8-19-2021

Adoption and Use of E-Grocery Shopping in the Context of the COVID-19 Pandemic: Implications for Transport Systems and Beyond

Gabriella Abou-Zeid
Portland State University

Adoption and Use of E-Grocery Shopping in the Context of the COVID-19 Pandemic:

Implications for Transport Systems and Beyond

by

Gabriella Abou-Zeid

A thesis submitted in partial fulfillment of the
requirements for the degree of

Master of Science
In
Civil and Environmental Engineering

Thesis Committee:
Kelly J. Clifton, Chair
Avinash Unnikrishnan
Jason Anderson
David Y. Yang

Portland State University
2021

Abstract

In 2020, the COVID-19 pandemic drastically impacted travel for in-person shopping, commute trips, global supply chains, and food business operations. Previously mundane tasks, like shopping for food and household items, became markedly different as new social distancing and mask guidelines were put in place to mitigate the spread of COVID-19. Concurrently, e-commerce sales in the U.S. skyrocketed. E-grocery pickup and delivery services saw unprecedented expansions. The adoption and use of e-grocery services have implications for equity and mobility, although the nature of the relationship of e-grocery to the latter is still unclear. Enhancing our understanding of the drivers of (and barriers to) online grocery shopping and its potential “stickiness”—or the extent to which e-grocery use will continue at the same or higher frequencies after the pandemic—is a prerequisite for unpacking current and future consequences of this ecommerce sector on people and transportation networks.

The goal of this work, then, is to 1) explore the drivers of adoption and use of e-grocery services in the context of the COVID-19 pandemic and 2) estimate “stickiness” of online grocery ordering behaviors. Survey data (N=2,266) capturing household and individual information on demographics, attitudes, and behaviors are employed in carrying out this goal. First, individual e-grocery delivery adoption is explored using a series of mixed logit models disaggregated by household income. Demographics, COVID-19 related variables, and attitudinal indicators hold significant explanatory power in estimating the probabilities individuals will fall into non-adopter, pre-pandemic adopter, or during-pandemic adopter categories.

Next, relationships between in-store and online grocery shopping trip rates are investigated utilizing random parameters Tobit and hurdle models. Model results demonstrate heterogeneous and often asymmetric relationships between shopping modes. Finally, whether or not households will retain (or increase) their already elevated e-grocery shopping behavior is examined. A random parameters binary logit model is applied to identify factors affecting the probability households a) ordered groceries online more often during the pandemic compared to before the pandemic, and b) expect to hold or increase the proportion of their groceries purchased online in the next year.

The culmination of results show attitudes and COVID-19 related variables are strong drivers of e-grocery adoption, use, and stickiness. With respect to attitudes in particular, households with shoppers who find shopping online for groceries to be easy and who know others who shop online for groceries have a higher likelihood of adopting and using e-grocery services, as well as continuing these behaviors in the future. COVID-19 related characteristics – including individual and household experiences related to employment, income, remote work, diagnosis, food insecurity, and changes in food shopping behaviors – were found to be significant across the suite of estimated models, demonstrating the sheer impact of the pandemic on household provisioning behaviors. Results from the "stickiness" analysis suggests households that are multimodal, below retirement age, and located in places with high e-grocery service availability are more likely to hold or increase their already elevated e-grocery usage. Households who have at least one member particularly vulnerable to COVID-19 or who reduced their in-store shopping frequency during the pandemic are also more likely to have e-grocery shopping "stick". Attitudes of household grocery shoppers also play a significant role: households whose shopper thinks it's easy to shop online have an almost 17%-point higher probability of holding or increasing their already elevated proportion of groceries purchased online.

The work concludes with a synthesis of findings, highlighting key drivers of and barriers to online grocery shopping, the impacts of the COVID-19 pandemic on e-grocery, and implications for transportation systems and practice. This discussion includes recommendations for policy and future work.

Dedication

To Kelly, Kristi and Amanda

for paving the way.

Acknowledgements

While I always hoped to go to graduate school, I could have never anticipated going to graduate school in the middle of a global pandemic. There are so many people who got me to, and then through, graduate school who I'd like to thank—although the words will never feel sufficient. I hope that I can only make you all proud with the work I continue to do. My accomplishments are all shared with you.

First and foremost, I want to acknowledge my advisor and committee chair, Dr. Kelly Clifton. Thank you for everything. I would not be finishing this degree today (seriously, because you're the *only* person who could have convinced me I could pursue an engineering degree) without your advocacy, support, encouragement, mentorship, and guidance. Thank you for taking a chance on an undergraduate student who knew nothing about transportation before participating in Portland State's Transportation Undergraduate Research Program (TURF). You go above and beyond to advocate for your students, for which I am so grateful. Your multidisciplinary expertise carries weight, and I will forever feel lucky to be a "Kelly student". I have learned so much from you and am a better student, researcher, and person because of it.

Thank you, also, to my committee members. Dr. Avinash Unnikrishnan, thank you for introducing me to Portland State through the TURF program. Your classes ignited my interest in coding and provided a solid foundation for learning econometric analyses. Your dedication to teaching and passion for the subjects comes through in your classes. Thank you for being so accessible and helpful with all my questions in class. If I ever teach, I aspire to follow your model. Dr. Jason Anderson's courses sparked my new-found interest in statistical modeling and econometric analysis. I am so grateful to have learned from you and appreciate all your guidance. Thank you for making econometrics more exciting than intimidating, and for meeting with me nearly every week during the development of my thesis. Your expertise informed every piece of statistical analysis in this document. Dr. David Yang introduced me to machine learning in his coursework, a subject I had always wanted to learn about but didn’t know where to start. Thank you, Dr. Yang, for making machine learning accessible (and fun to learn). I appreciate you going above and beyond to help your students (with all the Zoom we’ve all had to do this year, you still helped us all de-bug Python code and improve our models for who knows how many hours. Thank you.).

I’d also like to thank Dr. Christopher Monsere, Dr. Liming Wang, John MacArthur, and Dr. Jennifer Dill —your classes and expertise only reiterated Portland State was the best place for me to be. Additionally, thank you to the many University of Arizona faculty and staff in the College of Architecture, Planning and Landscape Architecture who got me here: Dr. Kristina Currans, Dr. Arlie Adkins, Dr. Joey Iuliano, Dr. Nicole Iroz-Elardo, Dr. Ladd Keith, Sean Kramer-Lazar, Dr. Clare Robinson and Dr. Philip Stoker. I’d also like to acknowledge Arturo Rodriguez, who I had the pleasure of working for at the University of Arizona’s Think Tank, and who had unmeasurable influence on the way I work and think.

To Dr. Kristina Currans and Amanda Howell: working with you and Kelly has been the dream team. I am in awe of both of you, personally and professionally. I cannot wait to see how your work continues to evolve. Thank you for everything and for playing an integral role in this work and my own development.

Thank you to Jaime Orrego-Oñate, Michael McQueen, Katherine Keeling, Darshan Chauhan, Jaclyn Schaefer, and Baxter Shandobil for being the best peers and support system for going to grad school in a pandemic. Thanks, too, to Kiley Melicker and Sam Parsons, for keeping us all afloat. I can't wait to see you all again soon.

I am additionally grateful for the financial and professional support provided by the Federal Highway Administration's (FHWA) Dwight D. Eisenhower Transportation Fellowship Program (DDETFP) and the National Institute for Transportation and Communities (NITC).

Last, I would like to thank my family. Mom, thank you for raising me to think I could accomplish anything, for being the best role model, and for letting me move back home when the pandemic hit. If I am half the person you are in my life, I'll have been successful. Dad, thank you for passing down your engineering-minded brain, for supporting me in all my endeavors, and for staying up until 3 AM at least once a week to help me with AP Calc homework back in the day. Mucio, I am beyond grateful that you are my family, and you have shaped so much of how I view the world. Thank you for your endless wisdom, guidance, and laughs. Dominique and Michael, my favorite (and only) sister and brother, thank you for growing up before me and helping me figure it all out. Cassie, the best cat that ever was, deserves thanks for getting me through the hard times. Finally, Nick—thank you for all your support and encouragement through this process, for fielding my stress about every model gone wrong in this thesis, and for being an ever-present grounding presence in my life.

Table of Contents

List of Tables

List of Figures

1 Introduction

In 2020, the COVID-19 pandemic drastically impacted travel for in-person shopping, commute trips, global supply chains, and food business operations. Previously mundane tasks, like shopping for food and household items, became markedly different as new social distancing and mask guidelines were put in place to mitigate the spread of COVID-19. Google Mobility data show trips to grocery stores and pharmacies were down 15% by April of 2020, on average, compared to baseline values from the beginning of 2020 (*1*). Consumers may have faced increased difficulties finding essential items given the impact of the pandemic on food supply chains (*2*) and the rise of "panic buying" (*3*, *4*). Agricultural supply chains have had to meet unprecedented demand, with online ordering becoming a key link in last-mile operations (*5*).

While the pandemic has stifled some industries (restaurants included (*6*)), e-commerce has accelerated. E-commerce sales in the U.S. increased almost 37% between the third quarters of 2019 and 2020 (*7*). Recent market research pins the 2020 increase of online grocery, or "e-grocery", shopping between 40% (*8*) and 53% (*9*) based on total sales. The increase, here, is likely because online grocery shopping has been touted as a safer shopping option during the pandemic. The Centers for Disease Control and Prevention (CDC) recommend using online pickup or delivery methods for grocery shopping to limit interaction with others and curb the spread of COVID-19 (*10*). In April of 2020, Amazon released information about its efforts to expand pickup services at Whole Foods from 80 to 150 stores, citing an 60% increase in capacity for online orders (*11*).

Photo by [Mick Haupt](#) on [Unsplash](#)

Adoption and use of online provisioning modes for groceries have important implications for equity. The effects of the pandemic exacerbated food insecurity, particularly for already vulnerable populations (*12*), with one study estimating 17 million more Americans would experience food insecurity in 2020 compared to 2018 (*13*). Figliozzi and Keeling (*14*) and Figliozzi and Unnikrishnan (*15*) provide extensive insights into how e-grocery and e-commerce services can improve equity outcomes for marginalized groups.

Adoption and use of online provisioning modes for groceries also have important, albeit nuanced, implications for transportation systems. Consider, first, online delivery methods. While grocery shopping for online delivery *may* substitute for in-person food shopping trips, the subsequent effects on the transportation system depend on the travel mode of both events (*16*). For example, if both trips are taken by car, the delivery trip may be more efficient overall (in terms of emissions and system demand) because of route optimization. On the other hand, if a trip walking to the store is replaced by a vehicle delivery trip, this online order effectively *increases* roadway demand and vehicle emissions.

Online pickup methods also have nuanced implications for our transport systems. Stores have set up limited space for curbside pickup in their parking lots. This shopping method may then, for example, reduce the volume of demand for parking at grocery stores, theoretically allowing most of that land to be used for another purpose. However, shoppers must still make a trip to the store. Assuming this trip is by car and consumers must wait some time to receive their orders, this trip may have a higher emissions footprint than an in-store shopping trip given idling for over 10 seconds generates more emissions than stopping and starting a car engine (*17*).

Recovery from the brunt of the pandemic is hopefully on the horizon. Currently, Google Mobility data show grocery and pharmacy trips up 2% compared to baseline data from the beginning of 2020 (*1*). Yet, it is likely that some aspects of the pandemic—e-grocery use included—will "stick". Forbes notes that online ordering is one of three changes related to grocery shopping that is here to stay in a post-pandemic era (*18*). Recently published research by Salon et al. (*19*) outline transformative changes related to telecommuting, air travel, active transportation use, and online grocery shopping as a result of the pandemic. Enhancing our understanding of the drivers of (and barriers to) online grocery shopping and its potential "stickiness"—or the extent to which e-grocery use will continue at the same or higher frequencies after the pandemic—is a prerequisite for unpacking current and future implications of this ecommerce sector on people and transportation networks.

The goal of this work, then, is to 1) explore the drivers of adoption and use of e-grocery services in the context of the COVID-19 pandemic, and 2) estimate "stickiness" of online grocery ordering behaviors. This work is carried out using survey data of persons who are primarily responsible for grocery shopping for their households, or who share this responsibility with other members. The remainder of this document is structured as follows. First, background on technology adoption and use is presented, with specific focus on ecommerce and online grocery shopping. Then, the survey data utilized in the study is described, along with externally appended datasets. The methods employed in the analyses are then presented. These include random parameters logit, Tobit, and hurdle models. Results from each step of the analysis are then discussed. The conclusion section synthesizes the culmination of findings to highlight key drivers of and barriers to online grocery shopping, the impacts of the COVID-19 pandemic on e-grocery, and implications for transportation systems.

2 Background and contribution

2.1 On technology adoption, e-commerce, and travel behavior

There exists an abundance of literature on theories of behavior explicitly related to or later applied to technology adoption, including (but certainly not limited to): Task-technology fit (TTF) (*20*, *21*), Theory of Planned Behavior (TPB) (*22*), Technology Acceptance Model (TAM) (*23*), Innovation Diffusion Theory (*24*), and the Motivation-Opportunity-Ability (MOA) model (*25*, *26*). For parsimony, this section is focused mainly on the adoption and use of e-commerce services for pickup and delivery during the COVID-19 pandemic and/or pertaining to groceries. See Lai (*27*), Droogenbroeck and Hove (*26*), and Abu-Shanab (*28*) for more comprehensive reviews of this broader set of frameworks.

2.1.1. Technology, e-commerce, and e-grocery adoption and use

Droogenbroeck and Hove (*26*) examined e-grocery adoption through surveys regarding use Collect & Go, a Belgian grocery pick-up service with online ordering. Using a binary logit model analysis, the authors found associations between both household and individual level characteristics, including age, education level, and presence of children. The authors found the models including both individual and household-level characteristics to have higher predictive power compared to models that only include individual characteristics, bolstering the argument that both are important when assessing adoption of e-grocery services.

In an evaluation of general e-commerce adoption, Naseri and Elliott (*29*) found that e-commerce adopters are more likely to be young, male, highly educated, and high income. While Dominici et al. (*30*) reported the same trends for income, age, and education specifically with respect to online grocery shopping, they said e-grocery shoppers were more likely to be women than men. Men are more likely to shop online in general (*26*), although women may be more likely to shop both in-store and online (*31*)—perhaps because they do more of household provisioning in general (*32*). Larger households, particularly those with children, have been linked with more frequent online provisioning habits (*31*). Household vehicle ownership has been associated with preferences for in-store food shopping opposed to online food shopping (*30*).

Additional fees associated with online ordering methods have proved to be a barrier to adoption for low-income households (*33*). A recent analysis of residents in Portland, OR demonstrated that Hispanic-Latino identifying populations and under-educated populations were less likely to receive deliveries during COVID-19, while low-income households and households with members over 65 were less likely to be subscribed to a delivery subscription service (*15*). Understanding the drivers of online shopping for food and household items will provide a picture of who *is* and *isn't* using such methods, highlighting barriers so that planners, practitioners, retailers, and government institutions with regulatory power might address them.

Age is a commonly cited factor in the digital divide, as older Americans' internet usage is increasing but still falls behind rates of other adults (*34*). Twenty-five percent of adults 65 and older never use the internet, compared to four percent of 50-64 year-olds, two percent of 30-49 year-olds, and one percent of 18-29 year-olds (*35*). Barriers associated with this group include (non-)ease of use, lack of knowledge of availability, and lack of technical support (*36*).

Major discrepancies in adoption of technologies exist across income groups, too. Higher incomes typically correspond with higher rates of online shopping (*26*, *37*). Recent findings from the Pew Research Center show striking differences in adoption of internet-related technologies by income (*38*). For example, while 93% of households earning $100,000 or more have broadband internet at home, only 57% of those earning less than $30,000 do. Further, 92% of households earning $100,000 or more have a computer at home, compared to 84% of households with $30,000-$99,999 incomes and 59% of households with income under $30,000. Fourteen percent of households earning less than $30,000 report not using the internet at all, compared to just one percent of those earning $75,000 or more and 2% earning $50,000-$75,000 (*35*). Income has been used as a moderating variable in analyses examining technology adoption (*39*, *40*). The adoption-focused analysis in this work hypothesizes that differences in drivers of e-grocery delivery adoption exist across income groups, suggesting a disaggregate modeling approach.

Built environment factors also play a role in the adoption (and use) of technologies. Residents of densely populated cities are more likely to exclusively shop online (*31*); this may be in part due to better access to internet (*41*) or due to the increased access to stores and restaurants offering online ordering methods. In a study of Belgian shoppers, Beckers et al. (*42*) noted that dense neighborhoods with high incomes and levels of education are expected to have higher numbers of online shoppers (*42*). Chen et al. found telehealth adoption rates trend positively with increasingly urban contexts (*43*). E-commerce and freight research have demonstrated a positive association between population density or urban context and online shopping (*41*, *44*).

Unsurprisingly, attitudes have been found to be significant indicators of e-commerce use in previous analysis of general and grocery online shopping (*26*, *37*, *45*, *46*). Using 1,580 survey responses of Danish e-commerce users—24% of whom had ordered groceries online—Frank and Peschel (*47*) developed a binary logit model to examine e-grocery adoption, as well as cluster analysis to develop e-grocery shopper typologies. The authors found that, when controlling for demographics, perceived social norm, compatibility with in-store shopping, and perceived advantage over in-store shopping are significant and positive predictors of online grocery shopping adoption. Further, the authors identify three segments of online shoppers, whose main priorities are 1) price, 2) time, and 3) trust / brand awareness. Features used to classify shoppers included e-grocery costs, products available, delivery speed and accuracy, time savings, times available to shop, personal service, and brand name. While no significant differences existed across groups in e-grocery shopping frequency, the authors noted the segment associated with price consciousness held the greatest share of weekly grocery shoppers.

Huang and Oppewal (*48*) employed a choice experiment of U.K. consumers. Their sample was built using intercept surveys of 152 grocery shoppers; under a quarter of these shoppers had previous experience shopping online for groceries. The authors hypothesized delivery costs would be the major factor affecting grocery shopping mode. However, their analysis revealed the effect on shopping mode choice of a 15-minute travel time increase was almost double that of a delivery fee increasing from zero to five pounds (roughly $6.90 USD). Factors associated with perceived costs, risks, convenience, and enjoyment were also found to influence the choice to shop online (or not). Hansen et al. (*49*) found compatibility with existing shopping behaviors, perceived advantages over in-store shopping, affirmative social norms, and low risk and complexity related to the Internet to differentiate e-grocery adopters from non-adopters. Piroth et al. (*50*) also found social norms to be a strong predictor of e-grocery adoption, while Hand et al. (*51*) noted level of satisfaction with shopping channels is an indicator of grocery adoption and continued use

Singh and Rosengren (*52*) provided an overview of switching *between* e-grocery retailers. Using 221 survey responses of e-grocery shoppers and structural equation modeling, the authors noted that poor customer service and item quality, along with high costs and technical problems with online platforms, are significant factors that push consumers to switch to other online retailers in their grocery shopping. Further, positive word-of-mouth about a particular online retailer and the availability of alternative products are significant in attracting consumers toward an online retailer. It is plausible that these factors attracting or detracting consumers between online retailers also influence adoption and continued use of e-grocery services when switching from traditional in-store shopping.

2.1.2. Travel behavior, online shopping, and transportation impacts

The relationship between traditional provisioning methods and online shopping for food and household items has serious implications for our transportation networks. However, the nature of the effects here are contingent on the substitutional versus complementary (or even asymmetric) relationship between online provisioning and traditional shopping modes (*31*, *53*). The lines between passenger travel and freight transport become increasingly blurred where delivery of goods can substitute for household trips (*16*). If new modes of shopping prevail, there need be changes to meet increasing demand. Transportation Network Companies (TNCs) may jump to fill this gap, delivering both people to locations and essential items to people (*5*). This integration of food delivery and TNCs has already been observed with UberEats.

In an extensive review of the impacts of e-commerce as related to transportation and freight travel, Rotem-Mindali and Weltevreden (*16*) explored a number of hypotheses related to contrasting substitutional and complementary relationships of e-shopping and in-person shopping. The authors reported that online ordering exhibits substitutional effects if this shopping mode replaces a trip made to a store to shop (as *might* be the case with deliveries). However, they noted that the *travel mode* substituted for is necessary to understand the net effect on our transport systems. For example, if a household substituted a driving trip for a delivery, the freight trip (also in a vehicle) may be more efficient, especially if other delivery trips can be chained together. Conversely, if a household member planned to walk to a store to shop but instead ordered items for delivery motorized vehicle, this may incur a net increase on roadway demand (along with increased emissions, which has further implications for air quality and climate change).

The increased system efficiency of online ordering is also contingent on a number of factors. With respect to delivery, Rotem-Mindali and Weltevreden (*16*) noted there is an inverse relationship between efficiency and delivery time frames. Where deliveries can be combined and chained together, scheduled routes can make such deliveries more efficient. However, when a strict timeline is imposed on deliveries, or where there is not enough demand to plan chained delivery trips, deliveries may have a negligible efficiency impact.

While the review provided by Rotem-Mindali and Weltevreden (*16*) focused on delivery, these notions extend to online pickup as well. Quicker turnaround of pickup trips compared to shopping events at the store may reduce the demand for parking. They may in turn, however, increase the demand for curb space so vehicles picking up groceries can be located near the front of the store. Trips made by car to pick up orders may also idle in the parking lot while waiting, releasing more emissions than the same trip made to the store where the car was parked during an in-person shopping event.

Rotem-Mindali and Weltevreden (*16*) stated online grocery shopping tends to substitute for in-person trips more than shopping online for other goods. In contrast, Farag et al. (*37*) found a positive relationship between in-store and online daily shopping trips (which included grocery trips), suggesting a complementary relationship. The uncertainty surrounding the nature of the relationship between online and in-person shopping for food and household items necessitates more investigation into behavioral drivers of both of these modes. This would allow for further analysis to parse out in which contexts substitutional versus other situations happen and extrapolate findings to estimate transport system impacts.

Although an extensive review is beyond the scope of this analysis, it is important to note impacts on the transportation system are closely tied to those on the environment, especially given the transportation sector is the largest contributor to greenhouse gas emissions in the U.S. (*54*). In a simulation study of e-grocery home delivery, Siikavirta et al. (*55*) found net greenhouse gas (GHG) emission impacts (based on km traveled/order) of all simulation studies involving e-grocery home delivery to be improvements (e.g., reductions in GHGs) over the status-quo of in-person shopping. The authors reported that wider delivery time bands can help improve efficiency outcomes of routes because of the planned optimization. However, the study utilized data for e-grocery shopping in the Helsinki metropolitan area; given the greater car dominance in the U.S. compared to Europe, these savings may not translate to U.S. context.

2.2 The future of e-grocery services

The COVID-19 pandemic is certainly expected to be a behavioral trigger. Untangling the current drivers and implications of e-grocery use and adoption is vital to understand future trends and consequences. A study conducted by The Food Industry Association showed 89% of surveyed consumers made changes to the way they grocery shop, noting spending on groceries online likely doubled during the pandemic (*56*). Market penetration of e-grocery services is still fairly low but may hit 55%-66% by 2024, depending on COVID-19 recovery (*57*).

It is unclear if changes made by households and individuals to their grocery shopping behaviors in response to the pandemic will prevail. In the context of other major life events, Hand et al. (*51*) found that major life events, like the birth of a child or health issues, trigger the adoption of online grocery shopping. However, the authors reported that after these events pass, there may be a reversal of adoption behavior. In a nationally representative survey examining behavioral "stickiness" around the pandemic, Salon et al. (*19*) found the share of U.S. residents who shop online a few times a month to increase from 21% pre-pandemic to 30% post-pandemic (based on consumer expectations). A McKinsey report hypothesizes surges in e-commerce to "stick" in the post-pandemic world, along with remote working and prevalence of e-health services (*58*).

2.3 Summary of key determinants

Based on the reviewed background literature in Sections 2.1-2.2, input variables hypothesized to have explanatory power in estimating e-grocery delivery adoption, online and in-store grocery trip rates, and the "stickiness" of e-grocery services fall into four broad categories:

1. Other provisioning frequencies
2. Household and respondent demographics, geographies
3. COVID-19 related characteristics
4. Household shopper attitudes

The data used in the analyses are described in Section 3.

2.4 Contribution of this work

2.4.1 Novel examination of e-grocery service adoption, use, and stickiness in the context of the COVID-19 pandemic

The COVID-19 pandemic is still ongoing, and data and analyses are being rapidly deployed to try to understand its vast societal impacts. This research contributes to this developing body of work by utilizing a novel dataset of household demographics, attitudes, and behaviors to paint a robust picture of the adoption, use, and "stickiness" of online grocery shopping. To the author's knowledge, no existing work 1) examines factors influencing pre-pandemic, during-pandemic, or non-adoption disaggregated by relative income levels, 2) explores the relationships between in-store, online delivery, and online pickup trip rates during the COVID-19 pandemic, and 3) examines determinants of households' retaining or increasing already heightened use of e-grocery services in the future within the context of the same dataset.

The collected, cleaned, and processed data in this study (described in greater detail in Section 3) form their own contribution. By the end of 2021, the data associated with this research will include four cross-sectional waves of survey responses by the end of 2021. These data will be publicly available. Additionally, a new dataset determining the availability and extent of Instacart service at the zip code level in the five-state study area was scraped from the web for this analysis. Those data are described in Appendix C along with other compiled datasets mentioned in Section 3.3 and are available upon request.

2.4.2 Methodological contributions

Another contribution to this work involves the use of advanced econometric analysis in the evaluation of the novel dataset. All econometric models are estimated with random parameters. Unobserved heterogeneity may arise due to unobservables, resulting in the possibility of effects of estimated parameters varying across observations. Estimation of random parameters attempts to capture these heterogeneous effects by allowing variation in parameter estimates within the observed data. Failing to address unobserved heterogeneity may lead to serious issues from model misspecification (including biased or inefficient parameter estimates) (*59*), explaining the growing body of research incorporating random parameters model frameworks (*60–64*). Additionally, with respect to multinomial logit model frameworks, random parameters estimation helps mitigate specification issues resulting from violation of the independence of irrelevant alternatives (IIA) assumption (*65*).

3 Data & Research Design

The primary goals of this work are to 1) explore the drivers of adoption and use of e-grocery services in the context of the COVID-19 pandemic and 2) estimate "stickiness" of online grocery ordering behaviors. This section describes the data and methods employed in achieving these goals. The primary data source comes from survey data in the second of four waves of surveys evaluating the impacts of COVID-19 on household provisioning for groceries across five U.S. states: Arizona, Florida, Michigan, Oregon, and Washington. The first wave of surveys was fielded in September and October of 2020, while the second wave was fielded in January and February of 2021. The survey was administered by Qualtrics to their commercially available general population panel[1]. The project for which the data were collected is led by Kelly Clifton, PhD (PI, Portland State University), Kristina Currans, PhD (Co-PI, University of Arizona), Amanda Howell, MURP (Co-PI, University of Oregon), and Rebecca Lewis, PhD (Co-PI, University of Oregon). This research is funded by the National Science Foundation (NSF) and the National Institute for Transportation and Communities (NITC). The data for this project are currently being prepared for public release[2].

3.1 Survey administration, data cleaning and processing

In the second wave of administered surveys, respondents were asked to provide insights into their household's shopping behaviors in the last four weeks. Demographic and attitudinal information were also collected. In order to be eligible to complete the survey,

---

[1] Qualtrics indicates an approximate 10% response rate for these survey distributions.
[2] More information about the data and project available upon request. Check the Sustainable Urban Planning & Engineering Research (SUPER) Lab website for updates: http://www.superlab.us/

participants were required to be the primary grocery shopper in their household, or else share the responsibility with other household members. Survey sample quotas were instituted based on household state, race of respondent (white alone/non-white alone), age (18-64/65+), household size (1,2, 3+), and household income ($0-$40k, $40-$80k, $80k+) to ensure sufficient representation of a diverse set of households in the sample. The associated survey instrument is provided in Appendix A: Wave 2 Survey Instrument.

During the data collection process, incoming responses were evaluated for quality and scrubbed if various quality criteria were not met (e.g., speeding through the survey, providing gibberish answers to open-ended question responses, failing an internal quality check, etc.). The data were processed in R (*66*) and additional quality-control indicators were developed flagging households with contradictory responses or those who provided invalid information (e.g., households indicating they received SNAP benefits along with income ranges and household sizes that would make them ineligible; respondents who said they had not adopted e-grocery delivery but who had non-zero e-grocery delivery frequencies in the past four weeks, etc.). For this analysis, respondents who were flagged with any quality checks were filtered out. The sample was also filtered to focus on households in metropolitan zip codes (*67*) who provided full income information, giving a final sample of 2,266 households.

3.2 Evaluated outcomes in analysis

In this subsection, the outcome variables analyzed in this research are described. A number of potential explanatory variables were selected based on the reviewed background literature in Section 2. Descriptive statistics for outcome variables and tested explanatory variables are provided in Appendix B: Descriptive statistics for outcome and explanatory variables.

3.2.1 E-grocery delivery adoption

Participating household grocery shoppers were categorized into one of three adoption phases for e-grocery delivery:

- Pre-pandemic adopter (did this for the first time prior to the start of the COVID-19 pandemic[3])
- During-pandemic adopter (did this for the first time after the start of the COVID-19 pandemic[3])
- Non-adopter (have not ever done this)

Based on the reviewed literature in Section 2, it was assumed that drivers of e-grocery delivery adoption would vary by household income level. Because of this, the data for the analysis examining drivers of e-grocery delivery adoption was disaggregated by income level in order to test for parameter transferability. Parameter transferability answers the question, "do the same parameter estimates for one income group readily apply to others or should separate models be estimated for each income group?". In the parameter transferability process, described in more detail in Section 4, separate models are estimated for each income group. Then, the final model specifications for each group are applied to the other group's datasets, and model fit is assessed using a parameter transferability test (*65*).

Survey respondents, and their households, resided in a diverse set of counties and sizes. To ensure household income was representative of costs of living associated with

[3] Referred to in the survey as March, 2020

place and household size, a relative measure of income was developed to scale household income based on these characteristics. First, the midpoint of collected income ranges in the survey was determined. Then, the income midpoint, along with household size and county, were first used to assign households to the Department of Housing and Urban Development's 2021 Section 8 Income Limits, which define 'Extremely Low Income', 'Very Low Income', and 'Low Income' households as those whose household incomes do not exceed 30%, 50%, and 80% of a county's median family income (*68*). These groups were consolidated into a "Low Income" segment for analysis.

To further differentiate higher income groups, methodology from California's Department of Housing and Community Development was applied, defining 'Median/Moderate' income households as those earning 80-120% of a county's median family income, and 'Above Moderate Income' households as those earning more than 120% of a county's median family income (*69*). These thresholds were rounded to the nearest $50. Households falling into these income categories were used as "Mid-Income" and "High-Income" segments in analysis.

3.2.2 Estimating numeric trip values

Shopping trips—both those *taken* by a household for traditional in-store shopping or online pickup, and those *generated* with an online delivery order—were of particular interest in this analysis. Household shoppers were asked how often their household traveled to a grocery store to shop, picked up an online grocery order at the store, or received an online grocery delivery order in the last four weeks. It was assumed survey respondents would be able to more accurately categorize their household's shopping behaviors in discrete categories versus providing numeric values. Response categories included:

1. None in the last four weeks
2. Once over the last four weeks
3. 2-3 times over the last four weeks
4. Once per week
5. 2-3 times per week
6. 4 or more times per week

Statistical methods exist for modeling such discrete, ordered categories, like the ordered probit model. A major drawback to this method is that only the probability of being in one of the extreme categories (e.g., either 1 or 6 in the discretization above) could be readily interpreted. Further, the relationship between independent variables and *trips* themselves—not probabilities of being in a certain trip-making category—were of interest, particularly to explore the relationships between different provisioning methods. Because of this, the discretization above was translated into numeric monthly trips based on assumed midpoints of the trip categories:

1. None in the last four weeks = 0 trips
2. Once over the last four weeks = 1 trip
3. 2-3 times over the last four weeks = 2.5 trips
4. Once per week = 4 trips
5. 2-3 times per week = 2.5 trips x 4 weeks = 10 trips
6. 4 or more times per week = 4.5 trips (an assumed value aiming to account for the 'or more' clause) x 4 weeks = 18 trips

Note that a trip is defined as a one-way journey from origin to destination. Respondents were asked about household shopping behaviors over the last four weeks to capture variations in food shopping strategies. Assuming households plan grocery shopping events on a weekly basis, the numeric values above were divided by four to generate weekly in-store, online pickup, and online delivery trip rates[4], which were treated as continuous data measures. This transformation allows for a) more flexible modeling specifications in line with analytical interests and b) adjustment of the timescale to one more relevant for household grocery shopping.

3.2.3 Stickiness of e-grocery services

In order to evaluate stickiness of e-grocery services, a dichotomous variable was created that took a value of one if a respondent indicated: 1) their household was ordering groceries online (delivery or pickup) more often compared to before the pandemic, and 2) their projection of household proportion of groceries purchased online for pickup or delivery (versus in-store) was expected to stay the same or increase a year from the time of the survey; else, the outcome value was zero.

The former condition was determined from survey Q38 (see the survey instrument in Appendix A). The latter condition was derived from two questions that asked about households' proportion of grocery shopping done online, both currently and asking respondents to project behaviors a year from now. Answer choices included:

1. All in-store
2. Mostly in-store
3. About 50-50
4. Mostly online
5. All online

[4] These measures are referred to as rates because they are imperfect measures of trips per month per week (not just trips per week). The numeric values of these measures can be fractional, and as such they are not referred to as simply *trips*.

To fulfill this latter condition, respondents had to indicate they expected their households to retain to increase their proportion of groceries purchased online a year from the survey data. Roughly one quarter of the sample is ordering groceries online more often compared to before the pandemic and are expected to hold or increase their proportion of groceries purchased online in the next year.

3.3 Data augmentation

A number of archived data sources were appended to the survey. These appended data are summarized in Appendix C: External datasets appended to the sample data, given the information may be useful for others seeking relevant data sources related to online shopping, the built environment, or COVID-19.

3.4 Data description

Table 1 shows some basic comparisons of sample averages to state-level population demographics. The survey questionnaire only captured the race of the responding household shopper, not of all members of the household. Household respondents identifying as white (non-Hispanic) are overrepresented in the sample compared to state populations. Additionally, a higher proportion of survey respondents have access to a computer and internet at home than in state populations[5]. Household size and income data are relatively similar between respondents and state populations.

Figure 1 through Figure 6 visualize basic demographic data of the sample. Figure 7 shows e-grocery delivery adoption status by income group (with all low-income

---

[5] See Section 5.1 (Limitations) for implications

categories consolidated; these represent the data segments in the models of e-grocery delivery adoption). A chi-square test demonstrates differences in those income and e-grocery delivery adoption distributions are not due to chance, $\chi^2(df=4)=19.94$, $p < 0.001$. Figure 8 summarizes respondent rankings of level of importance of various factors when grocery shopping. Figure 9 displays the distributions of respondent attitudes about technology and grocery shopping. Note that respondents were prompted to provide their attitudes about and perceptions of e-grocery shopping, even if they have never purchased groceries online before.

Table 1 Comparison of survey data to state population

		White (non-Hispanic), percent	Household size	Households with a computer, percent[1]	Households with internet access, percent[2]	Household income[3]
Arizona (N=451)	State population	54.1%	2.69	89.9%	81.8%	$57,232
	Survey sample	78.9%	2.32	95.8%	95.3%	$56,630
Florida (N=504)	State population	53.2%	2.65	89.8%	80.8%	$54,232
	Survey sample	76.4%	2.29	95.0%	95.4%	$58,968
Michigan (N=444)	State population	74.7%	2.49	88.0%	79.0%	$55,933
	Survey sample	82.9%	2.33	96.2%	95.7%	$57,477
Oregon (N=424)	State population	75.1%	2.51	91.8%	83.9%	$60,469
	Survey sample	75.7%	2.46	96.9%	98.3%	$61,132
Washington (N=443)	State population	67.5%	2.55	92.7%	86.5%	$71,386
	Survey sample	79.2%	2.40	96.2%	95.9%	$69,842

Notes:
All state population data compiled on 10/19/2020 from Census QuickFacts (https://www.census.gov/quickfacts) by state
1 For the state population, this is households with a computer at home; for our survey sample, this is the

proportion of respondents indicating they had access to a computer or tablet at home.
2 For the state population, this is households with a broadband internet subscription; for our survey sample, this is the proportion of respondents who indicated they had access to the internet at home.
3 For state populations, this is median household income converted from 2018 dollars to 2019 dollars using U.S. Consumer Price Index data; for our survey sample, this is the mean of income category midpoints.

