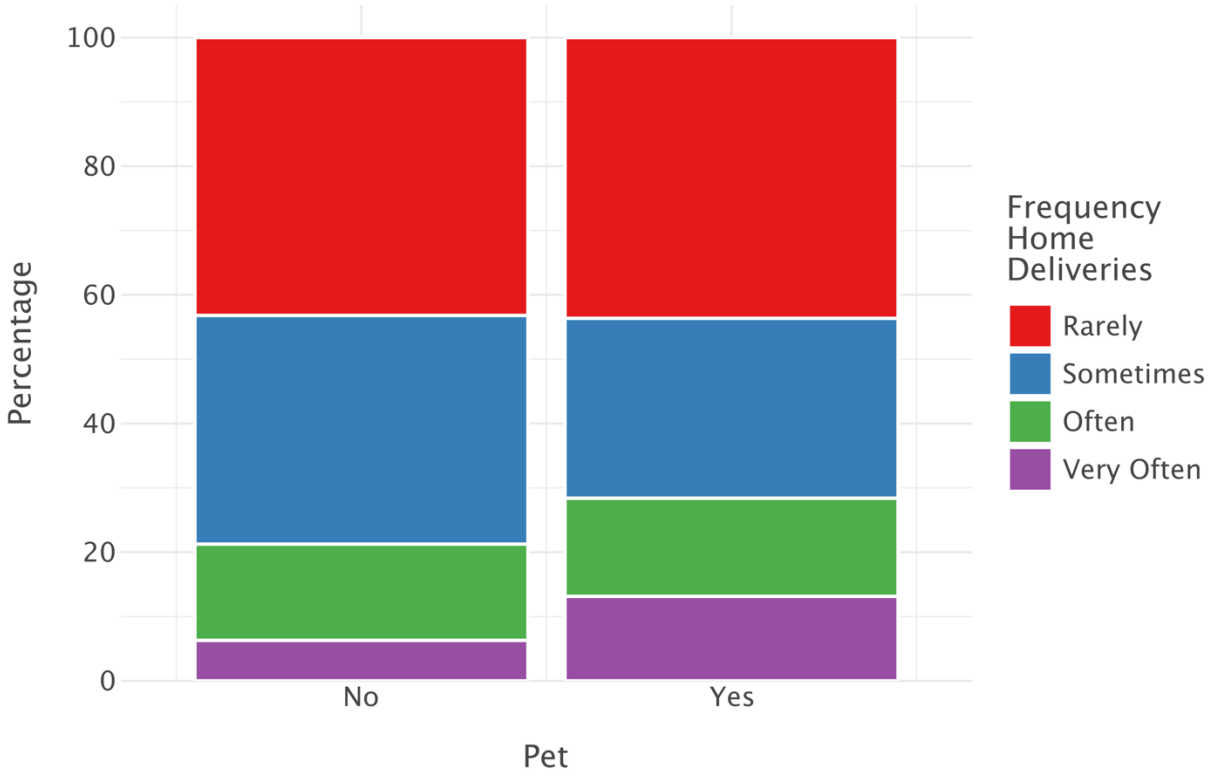

Figure 5.13: Home delivery frequency and potential fee for pet products

5.2.10 Other products (sports equipment, hobbies, toys, etc.)

No trend or major differences observed for other products.

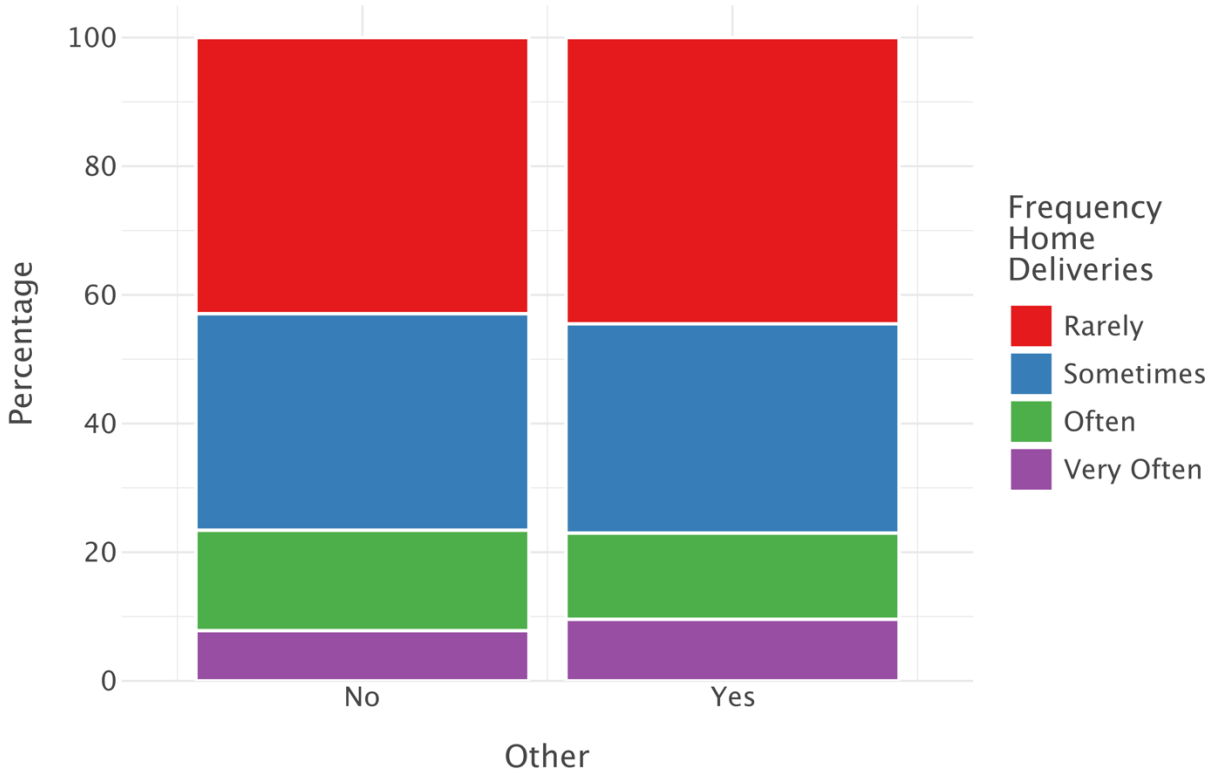

Figure 5.14: Home delivery frequency and potential fee for other products

5.3 SUMMARY

Overall, the results of this section are mostly novel yet intuitive. The potential impact of delivery fees on delivery frequency is clearly affected by the type of product ordered. On one hand for products like groceries, food, or pet products there is an intention of ordering less mostly for households that are in the “very often” category. On the other hand, products like electronics and other (sports equipment, hobbies, toys, etc.) do not seem to be affected by a delivery fee.

6.0 LOGISTIC MODELS FOR DELIVERY FEES

The previous section described products delivery rates and statistics about potential fee impacts on deliveries disaggregated by product. This section presents logistic results of models that seek to explain delivery fee sensitivity as a function of shopping and sociodemographic variables. In the first subsection the logistic model is introduced and in the second subsection the modeling results are discussed.

6.1 LOGISTIC REGRESSION BACKGROUND

The survey question related to the potential impact of delivery fees on ordering frequency has a binary outcome. The question is the following:

Some states have a delivery fee for online shopping. Please select any category where your household would order LESS OFTEN if a $0.50 delivery fee is applied to your delivery.

Respondents had to choose "yes" or "no" for each product described in the previous section. For an exploratory analysis of the variables that explain the respondent sensitivity to delivery fees a logistic regression model is adequate because it assumes that the choice is binary (e.g. yes/no or 1/0).

6.1.1 Formulation of the logistics model

More formally, a logistic regression models the probability of a binary outcome. The probability that the outcome is 1, i.e. $y_i = 1$ given x_i, is modeled using the logistic function (also known as the sigmoid function):

$$P(y_i = 1 \mid x_i) = \pi_i = \frac{1}{1 + e^{-z_i}}$$

Where the term $z_i = x_i^{\top}\beta$ is a linear combination of the independent variables. Using matrix and vector notation:

$$z = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p$$

where the matrix X (with n observations and p features) belong to the real numbers.

$$X \in R^{n \times p}$$

In this case, the intercept plus p coefficients must be estimated. The likelihood function is:

$$L(\beta) = \prod_{i=1}^{n} \pi_i^{y_i} (1 - \pi_i)^{1 - y_i}$$

The log-likelihood is:

$$l(\beta) = \sum_{i=1}^{n} [y_i \log(\pi_i) + (1 - y_i) \log(1 - \pi_i)]$$

and the optimization problem:

$$\hat{\beta} = \arg\max_{\beta} l(\beta)$$

There is no closed solution for this optimization problem and the beta coefficients are estimated using iterative optimization algorithms such as gradient descent, Newton-Raphson, or other non-linear optimization techniques.

6.1.2 Interpretation of the coefficients

In a logistic regression the interpretation of the coefficients is not as straightforward as in linear regression. Logistic regression coefficients represent the change in the log-odds of the outcome for a one-unit change in the predictor, holding all other predictors constant. A positive coefficient indicates that as the predictor variable increases, the log-odds of the outcome (i.e. having less deliveries if a delivery fee is introduced) occurring also increase. Conversely, a negative coefficient means the log-odds of the zero outcome (not having less deliveries if a delivery fee is introduced) decrease with an increase in the predictor. The coefficients for categorical variables represent the difference in the log-odds of the outcome for that category compared to the reference category. Another common interpretation of the coefficients is done after exponentiating the coefficients which results in odds ratios. The odd rations express the multiplicative change in odds of success (outcome one) for a one-unit change in the predictor.

6.2 RESULTS OF LOGISTIC MODELS

In all regressions, variable inflation factors (VIF) are quantified to ensure that levels are within recommended thresholds which ensures that the regression coefficients are not unreliable due to correlation among predictors. Regression model specifications are built manually one step at the time using the Bayesian Information Criteria (BIC) and checking the stability and consistency of successive regression results.

This subsection presents the results of the logistics models one product at the time. The models are estimated using only observations where the product analyzed was delivered. Only significant variables are presented plus the variable that indicates how many items of the product being analyzed were delivered last week. In all cases the format of the table follows the standard presentation of statistical estimations: variable, coefficient, standard error, *z* value, probability of the *z* value, and the intervals of the confidence interval.

6.2.1 Groceries

For groceries the results of the logistics model are presented in Table 6.1. The number of grocery deliveries is not significant at the 0.05 level. There are five significant variables.

- If cheaper is considered important then the probability of decreasing deliveries after a fee is introduced *increases*.
- If the household has an Amazon subscription probability of decreasing deliveries after a fee is introduced *decreases*.
- If the household visits discount stores the probability of decreasing deliveries after a fee is introduced *increases.*
- If the household is located in a large urban area the probability of decreasing deliveries after a fee is introduced *increases.*
- If saving time is considered important then the probability of decreasing deliveries after a fee is introduced *decreases*.

Table 6.1: Groceries logistic regression results

Variable	Coef.	Std. err.	*z*	$P > \|z\|$	[0.025	0.975]
Intercept	-0.159	0.349	-0.455	0.649	-0.843	0.525
Cheaper Imp.	0.743	0.240	3.097	0.002	0.273	1.214
Amazon subs.	-0.995	0.300	-3.321	0.001	-1.583	-0.408
Discount store	0.638	0.226	2.821	0.005	0.195	1.081
Large urban area	0.679	0.233	2.914	0.004	0.222	1.135
Saves time Imp.	-0.640	0.265	-2.414	0.016	-1.159	-0.120
Grocery Deliveries	0.119	0.067	1.767	0.077	-0.013	0.251

The results seem intuitive and may indicate that deliveries to cost conscious households in urban areas may be affected by a fee. Households with high value of time or with an Amazon subscription seem less sensitive to delivery fees.

6.2.2 Food (prepared food, restaurant deliveries)

For food the results of the logistics model are presented in Table 6.2. The number of food deliveries is not significant at the 0.05 level. There are two significant variables. The significant variables were already described in the previous subsection.

- If the household visits discount stores the probability of decreasing deliveries after a fee is introduced *increases.*
- If the household is located in a large urban area the probability of decreasing deliveries after a fee is introduced *increases.*

Table 6.2: Food logistic regression results

Variable	Coef.	Std. err.	*z*	*P* > |*z*|	[0.025	0.975]
Intercept	-1.349	0.201	-6.718	0.000	-1.742	-0.955
Discount store	0.597	0.218	2.733	0.006	0.169	1.025
Large urban area	0.703	0.232	3.033	0.002	0.249	1.157
Food Deliveries	0.095	0.063	1.511	0.131	-0.028	0.218

The results indicate that food deliveries to cost conscious households in urban areas may be affected by a fee.

6.2.3 Clothing/shoes

For clothing/shoes the results of the logistics model are presented in Table 6.3. The number of personal products deliveries is significant. There are four additional significant variables.

- If the household visits discount stores the probability of decreasing deliveries after a fee is introduced *increases* but the probability *decreases* if the household visits bog-box stores.
- If the household is located in a large urban area the probability of decreasing deliveries after a fee is introduced *increases.*
- If the household has higher income the probability of decreasing deliveries after a fee is introduced *decreases*.

Table 6.3: Clothing logistic regression results

Variable	Coef.	Std. err.	*z*	*P* > |*z*|	[0.025	0.975]
Intercept	-0.271	0.372	-0.729	0.466	-0.999	0.458
Large urban area	0.641	0.231	2.771	0.006	0.188	1.095
Big box store	-0.837	0.305	-2.739	0.006	-1.435	-0.238
Discount store	0.480	0.230	2.090	0.037	0.030	0.931
Income	-0.121	0.062	-1.953	0.050	-0.242	0.000
Clothing Del.	0.201	0.076	2.656	0.008	0.053	0.350

For clothing products, the results may indicate that the fee may affect deliveries lower income households in large urban areas that are cost conscious and tend to order frequently.

6.2.4 Personal care, beauty products

For personal care/beauty products the results of the logistics model are presented in Table 6.4.The number of personal products deliveries is highly significant. There are two additional significant variables.

- If the household visits discount stores the probability of decreasing deliveries after a fee is introduced *increases.*

- If having product options is considered NOT important then the probability of decreasing deliveries after a fee is introduced *increases*.

Table 6.4: Personal products logistic regression results

Variable	Coef.	Std. err.	*z*	$P > \|z\|$	[0.025	0.975]
Intercept	-1.556	0.231	-6.746	0.000	-2.008	-1.104
Discount Store	0.444	0.222	2.004	0.045	0.010	0.879
Options Not Imp.	0.812	0.374	2.170	0.030	0.078	1.545
Pers. Prod. Del.	0.318	0.086	3.704	0.000	0.150	0.486

For personal products the results seem to indicate that the fee may affect deliveries to cost conscious households that do not value having multiple options and tend to order frequently.

6.2.5 Miscellaneous products

For miscellaneous products the results of the logistics model are presented in Table 6.5. The number of miscellaneous products deliveries is NOT significant. There are three significant variables.

- If the household visits supermarkets or small/local stores the probability of decreasing deliveries after a fee is introduced *increases.*

- If comparing products is considered NOT important then the probability of decreasing deliveries after a fee is introduced *increases*.

Table 6.5: Misc. products logistic regression results

Variable	Coef.	Std. err.	*z*	$P > \|z\|$	[0.025	0.975]
Intercept	-2.947	0.579	-5.093	0.000	-4.081	-1.813
Supermarkets	1.605	0.543	2.956	0.003	0.541	2.668
Small Stores	0.491	0.194	2.524	0.012	0.110	0.872
Compare Not Imp.	0.846	0.280	3.025	0.002	0.298	1.394
Misc. Prod. Del.	0.089	0.069	1.291	0.197	-0.046	0.225

For miscellaneous products the results seem to indicate that the fee may affect deliveries to households that have alternative shopping options (supermarkets, small shops) and when comparing products is considered not important.

6.2.6 Home products/appliances/décor

For home products/appliances/décor the results of the logistics model are presented in Table 6.6.The number of personal products deliveries is highly significant. There are three significant variables.

- If the household visits supermarkets or discount stores the probability of decreasing deliveries after a fee is introduced *increases.*

- If the household has more members age 65+ then the probability of decreasing deliveries after a fee is introduced *decreases*.

Table 6.6: Home products logistic regression results

Variable	Coef.	Std. err.	*z*	*P* > |*z*|	[0.025	0.975]
Intercept	-2.467	0.637	-3.871	0.000	-3.716	-1.218
Discount	0.653	0.270	2.422	0.015	0.124	1.181
Supermarkets	1.183	0.585	2.023	0.043	0.037	2.329
Members 65+	-0.465	0.202	-2.306	0.021	-0.861	-0.070
Home Prod. Del.	0.169	0.097	1.747	0.081	-0.021	0.350

For home products, the results seem to indicate that the fee may affect deliveries to households that have alternative shopping options (supermarkets, discount stores). There is not a clear or single explanation for the significance of the variable related to household members 65+. It is possible that is related to mobility issues or other unmeasured factors for this subpopulation.

6.2.7 Electronic products/accessories

For electronic products and accessories, the results of the logistics model are presented in Table 6.7. The number of electronic products deliveries not significant. There are two significant variables.

- If the household visits small/local or discount stores the probability of decreasing deliveries after a fee is introduced *increases*

Table 6.7: Electronic products logistic regression results

Variable	Coef.	Std. err.	*z*	*P* > |*z*|	[0.025	0.975]
Intercept	-1.630	0.307	-5.313	0.000	-2.231	-1.029
Discount Store	0.746	0.268	2.783	0.005	0.221	1.271
Small Store	0.644	0.274	2.352	0.019	0.107	1.180
Electron.Pr. Del.	0.055	0.093	0.593	0.553	-0.127	0.238

6.2.8 Pet products

For pet products the results of the logistics model are presented in Table 6.8. The number of pet deliveries is highly significant, in fact it is the only significant variable.

- If the household has more pet product deliveries the probability of decreasing deliveries after a fee is introduced *increases.*

Table 6.8: Pet products logistic regression results

Variable	Coef.	Std. err.	*z*	*P* > |*z*|	[0.025	0.975]
Intercept	-1.130	0.139	-8.124	0.000	-1.402	-0.857
Pet Prod. Del.	0.304	0.075	4.034	0.000	0.156	0.451

6.2.9 Pharmacy products

For pharmaceutical products the results of the logistics model are presented in Table 6.9. The number of pharmaceutical products deliveries is not significant. There are two significant variables.

- If the respondent has age 65+ the probability of decreasing deliveries after a fee is introduced *decreases*
- If having more options is considered important then the probability of decreasing deliveries after a fee is introduced *decreases*.

Table 6.9: Pharmacy products logistic regression results

Variable	Coef.	Std. err.	*z*	*P* > |*z*|	[0.025	0.975]
Intercept	-0.603	0.250	-2.416	0.016	-1.092	-0.114
Age 65+	-1.628	0.754	-2.158	0.031	-3.106	-0.150
More Options	-0.692	0.265	-2.610	0.009	-1.211	-0.172
Pharm. Prod. Del.	0.111	0.099	1.124	0.261	-0.082	0.304

The results seem intuitive, for pharmacy products seems reasonable that access to more options is valuable and that the group of people age 65+ value more the convivence of home deliveries for pharmaceutical products.

6.2.10 Other products (sports equipment, hobbies, toys, etc.)

For other products the results of the logistics model are presented in Table 6.10. The number of other products deliveries is not significant. There is only one significant variable: visiting discount stores.

Table 6.10: Sports and other products logistic regression results

Variable	Coef.	Std. err.	*z*	*P* > |*z*|	[0.025	0.975]
Intercept	-1.265	0.222	-5.701	0.000	-1.700	-0.830
Discount Stores	0.647	0.262	2.470	0.014	0.134	1.161
Sports Prod. Del.	-0.010	0.080	-0.119	0.906	-0.166	0.147

- If the household visits discount stores the probability of decreasing other product deliveries after a fee is introduced *increases.*

6.3 SUMMARY

The results of the logistic models seem reasonable and introduce many insights that are novel and cannot be compared to previous findings in the literature.

The analysis of the impact of individual variables is done assuming that the impact of one independent variable on the dependent variable is estimated assuming that all other variables in the model remain unchanged – i.e. ceteris paribus. This assumption is violated if the regressors are not independent. In the regression results presented in this section

VIF values have been quantified, and the stability of the estimated coefficients has been checked to ensure that the interpretations are valid.

These are some of the key insights spotted in the modeling results:

- There are some common or repeated variables but in general each product category has its own unique profile regarding sensitivity to delivery fees.

- In all cases the signs of the significant variables seem intuitive, and they are always consistent if the same variable is found in more than one model which is a sign of the consistency of the data.

- Only for a few products (clothing, personal/beauty products, and pet products) the number of deliveries is a significant variable. These products seem to be more discretionary than food and groceries.

- A consistent result is that being located in a large urban area is a significant variable decreasing the frequency of deliveries for some products (groceries, food, clothing) with a fee. This result may be related easier access to good alternatives to e-commerce in large urban areas.

- Type of brick-and-mortar store visited seems to be important to explain how households may react to delivery fees. Visiting discount stores is the most repeated significant variable (for seven products) and there seems to be a strong indication that discount stores attract households that are more sensitive to delivery fees. Shopping in small/local stores – repeated three times – is also associated with more sensitivity to delivery fees.

- Overall, basic sociodemographic variables like income (clothing/shoes) and age (pharmaceutical and home products) are found in the models but it seems that using only sociodemographic variables to explain sensitivity to delivery fees is not enough to fully account for sensitivity to delivery fees.

7.0 MODELING DELIVERY RATES

This section presents the results of a model where delivery rate is the dependent variable, and the potential explanatory variables are all the socioeconomic and shopping variables that have been analyzed in previous sections. The dependent variable includes only observations from households that engage in e-commerce. In the first subsection the data is discussed, then negative binomial model is introduced, and finally the modeling results are discussed.

7.1 HOME DELIVERY DISTRIBUTION

The survey question best related to delivery rates is the following:

In a TYPICAL WEEK, approximately how many deliveries does your home receive? If unsure provide your best estimate *(range 0-20).*

The data provided by this type of question is typically modeled as count data. Traditionally, Poisson models have been used to model count data. In this section, a negative binomial model will be utilized.

A limitation of Poisson regression is that it assumes that the mean and variance are equal. The negative binomial model is more complex than the Poisson model, but it can account for overdispersion and highly skewed data. Overdispersion occurs when the variance of the data is higher than its mean. If overdispersion is not properly addressed can lead to the underestimation of standard errors and inflated test statistics.

The distribution of the count data is presented in Figure 7.1. It can be observed the distribution is right skewed with a mode of two and overdispersion.

