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Children, Income, and the Impact of Home-Delivery on Household Shopping Trips

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ABSTRACT

Expanding e-commerce and delivery benefit consumers with increased flexibility and convenience. However, there is a potential impact on vehicle miles traveled (VMT) by delivery and personal vehicles, and the resulting energy consumption, air quality, and congestion. Delivery trips could replace personal vehicle trips, but if not could add to (or supplement) shopping-related VMT for a given household. We examine the benefits of e-commerce to consumers and the impact on personal shopping trips, and how these differ across item types and household child status and income. We find that high-income households and households with children care relatively more about time saving from deliveries. We find that on average, deliveries substitute for 12% of vehicle shopping trips, but for 9% of purchases deliveries supplement personal shopping trips. Underlying these averages are two main types of households: those for whom all deliveries substitute for trips (between 55% and 70% of households) and those for whom all deliveries supplement trips (between 20% and 35% of households). There is significant heterogeneity across households with and without children and with high or low income with respect to the use of delivery. While time savings was more likely to motivate higher-income households and households with children to use delivery, this did not translate through to these households substituting for more of their trips; deliveries of prepared meals for both these categories of households are relatively more likely (15% for households with children, and 12% for higher-income households) to supplement, and not substitute for, personal trips.

Keywords: e-commerce, online shopping, energy, family life cycle, children, income

INTRODUCTION

E-commerce and delivery are growing quickly in the United States and across the world. Online retail sales almost doubled as a percent of U.S. retail sales between 2012 and 2017 (1,2). In addition, as of June 2018, more than 95 million people in the U.S. were paying for Amazon Prime (through which an annual fee gains the subscriber access to benefits such as free two-day shipping) subscriptions (3). This is close to 40% of the U.S. adult population. This expanding home delivery is associated with societal benefits and costs.

Benefits of home delivery include: time savings; increased choice of products and prices; and convenience (4–9). However, e-commerce and delivery also impact vehicle miles traveled (VMT) in the transportation system and resulting energy consumption, air quality, and congestion. Determining the extent of this impact is complex (10,11). If a delivery trip substitutes for a personal vehicle trip, the delivery truck may be less energy efficient than the vehicle replaced, but may decrease the total energy use and VMT in the system if multiple items are delivered on a given route. However, home delivery may add to overall shopping-related VMT if deliveries *supplement* (add to) the number of existing personal or household trips to the store. These supplemental home delivery trips may occur for various reasons: a household may order items that they could have purchased during an existing shopping trip; some deliveries may not have been purchased in the absence of a delivery option; and e-commerce may generate new demand for trips to a store or vice versa. Delivery trips may also replace trips that otherwise would have been made by walking or biking.

Empirical research to-date is mixed. Some suggest that e-commerce supplements in-store shopping, leading to an overall increase in shopping travel (9,12–14), while others suggest that it substitutes, leading to a decrease (15–18). Data from the National Household Travel Survey (NHTS) shows that from 2009 to 2018, the percentage of person-trips per household with the purpose of shopping decreased from 21% to 18%, and the per-person VMT associated with shopping decreased from 14% to 12% (19). This decrease may be related to the concurrent increased prevalence of home delivery, or may be related to other factors.

Shopping behavior and the use of e-commerce varies based on household characteristics. For example, in both 2009 and 2017, households with children of any age averaged close to twice as many deliveries than those without children. Households with both older teens and younger children averaged the largest increase in deliveries received per month (from 4 to 7) between 2009 and 2017 (19). In the literature, purchasing decisions have been found to be related to family life cycle characteristics including children in the home and household income (20–23). Children in the home can be a constraint on shopping time and flexibility (24), and higher income means less constraint on expenditure, but a higher opportunity cost of time. All of these factors likely influence choice of shopping mode. Empirical evidence relating time constraint or pressure to online shopping behavior is mixed. Ferrell (25) finds a negative correlation between online shopping frequency and in-store shopping frequency, particularly for consumers with greater time constraints. However, Lee et al. (9) find that those who reported being very busy or having increased time pressure were no more or less likely to shop online. Such heterogeneity in e-commerce use and underlying motivations suggest that the resulting impacts of delivery on household shopping trips may differ based on household characteristics that are largely defined by time and financial constraints, such as household income and the presence of children in the home. This motivates our focus in this paper.

In this paper, we examine the degree to which home delivery substitutes for and/or supplements household shopping trips. We consider impacts across two separate shopping trip modal categories: 1. vehicle (personal, taxi, or ride-hailing); and 2. non-vehicle (walking, biking, or public transit). We analyze purchases across four product categories (groceries, clothing, household items, and prepared meals). We drill down on two key household characteristics: income and the presence of children in the home. We test four hypotheses motivated largely by the role time saving and convenience play in delivery use, and the resulting impact on shopping travel, based on income and child status.

LITERATURE

Dating back to the 1980s researchers have grappled with the impact e-commerce would have on the transportation system and associated energy consumption or VMT (10,11). E-commerce may: *complement* shopping trips by generating new demand for, or supplementing, existing trips; *substitute for* shopping trips; *modify* shopping trips, such as change trip mode or timing; or have no systematic impact in shopping travel (26). Much of the current empirical evidence suggests that online shopping complements in-store shopping (9,12,14,27). However, some find that online shopping has saved individual trips to the store (15–18). However, the finding of complementarity often results from an observed positive correlation between internet shopping and store shopping frequency from cross-sectional data (27), which might result from other unobserved factors and should not be taken as definitive evidence that e-commerce *causes* more in-store shopping. On the other hand, studies that use an experimental stated-preference approach designed to avoid spurious correlation find online shopping to substitute for, rather than complement, in-store trips, at least in the context of grocery shopping (18).

Online shopping behavior varies across the population. Some studies find that urban shoppers tend to have a higher likelihood of shopping online (28,29), yet others find that different types of residence locations (urban, suburban, village, countryside) are associated with similar rates of online shopping (30,31). Further, results suggest that rates of online shopping do not appear to be impacted by built-environment features such as availability of nearby shopping opportunities, population density, shopping center accessibility, connectivity, transit accessibility, and land use (9,32–34). Online shopping tends to be associated with younger people, those with higher incomes, and those with higher levels of education (18,35–40).

Similarly, the impact of online shopping on shopping travel is not uniform across the population. Weltevreden and van Rietbergen (41), for example, find evidence of substitution in about a fifth of their respondents and complementarity in a similar proportion of other respondents. There is a dearth of work relating these impacts to consumer characteristics, which is one of our contributions.

DATA AND ANALYSIS METHODS

We use survey data collected in the Spring of 2018 as part of the WholeTraveler Transportation Behavior Study. This study was supported by the U.S. Department of Energy's (DOE's) Energy Efficient Mobility Systems (EEMS) program as part of the SMART Mobility Consortium, which strives to clarify energy implications and opportunities related to advanced mobility solutions.

Data

A sample of randomly selected addresses in the nine Bay Area California counties (Alameda, Contra Costa, Marin, Napa, San Francisco, San Mateo, Santa Clara, Solano, and Sonoma) was recruited to respond to an online survey via a mailed invitation letter followed by a reminder postcard. The household member who most recently had a birthday and was 18 years or older was asked to respond to the survey. The survey was administered in English only, online only, and could only be completed using a desktop or laptop computer. Respondents received a $10 Amazon gift card for completing the survey.

Of the 60,000 addresses invited 997 residents completed the entire survey, and 48 completed the first portion of the survey instrument (the part used for this analysis) for a total of 1,045 responses (1.74%). The response rate, while low, is consistent with other implementations using similar unsolicited mailings, such as the 2015-2017 California Vehicles Survey which had a 1.5% response rate overall (42). The full WholeTraveler survey instrument can be found in the supplementary materials of Spurlock et al. (43).

Sample Biases: Due to the design of the survey and the recruitment methodology, the sample of respondents is a selected sample, which should be taken into account when interpreting these results. Specifically, the 1045 respondents were more highly educated than the general population, with 83% reporting a college degree or higher. In contrast, according to the American Community Survey (ACS), 45% of the Bay Area population reported a college education or higher. Median income levels tended to be commensurate with the ACS for Alameda, Contra Costa, Marin, San Mateo, Santa Clara, and Sonoma counties. However, Solano County respondents tended to have slightly lower median incomes than indicated by the ACS, and San Francisco and Napa County respondents tended to have higher median incomes. Of the ACS sampled households, 24% in the Bay Area earned greater than $150,000 per year, compared with 39% in the WholeTraveler sample, indicating a bias overall in the WholeTraveler responses toward higher-income households. In addition, the Amazon gift card incentive may have attracted respondents that were more likely to be online shoppers than the general population, and results should be interpreted with this in mind.

