Title

Who Has Access to E-Commerce During the COVID-19 Pandemic in the Sacramento Region? Implications for Future E-Commerce and Shopping Tripmaking

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Who Has Access to E-Commerce During the COVID-19 Pandemic in the Sacramento Region? Implications for Future E-Commerce and Shopping Tripmaking

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16. Abstract

The COVID-19 pandemic brought about dramatic shifts in travel, including shopping trips. We investigated changes in e-shopping for food and non-food items by supplementing an April to May 2018 household travel survey (n=3,956 households) conducted by the Sacramento Area Council of Governments (SACOG) with a May 2020 follow-on panel survey (n=313 households) during one week early in the pandemic. Results demonstrate that impacts from added pickups and deliveries in the SACOG region during the first two months of the COVID-19 pandemic were limited and did not overwhelm curb management at retail, restaurant, and grocery establishments. Results also show that during the pandemic e-commerce tended to replace non-food shopping trips, but complemented restaurant and grocery trips. However, Forty percent of the sample households — predominantly lower income and/or older populations — still shopped only in-store for food while more affluent households appear to have isolated themselves from virus exposure through more extensive online shopping. We recommend extending the forms of accepted payment for online shopping and reducing fees and markups based upon payment method to reduce barrier to online shopping for those with limited resources. We identify possible consequences (e.g., more vehicle miles traveled and higher demand for curbside parking) if e-commerce food purchasing continues to grow post-pandemic or if in-person retail shopping returns to normal.

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Disclaimer

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Executive Summary

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Due to the COVID-19 pandemic, beginning in March 2020, many regions in the United States experienced rapid changes in travel patterns, with much of the populace staying at home for work and school and reducing out-of-home trips for shopping, entertainment, socializing, and personal business. This led to an increase in the use of retail purchase pick-up and delivery services, exacerbating concerns around curb management problems in large cities such as New York and San Francisco. However, do such concerns also apply in mid-sized cities? Does an increase in shopping from home lead to a proliferation of issues with pickups and deliveries? To gather more information about mid-sized California cities, we re-sampled participants from the 2018 Sacramento Area Council of Governments (SACOG) household travel survey (2018 HTS) of 8,191 individuals representing 3,956 households over a rolling six-week period from April to May 2018. This was the first region in the state to collect detailed information on e-commerce use, and use behavioral modeling to compare pre-pandemic shopping to pandemic-related shifts in consumer purchasing and receipt, for nine types of essential and non-essential commodities (including groceries, meals, clothing, paper products and cleaning supplies). We collect responses from 327 individual respondents, representing 313 households, in May 2020. We present descriptive statistics to examine changes to weekly shopping trips and online ordering during the pandemic to assess likely traffic and curb use impacts. The respondents were also asked about their prospective behavior once the pandemic ends and we consider if and how current changes might persist in the future based on their responses.

Results demonstrate that impacts to curb management in the SACOG region during the first two months of the COVID-19 pandemic and response were limited and did not overwhelm existing infrastructure at retail, restaurant, and grocery establishments. Pandemic-induced changes to retail shopping vary widely by commodity. Even though overall trip making fell 54 percent during the 2020 observation week compared with 2018, e-commerce ordering replaced a large percentage of non-food trips, with such deliveries down only two percent. On the other hand, e-commerce food deliveries rose 375 percent with purchases and pickups complementing restaurant and grocery trips (and potentially inducing some additional grocery trips). Even with that level of increase in deliveries, we find that e-commerce food purchases did not result in comparable reductions in in-person trips for food items (e.g., restaurant food, groceries, etc.), as 85 percent of food purchases among the sample population involved taking a trip.

Even facing a global pandemic, we observe that 40 percent of the sample population shopped only in-store for food during the observation week. Model results indicate that these shoppers were more likely to be older and from households earning below the median. Those households that did not change their shopping behavior during the pandemic may represent e-commerce laggards in the future. Conversely, more affluent populations demonstrated a strong shift toward e-commerce, shopping online for non-food items and complementing in-person food shopping with e-commerce during the pandemic. Taken together, these results signal a higher exposure risk in populations (e.g., older adults) that may be more vulnerable to serious complications from contracting COVID-19 and/or higher exposure to the virus due to performing essential work.

Demographic variables shown to be highly significant in explaining weekly shopping decisions prior to the pandemic (e.g., gender, household income, household size) do not explain changes to tripmaking and e-commerce ordering frequency during May 2020. This suggests that the major factors affecting pandemic shopping behavior may not be captured by demographic information collected by standard transportation data collection efforts. Lifestyle variables, such as household Amazon Prime memberships, positively and significantly affect the likelihood of households shopping online for food and non-food items. This points to: 1) the influence of non-food shopping services on food shopping and 2) a need to collect more household information (e.g., physical and digital subscriptions, credit card-based e-commerce incentives). Additionally, we find a large proportion of new e-commerce food shoppers; there was 25 percent signup rate for groceries and 22 percent for prepared food for those surveyed. Among these new users, we observe a strong shift toward shopping only online for food, as well as limiting the frequency of in person shopping. This safety-minded behavior may be tempered by high demand for and difficulty finding available delivery times, particularly for groceries.

In light of these results, we suggest improving future analyses by using consistent definitions of e-commerce and collecting more precise information about shopping, particularly online shopping. We also suggest strategies to expand e-commerce access — particularly for food — to a broader range of people by:

1) expanding the forms of payment accepted,

2) limiting item markups and/or fees based upon payment type, and

3) offering call-in order options.

We also address the curbside and parking implications of these demand shifts for different types of commodities (e.g., food, non-perishable items). Given the stated five to ten-year growth acceleration of retail e-commerce predicted by some experts (e.g., Mahmassani et al., 2020), we address the likelihood and implications that certain behaviors will persist after the pandemic. If food e-commerce continues to complement and/or begins to induce additional trips the sustainability benefits (e.g., lower vehicle miles traveled) from food e-commerce delivery economies of scale could diminish, while the demand for short-term parking and loading at restaurants could eclipse that of longer-term metered parking.