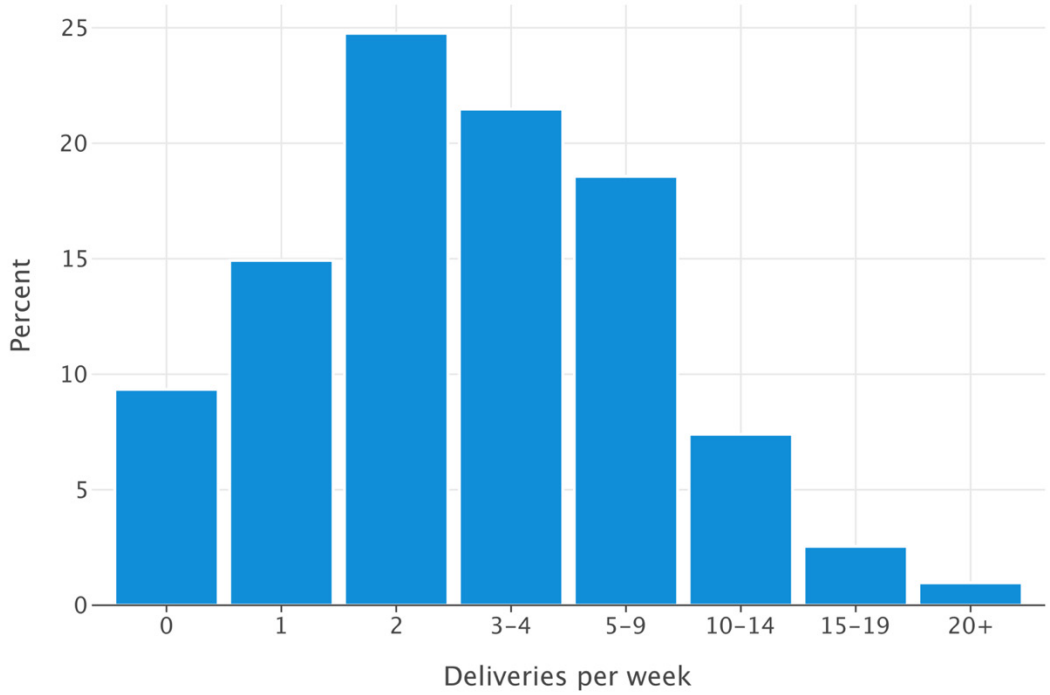

Figure 7.1: Deliveries per week (typical week)

7.2 NEGATIVE BINOMIAL REGRESSION BACKGROUND

Formally, if Y_i is a count response variable for observation i, and x_i is a vector of covariates then the Negative Binomial regression assumes:

$$Y_i \sim \mathbf{NB}(\mu_i, \theta)$$

where:

$$\mu_i = E[\, Y_i \mid x_i \,] = \exp(x_i^{\top}\beta)$$

The shape parameter is

$$\theta > 0$$

The variance is a function of the delivery rate μ and the shape parameter

$$\mathbf{Var}(Y_i \mid x_i) = \mu_i + \frac{\mu_i^2}{\theta}$$

The probability mass function (PMF) is:

$$P(Y_i = y_i) = \frac{\Gamma(y_i + \theta)}{y_i!\,\Gamma(\theta)}\left(\frac{\theta}{\theta + \mu_i}\right)^{\theta}\left(\frac{\mu_i}{\theta + \mu_i}\right)^{y_i}, \quad y_i = 0,1,2,..,n$$

The log-likelihood function (LLF) for n observations is:

$$l(\beta,\theta)=\sum_{i=1}^{n}\left[\log\Gamma\left(y_i+\theta\right)-\log\Gamma\left(y_i+1\right)-\log\Gamma\left(\theta\right)+\theta\log\left(\frac{\theta}{\theta+\mu_i}\right)+y_i\log\left(\frac{\mu_i}{\theta+\mu_i}\right)\right]$$

Where:

$$\mu_i=\exp(x_i^{\top}\beta)$$

The vector of parameters β are obtained by solving:

$$\left(\hat{\beta},\hat{\theta}\right)=\arg\max_{\beta,\theta}\mathrm{l}(\beta,\theta)$$

Solving this expression is equivalent to finding the vector of parameters β the maximizes the likelihood of the estimation or MLE parameters.

It is easy to see that Poisson regression is a special case of Negative Binomial regression when $\theta\rightarrow\infty$:

$$\mathbf{Var}(Y_i\mid x_i)=\mu_i+\frac{\mu_i^2}{\theta}$$

The shape parameter θ is sometimes expressed as the inverse of the dispersion parameter α:

$$\theta\ =\ 1/\alpha$$

In this case, if $\alpha\ =\ 0$ then the variance equals the mean (as in Poisson regression).

7.3 NEGATIVE BINOMIAL MODEL RESULTS

The results are provided in Table 7.1. The dependent variable is the number of weekly deliveries, and the potential explanatory variables are the socioeconomic and shopping variables that have been analyzed in previous sections. Only significant variables are presented in Table 7.1. The format of the table follows the standard presentation of statistical estimations: variable, coefficient, standard error, z value, probability of the z value, and the intervals of the confidence interval.

In all regressions, variable inflation factors (VIF) are quantified to ensure that levels are within recommended thresholds which ensures that the regression coefficients are not unreliable due to correlation among predictors. Regression model specifications are built manually one step at the time using the Bayesian Information Criteria (BIC) and checking the stability and consistency of successive regression results.

Table 7.1: Negative Binomial Model Statistics

Variable	Coef.	Std. err.	*z*	$P > \|z\|$	[0.025	0.975]
Intercept	0.403	0.133	3.044	0.002	0.144	0.663
# Online shoppers	0.216	0.037	5.832	0.000	0.143	0.288
# Online workers	0.102	0.035	2.904	0.004	0.033	0.171
Supermarkets visit	-0.429	0.095	-4.537	0.000	-0.614	-0.243
It is safer Imp.	0.222	0.056	3.955	0.000	0.112	0.332
Compare Imp.	0.225	0.058	3.879	0.000	0.111	0.339
Subs. Conv. Imp.	0.158	0.056	2.800	0.005	0.047	0.268
Amazon Subs.	0.311	0.075	4.149	0.000	0.164	0.458
Medical Subs.	0.248	0.066	3.778	0.000	0.119	0.376
HH Size 3+	0.059	0.021	2.796	0.005	0.018	0.101
HH Income 100k+	0.143	0.057	2.494	0.013	0.031	0.255
Age 35-44	0.167	0.068	2.440	0.015	0.033	0.300
Age 65+	-0.190	0.084	-2.269	0.023	-0.354	-0.026
alpha	0.290	0.028	10.347	0.000	0.235	0.345

7.3.1 Interpretation of the results

Unlike linear regression, the interpretation of the negative binomial coefficients is less direct because the model is non-linear. The coefficients in a negative binomial regression represent the change in the log of the expected count of the dependent variable for a one-unit increase in the independent variable, holding other variables constant. This is inferred from the formulation presented in the previous subsection.

A positive coefficient indicates that as the independent variable increases, the expected count of the dependent variable also tends to increase. A negative coefficient suggests that as the independent variable increases, the expected count of the dependent variable tends to decrease. But the increases and decreases are non-linear and related to the log of the expected count of the dependent variable.

The value of alpha indicates the degree of overdispersion. A larger alpha value suggests more overdispersion, while a statistically insignificant alpha value close to 0 indicates the data may be better modeled using a Poisson regression.

7.3.2 Analysis of the results

There are 12 significant variables which have been grouped to facilitate the interpretation.

- If the number of household members that usually spend time online shopping or working increases the expected number of deliveries *increases*. Note that the coefficient for shoppers is roughly double the coefficient for workers which signals the relative weight of the variables. These results are consistent with the distribution observed in the exploratory analysis of these variables.

- If the household visits supermarkets the expected number of deliveries *decreases*. This result is consistent with the distribution observed in the exploratory analysis of the variable associated to brick-and-mortar shopping.

- If safety, comparing products, or subscriptions are considered important the expected number of deliveries *increases*. This result is consistent with the distribution observed in the exploratory analysis of the attitudinal variables.

- If the household has Amazon or pharmaceutical subscriptions the expected number of deliveries *increases*. This result is consistent with the distribution observed in the exploratory analysis of the subscriptions variable.

- If the household has three or more members the expected number of deliveries *increases*. This result is consistent with the distribution observed in the exploratory analysis of the household variable.

- If the household income is $100,000 or higher the expected number of deliveries *increases*. This result is consistent with the distribution observed in the exploratory analysis of the income variable.

- If the respondent is in the 35-44 age group, the expected number of deliveries *increases* but if the respondent has age 65+ the expected number of deliveries *decreases*. These results are also consistent with the distribution observed in the exploratory analysis of the age variables.

7.3.3 Marginal effects

Marginal effects in negative binomial regression are interpreted as the change in the expected count of the outcome variable for a small increase in a predictor variable, while holding all other predictors constant. This interpretation is useful for understanding the effect of an explanatory variable on the rate deliveries. For a continuous predictor variable, the marginal effect is the derivative of the expected count with respect to that predictor.

Marginal effects are useful to interpret negative binomial coefficients because the relationship between predictors and the outcome is non-linear and it is difficult to directly interpret the coefficients themselves beyond the sign and relative magnitude. The model marginal effects at the mean values are presented in Table 7.2.

Table 7.2: Negative binomial marginal effects at mean values

Variable	Coef.	Std. err.	*z*	*P* > |*z*|	[0.025	0.975]
# Online shoppers	0.750	0.130	5.830	0.000	0.500	1.010
# Online workers	0.360	0.120	2.900	0.000	0.120	0.600
Use supermarkets	-1.500	0.330	-4.530	0.000	-2.150	-0.850
It is safer Imp.	0.780	0.200	3.950	0.000	0.390	1.160
Compare Imp.	0.790	0.200	3.880	0.000	0.390	1.180
Subs. Conv. Imp.	0.550	0.200	2.800	0.010	0.170	0.940
Amazon Subs.	1.090	0.260	4.160	0.000	0.570	1.600
Medical Subs.	0.870	0.230	3.770	0.000	0.420	1.320
HH Size 3+	0.210	0.070	2.790	0.010	0.060	0.350
HH Income 100k+	0.500	0.200	2.490	0.010	0.110	0.890
Age 35-44	0.580	0.240	2.440	0.010	0.110	1.050
Age 65+	-0.660	0.290	-2.270	0.020	-1.240	-0.090

7.3.4 Incident rate ratio

The Incidence Rate Ratio (IRR) is another measure that can be used to interpret the coefficients. The IRR provides the percentage change in the rate for a one-unit increase in the predictor and it is usually approximated by exponentiating the coefficients (the approximation works better for smaller coefficients). For example, the IRR for a -0.10 coefficient is calculated by exponentiating the coefficient (e^0.10 = 1.105) and this can be interpreted that for a one-unit increase in the independent variable the rate is expected to decrease by a factor of 1.105 (or 10.5%).

Table 7.3: Incident rate ratios

Variable	IRR
# Online shoppers	1.24
# Online workers	1.11
Use supermarkets	0.65
It is safer Imp.	1.25
Compare Imp.	1.25
Subs. Conv. Imp.	1.17
Amazon Subs.	1.36
Medical Subs.	1.28
HH Size 3+	1.06
HH Income 100k+	1.15
Age 35-44	1.18
Age 65+	0.83

7.4 SUMMARY

Overall, the results of the negative binomial model confirm some of the trends already observed in the exploratory analysis. The impacts of sociodemographic variables like age, household size, and income are also found in the literature though the specification of the variables may vary somewhat. However, most of the independent variables are attitudes, variables related to shopping characteristics, or variables related to exposure to e-commerce.

The analysis of the impact of individual variables is done assuming that the impact of one independent variable on the dependent variable is estimated assuming that all other variables in the model remain unchanged – i.e. ceteris paribus. This assumption is violated if the regressors are not independent. In the regression results presented in this section

VIF values have been quantified, and the stability of the estimated coefficients has been checked to ensure that the interpretations are valid.

It is worth noting that the variables that affect delivery rates are predominantly different from the variables that affect the sensitivity to potential delivery fees. This is an important finding that should inform future research efforts and policy decisions regarding e-commerce delivery fees.

8.0 MODELING DELIVERY RATES USING CENSUS DATA

This section presents the results of a model where delivery rate is the dependent variable, and the potential explanatory variables are those that can also be found in Census data. Therefore, all the attitudinal, e-commerce exposure, and shopping variables that have been analyzed in previous sections cannot be incorporated into the model. However, using the census data and a zero-inflated model it is possible to include all the households whether they engage in e-commerce and home deliveries or not. In the first subsection the data is discussed, then the zero-inflated negative binomial model is introduced, and finally the modeling results are discussed.

8.1 HOME DELIVERY DISTRIBUTION

The home delivery distribution utilizing all the households in the sample is presented in Figure 8.1. The households that do not engage in e-commerce have a zero-delivery rate and this explains the increase in the zero category. The need to use a zero-inflated model is given the large number of zero observations that cannot be accommodated by a negative binomial model where the mode of the distribution was two.

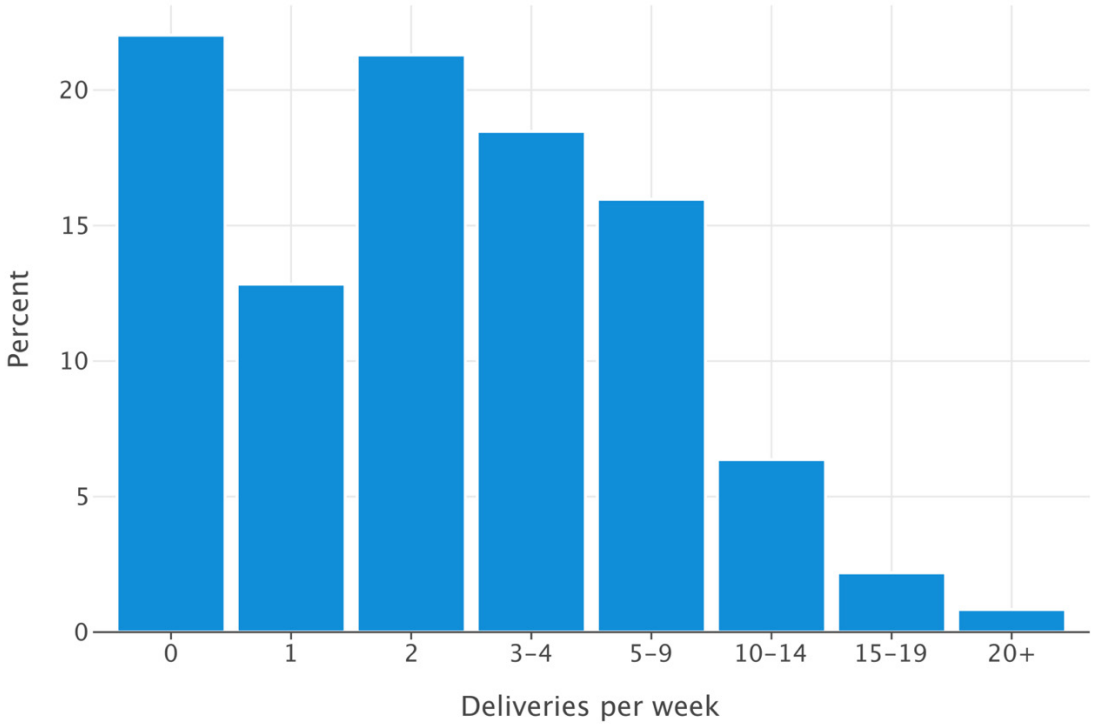

Figure 8.1: Deliveries per week (typical week) including all households

8.2 ZERO-INFLATED NEGATIVE BINOMIAL BACKGROUND

The Zero-Inflated Negative Binomial (ZINB) regression model is a statistical model used for count data (i.e., data representing the number of occurrences of an event) that exhibits two key characteristics: overdispersion and excess zeros. Overdispersion means the variance is higher than the mean (already confirmed in the previous section while the excess of zeros refers to having more zero counts than a standard negative binomial count model would predict.

ZINB models assume that the excess zeros are generated by a separate process from the count values and that the excess zeros can be modeled independently. The ZINB model combines two components: the negative binomial part models the count values, and the zero-inflation component models the excess zeros.

More formally, the Zero-Inflated Negative Binomial (ZINB) model is a mixture model combining a zero-generating process and a count process. For each observation i, let Y_i be the count outcome, x_i be the vector of covariates for the count model, and $\boldsymbol{z}_i$ the vector of covariates for the zero-inflation model.

8.2.1 Zero-generating process (structural zeros)

Let π_i be the probability that observation i comes from a process that always results in zero. This probability is modeled using a link function (e.g., logit or probit):

$$\pi_i = P(\textbf{structural zero}_i) = F(z_i^\top \gamma)$$

where $F(\cdot)$ is the cumulative distribution function (CDF) of the chosen distribution (logistic for logit, standard normal for probit), and γ is the vector of coefficients for the zero-inflation model.

8.2.2 Count process (sampling zeros and positive counts)

With probability $1 - \pi_i$, the count Y_i is generated from a Negative Binomial distribution with mean μ_i and dispersion parameter $\alpha > 0$. The mean μ_i is typically modeled using a log link function:

$$\log(\mu_i) = \mathbf{x}_i^\top \boldsymbol{\beta} \Longrightarrow \mu_i = \exp(\mathbf{x}_i^\top \boldsymbol{\beta})$$

where β is the vector of coefficients for the count model. The probability mass function (PMF) of the Negative Binomial distribution is:

$$P(Y_i = y_i|\mu_i, \alpha) = \frac{\Gamma(y_i + 1/\alpha)}{\Gamma(y_i + 1)\Gamma(1/\alpha)}\left(\frac{1}{1 + \alpha\mu_i}\right)^{1/\alpha}\left(\frac{\alpha\mu_i}{1 + \alpha\mu_i}\right)^{y_i}, \quad y_i = 0,1,2, \dots, n$$

8.2.3 Combined Model

The probability of observing a count y_i in the ZINB model is:

$$P(Y_i = y_i|x_i, z_i, \beta, \gamma, \alpha) =$$

$$\pi_i + (1 - \pi_i)P(Y_i = 0|\mu_i, \alpha) \qquad \textbf{if } y_i = 0$$

$$(1 - \pi_i)P(Y_i = y_i|\mu_i, \alpha) \qquad \textbf{if } y_i > 0$$

Where:

$$P(Y_i = 0|\mu_i, \alpha) = \left(\frac{1}{1 + \alpha\mu_i}\right)^{1/\alpha}$$

8.2.4 Estimation

The parameters of the ZINB model, β, γ, and α, are typically estimated using the method of Maximum Likelihood Estimation (MLE). For n independent observations, the likelihood function $L(\beta, \gamma, \alpha \mid y, X, Z)$ is the product of the probabilities for each observation:

$$L(\beta, \gamma, \alpha) = \prod_{i=1}^{n} P(Y_i = y_i|x_i, z_i, \beta, \gamma, \alpha)$$

The log-likelihood function $l(\beta, \gamma, \alpha)$ is the natural logarithm of the likelihood function:

$$l(\beta, \gamma, \alpha) = \log\big(L(\beta, \gamma, \alpha)\big) = \sum_{i=1}^{n} \log\big(P(Y_i = y_i|x_i, z_i, \beta, \gamma, \alpha)\big)$$

Specifically, for each observation i:

$$log\big(\pi_i + (1 - \pi_i)P(Y_i = 0|\mu_i, \alpha)\big) \qquad \textbf{if } y_i = 0$$

$$log(1 - \pi_i)P(Y_i = y_i|\mu_i, \alpha) \qquad \textbf{if } y_i > 0$$

The maximum likelihood estimates $\hat{\beta}$, $\hat{\gamma}$, $\hat{\alpha}$ are obtained by maximizing the log-likelihood function with respect to the parameters. This is typically done using numerical optimization

algorithms such as Newton-Raphson, BFGS, or other gradient-based methods. These algorithms iteratively update the parameter estimates until convergence is achieved.

The ZINB allows for more general data distributions but at the cost of higher complexity and longer or more difficult numerical convergence.

8.3 RESULTS OF THE ZINB MODEL

Of the household level variables that are useful to model home deliveries two are readily available from US census: income and household size. The results of the ZINB model estimation using income and household size are shown in Table 8.1. The format of the table follows the standard presentation of statistical estimations: variable, coefficient, standard error, z value, probability of the z value, and the intervals of the confidence interval. The main difference is that there are two types of variables: inflated variables for the binomial part (ZI) of the model and count variables for the count (NB) part of the model.

Table 8.1: ZINB model results

Variable	Coef.	Std. err.	z	$P > \|z\|$	[0.025	0.975]
Inflate Intercept	-0.348	0.497	-0.701	0.483	-1.321	0.625
Inflate Income	-0.576	0.164	-3.512	0.000	-0.897	-0.254
Inflate HH Size	-0.233	0.177	-1.315	0.188	-0.579	0.114
Intercept	0.368	0.107	3.447	0.001	0.159	0.577
Income	0.082	0.019	4.231	0.000	0.044	0.120
HH Size	0.205	0.024	8.563	0.000	0.158	0.252
alpha	0.573	0.059	9.793	0.000	0.459	0.688

8.3.1 Interpretation of the coefficients

The coefficients should be interpreted separately. For the inflated coefficients the interpretation is similar to the binomial regression coefficients: change in the variable should be interpreted as changes is the log-odds of the outcome. A positive coefficient indicates that as the predictor variable increases, the log-odds of the outcome (having zero deliveries) occurring also increase. Conversely, a negative coefficient means the odds of the outcome decrease with an increase in the predictor.

The interpretation of the count coefficients should be interpretated as in the binomial regression. The coefficients in a negative binomial regression represent the change in the log of the expected count of the dependent variable for a one-unit increase in the independent variable, holding other variables constant. A positive coefficient indicates that as the independent variable increases, the expected count of the dependent variable also tends to increase. A negative coefficient suggests that as the independent variable increases, the expected count of the dependent variable tends to decrease. The interpretation of alpha does not change either.

8.3.2 Analysis of the results

In the inflated part income is the only significant variable and has a negative coefficient.

- If household income increases the probability of having a zero-delivery household *decreases*.

In the count part both income and household size are significant variable and they both have positive coefficients.

- If the household size increases the expected number of deliveries *increases*.
- If the household income increases the expected number of deliveries *increases*.

As expected, alpha is positive and significant. All the signs are as expected from the literature review and previous analysis.

8.3.3 Applying the results

To apply the ZINB results to the population of Oregon it is necessary to first estimate the group sizes for Oregon. US Census (US Census, 2021) provides data for number of households in different income groups or brackets, see Table 8.2.

Table 8.2: Oregon Households by income

Interval	Number HHs	Margin of Error
Less than $10000	87,214	5,520
$10000–$14999	59,883	4,223
$15000–$19999	52,226	3,591
$20000–$24999	59,882	4,916
$25000–$29999	49,612	4,034
$30000–$34999	58,964	4,396
$35000–$39999	57,422	3,937
$40000–$44999	62,775	3,890
$45000–$49999	52,845	4,160
$50000–$59999	117,595	5,447
$60000–$74999	163,401	7,354
$75000–$99999	236,882	7,380
$100000–$124999	187,466	6,577
$125000–$149999	135,333	6,128
$150000–$199999	164,192	6,084
$200,000 or more	206,358	7,269

The Tables present not only the number of households but also the margin of error of the estimate. A similar table (with estimates and margin of errors) can be obtained for household size but disaggregated into family and non-family groups.