The design of our study enables us to make several meaningful contributions. We examine impacts across multiple shopping categories, shopping trip modes, and household characteristics. We do not rely only on hypothetical stated-preference experiments, which can be divorced from reality, or only cross-sectional revealed-preference data, which can limit insights to interpretation of correlations. Instead, we use a hybrid data-elicitation approach; we ask for information regarding actual trip and delivery behavior and then impose a counterfactual world where deliveries were not possible and ask for the shopping travel implications—thereby benefiting from a form of experimental manipulation, but rooting the information requested in the specific realities of respondents. In addition, we ask participants to report their motivations for ordering delivery.

Figure 1 shows the primary questions used to generate data for this analysis. Respondents were asked to report how many times in a recent typical week they took a shopping trip via: vehicle (e.g., personal vehicle, taxi, or ride-hailing) and non-vehicle (walking, biking, or public transit); and how many times they received deliveries. This was asked for each of four categories: 1. groceries (e.g., cereal, meat, produce, dairy, beans); 2. clothing, shoes, or accessories; 3. household items (e.g., paper towels, diapers, cleaning products, sunscreen); and 4. prepared meals (e.g., restaurant meals, take-out, meal delivery, cooking kit with prepared ingredients such as Blue Apron). They were then asked to report how many additional trips they would have taken (if any) if they could not have received the deliveries they reported in the first part of the question.

[Question 1]

WholeTraveler
TRANSPORTATION BEHAVIOR STUDY

*Please fill in how many times during a RECENT TYPICAL WEEK that you or someone in your household:

	Received a delivery from an online/phone order of...	Took a vehicle (e.g., personal vehicle, taxi, Uber, Lyft) to a store or restaurant to buy primarily...	Walked, biked or used public transit to get to a store or restaurant to buy primarily...	Did not purchase any of these items in a recent typical week
Groceries	0 deliveries	0 trips	0 trips	☐
Clothing, shoes or accessories	0 deliveries	0 trips	0 trips	☐
Household items	0 deliveries	0 trips	0 trips	☐
Prepared meals	0 deliveries	0 trips	0 trips	☐

[Question 2]

WholeTraveler
TRANSPORTATION BEHAVIOR STUDY

*We want to understand how home delivery affects how many shopping trips you or others in your household have to take.

Imagine, hypothetically, you could not order anything online and request home delivery, so that you could not receive the deliveries you reported in the previous question.

Think about the SAME RECENT TYPICAL WEEK. Please indicate whether lack of home delivery during that week would require you or someone in your household to take ADDITIONAL TRIPS (beyond those reported in the previous question) in order to make those purchases, or whether you would not make any additional trips (because you would be able to meet your needs by purchasing those items during trips you already reported in the previous question or by foregoing them altogether).

	Number of deliveries you reported in the previous question that you could no longer have delivered	If you could not have them delivered, the number of additional trips you would make to buy these items beyond the trips reported in the previous question		Would not have made any additional trips to buy these items if you couldn't have them delivered
		using a vehicle (e.g., personal vehicle, taxi, Uber, Lyft)	by walking, biking, or using public transit	
Groceries	1 delivery	0 additional trips	0 additional trips	☐
Clothing, shoes or accessories	1 delivery	0 additional trips	0 additional trips	☐
Household items	1 delivery	0 additional trips	0 additional trips	☐
Prepared meals	1 delivery	0 additional trips	0 additional trips	☐

Your responses from the previous question for reference:

	Received a delivery from an online/phone order of...	Took a vehicle (e.g., personal vehicle, taxi, Uber, Lyft) to a store or restaurant to buy primarily...	Walked, biked, or used public transit to get to a store or restaurant to buy primarily...
Groceries	1	0	0
Clothing, shoes or accessories	1	0	0
Household items	1	0	0
Prepared meals	1	0	0

Figure 1 Questions from the WholeTraveler Survey

Respondents were also asked two questions to better understand their preferences and motivations behind online shopping. First, "in general, what are the three things you like MOST about making purchases online with delivery rather than making purchases in a store?" with the response options: more environmentally friendly, saves time, more convenient, more options, saves money, easier to compare options and prices, don't have to interact with another person, less hassle, other (with an ability to specify), or not applicable. Second, "in general, what are the three things you like LEAST about making purchases online with delivery rather than making purchases in a store?" with response options: delivery charges, having to wait for delivery, less environmentally friendly, too much packaging to dispose of, harder to know what you're getting (e.g., fit, fabric, quality, freshness), less personal (i.e., don't get to interact with another person), having to mail back returns, harder to browse and get ideas or get exposed to new items, not supporting local businesses, other (with an ability to specify), or not applicable. We asked both of these questions to all survey participants as their opinions on what they like and do not like about delivery may have influenced whether they decide to use on-line shopping.

In addition, demographic and family structure information was collected and processed to generate variables used in this analysis including age; population density of the residential census block group; a binary indicator variable delineating households at or above the median income of the sample (the income option of $100,000 to $149,999) versus those below; and an indicator for whether the household includes children 18 years old or younger.

Data Cleaning

To screen out any respondents who clicked through without reading questions or answering meaningfully, we dropped 18 responses due to response times less than 12 minutes. We also removed: two that did not report household size, one that reported an age of 118 years, four because they were outliers with respect to number of children (six or more), one whose responses were inconsistent, and seven because they were outliers in their reported shopping behavior (more than two purchases per day on average for any single given item type). Overall, 33 respondents were dropped for the above specified reasons, leaving 1,012 remaining (97% of the original data).

Hypotheses

We use the data to test four specific hypotheses motivated largely by the role time saving and convenience play in delivery use, and the resulting impact on shopping travel, based on income and child status.

Hypothesis 1: Both households with children and higher-income households are more likely to be motivated to order delivery by the time-saving aspects of e-commerce compared to childless or lower-income households, because households with children are more time constrained (24,25) and higher-income households have a higher value of time given the higher opportunity cost of their time.

Hypothesis 2: Households with lower incomes are more likely to dislike monetary costs associated with e-commerce (such as delivery charges) compared with higher-income households.

Hypothesis 3: Households with children are relatively more likely than households without children to use delivery for household items (because of convenience and the bulkiness of items), whereas higher-income households are relatively more likely than lower-income households to use delivery for prepared meals and groceries (more luxury applications of delivery and associated convenience and time-saving).

Hypothesis 4: Both households with children and higher-income households are more likely than their counterparts to have deliveries substitute for shopping trips, which would maximize the use of delivery for time-savings.

Analysis Methods

Hypotheses 1 and **2** are tested using a series of pairwise t-tests. The primary analyses for **Hypotheses 3** and **4** were done using multinomial logit choice models. For **Hypothesis 3** we analyze the choice of purchase mode by modeling the choice between four alternatives: (1) delivery, (2) vehicle trip, (3) non-vehicle trip, or (4) no purchase. We define the set of potential purchase opportunities to be 56 (allowing for two purchases per day per item type during a week period). This is simply a scaling factor enabling us to interpret the resulting marginal estimates to be marginal changes in the probability of a household choosing delivery to make a purchase during the week in contrast to choosing delivery conditional on a purchase being made. We therefore assume that, for each of 56 potential purchase opportunities (t), a given household (i) has utility for purchase mode alternative (j) given by **Equation 1**.

$$U_{itj} = \beta_j' X_{ji} + \varepsilon_{itj} \tag{1}$$

where X_{ji} is a vector of household characteristics that describe heterogeneity across households both in terms of their shopping preferences, constraints, or needs, and in terms of shopping mode alternative availability. Specifically we include the following regressors: age; an indicator that is one if the household has income at or above the sample median, zero otherwise; an indicator that is one if the household has children that are 18 years of age or under, zero otherwise; and a variable designed to capture the availability or relative benefit or cost across purchase modes, which is the population density of the residential census block group. Population density has been shown to be a good proxy for availability and quality of public transit or potential ability to walk or bike (44,45).

