NATIONAL CENTER FOR UNDERSTANDING FUTURE
TRAVEL BEHAVIOR AND DEMAND

Final Project Report

The Effects of Changing Commutes on Home Delivery Activity

BY

Alison Conway
Email: aconway@ccny.cuny.edu

Fateme Rezapour Fardin
Email: frezapourfardin@ccny.cuny.edu

Yana Kucheva
Email: ykucheva@ccny.cuny.edu

Cosmo Bjorkenheim
Email: cbjorkenheim@ccny.cuny.edu

The City College of New York
160 Convent Avenue
New York, NY 10031

October 2025

TECHNICAL REPORT DOCUMENTATION PAGE

1. Report No. N/A	**2. Government Accession No.** N/A	**3. Recipient's Catalog No.** N/A	
4. Title and Subtitle The Effects of Changing Commutes on Home Delivery Activity		**5. Report Date** October 3, 2025 **6. Performing Organization Code** N/A	
7. Author(s) Alison Conway, https://orcid.org/0000-0002-2538-4501 Fateme Rezapour Fardin, https://orcid.org/0009-0001-8235-0770 Yana Kucheva, https://orcid.org/0000-0002-6986-7150 Cosmo Bjorkenheim, https://orcid.org/0009-0000-0897-2806		**8. Performing Organization Report No.** N/A	
9. Performing Organization Name and Address Department of Civil Engineering The City College of New York 160 Convent Avenue, New York, NY 10031		**10. Work Unit No. (TRAIS)** N/A **11. Contract or Grant No.** 69A3552344815 and 69A3552348320	
12. Sponsoring Agency Name and Address U.S. Department of Transportation, University Transportation Centers Program, 1200 New Jersey Ave, SE, Washington, DC 20590		**13. Type of Report and Period Covered** Final Report, 2023-2024 **14. Sponsoring Agency Code** USDOT OST-R	
15. Supplementary Notes N/A			
16. Abstract (see below)			
17. Key Words teleworking, home shopping, electronic commerce, delivery service, structural equation modeling		**18. Distribution Statement** No restrictions.	
19. Security Classif.(of this report) Unclassified	**20. Security Classif.(of this page)** Unclassified	**21. No. of Pages** 43	**22. Price** N/A

16. Abstract

In recent years, the rapid evolution of digital technologies has transformed various aspects of daily life, including introducing new opportunities for online shopping and teleworking. As virtual activities increasingly replace or complement in-person alternatives, related transportation activities for both passengers and goods are expected to change profoundly. While prior research has examined the socio-economic factors and built environment characteristics that influence these activities independently, few studies have examined the interaction between these activities, and the implications travel demand estimation and transportation planning.

Leveraging an existing household travel survey – the New York City Department of Transportation's Citywide Mobility Survey - this study used path analysis, a Structural Equation Modeling approach, to examine the impact of teleworking on (1) online shopping participation and (2) home delivery propensities for specific types of goods. Using this model structure enables exploration of the impact of teleworking on online shopping and home delivery behavior while also recognizing the effects of other exogenous variables and capturing the interconnections between online shopping and each of the delivery types.

Results from this study can inform local delivery approaches that take into account the daily activities of receivers. This report also identifies a number of recommended improvements for future travel surveys and models of home delivery activity to better capture delivery complexities.

Form DOT F 1700.7 (8-72) Reproduction of completed page authorized

DISCLAIMER

The contents of this report reflect the views of the authors, who are responsible for the facts and the accuracy of the information presented herein. This document is disseminated in the interest of information exchange. The report is funded, partially or entirely, under Grant No. 69A3552344815 and 69A3552348320 from the U.S. Department of Transportation's University Transportation Centers Program. The U.S. Government assumes no liability for the contents or use thereof.

ACKNOWLEDGMENTS

This research was partially supported by the National Center for Understanding Future Travel Behavior and Demand (TBD), a National University Transportation Center sponsored by the U.S. Department of Transportation (USDOT) under grant numbers 69A3552344815 and 69A3552348320. The authors would like to thank the TBD National Center and USDOT for their support of university-based research in transportation, particularly for the funding provided for this project. The authors also extend their thanks to Mila LeMorvan-Chevestre for her valuable contributions to the work presented in this report.

EXECUTIVE SUMMARY

Project Motivation

Online shopping, home deliveries, and teleworking have accelerated in recent years. These activities are expected to significantly impact freight and passenger travel demand. While many studies have been conducted to examine factors influencing online shopping and teleworking adoption, home delivery rates, and trade-offs between in-person and online work and shopping activities, the impact of teleworking on daily home delivery activities remains underexamined.

Project Approach

Using path analysis, a type of Structural Equation Modeling (SEM), this study investigates the effect of teleworking on an individual's daily likelihood to participate in four e-commerce-related activities - online shopping and at-home receipt of packages, groceries, and prepared meals while simultaneously controlling for out-of-home activity participation, demographics, household characteristics, and security factors. Comparison of model results for multiple activities simultaneously capture complexities that should be recognized in related travel demand models and in city logistics planning.

Key Model Results

Our results indicate that a number of factors significantly influence online shopping participation and delivery frequencies, but that these may vary depending on the delivery type. The following section briefly summarizes the significant model results.

Impacts of Teleworking

- Teleworkers are not more likely to participate in online shopping than non-teleworkers.
- Teleworkers do exhibit delivery behaviors distinct from non-teleworkers, and, in general, teleworking does increase the likelihood of receiving home deliveries. However, distinctions vary based on delivery type with the duration of telework.

Impacts of Other Time Uses

- Time spent at work, at home, in a store, or at a restaurant does not significantly impact the likelihood of receiving a grocery delivery.
- More time spent at home increases online shopping participation, as well as the likelihood of receiving a parcel delivery and receiving a prepared food delivery.
- More time traveling to work and working-out-of-home also increases the likelihood of receiving a parcel delivery.
- When explored on a daily basis, online shopping is not a substitute for in-store shopping, but is rather a complementary activity.
- Alternatively, spending time eating at a restaurant reduces the likelihood of a prepared food delivery on the same day.

Demographic Factors

- Men are less likely than women to shop online on a given day, and are less likely to receive package deliveries at home, but no gender differences are observed in food and grocery delivery propensities.
- Individuals in the highest income groups shop more online and receive more packages.

- No race or ethnicity variables were not significantly related to online shopping participation.
- Hispanic individuals were less likely to receive a package delivery to home; this may be due to greater use of alternative delivery locations.
- Hispanic individuals were more likely to receive a prepared food delivery compared to other groups.
- Black or African American individuals were more likely to receive a grocery delivery compared to other groups.
- Seniors (65+) were less likely to shop online compared to younger adults, and they received fewer prepared food deliveries.
- Adults aged 45 - 54 were less likely to shop online than all other non-senior adults.
- Survey respondents aged 18-24 were less likely to receive parcels compared to other age groups.
- Household intergenerational dynamics likely impact observed differences between age groups.

Household Characteristics and Structure

- In general, the likelihood of receiving a parcel delivery increases with household wealth.
- The likelihood of receiving a grocery delivery is significantly higher among the highest income category, while prepared food deliveries are higher among both the highest and lowest income groups compared to middle income receivers.
- Houses with multiple workers are more likely to receive prepared food deliveries.
- Households with small children (under 5) are more likely to shop online, and to receive deliveries of all types. More kids aged 5 to 15 also increases the likelihood of online shopping and the frequency of package deliveries
- Households with teenagers were found to shop less online.

Relationships between Delivery Types

- Online shopping participation is positively associated with all three types of deliveries.
- There is a weak positive relationship between grocery and prepared food deliveries, indicating that those receiving one type of food delivery are more likely to have the other type of food delivered as well.
- Although higher likelihood of package deliveries is positively associated with higher likelihood of receiving grocery deliveries, it is negatively associated with the likelihood of receiving prepared food.

Takeaways for Research and Practice

This study also produced recommendations for incorporating results into city logistics strategies, as well as for making improvements to future surveys and models of home delivery activity. Based on findings from the model, to realize transportation efficiencies, local authorities should explore implementing alternative delivery strategies in areas with high concentrations of traditional employment, as well as near alternative work locations from which teleworkers complete remote work, including formal and informal shared workspaces as well as in residential areas. Given that parents of young children are major consumers of home delivery, authorities should also considering aligning alternative delivery locations with spaces regularly visited by parents.

Specific areas of needed research improvement identified include: clearly differentiating online shopping participation and delivery activity; recognizing the impact of unique delivery characteristics such as value, time-sensitivity, handling requirements, lead time, and receiver ability to control delivery times; and more detailed evaluation of physical, time, and financial access impacts on shopping behavior choices.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

1 INTRODUCTION

The rapid evolution of digital technologies has transformed various aspects of daily life, with online shopping and teleworking emerging as significant trends. The COVID-19 pandemic further accelerated these shifts, reshaping consumer behavior and work habits globally. New York City (NYC), like most US and global cities, has seen rapid evolution of (1) work location and time flexibility and (2) adoption of online shopping alternatives for diverse commodities by varying shopper populations. It is expected that changes in work location – particularly the increased opportunity for some individuals to work from home at least a few days per week – could have profound impacts on the choice of location for shopping activities and on the likelihood of receiving home deliveries.

This study utilized an existing household travel survey, the New York City Department of Transportation's (NYC DOT) 2022 Citywide Mobility Survey (CMS). While prior research has explored factors influencing teleworking, online shopping, and home deliveries separately—and some studies have examined trade-offs between in-person and virtual activities—there remains a gap in understanding the interdependencies among these behaviors. To address this gap, this study employs path analysis, a Structural Equation Modeling (SEM) approach, to examine the relationships between teleworking adoption and online shopping participation and home delivery frequency. SEM allows us to capture the complex, bidirectional influences between these activities, providing a comprehensive understanding of their interplay in shaping future mobility and logistics trends. The results of this study can inform both urban freight planning practice and future research improvement.

2 LITERATURE REVIEW

Prior research has extensively examined the socio-economic factors, such as income, education, and household composition, as well as built environment characteristics, including urban density and access to transportation, that influence participation in virtual activities. These studies have also explored the trade-offs between different types of in-person and virtual activities, shedding light on how individuals balance the convenience of online options with the need for physical presence in various contexts, such as shopping, work, and social interactions.

2.1 Prior Studies: Online Shopping and Home Delivery

Many studies have been done in the context of online shopping and home deliveries to examine the factors influencing participation in these virtual activities. As detailed in the following section, these studies have typically focused on individual delivery types. These studies have produced mixed results regarding the influence of socioeconomic and built environment factors.

2.1.1 Online Shopping Participation and Home Delivery Frequencies

Wang and Zhou examined the rise of deliveries to residential units using a right-censored negative binomial model; their study examined factors including web use, education, age, race and household related variables [1]. Beckers et al. developed a logit regression model to analyze the relationship between socio-economic characteristics and willingness to shop online in Belgium [2]. Saphores & Xu used a negative binomial model to explore changes in online grocery shopping between 2009 and 2017 in the US [3]. Kirby-Hawkins et al. investigated the geography of corporate e-commerce sales in the UK grocery market using a spatial interaction model [4], while Dominici et al. developed a logit model to understand factors affecting online food purchasing in Italy [5]. Reiffer et al. used a binary regression model during COVID-19 in addition to logistic and Poisson regressions to examine both socio-demographic characteristics and travel behavior variable impacts on last-mile parcel delivery and online shopping behavior [6]. Kim & Wang, using an earlier version of the same survey used in this study, explored factors affecting retail, grocery, and food deliveries in New York City by developing an ordered probit and simultaneous equation models [7].