To apply the ZINB model it is necessary to have the joint distribution of household sizes and incomes. An estimation of this distribution can be obtained using US Census PUMS dataset (US Census, 2023). The estimated distribution (percentages) of households by income and household size is shown below in Table 8.3.

Table 8.3: Oregon Households by Income and HH size (percentages)

Income Interval	1	2	3	4	5	6+
Less than $14999	5.4	1.5	0.5	0.3	0.1	0.1
$15000–$24999	4.2	1.9	0.6	0.3	0.1	0.1
$25000–$49999	7.7	7.0	2.0	1.3	0.7	0.4
$50000–$74999	4.8	7.3	2.3	1.7	0.8	0.6
$75000–$99999	2.4	5.7	2.3	1.7	0.8	0.5
$100000–$149999	1.9	7.2	3.5	2.9	1.2	0.7
$150000–$199999	0.6	3.2	1.7	1.6	0.6	0.4
$200,000 or more	0.7	3.6	2.0	2.0	0.8	0.5

Applying the model, it is possible to estimate as a preliminary result that a household delivery fee of $0.50 in Oregon would likely bring a weekly revenue of over two million dollars. However, the estimation of the confidence intervals is beyond the scope of this research for several reasons. The estimation of the margin of errors of the joint income and household distribution is not trivial. Additionally, the variance covariance matrix of the of the ZINB model should be used to estimate confidence intervals and then apply a non-trivial and computationally expensive MC (Montecarlo) simulation process to the previous data. But there are other important aspects that should be analyzed: fee implementation scenarios (for example fee value and exceptions), seasonal variation, e-commerce growth projection, and economic uncertainties (growth, impact of tariffs). In addition, a follow up survey is strongly recommended to quantify the impact of delivery fees on delivery rates.

8.4 SUMMARY

A zero-inflated negative binomial model for home deliveries was estimated using income and household size variables and the results are intuitive as expected. The application of the model to census data was discussed as well as revenue estimation and sources of uncertainty. A follow study is required to analyze potential delivery fee implementation scenarios and to estimate confidence intervals.

9.0 FAIRNESS CONCEPTS AND FEE IMPACT QUANTIFICATION

Transportation fees and taxes, depending on how they are structured, can have different impacts on socioeconomic groups. This section presents a short overview of fairness principles and a general characterization of the fairness of a flat delivery fee. In the second part of this section there is quantification of the impact of a flat delivery fee in relation to gas taxes, distance traveled, household income, and poverty income levels.

9.1 FAIRNESS OF TRANSPORTATION FEES AND TAXES

Collecting and spending revenue for transportation regularly generates political debates over fairness, specifically concerning who should pay, how much, and where revenues should be spent. Concerns about transportation finance equity are not new and have historically played a role in shaping funding mechanisms (TRB, 2011).

9.1.1 Basic Principles to Assess Fairness

The literature has distinguished different principles, elements, or factors that determine the fairness of a transportation fee or tax (TRB, 2011), and these principles are useful to frame policy discussions or fairness analysis.

- Horizontal Equity: This principle indicates that individuals in similar situations should be treated similarly. In transportation, this means that two people driving the same type of vehicle for the same distance on the same road, or using the same transportation service, should ideally pay comparable fees or taxes.
- Vertical Equity: This principle indicates that individuals in different situations should be treated differently, with those who have a greater ability to pay contributing more. A transportation fee or tax is considered more vertically equitable if it places a proportionally smaller burden on lower-income households and a proportionally larger burden on higher-income households. For example, public transit reduced fares for low-income households is an example of vertical equity. The "Ability to Pay" principle is a more general principle that indicates that taxes and fees should be levied based on an individual or household's financial capacity, regardless of their direct use of a specific service, justifying even zero taxes or fees for some groups.
- User Pays Principle: This principle argues that those who directly benefit from a transportation service or infrastructure should be the ones to pay for it. Transportation tolls can be justified using this principle because they directly link payment to usage. This principle is related to horizontal equity, but these principles are not equivalent because the "user pays principle" is about who pays for what

they use, while "horizontal equity" is about ensuring that similar people or groups are treated the same by the tax or fee system.

- Cost Internalization: This factor relates to fairness in terms of accountability for the negative costs imposed on society by certain transportation choices, such as pollution, congestion, and noise. The principle here is that those who create more negative externalities should bear more of the cost of the externalities. Higher registration fees for high-emission vehicles or higher taxes for dirtier fuels are examples of this principle.
- Geographic Equity: This considers whether the distribution of transportation costs and benefits is fair across different geographic areas, such as urban versus rural regions. It involves ensuring that transportation funding supports the diverse needs of all geographic areas and does not disproportionately burden or benefit specific locations.
- Taxes and fees can also be discussed within the much broader principle of "Social Justice" that takes into account not only ability to pay but also includes historical disadvantages or systemic inequities and questions whether transportation policy and funding mechanisms foster social mobility and opportunities or whether perpetuate or alleviate historical or systemic injustices (Atkinson, 1983).

9.1.2 Progressive and regressive fees and taxes

There are other terms that are closely intertwined with the concepts of vertical and horizontal equity and often used interchangeably. The term progressive fee or tax describes the specific tax structure that implements vertical equity principle by imposing higher tax rates on higher incomes. A similar analogy can be used to describe the relationship between horizontal equity and a regressive tax or fee structure. For example, a flat gas tax applies the principle of horizontal equity because the tax amount is the same for all individuals and it is also regressive because the tax amount is independent of the income of the buyer.

In later sections of this draft report data analysis and modeling are used to identify the type of households that would pay a higher amount of delivery fees in relation to their household income and discuss issues related to the fairness of a potential household delivery fee.

9.2 GENERAL CHARACTERIZATION OF THE FAIRNESS OF A FLAT DELIVERY FEE

This subsection analyzes how a flat e-commerce delivery fee, charged per delivery, aligns with or conflicts with each of the principles of fairness.

9.2.1 Horizontal Equity

A flat e-commerce delivery fee generally aligns well with horizontal equity. If two individuals, regardless of their income or the value of their order, receive a delivery service, they both pay the same flat fee for that service. In this sense, "equals" (those receiving the same service) are treated "equally" in terms of the direct cost of the delivery fee.

9.2.2 Vertical Equity

A flat e-commerce delivery fee tends to be regressive and therefore conflicts with vertical equity. Since the fee is a fixed amount per delivery, it consumes a larger percentage of income from a lower-income individual compared to a higher-income individual. For example, a $1 delivery fee is a much more significant financial burden for someone with a low disposable income than for someone with a high income. It does not differentiate based on the customer's ability to pay.

9.2.3 Benefits Received (User Pays Principle)

A flat e-commerce delivery fee generally aligns with the User Pays Principle. The individual receiving the delivery service is directly paying for that specific service. The fee is a direct charge for the benefit of having goods transported to their doorstep.

9.2.4 Cost Internalization

A flat e-commerce delivery fee can partially contribute to cost internalization, but its effectiveness depends on what costs it is designed to cover. It is implausible that a set flat fee can properly account for externalities like increased traffic congestion, air pollution from delivery vehicles, or noise in residential areas.

9.2.5 Geographic Equity

A flat e-commerce delivery fee can conflict with geographic equity. If the fee is the same regardless of distance or location, it might disproportionately benefit those in more remote or less accessible areas (where the actual cost of delivery or the utilization of roadway infrastructure in terms of miles is higher) at the expense of those in denser, more easily served areas with shorter delivery trips.

9.2.6 Other aspects: transparency and choice

The transparency and accountability of a flat e-commerce delivery fee can vary. If the fee is clearly stated upfront and customers understand it's for the delivery service, it's transparent. However, if the revenue from these fees is not clearly linked to specific improvements in highway infrastructure related to e-commerce access and deliveries, then there could be a decrease in terms of perceived transparency regarding the utilization of the collected funds.

The fairness of a flat delivery fee in relation to alternatives varies greatly depending on the household circumstances and location and whether households have good alternatives – i.e., choice – or they are captive consumers – for example, if discount stores are the only viable option. For many, physical shopping at brick-and-mortar stores is a viable alternative, making the delivery fee a choice. However, for individuals with limited mobility, those in remote areas, or those without personal vehicles, e-commerce delivery might be a necessity rather than a convenience. In such cases, a flat fee can be seen more as an unavoidable cost.

9.3 QUANTIFYING DELIVERY FEE IMPACTS

A flat delivery fee is regressive. In this section, the goal is the goal is to quantify its regressivity in terms of household income and compare it to other transportation costs, such as fuel costs.

9.3.1 Delivery fee as a sales tax

A flat delivery fee can be compared to a sales tax. The impact of the fee increases rapidly for low-value orders as shown in the table below assuming a flat delivery fee of $0.50. A flat fee may foster order consolidation but may reduce demand for categories that have low value.

Table 9.1: Delivery fee as a sales tax

Order Cost	Sales Tax
$ 10	5.0%
$ 20	2.5%
$ 30	1.7%
$ 40	1.3%
$ 50	1.0%

9.3.2 Delivery fee as gasoline cost

Many shoppers have the option to drive to a store or to order online. To visualize the tradeoffs among distance traveled, fuel efficiency, and a flat $0.50 delivery fee the following table presents the breakeven distance (in miles) assuming that cost of gasoline is $4 per gallon.

Table 9.2: Delivery fee – distance traveled tradeoffs

MPG	Distance
15	1.88
20	2.50
25	3.13
30	3.75
35	4.38

9.3.3 Delivery fee as percentage of income

There are Federal Poverty Guidelines (FPL) shown below for year 2024. In addition, 200% of the FPL is a commonly used measure, particularly in the context of determining eligibility for various government assistance programs and tax credits. It is frequently used as a threshold for identifying low-income individuals and families.

Table 9.3: Federal Poverty Guidelines 2024

HH size	100% Poverty	200% Poverty
1	$15,060	$30,120
2	$20,440	$40,880
3	$25,820	$51,640
4	$31,200	$62,400
5	$36,580	$73,160
6	$41,960	$83,920

To quantify the impact of fees, the median delivery rate of 3 deliveries per week or 156 deliveries per year is assumed, as well as a flat $0.50 delivery fee. The table below shows that delivery fee can account for up to 0.5% of annual income assuming 3 weekly deliveries.

Table 9.4: Delivery fee – distance traveled tradeoffs

HH size	100% Poverty	$78 as % annual income
1	$15,060	0.52%
2	$20,440	0.38%
3	$25,820	0.30%
4	$31,200	0.25%
5	$36,580	0.21%
6	$41,960	0.19%

What might be a negligible amount for a high-income individual can be a significant and prohibitive financial barrier for someone on a stringent budget. This disparity can force lower-income individuals to absorb disproportionate costs, reducing their capacity for other essential expenditures, or to forgo necessary goods altogether, limiting their access to competitive online prices.

9.3.4 Annual fee costs and subscription costs

Assuming a $0.50 flat delivery fee, a median delivery frequency of three deliveries per week, the annual cost of the delivery fee totals $78. For a household earning $30,000 annually, a $78 annual delivery fee represents approximately 0.26% of their income. In stark contrast, for a household with an income above $150,000, the burden is closer to negligible, less than 0.05% of their income.

To put the median delivery fee in perspective, $78 is less than the annual Amazon Prime subscription at $139. However, Amazon offers discounts for young adults (18 to 24) who pay $69 per year. Amazon also offers a discount, annual cost of $84, for lower-income individuals that are eligible if they provide proof of participation in SNAP or an eligibility letter for Medicaid (Amazon, 2025).

The plot below indicates that the proportion of households in the lowest income category – less than $15,000 – does not decrease when households have an Amazon subscription.

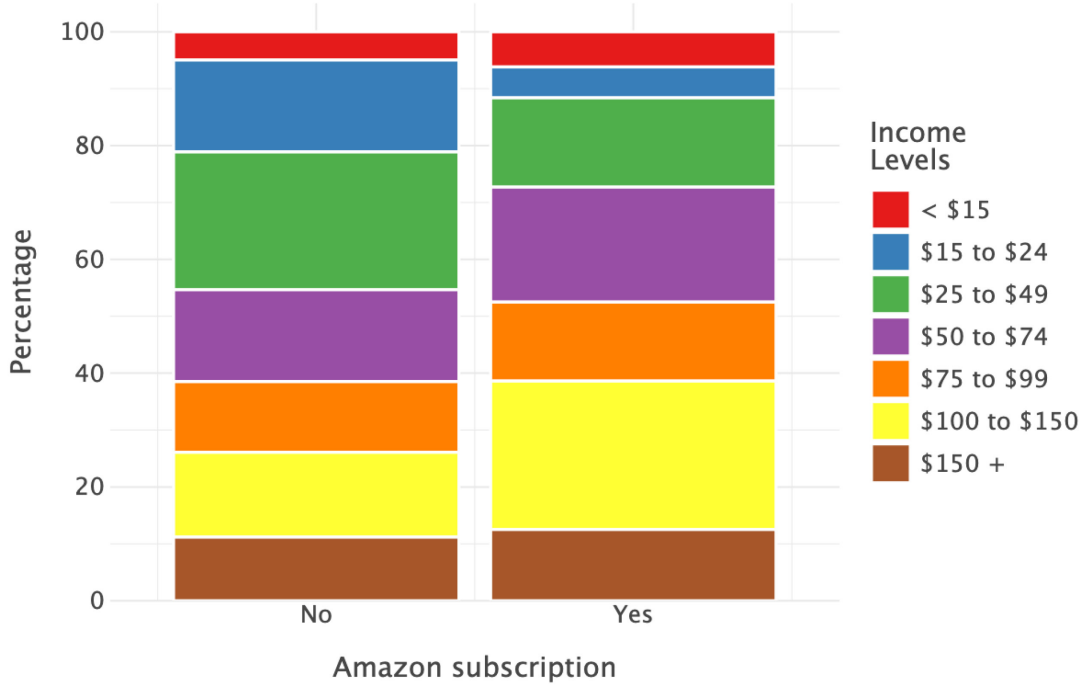

Figure 9.1: Income distribution by Amazon subscription

9.4 QUANTIFICATION OF FEE IMPACTS USING SURVEY DATA

This subsection uses survey data to quantify the impact of a potential $0.50 delivery fee as a cost that is shown in the graphs below as a percentage of household income.

9.4.1 Using federal poverty guidelines

The graph below shows the distribution using a KDE graph of the ratio between estimated annual delivery fees and income per household. The red curve is for households that qualify as low income according to the federal guidelines. It is possible to observe a long tail for the low-income households.

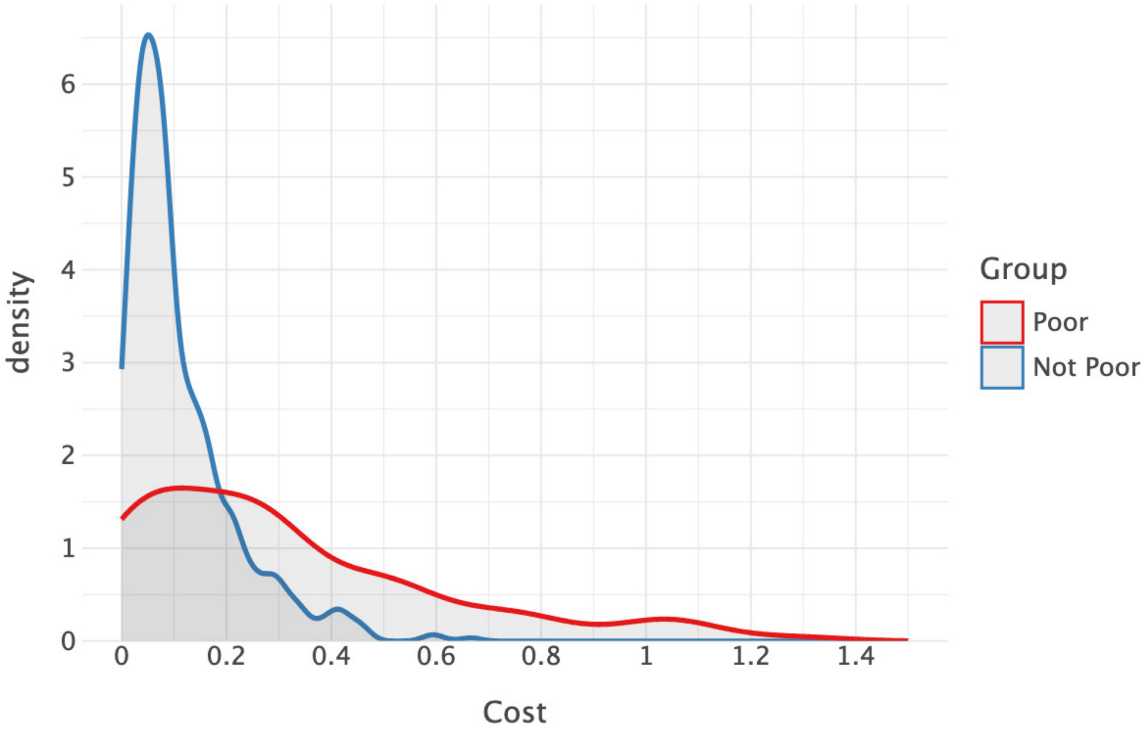

Figure 9.2: Income distribution by age group

A flat delivery fee is clearly regressive, and this can also be observed by analyzing the table with mean deliveries per income group. Income grows much faster than delivery rate by income.

Table 9.5: Deliveries per week by income group

Group	Income bracket	Mean delivery rate	Median delivery rate
Low	Less than $50k	3.0	2
Mid	$50k - $150k	4.3	3
High	More than $150k	5.3	4

The KDE graph with the three income groups determined using survey data is below and it is clear that the low-income group matches the curve observed in the previous graph for the poor group.

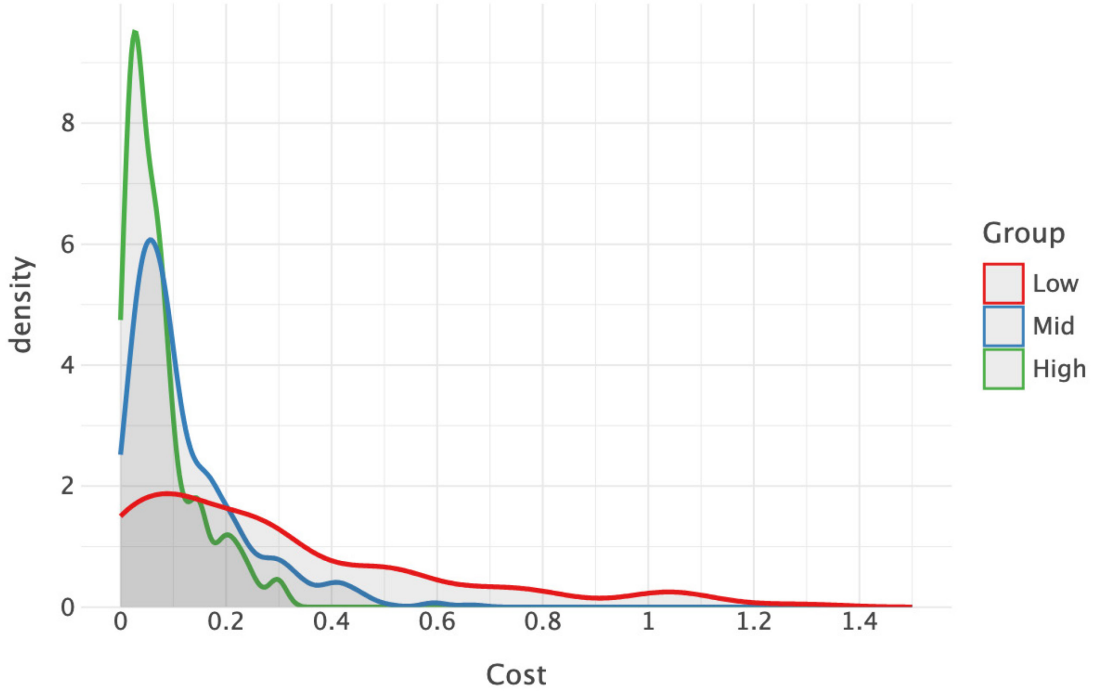

Figure 9.3: Income distribution by age group

9.5 SUMMARY

Different principles can be applied to analyze fairness. Studying whether a fee or tax is regressive, or progressive, is one of the most used approaches. The preliminary analysis presented in this section establishes that a flat delivery fee is regressive. The survey data show that mostly for low-income households that use home deliveries the annual cost of a $0.50 delivery will exceed 0.5% of the annual household income.

10.0 EXPLORATION OF SURVEY INCOME DISTRIBUTIONS

To understand why a fee is regressive, it is useful to first explore the distribution of income. This section documents descriptive results using basic socio-demographic variables that could be useful to analyze the fairness of a delivery fee. The survey question is always introduced first to facilitate the interpretation of the data.

10.1 INCOME

This subsection about income was already presented in the previous report, but it is repeated here because the other subsections are based on income distributions. The survey question and the groups related to income are the following:

Which category best represents last year's household income before taxes (2023 income)?

- Less than $15,000
- $15,000 to $24,999
- $25,000 to $49,999
- $50,000 to $74,999
- $75,000 to $99,999
- $100,000 to $150,000
- $150,000 to $200,000
- Greater than $200,000
- Prefer not to answer

Respondents were screened out if they preferred not to answer this question.

The distribution of respondents by income group is shown below and it has already been established that income is a significant positive variable regarding delivery frequency.

