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Final Project Report

**The Reverse Side of Online Shopping:  
Examining Sociodemographic and Built-  
Environment Determinants of Delivery  
Returns**

*BY*

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## **EXECUTIVE SUMMARY**

The rapid growth of e-commerce has created new transportation challenges through increased product returns, yet the behavioral determinants of delivery return patterns remain understudied from a consumer-centric perspective. This research develops a comprehensive econometric framework to analyze online shopping frequency, delivery return rates, and return channel preferences using data from the 2022 National Household Travel Survey (NHTS). We employ a multivariate modeling approach integrating probit ordered-response and probit fractional response models to examine three interconnected outcomes: (1) frequency of online goods purchases, (2) proportion of online purchases returned, and (3) distribution of returns across four channels (home pickup, post office, Amazon drop-off, and physical store). The modeling framework accounts for causal relationships between outcomes while controlling for unobserved factors that lead to correlations across the three dimensions just listed. Results reveal significant sociodemographic heterogeneity in online purchasing and return behavior. Women, teleworkers, individuals with higher formal education, and those with higher incomes tend to exhibit increased e-commerce engagement. Older adults and zero-vehicle households, in contrast, have lower online purchase participation and return accessibility. Built environment factors significantly influence return behaviors, with rural residents showing reduced return rates and limited access to Amazon drop-off locations, while individuals residing in areas with high retail density exhibit increased use of Amazon drop-off and physical store returns. The analysis reveals causal relationships where higher online shopping frequency is associated with increased return rates, and both shopping frequency and return rates jointly influence return channel choices. These findings have important implications for transportation planning and urban logistics, highlighting the need for policies that ensure equitable return access and the importance of integrating e-commerce return trips into travel demand models.

## INTRODUCTION

### The Rising Trend of E-commerce and Product Returns

The rise of e-commerce and on-demand services has fundamentally transformed and shifted how consumers shop and access products and services. This shift, fast-tracked by the global COVID-19 pandemic, is reflected in the growing reliance on online shopping for goods, food, and services. U.S. Department of Commerce data shows that e-commerce sales, which were already increasing in the years leading up to the pandemic, represented about 10-11% of total retail sales in the U.S. in 2019, but rose to 14.6% in 2020 (U.S. Census Bureau, 2025). While this share stabilized at 14-15% through 2021-2022, it has since resumed its upward trajectory, reaching 16.1% of total retail sales in 2024, indicating a continued preference for online shopping even as the immediate impact of the pandemic subsided. This national trend also reflects profound changes in individual-level shopping habits, with recent data indicating that 46% of the U.S. population makes at least one online purchase per week (Narvar, 2024).

The widespread adoption of online shopping has, in turn, brought about a major change in product return patterns. The act of returning merchandise has transitioned from a relatively rare occurrence in conventional retail settings to a commonplace aspect of the online shopping experience. Industry reports indicate that the return rate for items purchased online (hereafter referred to as “delivery returns” for simplicity) is substantially higher (approximately 20%) than for store-bought items (around 9%) (Narvar, 2024, and National Retail Federation, 2024). Before the COVID-19 pandemic, retail returns (combining both online and in-store purchases) followed a predictable pattern, with annual increases below 2% and total returns representing just 8.1% of sales in 2019 (National Retail Federation, 2023). However, subsequent acceleration of e-commerce adoption during the COVID-19 pandemic disrupted this long-standing stability, driving the total cost of returns from \$309 billion (8.1% of sales) in 2019 to \$890 billion (16.9%) by 2024 (National Retail Federation, 2024). At the individual consumer level, this transformation is evident in the fact that over a third (35%) of online shoppers return purchased items every one to three weeks (Narvar, 2024).

At the same time, consumer expectations for seamless returns have become standard in e-commerce, requiring retailers to integrate convenient return options as a core service rather than an added benefit. Leading brands now offer comprehensive omnichannel return networks, including home pickup, drop-off at mail carriers (USPS or UPS), drop-off at third-party locations (such as Amazon drop-off lockers, Walgreens, Kohl’s stores, or Whole Foods), and direct returns to brick-and-mortar stores (commonly referred to as BORIS: Buy Online and Return In-Store). Online consumers appear to prefer, purely if left to their choice, third-party drop-off points (37%) and mail carrier locations (31%), with few consumers stating that they prefer home pickup (13%) or storefront returns (10%) (Narvar, 2022). But, of course, these stated (desired) preferences are moderated by a variety of contextual factors in actual return behavior, such as return costs, extent of packaging required, and distance to return location (Narvar, 2024). In this regard, aggregate transaction data from 2024 does suggest a notable discrepancy between stated preferences and actual behavior, with return rates seemingly being higher through the BORIS channel than through other channels (Appriss Retail and Deloitte, 2024). This divergence points to a discord between preference and actual returns behavior, driven by contextual factors. Understanding these behavioral patterns is essential for optimizing return policies and designing systems that more closely align consumer choices with their stated preferences.

## **Implications of High Return Rates**

High delivery return rates, while convenient for consumers, have substantial financial, logistical, environmental, and transportation-related repercussions. In 2022, the financial burden of product returns in the U.S. amounted to \$817 billion, with a quarter originating from the online retail sector (Chevalier, 2023). High return volumes also pose logistical and operational challenges related to managing the return flow of goods, which require additional infrastructure, human power, and resources for sorting, processing, restocking, and disposing of returned items. Moreover, the increased transportation requirements associated with returns generate additional freight vehicle miles traveled (VMT) (as trucks transport returned items from consumers back to warehouses or processing centers), contributing to higher greenhouse gas emissions and exacerbating environmental concerns such as climate change and air pollution. This return transport logistics also increases truck traffic at residential locations or return points, potentially worsening traffic congestion in affected areas. Furthermore, the need for return processing facilities introduces new nodes to urban logistics networks, particularly for inspecting, repackaging, and redistributing returned items, thereby influencing land-use decisions and creating additional trip attraction points within metropolitan regions. Beyond the movement of goods, product returns also generate distinct consumer travel patterns. Consumer research demonstrates a substantial willingness to undertake dedicated return trips (the average return trip length is the order of 6 miles; Bowes, 2023), with rural consumers traveling nearly 50% farther than their urban counterparts (Bowes, 2023). These transportation impacts further vary across different return channels. For instance, while home pickup services eliminate consumer travel entirely, they increase delivery vehicle routing complexity; and while drop-off options distribute return trips across different facility types, they still generate millions of consumer vehicle trips annually. Collectively, these return-related movements, both freight and passenger, create significant pressure on transportation infrastructure that current planning frameworks have not adequately addressed.

## **Research Objectives**

Despite the well-documented impacts of delivery returns (see, for example, Tian and Sarkis, 2022, Zhang et al., 2023, and Ng, 2024), empirical research remains limited, particularly from a consumer-centric perspective. Existing studies primarily examine product characteristics, retailer policies, or individual order details, as we discuss in the next section, often overlooking how sociodemographic and built-environment factors influence product return behavior. The current research study seeks to bridge this gap by exploring the following three key questions: Who are the returners? Do frequent online shoppers also exhibit high return rates, or is the opposite true? How do return channel preferences vary across consumer characteristics? Addressing these questions can help design strategies to reduce return rates, optimize reverse logistics, and mitigate adverse environmental and transportation impacts, thereby enhancing the sustainability of e-commerce practices.

To achieve our research objectives, we utilize data from the 2022 National Household Travel Survey (NHTS), which includes responses on the frequency and channels of delivery returns within the past 30 days. Our analytic framework employs a multivariate approach, estimating:

- The frequency of online goods purchased within the past 30 days, using an ordered-response probit model,

- The proportion of purchased goods returned within the past 30 days, using a probit fractional response model, and
- The distribution of returns across four channels (home pickup, post office, Amazon drop-off, and physical store), using a probit fractional response model.

These models are integrated into a joint framework to capture the entire lifecycle of product purchase and return behavior, providing a comprehensive understanding of the factors shaping return decisions.

## REVIEW RELEVANT BACKGROUND

Current product returns research predominantly takes a retailer-centric perspective. A systematic review by Ahsan and Rahman (2021) identified six primary research thrusts reflecting key themes in the retail returns literature, including (1) returns service and logistics, (2) omnichannel returns, (3) returns policy, (4) returns cost and channel coordination, (5) customer purchase and returns behavior, and (6) customer satisfaction and risk (based on retailer service attributes). Of these, the thrust area, “customer purchase and returns behavior,” is the only category that considers a consumer-centric perspective rather than a retailer-centric one. Even within this category, consumer behavior literature has focused on the reasons behind product returns (see Ahsan and Rahman, 2021, Kar and Tripathy, 2022, and Das and Kunja, 2024) and consumer intentions when purchasing a product (see Ahsan and Rahman (2021) for a comprehensive discussion), but has not adequately investigated the impact of sociodemographic and built-environment factors on return patterns, as explicitly noted by Makkonen et al. (2021). This gap is also apparent in Karl's (2024) review of the e-commerce returns forecasting literature. After categorizing the factors used to evaluate product return behaviors across studies, Karl found that research heavily concentrated on product features and return policies, which appeared in over 90% of the studies, followed by customer purchase history in 48% of the studies. However, the connection between consumer sociodemographic characteristics and return behaviors received minimal attention. Only four papers (fewer than 16% of the studies in Karl's predictors summary table) investigated sociodemographic attributes (typically limited to age and income) using transaction data from specific retailers rather than broader cross-retailer consumer behavior datasets. This lack of focus on the effects of consumer attributes on return decisions creates a significant knowledge gap, particularly since consumer-level analyses can better inform transportation planning and policy interventions by revealing spatial patterns of return behavior, trip-chaining tendencies, and demographic variations in return channel preferences that are essential for infrastructure planning and sustainable logistics solutions. Stevenson and Rieck (2024) explicitly called for addressing this gap, recommending that future research should “examine how product type and customer demographics affect product returns and customer loyalty in an omnichannel context,” thereby highlighting the scholarly consensus on the need to better understand demographic influences on return behavior.

Interestingly, despite the fundamental link between returns and purchasing decisions, as a product must be bought to be returned, research has disproportionately focused on purchase behavior. This point is strongly emphasized in a recent review of online consumer shopping behavior by Singh and Basu (2023), who state, “Majority considered purchase intention or purchase behaviour as dependent variables. Post-purchase behaviour has been largely ignored.... Future researchers can focus on variables of post-purchase behaviour in their studies as a dependent variable.” Specifically, extensive e-commerce literature has demonstrated the significant influence of sociodemographic and built-environment (BE) factors, such as age, gender, income, residential density, and urbanity, on online purchasing behavior (see, for example, Dias et al., 2020, Figliozzi and Unnikrishnan, 2021, and Eriksson and Stenius, 2022). Given the relationship between online purchases and returns, it is reasonable to hypothesize that some of these sociodemographic and BE characteristics might also play a role in shaping return behavior. However, their impact on delivery returns remains largely unexplored. In particular, to date, information on the relationship between delivery return patterns and consumer characteristics comes primarily from descriptive industry reports, which fail to capture complex relationships or control for confounding variables. In the remainder of this section, we begin our overview with

such descriptive industry reports, followed by the very limited consumer-level multivariate modeling studies of the relationship between sociodemographic, built-environment characteristics, and delivery returns. Finally, we contextualize this literature, position our research to address the identified gaps, and highlight how our research contributes new knowledge to the field.

### **Descriptive Studies**

A consistent trend across industry reports is the generational divide in delivery return behaviors. The results highlight higher return rates among younger generations (Millennials and Gen Z) compared to older ones (Gen X and Baby Boomers) (see Hutt, 2023, Narvar, 2022, and Nashra, 2024). For example, European data indicates that the 18 to 24 age group returns approximately twice the number of items as their senior counterparts (65+ years) (Alvarez and Marsal, 2022). This aligns with the comfort younger shoppers have navigating e-commerce, their potentially lower investment in individual purchases, as well as their prevalent engagement in bracketing practices (buying multiple items with the intent to return some) (see Happy Returns, 2022, and Nashra, 2024). The age effect appears most pronounced in apparel returns, where recent surveys indicate that 51% of Gen Z consumers engage in bracketing (with 14% reporting they “always” do so), compared to just 36% of Gen X and 24% of Baby Boomer consumers (National Retail Federation, 2024). Additionally, younger shoppers are more likely to practice bracketing compared to their older counterparts. Gender differences are also evident, with men generally exhibiting higher online return propensity across most product categories except clothing, where return rates are comparable between genders (Nashra, 2024). This aligns with other findings indicating that millennial women prefer non-online return processes over men, because millennial women perceive non-online returns to be easier (USPS, 2017). Additionally, existing statistics reveal that income levels influence return behaviors. While higher income groups (\$100,000 or over) account for a larger share of returns than their population size (Narvar, 2022), the lowest income segment (\$0-25,000) is least likely to return items (Hutt, 2023), potentially due to fewer discretionary online purchases and fewer online purchases overall to begin with. One report examined returns by geographic location and found that urban and suburban shoppers account for most returns in absolute volume. However, when adjusted for population size, rural consumers exhibit disproportionately higher return rates than their urban and suburban counterparts (Narvar, 2022). This is further supported by the finding that a significant portion of the population (78%) is willing to travel up to 10 miles to a return location (Happy Returns, 2022).

Regarding preferred return channels, industry statistics indicate that convenient return processes have a significant influence on e-commerce return decisions. As already alluded to earlier, Baby Boomers, Millennials, and women generally find in-store returns easier than online returns compared to other demographic groups (see USPS, 2017, and Chevalier, 2023). Additionally, findings highlight a growing consumer preference for in-person returns, particularly box-free options, which are the preferred method for most consumers, with mail returns being the least desirable (Happy Returns, 2022). This convenience factor is likely a significant driver of return channel preference, especially for younger demographics who may not have easy access to printers for return labels.

### **Consumer-Level Econometric Studies**

While many industry reports provide general product return statistics disaggregated by age, gender, or income, as discussed in the previous section, our review identified only two scholarly articles

explicitly investigating the relationship between consumer demographic characteristics and return frequency.