2.1.2 Online Shopping Participation and Home Delivery During COVID-19

Several studies have specifically focused on understanding COVID-19 impacts on e-commerce-related behaviors. Adibfar et al. studied COVID-19 effects on online shopping behavior of users before, during, and after the COVID-19 pandemic using discrete choice models [8]. Colaço and De Abreu E Silva investigated online shopping and travel behavior before the COVID-19 pandemic (January–February 2020) and in its aftermath (April–May 2022) using a structural equation model and multigroup analysis [9]. Khaddar and Rahman Fatmi (2024) investigated telecommuting and teleshopping preferences using a multivariate ordered probit model [10]. Unnikrishnan & Figliozzi also analyzed home delivery purchases during COVID-19 lockdowns and before COVID-19 using ordered choice models [11].

2.1.3 Time Use Impacts of Online Shopping and Home Delivery

As digital alternatives have become increasingly widespread, researchers have examined how individuals allocate their time between in-person and virtual activities like shopping and work. Shen et al. investigated online grocery shopping versus in-person grocery shopping in Chicago using a series of binary logit models [12]. A similar study by Wang et al. investigated individuals’ choice of in-store and online grocery shopping in Canada using stated preference (SP) choice experiments [13]. Dias et al. (2020) compared online and in-person shopping and eating behaviors using a multivariate ordered probit model [14]. Kim and Wang also examined relationships between deliveries and in-store shopping trips [7].

2.1.4 Findings from Prior Studies: Socioeconomic Variables

Prior research has investigated the relationships between socioeconomic variables and online shopping participation or delivery frequencies. However, results have varied across locations, over time, and for different commodity types. The following sections summarize findings from prior studies for different socioeconomic characteristics.

2.1.4.1 Income

Reiffer et al. [6] found that higher-income households are more likely to engage in online shopping compared to lower-income ones. Adibfar et al. [8] detailed that income primarily affects the online purchasing of non-essential items such as electronics, clothing, and books. According to Shen et al. [12], the impact of household income on online grocery shopping has also evolved notably before and after COVID-19. Prior to the pandemic, higher-income groups were less inclined to use online grocery shopping services, but this trend changed during and after the pandemic, with significant increases in online grocery shopping among higher-income households, particularly in the short-term following the pandemic [12].

2.1.4.2 Race/Ethnicity

While research on race and ethnicity impacts on delivery frequency are limited, some US studies have identified differences in shopping and delivery propensities. Kim and Wang [7] and Saphores and Xu [3] both found that white individuals are more likely to shop online than African American or Asian individuals. Kim and Wang [7] found that African American and Hispanic individuals were more likely to receive food deliveries compared to white individuals. This result contrasts with a more recent study conducted by Wang et al. during the COVID 19 pandemic which found that Hispanic and African-American respondents showed a greater inclination toward adopting food delivery services compared to other racial groups [13].

2.1.4.3 Gender

In a 2017 study, Loo and Wang [15] found that that women are significantly more likely to spend time on e-shopping activities at home compared to males, but a 2023 study by Reiffer et al.[6] found males to be more likely to participate in online shopping and to have a positive attitude towards e-shopping. Shen et al. found an evolution over time in gender impacts on online grocery shopping; their study found that before COVID-19, gender did not significantly influence the likelihood of participation, but that adoption of these services by women increased rapidly during the pandemic [12]. In a 2021 study, Dominici et al. [5] found that women are more likely to order food online.

2.1.4.4 Age

Both Loo and Wang (in a pre-covid study) and Reiffer et al.(in a post-COVID study), found that younger adults, particularly those aged 25-45, are more likely to participate in online shopping, compared to those aged 45 and above [6], [15]. Reiffer et al. also found that people under 25 are more likely to order parcels online and that the likelihood of ordering parcels decreases as age increases [6]. In a study of delivery behaviors during the COVID-19 pandemic, Unnikrishnan and Figliozzi noted that the likelihood of receiving packages decreased with age [11].

According to Shen et al. [12], individuals aged 20-54 were more likely to engage in online grocery shopping (OGS) before the COVID-19 pandemic. However, after COVID-19, those aged 70-84 showed a greater tendency to use OGS. Contrarily, another post-COVID study by Colaço & De Abreu E Silva found that as people age, they increasingly prefer shopping in-store rather than online [9].

A study by Khaddar & Rahman Fatmi examined use of food delivery services during- and post-COVID, and found no significant changes for younger adults (18-34) and mixed results for older age groups, with a significant decrease in use after the pandemic for those aged 40-54 and 65 and above [10]. This result suggests that younger adults have maintained consistent use of online food delivery services, while older adults show varied retention rates post-COVID.

2.1.5 Findings from Prior Studies: Built Environment Factors

Accessibility factors also influence participation in online shopping and e-activities. Loo and Wang found that people with poorer access to public transport and shopping centers tend to spend more time on e-shopping at home [15]. Also, Kirby-Hawkins et al. found that the likelihood to shop online might be linked to the density of physical stores; less dense neighborhoods are more likely to shop online [4]. In addition to geographical access, the type of residency can also affect engagement in online activities. Shi et al. found that higher residential density has a positive impact on online shopping frequency, and also, higher accessibility to subway stations has an indirect and negative influence on e-shopping frequency [16]. Dias et al. (2020) found that residents of apartments and condos tend to engage less in online shopping and prefer in-person activities for groceries and dining out. The authors suggest that this higher tendency to dine out among apartment and condo dwellers may reflect a more dynamic lifestyle and a willingness to explore diverse food options [14].

2.1.6 Findings from Prior Studies: Daily Activity Tradeoffs

Reiffer et al. found that individuals who participate in more leisure activities and in-store shopping are more likely to shop online; however, doing weekend shopping has a negative impact and decreases this likelihood [6]. Aldo et al. found that people who buy online at least once a week tend to have a higher share of shopping trip frequency compared to those who never e-shop [17]. Kim and Wang found that in New York City, individuals who made a trip to a restaurant by car, have higher likelihood of receiving food deliveries [7].

2.2 Prior Studies: Teleworking

Teleworking is another virtual activity that has grown rapidly in recent years. A number of studies have also investigated the factors influencing telework participation, also producing mixed results regarding the influence of socioeconomic and built environment factors.

2.2.1 Teleworking

In an early study of teleworking, Singh et al. (2013) analyzed teleworking using a joint model of three dimensions—option, choice, and frequency of telecommuting [18]. More recently, Bhuiyan et al. studied the influence of community design and socio-demographic characteristics on teleworking using a multiple regression model [19]. Elldér (2020) investigated the impact of teleworking on daily trip activity, utilizing a range of regression models, including multivariate, logistic, multinomial, Tobit, and binomial [20]. Soler et al. (2021) examined the effects of teleworking and online shopping on transport demand across 27 using a classification model [21]. Campisi et al. (2022) also investigated the impact of teleworking on travel behavior [22]. Not many studies have specifically examined interactions of virtual work and shopping activities; however, Mohammadi et al. explored the interaction between working from home and online shopping frequency using a Generalized Structural Equation Model, which showed a positive causal relationship between WFH and online shopping [23].

2.2.2 Findings from Prior Studies: Socioeconomic Variables

2.2.2.1 Income

Singh et al. found that high-income households ($100K) are more likely to have the option of working from home, possibly because they are ‘‘high up the ladder’’ and can determine how they work themselves [18]. Soler et al. also found that individuals with higher incomes are more likely to telework than respondents with low incomes [21].

2.2.2.2 Race/Ethnicity

Asfaw found that in the United States during the COVID-19 pandemic, being Black or Hispanic, in comparison with being white, decreased the odds of teleworking by 7% and 16%, respectively, while being Asian increased the odds of teleworking by 13% white [24]. Another similar study conducted during the pandemic in the United States showed that Asian workers were the most likely to be able to work from home, followed by non-Hispanic and white workers. Only 16.2% of Hispanic workers and 19.7% of African American workers were able telework [25].

2.2.2.3 Gender

While Singh et al. found that married females telework more [18], Soler et al. found that males tend to telework more, while females prefer to work traditionally [21]. Loo & Wang found that gender is a significant variable for choosing whole-day home-based e-working, however this variable did not affect part-day home-based e-working [15].

2.2.2.4 Age

In an early study of teleworking, Singh et al. found that middle-aged individuals (36–50 years of age) are more likely to have the option to telework but are less likely to do so frequently relative to individuals of other age groups who also have the option to telecommute [18]. In 2021, Soler et al. found that young professionals tend to adopt teleworking more compared to seniors, possibly because young individuals have better information and communication technology skills [21].

2.2.3 Findings from Prior Studies: Built Environment Factors

Neighborhood design and access to public transit can affect individuals’ decisions about commuting to work or teleworking. Bhuiyan et al. found that community size is an important variable in determining teleworking participation, with residents of smaller to mid-size communities less likely to telework [19]. Their study also found that communities with more connected roadway infrastructures produce less teleworking. In another across the EU and UK, Soler et al. found that teleworking is more common in metropolitan areas or big cities than in rural areas since big companies are usually located in big cities [21].

2.2.4 Finding from Prior Studies: Daily Activity Tradeoffs

According to Elldér, individuals who telework full-time make fewer trips than those who do not telework, but part-day teleworkers make significantly more trips than non-teleworkers [20]. Campisi et al. found that teleworking can result in a smaller number of trips weekly, but that the net amount of distance traveled per person can be larger, as employees are more willing to commute farther, considering they will not commute as often [22].

2.3 Summary of Research Gaps and Limitations

The review of existing studies on online shopping, home deliveries, and teleworking shows that, while there has been a lot of valuable research in this area, there are still several important gaps that this study aims to address. First, most studies have relied on traditional regression-based approaches like binary logit, probit, or negative binomial models. These methods have been useful for identifying basic relationships, but they often fall short of capturing the complex relationships and indirect effects among factors that influence behavior. In this study, we used path analysis within a Structural Equation Modeling (SEM) framework (explained in Chapter 5), which makes it possible to examine both direct and indirect effects at the same time. This approach provides a more complete view of how demographics, daily activities, and teleworking interact with online shopping and different types of deliveries. Second, most studies looked at online shopping, deliveries, teleworking, and travel patterns separately, rather than as interconnected activities. This study takes a more integrated approach, looking at these behaviors together to better understand the bigger picture. Third, many previous studies relied on data collected before or during the COVID-19 pandemic, capturing short-term changes but not the longer-term adjustments that followed. This study uses post-COVID data, allowing us to explore how online shopping, deliveries, and teleworking behaviors have shifted in the years after the pandemic. Finally, while some research has touched on trade-offs between virtual and in-person activities, few studies have analyzed how daily routines and time-use patterns influence online shopping and delivery behaviors. By including these activity-based factors, our approach sheds light on how people reallocate their time between physical and digital activities.