Each household maximizes utility, and therefore the probability that household i chooses alternative j over all other alternatives $k \neq j$ for a given potential purchase opportunity is given by **Equation 2**.

$$P_{itj} = P[U_{itj} > U_{itk}, \forall k \neq j] = P[\varepsilon_{itj} - \varepsilon_{itk} < \beta_k' X_{ki} - \beta_j' X_{ji}, \forall k \neq j] \tag{2}$$

Because we model this relationship using multinomial logit, the standard assumption is that the errors are independently and identically distributed (IID) with type I extreme value distribution. In our case, because of the correlation within a household across purchase opportunities, particularly because we don't observe any attributes that vary within a household across purchase opportunities, we relax this assumption such that we assume errors are IID across households, but allow them to be correlated within a household. We do this by clustering the standard errors by household to reflect the fact that our observations are correlated across the 56 potential purchase opportunities within a household. The probability that household i chooses alternative j is modeled using **Equation 3**.

$$P(j|\beta_j, X_{itj}) = \frac{e^{\beta_j{}' X_{ij}}}{\sum_{k=1}^{4} e^{\beta_k{}' X_{ik}}} \quad (3)$$

We estimate this model pooled across all four item types (groceries; clothing, shoes, or accessories; household items; and prepared meals). We then estimate it separately for each of the four item types. In the item-specific cases, we assume 14 potential purchase opportunities per household in the modeled typical week, and the household choice is modeled using the same framework as presented in **Equations 1** through **3**, only now observations are limited to those relevant for each item type separately.

Intuitively, our modeling approach uses the framework of a discrete choice setting where the outcome is a zero-one indicator, but the primary feature being modeled is the proportion of the 56 hypothetic purchase opportunities (or 14 in the case of the item-specific estimations) where a household with characteristics X_{ji} chose alternative j for each alternative. We could do this using a fractional regression model, but only for one alternative at a time, rather than modeling across all alternatives simultaneously.

We test **Hypothesis 4** by taking advantage of the second part of the survey question and modeling the probability that a given reported delivery falls under one of three alternatives: 1. supplemental to existing shopping trips, 2. substitutes for a vehicle trip, or 3. substitutes for a non-vehicle trip. The multinomial logit modeling structure is the same as that described above, only now the set of choice events for each household is the number of deliveries reported in the first survey question for that household, and the alternatives are the three described above.

Summary Statistics

In **Table 1** and **Table 2** we present summary statistics across the analysis sample. **Table 1** summarizes various ways of looking at the outcome variables regarding purchase channels or modes used and trips replaced or not. On average each household makes 2.9 grocery, 1.8 household item, 1.7 prepared meal, and 1.1 clothing, shoe, or accessory purchases in a recent typical week. The extent to which these purchases are delivered ranges from 50 percent, in the case of clothing, shoes, or accessories, to 6 percent in the case of groceries. Most households, if they receive any deliveries in a particular category, receive one delivery for that category in a typical week, with very few receiving more. Depending on the item, 61 to 50 percent of deliveries replace a vehicle trip. To provide some context for the frequency of clothing, shoe, and accessory purchases (46) cite statistics indicating that U.S. women make 30 shopping trips for clothes and an additional 15 for shoes per year. Taking into account that our survey question also included “accessories” which could include a relatively large number of types of items, one per week seems reasonable.

TABLE 1 Summary Statistics: Outcome Variables

	N	mean	sd	min	max	N	mean	sd	min	max
	Groceries					Household Items				
Number of purchases (count)	1,012	2.93	2.01	0	14	1,012	1.80	1.62	0	12
Number of purchases as share of 14 (share)	1,012	0.21	0.14	0	1	1,012	0.13	0.12	0	0.86
Number of deliveries (count)	1,012	0.18	0.50	0	5	1,012	0.62	0.96	0	11
Reported zero deliveries (0,1)	1,012	0.86	0.35	0	1	1,012	0.59	0.49	0	1
Reported one delivery (0,1)	1,012	0.11	0.32	0	1	1,012	0.28	0.45	0	1
Reported two deliveries (0,1)	1,012	0.02	0.14	0	1	1,012	0.09	0.28	0	1
Reported three or more deliveries (0,1)	1,012	0.01	0.08	0	1	1,012	0.05	0.21	0	1
Deliveries as share of purchases (share)	959	0.06	0.18	0	1	846	0.33	0.39	0	1
Number of vehicle trips (count)	1,012	1.88	1.58	0	11	1,012	0.87	1.03	0	10
Number of non-vehicle trips (count)	1,012	0.87	1.53	0	11	1,012	0.31	0.81	0	8
None-substitution as share of deliveries (share)	142	0.30	0.44	0	1	417	0.28	0.41	0	1
Replaced vehicle trips as share of deliveries (share)	142	0.53	0.49	0	1	417	0.61	0.45	0	1
Replaced non-vehicle trips as share of deliveries (share)	142	0.17	0.36	0	1	417	0.11	0.29	0	1
	Prepared Meals					Clothing, Shoes, or Accessories				
Number of purchases (count)	1,012	1.73	2.00	0	12	1,012	1.14	1.39	0	13
Number of purchases as share of 14 (share)	1,012	0.12	0.14	0	0.86	1,012	0.08	0.10	0	0.93
Number of deliveries (count)	1,012	0.23	0.64	0	5	1,012	0.57	0.85	0	5
Reported zero deliveries (0,1)	1,012	0.85	0.36	0	1	1,012	0.60	0.49	0	1
Reported one delivery (0,1)	1,012	0.11	0.31	0	1	1,012	0.28	0.45	0	1
Reported two deliveries (0,1)	1,012	0.03	0.16	0	1	1,012	0.08	0.28	0	1
Reported three or more deliveries (0,1)	1,012	0.02	0.14	0	1	1,012	0.04	0.19	0	1
Deliveries as share of purchases (share)	662	0.13	0.28	0	1	614	0.50	0.42	0	1
Number of vehicle trips (count)	1,012	0.95	1.30	0	11	1,012	0.43	0.72	0	5
Number of non-vehicle trips (count)	1,012	0.56	1.27	0	11	1,012	0.14	0.52	0	7
None-substitution as share of deliveries (share)	157	0.35	0.46	0	1	403	0.40	0.47	0	1
Replaced vehicle trips as share of deliveries (share)	157	0.50	0.48	0	1	403	0.50	0.47	0	1
Replaced non-vehicle trips as share of deliveries (share)	157	0.16	0.35	0	1	403	0.10	0.28	0	1

Table 2 provides summary statistics of explanatory variables. Most of these variables are used in the analysis, but some are provided simply to better describe the sample of survey respondents.

Respondents are 46 years old on average. They are relatively evenly split between men and women. About 30 percent have children in the home and about 45 percent have at least a bachelor's degree. On average they commute about four days per week and about a quarter did so using public transit and or walking/biking in the seven days prior to taking the survey. The most frequently cited things liked most about shopping online with delivery were convenience and time-saving, while the most frequently cited thing liked least was the fact that with shopping online it was hard to know exactly what you are ordering without being able to see it in person.

TABLE 2 Summary Statistics: Explanatory Variables

	N	mean	sd	min	max
Child 18 or under (0,1)	1,012	0.28	0.45	0	1
Income: median or greater (0,1)	1,012	0.67	0.47	0	1
Age	1,012	46.18	15.03	19	94
Residence: population density	1,012	13.17	15.04	0.01	169.30
Female (0,1)	1,012	0.47	0.50	0	1
Education > Bachelor's (0,1)	1,012	0.45	0.50	0	1
Likes: convenience (0,1)	1,012	0.64	0.48	0	1
Likes: saves time (0,1)	1,012	0.59	0.49	0	1
Likes: easy to compare (0,1)	1,012	0.50	0.50	0	1
Dislikes: hard to know (0,1)	1,012	0.64	0.48	0	1
Dislikes: packaging (0,1)	1,012	0.40	0.49	0	1
Dislikes: mailing returns (0,1)	1,012	0.39	0.49	0	1
Dislikes: not supporting local (0,1)	1,012	0.39	0.49	0	1
Number of days per week commutes	1,012	4.28	1.39	0	7
Commuted via public transit within last 7 days (0,1)	1,012	0.25	0.43	0	1
Commuted via walk or bike within last 7 days (0,1)	1,012	0.25	0.43	0	1
Telecommuted within last 7 days (0,1)	1,012	0.19	0.40	0	1

A version of these summaries broken out by households with and without children, and by households above or below the sample median income is provided in the supplemental material in **Appendix A**.