Respondents indicated that once the pandemic is over, they plan to in-person non-food retail shopping. If so, in-person shopping trips may rise even more if the pandemic substitution effect of e-commerce on tripmaking shrinks. As concerns about virus transmission decrease with more widespread vaccination and immunity, many of those currently using grocery ordering platforms may return to in-person shopping, undercutting the growth of e-commerce.

As the state and nation progress toward post-pandemic life, emerging and pandemic-induced long-term changes in business (e.g., more outdoor sidewalk dining, increased curbside pickup) could compete for curb space with traditional curb uses, including long-term metered parking. Thus, policymakers will need to balance the needs of all types of curb users and make safety — both health and traffic-related — a priority.

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Introduction

COVID-19 travel and business restrictions and closures present an opportunity to gain insights into how individuals with varying levels of technological capability, internet-connectedness, personal mobility, and other key factors are managing their purchasing needs in a time of constrained travel. The transportation literature has long focused on the relationship between e-commerce[1] and online shopping and personal shopping trips, and recently the Sacramento Area Council of Governments (SACOG) addressed these questions in their 2018 household travel survey (HTS). Unfortunately, the unexpected shock of the pandemic has rendered much of the information collected from this survey outdated or irrelevant. For example, changes in consumer shopping may be generating second order effects (e.g., changes to curb use, changes in household car ownership) and even third order effects (e.g., changes to land use; it is important to develop a clearer picture of these pandemic-influenced behaviors, and how they could play out in the future. In this research we supplement the recent 2018 HTS data with online surveys conducted during the early months of the COVID-19 Stay at Home orders, to develop a greater understanding of current and future online shopping patterns.

Some pandemic effects may be here for years to come, and stakeholders at the local and regional levels will need to develop flexible strategies and infrastructure to deal with rapidly changing circumstances as counties and regions move forward with different stages of re-opening. Many cities (e.g., Los Angeles, Oakland, San Francisco) greatly relaxed or eliminated parking meter enforcement at the beginning of the Stay at Home orders and/or are exploring expedited temporary loading zone applications (e.g., Sacramento, Oakland) and permits as part of pilot programs. Additionally, companies are responding to the pandemic in many ways, such as implementing waiting lists for online shopping services (Ocado, 2020; Petrova, 2020; Perez, 2020), constructing more urban delivery centers (Martineau, 2020), converting closed retail locations into online fulfillment centers (Kang, 2020), or instituting specific fees for e-commerce parcels (Ziobro, 2020). These shifting market realities are presenting consumers with different options to choose from for their shopping needs compared to before the pandemic. We examine changes to household travel behavior under such circumstances.

Recent work has focused on shopping motivations and consumer attitudes in explaining shopping behavior (Punel and Stathopolous, 2017; Le and Ukkusuri, 2019), and preliminary work since the onset of the COVID-19 pandemic has shown marked shifts in shopping behavior (Holguín-Veras and Encarnacion, 20202; Wunderman Thomson, 2020). Additionally, new open-sourced datasets from private companies (Contentsquare, 2020; Google, 2020) and publicly available data have revealed dramatic shifts in the retail purchasing habits of American consumers in response to Stay at Home orders and uncertain economic circumstances. No studies to date, however, have examined both changes in online consumer purchasing and e-commerce delivery service operations or their collective impact on public infrastructure. This study fills in those gaps.

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[1] In this study, we adopt the United States Census definition of e-commerce, as: "sales of goods and services where the buyer places an order, or the price and terms of the sale are negotiated over an Internet, mobile device (M-commerce), extranet, Electronic Data Interchange (EDI) network, electronic mail, or other comparable online system. Payment may or may not be made online (Census, 2019)." We focus on business-to-consumer, as opposed to business-to-business shopping and e-commerce.

This research resurveys a sample of respondents from the 2018 HTS about their purchase habits across nine different types of commodities in three groups—food items (groceries, prepared meals), essential non-food items (childcare items, medication, cleaning supplies and paper products) and non-essential non-food items (clothing, home/office items) for a single week during May 2020. This time period coincided seasonally with data collection for the 2018 HTS and represents a time long enough after the onset of the pandemic for consumer behaviors to have had time to settle. By looking at a wide range of consumer items, we were able to compare travel patterns and purchasing behaviors for different demographic groups and between groups of consumers living at different population densities. Specifically, we compared: 1) the use of e-commerce channels (e.g., websites, such as Amazon) that were already on the rise prior to the pandemic (e.g., buying online for in-store pick up, buying online for delivery); 2) shopping mechanisms that have seen increased use because of the pandemic (e.g., curbside pickup, contactless delivery) that may or may not continue as restrictions are eased; and 3) in-store shopping. This study will aid policymakers to make decisions about curb space allocation, time of day parking incentives/restrictions, and conversion of sidewalk or street space to outdoor dining space.

In the next section we provide background information on: 1) online shopping and trips for shopping, 2) retail commerce and COVID-19, and 3) how the pandemic has affected business operations. We follow this with a discussion of our methods, a presentation of our interview and survey results, and finally local and regional policy recommendations based upon our findings.

Background: Framing the Analysis

Online shopping and tripmaking

An online shopping purchase can produce these three changes in travel:

1) It **substitutes** for in-person shopping thereby replacing a consumer trip to the store;

2) It generates or **induces** new trips that did not take place before or increases overall tripmaking, for example _____; and

3) It **supplements** or complements in-person shopping, as for example _______.

Holguín-Veras et al. (2006). We use this framework in this study to investigate whether, during the pandemic, e-commerce has been substituted for in person shopping trips, induced new shopping trips, or complemented existing trips to obtain the different commodities described above.

Commerce and COVID-19

Newly available retail data, legacy Census products, and rapidly produced results from the supply chain sectors shed some light on how consumer buying patterns have changed since the onset of the pandemic. Key questions we consider in this study are:

1. **What** goods are being purchased?
2. **How** are those goods being purchased: online, in-store, a combination?
3. **Where** does the consumer receive their purchases: door delivery, store pick up?