Figure 10.1: Survey income distribution

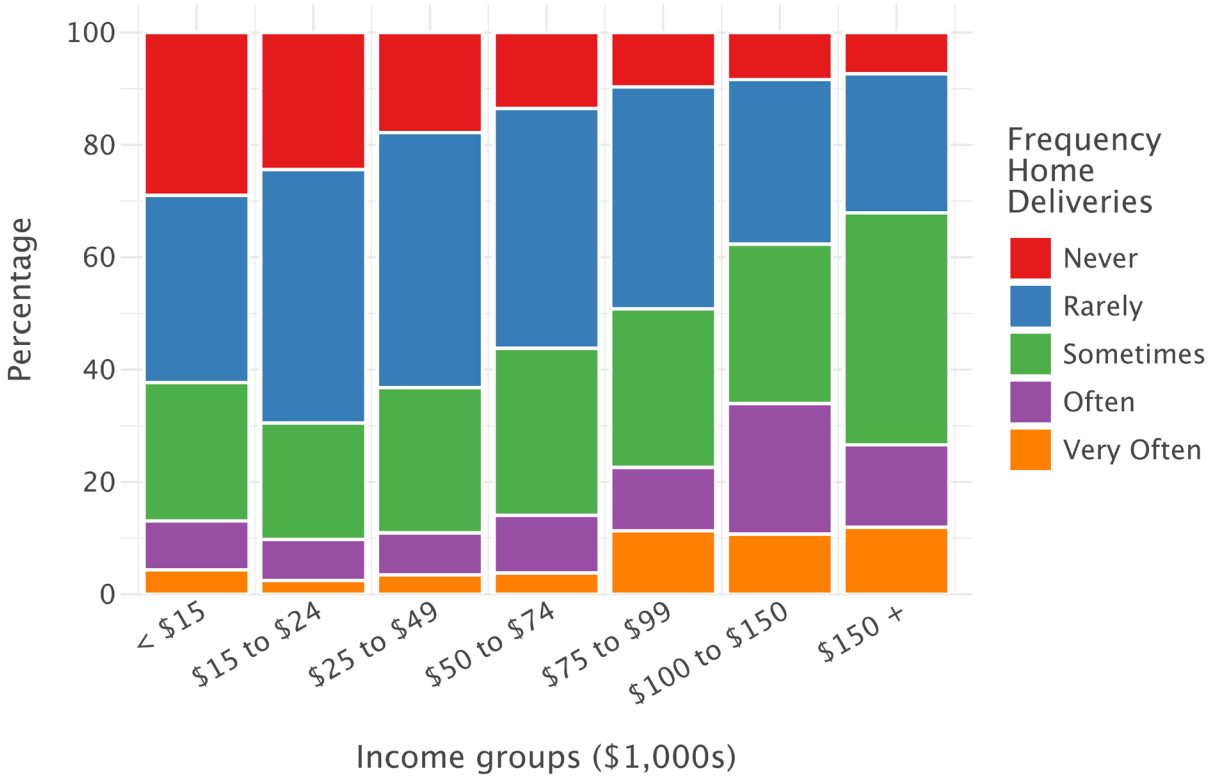

Figure 10.2: Home delivery frequency by income group

10.2 AGE

The survey question and the groups related to age are the following:

What is your age?

- Less than 18
- 18 to 24
- 25 to 34
- 35 to 44
- 45 to 54
- 55 to 64
- 65 to 74
- 75 or more
- Prefer not to answer

Respondents were screened out if they preferred not to answer this question. As shown in Figure 3.3 there is a non-linear relationship between age and income. The peak income is found for middle-aged adults between 45 and 54 years old. Young adults between 18 and 24 have the lowest income but tend to be more technologically savvy and likely to use more e-commerce deliveries than older adults.

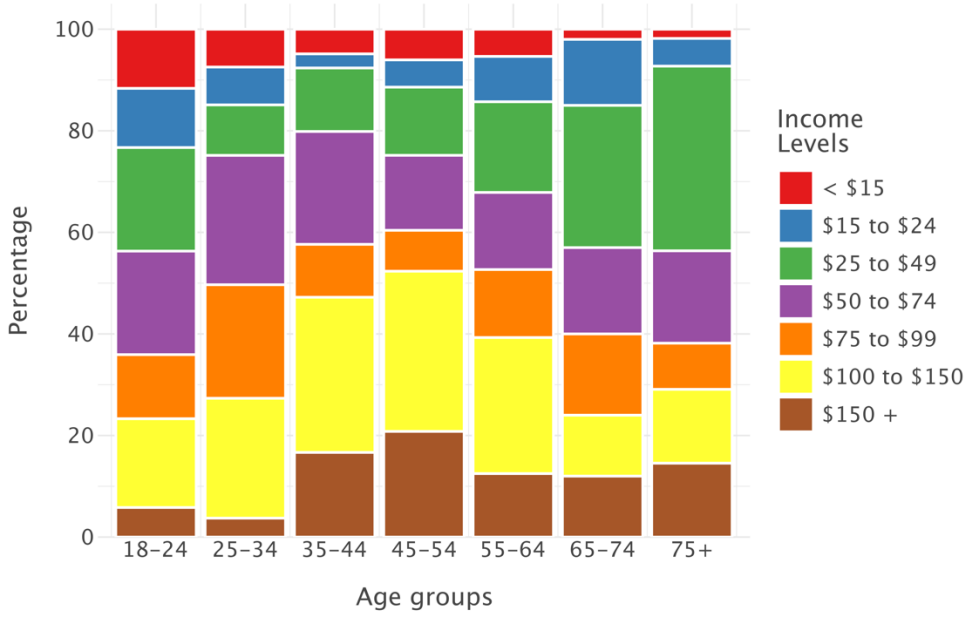

Figure 10.3: Income distribution by age group

Flipping the graph the same trends can be observed but perhaps with more clarity with respect to the income trend for 18–24-year-old group.

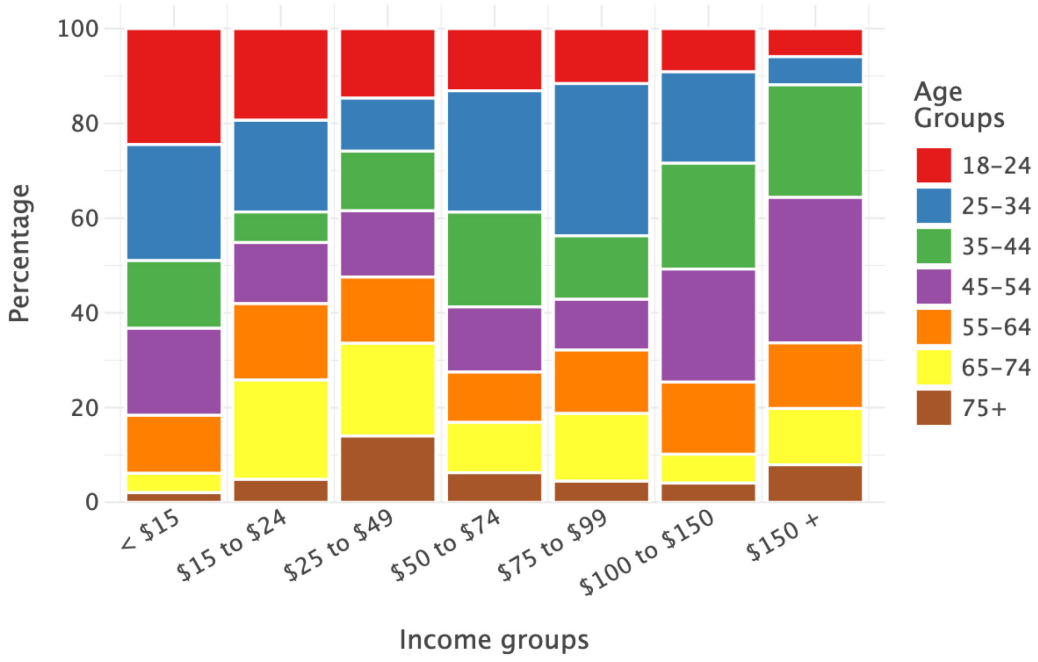

Figure 10.4: Age distribution by income group

10.3 GENDER

The survey question and the groups related to age are the following:

What is your gender?

- Female
- Male
- Non-binary
- Prefer not to answer

Respondents were screened out if they preferred not to answer this question. The non-binary category is not included in the analysis due to the low number of responses obtained for this category. Figure 3.5 indicates that in the survey males tend to have higher incomes than females.

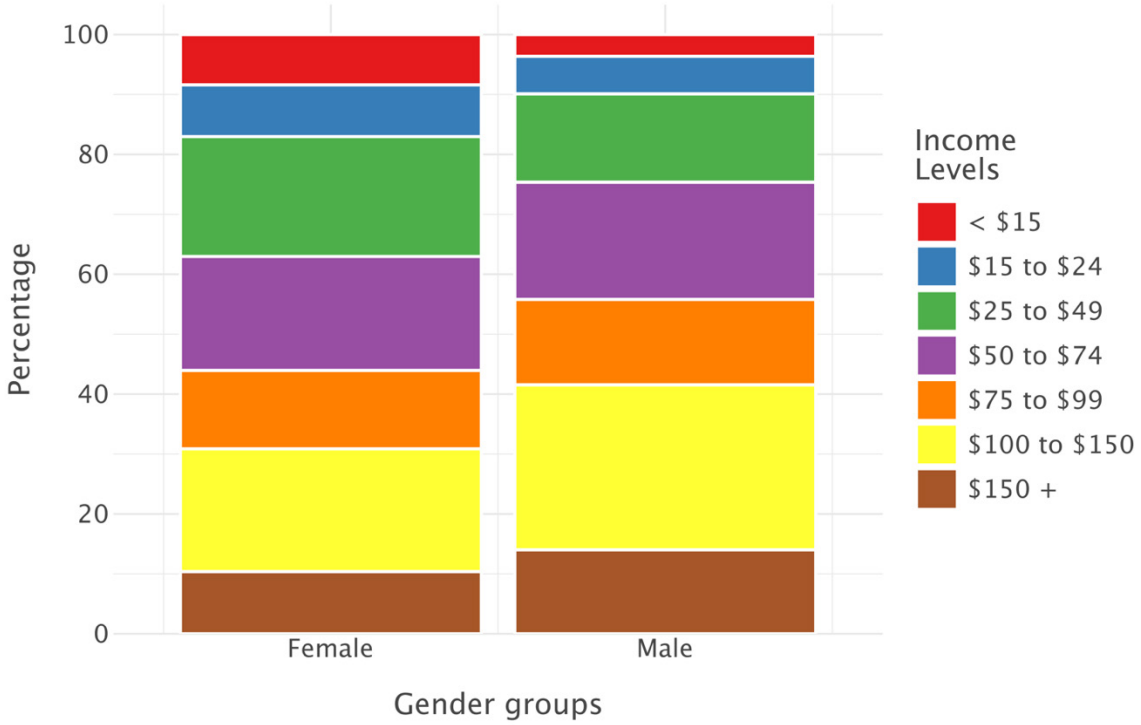

Figure 10.5: Income distribution by gender group

10.4 HOUSEHOLD SIZE

The survey question related to household size is the following:

How many people live in your household by age group? Provide a number for each group

- 0 to 17 years old
- 18 to 34 years old
- 35 to 64 years old
- 65 years old or more

Household size is obtained by summing the four groups and there is an adequate number of observations for household size in the range 1 to 6+. The distribution of household income by household size can be seen in Figure 3.9. There is not a clear trend across all income categories, but larger households tend to have more households in the over $100,000 annual income category. For households with an income below $25,000 or $50,000 the trend is not as clear.

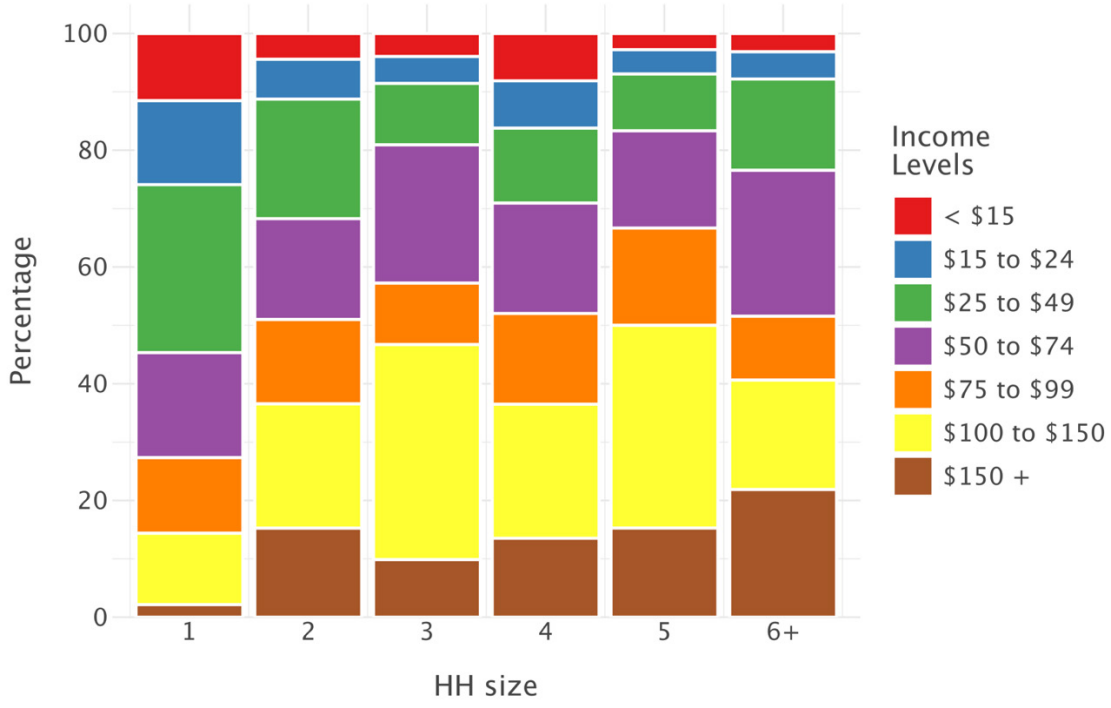

Figure 10.6: Income distribution by household size

10.5 RACE

The survey question for race is the following:

Which of the following options best describes the race or ethnicity of members of your household? *Select one or more options.*

- American Indian or Alaska Native
- Asian
- Black or African American
- Hispanic or Latino
- Native Hawaiian or Pacific Islander
- White
- Other

The income distribution by race can be seen in Figure 3.14 for all the groups with adequate number of responses. The group "Mixed White" is for households including "White" plus another race group. There is no clear trend in terms of race and income distribution in the survey responses.

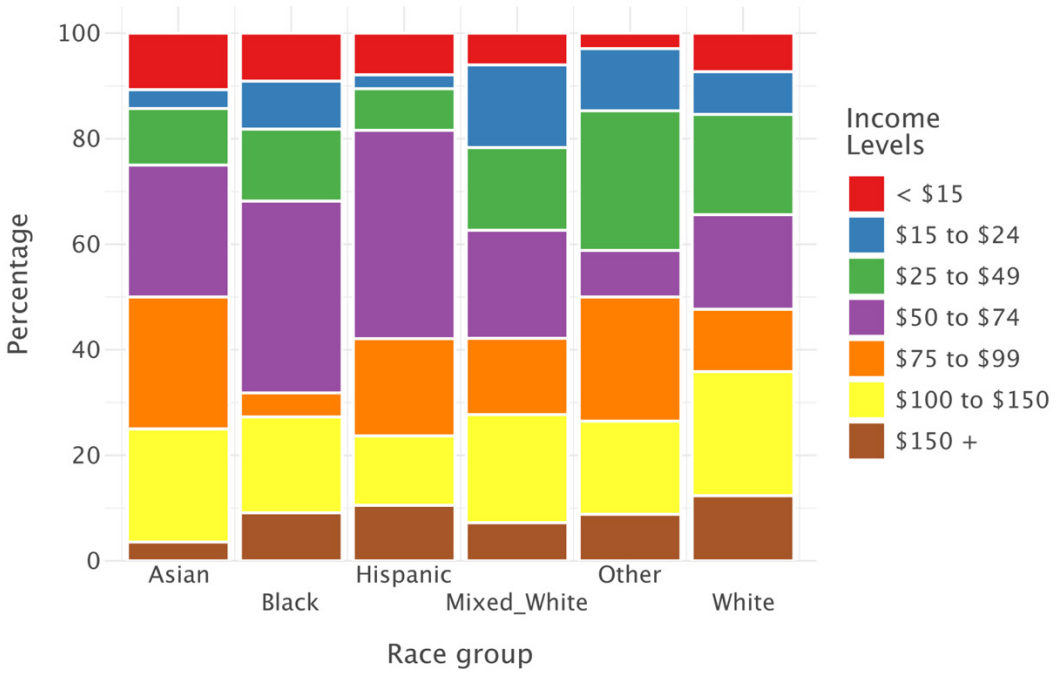

Figure 10.7: Income distribution by race groups

10.6 AREA TYPE

The survey question for area type is the following:

Which of the following best describes the area where you live?

- Large city
- Small town or city
- Suburban area
- Rural area

The distribution of income by area type can be seen in Figure 3.20. The differences seem small, but "Suburban area" shows a lower percentage of households with annual income below $25,000 and a higher percentage of households with annual income above $100,000.

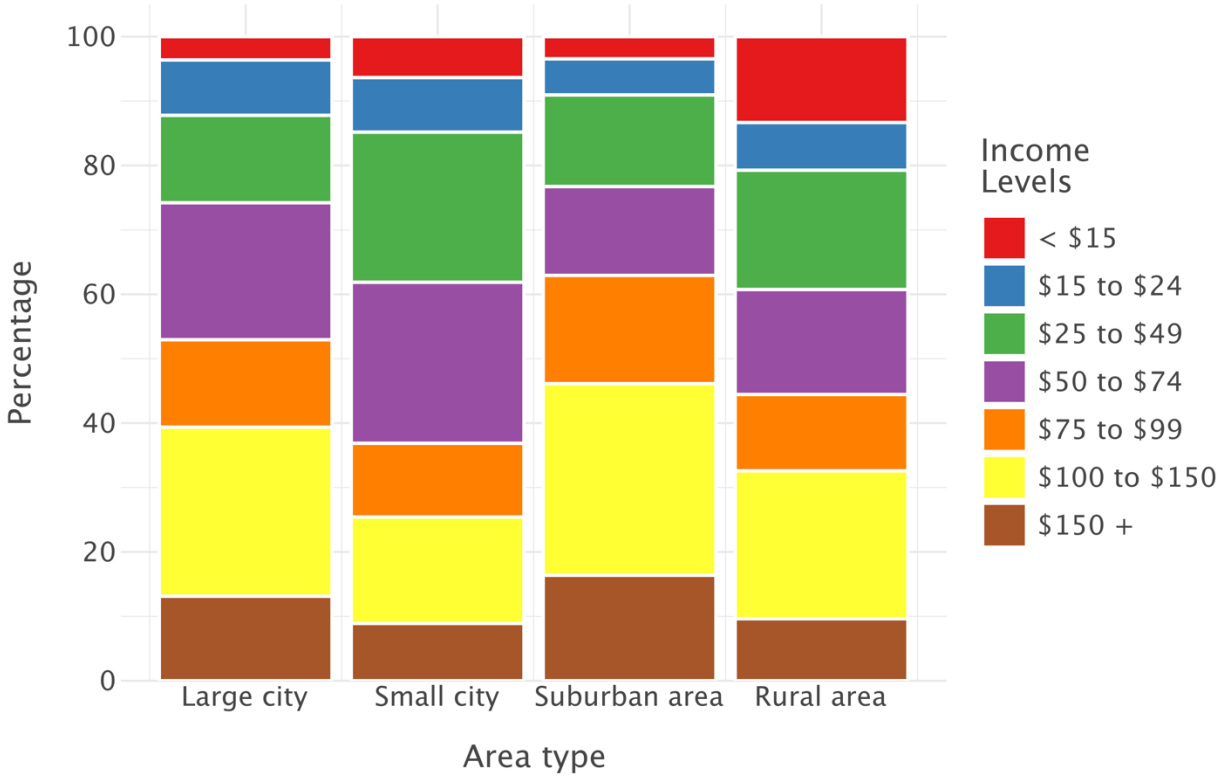

Figure 10.8: Income distribution by area type

10.7 HH MEMBERS WITH DISABILITIES

The survey question related to HH members with disabilities is the following:

Disabilities can affect the way people travel and buy. How many household members have difficulty walking, climbing stairs, reaching, lifting, or carrying? *(range 0-3+)*

There is an adequate number of observations in the groups with 0, 1, 2+ members with disabilities. The income distribution by number of HH members with a disability can be seen in Figure 3.22. There is a clear trend, households with zero members show a much lower percentage of households with annual income below $25,000 and a much higher percentage of households with annual income above $100,000. Having household members with disabilities does seem to negatively affect household income and this trend is also observed in the NHTS data.

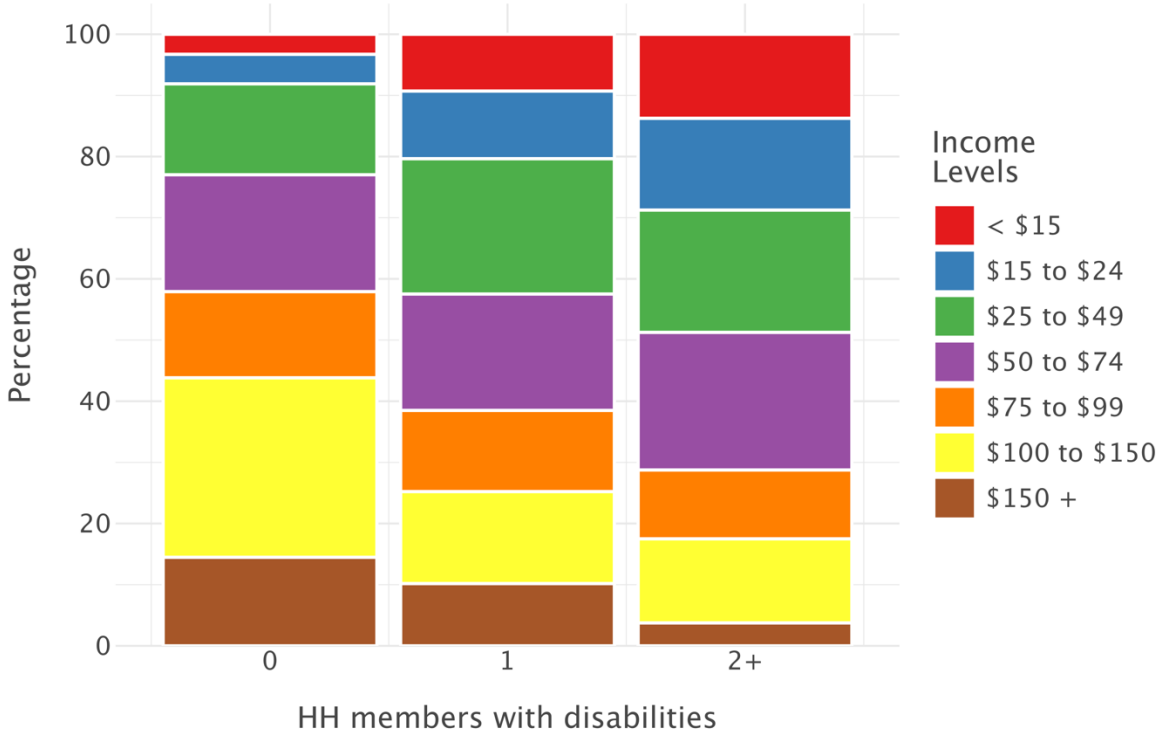

Figure 10.9: Income distribution by number of HH members with a disability

10.8 HH MEMBERS WITH ONLINE ACTIVITIES

The survey question for this subject is the following:

How many household members usually spend time ONLINE doing these activities *(range 0-3+):*

- Shopping
- Working

10.8.1 HH members that shop online

The distribution of household income by the number of household members that usually shop online can be seen in Figure 4.2. The Figure shows that there is a clear trend, households with more online shoppers have a much lower percentage of households with annual income below $25,000 and a much higher percentage of households with annual income above $100,000.

Figure 10.10: Income distribution by number of online shoppers

10.8.2 HH members that work online

The income distribution by the number of household members that usually work online can be seen in Figure 4.4. Again, there is a positive correlation between income and number of online workers. Households with more online workers have a lower percentage of households with annual income below $25,000 and a substantially higher percentage of households with annual income above $100,000.