RESULTS

Attitudes Towards E-commerce

As seen in Table 2 above, a large percentage of our sample indicated that one of the top three things they liked about online shopping is that it saves time (59%) and is convenient (64%). This is consistent with the previous findings that online shopping and home delivery save time and are more convenient. In addition, 50% selected ease of comparing items. Lower percentages of respondents selected saving money (32%), lower hassle (34%), and enabling access to more options (29%).

For the perceived disadvantages of online shopping, by far the most frequently selected item was the difficulty of knowing what one is getting online (65%). Other dislikes included delivery charges (35%), having to wait for delivery (33%), not supporting local businesses (39%), having to mail back returns (39%), and having to deal with excessive packaging (40%). The degree to which e-commerce was perceived to hurt or help the environment was not a major driver around preferences either way.

Figure 2 compares these attitudinal factors between those with and without children and those with higher versus lower household income. Results support **Hypotheses 1** and **2**. Households with children valued time savings and convenience relatively more than those without, and they additionally valued monetary savings relatively less. For high income households, time savings, more options, and knowing what one is getting are more important than for low income households; low hassle and delivery charges were relatively more important for lower income households.

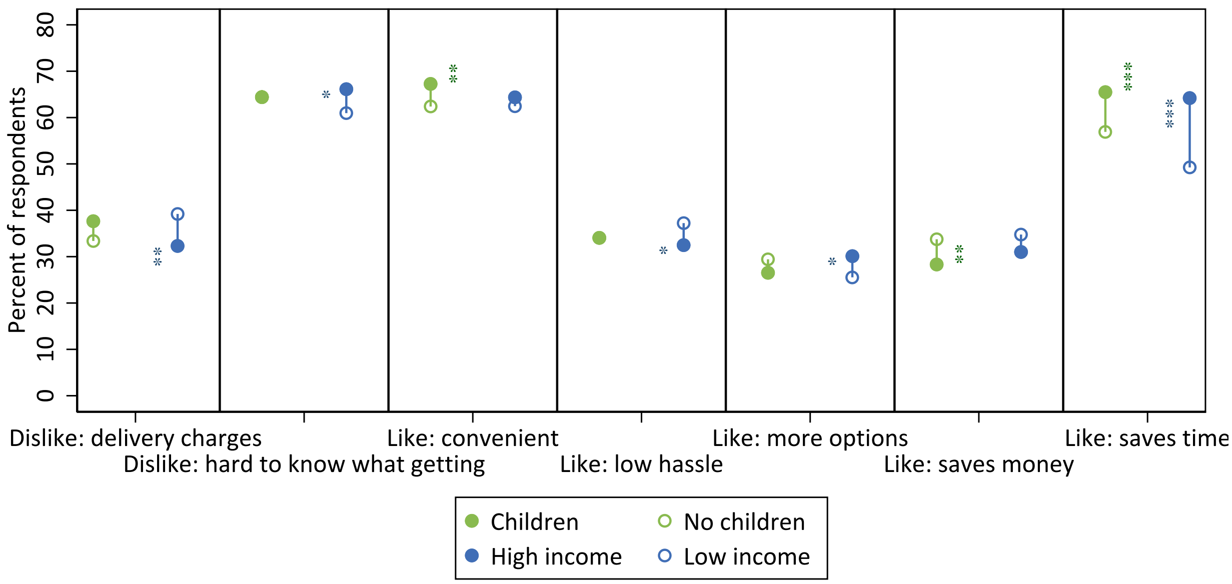


Figure 2 Likes and Dislikes of Online Shopping Differentiated by Subpopulations
***p < 0.01, **p < 0.05, *p < 0.1 (asterisks shown stacked vertically alongside plotted points)

Purchase Behavior: Modes and Magnitude

Figure 3 summarizes purchase mode, or channel, use in aggregate. The data underlying all bar graphs are reported in **Appendix B.** While groceries are the most frequently purchased (close to three times per household on average in a week), they are delivered the least. Conversely, clothing, shoes, or accessories and household items are delivered proportionally the most; clothing, shoes, or accessories are purchased least frequently but are more likely to be delivered than purchased via a shopping trip. Groceries and prepared meals are the most likely to be purchased via a non-vehicle shopping mode.

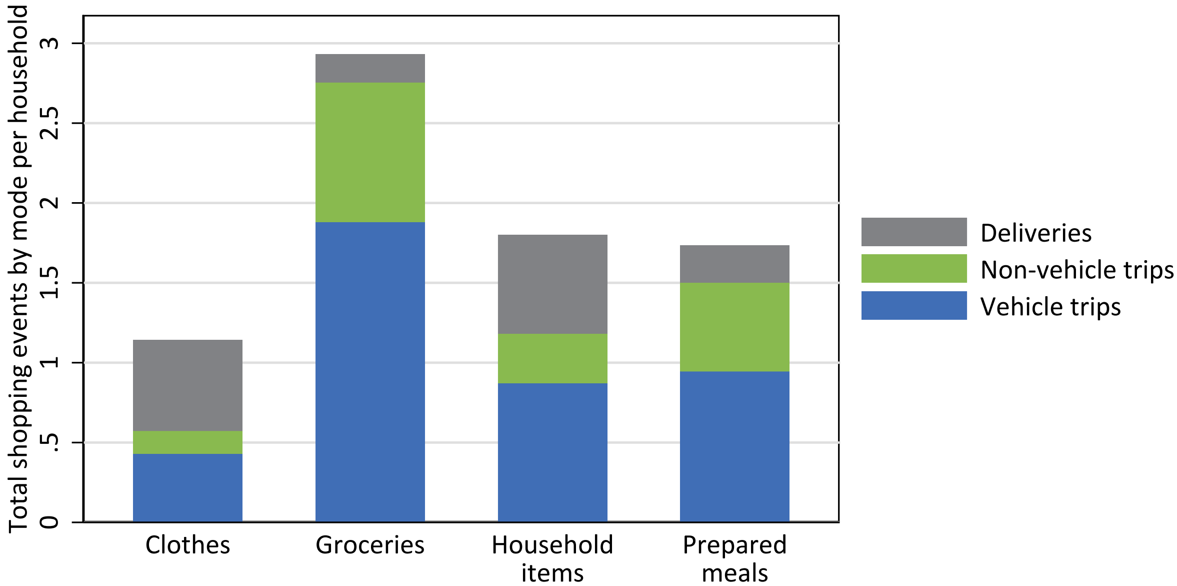
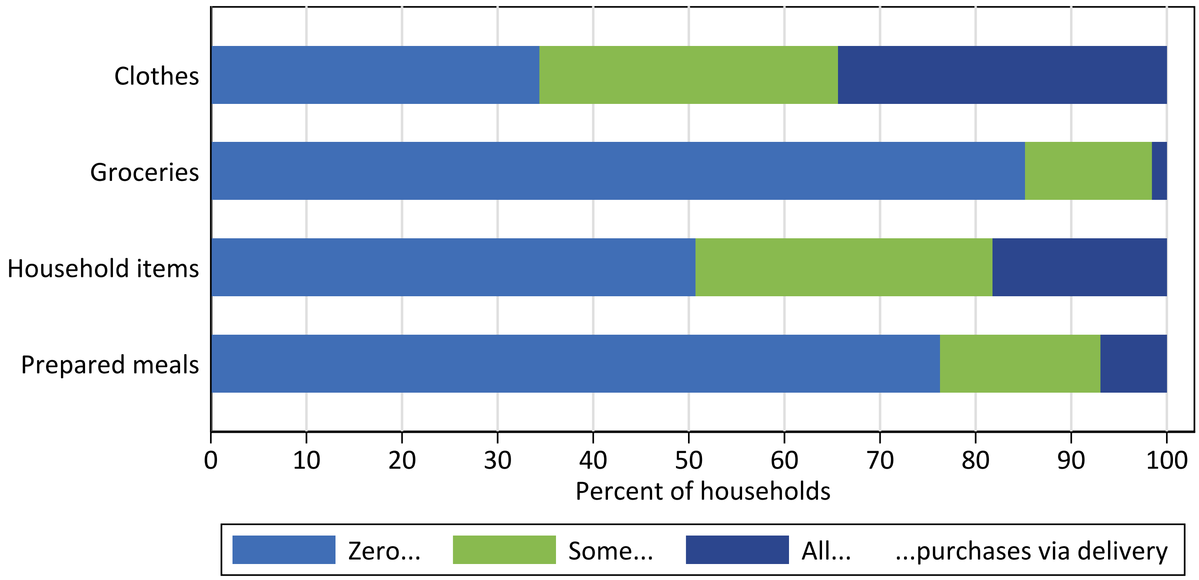