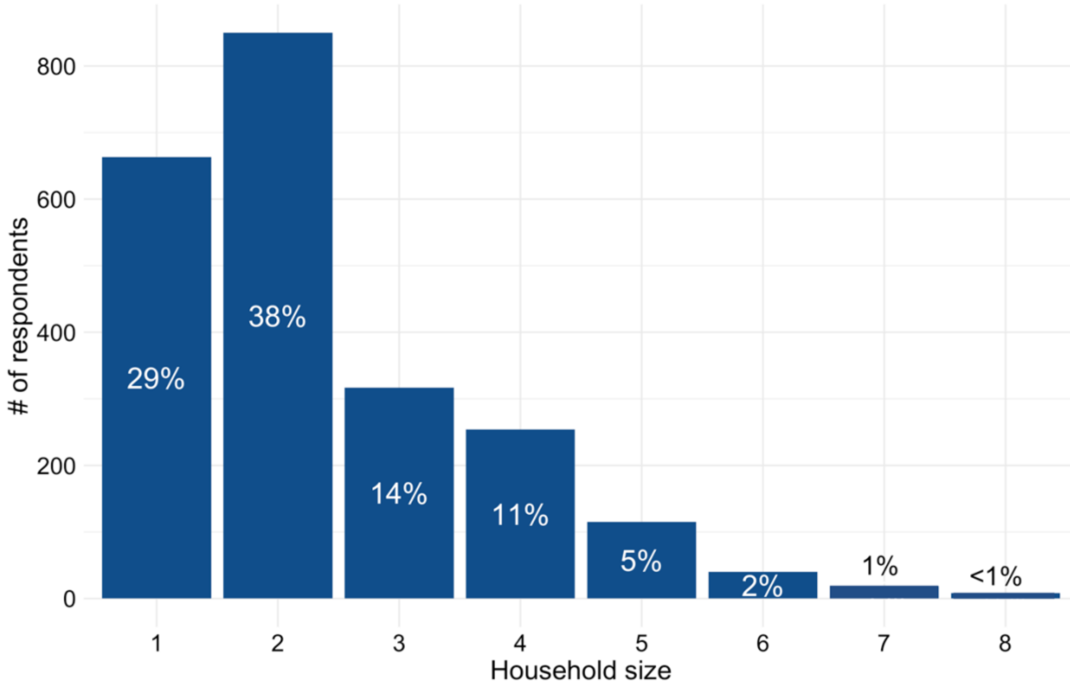

Figure 1 Household size distribution for sample (N=2,266)

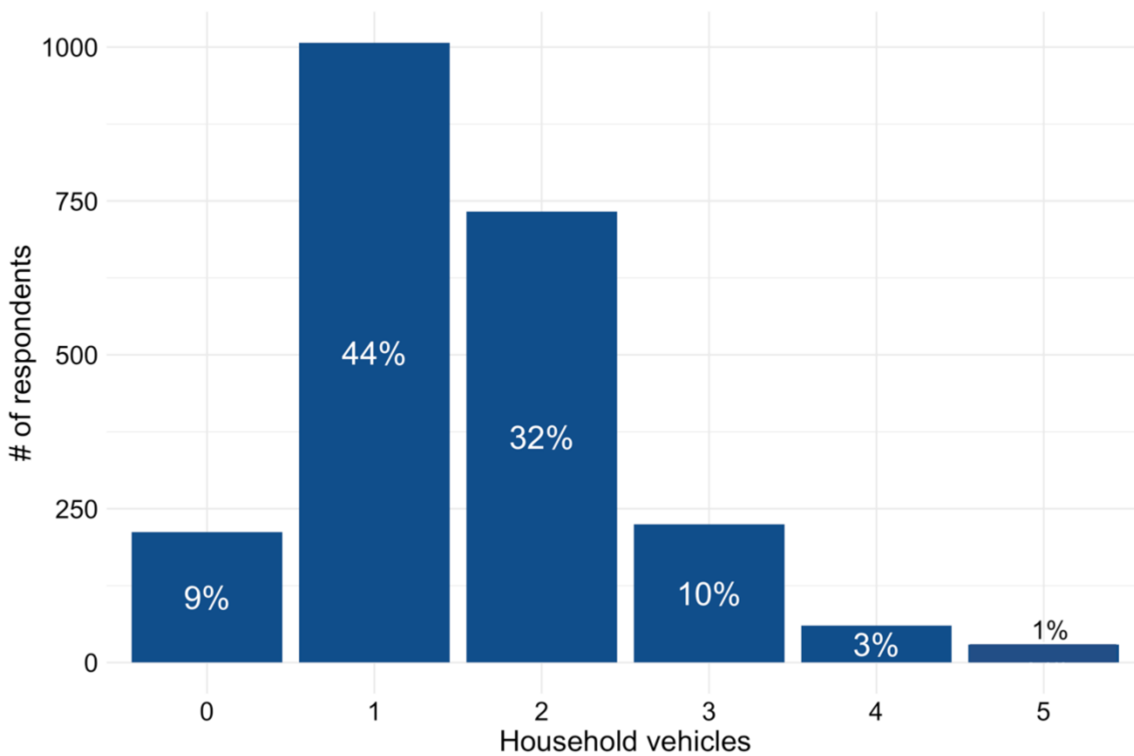

Figure 2 Household vehicle distribution for sample (N=2,266)

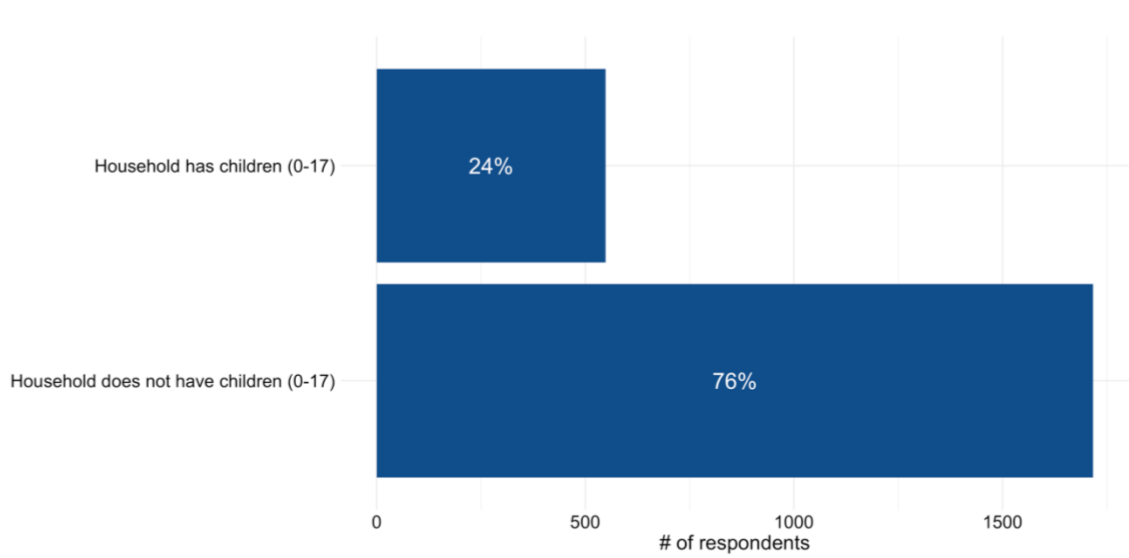

Figure 3 Household child status for sample (N=2,266)

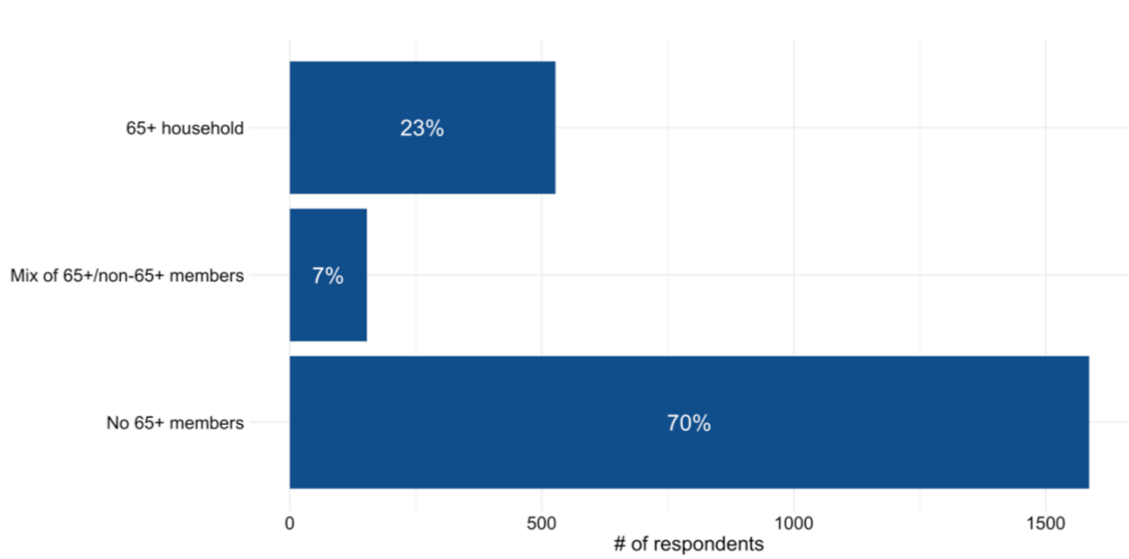

Figure 4 Household age profile for sample (N=2,266)

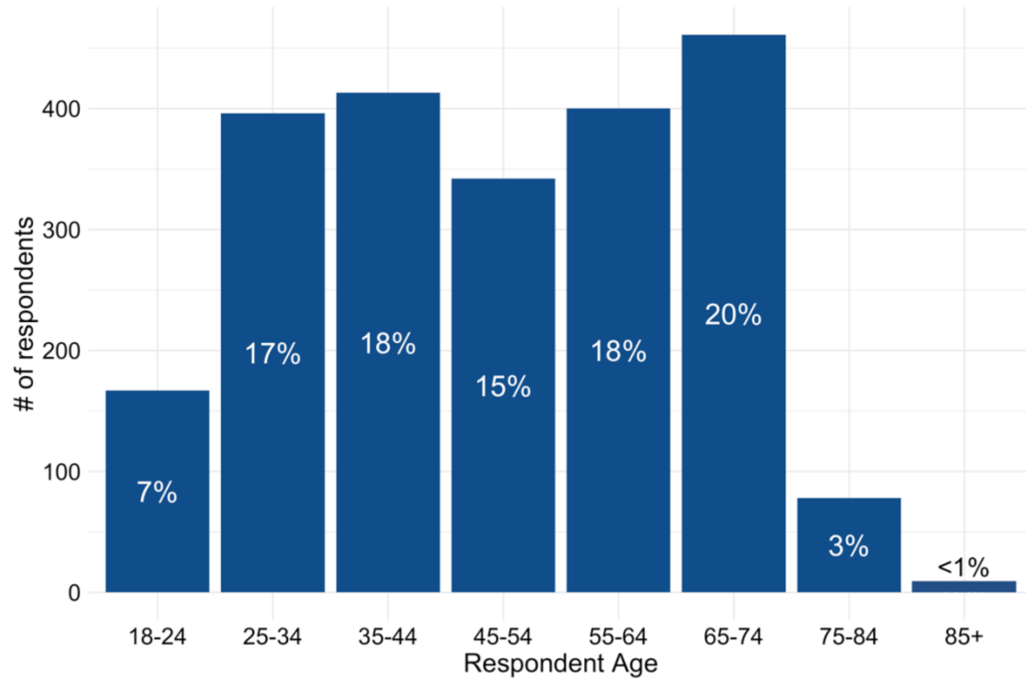

Figure 5 Respondent age category for sample (N=2,266)

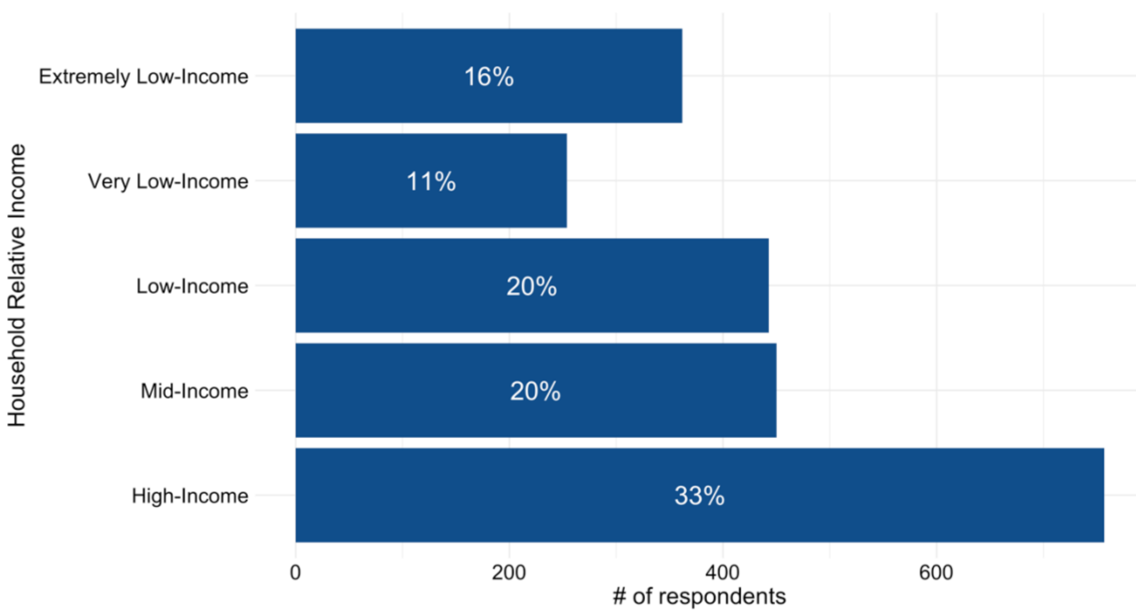

Figure 6 Household income level distribution in sample (N=2,266)

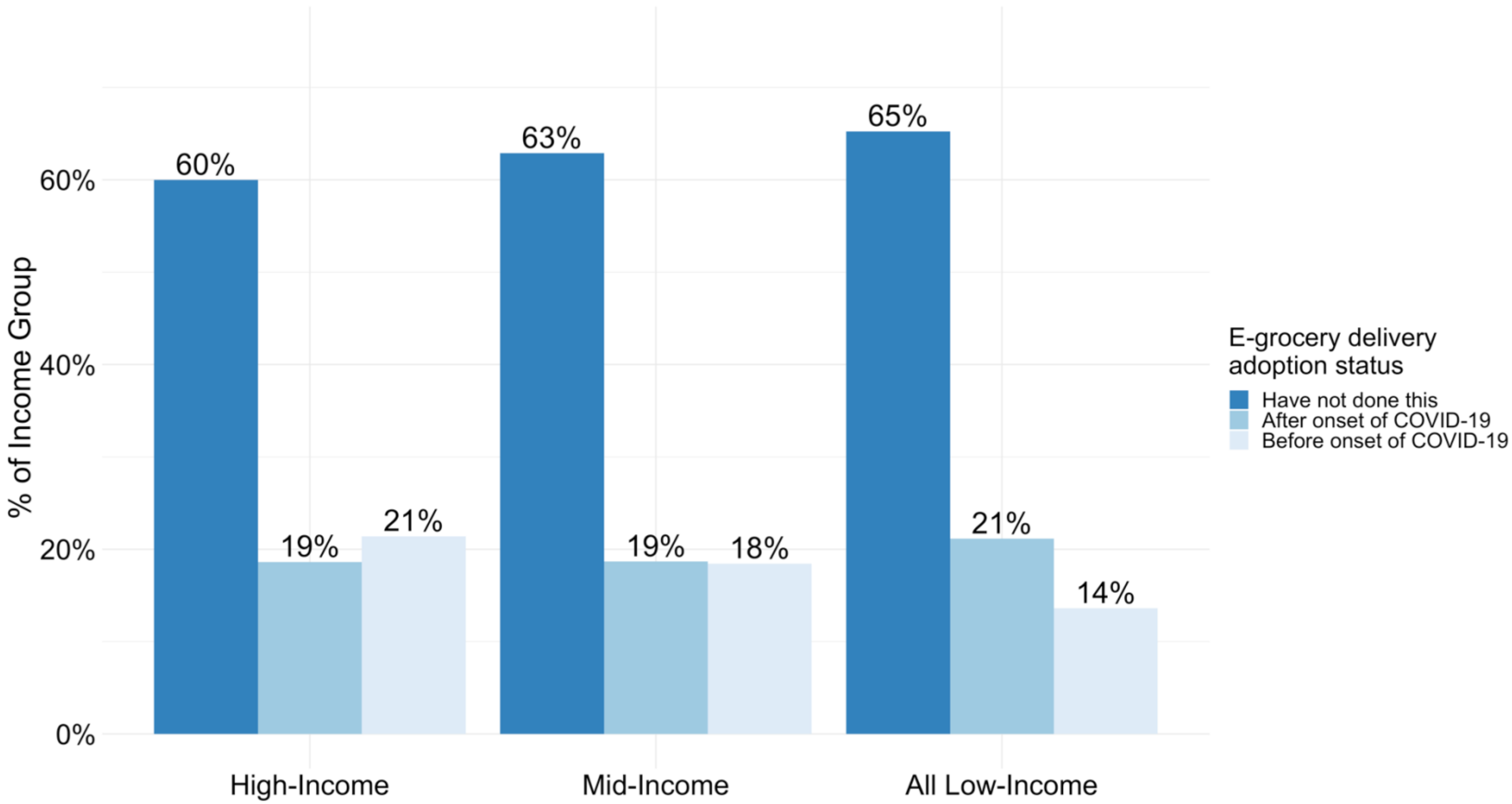

Figure 7 E-grocery delivery adoption status by relative income group

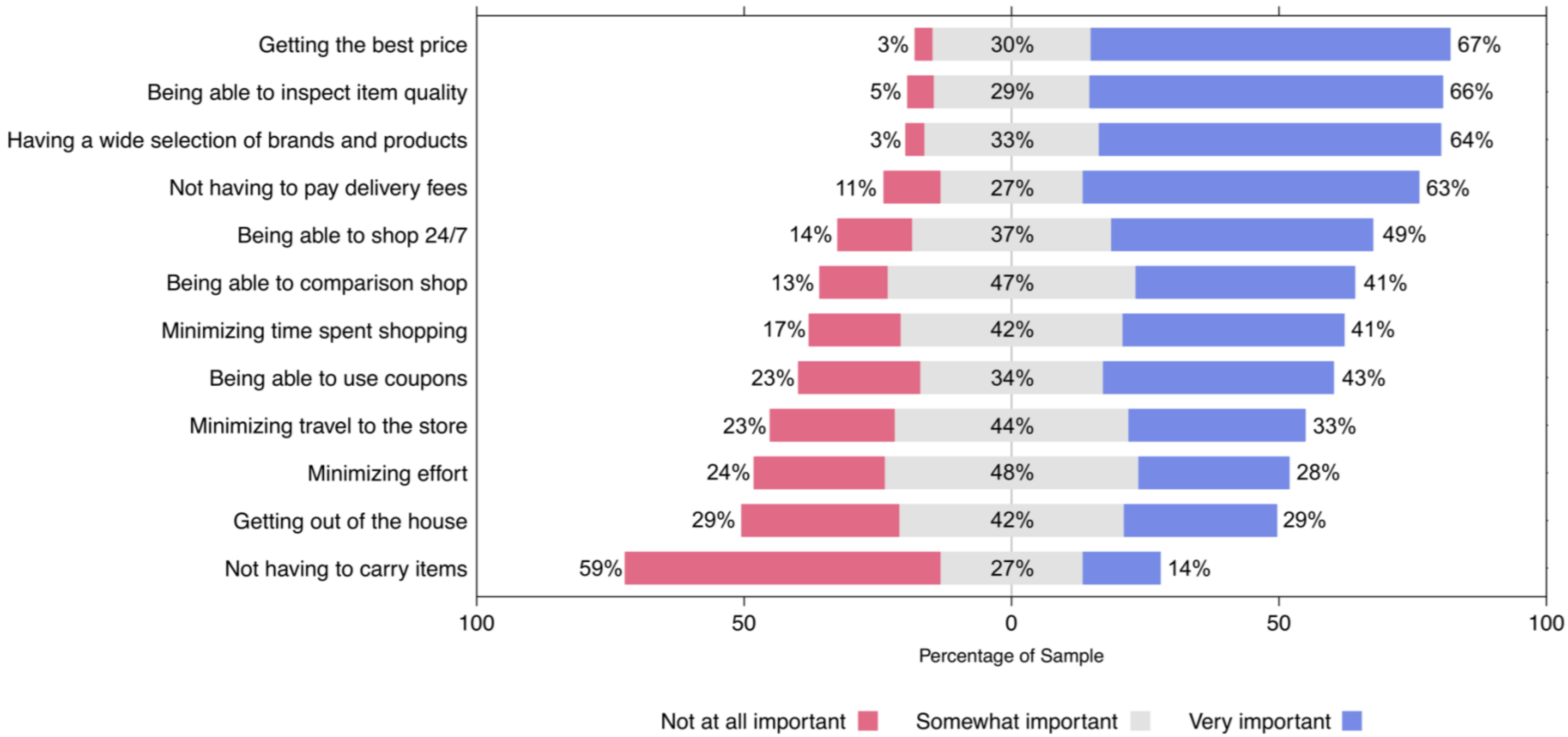

Figure 8 Respondent rankings of relative importance of various factors when grocery shopping

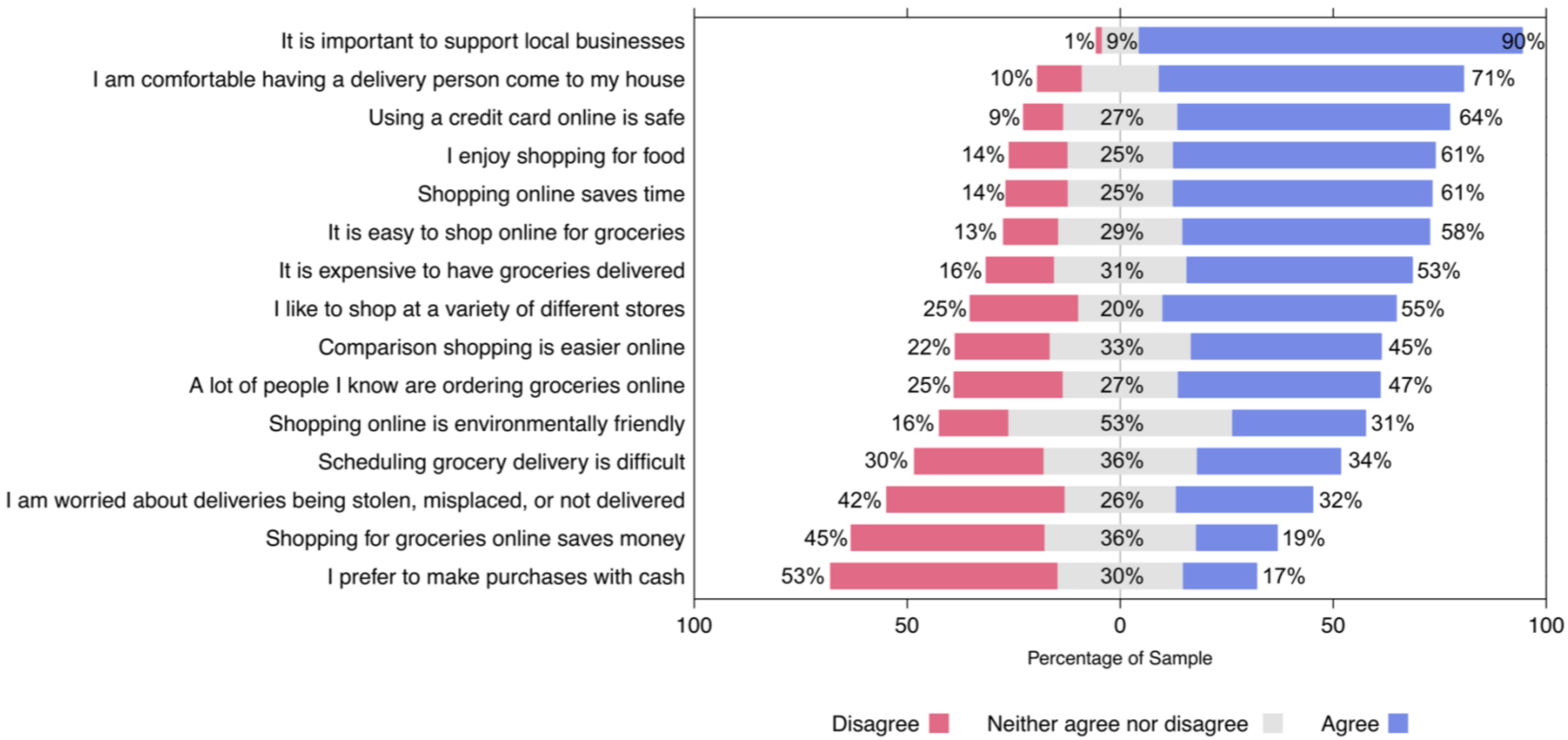

Figure 9 Respondent attitudes about grocery shopping and technology

3.5 Model Development

This section describes the development of models used to examine e-grocery delivery adoption, weekly grocery trip generation rates, and the stickiness of e-grocery services. All models were implemented in NLogit 5 software (*70*) using a forward stepwise approach (i.e., explanatory variables were added one-by-one to the model). Only those explanatory variables significant at a 90% confidence level were carried forward after each step[6]. This process was repeated, iterating through the list of independent variables provided in Appendix B until no new significant parameters were discovered, and no increase in log-likelihood was achieved. Variables that were highly correlated (Pearson's correlation ±0.70)—including variables derived from combinations of others— were not tested within utility functions together to avoid potential multicollinearity issues. Variance inflation factors (VIF) were also assessed after model estimation to check for any collinearity problems.

Unobservables in the models may generate unobserved heterogeneity, where the effects of estimated parameters vary across observations. For example, the literature demonstrates younger people are more likely to adopt and use e-commerce in general (*29*, *30*), and so we might expect younger age groups to be positively associated with the adoption and use of e-grocery services. However, younger people are also less vulnerable

[6] The one exception is state indicator variables were included in all models, regardless of significance. Because the survey data contains observations from five different states, indicator variables flagging state location were included in all models, regardless of significance. Washington was selected as a reference case, given the higher e-grocery shopping frequencies seen in Figure 14 and its position as a tech hub, given Amazon and Microsoft are headquartered there.

to the negative health impacts of the COVID-19 pandemic, so they may be less likely to use e-grocery delivery services for their safety aspects, at least. Without knowing each individual's full suite of attitudes about technology and the pandemic along with their age, we might expect heterogeneous effects of age on e-grocery service use and adoption. To account for this and other potential heterogeneous effects, random parameters were estimated for <u>all</u> models in the presented analyses after the forward stepwise process was completed. All estimated random parameters were assumed to be normally distributed. Use of this distribution allows for straightforward interpretations of the percentage of the sample where the direction of effect is above or below zero based on the parameter mean and standard deviation. Additionally, this distribution is adopted for many random parameters studies given it generally results in the best model fit compared to other tested distributions (*63–65*, *71*). In all models, a random parameter was considered significant if the z-statistic for the standard deviation indicated significance at a 90% confidence level. With respect to the multinomial logit model, estimating random parameters (i.e., a mixed logit model) additionally addresses issues that might otherwise arise due to violation of independence of irrelevant alternatives (IIA) assumptions (*65*).

All random parameters models are solved using a (simulated) maximum likelihood estimation (MLE) approach. Due to the complexities involved in solving the log-likelihood functions in random parameters frameworks, a best-practice simulation approach with 500 Halton draws is used (*72–75*). All estimated random parameters models were compared to their corresponding fixed parameter models with the following version of the log-likelihood ratio test (*65*):

$$\chi^2 = -2[LL(\beta_{FP}) - LL(\beta_{RP})] \qquad \textit{Eq. 1}$$

where $LL(\beta_{FP})$ and $LL(\beta_{RP})$ are the log-likelihood values at convergence of the fixed parameter and random parameter models, respectively, and χ^2 is a test statistic for comparison with critical values in a chi-square distribution table equal to the number of significant random parameters estimated in each mixed model[7].

3.5.1. Mixed Logit Models of Online Grocery Adoption

A multinomial logit model (MNL) framework was utilized to explore factors related to the adoption of e-grocery delivery. Given potential structural differences in adoption factors across income levels, segmented models were developed for three groups of respondents (low-income, mid-income, and high-income) in order to determine if estimated parameters were transferable across income groups. These income groups are based on the relative income levels described in Section 3.2.1, with the low-income group comprising extremely low-, very low-, and low-income households. As described in Section 3.2.1, e-grocery delivery adoption status was parsed into three groups: non-adopters, pre-pandemic adopters, and during-pandemic adopters.

In the MNL model framework, each respondent *n* is expected to fall into the adoption-status *i* that affords them the highest utility, *U*:

$$U_{in} = \boldsymbol{x}_{in}\beta + \varepsilon_{in} \qquad \textit{Eq. 2}$$

[7] This comparison was conducted for all mixed and fixed-parameter models, but due to their 1) illumination of heterogeneous effects and 2) ability to address violation of the IIA assumption for multinomial logit models, all random parameter models were retained as the final models presented.

where $\boldsymbol{x}$ is a vector of characteristics for respondent *n* for category *i* and β is a vector of estimated parameters (*76*). The probability that respondent *n* will fall into the non-adopter (N), pre-pandemic adopter (B), or during-pandemic adopter (A) categories can be represented as:

$$P_n(i) = \frac{e^{x_{in}\beta_i}}{\sum_{i=N,B,A} e^{x_{in}\beta_i}} \qquad \textit{Eq. 3}$$

Because each respondent is expected to fall into the category that offers the greatest utility, a respondent would be expected to belong to category *i* when

$$Prob(U_{in} > U_{nj}), \text{ where } i, j \text{ are in N,B,A and } i \neq j. \qquad \textit{Eq. 4}$$

In estimating random parameters for the MNL (a mixed logit model), Eq. 3 changes to

$$P_n(i \mid \psi) = \int_x \frac{e^{x_{in}\beta_i}}{\sum_{i=N,B,A} e^{x_{in}\beta_i}} f(\beta|\psi)d\beta \qquad \textit{Eq. 5}$$

where $P_n(i \mid \psi)$ is the weighted probability a respondent *n* will fall into category *i* (here, into N,B, or A), $f(\beta|\psi)$ is the density function of β, and ψ is a vector of parameters associated with the density function (*65*).

Recall that all estimated random parameters were assumed to follow a normal distribution. The simulated log-likelihood function in the mixed logit model is then

$$LL = \sum_{n=1}^{N} \sum_{i=1}^{I} \delta_{in} \ln[P_n(i \mid \psi)] \qquad \textit{Eq. 6}$$

for *n* of *N* total observations and *i* of *I* total outcomes where δ_{in} is one if the outcome for respondent *n* is *i* and zero otherwise (*65*).

To assess if each model was a significant improvement over a constants-only model, a log-likelihood ratio test was performed. In the log-likelihood ratio test,

$$\chi^2 = -2[LL(\beta_0) - LL(\beta_{X_1})] \quad \textit{Eq. 7}$$

where $LL(\beta_0)$ is the log-likelihood of the constants-only model, $LL(\beta_{X_1})$ is the log-likelihood of each mixed-logit model at convergence, and χ^2 is a test statistic for comparison with critical values in a chi-square distribution table with the difference in parameters between the two models as the degrees of freedom. If the observed χ^2 is greater than the expected value of the distribution based on the appropriate degrees of freedom, the null hypothesis that the two models are statistically equivalent can be rejected. These log-likelihood values were also used to estimated McFadden's Pseudo R^2 to assess goodness-of-fit, where

$$McFadden's\ Pseudo\ R^2 = 1 - \frac{LL(\beta_{X_1})}{LL(\beta_0)} \quad \textit{Eq. 8}$$

and values of 0.2-0.4 indicate excellent fit (*77*).

To test if the estimated parameters were transferable across income groups, the following log-likelihood ratio test using the mixed model log-likelihoods at convergence was used (*65*):

$$\chi^2 = -2\left[LL\left(\beta_{X_1X_2}\right) - LL(\beta_{X_1})\right] \quad \textit{Eq. 9}$$

where $LL\left(\beta_{X_1X_2}\right)$ is the convergence log-likelihood for model X_1 using the sample data from model X_2, $LL(\beta_{X_1})$ is the convergence log-likelihood for model X_1, χ^2 is a test statistic for comparison with critical values in a chi-square distribution table with the number of parameters in $\beta_{X_1X_2}$ as the degrees of freedom, and X_1 and X_2 represent the final, random parameters models developed from two separate data segments, either low-income, mid-income, or high-income. This test was completed for each pair of models, resulting in six total tests. Then, the parameters, β, are fixed to their values from X_1, and constant start values are assigned the respective constant values from X_1. This model is estimated using the segment data for model X_2, giving $\beta_{X_1 X_2}$.

In addition to regression coefficients, marginal effects were computed for significant variables. Marginal effects represent the change in the probability of an alternative being chosen for a one-unit increase in continuous variables, and are calculated as:

$$\frac{\partial P_n(i)}{\partial \boldsymbol{x}_{ni}} = \frac{\partial \boldsymbol{x}_{in}\beta}{\partial \boldsymbol{x}_{ni}} P_{ni}(1 - P_{ni}) \qquad \textit{Eq. 10}$$

For indicator variables, marginal effects are estimated as the change in probability from absence to presence of an indicator, *b*:

$$ME_b = Prob[y \mid \bar{x}_{(b)}, b = 1] - Prob[y \mid \bar{x}_{(b)}, b = 0] \qquad \textit{Eq. 11}$$

where $\bar{x}_{(b)}$ represents the mean values of the other variables present in the model, held constant.

3.5.2. Trip generation models

This section describes the modeling approaches for the trip outcomes described in Section 3.2.2. As a reminder, *trips* refer to those taken for in-store and online pickup grocery shopping and those generated for the delivery of online grocery orders. Further, the trip rates reflect one-way journeys from origin to destination points.

Recall that numeric values for trips were determined for four weeks' time and divided by four to obtain a weekly estimate. Because of this, there are fractional measures of trips. These measures are then assumed to be continuous and called weekly trip *rates*, although they are rough measures of trips per week[8]. Such trip rates could not be negative, which influenced the choice of modeling approaches for weekly in-store, online pickup, and online delivery grocery shopping rates.

3.5.2.1 Tobit regression models for in-store grocery shopping

The distribution of weekly in-store grocery shopping trip rates is displayed in Figure 10. Although the data were assumed to be continuous, the non-negative nature of trip-making caused concern in adopting ordinary-least squares (OLS) regression methods[9]. The Tobit model, first proposed by Tobin (*78*), is an attractive alternative as it accounts for censoring at zero; ignoring this for multiple linear regression may produce biased coefficient estimates (*79*) and non-zero predicted values (*80*). Tobit models have been applied in transportation research to analyze, for example, accident frequencies (*60*, *62*, *71*, *81*), vehicle miles traveled (*82*, *83*), activities and travel times (*84*), and trip generation (*85*).

---

[8] Additionally, note the distributions in the following subsections divide households into discrete trip rates for each category. While this is a result, again, of the numeric coding of qualitative trip making categories, the data are assumed to be continuous in this analysis.

[9] Additional implications of assuming a continuous outcome variable with only discrete observations are discussed in the Conclusions section.

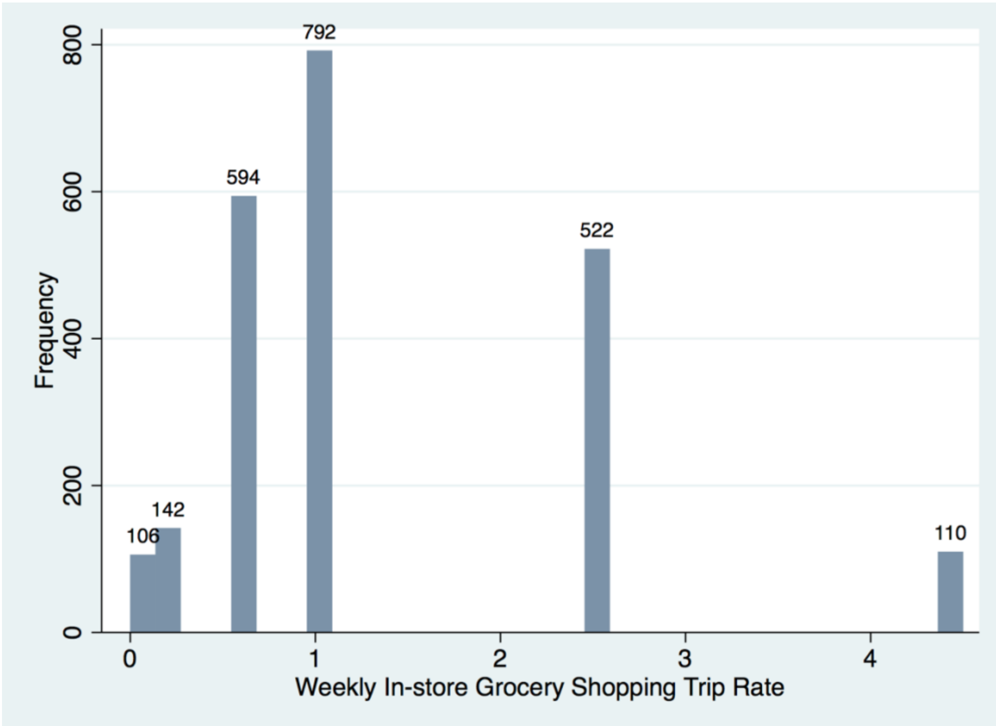

Figure 10 Histogram of weekly in-store grocery shopping trip rates

A key advantage of Tobit regression is its ability to model distributions with large clusters of data at zero, typical of left-censored data. In this example, just under five percent of respondent's households had zero in-store grocery shopping trips in the last four weeks. While this is by no means a substantial cluster of the data at zero, analyses where Tobit regressions have been applied vary in their extent of censoring. In an analysis conducted by Anastasopoulos et al. (*71*) that utilized Tobit regression, 65 of 200 road segments (33%) had no observed accidents. In another example, only 12% of the 1,038 observations used for Tobit regression surrounding accident rates were zero-valued (*62*). Given some flexibility in this, and due to the non-negative nature of the data, a Tobit model was used to estimate weekly in-store grocery shopping trip rates.

The formulation for the Tobit model is focused on an uncensored, latent variable y^*:

$$y^* = \boldsymbol{x}\beta + \varepsilon \qquad \textit{Eq. 12}$$

where **x** is a vector of respondent or household characteristics, β is a vector of estimated parameters, and ε is the associated normally distributed error term (*76*, *80*). The observed and censored *y*, in this case, weekly in-store grocery shopping trip rates, relate to y* through an index function, where

$$\begin{aligned} y &= 0 & y^* &\leq 0 \\ y &= y^* & y^* &> 0 \end{aligned} \qquad \textit{Eq. 13}$$

The value of *y** follows traditional linear regression assumptions, namely that $E[y^*|\boldsymbol{x}] = \boldsymbol{x}\beta$. However, the censored variable *y* is of interest, and its expected value is

$$E[y|\boldsymbol{x}] = \Phi\left(\frac{\boldsymbol{x}\beta}{\sigma}\right)(\boldsymbol{x}\beta + \sigma\lambda) \qquad \textit{Eq. 14}$$

where Φ is the CDF of the standard normal distribution, and λ is the inverse Mills ratio (IMR), defined as

$$\lambda = \frac{\phi[\frac{0-x\beta}{\sigma}]}{1-\Phi[\frac{0-x\beta}{\sigma}]} = \frac{\phi(\frac{x\beta}{\sigma})}{\Phi(\frac{x\beta}{\sigma})} \qquad \textit{Eq. 15}$$

where ϕ is the PDF of the standard normal distribution.

Again, random parameters were estimated to attempt to capture unobserved heterogeneity given the included (and potentially missing) variables relevant to in-person grocery shopping. Random parameters in the Tobit model are estimated as

$$\beta_n = \beta + \psi_n \qquad \textit{Eq. 16}$$

where β_n is a vector of random parameters to be estimated, β is vector of the corresponding parameter means, and ψ_n is a vector of randomly distributed (in this analysis, normally distributed) terms (*71, 76*). In the fixed parameters Tobit model, the log-likelihood function is (*76*):

$$LL = \sum_{y_i>0} -\frac{1}{2}\left[\log(2\pi) + \ln(\sigma^2) + \frac{(y_i - \boldsymbol{x}_i\beta)^2}{\sigma^2}\right] + \sum_{y_{i=0}} \ln\left[1 - \Phi\left(\frac{\boldsymbol{x}_i\beta}{\sigma}\right)\right] \quad \textit{Eq. 17}$$

In the case of random parameters estimation (assuming all parameters are normally distributed), Eq. 17 is rewritten as (*71, 86*)

$$LL = \sum_{\forall n} \ln \int_{\psi_n} \phi(\psi_n) \mathrm{P}(y_n^*|\psi_n) d\psi_n \quad \textit{Eq. 18}$$

where all variables are as previously defined.

As with the mixed logit model a log-likelihood ratio test (Eq. 8) is used to compare the estimated model with a constants-only model. As an additional assessment of model fit, a Maddala Pseudo-R^2 (*87*) value was calculated as follows, given its prevalence in use for Tobit regressions (*81, 88, 89*):

$$R^2_{Maddala} = 1 - e^{\frac{-2[LL(\beta) - LL(0)]}{N}} \quad \textit{Eq. 19}$$

where $LL(\beta)$ is log-likelihood of the best-fit model, $LL(0)$ is the log-likelihood of the constants only model, and N is the number of observations.

The estimated coefficients in the Tobit model express the relationship between the independent variables and y*. This necessitates some reconfiguration to obtain effects of interest on the censored y. Assuming a normally distributed error term and accounting for left censoring at zero, McDonald and Mofitt (*90*) suggest such a configuration where, for a given observation i,

$$\frac{\partial E[y_i|\boldsymbol{x_i}]}{\partial \boldsymbol{x_i}} = \mathrm{Prob}[y_i > 0] \frac{\partial E[y_i\,|\boldsymbol{x}_i, y_i\ > 0]}{\partial \boldsymbol{x}_i} + \quad \textit{Eq. 20}$$

$$E[y_i \,|\boldsymbol{x}_i, y_i > 0]\frac{\partial \text{Prob}[y_i > 0]}{\partial \boldsymbol{x}_i}$$

Here, changes in independent variables influence the conditional mean (i.e., where $y^* > 0$) and the probability that y^* will be non-zero (and positive). Note that, for indicator variables (the majority of those included in analysis), marginal effects are interpreted as the difference in the expected value of *y* when the variable shifts from zero to one.

3.5.2.2. Cragg hurdle regression models for online grocery pickup and delivery trips

The distributions of weekly online grocery pickup and delivery shopping trip rates are displayed in Figure 11 and Figure 12. Both the nature of the data and theoretical considerations influenced the modeling choice for online grocery pickup and delivery trip rates. First, a substantial portion of the sample did not buy groceries online in the last four weeks (75% each for pickup and delivery). While Tobit models are equipped to handle censoring of dependent variables (which was theoretically aligned with in-store grocery shopping, given it is the traditional method), it is less apt for cases where an inflated number of zero values are observed (*91*), as is expected with these newer online provisioning modes. Cragg (*92*) proposed extensions of the Tobit model, often referred to as hurdle models, that estimate the participation in the behavior separately from the observed frequencies. The hurdle model adopted here first estimates the use of e-grocery delivery or pickup with a binary probit participation model. Frequency of use is then estimated with a truncated regression.

3.5.2.2.1. The ordinal probit participation model

Binary outcomes for weekly use of e-grocery pickup and delivery were defined as one if the weekly shopping trip rate was greater than zero, and zero otherwise. The binary probit

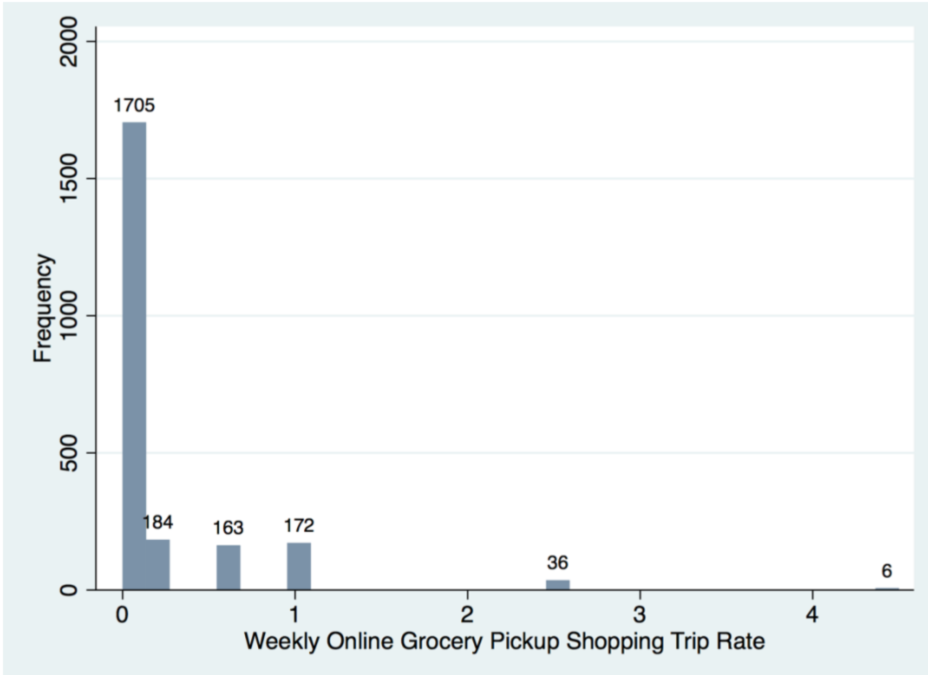

Figure 11 Histogram of weekly online grocery pickup shopping trip rates

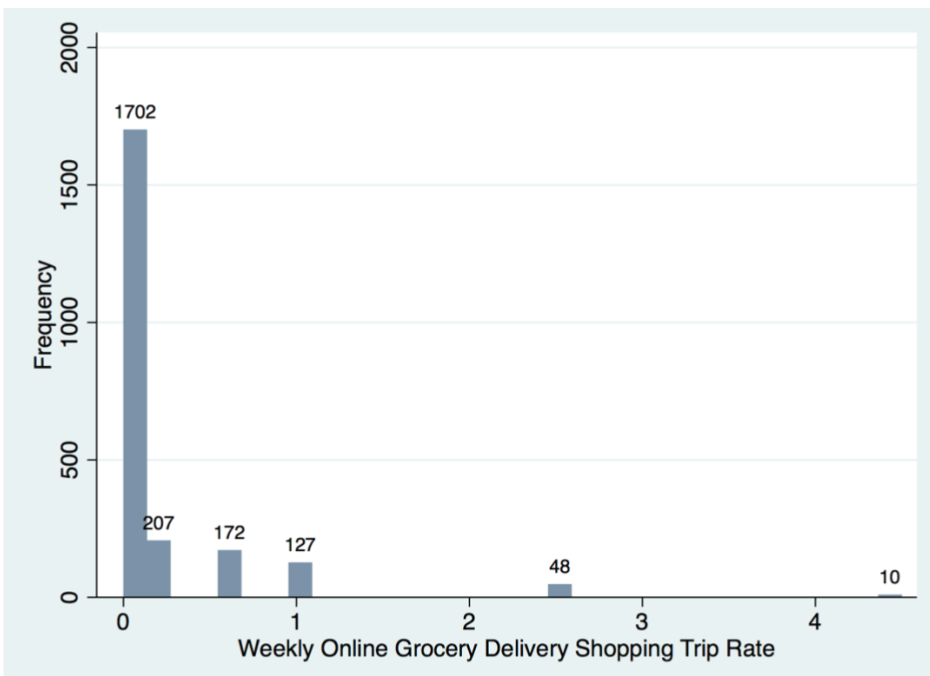

Figure 12 Histogram of weekly online grocery delivery shopping trip rates

participation model stems from random utility relationships presented in Section 3.5.1 for the mixed logit model. The probability of participation (here, in ordering groceries online for pickup or delivery) for a respondent *n* is generally denoted as

$$P_n(1) = \text{Prob}(\boldsymbol{x}_{1n}\beta_1 - \boldsymbol{x}_{0n}\beta_0 > \varepsilon_{0n} - \varepsilon_{1n}). \quad \textit{Eq. 21}$$

In the case of the binary probit, ε_{0n} and ε_{1n} are assumed to be normally distributed and (*76*)

$$P(1\,|\boldsymbol{x}) = \int_{-\infty}^{\boldsymbol{x}'\beta} \phi\,(t)dt = \Phi(\boldsymbol{x}'\beta). \quad \textit{Eq. 22}$$

In the random parameters probit model, the vector of parameter estimates is added to a randomly distributed (here, normally distributed) term as displayed for the random parameters Tobit model in Eq. 16.