Makkonen et al. (2021) investigated the interplay between consumer demographics and online product return frequency using cumulative odds ordinal logistic regression. Data were collected through a direct survey of 560 Finnish online shoppers, who were asked to report their average product return frequency categorized into three ordinal levels: less frequently than yearly, yearly, and monthly. Contrary to broader trends highlighted in the previous section, Makkonen et al. (2021) found that women had 2.1 times higher odds of being more frequent returners than men. The study also found a negative correlation between age and return frequency, corroborating insights from industry reports on generational variations in return behavior. Specifically, younger consumers were more likely to be frequent returners, with, on average, every year of being younger associated with about a 3% higher chance of returning. Additionally, those shopping online more frequently (monthly or weekly) had substantially higher odds (3.7 and 5.9 times, respectively) of being frequent returners compared to online shoppers who made purchases only yearly, demonstrating a clear relationship between online purchases and returns.

Kar et al. (2022) employed multinomial logistic regression to model return frequency categorized as “rarely,” “few times,” and “often” as a function of individuals’ demographics (age, gender, profession, income). They utilized a sample of 619 observations from a survey conducted in India. The results highlighted some notable shifts in behavior when comparing the effects of explanatory variables across the three return frequency categories. Starting with the effect of age, younger age groups (58 years or younger) exhibited a higher propensity to return products (compared to those 59 or older), a finding that is consistent with Makkonen et al. (2021). Regarding gender, Kar et al. (2022) identified a U-shaped relationship between several variables and return frequency. Men were less likely to return “a few times” but more likely to return “often” compared to “rarely.” A similar pattern was also observed with income. Lower-income groups were less likely to return a “few times” compared to “rarely,” but more likely to return “often” compared to “rarely.” Additionally, regarding the individual’s profession, the likelihood associated with the student group changed from being negative with the “few times” frequency category to positive with the “often” category when compared to “rarely.” Lastly, return frequency changed with the amount spent per month on online purchases. Individuals with higher spending levels were less likely to return a “few times” compared to “rarely,” but more likely to return “often.”

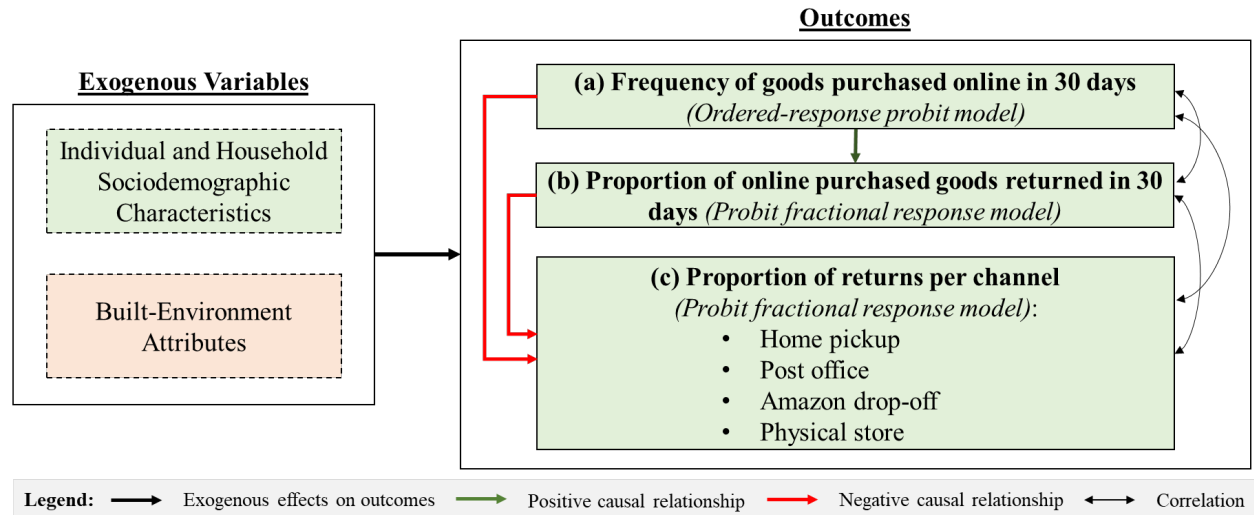
### **Current Research in Context**

This study proposes an analytical framework, presented in Figure 1, for modeling online shopping and return behaviors. It employs a multivariate econometric approach to estimate three outcomes (positioned on the right side of Figure 1): (a) the frequency of goods purchased online in the past 30 days; (b) the proportion of online purchased goods returned (or “delivery returns”) in the past 30 days; and (c) the proportion of returns per channel (home pickup, post office, Amazon drop-off, and physical store). These outcomes are estimated using a wide range of exogenous variables representing individual and household characteristics, as well as their residential built environment (see the left side of Figure 1, and the solid-line arrow from the block labeled “Exogenous Variables” to the “Outcomes” block), providing a comprehensive understanding of online shopping and return behavior patterns. The modeling framework includes an ordered-response probit model to analyze the frequency of online purchases, a probit fractional response model to estimate the percentage of purchases returned, and another multinomial probit fractional response model to estimate the distribution of returns across the four channels, with each model type labeled in parentheses next

to its corresponding outcome in Figure 1. These models are integrated into a joint framework that accounts for unobserved lifestyle and attitudinal factors affecting multiple outcomes. By controlling for these unobserved factors, which create correlations among outcomes (double-sided curved arrows to the right of the boxes under the “outcomes” panel on the right side of Figure 1), we can estimate the “true” causal effect of one outcome on another (such as the effect of shopping frequency on return rate). For example, individuals who value convenience (an unobserved factor) may shop online more frequently to avoid in-person shopping hassles; however, they may be less inclined to return items due to the effort involved in packaging and arranging drop-offs. However, when they do make returns, they might favor home pickup or local mail carriers over dedicated trips to Amazon drop-off centers or physical stores. Simultaneously, a positive causal effect could exist where more online shopping leads to higher return rates, perhaps because frequent online shoppers become more comfortable with the return process or because higher purchase volumes naturally result in a greater number of items that do not meet expectations. In this scenario, ignoring the negative correlation between online purchase frequency and return proportion due to the unobserved factor of convenience preference would underestimate the true effect of purchase frequency on return proportion. Moreover, while the previous example posited that online purchase frequency drives return proportion, the reverse could also apply, where individuals who are more willing to return items may shop online more frequently, viewing returns as a safety net that mitigates purchase risk. Similarly, preferences for return channels could influence, or be influenced by, both purchase frequency and return rates. Our joint system, after accounting for associations induced by unobserved correlations, allows us to test the direction of causality and identify the relationships that best fit the data. However, in joint limited dependent variable models such as ours, only recursive effects of one endogenous observed variable on the underlying propensity of another variable are permitted due to logical consistency (see Bhat, 2015 for details). Therefore, our joint system estimates alternative directions of recursivity among the three outcomes to determine the configuration that best fits the data (as elaborated in the “Endogenous Effects and Correlations” Section). Our final recursive configuration, based on the empirical analysis, reveals that the frequency of goods purchased online in the last 30 days (Outcome (a)) directly affects the proportion of online purchased goods returned in the last 30 days (Outcome (b)), while both the online purchase frequency and the proportion of returned goods (Outcomes (a) and (b)) directly influence the proportion of returns by different channels (Outcome (c)). These causal effects are indicated by solid, color-coded unidirectional arrows in the rightmost panel of Figure 1.

Within the context of existing research and the proposed framework (as presented in Figure 1), the current research contributes to the existing body of knowledge in five distinct ways. First, we investigate the understudied topic of online product returns from a consumer-centric perspective. More importantly, we move beyond the conventional analysis of general return probability or overall return frequency to quantify the specific impacts of exogenous variables on delivery return frequency at the individual channel level. This channel-specific approach addresses a significant gap in the literature, as previous studies have not differentiated between return channels, despite the substantial variations in their operational implications. This differentiation is particularly significant because different return channels produce distinctive effects across multiple sectors, including transportation, warehousing, and retail operations. Second, we employ advanced consumer-level econometric models, rather than descriptive statistics, to analyze return behavior within the U.S. consumer landscape. In contrast, the only two earlier studies that employed some form of econometric modeling, as discussed in the previous section, were conducted outside the U.S. Third, we incorporate a comprehensive set of individual and household

characteristics, as well as built-environment variables (such as urbanity, residential density, and proximity to retail and return establishments) that capture accessibility factors (positioned on the left side of Figure 1). Fourth, we utilize a more granular measure of delivery return frequency based on the actual number of returns an individual makes over a defined one-month period. This contrasts with existing studies that often rely on consumers’ generalized perceptions of their “usual” return frequency, subsequently categorized into broad temporal bins (such as yearly, monthly, and often). Our approach provides a temporally specific and normalized measure based on concrete return events. Fifth, to our knowledge, this is the first research study to employ a comprehensive econometric approach to simultaneously investigate online shopping and delivery return behaviors.



**Figure 1 Analytical Framework for Modeling Online Shopping Frequency, Delivery Return Rates, and Channel Distribution**

## DATA AND VARIABLE DESCRIPTION

### The Survey

The primary data source for this research is the 2022 National Household Travel Survey (NHTS), the most recent nationally representative survey that collects information on the travel habits and demographics of individuals and households (Federal Highway Administration, 2022). The survey was conducted from January 20, 2022, to January 19, 2023 (Ipsos, 2023). Households across the U.S. population received a mailed invitation explaining the survey and encouraging their involvement. In the invitation letter, respondents were asked to report their responses using an online system, but they also had the option to request and submit paper mail-in surveys. For each household, the survey collected information on individual member characteristics (age, gender, race/ethnicity, education level, driver's license status, employment status (income, vehicle ownership, home ownership, type, and other attributes). Household members aged 16 and older reported their personal travel across all transportation modes (cars, bikes, buses, trains, and walking), online shopping and return habits, changes in trip patterns, and detailed information about each journey taken on their designated travel diary day. Pertinent to this research, we analyze responses to the following two questions (verbatim) from the 2022 NHTS survey from each individual in each sampled household:

1. Online Purchases:

- Question: "In the past 30 days, how many times did this person personally purchase *goods* online and have it delivered to their home?"
- Outcome: This response is used as Outcome (a) in Figure 1.

2. Online Purchase Returns:

- Question: "In the past 30 days, how many times has this person personally returned an online purchase that was delivered to their home by:"
  - o Home pickup
  - o Taking it to a post office/UPS/FedEx/similar
  - o Taking it to an Amazon drop-off center
  - o Taking it directly to the store
- Outcomes:
  - o The sum of all responses to the second question divided by the total number of online goods purchases from the first question constitutes Outcome (b) in Figure 1.
  - o The distribution of responses across these return channels, derived from the responses to the second question, represents Outcome (c) in Figure 1.

The survey questions' wording explicitly captures online shopping behaviors at the individual level within households by using the phrasing "this person" rather than household-level terminology. This design presents an analytical choice between aggregating values across household members or conducting analysis at the individual level. We selected individual-level analysis to examine behavioral heterogeneity based on person-specific characteristics such as age, gender, race, employment status, and telework arrangements. This approach preserves important variations in online shopping and return behaviors that would be obscured through household aggregation. This approach also facilitates a more direct comparison with existing literature, which predominantly focuses on individual-level behavior (see Suel, 2016, Shah et al., 2021, and Le et al., 2022).

Overall, the survey collected data from 16,997 individuals. Of these, 10,363 individual responses with complete data on shopping and returning choices were retained for the final

analysis. Specifically, for our analysis, we excluded respondents who were under 18 years old, had missing gender information, had unspecified household income, did not provide the number of goods delivered in the past 30 days, or had inconsistent return data (where the sum of returns by channel differed from the total reported returns or reported more returns than purchases). Out of the 10,363 individual responses, 6,518 individuals indicated that they had made at least one delivery return (i.e., returned at least one good that was purchased online) in the last month.

To enrich the original public NHTS survey data with residential context, we appended supplementary data from multiple sources at varying geographic resolutions due to NHTS data privacy restrictions. At the Census Block Group (CBG) level, we obtained population density and walkability information from the restricted-access portion of the 2022 NHTS<sup>1</sup>. For county-level characteristics, we utilized the U.S. Census Bureau’s County Business Patterns (CBP) data series, which employs the North American Industry Classification System (NAICS), specifically NAICS Sector 44-45 (Retail Trade), to determine the number of retail establishments per county. This county-level aggregation was necessary as NHTS data privacy limitations prevented access to CBG or census tract-level residential locations. Additionally, we leveraged OpenStreetMap (OSM) data to determine the number of post offices and the number of third-party return points per county. Third-party return points were defined as the presence of establishments belonging to the following retailers: Kohl’s, Whole Foods, CVS, and Walgreens. These specific retailers were chosen as a proxy for third-party return points due to their established partnerships with major e-commerce platforms, most notably Amazon, to facilitate the return of online purchases.

## Outcome Variables

The descriptive statistics of the specific outcome variables explored in this study are summarized in Table 1 and Table 2.

The first outcome variable refers to the frequency of online goods purchases made by the individual in the last month (hereafter referred to as “frequency of online shopping” for ease of presentation). The response categories include: 0 purchases, 1-2 purchases, 3-4 purchases, 5-9 purchases, and 10 or more purchases per month (30 days). As presented in Table 1, a total of 3,845 individuals, representing 37.1% of the sample, reported that they had not made any online purchases in the 30 days preceding the survey completion date. Of those who reported shopping online, 47.9% made between 1 and 9 purchases, while 15% made 10 or more purchases.

The second outcome variable measures the proportion of online purchased goods returned in the past 30 days (or simply the “delivery return rate” as shown in the final column in Table 1). As previously discussed, this outcome depends on both the total frequency of online shopping and the total number of returns. To illustrate this relationship, Table 1 shows a positive association between delivery returns and the frequency of online shopping. For individuals who shop online 1 to 2 times a month, only 10.9% (= 9.0% + 1.9%) made at least one return. This percentage rises to 18.0% (= 11.0% + 4.8% + 2.2%) for those shopping 3-4 times, 28.8% (= 13.9% + 8.1% + 6.8%) for those shopping 5-9 times, and 41.8% (= 13.0% + 9.7% + 19.1%) for those shopping 10 or more times online. The last column of Table 1 presents the average and standard deviation of the

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<sup>1</sup> The Walkability Index, originally defined by the U.S Environmental Protection Agency (EPA) as a continuous variable ranging from 1 to 20, was provided in the NHTS restricted data file in 10 categorical ranges: (1) 1-2; (2) 2-4; (3) 4-6; (4) 6-8; (5) 8-10; (6) 10-12; (7) 12-14; (8) 14-16; (9) 16-18; (10) 18-20. Higher-numbered categories represent more walkable environments than lower-numbered categories. Similarly, population density was available in 8 categorical ranges: (1) 0-99; (2) 100-499; (3) 500-999; (4) 1,000-1,999; (5) 2,000-3,999; (6) 4,000-9,999; (7) 10,000-24,999; (8) 25,000-999,999 [people per square mile].

proportion of delivery returns for each online shopping frequency category, which directly refers to the second outcome variable (i.e., Outcome (b) in Figure 1). Overall, the average delivery return rate in the dataset is 8.6%, with a standard deviation of 20.0%.