3 METHODOLOGY

3.1 Research Objective

This study aimed to answer the following primary research question:

Does teleworking (full-time or part-time) increase the daily likelihood of an individual:

1. *participating in online shopping;*
2. *having a package delivered to their home;*
3. *having groceries delivered to their home; or*
4. *having prepared food delivered to their home?*

3.2 Data Source

This study used data from the New York City (NYC) Department of Transportation's 2022 Citywide Mobility Survey (CMS) [26]. This survey was carried out between September 28 and November 17, 2022, and notably is the first citywide household travel survey conducted since restrictions were lifted following the COVID-19 pandemic. The survey dataset is composed of five comprehensive tables; we use variables from four of these five tables (Household, Person, Day, and Trip) to construct our analysis dataset. To construct the final dataset, records from four source CMS tables were joined using household and person IDs common to all four tables.

In total, 6,886 participants completed the CMS, reporting 15,925 days of daily trip and delivery activity. Since the focus of this study is on teleworking, only working adults aged 18 and over who provided complete trip and delivery activity on a given day were included in this analysis. The final sample included 2,062 participants. Of these, 598 individuals completed the survey for seven days, 475 answered the questionnaire for only a single day, and 990 participants completed the survey for between 2 and 6 days. The final dataset consisted of 9,527 unique person-days.

3.3 Model Construction

This study used a Structural Equation Modeling approach to examine the impact of teleworking on (1) online shopping participation and (2) home delivery propensities for specific types of goods. Using this model structure enabled exploration of the impact of teleworking on online shopping and delivery behavior while also recognizing the effects of other exogenous variables and capturing the interconnections between online shopping and each of the delivery types. This structure captures complexities that are important for planners and future researchers to consider in estimating passenger and freight travel demand impacts from changing consumer preferences and work patterns. A conceptual model is shown in Figure 1.

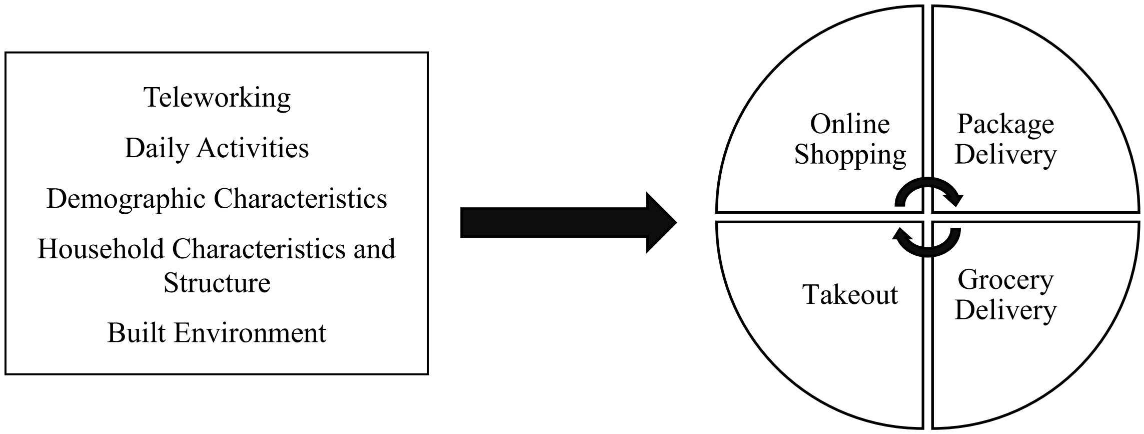


Figure 3-1 Conceptual Mode

3.3.1 Endogenous Variables

This study investigated four endogenous variables: online shopping participation and deliveries of three types of goods: packages, groceries, and prepared food. The three delivery types are expected to have very different demand profiles based on the characteristics of the goods and the frequency with which they are typically purchased.

- **Packages** include a wide variety of items, which may be purchased with varying lead times for delivery. Most packages will not be temperature sensitive, but they may vary in value from very inexpensive to very expensive.
- **Groceries** include food and other personal and household care items (e.g. toiletries, cleaning products). Groceries are very often temperature-sensitive, requiring the receiver to be home at or close to the time of delivery to sort and stow the goods. Groceries may be pre-ordered or may be purchased on-demand for same day or even immediate delivery.
- **Prepared food** is also typically temperature-sensitive, and is usually ordered on-demand for immediate consumption. Like for groceries, receiving prepared food may require an interaction with a delivery provider, but unlike groceries, will not require significant time for sorting.

In the CMS, for each day of reported activity, each respondent detailed whether they shopped online and whether they received a package, grocery, or prepared meal delivered to their home. For each activity, a binary variable was constructed, equal to 1 if a respondent shopped online or received a specific delivery type on that day, and zero if the respondent did not. Online shopping was observed on 1,715 person-days (18.0% of the total). Package deliveries to homes occurred on 2,736 person-days (28.7%), while grocery and prepared food deliveries were observed on 209 (2.2%) and 750 (7.9%) person-days, respectively.

3.3.2 Exogenous Variables

Exogenous variables of interest, in addition to teleworking participation, included other daily activities that might influence online shopping and daily delivery propensity, demographic characteristics, household characteristics and structure, and built environment variables.

3.3.2.1 Teleworking Variables

Three different binary teleworking variables were included in the model for different intensities of teleworking:

- **Short duration telework** was set equal to one if the respondent teleworked less than one hour in a day.
- **Part-time telework** was set equal to one if the respondent teleworked between one and six hours.
- **Full-time Telework** was set equal to one for any person-day on which the respondent teleworked for more than 6 hours.

Table 5-1 summarizes the observed data for each teleworking variable. This data was obtained from the CMS Day Table.

Table 3-1 Teleworking Variables

Description	# Observed Person-Days	% Observed Person-Days
Short-duration telework (<1hr)	283	3.0%
Part-time telework (1hr-6 hrs)	1058	11.1%
Full-time telework (6 hrs+)	2696	28.3%
Did not telework	5371	56.4%
Preferred not to answer	119	1.2%

3.3.2.2 Time Use Variables

Five continuous variables were calculated to investigate the impacts of daily time use:

- **Time spent grocery shopping** is calculated as the total travel time for grocery shopping trips plus the time spent at the store.
- **Time spent routine shopping** is calculated as the total travel time for routine shopping trips (e.g., pharmacy visits) plus the time spent at the store.
- **Time spent major shopping** is calculated as the total travel time for shopping for major items (e.g., furniture, car) plus the time spent at the store.
- **Time spent having a meal** is calculated as the sum of travel time for dining out, getting coffee, or take-out, plus the time spent at the establishment.
- **Time spent at work** is calculated as the total travel time for primary work, work-related (e.g., meetings, deliveries, worksites), or other work-related activities, plus the time spent at the workplace.
- **Time spent at home** is calculated as the sum of time spent at home.

Each time estimate includes the duration of the trips to the location and the time spent at the location, except for time spent at home, which excludes any travel time. Table 5-2 summarizes the basic statistics for each observed time use variable.

Table 3-2 Other Time Use Variables

Description	Mean (hour)	Standard Deviation (hour)
Time spent grocery shopping	0.172	0.547
Time spent routine shopping	0.116	0.508
Time spent major shopping	0.027	0.354
Time spent having a meal	0.453	0.975
Time spent at work	3.894	4.941
Time spent at home	14.497	6.391

3.3.2.3 Demographic Characteristics

Based on findings from prior research, four categories of demographic variables were included in the model.

- **Age** is categorized into six groups: 18-24, 25-34, 35-44, 45-54, 55-64, and 65 years old and older.
- **Gender** is categorized into four groups: Female, Male, Non-binary, and preferred not to answer.
- **Race** is categorized into eight groups: African American or Black, American Indian or Alaska Native, Asian, Native Hawaiian or other Pacific Islander, White, Multiracial, and Other race.
- **Ethnicity** is categorized into three groups: Hispanic (Mexican, Mexican American, Chicano, Puerto Rican, Dominican, Cuban, Another Hispanic, Latino, or Spanish origin), Not Hispanic (Not of Hispanic, Latino, or Spanish origin), and no answer.

Each of these variables is a categorical variable. For modeling, each categorical variable was re-coded into a binary variable equal to one if a respondent belonged to a specific category. Table 3 summarizes the respondent demographics in the final dataset. In Table 5-3, two frequencies are provided; the person frequency indicates the share of individuals represented in the data sample described by that characteristic, while the person-day frequency represents the total number of days observed for a person with that characteristic.

Table 3-3 Demographic Variables

Variable Category	Description	# Observed Person-Days	% Observed Person-Days	# Observed People	% Observed People
Age of Respondent	18-24	427	4.50%	90	4.40%
	25-34	2876	30.20%	597	29.00%
	35-44	2862	30.00%	590	28.60%
	45-54	1736	18.20%	387	18.80%
	55-64	1193	12.50%	284	13.80%
	65 years old and older	433	4.50%	114	5.50%
Gender	Female	4795	50.30%	1040	50.40%
	Male	4326	45.40%	916	44.40%
	Nonbinary	109	1.10%	26	1.30%
	Preferred not to answer	297	3.10%	80	3.80%
Race	African American or Black	1088	11.40%	248	12.00%
	American Indian or Alaska Native	33	0.30%	8	0.40%
	Asian	1714	18.00%	368	17.80%
	Native Hawaiian or Pacific Islander	17	0.20%	3	0.10%
	Other	528	5.50%	106	5.10%
	White	4626	48.60%	968	46.90%
	Multiracial	717	7.50%	157	7.60%
	No Response	804	8.40%	204	9.90%
Ethnicity	Hispanic	1927	20.20%	398	19.30%
	Not Hispanic	7600	71.30%	1444	70.00%
	Preferred not to answer	806	8.50%	220	10.70%

3.3.2.4 Household Characteristics and Household Structure

To investigate how household characteristics and structure influence shopping and deliveries, the model included several household-specific variables:

- **Household size** is the number of people in a household.
- **Household income** is the amount of income earned by the households' residents, and is categorized into six groups: Under \$25k, \$25k-\$50k, \$50k-\$75k, \$75k-\$100k, \$100-\$200k, \$200k or more, and no answer.
- **Number of vehicles** is the number of vehicles available to the household.
- **Number of workers** is the number of working adults living in the household.
- **Number of residents in the household belonging to specific age categories** is the number of household residents belonging to each age category, including young children (under 5), school aged children (5-15), older teenagers (16-17), and adult categories as defined for the age variable detailed in section 5.3.2.3.

Like the demographic variables, household income was coded as a categorical variable equal to one if a respondent belonged to a specific income category. Results for the two wealthiest income categories from the original survey (\$200k to \$500k and \$500k+) were combined due to a very low number of observations in the highest original income category. All other household variables were included as integer values. As in Table 5-3, Table 5-4 presents two observed frequencies for each household variable.