3.5.2.2.1. Cragg's hurdle model

In Cragg's (*92*) proposed hurdle model, the binary probit model is then combined with a truncated regression for estimating participation and frequency, respectively, with a density expressed as (*93, 94*):

$$f(y\mid \boldsymbol{x_1},\boldsymbol{x_2}) = [1-\Phi(\boldsymbol{x_1\gamma})]^{1[y=0]}\{\Phi(\boldsymbol{x_1}\gamma)[(\boldsymbol{x_2\beta}/\sigma)]^{-1}[\phi(\{y-\boldsymbol{x_2\beta}\}/\sigma)/\sigma]\}^{1[y>0]} \quad \textit{Eq. 23}$$

where $\boldsymbol{x_1}$ and $\boldsymbol{x_2}$ are vectors of sample characteristics included in the participation and frequency components, respectively, γ and β are their associated coefficient vectors, and all other variables are as previously defined. As Burke (*93*) notes, the probit and truncated regression can be estimated separately. Wooldridge (*80*) provides a detailed discussion of the truncated regression, while Altman et al. (*95*) develop a random parameters truncated regression model, as was done in this analysis. While the participation and frequency models are estimated separately, the unconditional (i.e., for all values of *y*) expected outcome depends on the model specifications of both the participation and frequency models (*93*)

$$E[y \mid \boldsymbol{x_1}, \boldsymbol{x_2}] = \Phi(\boldsymbol{x_1\gamma})\{\boldsymbol{x_2\beta} + \sigma \times \lambda\left(\frac{\boldsymbol{x_2\beta}}{\sigma}\right)\} \qquad \textit{Eq. 24}$$

For a continuous variable *j*, the unconditional marginal effects are then (*93*)

$$\frac{\partial E[y \mid \boldsymbol{x_1}, \boldsymbol{x_2}]}{\partial x_j} = \gamma_j \phi(\boldsymbol{x_1\gamma}) \times \left\{\boldsymbol{x_2\beta} + \sigma \times \lambda\left(\frac{\boldsymbol{x_2\beta}}{\sigma}\right)\right\} + \Phi(\boldsymbol{x_1\gamma}) \times \beta_j[1 - \lambda\left(\frac{\boldsymbol{x_2\beta}}{\sigma}\right)\{\boldsymbol{x_2\beta} + \sigma \times \lambda\left(\frac{\boldsymbol{x_2\beta}}{\sigma}\right)\} \qquad \textit{Eq. 25}$$

Eq. 25 demonstrates the connection between the participation and frequency models. As Burke (*93*) notes, even if x_j belongs only to x_1 or x_2 (but not both), the marginal effect depends on both $x_1\gamma$ and $x_2\beta$. Note that, for indicator variables, the marginal effect is computed based on Eq. 25 as the difference in the expected value of *y* when the variable shifts from zero to one, all other variables held constant at their means.

Both components (participation and frequency) of the final estimated hurdle model were compared constants-only versions using Eq. 8, and McFadden's Psuedo-R^2 (*77*) was calculated using Eq. 9.

3.5.3. Binary logit model for future use

A binary logit model was used to explore the stickiness of e-grocery services. As described in Section 3.2.3, the outcome variable in this model equaled one if a respondent indicated 1) their household was ordering groceries online (delivery or pickup) more often compared to before the pandemic and 2) they expect the proportion of their household's groceries purchased online (for pickup or delivery, compared to in-store) would stay the same or increase a year from the time of survey fielding.

The binary logit is simply a special case of the MNL presented in Section 3.5.1 where the outcome variable is dichotomous. In the case of this analysis and the binary logit model framework, the probability a respondent's household will hold or increase their already elevated proportion of purchasing groceries online is represented as (*76*)

$$Prob(Y = 1 \mid \boldsymbol{x}) = \frac{e^{x\beta}}{1 + e^{x\beta}} \qquad \textit{Eq. 26}$$

In the random parameters binary logit model, Eq 27. becomes Eq. 28 in this special case of Eq. 5, and the simulated log-likelihood function is the same as Eq. 6.

$$P_n(i \mid \psi) = \int_{\boldsymbol{x}} \frac{e^{x\beta}}{1 + e^{x\beta}} f(\beta|\psi) d\beta \qquad \textit{Eq. 27}$$

Again, a log-likelihood ratio test (Eq. 8) to compare the estimated model to the constants-only model was performed, and McFadden's Pseudo-R^2 (Eq. 9) was calculated as an additional assessment of model fit. Marginal effects for continuous and indicator variables were calculated as defined in Eq. 10 and Eq. 11, respectively.

4 Results and Discussion

In 2019, the analytics company Gallup posted an article titled "Online Grocery Shopping Still Rare in U.S." (*96*). Data were presented on U.S. adults' in-store grocery and e-grocery shopping frequencies. The data, collected by Gallup in a survey of consumer habits in July of that year, showed 88% of U.S. adults ordered groceries online for pickup or delivery less than once a month (or never).

In-store and e-grocery shopping frequencies from the survey data for this study were compiled for comparison to the Gallup poll. Recall the survey data used throughout this study are from the second of four waves of surveys associated with a larger project. Data from the first wave of surveys were also organized for comparison with the Gallup poll.[10] The Gallup data are nationally representative. For better parity in the comparison, both waves' respective datasets were weighted by household size, income, and the presence of children in the household at a state level[11].

Figure 13 shows the comparison of in-store the Wave 2 in-store shopping frequencies are higher than those in Wave 1. This may coincide with vaccination rollouts or lifted restrictions across the study areas. In Figure 14, e-grocery delivery and pickup frequencies observed in the survey data sit in contrast to the Gallup poll data. E-grocery use is slightly higher in the Wave 2 cross-section than in Wave 1, even as Wave 2 respondents also exhibited higher in-store shopping rates. Together, the figures suggest

---

[10] The two surveys are cross-sectional and do not represent a panel. The Wave 1 data were cleaned, processed, filtered, and subset in the same way described for Wave 2

[11] This is the only section in this document where data from survey Wave 1 and weighting is used. There are slight differences in how the first and second waves defined e-grocery shopping, given different survey instruments were used across waves. More information about Wave 1 and the survey weighting process is available upon request.

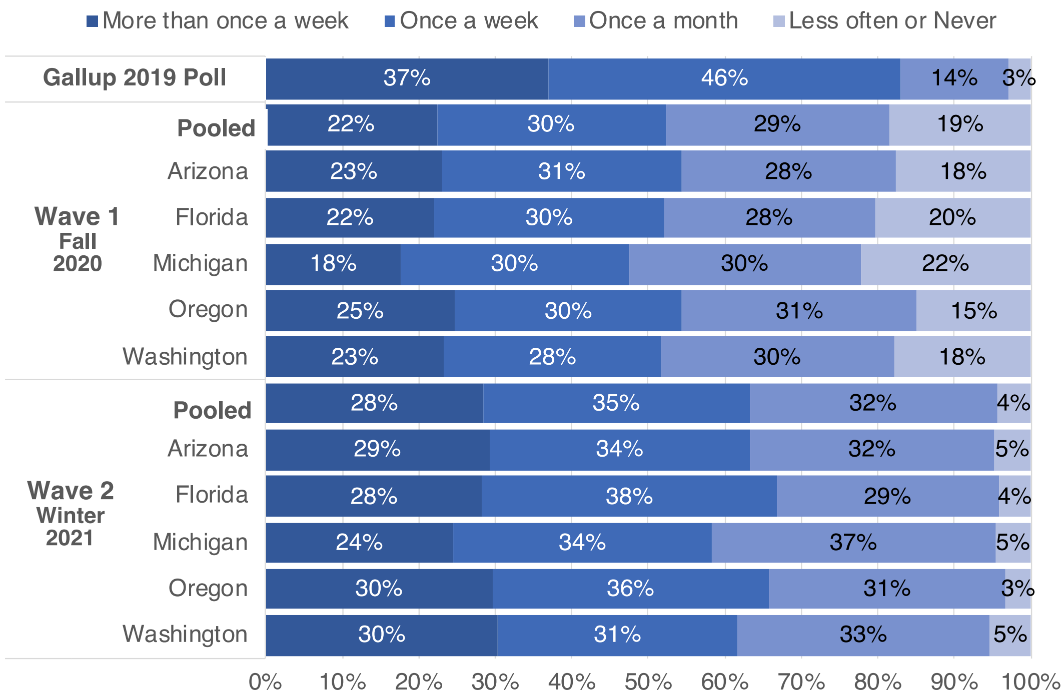

Figure 13 In-store shopping frequency: comparison of Gallup data to survey data

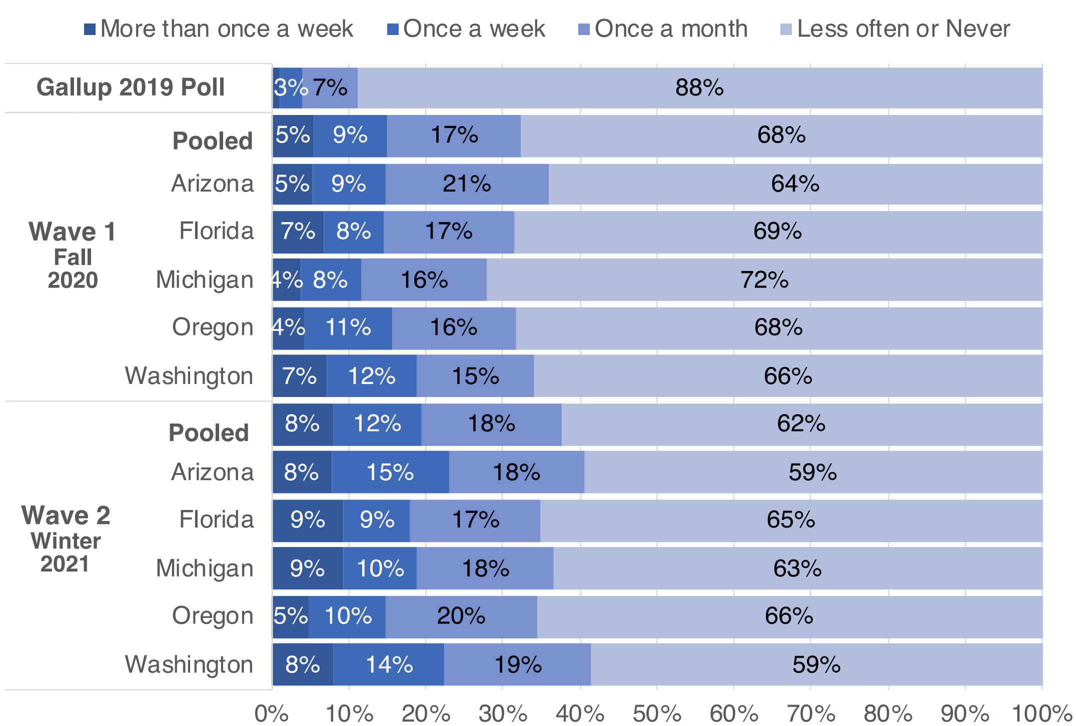

Figure 14 E-grocery delivery or pickup shopping frequency: comparison of Gallup data to survey data[12]

that while consumers may be getting more comfortable with resuming in-store grocery shopping, e-grocery usage rates show no sign of slowing down.

This remainder of this section presents and discusses results of the suite of estimated models. Model results related to e-grocery adoption (for delivery), use, and stickiness are discussed individually in their own subsections. The broader context of the culmination of findings, including implications for policy and transport systems overall, are left for the conclusions section.

4.1 E-grocery delivery adoption

The estimated mixed logit models for low-income, mid-income, and high-income household shoppers' e-grocery delivery adoption are presented in Table 2**,** Table 3, and Table 4, respectively. While aggregate descriptive statistics for tested variables across analyses are presented in Appendix B, Appendix D provides disaggregate descriptive statistics by income level for significant variables for the e-grocery delivery adoption models.

All models were significant improvements over their constants-only models with over 99% confidence based on Eq. 8. Two parameters each were found to be significantly random with normal distributions in the mid-income and high-income models, while four were discovered in the low-income model. From Eq. 1, the mixed logit models were a significant improvement over the fixed-parameter models with 91% confidence for low-

---

[12] Note: "More than once a week" for Gallup poll is 1%. The data only add to 99% likely due to rounding, as percentages from the Gallup article were only given to the ones' place.

income, 99% confidence for mid-income, and 94% confidence for high-income segments, respectively.

First, a formal write-up of model results is presented. Then, graphics highlighting a series of scenario analyses are offered.

Table 2 E-grocery delivery adoption for shoppers from low-income households

	Coef.	Std. Error	z-stat		Marginal effects: Pre-Pandemic Adopter	Marginal effects: During-Pandemic Adopter	Marginal effects: Non-Adopter
Pre-Pandemic Adopter							
Constant	-0.882	0.934	-0.94				
HH income is 'Extremely Low Income'	-1.132	0.333	-3.40	***	-0.026	0.012	0.014
HH located in Arizona	-0.325	0.401	-.81		-0.005	0.002	0.003
HH located in Florida	0.328	0.401	.82		0.006	-0.003	-0.003
HH located in Michigan	-0.162	0.395	-.41		-0.003	0.001	0.002
HH located in Oregon	-0.561	0.423	-1.33		-0.008	0.003	0.005
When grocery shopping, being able to inspect items for quality is not important	0.799	0.428	1.87	*	0.006	-0.003	-0.003
When grocery shopping, not having to carry items is very important	0.591	0.324	1.83	*	0.013	-0.008	-0.006
Knows others who are ordering groceries online	0.869	0.298	2.92	***	0.043	-0.025	-0.018
Thinks it is easy to shop online for groceries	1.588	0.357	4.45	***	0.105	-0.056	-0.050
Disagrees that scheduling grocery delivery is difficult	1.053	0.312	3.38	***	0.033	-0.016	-0.017
During-Pandemic Adopter							
Constant	-1.457	0.932	-1.56				
Age 18-24	1.480	0.492	3.01	***	-0.004	0.020	-0.016
HH income is 'Extremely Low Income'	-0.705	0.323	-2.18	**	0.007	-0.023	0.016
HH's preferred grocery store is not easy to get to from home	1.246	0.489	2.55	**	-0.002	0.007	-0.005
HH located in Arizona	0.217	0.389	.56		-0.002	0.004	-0.003
HH located in Florida	0.738	0.392	1.89	*	-0.007	0.017	-0.009
HH located in Michigan	0.068	0.389	.18		-0.001	0.001	-0.001
HH located in Oregon	-0.525	0.421	-1.25		0.003	-0.008	0.005

HH is purchasing more groceries each shop compared to before the COVID-19 pandemic	0.653	0.242	2.69	***	-0.014	0.034	-0.020
HH dissatisfied with item quality when in-store shopping during the COVID-19 pandemic	1.220	0.463	2.64	***	-0.002	0.008	-0.006
When grocery shopping, not having to carry items is very important	0.707	0.318	2.23	**	-0.009	0.020	-0.010
Knows others who are ordering groceries online	1.224	0.284	4.31	***	-0.035	0.073	-0.038
Thinks it is easy to shop online for groceries	1.465	0.339	4.32	***	-0.051	0.110	-0.058
Disagrees that scheduling grocery delivery is difficult	0.768	0.419	1.83	*	-0.015	0.039	-0.024
Standard deviation of parameter, normally distributed	2.004	0.963	2.08	**			
Non-Adopter							
Age 18-24	1.101	0.518	2.13	**	-0.003	-0.012	0.015
Age 25-34	-0.315	0.308	-1.02	*	0.004	0.004	-0.008
Standard deviation of parameter, normally distributed	1.639	0.761	2.15	**			
Currently employed	-0.442	0.250	-1.77	*	0.008	0.011	-0.019
All members of HH are age 65+	0.756	0.361	2.09	**	-0.006	-0.007	0.013
HH has access to more than one vehicle	0.497	0.268	1.86	*	-0.007	-0.009	0.016
Travels to the grocery store by vehicle only [driver or passenger], no other modes	0.694	0.295	2.35	**	-0.014	-0.022	0.036
Standard deviation of parameter, normally distributed	1.189	0.649	1.83	*			
HH dwelling unit does not require delivery personnel to request access	0.589	0.306	1.93	*	-0.022	-0.029	0.051
Zip code population density (population per square mile, ln transformed)	-0.169	0.086	-1.97	**	0.058	0.076	-0.134
HH has not changed grocery stores in response to the COVID-19 pandemic	0.712	0.282	2.52	**	-0.024	-0.030	0.054
HH has not changed in-store grocery shopping frequency compared to before the start of the COVID-19 pandemic	1.072	0.280	3.83	***	-0.023	-0.027	0.050

Disagrees that HH members are too tired to cook in response to the COVID-19 pandemic	0.534	0.248	2.16	**	-0.009	-0.011	0.019
When grocery shopping, being able to inspect items for quality is very important	0.647	0.247	2.62	***	-0.016	-0.024	0.040
When grocery shopping, minimizing travel to the store is not important	1.249	0.536	2.33	**	-0.003	-0.005	0.008
Standard deviation of parameter, normally distributed	1.804	0.850	2.12	**			
When grocery shopping, not having to pay any delivery fees is very important	0.831	0.264	3.15	***	-0.024	-0.034	0.057
Is uncomfortable with delivery personnel coming to their home	1.850	0.565	3.28	***	-0.004	-0.007	0.011
Model summary							
# of observations	1,059						
Log-likelihood at convergence	-687.44						
Log-likelihood of fixed-parameter model	-691.33						
Log-likelihood constants-only	-930.30						
McFadden's Pseudo-R2	0.26						

HH = Household
*** p < 0.01 ** p < 0.05 * p < 0.1

Table 3 E-grocery delivery adoption for shoppers from mid-income households

	Coef.	Std. Error	z-stat		Marginal effects: Pre-Pandemic Adopter	Marginal effects: During-Pandemic Adopter	Marginal effects: Non-Adopter
Pre-Pandemic Adopter							
Constant	-0.097	1.356	-0.07				
No HH members are age 65+	1.290	0.781	1.65	*	0.049	-0.018	-0.030
HH located in Arizona	-1.852	1.060	-1.75	*	-0.019	0.007	0.012
HH located in Florida	-1.171	1.165	-1.01		-0.010	0.003	0.007
HH located in Michigan	-0.232	0.943	-0.25		-0.002	0.001	0.001
HH located in Oregon	-0.373	0.942	-0.40		-0.004	0.001	0.002
When grocery shopping, minimizing level of effort is very important	0.969	0.689	1.41	*	0.017	-0.006	-0.011
When grocery shopping, not having to carry items is very important	1.762	0.851	2.07	**	0.018	-0.007	-0.011
Is comfortable having a delivery person come to their home	0.319	0.922	0.35	*	0.109	-0.035	-0.075
Standard deviation of parameter, normally distributed	4.308	1.494	2.88	***			
Thinks it is easy to shop online for groceries	2.789	0.956	2.92	***	0.114	-0.047	-0.067
Does not think it is expensive to have groceries delivered	2.240	0.857	2.61	***	0.030	-0.012	-0.018
During-Pandemic Adopter							
Constant	-2.215	1.391	-1.59				
Age 55-64	1.683	0.731	2.30	**	-0.005	0.018	-0.014
Education level is college degree or higher	0.392	0.593	0.66	*	-0.016	0.057	-0.042
Standard deviation of parameter, normally distributed	*2.441*	*1.027*	*2.38*	**			
Is a homemaker	1.544	0.875	1.76	*	-0.003	0.009	-0.005
Is employed and working from home exclusively.	1.469	0.617	2.38	**	-0.006	0.023	-0.016
HH located in Arizona	0.485	0.787	0.62		-0.002	0.008	-0.006
HH located in Florida	1.411	0.884	1.60		-0.004	0.017	-0.013
HH located in Michigan	1.584	0.878	1.80	*	-0.007	0.022	-0.015

HH located in Oregon	1.420	0.850	1.67	*	-0.005	0.017	-0.012
HH member(s) were diagnosed with COVID-19	1.474	0.803	1.84	*	-0.004	0.014	-0.010
HH worried that food would run out before having money to buy more	1.253	0.561	2.23	**	-0.008	0.025	-0.017
Is comfortable having a delivery person come to their home	2.249	0.692	3.25	***	-0.034	0.119	-0.086
Thinks it is easy to shop online for groceries	3.211	0.906	3.54	***	-0.054	0.179	-0.124
Non-Adopter							
Travels to the store by vehicle only [driver or passenger], no other modes	2.166	0.730	2.97	***	-0.061	-0.086	0.147
Vehicles per HH member	1.074	0.551	1.95	*	-0.027	-0.039	0.066
HH has not changed in-store grocery shopping frequency in response to the pandemic	1.393	0.477	2.92	***	-0.022	-0.029	0.051
Is satisfied with in-store safety measures when shopping in-store during the COVID-19 pandemic	1.088	0.501	2.17	**	-0.027	-0.040	0.067
When grocery shopping, getting the best price available is very important	1.334	0.476	2.80	***	-0.030	-0.039	0.069
When grocery shopping, minimizing travel to the store is not important	1.058	0.546	1.94	*	-0.007	-0.011	0.017
Does not know others who are ordering groceries online	1.652	0.661	2.50	**	-0.008	-0.012	0.020
Agrees that scheduling grocery delivery is difficult	1.023	0.542	1.89	*	-0.009	-0.013	0.022
Disagrees that shopping online is environmentally friendly	1.979	0.731	2.71	***	-0.009	-0.012	0.020
Model summary							
# of observations	450						
Log-likelihood at convergence	-275.57						
Log-likelihood of fixed-parameter model	-279.90						
Log-likelihood constants-only	-412.55						
McFadden's Pseudo-R2	0.33						

HH = Household

*** $p < 0.01$ ** $p < 0.05$ * $p < 0.1$

Table 4 E-grocery delivery adoption for shoppers from high-income households

	Coef.	Std. Error	z-stat		Marginal effects Pre-Pandemic Adopter	Marginal effects During-Pandemic Adopter	Marginal effects Non-Adopter
Pre-Pandemic Adopter							
Constant	-1.104	0.735	-1.50				
HH located in Arizona	-0.255	0.445	-0.57		-0.005	0.001	0.004
HH located in Florida	-0.319	0.439	-0.73		-0.007	0.002	0.005
HH located in Michigan	-0.167	0.452	-0.37		-0.003	0.001	0.002
HH located in Oregon	-0.187	0.434	-0.43		-0.004	0.001	0.003
Is comfortable having a delivery person come to their home	1.365	0.375	3.64	***	0.120	-0.034	-0.086
Is not worried about deliveries being stolen, misplaced, or not delivered	0.230	0.355	0.65	*	0.038	-0.010	-0.028
Standard deviation of parameter, normally distributed	1.594	0.778	2.05	**			
When grocery shopping, minimizing level of effort is very important	0.569	0.283	2.01	**	0.021	-0.006	-0.015
When grocery shopping, being able to easily comparison shop is very important	0.692	0.310	2.24	**	0.029	-0.008	-0.022
Knows others who are ordering groceries online	0.965	0.289	3.34	***	0.065	-0.022	-0.043
Thinks it is easy to shop online for groceries	1.164	0.375	3.10	***	0.092	-0.027	-0.065
Disagrees that scheduling grocery delivery is difficult	0.687	0.298	2.31	**	0.027	-0.009	-0.018
Agrees shopping online saves time	0.776	0.334	2.33	**	0.059	-0.018	-0.041
During-Pandemic Adopter							
Constant	-2.748	1.008	-2.73				
Age 18-24	1.322	0.593	2.23	**	-0.002	0.008	-0.005
All members of HH are age 65+	2.045	0.579	3.53	***	-0.006	0.041	-0.035
Vehicles per HH member	0.757	0.478	1.58	*	-0.016	0.055	-0.039

HH dwelling unit has a protected place to leave deliveries (e.g., covered porch, building locker, garage, etc.)	1.276	0.530	2.41	**	-0.032	0.093	-0.061
HH located in Arizona	-0.492	0.529	-0.93		0.002	-0.007	0.005
HH located in Florida	-0.171	0.488	-0.35		0.001	-0.003	0.002
HH located in Michigan	0.109	0.518	0.21		-0.001	0.002	-0.001
HH located in Oregon	0.018	0.509	0.04		0.000	0.000	0.000
HH is shopping at fewer grocery stores in response to the COVID-19 pandemic	1.023	0.393	2.60	***	-0.017	0.049	-0.032
HH is shopping at more grocery stores in response to the COVID-19 pandemic	1.354	0.620	2.18	**	-0.005	0.012	-0.007
HH is placing orders for restaurant delivery more often compared to before the COVID-19 pandemic	1.395	0.373	3.74	***	-0.021	0.048	-0.027
Knows others who are ordering groceries online	1.280	0.364	3.51	***	-0.029	0.071	-0.042
Thinks it is easy to shop online for groceries	-0.339	0.636	-0.53	*	-0.019	0.050	-0.031
Standard deviation of parameter, normally distributed	2.524	0.876	2.88	***			
Disagrees that scheduling grocery delivery is difficult	1.201	0.395	3.04	***	-0.016	0.038	-0.023
Agrees shopping online saves time	0.623	0.361	1.73	*	-0.015	0.036	-0.022
Non-Adopter							
All members of HH are age 65+	1.753	0.471	3.72	***	-0.017	-0.030	0.047
Vehicles per HH member	0.654	0.368	1.78	*	-0.042	-0.033	0.075
Travels to the store by vehicle only [driver or passenger], no other modes	0.979	0.386	2.54	**	-0.063	-0.046	0.109
There are several grocery stores in walking distance from HH dwelling unit	0.542	0.296	1.84	*	-0.010	-0.006	0.016
HH has not changed in-store grocery shopping frequency in response to the pandemic	0.750	0.267	2.81	***	-0.027	-0.017	0.044
Disagrees that HH has less time to shop compared to before the COVID-19 pandemic	0.881	0.254	3.48	***	-0.042	-0.032	0.074
Is satisfied with time spent waiting (e.g., to get in the store, in line at checkout, etc.) when shopping in-store during the COVID-19 pandemic	0.710	0.238	2.98	***	-0.030	-0.023	0.053
When grocery shopping, not having to pay delivery fees is very important	0.836	0.247	3.38	***	-0.036	-0.024	0.059

Model summary	
# of observations	757
Log-likelihood at convergence	-533.90
Log-likelihood of fixed-parameter model	-536.71
Log-likelihood constants-only	-718.85
McFadden's Pseudo-R2	0.26

HH = Household

*** p < 0.01 ** p < 0.05 * p < 0.1

4.1.1 Mixed logit model results

With respect to parameter transferability, the results from Eq. 7 are shown in Table 5. The results indicate the parameters are not separable—and that e-grocery delivery adoption should be modeled separately for the income groups—with over 99% confidence. McFadden Psuedo-R^2 values of 0.26, 0.33, and 0.26 for the low-income, mid-income, and high-income models, respectively, indicate excellent model fit (*77*).

Table 5 Parameter transferability chi-square test statistics and degrees of freedom based on Eq.9

X_1	X_2		
	Low-Income	Mid-Income	High-Income
Low-Income		556.15 (31)	244.92 (35)
Mid-Income	101.50 (37)		129.11 (35)
High-Income	124.90 (36)	298.02 (31)	

Household and respondent demographics, geographics, and dwelling unit characteristics

With respect to age, household shoppers aged 18-24 in low-income households have a 0.020 higher probability of being during-pandemic adopters, but also a 0.015 higher probability of being non-adopters. This same age group in high-income households have a 0.007 higher probability of being during-pandemic adopters. The positive effect with respect to during-pandemic adoption aligns with literature demonstrating higher adoption and use of technologies in younger age cohorts (*26*, *97*). The finding that 18-24 year old shoppers from low-income households have a higher probability of being non-adopters seems multifaceted: younger individuals tend to have lower incomes overall, at least until retirement age (*98*). Combined with low relative household income, the cost barrier to online shopping for groceries may outweigh perceived benefits. Further, this age group had lower risk of serious illness due to COVID-19, and a lower perceived risk of shopping in-store during the pandemic may also influence this finding.

For low-income households, the estimated parameter for shoppers aged 25-34 was found to be significantly random with a normal distribution in estimating non-adoption of e-grocery delivery. A parameter mean of -0.315 and standard deviation of 1.639 suggests 42% of 25-34 year old shoppers from low-income households have a higher probability of being non-adopters, while 58% have a lower probability. Similar to the findings for the 18-24 year-old cohort, this heterogeneity could be explained by younger groups' higher propensity to adopt and use technology combined with their lower relative risks associated from contracting COVID-19. Household-level age profiles generally mimic existing literature associations between age and technology adoption. Shoppers in households where all members are aged 65 or older have higher non-adoption probabilities in the low-income and high-income households. For the mid-income cohort, shoppers in households where no members are 65 or older have a higher probability of being pre-pandemic adopters of e-grocery delivery.

In contrast, shoppers aged 55-64 from mid-income households have a 0.018 higher probability of being during-pandemic adopters, while being in a household where no members are aged 65 or older increases the probability of being a pre-pandemic adopter in the middle-income segment. For the high-income cohort, shoppers in households where all members are aged 65 or older have a 0.041 higher probability of being during-pandemic adopters. While this may seem counterintuitive given the negative trend between age and e-grocery adoption (*26*), e-grocery delivery may have been used as a protective measure for this group during the COVID-19 pandemic given higher vulnerability to the associated health risks. Additionally, technology use and adoption trend positively with higher income levels (*26*, *37*).

In line with this is the finding related to extremely low-income households. While the middle- and high-income cohorts are homogenous in their relative income levels, the low-income group includes low, very low, and extremely low-income categories as defined in Section 3.2.1. Shoppers in extremely low-income households have 0.026 and 0.023 lower probabilities of being pre-pandemic and during pandemic-adopters. Currently employed shoppers from low-income households have a 0.019 lower probability of being e-grocery delivery non-adopters. Grocery delivery may be especially beneficial for this cohort given the complex time constraints faced by low-income households (*99*), particularly if they are engaged in essential work that cannot be performed remotely.

Shoppers from mid-income households who are employed but exclusively working from home, or who are homemakers, have 0.023 and 0.009 higher probabilities of being during-pandemic adopters, respectively. Grocery delivery may be attractive to these groups as they may typically be home during the day and have more flexibility regarding grocery delivery windows. The estimated parameter for responding shoppers from mid-income households with a college degree or high education was determined to be a significant random parameter, normally distributed, with a mean of 0.392 and a standard deviation of 2.441. This implies the effect of having a college education or higher on during-pandemic adoption probability is positive for 56% of this cohort and negative for 44%.

Existing literature does present some mixed results regarding education level and technology adoption, including e-grocery shopping. For example, Abu-Shanab (*28*) finds education level to significantly moderate technology adoption related to internet banking, where higher-education individuals had greater propensities to use it. Droogenbroeck and Hove (*26*) find higher-education individuals to also be more likely to adopt an e-grocery pickup service. In contrast, Hui and Wan (*100*) find education level to be insignificant in a discriminant analysis of propensity to use online grocery services, as do Frank and Peschel (*47*) in a model of e-grocery adoption. In an older review, Zmud (*101*) finds more highly educated individuals are less likely to utilize management information systems. Additional information on education as related to the employment sector of the individual may help further parse out this result, especially given the heterogeneity of employment sectors of mid-income households (*102*). Loss of income in previously well-paying jobs in this population may influence during-pandemic adoption status, although an indicator for a decrease in household income due to the pandemic was not found to be significant individually or interacted with education level.

Model results indicate car use, reliance, and access to be key determinants of e-grocery delivery adoption status across income levels. A one-unit increase in the ratio of vehicles per household member is associated with 0.066 and 0.075 higher probabilities of being non-adopters for shoppers in mid-income and high-income households, respectively. Shoppers in mid-income and high-income households who typically travel to the store by vehicle-only (no other modes) have 0.147 and 0.109 high probabilities of being non-adopters, respectively—10-15% points higher than multimodal travelers. For shoppers in the low-income cohort, being in a household with access to more than one vehicle is associated with a 0.016 higher probability of being a non-adopter.

A one-unit unit increase in the ratio of vehicles per household member is also associated with 0.055 higher probability of being during-pandemic adopters for shoppers in high-income households. In the low-income model, the estimated parameter for typical grocery store travel mode being vehicle-only was found to be a normally distributed random parameter, with a mean of 0.694 and standard deviation of 1.189. This suggests 72% of vehicle-travel-only shoppers in this cohort have higher probabilities of being non-adopters compared to multimodal travelers, while 28% have lower probabilities.

The heterogeneity in relationships between vehicle ownership and use and e-grocery delivery adoption are in line with literature findings. On one hand, vehicle ownership and use expand mobility for households, enhancing access to food shopping opportunities (*99*, *103*) and perhaps reducing the need for or benefit of an e-grocery delivery service. In contrast, vehicle ownership has been found to positively trend with use of e-commerce (*104*, *105*), although Rotem-Mindali and Weltevreden (*16*) note a complementary relationship between trip making and grocery shopping is plausible.

A related discussion concerns store access. Shoppers from high-income households who indicated they had several grocery stores within walking distance from home have a 0.016 higher probability of being a non-adopter. When stores are easy to access, the utility of e-grocery delivery services would be expected to decrease. On the other hand, respondents in low-income households whose preferred grocery store is not easy to get to from home have a 0.007 higher probability of adopting e-grocery delivery during the pandemic. Here, e-grocery delivery would be expected to fill a gap in access to food; during-pandemic significance may relate to increased time constraints essential workers in lower-income employment sectors face (*106*). Population density of the home-location zip code trended negatively with being a non-adopter in this income cohort as well, with each percent increase in population density being associated with 0.134 lower probability of non-adoption. While areas with higher population densities might be thought to have easier access to grocery stores by virtue of having more of them, these areas may also have the most e-grocery delivery service availability along with shorter travel times and potentially tighter delivery schedule estimates.

Various characteristics of shoppers' household dwelling units were found to be significant across the models, albeit in different contexts. Responding shoppers in low-income households whose dwelling unit does not require delivery personnel to request access have a 0.051 higher probability of being a non-adopter. Further, shoppers in this income cohort who are uncomfortable with delivery personnel coming to their house have a 0.011 higher probability of non-adoption. In mid-income shoppers, respondents who *are* comfortable having delivery personnel come to their home have 0.119 higher probabilities of during-pandemic adoption. Similarly, shoppers in high-income households who are comfortable having delivery personnel come to their home have a 0.120 higher probability of having adopted e-grocery delivery before the onset of the pandemic. Also in the high-income model, shoppers whose dwelling units have a protected place to leave deliveries have a 0.093 higher probability of being during-pandemic adopters.

The estimated parameter for household shoppers being comfortable with delivery personnel coming to their home was found to be random and normally distributed in the mid-income model for pre-pandemic adoption with a mean of 0.319 and a standard deviation of 4.308. This indicates 53% of these individuals have a higher probability of being pre-pandemic adopters, while 47% have a lower probability. Although variables directly related to the pandemic were not tested for pre-pandemic adoption significance, responses in this case could reflect apprehension about delivery personnel currently coming to home due to the COVID-19 pandemic.

In the high-income model, the estimated parameter for shoppers not being worried about deliveries being stolen, misplaced, or not delivered was found to be random and normally distributed for pre-pandemic adoption with a mean of 0.230 and a standard deviation of 1.594. This suggests that 56% of shoppers who are not worried about stolen or misplaced deliveries are more likely to have adopted e-grocery delivery before the start of the pandemic, while 44% are less likely. The positive effect might be attributed to the level of comfort in receiving deliveries in general due to lack of theft concerns. In contrast, the negative effect might be accounted for by shoppers in households who don’t typically order items for delivery, and who are subsequently not worried about package theft in general.

Overall, the trends related to shoppers’ household dwelling units indicate that confidence in delivery security significantly pulls mid- and high-income households to adopt e-grocery delivery, but lack of security doesn’t necessarily influence non-adoption. Conversely, for responding shoppers in low-income households, lack of security (indicated by dwelling units not requiring delivery personnel to request access) is a push factor away from adoption, but having security is not a significant determinant of adoption, indicating other factors may be more important adoption drivers for this population.

Household home state was included across the models as controls for COVID-19 policies and differences in built environments across states. Washington state was excluded, making it an independent reference group for interpretation effects. Low-income shoppers in Florida have a 0.017 higher probability of adopting e-grocery delivery during the pandemic. At the beginning of survey fielding, Florida did not have a statewide mask mandate, ban on gatherings, or stay-at-home order in effect (Washington had all three) (*107–109*). Additionally, data from the New York Times demonstrate Florida counties had an average of about 1,690 new cases per 100,000 population in the four weeks prior to survey fielding, while Washington counties had an average of about 804 new cases per 100,000 population (*110*). Given the lack of protections in place and higher case rates, those concerned about contracting COVID-19 at grocery stores in Florida may have, in turn, adopted e-grocery delivery. The state indicator for Florida was interacted with an indicator for households where all members were 65 and older to try and further parse out this effect, but the interaction was not significant.

Mid-income shoppers located in Oregon and Michigan have 0.022 and 0.017 higher probabilities of adopting e-grocery delivery during the pandemic compared to Washington. Both states had lower cumulative and during-fielding COVID-19 cases averaged across counties per 100,000 population, and Oregon had a stay-at-home order, mask mandate, and ban on gatherings in place. Further investigation into county-level policies or e-grocery delivery accessibility across states may help explain these effects.

COVID-19 related indicators

The influence of the pandemic on the probability of non-adoption and during-pandemic adoption is reflected across the models, differentiating these adoption levels from pre-pandemic adoption. In the low-income model, shoppers whose households are purchasing more groceries each time they shop have a 0.034 higher probability of being during-pandemic adopters. Making purchases in this manner may have enabled shoppers and their households to utilize e-grocery services while minimizing additional costs. By purchasing more groceries with each shop, fewer overall orders would be required, reducing paid delivery costs. Further, e-grocery apps may offer free delivery after a certain level of expenditure.

Shoppers from low-income households who are dissatisfied with in-store grocery item quality have a 0.008 higher probability of being in-pandemic adopters. In contrast, those who were satisfied with safety measures taken by their grocery stores when shopping in-person from mid-income households have 0.067 higher probabilities of being non-adopters. Both results indicate the role (dis)satisfaction with in-store shopping has in pushing or pulling individuals toward e-grocery services in the context of the COVID-19 pandemic.

Middle-income shoppers in households where at least one member (including the respondent) was diagnosed with COVID-19 have a 0.014 higher probability of being during-pandemic adopters. This may be because e-grocery delivery was used as a provisioning strategy during quarantine periods. It is important to note, however, that time of adoption during the pandemic relative to contracting COVID-19 was not distinguished. This complicates the interpretation here and could explain the lack of significance of a COVID-19 diagnosis on adoption status for low- and high-income households.

Shoppers in high-income households who are shopping at fewer grocery stores in response to the pandemic have a 0.049 higher probability of being a during-pandemic adopter. Curiously, shoppers in this income cohort whose households are shopping at more grocery stores in response to the pandemic have a 0.012 higher probability of during-pandemic adoption. Shoppers in low-income households who have not changed grocery stores in response to the pandemic and who have not changed in-store grocery shopping frequencies have 0.054 and 0.050 higher probabilities of being non-adopters, respectively. Similarly, shoppers from mid-income and high-income households whose in-store shopping frequencies did not change in response to the pandemic have 0.051 and 0.044 higher probabilities of being non-adopters, respectively. Further, low-income shoppers who disagreed that their household members were too tired to cook in response to the COVID-19 pandemic have 0.019 higher probabilities of being non-adopters. This combination of results might simply indicate that pandemic-related behavioral changes in general, regardless of the change, have a domino effect on other behavioral changes like e-grocery adoption. Lack of behavioral change related to grocery provisioning, too, seems to trend positively with non-adoption.