Blackwell et al. (2006)

Some consumer items, like food, are purchased more frequently than others such as clothing. Households predominantly use e-commerce as: 1) a substitute for shopping trips or 2) to supplement shopping trips (i.e., to attain additional goods not found in-person) (Spurlock et al. 2020). The type of items that are purchased, such as perishable vs. non-perishable groceries items, influences whether they are more likely to be purchased in store or on line (Suel and Polak, 2018). A purchaser's education, mobility, and their experience using the Internet is also a factor in their propensity to make online purchases (Rotem-Mindali, 2010). The availability of parcel lockers (also known as pick up or collection points also positively influences e-commerce adoption (Yuen et al., 2018). Females, individuals in highly populated areas, particularly with children may be more likely to shop online (Jaller and Pahwa, 2020).[2]

Just after the onset of the pandemic consumer spending initially contracted significantly, though spending on food remained stable and even increased as families ate more meals at home (McKinsey, 2020; Salon et al., 2020). In addition,

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[2] This study used the American Time Use Survey (a one-day survey of a representative sample of the US population).

consumers tried online shopping for many different types of commodities for the first time as a result of Stay at Home orders (McKinsey, 2020; Salon et al., 2020).

Effect of pandemic on retail commerce, deliveries, and curb space

The pandemic has not only introduced shocks to consumption but also to the availability of goods. Multiple representatives from large delivery and shipping providers described the shock to the retail supply chain as akin to the volume of Cyber Monday (one of the busiest shopping days of the year) every day for months (Mahmassani et al., 2020). Online grocery providers, flooded with new signups and spikes in demand, had to restrict delivery windows, encourage shoppers to share delivery slots with neighbors, or quickly deploy new tiered service models (i.e., giving priority to some customers over others) (Ocado, 2020; Griswold, 2020; Perez, 2020; Petrova, 2020). Additionally, many previously in-person retailers — both in the food/beverage and non-food industries — had to rapidly alter their operations by, for example, offering curbside pickup, or setting up outdoor tables to service customers, to comply with local or regional health and safety regulations (Griswold, 2020).

Prior to the pandemic, documented data flows between private Transportation Network Companies (TNCs) like Uber or Lyft and the public sector indicated a shared focus on curbside management as an important operations and policy topic, particularly in a time of changing demand and supply (Butrina et al., 2020).[3]

The use of curb space for commercial deliveries, including how long they take, depends on the type of commodity being delivered (Schmid et al., 2018). Peak delivery demand often coincides with peak travel demand (Chen et al. 2016). E-commerce deliveries and pickups could present similar issues. During a time of decreased travel demand, like now, these particular issues may not be as pressing, but the curb still presents a space for both conflict and cooperation between public and private entities, as well as consumers.

Methodology

To examine how shopping has changed in response to COVID-19, assess whether such changes are likely to persist, and examine the impact on traffic and curb management, we compared survey responses from the SACOG) 2018 HTS from April and May 2018, with those from a survey of subset of the same respondents collected in May 2020.[4] We then examine how the demographic and other characteristics of the respondents were related to any changes in their shopping behavior.

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[3] One unexpected result of the COVID-19 pandemic has been the open sourcing of privately held datasets. Many have been made publicly available to help with pandemic research, but others have shed light on changes in travel and shopping behavior. For a more detailed discussion of results from such datasets, please see Dennis, Forscher, and Jaller (2020).

[4] This is known as a panel data collection approach.

2018 HTS data and 2020 online survey

The 2018 HTS collected travel data from 8,321 individuals representing 4,010 households over a rolling six-week period.[5] Those responding to the survey were divided into two groups. A total of 4,674 individuals (about 57 or the total) representing 2,875 households (about 73 percent) installed a smartphone application for use during the observation week (beginning on a Tuesday and ending on a Monday), which provided seven days of contiguous data — this was the rMoves sample in Table 1 below. The app passively tracked their location and prompted them to enter details about every trip taken, and participants also filled out daily surveys regarding their e-commerce purchases and demographic information (both individual and household). The other respondents — the rOnline sample — reported data for a single travel day (either a Tuesday, Wednesday, or Thursday). Participants in the rOnline sample completed one daily survey, self-reporting their tripmaking (including locations and purposes), e-commerce behavior, and demographic information (both individual and household).

[5] There was a total of 8,191 individuals and 3,956 households in the cleaned 2018 sample.

Table 1. Demographic comparisons of sample groups[6]

	SACOG Region 2017 1-year ACS Percent (2,498,563 persons, 887,945 households)	2018 SACOG HTS Percent (8,191 persons, 3,956 households)	2018 rMoves (7 day) Percent (5,967 persons, 2,875 households)	2020 COVID-19 Subsample in 2018 Percent (671 persons*, 313 households)	2020 COVID-19 Respondent Subsample in 2020 Percent (327 persons*, 313 households)
Age (person					
Younger than 35	46	38	45	42	20
35 - 64	39	41	43	45	58
65 or older	15	21	12	13	22
Gender (person)					
Female-identifying	49	54	54	60	54
Male-identifying	51	44	45	37	45
Other Gender identity	-	0	0	1	0
Prefer not to answer	-	2	1	2	1
Household Income (household)					
Under $50,000	37	29	25	18	7
$50,000 - $74,999	17	17	17	17	10
$75,000 - $99,999	13	14	15	14	10
$100,000 or more	33	27	31	42	42
No Response	-	-	-	-	25

[6] In total, there were 2,838 useable household weeks for the rMoves sample and 313 household weeks from the 2020 COVID-19 subsample.

	SACOG Region 2017 1-year ACS Percent (2,498,563 persons, 887,945 households)	2018 SACOG HTS Percent (8,191 persons, 3,956 households)	2018 rMoves (7 day) Percent (5,967 persons, 2,875 households)	2020 COVID-19 Subsample in 2018 Percent (671 persons*, 313 households)	2020 COVID-19 Respondent Subsample in 2020 Percent (327 persons*, 313 households)
Prefer not to answer	-	13	12	9	6
Household Size (household)					
1 person	25	39	40	30	24
2 persons	34	37	35	47	45
3 persons	16	11	11	9	12
4 or more persons	25	13	14	20	18

* Detailed demographic information about all household members is not available from the 2020 COVID-19 subsample (due to survey response fatigue concerns). 2020 person-level variables represent the respondent in 2020, meaning that the person-level variables in the 2020 subsample are not directly comparable to the other columns.