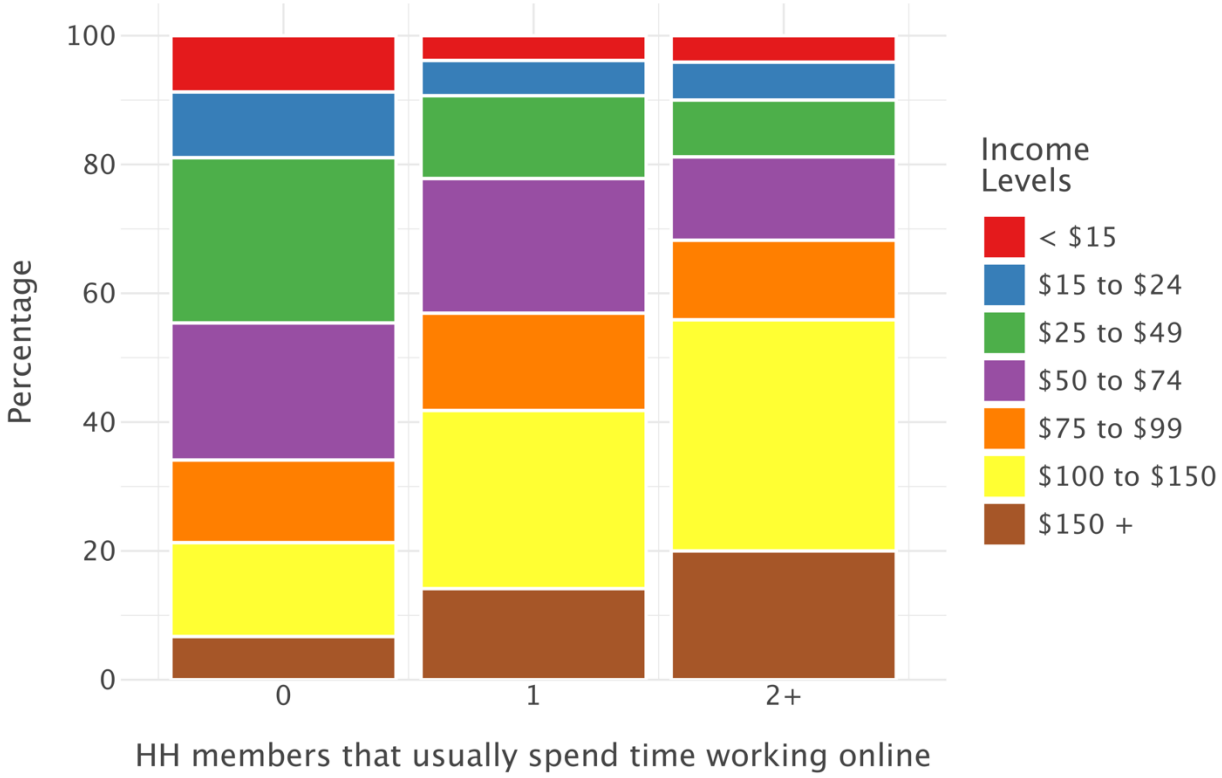

Figure 10.11: Income distribution by number of online workers

10.9 ONLINE EXPENDITURES

Finally, the relationship between household income and household spending is analyzed. The survey question related to online spending is the following:

Approximately, how much does your household spend on home deliveries during a typical week? If unsure, please provide your best estimate.

- Less than $50
- $50 to $100
- $100 to $200
- $200 to $350
- $350 to $500
- More than $500

As expected, Figure 3.6 shows that households in higher spending categories show a lower share of households with annual income below $25,000 and a higher percentage of households with annual income above $100,000.

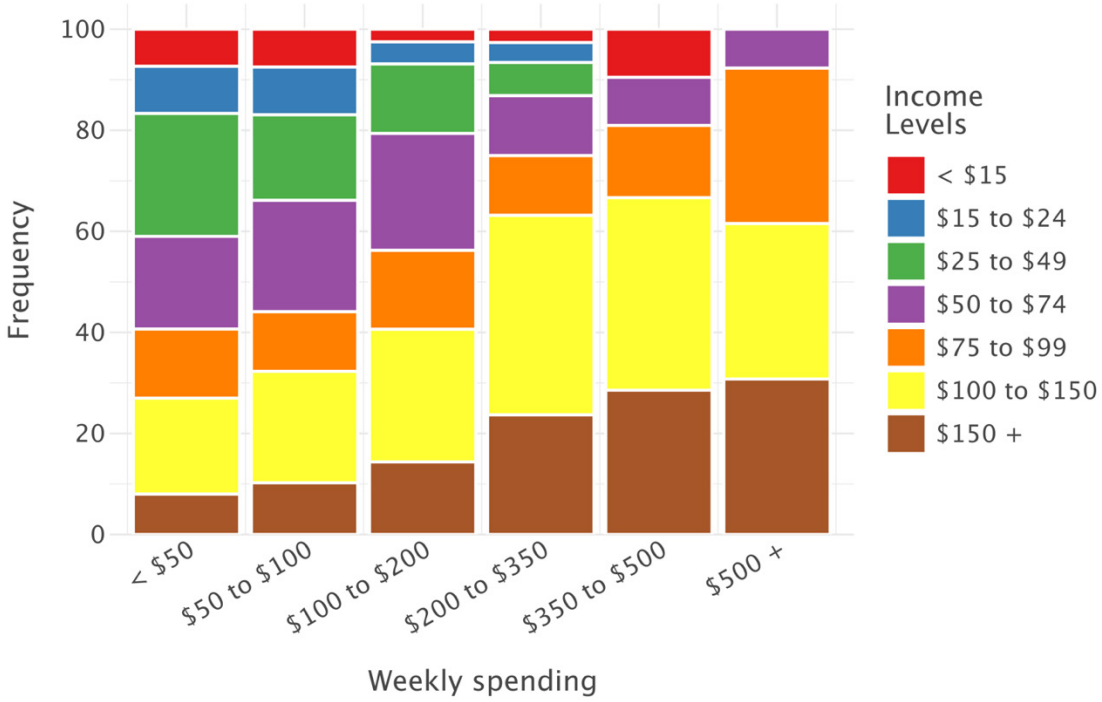

Figure 10.12: Income distribution by level of online spending

10.10 SUMMARY

This section presents an exploratory analysis of the relationship between household income and some key sociodemographic variables. The data show trends that are relevant for a fairness analysis. For example, households with members who have a disability have a lower income and this is also confirmed at the national level in the US (Merchant et al., 2025). Other observations that may impact the fairness analysis is that young adults tend to have lower incomes than older adults though they tend to engage more on online activities and e-commerce than older adults. Higher income is also observed for males, but it was previously established that gender does not significantly impact the number of home deliveries.

11.0 CHARACTERIZATION OF HIGH-IMPACT HOUSEHOLDS

This section identifies the household variables or factors that indicate regressivity of a flat household delivery fee. Logistic models are estimated to elicit the socio-demographic, attitudinal, and shopping variables that profile the type of household that may be more affected by a delivery fee as a percentage of household income. In the first subsection, the logistic model is introduced, and in the second subsection the modeling results are discussed.

11.1 MODELING FRAMEWORK

Given that the delivery fee has been implement as a flat fee in other states, it is assumed that the relative impact of the fee can be estimated by the ratio between the number of deliveries and the household income.

The goal is to elicit the sociodemographic, attitudinal, and shopping variables that profile the type of household that may be more affected by a delivery fee. A logistic model is proposed where the binary dependent variable is 1 if the household belongs to the upper tertile of the ratio between the number of deliveries and household income. Regressions are estimated for all products and for each type of product. The models are estimated using only observations where the product analyzed was delivered.

In all regressions, variable inflation factors (VIF) are quantified to ensure that levels are within recommended thresholds, which ensure that the regression coefficients are not unreliable due to correlation among predictors. Regression model specifications are built manually one step at a time using the Bayesian Information Criteria (BIC) and checking the stability and consistency of successive regression results.

Only significant variables are presented. In all cases the format of the regression result tables follows the standard presentation of statistical estimations: variable, coefficient, standard error, z value, probability of the z value, and the intervals of the confidence interval. The interpretation of the regression coefficients for logistic regressions was already discussed when analyzing sensitivity to a delivery fee.

11.2 RESULTS ALL PRODUCTS

The survey question best related to overall delivery rates for all types of products is the following:

In a TYPICAL WEEK, approximately how many deliveries does your home receive? If unsure, provide your best estimate *(range 0-20).*

For all products (typical week), the results of the logistics model are presented in Table 6.10. There are eight significant variables.

Table 11.1: Sports and other products logistic regression results

Variable	Coef.	Std. err.	*z*	*P* > |*z*|	[0.025	0.975]
Intercept	-1.496	0.356	-4.202	0.000	-2.194	-0.798
# HH Disabilities	0.469	0.111	4.206	0.000	0.250	0.687
Hard to travel	0.451	0.112	4.040	0.000	0.232	0.670
Supermarket store	-1.483	0.296	-5.002	0.000	-2.064	-0.902
Discount store	0.707	0.176	4.005	0.000	0.361	1.052
# Online shoppers	0.432	0.103	4.179	0.000	0.229	0.635
Age 18 to 24	0.884	0.239	3.697	0.000	0.415	1.352
It is safer	0.395	0.123	3.220	0.001	0.155	0.635
Amazon subs.	0.435	0.228	1.913	0.056	-0.011	0.881

A positive sign indicates that the probability of being in the upper tertile of the ratio between the number of deliveries and household income increases as the predictor increases. Then, for positive coefficients, the delivery fee becomes *more regressive* as the predictor increases. A negative coefficient will have the opposite interpretation; for negative coefficients the delivery fee becomes *less regressive* as the predictor increases.

- As the number of household members with a disability increases the delivery fee becomes *more regressive*.
- If it is better to use home deliveries because it is hard to travel or because it is considered safer, then the delivery fee becomes *more regressive*.
- If a household shops at discount stores, then the delivery fee becomes *more regressive*. The opposite effect is found if the household shops at supermarkets.
- If a household has an Amazon subscription or more members that shop online, then the delivery fee becomes *more regressive*.
- Finally, the delivery fee becomes *more regressive* if the respondent is in the age group 18-24, and this is congruent with trends related to relatively higher delivery frequency and lower income for this age group.

11.3 RESULTS FOR EACH PRODUCT

The survey question related to product delivery frequency for each product is the following:

For each of the following categories, approximately how many home deliveries took place LAST week? *(range 0-8)*

- Groceries
- Prepared food, restaurant deliveries

- Clothing/shoes
- Personal care, beauty products
- Miscellaneous supplies
- Home products/appliances/décor
- Electronic products/accessories
- Pet products
- Pharmacy products
- Other (sports equipment, hobbies, toys, etc.)

For each product the results of the logistics model are presented in the following subsections.

11.3.1 Groceries

For groceries the results of the logistics model are presented in Table 6.1. There are five significant variables.

Table 11.2: Groceries logistic regression results

Variable	Coef.	Std. err.	z	$P > \|z\|$	[0.025	0.975]
Intercept	-1.036	0.320	-3.243	0.001	-1.662	-0.410
PO distance	0.123	0.032	3.870	0.000	0.060	0.184
Big box store	-1.125	0.305	-3.684	0.000	-1.723	-0.526
Discount store	0.719	0.245	2.933	0.003	0.239	1.200
Female	0.552	0.234	2.361	0.018	0.094	1.011
It is cheaper	0.357	0.157	2.276	0.023	0.050	0.665

A positive sign indicates that the probability of being in the upper tertile of the ratio between the number of deliveries and household income increases as the predictor increases.

- As the distance between the household and the nearest Post Office increases the delivery fee becomes *more regressive*.
- If it is better to use home deliveries because it is considered cheaper, then the delivery fee becomes *more regressive*.
- If a household shops at discount stores, then the delivery fee becomes *more regressive*. The opposite effect is found if the household shops at big box stores (Walmart, COSTCO, Target, etc.).
- Finally, the delivery fee becomes *more regressive* if the responded identifies as female.

11.3.2 Food (prepared food, restaurant deliveries)

For food the results of the logistics model are presented in Table 6.2. There are four significant variables. A positive sign indicates that the probability of being in the upper tertile of the ratio between the number of deliveries and household income increases as the predictor increases.

- As the distance between the household and the nearest Post Office increases the delivery fee becomes *more regressive*.
- As the number of household members with a disability increases the delivery fee becomes *more regressive*.
- For households located in suburban areas the delivery fee becomes *less regressive*.
- Finally, the delivery fee becomes *more regressive* if the respondent is in the age group 18-24.

Table 11.3: Food logistic regression results

Variable	Coef.	Std. err.	*z*	$P > \|z\|$	[0.025	0.975]
Intercept	-1.365	0.219	-6.240	0.000	-1.793	-0.936
PO distances	0.106	0.034	3.099	0.002	0.039	0.173
Age 18 to 24	1.037	0.306	3.384	0.001	0.436	1.637
Suburban area	-0.679	0.287	-2.363	0.018	-1.243	-0.116
# HH Disabilities	0.397	0.148	2.676	0.007	0.106	0.688

11.3.3 Clothing/shoes

For clothing/shoes the results of the logistics model are presented in Table 6.3. There are seven significant variables. A positive sign indicates that the probability of being in the upper tertile of the ratio between the number of deliveries and household income increases as the predictor increases.

- As the distance between the household and the nearest Post Office increases the delivery fee becomes *more regressive*.
- For households located in suburban areas the delivery fee becomes *less regressive*.
- As the number of household members with a disability increases the delivery fee becomes *more regressive*.
- If a household shops at discount stores, then the delivery fee becomes *more regressive*. The opposite effect is found if the household shops at supermarkets.
- If it is better to use home deliveries because it saves time, then the delivery fee becomes *less regressive*.
- Finally, the delivery fee becomes *less regressive* for older respondents.

Table 11.4: Clothing logistic regression results

Variable	Coef.	Std. err.	*z*	*P* > |*z*|	[0.025	0.975]
Intercept	-0.035	0.417	-0.084	0.933	-0.851	0.782
PO distance	0.096	0.034	2.797	0.005	0.029	0.163
Suburban area	-0.970	0.314	-3.089	0.002	-1.586	-0.355
# HH Disabilities	0.553	0.160	3.461	0.001	0.240	0.866
Discount store	0.672	0.251	2.678	0.007	0.180	1.165
Supermarkets store	-0.803	0.362	-2.219	0.027	-1.512	-0.094
It saves time	-0.467	0.219	-2.130	0.033	-0.897	-0.037
Age	-0.256	0.078	-3.265	0.001	-0.409	-0.102

11.3.4 Personal care, beauty products

For personal care/beauty products the results of the logistics model are presented in Table 6.4. There are four significant variables. A positive sign indicates that the probability of being in the upper tertile of the ratio between the number of deliveries and household income increases as the predictor increases.

- If a household indicates that a delivery fee will result in ordering less frequently this product category (personal care), then the delivery fee becomes *more regressive*. This is the only category where this type of variable is significant.

- As the distance between the household and the nearest Post Office increases the delivery fee becomes *more regressive*.

- As the number of household members with a disability increases the delivery fee becomes *more regressive*.

- If it is better to use home deliveries because it saves time, then the delivery fee becomes *less regressive*.

Table 11.5: Personal products logistic regression results

Variable	Coef.	Std. err.	*z*	*P* > |*z*|	[0.025	0.975]
Intercept	-1.547	0.289	-5.362	0.000	-2.113	-0.982
Order less often	0.788	0.244	3.224	0.001	0.309	1.266
# HH Disabilities	0.581	0.149	3.904	0.000	0.289	0.873
It saves time	-0.662	0.221	-2.998	0.003	-1.094	-0.229
PO distance	0.116	0.033	3.508	0.000	0.051	0.181

11.3.5 Miscellaneous products

For miscellaneous products the results of the logistics model are presented in Table 6.5. There are six significant variables. A positive sign indicates that the probability of being in the upper tertile of the ratio between the number of deliveries and household income increases as the predictor increases.

- As the distance between the household and the nearest Post Office increases the delivery fee becomes *more regressive*.
- As the number of household members with a disability increases the delivery fee becomes *more regressive*.
- If a household shops at discount stores, then the delivery fee becomes *more regressive*.
- If a household has a big box store (Walmart, COSTCO, etc.) subscription, then delivery fee becomes *less regressive*.
- If it is better to use home deliveries because it is hard to travel, then the delivery fee becomes *more regressive*.
- Finally, the delivery fee becomes *more regressive* if the respondent is in the age group 18-24

Table 11.6: Misc. products logistic regression results

Variable	Coef.	Std. err.	*z*	$P > \|z\|$	[0.025	0.975]
Intercept	-1.720	0.239	-7.199	0.000	-2.188	-1.252
# HH Disabilities	0.355	0.126	2.813	0.005	0.108	0.603
Discount store	0.817	0.209	3.899	0.000	0.406	1.227
Age 18 to 24	0.776	0.280	2.772	0.006	0.227	1.324
Big Box subs.	-0.567	0.203	-2.796	0.005	-0.964	-0.170
PO distance	0.062	0.028	2.217	0.027	0.007	0.117
Hard to travel	0.374	0.130	2.875	0.004	0.119	0.628

11.3.6 Home products/appliances/décor

For home products/appliances/décor the results of the logistics model are presented in Table 6.6. There are six significant variables. A positive sign indicates that the probability of being in the upper tertile of the ratio between the number of deliveries and household income increases as the predictor increases.

- As the distance between the household and the nearest Post Office increases the delivery fee becomes *more regressive*.
- If a household shops at discount stores, then the delivery fee becomes *more regressive*. The opposite effect is found if the household shops at supermarkets.

- If a household has a big box store (Walmart, Costco, etc.) subscription, then delivery fee becomes *less regressive*.

- If it is better to use home deliveries because it is hard to travel or because it is considered cheaper, then the delivery fee becomes *more regressive*.

Table 11.7: Home products logistic regression results

Variable	Coef.	Std. err.	*z*	$P > \|z\|$	[0.025	0.975]
Intercept	-0.042	0.465	-0.091	0.928	-0.953	0.869
PO distance	0.167	0.040	4.166	0.000	0.089	0.246
Supermarket store	-1.920	0.432	-4.442	0.000	-2.767	-1.073
Cheaper	0.494	0.196	2.524	0.012	0.110	0.878
Big Box subs.	-0.956	0.295	-3.240	0.001	-1.534	-0.378
Hard to travel	0.406	0.195	2.079	0.038	0.023	0.788
Discount store	0.698	0.296	2.358	0.018	0.118	1.277

11.3.7 Electronic products/accessories

For electronic products and accessories, the results of the logistics model are presented in Table 6.7. There are four significant variables. A positive sign indicates that the probability of being in the upper tertile of the ratio between the number of deliveries and household income increases as the predictor increases.

- As the distance between the household and the nearest Post Office increases the delivery fee becomes *more regressive*.

- If it is better to use home deliveries because it is hard to travel, then the delivery fee becomes *more regressive*. The opposite impact is found if it is better to use home deliveries because it saves time.

- Finally, the delivery fee becomes *more regressive* if the respondent is in the age group 18-24

Table 11.8: Electronic products logistic regression results

Variable	Coef.	Std. err.	*z*	$P > \|z\|$	[0.025	0.975]
Intercept	-1.273	0.300	-4.244	0.000	-1.860	-0.685
PO distance	0.143	0.040	3.542	0.000	0.064	0.222
Hard to travel	0.588	0.187	3.149	0.002	0.222	0.954
Age 18 to 24	1.037	0.368	2.820	0.005	0.316	1.758
It saves time	-0.431	0.220	-1.951	0.050	-0.913	-0.051

11.3.8 Pet products

For pet products the results of the logistics model are presented in Table 6.8. There are six significant variables. A positive sign indicates that the probability of being in the upper tertile of the ratio between the number of deliveries and household income increases as the predictor increases.

- As the distance between the household and the nearest Post Office increases the delivery fee becomes *more regressive*.
- If it is better to use home deliveries because it is hard to travel, then the delivery fee becomes *more regressive*. The opposite impact is found if it is better to use home deliveries because it provides more options.
- If a household shops at discount stores, then the delivery fee becomes *more regressive*. The opposite effect is found if the household shops at supermarkets.
- Finally, the delivery fee becomes *more regressive* if the responded identifies as female.

Table 11.9: Pet products logistic regression results

Variable	Coef.	Std. err.	*z*	$P > \|z\|$	[0.025	0.975]
Intercept	-0.788	0.467	-1.687	0.092	-1.703	0.127
PO distance	0.122	0.036	3.387	0.001	0.052	0.193
Supermarket store	-2.038	0.457	-4.465	0.000	-2.933	-1.143
Discount store	0.968	0.297	3.263	0.001	0.386	1.549
Female	0.940	0.303	3.101	0.002	0.346	1.535
More options	-0.545	0.197	-2.759	0.006	-0.931	-0.158
Hard to travel	0.443	0.193	2.294	0.022	0.064	0.821

11.3.9 Pharmacy products

For pharmaceutical products the results of the logistics model are presented in Table 6.9. There are five significant variables. A positive sign indicates that the probability of being in the upper tertile of the ratio between the number of deliveries and household income increases as the predictor increases.

- As the distance between the household and the nearest Post Office increases the delivery fee becomes *more regressive*.
- If it is better to use home deliveries because it is hard to travel, then the delivery fee becomes *more regressive*.
- If a household shops at discount stores, then the delivery fee becomes *more regressive*. The opposite effect is found if the household shops at supermarkets.
- Finally, the delivery fee becomes *more regressive* if the responded identifies as female.

Table 11.10: Pharmacy products logistic regression results

Variable	Coef.	Std. err.	z	$P > \|z\|$	[0.025	0.975]
Intercept	-1.252	0.425	-2.947	0.003	-2.084	-0.419
PO distance	0.086	0.037	2.339	0.019	0.014	0.158
Supermarket store	-1.204	0.408	-2.952	0.003	-2.003	-0.404
Discount store	0.983	0.288	3.419	0.001	0.420	1.547
Female	0.766	0.275	2.784	0.005	0.227	1.305
Hard to travel	0.403	0.177	2.278	0.023	0.056	0.749

11.4 SUMMARY

The analysis of the impact of individual variables is done assuming that the impact of one independent variable on the dependent variable is estimated assuming that all other variables in the model remain unchanged – i.e., ceteris paribus. This assumption is violated if the regressors are not independent. In the regression results presented in this section, VIF values have been quantified, and the stability of the estimated coefficients has been checked to ensure that the interpretations are valid.

The results of the logistic models show some consistent trends and regressor (variable) signs. The sign and interpretation of the regressors can be analyzed in terms of their association with household income. Some variables can be considered as signaling lower income. In this group it is possible to include variables such as using discount stores, having household members with disabilities, identifying as female, using home deliveries because it is cheaper, or belonging to the 18-24 age group. Other group of variables can be considered as signaling higher income. In this group it is possible to include variables such as being in a suburb or using home deliveries because it saves time.