Shoppers in high-income households who are placing orders for restaurant delivery (online or otherwise) more often compared to before the start of the pandemic have a 0.048 higher probability of being during-pandemic adopters. Higher-income households may have more resources to spend on convenience food shopping—including restaurant takeout and e-grocery delivery—which may explain the positive association here. Shoppers in this income cohort who do not feel their households have less time to shop compared to before the pandemic have 0.074 higher probabilities of being non-adopters. Those shoppers who were satisfied with time spent waiting at grocery stores when shopping in-person have a 0.053 higher probability of being a non-adopter. While higher-income households may be more willing to incur costs to save time spent traveling (*111*), the trend in reverse seems to be at play here. Namely, shoppers from high-income households who have *not* experienced time burdens associated with traditional grocery shopping modes are more likely to be non-adopters of e-grocery delivery, perhaps because time savings is less important in these cases.

Respondent attitudes

Shopper attitudes hold explanatory power for e-grocery delivery adoption status throughout the models and highlight some of the variance across both income groups and adoption levels. A few key attitudinal indicators were shared by income cohorts. Shoppers who know others who shop for groceries online have higher probabilities of during-pandemic and pre-pandemic adoption. In the low-income model, these individuals have 0.043 and 0.073 higher probabilities of being pre-pandemic and during pandemic adopters, respectively. In the high-income model, these shoppers have 0.065 and 0.071 higher probabilities of being pre-pandemic and during pandemic adopters, respectively. Shoppers from mid-income households who indicated they did *not* know other people ordering groceries online have a 0.020 higher probability of being a non-adopter of e-grocery delivery. This suite of results is consistent with the literature surrounding online grocery shopping and technology adoption in general: Frank and Peschel (*47*) find perceived social norms to be a strong predictor of e-grocery adoption even after controlling for demographics, while Singh and Rosengren (*52*) note that positive word-of-mouth about a particular online retailer is a significant pull factor driving switching between online grocery retailers.

Shoppers in low-income households who indicated not having to carry items is very important when grocery shopping have 0.020 and 0.013 higher probabilities of being during-pandemic and pre-pandemic adopters, respectively. In the mid-income cohort, these shoppers have a 0.018 higher probability of being pre-pandemic adopters. The direction of effect with respect to this attitude is intuitive, as having groceries delivered certainly reduces the amount of carrying one must do. Interactions of this attitude with indicators for respondents (or household members) having a limited mobility condition, traveling to the store by non-auto modes only or being part of zero-car households, and not being able to easily get to the grocery store from home were tested, but not found to be significant. This attitude may capture these factors, and others, in a complex manner that could be examined further in future work.

Ease of shopping online positively affected pre-pandemic and during-pandemic adoption probabilities across income cohorts, with higher effect sizes in low- and mid-income cohorts. For the low-income model, shoppers who think it is easy to shop for groceries online have 0.105 and 0.110 higher probabilities of being a pre-pandemic or during pandemic adopter, respectively. Shoppers with this attitude from mid-income households have 0.114 and 0.179 higher probabilities of pre-pandemic and during pandemic adoption, respectively. Those shoppers from high-income households have a 0.092 higher probability of being a pre-pandemic adopter. The estimated parameter for perceived ease of online shopping was found to be random and normally distributed with respect to during-pandemic adoption for respondents from high-income households. With a parameter mean of -0.339 and a standard deviation of 2.524, 45% of shoppers from high-income households who think it is easy to shop online for groceries have a higher probability of adopting e-grocery delivery during the pandemic, while 55% have a lower probability. While the positive effect is expected, the negative effect may occur if other factors that would deter one from ordering groceries online (cost, availability of items, service, etc.) may lead to individuals being less likely to adopt e-grocery delivery even if they think it is easy to do so.

Shoppers from high-income households who disagree that scheduling e-grocery delivery is difficult have 0.027 and 0.038 higher probabilities of being pre-pandemic and during pandemic adopters, respectively. In low-income households, shoppers who disagree that scheduling grocery delivery is difficult have a 0.033 higher probability of being pre-pandemic adopters. With respect to during-pandemic adoption, this effect of this attitude in low-income household shoppers exhibited heterogeneity. The estimated during-pandemic parameter for low-income shoppers who disagree scheduling e-grocery delivery is difficult was random and normally distributed with a mean of 0.786 and a standard deviation of 2.004. This reveals 65% of shoppers from low-income households with this attitude have a higher probability of during-pandemic adoption, while 35% have a lower probability. On the other hand, shoppers who *agreed* scheduling e-grocery delivery is difficult in mid-income households have a 0.022 higher probability of being a non-adopter.

Overall, the attitudes related to ordering ease and scheduling difficulty factors signal ease as a key determinant of adoption, regardless of income. Existing literature supports this for online grocery shopping acceptance (*52*, *112*). While effect sizes were highest with respect to mid-income household consumers and perceived ease of ordering groceries online, both ease of online ordering and perceived (lack of) difficulty in scheduling grocery delivery were strong determinants of adoption in low-income households. Heterogeneity, and in particular the negative effects of the two random parameters on during-pandemic adoption, initially seem counterintuitive. These may be observed because other factors, including cost, ease of in-store shopping because of car ownership, or lack of concern of contracting COVID-19 while shopping in-store have stronger push effects away from adoption for some individuals.

The importance of inspecting items for quality when grocery shopping was a significant determinant of adoption status for respondents in low-income households. Those shoppers who note being able to inspect items for quality is very important when grocery shopping have a 0.040 higher probability of being a non-adopter. Low-income shoppers who say being able to inspect items for quality when grocery shopping is not at all important have a 0.006 higher probability of being a pre-pandemic adopter. These effects align with expectations and existing literature. Using interviews of 28 low-income primary shoppers in New York, Webber et al. (*113*) found that product quality was a major factor of importance for low-income households in their food shopping. Participants noted inspecting items for quality was important to gauge how fresh the food was, and subsequently how long it was going to last—they expressed dismay at making purchases of items only to arrive home and realize items were past expiration dates or otherwise spoiled.

Cost-related factors are present across the models. Shoppers who indicated not having to pay any delivery fees was very important in both high- and low-income households have 0.059 and 0.057 higher probabilities of being non-adopters. High-income shoppers for whom comparison shopping is very important have a 0.029 higher probability of being pre-pandemic adopters. For mid-income shoppers, those who do not think having groceries delivered is expensive have a 0.030 higher probability of being pre-pandemic adopters, while those who say getting the best price on groceries is very important have a 0.069 higher probability of being non-adopters.

Price, and associated factors, seem to obviously attract or detract individuals from adopting e-grocery delivery regardless of income. This is dependent on how costs are perceived, which may differ by income groups. Based on results, high-income consumers may see e-grocery services as valuable for comparison shopping if they believe online venues provide additional places to price-compare along with retail stores. Mid-income consumers, in contrast, may believe the best prices on items are found in-store, pushing those who think getting the best price is important away from e-grocery.

For shoppers who indicated minimizing travel to the grocery store is not very important, those who were from mid-income households have a 0.017 higher probability of being a non-adopter. The estimated parameter for this attitude in the low-income model with respect to non-adoption was random and normally distributed with a mean of 1.249 and standard deviation of 1.804. This suggests the attitude has a positive effect on the probability of non-adoption for 76% of low-income shoppers, and a negative effect for 24%. The positive effect, for both low- and mid-income shoppers, is intuitive: if travel reduction is not a primary concern, the travel reduction provided by e-grocery delivery may not be a strong incentive for adoption. The negative effect in the low-income cohort may reflect a mismatch between transportation reliability and viability of e-grocery delivery use. Because low-income populations may exhibit lower rates of car ownership and heavier reliance on transit or walking (*114–116*), minimizing travel to the store may be very important. However, barriers associated with e-grocery delivery for this population, which could include cost, may prevent adoption despite the benefits it would provide.

Shoppers who indicated minimizing level of effort when grocery shopping have 0.017 and 0.021 higher probabilities of being pre-pandemic adopters in the mid-income and high-income households. For shoppers with this attitude, e-grocery delivery may have a higher utility than in-store shopping due to lower overall effort required to complete this daily task (e.g., planning transportation to and from the store, shopping time, carrying groceries, etc.). Additionally, high-income shoppers who agree shopping online saves time have 0.059 and 0.036 higher probabilities of being pre-pandemic and during-pandemic adopters, respectively.

Mid-income shoppers who disagree that shopping online is environmentally friendly have a 0.020 higher probability of being a non-adopter. More in-depth analysis into consumer opinions about e-grocery delivery and environmental benefits or detriments would be useful to better understand how attitudes about the environment inform this shopping mode. If consumers think getting items delivered is environmentally harmful (based on packaging, emissions, etc.) and that belief extends to e-grocery shopping, this may act as a deterrent from adoption. It is important to note there is some nuance involved with environmental impacts of e-grocery delivery. If groceries are delivered to a household by car, the emissions of that trip are the same as household driving to purchase groceries at the store, differences in vehicle efficiency and routing aside. If groceries can be delivered by non-automobile modes—by e-cargo delivery bikes, for example—or if demand and timing are such that grocery deliveries can be made to multiple households in a neighborhood within a single trip, the carbon-intensity of e-grocery delivery may dip below that for a traditional in-store shopping, at least with respect to the trip.

Mid-income shoppers who indicated their households were worried that food would run out before having money to purchase more have a 0.03 higher probability of adopting e-grocery delivery during the pandemic. Pandemic 'hoarding' combined with inflated prices for essential items may have spurred such worries, driving mid-income households to look to alternate online venues for groceries. While it is curious that no similar indicators of food insecurity presented themselves in the low-income model, or in prediction of non-adoption across models, existing literature and reporting offer insights.

In a study COVID-19 impacts on low- and mid-income households in Bangladesh, Ruszczyk et al. (*117*) note that interviews with middle-income households reveal they, in some cases, may suffer during the pandemic due to decreases in income while still earning too much to qualify for federal support. Despite expansions of aid during the COVID-19 pandemic, some middle-income households may find themselves in similar situations—eloquently highlighted in a New York Times article titled "Just Because I have a Car Doesn't Mean I have Enough Money to Buy Food" (*118*). A Tufts article notes that middle-income households may be experiencing food insecurity for the first time during the pandemic, and subsequently may not have experience shopping with SNAP or WIC benefits (*119*). A report by the Food Research and Action Center notes that households earning $50,000-$74,999 who sometimes or often did not have enough food to eat increased from 3% to 8% between 2018 and the pandemic; for households earning $35,000-$49,999, the share experiencing food insecurity increased from 5% to 12% (*120*, *121*). That being said, the lowest-earning households still experienced sharp increases in food insecurity, with the share of those earning $25,000-$34,999 increasing from 8% to 16%, and for those earning less than $25,000, from 11% to 28%.

4.1.2. Simulated scenarios

A series of scenarios exploring mixed logit model results were developed using NLogit 5's scenario simulations (*70*). The simulated scenarios represent the changes in group assignment according to the model for fixed changes in the data. The disaggregate income models classify individuals in the data into e-grocery delivery adoption groups as shown in Figure 15:

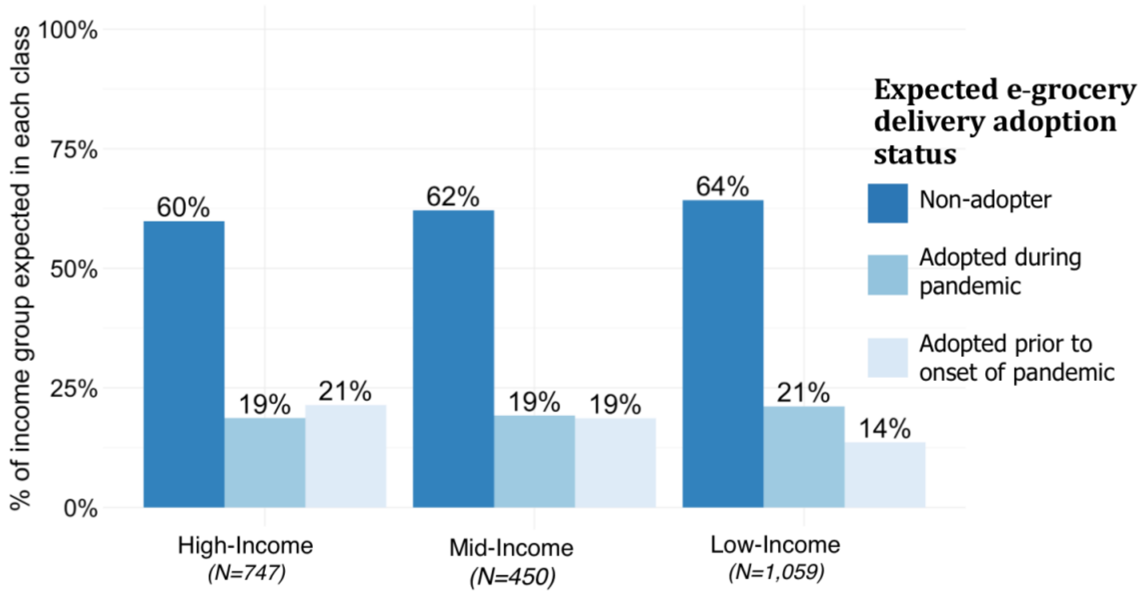

Figure 15 Expected e-grocery delivery adoption classifications based on disaggregate models

The scenario analysis examines how the baseline group distributions for each income group would change based on a series of "what if" hypotheticals about the data (e.g., they could answer, "What share of shoppers would the model assign in non-adoption, during-pandemic adoption, and pre-pandemic adoption groups if all shoppers had more than one vehicle? What is the difference between these assignments and baseline assignments based on the observed data?"). Note that this analysis is purely exploratory, as the model results are being applied to the same data used to generate them. However, such an analysis visualizes how distributions in e-grocery delivery adoption would be expected to change given hypothetical scenarios.

4.1.2.1 Delivery fees in low- and high-income segments

Scenario 1 (S1): What if <u>not having to pay delivery fees is very important</u> across <u>low-income</u> and <u>high-income</u> observations? Scenario 1A (S1A): What if <u>not having to pay delivery fees is very important</u> and shoppers are from <u>extremely low-income</u> households?

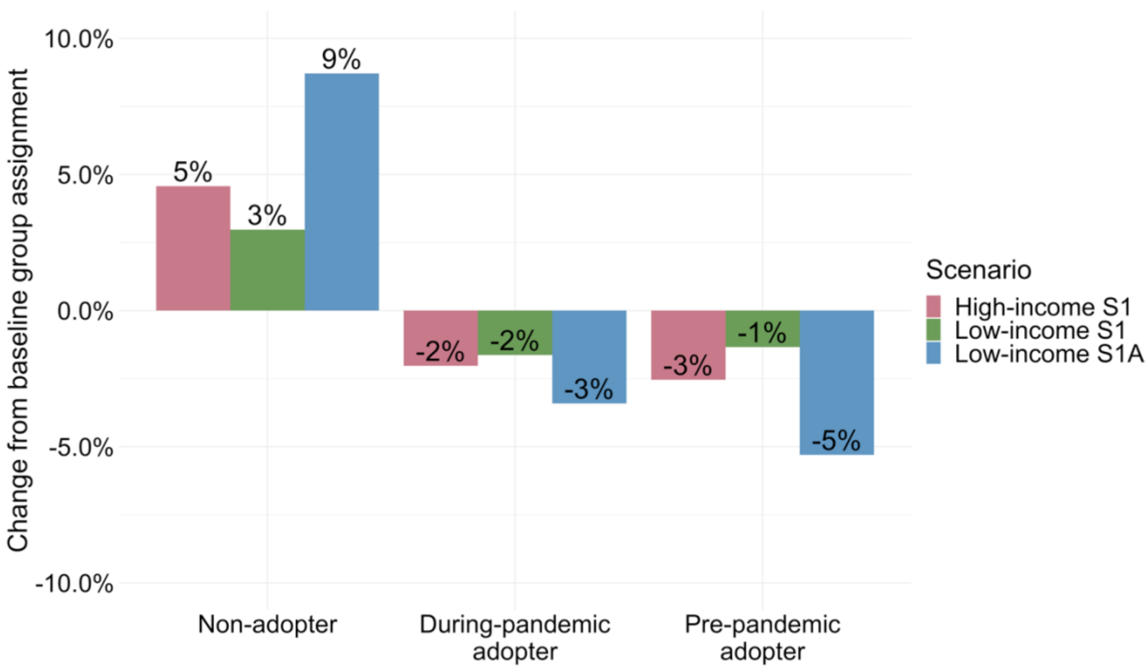

Figure 16 Low- and High-income household delivery fees scenarios

Figure 16 visualizes the scenarios. If all shoppers in the low-income and high-income cohorts indicated not having to pay delivery fees is very important, the share of non-adopters would be higher than model baseline expectations in the high-income cohort than the low-income one. However, if low-income individuals share this attitude and are also from extremely low-income households, the expected change in share of non-adopters is 9%-points greater, compared to just a 5%-points greater in high-income households. This suggests that while not wanting to pay delivery fees is associated with higher probabilities of non-adoption in both high- and low-income cohorts, the attitude combined with extreme financial constraints suggests an even greater expected share of non-adopters more than the individual attitude does alone.

4.1.2.2 Transportation related scenarios

Scenario 2A (S2A): What if all low-income shoppers are from <u>extremely low-income</u> households, do <u>not have more than one vehicle</u>, and their <u>preferred grocery store is not easy to get to from home</u>?

Scenario 2B (S2B): What if all shoppers in <u>low-income</u> households are from households that do <u>not have more than one vehicle</u>, and their <u>preferred grocery store is not easy to get to from home</u>?

Scenario 2 (S2): What if all shoppers in <u>mid- and high-income</u> households usually travel to the store by <u>vehicle only</u> (no other mode) and have <u>one vehicle for each member</u> of the household?

Two different scenarios are explored for low-income households, while the same scenario is applied to mid- and high-income households given the common transport-related variables between their associated models. In Figure 17, the simulated decrease in the share of non-adoption observations when all households are the most financially constrained (S2A) is half that when incomes are left at their sample values. This, again, suggests households with the most constrained incomes may face the greatest cost barriers in adopting e-grocery services compared to other low-income households.

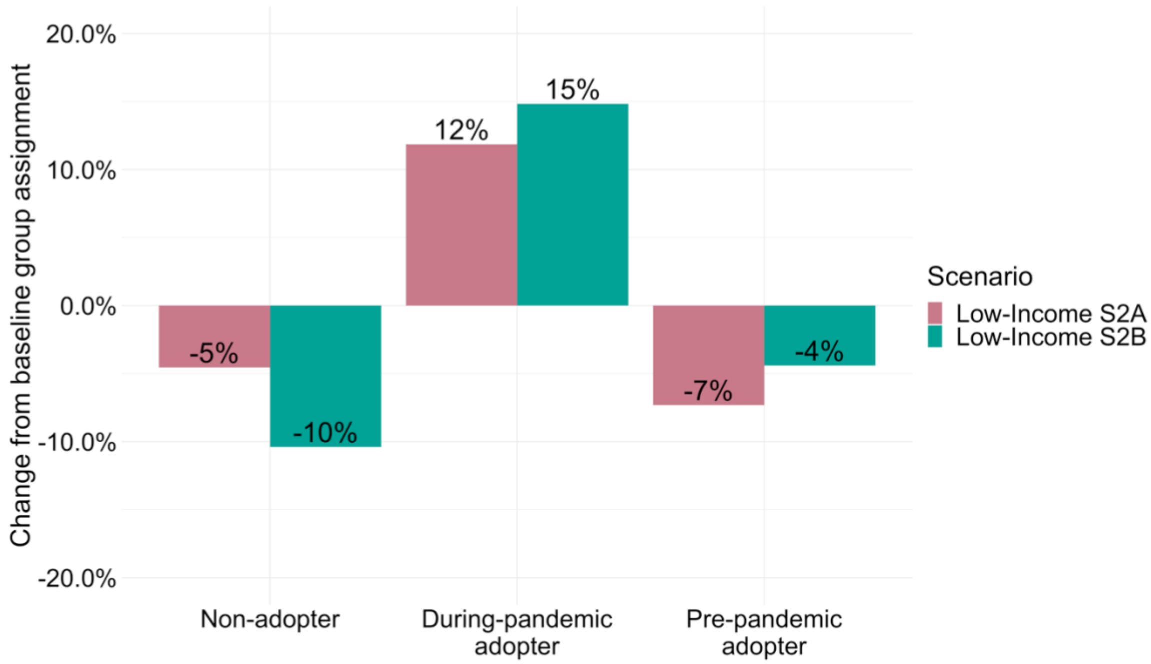

Figure 17 Low-income household transportation scenarios

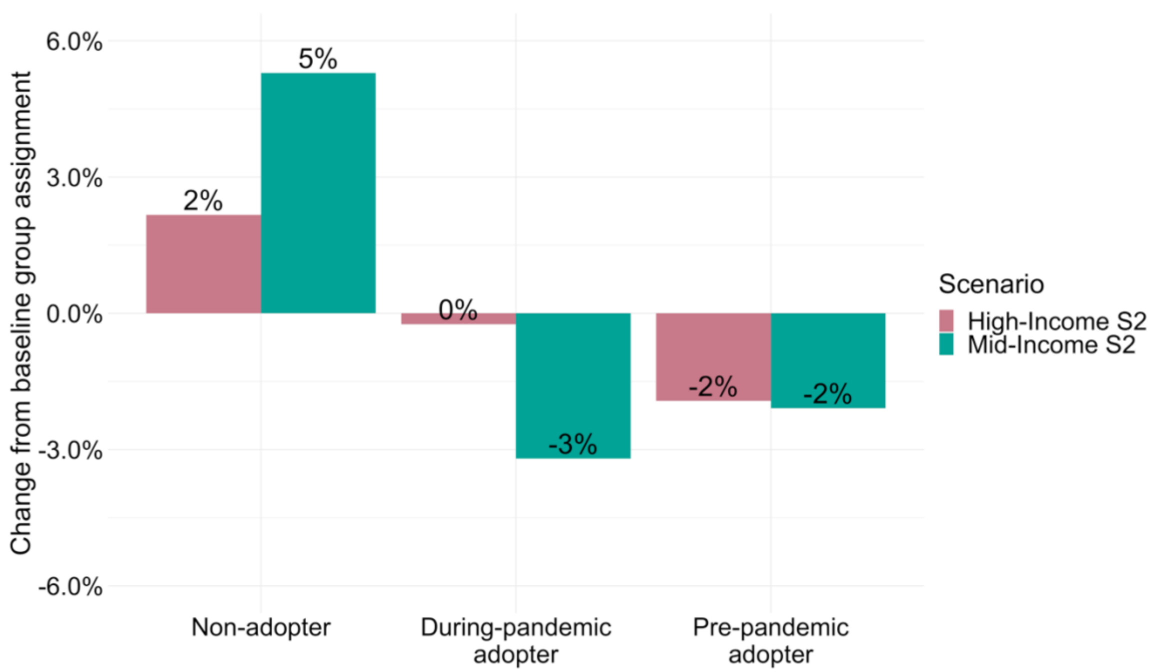

Figure 18 Mid- and High-income household transportation scenario

Figure 18 shows the simulated change in non-adoption when all mid-income households 1) have one vehicle for every household member and 2) typically travel to the store by vehicle only is higher than for that when these conditions apply to high-income households. Given higher income households are usually expected to have higher usage rates of e-commerce in general (*26*, *37*), they may be more inclined to adopt e-grocery delivery services for perceived benefits, even if they have sufficient auto access and typically drive to the store.

4.1.2.3 COVID-19 related scenarios

Scenario 3A (S3A): What if all shoppers in <u>low-income</u> households indicate their households are <u>purchasing more groceries each time they shop</u> and are <u>dissatisfied with item quality</u> when shopping in-store during the pandemic?
Scenario 3B (S3B): What if all shoppers in <u>mid-income</u> households are currently employed and <u>working exclusively remotely</u>, and at least one person in their households was <u>diagnosed with COVID-19?</u>
Scenario 3C (S3C): What if all shoppers in <u>high-income households</u> are shopping at <u>fewer grocery stores</u> and <u>placing orders for restaurant delivery more often</u> during the pandemic?

Given the different significant COVID-19-related effects across income models, a unique scenario was applied to each income group, although they are plotted together in Figure 19. COVID-19 diagnosis only appeared to be significant in predicting e-grocery during-pandemic adoption in the mid-income cohort, which sees the highest simulated increase in during-pandemic adoption across scenarios.

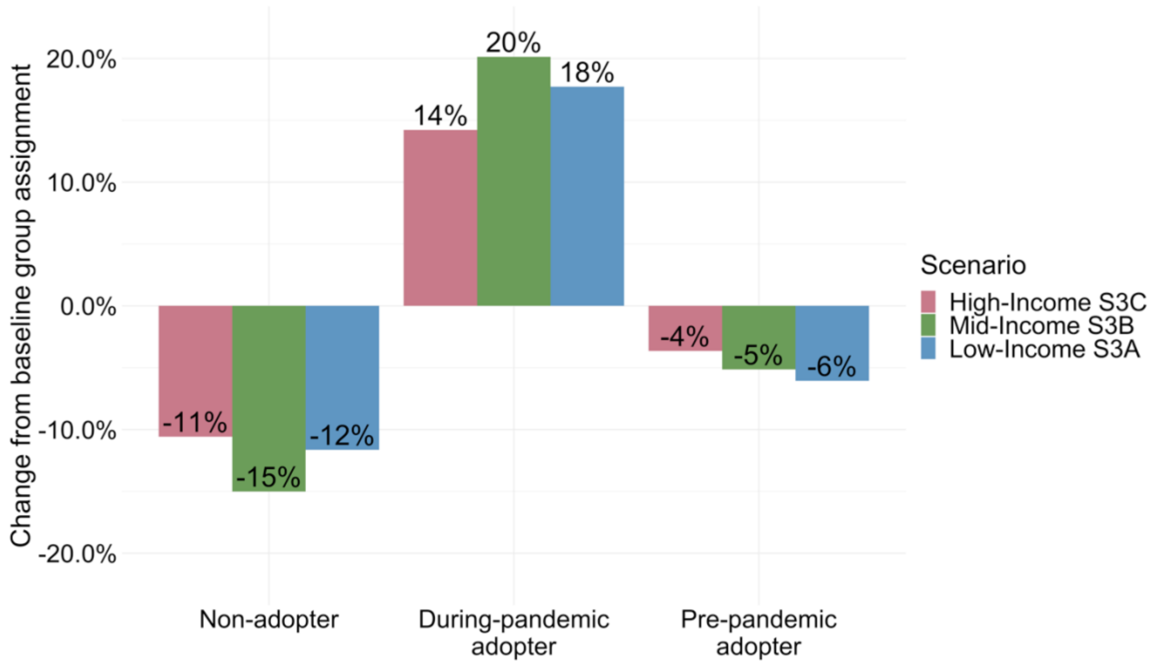

Figure 19 COVID-19 related scenarios

4.1.2.4 Ease of use and social norms

Scenario 4 (S4): What if all shoppers from <u>all households</u> indicated they think <u>it is easy to shop online for groceries</u>? Scenario 4A (S4A): What if all <u>low-income</u> and <u>high-income</u> household shoppers indicated they think <u>it is easy to shop online for groceries</u>, and they <u>know others who are ordering groceries online</u>?

Ease of use was a common significant explanatory variable across income models, while an indicator of social norm influence (knowing others who order groceries online) was significant in the low- and high-income models. Figure 20 demonstrates upward shifts in expected observation shares in both pre-pandemic and during-pandemic adoption categories. When combined with attitudes regarding social norms in the low- and high-income cohorts, these shifts are more dramatic.

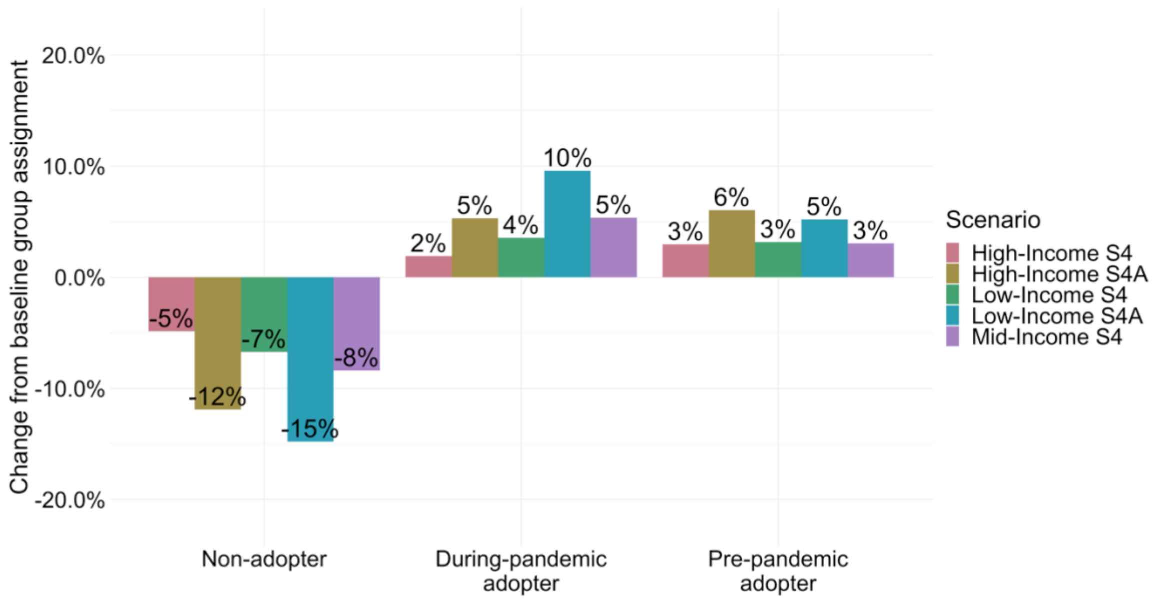

Figure 20 Ease of use and social norm scenarios

4.2 Exploratory analysis of shopping events

In this section, exploratory results from three models are presented, one each estimating weekly grocery in-store, online pickup, and online delivery shopping trip rates. Of key importance to these models was the direction of effect on weekly trip rates of other provisioning frequencies. In addition to grocery provisioning, weekly restaurant provisioning frequencies were tested as explanatory variables, as it was hypothesized there may be trade-offs or synergies between provisioning for food at restaurants and grocery stores. These relationships are summarized in Table 6 and discussed in this section. Major implications are saved for the conclusions section. A formal write-up of other model results can be found in Appendix E: Extended results of trip rate models.

Table 6 Summary of effect directions of other provisioning modes on weekly in-store, online pickup, and online delivery grocery trip rates

Explanatory variables (weekly grocery or restaurant trip rates)	Outcome variables in separate models (weekly grocery trip rates)		
	Grocery in-store	Grocery online pickup	Grocery online delivery
Grocery in-store		+ / -	
Grocery online pickup	+ / -		+
Grocery online delivery	+ / -	+	
Restaurant dine-in	+ / -	*n.s.*	
Restaurant drive-thru	+ / -	-	
Restaurant online pickup	*n.s.*	+ / -	
Restaurant online delivery	*n.s.*	*n.s.*	+

n.s. = not significant, and not included in final model specification
\+ / - indicates a heterogeneous effect due to the parameter being significantly random with normal distribution

4.2.1. Household weekly in-store grocery trip rates

Results from the Tobit regression of weekly in-store grocery trip rates are displayed in Table 7. A log-likelihood ratio test demonstrates significant improvement of the final model over the constants-only model, χ^2(df=22)=460.93, $p < 0.01$, and the fixed parameters model, χ^2(df=9)=83.42, $p < 0.01$, with over 99% confidence. All marginal effects represent the change in weekly in-story grocery trip rates, on average.

Table 7 Final Random Parameters Tobit model specification for weekly in-store grocery trip rates

	Coef.	Std. Error	z-stat	Marg. Eff.	
Constant	0.547	0.087	6.29		***
Other provisioning frequencies					
Weekly online pickup frequency	0.103	0.042	2.46	0.097	**
Standard deviation of parameter, normally distributed	0.239	0.035	6.89		***
Weekly online delivery frequency	-0.266	0.039	-6.81	-0.251	***
Standard deviation of parameter, normally distributed	0.227	0.032	7.17		***
Weekly restaurant dine-in frequency	0.113	0.030	3.83	0.107	***
Standard deviation of parameter, normally distributed	0.123	0.024	5.07		***

Weekly restaurant drive-thru frequency	0.182	0.022	8.40	0.171	***
Standard deviation of parameter, normally distributed	0.119	0.016	7.36		***
Household and respondent demographics, geographies					
HH size	0.104	0.015	6.79	0.098	***
Standard deviation of parameter, normally distributed	0.103	0.006	16.08		***
HH has access to more than one vehicle	0.078	0.041	1.93	0.073	*
Standard deviation of parameter, normally distributed	0.269	0.025	10.65		***
HH received SNAP assistance	0.172	0.056	3.08	0.162	***
Standard deviation of parameter, normally distributed	0.649	0.046	14.20		***
HH's preferred grocery stores are easy to get to from home	0.209	0.066	3.15	0.197	***
There are no grocery stores in walking distance of household dwelling unit	-0.113	0.037	-3.08	-0.106	***
HH located in Arizona	-0.054	0.058	-0.93	-0.051	
HH located in Florida	0.026	0.054	0.48	0.024	
HH located in Michigan	-0.109	0.058	-1.89	-0.102	*
HH located in Oregon	0.049	0.057	0.87	0.046	
COVID-19 Related Variables					
At least one member of HH had received at least one dose of COVID-19 vaccine	0.111	0.052	2.15	0.105	**
At least one HH member experienced a temporary layoff, furlough, or permanent job-loss during the pandemic	0.110	0.040	2.75	0.104	***
Standard deviation of parameter, normally distributed	0.374	0.031	12.15		***
HH is shopping at fewer grocery stores in response to the COVID-19 pandemic	-0.182	0.037	-4.91	-0.172	***
HH has less time to shop since before the start of the COVID-19 pandemic	-0.109	0.063	-1.74	-0.103	*
Respondent attitudes					
Enjoys shopping for food	0.204	0.039	5.30	0.192	***
Likes to shop at a variety of grocery stores	0.118	0.038	3.11	0.111	***
When grocery shopping, minimizing time spent shopping is very important	-0.197	0.040	-4.88	-0.185	***
When grocery shopping, minimizing travel to the store is very important	-0.111	0.042	-2.66	-0.104	***
When grocery shopping, being able to inspect items for quality is very important	0.250	0.039	6.38	0.235	***
Standard deviation of parameter, normally distributed	0.352	0.021	16.75		***
Model summary					
Sigma	0.825	0.012	71.56		***
# of observations	2,266				
Log-likelihood at convergence	-3168.29				
Log-likelihood of fixed-parameter model	-3210.00				

Log-likelihood constants-only	-3398.76
Maddala Pseudo-R^2	0.18
*** $p < 0.01$ ** $p < 0.05$ * $p < 0.1$	

4.2.2. Household weekly online grocery pickup trip rates

Results from the hurdle regression of weekly online pickup grocery trip rates are displayed in Table 8. Log-likelihood ratio tests for the participation, $\chi^2(df=24)=693.17$, and frequency, $\chi^2(df=13)=151.80$, $p < 0.01$, models demonstrate a superior fit over the constants-only models with over 99% confidence. Additionally, Eq. 1 shows the frequency model is a significant improvement in terms of fit from the fixed-parameter version with over 99% confidence, $\chi^2(df=3)=25.61$. McFadden's Pseudo-R^2 values for the model components approach or exceed 0.2, suggesting good to excellent fit (*77*).

Table 8 Final random parameters hurdle model specification for weekly online grocery pickup trip rates

	Participation model (binary probit)		Structural model (truncated regression)		Marg. Eff.
	Coef. (Std. Error)	z-stat	Coef. (Std. Error)	z-stat	
Constant	-2.67 (0.251)	-10.64	0.128 (0.139)	0.92	
Other provisioning frequencies					
Weekly online grocery delivery frequency			0.348*** (0.048)	7.31	0.046
Weekly restaurant drive-thru frequency			-0.116** (0.048)	-2.40	-0.015
Weekly in-store grocery shopping frequency			0.171*** (0.040)	4.29	0.023
Standard deviation of parameter, normally distributed			0.230*** (0.021)	10.87	
Weekly restaurant online-pickup frequency			0.164*** (0.052)	3.17	0.022
Standard deviation of parameter, normally distributed			0.219*** (0.031)	6.98	
Household and respondent demographics, geographies					
R is age 25-34	0.173* (0.091)	1.900			0.025
Standard deviation of parameter, normally distributed	0.608*** (0.085)	7.150			
R identifies as male	0.158* (0.081)	1.950			0.023

R is unemployed and not looking for work	-0.459*** (0.171)	-2.680			-0.061
At least one HH member experienced a temporary layoff, furlough, or permanent job-loss during the pandemic			-0.262*** (0.087)	-2.99	-0.034
HH has children (<18 years old)	0.408*** (0.079)	5.150			0.062
Standard deviation of parameter, normally distributed	0.357*** (0.066)	5.370			
Zero-car HH	-0.523*** (0.127)	-4.120			-0.068
HH has internet access at home	0.558** (0.231)	2.420			0.071
HH located in Arizona	0.108 (0.112)	0.960	0.010 (0.121)	0.08	0.017
HH located in Florida	0.074 (0.112)	0.660	-0.091 (0.128)	-0.71	-0.002
HH located in Michigan	0.063 (0.112)	0.560	-0.019 (0.122)	-0.16	0.006
HH located in Oregon	-0.220* (0.121)	-1.820	-0.117 (0.136)	-0.86	-0.044
Standard deviation of parameter, normally distributed	0.333*** (0.087)	3.840			
COVID-19 Related Variables					
At least one member of HH was diagnosed with COVID-19	0.200* (0.108)	1.850			0.030
HH is shopping in-person at the grocery store less often since the start of the pandemic	0.326*** (0.075)	4.370			0.048
HH is shopping at fewer grocery stores in response to the COVID-19 pandemic			0.141* (0.079)	1.79	0.019
R is dissatisfied with available selection of products when shopping in-person			0.239** (0.113)	2.11	0.034
R is dissatisfied with safety measures by the store taken when shopping in-person	0.282** (0.132)	2.140			0.042
HH is ordering restaurant food for delivery more often compared to before the start of the pandemic	0.269*** (0.077)	3.480			0.040
Standard deviation of parameter, normally distributed	0.339*** (0.062)	5.480			
HH is planning ahead before shopping more often compared to before the start of the COVID-19 pandemic	0.128* (0.073)	1.760			0.018
Standard deviation of parameter, normally distributed	0.323*** (0.054)	6.020			
Respondent attitudes					

When grocery shopping, being able to inspect items for quality is very important^	-0.377*** (0.075)	-5.000	-0.217*** (0.082)	-2.64	-0.087
Standard deviation of parameter, normally distributed			0.467*** (0.044)	10.63	
When grocery shopping, minimizing time spent shopping is very important	0.196*** (0.074)	2.670			0.029
When grocery shopping, getting out of the house is very important	0.149* (0.081)	1.840			0.022
Likes to shop at a variety of grocery stores	0.222*** (0.078)	2.840			0.032
Knows others who are ordering groceries online	0.420*** (0.075)	5.600			0.062
Thinks it is easy to shop online for groceries	0.756*** (0.091)	8.280			0.109
Thinks shopping online saves money	0.595*** (0.085)	6.990	0.212*** (0.081)	2.61	0.132
Thinks shopping online saves time	0.214** (0.084)	2.540			0.031
Enjoys shopping for food	-0.199** (0.080)	-2.480			-0.029
Model Summary					
Sigma			0.605*** (0.025)	24.12	
# of observations	2,266		2,266 (561 non-zero observations)		
Log-likelihood at convergence	-921.59		-337.82		
Log-likelihood of fixed-parameter model	-922.99		-350.62		
Log-likelihood constants-only	-1268.17		-413.72		
McFadden's Pseudo-R^2	0.27		0.18		

*** $p < 0.01$ ** $p < 0.05$ * $p < 0.1$

Notes:

^ Marginal effect for probit model alone is -0.092

4.2.3. Household weekly online grocery delivery trip rates

Results from the hurdle regression of weekly online pickup grocery trip rates are displayed in Table 9. Log-likelihood ratio tests for the participation, χ^2(df=30)=831.88, and frequency, χ^2(df=13)=746.31, $p < 0.01$, models demonstrate a superior fit over the constants-only models with over 99% confidence. Additionally, Eq. 1 shows the participation model is a significant improvement in terms of fit from the fixed-parameter version with over 90% confidence, $\chi^2(df=8)=13.55$. McFadden's Pseudo-R^2 values for the model components approach or exceed 0.2, suggesting good to excellent fit (*77*).