The third outcome variable captures the distribution of delivery returns across four channels: home pickup (HP), post office (PO), Amazon drop-off (AD), and physical store (PS). Table 2 illustrates this distribution. For each category of total number of returns (first column in Table 2), which serves as the numerator in Outcome (b) (i.e., the proportion of returns out of total online purchases), the table presents the mean and standard deviation of the proportion of returns through each of the four channels, corresponding to Outcome (c) in Figure 1. Note that the sum of the percentages across the four channels is 100% for each total return number category. PO services (including mail carriers such as the United States Postal Service, UPS, and FedEx) dominate across all return frequency categories, averaging 49.4% of returns, while home pickup remains consistently low at just 6.8%. However, within individual channels, we observe large variations across different return frequency categories with no specific trend. For example, PO usage peaks at 53.8% for customers with two returns, decreases for the 3-4 return categories (46.8% and 43.0% respectively), increases again for the 5-return category (49.1%), then decreases for the 6+ category (45.2%). Similarly, PS usage peaks dramatically at 30.5% for the 3-return category before declining substantially for higher return frequencies. AD usage also follows an inconsistent pattern, ranging from 16.6% to 25.3% across categories with no clear directional trend. These seemingly erratic trends at the aggregate level, combined with high standard deviations (ranging from 18.0% to 50.0%), point to highly heterogeneous decision-making processes among consumers, highlighting the need for multivariate modeling approaches that can recognize and address this individual-level heterogeneity in return channel choice based on individual/household characteristics as well as environmental and contextual factors.

**Table 1 Descriptive Statistics for Online Shopping Frequency and Delivery Return Rate**

Frequency of online shopping per month	No. (%) of observations	No. of delivery returns				Average (st dev.) delivery return rate
		(X=0)	1	2	(3+)	
<b>0</b>	3845 (37.1%)	<i>No online goods purchases made.</i>				
<b>1-2</b>	1870 (18.0%)	1665 (89.1%)	169 (9.0%)	36 (1.9%)	0 (0.0%)	8.2% (24.9%)
<b>3-4</b>	1434 (13.8%)	1175 (82.0%)	158 (11.0%)	69 (4.8%)	32 (2.2%)	8.1% (19.8%)
<b>5-9</b>	1664 (16.1%)	1184 (71.2%)	232 (13.9%)	135 (8.1%)	113 (6.8%)	9.4% (18.6%)
<b>10+</b>	1550 (15.0%)	902 (58.2%)	201 (13.0%)	151 (9.7%)	296 (19.1%)	8.7% (14.4%)
<b>Total</b>	10363 (100.0%)	4926 (75.6%)	760 (11.7%)	391 (6.0%)	441 (6.8%)	8.6% (20.0%)

**Table 2 Descriptive Statistics for Distribution of Delivery Returns by Channel (conditional on an online purchase)**

Total No. of delivery returns	No. (%) of observations	Average (st dev.) proportion of returns through each channel			
		HP*	PO*	AD*	PS*
<b>0</b>	4926 (75.6%)	<i>No delivery returns made.</i>			
<b>1</b>	760 (11.7%)	7.1% (25.7%)	49.2% (50.0%)	22.9% (42.0%)	20.8% (40.6%)
<b>2</b>	391 (6.0%)	5.8% (19.9%)	53.8% (41.0%)	21.0% (34.1%)	19.4% (31.5%)
<b>3</b>	163 (2.5%)	6.1% (21.0%)	46.8% (34.7%)	16.6% (28.8%)	30.5% (30.9%)
<b>4</b>	107 (1.6%)	8.4% (19.7%)	43.0% (34.0%)	24.3% (27.6%)	24.3% (26.3%)
<b>5</b>	68 (1.0%)	4.7% (18.0%)	49.1% (37.9%)	22.1% (30.2%)	24.1% (30.2%)
<b>6+</b>	103 (1.6%)	8.4% (18.5%)	45.2% (29.5%)	25.3% (26.8%)	21.1% (20.6%)
<b>Total</b>	6518 (100.0%)	6.8% (22.8%)	49.4% (43.9%)	22.0% (36.8%)	21.8% (35.3%)

\*Home pickup (HP); Post office (PO); Amazon drop-off (AD); Physical store (PS).

### Exogenous Variables

Table 3 presents a comparative snapshot of our sample’s key individual and household-level sociodemographic, employment, and residential characteristics against the benchmark of the 2022 American Community Survey (ACS) 5-year estimates, which serves as a proxy for the broader U.S. population. Specifically, the columns in Table 3 provide percentage distributions for three groups: (i) “All Respondents” (our total sample of 10,363 individuals), (ii) “% in ACS” (the corresponding percentage distribution from the ACS), and (iii) “Returners” (a subsample of 6,518 respondents with at least one delivery return).

Comparing the “All Respondents” and “% in ACS” columns reveals several sample deviations from the national population. Older adults, particularly those aged 56 and above, are overrepresented, while younger adults (18-25) are underrepresented. This underrepresentation may reflect younger adults’ lower response rates to traditional mail surveys and their limited availability due to early career, educational, and family obligations. Consistent with patterns in survey participation (see Jang and Vorderstrasse, 2019, Lallukka et al., 2020, and Wu et al., 2022), our sample shows a higher proportion of white individuals, those holding Bachelor’s and Graduate degrees, and individuals in the middle to upper-middle income brackets. We also observed fewer households with zero or one vehicle and a higher proportion with two or more vehicles. Employment characteristics also diverged, with a higher proportion of employed individuals and fewer not employed compared to the ACS. Conversely, non-teleworkers and students were underrepresented, potentially due to the mail-based administration and the mobility of the student population. These deviations highlight the limitations of simple univariate analyses, which examine each variable in isolation and overlook the interdependent relationships among variables. To rigorously identify both independent and interactive effects, and to facilitate the generalizability of findings, multivariate analysis is more desirable. In fact, despite sample departures from ACS

benchmarks, the large number of observations across diverse combinations of variables enables the identification of meaningful patterns. Furthermore, NHTS' non-endogenous sampling approach strengthens the efficiency of unweighted analysis for drawing inferences about individual-level relationships in the broader U.S. population, as supported by established econometric principles (see Wooldridge, 1995, and Solon et al., 2015).

While univariate comparisons do not address confounding or interaction effects, they remain a valuable starting point for data exploration. They offer transparency, highlight key sample characteristics, and provide context that guides model specification. Examining the distribution differences between the "All Respondents" group and the "Returners" subsample reveals several noteworthy patterns. The Returners subsample shows a slightly higher percentage of women compared to the overall respondent pool. Regarding race, Returners exhibit a higher proportion of White individuals and a lower proportion of Black or African American and "Other" individuals compared to the sample, suggesting a potential skew in return behavior across racial identities. The formal educational attainment of Returners also leans slightly towards higher degrees, with a higher percentage holding Bachelor's and Graduate degrees. Similarly, the household income distribution of Returners indicates a trend toward higher income brackets and a lower representation in the lowest income tier. Vehicle ownership and household lifecycle classification trends remain largely consistent between the two groups. Moving to employment characteristics, the Returners subsample has a higher percentage of employed individuals and teleworkers but a similar percentage of students compared to the full sample. Finally, the table shows only slight differences in residential location characteristics, suggesting that the geographical makeup of the Returners subsample closely mirrors that of the overall respondent pool.

**Table 3 Sample Distribution of Exogenous Variables**

Variable	% of All Respondents (N=10,363)	% in ACS	% of Returners (N=6,518)	Variable	% of All Respondents (N=10,363)	% in ACS	% of Returners (N=6,518)
<b>Individual/Household Sociodemographics</b>				<b>Residential Location Attributes</b>			
<b>Gender</b>				<b>CBG Population Density (persons per square mile)</b>			
Female	50.7	51.0	53.6	0 to 499	26.3	--	25.5
Male	49.3	49.0	46.4	500 to 1999	21.3	--	21.5
<b>Age</b>				2000 to 9999	42.7	--	43.6
18 to 25	9.1	12.1	6.8	10000 to 24999	6.5	--	6.1
26 to 40	21.9	26.1	23.4	25000+	3.2	--	3.3
41 to 55	21.4	24.1	23.2	<b>CBG Walkability Index</b>			
56 to 64	17.2	16.5	17.7	1 ≥ and < 4	9.2	--	8.4
65 or more	30.4	21.2	28.9	4 ≥ and < 8	39.1	--	39.8
<b>Race</b>				8 ≥ and < 12	24.2	--	24.1
White	83.3	65.9	86.3	12 ≥ and < 16	20.9	--	20.8
Black or African American	7.5	12.4	5.8	16 ≥ and ≤ 20	6.6	--	6.9
Asian	5.3	5.8	5.1	<b>Area Type<sup>#</sup></b>			
Other	3.9	15.9	2.8	Inside urbanized areas	69.8	70.9	71.7
<b>Formal Education Level</b>				Inside urban clusters	8.7	9.6	7.8
Less than a Bachelor's degree	53.8	56.9	44.7	Rural	21.5	19.5	20.5
Bachelor's degree	26.4	29.7	30.9	<b>Number of Retail Establishments in County of Residence</b>			
Graduate degree	19.8	13.4	24.4	0 to 149	11.0	--	9.7
<b>Household Income (gross)</b>				150 to 399	13.8	--	13.1
Less than \$25,000	11.4	16.0	7.5	400 to 1199	24.7	--	24.1
\$25,000-\$49,999	16.7	17.8	13.8	1200 to 2999	26.4	--	27.5
\$50,000-\$99,999	32.2	29.1	33.0	3000 to 5999	12.7	--	13.5
\$100,000-\$149,999	20.7	16.9	23.1	6000+	11.4	--	12.1
\$150,000-\$199,999	8.3	8.7	9.9	<b>Number of Third-Party Return Points in County of Residence</b>			
\$200,000+	10.7	11.5	12.7	0 to 2	20.1	--	18.5
<b>Number of Motorized Vehicles</b>				3 to 5	9.3	--	8.6
0	5.0	8.3	4.0	6 to 14	18.4	--	17.8
1	25.0	32.6	23.2	15 to 39	27.4	--	28.8
2	43.1	37.0	45.1	40 to 89	14.4	--	15.6
3+	26.9	22.1	27.7	90+	10.4	--	10.7

Variable	% of All Respondents (N=10,363)	% in ACS	% of Returners (N=6,518)	Variable	% of All Respondents (N=10,363)	% in ACS	% of Returners (N=6,518)
<b><i>Life Cycle Classification</i></b>				<b><i>Number of Post Office Locations in County of Residence</i></b>			
One adult, no children	15.8	17.4	16.6	0 to 2	15.4	--	14.0
2+ adults, no children	54.7	55.2	54.5	3 to 5	13.6	--	12.6
One adult, with children	2.8	3.6	2.9	6 to 14	27.2	--	25.6
2+ adults, with children	26.7	23.8	26.0	15 to 24	16.0	--	23.9
<b>Employment Characteristics</b>				25 to 114	23.6	--	19.6
<b><i>Employment Status</i></b>				115+	4.2	--	4.3
Not employed	48.9	30.9	42.5	<b><i>Region</i></b>			
Employed	51.1	69.1	57.5	Northeast	17.2	17.2	18.0
<b><i>Telework Arrangements</i></b>				Midwest	23.7	20.7	23.1
Daily	11.1	11.3	14.3	West	21.8	23.7	22.6
At least one time per week	10.4			13.0	South	37.3	38.4
No telework	29.6	57.8	30.2				
<b><i>Student</i></b>							
Yes	6.3	9.6	6.1				
No	93.7	90.4	93.9				

# The urban area classification for each surveyed household in the NHTS dataset is derived from the U.S. Census Bureau's 2020 standards and their corresponding TIGER/Line Shapefiles. Urbanized Areas (UAs) contain 50,000 or more people per Census Block Group, while Urban Clusters (UCs) contain at least 2,500 but fewer than 50,000 people per Census Block Group. All territory outside these urban definitions is considered rural (U.S. Census Bureau, 2020).

## METHODOLOGY

The empirical analysis examines three interrelated aspects of online shopping behavior through a multivariate econometric framework. The first outcome variable,  $y_1$ , is an ordered categorical measure capturing the frequency of online shopping per month, where responses are naturally ranked across discrete categories representing different intensity levels of shopping frequency, including zero, 1-2, 3-4, 5-9, and 10+. The second outcome,  $y_2$ , is a binary fractional response measuring the delivery return rate, capturing the proportion of online purchases that consumers return relative to their total purchases. The third outcome,  $y_3$ , extends the delivery return behavior to a multinomial fractional response involving the distribution of delivery returns across different channels, such as the fractions of products returned through home pickup, post office, Amazon drop-off, and physical store alternatives.

In the following mathematical formulation, we suppress the individual index  $q$  for notational simplicity while deriving the likelihood contribution for each individual  $q$ . We develop the estimation procedure for the complete case when all three outcomes are observed. However, the availability of outcomes depends on individuals' shopping and return behaviors, requiring modifications to the likelihood function for different scenarios. The first scenario applies when respondents indicate zero online purchases in the last month. In this case, the shopping frequency outcome ( $y_1$ ) is observed, but the return rate ( $y_2$ ) and return channel allocation ( $y_3$ ) outcomes are not available since no purchases were made. Accordingly, the likelihood contribution reduces to the marginal univariate probability of the observed shopping frequency category. The second scenario applies to individuals who make one or more online purchases but choose to return zero items. In this case, both shopping frequency ( $y_1$ ) and return rate ( $y_2$ ) outcomes are observed, but the return channel allocation ( $y_3$ ) is not available since no returns occurred. The likelihood contribution becomes the marginal bivariate probability of the observed shopping frequency and return rate.