Figure 3 Shopping events per household in a typical week, by vehicle, non-vehicle, or delivery
The data underlying this graph are reported in **Appendix B.**

Heterogeneity in Purchase Modes and Magnitude

Figure 4 shows purchase mode patterns across households. In general households appear to be one of two types: using delivery for all purchases, or using it for none (**Figure 4a**). **Figure 4b** shows that high-income households are significantly more likely to make all of their household item purchases via delivery, and significantly less likely to receive no deliveries across all four item types. Households with children are significantly less likely to receive no deliveries of household items compared to those without children. These results support **Hypothesis 3.**

(a)



(b)

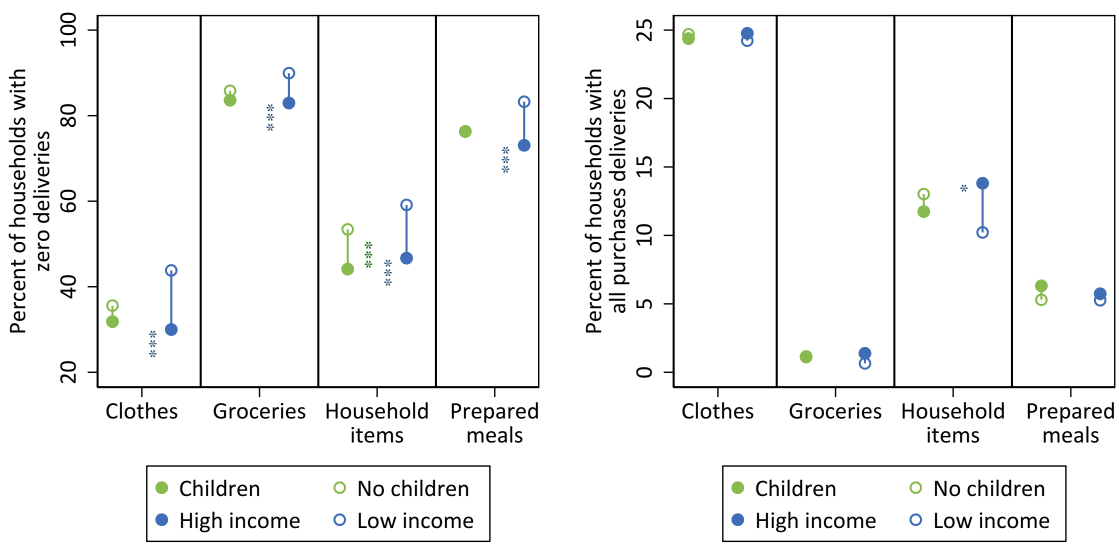


Figure 4 Percent of households that received zero, some, or all purchases via delivery (a), and breakdown of the prevalence of the two ends of the distribution by household characteristic (b)

(a) The data underlying this graph are reported in **Appendix B.**

(b) ***p < 0.01, **p < 0.05, *p < 0.1 (asterisks shown stacked vertically alongside plotted points)

Multinomial Logit Results Relating Purchase Channel Choice to Household Demographics

The marginal effect estimates from the multinomial logit analysis of purchase channel choice are presented in **Table 3**. The full model output including coefficient estimates, standard errors, confidence intervals, and extensive fit statistics can be found in **Appendix C**. These results show that households with children are more likely to make more frequent purchases across all item types while higher income households are only likely to make more frequent purchases of prepared meals. Consistent with **Hypothesis 3**, higher-income households are more likely to receive deliveries overall, and across all item types. The results indicate that, for any one of the 56 potential purchase opportunities in a typical week, high-income households are 0.8 percentage points more likely to choose delivery relative to low-income households. Over the whole week (treating each purchase opportunity as independent), the probability that a high-income household had at least one delivery is 44 percentage points higher than for a low-income household. Also consistent with **Hypothesis 3**, households with children are more likely to make more delivery purchases, particularly for household items and clothing, shoes, or accessories, as well as more vehicle shopping trips across all item types other than prepared meals compared to households with no children. We conducted an additional analysis, the results of which are presented in **Appendix D and E**, in which we separate out the effect of a household having at least one younger child (eight years or younger) from households with children all over the age of eight. That analysis showed that the tendency towards more delivery is most strongly driven by the presence of younger children. Results regarding respondent age and location also stand out. Age enters the model linearly, so a case in which the effect of age is negative, for example, can be interpreted as a case where relative youth (i.e., younger people relative to older people), is associated with a lower likelihood of exhibiting that outcome. Specifically, relative youth is associated with more deliveries, particularly for prepared meals and clothing. Younger people were also relatively more likely than older people to make grocery purchases via vehicle (and make fewer grocery purchases). They also tended to purchase prepared meals more, and take non-vehicle modes more and vehicles less to make those purchases. Higher residential population density is associated with fewer purchases, less vehicle-dependence for shopping, and more use of non-vehicle modes.

TABLE 3 Purchase Channel Choice Multinomial Logit Marginal Effects

	Delivery	No Purchase	Vehicle	Non-Vehicle
All Item Types Pooled				
Age	-0.000146***	0.0002	0.0000	-0.0001
Income: median or greater	0.00790***	-0.0070	0.0034	-0.0043
Child 18 or under	0.00494***	-0.0183***	0.0101***	0.0033
Residence: population density	0.0001	0.000538**	-0.00126***	0.000667***
McFadden's R2: 0.0117 McFadden's Adjusted R2: 0.011 Count R2: 0.864				
Observations 56,672			Households 1,012	
Separated by Item Type		**Groceries**		
Age	-0.0001	-0.000828***	0.000731***	0.0002
Income: median or greater	0.00474***	-0.0057	0.0092	-0.0082
Child 18 or under	0.0017	-0.0326***	0.0245***	0.0064
Residence: population density	0.0000	0.00122***	-0.00254***	0.00131***
McFadden's R2: 0.017 McFadden's Adjusted R2: 0.015 Count R2: 0.791				
Observations 14,168			Households 1,012	
		Household Items		
Age	0.0000	-0.0004	0.0002	0.0001
Income: median or greater	0.00927***	-0.0028	-0.0011	-0.0054
Child 18 or under	0.00823**	-0.0181**	0.0112**	-0.0013
Residence: population density	0.0000	0.000601**	-0.00122***	0.000575***
McFadden's R2: 0.013 McFadden's Adjusted R2: 0.010 Count R2: 0.871				
Observations 14,168			Households 1,012	
		Prepared Meals		
Age	-0.000320***	0.00184***	-0.000870***	-0.000647***
Income: median or greater	0.00563***	-0.0137*	0.00920*	-0.0011
Child 18 or under	0.0005	-0.0023	-0.0018	0.0036
Residence: population density	0.0001*	0.0002	-0.000934***	0.000634***
McFadden's R2: 0.021 McFadden's Adjusted R2: 0.018 Count R2: 0.876				
Observations 14,168			Households 1,012	
		Clothing, Shoes, or Accessories		
Age	-0.000160*	0.0003	-0.0002	0.0000
Income: median or greater	0.0106***	-0.0045	-0.0040	-0.0022
Child 18 or under	0.0101***	-0.0220***	0.00781**	0.0040
Residence: population density	0.0000	0.0001	-0.000353*	0.000210***
McFadden's R2: 0.011 McFadden's Adjusted R2: 0.007 Count R2: 0.918				
Observations 14,168			Households 1,012	

Note: Standard errors clustered at the individual level. Frequency weighted by number of purchase opportunities by mode for each household. Omitted Categories (No purchase).
*** p<0.01, ** p<0.05, * p<0.1

Overall Degree of Supplementation and Substitution of Delivery for Shopping Trips

If users were not able to have deliveries, they would change their shopping behaviors. **Figure 5** shows how purchase trips are affected by the availability of delivery. In the figure the 100% mark reflects the number of shopping trips that would be made if delivery was not available. Looking at the total changes we see that:

1. Delivery replaced 12 percentage points worth of vehicle trips.
2. Delivery replaced three percentage points worth of non-vehicle trips.
3. Delivery added nine percentage points worth of extra goods transportation activities (via delivery vehicle).