Table 9 Final random parameters hurdle model specification for weekly online grocery delivery trip rates

	Participation model (binary probit)		Structural model (truncated regression)		Marg. Eff.
	Coef. (Std. Error)	z-stat	Coef. (Std. Error)	z-stat	
Constant	-2.277 (0.393)	-5.79	-2.711 (1.117)	-2.43	
Other provisioning frequencies					
Weekly online grocery pickup frequency			0.637*** (0.200)	3.18	0.029
Weekly online restaurant delivery frequency			0.748*** (0.170)	4.39	0.035
Household and respondent demographics, geographies					
R is working from home/remotely exclusively	0.343*** (0.118)	2.92			0.035
All members of HH are 65 or older	-0.526*** (0.134)	-3.92			-0.049
HH size			0.192* (0.112)	1.71	0.009
Standard deviation of parameter, normally distributed			0.202*** (0.050)	4.01	
HH has children (<18 years old)	0.362*** (0.110)	3.3			0.036
Standard deviation of parameter, normally distributed	0.609*** (0.088)	6.89			
HH received SNAP assistance	-0.555*** (0.143)	-3.89			-0.050
Standard deviation of parameter, normally distributed	0.493*** (0.123)	4.02			
HH has access to more than one vehicle	-0.495*** (0.104)	-4.75			-0.048
Standard deviation of parameter, normally distributed	1.083*** (0.083)	13.06			
Travels to the store by vehicle only [driver or passenger], no other modes	-0.540*** (0.113)	-4.77			-0.056
Standard deviation of parameter, normally distributed	0.696*** (0.058)	11.95			

HH dwelling unit has a protected place to leave deliveries (e.g., covered porch, building locker, garage, etc.)	0.419*** (0.117)	3.58	0.976** (0.469)	2.08	0.073
HH dwelling unit requires delivery personnel to request access	0.359*** (0.111)	3.23			0.036
Population density of HH zip code (people per square mile, ln transformed)	0.148*** (0.037)	4.02			0.014
HH located in Arizona	-0.159 (0.142)	-1.12	-0.277 (0.423)	-0.65	-0.027
HH located in Florida	0.137 (0.140)	0.98	-0.384 (0.409)	-0.94	-0.004
HH located in Michigan	-0.194 (0.147)	-1.32	-0.070 (0.417)	-0.17	-0.021
HH located in Oregon	-0.235 (0.148)	-1.58	-0.648 (0.484)	-1.34	-0.047
COVID-19 Related Variables					
At least one household member is particularly vulnerable to COVID-19	0.224** (0.095)	2.37			0.022
R is satisfied with safety measures by the store taken when shopping in-person	-0.372*** (0.102)	-3.64			-0.037
HH is shopping at all different grocery stores in response to the COVID-19 pandemic	0.969*** (0.202)	4.79			0.106
HH has not changed in-store grocery shopping frequency since before the start of the COVID-19 pandemic	-0.617*** (0.099)	-6.21			-0.061
HH is going in-store grocery shopping less frequently since before the start of the COVID-19 pandemic			0.682** (0.298)	2.29	0.031
HH is ordering restaurant food for delivery more often since before the start of the COVID-19 pandemic	0.836*** (0.099)	8.4			0.090
HH dining in at restaurants less often since before the start of the COVID-19 pandemic			-0.763*** (0.308)	-2.47	-0.036
Respondent attitudes					
When grocery shopping, being able to inspect items for quality is very important	-0.288*** (0.095)	-3.03			-0.028
When grocery shopping, being able to use coupons is very important	-0.217** (0.096)	-2.27			-0.021

When grocery shopping, minimizing travel to the store is very important	0.341*** (0.097)	3.5			0.034
When grocery shopping, not having to pay any delivery fees is very important	-0.674*** (0.097)	-6.97			-0.069
When grocery shopping, not having to carry items is very important	0.710*** (0.120)	5.93	0.656** (0.308)	2.13	0.115
When grocery shopping, being able to comparison shop is very important	0.240** (0.098)	2.44			0.023
Standard deviation of parameter, normally distributed	0.359*** (0.072)	5.01			
Knows others who are ordering groceries online	0.468*** (0.097)	4.81			0.046
Thinks it is easy to shop online for groceries	1.317*** (0.122)	10.82			0.124
Thinks shopping online saves money	0.236** (0.112)	2.11			0.024
Standard deviation of parameter, normally distributed	1.087*** (0.107)	10.12			
Agrees that scheduling grocery delivery is difficult	-0.307*** (0.101)	-3.03			-0.029
R is comfortable with delivery personnel coming to their home	0.490*** (0.115)	4.25			0.046
Standard deviation of parameter, normally distributed	0.312*** (0.051)	6.12			
R thinks it's important to support local businesses^	-0.715*** (0.146)	-4.9	-0.869** (0.348)	-2.49	-0.135
Standard deviation of parameter, normally distributed	0.689*** (0.054)	12.65			
Model Summary					
Sigma			1.413*** (0.151)	9.38	
# of observations	2,266		2,266 (564 non-zero observations)		
Log-likelihood at convergence	-855.56		-388.07		
Log-likelihood of fixed-parameter model	-862.33		-388.39		
Log-likelihood constants-only	-1271.50		-761.22		
McFadden's Pseudo-R^2	0.33		0.49		
*** p < 0.01 ** p < 0.05 * p < 0.1					
Notes:					
^ Marginal effect for truncated regression model alone is -0.121					

4.2.4. Summary of relationships between provisioning methods

<u>In-store shopping and e-grocery pickup</u>

In the model of weekly in-store grocery trip rates, the estimated parameter for weekly online pickup grocery trip rate has a mean of 0.103 and standard deviation of 0.239, suggesting a positive effect on in-store trip rates for 66% of households, and a negative effect for 33%. In the model of weekly online grocery pickup trip rates, the estimated parameter for weekly in-store grocery trip rates was determined to be random with a normal distribution in the frequency model. The parameter mean and standard deviation are 0.171 and 0.230, which suggests that weekly in-store grocery pickup trip rates have a positive effect on weekly online pickup grocery trip rates for 77% of households, and a negative effect for 23%. Relationships, here, are totally heterogeneous, and further research is required to unpack them. They may be substitutional, complementary, or asymmetric.

<u>In-store shopping and e-grocery delivery</u>

Weekly e-grocery delivery trip rates were found to be random with a normal distribution in the weekly in-store grocery trip rate model. The estimated parameter mean and standard deviation are -0.266 and 0.227, indicating a positive effect on in-store trip rates for 12% of households and a negative effect for 88% of households. Weekly in-store grocery trip rates were not found to be significant in the weekly e-grocery delivery trip rate model. This suggests a one-directional and heterogeneous relationship between in-store grocery and e-grocery delivery shopping, with the majority of households being characterized by a one-way substitution-leaning relationship from e-grocery delivery to in-store grocery.

E-grocery pickup and e-grocery delivery

Weekly online delivery grocery trip rates have a positive effect on weekly e-grocery pickup trip rates; the direction of effect is the same in the reverse relationship. This suggests that households' e-grocery delivery and pickup frequencies have a complementary relationship. This is likely because many attitudes or perceived benefits regarding online shopping overlap in their applicability to e-grocery delivery and pickup.

In-store grocery, e-grocery pickup, and e-grocery delivery and restaurant provisioning

With respect to weekly in-store grocery trip rates, estimated parameters for restaurant dine-in and restaurant drive-thru trip rates were random with normal distributions. The parameter mean for weekly restaurant dine-in trip rates is 0.113 with a standard deviation of 0.123, revealing a positive effect on weekly in-store grocery trip rates for 82% of households, and negative effect for 18%. Weekly restaurant drive-through trip rate has a positive effect on weekly in-store grocery trip rate for 93% of households and a negative effect for 7% of households, given the parameter mean of 0.182 and standard deviation of 0.119.

Weekly restaurant drive-thru trip rates were negatively related to weekly e-grocery pickup trip rates. The estimated parameter for weekly restaurant online pickup trip rates was random with a normal distribution. The parameter mean and standard deviation are 0.164 and 0.219, respectively. This suggests that weekly restaurant online pickup trip rates have a positive effect on weekly online pickup grocery trip rates for 77% of households, and a negative effect for 23%. Weekly online restaurant delivery trip rates had a positive relationship with weekly e-grocery delivery trip rates.

4.3 Stickiness of elevated proportion of grocery shopping done online

Results from the binary logit estimating the stickiness of the proportion of household grocery shopping done online are presented in Table 10**.** Recall the outcome variable here is equal to one if household shoppers indicated their households are 1) ordering groceries online more often compared to before the start of the pandemic and 2) expecting to retain or increase the proportion of their grocery shopping done online (for pickup or delivery) looking one year to the future. A log-likelihood ratio test demonstrates significant improvement of the final model over the constants-only model, χ^2(df=22)=595.43, with over 99% confidence. The random parameters model is a significant improvement over the fixed parameters version, χ^2(df=4)=9.16, with 96% confidence based on Eq. 1.

Table 10 Final random parameters binary logit model of e-grocery "stickiness"

	Coef.	Std. Error	z-stat	Marg. Eff.	
Outcome: =1 if responding household shopper indicated 1) their household is ordering groceries online more often compared to before the start of the pandemic and 2) their household's proportion of groceries purchased online is expected to stay the same or increase in the next year; =0 otherwise (reference)					
Constant	-3.775	0.371	-10.17		
Household and respondent demographics, geographies					
R is employed and working from home exclusively.	0.192	0.118	1.62	0.033	*
All members of HH are 65 or older	-0.284	0.125	-2.27	-0.048	**
HH has children (<18 years old)	0.118	0.113	1.05	0.020	**
Standard deviation of parameter, normally distributed	1.664	0.155	10.74		***
Uses multiple travel modes for going to the store to shop in-person	0.212	0.113	1.88	0.036	*
Instacart is available in respondent zip code	0.766	0.303	2.53	0.130	**
County % population with low access to grocery stores	0.009	0.006	1.42	0.002	*
Standard deviation of parameter, normally distributed	0.030	0.003	9.33		***
HH located in Arizona	0.002	0.144	0.01	0.000	
HH located in Florida	0.036	0.140	0.26	0.006	
HH located in Michigan	-0.176	0.144	-1.23	-0.030	
HH located in Oregon	-0.264	0.153	-1.73	-0.045	*

COVID-19 Related Variables					
HH member(s) were diagnosed with COVID-19	0.230	0.149	1.55	0.039	**
Standard deviation of parameter, normally distributed	1.424	0.217	6.56		***
At least one household member is particularly vulnerable to COVID-19	0.355	0.094	3.79	0.060	***
HH is going in-store grocery shopping less frequently since before the start of the COVID-19 pandemic	0.933	0.096	9.67	0.158	***
Respondent attitudes					
When grocery shopping, being able to inspect items for quality is very important	-0.329	0.093	-3.53	-0.056	***
When grocery shopping, minimizing travel to the store is very important	0.188	0.098	1.91	0.032	*
When grocery shopping, not having to carry items is very important	0.327	0.121	2.7	0.055	***
Is comfortable with delivery personnel coming to their home	0.274	0.115	2.37	0.046	**
Prefers cash when grocery shopping	-0.598	0.141	-4.25	-0.102	***
Knows others who are ordering groceries online	0.494	0.096	5.16	0.084	***
Thinks it is easy to shop online for groceries	0.990	0.120	8.28	0.168	***
Agrees shopping online saves time	0.382	0.113	3.37	0.065	***
Agrees shopping online saves money	0.360	0.114	3.17	0.061	***
Standard deviation of parameter, normally distributed	1.530	0.161	9.52		***
Model summary					
# of observations	2,266				
Log-likelihood at convergence	-979.27				
Log-likelihood of fixed-parameter model	-983.85				
Log-likelihood constants-only	-1276.99				
McFadden's Pseudo-R^2	0.23				
*** p < 0.01 ** p < 0.05 * p < 0.1					

Household and respondent demographics, geographics, and dwelling unit characteristics

Households where all members are 65 or older have a 0.048 lower probability of retaining or increasing their proportion of groceries purchased online. This aligns with general e-commerce (*31*, *37*) and e-grocery (*26*) literature demonstrating an overall negative trend between age and use of these technologies. It is important to note e-grocery services may be particularly advantageous in this population. For example, as driving cessation occurs with aging (*122*), e-grocery delivery services may help older households in this transition their mobility patterns without disrupting fulfillment of food provisioning needs. Because of this, efforts should be made to help understand and overcome barriers older households may face in using e-grocery services[13].

The estimated parameter for households with children was random with a normal distribution. The parameter mean of 0.118 and standard deviation of 1.664 suggest households with children are more likely to retain or increase their proportion of groceries purchased online in 53% of households, while the reverse is true for the remaining 47%. Larger households, particularly those with children, have been linked with more frequent online provisioning habits (*31*). In contrast, traditional in-store shopping trips may be conveniently trip-chained with children's school or extracurricular activities. If households anticipate such activities to resume at regular frequencies next year, the utility of e-grocery services may decline—particularly if other factors, like cost, are a concern.

Households whose responding shopper is currently working exclusively from home have a 0.033 higher probability of retaining or increasing e-grocery shopping proportion. E-grocery services may be especially convenient for remote workers. For example, less constraints on e-grocery delivery windows might exist if a household member will reliably be home to receive an order most of the day. E-grocery pickup orders could be planned around working hours at home and would presumably require less time to pick up than an in-store shopping trip. A recent McKinsey study anticipates some remote work will persist in a post-pandemic era (*123*). Household shopper

[13] To complement collected survey data, focus groups with a variety of populations, including older adults, are currently being designed.

anticipation of continuing remote work, along with the synergies present between remote work and online grocery shopping may be responsible for this positive effect.

Households who typically rely on multiple modes to travel to the grocery store (compared to those who travel by car only) have a 0.036 higher probability of holding or increasing their e-grocery shopping proportion in the future. A number of interaction terms were tested with this variable, including income and car-ownership level, to try and unpack this result, but were not found to be significant. This effect may be a function of transportation or shopping constraints and preferences.

Households may travel to the store using multiple modes due to transportation constraints. Taking a grocery shopping trip via "slow" modes, like walking, biking, or taking transit may involve more hassle taking large grocery orders back home. If households rely more on these modes, perhaps due to low or no vehicle ownership, the e-grocery delivery in particular may be more convenient than in-store shopping. E-grocery pickup may additionally offer time- and travel-savings benefits over in-store shopping, which could be beneficial for households where a single vehicle is shared between multiple household members. Alternatively, some of the diverse set of factors influencing multimodal travel choices (*124*) may be correlated with increased propensity for "multimodal" shopping behavior.

There exists heterogeneity in multimodal travelers (*125*). Some households may rely on "slow" modes and exhibit lower rates of vehicle ownership by choice versus due to constraints. Brown (*126*) shows that these "car-free" households make up the minority of zero-car households and tend to have higher incomes which trends positively with e-commerce in general (*26, 37*). The potential burden of additional costs associated with e-grocery services may present less of a barrier for higher income, multimodal households compared to those that are lower income, creating a disparity in the ability to start or continue utilizing e-grocery services.

Households living in zip codes where Instacart is available have a 0.130 higher probability of retaining or increasing their already-elevated proportion of grocery shopping online. The direction of effect here is intuitive. Given some estimates put Instacart's e-grocery market share at more than 50% (*127*), this variable likely serves as a proxy for overall availability of e-grocery and pickup services within a zip code. The estimated parameter for percentage of a household's county population with low access to grocery stores, defined by the U.S. Department of Agriculture Economic Research Service's Food Environment Atlas as the population living more than a mile from a supermarket in urban areas (*128*), was random with a normal distribution. With a mean of 0.009 and standard deviation of 0.030, the parameter suggests this variable has a positive effect on the probability of retaining or increasing the proportion of grocery shopping done online for 62% of households and negative effect for the remaining 38%. The positive effect may be explained in that households in low-access areas benefit from online grocery delivery in particular to fill an "accessibility gap" to food stores. However, such areas may also have fewer stores that offer e-grocery services, limiting availability. Expansion of online-exclusive retailers or third-party intermediaries between consumers and grocery stores that deliver to these areas may help mitigate this negative effect.

Households located in Oregon have a 0.045 lower probability of retaining or increasing e-grocery their elevated e-grocery shopping proportions compared to those located in Washington. Instacart availability and access to grocery stores are controlled for in the model, but there could be a number of factors contributing to the difference here. The effect could be cost related; Washington has no income taxes, which may leave households with more resources to spend on food shopping that includes additional e-grocery related fees compared to those in Oregon. The difference may also be cultural. With tech giants like Amazon and Microsoft headquartered in Washington, a larger portion of the population may have more favorable views on technology and online ordering that influence the difference. However, households located in other states exhibited no significant differences in their projected same or higher levels of e-grocery shopping proportions.

COVID-19 related indicators

The estimated parameter for households where at least one member was diagnosed with COVID-19 is random and normally distributed with a mean of 0.230 and a standard deviation of 1.424. This indicates a positive effect on the probability of holding or increasing the proportion of grocery shopping online for 56% of households and a negative effect for 44%. The heterogeneity here may be related to the heterogeneity associated with attitudes about COVID-19. For example, those who anticipate a full societal recovery a year from now may be more likely to resort back to traditional provisioning behaviors, while those who have concerns about the lasting impacts of the pandemic may be more likely to continue using e-grocery services as a protective measure. The positive effect may also be attributed to those households where a member had COVID-19 being more reliant on e-grocery services to provision, making these households more familiar and comfortable with the services.

Households where at least one member is particularly vulnerable to COVID-19 have a 0.060 higher probability of holding or increasing e-grocery proportion. Some vulnerable groups, for example those with compromised immune systems, may not be able to get vaccinated and as such, their households may continue to rely on e-grocery services due to potential health concerns surrounding COVID-19 or other diseases.

Finally, households who shopped in-person less often compared to the start of the pandemic have a 0.158 higher probability of holding or increasing e-grocery proportion. In other words, households who shopped in-person less often during the pandemic are almost 16% points more likely to retain or increase their already elevated e-grocery shopping proportions. This demonstrates a strong relationship between changed in-store shopping habits during the pandemic and greater overall "stickiness" of online grocery shopping in the future.

Respondent attitudes

A number of attitudinal variables held significant explanatory power in the model. Households where shoppers say not having to carry items at the grocery store is very important have 0.055 higher probabilities of holding or increasing e-grocery proportion. This direction of effect is as expected. Given both e-grocery delivery and e-grocery pickup limit the amount of grocery carrying one must do, it is likely that shoppers who think not having to carry items is very important have a higher perceived value of e-grocery services.

Households whose shoppers who indicated being able to inspect items for quality is very important when grocery shopping have a 0.056 lower probability of holding or increasing their proportion of online grocery shopping. This is intuitive, given in-store shopping allows consumers to inspect products before purchasing, while e-grocery shopping does not. Additionally, respondents who prefer to pay with cash have a 0.102 lower probability of holding or increasing their proportion of e-grocery shopping. If this latter preference is linked to not being able to access a bank account, increasing access to online payment methods (pre-paid Visas, for example) may help mitigate this potential barrier created by online-only payment options when ordering groceries online.

Households whose shoppers who say minimizing travel to the store is very important have a 0.032 higher probability of holding or increasing e-grocery proportion, while households whose shoppers who are comfortable with delivery personnel coming to their home have a 0.046 higher probability of holding or increasing their online grocery shopping proportion. The latter finding is likely more strongly associated with use of e-grocery delivery versus pickup methods. Households where shoppers know others who are ordering groceries online have a 0.084 higher probability of holding or increasing e-grocery proportion, emphasizing the influence of social norms on behavior, as literature specifically pertaining to e-grocery shopping has demonstrated (*47, 52*).

Households where shoppers think it is easy to shop for groceries online have a 0.168 higher probability of holding or increasing e-grocery proportion. This same trend is seen in the models of weekly online delivery and pickup trip rates. While respondents who agree shopping online saves time have 0.065 higher probabilities of holding or increasing e-grocery proportion, the estimated parameter for respondents who agree online shopping saves money was found to be random and normally distributed. The parameter mean of 0.360 and standard deviation of 1.530 translate to a positive effect of the attitude on the probability of holding or increasing e-grocery proportion for 59% of households and a negative effect for 41%. While the positive effect is intuitive given the perceived benefits of online shopping cost savings based on the attitude, the negative effect may arise because other perceived disadvantages—delivery or pickup windows out of alignment with schedules, unavailability of wanted items, etc.—outweigh the expected cost savings.

4.*3.1 A note on future work with machine learning comparisons*

Given the growing body of work demonstrating the superior predictive power of machine learning methods compared to traditional econometric ones (*129–133*), four machine learning models were developed for comparison with the random parameter binary logit model. Support vector machine (SVM), artificial neural network (ANN), random forest (RF), and decision tree (DT) supervised learning models for classification were developed in Python[14] using Scikit-learn[15], with the exception of the ANN model, which was created a tuned using Keras[16] and TensorFlow[17] with a Scikit-learn wrapper. The same observations used to develop the binary logit (and used throughout this work) was split in a 9:1 training and validation set, stratified by the outcome variable. Input features were reduced to a limited set from the data in Appendix B based on prior model results;

---

[14] Python Software Foundation. Python Language Reference, version 3.7.9. Available at http://www.python.org

[15] Pedregosa, F., G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and É. Duchesnay. Scikit-Learn: Machine Learning in Python. *Journal of Machine Learning Research*, Vol. 12, No. 85, 2011, pp. 2825–2830.

[16] Chollet, F. *Keras*. GitHub, 2015.

[17] Abadi, M., A. Agarwal, P. Barham, E. Brevdo, Z. Chen, C. Citro, G. S. Corrado, A. Davis, J. Dean, M. Devin, S. Ghemawat, I. Goodfellow, A. Harp, G. Irving, M. Isard, Y. Jia, R. Jozefowicz, L. Kaiser, M. Kudlur, J. Levenberg, D. Mane, R. Monga, S. Moore, D. Murray, C. Olah, M. Schuster, J. Shlens, B. Steiner, I. Sutskever, K. Talwar, P. Tucker, V. Vanhoucke, V. Vasudevan, F. Viegas, O. Vinyals, P. Warden, M. Wattenberg, M. Wicke, Y. Yu, and X. Zheng. TensorFlow: Large-Scale Machine Learning on Heterogeneous Distributed Systems.

additionally, while the binary logit was estimated using separate indicator variables for all levels of categorical variables, ordered categorical variables were converted into numeric labels for machine learning model training to reduce redundancy.

A grid search process was employed in hyperparameter tuning with four-fold cross validation. The models were scored on cross-entropy (loss), but additional metrics (accuracy, precision, recall, f1, ROC) were analyzed. Differences between metrics in the training and validation sets were compared to assess overfitting. Based on the suite of metrics examined and low overfitting, the ANN model was selected as the best and carried forward to compare predictive power with the estimated random parameters binary logit model.

The data used as a test set included 423 observations that came from responses to the same survey instrument in Appendix A, collected contemporaneously with those used throughout this analysis, but from a different panel[18]. In terms of accuracy, the random parameters binary logit model actually outperformed the estimated ANN. Alternative (to backpropagation) optimization methods may help boost the predictive power of the ANN, as was demonstrated by Mokhtarimousavi et al. (*131*). Because of this, a full discussion or presentation of results for this comparative analysis is not presented. However, it is mentioned as further development of this work is ongoing.

---

[18] These test set data were from a survey panel from AmeriSpeak's NORC; as previously mentioned, the data throughout this survey were collected via Qualtrics through an internal Qualtrics panel.

5 Conclusions

The culmination of this work demonstrates the importance of both household and demographic influences on adoption and use of e-grocery services. Further, the impacts of the COVID-19 pandemic on these behaviors are not insignificant. In fact, COVID-19 related variables exhibited significance in all the presented analysis. While increasing vaccination rates are starting to suggest a recovery period from the pandemic, the future is still full of uncertainty. Models can help us attempt to forecast future conditions, albeit with many assumptions. The binary logit analysis suggests households that are multimodal, below retirement age, and located in places with high e-grocery service availability are more likely to hold or increase their already elevated e-grocery usage. Households who have at least one member particularly vulnerable to COVID-19 or who reduced their in-store shopping frequency during the pandemic are also more likely to have e-grocery use “stick”.

The presented analyses also flag some potential barriers to adoption and use of e-grocery services. If we are to agree that, at face value, e-grocery services have objective benefits for people and households, then researchers, planners, and policymakers should aim to mitigate these barriers. Concurrently, we must also try and understand the implications of the expansion of e-commerce on travel behavior and transportation systems. The weekly trip rate analyses only emphasized the complexity surrounding the relationships between in-store and online grocery shopping. The remainder of this section first presents some limitations of the presented work, and then synthesizes key themes and proposes plans for future research.

5.1 Limitations

The present data and proposed analysis do have some key limitations. First, the Qualtrics survey panel recruits and invites panelists to take the survey via email, and the survey is only fielded online. Because of this, the sample of respondents may be biased toward those who readily have access to the internet and who are more comfortable navigating the web. Note that the comparison offered in Table 1 supports this (and also indicates an overrepresentation of white respondents). Sample respondents may have more favorable attitudes toward the utility of technology and buying items online, or other bias. As an extension to the project on which this work is based, focus groups are being planned to try and capture attitudes toward and barriers to ordering groceries online for populations that may be more technology averse.

Second, the trip generation models rely on estimated rates that are treated as continuous, although only discrete trips and rates are observed, resulting in some implications for model interpretation. Use of models suited for continuous data on these estimated trip rates may result in biased or inefficient parameter estimates given the discrete distribution. As discussed in Winship and Mare (*134*), some research demonstrates the difference between methods for continuous and discrete variables are minor and offer enhanced flexibility (*135*, *136*), although this is still debated. Interpretation of the magnitude (versus direction) of effect must be taken with caution and as such, the trip generation model results were primarily focused on presenting relationships in terms of the direction of effect instead of the magnitude and direction.

Additionally, while many (but not all—(*37*, *104*, *137*, *138*)) studies evaluating the relationship between online ordering and traditional in-store shopping utilize structural equation modeling (SEM) to address endogeneity and explore indirect relationships (*41*, *105*, *139*, *140*), online and in-store trip rate frequencies are modeled separately here. This decision was made based on the complex nature of the data distributions. As Saphores and Xu (*104*) note, interpreting SEM results is difficult when data distributions are not continuous. Although the trip rate frequency data are being assumed to be continuous, the presence of zeros in the online grocery shopping trip rates necessitated a two-step modeling approach, the first step of which involves a dichotomous participation model. Additionally, the relationships at hand are not recursive in nature (if all shopping modes are expected to influence others), so simultaneous estimation with readily available software and differing distributions among variables presents difficulties. Future work evaluating the relationships at hand utilizing SEM, simultaneous equation frameworks, or instrumental variables would enhance the presented results of the separate models. Additionally, adapting the survey framework to a diary format versus asking about the last four weeks of behavior may allow researchers to ask about numeric trip frequencies directly, reducing error introduced by estimating numeric trips from qualitative categories.

Third, while survey respondents were required to either be the primary shopper in their household, or else share the responsibility with others, perceptions and attitudes captured in the survey are their own. Droogenbroeck and Hove (*26*) illuminate the importance of both household and individual characteristics in online grocery shopping use and adoption. Because the survey captures attitudes and preferences of just one household member, there may exist discrepancies between these attitudes and preferences with household behavior. Such discrepancies could influence results in the weekly grocery trip rates and projection of future online ordering behaviors.

Fourth, the closest spatial resolution of households' home locations captured by the survey was the zip code. This severely limits the ability to characterize the localized built environment of survey respondents, which has strong ties to travel behavior (*141–144*). A similar research effort, perhaps with a more restricted study area, that captured households' home location to the neighborhood level would allow for more exploration of built environment influences on e-grocery adoption and use.

Finally, the missing piece across this analysis is household expenditure levels. Shopping trips, particularly those for food provisioning, are intricately tied together with expenditure levels (*145*). Two households with drastically different incomes and different budgets for food may make the same number of trips to the grocery store, allocating the proportion of their budgets over the same number of shopping events. In another theoretical example, low-income households, for example, may have to purchase less items overall if resources for food are constrained. However, purchases may occur in one trip to the store where the whole food budget is used for a given time frame, or in a series of more frequent trips spending less each trip. Lack of expenditure data may explain why income was not a significant explanatory variable in the presented trip models. A third wave of the survey on which this work was based asks a question about household expenditures on food, which offers a valuable avenue for future work.

5.2 Perceived ease of use and social networks are key determinants of e-grocery adoption, use, and "stickiness"

The attitudinal indicator for household shoppers who thought it was easy to shop for groceries online was a strong, positive predictor of e-grocery delivery adoption, e-grocery delivery and pickup use, and e-grocery stickiness. The indicator for household shoppers who know other people who are ordering groceries online was also a positive predictor of e-grocery delivery adoption and e-grocery delivery and pickup use. The scenarios presented in Section 4.1.2.4 visualize this from an e-grocery delivery adoption standpoint. Given the magnitude of effects of these variables, it seems increasing familiarity with online grocery shopping platforms through social networks may help overcome some barriers to use of e-grocery services. As part of the larger project in which this analysis is part of, focus groups are being designed to better understand how more tech-comfortable household and community members might enable those more tech-averse around them to get online, should perceived benefits of doing so exist.

5.3 COVID-19 contexts

The models show the widespread impacts of the COVID-19 pandemic on the explored outcomes. Changes (or not) in provisioning behavior, job loss, remote work, and satisfaction (or not) with in-store shopping channels, along with COVID-19 diagnoses and vulnerability, held significant explanatory power in the presented models. It is uncertain whether or not the same behaviors would be observed without the pandemic. Future work can continue to explore pre-pandemic, during-pandemic, and, at some point, "post-pandemic" behaviors. Some of the presented analysis might be repeated with the third or fourth waves of cross-sectional surveys on this note; longitudinal studies will also be important in evaluating the pandemic's lasting influence.

5.4 E-grocery and e-commerce transportation system impacts

In tandem with efforts to expand access to e-grocery services should be those to understand how heightened levels of, in the case of food, local e-commerce are impacting our transportation systems. As seen in this analysis, the answer is not clear cut, and further data collection and research are necessary.

Recall that relationships between shopping modes may be substitutional, complementary, or asymmetric (*31*, *53*). Given the complexities involved in both shopping for food, comfort with online shopping modes, and travel behavior, it is not necessarily surprisingly that the effects of other provisioning methods on in-store grocery shopping are not homogenous. The exploratory analysis of trip rates revealed, for example, that weekly in-store grocery trip rates are expected to decrease as weekly online delivery grocery trip rates increase for the majority of households. This suggests a one-directional, substitutional-leaning relationship. However, for a smaller proportion of households, weekly in-store grocery trip rates trend positively as online delivery trip rates increase, suggesting a complementary-leaning relationship in this direction.

Online delivery is differentiated from the other provisioning modes in that it *generates* a trip *to* the household from an external source, while the other modes require a household member to *make* a trip. This trade off may explain why the only negative mean across the estimated provisioning frequency explanatory variables in the in-store trip rate model is for e-grocery delivery. This mode is the only tested provisioning mode where the relationship with in-store shopping leans toward substitutional versus complementary for the majority of households. Additionally, online delivery may be thought of as the provisioning mode offering the least exposure risk to COVID-19, given a courier may leave items at a respondent's doorstep, requiring no in-person contact.

With respect to online ordering, the positive trend association between grocery delivery and pickup may simply indicate that using one online mode increases the rate of use for another, even if for the same goods. Households that have not changed their in-store grocery shopping frequencies or who are shopping in-store for groceries less frequently due to the pandemic are expected to generate higher weekly online grocery delivery trip rates. These variables may hint at a long-term substitutional relationship between in-store grocery shopping and online grocery delivery. Future work that utilizes simultaneous estimation would greatly enhance the results of the exploratory analysis here.

Forming a more robust understanding about the relationship between these trip types and shopping modes may encourage researchers and practitioners to more explicitly consider online-generated freight and pickup trips in regional and development-level transportation planning. Although activity-based models made significant advancements in mapping transportation systems compared to traditional trip-based frameworks (*146–148*), they rely on the premise that transportation is a *derived demand for activities*. While this has been critiqued on the basis that transportation, in some situations, has an intrinsic positive utility (*149–151*), it may also fall short in describing *food* shopping trips. For some, the *activity* of shopping for food in-store—getting out of the house, walking through the aisles—may be a secondary driver for travel to the store. However, the primary driver for these trips is not the activity itself, but the *expenditure*—

households need food, so they must purchase it. Efforts to incorporate expenditure data, given its strong relationship with shopping trips (*145*), is vital[19] Understanding the relationship between these inputs to online provisioning behaviors may help begin to bridge the gap between activity model frameworks and the next frontier in transportation demand modeling.

These gaps extend to development-level estimations of transportation impacts. Trip generation estimation at the development level was historically based on the Institute of Transportation Engineers (ITE)'s handbook and data (*152*). These data and this approach have been criticized for focusing solely on suburban contexts and vehicle trips, and for being insensitive to demographics and socioeconomic contexts—resulting in a slew of new work to try to update the data and methodology associated with transportation impact analyses (*141*, *153–157*). The next generation of updates to this work should more thoroughly dive into freight estimation. In particular, this should expand the existing section on freight trips to consider demands on the curb, including allocation for and potential conflicts between services (e.g., TNCs, service vehicles, delivery trucks).

There may well be a gap between the potential of online ordering methods and their actual performance. For example, online delivery methods have the potential to fill a transportation "gap" to help households without access to reliable transportation obtain food and household items. However, if there are barriers to ordering food for online

[19] Expenditure data are currently being collected in the third wave of surveys associated with this research

delivery, whether they be in the form of excess costs, access to technology, or availability of stores offering such services, online methods are not meeting this potential.

5.5 Barriers and strategies

As seen in the e-grocery delivery adoption models and analysis, both low- and high-income households' shoppers who indicate not having to pay any delivery fees when grocery shopping is very important have higher likelihoods of non-adoption. However, additional costs are more likely a barrier for low-income households.

E-grocery services may be particularly valuable for this population. Low-income households (along with non-white and rural households) tend to have lower levels of access to grocery stores in their neighborhoods (*158–160*). As Clifton (*99*) notes, low-income households face a unique suite of income, mobility, and time constraints compared to their higher-income counterparts. Income is a strong predictor of vehicle ownership (*116*, *161*, *162*), and low-income households exhibit greater reliance on "slower" (than car) modes, like transit and walking (*114–116*). They may also face longer commutes (*163*). Low-income individuals working in low-wage, but essential, sectors during the pandemic may face both physical and mental burdens associated with working in high-stress, high-risk environments (*106*), adding additional constraints to time and effort allotted to performing daily tasks, like grocery shopping.

To this end, subsidies for e-grocery delivery may help to reduce disparities in access to food for low-income households and others for whom e-grocery services may be particularly beneficial, like older households. Figliozzi and Unnikrishnan (*15*) discuss a variety of mechanisms through which such subsidies might occur, like in partnerships with logistics service providers or in collaboration with transit agencies. Considering access to food as social determinant of health, additional partnerships between e-grocery service leaders and healthcare companies may be fruitful. In a recent example, WellCare, a Tampa-based healthcare company, entered a partnership with Shipt to provide free grocery delivery to its Medicare members through 2020 (*164*).

While access to the internet[20] only showed significant explanatory power in the model of weekly e-grocery pickup trip rates, being able to connect to the web from home likely increases the ease of shopping for groceries online. The benefits of expansion of broadband internet access are not, of course, limited to e-grocery ease of use. A Brookings report outlines the social and economic benefits brought by broadband access—as well as the barriers to more widespread expansion, given access is far from universal, even in urban areas (*165*). Offering subsidies, enhancing digital skills, and working to fill current gaps in the broadband network should be key priorities to advance this important "infrastructure".

Finally, those households with shoppers who prefer to pay for groceries in cash had a probability of having their e-grocery behaviors "stick" 10% points lower than those who were neutral about payment type or who did not prefer cash. While interactions between this variable and income or debit card access were not significant, unbanked households likely face barriers to e-commerce in general. Availability of alternative payment methods, which have seen much grown in Latin America, may help to mitigate this barrier (*166*, *167*).

[20] Access to a smartphone and data plan were also tested in the models, but not found to be significant

6 References

1. Google LLC. *Google COVID-19 Community Mobility Reports*.
2. Aday, S., and M. S. Aday. Impact of COVID-19 on the Food Supply Chain. *Food Quality and Safety*, Vol. 4, No. 4, 2020, pp. 167–180. https://doi.org/10.1093/fqsafe/fyaa024.
3. Daly, J. Psychology of Panic Buying and How the Pandemic Has Changed Consumer Behaviour. *ABC News*. https://www.abc.net.au/news/rural/2021-03-16/how-the-covid-19-pandemic-has-changed-consumer-behaviour/13250360. Accessed Mar. 16, 2021.
4. Moore, A. How the Coronavirus Created a Toilet Paper Shortage. NC State College of Natural Resources News, May 19, 2020.
5. Gray, R. S. Agriculture, Transportation, and the COVID-19 Crisis. *Canadian Journal of Agricultural Economics*, Vol. 68, No. 2, 2020, pp. 239–243. https://doi.org/10.1111/cjag.12235.
6. The National Restaurant Association. *COVID-19 Restaurant Impact Survey V: Key Findings*. 2020.
7. *Quarterly Retail E-Commerce Sales: 3rd Quarter 2020*. Publication CB20-171. U.S. Department of Commerce, Washington, D.C., 2020.
8. Redman, R. Online Grocery Sales to Grow 40% in 2020. *Supermarket News*. https://www.supermarketnews.com/online-retail/online-grocery-sales-grow-40-2020. Accessed Mar. 16, 2021.
9. Kats, R. Online Grocery Sales Will Increase by Nearly 53% This Year. *eMarketer Insider Intelligence*. https://www.emarketer.com/content/online-grocery-sales-will-increase-by-nearly-53-this-year. Accessed Mar. 16, 2021.
10. CDC. Running Essential Errands: Grocery Shopping, Take-Out, Banking, and Getting Gas. *Centers for Disease Control and Prevention*. http://www.cdc.gov/coronavirus/2019-ncov/daily-life-coping/essential-goods-services.html. Accessed Mar. 16, 2021.
11. Landry, S. New Ways We're Getting Groceries to People during the COVID-19 Crisis. *About Amazon*. https://www.aboutamazon.com/news/company-news/new-ways-were-getting-groceries-to-people-during-the-covid-19-crisis. Accessed Mar. 13, 2021.
12. Wolfson, J. A., and C. W. Leung. Food Insecurity and COVID-19: Disparities in Early Effects for US Adults. *Nutrients*, Vol. 12, No. 6, 2020, p. 1648. https://doi.org/10.3390/nu12061648.
13. Gundersen, C., M. Hake, A. Dewey, and E. Engelhard. Food Insecurity during COVID-19. *Applied Economic Perspectives and Policy*, Vol. 43, No. 1, 2021, pp. 153–161. https://doi.org/10.1002/aepp.13100.
14. Figliozzi, M., and K. Keeling. E-Grocery Home Delivery Impacts on Food Distribution, Access and Equity: A Portland Case Study. *Civil and Environmental Engineering Faculty Publications and Presentations*, Vol. 544, 2019.
15. Figliozzi, M., and A. Unnikrishnan. Home-Deliveries before-during COVID-19 Lockdown: Accessibility, Environmental Justice, Equity, and Policy Implications.

Transportation Research Part D: Transport and Environment, Vol. 93, 2021, p. 102760. https://doi.org/10.1016/j.trd.2021.102760.

16. Rotem-Mindali, O., and J. W. J. Weltevreden. Transport Effects of E-Commerce: What Can Be Learned after Years of Research? *Transportation*, Vol. 40, No. 5, 2013, pp. 867–885. https://doi.org/10.1007/s11116-013-9457-6.
17. U.S. Department of Energy. *Idling Reduction for Personal Vehicles*. Publication DOE/CHO-AC-06CH11357-1502. Washington, D.C., 2015, pp. 1–2.
18. Morgan, B. 3 Lasting Changes To Grocery Shopping After Covid-19. *Forbes*. https://www.forbes.com/sites/blakemorgan/2020/12/14/3-lasting-changes-to-grocery-shopping-after-covid-19/. Accessed Mar. 16, 2021.
19. Salon, D., M. W. Conway, D. C. Silva, R. S. Chauhan, S. Derrible, A. (Kouros) Mohammadian, S. Khoeini, N. Parker, L. Mirtich, A. Shamshiripour, E. Rahimi, and R. M. Pendyala. The Potential Stickiness of Pandemic-Induced Behavior Changes in the United States. *Proceedings of the National Academy of Sciences*, Vol. 118, No. 27, 2021. https://doi.org/10.1073/pnas.2106499118.
20. Goodhue, D. L., and R. L. Thompson. Task-Technology Fit and Individual Performance. *MIS Quarterly*, Vol. 19, No. 2, 1995, pp. 213–236. https://doi.org/10.2307/249689.
21. Klopping, I. M., and E. McKinney. Extending the Technology Acceptance Model and the Task-Technology Fit Model to Consumer E-Commerce. *Information Technology, Learning, and Performance Journal*, Vol. 22, No. 1, 2004, pp. 35–48.
22. Ajzen, I. From Intentions to Actions: A Theory of Planned Behavior. In *Action Control: From Cognition to Behavior* (J. Kuhl and J. Beckmann, eds.), Springer, Berlin, Heidelberg, pp. 11–39.
23. Davis, F. D. Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly*, Vol. 13, No. 3, 1989, pp. 319–340. https://doi.org/10.2307/249008.
24. Rogers, E. M. Diffusion of Preventive Innovations. *Addictive Behaviors*, Vol. 27, No. 6, 2002, pp. 989–993. https://doi.org/10.1016/S0306-4603(02)00300-3.
25. Maclnnis, D. J., and B. J. Jaworski. Information Processing from Advertisements: Toward an Integrative Framework. *Journal of Marketing*, Vol. 53, No. 4, 1989, pp. 1–23. https://doi.org/10.2307/1251376.
26. Droogenbroeck, E. V., and L. V. Hove. Adoption of Online Grocery Shopping: Personal or Household Characteristics? *Journal of Internet Commerce*, Vol. 16, No. 3, 2017, pp. 255–286. https://doi.org/10.1080/15332861.2017.1317149.
27. Lai, P. C. The Literature Review of Technology Adoption Models and Theories for the Novelty Technology. *Journal of Information Systems and Technology Management*, Vol. 14, No. 1, 2017, pp. 21–38. https://doi.org/10.4301/s1807-17752017000100002.
28. Abu-Shanab, E. A. Education Level as a Technology Adoption Moderator. In *2011 3rd International Conference on Computer Research and Development*, No. 1, 2011, pp. 324–328.
29. Naseri, M. B., and G. Elliott. Role of Demographics, Social Connectedness and Prior Internet Experience in Adoption of Online Shopping: Applications for Direct

Marketing. *Journal of Targeting, Measurement and Analysis for Marketing*, Vol. 19, No. 2, 2011, pp. 69–84. https://doi.org/10.1057/jt.2011.9.