When analyzing the sensitivity to delivery fees it was found that the type of brick-and-mortar store visited seems to be important to explain how households may react to delivery fees. In these models visiting discount stores in the most repeated significant variable (for seven products) and the regression results in this section seems to confirm that discount stores attract households that are more sensitive to delivery fees and more affected by a delivery fee as a percentage of income.

Some variables can also be analyzed in terms of transportation accessibility. Disabilities can affect the way people travel and shop. With a disability, it is likely harder to travel and shop at physical stores and this seems to be reflected in the regression results. The regression results also indicate that lower-income households use more home deliveries when it is harder to travel or when they are located farther away as measured by distance to the nearest Post Office. These results have significant implications in terms of fairness and policy recommendations as discussed in later sections.

12.0 CONSIDERATIONS FOR RURAL AND LOW-INCOME HOUSEHOLDS IN OREGON

The previous section has identified the variables that determine what type of households are most affected by the regressive aspect of a flat delivery fee. This section focuses on two groups of Oregonian households: rural and low-income. Travel data and patterns from the 2010 Oregon Household Activity Survey (OHAS) data are utilized to discuss the potential impact of a flat delivery fee. The concept of store deserts is introduced first because it is relevant to discuss fee fairness for rural and low-income households.

12.1 STORE AND FOOD DESERTS

The literature has explored the equity issues related to discount stores and the presence of food or retail deserts. A retail desert can be defined as a geographic area that lacks access to essential retail services, including grocery stores, supermarkets, and other vital amenities. In rural areas, retail deserts can emerge due to geographic isolation, limited public transportation, or lack of customers, forcing residents to travel long distances to procure basic necessities. In urban areas, retail deserts are typically occupied by a low-income or disadvantaged community. A food desert is defined as an urban area in which it is difficult to buy affordable and good-quality or nutritious food. This lack of access is often due to the absence of supermarkets, grocery stores, or other retailers carrying healthy options, forcing residents to rely on highly processed or high-calorie alternatives. Households located in food desert areas may pay higher prices for groceries or incur a greater travel cost to access the large food retailer that may offset the savings available at these stores (Blanchard & Lyson, 2007).

The concentration of discount or dollar stores is often a key feature of retail and food deserts. Residents in these areas, particularly minority residents of small towns and rural areas, tend to spend a larger portion of their income at these types of retailers (Feng et al., 2023). In these locations, dollar stores frequently serve as the most affordable and convenient option for low-income households to purchase meal essentials, snack foods, household supplies, and entertainment items (Reimold et al., 2024). According to Reuter (2023) the typical Dollar General customer provides a clear illustration of this demographic: they are often low-to-middle-income customers with a high school education, living in rural and suburban areas. This profile is supported by the chain's footprint, as approximately 75% of Dollar General stores are located in towns with fewer than 20,000 residents.

Research also shows that retail patterns vary by neighborhood income and low-income neighborhoods have lower retail employment density for retail overall and several types of retail, including supermarkets, drugstores, food services, and laundry. Some low-income neighborhoods have a higher density of supermarket establishments, but after controlling for population they have lower employment density, smaller establishments and fewer chain supermarkets (Schuetz et al., 2012). It has also been observed that once a dollar store enters a food desert, that area is more likely to remain without access to a supermarket and higher-quality

food options (Chenarides et al., 2021). The presence of a food or retail desert is problematic for vulnerable segments of the population – such as poor, low-income individuals, and the disabled – for whom it may not be feasible to shop at retailers found in high-income neighborhoods because of travel cost and time considerations (Blanchard & Lyson, 2007). The potential of home grocery deliveries to alleviate the burden of living in a food desert has been discussed in the literature and it is a valid option, but not a panacea (Keeling & Figliozzi, 2019).

12.2 RURAL DEMOGRAPHICS AND TRAVEL PATTERNS

Rural Oregon households exhibit distinct demographic and travel characteristics that set them apart from their urban and suburban counterparts. Unless noted otherwise the figures and data in this subsection have been sourced from the analysis of the 2010 OHAS data done by Bricka (2019) .

Rural households generally have the largest average household sizes among all place types. They also tend to report the highest average number of children per household. Regarding income, the trends are more mixed. Vehicle ownership is highest in rural areas with almost half (46%) of rural households owning more vehicles than they have workers. This high vehicle ownership underscores their significant reliance on private transportation. Non-auto modes such as walking, biking, or public transit are severely limited or often non-existent in these dispersed rural locales, making it challenging to serve such trips.

Persons living in rural place types, or "spoke" areas (which include rural, rural near major city, and MPO low density), report some of the lowest person trip rates daily (e.g., 3.5 trips for rural, rural near major center). This means they make fewer trips per person on a typical weekday compared to the statewide average of 3.7 trips. Despite making fewer trips, individuals in rural households travel significantly longer distances daily. Residents of rural place types report the highest daily trip miles (44 miles), which is 18 miles above the state average of 26 miles. Spoke households, which include rural, report about 40% more miles traveled on a typical weekday (37 miles per day). Rural residents also spend the most time traveling daily (87 minutes for rural, 81 minutes for rural near major center), compared to other place types. However, despite longer distances, their trip durations are only about 10% higher than those reported by households in other regions, potentially due to faster auto modes and/or less congestion.

Rural areas are highly auto dependent, with 91% of trips made by auto. This is the highest auto usage among all land use types, reflecting lower density, where residential and commercial areas are separated, making walking, biking, or transit less feasible due to longer trip lengths and dispersed locations. Non-auto modes like walk, bike, and transit are severely limited or non-existent in rural locales.

Rural residents report a higher level of personal errands and shopping trips on a typical weekday compared to those living in more metropolitan areas. For rural households, work trips averaged 20% of the total, with social/recreation trips also at 20%. Work trips are consistently 3-4 miles longer than non-work trips for each home-destination pair in rural areas, and trips that stay outside "spoke" boundaries are the shortest. Spoke workers travel an average of 11 miles for work. Rural residents (spoke group) have the greatest variation in their trip destination locations, with 40% of trips going to "hub" locations (higher density areas), 27% to "hybrid" locations, and

only 33% remaining within the spoke place types. This indicates a reliance on denser urban centers for various needs.

12.3 LOW-INCOME DEMOGRAPHICS AND TRAVEL PATTERNS

Oregon's lower-income households, specifically those reporting an annual income of less than $25,000, also exhibit distinct demographic traits and travel behaviors. This income bracket represents a significant segment of the population, often facing unique mobility challenges. Unless noted otherwise the figures and data in this subsection has been sourced from the analysis of the 2010 OHAS data done by Bricka (2019) .

Households with the lowest-income categories tend to live in "hub" rather than "spoke" place types, which are typically denser areas with more diverse job and activity opportunities. Households with incomes under $25,000 tend to report shorter-than-expected trips compared to higher-income households. For instance, in Oregon statewide, persons in households with incomes less than $25,000 average 3.4 trips per day, traveling 20 miles and spending 76 minutes, compared to 3.9 trips, 31 miles, and 76 minutes for those earning $75,000 or more.

Table 12.1: Travel Metrics by HH Income – Source Bricka (2019)

HH Income	Person Trips	Daily Trip Miles	Daily Travel Time
Less $25k	3.4	20	76
$25k-$50k	3.5	25	73
$50k-$75k	3.7	26	72
$75k +	3.9	31	76

No vehicle ownership is associated with low-income levels. Auto travel is the dominant mode across Oregon, accounting for 82% of all trips statewide. However, adults in zero-vehicle households primarily rely on walking, transit, or being an auto passenger. Only 9% of their trips are as auto drivers, using borrowed or company-owned vehicles. This highlights a constrained mobility choice for these households. Furthermore, transit riders in Oregon are disproportionately low-income, with 42% of transit trips made by travelers from households earning less than $25,000 annually and 25% earning between $25,000 and $50,000 annually. The average transit trip is 6 miles long and takes 45 minutes, with work trips being the longest (9 miles, 51 minutes).

For OHAS 2010 survey respondents who report a disability, most trips are for personal errands (including medical appointments), social/recreational activities, and shopping, with lower levels of travel for work and school. Persons with disabilities are also more likely to live in higher-density urban areas where it is easier to access services.

National (NHTS) data also show that low-income households have cheaper, older, and less fuel-efficient vehicles than high-income households (Bauer et al., 2021).

12.4 FAIRNESS IMPLICATIONS

The principle of horizontal equity suggests that individuals in comparable economic circumstances should bear an equivalent burden. While a flat delivery fee imposes a uniform charge per delivery on all users, it may overlook critical contextual differences in consumer needs and reliance on delivery services.

12.4.1 Geographic equity and rural households

The principle of geographic equity assesses whether a tax disproportionately burdens different geographical regions. A flat delivery fee can indeed introduce nuanced issues concerning geographic equity. Rural Oregon residents are frequently compelled to traverse significantly greater distances for employment, education, and essential goods and services, leading to inherently higher travel costs by personal vehicle. This situation is compounded by the typical absence or severe limitation of public transit options in rural locales, which are often robust in urban centers.

Rural communities often face challenges such as "retail deserts" and a lack of accessible physical retail outlets. For elderly, disabled, or lower-income rural residents who might lack reliable personal vehicles or access to public transportation, e-commerce delivery services are not a luxury but a "critical lifeline". The COVID-19 pandemic has shown that access to home deliveries can enhance access to basic goods for vulnerable populations (M. Figliozzi & Unnikrishnan, 2021b). A fixed delivery fee makes essential commodities more expensive for these already economically disadvantaged populations in rural areas, penalizing individuals for a lack of choice and potentially limiting their access to healthy food options or vital supplies, thereby potentially reinforcing existing socioeconomic disparities.

On the other hand, given that rural households travel significantly longer distances for shopping and errands, the benefits of home delivery in terms of reducing travel burden and time are substantial, making this a clear case of direct benefit for direct payment of a fee. In addition, in Oregon, rural households may benefit from paying a flat delivery fee instead of a flat gasoline tax. This is because rural households tend to own less-fuel-efficient vehicles (McMullen et al., 2010), on average, even though they drive more miles than urban households.

Summarizing, for a rural household, particularly those in "retail deserts" or with limited mobility, delivery may be a necessity to access essential groceries, medications, or other vital supplies. This is particularly important when the household has low or no vehicle ownership. In contrast, an urban household with similar income and numerous retail alternatives might use delivery purely for convenience.

12.4.2 Urban low-income households

For low-income households in urban areas, the fairness analysis depends on vehicle ownership. Low-income households without a vehicle living in a retail desert are likely to benefit the most from a reduction in the delivery fee burden.

Low-income households with a vehicle already pay the highly regressive flat gasoline tax and vehicle registration tax. A reduction in the delivery fee would be highly recommended if home deliveries reduce the need to travel long distances to access essentials using low-fuel-efficiency vehicles. In this particular case, it would be ideal to incentivize the utilization of electric delivery vehicles to reduce emissions.

12.5 CONSIDERATIONS FOR EQUITABLE FEE STRUCTURES

Given these regressive impacts, the introduction of flat delivery fees should be approached with caution. Policymakers and retailers might consider implementing sliding-scale pricing mechanisms, fee exemptions for low-income or elderly households, or incentive structures that encourage order consolidation without penalizing necessity. This mirrors concepts in transportation finance where remedies for inequities, such as toll rebates or subsidies, or improved alternative services, have been proposed. For instance, some road pricing proposals sometimes included "lifeline" credits for low-income motorists (Manville et al., 2022).

Given Oregon distinct tax structure, characterized by a progressive income tax and the absence of a sales tax, the regressivity of a flat delivery fee – e.g., $78 per year assuming three deliveries per week – counters the lack of a sales tax, which is typically regressive as lower-income households spend a larger proportion of their income on taxable goods.

12.5.1 Leveraging Existing Progressive Tax Structures

Oregon already has an Earned Income Tax Credit (EITC). A substantial increase in the Oregon EITC, or the creation of a new, targeted refundable credit for essential services, could provide direct financial relief to low- and moderate-income households. Refundable credits are particularly potent because they can provide a refund even if a household owes no income tax, thus directly benefiting those with the lowest incomes.

12.5.2 Direct Subsidies and Program Integration

Beyond tax credits, Oregon could explore direct subsidy mechanisms or integrate fee relief into existing social service programs. A means-tested voucher or subsidy program could be established, perhaps administered through the Oregon Department of Human Services (DHS) or a similar agency. This program would provide direct financial assistance to eligible households to cover the annual delivery fee. Eligibility could be tied to participation in other established benefit programs, such as the Supplemental Nutrition Assistance Program (SNAP) or Temporary Assistance for Needy Families (TANF), to reduce administrative overhead and ensure that relief reaches those most in need.

Furthermore, partnerships between the state and delivery service providers could be forged. Note that Amazon already provides a discount for eligible low-income households as discussed earlier. This model is akin to how certain essential services are subsidized for low-income populations, recognizing that access to convenient food delivery or essential products – especially in retail deserts – can improve health outcomes and reduce other costs, such as transportation expenses for individuals with limited mobility or childcare costs for parents.

12.5.3 User, administrative, and budget burden

New programs or expansions of existing ones require robust administrative infrastructure. Designing systems that minimize bureaucratic hurdles for both applicants and administrators would be paramount to ensure efficient and equitable distribution of benefits. For users, it may be simpler to receive direct subsidies or reduced fees through providers, but in this case, the willingness of delivery service companies to participate and collaborate would be essential. Incentives, such as increased market access to underserved populations or positive public relations, could encourage their involvement.

Finally, any proposed relief mechanism would require a funding source. Part of the delivery fee revenues could be used to provide relief to qualifying lower-income households.

12.6 BEHAVIORAL RESPONSES AND BROADER IMPACTS

Economic theory suggests that consumers adjust their behavior in response to cost signals. For households that are most sensitive to delivery fees, a flat delivery fee is likely to prompt behavioral shifts such as consolidating orders, reverting to in-store shopping, or using less convenient alternatives. However, if delivery is the only practical option, these households may incur a less visible but still real cost in terms of reduced access.

12.6.1 Home Deliveries and emissions

A flat gasoline tax does incentivize the purchase and use of more fuel-efficient or less polluting vehicles by increasing the cost of fuel. However, it is considered a "blunt and imprecise instrument" for this purpose, as it does not differentiate between varying damages inflicted by different vehicle types – e.g., old-high-emission vs. modern-low-emission hybrid or electric vehicles (TRB, 2011).

Order consolidation can reduce the number of deliveries and lead to more efficient routing; customer density and the number of deliveries per route are key to determining the efficiency of the delivery route (M. A. Figliozzi, 2007). But actual emissions are dependent on many real-world factors such as vehicle type, depot location, congestion, and delivery time windows (Aziz et al., 2022; M. Figliozzi, 2010; M. A. Figliozzi, 2011).

A flat delivery fee, therefore, could have a weak effectiveness in internalizing the full spectrum of negative externalities associated with e-commerce delivery operations. While it provides a general incentive to reduce overall delivery demand, it fails to differentiate the varying marginal emissions inherent in different delivery scenarios. Deliveries to remote, sparsely populated rural locations have higher logistical, fuel, and environmental footprints due to longer distances and lower delivery density compared to dense urban areas.

12.7 SUMMARY

A flat delivery fee is regressive, but the impacts of a delivery fee on rural households are different from the impacts on urban low-income households. For rural households a flat delivery fee may be less regressive than an increase in the flat gas tax. For urban low-income households

a flat delivery fee may hinder access to home deliveries, which is especially negative if the household is in a retail desert.

Oregon has the potential to leverage existing progressive tax structures and programs, but potential user, administrative, and budget burdens should be carefully analyzed. A delivery fee could increase delivery efficiency and reduce emissions if orders are consolidated, but there are many variables affecting actual delivery distances and emissions, and further research is necessary to better understand all the implications in this regard.

13.0 ROAD INFRASTRUCTURE MAINTENANCE AND E-COMMERCE FEES

Based on a suggestion from the research coordinator (M. Bagwell, personal communication, August 22, 2025), this section of the report addresses topics that are not explicatively considered in any of the work plan tasks and therefore are considered separately in this section. These topics include: (a) a survey of other states' policies and statutes on e-commerce delivery fees, with a focus on fee justifications related to highway maintenance costs; (b) considerations regarding the viability of these fees to maintain roadway infrastructure affected by e-commerce; and (c) project survey findings regarding socio-economic status (SES) considerations in Oregon. Point (c) is discussed later in the report's recommendations for future data collection efforts and the final section.

13.1 SURVEY OF CURRENT STATE POLICIES AND ROADWAY MAINTENANCE

Both Colorado and Minnesota have implemented retail delivery fees, with varying justifications related to maintaining roadway infrastructure and mitigating other impacts of e-commerce.

13.1.1 Colorado

In Colorado, the legislative declaration for Senate Bill 21-260 explicitly identifies the impact of increasing retail deliveries on transportation infrastructure (Colorado Retail Delivery Fees, 2023). The Colorado general assembly found that the demand for retail deliveries has risen and is expected to continue growing significantly, which will increase both traffic and associated motor vehicle emissions, leading to additional costs for the state. This increased usage has accelerated and is projected to continue to accelerate the deterioration of surface transportation system infrastructure. Consequently, the state, counties, and municipalities are required to perform more maintenance and reconstruction of state highways, county roads, and city streets. The imposition of reasonably calculated retail delivery fees is intended to account for the use of the transportation system related to these deliveries and generate the necessary revenue to mitigate their impact on transportation system infrastructure.

Beyond infrastructure deterioration, Colorado's retail delivery fee is justified by other significant impacts:

- Traffic Congestion: the legislation cites World Economic Forum estimates forecasting a substantial increase in delivery vehicles on roads by 2030, leading to a corresponding increase in traffic congestion. The Nonattainment Area Air Pollution Mitigation Enterprise, funded in part by these fees, aims to support eligible projects that reduce traffic, including demand management projects encouraging alternatives to driving alone, thereby reducing travel delays, engine idle time, and unproductive fuel consumption.

- Environmental and Health Impacts (Air Pollution and Greenhouse Gas Emissions): Increased retail deliveries contribute to motor vehicle emissions that cause adverse environmental and health impacts. Specifically, there is increased local air and greenhouse gas pollution at the community level from idling delivery vehicles in neighborhoods. These emissions include ozone precursors, particulate matter pollutants, other hazardous air pollutants, and greenhouse gases, which contribute to adverse environmental effects like climate change and negative human health outcomes. The state's strategy, supported by these fees, includes creating several enterprises with distinct purposes to address these issues:

    - The Community Access Enterprise aims to equitably reduce and mitigate adverse environmental and health impacts of air pollution and greenhouse gas emissions from retail delivery vehicles at the community level, primarily by supporting the widespread adoption of electric motor vehicles and electric alternatives.

    - The Clean Fleet Enterprise focuses on reducing and mitigating adverse environmental and health impacts from air pollution and greenhouse gas emissions produced by fleet vehicles (including those for retail deliveries and transportation network company rides) by supporting fleet electrification.

    - The Clean Transit Enterprise works to reduce and mitigate adverse environmental and health impacts from retail delivery emissions by supporting the replacement of existing gasoline and diesel public transit vehicles with electric motor vehicles and providing associated recharging infrastructure.

    - The Nonattainment Area Air Pollution Mitigation Enterprise is specifically created to mitigate environmental and health impacts of increased air pollution from motor vehicle emissions in nonattainment areas, particularly those resulting from the growth in retail deliveries and prearranged rides.

Recent legislation in Colorado (Senate Bill 23-143) also acknowledges the administrative costs for retailers associated with these fees and emphasizes that they should primarily be imposed on retailers large enough to absorb these costs without significant economic harm. As a result, an exemption from retail delivery fees was created for retailers with retail sales of $500,000 or less in the previous calendar year. Retailers are also given the option to pay the retail delivery fee and associated enterprise fees on behalf of the purchaser, rather than itemizing it separately.

13.1.2 Minnesota

In Minnesota (MN Legislature, 2024), the retail delivery fee is intended for "road improvement and food delivery". While the legislation does not explicitly detail the deterioration of infrastructure specifically by e-commerce deliveries, the fee is designated for "road improvement" which suggests an underlying recognition of the need for funds to maintain the road network, which would inherently be impacted by increased delivery traffic. The proceeds from the retail delivery fee are deposited into the transportation advancement account, indicating a general purpose of funding transportation system needs.

The Minnesota legislation does not explicitly list congestion or pollution as direct justifications for the retail delivery fee itself. However, the proceeds being directed to a "transportation advancement account" implies a broader benefit to the transportation system. The fee's description as a "road improvement and food delivery fee" on invoices points to a direct link with supporting the physical infrastructure.
Minnesota's retail delivery fee is set at 50 cents for each transaction that equals or exceeds a threshold amount of $100, excluding specific exempt items. Key exemptions include:

- Retail deliveries to a tax-exempt purchaser.
- Deliveries made on motor vehicles requiring a specific permit under chapter 169 or 221.
- Deliveries resulting from retail sales of food and food ingredients, prepared food, or sales by a food and beverage service establishment.
- Deliveries resulting from retail sales of drugs, medical devices, accessories and supplies, or baby products.
- Small businesses are also exempt: a retailer with less than $1,000,000 in retail sales in the previous calendar year, or a marketplace provider facilitating sales for a retailer with less than $100,000 in retail sales in the previous calendar year.

Retailers have the option to collect the fee from the purchaser or pay it themselves. If collected, it must be shown as a separate item on the receipt labeled "road improvement and food delivery fee". The fee is applied once per transaction, irrespective of the number of shipments or items, and is generally nonrefundable unless the delivery itself is canceled.