Delivery affected shopping trips most for clothing and least for groceries. The proportion of deliveries that substituted for vehicle trips is similar to the proportion of deliveries that supplemented existing trips for all except household items.

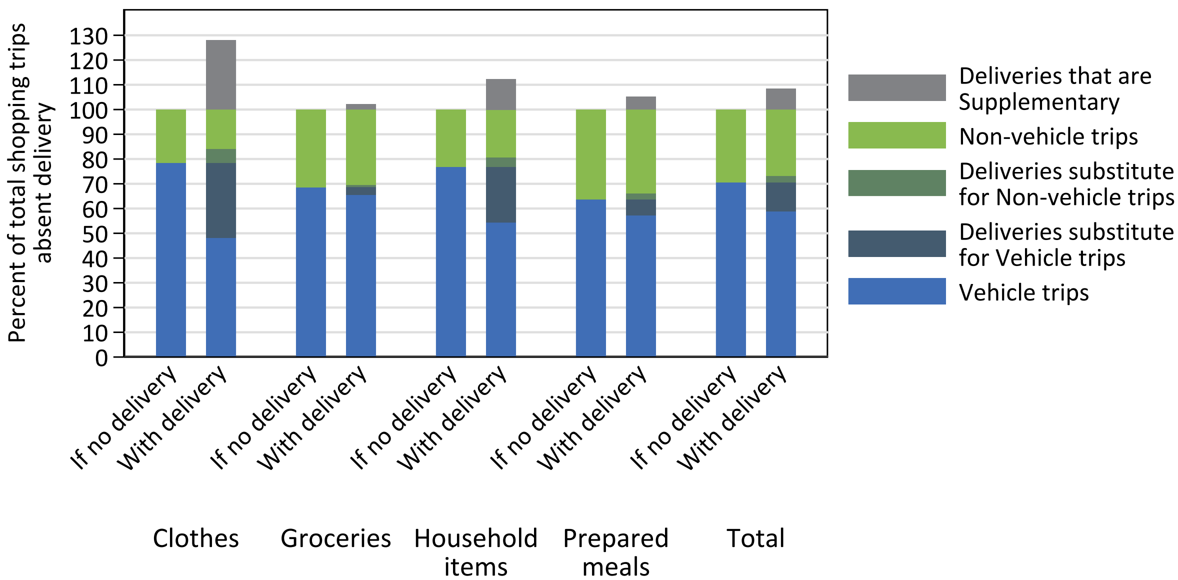


Figure 5 Overall degree of substitution and supplementation of delivery for household shopping trips

The data underlying this graph are reported in **Appendix B.**

Heterogeneity in the Degree of Supplementation and Substitution of Delivery for Shopping Trips

Similar to overall purchase patterns, the degree of supplementation or substitution is highly dichotomous across households, at least within the week-long timeframe for which data was requested from respondents (**Figure 6a**). For about 55% to 70% of households, deliveries perfectly substituted for existing trips, while for 20% to 35% of households, deliveries perfectly supplemented existing trips. Clothing deliveries have more of an equal balance across the two sides of the spectrum (55% perfect substitution, 35% perfect supplementation), whereas groceries and household items exhibit the most asymmetry (65%-70% perfect substitution, 20%-25% perfect supplementation).

As shown in **Figure 6b**, for household items and prepared meals, counter to **Hypothesis 4**, households with children were significantly less likely to have all deliveries substitute for trips and more likely to have all deliveries supplement trips. Whereas consistent with **Hypothesis 4**, high-income households were less likely to have all their deliveries supplement trips compared to low-income households in the case of clothing and prepared meals.

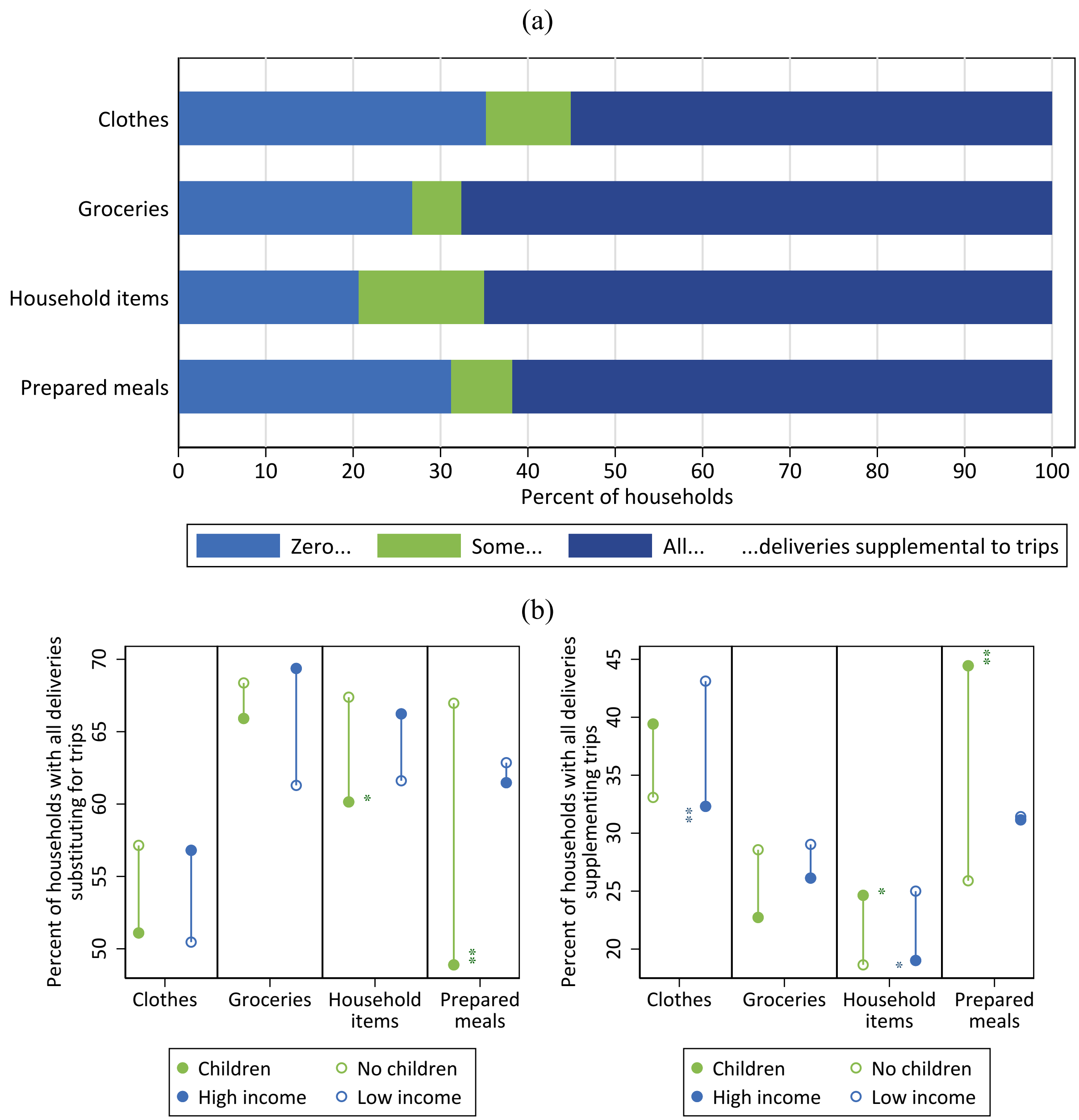


Figure 6 Percent of households for whom zero, some, or all deliveries supplemented shopping trips (a), and the breakdown of the two ends of the distribution by household characteristic (b)

(a) The data underlying this graph are reported in **Appendix B.**

(b) ***p < 0.01, **p < 0.05, *p < 0.1 (asterisks shown stacked vertically alongside plotted points)

Multinomial Logit Results Relating Supplementation and Substitution of Delivery for Shopping Trips to Household Demographics