Table 3-4 Household Variables

Variable Category	Description		# Observed Person-Days	% Observed Person-Days	# Observed People	% Observed People
Annual Income	Under $25k		579	6.10%	129	6.30%
	$25k-$50k		1188	12.50%	257	12.50%
	$50k-$75k		1497	15.70%	328	15.90%
	$75k-$100k		1453	15.30%	289	14.00%
	$100-$200k		2693	28.30%	572	27.70%
	$200k or more		1446	15.20%	313	15.20%
	Preferred not to answer		671	7.00%	174	8.40%
Number of Vehicles	No Vehicle		4540	47.70%	994	48.20%
	1 Vehicle		3694	38.80%	787	38.20%
	2 Vehicle		1019	10.70%	226	11.00%
	3 Vehicle		274	2.90%	55	2.70%
Number of Workers	No Worker		101	1.10%	31	1.50%
	1 Worker		4128	43.30%	926	44.90%
	2 Workers		4412	46.30%	916	44.40%
	3 Workers		681	7.10%	145	7.00%
	4 Workers or more		205	2.20%	44	2.10%
Number of Residents	1 Person		3184	33.40%	601	29.10%
	2 People		2604	27.30%	693	33.60%
	3 People		1726	18.10%	357	17.30%
	4 People		1269	13.30%	257	12.50%
	5 People		484	5.10%	100	4.80%
	6 People and more		260	2.70%	54	2.60%
Number of Residents by Age	Under 5	0	8578	90.00%	1868	90.60%
		1	752	7.90%	155	7.50%
		2	192	2.00%	38	1.80%
		3	5	0.10%	1	0.00%
	5-15	0	7593	79.70%	1664	80.70%
		1	1221	12.80%	251	12.20%
		2	588	6.20%	122	5.90%
		3	88	0.90%	17	0.80%
		4	37	0.40%	8	0.40%
	16-17	0	9003	94.50%	1951	94.60%
		1	496	5.20%	106	5.10%
		2	28	0.30%	5	0.20%
	18-24	0	8313	87.30%	1807	87.60%
		1	926	9.70%	194	9.40%
		2	236	2.50%	48	2.30%
		3	52	0.50%	13	0.60%
	25-34	0	5847	61.40%	1306	63.30%
		1	2141	22.50%	441	21.40%
		2	1394	14.60%	283	13.70%
		3	109	1.10%	26	1.30%
		4	36	0.40%	6	0.30%
	35-44	0	6021	63.20%	1337	64.80%
		1	2248	23.60%	458	22.20%
		2	1228	12.90%	259	12.60%
		3	30	0.30%	8	0.40%
	45-54	0	7095	74.50%	1527	74.10%
		1	1774	18.60%	396	19.20%
		2	638	6.70%	135	6.50%
		3	20	0.20%	4	0.20%
	55-64	0	7602	79.80%	78.70%	78.70%
		1	1489	15.60%	16.30%	16.30%
		2	426	4.50%	4.80%	4.80%
		3	10	0.10%	0.10%	0.10%
	65 years old and older	0	8605	90.30%	1869	90.60%
		1	731	7.70%	157	7.60%
		2	178	1.90%	34	1.60%
		3	6	0.10%	1	0.00%
		4	7	0.10%	1	0.00%

3.3.2.5 Built Environment

As detailed in the literature review, the built environment in which a respondent lives may influence shopping and delivery behavior by providing opportunities for alternative out-of-home activities and by influencing the real or perceived security of delivered goods. Deliveries to larger or more densely developed buildings are likely to be more exposed to potential theft due to an increased amount of foot traffic past doors and lobbies. However, some buildings may be equipped with secure delivery alternatives, including doorman-attended desks. In this study, our ability to control for built environment was limited by the geographic aggregation of the dataset. However, to assess the potential influence of security concerns, we included two proxy variables:

- **Residency type** identifies the type of building in which the respondent lives. Six building types were considered in the model (see Table 5-5). The “Other” category includes senior or age-restricted apartments/condos, manufactured home/mobile home/trailer, dorm, group quarters, institutional housing, and other alternative living spaces (e.g., boat, RV, van).
- **Alternative package delivery location** is where the respondent reported that a delivery would occur if the respondent was not home to accept it. Potential responses are detailed in Table 5-5.

While a previous study by Kim and Wang [7] using an earlier version of the CMS investigated the alternative delivery location as a endogenous variable, this study treats it as an exogenous variable.

Table 3-5 Built Environment Variables

Variable Category	Description	# Observed Person-Days	% Observed Person-Days	# Observed People	% Observed People
Residency Type	Detached single-family house	971	10.20%	215	10.40%
	Attached single-family house	809	8.50%	171	8.30%
	Building with 2-4 units	1224	12.80%	252	12.20%
	Building with 5-49 units	3469	36.40%	751	36.40%
	Building with 50+ units	2906	30.50%	634	30.70%
	Other	148	1.60%	39	1.90%
Alternative Package Delivery Location	Lobby	3621	38.00%	778	37.70%
	Doorstep	3601	37.80%	752	36.50%
	Doorman	1080	11.30%	249	12.10%
	Other than Home	1060	11.10%	235	11.40%
	No Response	165	1.70%	48	2.30%

3.3.3 Correlation Analysis

A correlation analysis was conducted in Python using the Spearman method. No substantial correlations were observed for any variables except for the two teleworking variables.

3.4 Model Implementation

Path analysis, a type of Structural Equation Modeling (SEM) [27], was implemented in RStudio. Path analysis is a more general model where all variables are still manifest, but endogenous variables are allowed to explain other endogenous variables. Although SEMs can include latent endogenous variables, the present application is restricted to the case where all endogenous variables are observed. The general path analytical model is described as:

(Eq. 1)

where:

- ***Y*** is a ($N_Y \times 1$) column vector of endogenous variables (N_Y = number of endogenous variables),
- ***X*** is a ($N_X \times 1$) column vector of exogenous variables (N_X = number of exogenous variables),
- is a ($N_Y \times 1$) column vector of intercept terms,
- ***B*** is a ($N_Y \times N_Y$) matrix of structural coefficients from endogenous to other endogenous variables,
- is a ($N_Y \times N_X$) matrix of structural coefficients from exogenous to endogenous variables, and
- is a ($N_Y \times 1$) column vector of error terms of endogenous variables.

3.5 Further Exploration

Once model results were estimated and evaluated, some additional data analysis was conducted to further explore significant observed relationships. These procedures are detailed in the Appendix.

3.6 Survey Limitations

There are a number of limitations to the CMS dataset that may impact the results of this study:

- NYC is a relatively unique environment in the US, with high density and transit dependence; as a result, behavioral results may not be directly transferable to other cities.
- The final dataset, limited to workers aged 18 and over, is not a representative sample of all NYC residents.
- The CMS relied on app-based inputs of trip information. Use of this technology may have biased response rates and resulted in human input errors (e.g. trips with a destination but no known origin).
- Trip diaries provide information about the time spent in a specific location, but do not provide a breakdown of specific activities occurring at that location.
- Trip diary completeness varies between respondents in the CMS, with completed days varying from one to seven. To maximize use of the dataset, this study analyzed time tradeoffs occurring on individual person-days.
- The CMS aggregated data into large survey zones that cover broad geographic areas; as a result, it was not possible to investigate the impacts of specific built environment variables such as local business or transit availability.
- The delivery security variables included in the model serve only as a proxy for expected package security.
- The teleworking variable defined in the current CMS is not location-specific.
- The CMS currently identifies whether or not the survey respondent shopped online on a given day, and whether or not the respondent's household received a delivery of a specific type of product. However, multiple household residents may have different shopping activities on a given day, and multiple packages might be received on a given day. As a result, the online shopping variable represents the behavior of only one resident, while delivery activity may result from decisions of multiple actors.

4 MODEL RESULTS

4.1 Model Fitness

The measurements of model fitness are provided in Table 6-1. The model fitness results show that the proposed model is a good fit for the dataset.

Table 4-1 Measures of Model Fitness

Fit Index	Value	Interpretation
Comparative Fit Index (CFI): Assesses model fit by comparing it to a baseline model [28].	0.987	Above 0.95 indicates a good fit.
Root Mean Square Error of Approximation (RMSEA): Assesses how far a hypothesized model is from a perfect model [29].	0.006	Below 0.05 indicates excellent fit; below 0.08 is acceptable.
Standardized Root Mean Square Residual (SRMR): Measures the average standardized difference between observed and predicted correlations [30].	0.004	Below 0.05 indicates a very good fit.

4.2 Significant Findings

The full results from the SEM are presented in Table 6-2 (next page). The following sections detail the identified impacts of teleworking and other exogenous and endogenous variables on online shopping participation and delivery activity.

4.2.1 Time Use

The model did identify significant relationships between teleworking variables and likelihood of receiving each type of delivery, and between other times uses and both online shopping participation and likelihood of receiving parcel and prepared food deliveries.

Teleworking: No type of teleworking significantly impacts the likelihood of online shopping. Teleworking participation does impact delivery frequencies in several ways. Both individuals who telework full-time (more than 6 hours) and those who telework minimally (< 1 hour) are more likely to receive parcels compared to those who do not telework at all and those who are part-time teleworkers. However, part-time teleworkers (1 to 6 hours) are significantly more likely to receive grocery and prepared food deliveries than those who do not telework part-time. Some further exploration of time use differences between subgroups of teleworkers are detailed in the appendix in section A.1.

Other time uses: Notably, the likelihood of receiving a grocery delivery is not significantly related to any same-day time use. The models do identify several significant relationships between other time uses and the frequency of online shopping or receiving deliveries of specific types of goods. More time spent at home increases the likelihood of an individual shopping online on a given day. More time spent at home also increases the likelihood that an individual receives a parcel or prepared food delivery to their household. Spending time at an out-of-home workplace increases the likelihood of receiving a package, but not of shopping online. The likelihood of shopping online increases with the amount of time that a person spends in a store, while the likelihood of receiving a prepared food delivery decreases with time spent at a restaurant.

Table 4-2 Structural Equation Model Results

Exogenous Variables	Model							
	Online Shopping		Package Delivery		Grocery Shopping		Prepared Food	
	Coeff.	P-Value	Coeff.	P-Value	Coeff.	P-Value	Coeff.	P-Value
Teleworking Variables								
Teleworking > 6 hrs			0.061	0				
Teleworking 1-6 hrs					0.011	0.065	0.022	0.028
Teleworking< 1 hr			0.064	0.022				
Daily Activity Variables								
Time Spent at Home	0.004	0	0.002	0.026			0.001	0.035
Time Spent at Work			0.002	0.025				
Time Spent Routine Shopping	0.015	0.065						
Time Spent Having a Meal							-0.008	0.002
Socio-Economic Variables								
Race								
African American					0.013	0.017		
Multiracial			0.069	0.001				
Ethnicity								
Hispanic			-0.048	0			0.019	0.011
Respondent Age								
Age 18 to 24			-0.066	0.001				
Age 45 to 54	-0.03	0.004						
Age 65 +	-0.055	0.001					-0.046	0
Income								
$200k or more	0.038	0.003	0.118	0	0.01	0.071	0.018	0.049
$100k-$200k			0.055	0				
Under $25k							0.032	0.02
Preferred Not to Answer	-0.05	0.001						
Household Structure								
Residents under 5	0.036	0.004	0.069	0	0.015	0.016	0.024	0.006
Residents age 5 to 15	0.016	0.015	0.031	0				
Residents age 16 to 17	-0.058	0						
Residents age 35 to 44	0.019	0.08						
Residents age 45 to 54							-0.024	0.002
Residents age 55 to 64			0.037	0.004				
Number of Workers							0.015	0.001
Gender								
Male	-0.023	0.005	-0.029	0.001				
Built Environment Variables								
Other than Home	-0.031	0.009	-0.094	0				
Doorman	0.037	0.007	0.092	0				
Endogenous Variables								
Online Shopping			0.239	0	0.039	0	0.104	0
Package Delivery					0.006	0.144	-0.012	0.063
Grocery Delivery							0.059	0.027

4.2.2 Demographic Factors

The models did identify a number of significant relationships between respondent demographics and the endogenous variables.