30. Dominici, A., F. Boncinelli, F. Gerini, and E. Marone. Determinants of Online Food Purchasing: The Impact of Socio-Demographic and Situational Factors. *Journal of Retailing and Consumer Services*, Vol. 60, 2021, p. 102473. https://doi.org/10.1016/j.jretconser.2021.102473.
31. Jaller, M., and A. Pahwa. Evaluating the Environmental Impacts of Online Shopping: A Behavioral and Transportation Approach. *Transportation Research Part D: Transport and Environment*, Vol. 80, 2020, p. 102223. https://doi.org/10.1016/j.trd.2020.102223.
32. Southerton, D. Analysing the Temporal Organization of Daily Life:: Social Constraints, Practices and Their Allocation. *Sociology*, Vol. 40, No. 3, 2006, pp. 435–454. https://doi.org/10.1177/0038038506063668.
33. Rummo, P. E., M. A. Bragg, and S. S. Yi. Supporting Equitable Food Access During National Emergencies—The Promise of Online Grocery Shopping and Food Delivery Services. JAMA Health Forum, Mar 27, 2020.
34. Pew Research Center. Demographics of Internet and Home Broadband Usage in the United States. *Pew Research Center: Internet, Science & Tech*. https://www.pewresearch.org/internet/fact-sheet/internet-broadband/. Accessed Apr. 6, 2020.
35. Perrin, A., and S. Atske. 7% of Americans Don't Use the Internet. Who Are They? Pew Research Center, Apr 02, 2021.
36. Lee, C., and J. F. Coughlin. PERSPECTIVE: Older Adults' Adoption of Technology: An Integrated Approach to Identifying Determinants and Barriers. *Journal of Product Innovation Management*, Vol. 32, No. 5, 2015, pp. 747–759. https://doi.org/10.1111/jpim.12176.
37. Farag, S., K. J. Krizek, and M. Dijst. E-Shopping and Its Relationship with In-store Shopping: Empirical Evidence from the Netherlands and the USA. *Transport Reviews*, Vol. 26, No. 1, 2006, pp. 43–61. https://doi.org/10.1080/01441640500158496.
38. Vogels, E. A. Digital Divide Persists Even as Americans with Lower Incomes Make Gains in Tech Adoption. Pew Research Center, Jun 22, 2021.
39. Brown, S. A., and V. Venkatesh. Model of Adoption of Technology in Households: A Baseline Model Test and Extension Incorporating Household Life Cycle. *MIS Quarterly*, Vol. 29, No. 3, 2005, pp. 399–426. https://doi.org/10.2307/25148690.
40. Chawla, D., and H. Joshi. The Moderating Effect of Demographic Variables on Mobile Banking Adoption: An Empirical Investigation. *Global Business Review*, Vol. 19, No. 3_suppl, 2018, pp. S90–S113. https://doi.org/10.1177/0972150918757883.
41. Farag, S., T. Schwanen, M. Dijst, and J. Faber. Shopping Online and/or in-Store? A Structural Equation Model of the Relationships between e-Shopping and in-Store Shopping. *Transportation Research Part A: Policy and Practice*, Vol. 41, No. 2, 2007, pp. 125–141. https://doi.org/10.1016/j.tra.2006.02.003.

42. Beckers, J., I. Cárdenas, and A. Verhetsel. Identifying the Geography of Online Shopping Adoption in Belgium. *Journal of Retailing and Consumer Services*, Vol. 45, 2018, pp. 33–41. https://doi.org/10.1016/j.jretconser.2018.08.006.
43. Chen, J., A. Amaize, and D. Barath. Evaluating Telehealth Adoption and Related Barriers Among Hospitals Located in Rural and Urban Areas. *The Journal of Rural Health*, 2020, pp. 1–11. https://doi.org/10.1111/jrh.12534.
44. Cheng, C., T. Sakai, A. Alho, L. Cheah, and M. Ben-Akiva. Exploring the Relationship between Locational and Household Characteristics and E-Commerce Home Delivery Demand. *Logistics*, Vol. 5, No. 2, 2021, p. 29. https://doi.org/10.3390/logistics5020029.
45. Mehrolia, S., S. Alagarsamy, and V. M. Solaikutty. Customers Response to Online Food Delivery Services during COVID-19 Outbreak Using Binary Logistic Regression. *International Journal of Consumer Studies*, Vol. n/a, No. n/a. https://doi.org/10.1111/ijcs.12630.
46. McCloskey, D. W. The Importance of EAse of Use, Usefulness, and Trust to Online Consumers: An Examination of the Technology Acceptance Model with Older Consumers. *Journal of Organizational and End User Computing*, Vol. 18, No. 3, 2006. https://doi.org/10.4018/978-1-59904-945-8.
47. Frank, D.-A., and A. O. Peschel. Sweetening the Deal: The Ingredients That Drive Consumer Adoption of Online Grocery Shopping. *Journal of Food Products Marketing*, Vol. 26, No. 8, 2020, pp. 535–544. https://doi.org/10.1080/10454446.2020.1829523.
48. Huang, Y., and H. Oppewal. Why Consumers Hesitate to Shop Online: An Experimental Choice Analysis of Grocery Shopping and the Role of Delivery Fees. *International Journal of Retail & Distribution Management*, Vol. 34, No. 4/5, 2006, pp. 334–353. https://doi.org/10.1108/09590550610660260.
49. Hansen, T., F. Cumberland, and H. S. Solgaard. Determinants of Consumers' Adoption of Online Grocery Shopping. *European Advances in Consumer Research*, Vol. 7, 2005, pp. 276–277.
50. Piroth, P., M. S. Ritter, and E. Rueger-Muck. Online Grocery Shopping Adoption: Do Personality Traits Matter? *British Food Journal*, 2020. https://doi.org/10.1108/BFJ-08-2019-0631.
51. Hand, C., F. Dall'Olmo Riley, P. Harris, J. Singh, and R. Rettie. Online Grocery Shopping: The Influence of Situational Factors. *European Journal of Marketing*, Vol. 43, No. 9/10, 2009, pp. 1205–1219. https://doi.org/10.1108/03090560910976447.
52. Singh, R., and S. Rosengren. Why Do Online Grocery Shoppers Switch? An Empirical Investigation of Drivers of Switching in Online Grocery. *Journal of Retailing and Consumer Services*, Vol. 53, 2020. https://doi.org/10.1016/j.jretconser.2019.101962.
53. Mokhtarian, P. L. A Conceptual Analysis of the Transportation Impacts of B2C E-Commerce. *Transportation*, Vol. 31, No. 3, 2004, pp. 257–284. https://doi.org/10.1023/B:PORT.0000025428.64128.d3.

54. U.S. EPA. Sources of Greenhouse Gas Emissions. *U.S. Environmental Protection Agency*. https://www.epa.gov/ghgemissions/sources-greenhouse-gas-emissions. Accessed Jun. 11, 2020.
55. Siikavirta, H., M. Punakivi, M. Kärkkäinen, and L. Linnanen. Effects of E-Commerce on Greenhouse Gas Emissions: A Case Study of Grocery Home Delivery in Finland. *Journal of Industrial Ecology*, Vol. 6, No. 2, 2002, pp. 83–97. https://doi.org/10.1162/108819802763471807.
56. Redman, R. It's a New Scene for Grocery Shopping as Pandemic Changes Behaviors. Supermarket News, Jun 12, 2020.
57. Keyes, D. THE ONLINE GROCERY REPORT: Coronavirus Is Accelerating US Online Grocery Shopping Adoption—Here Are the Market Stats, Trends and Companies to Know. Business Insider, Feb 03, 2021.
58. Kohli, S., B. Timelin, V. Fabius, and S. M. Veranen. *How COVID-19 Is Changing Consumer Behavior – Now and Forever*. 2020.
59. Mannering, F. L., V. Shankar, and C. R. Bhat. Unobserved Heterogeneity and the Statistical Analysis of Highway Accident Data. *Analytic Methods in Accident Research*, Vol. 11, 2016, pp. 1–16. https://doi.org/10.1016/j.amar.2016.04.001.
60. Anderson, J., and S. Hernandez. Heavy-Vehicle Crash Rate Analysis: Comparison of Heterogeneity Methods Using Idaho Crash Data. *Transportation Research Record*, Vol. 2637, No. 1, 2017, pp. 56–66. https://doi.org/10.3141/2637-07.
61. Anderson, J., and S. Hernandez. Roadway Classifications and the Accident Injury Severities of Heavy-Vehicle Drivers. *Analytic Methods in Accident Research*, Vol. 15, 2017, pp. 17–28. https://doi.org/10.1016/j.amar.2017.04.002.
62. Zeng, Q., H. Wen, H. Huang, and M. Abdel-Aty. A Bayesian Spatial Random Parameters Tobit Model for Analyzing Crash Rates on Roadway Segments. *Accident Analysis & Prevention*, Vol. 100, 2017, pp. 37–43. https://doi.org/10.1016/j.aap.2016.12.023.
63. Anastasopoulos, P. Ch. Random Parameters Multivariate Tobit and Zero-Inflated Count Data Models: Addressing Unobserved and Zero-State Heterogeneity in Accident Injury-Severity Rate and Frequency Analysis. *Analytic Methods in Accident Research*, Vol. 11, 2016, pp. 17–32. https://doi.org/10.1016/j.amar.2016.06.001.
64. Anastasopoulos, P. Ch., and F. L. Mannering. The Effect of Speed Limits on Drivers' Choice of Speed: A Random Parameters Seemingly Unrelated Equations Approach. *Analytic Methods in Accident Research*, Vol. 10, 2016, pp. 1–11. https://doi.org/10.1016/j.amar.2016.03.001.
65. Washington, S., M. Karlaftis, F. Mannering, and P. Anastasopoulos. *Statistical and Econometric Methods for Transportation Data Analysis*. Chapman and Hall/CRC, Boca Raton, 2011.
66. R Core Team. R: A Language and Environment for Statistical Computing. Presented at the R Foundation for Statistical Computing, Vienna, Austria, 2017.
67. USDA Economic Research Service. Rural-Urban Commuting Area Codes. https://www.ers.usda.gov/data-products/rural-urban-commuting-area-codes.aspx. Accessed Jun. 14, 2021.

68. U.S. Department of Housing and Urban Development. *Methodology for Determining Section 8 Income Limits*. Washington, D.C., 2020.
69. California Department of and Housing and Community Development. Income Limits. *CA.gov*. https://www.hcd.ca.gov/grants-funding/income-limits/index.shtml. Accessed Jun. 26, 2021.
70. Greene, W. H. *NLogit Version 5 Reference Guide*. Plainview, NY, 2012.
71. Anastasopoulos, P. Ch., F. L. Mannering, V. Shankar, and J. E. Haddock. A Study of Factors Affecting Highway Accident Rates Using the Random-Parameters Tobit Model. *Accident Analysis & Prevention*, Vol. 45, 2012, pp. 628–633. https://doi.org/10.1016/j.aap.2011.09.015.
72. Train, K. E. *Discrete Choice Methods with Simulation*. Cambridge University Press, 2003.
73. Train, K. E. *Halton Sequences for Mixed Logit*. 1999, pp. 1–18.
74. Bhat, C. R. Simulation Estimation of Mixed Discrete Choice Models Using Randomized and Scrambled Halton Sequences. *Transportation Research Part B: Methodological*, Vol. 37, No. 9, 2003, pp. 837–855. https://doi.org/10.1016/S0191-2615(02)00090-5.
75. Halton, J. H. On the Efficiency of Certain Quasi-Random Sequences of Points in Evaluating Multi-Dimensional Integrals. *Numerische Mathematik*, Vol. 2, No. 1, 1960, pp. 84–90. https://doi.org/10.1007/BF01386213.
76. Greene, W. H. *Econometric Analysis*. Prentice Hall, New Jersey, 2002.
77. McFadden, D. Quantitative Methods for Analyzing Travel Behaviour on Individuals: Some Recent Developments. In *Behavioural Travel Modelling* (D. A. Hensher and P. R. Stopher, eds.), Croom Helm.
78. Tobin, J. Estimation of Relationships for Limited Dependent Variables. *Econometrica*, Vol. 26, No. 1, 1958, pp. 24–36. https://doi.org/10.2307/1907382.
79. Milton, J., and F. Mannering. The Relationship among Highway Geometrics, Traffic-Related Elements and Motor-Vehicle Accident Frequencies. *Transportation*, Vol. 25, No. 4, 1998, pp. 395–413. https://doi.org/10.1023/A:1005095725001.
80. Wooldridge, J. M. *Introductory Econometrics: A Modern Approach*. South-Western, Cengage Learning, Mason, OH, 2013.
81. Anastasopoulos, P. Ch., A. P. Tarko, and F. L. Mannering. Tobit Analysis of Vehicle Accident Rates on Interstate Highways. *Accident Analysis & Prevention*, Vol. 40, No. 2, 2008, pp. 768–775. https://doi.org/10.1016/j.aap.2007.09.006.
82. Boarnet, M. G., and X. Wang. Urban Spatial Structure and the Potential for Vehicle Miles Traveled Reduction: The Effects of Accessibility to Jobs within and beyond Employment Sub-Centers. *The Annals of Regional Science*, Vol. 62, No. 2, 2019, pp. 381–404. https://doi.org/10.1007/s00168-019-00900-7.
83. Shin, E. J. Commuter Benefits Programs: Impacts on Mode Choice, VMT, and Spillover Effects. *Transport Policy*, Vol. 94, 2020, pp. 11–22. https://doi.org/10.1016/j.tranpol.2020.05.001.
84. Liu, C., Y. O. Susilo, and A. Karlström. Jointly Modelling Individual's Daily Activity-Travel Time Use and Mode Share by a Nested Multivariate Tobit Model System. *Transportmetrica A: Transport Science*, Vol. 13, No. 6, 2017, pp. 491–518. https://doi.org/10.1080/23249935.2017.1298682.

85. Chang, J. S., D. Jung, J. Kim, and T. Kang. Comparative Analysis of Trip Generation Models: Results Using Home-Based Work Trips in the Seoul Metropolitan Area. *Transportation Letters*, Vol. 6, No. 2, 2014, pp. 78–88. https://doi.org/10.1179/1942787514Y.0000000011.
86. Brown, S., W. H. Greene, M. N. Harris, and K. Taylor. An Inverse Hyperbolic Sine Heteroskedastic Latent Class Panel Tobit Model: An Application to Modelling Charitable Donations. *Economic Modelling*, Vol. 50, 2015, pp. 228–236. https://doi.org/10.1016/j.econmod.2015.06.018.
87. Maddala, G. S. *Limited-Dependent and Qualitative Variables in Econometrics*. Cambridge University Press, 1986.
88. Anastasopoulos, P. Ch., V. N. Shankar, J. E. Haddock, and F. L. Mannering. A Multivariate Tobit Analysis of Highway Accident-Injury-Severity Rates. *Accident Analysis & Prevention*, Vol. 45, 2012, pp. 110–119. https://doi.org/10.1016/j.aap.2011.11.006.
89. Anderson, J., R. Sirupa, S. Kothuri, and A. Unnikrishnan. *Understanding Factors Affecting Arterial Reliability Performance Metrics*. 2019.
90. McDonald, J. F., and R. A. Moffitt. The Uses of Tobit Analysis. *The Review of Economics and Statistics*, Vol. 62, No. 2, 1980, pp. 318–321. https://doi.org/10.2307/1924766.
91. Eisenberg, T., T. Eisenberg, M. T. Wells, and M. Zhang. Addressing the Zeros Problem: Regression Models for Outcomes with a Large Proportion of Zeros, with an Application to Trial Outcomes: Addressing the Zeros Problem. *Journal of Empirical Legal Studies*, Vol. 12, No. 1, 2015, pp. 161–186. https://doi.org/10.1111/jels.12068.
92. Cragg, J. G. Some Statistical Models for Limited Dependent Variables with Application to the Demand for Durable Goods. *Econometrica*, Vol. 39, No. 5, 1971, pp. 829–844. https://doi.org/10.2307/1909582.
93. Burke, W. J. Fitting and Interpreting Cragg's Tobit Alternative Using Stata. *The Stata Journal*, Vol. 9, No. 4, 2009, pp. 584–592. https://doi.org/10.1177/1536867X0900900405.
94. Wooldridge, J. M. *Econometric Analysis of Cross Section and Panel Data, Second Edition*. MIT Press, 2010.
95. Altman, I., J. Bergtold, D. Sanders, and T. Johnson. Willingness to Supply Biomass for Bioenergy Production: A Random Parameter Truncated Analysis. *Energy Economics*, Vol. 47, 2015, pp. 1–10. https://doi.org/10.1016/j.eneco.2014.10.016.
96. Jones, J. M., and S. Kashanchi. Online Grocery Shopping Still Rare in U.S. Gallup, Aug 20, 2019.
97. Porter, C. E., and N. Donthu. Using the Technology Acceptance Model to Explain How Attitudes Determine Internet Usage: The Role of Perceived Access Barriers and Demographics. *Journal of Business Research*, Vol. 59, No. 9, 2006, pp. 999–1007. https://doi.org/10.1016/j.jbusres.2006.06.003.
98. Semega, J., M. Kollar, E. A. Shrider, and J. F. Creamer. *Income and Poverty in the United States: 2019*. Washington, D.C., 2019, p. 88.

99. Clifton, K. J. Mobility Strategies and Food Shopping for Low-Income Families: A Case Study. *Journal of Planning Education and Research*, Vol. 23, No. 4, 2004, pp. 402–413. https://doi.org/10.1177/0739456X04264919.
100. Hui, T.-K., and D. Wan. Who Are the Online Grocers? *The Service Industries Journal*, Vol. 29, No. 11, 2009, pp. 1479–1489. https://doi.org/10.1080/02642060902793334.
101. Zmud, R. W. Individual Differences and MIS Success: A Review of the Empirical Literature. *Management Science*, Vol. 25, No. 10, 1979, pp. 966–979.
102. Bui, Q. The Most Common Jobs For The Rich, Middle Class And Poor. *NPR*. https://www.npr.org/sections/money/2014/10/16/356176018/the-most-popular-jobs-for-the-rich-middle-class-and-poor. Accessed Jun. 23, 2021.
103. Fitzpatrick, K., and M. Ver Ploeg. On the Road to Food Security? Vehicle Ownership and Access to Food. Presented at the Research on Connections between Health and SES Using PSID Data, 2010.
104. Saphores, J.-D., and L. Xu. E-Shopping Changes and the State of E-Grocery Shopping in the US - Evidence from National Travel and Time Use Surveys. *Research in Transportation Economics*, Vol. 87, 2021, p. 100864. https://doi.org/10.1016/j.retrec.2020.100864.
105. Zhou, Y., and X. (Cara) Wang. Explore the Relationship between Online Shopping and Shopping Trips: An Analysis with the 2009 NHTS Data. *Transportation Research Part A: Policy and Practice*, Vol. 70, 2014, pp. 1–9. https://doi.org/10.1016/j.tra.2014.09.014.
106. Kantamneni, N. The Impact of the COVID-19 Pandemic on Marginalized Populations in the United States: A Research Agenda. *Journal of Vocational Behavior*, Vol. 119, 2020, p. 103439. https://doi.org/10.1016/j.jvb.2020.103439.
107. The Centers for Disease Control. U.S. State and Territorial Stay-At-Home Orders: March 15 – December 31 by County by Day. *Data.CDC.gov*. https://data.cdc.gov/Policy-Surveillance/U-S-State-and-Territorial-Stay-At-Home-Orders-Marc/y2iy-8irm.
108. The Centers for Disease Control. U.S. State and Territorial Gathering Bans: March 11-December 31, 2020 by County by Day. *Data.CDC.gov*. https://data.cdc.gov/Policy-Surveillance/U-S-State-and-Territorial-Stay-At-Home-Orders-Marc/y2iy-8irm.
109. The Centers for Disease Control. U.S. State and Territorial Public Mask Mandates From April 10, 2020 through March 22, 2021 by County by Day. *Data.CDC.gov*. https://data.cdc.gov/Policy-Surveillance/U-S-State-and-Territorial-Stay-At-Home-Orders-Marc/y2iy-8irm.
110. The New York Times. Coronavirus (Covid-19) Data in the United States. https://github.com/nytimes/covid-19-data.
111. Tseng, Y.-Y., and E. T. Verhoef. Value of Time by Time of Day: A Stated-Preference Study. *Transportation Research Part B: Methodological*, Vol. 42, No. 7, 2008, pp. 607–618. https://doi.org/10.1016/j.trb.2007.12.001.
112. Kurnia, S., and A. J. Chien. The Acceptance of Online Grocery Shopping. Presented at the 16th Bled eCommerce Conference eTransformation, Bled, Slovenia, 2003.

113. Webber, C. B., J. Sobal, and J. S. Dollahite. Shopping for Fruits and Vegetables. Food and Retail Qualities of Importance to Low-Income Households at the Grocery Store. *Appetite*, Vol. 54, No. 2, 2010, pp. 297–303. https://doi.org/10.1016/j.appet.2009.11.015.
114. Giuliano, G. Low Income, Public Transit, and Mobility. *Transportation Research Record*, Vol. 1927, No. 1, 2005, pp. 63–70. https://doi.org/10.1177/0361198105192700108.
115. Tal, G., and S. Handy. Travel Behavior of Immigrants: An Analysis of the 2001 National Household Transportation Survey. *Transport Policy*, Vol. 17, No. 2, 2010, pp. 85–93.
116. Pucher, J., and J. L. Renne. Socioeconomics of Urban Travel. Evidence from the 2001 NHTS. *Nr. 3*, 2003.
117. Ruszczyk, H. A., M. F. Rahman, L. J. Bracken, and S. Sudha. Contextualizing the COVID-19 Pandemic's Impact on Food Security in Two Small Cities in Bangladesh. *Environment and Urbanization*, Vol. 33, No. 1, 2021, pp. 239–254. https://doi.org/10.1177/0956247820965156.
118. Arango, T., and B. A. Kenneally. 'Just Because I Have a Car Doesn't Mean I Have Enough Money to Buy Food.' *The New York Times*, Sep 03, 2020.
119. Baskin, K. Food Insecurity in the Age of COVID-19. *Tufts Now*, Apr 30, 2020.
120. Whitmore Schanzenbach, D. *Not Enough to Eat: COVID-19 Deepens America's Hunger Crisis*. Washington, D.C., 2020.
121. Bloch, S. Study: 29 Million American Adults Don't Have Enough to Eat—a Threefold Increase since 2018. *The Counter*, Sep 15, 2020.
122. Rosenbloom, S. Driving Cessation Among Older People: When Does It Happen and What Impact Does It Have? *Transportation Research Record*, Vol. 1779, No. 1, 2001, pp. 93–99. https://doi.org/10.3141/1779-13.
123. Lund, S., A. Madgavkar, J. Manyika, S. Smit, K. Ellingrud, M. Meany, and O. Robinson. *The Future of Work after COVID-19 | McKinsey*. 2021.
124. Clauss, T., and S. Döppe. Why Do Urban Travelers Select Multimodal Travel Options: A Repertory Grid Analysis. *Transportation Research Part A: Policy and Practice*, Vol. 93, 2016, pp. 93–116. https://doi.org/10.1016/j.tra.2016.08.021.
125. Hunecke, M., S. Groth, and D. Wittowsky. Young Social Milieus and Multimodality: Interrelations of Travel Behaviours and Psychographic Characteristics. *Mobilities*, Vol. 15, No. 3, 2020, pp. 397–415. https://doi.org/10.1080/17450101.2020.1732099.
126. Brown, A. Car-Less or Car-Free? Socioeconomic and Mobility Differences among Zero-Car Households. *Transport Policy*, Vol. 60, 2017, pp. 152–159. https://doi.org/10.1016/j.tranpol.2017.09.016.
127. Cox, A. Is Instacart Headed to Be America's Top Grocer? *FreightWaves*, Mar 10, 2021.
128. USDA Economic Research Service. Food Environment Atlas Documentation. https://www.ers.usda.gov/data-products/food-environment-atlas/documentation/. Accessed Jun. 14, 2021.
129. Mokhtarimousavi, S., J. C. Anderson, A. Azizinamini, and M. Hadi. Improved Support Vector Machine Models for Work Zone Crash Injury Severity Prediction

and Analysis. *Transportation Research Record*, Vol. 2673, No. 11, 2019, pp. 680–692. https://doi.org/10.1177/0361198119845899.

130. Mokhtarimousavi, S., J. C. Anderson, M. Hadi, and A. Azizinamini. A Temporal Investigation of Crash Severity Factors in Worker-Involved Work Zone Crashes: Random Parameters and Machine Learning Approaches. *Transportation Research Interdisciplinary Perspectives*, Vol. 10, 2021, p. 100378. https://doi.org/10.1016/j.trip.2021.100378.
131. Mokhtarimousavi, S., J. C. Anderson, A. Azizinamini, and M. Hadi. Factors Affecting Injury Severity in Vehicle-Pedestrian Crashes: A Day-of-Week Analysis Using Random Parameter Ordered Response Models and Artificial Neural Networks. *International Journal of Transportation Science and Technology*, Vol. 9, No. 2, 2020, pp. 100–115. https://doi.org/10.1016/j.ijtst.2020.01.001.
132. Iranitalab, A., and A. Khattak. Comparison of Four Statistical and Machine Learning Methods for Crash Severity Prediction. *Accident Analysis & Prevention*, Vol. 108, 2017, pp. 27–36. https://doi.org/10.1016/j.aap.2017.08.008.
133. Li, Z., P. Liu, W. Wang, and C. Xu. Using Support Vector Machine Models for Crash Injury Severity Analysis. *Accident Analysis & Prevention*, Vol. 45, 2012, pp. 478–486. https://doi.org/10.1016/j.aap.2011.08.016.
134. Winship, C., and R. D. Mare. Regression Models with Ordinal Variables. *American Sociological Review*, Vol. 49, No. 4, 1984, pp. 512–525. https://doi.org/10.2307/2095465.
135. Labovitz, S. The Assignment of Numbers to Rank Order Categories. *American Sociological Review*, Vol. 35, No. 3, 1970, pp. 515–524. https://doi.org/10.2307/2092993.
136. Kim, J.-O. Multivariate Analysis of Ordinal Variables. *American Journal of Sociology*, Vol. 81, No. 2, 1975, pp. 261–298.
137. Farag, S., T. Schwanen, and M. Dijst. Empirical Investigation of Online Searching and Buying and Their Relationship to Shopping Trips. *Transportation Research Record*, Vol. 1926, No. 1, 2005, pp. 242–251. https://doi.org/10.1177/0361198105192600128.
138. Weltevreden, J. W. J., and T. V. Rietbergen. E-Shopping Versus City Centre Shopping: The Role of Perceived City Centre Attractiveness. *Tijdschrift voor Economische en Sociale Geografie*, Vol. 98, No. 1, 2007, pp. 68–85. https://doi.org/10.1111/j.1467-9663.2007.00377.x.
139. Cao, X. J., 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, 2012, pp. 957–974. https://doi.org/10.1007/s11116-011-9376-3.
140. Ferrell, C. E. Home-Based Teleshopping and Shopping Travel: Where Do People Find the Time? *Transportation Research Record*, Vol. 1926, No. 1, 2005, pp. 212–223. https://doi.org/10.1177/0361198105192600125.
141. Currans, K. M. Issues in Trip Generation Methods for Transportation Impact Estimation of Land Use Development: A Review and Discussion of the State-of-the-Art Approaches. *Journal of Planning Literature*, Vol. 32, No. 4, 2017, pp. 335–345. https://doi.org/10.1177/0885412217706505.

142. Jiao, J., A. V. Moudon, and A. Drewnowski. Grocery Shopping: How Individuals and Built Environments Influence Choice of Travel Mode. *Transportation Research Record*, Vol. 2230, No. 1, 2011, pp. 85–95. https://doi.org/10.3141/2230-10.
143. Cervero, R., and K. Kockelman. Travel Demand and the 3Ds: Density, Diversity, and Design. *Transportation Research Part D: Transport and Environment*, Vol. 2, No. 3, 1997, pp. 199–219. https://doi.org/10.1016/S1361-9209(97)00009-6.
144. Handy, S., X. Cao, and P. Mokhtarian. Correlation or Causality between the Built Environment and Travel Behavior? Evidence from Northern California. *Transportation Research Part D: Transport and Environment*, Vol. 10, No. 6, 2005, pp. 427–444. https://doi.org/10.1016/j.trd.2005.05.002.
145. Vickerman, R. W., and T. A. Barmby. The Structure of Shopping Travel: Some Developments of the Trip Generation Model. *Journal of Transport Economics and Policy*, Vol. 18, No. 2, 1984, pp. 109–121.
146. Hägerstrand, T. What about People in Regional Science? *Papers in Regional Science*, Vol. 24, No. 1, 1970, pp. 7–24.
147. Bates, J. History of Demand Modelling. In *Handbook of Transport Modelling* (D. A. Hensher and K. J. Button, eds.), Emerald Group Publishing Limited, pp. 11–34.
148. Chu, Z., L. Cheng, and H. Chen. A Review of Activity-Based Travel Demand Modeling. 2012, pp. 48–59. https://doi.org/10.1061/9780784412442.006.
149. Mokhtarian, P. L., I. Salomon, and L. S. Redmond. Understanding the Demand for Travel: It's Not Purely "Derived." *Innovation: The European Journal of Social Science Research*, Vol. 14, No. 4, 2001, pp. 355–380. https://doi.org/10.1080/13511610120106147.
150. Mokhtarian, P. L., and I. Salomon. How Derived Is the Demand for Travel? Some Conceptual and Measurement Considerations. *Transportation Research Part A: Policy and Practice*, Vol. 35, No. 8, 2001, pp. 695–719. https://doi.org/10.1016/S0965-8564(00)00013-6.
151. Singleton, P. A. Chapter 14 - Exploring the Positive Utility of Travel and Mode Choice: Subjective Well-Being and Travel-Based Multitasking during the Commute. In *Mapping the Travel Behavior Genome* (K. G. Goulias and A. W. Davis, eds.), Elsevier, pp. 259–277.
152. Institute of Transportation Engineers. *Institute of Transportation Engineers' Trip Generation Handbook*. Institute of Transportation Engineers, Washington, D.C., 2014.
153. Clifton, K. J., K. M. Currans, A. C. Cutter, and R. Schneider. Household Travel Surveys in Context-Based Approach for Adjusting ITE Trip Generation Rates in Urban Contexts. *Transportation Research Record,* Vol. 2307, No. 1, 2012, pp. 108–119. https://doi.org/10.3141/2307-12.
154. Clifton, K. J., K. M. Currans, and C. D. Muhs. Adjusting ITE's Trip Generation Handbook for Urban Context. *Journal of Transport and Land Use*, Vol. 8, No. 1, 2015, pp. 5–29.
155. Currans, K. M., G. Abou-Zeid, K. J. Clifton, A. Howell, and R. Schneider. Improving Transportation Impact Analyses for Subsidized Affordable Housing Developments: A Data Collection and Analysis of Motorized Vehicle and Person

Trip Generation. *Cities*, Vol. 103, 2020, p. 102774. https://doi.org/10.1016/j.cities.2020.102774.
156. Weinberger, R., S. Dock, L. Cohen, J. D. Rogers, and J. Henson. Predicting Travel Impacts of New Development in America's Major Cities: Testing Alternative Trip Generation Models. *Transportation Research Record*, Vol. 2500, No. 1, 2015, pp. 36–47. https://doi.org/10.3141/2500-05.
157. Millard-Ball, A. Phantom Trips: Overestimating the Traffic Impacts of New Development. *Journal of Transport and Land Use*, Vol. 8, No. 1, 2015, pp. 31–49.
158. Larson, N. I., M. T. Story, and M. C. Nelson. Neighborhood Environments: Disparities in Access to Healthy Foods in the U.S. *American Journal of Preventive Medicine*, Vol. 36, No. 1, 2009, pp. 74-81.e10. https://doi.org/10.1016/j.amepre.2008.09.025.
159. Morland, K., S. Wing, A. Diez Roux, and C. Poole. Neighborhood Characteristics Associated with the Location of Food Stores and Food Service Places. *American Journal of Preventive Medicine*, Vol. 22, No. 1, 2002, pp. 23–29. https://doi.org/10.1016/S0749-3797(01)00403-2.
160. Berg, N., and J. Murdoch. Access to Grocery Stores in Dallas. *International Journal of Behavioural and Healthcare Research*, Vol. 1, No. 1, 2008, pp. 22–37. https://doi.org/10.1504/IJBHR.2008.018449.
161. Howell, A., K. Currans, S. Gehrke, G. Norton, and K. Clifton. Transportation Impacts of Affordable Housing: Informing Development Review with Travel Behavior Analysis. *Journal of Transport and Land Use*, Vol. 11, No. 1, 2018, p. 103. https://doi.org/10.5198/jtlu.2018.1129.
162. Giuliano, G., and J. Dargay. Car Ownership, Travel and Land Use: A Comparison of the US and Great Britain. *Transportation Research Part A: Policy and Practice*, Vol. 40, No. 2, 2006, pp. 106–124. https://doi.org/10.1016/j.tra.2005.03.002.
163. Shen, Q. Spatial and Social Dimensions of Commuting. *Journal of the American Planning Association*, Vol. 66, No. 1, 2000, pp. 68–82. https://doi.org/10.1080/01944360008976085.
164. Shipt. WellCare Partners with Shipt to Provide Delivery to Medicare Members. *Shipt Newsroom*. https://corporate.shipt.com/news/wellcare-partners-with-shipt-to-provide-free-grocery-delivery-memberships-to-medicare-advantage-memb. Accessed Jun. 27, 2021.
165. Tomer, A., L. Fishbane, A. Siefer, and B. Callahan. Digital Prosperity: How Broadband Can Deliver Health and Equity to All Communities. Brookings, Feb 27, 2020.
166. Lehr, L. Cash Payments for E-Commerce--Sticky, and Growing. LinkedIn, Mar 21, 2017.
167. Cision PR Newswire. SafetyPay Drives Inclusion in E-Commerce for Consumers without a Bank Account or a Credit Card. https://www.prnewswire.com/news-releases/safetypay-drives-inclusion-in-e-commerce-for-consumers-without-a-bank-account-or-a-credit-card-300289432.html. Accessed Jun. 27, 2021.
168. Wilson, R., and A. Din. Understanding and Enhancing the U.S. Department of Housing and Urban Development's ZIP Code Crosswalk Files. *Cityscape: A Journal of Policy Development and Research*, Vol. 20, No. 2, 2018, p. 18.

169. U.S. Department of Housing and Urban Development. HUD USPS ZIP Code Crosswalk Files. *Office of Policy Development and Ressearch*. https://www.huduser.gov/portal/datasets/usps_crosswalk.html. Accessed Jun. 14, 2021.
170. The Centers for Disease Control. Reporting COVID-19 Vaccination Demographic Data. *Centers for Disease Control and Prevention*. http://www.cdc.gov/coronavirus/2019-ncov/vaccines/distributing/demographics-vaccination-data.html. Accessed Jun. 26, 2021.
171. The Centers for Disease Control. Estimates of Vaccine Hesitancy for COVID-19. *Centers for Disease Control and Prevention*. https://data.cdc.gov/stories/s/Vaccine-Hesitancy-for-COVID-19/cnd2-a6zw/. Accessed Jun. 26, 2021.
172. Atkinson, T., J. Dolmas, C. Koch, E. Koenig, K. Mertens, A. Murphy, and K.-M. Yi. Mobility and Engagement Index. *Federal Reserve Bank of Dallas*. https://www.dallasfed.org/research/mei.aspx. Accessed Jun. 26, 2021.
173. Thill, J.-C., and M. Kim. Trip Making, Induced Travel Demand, and Accessibility. *Journal of Geographical Systems*, Vol. 7, No. 2, 2005, pp. 229–248.
174. Kitamura, R. A Dynamic Model System of Household Car Ownership, Trip Generation, and Modal Split: Model Development and Simulation Experiment. *Transportation*, Vol. 36, No. 6, 2009, pp. 711–732. https://doi.org/10.1007/s11116-009-9241-9.
175. Purvis, C. L., M. Iglesias, and V. A. Eisen. Incorporating Work Trip Accessibility in Nonwork Trip Generation Models in San Francisco Bay Area. *Transportation Research Record*, Vol. 1556, No. 1, 1996, pp. 37–45. https://doi.org/10.1177/0361198196155600106.
176. Li, W., Y. Li, X. (Jeff) Ban, H. Deng, H. Shu, and D. Xie. Exploring the Relationships between the Non-Work Trip Frequency and Accessibility Based on Mobile Phone Data. *Transportation Research Record*, Vol. 2672, No. 42, 2018, pp. 91–102. https://doi.org/10.1177/0361198118774170.
177. Handy, S. Regional Versus Local Accessibility: Implications for Nonwork Travel. *Transportation Research Record 1400*, 1993, pp. 58–66.
178. Anderson, M., and A. Perrin. *Tech Adoption Climbs Among Older Adults*. Washington, D.C., 2017.
179. USDA FNS. FNS Launches the Online Purchasing Pilot. https://www.fns.usda.gov/snap/online-purchasing-pilot. Accessed Mar. 18, 2021.
180. Buldeo Rai, H., S. Verlinde, and C. Macharis. Unlocking the Failed Delivery Problem? Opportunities and Challenges for Smart Locks from a Consumer Perspective. *Research in Transportation Economics*, Vol. 87, 2021, p. 100753. https://doi.org/10.1016/j.retrec.2019.100753.
181. Buldeo Rai, H., S. Verlinde, and C. Macharis. The “next Day, Free Delivery” Myth Unravelled: Possibilities for Sustainable Last Mile Transport in an Omnichannel Environment. *International Journal of Retail & Distribution Management*, Vol. 47, 2018. https://doi.org/10.1108/IJRDM-06-2018-0104.
182. Kelly, H. To Save Their Neighborhood Small Businesses, People Are Rebelling against Delivery Apps. *Washington Post*, May 13, 2020.

Appendix A: Wave 2 Survey Instrument

Start of Block: Introduction

Q1 We are interested in how you shop for food and other household items.

This short survey includes questions about:
You and your household; Online and in-store shopping; Delivery and pick up;
This research is funded by the National Science Foundation and the National Institute for Transportation Communities.

Thank you for taking the time to complete our survey.

Q2
To participate in this study, we require that you read and accept the terms of informed consent. Your responses will remain completely anonymous.
Project Title: Consumer Responses to Household Provisioning During COVID-19 Crisis and Recovery
Sponsor/funders: National Science Foundation and National Institute of Transportation and Communities
Principal Investigator: Kelly J. Clifton, PhD, Portland State University
Researcher Contact: covidshopping@pdx.edu / 510-698-2986

Click here to view or download a copy of the terms

Q3 By clicking "Accept," you affirm that you are over the age of 18 and agree to the terms.

○ Accept

○ Decline

Skip To: End of Block If Q3 = Decline

End of Block: Introduction

Start of Block: Respondent Demographics

Q4 To start, we want to ask you a few questions about you and your household.

Q5 What is your age?

- ○ 18-24
- ○ 25-34
- ○ 35-44
- ○ 45-54
- ○ 55-64
- ○ 65-74
- ○ 75-84
- ○ 85+
- ○ Prefer not to say

Q6 What is your ZIP code?

Q7 How would you describe yourself?

Select all that apply.

- ☐ White or European American
- ☐ Black or African American
- ☐ American Indian or Alaska Native
- ☐ Asian or Asian American
- ☐ Native Hawaiian or Pacific Islander
- ☐ Hispanic or LatinX
- ☐ Other ____

☐ ⊗Prefer not to say

Q8 How do you identify?

- ◯ Woman
- ◯ Man
- ◯ Transgender woman
- ◯ Transgender man
- ◯ Non-binary
- ◯ Prefer to self-describe ____
- ◯ Prefer not to say

Q9 What is the highest degree or level of school you have completed?

- ◯ College degree or higher
- ◯ Some college but no degree
- ◯ Vocational degree or certificate
- ◯ High school diploma or GED
- ◯ Less than high school
- ◯ Other: ____

Q10

We want to ask you a few questions about **your household**. We define a household as ***people that live together as an economic unit*** - meaning you share a budget: you earn and spend financial and other resources together.
For some people, the number of people in your household may be smaller than the number of people you live with.
For example, you may live with roommates or your parents but do not share your income and are responsible for your own grocery shopping and your portion of expenses, such as rent or utilities. If that were the case, your household would only include you and your household size would be 1/

Keep this in mind as you answer the following questions about **your household**.

Q11 Are you the person who usually does the grocery shopping in **your household**?

- ○ Yes
- ○ I share this task with other members of my household
- ○ No

Q12
How many people are in **your household** including yourself?

- ○ 1
- ○ 2
- ○ 3
- ○ 4
- ○ 5
- ○ 6
- ○ 7
- ○ 8+

Display This Question:
If Q12 != 1

Q13 Who else is part of **your household** *(people who live together as an economic unit)*?

Select all that apply.

- ▢ Spouse/partner
- ▢ Children (Under 18)
- ▢ Adult children (18+)
- ▢ Parents and/or grandparents

- [ ] Siblings
- [ ] Extended family (e.g., nephews, aunts, etc.)
- [ ] Roommates
- [ ] Other ____
- [ ] ⊗Prefer not to say

Display This Question:
If Q12 != 1

Q14 Please select the age categories of the **other people in your household**. Note that you only need to select age categories once even if two or more people are in the same age category.

- [ ] Under 5
- [ ] 5-9
- [ ] 10-14
- [ ] 15-17
- [ ] 18-24
- [ ] 25-34
- [ ] 35-44
- [ ] 45-54
- [ ] 55-64
- [ ] 65-74
- [ ] 75-84

☐ 85+

☐ ⊗Prefer not to say

Q15 Information about income is very important to help us understand your household's resources. Please make a selection below about **your household income** in 2020 before taxes. (Reminder that we define a household as ***people that live together as an economic unit***.)

○ My household income in 2020 before taxes was LESS than $100,000.

○ My household income in 2020 before taxes was MORE than $100,000.