Table 4 shows the marginal effect from a multinomial regression modeling the choice that a delivery supplements trips, substitutes for a vehicle trip, or substitutes for a non-vehicle trip. The full model output including estimated coefficients, standard errors, confidence intervals, and extensive fit statistics can be found in **Appendix C**. Reinforcing the results shown in **Figure 6**, **Table 4** shows that households with children were more likely to have deliveries supplement existing trips and less likely to have them substitute for vehicle trips overall; for prepared meals in particular deliveries for these households are relatively more likely to supplement existing trips with a marginal effect that is both large (15 percentage points) and significant. While **Figure 6** depicted higher income households being less likely to have *all* their deliveries supplement trips, here we see that in contrast to **Hypothesis 4**, higher-income household's deliveries are not systematically more or less likely than those of low-income households to either supplement or substitute trips with one exceptions; in the case of prepared meals high income households are actually more likely to supplement shopping trips (12 percentage points), and less likely to substitute for vehicle trips (16 percentage points). Relative youth is associated with more supplementation and less substitution for vehicle trips (especially for household items and clothing, shoes, or accessories) and more substitution for non-vehicle trips (especially for prepared meals). High population density is associated with more substitution for non-vehicle trips, less supplementation (in the case of groceries), and less substitution for vehicle trips (in the case of prepared meals and clothing, shoes, or accessories). It should be noted that the model for grocery purchases alone is under-powered, lacks satisfactory fit, and provides little in the way of meaningful results, but is included for completeness, so even the one significant result regarding population density should interpreted with caution.

TABLE 4 Substitution/Supplementation Choice Multinomial Logit Marginal Effects

	Delivery is supplemental to trips	Delivery substitutes for vehicle trip	Delivery substitutes for non-vehicle trip
All Item Types Pooled			
Age	-0.00282**	0.00467***	-0.00185**
Income: median or greater	-0.0341	0.0272	0.0069
Child 18 or under	0.0878**	-0.0353	-0.0525*
Residence: population density	0.0009	-0.0037	0.00285**
McFadden's R2: 0.040	McFadden's Adjusted R2: 0.031	Count R2: 0.513	
	Observations 1,619	Households 622	
Separated by Item Type		**Groceries**	
Age	-0.0016	0.0028	-0.0012
Income: median or greater	-0.0464	0.1270	-0.0806
Child 18 or under	-0.0467	-0.0363	0.0830
Residence: population density	-0.00644*	-0.0005	0.00691**
McFadden's R2: 0.049	McFadden's Adjusted R2: -0.034	Count R2: 0.506	
	Observations 180	Households 142	
		Household Items	
Age	-0.00307*	0.00457***	-0.0015
Income: median or greater	-0.0596	0.0473	0.0123
Child 18 or under	0.0807	-0.0127	-0.0680*
Residence: population density	0.0001	-0.0019	0.0018
McFadden's R2: 0.034	McFadden's Adjusted R2: 0.008	Count R2: 0.582	
	Observations 672	Households 417	
		Prepared Meals	
Age	-0.0003	0.00540*	-0.00514**
Income: median or greater	0.115**	-0.159***	0.0440
Child 18 or under	0.153***	-0.0751	-0.0775
Residence: population density	0.0021	-0.00369*	0.0016
McFadden's R2: 0.082	McFadden's Adjusted R2: 0.021	Count R2: 0.506	
	Observations 235	Households 157	
		Clothing, Shoes, or Accessories	
Age	-0.00488**	0.00441**	0.0005
Income: median or greater	-0.0644	0.0704	-0.0060
Child 18 or under	0.0728	-0.0372	-0.0357
Residence: population density	0.0029	-0.00752***	0.00458***
McFadden's R2: 0.061	McFadden's Adjusted R2: 0.033	Count R2: 0.549	
	Observations 577	Households 403	

Note: Standard errors clustered at the household level. Frequency weighted by number of deliveries for each household for each item type. Omitted Category (Delivery replaces a vehicle trip).
*** p<0.01, ** p<0.05, * p<0.1

DISCUSSION AND CONCLUSION

As a whole, we find that the question of how increased online shopping and expanded goods delivery affect household shopping trips has a nuanced and complicated answer. We found in aggregate evidence to support the subset of the literature (15–18) that has found more substitution for vehicle trips on net as opposed to supplementation. However, there is significant heterogeneity in shopping mode choice and in the degree to which engagement in e-commerce supplements or substitutes for shopping trips. Interestingly, consistent with Weltevreden and van Rietbergen (41), we found that for a large proportion of our sample deliveries either fully substitute for (55% to 70%) or fully supplement (20% to 35%) shopping trips. This is in contrast to all households using deliveries to both supplement and substitute for a little of their shopping trips. This may relate to the relatively short timeframe of the date requested (a single week's worth of purchases), but stands out nonetheless.

We found evidence consistent with all of our Hypotheses with one interesting exception. We found, consistent with **Hypothesis 1** and previous literature (4,5,7,8), that time-savings and convenience, among other factors, are important to consumers when considering whether or not to make a purchase online, and specifically time-saving is more of a motivating factor for higher income households and households with children relative to their counterparts. In addition, consistent with **Hypothesis 2**, lower income people were more likely to be negatively influenced by delivery charges. However, the motivation for time-savings related to delivery utilization and the degree to which these deliveries substitute and supplement for shopping trips was mixed. On the one hand, consistent with **Hypothesis 3**, higher-income households are more likely to receive deliveries overall, and across all item types. Households with children were also relatively more likely to choose delivery, particularly for household items and clothing, compared to households with no children. On the other hand, however, the time-saving motivation for these categories of households did not translate through to these deliveries being relatively more likely to substitute for shopping trips. Indeed, prepared meal purchase behavior is an interesting case demonstrating significant distinctions between high- and low-income households and households with and without children. Households with children (by 15 percentage points) and higher-income households (by 12 percentage points) are significantly more likely to have prepared meal delivery supplement trips relative to their counterparts. This speaks to the fact that increased convenience and time-saving aspects of meal delivery may actually substitute more for cooking at home, rather than for a trip to a restaurant. Indeed, for higher income households prepared meal delivery, which they're more likely to order relative to lower income households, is actually significantly less likely (by 16 percentage points) to substitute for a vehicle trip relative to lower income households. These results suggest that the marginal activities for those that are either more time constrained or have a higher opportunity cost of time isn't necessarily the time it takes to make a shopping trip, but appears more so to be the time involved in other activities, such as preparing meals. In future research a more comprehensive modeling of the direct relationship between time-constraints and preferences for time-savings across a variety of dimensions (not just shopping trips) would help to shed more light on the motivations for online shopping with delivery in different contexts.