Table 1 provides information on the age, gender, household income and household size for the participants in the 2018 HTS sample, the rMoves respondents in 2018, and the 2020 subsample (discussed below) compared to the results from the 2017 1-year American Community Survey (ACS) estimates for the six county SACOG region. All samples skew older than the ACS, although the rMoves and 2020 subsample have a dearth of respondents 75 and older. Additionally, all samples skew toward female-identifying respondents, who have been shown to shop more, likely due to family structures (Jaller and Pahwa 2020; Srinivasan and Bhat, 2005; Farag et al., 2005). This could mean a higher than regionally representative number of shopping trips among our sample populations, which we address by controlling for gender in the model. Additionally, all samples are toward the higher end of the income spectrum compared to the ACS (i.e., earning $100,000 or more), signaling a likely higher number of purchases; again, this is controlled for in the model. There is a higher prevalence of smaller households (i.e., 13 percent more two-person households in 2018 and 11% more in 2020,) in the sample populations as well, which might suppress the number of shopping trips.

Comparing the subsample population in 2018 to 2020, there is a 6 person drop in single-person households, a 16 person shift toward away households earning below $75,000, and a 22 percent shift toward individuals over the age of 35, which is partly expected given the two-year time difference in data collection and the age categories used during data collection. The gender split is slightly more balanced in 2020 (54-person female-identifying and 45 percent male-identifying) than in 2018 (60 percent female-identifying and 37 percent male-identifying); however, it is still skewed toward female-identifying respondents when compared with the region. In the one-time survey in 2020, age and gender information were only collected about the respondent and not about the rest of the household (to limit survey response fatigue compared with the week-long data collection period in 2018), which partly explains the differences in distributions at each time point. Household income and size were collected at the household level, reflecting changes to household circumstances and makeup. We do not feel that the differences in subsample makeup render them incomparable but instead that it is important to account for these factors in any demographic-level comparisons.

We re-contacted 4,658 of the original 8,191 respondents from 2018 to recruit them for a new survey using the online Qualtrics platform. A total of 327 individuals completed the survey, representing 313 households from the 2018 HTS sample.[7] All households completing the survey in 2020 where part of a group in the 2018 study who installed a smartphone application that passively tracked their location and prompted them to enter details about every trip taken, during a full week (beginning on a Tuesday and ending on a Monday). They also filled out daily surveys regarding their e-commerce purchases and demographic information (both individual and household), which provided seven days of contiguous data. This new subsample (the "panel households”) represented roughly four percent of the 2018 HTS individual respondents and seven percent of the households.

The 2020 online survey focused on pre- and post-COVID shopping behavior for nine categories of goods, far beyond the two broad categories used in 2018, and included questions about the respondents’ motivations for, attitudes toward, and ease of use of, online shopping. The survey was released on Monday, May 25, 2020[8] and was closed to new responses one week later on June 1, 2020; two reminder emails were sent to respondents who had not completed their surveys, and 99 percent of respondents submitted their completed surveys by the closing date.

Respondents reported the number of in-person shopping trips taken for the week spanning Sunday, May 17 to Saturday, May 23, 2020 (counting one back and forth trip as a single trip), allowing for direct comparisons between 2018 and 2020. They were asked about the number of e-commerce purchases made, and the number of deliveries and pickups made from those e-commerce purchases for each commodity type. Respondents additionally reported changes (less or more) in their behavior from a typical week in January or February 2020 (prior to the COVID-19 pandemic) for: 1) tripmaking, e-commerce purchases, and delivery and pick up frequencies; 2) purchase sizes; 3) distances traveled; and 4) modes used for in-person trips. For this analysis, we focus on changes in their frequency of purchases, deliveries and pickups, and order sizes.

Analytical approach

For the purposes of this analysis, we aggregated all household trips and shopping events from the 2018 HTS into household days. We then aggregated the data again into household weeks to make the two datasets more comparable.[9]

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[7] Of those re-contacted, 537 expressed interest in participating in the new study. When contacted to enroll in the study, 440 individuals responded to the solicitation. This represents an 82 percent click-through rate, and a 74 percent completion rate of those who responded to the solicitation. Those who completed the survey represented a 61 percent completion rate overall.
[8] George Floyd was murdered by police officers on this same day; the protests arising in part as a response to this may have affected response rates.
[9] This was done, since the May 2020 survey asked respondents to report their household’s shopping behavior for an entire week at once, rather than having respondents report daily activity for seven days consecutively as in the 2018.

Person-level demographics (e.g., age, gender identity) collected for both surveys represent those of the primary respondent for each household (with primary respondents matched between 2018 and 2020 to retain consistent demographics).[10]

All the 2018 respondents reported on their daily e-commerce activities (receiving deliveries and online shopping events) and shopping trips. For each day, respondents reported on the primary purpose of each trip made (as recording multi-purpose trips with a single destination was not an option presented to respondents during the 2018 HTS possible). However, for multi-destination trips, we counted each segment of the trip as a separate trip to an individual destination, and assigned each segment a specific purpose. In 2028, respondents only reported whether they made an online or received a delivery each day. In 2020, respondents reported not only on each trip's purpose but also the number of purchases and/or deliveries each day, and what they were. In addition, the 2018 HTS only distinguished between food (groceries, or prepared meals) and non-food purchases, whereas the 2020 Survery collected more detailed information about the specific non-food item purchased, as shown in Table 3.

The e-commerce variables in the 2018 HTS were recorded as binary responses on a given day (i.e., did a respondent make an online purchase or receive a delivery?), rather than the number of events (i.e., the number of purchases or deliveries) on a given day, meaning they are capped at one, while trip counts are not capped for any given day.

[10] Depending upon household structure, many shopping trips are conducted on behalf of the entire household (e.g., grocery shopping, picking up take-out, etc.) so assigning the person-level variables of the primary household respondents who provided the majority of data for their household (in many cases they were the only respondent) to a household trip best represents the household's tripmaking motivations for the week overall.