○ Don't know

○ Prefer not to say

Display This Question:
If Q15 = My household income in 2020 before taxes was LESS than $100,000.

Q16 Would you please give your best guess about **your household income** in 2020 before taxes?

○ Less than $19,999

○ $20,000 - $39,999

○ $40,000 - $59,999

○ $60,000 - $79,999

○ $80,000 - $99,999

○ Don't know

○ Prefer not to say

Display This Question:
If Q15 = My household income in 2020 before taxes was MORE than $100,000.

Q17 Would you please give your best guess about **your household income** in 2020 before taxes?

○ $100,000 - $119,999

○ $120,000 - $139,999

○ $140,000 - $159,999

○ $160,000 - $179,999

○ $180,000 - $199,999

○ $200,000 or more

○ Don't know

○ Prefer not to say

Q18 Do **you or other members of your household** currently receive any of the following forms of assistance?

Select all that apply.

▢ Unemployment benefits

▢ SNAP (Supplemental Nutrition Assistance Program, i.e. food stamps)

▢ WIC (Women Infants and Children)

▢ Other food assistance ____

▢ ⊗None of these

▢ ⊗Prefer not to say

Q19 Does **your household** have access to a debit and/or credit card to use for online purchases?

- ○ Yes
- ○ No
- ○ Prefer not to say

Q20 Do you live with anyone else that you do not consider to be part of **your economic household**? (E.g., roommates)

- ○ Yes
- ○ No
- ○ Other ____

End of Block: Household Information

Start of Block: Transportation and Housing

Q21 How many functioning automobiles (including motorcycles) does **your household** own or lease? (Do not include motor homes or RVs).

- ○ 0
- ○ 1 ____
- ○ 2
- ○ 3
- ○ 4
- ○ 5 or more

Q22 How many people in **your household** have a valid drivers license?

- ○ 0
- ○ 1
- ○ 2
- ○ 3
- ○ 4
- ○ 5 or more

Q23 How many adults in **your household** have access to a functioning bicycle?

- ◯ 0 ____
- ◯ 1
- ◯ 2
- ◯ 3
- ◯ 4
- ◯ 5+

Q24 Does anyone in **your household** have a medical condition that limits mobility?

Check all that apply.

- ▢ I have a condition that limits my mobility.
- ▢ Someone else in my household has a condition that limits their mobility.
- ▢ ⊗Prefer not say
- ▢ ⊗None of the above

Q25 Please indicate the extent to which the following statements apply to **your household**.

My/Our preferred grocery store is easy to get to.	◯ Disagree	◯ Agree	◯ Neither agree nor disagree
There are grocery stores within walking distance from home.	◯ Yes, there are several grocery stores within walking distance from home.	◯ There are no grocery stores within walking distance from home.	◯ Yes, there is one grocery store within walking distance from home.
My/Our preferred restaurants are easy to get to.	◯ Disagree	◯ Agree	◯ Neither agree nor disagree
There are restaurants within walking distance from home.	◯ Yes, there are many restaurants within walking distance from home.	◯ There are no restaurants within walking distance from home.	◯ Yes, there are a few restaurants within walking distance from home.

Q26 Please select the option that best describes your housing unit:

- ◯ Single-family home, detached
- ◯ Townhouse, row house, or attached single family
- ◯ Apartment or condominium
- ◯ Mobile home or RV
- ◯ I am currently houseless.
- ◯ Other ____

Q27 In thinking about **your housing unit**, please indicate whether the following are true.

	Yes	No	Don't know
There is a protected place to leave deliveries (e.g., covered porch, building locker, garage, etc.).	◯	◯	◯
Delivery personnel have to request access (e.g., enter a code, get buzzed in, go through a front gate, etc.) to get to my/our unit.	◯	◯	◯

End of Block: Transportation and Housing
Start of Block: Technology Access

Q28 Does **your household** have...

Internet service at home?	◯ Yes	◯ No	◯ Don't know
Access to a computer, laptop, and/or tablet?	◯ Yes	◯ No	◯ Don't know
Access to a smartphone?	◯ Yes	◯ No	◯ Don't know
Data plan for smartphone(s)?	◯ Yes	◯ No	◯ Don't know

Q29 Please indicate the extent to which you agree or disagree with the following statements.

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree	Not applicable
I/We are satisfied with the quality of my/our internet service.	○	○	○	○	○	○
I/We have access to enough internet-connected devices (computers, tablets, smartphones, etc.) to meet my/our needs.	○	○	○	○	○	○
My/Our smartphone plans have sufficient data.	○	○	○	○	○	○

End of Block: Technology Access

Start of Block: Grocery Block

Q30 Next we are going to ask a series of questions about **your household's** grocery shopping. We define groceries as:
Food items - such as meat, vegetables, dairy, bread and bakery items, canned and dried foods, packaged and frozen foods, beverages, etc.; Household items - kitchen and bathroom supplies, cleaning products, toiletries, other personal products, etc.
We are interested in your **in-store shopping** and **online ordering** of groceries. This includes all grocery retailers, including local supermarkets, specialty food stores, superstores, and online-only stores.

We will also ask you about **ordering meals online from restaurants**. For these online restaurant orders, we will ask about pick-up (curbside, parking lot, at store, e.g.) and delivery choices.

Q31
In the last four weeks, how often did your household...

	None in the last four weeks	Once over the last four weeks	2-3 times over the last four weeks	Once per week	2-3 times per week	4 or more times per week
Travel to a store to grocery shop	○	○	○	○	○	○
Pick up an online grocery order at the store	○	○	○	○	○	○
Receive an online grocery delivery	○	○	○	○	○	○
Have someone outside the household get groceries for me/us	○	○	○	○	○	○
Visit a food bank or other supportive service to get groceries *(After you respond to this question, press the green arrow to advance).*	○	○	○	○	○	○

Q32 In the last four weeks, how often did your household...

	None in the last four weeks	Once over the last four weeks	2-3 times over the last four weeks	Once per week	2-3 times per week	4 or more times per week
Eat at a restaurant (indoor or outdoor dining)	○	○	○	○	○	○
Go through a restaurant drive-thru	○	○	○	○	○	○
Pick up an online restaurant order	○	○	○	○	○	○
Receive an online restaurant delivery	○	○	○	○	○	○
Receive a meal delivery from a supportive service (e.g., Meals on Wheels) *(After you respond to this question, press the green arrow to advance).*	○	○	○	○	○	○

Q33 Please indicate the degree to which you agree to the following statements.

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
Using a credit card online is safe.	○	○	○	○	○
I/We are comfortable having a delivery person come to my/our house.	○	○	○	○	○
Cooking is enjoyable.	○	○	○	○	○
I/We are worried about deliveries being stolen, misplaced, or not delivered.	○	○	○	○	○
I/We prefer to make purchases with cash.	○	○	○	○	○

Q34 How does your household **travel to** the store to shop for groceries or pick up a grocery order?

Select all that apply.

- ☐ Personal automobile, motorcycle, or moped (drive or ride as passenger)
- ☐ Carshare (e.g., Zipcar, Enterprise CarShare)
- ☐ Ridehail service (e.g., Uber, Lyft, etc.) or taxi
- ☐ Public transit or paratransit (e.g., bus, light rail, subway, streetcar, people mover)
- ☐ Bicycle (personal, bikeshare, e-bike)
- ☐ Walk or use a wheelchair
- ☐ ⊗I/we never travel to the grocery store
- ☐ Other: ____

Q35 Please indicate the extent to which the following statements apply to **your household**.

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
I/We enjoy shopping for food.	○	○	○	○	○
I/We like to shop at a variety of different stores.	○	○	○	○	○
A lot of people I/we know are ordering groceries online.	○	○	○	○	○
It is important to support local businesses.	○	○	○	○	○
A lot of people I/we know are ordering restaurant meals online.	○	○	○	○	○

Q36 We want to know about **your perceptions of online grocery shopping** even if you have not shopped for groceries online previously. What is your impression of the following:

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
It is easy to shop online for groceries.	◯	◯	◯	◯	◯
Shopping for groceries online saves money.	◯	◯	◯	◯	◯
Scheduling grocery delivery may be difficult.	◯	◯	◯	◯	◯
Shopping online saves time.	◯	◯	◯	◯	◯
Comparison shopping is easier online.	◯	◯	◯	◯	◯
It is expensive to have groceries delivered.	◯	◯	◯	◯	◯
Shopping online is environmentally friendly.	◯	◯	◯	◯	◯

Q37 In response to the COVID-19 pandemic, my household...

Generally buys...	◯ More groceries each time I/we shop	◯ Less groceries each time I/we shop	◯ No change
Has changed the day or time when I/we shop to avoid crowds	◯ Yes, always	◯ Yes, sometimes	◯ No change
Shops for groceries at...	◯ More stores than before	◯ Fewer stores than before	◯ No change
Shops at different stores than before	◯ Yes, all the stores are different	◯ Yes, some of the stores are different	◯ No change

Q38 Compared to before the start of the COVID-19 pandemic (March 2020), my household is currently...

	We have not done this	Less often	About the same	More often	Don't know
Going to the store to shop for groceries...	◯	◯	◯	◯	◯
Ordering groceries online...	◯	◯	◯	◯	◯
Dining in person at restaurants...	◯	◯	◯	◯	◯
Picking up food from a restaurant or going through a drive-thru...	◯	◯	◯	◯	◯
Placing a restaurant order for delivery...	◯	◯	◯	◯	◯
Planning ahead before I/we shop...	◯	◯	◯	◯	◯
Experiencing longer lines or waits at the grocery store... *After you respond to this question, press the green arrow to advance.*	◯	◯	◯	◯	◯

Display This Question:
If Q38 = Ordering groceries online... [We have not done this]

Q39 Do the grocery stores where you currently shop offer online ordering for pick-up or delivery as an option?

- Yes
- No
- Don't know

Q40 Approximately what proportion of **your household's** grocery shopping is **currently** done by shopping in-store vs. ordering online (for pick-up or delivery)?

- All in-store
- Mostly in-store
- About 50-50
- Mostly online
- All online

Q41
Have you <u>ever</u> ordered any of the following <u>online or with a smartphone</u>?

	Yes	No	Don't know
Groceries for <u>delivery</u>	○	○	○
Groceries for <u>pick up</u> at store (curbside, parking lot, or in-store)	○	○	○
Food from a restaurant for <u>delivery</u>	○	○	○
Food from a restaurant for <u>pick up</u>	○	○	○
Other goods online for <u>delivery</u> (e.g., clothing, electronics, books)	○	○	○
Other goods online for <u>pick up</u> (e.g., clothing, electronics, books)	○	○	○

Display This Question:
If Q18 = SNAP (Supplemental Nutrition Assistance Program, i.e. food stamps)

Q42 Have you ever used your SNAP benefits to pay for an online grocery order?

○ Yes

○ No

Display This Question:
If Q42 = Yes

Q43 What was your experience using your SNAP benefits online?

____

Display This Question:
If Q41 = Groceries for <u>delivery</u> [Yes]
Or Q41 = Food from a restaurant for <u>delivery</u> [Yes]
Or Q41 = Other goods online for <u>delivery</u> (e.g., clothing, electronics, books) [Yes]
Or Q41 = Groceries for <u>pick up</u> at store (curbside, parking lot, or in-store) [Yes]
Or Q41 = Other goods online for <u>pick up</u> (e.g., clothing, electronics, books) [Yes]
Or Q41 = Food from a restaurant for <u>pick up</u> [Yes]
Carry Forward Selected Choices from "Q41"

Q44 When was the first time you ever ordered this online or with a smartphone?

	Before March 2020	After March 2020 (since the start of the COVID-19 pandemic)
Groceries for delivery	○	○
Groceries for pick up at store (curbside, parking lot, or in-store)	○	○
Food from a restaurant for delivery	○	○
Food from a restaurant for pick up	○	○
Other goods online for delivery (e.g., clothing, electronics, books)	○	○
Other goods online for pick up (e.g., clothing, electronics, books)	○	○

Display This Question:
If Device = not_mobile

Q45

When it comes to your household's decisions about how and where to shop for groceries, how important are the following factors? Drag and drop each item into the corresponding bucket.

Very important	Somewhat important	Not at all important
______ Wanting to get out of the house	______ Wanting to get out of the house	______ Wanting to get out of the house
______ Being able to inspect items for quality	______ Being able to inspect items for quality	______ Being able to inspect items for quality
______ Minimizing time spent shopping	______ Minimizing time spent shopping	______ Minimizing time spent shopping
______ Having a wide selection of brand and products to choose from	______ Having a wide selection of brand and products to choose from	______ Having a wide selection of brand and products to choose from
______ Being able to redeem coupons	______ Being able to redeem coupons	______ Being able to redeem coupons
______ Minimizing level of effort	______ Minimizing level of effort	______ Minimizing level of effort
______ Being able to easily comparison shop	______ Being able to easily comparison shop	______ Being able to easily comparison shop
______ Getting the best price available	______ Getting the best price available	______ Getting the best price available
______ Minimizing travel to the store	______ Minimizing travel to the store	______ Minimizing travel to the store
______ Not having to pay delivery fees	______ Not having to pay delivery fees	______ Not having to pay delivery fees
______ Being able to shop at any time	______ Being able to shop at any time	______ Being able to shop at any time
______ Not having to carry items	______ Not having to carry items	______ Not having to carry items

Display This Question:
If Device = mobile

Q46
When it comes to your household's decisions about how and where to shop for groceries, how important are the following factors?

	Very important	Somewhat important	Not at all important
Wanting to get out of the house	○	○	○
Being able to inspect items for quality	○	○	○
Minimizing time spent shopping	○	○	○
Having a wide selection of brand and products to choose from	○	○	○
Being able to redeem coupons	○	○	○
Minimizing level of effort	○	○	○
Being able to easily comparison shop	○	○	○
Getting the best price available	○	○	○
Minimizing travel to the store	○	○	○
Not having to pay delivery fees	○	○	○
Being able to shop at any time	○	○	○
Not having to carry items *After you respond to this question, press the green arrow to advance.*	○	○	○

Q47 In your household's experiences with shopping for groceries in-store, how satisfied have you been with the following:

	Very dissatisfied	Dissatisfied	Neutral	Satisfied	Very satisfied	Not applicable
Availability of items	○	○	○	○	○	○
Quality of items	○	○	○	○	○	○
Selection of items to choose from	○	○	○	○	○	○
Measures taken by stores to ensure customer safety	○	○	○	○	○	○
Time spent waiting (e.g., to get into the store, in line at checkout, etc.) *After you respond to this question, press the green arrow to advance.*	○	○	○	○	○	○

Display This Question:
If Q41 = Groceries for <u>pick up</u> at store (curbside, parking lot, or in-store) [Yes]
And Q41 = Groceries for <u>delivery</u> [Yes]

Q48 In your household's experiences with ordering groceries online, how satisfied have you been with the following:

	Very dissatisfied	Dissatisfied	Neutral	Satisfied	Very satisfied	Not applicable
Order accuracy	○	○	○	○	○	○
Availability of items	○	○	○	○	○	○
Quality of items	○	○	○	○	○	○
Item substitutions, if needed	○	○	○	○	○	○
Bagging of items	○	○	○	○	○	○
The online stores or smartphone apps	○	○	○	○	○	○
The process for grocery pick up	○	○	○	○	○	○
The scheduled arrival of deliveries	○	○	○	○	○	○
The service provided by delivery personnel *After you respond to this question, press the green arrow to advance.*	○	○	○	○	○	○

Display This Question:
If Q41 = Groceries for <u>pick up</u> at store (curbside, parking lot, or in-store) [Yes]
And Q41 = Groceries for <u>delivery</u> [No]

Q49 In your household's experiences with ordering groceries online, how satisfied have you been with the following:

	Very dissatisfied	Dissatisfied	Neutral	Satisfied	Very satisfied	Not applicable
Order accuracy	○	○	○	○	○	○
Availability of items	○	○	○	○	○	○
Quality of items	○	○	○	○	○	○
Item substitutions, if needed	○	○	○	○	○	○
Bagging of items	○	○	○	○	○	○
The online stores or smart phone apps	○	○	○	○	○	○
The process for grocery pick up *After you respond to this question, press the green arrow to advance.*	○	○	○	○	○	○

Display This Question:
If Q41 = Groceries for <u>pick up</u> at store (curbside, parking lot, or in-store) [No]
And Q41 = Groceries for <u>delivery</u> [Yes]

Q50 In your household's experiences with ordering groceries online, how satisfied have you been with the following:

	Very dissatisfied	Dissatisfied	Neutral	Satisfied	Very satisfied	Not applicable
Order accuracy	○	○	○	○	○	○
Availability of items	○	○	○	○	○	○
Quality of items	○	○	○	○	○	○
Item substitutions, if needed	○	○	○	○	○	○
Bagging of items	○	○	○	○	○	○
The online stores or smart phone apps	○	○	○	○	○	○
Scheduled arrival of deliveries	○	○	○	○	○	○
The service provided by delivery personnel *After you respond to this question, press the green arrow to advance.*	○	○	○	○	○	○

Display This Question:
If Q41 = Groceries for <u>delivery</u> [Yes]

Q51
Which online services has your household used to have **groceries delivered**?
Select all that apply.

▢ Amazon

▢ Instacart

▢ Shipt

▢ Peapod

- [ ] Mercato
- [ ] Postmates
- [ ] Direct from grocery store
- [ ] Other: ____
- [ ] ⊗Don't know

Display This Question:
If Q41 = Groceries for <u>delivery</u> [Yes]

Q52
Where did you have your grocery orders delivered to?

Select all that apply.

- [ ] Home
- [ ] Friend or a family member's home
- [ ] Workplace
- [ ] Secure locker (e.g., Amazon Hub Locker)
- [ ] Other: ____

Q53
Approximately what proportion of **your household's** grocery shopping do you anticipate being done by shopping in-store vs. ordering online (for pick-up or delivery) **this time next year**?

- ○ All in-store
- ○ Mostly in-store
- ○ About 50-50
- ○ Mostly online
- ○ All online

End of Block: Grocery Block

Start of Block: Restaurant Meals

Q54
Compared to before the start of COVID-19 pandemic (March 2020), my household...

	Disagree	Neither agree nor disagree	Agree
Has less time to cook and prepare meals.	○	○	○
Is often too tired/not motivated to prepare meals.	○	○	○
Has less time to go grocery shopping.	○	○	○
Has a renewed interest in cooking at home.	○	○	○

Q55 Please indicate the extent to which the following statements about **restaurants** apply to **your household**.

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
Getting food from a restaurant is a treat.	◯	◯	◯	◯	◯
It is important to support local restaurants.	◯	◯	◯	◯	◯
The quality of restaurant food is better than I/we can prepare.	◯	◯	◯	◯	◯
As a quality check, please select "Strongly disagree" here.	◯	◯	◯	◯	◯
I/We like the variety of foods available from restaurants.	◯	◯	◯	◯	◯
I/We are willing to pay more to have food delivered.	◯	◯	◯	◯	◯
I/We are willing to wait longer to have food delivered.	◯	◯	◯	◯	◯
I/We are concerned about food arriving at the wrong temperature.	◯	◯	◯	◯	◯
I/We often don't feel like leaving the house. *After you respond to this question, press the green arrow to advance.*	◯	◯	◯	◯	◯

Display This Question:
If Q32 != Receive an online restaurant delivery [None in the last four weeks]
Or Q32 != Pick up an online restaurant order [None in the last four weeks]

Q56
Which online services have your household used to order restaurant meals for delivery or pick-up?

Select all that apply.

- ☐ Uber Eats
- ☐ Caviar
- ☐ DoorDash
- ☐ Grubhub
- ☐ Postmates
- ☐ Seamless
- ☐ Eat24
- ☐ Direct from restaurant
- ☐ Other: ____
- ☐ ⊗None of the above

End of Block: Restaurant Meals

Start of Block: Wellbeing

Q57 Please indicate how often you or your household experienced the following in the past four weeks.

	Often true	Sometimes true	Never true	Prefer not to say
I/We worried my/our food would run out before I/we got money to buy more.	○	○	○	○
The food that I/we bought just didn't last, and I/we didn't have money to get more.	○	○	○	○

Q58
Since the start of the COVID-19 pandemic, have **you or members of your household** experienced any of the following?

	Yes	No	Not applicable	Prefer not to say
Temporary lay-off or furlough	○	○	○	○
Permanent loss of job	○	○	○	○
Significant decrease in income compared to 2019	○	○	○	○
Worked from home more	○	○	○	○
Concerns about housing stability	○	○	○	○

Q59 Are **you** or is **anyone you live with...**

Currently recovering from COVID-19?	◯ Yes ◯ No ◯ Not sure ◯ Prefer not to say
Previously recovered from COVID-19?	◯ Yes ◯ No ◯ Not sure ◯ Prefer not to say
Vulnerable to COVID-19 (e.g., has underlying conditions, is immunocompromised)?	◯ Yes ◯ No ◯ Not sure ◯ Prefer not to say
Currently quarantining due to known exposure to COVID-19?	◯ Yes ◯ No ◯ Not sure ◯ Prefer not to say
Vaccinated for COVID-19 (at least one dose)?	◯ Yes ◯ No ◯ Not sure ◯ Prefer not to say

End of Block: Wellbeing

Start of Block: Employment and Schooling

Q60 I am currently (pick all that apply):

▢ Employed

▢ Out of work but looking for work.

▢ Out of work and not looking for work.

▢ Retired

▢ Student

▢ Homemaker

▢ Other ____

Display This Question:
If Q60 = Employed

Q61 Which of the following best describes your current work situation?

◯ I am working outside of my home exclusively.

◯ I am working from home/remotely exclusively.

◯ I sometimes work outside of my home and sometimes work from home/remotely.

◯ Other ____

Display This Question:
If Q60 = Student

Q62 Which of the following best describes your current school situation?

◯ I am attending school in-person, exclusively

◯ I am attending school online or remote classroom, exclusively

◯ I am attending school in a hybrid model: in-person and online

◯ Other ____

Display This Question:
If Q12 != 1
Q63
How many other people **in your household** are currently employed?

◯ 0

◯ 1

◯ 2

◯ 3

◯ 4 or more

◯ Prefer not to say

Display This Question:
If Q63 = 1
Or Q63 = 2
Or Q63 = 3
Or Q63 = 4 or more

Q64 Which of the following best describes the current work situation of members of your household? Select all that apply.

▢ A member of my household works outside of the home exclusively.

▢ A member of my household works from home/remotely exclusively.

▢ A member of my household sometimes works outside of the home and sometimes works from home/remotely.

☐ Other ____

Display This Question:
If Q14 = 5-9
Or Q14 = 10-14
Or Q14 = 15-17

Q65 In the last month, the **school-aged children** in my home have been:
Select all that apply.

☐ Attending school in-person, exclusively

☐ Attending school online or remote classroom, exclusively

☐ Attending school in a hybrid model: in-person and online

☐ Not attending school on a regular basis

☐ In daycare outside the home

☐ None of the above

Display This Question:
If Q14 = Under 5
Q66 In the last month, the **pre-school aged** children in my home have been:
Select all that apply.

☐ Attending preschool online

☐ In daycare or preschool outside the home

☐ None of the above

End of Block: Employment and Schooling
Start of Block: Share
Q67 Is there anything you would like to share with us about your experiences shopping for food and household items?

Appendix B: Descriptive statistics for outcome and explanatory variables

Table A Descriptive statistics for variables tested in analysis^

	Mean	Std. Deviation	Min	Max
Outcome variables				
Household shopper e-grocery delivery adoption status				
Have not done this (Non-adopter)	0.630	0.483	Dichotomous variable (0/1)	
After onset of COVID-19 (During-pandemic adopter)	0.198	0.399	Dichotomous variable (0/1)	
Before onset of COVID-19 (Pre-pandemic adopter)	0.172	0.377	Dichotomous variable (0/1)	
Household weekly trip rates				
Weekly in-store grocery trip rate	1.323	1.062	0	4.5
Weekly online grocery pickup trip rate	0.193	0.474	0	4.5
Weekly online grocery delivery trip rate	0.199	0.523	0	4.5
Used e-grocery pickup in last four weeks	0.248	0.432	Dichotomous variable (0/1)	
Used e-grocery delivery in last four weeks	0.249	0.432	Dichotomous variable (0/1)	
Household e-grocery "stickiness"				
Household is ordering groceries online more often compared to before the pandemic and will hold or increase the proportion of their grocery shopping done online in the next year	0.251	0.434	Dichotomous variable (0/1)	
Explanatory variables				
Other provisioning frequencies				
Weekly restaurant dine-in trip rate	0.324	0.638	0	4.5
Weekly restaurant drive-thru trip rate	0.673	0.849	0	4.5
Weekly restaurant online pickup trip rate	0.369	0.613	0	4.5
Weekly restaurant online delivery trip rate	0.277	0.590	0	4.5
Household (HH) and respondent demographics, geographies				
HH size	2.357	1.353	1	8
HH vehicles	1.559	0.972	0	5
HH has more than one vehicle	0.462	0.499	Dichotomous variable (0/1)	
HH vehicles / HH size	0.760	0.459	Dichotomous variable (0/1)	
HH drivers	1.711	0.845	0	5
HH workers	1.214	1.175	0	5
Zero-car HH	0.094	0.291	Dichotomous variable (0/1)	
HH's typical travel mode to the grocery store				

Travels to the grocery store by vehicle only [driver or passenger], no other modes	0.806	0.395	Dichotomous variable (0/1)
Uses multiple travel modes for going to the store to shop in-person	0.194	0.395	Dichotomous variable (0/1)
At least one household member has condition that limits mobility	0.239	0.426	Dichotomous variable (0/1)
HH includes children 0-9 years old	0.151	0.358	Dichotomous variable (0/1)
HH includes children 0-17 years old	0.242	0.429	Dichotomous variable (0/1)
Respondent race and gender characteristics			
Is Female	0.677	0.468	Dichotomous variable (0/1)
Is Female and the primary (sole) grocery shopper for the household	0.559	0.497	Dichotomous variable (0/1)
Is Male	0.308	0.462	Dichotomous variable (0/1)
Is white alone (not Hispanic or Latino)	0.786	0.410	Dichotomous variable (0/1)
Respondent educational attainment and employment			
Educational attainment is college degree or higher	0.513	0.500	Dichotomous variable (0/1)
Educational attainment is less than college degree	0.487	0.500	Dichotomous variable (0/1)
Is currently employed	0.499	0.500	Dichotomous variable (0/1)
Is currently employed and working from home exclusively	0.162	0.368	Dichotomous variable (0/1)
Is currently employed and working outside of home exclusively	0.241	0.428	Dichotomous variable (0/1)
Is currently employed and working from home and outside the home	0.083	0.276	Dichotomous variable (0/1)
Is currently unemployed and looking for work	0.088	0.283	Dichotomous variable (0/1)
Is currently unemployed and not looking for work	0.063	0.243	Dichotomous variable (0/1)
Is retired	0.262	0.440	Dichotomous variable (0/1)
Is a student	0.037	0.188	Dichotomous variable (0/1)
Is a homemaker	0.089	0.284	Dichotomous variable (0/1)
Respondent age			
18-24	0.074	0.261	Dichotomous variable (0/1)
25-34	0.175	0.380	Dichotomous variable (0/1)
35-44	0.182	0.386	Dichotomous variable (0/1)
45-54	0.151	0.358	Dichotomous variable (0/1)

55-64	0.177	0.381	Dichotomous variable (0/1)
65-74	0.203	0.403	Dichotomous variable (0/1)
75+	0.038	0.192	Dichotomous variable (0/1)
Household age profile			
No 65+ members	0.700	0.458	Dichotomous variable (0/1)
Mix of 65+/non-65+ members	0.068	0.251	Dichotomous variable (0/1)
65+ household	0.233	0.423	Dichotomous variable (0/1)
HH lifecycle			
Single-person HH, not 65+	0.183	0.387	Dichotomous variable (0/1)
Single-person HH, 65+	0.110	0.313	Dichotomous variable (0/1)
2+ Person HH, Has Children	0.242	0.429	Dichotomous variable (0/1)
2+ Person HH, No Children, 65+	0.123	0.328	Dichotomous variable (0/1)
2+ Person HH, No Children, Mix <65/65+	0.053	0.224	Dichotomous variable (0/1)
2+ Person HH, No Children, not 65+	0.289	0.454	Dichotomous variable (0/1)
HH actual and relative income			
$39,000 or less	0.350	0.477	Dichotomous variable (0/1)
$40,000 - $79,999	0.324	0.468	Dichotomous variable (0/1)
$80,000 - $119,999	0.183	0.387	Dichotomous variable (0/1)
$120,000 or more	0.143	0.350	Dichotomous variable (0/1)
Extremely low income	0.160	0.366	Dichotomous variable (0/1)
Very low income	0.112	0.316	Dichotomous variable (0/1)
Low income	0.195	0.397	Dichotomous variable (0/1)
Extremely low, very low, low income (combined category)	0.467	0.499	Dichotomous variable (0/1)
Median / moderate (Mid) income	0.199	0.399	Dichotomous variable (0/1)
Above median / moderate (High)	0.334	0.472	Dichotomous variable (0/1)
HH's food didn't last and they didn't have money to buy more, or household was worried food would runout before funds to buy more were available	0.331	0.471	Dichotomous variable (0/1)
HH's food didn't last and they didn't have money to buy more	0.243	0.429	Dichotomous variable (0/1)

HH was worried food would run out before funds to buy more were available	0.301	0.459	Dichotomous variable (0/1)	
HH receives SNAP assistance	0.141	0.348	Dichotomous variable (0/1)	
HH receives unemployment benefits	0.108	0.311	Dichotomous variable (0/1)	
HH state				
Arizona	0.199	0.399	Dichotomous variable (0/1)	
Florida	0.222	0.416	Dichotomous variable (0/1)	
Michigan	0.196	0.397	Dichotomous variable (0/1)	
Oregon	0.187	0.390	Dichotomous variable (0/1)	
Washington (reference)	0.195	0.397	Dichotomous variable (0/1)	
Population per square mile of HH's zip code	3010.221	3362.953	6.718	41,298.541
Instacart is available in HH's zip code	0.967	0.178	Dichotomous variable (0/1)	
Number of big-box or grocery store brands available for Instacart pickup or delivery in HH's zip code	11.639	4.791	0	18
HH Dwelling type				
Single-family home or townhouse	0.669	0.471	Dichotomous variable (0/1)	
Apartment or condominium	0.275	0.447	Dichotomous variable (0/1)	
HH dwelling unit has a protected place to leave deliveries (e.g., covered porch, building locker, garage, etc.)	0.772	0.419	Dichotomous variable (0/1)	
HH dwelling unit does not have a protected place to leave deliveries	0.223	0.416	Dichotomous variable (0/1)	
HH dwelling unit requires delivery personnel to request access	0.182	0.386	Dichotomous variable (0/1)	
HH dwelling unit does not require delivery personnel to request access	0.809	0.393	Dichotomous variable (0/1)	
HH's preferred grocery store is easy to get to from home	0.926	0.262	Dichotomous variable (0/1)	
HH has no grocery stores in walking distance of home	0.448	0.497	Dichotomous variable (0/1)	
HH has several grocery stores in walking distance of home	0.229	0.420	Dichotomous variable (0/1)	
Tech access and satisfaction				
HH has internet access at home	0.961	0.193	Dichotomous variable (0/1)	
HH does not have internet access at home	0.038	0.192	Dichotomous variable (0/1)	

HH has access to a computer at home	0.960	0.196	Dichotomous variable (0/1)
HH does not have access to a computer at home	0.040	0.196	Dichotomous variable (0/1)
HH members have access to a dataplan for cellphone	0.920	0.272	Dichotomous variable (0/1)
HH members do not have access to a dataplan for cellphone	0.059	0.236	Dichotomous variable (0/1)
HH is satisfied with internet quality	0.754	0.431	Dichotomous variable (0/1)
HH is not satisfied with internet quality	0.131	0.338	Dichotomous variable (0/1)
HH has enough tech devices to meet their needs	0.899	0.301	Dichotomous variable (0/1)
HH does not have enough tech devices to meet their needs	0.054	0.226	Dichotomous variable (0/1)
HH has sufficient data for a dataplan	0.854	0.353	Dichotomous variable (0/1)
HH does not have sufficient data for a dataplan	0.069	0.254	Dichotomous variable (0/1)
COVID-19 related variables			
At least one HH member experienced ______ due to the COVID 19 pandemic:			
Temporary layoff, furlough, or permanent job-loss during the pandemic	0.304	0.460	Dichotomous variable (0/1)
Decrease in income	0.333	0.471	Dichotomous variable (0/1)
More remote work	0.375	0.484	Dichotomous variable (0/1)
Concerns about housing stability	0.228	0.420	Dichotomous variable (0/1)
At least one HH member was diagnosed with COVID-19	0.104	0.306	Dichotomous variable (0/1)
At least one HH member is particularly vulnerable to COVID-19	0.417	0.493	Dichotomous variable (0/1)
At least one HH member received at least one dose of COVID-19 vaccine	0.132	0.339	Dichotomous variable (0/1)
HH pandemic-related changes to amount of groceries purchased			
No change	0.494	0.500	Dichotomous variable (0/1)
Less groceries each time I/we shop	0.091	0.288	Dichotomous variable (0/1)
More groceries each time I/we shop	0.415	0.493	Dichotomous variable (0/1)
HH pandemic-related changes to shopping times to avoid crowds			
No change	0.425	0.494	Dichotomous variable (0/1)
Yes, sometimes	0.366	0.482	Dichotomous variable (0/1)

Yes, always	0.209	0.407	Dichotomous variable (0/1)
HH pandemic-related changes to number of stores grocery shopped at			
No change	0.467	0.499	Dichotomous variable (0/1)
Fewer stores than before	0.468	0.499	Dichotomous variable (0/1)
More stores than before	0.065	0.246	Dichotomous variable (0/1)
HH pandemic-related changes to grocery stores			
No change	0.763	0.425	Dichotomous variable (0/1)
Yes, some of the stores are different	0.199	0.399	Dichotomous variable (0/1)
Yes, all the stores are different	0.038	0.191	Dichotomous variable (0/1)
In-store grocery shopping frequency compared to before the pandemic			
About the same	0.516	0.500	Dichotomous variable (0/1)
Less often	0.372	0.483	Dichotomous variable (0/1)
More often	0.081	0.273	Dichotomous variable (0/1)
Restaurant dine-in frequency compared to before the pandemic			
About the same	0.105	0.306	Dichotomous variable (0/1)
Less often	0.557	0.497	Dichotomous variable (0/1)
Restaurant drive-thru frequency compared to before the pandemic			
About the same	0.338	0.473	Dichotomous variable (0/1)
Less often	0.180	0.385	Dichotomous variable (0/1)
More often	0.361	0.480	Dichotomous variable (0/1)
Restaurant deliveries frequency compared to before the pandemic			
About the same	0.231	0.422	Dichotomous variable (0/1)
Less often	0.117	0.321	Dichotomous variable (0/1)
More often	0.275	0.447	Dichotomous variable (0/1)
HH planning ahead prior to grocery shopping compared to before the pandemic			
About the same	0.540	0.499	Dichotomous variable (0/1)
Less often	0.030	0.171	Dichotomous variable (0/1)

More often	0.382	0.486	Dichotomous variable (0/1)	
HH members have less time to cook compared to before the pandemic				
Agree	0.079	0.270	Dichotomous variable (0/1)	
Disagree	0.672	0.470	Dichotomous variable (0/1)	
HH members are too tired to cook compared to before the pandemic				
Agree	0.265	0.442	Dichotomous variable (0/1)	
Disagree	0.451	0.498	Dichotomous variable (0/1)	
HH members have less time to grocery shop compared to before the pandemic				
Agree	0.112	0.316	Dichotomous variable (0/1)	
Disagree	0.654	0.476	Dichotomous variable (0/1)	
HH average county cumulative COVID-19 cases per 100,000 population in last four weeks	5,225.622	2,226.957	1,184.572	14,075.539
HH average county cumulative COVID-19 deaths per 100,000 population in last four weeks	92.275	52.003	12.936	264.462
HH average county new COVID-19 cases per 100,000 population in last four weeks	1,390.979	912.969	269.109	3,751.886
HH average county new COVID-19 deaths per 100,000 population in last four weeks	19.981	13.259	1.207	72.087
HH county percentage (*100) vaccinated residents	21.237	2.790	10.900	49.500
HH county percentage (*100) vaccinated residents over 18	26.876	3.087	14.300	53.300
HH county percentage (*100) vaccinated residents over 64	61.748	6.543	30.000	88.600
Federal Reserve Bank of Dallas Mobility and Engagement (MEI) Index, in percentage*100 for HH county	-52.738	10.007	-77.741	-18.551
HH county percentage of residents hesitant to receive COVID-19 vaccine	0.165	0.035	0.090	0.260
HH county percentage of residents strongly hesitant to receive COVID-19 vaccine	0.077	0.017	0.050	0.120
CDC COVID-19 Vaccine Coverage Index (CVAC) for HH county	0.529	0.207	0.110	0.970
State policy level				
Low Restrictions (AZ & FL)	0.421	0.494	Dichotomous variable (0/1)	

Mid-Restrictions (MI)	0.196	0.397	Dichotomous variable (0/1)	
High Restrictions (OR & WA)	0.383	0.486	Dichotomous variable (0/1)	
CDC Social Vulnerability Index (SVI) for county compared to all U.S.	0.529	0.221	0.007	0.990
CDC Social Vulnerability Index (SVI) for county compared to respective state	0.415	0.255	0	0.9878
Percentage(*100) of HH's county population not within 1 mile of a grocery store	19.954	8.008	1.260	56.730
Household responding shopper attitudes about grocery shopping and technology				
When grocery shopping, getting out of the house is not at all important	0.293	0.455	Dichotomous variable (0/1)	
When grocery shopping, getting out of the house is very important	0.285	0.451	Dichotomous variable (0/1)	
When grocery shopping, being able to inspect items for quality not at all important	0.048	0.213	Dichotomous variable (0/1)	
When grocery shopping, being able to inspect items for quality is very important	0.659	0.474	Dichotomous variable (0/1)	
When grocery shopping, minimizing time spent shopping is not at all important	0.170	0.376	Dichotomous variable (0/1)	
When grocery shopping, minimizing time spent shopping is very important	0.413	0.492	Dichotomous variable (0/1)	
When grocery shopping, having a wide selection of brands and products to choose from is not at all important	0.034	0.180	Dichotomous variable (0/1)	
When grocery shopping, having a wide selection of brands and products to choose from is very important	0.638	0.481	Dichotomous variable (0/1)	
When grocery shopping, being able to use coupons is not at all important	0.226	0.419	Dichotomous variable (0/1)	
When grocery shopping, being able to use coupons is very important	0.430	0.495	Dichotomous variable (0/1)	
When grocery shopping, minimizing level of effort is not at all important	0.243	0.429	Dichotomous variable (0/1)	
When grocery shopping, minimizing level of effort is very important	0.281	0.449	Dichotomous variable (0/1)	
When grocery shopping, being able to comparison shop is not at all important	0.126	0.332	Dichotomous variable (0/1)	
When grocery shopping, being able to comparison shop is very important	0.409	0.492	Dichotomous variable (0/1)	
When grocery shopping, getting the best price available is not at all important	0.031	0.174	Dichotomous variable (0/1)	

When grocery shopping, getting the best price available is very important	0.671	0.470	Dichotomous variable (0/1)
When grocery shopping, minimizing travel to the store is not at all important	0.232	0.422	Dichotomous variable (0/1)
When grocery shopping, minimizing travel to the store is very important	0.329	0.470	Dichotomous variable (0/1)
When grocery shopping, not having to pay delivery fees is not at all important	0.105	0.306	Dichotomous variable (0/1)
When grocery shopping, not having to pay delivery fees is very important	0.628	0.484	Dichotomous variable (0/1)
When grocery shopping, being able to shop 24/7 is not at all important	0.138	0.345	Dichotomous variable (0/1)
When grocery shopping, being able to shop 24/7 is very important	0.488	0.500	Dichotomous variable (0/1)
When grocery shopping, not having to carry items is not at all important	0.588	0.492	Dichotomous variable (0/1)
When grocery shopping, not having to carry items is very important	0.144	0.351	Dichotomous variable (0/1)
Agrees using a credit card online is safe	0.638	0.481	Dichotomous variable (0/1)
Disagrees using a credit card online is safe.	0.091	0.288	Dichotomous variable (0/1)
Is comfortable having a delivery person come to their house	0.714	0.452	Dichotomous variable (0/1)
Is not comfortable having a delivery person come to their house	0.102	0.303	Dichotomous variable (0/1)
Is worried about deliveries being stolen, misplaced, or not delivered	0.320	0.467	Dichotomous variable (0/1)
Is not worried about deliveries being stolen, misplaced, or delivered	0.416	0.493	Dichotomous variable (0/1)
Prefers to make purchases with cash	0.172	0.377	Dichotomous variable (0/1)
Enjoys food shopping	0.614	0.487	Dichotomous variable (0/1)
Does not enjoy food shopping	0.135	0.342	Dichotomous variable (0/1)
Likes to shop at a variety of stores	0.548	0.498	Dichotomous variable (0/1)
Knows others who are ordering groceries online	0.474	0.499	Dichotomous variable (0/1)
Does not know others who are ordering groceries online	0.253	0.435	Dichotomous variable (0/1)
Agrees it's important to support local businesses	0.899	0.301	Dichotomous variable (0/1)
Thinks it's easy to shop online	0.579	0.494	Dichotomous variable (0/1)
Disagrees that it's easy to shop online	0.127	0.333	Dichotomous variable (0/1)
Thinks shopping online for groceries saves money	0.189	0.392	Dichotomous variable (0/1)

Disagrees that shopping online for groceries saves money	0.452	0.498	Dichotomous variable (0/1)
Agrees it is expensive to have groceries delivered	0.336	0.472	Dichotomous variable (0/1)
Disagrees it is expensive to have groceries delivered	0.301	0.459	Dichotomous variable (0/1)
Thinks shopping online saves time	0.607	0.488	Dichotomous variable (0/1)
Disagrees that shopping online saves time	0.143	0.351	Dichotomous variable (0/1)
Thinks comparison shopping is easier online	0.446	0.497	Dichotomous variable (0/1)
Disagrees that comparison shopping is easier online	0.220	0.414	Dichotomous variable (0/1)
Thinks it is expensive to have groceries delivered	0.529	0.499	Dichotomous variable (0/1)
Disagrees it is expensive to have groceries delivered	0.158	0.364	Dichotomous variable (0/1)
Thinks shopping online is environmentally friendly	0.312	0.463	Dichotomous variable (0/1)
Disagrees shopping online is environmentally friendly	0.160	0.367	Dichotomous variable (0/1)
Satisfaction with in-store grocery shopping experiences			
Satisfied, availability of items	0.656	0.475	Dichotomous variable (0/1)
Dissatisfied, availability of items	0.154	0.361	Dichotomous variable (0/1)
Satisfied, quality of items	0.827	0.379	Dichotomous variable (0/1)
Dissatisfied, quality of items	0.038	0.192	Dichotomous variable (0/1)
Satisfied, selection of items to choose from	0.741	0.438	Dichotomous variable (0/1)
Dissatisfied, selection of items to choose from	0.102	0.302	Dichotomous variable (0/1)
Satisfied, safety measures taken by stores to ensure customer safety	0.751	0.432	Dichotomous variable (0/1)
Dissatisfied, safety measures taken by stores to ensure customer safety	0.066	0.249	Dichotomous variable (0/1)
Satisfied, time spent waiting (e.g., to get into the store, in line at checkout, etc.)	0.562	0.496	Dichotomous variable (0/1)
Dissatisfied, time spent waiting	0.155	0.362	Dichotomous variable (0/1)

^Notes: Not all levels of multilevel variables may be shown, in particular those that a) comprise <3% or >97% of the sample or b) those that were not used other than as a reference level. Dichotomous variables are equal to 1 if the condition listed holds and are 0 otherwise. The ‘mean’ of dichotomous variables is representative of the percentage of the sample for which the expressed condition is true.