### Ordered Response Component

The modeling of shopping frequency ( $y_1$ ) utilizes an ordered-response probit framework. The fundamental assumption underlying this approach is that there exists an unobserved continuous latent variable  $y_1^*$  representing an individual's propensity for online shopping:

$$y_1^* = \boldsymbol{\beta}'\mathbf{x} + \varepsilon, \quad y_1 = k \quad \text{if} \quad \psi_{k-1} < y_1^* < \psi_k, \quad (1)$$

where  $\mathbf{x}$  is an  $(L \times 1)$  vector of exogenous variables (excluding a constant),  $\boldsymbol{\beta}$  is a corresponding  $(L \times 1)$  vector of coefficients to be estimated, and  $\varepsilon$  is a random error term assumed to be standard normally distributed (the scale of  $\varepsilon$  is not identified and so is arbitrarily set to one). Also, let  $k \in \{1, 2, \dots, K = 5\}$  represent the ordered-response level for outcome  $y_1$ , where  $K$  is the highest level corresponding to variable  $y_1$  ( $K=5$  corresponding to the five levels of frequency of monthly online shopping: 0, 1-2, 3-4, 5-9, 10+). The latent count propensity  $y_1^*$  is mapped to the observed count variable  $y_1$  by the thresholds  $\psi_k$ . The threshold parameters satisfy the ordering constraint  $-\infty = \psi_0 < \psi_1 < \psi_2 < \dots < \psi_{K-1} < \psi_K = +\infty$ . Also, define the vector of thresholds (to be estimated) as:  $\tilde{\boldsymbol{\psi}} = (\psi_1, \dots, \psi_{K-1})'$ .

## Fractional Response Components

The model for delivery return rates ( $y_2$ ) employs a binary probit fractional response framework explicitly designed to handle fractional outcome variables constrained to the unit interval  $y_2 \in [0,1]$ . The return channel allocation outcome ( $y_3$ ) is estimated using a multinomial fractional response model with four alternatives. In this section, we treat the binary fractional response model as a special case of a multinomial response model with just two alternatives, providing a unified mathematical framework for both the  $y_2$  and  $y_3$  outcomes.

Let  $c$  be the index for the fractional response outcomes, where  $c = 2$  corresponds to the return rate outcome and  $c = 3$  to the return channel outcome (we use this unconventional notation to be consistent with the notation of  $y_2$  for the return rate outcome and  $y_3$  for the return channel). For each outcome  $c$ , let  $h_c$  denote an index for the alternatives within the outcome, where  $h_c \in \{1, 2, \dots, H_c\}$  and  $H_c$  represents the total number of alternatives for fractional outcome variable  $c$ . Specifically, for outcome  $c = 2$  (return rate),  $h_2 \in \{1, H_2=2\}$ , where alternative 1 corresponds to “online purchased goods not returned” and alternative 2 corresponds to “online purchased goods returned”. For outcome  $c = 3$  (return channels),  $h_3 \in \{1, 2, 3, H_3=4\}$ , where alternative 1 corresponds to “home pickup,” alternative 2 to “post office,” alternative 3 to “Amazon drop-off,” and alternative 4 to “physical store” returns. Next, let  $y_{c,h_c}$  be the observed fraction allocated to alternative  $h_c$  within outcome  $c$ . By definition, the following must be true:

$$0 \leq y_{c,h_c} \leq 1, \text{ and } \sum_{h_c=1}^{H_c} y_{c,h_c} = 1 \text{ for each of } c = 2 \text{ and } c = 3. \quad (2)$$

A common approach to analyzing fractional outcomes, as suggested by Papke and Wooldridge (1996), is to model the conditional expectation of a fractional dependent variable via a non-linear function  $G(\cdot)$ , which can take the form of a logistic function or the standard normal cumulative distribution function since they satisfy the bounded, unit-sum nature of the conditional means of fractional variables. Sivakumar and Bhat (2002) extended Papke and Wooldridge’s framework to the multinomial case to simultaneously handle multiple fractional outcomes. Their work demonstrated that the specifications commonly used for binary response variables in the univariate case can be naturally extended to describe the conditional means of fractional responses in the multinomial setting. In particular, the specifications typically employed to model individual choices among  $M$  mutually exclusive alternatives may be adapted to describe the conditional means of fractional responses in the multinomial fractional context, since they inherently satisfy the bounded, unit-sum nature required for conditional means of fractional variables. However, unlike Sivakumar and Bhat (2002), who utilize the multinomial logit functional form for function  $G(\cdot)$ , our specification employs a multinomial probit (MNP) functional form because of the ease of developing correlations across the many outcomes in our model system. Specifically, we adapt the standard latent utility specification for each alternative following the MNP framework, but customized to fractional allocations. For the  $c^{th}$  fractional outcome, we assume that individuals have latent propensities for each alternative  $h_c$  that determine the fractional allocation across alternatives. The usual random utility structure for each alternative  $h_c$  is:

$$U_{c1} = 0 \text{ (Reference alternative - normalized to zero),}$$

$$U_{ch_c} = \gamma'_{ch_c} \mathbf{z}_c + \zeta_{ch_c} = V_{ch_c} + \zeta_{ch_c} \text{ for } h_c > 1, \quad (3)$$

where  $z_c$  is an  $(A \times 1)$  vector of exogenous variables (including a constant), as well as possibly the observed values of other endogenous variables,  $\gamma_{ch_c}$  is an  $(A \times 1)$  column vector of corresponding alternative-specific coefficients,  $V_{ch_c}$  is the systematic utility, and  $\zeta_{ch_c}$  is assumed to be a normal error term. Let  $\zeta_c$  be an  $(H_c \times 1)$  vector  $\zeta_c = (\zeta_{c,1}, \zeta_{c,2}, \dots, \zeta_{c,H_c})'$ . Then, we assume  $\zeta_c \sim MVN_{H_c}(\mathbf{0}_{H_c}, \Lambda_c)$ . Appropriate scale and level normalization must be imposed on  $\Lambda_c$  for identification. Since only utility differentials matter at each choice occasion (because the fractions must add up to one across all alternatives  $h_c$  for each  $c$ , only the elements of the  $(H_c - 1) \times (H_c - 1)$  covariance matrix  $\tilde{\Lambda}_c$  of the error differentials  $\tilde{\zeta}_{c,h_c} = \zeta_{c,h_c} - \zeta_{c,1}$  ( $h_c \neq 1$ ) are estimable (with utility differentials taken with respect to the first alternative). Note that for the binary case of return rates ( $H_2=2$ ), no elements of the covariance matrix are estimable and accordingly  $\tilde{\Lambda}_2 = 1$ . On the other hand, for the return channel model ( $H_3=4$ ), we imposed zero correlations and scale invariance within the multinomial return channel component to address identification constraints commonly encountered in multinomial models that rely solely on individual-specific variables. As demonstrated by Bunch (1991) and Keane (1992), the full error covariance matrix in such settings becomes challenging to identify empirically in the absence of alternative-specific covariates. Given that our model specification fits this situation, we assume that  $\Lambda_3 = 0.5 \times IDEN_{H_3}$ , where  $H_3=4$  in our current empirical context. Accordingly, the difference matrix for the return channel outcome  $\tilde{\Lambda}_3$  takes the size  $((H_3-1) \times (H_3-1))$ , with the matrix as follows in our empirical analysis:

$$\tilde{\Lambda}_3 = \begin{bmatrix} 1 & 0.5 & 0.5 \\ & 1 & 0.5 \\ & & 1 \end{bmatrix}$$

Lastly, for use later in the report, we define an  $(A \times H_c)$  matrix  $\gamma_c = (\gamma_{c1}, \gamma_{c2}, \dots, \gamma_{cH_c})$  and

$$\mathbf{B} = \begin{pmatrix} \beta' \mathbf{x} \\ 0 \\ \gamma_2' z_2 \\ 0 \\ \gamma_3' z_3 \end{pmatrix} (1 + H_2 + H_3) \times 1 \text{ vector.}$$

### Quasi-Likelihood Estimation Setup

In the quasi-likelihood estimation set-up, we use a function  $G_{c,h_c}$  for each of  $c=2$  and  $c=3$  such that

$0 < G_{c,h_c} < 1$  and  $\sum_{h_c=1}^{H_c} G_{c,h_c} = 1$  for  $c = 2$  and  $c = 3$ . The properties specified above for  $G_{c,h_c}$  ensure

that the predicted fractions will lie in the interval  $(0,1)$  and will sum to 1 for the return/no return fractional rates conditional on a purchase, as well as sum to one across the four return channels conditional on a return. To satisfy the conditions above along each of the return fraction rate and return channel marginals, while also enabling easy incorporation of jointness across the three dimensions of purchase frequency, return fraction rate, and return channel fraction, we first determine the probability  $[\text{Prob}(y_1 = m_1, h_2 = m_2, h_3 = m_3)]$  for the event that the individual has the

observed purchase frequency of  $y_1 = m_1$  and for each of the possible discrete states  $m_2$  that  $h_2$  may take and each of the possible discrete states of  $m_3$  that  $h_3$  may take. Then, denoting  $1(\cdot)$  as a dummy variable taking the value one if the expression in parenthesis is true, the quasi-likelihood function to be maximized may be specified as follows:

$$L(\boldsymbol{\delta}) = \prod_{m_1} \prod_{m_2} \prod_{m_3} [\text{Prob}(y_1 = m_1, h_2 = m_2, h_3 = m_3)]^{1(y_1=m_1) \times y_2 \times y_3 \times h_3}, \quad (4)$$

where  $\boldsymbol{\delta}$  is the collection of parameters to be estimated:

$\boldsymbol{\delta} = \left( \boldsymbol{\beta}', \boldsymbol{\psi}', \text{Vech}(\boldsymbol{\gamma}_1)', \text{Vech}(\boldsymbol{\gamma}_2)', [\text{Vechup}(\boldsymbol{\Xi})]' \right)'$ , the operator "Vech(.)" row-vectorizes all the non-zero elements of the matrix/vector on which it operates, and the operator Vechup(.) row-vectorizes the upper diagonal elements of a matrix. The computation of the probability expression above needs additional setup. We first consolidate the covariance matrix of the error terms in the ordered response and the differenced (from the first alternative) error terms for each of the returns/no returns and return channel as follows:

$$\boldsymbol{\Xi}_1 = \begin{bmatrix} \text{Var}(\varepsilon) & \text{Cov}(\varepsilon, \tilde{\zeta}_{2,2}) & \text{Cov}(\varepsilon, \tilde{\zeta}_{3,2}) & \text{Cov}(\varepsilon, \tilde{\zeta}_{3,3}) & \text{Cov}(\varepsilon, \tilde{\zeta}_{3,4}) \\ & \text{Var}(\tilde{\zeta}_{2,2}) & \text{Cov}(\tilde{\zeta}_{2,2}, \tilde{\zeta}_{3,2}) & \text{Cov}(\tilde{\zeta}_{2,2}, \tilde{\zeta}_{3,3}) & \text{Cov}(\tilde{\zeta}_{2,2}, \tilde{\zeta}_{3,4}) \\ & & \text{Var}(\tilde{\zeta}_{3,2}) & \text{Cov}(\tilde{\zeta}_{3,2}, \tilde{\zeta}_{3,3}) & \text{Cov}(\tilde{\zeta}_{3,2}, \tilde{\zeta}_{3,4}) \\ & & & \text{Var}(\tilde{\zeta}_{3,3}) & \text{Cov}(\tilde{\zeta}_{3,3}, \tilde{\zeta}_{3,4}) \\ & & & & \text{Var}(\tilde{\zeta}_{3,4}) \end{bmatrix}$$

$$= \begin{bmatrix} 1.0 & \text{Cov}(\varepsilon, \tilde{\zeta}_{2,2}) & \text{Cov}(\varepsilon, \tilde{\zeta}_{3,2}) & \text{Cov}(\varepsilon, \tilde{\zeta}_{3,3}) & \text{Cov}(\varepsilon, \tilde{\zeta}_{3,4}) \\ & 1.0 & \text{Cov}(\tilde{\zeta}_{2,2}, \tilde{\zeta}_{3,2}) & \text{Cov}(\tilde{\zeta}_{2,2}, \tilde{\zeta}_{3,3}) & \text{Cov}(\tilde{\zeta}_{2,2}, \tilde{\zeta}_{3,4}) \\ & & 1.0 & 0.5 & 0.5 \\ & & & 1.0 & 0.5 \\ & & & & 1.0 \end{bmatrix}.$$

The matrix  $\boldsymbol{\Xi}_1$  corresponds to the error differences taken with respect to the first alternative for the returns ( $y_2$ ) and the return channel ( $y_3$ ) model components. To compute the probability in the quasi-likelihood function, we however, need the covariance matrix corresponding to the error term differences taken with respect to any alternative  $h_2 = m_2$  for  $y_2$ , and  $h_3 = m_3$  for  $y_3$ . To obtain this covariance matrix, first define a zero element matrix  $\mathbf{D}$  of size  $[1+H_2+H_3] \times [1+(H_2-1)+(H_3-1)]$ . Place a value of '1' as the first element of  $\mathbf{D}$ , then position an identity matrix of size  $(H_2-1)$  in the third through  $1+H_2$  rows and the second through  $H_2$  columns. Next position another identity matrix of size  $(H_3-1)$  starting from the  $(3+H_2)^{th}$  row through the  $(1+H_2+H_3)^{th}$  row and the  $(1+H_2)^{th}$  column through the  $[H_2+H_3-1]^{th}$  column. Next, define a zero element matrix  $\mathbf{M}_{m_2, m_3}$  of size  $[1+(H_2-1)+(H_3-1)] \times [1+H_2+H_3]$ . Place a value of '1' as the first element of the matrix (this is for the ordered-response error term). Next, leaving alone column  $m_2$ , insert an identity matrix of size  $(H_2-1)$  in rows 2 to  $H_2$  and columns 2 to  $H_2+1$ , followed by a column of '-1' values in column  $m_2$  in rows 2 to  $H_2$ . Also, leaving alone column  $m_3$ , insert an identity matrix of size  $(H_3-1)$  in rows  $(H_2+1)$

to  $1+(H_2-1)+(H_3-1)$  and columns  $(H_2+2)$  to  $(1+H_2+H_3)$ , followed by a column of ‘-1’ values in column  $m_3$  in rows  $(H_2+1)$  to  $1+(H_2-1)+(H_3-1)$ .