Table 2. Shopping variables in the 2018 SACOG HTS

Variable Name:	Non-food shopping	Food shopping	Unspecified shopping
E-commerce/online shopping	-*delivery_athome*: Travel day delivery: Received packages at home (e.g., FedEx, UPS, USPS) -*delivery_atwork*: Travel day delivery: Received personal packages at work (e.g., FedEx, UPS, USPS)	-*delivery_food*: Food was delivered to home (e.g., take-out, groceries)	-*shoponline*: Personally purchased anything online on travel day
In-person shopping	-*to_other_routine_shopping*: A trip ending at another routine shopping area (e.g., CVS, clothing)	-*to_grocery*: A trip ending at a grocery store -*to_meal*: A trip ending at an establishment labeled “Dine out/get coffee or take-out”	

Taken together, the e-commerce and in-person shopping variables create a nearly complete view of the purchase and receipt options available to this sample of residents for food and non-food commodities in the SACOG region in 2018. It is important to note that while e-commerce variables match directly with only one step in a shopping journey (i.e., *shoponline* and purchase, *delivery_athome* and receipt of goods), in-person trips cannot be directly matched as it is ambiguous whether or not a purchase was made on a shopping trip. As our analysis is concerned with shopping behavior and trends, understanding in-person tripmaking by purposes is sufficient, although tripmaking and purchase-making by commodity would add richness in the future.

In comparison to the 2018 HTS data, in 2020 respondents reported all of their household’s behavior for an entire week via one online survey and reported purchases at a much higher level of commodity detail than in 2018; the interaction between the 2020 and 2018 commodity types is shown in Table 3. Additionally, the 2020 survey collected numerical data for e-commerce purchases (rather than binary variables), meaning that tripmaking and e-commerce analyses are more comparable within the 2020 sample than within the 2018 sample. Comparisons from the 2018 sample to the 2020 sample are assumed to be equivalent for tripmaking. To account for differences in variable types for e-commerce activities, we compare the number of days during which a particular e-commerce activity was recorded in 2018 (e.g., a household made an e-commerce purchase on five of the seven observation days) with the number of e-commerce activities reported during the observation week in 2020 (e.g., a household made five e-commerce purchases during the observation week).

Table 3. Comparison of commodity categories between the 2018 HTS and the 2020 supplement

Survey	Parcel (non-food)	Food	
2018 HTS	-Other routine shopping; -FedEx, UPS, USPS packages	-Groceries	-Take-out, meals
2020 Supplement	-Clothing; -Paper products and cleaning supplies;* -Home office items; -Medication;* -Childcare items;* -Other non-food items	-Groceries	-Prepared meal or beverages (i.e., from a restaurant or a café)
		-Other food items (e.g., specialty foods, farmer's markets, farm boxes, meal preparation kits)	

*Indicates an essential non-food commodity; all food commodities are considered essential

Modeling approach

Using the subsample responses from both 2018 and 2020 we estimated a multinomial logit (MNL) model with four possible household outcomes during the observation week: 1) no shopping, 2) only in-person shopping, 3) only online shopping, and 4) both in-person and online shopping.[11] As these four outcomes are mutually exclusive for any given week, a MNL model was selected to provide a view of what variables influence the likelihood of each outcome.[12] MNL models can be used for example, to answer how much more likely a female-identifying individual is to shop online for food than a male-identifying- individual both pre- and post-pandemic.[13] This type of framework is useful for analyzing population level demographic differences in behavior and can be used to produce estimates for behavior in light of different policy

[11] We use a multinomial logit model with both 2018 HTS data and 2020 survey results. Logit models, like probit models, can be used to estimate the influence of independent variables on dependent binary or multinomial variables. Logit models differ from probit models primarily in the way they transform linear relationships into non-linear ones. Logit models use cumulative logistic distributions, whereas probit models use cumulative standard normal distributions.
[12] This approach is similar to Jaller and Pahwa (2020),
[13] Formally, the model produces an estimate of the effect of selected explanatory variables on the log of the probability of an individual choosing a particular shopping outcome when compared to the base alternative of in-person shopping.

interventions. Importantly, MNL models do not assign any causal relationship between variables, they only provide an explanation of differences.

Study limitations

The 2018 HTS data presented a few challenges, as mentioned previously, primarily related to the time lag between online purchases, pickups, and delivery events, which could result in: 1) missing purchases for deliveries on day one and missing deliveries for purchases made on day seven of a seven-day long observation window, 2) mismatched commodity category specificity for purchases vs. deliveries, 3) confusion over whether call-in orders constitute an online purchase, and 4) the inability for respondents to recognize whether particular deliveries and/or trips were related to online purchases (e.g., buy online/pick up in store transactions), or to accurately report the number of deliveries resulting from each purchase. The boundary issue of purchases and deliveries should be addressed with a large enough sample size, but as our results demonstrate, the lack of granularity pertaining to commodity types limits the usefulness of the 2018 HTS data for understanding curbside activities.

Additionally, SACOG's decision to omit food deliveries to work locations in their survey may mask a behavior that was on the rise in 2018, limiting our ability to make comparisons between 2020 and 2018. We expect that the prevalence of deliveries to work locations plummeted due to Stay at Home orders at the time of our survey, meaning that some downtown locations with busy curbsides in 2018 were not being used for food or other deliveries during the early months of the pandemic. Similarly, the time lags between purchases and deliveries/pick-ups (e.g., e-click to door or e-click to collect time purchases) varies widely by commodity. It is important to note that grocery and food orders could not be scheduled far in advance (e.g., up to two weeks) in 2018, and instant and two-hour deliveries for non-food items were just being launched in many metro areas.

By aggregating daily observations into household weeks, we lose the ability to explore variations between weekdays and weekends; however, we feel that the ability to explain weekly shopping behavior provides more information than the ability to predict the likelihood of shopping on any particular day.

One other limitation with any retrospective survey data collection effort is respondent recall. Daily surveys minimize lack of recall issues in comparison to weekly or monthly surveys. Asking respondents to recall their monthly behavior, l is a difficult task, even prior to the pandemic. Our qualitative data reveal somewhat of a mismatch between respondents' recollections and their actual behavior, similar to what Hamar et al. (2016) found, 57 percent of respondents in our study stated that their weekly grocery shopping trip frequency had decreased since the pandemic. However, our analysis found that only 13 percent actually made fewer trips during the observation week than in 2018. For this reason, we present only numerical results and do not use the qualitative responses (more/less) in our analysis. Such mismatch issues, along with recall considerations, make repeated observations of panel populations all the more important.