Gender: No significant differences were observed in delivery likelihoods for groceries or prepared food between men, women, and individuals identifying as non-binary. Model results do suggest that men are less likely than women to shop online on a given day, and are less likely to receive package deliveries at home.

Age: Survey respondents aged 18-24 were less likely to receive parcels compared to other age groups. Seniors (65+) were less likely to shop online, and they received fewer prepared food deliveries. Those aged 45 - 54 were less likely to shop online than other age groups, except seniors. Further exploration of household age dynamics is detailed in the appendix in section A.2.

Race and ethnicity: No significant differences were observed across races and ethnicities with regard to the likelihood of shopping online. However, the model did identify several differences in delivery likelihoods among demographic groups. Multiracial individuals were more likely to receive packages. African Americans were more likely to receive grocery deliveries. Hispanic individuals were found to be less likely to receive a package delivery at home on a given day, but more likely to receive prepared food deliveries. Further exploration of home delivery of parcels to Hispanic individuals is provided in the appendix in section A.3.

4.2.3 Household Characteristics and Structure

Income: Individuals belonging to the two highest household income groups ($100k+) were significantly more likely to shop online and to receive package deliveries compared to other income groups, with that likelihood increasing with more wealth. Only the highest income group was significantly more likely to receive a grocery delivery. Both the highest and lowest income groups were significantly more likely to receive a prepared food delivery.

Number of workers: As the number of workers in the family increased, so too did the likelihood of prepared food deliveries.

Household age structure: The number and ages of children in the household impacted behavior in several ways. Having young children (under 5) and school-age children (5-15) in the household increased the likelihood of shopping online and receiving package deliveries. As the number of children under 5 years old increased, the likelihood of receiving grocery and prepared food also increased. Having more adults between 35 to 44 in the household increased the likelihood of online shopping, while having 16 - 17 year-old teenagers decreased the likelihood of online shopping. Having more adults aged 55-64 decreased package deliveries and having more 45-54 year olds in a household decreased the likelihood of receiving prepared food deliveries. These findings regarding the impacts of adult ages are complex, and are likely influenced by household intergenerational dynamics. As previously noted, further exploration of household age dynamics is detailed in the appendix in section A.2.

Household size and number of vehicles were not significant predictors of online shopping participation or likelihood of receiving a delivery of any type.

4.2.4 Built Environment Factors

The **alternative delivery location** variable was found to significantly influence online shopping and some delivery types, while **building type** was not found to have a significant impact. Respondents whose delivery alternative is a doorman (the most secure option) are more likely to both shop online and receive package deliveries. Those whose primary alternative for unattended package delivery is delivery to a non-home location (indicating a lack of secure home-based options) are less likely to shop online and receive fewer package deliveries. Delivery alternatives have no impact on grocery and prepared meal deliveries, which are typically attended and usually do not require the use of an alternative delivery location, regardless of the home environment.

4.2.5 Relationship between Online Shopping and Delivery Types

Online shopping was positively associated with receiving all three delivery types: packages, groceries, and takeout. A weak positive relationship was observed between grocery and prepared food deliveries, indicating that those receiving one type of food delivery are more likely to have the other type of food delivered as well. Although receiving package deliveries is positively associated with receiving grocery deliveries, it is negatively associated with receiving prepared food.

5 DISCUSSION

5.1 Impacts of Teleworking

Contrasting the findings from Mohammadi et al. [23], results of this study indicate that teleworkers are not more likely to participate in online shopping than non-teleworkers. This study did find that teleworkers have delivery behaviors distinct from non-teleworkers, but also found that those distinctions vary with the duration of telework. Full-time teleworkers receive more parcel deliveries than part-time teleworkers and non-teleworkers, while part-time teleworkers receive more grocery and prepared food deliveries than other teleworkers and non-teleworkers. As detailed in the appendix in section A.1, these distinctions may be due to a lower total time spent working in any format (in person or teleworking) for part-time teleworkers vs. other worker types.

5.2 Impacts of Other Time Uses

The positive relationship between time spent at home and likelihood of receiving a parcel delivery likely reflects a general preference to have goods delivered when receivers are home to minimize risk of damage or theft. Prepared food is typically ordered on-demand for immediate consumption, and is temperature-sensitive and perishable, so it is unsurprising that the likelihood of receiving this type of delivery to home increases with time spent at home. Increased dependence on package deliveries for individuals spending more time traveling to work and working-out-of-home is likely a result of reduced time availability for shopping, whether in-store or online. The positive relationship between time spent at home and online shopping participation – and the lack of significant relationship between time spent at work and online shopping – indicates that individuals may have more opportunities to shop when at home compared to time spent at work, where there might be more oversight of activities or other time demands.

The positive relationship between shopping online and the time spent shopping in a store suggests that online shopping is not a substitute for in-store shopping, but is rather a complementary activity when explored on a daily basis. Some individuals have a higher propensity for shopping, regardless of the mechanism, or participate in omni-channel shopping, such as ordering a good online and then picking it up in-store, or window-shopping followed by an online search for a better price. Findings from other studies suggest similar results [30], [31]. Alternatively, spending time eating at a restaurant reduces the likelihood of a prepared food delivery on the same day, suggesting that in this case, delivery is substituting an out-of-home activity. This result is expected, as individuals generally consume a finite number of meals in a day, so would be less likely to order another meal after consuming one outside of home.

5.3 Time Use Insensitivity of Grocery Shopping

Time spent at work, at home, in a store, or at a restaurant does not significantly impact the likelihood of receiving a grocery delivery. This may be due to the differing nature of groceries compared to other packages and prepared food. Many, although not all, grocery deliveries are pre-ordered with lead times of up to a week. Grocery shopping is generally a more time-consuming activity than ordering prepared food, as it often involves selecting a relatively large number of items. Groceries are usually temperature sensitive, requiring a receiver to be home. Because of this, receivers can typically select a fixed time window of one to two hours when groceries will arrive, allowing the delivery to be scheduled around other out-of-home activities. When groceries arrive, the receiver may need to immediately expend additional time sorting and stowing the goods. For groceries, the receiver typically has considerable control over the delivery timing, and likely schedules this activity to occur at a convenient day and time, regardless of overall activities completed during the day. Findings from a previous study show that a higher frequency of in-person meal activities is associated with a higher propensity for online grocery shopping [14]. It is possible that those who eat out often find something appealing and decide to try it at home, thus potentially leading to more online grocery shopping in the process of obtaining the specialty dish or ingredients.

5.4 Demographic Factors

Findings regarding higher online shopping propensity among women align with Reiffer et al. [6], but contrast with Loo and Wang [15], who found opposite results. The lack of gender significance in online food shopping contradicts prior findings from Shen et al. [12] and Dominici et al. [5], who found that women are more likely to order food online. Discrepancies in findings may be due to evolution over time, as noted by Shen et al. [12].

Age factors can be better understood based on the results from the analysis of household intergenerational dynamics described in the appendix in section A.2. Very young adults (18-24) living independently may have less disposable income, and therefore may receive less package deliveries of retail goods. Individuals in this age group – especially those living in a family household – may also still rely on older adults to purchase some of their goods. Thirty-five to 44 year olds are likely technology savvy and are most likely to live in households with small kids; therefore, they rely more on online shopping. This result is consistent with findings from prior studies [6], [15]. Forty-five to 54 year olds are most likely to have children in school and other related activities, likely increasing their out-of-home time demands, and they are most likely to have older teenagers and young adult offspring with some independence to conduct their shopping activities. Fifty-five to 64 year olds have fewer children living in the household than other adult age groups except seniors, who may have more mobility challenges to in-store shopping. As a result, the 55-64 year olds have relatively less need for delivery of retail goods. Seniors are likely less tech savvy than younger adults, conducting less online shopping as a result. Seniors are also less-likely to have work-related demands that constrain time availability for cooking.

Race and ethnicity results regarding prepared food deliveries are consistent with findings from Wang et al. [32]. Observed differences in grocery and prepared meal deliveries may result from differential geographic access to fresh food options [34, 35], variable time constraints [34], or financial barriers to online shopping [37, 38, 39]. The lower likelihood of package delivery to home for Hispanic respondents observed in this study could be due to a higher propensity among Hispanic individuals to receive deliveries at a non-home location, as detailed in the appendix in section A.3.

5.5 Household Income

Results from this study indicate that, in general, the likelihood of receiving a parcel delivery increases with household wealth. This result is consistent with Reiffer et al. [6]. The relationship between income and food deliveries is more complex. While grocery deliveries are significantly more likely only among the highest income group, prepared food deliveries are more likely among both the highest and lowest income groups. Prior studies have found that high-income areas have more online food delivery options [35]. Low-income households may face barriers to online shopping, such as low control over food selection and perceived higher prices [36]. Additionally, online grocery shopping is often linked to healthy foods, which have been found to appeal more to high-income individuals [37]. Consequently, low-income households rely more on convenience foods, like takeout and fast food, due to time and financial constraints [38].

5.6 Household Responsibilities

Houses with multiple workers are likely more reliant on prepared food due to having less time to available to cook. Households with small children (under 5) are more likely to shop online, and to receive deliveries of all types. This is likely due to the time demands of childcare activities, and to the relative difficulty of traveling to out-of-home opportunities with small children. The number of kids aged 5 to 15 increases the likelihood of online shopping and the frequency of package deliveries, likely reflecting more purchases of retail goods needed for school-aged children. These results are similar to findings from Spurlock et al., which found that households with children are more likely to choose delivery for household items and also they are more likely to have prepared meal delivery due to convenience and time saving aspects [39]. Wang and Zhou also found similar results, that households with children 0-15 tended to receive more deliveries [1].

Households with teenagers were found to shop less online. This could be due to different factors. First, the survey sample did not include 16 and 17 year olds as respondents; these teenagers may be completing their own online shopping independently and are therefore not reflected in the household response. Sixteen and 17 year olds may also be independently completing out-of-home shopping tasks, reducing the household demand for online shopping.

5.7 Relationships between Delivery Types

There is a weak positive relationship between grocery and prepared food deliveries, indicating that those receiving one type of food delivery are more likely to have the other type of food delivered as well. This result reinforces findings from previous studies [10], [14]. Although higher likelihood of package deliveries is positively associated with higher likelihood of receiving grocery deliveries, it is negatively associated with the likelihood of receiving prepared food. The reason for this distinction is not clear.