Next, define a set of lower thresholds  $\boldsymbol{\psi}_{low} = (\psi_{m_1-1}, -\infty_{H_2+H_3-2})'$ , and upper thresholds  $\boldsymbol{\psi}_{high} = (\psi_{m_1}, \mathbf{0}_{H_2+H_3-2})'$ . Then we may write:

$$[\text{Prob}(y_1 = m_1, h_2 = m_2, h_3 = m_3)] = \int_{D_r} \phi[\mathbf{r} | (\mathbf{M}_{m_2, m_3} \mathbf{B}), (\mathbf{M}_{m_2, m_3} \mathbf{D} \boldsymbol{\Xi} \mathbf{D}' \mathbf{M}'_{m_2, m_3})] d\mathbf{r}, \quad (5)$$

where  $\phi(\cdot)$  refers to the standard multivariate normal density function, and the integration domain  $D_r = \{\mathbf{r} : \boldsymbol{\psi}_{low} < \mathbf{r} < \boldsymbol{\psi}_{high}\}$  is the multivariate region of integration. The quasi-likelihood function for the entire sample is constructed as the product of individual-level quasi-likelihood contributions across all observations. In our empirical context, each individual likelihood requires the evaluation of a five-dimensional integral over the multivariate normal density function, which poses significant computational challenges using classical numerical integration methods. To address this computational burden, we employ Bhat’s (2018) matrix-based approximation method for evaluating multivariate normal cumulative distribution functions (MVNCD). This approach provides a computationally efficient and numerically stable framework for approximating the high-dimensional integrals inherent in the trivariate fractional response system.

## EMPIRICAL RESULTS

In developing the final specification, we explored various combinations of variables and functional forms. Initially, all variables in grouped form (such as income, CBG-level walkability index, CBG-level population density), categorical form (such as gender, race, and household lifecycle classification), and a naturally discrete form (such as number of motorized vehicles in the household) were included at their most granular level. We gradually consolidated them based on statistical significance. For continuous variables, such as age and telework frequency, we tested various functional forms, including linear, logarithmic, piecewise linear, and dummy variable representations, to identify the optimal specifications. Our analysis indicated that representing age and telework days as dummy variables provided the best fit. The CBG-level walkability index was transformed from its original 10 categorical ranges into a continuous variable (1-10) for the final model specification, as our testing revealed this linear approach provided better statistical fit than categorical dummy variables. Additionally, we tested three representations of continuous location-based infrastructure variables: raw counts, density per population (establishments per capita), and density per area (establishments per square mile). For the online shopping frequency model, the two significant predictors were retail establishment density per 100 people (continuous form) and binary post office density per square mile greater than 0.75 (90<sup>th</sup> percentile). Specific threshold-based variables proved most effective for the delivery returns models: retail establishment density per square mile above the 90<sup>th</sup> percentile, post office density per square mile above the 90<sup>th</sup> percentile, and third-party return points per 10,000 capita above the 50<sup>th</sup> percentile. We also explored potential interaction effects among key demographic and socioeconomic factors, but found no statistically significant interactions, even at a marginal confidence level of 75%. At each step of this iterative process, we removed variables that lacked statistical significance or failed to substantially improve the model fit, using likelihood ratio tests to validate each more parsimonious specification. This methodical approach optimized statistical efficiency while minimizing estimation bias from overfitting and multicollinearity, leading to the final specification presented in Table 4.

Technically, the parameters in the “Frequency of Online Shopping” column of this table represent the elements of the  $\beta$  vector, which reflects the effect of exogenous variables on the latent propensity underlying the ordinal shopping frequency outcome. The parameters presented in the remaining columns represent elements of the  $\gamma_c$  matrices, which reflect the effects of exogenous variables on the systematic utilities for the fractional response components (relative to the reference alternative). However, for the binary delivery return rate model, parameters directly relate to the probability of returns (since this is a two-alternative fractional response where the probability of the second alternative equals the expected fraction). Not all included variables achieve statistical significance at the 95% level. In fact, we retained two variables that are significant only at the 87% level (a t-statistic threshold of 1.53). Robustness checks confirmed that excluding these variables did not materially affect the sign, magnitude, or significance of other parameter estimates. Given their theoretical importance and the consistent results across specifications with and without these variables, we included them to maintain model completeness. By being more inclusive in retaining exogenous variables, we hope that our findings will offer valuable insights for future investigations. Also, a dash (“--”) next to a variable indicates that the corresponding coefficient is not applicable to that specific outcome variable. A blank cell implies that the exogenous variable did not have a statistically significant association with the outcome. Finally, in some cases, the same coefficient (and t-statistic) may appear across columns or rows (or both) because earlier tests of coefficient equality could not be rejected.

**Table 4 Estimation Results**

Variable	Frequency of Online Shopping		Delivery Return Rate		Delivery Return Channel (base: Home Pickup)					
	Coef.	t-stat	Coef.	t-stat	Post Office		Amazon Drop-off		Physical Store	
					Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
<b>Individual/Household Sociodemographics</b>										
<i>Gender (Base: Man or Other)</i>										
Woman	0.227	10.46	0.133	1.97					0.281	2.77
<i>Age (Base: 26 to 55 years)</i>										
18 to 25									-0.579	-2.30
56 to 64			-0.140	-1.96						
65 or more	-0.070	-2.45	-0.140	-1.96	0.212	2.18				
<i>Race</i>										
White (Base: Not white)					0.246	2.21				
Black or African American (Base: Not Black or African American)	-0.212	-4.86								
Asian (Base: Not Asian)			0.270	2.18						
<i>Formal Education Level (Base: Less than a Bachelor's degree)</i>										
Bachelor's degree	0.304	11.19	0.136	1.84	0.244	3.57	0.244	3.57		
Graduate degree	0.393	12.81	0.136	1.84	0.244	3.57	0.244	3.57		
<i>Household Income (Base: Less than \$25,000)</i>										
\$25,000-\$49,999	0.219	4.90								
\$50,000-\$74,999	0.373	8.26					0.209	2.02		
\$75,000-\$99,999	0.542	12.73					0.209	2.02		
\$100,000-\$149,999	0.542	12.73					0.141	1.88		
\$150,000+	0.666	14.16								
<i>Number of Motorized Vehicles (Base: &gt;0 Vehicles)</i>										
Zero vehicles	0.128	2.14	-0.194	-2.09	-0.376	-2.80	-0.376	-2.80		
<i>Life Cycle Classification</i>										
2+ adults (Base: One adult)	-0.175	-5.15								
Presence of children (Base: No children present)	-0.142	-3.79	0.137	1.82					0.136	1.53
<b>Employment Characteristics</b>										
<i>Employment Status (Base: Not employed)</i>										
Employed	0.133	4.75								
<i>Telework Arrangements (Base: No telework)</i>										
Telework daily	0.269	6.96	0.133	1.74	-0.229	-2.27	-0.341	-3.01	-0.295	-2.63
Telework at least once per week	0.165	4.06	0.133	1.74	-0.229	-2.27	-0.341	-3.01	-0.295	-2.63

Variable	Frequency of Online Shopping		Delivery Return Rate		Delivery Return Channel (base: Home Pickup)					
	Coef.	t-stat	Coef.	t-stat	Post Office		Amazon Drop-off		Physical Store	
					Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
<b>Residential Location Attributes</b>										
<i>CBG Population Density (persons per square mile)</i>										
10,000 or higher	-0.095	-2.39								
<i>CBG Walkability Index</i>										
Walkability Index [range:1-10]	-0.013	-2.27								
<i>Area Type (Base: Urban or Suburban)</i>										
Rural			-0.166	-1.80			-0.681	-2.97		
<i>Retail Establishments in County of Residence</i>										
Retail establishment density (establishments per 100 people) [range: 0.02-1.54]	-0.252	-1.85								
Retail establishments density per square mile > 7.95 (90th percentile)					-0.308	-2.59	0.473	2.49	0.389	1.93
<i>Third-Party Return Points in County of Residence (Base: Third-party return points per 10,000 capita ≤ 0.3)</i>										
Third-party return points per 10,000 capita > 0.3 (50 <sup>th</sup> percentile)			0.076	2.32			0.204	2.05		
<i>Post Offices in County of Residence</i>										
Post Office density per mile squared > 0.75 (90 <sup>th</sup> percentile)	0.059	1.59			0.222	1.78				
<i>Region (Base: Northeast or South)</i>										
West					-0.113	-1.53			-0.113	-1.85
Midwest					-0.270	-2.98				
<b>Thresholds and Constants</b>										
Constant			-1.432	-13.80	-0.203	-1.21	-0.921	-5.68	-0.562	-4.30
Threshold 0 1	0.108	1.47								
Threshold 1 2	0.613	8.32								
Threshold 2 3	1.012	13.72								
Threshold 3 4	1.594	21.52								
<b>Endogenous Variables</b>										
Frequency of online shopping > 5 per month			0.141	1.85						
Frequency of online shopping									-0.010	-1.75
Delivery return rate (0-1)					-0.444	-3.28			-0.505	-3.16
<b>Correlations</b>										
Frequency of Online Shopping	1.000	--	-0.077	-1.20	0.477	9.47	0.430	6.87	0.303	3.78
Delivery Return Rate			1.000	--	-0.026	-0.06	-0.027	-0.05	0.102	1.02
Post Office Return Channel					1.000	--	--	--	--	--
Amazon Drop-off Return Channel							1.000	--	--	--
Physical Store Return Channel									1.000	--

## **Exogenous Variable Parameter Estimates**

### **Individual/Household Sociodemographics**

The results in Table 4 clearly reveal that demographic factors statistically significantly influence consumers' online shopping behaviors, delivery return patterns, and channel preferences. Women exhibit a higher propensity for frequent online purchases compared to men, aligning with a recent study using similar NHTS 2022 data (Sharda et al., 2024) and other research indicating higher female participation rates in e-commerce (see Pradhana and Sastiono, 2019, CapitalOne, 2024, and Tutar et al., 2024). However, it is important to note here that the empirical evidence on gender differences remains mixed, with some studies finding minimal gender gaps or even slightly higher male participation in certain online shopping activities (Intel, 2024a), suggesting that gender effects may vary by product category, platform, or regional context. Unfortunately, the NHTS survey, like the data used in many earlier studies of online purchasing behavior (see Le et al., 2022, and Shah et al., 2024), did not distinguish between product categories or platform of purchase. Overall, we hypothesize that the observed higher online shopping frequency among women is likely an extension of their offline shopping patterns driven by their traditional role as primary household shoppers (Numerator, 2022), and their stronger motivation by hedonic factors such as pleasure, entertainment, and mood improvement compared to men's more need-based shopping approach (Nair et al., 2022, and Tarka et al., 2022). Additionally, the results in Table 4 indicate that women's increased shopping activity translates to proportionally higher return probabilities and stronger preferences for physical store return channels compared to men. This likely reflects women's dominance in high-return categories such as fashion and beauty, where sizing issues and "bracketing" practices (ordering multiple sizes or colors with the intent to return some) result in elevated return rates (Intel, 2024b).

Generational differences also significantly influence consumer behavior in the e-commerce space. Older adults show a reduced propensity for online shopping (among those 65 years or older compared to their younger counterparts) and delivery returns (among those 56 years or older compared to their younger peers). Such age effects on frequent online shopping and return habits are well-documented (see Intel, 2024b, and CapitalOne, 2025) based on the Technology Acceptance Model and the Theory of Planned Behavior, both of which suggest that generational differences stem from older adults' lower comfort with digital interfaces, perceived lack of value compared to traditional shopping, concerns about online security, less trust in digital environments and brands, and a preference for conventional in-person shopping experiences (see Wu and Song, 2021, Abdul Wahid and Ismail, 2022, and Llorente-Barroso et al., 2024). Adults 65 years and above also favor post office returns, likely due to familiarity and ease of use of this channel of returns. Conversely, younger adults (ages 18-25), who have grown up with the internet and mobile technology and thus find digital communication natural and convenient (often referred to as "digital natives"), show a significantly lower preference for physical store returns, as also supported by recent statistics (Intel, 2024b).

With regards to race effects, Black or African American individuals exhibit lower online shopping propensity, potentially linked to having the lowest internet penetration rates in the U.S. (Pew Research Center, 2024). In contrast, Asian individuals show a higher likelihood of returning online purchases compared to other racial groups, while White individuals are more inclined to use mail carriers for returns. Given the limited attention these racial variations have received, further research is needed to understand the underlying drivers behind these behaviors.

Higher formal education (Bachelor's degree or higher relative to "less than a Bachelor's degree") increases the propensity of online shopping and the proportion of online purchases that

are returned. These relationships may be attributed to the association between higher education and enhanced digital literacy (Mamedova and Pawlowski, 2018), leading to greater comfort navigating online platforms and a reduced perception of risk in online transactions (see Angelovska Stankov, 2023, and Ullah et al., 2025). Higher educational attainment not only encourages e-commerce engagement, but also expands consumers' repertoire of return management strategies. Specifically, consumers with a Bachelor's degree or higher show a stronger inclination towards both post office and Amazon-based returns compared to those without a Bachelor's degree. This preference potentially stems from the self-service nature of these channels, often involving machine interactions and code scanning rather than direct human assistance.

Similarly, higher income levels increase the propensity of online shopping, likely due to increased purchasing power. Affluent individuals may also place a higher value on convenience, which is consistently cited as a primary driver for online shopping (see Snap Inc, 2021, and Gupta et al., 2023). Furthermore, higher income often coincides with greater access to the necessary technology and reliable internet services required for online transactions. In contrast, income does not directly affect the propensity to make delivery returns, but it does influence return channel preferences. When examining these preferences, we observe a U-shaped pattern with middle-to-high-income households (\$50,000-\$149,999) having a higher likelihood of selecting Amazon-based drop-offs compared to both low-income (less than \$50,000) and high-income households (over \$150,000).

Aligning with prior research (see, for example, Dias et al., 2020, and Kim and Wang, 2021), zero-vehicle households exhibit an increased propensity for online purchasing, likely as a means to compensate for limited transportation access. However, this lack of vehicle access may also make returning online purchases more challenging, potentially explaining their lower proportion of returns. Regarding return channel preferences, zero-vehicle households show a reduced preference to use post office and Amazon drop-off alternatives for returns (relative to physical store returns and home pickup).

Family structure also creates noteworthy patterns in online shopping behavior. Individuals in households with two or more adults (relative to sole-adult individuals) and those with children in the household (relative to those without children) have a lower propensity to shop online. This aligns with Titiloye et al.'s (2024) recent latent segmentation study, which revealed that "Traditional in-store shoppers" often include households with children aged 5-18, and "Exclusive online shoppers" are typically single-person households. However, this result contrasts with other studies (see Dias et al., 2020, and Kim and Wang, 2021, for examples), which observed that larger households are more prone to both frequent online and in-store shopping. At the same time, our findings indicate that households with children show a higher return rate of online purchases, particularly through physical stores, presumably because of the practicalities of shopping for children (such as the need to assess sizing and fit in person or the desire for immediate resolutions and exchanges offered by physical returns).