It is also important to note that households were presented with a fundamentally different set of options during the observation week than they would otherwise have been. Many retail stores were closed for in-person operations, in-person dining was restricted, and stores that were open were adapting to changing guidelines regarding occupancy, mask wearing, and sanitation. Additionally, as we mentioned previously, the retail e-commerce landscape has changed since 2018, so we cannot attribute all the observed variation between 2018 and 2020 to pandemic-induced changes alone. Our results are useful because of the fundamentally different reality in which households were shopping, particularly in analyzing households that do and do not adopt e-commerce when faced with a deadly pandemic.

Results and Discussion

Overview

To examine pandemic-induced changes to retail shopping patterns, we first analyzed in-person and online shopping behavior from the pre-pandemic 2018 HTS to determine how representative the panel households were of the entire 2018 HTS sample. Table 4. Average tripmaking and delivery rates in 2018

	All rMoves households (n = 2,838)		2020 COVID-19 subsample households (n = 313)	
Purpose of Trip	**Average household trips per week**	**Average number of day per week with deliveries**	**Average household trips per week**	**Average number of days per week with deliveries**
For groceries	2.97	-	3.13	-
For meals	5.51	-	5.91	-
Home deliveries of food	-	0.10	-	0.14
To other routine shopping	2.93	-	3.18	-
Home deliveries of non-food	-	1.46	-	1.62
Online purchase	-	1.10	-	1.10

Table 4 shows the average number of weekly household trips and average number of deliver days per week for food and non-food items for each group. Most trips were for food, whereas deliveries were primarily for non-food items. Both groups had the same average number of days per week with deliveries. The panel households took more trips per week and received deliveries on more days of the week than the rest of the sample. TFor both groups there here were more days with deliveries than purchases, which could be due to single online orders leading to deliveries on multiple days or deliveries of purchases made prior to the observation week (i.e., someone made a purchase before beginning the survey period and received a package during the survey period). However, one would expect that with a large enough sample, this purchase/delivery mismatch during the observation period would even out. The households present in the 2020 COVID-19 subsample had a higher rate of tripmaking than the rMoves sample overall which may be due to products being unavailable at the time of purchase due to the pandemic, requiring multiple trips; however, these differences were not significant at a 95 percent confidence level.

Below we present the results of our analysis of the panel household respondents, for food and non-food purchases in 2018 and 2020.

Non-food shopping

We modelled food and non-food weekly shopping patterns separately because we hypothesize that the motivations for food and non-food purchases are quite different, as evidenced by the rates shown in Table 5. Separate treatment further allowed us to examine whether e-commerce food purchases add to (supplement) or replace trips (substitute for) food trips. The explanatory variables in each model are associated with one type of shopping to examine the existence of a link between food and non-food shopping behaviors (e.g., does an Amazon Prime membership change one's food shopping behavior?).

Table 5. Rates of shopping patterns in 2018

	Percent of rMoves sample (n=2,838)		Percent of 2020 COVID-19 subsample (in 2018) (n=313)	
Weekly Pattern	**Non-food**	**Food**	**Non-food**	**Food**
Only in-person shopping	27.4	88.4	26.3	87.5
Both in-person and online shopping	44.2	7.7	51.7	9.8
Only online shopping	14.5	0.2	12.5	0.0
No shopping	13.9	3.7	9.4	2.8
	100	100	100	100

As mentioned previously, we estimate one model each for food and non-food and commodities. To achieve these comparisons in a single model, we include parameters that apply to both observation years (2018 and 2020) as well as parameters that only apply to 2020; this allows us to interpret the 2020 parameters as the change above and beyond observable differences and potentially due to pandemic-induced behavior.

Non-food model results are presented in Table 6.

Table 6. Non-food MNL model results

Number of Parameters	135
Number of Observations	626
Null Log-Likelihood	-867.82
Fitted Log-Likelihood	-677.91
Rho-Squared	0.22
Rho-Bar-Squared	0.06

	2018 & 2020 Parameters		2020 COVID-19 subsample parameters	
	Parameter	Std. error	Parameter	Std. error
Alternative specific constant - No shopping	**-2.09****	**0.87**	**2.88****	**1.26**
Alternative specific constant - Online only	**-1.22***	**0.70**	-0.05	1.23
Alternative specific constant - Both in-person and online	-0.20	0.53	-0.42	1.06
Single Person HH - No shopping	0.55	0.61	-0.32	1.00
Single Person HH - Online only	0.46	0.53	0.07	1.04
Single Person HH - Both in-person and online	**-0.92****	**0.38**	1.15	0.90
Three+ Person HH - No shopping	-0.98	1.15	-0.03	1.38
Three+ Person HH - Online only	0.14	0.86	-0.31	1.11
Three+ Person HH - Both in-person and online	0.50	0.58	-0.13	0.84

	2018 & 2020 Parameters		2020 COVID-19 subsample parameters	
	Parameter	Std. error	Parameter	Std. error
At least one child in HH - No shopping	0.87	1.11	0.64	1.51
At least one child in HH - Online only	0.03	0.87	2.02	1.33
At least one child in HH - Both in-person and online	-0.54	0.59	0.53	1.10
HH Income < 50k - No shopping	-0.75	0.75	0.59	1.19
HH Income < 50k - Online only	-0.09	0.55	-1.50	1.45
HH Income < 50k - Both in-person and online	0.00	0.52	0.25	0.98
HH Income 75 - 100k - No shopping	-0.66	0.94	-0.40	1.32
HH Income 75 - 100k - Online only	**-1.44***	**0.76**	**2.39****	**1.16**
HH Income 75 - 100k - Both in-person and online	0.26	0.52	-0.44	0.91
HH Income 100k+ - No shopping	0.27	0.80	0.40	1.05
HH Income 100k+ - Online only	**-1.19***	**0.65**	**2.98*****	**1.00**
HH Income 100k+ - Both in-person and online	0.49	0.47	0.05	0.79
HH Income unknown - No shopping	**1.91****	**0.83**	-1.15	1.34
HH Income unknown - Online only	-1.53	1.17	2.70	1.67
HH Income unknown - Both in-person and online	0.50	0.65	0.46	1.22
COVID-related HH income reduction - No shopping			-0.08	0.56