6 CONCLUSIONS AND RECOMMENDATIONS FOR FUTURE RESEARCH AND PRACTICE

6.1 Implications for Local Delivery Planning

Results from this study, and future studies that address the remaining gaps identified, can help to inform more integrated planning that leverages the relationships between personal activities – including working - and goods movements to achieve new efficiencies. For example, based on the results of this study, the following solutions should be investigated:

- Since full-time teleworkers and individuals who generally spend more time at home demand more package deliveries, but so too do those who spend a lot of time at out-of-home work locations, authorities might consider:
  - Working with residential buildings or neighborhood associations to implement centralized delivery points for secure package receiving.
  - Locating package delivery alternatives such as lockers or pick-up points at common alternative work locations, such as coffee shops or coworking spaces.
  - Locating package delivery alternatives such as lockers or pick-up points in publicly accessible spaces in areas with high employment concentrations.
- Since the presence of children in a household also increases demand for packages, authorities might also consider locating package delivery alternatives close to childcare facilities, schools, or playgrounds.
- In areas where package security is a concern, residents may benefit from more secure alternative delivery locations such as lockers and pick-up points. These solutions have the potential to reduce security barriers for online shopping opportunities, and could potentially facilitate increased replacement of store trips for those currently unable to shop online.
- Given the perishability, it is unlikely that direct-to-home deliveries of groceries or prepared food could be replaced with delivery to an alternative pick-up point. However, efficient direct-to-home groceries delivery services might help to facilitate access to healthy food alternatives for time constrained populations and for residents with limited local shopping access. Assessing the potential impacts of such solutions will require more careful evaluation of the accessibility factors that influence (or inhibit) shopping choices.

6.2 Differentiating Shopping and Deliveries

This study found that more online shopping is positively associated with receiving more package deliveries, grocery deliveries, and takeout deliveries. This reinforces findings from Colaço and De Abreu E Silva, who found that having online shopping preferences positively affects online grocery shopping and meal deliveries [40]. However, some contrasting results from this study emphasize an important point: while results do indicate that deliveries of all types are positively associated with online shopping participation, one online shopping event does not necessarily translate to one home delivery event. For example, individuals with limited time availability for online shopping during the week may concentrate time spent online shopping on a weekend day. However, if they order from multiple retailers, or even order multiple items from the same retailer, that one day of shopping might translate into multiple days of package deliveries. Alternatively, a shopper ordering online from the same retailer might occasionally have the alternative to aggregate orders from multiple days on a fixed delivery day. Additionally, deliveries to a household might reflect goods ordered by multiple shoppers living in the same household, or may include goods purchased in-store (not online) for delivery. In survey design and in model development, these activities should not be conflated.

6.3 Recognizing Complex Delivery Characteristics

Home deliveries vary in value, temperature sensitivity/perishability, lead time between ordering and delivery, handling time for receiving, and the extent to which the receiver controls the arrival time. The differences in significant predictors observed across delivery types in this study reveal several complexities that arise in understanding activity trade-offs. For example:

- Deliveries that are high in value require either a present receiver or a secure delivery alternative. Receivers of high value goods may be more likely to change their location (e.g. stay home) to receive a delivery, while individuals without access to a secure delivery location are less likely to shop online or to receive a delivery to home.
- Goods that are temperature sensitive or perishable generally require the receiver to be present, making delivery likely to occur when a receiver is home and making secure delivery alternatives a less critical factor for these delivery types.
- Receivers have varying control over delivery times for different types of goods. For example, for parcels the receiver may define a delivery day while for groceries or prepared food they can define a delivery hour. This ability (or lack thereof) to control the delivery time may influence the receivers' daily time and location decisions. For example, high value package receivers may need to consider delivery time uncertainty in arranging their daily activities and plan to spend more time at home, while a grocery receiver facing less uncertainly can plan the delivery around other daily activities, limiting the additional time needed to be spent at home.
- Receivers may need to dedicate varying amounts of time and attention to different delivery activities. For example, parcel deliveries to a relatively secure location may require no interaction with a delivery person, and little time commitment from the receiver. Alternatively, a large grocery delivery might require the receiver to dedicate a large amount of time to sorting and stowing goods at the time of delivery. This may affect the receiver's ability to receive a delivery while conducting an activity like teleworking.

In future studies, delivery activity diaries should carefully distinguish between delivery types, and collect detailed information about these characteristics of individual delivery events.

6.4 Accessibility Factors

This study has revealed a number of accessibility dimensions that may influence the feasibility of both online shopping and out-of-home alternatives. For example, accessibility to shopping opportunities may be influenced by geographic proximity to shopping or dining options, affordability of online and in-store purchases and access to credit cards or bank accounts, individual time availability to accomplish an activity, and other individual and household factors, such as mobility impairments or the presence of small children, that may make an out-of-home trip more difficult to accomplish.

However, data limitations did not allow for detailed evaluation of many of these factors. To allow for more detailed evaluation of built environment factors by leveraging secondary data sources data sources, future surveys should identify respondent home locations with finer geographic detail, such as a zip code or census tract. Future surveys should also include specific questions about the cost and accessibility factors and individual and household constraints that influence the choice to purchase a good online vs. in-store.

6.5 Other Survey Improvements

Finally, as noted in section 5.6 there were a number of other survey limitations identified in this study. The following are specific potential improvements identified for future surveys to address these limitations:

- To allow for more precise evaluation of impacts due to at-home telework compared to remote telework from another location, future studies should clearly distinguish between the two.
- To more precisely quantify household online shopping and household deliveries, future studies should consider collecting inputs from all household residents, and distinguishing package delivery events not as a binary yes/no variable but as a precise number of packages by type.
- To capture time trade-offs that may occur over a longer timeframe than a single day (e.g a lag between an in-store or online shopping activity and a delivery event), future studies should investigate using a longer analysis period, for example activities completed during a full week rather that a single day.
- To more precisely identify the overall activity time savings associated with specific delivery types (e.g. time savings from both shopping and cooking realized from prepared food deliveries), future research should investigate other data sources, such as time-use surveys.

7 REFERENCES

[1] X. (Cara) Wang and Y. Zhou, "Deliveries to residential units: A rising form of freight transportation in the U.S.," *Transp. Res. Part C Emerg. Technol.*, vol. 58, pp. 46–55, Sep. 2015, doi: 10.1016/j.trc.2015.07.004.

[2] J. Beckers, I. Cárdenas, and A. Verhetsel, "Identifying the geography of online shopping adoption in Belgium," *J. Retail. Consum. Serv.*, vol. 45, pp. 33–41, Nov. 2018, doi: 10.1016/j.jretconser.2018.08.006.

[3] J.-D. Saphores and L. Xu, "E-shopping changes and the state of E-grocery shopping in the US - Evidence from national travel and time use surveys," *Res. Transp. Econ.*, vol. 87, p. 100864, Jun. 2021, doi: 10.1016/j.retrec.2020.100864.

[4] E. Kirby-Hawkins, M. Birkin, and G. Clarke, "An investigation into the geography of corporate e-commerce sales in the UK grocery market," *Environ. Plan. B Urban Anal. City Sci.*, vol. 46, no. 6, pp. 1148–1164, Jul. 2019, doi: 10.1177/2399808318755147.

[5] A. Dominici, F. Boncinelli, F. Gerini, and E. Marone, "Determinants of online food purchasing: The impact of socio-demographic and situational factors," *J. Retail. Consum. Serv.*, vol. 60, p. 102473, May 2021, doi: 10.1016/j.jretconser.2021.102473.

[6] A. S. Reiffer, J. Kübler, M. Kagerbauer, and P. Vortisch, "Agent-based model of last-mile parcel deliveries and travel demand incorporating online shopping behavior," *Res. Transp. Econ.*, vol. 102, p. 101368, Dec. 2023, doi: 10.1016/j.retrec.2023.101368.

[7] W. Kim and X. (Cara) Wang, "To be online or in-store: Analysis of retail, grocery, and food shopping in New York city," *Transp. Res. Part C Emerg. Technol.*, vol. 126, p. 103052, May 2021, doi: 10.1016/j.trc.2021.103052.

[8] A. Adibfar, S. Gulhare, S. Srinivasan, and A. Costin, "Analysis and modeling of changes in online shopping behavior due to Covid-19 pandemic: A Florida case study," *Transp. Policy*, vol. 126, pp. 162–176, Sep. 2022, doi: 10.1016/j.tranpol.2022.07.003.

[9] R. Colaço and J. De Abreu E Silva, "Interactions between Online Shopping, In-Store Shopping and Weekly Travel Behavior: An Analysis Before and in the Aftermath of COVID-19 in Lisbon, Portugal," *Transp. Res. Rec. J. Transp. Res. Board*, p. 03611981231194628, Aug. 2023, doi: 10.1177/03611981231194628.

[10] S. Khaddar and M. Rahman Fatmi, "Modeling Telecommuting and Teleshopping Preferences in the Post-Pandemic Era," *Transp. Res. Rec. J. Transp. Res. Board*, p. 03611981231222238, Jan. 2024, doi: 10.1177/03611981231222238.

[11] A. Unnikrishnan and M. Figliozzi, "A Study of the Impact of COVID-19 on Home Delivery Purchases and Expenditures," *Civ. Environ. Eng. Fac. Publ. Present.*, Jan. 2020, [Online]. Available: https://pdxscholar.library.pdx.edu/cengin_fac/557

[12] H. Shen, F. Namdarpour, and J. Lin, "Investigation of online grocery shopping and delivery preference before, during, and after COVID-19," *Transp. Res. Interdiscip. Perspect.*, vol. 14, p. 100580, Jun. 2022, doi: 10.1016/j.trip.2022.100580.

[13] K. Wang, Y. Gao, Y. Liu, and K. Nurul Habib, "Exploring the choice between in-store versus online grocery shopping through an application of Semi-Compensatory Independent Availability Logit (SCIAL) model with latent variables," *J. Retail. Consum. Serv.*, vol. 71, p. 103191, Mar. 2023, doi: 10.1016/j.jretconser.2022.103191.

[14] F. F. Dias *et al.*, "A comparison of online and in-person activity engagement: The case of shopping and eating meals," *Transp. Res. Part C Emerg. Technol.*, vol. 114, pp. 643–656, May 2020, doi: 10.1016/j.trc.2020.02.023.