### Employment Characteristics

Our analysis also explored the relationship between employment status, telework arrangements, and e-commerce behaviors. Employment status is associated with a higher propensity for online shopping, likely because online shopping offers convenience amidst time constraints. In contrast, telework significantly impacts all measured aspects, a finding supported by various recent studies (see Mohammadi et al., 2024; Shah et al., 2024; Sharda et al., 2024, and Hensher et al., 2025). Several factors likely contribute to the observed positive impact of telework on online shopping

and return propensity. First, teleworkers' enhanced Information and Communications Technology (ICT) skills and tech-savviness are key, as these directly correlate with more frequent online shopping (Kim et al., 2023). Second, the work-from-home setting provides increased opportunities and convenience for online shopping, particularly with extended time spent on computers, allowing for seamless browsing and purchases during breaks. Third, without daily commutes, people have fewer opportunities to combine errands through trip chaining, making online shopping a more appealing alternative to driving out specifically for purchases. Telework also directly affects return channel preferences, with teleworkers (relative to non-teleworkers) exhibiting a higher probability of using the "home pick-up" option rather than using post offices, Amazon drop-off locations, and physical stores for returning goods. Ultimately, these findings highlight how telework arrangements uniquely interact with e-commerce ecosystems, with significant implications for last-mile logistics strategies.

### Residential Location Attributes

The relationship between residential accessibility and online shopping remains a rather contested subject. The literature presents mixed evidence, with some studies supporting the innovation-diffusion theory (i.e., higher urban online adoption), and others favoring the efficiency theory (i.e., higher adoption in areas with limited physical retail access) (see Cheng et al., 2021, and Titiloye et al., 2024). Our analysis contributes to this subject by examining how residential spatial characteristics influence online shopping and returning behaviors. The results reveal that individuals residing in high population density and walkability areas have a lower online shopping propensity, suggesting that neo-urbanist physical environments (that is, high density environments with land-use mixing) preserve traditional retail's competitive advantages by reducing the convenience differential that typically drives e-commerce adoption. On the other hand, rural residents are less likely to return online purchases, particularly via the Amazon drop-off channel, compared to urban or suburban dwellers. This likely results from limited return infrastructure and fewer drop-off locations in rural areas. Conversely, greater access to third-party return points (i.e., stores partnered with major platforms such as Amazon) leads to a higher proportion of returns and a greater drop-off probability through the Amazon drop-off channel.

Proximity to retail and return establishments also has effects on purchasing and return preferences. While individuals residing in counties with high retail establishment density have a reduced propensity to shop online, those residing in counties with a high density of third-party return points (by way of having more than 0.3 return points per 10,000 individuals in the county) have a higher return rate for their online-purchased items. Individuals living in counties with a retail establishment density of more than 7.95 establishments per square mile also show a reduced probability of selecting post office returns, but a higher probability of choosing Amazon drop-off and physical store return channels. Conversely, and as one would expect, individuals living in areas in the higher-than-90<sup>th</sup> percentile of counties in terms of post office density per square area have a higher predisposition to choose post offices as their return channel.

Finally, Table 4 indicates that regional factors influence return channel preferences, though these variables primarily serve as controls to ensure a more accurate estimation of individual-level effects.

### Thresholds and Constants

Note that the threshold values reported in the "Thresholds and Constants" panel do not have any substantive interpretations on their own. These values serve solely as a mapping mechanism to

translate the underlying propensity to the actual observed ordinal category for the online shopping frequency. For the delivery returns model, the constant again simply adjusts for the share of returns across the entire sample after accounting for the exogenous (and endogenous causal) effects. Similarly, for the return channel model, the constants adjust for the shares in the sample of each return channel after accounting for all observable and endogenous covariates.

### **Endogenous Effects and Correlations**

The two bottom panels of Table 4 present the estimated endogenous effects and the estimated error correlations (corresponding to the covariance matrix  $\Xi_1$ ).

The endogenous variable parameters in Table 4 represent the estimated causal effects of variables on each other after controlling for unobserved error correlations shown in the bottom panel of the table. By explicitly modeling these error correlations, we can better disentangle “true” causal effects from spurious associations arising from unobserved variables (Bhat, 2015). In determining the causal pathways, as discussed in detail in Bhat (2015), multivariate model systems with limited dependent variables can only accommodate structural effects in a single direction due to logical consistency considerations. Furthermore, cyclical relationships are not permissible where observed endogenous variable A affects the underlying latent propensity for variable B, observed endogenous variable B affects the underlying latent propensity for variable C, and observed variable C affects the latent propensity for variable A. After empirically testing all six permissible causality pathways to identify the specification with the optimal fit, we arrived at the final configuration presented in Table 4. Our recursive specification reveals that the frequency of goods purchased online in the last 30 days (i.e., frequency of online shopping) directly affects the proportion of online purchased goods returned in the last 30 days (i.e., delivery return rate), while both online purchase frequency and the proportion of returned goods directly influence the proportion of returns through various channels. We also tested various functional forms of the endogenous variables. The binary form for online shopping frequency (greater than 5 times per month) performed best for estimating the causal effect of shopping on delivery return rate, while the continuous forms of online shopping frequency and delivery return rate were most effective for modeling causal relationships affecting return channel preference.

Regarding the empirical interpretations of the endogenous effects and correlations, the results reveal a positive causal effect of online shopping frequency on delivery return propensity, indicating that individuals who make more than five online purchases with home delivery in the last 30 days exhibit higher return rates than those who make five or fewer purchases. This positive causal effect could possibly arise from “bracketing” behavior, where shoppers strategically order multiple variants of the same item (such as different sizes, colors, or styles) with the explicit intention of keeping only the best-fitting option and returning the rest. However, the negative error correlation between these outcomes suggests the presence of unobserved factors that simultaneously increase purchase frequency while decreasing return rates. This pattern could reflect several underlying reasons. For example, experienced online shoppers may develop better product selection skills, thereby reducing the need for returns despite higher purchase volumes. Alternatively, convenience-oriented consumers may shop online frequently but find returns burdensome, leading them to keep marginal purchases. The negative correlation indicates that a model ignoring this unobserved heterogeneity would substantially underestimate the “true” causal effect of purchase frequency on returns.

Online shopping frequency, from a causal standpoint, also negatively affects the choice of physical store return channels, indicating that frequent online shoppers are more likely to avoid in-

store returns. The interpretation of the correlation effects between online shopping frequency and return channel choice is somewhat tricky because the model only allows comparisons relative to the home pickup option. The positive correlations between online purchase frequency and non-home pickup return options (post office, Amazon drop-off, and physical store) suggest that unobserved factors that increase online shopping propensity also increase the likelihood of using non-home pickup return platforms relative to the home pickup alternative.

Lastly, the delivery return rate exerts negative causal effects on both post office and physical store return channel choice, suggesting that higher return volumes discourage the use of these channels relative to home pickup and Amazon drop-offs. The error correlations between delivery return rates and non-home return channel choices (relative to the home return channel) are generally statistically insignificant, indicating limited common unobserved factors affecting the return rate and return platform decisions.

### Goodness-of-Fit Measures

To establish the value of our integrated modeling framework, we compare its performance against two distinct benchmarks: first, an independent model that neglects correlations among outcomes; and second, a simplified “thresholds/constants-only” model, which relies solely on frequency thresholds for online shopping and constant terms for the delivery return and return channel preference components. Table 5 presents comprehensive diagnostics that demonstrate the joint model’s improved performance across all examined dimensions. The Bayesian Information Criterion statistic, defined as  $\left[ \text{BIC} = -L(\hat{\delta}) + 0.5 \times (\# \text{ of model parameter}) \times \log(\text{sample size}) \right]$ ,

where  $L(\hat{\delta})$  is the log-likelihood value at convergence, consistently yields a lower value for our multivariate model compared to both the independent and thresholds/constants-only alternatives. The higher values of the average probability of correct prediction and the adjusted likelihood ratio index  $\bar{\rho}^2$  for the joint model further support its superior performance. The  $\bar{\rho}^2$  index is calculated as follows:

$$\bar{\rho}^2 = 1 - \frac{L(\hat{\delta}) - M}{L(c)} \quad (6)$$

In the above equation,  $L(c)$  represents the constants-only log-likelihood function at convergence, and  $M$  is the number of parameters estimated in the model (excluding the constants and thresholds). Additionally, formal likelihood ratio testing provides conclusive validation of our joint modeling approach. The test strongly rejects the null hypothesis of independence ( $p < 0.000001$ ), indicating that the unrestricted error covariance structure substantially improves model performance compared to the restricted alternative. Also, the negligible p-value indicates that under the null hypothesis of independence, the probability of observing a test statistic this large or larger is virtually zero.

In addition to the overall fit measures, we evaluate model performance at both aggregate and disaggregate levels across various market segments to confirm that the superior performance of the joint model is not simply a result of overfitting (following Ben-Akiva and Lerman, 1985, market segment validation framework, page 208). At the disaggregate level, we derive the implied predictive log-likelihood values for the joint and independent models and compare their performance using an informal chi-squared predictive log-likelihood ratio test. At the aggregate level, we employ several validation techniques depending on the dependent variable. For the ordinal online shopping frequency variable, we analyze predicted versus observed shares at each

ordinal level, considering both the entire sample and each market segment. For the delivery return rate and channel preference variables, we compare the predicted expected fractions to the average of the observed fractions at each ordinal level, conducting this analysis for both the overall sample and individual segments. We conclude by measuring relative model effectiveness through Weighted Absolute Percentage Error (WAPE) calculations to quantify the joint model’s advantage over independent alternatives.

Table 6 presents these diagnostic measures for six consumer segments categorized by demographic and geographic characteristics, including gender, age, remote work status, area of residence, and local retail density. The findings uniformly indicate that the joint modeling approach outperforms the independent alternative across every segment analyzed. Informal predictive log-likelihood ratio evaluations (shown in the third numerical row of Table 6) favor the joint specification over the independent specification for all consumer segments under investigation. Additionally, the joint approach generates forecasted proportions that align more accurately with observed data, as evidenced by lower WAPE values relative to the independent modeling approach in every segment category.

**Table 5 Data Fit Measures**

<b>Summary Statistics</b>	<b>Multivariate model</b>	<b>Independent model</b>	<b>Thresholds/ Constants-only model</b>
Log-likelihood at convergence	-18960.974	-19036.831	-19906.183
Number of parameters	67	60	8
Bayesian Information Criterion (BIC)	19270.715	19314.211	19943.167
Adjusted likelihood ratio index ( $\bar{\rho}^2$ )	0.045	0.041	--
Likelihood ratio test versus multivariate model	--	LR=151.714>> $\chi^2_{(7,0.000001)} = 40.522$	LR=1890.418>> $\chi^2_{(59,0.000001)} = 125.665$
Average probability of correct prediction	0.236	0.229	0.192

**Table 6 Aggregate and Disaggregate Measures of Fit on Various Market Segments of the Estimation Sample**

Market Segment	Entire Sample		Gender: Women		Age: 65 years or more	
Measures of Fit	Joint Model	Independent Model	Joint Model	Independent Model	Joint Model	Independent Model
Number of observations	10363		5253		3170	
Log-likelihood	-18960.97	-19036.83	-10117.17	-10157.25	-5513.23	-5540.84
Informal predictive likelihood ratio test	151.72 > $\chi^2_{(7,0.05)} = 14.07$		80.16 > $\chi^2_{(7,0.05)} = 14.07$		55.22 > $\chi^2_{(7,0.05)} = 14.07$	
Online shopping frequency WAPE	0.3%	1.1%	0.6%	1.0%	0.8%	2.8%
Average delivery return rate WAPE	2.3%	6.2%	5.8%	7.4%	3.0%	10.2%
Average proportion of returns through HP WAPE	11.6%	18.4%	16.5%	25.3%	12.9%	22.0%
Average proportion of returns through PO WAPE	2.7%	3.8%	3.0%	5.1%	5.3%	12.0%
Average proportion of returns through AD WAPE	8.2%	9.7%	12.7%	13.7%	8.0%	16.5%
Average proportion of returns through PS WAPE	9.9%	11.2%	7.7%	9.7%	10.1%	18.8%
<hr/>						
Market Segment	Telework Arrangement: Telework Daily		Area Type: Rural		Retail Establishments in County of Residence: density per square mile > 7.95	
Measures of Fit	Joint Model	Independent Model	Joint Model	Independent Model	Joint Model	Independent Model
Number of observations	1150		2222		1012	
Log-likelihood	-2461.42	-2472.83	-3792.50	-3799.81	-1891.40	-1899.69
Informal predictive likelihood ratio test	22.82 > $\chi^2_{(7,0.05)} = 14.07$		14.62 > $\chi^2_{(7,0.05)} = 14.07$		16.58 > $\chi^2_{(7,0.05)} = 14.07$	
Online shopping frequency WAPE	1.5%	2.3%	2.5%	3.6%	0.3%	4.1%
Average delivery return rate WAPE	3.5%	9.6%	7.1%	10.5%	2.3%	13.0%
Average proportion of returns through HP WAPE	16.0%	24.9%	18.6%	25.9%	14.7%	19.4%
Average proportion of returns through PO WAPE	2.6%	5.6%	4.6%	5.9%	2.8%	3.8%
Average proportion of returns through AD WAPE	11.6%	21.5%	12.1%	17.1%	9.7%	9.8%
Average proportion of returns through PS WAPE	12.0%	15.2%	12.7%	14.2%	11.2%	14.2%