	2018 & 2020 Parameters		2020 COVID-19 subsample parameters	
	Parameter	Std. error	Parameter	Std. error
COVID-related HH income reduction - Online only			0.22	0.55
COVID related HH income reduction - Both in-person and online			0.32	0.51
At least 85th percentile population density - No shopping	-0.32	0.65	0.60	0.81
At least 85th percentile population density - Online only	0.09	0.52	**-1.25***	**0.75**
At least 85th percentile population density - Both in-person and online	-0.40	0.41	0.19	0.63
Apartment - No shopping	**1.33****	**0.60**	**-2.10*****	**0.79**
Apartment - Online only	0.06	0.51	-0.15	0.73
Apartment - Both in-person and online	-0.01	0.42	-0.64	0.66
Work-from-Home for 1 day - No shopping	0.22	1.00	-0.72	1.85
Work-from-Home for 1 day - Online only	-1.36	1.17	2.16	1.82
Work-from-Home for 1 day - Both in-person and online	0.34	0.62	-0.44	1.52
Work-from-Home for 2 days - No shopping			0.13	1.06
Work-from-Home for 2 days - Online only			-0.23	1.07
Work-from-Home for 2 days - Both in-person and online			-0.46	1.11
Work-from-Home for 3 or more days - No shopping	1.12	0.89	-1.35	1.01
Work-from-Home for 3 or more days - Online only	-0.48	1.19	0.22	1.28

	2018 & 2020 Parameters		2020 COVID-19 subsample parameters	
	Parameter	Std. error	Parameter	Std. error
Work-from-Home for 3 or more days - Both in-person and online	0.81	0.60	**-1.23***	**0.75**
Age < 35 - No shopping	**1.13***	**0.62**	-1.05	0.82
Age < 35 - Online only	0.45	0.51	0.42	0.74
Age < 35 - Both in-person and online	**0.64***	**0.38**	-0.72	0.64
Age > 65 - No shopping	0.79	0.66	-0.36	0.83
Age > 65 - Online only	-0.07	0.60	0.36	0.79
Age > 65 - Both in-person and online	0.18	0.41	-0.53	0.66
Female-identifying - No shopping	-0.23	0.51	-0.41	0.66
Female-identifying - Online only	0.17	0.44	0.77	0.65
Female-identifying - Both in-person and online	0.03	0.30	0.03	0.52
Respondent had a travel disability - No shopping	**2.34****	**1.03**	**-2.96****	**1.24**
Respondent had a travel disability - Online only	1.40	0.91	-0.99	1.13
Respondent had a travel disability - Both in-person and online	**1.41***	**0.84**	-1.31	1.05
Unknown disability status - No shopping			0.20	0.49
Unknown disability status - Online only			0.14	0.52
Unknown disability status - Both in-person and online			-0.06	0.48

	2018 & 2020 Parameters		2020 COVID-19 subsample parameters	
	Parameter	Std. error	Parameter	Std. error
Amazon Prime: member since at least 2018 - No shopping	**-0.91***	**0.52**	0.96	0.65
Amazon Prime: member since at least 2018 - Online only	**0.89****	**0.45**	-0.27	0.61
Amazon Prime: member since at least 2018 - Both in-person and online	**0.78****	**0.31**	0.02	0.51
Restaurant Delivery: COVID-19 signup - No shopping			-0.41	1.41
Restaurant Delivery: COVID-19 signup - Online only			0.67	1.10
Restaurant Delivery: COVID-19 signup - Both in-person and online			0.08	1.08
Shared burden for some shopping needs - No shopping			-0.62	0.61
Shared burden for some shopping needs - Online only			-0.32	0.59
Shared burden for some shopping needs - Both in-person and online			**1.11****	**0.56**
Shared burden for all shopping needs - No shopping			-0.53	0.57
Shared burden for all shopping needs - Online only			-0.45	0.56
Shared burden for all shopping needs - Both in-person and online			0.41	0.55
Shopping on behalf of immediate family members only - No shopping			0.23	0.45
Shopping on behalf of immediate family members only - Online only			**-0.82***	**0.49**
Shopping on behalf of immediate family members only - Both in-person and online			0.28	0.45
Shopping on behalf of non-immediate family members only - No shopping			-0.69	0.63

	2018 & 2020 Parameters		2020 COVID-19 subsample parameters	
	Parameter	Std. error	Parameter	Std. error
Shopping on behalf of non-immediate family members only - Online only			**-1.27***	**0.66**
Shopping on behalf of non-immediate family members only - Both in-person and online			-0.18	0.58
Shopping for both immediate family and others - No shopping			**-1.48***	**0.82**
Shopping for both immediate family and others - Online only			**-2.09*****	**0.79**
Shopping for both immediate family and others - Both in-person and online			-0.96	0.64
COVID-19 related reduction in employment - No shopping			-0.41	0.79
COVID-19 related reduction in employment - Online only			-0.46	0.78
COVID-19 related reduction in employment - Both in-person and online			-0.11	0.74
Female-identifying respondents living with children - No shopping			-0.04	1.08
Female-identifying respondents living with children – Online only			**-2.00***	**1.11**
Female-identifying respondents living with children - Both in-person and online			0.46	1.04

We compared the demographic and other characteristics of the respondents who engaged 1) in-person only shopping to: 2) shopping both in-person and online, 3) shopping only online, and 4) no shopping during the observation week to examine how different sections of the population behaved in response to COVID-19.

The results for both 2018 and 2020 show that for both years most households in the SACOG region only shopped online for non-food items. During the survey week in 2020, few if any households shopped for non-food items at all, suggesting that there were viewed as non-essential items at that time. This coincides with a steep decline in retail and recreational trips in the region and the nation, as persons appear to have been sheltering in place at this time.

As evidenced by the negative alternative specific constants (ASCs) for the combined 2018 and 2020 parameters, the default shopping behavior in both observation years is to shop only in-person for non-food items; this result suggests that households in the SACOG region are less likely to use e-commerce for non-food items. The additional effect of 2020—some of which can be explained by pandemic-induced behavior changes—is that all else equal, households in the SACOG region were not shopping at all for non-food items in the observation week, potentially foregoing non-essential purchases in lieu of food. This result is consistent with the decline in retail and recreational tripmaking in the region, as well as national trends indicating a dip in overall retail (Google, 2020; Contentsquare, 2020).