[15] B. P. Y. Loo and B. Wang, “Factors associated with home-based e-working and e-shopping in Nanjing, China,” *Transportation*, vol. 45, no. 2, pp. 365–384, Mar. 2018, doi: 10.1007/s11116-017-9792-0.
[16] K. Shi, R. Shao, J. De Vos, and F. Witlox, “Do e-shopping attitudes mediate the effect of the built environment on online shopping frequency of e-shoppers?,” *Int. J. Sustain. Transp.*, vol. 17, no. 1, pp. 41–51, Jan. 2023, doi: 10.1080/15568318.2021.1983676.
[17] A.-L. Aldo, B. Andreas, and L. Martin, “Exploring the associations between E-shopping and the share of shopping trip frequency and travelled time over total daily travel demand,” *Travel Behav. Soc.*, vol. 31, pp. 202–208, Apr. 2023, doi: 10.1016/j.tbs.2022.11.007.
[18] P. Singh, R. Paleti, S. Jenkins, and C. R. Bhat, “On modeling telecommuting behavior: option, choice, and frequency,” *Transportation*, vol. 40, no. 2, pp. 373–396, Feb. 2013, doi: 10.1007/s11116-012-9429-2.
[19] M. A. A. Bhuiyan, S. M. Rifaat, R. Tay, and A. De Barros, “Influence of Community Design and Sociodemographic Characteristics on Teleworking,” *Sustainability*, vol. 12, no. 14, p. 5781, Jan. 2020, doi: 10.3390/su12145781.
[20] E. Elldér, “Telework and daily travel: New evidence from Sweden,” *J. Transp. Geogr.*, vol. 86, p. 102777, Jun. 2020, doi: 10.1016/j.jtrangeo.2020.102777.
[21] J. R. L. Soler, P. Christidis, and J. M. Vassallo, “Teleworking and Online Shopping: Socio-Economic Factors Affecting Their Impact on Transport Demand,” *Sustainability*, vol. 13, no. 13, pp. 1–24, 2021.
[22] T. Campisi, G. Tesoriere, M. Trouva, T. Papas, and S. Basbas, “Impact of Teleworking on Travel Behaviour During the COVID-19 Era: The Case Of Sicily, Italy,” *Transp. Res. Procedia*, vol. 60, pp. 251–258, Jan. 2022, doi: 10.1016/j.trpro.2021.12.033.
[23] M. Mohammadi *et al.*, “The interaction between the recent evolution of working from home and online shopping,” *Transportation*, Jun. 2024, doi: 10.1007/s11116-024-10506-4.
[24] A. Asfaw, “Racial and Ethnic Disparities in Teleworking Due to the COVID-19 Pandemic in the United States: A Mediation Analysis,” *Int. J. Environ. Res. Public. Health*, vol. 19, no. 8, p. 4680, Apr. 2022, doi: 10.3390/ijerph19084680.
[25] “Not everybody can work from home: Black and Hispanic workers are much less likely to be able to telework,” Economic Policy Institute. Accessed: Jul. 30, 2024. [Online]. Available: https://www.epi.org/blog/black-and-hispanic-workers-are-much-less-likely-to-be-able-to-work-from-home/
[26] New York City Open Data, “2022 Citywide Mobility Survey Dataset.” [Online]. Available: https://data.cityofnewyork.us/browse?Data-Collection_Data-Collection=Citywide+Mobility+Survey&tags=2022&sortBy=relevance&pageSize=20
[27] R. O. Muller, *Basic principles of structural equation modeling: An introduction to LISREL and EQS*. Springer Science & Business Media, 2012. [Online]. Available: https://www.google.com/books/edition/Basic_Principles_of_Structural_Equation/OOvpBwAAQBAJ?hl=en&gbpv=0
[28] S. van Laar and J. Braeken, “Understanding the Comparative Fit Index: It’s all about the base!,” vol. 26, no. 26.
[29] Y. Xia and Y. Yang, “RMSEA, CFI, and TLI in structural equation modeling with ordered categorical data: The story they tell depends on the estimation methods,” *Behav. Res. Methods*, vol. 51, no. 1, pp. 409–428, Feb. 2019, doi: 10.3758/s13428-018-1055-2.

[30] X. J. Cao, Z. Xu, and F. Douma, "The interactions between e-shopping and traditional in-store shopping: an application of structural equations model," *Transportation*, vol. 39, no. 5, pp. 957–974, Sep. 2012, doi: 10.1007/s11116-011-9376-3.
[31] S. Farag, T. Schwanen, and M. Dijst, "Empirical Investigation of Online Searching and Buying and Their Relationship to Shopping Trips," *Transp. Res. Rec.*, 1926.
[32] X. (Cara) Wang, W. Kim, J. Holguín-Veras, and J. Schmid, "Adoption of delivery services in light of the COVID pandemic: Who and how long?," *Transp. Res. Part Policy Pract.*, vol. 154, pp. 270–286, Dec. 2021, doi: 10.1016/j.tra.2021.10.012.
[33] C. Gordon, M. Purciel-Hill, N. R. Ghai, L. Kaufman, R. Graham, and G. Van Wye, "Measuring food deserts in New York City's low-income neighborhoods," *Health Place*, vol. 17, no. 2, pp. 696–700, Mar. 2011, doi: 10.1016/j.healthplace.2010.12.012.
[34] L. S. Taillie, "Who's cooking? Trends in US home food preparation by gender, education, and race/ethnicity from 2003 to 2016," *Nutr. J.*, vol. 17, no. 1, p. 41, Apr. 2018, doi: 10.1186/s12937-018-0347-9.
[35] J. C. Hoenink *et al.*, "Socioeconomic distribution of food outlet availability through online food delivery services in seven European countries: A cross-sectional study," *Health Place*, vol. 84, p. 103135, Nov. 2023, doi: 10.1016/j.healthplace.2023.103135.
[36] A. C. B. Trude, C. M. Lowery, S. H. Ali, and G. M. Vedovato, "An equity-oriented systematic review of online grocery shopping among low-income populations: implications for policy and research," *Nutr. Rev.*, vol. 80, no. 5, pp. 1294–1310, Apr. 2022, doi: 10.1093/nutrit/nuab122.
[37] S. A. French, C. C. Tangney, M. M. Crane, Y. Wang, and B. M. Appelhans, "Nutrition quality of food purchases varies by household income: the SHoPPER study," *BMC Public Health*, vol. 19, no. 1, p. 231, Feb. 2019, doi: 10.1186/s12889-019-6546-2.
[38] T. Dubowitz, D. Acevedo-Garcia, J. Salkeld, A. C. Lindsay, S. V. Subramanian, and K. E. Peterson, "Lifecourse, immigrant status and acculturation in food purchasing and preparation among low-income mothers," *Public Health Nutr.*, vol. 10, no. 4, pp. 396–404, Apr. 2007, doi: 10.1017/S1368980007334058.
[39] C. A. Spurlock, A. Todd-Blick, G. Wong-Parodi, and V. Walker, "Children, Income, and the Impact of Home Delivery on Household Shopping Trips," *Transp. Res. Rec. J. Transp. Res. Board*, vol. 2674, no. 10, pp. 335–350, Oct. 2020, doi: 10.1177/0361198120935113.
[40] R. Colaço and J. De Abreu E Silva, "Are we moving online? Assessing the interactions between telework and grocery purchases, eating out and meal deliveries," *Transp. Res. Part Policy Pract.*, vol. Volume 195, 2025, doi: 104461.

APPENDIX: FURTHER DATA EXPLORATION

A.1 Time Use of Teleworkers

To further explore the difference in behavior for different groups of teleworkers – specifically the unique delivery behaviors among part-time teleworkers - the distributions of time spent at home and time spent at work were plotted for each teleworker group: full-time, part-time, minimal, and non-teleworkers. Before plotting, the dataset was segmented based on whether or not the teleworkers spent any time working at a non-home location, and those who did not visit any other work location (56 percent for full-time teleworkers, 60.2 percent for part-time teleworkers, 53.4 percent for minimal teleworkers, and 51.8 percent for non-teleworkers). Then, for each subset, the time spent at home by those who did and did not visit an out-of-home workplace (Figures A-1 and A-2) was plotted. The time spent at out-of-home work locations was also plotted for those who spent any time at an out-of-home-work location (Figure A-3).

This analysis produced the following observations:

- Compared to other groups, a notably larger portion of full-time teleworkers who do not visit an out-of-home workplace do not leave their home at all.
- Among the workers who do visit an out of home workplace, part-time teleworkers spend less time at out-of-home workplaces and significantly more time at home. This suggests that these workers are not supplementing in-office work with at-home work, but rather are working part time and spending more total time at home.

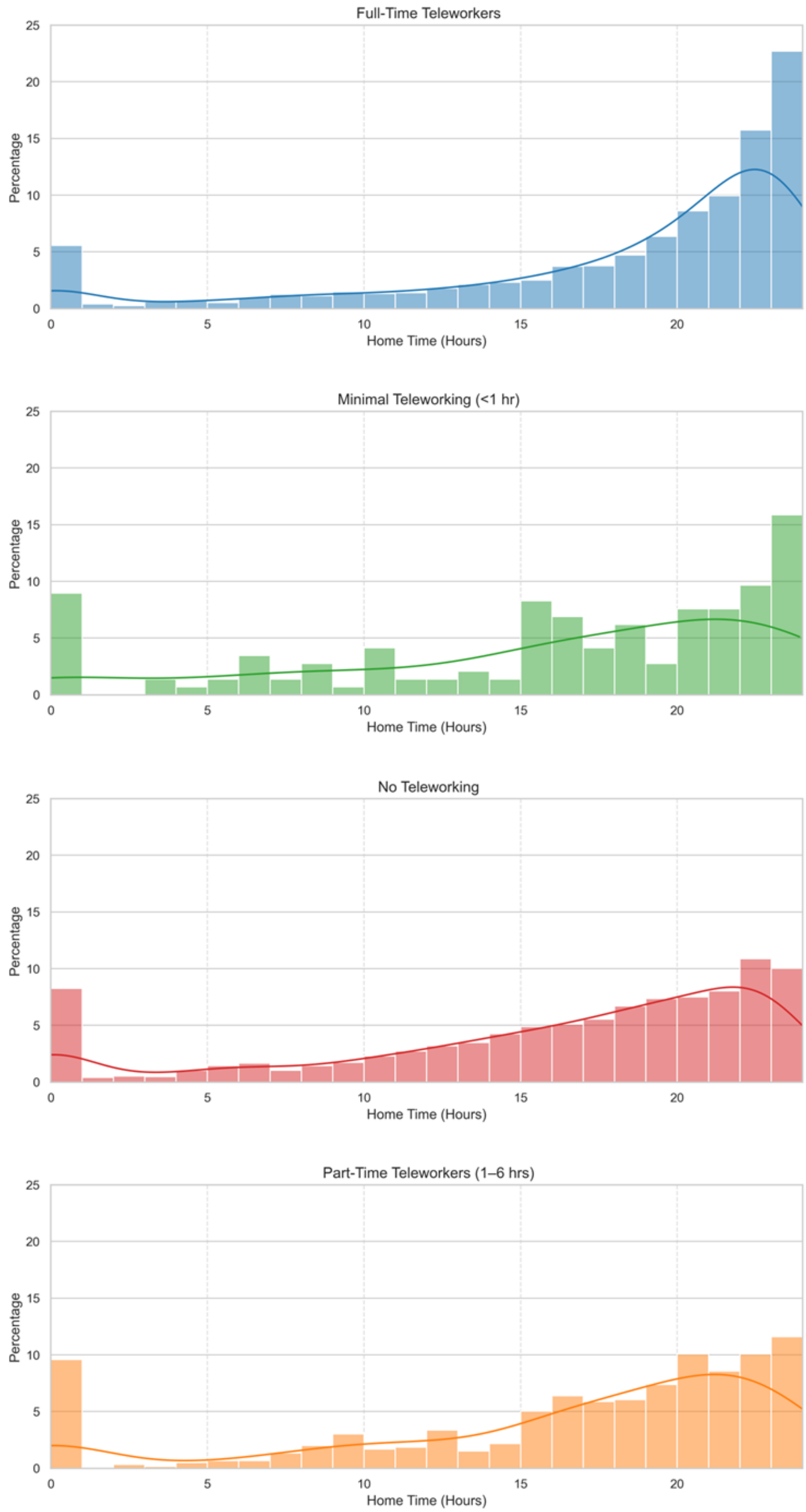
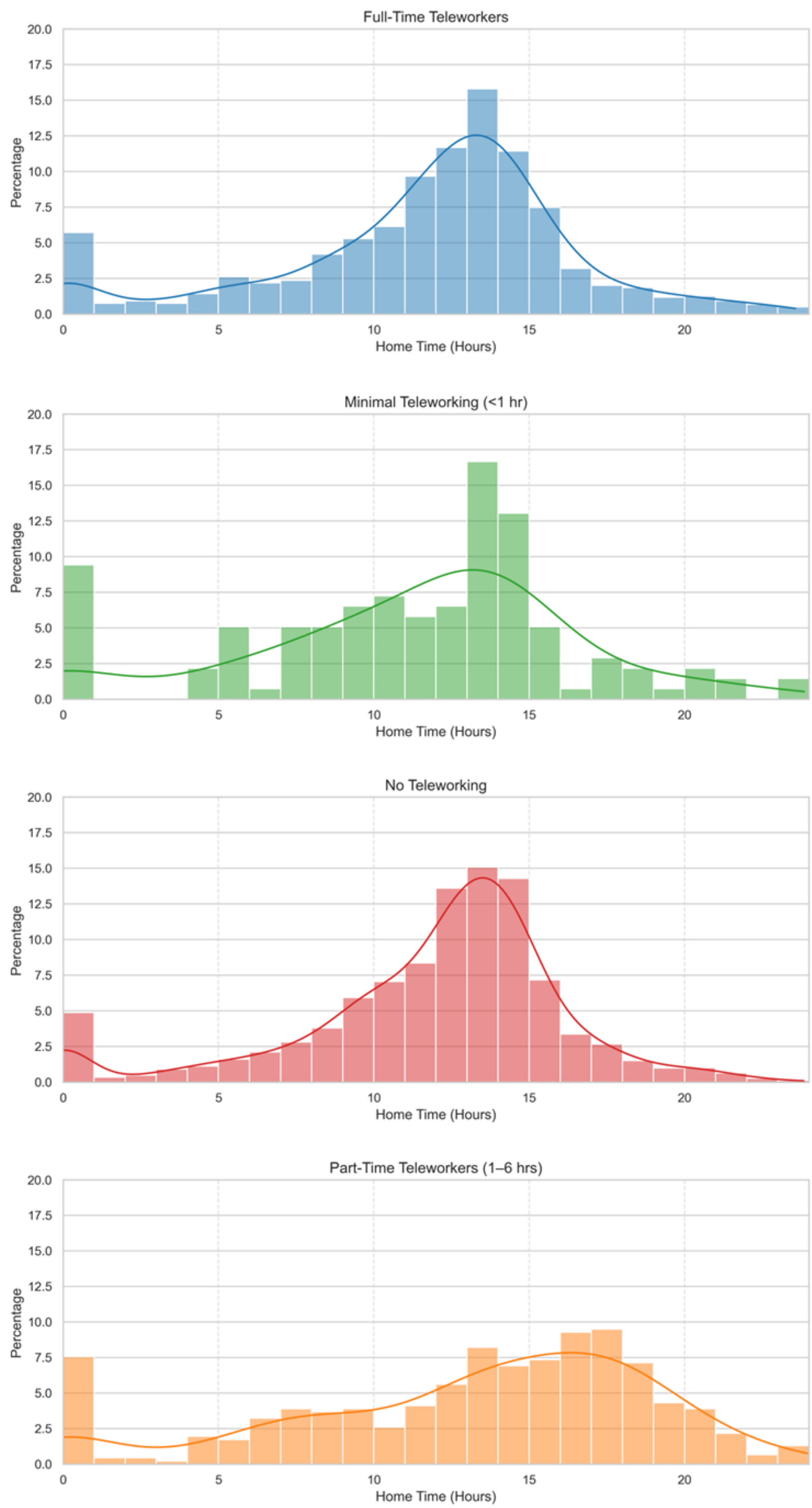