Appendix C: External datasets appended to the sample data

C.1 Building zip code to county crosswalk file
Many of the available relevant datasets to join to the collected survey data reported statistics at the county level. Therefore, it was necessary to develop a crosswalk file between zip codes (which were provided by survey respondents) and counties. The U.S. Department of Housing and Urban Development publishes zip code to county relationship files based on 2010 census geographies (*168*). Data for the zip code to county crosswalk were pulled from the HUD website (*169*). Because a given zip code may fall into multiple counties, the zip code was assigned to the county that the highest share of its population resided in, where applicable.

C.2 Rural-urban commuting area codes
The U.S. Department of Agriculture Economic Research Service (USDA ERA) publishes classifications on a rural-metropolitan continuum based on population density, level of urbanization, and commuting patterns (*67*). Although the most recent classifications rely on the 2010 decennial census and 2006-2010 American Community Survey, the data offer one of the only readily available composite measures of rural, small town, micropolitan, and metropolitan area classifications at the zip code level. These data were joined to the collected survey data at the zip code level. For this analysis, the survey dataset was then limited to include respondents living in metropolitan zip-codes only, where both e-grocery and in-store grocery shopping opportunities would be most likely to exist.

C.3 County populations with low access to grocery stores
The USDA ERA also publishes the Food Environment Atlas, which includes data on access and proximity to grocery stores at the county level (*128*). A measure indicating the percentage of the county population with low access to grocery stores, defined for urban areas as living more than a mile from a supermarket, was linked to the survey data at the county level. This measure was tested across the presented analysis in this document to see if there was a connection between respondents living in low-access counties and utility of e-grocery services, delivery in particular.

C.4 Database of Instacart availability and number of stores
In order to form a measure of relative availability and potential prevalence of e-grocery delivery or pickup service, data were scraped from the Instacart website delineating if a) Instacart service was available in each respondent's zip code, and b) the number of grocery and big-box store brands available through Instacart (which was 0 where Instacart was not available). Python[21] and Selenium[22] were employed in the data scraping process. While certainly an imperfect measure—Instacart is not the only app through which groceries can be delivered. However, its use as a proxy for availability of e-

[21] Python Software Foundation. Python Language Reference, version 3.7.9. Available at http://www.python.org
[22] See https://www.selenium.dev/selenium/docs/api/javascript/index.html

grocery services was thought to be appropriate given its sizeable market share (some estimate 50% or more (*127*)).

C.5 COVID-19 related data

C.5.1 Policies

Policy data at the state level were appended to the survey, using December 23, 2020 as a benchmark date for policies being in place (or not)[23] . Whether or not statewide mask mandates, stay at home orders, or bans on gatherings were in place on the benchmark date were summarized for each state based on data from the Centers for Disease Control (*107–109*). The state policies are summarized in Table C1:

Table C1 Survey state policy summaries

State	Mask mandate	Stay at home order	Ban on gatherings	Policy level
Arizona	No	No	No	Low restrictions
Florida	No	No	No	Low restrictions
Michigan	Yes	No	Yes	Mid restrictions
Oregon	Yes	Yes	Yes	High restrictions
Washington	Yes	Yes	Yes	High restrictions

Because these policies were summarized at the state level, state indicators and policy indicators were tested separately in analysis. Overall, state indicators performed better, likely because they capture both policy and built environment differences across states (although significant differences in outcomes rarely varied by state or policy level)

C.5.2 Case and death rates

Data from The New York Times Github repository tracking COVID-19 cases and deaths at the county level (*110*) were downloaded and aggregated for the four weeks prior to survey fielding (starting December 23, 2020). Both total cumulative and new cases and deaths across the four weeks were averaged and converted to rates per 100,000 county population. The data were then appended to the survey at the county level for testing in analyses.

C.5.3 Vaccination rates

CDC metrics describing the percentage of fully vaccinated population at the county level (*170*) was appended to respondent's home counties. An additional CDC published measure describing the percent of a county's population that indicated being hesitant or strongly hesitant to receive a vaccine (*171*) was appended. It was hypothesized that household shoppers' and their households' behavior related to online and in-person grocery shopping might be impacted by widespread vaccination level. Namely, perhaps

[23] This was approximately four weeks prior to survey fielding, and the survey asked about participant's last four weeks of behavior.

consumers in areas with higher vaccination rates would show higher levels of in-person shopping. Else, areas with high vaccination rates may be culturally more worried about contracting COVID-19, and may exhibit higher rates of e-grocery shopping.

C.5.4 CDC Social Vulnerability Index (SVI), COVID-19 Vaccine Coverage (CVAC) Index

The CDC's SVI describes a communities' vulnerability to disaster based on a suite of characteristics related to socioeconomic and demographic conditions (*171*), with zero indicating least vulnerable communities and one indicating the most vulnerable. Measures comparing counties SVI to counties within the same state as well as to counties in the U.S. overall were appended to the sample. The CDC also compiled the CVAC Index, which captures challenges related to vaccine rollout in a given county based on characteristics related to healthcare, resources, and vaccine histories (*171*). The CVAC Index appended to the sample takes a value of zero in the counties expected to face the least challenge for vaccination rollout, and one for those expected to face the greatest.

C.5.5 The Federal Reserve Bank of Dallas Mobility and Engagement Index (MEI)

The Federal Reserve Bank of Dallas compiled the MEI to assess deviations from baseline mobility patterns (data from January and February of 2020) based on cell phone data (*172*). The county-level index is presented in percentage difference (x100) in mobility compared to baseline data depending on trip times, distances, and locations (at or away from home). It was hypothesized that households located in areas with less engagement compared to baseline values may rely more on e-grocery services.

Appendix D: Descriptive statistics for significant variables in e-grocery delivery adoption models, disaggregated by income level

Table D.1 Low-income e-grocery delivery adoption model descriptives

	Mean	Std. Dev.	Min	Max
Outcome: E-grocery delivery status				
Non-adopter	0.653	0.476	Dichotomous variable (0/1)	
During-pandemic adopter	0.212	0.408	Dichotomous variable (0/1)	
Pre-pandemic adopter	0.136	0.343	Dichotomous variable (0/1)	
HH income is 'Extremely Low Income'	0.342	0.474	Dichotomous variable (0/1)	
Age 18-24	0.101	0.301	Dichotomous variable (0/1)	
Age 25-34	0.201	0.401	Dichotomous variable (0/1)	
Currently employed	0.378	0.485	Dichotomous variable (0/1)	
All members of HH are age 65+	0.206	0.404	Dichotomous variable (0/1)	
HH has access to more than one vehicle	0.308	0.462	Dichotomous variable (0/1)	
Travels to the grocery store by vehicle only [driver or passenger], no other modes	0.744	0.436	Dichotomous variable (0/1)	
HH dwelling unit does not require delivery personnel to request access	0.815	0.388	Dichotomous variable (0/1)	
Zip code population density (people per square mile)	3,192.509	3,501.205	10.037	41,168.847
HH located in Arizona	0.180	0.385	Dichotomous variable (0/1)	
HH located in Florida	0.211	0.408	Dichotomous variable (0/1)	
HH located in Michigan	0.205	0.404	Dichotomous variable (0/1)	
HH located in Oregon	0.190	0.392	Dichotomous variable (0/1)	
HH's preferred grocery store is not easy to get to from home	0.041	0.197	Dichotomous variable (0/1)	
HH is purchasing more groceries each shop compared to before the COVID-19 pandemic	0.402	0.490	Dichotomous variable (0/1)	
HH has not changed grocery stores in response to the COVID-19 pandemic	0.754	0.431	Dichotomous variable (0/1)	
HH has not changed in-store grocery shopping frequency compared to before the start of the COVID-19 pandemic	0.517	0.500	Dichotomous variable (0/1)	
HH dissatisfied with item quality when in-store shopping during the COVID-19 pandemic	0.046	0.210	Dichotomous variable (0/1)	

When grocery shopping, not having to carry items is very important	0.188	0.391	Dichotomous variable (0/1)
When grocery shopping, being able to inspect items for quality is not important	0.054	0.226	Dichotomous variable (0/1)
When grocery shopping, being able to inspect items for quality is very important	0.641	0.480	Dichotomous variable (0/1)
When grocery shopping, minimizing travel to the store is not important	0.214	0.410	Dichotomous variable (0/1)
When grocery shopping, not having to pay any delivery fees is very important	0.664	0.472	Dichotomous variable (0/1)
Knows others who are ordering groceries online	0.415	0.493	Dichotomous variable (0/1)
Thinks it is easy to shop online for groceries	0.548	0.498	Dichotomous variable (0/1)
Disagrees that scheduling grocery delivery is difficult	0.262	0.440	Dichotomous variable (0/1)
Disagrees that HH members are too tired to cook in response to the COVID-19 pandemic	0.391	0.488	Dichotomous variable (0/1)
Is uncomfortable with delivery personnel coming to their home	0.106	0.308	Dichotomous variable (0/1)

Table D.2 Mid-income e-grocery delivery adoption model descriptives

	Mean	Std. Dev.	Min	Max
Outcome: E-grocery delivery status				
Non-adopter	0.629	0.483	Dichotomous variable (0/1)	
During-pandemic adopter	0.187	0.390	Dichotomous variable (0/1)	
Pre-pandemic adopter	0.184	0.388	Dichotomous variable (0/1)	
Age 55-64	0.167	0.373	Dichotomous variable (0/1)	
No HH members are age 65+	0.676	0.468	Dichotomous variable (0/1)	
Education level is college degree or higher	0.600	0.490	Dichotomous variable (0/1)	
Is a homemaker	0.082	0.275	Dichotomous variable (0/1)	
Is employed and working from home exclusively.	0.169	0.375	Dichotomous variable (0/1)	
Travels to the store by vehicle only [driver or passenger], no other modes	0.856	0.352	Dichotomous variable (0/1)	

Vehicles per HH member	0.817	0.443	0	3
HH located in Arizona	0.251	0.434	Dichotomous variable (0/1)	
HH located in Florida	0.200	0.400	Dichotomous variable (0/1)	
HH located in Michigan	0.200	0.400	Dichotomous variable (0/1)	
HH located in Oregon	0.167	0.373	Dichotomous variable (0/1)	
HH member(s) were diagnosed with COVID-19	0.131	0.338	Dichotomous variable (0/1)	
HH worried that food would run out before having money to buy more	0.222	0.416	Dichotomous variable (0/1)	
HH has not changed in-store grocery shopping frequency in response to the pandemic	0.536	0.499	Dichotomous variable (0/1)	
Is satisfied with in-store safety measures when shopping in-store during the COVID-19 pandemic	0.769	0.422	Dichotomous variable (0/1)	
When grocery shopping, minimizing level of effort is very important	0.269	0.444	Dichotomous variable (0/1)	
When grocery shopping, not having to carry items is very important	0.124	0.330	Dichotomous variable (0/1)	
When grocery shopping, getting the best price available is very important	0.667	0.472	Dichotomous variable (0/1)	
When grocery shopping, minimizing travel to the store is not important	0.238	0.426	Dichotomous variable (0/1)	
Does not think it is expensive to have groceries delivered	0.171	0.377	Dichotomous variable (0/1)	
Is comfortable having a delivery person come to their home	0.709	0.454	Dichotomous variable (0/1)	
Thinks it is easy to shop online for groceries	0.604	0.489	Dichotomous variable (0/1)	
Does not know others who are ordering groceries online	0.247	0.431	Dichotomous variable (0/1)	
Agrees that scheduling grocery delivery is difficult	0.302	0.459	Dichotomous variable (0/1)	

Disagrees that shopping online is environmentally friendly	0.164	0.371	Dichotomous variable (0/1)

Table D.3 High-income e-grocery delivery adoption model descriptives

	Mean	Std. Dev.	Min	Max
Outcome: E-grocery delivery status				
Non-adopter	0.600	0.490	Dichotomous variable (0/1)	
During-pandemic adopter	0.186	0.389	Dichotomous variable (0/1)	
Pre-pandemic adopter	0.214	0.410	Dichotomous variable (0/1)	
Age 18-24	0.048	0.213	Dichotomous variable (0/1)	
All members of HH are age 65+	0.259	0.438	Dichotomous variable (0/1)	
Vehicles per HH member	0.913	0.414	Dichotomous variable (0/1)	
Travels to the store by vehicle only [driver or passenger], no other modes	0.864	0.343	Dichotomous variable (0/1)	
There are several grocery stores in walking distance from HH dwelling unit	0.231	0.422	Dichotomous variable (0/1)	
HH dwelling unit has a protected place to leave deliveries (e.g., covered porch, building locker, garage, etc.)	0.853	0.354	Dichotomous variable (0/1)	
HH located in Arizona	0.194	0.396	Dichotomous variable (0/1)	
HH located in Florida	0.252	0.434	Dichotomous variable (0/1)	
HH located in Michigan	0.181	0.385	Dichotomous variable (0/1)	
HH located in Oregon	0.196	0.397	Dichotomous variable (0/1)	
HH is shopping at fewer grocery stores in response to the COVID-19 pandemic	0.466	0.499	Dichotomous variable (0/1)	
HH is shopping at more grocery stores in response to the COVID-19 pandemic	0.077	0.266	Dichotomous variable (0/1)	
HH is placing orders for restaurant delivery more often compared to before the COVID-19 pandemic	0.293	0.455	Dichotomous variable (0/1)	
HH has not changed in-store grocery shopping frequency in response to the pandemic	0.505	0.500	Dichotomous variable (0/1)	
Disagrees that HH has less time to shop compared to before the COVID-19 pandemic	0.692	0.462	Dichotomous variable (0/1)	

Is satisfied with time spent waiting (e.g., to get in the store, in line at checkout, etc.) when shopping in-store during the COVID-19 pandemic	0.625	0.484	Dichotomous variable (0/1)
When grocery shopping, minimizing level of effort is very important	0.276	0.447	Dichotomous variable (0/1)
When grocery shopping, being able to easily comparison shop is very important	0.400	0.490	Dichotomous variable (0/1)
When grocery shopping, not having to pay delivery fees is very important	0.576	0.494	Dichotomous variable (0/1)
Is comfortable having a delivery person come to their home	0.746	0.435	Dichotomous variable (0/1)
Is not worried about deliveries being stolen, misplaced, or not delivered	0.480	0.500	Dichotomous variable (0/1)
Knows others who are ordering groceries online	0.534	0.499	Dichotomous variable (0/1)
Thinks it is easy to shop online for groceries	0.608	0.488	Dichotomous variable (0/1)
Disagrees that scheduling grocery delivery is difficult	0.328	0.469	Dichotomous variable (0/1)
Agrees shopping online saves time	0.608	0.488	Dichotomous variable (0/1)

Appendix E: Extended results of trip rate models

E.1 Weekly in-store grocery trip rates

Household and respondent demographics, geographics, and dwelling unit characteristics
Estimated parameters for household size, along with indicators for households having access to more than one vehicle and households receiving SNAP benefits, were found to be random and normally distributed. The parameter for household size has a mean of 0.104 and standard deviation of 0.103, indicating it has a positive effect on weekly in-store grocery trip rates for 84% of households and a negative effect for 16%. Trip literature generally supports the finding that larger households generate more trips in general (*173*). However, key information about expenditures could help unpack the negative effect. While a larger household may purchase more food, purchases could be distributed among any number of trips shared by household members. A household may, for example, only generate one trip to the store a week, but purchase more groceries in a single trip than a household of the same size, who breaks their purchase into two trips.

A similar logic might be extended to the random parameter estimated for SNAP recipients, which has a mean of 0.172 and a standard deviation of 0.649. This indicates receiving SNAP benefits has a positive effect on weekly in-store grocery trip rates for 60% of households, and negative effect for the remaining 40%. A household receiving SNAP benefits may make fewer trips to the store around when their benefits are distributed, stockpiling groceries for the month. Conversely, a household may use their benefits in smaller increments throughout the month, supplementing their benefits with income as it comes in.

Sixty-two percent of households who have access to more than one vehicle have higher weekly in-store grocery trip rates compared to those who don't, while 38% have lower trip rates. This is indicated by the associated parameter mean of 0.078 and standard deviation of 0.269. A positive effect of car ownership on trip making (particularly, of course, on vehicle trips) has been demonstrated in the literature (*174*, *175*). With respect to grocery shopping, vehicles may boost the ease and convenience of traveling to the store, possibly leading to more trips. However, a household can likely transport more groceries from a given shopping trip in a vehicle compared to other modes, like transit, walking, or biking. Because of this, vehicle-owning households may be able to fulfill their food shopping needs in fewer trips.

The importance of perceived accessibility to grocery stores is demonstrated in the model. If a household's preferred grocery store is easy to get to from home, their weekly in-store grocery trip rate is expected to be higher. Conversely, if there are no grocery stores in walking distance of home, a household's weekly in-store grocery trip rate is expected to be lower. These results suggest households with better access to grocery stores, measured subjectively and in terms of travel distances, will generate more weekly in-store shopping trips. Differences exist in the literature on this matter. Li et al. (*176*), using a measure of accessibility based on travel costs, find a positive relationship between accessibility and non-work travel. In contrast, Handy (*177*) finds higher levels of local and regional accessibility do not impact shopping trip frequency, although they are associated with lower travel distances. These discrepancies likely stem from differences in how accessibility is measured (*173*).

Of the state control variables, households located in Michigan are expected to have lower weekly in-story grocery trip rates compared to those in Washington. At the time of survey fielding, Washington had a statewide stay at home order, mask mandate, and ban on gatherings, while Michigan had no stay-at-home order. It's possible that households in Michigan opted to shop for groceries in-person less often to avoid exposure to COVID-19 due to the looser statewide restrictions. Given the survey was fielded in January and February, this may also be related to snowy weather conditions in Michigan limiting in-person travel overall—although rainy weather conditions in Washington, depending on location, may have also deterred in-person travel during this time.

COVID-19 related indicators

Households where at least one member received at least the first dose of COVID-19 vaccines are associated with higher weekly in-store grocery trip rates. Increased comfort in resuming typical in-store shopping behaviors due to decreased risk of getting seriously ill from COVID-19 may influence this result. Likely, there is a positive trend between in-store trip making and vaccinated individuals as well as individuals not concerned about contracting COVID-19, although only the former is explicitly demonstrated by the model.

The estimated indicator parameter for households where least one member experienced a temporary layoff, furlough, or permanent job loss due to the pandemic was found to be random and normally distributed. This indicates 62% of households with this experience have higher weekly in-store grocery trip rates, while 38% have lower trip rates. Household income and an indicator for households who experienced a decrease in income during the pandemic were not found to be significant in this model. However, job instability is likely associated with worries about or actual decreases in income, which might be expected to disrupt food shopping due to (actual or expected) constrained resources. In contrast, a household may go to the store to shop more frequently under these conditions, purchasing fewer groceries at a time based on paycheck schedules. Again, information on household food expenditures, and the timeframe at which household income is received, would greatly inform this finding.

Households that are shopping at fewer stores in response to the COVID-19 pandemic are expected to have lower weekly in-store trip rates, as are households who have less time to shop compared to before the start of the pandemic. Assuming a household would make a fixed number of trips to each store they shop at, the former finding being associated with a lower trip rate follows expectations. Additionally, it makes sense that households who are under increased time constraints due to the pandemic would undergo fewer in-person shopping trips in a given week.

Household shopper attitudes

A handful of household shopper attitudes were found to be significantly associated with weekly in-store grocery trip rates in the expected directions. Households where shoppers indicated they enjoyed shopping for food were associated with higher weekly in-store grocery trip rates. Those where shoppers like to shop at a variety of stores are expected to have higher rates. On the other hand, households where shoppers indicated that minimizing time spent shopping and minimizing travel to the grocery store were very important were expected to have lower trip rates.

An indicator for shoppers who said being able to inspect items for quality when grocery shopping is very important was found to be random and normally distributed with a mean of 0.250 and a standard deviation of 0.352. This indicates a positive trend between this attitude and weekly in-store grocery trip rates for 76% of households, and a negative trend for 24%. Interpretation of the positive trend is intuitive: in order to inspect the quality of various items when shopping, a household shopper would be expected to travel to the store more often to do so. Yet, the reverse is also intuitive. In a study of low-income households, Webber et al. (*113*) found that product quality was a major factor of importance in food shopping. Fresh food lasts longer, and participants noted that inspecting item quality was an indicator for its respective shelf life. It follows that respondents who enjoy inspecting items for quality may be doing this so that purchases last longer and fewer trips to the store are required in a given time period.

E.2 Weekly online grocery pickup trip rates

Household and respondent demographics, geographics, and dwelling unit characteristics
In the participation model, the estimated parameter for shopper age 25-34 was found to be random and normally distributed with a mean of 0.173 and standard deviation of 0.608. This indicates that households with shoppers in this age group are more likely to place an online pickup grocery order for 61% of households, and less likely for 39%. In an overlapping age cohort (31-40 year olds), Droogenbroeck and Hove (*26*) found a higher probability of use of an online pickup grocery service compared to the reference group of 18-30 year olds, and a negative trend of age on use thereafter. The positive result here also aligns literature finding that younger exhibit higher rates of online shopping compared to older groups (*31*, *37*). The negative facet of the heterogeneous effect here could stem from the fact that this age group is less susceptible to serious health problems as a result of contracting COVID-19, which may decrease the utility of online pickup from a safety standpoint relative to older age groups.

Households where the responding shopper is male are expected to have higher weekly online pickup grocery trip rate. Men are more likely to shop online in general (*26*), although women may be more likely to shop both in-store and online (*31*)—perhaps because they do more of household provisioning in general (*32*). In the participation model, the estimated parameter for households with children was found to be random and normally distributed with a mean of 0.408 and a standard deviation of 0.357. Households with children are thus expected to have higher weekly online pickup grocery trip rates in 87% of households, and lower rates in 13% of households. Larger households, particularly those with children, have been linked with more frequent online provisioning habits (*31*). Children might introduce additional time constraints on households, making online ordering options more attractive. The negative effect might be observed for a variety of reasons. Online pickup still requires a trip to the store. If shoppers have young children with them, additional time waiting spent waiting in the car may be undesirable if children grow restless. Trips to the store may also be chained with trips to and from children's school or extracurricular activities, which may not always align with online pickup windows.

Households where the responding shopper was unemployed and not looking for work are expected to have lower weekly online pickup grocery trip rates. Households where at least one member experienced a temporary layoff, furlough, or permanent job-loss during the pandemic are also associated with lower rates. Similar to the findings in the weekly in-store grocery trip rate model, household income and an indicator for households who experienced a decrease in income during the pandemic were not found to be significant here. These employment-related characteristics may, however, reflect existing or anticipating constraints on household income and resources available for food shopping. The strict negative trends here compared to the previously observed heterogeneity may be due to additional fees—for example, third party app fees or servicing fees—associated with online grocery pickup.

Zero-car households are associated with lower weekly online pickup trip rates. The direction of this effect is as expected. Unlike online grocery delivery, online grocery pickup still requires travel to the store. One perceived benefit of online pickup compared to in-store shopping during the pandemic, besides any assumed time savings, is that groceries are loaded into one's vehicle with minimal exposure to others. Grocery stores with curbside pickup options typically have reserved parking or curb space for this purpose. In order for zero-car households to shop this way, they may need to borrow vehicles from others, posing additional hassle associated with grocery pickup.

In contrast, households with internet access are associated with higher weekly online pickup grocery trip rates. Internet—or else a data plan, an indicator for which was not significant in this model—is a prerequisite for ordering online in general. Being able to do so from home enhances the relative ease of this action, potentially increasing the attractiveness of online grocery pickup. Without internet at home, households may have to place online orders using public Wi-Fi hotspots, adding an additional step—and barrier—to ordering groceries online.

Of the state control variables, the estimated parameter for households in Oregon was found to be random with a normal distribution in the participation model. The parameter mean of -0.220 and standard deviation of 0.333 suggest 25% of households located in Oregon have higher probabilities of placing an online grocery pickup order compared to those in Washington, with a lower probability observed in the remaining 75%. Oregon and Washington both had statewide mask mandates, stay at home orders, and bans on large gatherings in place at the time of survey fielding. However, in the four weeks prior to survey fielding (the timeframe in which survey respondents were asked about their behaviors), Oregon counties experienced fewer new COVID-19 cases on average compared to Washington counties. Lower perceived COVID-19 risks in Oregon may influence this result.

COVID-19 related indicators

Households where at least one member was diagnosed with COVID-19 have higher weekly online pickup grocery trip rates. This may signal household utilization of online grocery pickup to avoid exposure to others during or after contracting COVID-19.

Changes in provisioning in response to the COVID-19 pandemic also offered explanatory power. Households where shoppers indicated they were shopping in-person at grocery stores less often since before the start of the pandemic, and those who were shopping at fewer grocery stores in response to the pandemic, have higher rates. This supports a hypothesis that online pickup was perhaps used to make up for lower in-person shopping rates and fewer shopping destinations due to the pandemic, likely changes that were made as safety precautions.

The estimated parameter for households ordering restaurant food for delivery more often compared to before the start of the pandemic was found to be random with normal distribution. The parameter mean of 0.269 and standard deviation of 0.339 indicate a positive effect of this behavior on weekly online pickup grocery trip rates for 71% of households, and a negative effect for 29%. Similar to the relationship between the outcome variable and online restaurant pickup trip rates, the heterogeneity here may be due to a positive association between use of online ordering methods and a negative association between restaurant and grocery provisioning.

The estimated parameter for households who are planning ahead before shopping more often compared to before the start of the COVID-19 pandemic is random and normally distributed with a mean of 0.128 and a standard deviation of 0.323. This indicates a positive association between the indicator and weekly online pickup grocery trip rates for 65% of households and a negative association for 35%. The heterogeneity here may be capturing differences in perceived benefits of online pickup as it relates to household planning. For some, online pickup (or delivery) ordering may require more advance planning, as consumers must go on to the relevant website or app and select items to schedule for pickup in advance. In contrast, consumers may plan in advance but can also make unplanned purchases within the store with traditional in-store shopping. On the other hand, some may view online purchasing methods as simplifying their planning efforts given only needed items can be added to their online carts.

Dissatisfaction with in-store shopping selection and safety measures taken by stores were both positive predictors of online pickup grocery trip rates. Households where respondent shoppers indicated they were dissatisfied with in-store shopping selection are expected to have higher weekly online grocery pickup trip rates. Those who said they were dissatisfied by safety measures taken in store are also associated with higher rates. The online marketplace may offer consumers a wider selection when in-store supply is constrained, as has been the case during the COVID-19 pandemic (*3*, *4*). Online pickup also offers a safer method of shopping during the pandemic due to reduced exposure to others in close quarters, especially when consumers care about, and are dissatisfied with, safety measures (or lack thereof) implemented by stores.

Household shopper attitudes

A number of attitudinal variables have explanatory power for weekly online grocery pickup trip rates. The estimated parameter for household shoppers who noted being able to inspect items for quality is very important was significant in both the participation and frequency model and was found to be random with a normal distribution in the latter. Households with shoppers who held this attitude were associated with a lower probability of using online grocery pickup. In the frequency model, the estimated parameter for this indicator had a mean of -0.217 and a standard deviation of 0.467. This indicates a positive effect of the indicator on weekly online pickup grocery trip rates for 32% of households and a negative effect for 68%. The negative effects in both the participation and frequency model may follow from such households preferring in-store shopping methods to online ones, where items, especially produce, can be assessed prior to purchase. There are different plausible reasons for the positive effect in the frequency model. Even though items in online pickup orders are not selected by shoppers themselves, shoppers may review their purchases in their cars before heading home with their groceries, allowing them to inspect and potentially exchange items.

The attitudinal indicators with the greatest magnitude of effect—not only in comparison to other attitudes, but to all other explanatory variables for which parameters were estimated— are those for household shoppers who think it is easy to shop for groceries online. This attitude is associated households having higher weekly online pickup grocery trip rates. Where household shoppers think shopping for groceries online saves money, their households are expected to have higher online pickup grocery trip rates. Together, these attitudes reflect that ease of use and cost savings may be major pull factors toward grocery online pickup methods. Despite additional costs that could be incurred for grocery pickup (third-party app fees or other service fees, for example), some online platforms may embed coupons or offer other online-exclusive deals to using consumers, increasing the attractiveness of such shopping modes.

Households where shoppers indicated minimizing time spent shopping is very important are associated with higher weekly online pickup grocery trip rates, as are those who indicated online shopping saves time. In contrast, households where respondents indicated they enjoy shopping for food are associated with lower online pickup grocery trip rates. These variables may represent seemingly opposite consumer attitudes toward shopping; those who enjoy shopping for food may not mind spending time doing so, while those who aim to minimize time may do so in order to avoid the task of shopping, particularly if it feels like a chore. These attitudes may be markers for populations who are more likely to use grocery pickup in the future (i.e., those who enjoy time savings) and those who are less likely (i.e., those who like shopping).

Households where responding shoppers indicate they know others who are shopping for groceries online are expected to have higher weekly online pickup trip rates. This likely reflects the power of social norms on behavior, which has been previously demonstrated in literature specifically pertaining to e-grocery shopping (*47*, *52*). Households where shoppers say they like to shop at a variety of stores are expected to have higher weekly online grocery trip rates, while those where shoppers indicate that getting out of the house is very important when grocery shopping are also associated with higher rates. Online pickup as a shopping mode may more easily allow consumers to pick up items from a variety of stores in less time than it would take to go shopping in each store individually, providing a time savings benefit. Additionally, online pickup ordering may allow consumers to reap perceived benefits of this shopping mode over in-store shopping—less risk of contracting COVID-19, time savings, minimized shopping effort, etc. —while still being able to get out of the house, a benefit over online grocery delivery.

E.3 Weekly online grocery delivery trip rates

Household and respondent demographics, geographics, and dwelling unit characteristics
Households whose responding shopper is currently working exclusively from home are expected to have higher weekly online grocery delivery trip rates. Having a household member regularly home during the day to receive groceries likely expands available delivery windows a household can choose from, potentially increasing the convenience of this shopping mode. Households where all members are 65 or older, on the other hand, are associated with lower weekly online grocery delivery trip rates. This generally aligns with lower e-commerce rates observed in older populations (*31, 37*). However, given the increased risk of major illness due to COVID-19 for this population, as well as the more limited mobility patterns associated with aging (*122*), e-grocery delivery services seem like they would have a high utility. Although this population's internet usage is rising (*178*), focus groups with members of this population may provide key insights about current barriers to and perceived benefits of e-grocery delivery, which can then be used to facilitate strategies easier access.

Parameters estimated for a number of household demographics—including household size and indicators for households including children, receiving SNAP assistance, having access to more than one vehicle, and traveling to the store by vehicle only— were found to be random, normally distributed parameters. The parameter estimated for household size had a mean of 0.192 and a standard deviation of 0.202, indicating a positive effect on weekly online grocery delivery trip rates for 83% of households and a negative trend for 17% of households. The random parameter for households with children has a mean of 0.362 and a standard deviation of 0.609. This suggests households with children have higher weekly online grocery delivery trip rates for 72% of households, and lower rates for 28% of households. Larger households, particularly those with children, have been linked with more frequent online provisioning habits (*31*).One potential explanation for the negative trend may have to do with cost. Expenditures for larger households are likely higher, and those higher expenditures along with online delivery costs (e.g., delivery fees, tips, higher price-points, etc.) may deter these households from using e-grocery delivery as frequently. With respect to children, another possible explanation is that other shopping modes—like in-store shopping or online pickup—may be trip-chained to other activities surrounding children, including school pickups and drop-offs or extracurricular activities. If a traditional in-store trip, or online pickup event, can be easily scheduled surrounding other activities, the perceived benefits of online delivery may not outweigh the negative aspects, including cost.

The random parameter for households receiving SNAP benefits had a mean of -0.555 and a standard deviation of 0.143, indicating a positive trend with weekly online grocery delivery trip rates for 13% of households and a negative trend for 87%. In April of 2019, USDA launched a pilot program for use of SNAP benefits online at participating retailers in New York; by September of 2020, the pilot had been expanded to more than 40 states, including the five states survey respondents were located in (*179*). The pilot allowed SNAP recipients to use their benefits on eligible items online for the first time, which may explain the positive trend here. However, barriers were still in place. SNAP benefits could not, for example, be used to cover delivery fees. Additionally, benefits could only be used online at two stores in the five survey states—Walmart and Amazon—limiting selection. On top of the additional costs already associated with online delivery, the culmination of these factors likely helps explain the negative effect for the majority of households.

Variables related to vehicle use and ownership had heterogeneous effects on weekly online grocery delivery trip rates. The random parameters estimated for households having access to more than one vehicle and for households traveling to the store by vehicle only had means of -0.495 and -0.540 and standard deviations of 1.083 and 0.696, respectively. For households having access to more than one vehicle, this translates to a positive effect on weekly online grocery delivery trip rates for 32% of households and a negative effect for 68%. For households whose primary travel mode to the store is vehicle only, this translates to a positive effect on rates for 22% of households and a negative effect for the remaining 78%. The negative effects of these variables on weekly online grocery delivery trip rates likely has to do with access and shopping convenience. Vehicle owning- and using- households may more easily travel to the store compared to slower modes like walking and transit, in general. Additionally, it is easier to carry groceries back home in a vehicle compared to other modes. As such, vehicle ownership and reliance may decrease the utility of e-grocery delivery. However, the positive trend may be associated with COVID-19, as the benefits of e-grocery delivery during this time extend beyond transportation convenience to include offering a safer way to grocery shop by reducing exposure to others. The perceived safety benefits may make e-grocery delivery an attractive shopping mode even for those who can easily access a grocery store in-person.

Indicators related to dwelling unit security offered positive explanatory power on weekly online grocery delivery trip rates. Households whose homes have a protected place to leave deliveries (e.g., covered porch, building locker, etc.) are expected to have 0.073 higher weekly online grocery delivery trip rates, while households whose home requires delivery personnel to request access to drop off packages (e.g., keycard access apartment buildings; gated communities) are associated with higher weekly online delivery rates. These effects make sense given home tends to be consumers' preferred place to receive deliveries but security is a major concern (*180*, *181*).

Population density of households' zip codes is positively related to weekly online grocery delivery trip rates. Although the sample was limited to metropolitan zip codes, the significance here indicates that households in more urban areas have higher online grocery delivery rates, likely a function of higher densities of grocery stores in such areas and, subsequently, increased availability of a variety of stores with e-grocery delivery options.

COVID-19 related indicators

While behavioral changes in response to the pandemic with regard to certain provisioning methods were previously discussed, other variables related to COVID-19 offered significant explanatory power in the model. Households where at least one member was particularly vulnerable to COVID-19—perhaps due to age or pre-existing health conditions—are associated with higher weekly online grocery delivery trip rates. This suggests e-grocery delivery may be utilized by some vulnerable populations to reduce risk of exposure to COVID-19 relative to in-store shopping. In contrast, households where responding shoppers expressed they were satisfied with safety measures taken by their grocery stores when shopping in person are expected to have lower weekly online grocery delivery trip rates.

Households who are shopping at all different grocery stores in response to the COVID-19 pandemic are associated with higher weekly online grocery delivery trip rates. Unsatisfactory experiences shopping at pre-pandemic preferred grocery stores, which may include constrained supplies, may have pushed households to switch from their traditional stores to new ones. New stores may also include online markets, which offers a possible explanation for the positive trend here.

Respondent attitudes

Many attitudinal variables were found to be linked with weekly online grocery delivery trip rates. Households where responding shoppers indicated being able to inspect items for quality is very important when grocery shopping are expected to have lower weekly online grocery delivery trip rates. This direction of effect is expected, given that shoppers are not able to inspect items before receiving them in a grocery delivery order. The parameter estimated for households where shoppers noted being able to comparison shop is very important is random and normally distributed with a mean of 0.240 and a standard deviation of 0.359. This reveals the attitude has a positive effect on e-grocery delivery trip rates for 75% of households and a negative effect for 25%. This heterogeneity may arise based on *how* shoppers prefer to comparison shop. The positive effect might be explained in that the online market expands available selection and products that shoppers may not find in-store, allowing for more extensive comparison shopping. In contrast, comparison shopping may be more easily performed within a single grocery store without having to search across multiple marketplaces or do online research.

Three explicit cost related variables have significant explanatory power in the model. Households whose responding shoppers said being able to use coupons is very important when grocery shopping are associated with lower weekly e-grocery delivery trip rates. In-store coupons may still be more readily available than online ones, particularly for online retailers not connected to an existing big-box grocery store. Households where shoppers indicated not having to pay any delivery fees is very important are expected to have lower weekly e-grocery delivery trip rates, signaling costs associated with delivery as a deterrent to online grocery delivery shopping for these households. The estimated parameter for households whose shoppers think shopping online saves money is random and normally distributed with a mean of 0.236 and standard deviation of 1.087. This suggests households whose shoppers hold this attitude have higher weekly e-grocery delivery trip rates for 59% of households, but lower rates for 41%. The positive effect is intuitive, as consumers who see cost-savings associated with online ordering may reap this perceived benefit by using e-grocery delivery more frequently. However, the negative effect may reveal that either hassles associated with e-grocery services—scheduling orders, substitutions, etc.—or else preference of offline grocery shopping experiences outweigh perceived cost savings for some households.

Indicators related to ease were also key determinants of weekly online grocery delivery trip rates. Households whose responding shopper thinks shopping online for groceries is easy are associated with higher weekly e-grocery delivery trip rates. Additionally, households where respondents indicated they believe scheduling e-grocery delivery is difficult are expected to have lower weekly e-grocery delivery trip rates. This continues trends observed in earlier analyses. This positive trend follows that observed in the weekly online grocery pickup trip rate model. Ease of use was also positively associated with pre-pandemic and during-pandemic e-grocery delivery adoption.

Households whose shoppers say they others who are shopping for groceries online have higher weekly e-grocery delivery trip rates. This attitude was also positively associated with weekly e-grocery pickup trip rates. Again, this demonstrates the power of social norm in influencing behavior related to e-grocery services (*47*, *52*). The estimated parameter for households where responding shoppers indicated they are comfortable with delivery personnel coming to their home is random and normally distributed. The parameter mean of 0.490 and standard deviation of 0.312 suggest comfort with delivery personnel has a negative effect on weekly e-grocery delivery trip rates in just 6% of households, but a positive effect in the other 94%. Knowing others participating in online grocery ordering, as well as being comfortable with groceries being delivered to the home, seem likely to influence acceptance and use of this provisioning mode. The negative association between comfort with delivery personnel and weekly e-grocery delivery may stem from the difference between groceries and other goods. While a consumer may feel comfortable about other items being delivered to home, there may be specific concerns about groceries—tampering with food or other security-related factors—that would reduce e-grocery delivery frequency.

Households where shoppers say minimizing travel to the grocery store is very important are expected to have higher e-grocery delivery trip rates, as are households where shoppers indicated not having to carry items is very important. Reducing trip-making for households certainly seems to be a major benefit of e-grocery delivery. Additionally, couriers may leave groceries at a household's doorsteps, limiting the amount of carrying one must do being from the front door to the kitchen. Although interactions between these variables, along those related to car ownership and use, were not significant, they are theoretically expected to be related. Households reliant on non-auto modes, like transit, walking, and biking, may see extra benefits in minimizing travel to the store and not having to carry items, given the slower pace and more limited storage capacity of these modes.

The parameter estimated for households whose responding shoppers claim it's important to support local businesses is random with a normal distribution. With a mean of -0.715 and standard deviation of 0.689, this attitude positively effects weekly e-grocery delivery trip rates for 15% of households and negative effects 85%. The negative effect makes sense, given third-party apps typically reduce profits for businesses (and for small ones in-particular) (*182*), and given local businesses may be less likely to offer e-grocery delivery services. However, for those businesses that do, e-grocery delivery may be a good way to support those businesses for COVID-19 weary consumers during the pandemic, or for businesses who have limited in-store shopping hours.