Table 13.1: Comparison of Colorado and Minnesota Retail Delivery Fees

	Colorado	Minnesota
Implementation	July 1, 2022	July 1, 2024
Applicability	All retail sales delivered by motor vehicles; applies to all deliveries regardless of order value.	In-state and out-of-state sellers, marketplace facilitators; applies only on transactions over $100
Fee Amount	$0.29 per delivery (initially $0.27, adjusted for inflation)	$0.50 per delivery
Application per transaction	Applied once per retail sale, regardless of number of deliveries	Applied once per retail sale (same as CO)
Collection Method	Retailer collects from purchaser and remits to Department of Revenue (DOR). Retailer may elect to pay the fee on behalf of the purchaser. DOR collects all fees simultaneously on behalf of the state and enterprises.	Retailer may, but is not required to, collect the fee from the purchaser. If collected, the retailer remits to the commissioner. Third-party entities used for sales tax collection can also be elected for delivery fee collection.
Business Exemption Threshold	Businesses with less than $500,000 in annual sales	Businesses with less than $1,000,000 in annual sales
Itemization	If collected, fees must be shown as one item: "Retail Delivery Fees" separate from price and other taxes/fees. Not itemized if retailer pays on behalf of purchaser.	If collected from purchaser, must be shown as a separate item labeled "road improvement and food delivery fee" on the receipt/invoice.
Itemization Flexibility	Retailers can itemize the fee on receipts or embed it into the final product price	Retailers can itemize the fee on receipts or embed it into the final product price
Revenue Use	Distributed across various transportation and environmental funds, including clean fleet and air pollution mitigation	Not explicitly mentioned in the legislation.
Use of Funds	Primarily for: road infrastructure maintenance and mitigating environmental and health impacts from vehicle emissions (through various state enterprises for EV charging, fleet electrification, public transit electrification, and air pollution mitigation in	The balance of proceeds is deposited into the transportation advancement account for road improvement and food delivery. Primarily allocated to local governments, including cities, towns, and counties, with 1% for food assistance programs and covers the Commissioner's costs of

	Colorado	Minnesota
	nonattainment areas). Also, for multimodal transportation projects.	collection, administration, and enforcement.
Tax Treatment	Fee is not considered a tax	Fee is not considered a tax
Policy Focus	Clear and specific allocation to designated initiatives: clean transportation initiatives, reducing transportation-related emissions, etc.	Targeted at higher-value transactions, supporting transportation infrastructure and food assistance programs
Exemptions	Retailers with $500,000 or less in retail sales in the previous calendar year. Deliveries of tangible personal property exempt from state sales tax or to a purchaser exempt from state sales tax.	Retail deliveries to tax-exempt purchasers. Deliveries on motor vehicles requiring specific permits. Retail sales of food/food ingredients, prepared food, or sales by a food and beverage service establishment. Retail sales of drugs, medical devices, accessories/supplies, or baby products [466(5)]. Small businesses: Retailers with less than $1,000,000 in retail sales in previous calendar year, or marketplace providers for retailers with less than $100,000.
Inflation Adjustment	Yes, annually adjusted for inflation based on the Denver-Aurora-Lakewood Consumer Price Index, provided inflation is positive and results in at least a one-cent increase in the total fee, capped at 5%.	Not explicitly mentioned in the legislation.
Refund Policy	If retailer pays on behalf of purchaser, purchaser not entitled to refund for exempt deliveries, but retailer may claim refund. No general refund for returns/cancellations explicitly stated for the state fee.	Nonrefundable if items are returned or a refund/credit is equal to or less than purchase price. Refundable if the retail delivery is canceled by any party.

13.2 ESTIMATING E-COMMERCE DELIVERY FEES TO MAINTAIN ROADWAY INFRASTRUCTURE

To accurately estimate roadway infrastructure costs related to e-commerce delivery costs, a comprehensive analysis is required. A full accounting must integrate the direct and indirect expenses that e-commerce logistics inflict on public roadways, including wear-and-tear, congestion, and environmental impact. To understand the challenges of this task it is useful to borrow some concepts from highway cost allocation studies (HCAS).

The main purpose of a HCAS is to determine the fair share of highway-related costs that each user class, such as different vehicle types, should pay for the system's construction, maintenance, and operation. By comparing the costs each user class is responsible for, these studies evaluate the equity of the existing tax and fee structure and provide a basis for recommending adjustments to ensure a more equitable distribution of the financial burden.

13.2.1 Oregon HCAS

Oregon's HCAS is a comprehensive analysis that determines the cost responsibility for Oregon's highway system and the latest is for the 2023-25 biennial (Kitchen et al., 2023).

A primary purpose of Oregon's HCAS is to ensure that different classes of vehicles, from light-duty passenger cars to heavy-duty trucks, pay their fair share of the costs they impose on the road network. The is a key tool for policymakers to evaluate the equity of the state's highway user fee structure. The study's methodology is based on the principle that the costs of building, maintaining, and operating the highway system should be borne by those who use it, in proportion to the costs they generate.

The HCAS divides highway expenditures into different categories, including costs related to pavement, bridges, and common costs that do not vary with use, such as administration and safety programs. For costs that are directly related to vehicle use, the study allocates them based on factors like vehicle miles traveled (VMT), gross vehicle weight, and axle configurations. This is particularly important for heavy vehicles, which cause significantly more pavement damage than lighter vehicles. The study's findings are then used to calculate an "equity ratio" for each vehicle class, which compares the fees paid by that class to the costs it is responsible for. An equity ratio greater than 1.0 indicates a class is paying more than its share, while a ratio less than 1.0 indicates it is underpaying.

13.2.2 Challenges of Estimating E-Commerce's Impact Using a HCAS

Estimating the impact of an economic sector, like e-commerce, on a Highway Cost Allocation Study (HCAS) presents several challenges, primarily because e-commerce fundamentally alters transportation patterns in ways that are difficult to measure and quantify. The Oregon HCAS, for example, is designed to allocate highway costs to different vehicle classes, such as light and heavy vehicles, based on the costs they impose on the system. While the study is detailed, it does not explicitly address the complexities introduced by e-commerce.

Some of the key challenges include:

- Vehicle Data Collection and Disaggregation: E-commerce changes freight and delivery patterns from traditional business-to-business (B2B) to more complex business-to-consumer (B2C) models. This shift can introduce challenges in data collection. In Oregon, the HCAS relies on data from weigh-in-motion (WIM) sensors to understand heavy vehicle loads and distributions. While this is effective for commercial freight, it may not capture the full scope of e-commerce activity, which includes an increase in both light-duty and heavy-duty deliveries.

- E-commerce has led to a proliferation of delivery vans and smaller trucks. A traditional HCAS might group these vehicles into broad categories, potentially missing the nuance of their specific road use. The Oregon study, for example, separates vehicles into a "1 to 10,000 pound" light-duty class and several heavy-duty classes. E-commerce can increase overall VMT for smaller vehicles that make more frequent, spatially dispersed trips for last-mile delivery, even if these last-mile delivery vehicles are not carrying heavy loads. A traditional HCAS, which often places a greater cost burden on heavy vehicles due to their impact on pavement, may not fully account for the road wear and congestion caused by a high volume of lighter vehicles.

The core principle of a HCAS is that users should pay in proportion to the costs they impose. However, some costs, such as those for adding highway capacity or administrative functions, are considered "common costs" that do not vary directly with use. E-commerce complicates the allocation of these costs as detailed below.

- Congestion costs: the increase in delivery vehicles, especially during peak hours, contributes to traffic congestion. While the Oregon HCAS considers "congested (or peak-period) PCE-VMT" (passenger-car equivalence-vehicle miles traveled) to allocate common costs, it's challenging to isolate the specific portion of congestion attributable to e-commerce versus other economic activities.

- Road Network Utilization: E-commerce delivery services often utilize local roads and city streets more heavily than large, inter-city commercial trucks, which are a focus of many HCAS. The Oregon study's methodology includes state, federal, and local government expenditures, but separating the cost responsibility for e-commerce deliveries on local streets from other vehicle use can be complex. The study acknowledges that there are no single "right" allocators for costs that do not vary with use.

- Uncertainty: The Oregon study acknowledges that relying on forecasts for future periods can introduce error compared to using historical data. The rapid and ongoing evolution of e-commerce makes it difficult to forecast its future impact on traffic and infrastructure costs with a high degree of certainty.

- Light commercial vehicles (under 10,000 lbs.) are analyzed as "light vehicles" in the HCAS. They are responsible for a significant portion of overall highway expenditures, especially in areas like modernization, maintenance, and projects aimed at adding capacity, which are allocated using factors like Congested PCE-VMT. They contribute primarily through fuel

taxes and registration fees. The recent studies indicate they are projected to underpay their cost responsibility, a trend influenced by the evolving mix of highway investments and updated data.

The delivery fee impacts mostly final consumers, but in broad terms e-commerce can be broken down into (a) business to business (B2B) and (b) business to consumer (B2C) transactions. It debatable whether a delivery fee should capture mostly the B2C cost or cover the infrastructure costs all types of e-commerce. Completely separating the impacts of e-commerce on transportation infrastructure between B2B and B2C is not possible due to their shared use of networks and blended logistics. However, it may be possible to disaggregate them to some degree by analyzing their distinct logistical characteristics.

13.3 SUMMARY

Summarizing, there are only two states currently imposing a retail delivery fee and the justification of the fee in terms of e-commerce related infrastructure maintenance costs is more explicit in Colorado's legislation. Regarding the estimation of the actual costs of e-commerce in terms of infrastructure maintenance, it has been shown that this is a complex problem and there is no straightforward method to estimate the value of a delivery fee that compensates for roadway infrastructure costs. Separating B2C and B2C infrastructure costs is also challenging. Recommended data collection efforts to address these challenges are presented in the following section.

14.0 DATA COLLECTION RECOMMENDATIONS

This section discusses data collection trends and evaluates existing and potential data sources for analyzing the impacts of potential household e-commerce delivery fees and provides recommendations for future data collection efforts.

14.1 HOUSEHOLD DATA COLLECTION TRENDS

Household Travel Surveys (HTS) are critical tools for transportation and urban planning, providing essential data on travel behavior, socioeconomic factors, and the impact of evolving technologies and societal shifts. The household travel data collection efforts started in the 1960s and have changed significantly accompanying the evolution of travel patterns, modes, and data collection technologies. Despite the rise of new data sources, HTS remain indispensable, particularly for understanding nuanced travel motivations and individual-level insights not captured by aggregate data.

Current trends in household travel surveys include shifts to more frequent data collection and new passive data sources like mobile phone data, changes in survey methodology to include web and mail options instead of phone interviews, and increased focus on emerging mobility modes. Data collection efforts are becoming more integrated and partnerships are forming to address challenges like declining response rates and privacy concerns, as well as the bias towards tech-savvy populations (Lawson et al., 2023).

14.1.1 General trends

Some of the key trends related to household data collection approaches and analysis include:

- Given the declining response rates, researchers have developed response-propensity models to examine drop-out mechanisms and participation probabilities. In one study education was identified as an explanatory variable (Wittwer et al., 2024), however it is still too early to identify factors or trends that apply to multiple studies.

- Compounding the problem of declining response rates is the fact that household travel surveys are expensive. A potential solution is the utilization of mixed-mode surveys and new technologies to complement traditional household travel surveys designs. Though, the amount of bias generated by mixed-mode surveys remains an open question (Bayart & Simas, 2024).

- Traditionally decennial, many HTSs are moving to more frequent (e.g., biennial or continuous) collection cycles to capture rapid changes in travel behavior (e.g., e-commerce, micromobility, remote work) and provide up-to-date inputs for modeling. A recurrent sampling strategy includes a large initial survey followed by smaller and evenly timed surveys (Lawson et al., 2023).

- Smartphone apps are increasingly common since 2018, with 40-75% usage in reported surveys, leading to higher and more reliable trip counts and online surveys have largely replaced paper-based methods (Selby, 2025).

- Combining methods like smartphone apps, online surveys, and phone interviews allows for greater flexibility in data collection and helps overcome declining response rates and demographic biases (Harding et al., 2025).

- Collaborative efforts between Metropolitan Planning Organizations (MPOs), State Departments of Transportation (SDOTs), and other agencies are growing. This involves joint collection effort through partnerships and add-on samples – where local jurisdictions purchase additional samples using the same methodology – and consolidated programs to achieve economies of scale, harmonize data, and stabilize funding (Lawson et al., 2023).

- Incentives are universal, with differential incentives for hard-to-reach groups. Targeted oversampling by geography (e.g., block group demographics) and convenience samples are used. Public awareness campaigns, partnerships with community organizations, and simplified invitation/login processes (e.g., removing account creation requirements) are proving effective in boosting participation and reducing bias (Harding et al., 2025).

- HTS are evolving to capture new realities like remote work, online shopping, and the use of active transportation modes. Questions are being updated to cover remote work frequency and new transport options like ride-sharing services (Harding et al., 2025).

14.1.2 Shopping trips and e-commerce

Travel, shopping, and e-commerce activity data collection has its own challenges, some of the key issues include:

- For shopping and ecommerce, the utilization of Computer-Assisted Web Interview (CAWI) surveys is commonly used in market research where respondents answer a questionnaire directly on a website or web page. The software "assists" by guiding the respondent through the survey with self-routing logic, displaying multimedia content, and collecting data in real-time, allowing for efficient and relatively inexpensive data capture and broad geographic reach. For travel and e-commerce related research it is important to capture typical travel behavior but add information capture related to online shopping behavior, attitudes regarding shopping online, instore, and technological attitudes (Bönisch et al., 2024).

- There is also a tradeoff regarding integration of e-commerce/shopping surveys into traditional surveys or a dedicated survey (Gardrat, 2024). The main tradeoffs are cost, sample size, information accuracy, and information quantity.

- Another aspect of e-commerce data is acquisition of delivery vehicles data and behavior that is constrained by a competitive climate that encourages secrecy and data protection of vast amounts of GPS data that could be used to estimate travel patterns.

14.1.3 Household survey costs

Surveys must be responsive to policy needs and affordable, especially given insufficiently funded statistical systems and rising data collection costs, the average cost of a common face-to-face household survey is $170 per household (Carletto et al., 2022) but costs have increased after COVID-19.

There have been recent efforts to document and compare large household travel survey costs across different agencies and locations. Nominal cost per completed household sample is going up and typically range between $150 and $250 per household (Straub et al., 2025). And this range was confirmed by another source (Selby, 2025). On the other hand, a web-based shopping and ecommerce survey is on the other of $20 to $30 per household including survey design. This is a significant difference, and the needed sample size and goals of the study and research questions may be used to justify either approach. It remains unclear whether expensive household GPS data collection methods are needed to study e-commerce deliveries if the complexity and cost of GPS data collection does not allow the inclusion of questions related to shopping attitudes and habits or products purchased.

Summarizing, the landscape of household surveys, particularly HTS, is undergoing significant transformation. The challenges of declining response rates, data quality, and rapid shifts in societal behavior and technology necessitate a proactive approach to modernization. Innovations in data collection modes (smartphone apps, web surveys, mixed-mode designs), sampling techniques, objective measurement, and the integration of traditional surveys with new data sources are crucial. Given these general household data collection trends, the report will now evaluate specific data sources like NHTS and OTS.

14.2 CURRENT AND FUTURE DATA SOURCES

There are two main data sources that could be useful in future efforts to analyze the impacts of potential household e-commerce delivery fees and provide a foundation for future data collection efforts. The first dataset is the National Household Travel Survey (NHTS) and the second is the Oregon Travel Survey (OTS).

14.2.1 NHTS DATA

The National Household Travel Survey (NHTS) is a comprehensive, periodic survey conducted by the Federal Highway Administration (FHWA) with support from the Oak Ridge National Laboratory (ORNL). It is the leading source of nationwide data on the travel behavior, providing a detailed inventory of daily, non-commercial trips by all modes of transportation. The survey collects data from a nationally representative sample of households and individuals, including information on trip purpose, means of travel (car, walk, bus, etc.), travel time, and time of day. This rich dataset allows researchers and policymakers to analyze travel patterns, understand how travel characteristics are changing over time, and study the relationship between demographics and travel (ORNL, 2025).

The NHTS data collection methodology has evolved over the years to adapt to technological changes and improve accuracy. Historically, it relied on in-home interviews and then telephone surveys. The most recent surveys have shifted to a "push-to-web" approach, where households receive a mailed invitation with a link and secure password to complete the survey online. Respondents are asked to provide demographic details about their household, its vehicles, and its members. Then, each eligible household member (ages 5 and older) is asked to report every trip they took during a 24-hour travel period. The use of an address-based sampling frame allows for the inclusion of cellphone-only households, and the data collection is distributed across all 365 days of the year to account for seasonal and day-of-week variations. The data is often supplemented with information from the U.S. Census Bureau to provide additional context.

The NHTS has also evolved to address the significant shift toward e-commerce and home deliveries by adding specific questions and new data variables to its surveys. As online shopping and delivery services became more prevalent, especially following the COVID-19 pandemic, the traditional person-trip focus of the NHTS for shopping-related travel was no longer sufficient to provide a complete picture of travel demand. To better understand these new trends, the NHTS now collects data on a variety of delivery-related behaviors.

The most recent iterations of the NHTS, starting in 2009 and greatly expanded in the 2022 survey, have included specific questions to capture the impact of home deliveries on travel behavior. This includes asking respondents about the frequency and type of online purchases they have had delivered to their home over a specific period. The delivery period of time changes slightly, from “the past month” to “in the past 30 days”. Overall, the questions are now much more granular, differentiating between goods delivery services (like Amazon or Walmart), food delivery services (such as Uber Eats or DoorDash), and grocery delivery services (like Instacart). The survey also asks about return behavior, specifically whether online purchases were returned via home pickup, a drop-off location (e.g., Post Office, FedEx), or directly to a physical store.

The evolution of the most relevant question related to e-commerce are provided in the table below.

Table 14.1: NHTS e-commerce questionnaire evolution

YEAR	Question
2009	• In the past month, how many times did you personally purchase something through the Internet? [purchase] • How many of these purchases were delivered to your home? [deliver]
2017	• In the past 30 days, how many times did you purchase something online and have it delivered? [deliver]
2022	• In the past 30 days, how many times did you personally purchase something online and have delivered to your home? [deliver] • How many times in the past 30 days you personally purchase the following online and have it delivered to your home? ○ goods delivery service (amazon, walmart, etc.) [deliv_good] ○ food delivery service (uber eats, door dash, etc.) [deliv_food] ○ grocery delivery services (amazon fresh, instacart, etc.) [deliv_groc] ○ service delivery (home health care, home schooling) [deliv_pers]

It is possible to see that the 2009 question related to home deliveries was very general and that the 2022 survey provides a much higher level of detail and specificity. Because the variable "deliver" was maintained in the last three editions of the NHTS it is possible to compare results over time.

A recent paper (Ha, 2025) models and compares the significant variables affecting the number of deliveries using data for the head of the household. Note that most studies have reported on household level estimations, but this research focuses on the person level because the emphasis of the research is on socioeconomic variations at the person-level.

The variable [deliver] was used to estimate Zero-Inflated Negative Binomial (ZINB) regression models for 2009, 2017, and 2022 editions of the NHTS. The ZINB model is particularly suited for this analysis because a significant portion of the population (62% in 2009, 44% in 2017, and 27% in 2022) reports zero online deliveries, indicating an "excess of zeros" that standard count models cannot effectively handle.

As previously discussed, a ZINB model consists of two main components: a logit model that predicts the likelihood of an individual having zero online deliveries (i.e., not engaging in online shopping) and a count model that estimates the number of online deliveries for individuals who made at least one purchase. Generally, a negative coefficient in the logit model and a positive coefficient in the count model imply a positive association with online delivery engagement.

Table 14.2 presents the results of models that aim to identify the determinants of online delivery frequency across three waves of the National Household Travel Survey (NHTS). But before discussing possible trends it is useful to introduce some caveats, Table 14.3 shows that the

number of respondents have dramatically decrease between 2017 and 2020 and that the model fit, using pseudo R square, was never great but has also decreased over time from 0.080 to 0.027.

One of the most notable overarching trends revealed in Table 14.2 is the widespread growth in online shopping across diverse demographics, as reflected by the declining share of individuals reporting no online purchases and a marked increase in frequent online shoppers between 2009 and 2022. This shift is attributed to expanded digital infrastructure, changing economic conditions, and the accelerated adoption of e-commerce during the COVID-19 pandemic.

Table 14.2: ZINB models for NHTS [deliver] variable (Ha, 2025)

	2009	2009	2017	2017	2022	2022
Variable	**ZI**	**NB**	**ZI**	**NB**	**ZI**	**NB**
Intercept	-0.683*	0.445*	-0.496*	1.29*	0.399*	1.731*
Age	0.056*	-0.002*	0.029*	-0.009*	-0.005*	-0.006*
Female (ref: Male)	-0.305*	0.077*	-0.555*	0.142*	-0.573*	0.146*
Bachelor's degree + (ref: No 4-year degree)	-1.382*	0.169*	-1.292*	0.169*	-1.157*	0.076*
Driver (ref: Not driver)	-1.888*	0.299*	-1.291*	0.036*	-1.076	0.084
Black or African American (ref: White)	1.021*	-0.164*	0.705*	-0.321*	0.503*	-0.083*
Asian (ref: White)	0.889*	-0.179*	0.941*	-0.177*	0.772*	-0.112*
Other race (ref: White)	1.198*	-0.02	0.609*	-0.023	0.595*	-0.23*
Middle income HH (ref: Low income HH)	-0.996*	0.120*	-0.738*	0.172*	-0.208*	0.208*
High income HH (ref: Low income HH)	-1.651*	0.359*	-1.183*	0.410*	-0.138	0.375*
Not worker (ref: Worker (never WFH))	0.291*	-0.044*	0.313*	-0.012	0.598*	-0.029
Worker (WFH) (ref: Worker (never WFH))	-1.246*	0.254*	-1.016*	0.144*	-1.028*	0.151*
MSA < 1 million (ref: Not MSA)	-0.126*	-0.078*	-0.049*	-0.059*	-0.292*	-0.030
MSA ≧ 1 million (no rail) (ref: Not MSA)	-0.356*	-0.067*	-0.238*	-0.009	-0.464*	0.047
MSA ≧ 1 million (with rail) (ref: Not MSA)	-0.348*	0.013	-0.313*	0.047*	-0.412*	0.085
Alpha	1.565*		1.041*		0.808*	

* Indicates significance at $p < 0.01$.

Table 14.3: Model fit and sample size (Ha, 2025)

Variable	2009	2017	2022
Pseudo R-squared	0.080	0.049	0.027
N	262,506	230,472	14,423

There are mostly consistent trends. Income and worker are key variable as denoted by the absolute magnitude of the estimated coefficients. Income-based disparities in online shopping participation have declined over time, with middle- and high-income households becoming less distinct from low-income households in their likelihood of reporting zero online deliveries by 2022. This indicates a greater adoption of online shopping among lower-income groups. Despite

this narrowing participation gap, high-income households continue to make more online deliveries, reflecting differences in disposable income and purchasing power, with their delivery frequency peaking in 2017 and stabilizing in 2022.

Employment status also significantly shapes online shopping behavior. Unemployed individuals were consistently more likely to report zero online deliveries, and this gap widened over time. Conversely, remote workers (WFH) were consistently and significantly less likely to report zero online deliveries, indicating higher digital engagement. The count model suggests that the differences in delivery frequency between WFH and non-WFH workers narrowed over time, showing no significant differences between these groups from 2017 to 2022.

Educational attainment strongly correlates with online delivery behavior, with individuals possessing a bachelor's degree or higher consistently more likely to engage in online deliveries. In 2022, highly educated individuals were 69% less likely to report zero online deliveries compared to those with lower educational attainment. The widening divide in the logit model suggests that online shopping has increasingly become an integral part of daily consumption for this highly educated group. However, the count model shows that while highly educated individuals initially had more deliveries, this effect weakened by 2022, implying that online shopping is becoming more common even among less educated individuals, thereby slowing the growth rate among the highly educated.

For driver status, individuals who are drivers were consistently less likely to report zero online deliveries across all survey waves. In 2022, drivers were 66% less likely than non-drivers to report no online deliveries. However, the count model reveals a diminishing gap in delivery frequency between drivers and non-drivers, suggesting that while drivers were early adopters, non-drivers have increasingly engaged with e-commerce, leading to a narrowing of the frequency gap.