Figure 0-1 Time Spent at Home by Those Not Visiting an Out-of-Home Work Location



-

Figure 0-2 Time Spent at Home by Individuals Visiting an Out-of-Home Work Location

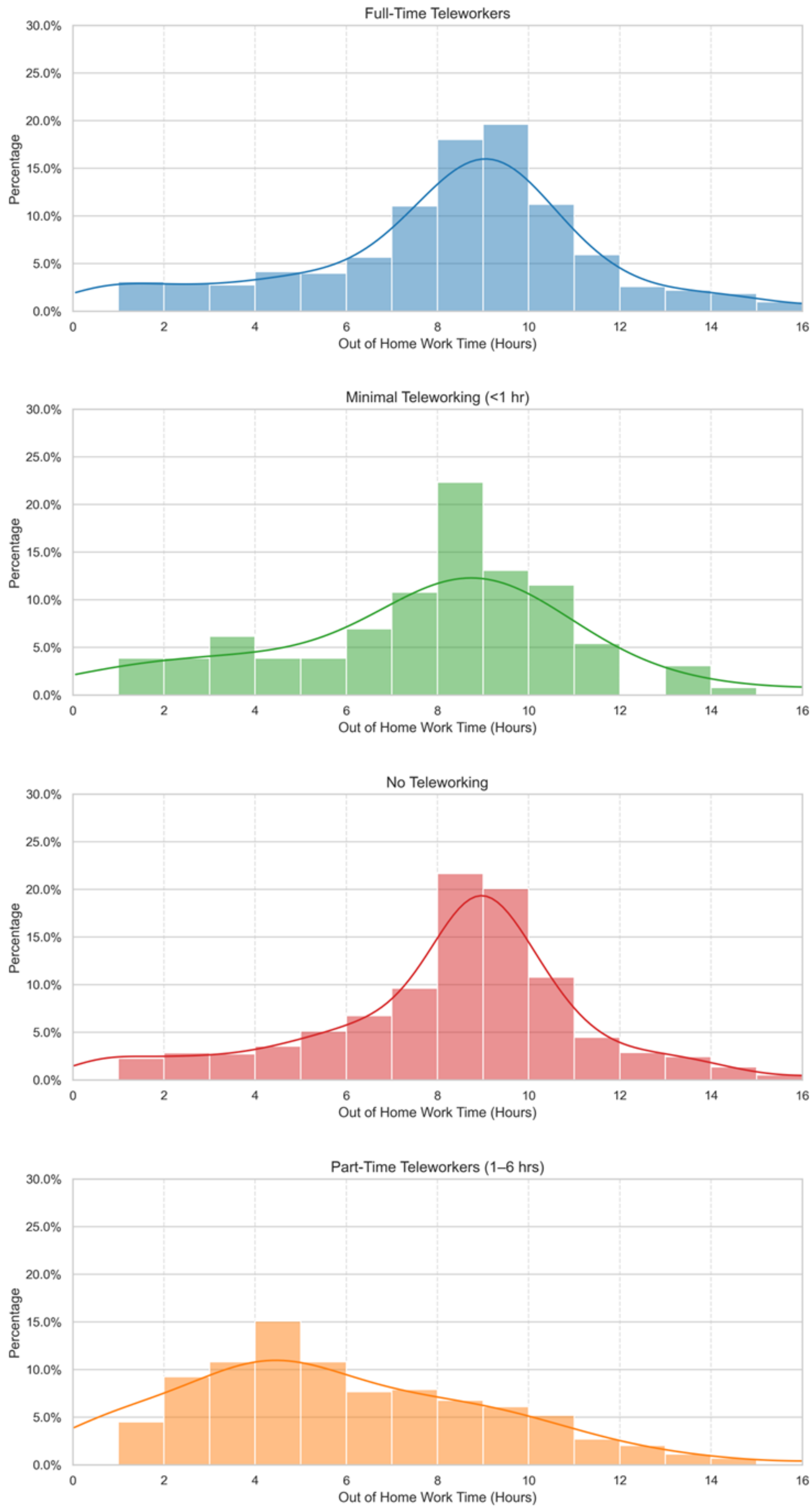


Figure 0-3 Time Spent by Individuals at an Out-of-Home Workplace

A.2 Household Intergenerational Dynamics

Adults in the different working age groups demonstrate different shopping patterns. It is expected that their behaviors may be influenced by the presence of other household residents of varying ages. To better understand this dynamic, we cross-tabulated the age groups of respondents with the age groups of all other residents in their households. This cross-tabulation is detailed in Table A.1.

Table 0-1 Respondent Age vs. Household Age Structure

Household Resident Ages	# Residents	Respondent Age					
		18-24	25-34	35-44	45-54	55-64	65+
Under 5	1	3.3	6.1	17.3	3.3	0.1	2.1
	2+	0.0	1.1	5.5	0.4	0.0	0.0
5-15	1	13.8	5.3	18.6	21.3	8.8	0.2
	2+	0.9	2.1	13.6	13.9	1.4	0.2
16-17	1	11.2	1.6	5.1	12.0	4.0	0.0
	2+	0.0	0.0	0.6	0.0	1.0	0.0
18-24	1	63.0	5.6	5.4	12.6	9.6	1.6
	2+	37.0	0.5	0.2	4.3	3.0	0.0
25-34	1	19.0	50.2	13.2	5.3	10.3	5.3
	2+	7.3	49.8	1.0	0.4	2.1	3.0
35-44	1	4.7	7.7	57.4	17.3	3.9	3.5
	2+	4.0	0.2	42.6	0.4	0.6	0.5
45-54	1	21.3	3.0	8.3	64.9	18.4	3.0
	2+	3.0	1.2	0.0	35.1	0.0	0.0
55-64	1	18.0	6.1	5.2	10.3	71.8	12.0
	2+	5.4	1.0	1.6	0.1	28.2	0.0
65+	1	7.7	4.1	6.4	8.0	6.5	58.2
	2+	3.0	1.7	1.9	2.6	2.6	41.8

As can be seen in Table A-1, the complexity of ages living in a household varies considerably across respondent age groups:

- Some 18 to 24 year olds live in family households with siblings or children of all ages, parents, and grandparents, while others live in households with other young adults.
- 25 to 34 year olds mostly live with other young adults. Some have children, and some live with older adults, possibly their parents.
- 34 to 44 year olds are most likely to have small children, and many have school aged children. A few live with older adults.
- 45 to 54 year olds are most likely to have school-aged children, older teenagers, and young adults living in their households.
- 55 to 64 year olds have fewer children and teenagers, but more young adults living with them.
- Seniors mostly live with other seniors and older adults, and few live with children.

These findings can inform interpretation of the age-related variables discussed in section 6.2.2.

A.3 Parcel Deliveries to Hispanic Receivers

Based on model results, Hispanic individuals are just as likely to shop online as non-Hispanics, but are significantly less likely to receive a package delivery to home. To investigate this disconnect, an alternative variable from the 2022 CMS not included in our model was investigated. While a stable daily choice model of deliveries to alternative locations could not be developed as part of this study due to the limited sample size, it is possible to identify the reported ethnicities of individuals who received package deliveries to work and to other non-home locations (e.g. parcel stores and lockers).

In the overall CMS sample, more than 60 percent of the individuals who received deliveries to alternative locations were Hispanic, a share much higher than the 19% sample population. This result suggests that the lower likelihood of package deliveries to home for Hispanic receivers with the same rate of shopping participation may be due to a higher propensity for receiving deliveries to alternative locations.