## DISCUSSION AND POLICY IMPLICATIONS

### ATE Computations

The coefficient estimates presented in the previous section do not directly quantify the actual effects of variables on outcomes, nor do they provide interpretable magnitudes of impact. The directional effects of variables on underlying propensities cannot be translated directly into effects on expected values or outcome probabilities. For example, a positive coefficient for women indicates a higher propensity for frequent online purchases compared to men, but does not quantify the magnitude of change in expected monthly shopping frequency between genders. Similarly, negative coefficients for daily telework on return channel alternatives only indicate effects relative to the reference alternative (home pickup), not the absolute change in the expected fraction allocated to each channel. This limitation arises from several methodological features of our framework. First, the nonlinear transformations inherent in ordered probit and fractional response models mean that coefficients affect latent utilities rather than observed outcomes directly. Second, the recursive structure creates multiple pathways for variables to influence outcomes, involving both direct and indirect effects that ripple through the causal chain. Third, the estimated error correlation matrix captures systematic heterogeneity in how individuals respond to changes in explanatory variables, further complicating the interpretation of coefficients. Therefore, to obtain economically meaningful effect sizes, we compute Average Treatment Effects (ATEs). An ATE is a metric that quantifies the expected change in outcomes when moving from a “base level” to a “treatment level” for any given exogenous variable. For the online shopping frequency outcome, ATE measures the change in the expected count of monthly purchases:

$$E[y_1 | \mathbf{x}] = \sum_{k=1}^5 t_k \times P(y_1 = k | \mathbf{x}) \quad (7)$$

$$P(y_1 = k | \mathbf{x}) = \sum_{m_2=1}^2 \sum_{m_3=1}^4 P(y_1 = m_1, h_2 = m_2, h_3 = m_3 | \mathbf{x}, \mathbf{z}_1, \mathbf{z}_2)$$

where  $P(y_1 = k | \mathbf{x})$  represents the probability that an individual with characteristics  $\mathbf{x}$  falls into shopping frequency category  $k$ .  $P(y_1 = k | \mathbf{x})$  is multiplied by its corresponding midpoint value  $t_k$  (0, 1.5, 3.5, 7, and 10 purchases per month for categories 1-5, respectively) rather than by the category index numbers. For the fractional response outcomes, we compute ATEs as changes in the expected fraction or probability of each outcome, given the individual’s characteristics and the recursive dependencies in our system. For the expected delivery return rate:

$$E[y_{2,2} | \mathbf{x}, \mathbf{z}_2, \mathbf{z}_3] = \sum_{m_1=1}^5 \sum_{m_3=1}^4 P(y_1 = m_1, h_2 = m_2, h_3 = m_3 | \mathbf{x}, \mathbf{z}_2, \mathbf{z}_3) \quad (8)$$

For the expected delivery return channel fractions:

$$E[y_{3,h_3} | \mathbf{x}, \mathbf{z}_2, \mathbf{z}_3, E[y_{2,2} | \mathbf{x}, \mathbf{z}_2, \mathbf{z}_3]] = \sum_{m_1=1}^5 \sum_{m_2=1}^2 P(y_1 = m_1, h_2 = m_2, h_3 = m_3 | \mathbf{x}, \mathbf{z}_2, \mathbf{z}_3) \quad (9)$$

ATEs can be computed for transitions between any variable states. For presentation clarity, we report ATEs for transitions between extreme categories of each variable. For categorical variables, we compare the lowest to highest categories. For continuous variables, we report ATEs for changes from low to high levels: from level 1 to level 9 for the Walkability Index (which ranges

from 1 to 10) and from the 10<sup>th</sup> to 90<sup>th</sup> percentile for retail establishment density (establishments per 100 people).

Table 7 summarizes the computed ATEs for each variable. For example, the interpretation of the first numeric row corresponding to the gender variable is as follows: On average, a woman is estimated to make 22.8% more online purchases per month, has a 23.3% higher delivery return rate, a 12.3% lower home pickup fraction, 6.1% lower post office return fraction, 6.0% lower Amazon drop-off fraction, and 43.2% higher physical store return fraction, compared to a man with all other variables held constant. Similar interpretations apply to all other variables reported in the table. These ATEs represent the total effects resulting from both direct and indirect pathways through the recursive system. We can also observe that some variables, which lack direct effects based on the Table 4 coefficients, still exhibit notable ATE effects through indirect channels. For example, household income does not directly affect the delivery return rate but still generates a positive 9.0% ATE through its influence on shopping frequency.

**Table 7 ATE Results**

Variable	Base	Treatment	% Shift in Frequency of Online Shopping	% Shift in Delivery Return Rate	% Shift in Return Channel Share			
					Home Pickup	Post Office	Amazon Drop-off	Physical Store
<b>Individual/Household Sociodemographics</b>								
Gender	Male	Female	22.8	23.3	-12.3	-6.1	-6.0	43.2
Age	18 to 25	56 or more	-6.2	-21.0	-32.3	9.7	-18.8	108.8
Race	White	Black	-18.2	-1.8	21.1	-19.4	11.1	9.7
Race	White	Asian	0.0	55.3	21.5	-21.0	12.3	7.9
Formal Education Level	Less than a Bachelor's degree	University degree	42.9	31.4	-26.0	16.7	24.2	-13.8
Household Income	Less than \$50,000	Over \$100,000	118.2	9.4	-6.8	-1.6	21.9	-1.8
Number of Vehicles	>0 Vehicles	Zero vehicles	11.8	-30.2	71.6	-19.4	-26.5	-23.4
Life Cycle Classification	No children present	Children present	-13.4	17.4	-5.7	-3.3	-2.2	16.4
	1 adult; no children	2+ adults; no children	-14.2	-5.4	-2.5	0.4	0.5	3.1
<b>Employment Characteristics</b>								
Employment Status and Telework Arrangements	Not employed	Employed + No telework	12.1	-20.2	-39.1	7.7	29.3	21.9
	Employed + No telework	Employed + Daily telework	27.5	29.6	65.2	-7.1	-22.4	-19.5
<b>Residential Location Attributes</b>								
CBG Population Density (persons per square mile)	Lower than 10,000	10,000 or higher	-8.3	-0.8	-0.1	0.0	-0.1	0.4
CBG Walkability Index	Level 1 <sup>#</sup>	Level 9 <sup>#</sup>	-9.0	-0.9	-0.1	0.0	-0.1	0.5
Area Type	Urban/Suburban	Rural	0.0	-25.9	23.4	9.4	-64.9	11.3
Retail Establishments	Low (density<10 <sup>th</sup> percentile)	High (density>90 <sup>th</sup> percentile)	-8.7	-0.8	-8.5	-33.2	108.7	78.7
Third-party Drop-off points	Low (density<50 <sup>th</sup> percentile)	High (density>50 <sup>th</sup> percentile)	0.0	14.2	-7.5	-3.5	32.0	-4.2
Post Offices	Low (density<90 <sup>th</sup> percentile)	High (density>90 <sup>th</sup> percentile)	5.5	0.5	-17.6	18.9	-10.1	-10.1
<b>Endogenous Variables</b>								
Frequency of Online Shopping	1	7	n.a	18.0	6.7	2.8	3.5	-18.4
Delivery Return Rate (0-1)	0.1	0.9	n.a	n.a	43.1	-25.9	21.6	-36.7

<sup>#</sup>Refer to footnote 1 for details about walkability levels

## **Sociodemographic Heterogeneity in E-commerce Behavior**

Our ATE analysis uncovers significant sociodemographic heterogeneity in online shopping and return behaviors, clearly indicating that “one-size-fits-all” approaches to addressing urban freight and logistics challenges are likely insufficient. Rather, a thorough understanding of the diverse sociodemographic patterns of online ordering and returns is necessary to inform logistics planning to serve all community segments.

Our analysis reveals that women exhibit significantly higher online shopping engagement (+22.8%) and return rates (+23.3%) compared to men. Notably, they also show a strong preference for physical store returns (43.2% increase), while reducing reliance on other return channels. This strong inclination suggests that online purchasing is likely fostering strategic trip chaining for many women. The convenience of buying online appears to create subsequent opportunities for in-person store visits, allowing for combining product returns with new purchases, product exploration, and other retail errands. This behavioral hypothesis is supported by survey results indicating that a significant proportion of consumers (e.g., 42% in a Narvar (2022) study) choose in-store returns specifically to shop for other items. Rather than simply replacing physical shopping, online purchases may be reshaping and even increasing certain types of store visits for women, solidifying the physical store’s role as an essential hub. Retailers can leverage these insights to optimize the physical return experience, particularly for women-oriented products. Practical strategies could include positioning return counters conveniently (e.g., near women’s clothing sections), offering dedicated return areas for frequently returned items such as apparel and cosmetics, or providing express return services for common women’s purchases. This fundamentally shows the retail industry’s urgent need to fully adapt to a truly hybrid ecosystem, seamlessly integrating online and offline channels instead of treating them as separate operations.

Further analysis by generational segments reveals several shopping mobility and accessibility issues associated with age. While a reduced online shopping frequency among older adults is a well-established observation (our data shows a 6.2% decrease for those 56 or more compared to 18-25), the reduced delivery return rate (-21.0%) for this demographic is even more substantial. This suggests that the barriers older adults face in the e-commerce ecosystem extend beyond initial purchasing to the crucial reverse logistics phase. This is rather ironic given that older adults frequently perceive the usefulness of online shopping to avoid physical mobility challenges associated with traditional retail, such as difficulties with standing in checkout lines, carrying heavy packages, and navigating crowded stores (Wu and Song, 2021). Yet, current return logistics systems effectively force them back into these challenging physical environments, negating many accessibility benefits of e-commerce. To address this, retailers and logistics providers should consider developing tailored return programs for older adults, such as specialized elderly-focused home pickup services, to enhance equitable access to the full e-commerce cycle.

Our findings point to clear variations in shopping and return behavior based on formal education attainment and income, highlighting a significant socioeconomic digital divide within the e-commerce ecosystem. University-educated consumers make online purchases more frequently, return items at higher rates, and use Amazon drop-off points more often. This pattern likely reflects how higher education correlates with enhanced digital literacy and greater awareness of consumer rights and return policies (see Valarezo et al., 2020, Nguyen et al., 2024, and Singh et al., 2024), enabling a more strategic navigation of e-commerce systems. Similarly, high-income households (\$100,000+) show a 118.2% higher online shopping engagement and greater use of Amazon drop-off locations (+21.9%) relative to low-income households (less than \$50,000). While income does not directly affect return rates, frequent shopping among affluent consumers

indirectly shapes return patterns, possibly through increased familiarity with the e-commerce landscape and policies, or even bracketing, enabled by their substantial purchasing power (as indicated by Narvar (2022)). These patterns align with Valarezo et al.'s (2020) observation that “education and digital skills diminish the costs of using internet services; economic variables, income, and employment situation, increase the benefits.” Ultimately, these relationships suggest that higher-income consumers, leveraging their greater purchasing power, digital literacy, and access to technology, are better equipped for frequent online purchases on platforms such as Amazon, directly contributing to their higher utilization of Amazon drop-off channels. In contrast, lower-income shoppers, who may be less experienced with the e-commerce ecosystem or perhaps gravitate towards cheaper shopping websites, might encounter less convenient return options or even platforms that offer no returns at all. Ultimately, these results highlight the need for targeted digital literacy programs and policy interventions to bridge the e-commerce divide. Specifically, initiatives should focus on: (1) increasing digital access/literacy and platform navigation skills among lower education and income consumers, (2) improving awareness of return policies and consumer rights, and (3) ensuring equitable access to convenient return infrastructure across consumers. Such efforts would help democratize e-commerce participation and ensure all consumers can fully benefit from online shopping opportunities. At the same time, retailers could leverage this information to optimize their returns infrastructure to meet varying preferences and needs. For instance, a retirement community would still require robust physical return options, while college towns can leverage automated parcel lockers more effectively.

Beyond education and income, individuals in vehicle-less households face additional disadvantages in their return journey (30.2% decrease in delivery return rate), revealing how transportation constraints fundamentally limit participation in the complete e-commerce cycle. Compounding this, our analysis shows that individuals in these vehicle-less households are 71.6% more likely to utilize the home pickup option for returns, which often involves a direct cost to the consumer (e.g., a specific pickup fee deducted from the refund or requiring a premium subscription). This suggests that, if not carefully designed, return policies may inadvertently create a form of socio-economic discrimination against car-free households and raise important policy questions regarding the responsibility of retailers and municipalities to collaboratively ensure equitable and affordable return access in transportation-disadvantaged communities. Specifically, strategic public-private partnerships could be established to develop reliable return infrastructure in transit- and active-transport dependent communities, potentially integrating return facilities with existing transit hubs. This involves expanding the deployment of parcel and smart lockers beyond current limited placements (e.g., multifamily apartment complexes, universities, airports) to ensure comprehensive coverage at public transport stations, following models already implemented across Europe (PYMNTS, 2023). Similarly, integrating return logistics with public transit planning would recognize return trips as an emerging transportation need requiring multimodal solutions. Urban planning policies could further address this through zoning and development incentives to ensure accessibility to return infrastructure in transportation-disadvantaged neighborhoods.

Finally, our results suggest that online shopping is far from being a seamless solution for parents. Instead, e-commerce may introduce unforeseen complications for busy households with children. Their higher return rates, coupled with the need to return items in person, could negate the very convenience online shopping promises, forcing them to integrate additional errands into their already complex schedules. Retailers, therefore, have an opportunity to enhance the virtual shopping and return experience for these households. This could involve optimizing online product descriptions and sizing tools, for instance, through AI-driven fit recommendations for children's

apparel, which are proven to reduce return rates (Bold Metrics, 2025). Additionally, providing enhanced customer service for common children's products or exploring streamlined home pickup options could further reduce the need for in-person store visits. Simultaneously, there is potential to encourage more frequent online shopping among larger households (2+ adults, no children) through tailored incentives such as family plans or account options (e.g., Amazon Family; Amazon, 2025), ensuring e-commerce genuinely serves all household configurations.

### **Relationship between Teleworking and E-commerce Patterns**

A growing body of research reveals how the telework revolution, accelerated by the COVID-19 pandemic, has created ripple effects across various aspects of life, including altering engagement in out-of-home activities (Kothawala et al., 2025), reshaping weekly production of maintenance and leisure trips (Asmussen et al., 2024), as well as significantly impacting the propensity for e-commerce engagement (see Mohammadi et al., 2024; Shah et al., 2024; Sharda et al., 2024, and Hensher et al., 2025).