Regarding gender, females consistently demonstrate higher online delivery engagement than males. In 2009, females were 26% less likely than males to report zero online deliveries, a disparity that widened significantly by 2017 and 2022, where the odds for females reporting zero deliveries were 56% of those for males. The count model further supports this, showing that females consistently made more online deliveries, and this effect became more pronounced and then stabilized after 2017. These findings suggest that gender disparities in e-commerce engagement have persisted over time.

Examining racial disparities, White individuals were consistently less likely to report zero online deliveries compared to Black, Asian, and other racial groups. While the participation gap for Black respondents has declined over time, it persists. The count model for Black respondents indicates that the delivery frequency gap with White individuals widened from 2009 to 2017 before narrowing by 2022. For Asian respondents, both logit and count models suggest a stable racial gap, although by 2022, Asian individuals showed greater engagement with online shopping than in previous years.

Geographic factors tend to have lower coefficients, and they are not significant at the 0.01 level in 2022. But it seems that in 2009 and 2017, metropolitan statistical area (MSA) type significantly influenced online shopping participation and frequency. Individuals in MSAs,

especially those with populations over one million, were consistently less likely to report zero online deliveries compared to those in non-MSA areas, suggesting an increasing divide in participation for rail-connected MSAs.

Regarding age there is a change in the trend, the logit models show a significant shift: older adults were initially less likely to engage in online shopping in 2009 and 2017 (positive coefficients), but by 2022, they became more likely to engage (negative coefficient). This change, confirmed by interaction terms, suggests increased digital adoption among seniors, possibly accelerated by the pandemic's influence on their familiarity with online platforms. The count models, while consistently showing that younger individuals tend to make more online deliveries, also indicate that the frequency gap between younger and older adults narrowed by 2022, meaning older adults not only adopted online shopping but also increased their usage frequency.

In summary, the results from Table 14.2 underscore a widespread growth in online shopping across diverse demographics, with a general trend towards narrowing disparities in participation (e.g., age, income) but persistent or even widening gaps in engagement based on education and employment status. Individuals with more financial resources, higher education, and those working from home tend to engage more frequently in online deliveries.

14.2.2 Future NHTS efforts

According to the FHWA the 2024 NHTS is underway and data collection activities started on November 1, 2024 (FHWA, 2025). The 2024 data is part of the NextGen NHTS program that started with the 2022 dataset and focuses on providing national travel behavior data more frequently (biennial surveys) but with a smaller dataset (approximately 7500 households). The large decrease in sample size was shown in Table 14.3.

For e-commerce and home delivery trend analysis, more frequent data collection is highly valuable and will provide a way to study nationwide trends regarding e-commerce growth and trends regarding the importance of different socioeconomic factors. The NHTS is the only survey that has collected e-commerce delivery data in a somewhat consistent way since 2009.

14.2.3 OTS Data

In the state of Oregon there is another highly relevant and valuable data collection effort underway, the Oregon Travel Study (OTS). According to the Oregon Modeling Statewide Collaborative (OMSC) travel information was collected from approximately 21,000 households (OMSC, n.d.). Unfortunately, the OTS survey data will not be available by Dec 2025/ Jan 2026 (M. Bagwell, personal communication, August 22, 2025).

Though the data is not available, it is possible to highlight questions in the general questionnaire that will be valuable to support the research conducted in this research.

14.2.4 OTS Delivery Day

There is question about "delivery day" that may be useful to understand the socioeconomic groups that engage in e-commerce and home deliveries. The question is the following:

We want to know how delivery and household services contribute to travel.
On (a specific day), which of the following occurred? *Select all that apply.*

- Received packages at home (e.g., USPS, FedEx, UPS)
- Received personal packages at work
- Received packages at another location (e.g., Amazon locker, package pick-up point)
- Take-out/prepared food delivered to home
- Groceries delivered to home
- Someone came to do work at home (e.g., babysitter, housecleaning, lawn)
- Other item delivered to home (e.g., appliance)
- None of the above

14.2.5 OTS Delivery Frequency

There is a question about delivery frequency that may be useful to study that socioeconomic factors that are associated to home deliveries. The question is the following:

Approximately how many home deliveries did you receive from online orders over the last seven days? This includes food, groceries, clothing, and any other items delivered to your residence.

- None
- 1-2
- 3-5
- 6-10
- 11-15
- 15+

The data obtained with this question is of ordinal type and it may be possible to estimate ordinal models. However, the data is not of interval or count type. Therefore, it is not possible the estimation of ZINB or NB models that can be used to directly compare results with the NHTS

data or with this research project. However, the OTS data contains detailed individual and household travel/trip data and therefore the OTS data may be useful to try to understand the substitution or complementary effects of e-commerce and household shopping trips.

14.2.6 OTS E-commerce survey

There has been a data collection effort to complement the general OTS survey data with a focused e-commerce dataset. However, this research effort has not had access to this potential source of data and therefore it is not possible to discuss how this dataset may be used in the future.

14.2.7 Limitations of existing data sources

The NHTS data is valuable because since 2009 is collecting data about home deliveries and it is expected that there will be frequent updates. An advantage of the NHTS is that it is possible to link e-commerce shopping with other trip, personal, and household variables.

However, the latest version of NHTS data still have some key limitations:

The NHTS survey questions gather information about the number of e-commerce monthly purchases. It is not clear whether respondents can accurately remember the number of monthly purchases.

1. There is no disaggregated data about product purchases or amount spent on e-commerce deliveries.

2. The NHTS data does not include any data related to e-commerce or home delivery preferences. Therefore, shopping attitudes are likely a confounding variable in the relationship between e-shopping and in-store shopping.

3. The NHTS data does not include any data related to e-commerce shopping or delivery subscriptions.

Regarding the OTS data, since it was not possible to access the data, it is unknown if the OTS data will include the necessary product detail and or shopping variables and attitudes that are necessary to provide a reasonable understanding of the complex relationships between in-store and e-commerce shopping. It is also unknown the sample size of the current dataset or the frequency or dates of future data collection efforts.

14.3 RECOMMENDATION FOR FUTURE DATA COLLECTION EFFORTS

E-commerce is evolving quickly, and the implementation of a delivery fee bring about new challenges, especially regarding measurement of e-commerce related road maintenance costs. The recommendations for future data collection efforts are multiple and grouped into six areas.

14.3.1 Shopping-centered data collection

To understand home deliveries, it is critical to understand how households shop online and at physical brick-and-mortar stores. While traditional household transportation data collection has focused on trips, the motivation for using e-commerce is not solely based on reducing trips. Therefore, understanding consumer shopping options, attitudes, and habits is essential for comprehending home delivery demand.

14.3.2 Socioeconomic factors and fee sensitivity

The findings presented in this research regarding a delivery fee sensitivity are novel, moreover, this is the first research effort to study household delivery fees. Therefore, it is important that future research efforts build on this foundational knowledge when planning future data collection efforts. The findings suggest that each product has a unique profile regarding sensitivity to delivery fees. It is important to have data collection efforts that include a set of products that account for most of the deliveries but also a set of products that is diverse enough to capture differences in attitudes and socioeconomic factors across products.

14.3.3 More Frequent and less expensive data collection

E-commerce is evolving quickly, and this is an area where more frequent data collection efforts are necessary. Biennial data collection efforts can track the evolution of households shopping patterns, shopping trips, and home deliveries. To reduce data collection costs well-designed web-based surveys can capture the key trends and factors while reducing data collection costs and analysis. Partnering in federal efforts like the NHTS can provided detailed trip data and frequent updates at a reduced cost with the advantage that the NHTS is now including more online shopping and home delivery related questions.

14.3.4 Revenue potential and exemptions

This research identified the key socioeconomic factors that impact the frequency of home deliveries and the estimated revenue potential of a delivery fee. Though, as e-commerce evolves and growth it will be valuable to update and expand data collection efforts to include more products. It is also important to measure the impact of potential product exemptions (e.g. groceries, medicines) and for certain groups (e.g. households under poverty or low-income thresholds).

14.3.5 Fairness data needs

The research findings indicate that households with specific characteristics are more susceptible to a delivery fee regressive impact. The findings also strongly suggest that each product has a unique profile regarding sensitivity to delivery fees. This research has no access to OTS data, but it speculates that data from the more detailed OTS data may be useful to evaluate shopping trip gasoline tax expenditures for households in rural areas taking into account household income, vehicle type, and fuel efficiency. Fuel efficiency is a key data element needed to evaluate fairness of existing gas taxes and future delivery fees. The research findings showed that the sensitivity to a potential delivery fee is highly dependent on the type of brick-and-mortar store

visited and the type of product purchased. More detailed OTS data may be useful to provide additional understanding in terms of fairness, but this is something that will be revealed when the OTS data is available.

14.3.6 E-commerce Infrastructure impacts

The impacts of e-commerce on roadway infrastructure are difficult to identify and measure. Some of the key data challenges include:

- It is hard to separate the operations of retail companies that offer both brick-and-mortar and home delivery shopping options. There may be a common supply chain from up to and including warehouse and distribution center facilities and only the last-mile delivery trip may be different.

- E-commerce may substitute trips to stores by delivery vehicle trips. The number of trips and vehicles utilized by consumers and delivery companies may affect the accounting of net infrastructure impacts.

- Number of trips and vehicle types (size, engine types, etc.) are also important to evaluate congestion and environmental impacts.

- A large proportion of last-mile delivery miles takes place on local street networks that have different infrastructure design and maintenance costs. The type of e-commerce related vehicles used in the core transportation network (interstates, U.S. highways, and state highways) is different from of the e-commerce related vehicles used in county, city streets, and other parts of the network.

14.4 SUMMARY

Traditionally household travel surveys have focused on person or household travel data. Questions to understanding shopping and e-commerce impacts have recently been added to surveys. In general, transportation planners have less access to detailed freight and e-commerce data due to the proprietary nature of much of the private sector data, privacy concerns, and lack of standardization across the logistics industry. This section provides some recommendations for future data collection efforts. Because data collection costs are a key constraint, survey data collection trends and costs are discussed. For e-commerce related data collection efforts it is important to analyze tradeoffs among survey type, costs, and size and whether detailed GPS based surveys are needed. Any future data collection effort that provides data to address some of the above points will be a valuable source to identify e-commerce impacts on roadway infrastructure.

15.0 CONCLUSIONS AND RECOMMENDATIONS

The analysis undertaken in this study provides the first comprehensive examinations of the potential revenue and equity implications of an e-commerce household delivery fee. Several major findings emerge from the literature review, survey data, statistical modeling, and analysis.

E-commerce activity has become deeply embedded in household consumption patterns. The survey results confirm that most Oregon households regularly use home deliveries for groceries, prepared food, clothing, electronics, pharmaceuticals, and other everyday products. Delivery frequency is strongly correlated with household characteristics such as age, income, and household size. Younger and higher-income households, particularly those with subscriptions to platforms such as Amazon Prime or grocery delivery services, are the most frequent users of delivery services. At the same time, some older adults exhibit a reliance on deliveries, especially pharmaceuticals, indicating that deliveries are not simply a matter of convenience but also serve important accessibility functions.

This section consolidates the key findings, key insights, and recommendations derived from this research.

15.1 KEY FINDINGS

E-commerce has experienced substantial and sustained growth, transforming retail landscapes both nationally and within Oregon. E-commerce sales escalated from approximately 7% of total retail sales in 2015 to 16% in 2024, a trend further accelerated by the global COVID-19 pandemic and projected to continue its double-digit annual growth due to demographic shifts, technological advancements, and the rise of delivery subscription models. This growth presents a compelling opportunity for a stable, long-term revenue source for transportation funding, particularly as ODOT faces declining real-term revenues from fuel taxes due to increased fuel efficiency and electric vehicle adoption.

Several U.S. states have already moved to implement retail delivery fees to address transportation infrastructure needs, with Colorado and Minnesota serving as prominent examples. Colorado's fee was implemented in July 2022, initially charging $0.28 and later adjusted to $0.29. Colorado’s fee is adjusted annually in July and is explicitly justified by the increased traffic, emissions, and accelerated deterioration of infrastructure caused by rising delivery volumes. Minnesota, following suit in July 2024, imposes a $0.50 fee on retail deliveries exceeding $100, allocating funds for "road improvement and food delivery". Both states have introduced exemptions for small businesses and offer flexibility for retailers in how the fee is itemized or integrated into product pricing to mitigate administrative burdens and consumer resistance.

Exploratory analysis of this survey data identified several sociodemographic factors strongly influencing home delivery frequency: higher-income households, larger household sizes, and

individuals in the 35-44 age group are associated with more frequent deliveries, while those aged 65 and above tend to have fewer deliveries. Households in large urban areas also exhibit more frequent deliveries. Conversely, variables such as gender, race, and the presence of household members with disabilities showed less clear or consistent impacts on overall delivery frequency.

Shopping-specific variables and consumer attitudes emerged as significant predictors of e-commerce engagement. A clear positive correlation exists between the number of household members who typically shop or work online and the frequency of home deliveries. Subscriptions, particularly Amazon Prime and pharmaceutical subscriptions, are strongly linked to higher delivery rates. Consumer attitudes play a crucial role, with "it saves time," "more options," and "more comparisons" being significant motivators for online shopping. The type of physical stores visited also has an impact: households that frequently visit supermarkets tend to have lower home delivery frequencies, while those visiting big-box stores show higher frequencies.

Analysis of product-specific deliveries indicated that groceries, prepared food, clothing, and miscellaneous items are the most frequently delivered categories. Crucially, the sensitivity to a potential $0.50 delivery fee varies by product type. Households that order groceries, prepared food, and pet products often expressed a higher likelihood of reducing orders if a fee were applied. In contrast, electronic and "other" products (like sports equipment or hobbies) showed less sensitivity to such a fee. Common variables increasing fee sensitivity include the perception that e-commerce is "cheaper," frequenting discount stores, and residing in a large urban area. Conversely, factors reducing fee sensitivity include holding an Amazon subscription, valuing time savings, higher household income, and – for pharmaceutical products only – being aged 65 or older. The number of deliveries was a significant predictor of fee sensitivity only for clothing, personal/beauty, and pet products, suggesting these are more discretionary categories.

Negative Binomial (NB) models, specifically for households engaging in e-commerce, reiterated the importance of the number of online shoppers/workers, supermarket visits (negative impact), and attitudes such as valuing safety, comparison, and subscription convenience in predicting overall delivery rates. Household size (three or more members), income over $100,000, and being in the 35-44 age group positively correlated with higher delivery rates, while those aged 65 and above showed decreased rates.

This research finds that a flat e-commerce delivery fee follows the User Pay Principle but is regressive. Quantifying this, a $0.50 fee translates to a 5.0% sales tax equivalent on a $10 order, decreasing for higher-value purchases. For low-income households, particularly those at 100% of the Federal Poverty Line, a median of three deliveries per week (equating to $78 annually) can represent up to 0.52% of their annual income for a single-person household, a burden that is significantly higher than for high-income households. The analysis characterizing high-impact households (those in the upper tertile of the delivery-to-income ratio) identified vulnerable groups, including households with members having disabilities, those for whom travel is difficult, individuals shopping at discount stores, young adults (18-24), frequent online shoppers, and females, as being disproportionately affected by the regressive nature of the fee.

The impacts of a delivery fee on rural and low-income households manifest differently. For urban low-income households, the fairness hinges on vehicle ownership; those without vehicles in retail deserts stand to benefit most from reduced delivery fee burdens. Rural Oregon residents

often face "retail deserts" and limited public transportation, making e-commerce deliveries a valuable option rather than a mere convenience. For these households, a flat delivery fee might surprisingly be less regressive than an increase in the flat gasoline tax. For lower-income households that own older, less fuel-efficient vehicles and drive longer distances increases in the flat gas tax and vehicle registration fee may be more regressive than a delivery fee.

Lastly, the estimation of e-commerce-related roadway infrastructure costs is highly complex, involving challenges in disaggregating vehicle data, accounting for congestion, and allocating costs across different road networks and business models (B2B vs. B2C).

15.2 KEY INSIGHTS

The growing e-commerce sector presents a multifaceted challenge and opportunity for state transportation agencies like ODOT. While it offers a promising, expanding revenue base to offset declining fuel tax revenues, the inherent regressivity of a flat delivery fee demands consideration. The research highlights that the utility of e-commerce extends beyond mere convenience for certain vulnerable populations, particularly those in retail deserts or individuals with disabilities, for whom home deliveries provide essential access to goods and services that might otherwise be unattainable.

The review of existing state policies shows that Colorado and Minnesota have taken different approaches to implementing delivery fees, each with trade-offs. Colorado's low per-delivery fee applies broadly, with revenue earmarked for transportation and environmental programs, while Minnesota applies a higher fee only to orders exceeding $100, with explicit exemptions for groceries, baby products, and medicines. Both programs confirm that such fees can generate tens of millions of dollars annually but also highlight the political and administrative challenges of balancing revenue generation with fairness.

A critical insight derived from this study is the distinction between factors driving overall home delivery rates and those influencing a household sensitivity to a delivery fee. While income, household size, and online engagement strongly predict delivery frequency, fee sensitivity is shaped by a more complex interplay of attitudes (e.g., valuing "cheaper" over "saves time"), shopping habits (e.g., preference for discount stores), and geographical context (e.g., large urban areas offering alternatives). This implies the complexity of designing a delivery fee that is not regressive.

There are distinct behavioral responses that consumers might exhibit in the face of delivery fees. High delivery fees could incentivize order consolidation or a return to in-store shopping. But for households with limited mobility or in areas lacking retail alternatives, the fee would simply impose an unavoidable cost, limiting access to competitively priced goods and potentially impacting their financial well-being.

The challenge of attributing e-commerce-specific costs to roadway infrastructure is considerable. For example, traditional Highway Cost Allocation Studies (HCAS) are not designed to precisely disentangle the wear-and-tear, congestion, and environmental impacts caused by the proliferation of diverse delivery vehicles (from light vans to heavier trucks) operating across various road networks (interstates, local streets). This methodological gap underscores the difficulty in

scientifically justifying a specific fee amount solely based on direct infrastructure impact, often necessitating a broader justification that includes societal benefits and environmental mitigation, as seen in Colorado's approach. The increasing use of electric delivery vehicles, while mitigating emissions, does not necessarily reduce congestion or direct roadway wear-and-tear, adding another layer of complexity to cost internalization efforts.

Regarding data needs, the existing limitations in current national (NHTS) and state (OTS) data collection efforts regarding detailed product purchases, spending amounts, shopping attitudes, and subscription data pose a significant constraint on comprehensive policy analysis. While these surveys are evolving to capture more e-commerce data, the need for more granular, shopping-centric, and cost-effective data collection is essential to fully understand the intricate relationships between e-commerce and travel behavior and to perfect the design of a delivery fee. The trade-off between the depth of data (e.g., GPS-based trip data vs. attitudinal surveys) and collection cost remains a critical consideration for future research.

15.3 KEY RECOMMENDATIONS

A proposed delivery fee structure could incorporate mechanisms to mitigate its inherent regressivity. Leveraging Oregon's existing progressive tax structure, such as an increase in the Oregon Earned Income Tax Credit (EITC) or the creation of a new, targeted refundable credit for essential services, could provide direct financial relief to low- and moderate-income households most affected by the fee. Oregon could explore direct subsidy mechanisms or integrate fee relief into existing social service programs, administered through agencies like the Oregon Department of Human Services, with eligibility tied to participation in other benefit programs like SNAP or TANF. Partnerships with delivery service providers – like Amazon's existing discounts for eligible low-income households – should also be explored and incentivized to streamline the delivery of benefits and reduce administrative burdens for users.

The justification for the delivery fee should be clearly articulated and transparently linked to specific transportation infrastructure improvements. While revenue generation is a primary goal, public acceptance and perceived fairness are enhanced when the collected funds are explicitly tied to mitigating the impacts of e-commerce deliveries, such as local road maintenance, congestion reduction, and promoting clean fleet transitions. This requires a clear allocation of funds, moving beyond general "road improvement" to specified initiatives, similar to Colorado's detailed breakdown into multimodal transportation projects, clean fleet transitions, and air pollution mitigation.

Both Colorado and Minnesota have introduced exemptions for small businesses and offer flexibility for retailers in how the fee is itemized or integrated into product pricing to mitigate administrative burdens and consumer resistance. There are political and administrative challenges when balancing revenue generation and fairness. The administration cost and implementation complexity of a delivery fee can also change if there are exceptions (e.g. for the delivery of groceries or pharmaceutical products) or exemptions for low value orders or small businesses. Oregon does not have a sales tax it is important to consider implementation costs because they may be higher than in Colorado or Minnesota. The cost of implementing and administering a retail delivery fee is outside the scope of this research but should be carefully considered.

Future data collection efforts must be strategically enhanced to provide more granular and actionable insights. A shopping-centered data collection approach is crucial, moving beyond traditional trip-based data to understand the underlying motivations, attitudes, and habits influencing both online and in-store shopping decisions. This would encompass:

- Product-Specific and Exemption Analysis: future surveys should collect detailed information on a broader and more diverse range of products, allowing for a deeper understanding of varying fee sensitivities across different goods. This is essential for evaluating the revenue and equity impacts of potential exemptions for essential items like groceries and medicines.

- Socioeconomic Factors and Vulnerable Groups: continued and more targeted data collection focusing on high-impact households – including those with disabilities, young adults, low-income individuals, and rural residents – is vital to inform precisely tailored relief strategies and ensure equitable policy outcomes.

- Frequent and Cost-Effective Data Collection: given the rapid evolution of e-commerce, biennial, well-designed web-based surveys are recommended to track evolving shopping patterns and delivery trends. Partnering with federal initiatives like the National Household Travel Survey (NHTS) can provide valuable, frequent updates and detailed trip data at a reduced cost, particularly as the NHTS increasingly incorporates e-commerce-related questions. The insights from such cost-effective methods should be prioritized over highly expensive GPS-based surveys if they better capture attitudinal and product-specific data.

Oregon should invest in research and methodologies to better quantify the specific impacts of e-commerce deliveries on roadway infrastructure. This involves addressing the challenges highlighted in the report, such as separating the impacts of business-to-business (B2B) versus business-to-consumer (B2C) transactions, accounting for the different vehicle types and their unique wear-and-tear on various road networks (e.g., local streets versus interstates), and precisely measuring congestion and environmental impacts. Such granular data will provide a more robust and defensible basis for determining appropriate fee levels and justifying the allocation of funds to specific infrastructure projects.

Policymakers should carefully consider the broader economic impacts of a delivery fee, including its potential effects on cross-border shopping and local brick-and-mortar retailers. As Oregon currently lacks a sales tax, a delivery fee could introduce competitive dynamics with neighboring states, influencing consumer choices. Comprehensive economic modeling should be undertaken to project these broader impacts and inform policy adjustments that balance revenue objectives with the health of the retail sector and regional economic competitiveness.

Finally, it is recommended that a delivery fee is designed as part of a comprehensive transportation funding package because a delivery fee alone would not provide a complete solution to ODOT's long-term transportation funding problems. It is also recommended that the delivery fee revenue can be adjusted by inflation or the rate of increase of transportation infrastructure maintenance costs.

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