REFERENCES

1. U.S. Census Bureau News: Quarterly Retail E-Commerce Sales 4th Quarter 2012 Publication CB13-24 [Internet]. U.S. Census Bureau. Washington, D.C.; 2013. Available from: https://www2.census.gov/retail/releases/historical/ecomm/12q4.pdf
2. U.S. Census Bureau News: Quarterly Retail E-Commerce Sales 4th Quarter 2017 Publication CB18-21 [Internet]. U.S. Census Bureau. 2018. Available from: https://www2.census.gov/retail/releases/historical/ecomm/17q4.pdf
3. Statista. Number of Amazon Prime Members in the United States as of December 2018 (in Millions) [Internet]. Statista - The Statistics Portal. 2019 [cited 2019 Apr 23]. Available from: https://www.statista.com/statistics/546894/number-of-amazon-prime-paying-members/
4. Darian JC. In-home shopping: Are there consumer segments? J Retail. 1987;63(2):163–86.
5. Harris P, Dall'Olmo Riley F, Riley D, Hand C. Online and store patronage: a typology of grocery shoppers. Int J Retail Distrib Manag [Internet]. 2017 Jan;45(4):419–45. Available from: https://doi.org/10.1108/IJRDM-06-2016-0103
6. Chu J, Chintagunta P, Cebollada J. Research Note—A Comparison of Within-Household Price Sensitivity Across Online and Offline Channels. Mark Sci [Internet]. 2008 Mar;27(2):283–99. Available from: https://doi.org/10.1287/mksc.1070.0288
7. Sabatini F. Can a click buy a little happiness? The impact of business-to-consumer e-commerce on subjective well-being (12/2011) [Internet]. Economics and Econometrics Research Institute (EERI) Research Paper Series. Brussels: Economics and Econometrics Research Institute (EERI); 2011. Available from: https://www.econstor.eu/handle/10419/142619
8. Chintagunta PK, Chu J, Cebollada J. Quantifying Transaction Costs in Online/Off-line Grocery Channel Choice. Mark Sci [Internet]. 2012 Dec;31(1):96–114. Available from: https://doi.org/10.1287/mksc.1110.0678
9. Lee RJ, Sener IN, Mokhtarian PL, Handy SL. Relationships between the online and in-store shopping frequency of Davis, California residents. Transp Res Part A Policy Pract. 2017 Jun;100:40–52.
10. Salomon I. Telecommunications and Travel: Substitution or Modified Mobility? J Transp Econ Policy [Internet]. 1985;19(3):219–35. Available from: http://www.jstor.org/stable/20052753
11. Salomon I. Telecommunications and travel relationships: a review. Transp Res Part A Gen [Internet]. 1986;20(3):223–38. Available from: http://www.sciencedirect.com/science/article/pii/0191260786900968
12. Cao X, Douma F, Cleaveland F. Influence of E-Shopping on Shopping Travel Evidence from Minnesota's Twin Cities. Transp Res Rec. 2010;(2157):147–54.
13. Zhou Y, Wang XC. Explore the relationship between online shopping and shopping trips: An analysis with the 2009 NHTS data. Transp Res Part A Policy Pract. 2014 Dec;70:1–9.
14. Ding Y, Lu H. The interactions between online shopping and personal activity travel behavior: an analysis with a GPS-based activity travel diary. Transportation (Amst). 2017 Mar;44(2):311–24.
15. Sim LL, Koi SM. Singapore's internet shoppers and their impact on traditional shopping patterns. J Retail Consum Serv. 2002;9(2):115–24.

16. Tonn BE, Hemrick A. Impacts of the Use of E-Mail and the Internet on Personal Trip-Making Behavior. Soc Sci Comput Rev. 2004;22:270–80.
17. Weltevreden JWJ, van Rietbergen T. E-shopping versus city centre shopping: The role of perceived city centre attractiveness. Tijdschr voor Econ en Soc Geogr. 2007;98(1):68–85.
18. Suel E, Polak JW. Development of joint models for channel, store, and travel mode choice: Grocery shopping in London. Transp Res Part A Policy Pract. 2017 May;99:147–62.
19. McGuckin N, Fucci A. Summary of Travel Trends: 2017 National Household Travel Survey. Publication FHWA-PL-18-01. 2018.
20. Lansing JB, Morgan JN. Consumer Finances over the Life Cycle. Consum Behav. 1955;2:36–50.
21. Brown A, Deaton A. Surveys in Applied Economics: Models of Consumer Behaviour. Econ J [Internet]. 1972 Dec;82(328):1145–236. Available from: https://doi.org/10.2307/2231303
22. Wagner J, Hanna S. The Effectiveness of Family Life Cycle Variables in Consumer Expenditure Research. J Consum Res. 1983;10:281–91.
23. Burningham K, Venn S, Christie I, Jackson T, Gatersleben B. New motherhood: a moment of change in everyday shopping practices? Martens DMJK, Lydia D, editors. Young Consum [Internet]. 2014 Jan;15(3):211–26. Available from: https://doi.org/10.1108/YC-11-2013-00411
24. Kwan M-P. Gender differences in space-time constraints. Area [Internet]. 2000 Jun 1 [cited 2020 May 6];32(2):145–56. Available from: http://doi.wiley.com/10.1111/j.1475-4762.2000.tb00125.x
25. Ferrell CE. Home-Based Teleshopping and Shopping Travel: Where Do People Find the Time? Transp Res Rec [Internet]. 2005 Jan;1926(1):212–23. Available from: https://doi.org/10.1177/0361198105192600125
26. Shao J, Yang H, Xing X, Yang L. E-commerce and traffic congestion: An economic and policy analysis. Transp Res PART B-METHODOLOGICAL. 2016 Jan;83:91–103.
27. Zhen F, Cao X (Jason), Mokhtarian PL, Xi G. Associations Between Online Purchasing and Store Purchasing for Four Types of Products in Nanjing, China. Transp Res Rec [Internet]. 2016 Jan;2566(1):93–101. Available from: https://doi.org/10.3141/2566-10
28. Pérez-Hernández J, Sánchez-Mangas R. To have or not to have Internet at home: Implications for online shopping. Inf Econ Policy. 2011;23:213–26.
29. Sener IN, Reeder PR. An examination of behavioral linkages across ICT choice dimensions: Copula modeling of telecommuting and teleshopping choice behavior. Environ Plan A. 2012;44:1459–78.
30. Winslott Hiselius L, Smidfelt Rosqvist L, Adell E. Travel behaviour of online shoppers in Sweden. Transp Telecommun J. 2015;16(1):21–30.
31. Smidfelt Rosqvist L, Winslott Hiselius L. Online shopping habits and the potential for reductions in carbon dioxide emissions from passenger transport. J Clean Prod. 2016;131:163–9.
32. Krizek KJ, Li Y, Handy SL. Spatial Attributes and Patterns of Use in Household-Related Information and Communications Technology Activity. Transp Res Rec J Transp Res Board. 2005;1926:252–9.
33. Ren F, Kwan M-P. The Impact of Geographic Context on E-Shopping Behavior. Environ Plan B Plan Des [Internet]. 2009 Jan;36(2):262–78. Available from:

https://doi.org/10.1068/b34014t
34. Lee RJ, Sener IN, Handy SL. Picture of Online Shoppers Specific Focus on Davis, California. Transp Res Rec. 2015;2496:55–63.
35. Soopramanien DGR, Robertson A. Adoption and usage of online shopping: An empirical analysis of the characteristics of "buyers" "browsers" and "non-internet shoppers." J Retail Consum Serv. 2007;14:73–82.
36. To P-L, Liao C, Lin T-H. Shopping motivations on Internet: A study based on utilitarian and hedonic value. Technovation [Internet]. 2007;27(12):774–87. Available from: http://www.sciencedirect.com/science/article/pii/S0166497207000144
37. Hashim A, Ghani EK, Said J. Does consumers' demographic profile influence online shopping?: An examination using Fishbein's theory. Can Soc Sci. 2009;5(6):19–31.
38. Burkolter D, Kluge A. Online Consumer Behavior and Its Relationship with Socio-Demographics, Shopping Orientations, Need for Emotion, and Fashion Leadership. J Bus Media Psychol. 2011;2:20–8.
39. Cao XJ, Xu Z, Douma F. The interactions between e-shopping and traditional in-store shopping: an application of structural equations model. Transportation (Amst). 2012 Sep;39(5):957–74.
40. Mintel Oxygen Reports. Online Grocery Shopping. London; 2014.
41. Weltevreden JWJ, van Rietbergen T. The implications of e-shopping for in-store shopping at various shopping locations in the Netherlands. Environ Plan B Plan Des. 2009;36:279–99.
42. Fowler M, Cherry T, Adler T, Bradley M, Richard A. 2015–2017 California Vehicle Survey Consultant Report. CEC-200-2018-006 [Internet]. California Energy Commission. 2018. Available from: https://ww2.energy.ca.gov/2018publications/CEC-200-2018-006/CEC-200-2018-006.pdf
43. Spurlock CA, Sears J, Wong-Parodi G, Walker V, Jin L, Taylor M, et al. Describing the users: Understanding adoption of and interest in shared, electrified, and automated transportation in the San Francisco Bay Area. Transp Res Part D Transp Environ. 2019;71:283–301.
44. Reilly M, Landis John. The influence of built-form and land use on mode choice: Evidence form the 1996 Bay Area Travel Survey. Publication IURD WP 2002-4. Berkeley; 2002.
45. Chen C, Gong H, Paaswell R. Role of the built environment on mode choice decisions: additional evidence on the impact of density. Transportation (Amst) [Internet]. 2008;35:285–99. Available from: https://doi.org/10.1007/s11116-007-9153-5
46. Johnson E. The Real Cost of Your Shopping Habits [Internet]. Forbes. 2015 [cited 2020 Feb 13]. Available from: https://www.forbes.com/sites/emmajohnson/2015/01/15/the-real-cost-of-your-shopping-habits/#5b83a5e01452