The evidence from our analysis aligns with broader research, demonstrating that flexible work arrangements have a significant influence on e-commerce engagement. Individuals who are employed, even without telework, show a 13.4% higher online purchase frequency compared to unemployed individuals, suggesting that the structure of employment itself, regardless of work location, supports greater e-commerce engagement. This trend intensifies with telework adoption, as daily teleworkers exhibit a 27.5% higher online shopping frequency compared to their non-teleworking employed counterparts, presumably attributable to ICT skills, time flexibility, and the reduced need for external travel, as discussed previously. These same factors, combined with the positive causal relationship between online shopping frequency and returns, translate into daily teleworkers showing 29.6% higher delivery return rates. This segment also demonstrates a striking shift towards home-based return solutions, with a 65.2% increase in home pickup utilization. This preference is obviously a direct manifestation of teleworkers' increased presence at home, making scheduled pickups exceptionally convenient while reducing the need for out-of-home errands. It also points to how trip chaining with commute journeys appears to facilitate returns at non-home locations. Overall, the growing reliance on home-based delivery and return pickup services among teleworkers may heighten their risk of "cabin fever" (see Mokhtarian and Salomon, 2001, and Colaço and de Abreu e Silva, 2025).

These findings have practical implications for various sectors. First, employers can design certain return programs or collaborate with mail carriers or private providers to provide their in-person and hybrid workers with some return infrastructure. Second, businesses can capitalize on teleworkers' heightened preference for online shopping by crafting targeted marketing strategies that speak directly to the unique needs and shopping patterns of remote workers, as suggested by Mohammadi et al. (2024). Similarly, reverse logistics operators can incorporate these insights when deciding where to locate return infrastructure, recognizing the fundamental shift in demand from employment-centered return facilities toward residential-focused collection networks. Alternatively, retailers could reimagine their physical return infrastructure by integrating return centers with experiential spaces, such as co-located cafes, community centers, or recreational facilities, effectively transforming routine return processes into more appealing activities. Such an approach could simultaneously counter the isolation of remote work while optimizing retailers' reverse logistics operations. Third, transportation planners must reconsider how the spatial redistribution of work activities influences not just commuting patterns but also the movement of

goods and people. We provide a detailed discussion of the impacts of e-commerce on transportation and freight planning, as well as broader travel demand, in the following sections.

### **Spatial Patterns of E-commerce**

Beyond individual-level factors and teleworking arrangements, our analysis highlights how residential location attributes and access to retail and return establishments fundamentally shape e-commerce behaviors, particularly regarding return channel choices.

While increasing walkability or population density lead to only marginal decreases in online purchase frequency (9.0% and 8.3%, respectively) with minimal impact on return rate or channel choice, the broader urban-rural distinction significantly influences both aspects. Individuals in rural areas exhibit a notably lower delivery return rate (-25.9%) and a significant 64.9% shift away from Amazon Drop-off locations. Individuals in rural areas compensate instead with increased reliance on home pickup (+23.4%), physical store (+11.3%), and post office returns (+9.4%). This trend clearly reveals a persistent urban-rural divide in e-commerce logistics, where the “last-mile” problem in e-commerce has a corresponding “first-mile” challenge in returns. Specifically, more densely urbanized areas often provide a wider array of convenient return options that support efficient reverse logistics and reduce vehicle dependence. In contrast, spatially sparse rural areas often place a greater burden on both consumers and retailers, frequently resulting in longer trips to access return services. These findings have substantive policy implications for rural transportation planning and service delivery, suggesting that addressing rural connectivity requires coordinated investment in both digital infrastructure and physical return networks, including enhanced postal services, mobile collection points, or incentivized regional consolidation centers.

Taking a closer look at specific retail and return infrastructure reveals much more pronounced impacts on return channel utilization. Consumers residing in areas with high retail establishment density show only modest decreases in online shopping frequency, yet demonstrate massive shifts toward Amazon drop-offs (+108.7%) and physical store returns (+78.7%), coupled with substantial reductions in post office and home pickup, for product returns. This effect challenges the simplistic view that e-commerce makes physical retail obsolete. In this context, retail establishments are becoming crucial nodes not just for sales but also for reverse logistics, integrating the online and offline shopping experiences. Urban planners should recognize and actively support the dual function of retail spaces as both sales points and e-commerce fulfillment/return centers. Zoning regulations might need to adapt to allow for or encourage the integration of drop-off points, lockers, and even small-scale reverse logistics operations within traditional retail corridors. In addition to retail infrastructure, areas with high third-party drop-off location density experience significant shifts toward Amazon drop-offs (+32.0%), while post office density directly drives post office return usage. Again, this pattern strongly suggests that existing commercial infrastructure continues to reshape logistics patterns and that consumers are driven by convenience and proximity when choosing return channels. Public entities, including city planning departments and transportation agencies, can leverage this insight to strategically optimize return operations and minimize their traffic externalities. This could potentially include justifying the designation of specific areas for return hubs, offering incentives for co-locating return services in transit-accessible locations, and integrating smart lockers into public spaces such as transit stations or community centers.

## **Impact on Urban Logistics and Travel Demand**

The overall rise in e-commerce, which both directly and indirectly induces higher return rates and fundamentally alters channel preferences (see endogenous effect panel in Table 7), makes it more critical than ever to plan and design urban systems that account for multifaceted delivery return behaviors.

The urban planning literature has extensively examined the implications of expanding e-commerce, particularly focusing on warehouse distribution and its impacts on traffic and infrastructure requirements (Giuliano et al., 2025; Kumar and Chidambara, 2024). As the demand for expedited deliveries with narrow time windows increases, retailers have also implemented multi-scale logistics strategies. This evolution has led to the continued expansion of large fulfillment centers, significantly altering regional land use patterns and intensifying highway freight traffic, while smaller sorting and delivery hubs have strategically emerged near residential areas. And while traditional carriers such as FedEx and UPS are still key, there is a growing reliance on independent contractors using personal cars for deliveries (Rutter et al., 2017). Interestingly, recent research has identified a prevalent “infill” growth pattern in the geographical footprint of e-commerce logistics networks (Giuliano et al., 2025). This development, consistent with e-commerce demands for population proximity and rapid delivery times, places additional pressure on already constrained urban resources, including road capacity and freight management systems. What is particularly challenging is that this urban resource strain now operates in a bidirectional manner. The forward logistics of e-commerce delivery have been supplemented by an equally demanding reverse logistics system handling returns, the combination of which then creates new spatial patterns and infrastructure needs that current urban planning frameworks are ill-equipped to address. These transformations, from expansive warehousing facilities to neighborhood-scale drop-off and pick-up points, necessitate comprehensive planning revisions. Zoning and land-use policies need to be reevaluated to accommodate return facilities through appropriate restrictions and flexibility. Cities must also reconsider parking allocation, curb management, and integration of logistics infrastructure within existing urban environments. To adapt effectively, urban planners could also innovatively shape policies by leveraging underutilized retail spaces of various sizes or integrating these facilities into new developments, especially in densely populated areas, to minimize consumer travel and rationalize delivery vehicle routes.

Beyond planning, the integration of delivery returns into our daily routines will undoubtedly lead to significant shifts in personal travel patterns and activity engagement, adding complexity to understanding the overall impact of online shopping. While researchers have extensively studied the effects of widespread adoption of online shopping on travel demand, often categorizing them as complementarity, substitution, or modification (see Le et al., 2022, for an extensive review), the sheer growth of product returns as a direct consequence of this e-commerce adoption will undeniably induce new return trips and generate additional vehicle miles traveled (VMT), impacting either the passenger or freight side of transportation, or both.

The aforementioned emerging dynamic necessitates analyzing delivery return trips through established travel behavior frameworks to understand how they fit into daily mobility patterns. Travel behavior research has long recognized that most travel represents a derived demand for activity participation. Since travel is largely a derived demand for activity participation, we need to examine how return activities interact with the familiar “mandatory,” “maintenance,” and “discretionary” activity categories central to activity-based travel demand models. In fact, product returns essentially constitute a new subset of maintenance-type activities, yet they possess

distinctive characteristics regarding destination options, timing constraints, and transportation mode choices. Importantly, these return trip attributes vary significantly across different population segments. For instance, our research indicates that women, university-educated individuals, and high-income individuals are likely to generate more return trips than their counterparts. However, the precise Vehicle Miles Traveled (VMT) and associated externalities of these trips will depend on multiple factors, including trip timing, distances traveled, trip-chaining practices, and mode choice for return trips. Supporting evidence related to trip-chaining and mode choice appears in recent research on automated parcel lockers, which found that 79% of trips to these facilities were made by private vehicles and that 44% were integrated into multi-purpose trip chains (Ha et al., 2022). Additionally, certain population groups, including women, older individuals, those with children, employed individuals working from the in-person workplace location, and those living in areas with a high density of retail establishments, tend to make return trips more frequently to physical store locations, rather than to other destination types, further influencing return trip attributes. Moreover, proximity to return infrastructure and destinations can also influence destination and mode choices. For instance, in areas with a high density of third-party drop-off points or post offices, individuals may frequently opt for walking or public transit for their return trips. To accurately capture such nuanced travel behaviors and enable more robust forecasting and policy interventions, data collection efforts need to be expanded. Existing data sources often lack the granularity needed to fully understand return trip dynamics. Specifically, surveys need to be designed to learn more about key attributes currently missing or significantly underrepresented in traditional travel surveys:

- Product Type: How does the type of product purchased influence return likelihood and channel choice (e.g., apparel vs. electronics)?
- Delivery and Return Timeline: How do delivery speed and return window policies affect consumer behavior and the timing of return trips?
- Channel Specifics: Detailed reasons for choosing a particular return channel beyond convenience, including cost, perceived effort, and specific service offerings.
- Trip Attributes for Returns: Data on the exact mode of transportation used for return trips, distances, timings, and whether these trips are chained with other activities (e.g., shopping, work, errands).
- Socio-demographic and Work Arrangements: More granular data on household composition, employment types, and telework arrangements to refine segmentation.

Additionally, since shopping and returning activities do not typically occur on a daily basis, using one-day travel diary data and cross-sectional surveys might not provide a comprehensive picture of shoppers' full behavioral patterns. Future research should implement extended observation periods or longitudinal survey designs that track the evolution of shopping patterns, channel preferences, and return behaviors over time.

## CONCLUSIONS AND LIMITATIONS

In the current study, we have employed a rigorous econometric framework to unravel the complex interplay of factors influencing online shopping purchase frequency, return rates, and preferences for different return channels among U.S. consumers, leveraging the comprehensive NHTS 2022 dataset. By utilizing ordered-response probit and probit fractional response models, we have provided insights into how sociodemographic characteristics, household attributes, and residential location characteristics shape e-commerce-related travel behaviors. Our results indicate that sociodemographics play an important role in online shopping engagement as well as return channel preferences. The emergence of telework as a powerful driver of e-commerce behavior is also noteworthy. Teleworkers both shop and return more frequently while using all non-home pickup return channels less often than non-teleworkers, suggesting unique trip-chaining strategies. In addition, residential built environment attributes influence product return behavior. Specifically, urban density, walkability, and proximity to return infrastructure affect return rates and channel choices, demonstrating that physical context remains relevant even in digital commerce. More importantly, after controlling for the effects of unobserved variables across the three dimensions studied, we identified direct causal relationships between increased online shopping, returns, and subsequent channel effects. This causal link confirms that higher shopping frequency directly drives return behavior, which in turn influences channel selection, creating a connected chain of consumer decisions.

The results from this study have implications for retailers designing return strategies and transportation planners anticipating travel impacts. In particular, the findings point toward the need for an integrated e-commerce-driven transportation policy approach that acknowledges returns as a distinct and increasingly significant generator of transportation demand with unique equity, efficiency, and sustainability implications. Such an approach would recognize return infrastructure as an essential element of the transportation system, ensure multimodal and equitable access to return options, and integrate return logistics considerations into broader transportation planning processes.

Of course, while this study offers valuable insights into e-commerce return behaviors, there is substantial scope for further research in this area in the future. First, our analysis relied on a combined frequency measure for online goods purchases, as the NHTS survey did not distinguish between product categories. The absence of product-level detail may conflate demographic effects with product preferences; for example, observed gender differences may reflect variation in purchase types (e.g., apparel vs. electronics) rather than intrinsic behavioral differences. In addition, the NHTS dataset lacked information about purchasing platforms, available return alternatives, distances to return facilities, and associated costs, all of which are likely to influence consumers' return channel decisions. Consequently, we could not observe the complete choice set from which consumers made their selections, nor the alternative-specific attributes that influenced their decisions. Second, the NHTS grouped return options into broad categories, potentially obscuring distinctions between functionally different alternatives. For example, Amazon drop-off locations differ from generic parcel lockers in accessibility, hours, and user experience. More granular channel categorization in future surveys would better capture nuanced consumer preferences and behaviors. Third, our analysis was constrained by county-level data, likely masking intra-county variation in return infrastructure. Finer geographic resolution in future studies would improve estimates of how proximity to facilities, particularly small-scale infrastructure such as parcel lockers, influences return channel choice. Fourth, a comprehensive understanding of return behavior requires situating online returns within the broader context of

omnichannel retail participation. Consumers likely make integrated decisions across online and in-store channels, balancing purchase and return convenience based on anticipated needs, patterns not fully captured by our model. Moreover, the causal relationship we identified between online shopping frequency and return behavior may not be uniform across all consumers. Some may exhibit reverse causality, where return policies and channel preferences influence initial purchase decisions. Future research employing latent segmentation methods could reveal distinct consumer types, such as “strategic returners,” who select platforms based on return logistics, and “impulse buyers,” whose high shopping frequency drives return activity, providing more targeted insights for retailers and policymakers. Finally, while our study adopted an individual-level perspective, future research should explore whether e-commerce return decisions are better understood through a household lens. This question parallels longstanding debates in transportation research over the appropriate unit of analysis, particularly in the context of residential location, vehicle ownership, and the division of shopping and maintenance tasks (see Ho and Mulley, 2015, Hu et al., 2023, and Palma et al., 2024 for an extensive review). Suel (2016) highlights similar considerations in online shopping, noting that decision-makers are often classified as individuals, households, or “main shoppers.” In the context of returns, households may consolidate items, allocate return tasks based on convenience or expertise, or make joint decisions based on household logistics. For example, one household member, the “main returner,” may routinely handle all returns, irrespective of who made the purchase. Recognizing these intra-household dynamics may reveal patterns that are obscured by an individual-level approach and improve our understanding of return behaviors.

In conclusion, the rise of delivery returns represents an emerging intersection of digital commerce, consumer behavior, and urban mobility, with meaningful implications for sustainability, infrastructure planning, and equity. Notwithstanding the many directions along which the current research may be extended in future investigations, this study makes important contributions to advancing our understanding of the behavioral, spatial, and logistical dimensions of return activity, informing the development of more resilient, efficient, and consumer-responsive retail and transportation systems.

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