Both in-person and online

Respondents: 1) with an Amazon Prime membership, 2) under the age of 35, or 3) indicating a travel-related disability were more likely to shop both online as well as in-person, than to shop only in-person across both observation years. This suggests that having grown up in the age of the internet positively influences online shopping behavior for some individuals, and online shopping may extend benefits to individuals who may have difficulty traveling. Conversely, smaller households are less likely to exhibit this behavior; they are more likely to shop only in-person compared to larger households.

Looking only at 2020, those households that shared some, but not all, shopping responsibilities among more than one individual are also more likely to shop both in-person and online, while households that worked-from-home for three or more days were less likely to shop some online and more likely to shop only in-person.

Online only

More Households earning the median regional income (in the $50,000 to $75,000 range) are more likely to shop only online compared to affluent households (those with incomes greater than $75,000).

While households with Amazon Prime memberships are more likely to shop *only* online than other households in the sample, households with Amazon Prime memberships are still most likely to shop *only* in-person. The effect of the pandemic was not statistically significant for households with Amazon Prime memberships; however, the magnitude indicates a shift toward no shopping for non-food items. This represent a major shift from previous research, which found that households with an above median income were more likely to shop both in-store and online [compared to what?], whereas we observe higher-income households are more likely to shop *only* in-store (Jaller and Pahwa, 2020; Srinivasan and Bhat, 2005; Farag et al., 2005).

The data from 2020 shows a drastic shift among more affluent households toward online shopping, potentially as a way to avoid virus exposure. Households with more financial means are better able to limit contact with the outside world for their non-food shopping than their less affluent counterparts. It appears though that more wealthier households are now substituting on line for in-person shopping trips, whereas pre-pandemic online shopping mostly supplemented non-food in-person shopping without reducing the overall number of shopping trips. Additionally, in 2020, we find that female-identifying respondents living with children are less likely to shop both in-person and online [than before, than females without children, or than males with children?].

No shopping

As discussed previously, post-pandemic more households are foregoing non-food shopping altogether in a given week. In both 2018 and 2020, respondents who indicated that they had a travel-related disability were more likely not to shop in a given week than those without a disability. Respondents under the age of 35 were also more likely to go without shopping than those over age 35, as were those who lived in apartments compared to those living in houses.

[How did this change, if at all, pre- and post-pandemic? In the next paragraph you imply that at least for these 3 groups they started to do more in-person shopping after the pandemic.] One the pandemic set in, respondents who shouldered the shopping responsibilities for those outside their own home were less likely not to shop during the observation week than was the case before the pandemic, as were respondents with disabilities and those living in apartments perhaps due to the need to stock up on necessary household items and/or medicine.

Other demographic variables

Overall, the model does not yield significant results for differences in pandemic-related employment or reduced incomes, suggesting that these shocks had not yet translated into changes in shopping behavior. Household size is not significant either and neither is the effect of households earning below the median income. The behavior of older respondents was not r significantly different from that of middle-aged respondents. This does not confirm previous results (Jaller and Pahwa, 2020), but it also does not negate them.

Few previous studies have looked at the effect of residential density or city size. Some studies covered entire Metropolitan Statistical Area (e.g., Jaller and Pahwa, 2020), while other have examined only at a single city or part of a city (e.g., Lee et al., 2017). We find no significant results for both observation years combined, for 2020 those households in population-dense regions tend to be less likely to shop only online. Without more observations, it is difficult to draw conclusions from this result. Some previous studies only found significant relationships by combining density measures with other demographic variables (Jaller and Pahwa, 2020), while others conducted at the regional level found a positive correlation between residential density and online shopping (Spurlock et al., 2020; Dias et al., 2020).

Summary

Taken as a whole, the model demonstrates an overall trend away from shopping for non-food items after the pandemic (in the observation week), with more affluent households increasingly likely to opt for online only purchases. Hhouseholds with a responsibility to shop for others were more likely to continue shopping in person during the pandemic, likely due to the need to deliver goods to others.

The relatively small sample (i.e., 313 households with only one observation per household), may be responsible for the lack of statistical significance in the findings, but it may also be due to the fact that previously significant factors explaining shopping are less important during a pandemic. For example, while Amazon Prime membership is a highly significant variable in both observation years, the added effect of it in 2020 is not significant, suggesting that variables correlated with online purchasing prior to the pandemic were not as important during the observation week. Furthermore, signing up for an e-commerce restaurant delivery service during the pandemic does not have a significant effect on non-food purchasing, which challenges the influence of food purchasing on non-food purchasing put forward by Dias et al. (2020).

Food shopping

We examine results for food shopping in a similar fashion as for non-food, with one exception. The food model excluded all parameters associated with ordering online only in 2018, since no respondents picked this option. Thus, 2020 online only parameters in the food model cannot be interpreted as the influence of 2020 beyond 2018, but instead only as the influence of 2020. All other parameters remain interpretable as in the non-food model. Additionally, the food model drops some explanatory variables used in the non-food model, as these are associated with a very low number of observed choices, causing specification errors. We did not introduce any new variables into the food model that were not included in the non-food model.

Table 7. Food MNL model results

Number of Parameters	71
Number of Observations	626
Null Log-Likelihood	-777.78
Fitted Log-Likelihood	-388.75
Rho-Squared	0.50
Rho-Bar-Squared	0.41

	2018 & 2020 parameters		2020 COVID-19 subsample parameters	
	Parameter	Std. error	Parameter	Std. error
ASC No shopping	**-6.05*** **	**1.35**	**3.58***	**1.99**
ASC Online only			**-3.62*** **	**1.35**
ASC Both in-person and online	**-2.69*** **	**0.67**	**2.38*** **	**0.83**
Single Person HH - No shopping	**1.86** **	**0.85**	-2.65	1.88
Single Person HH - Online only			-1.25	1.22
Single Person HH - Both in-person and online	**-2.05*** **	**0.79**	**1.69***	**0.91**
HH Income < 50k - No shopping	-0.15	1.10	-1.27	2.14
HH Income < 50k - Online only			-0.09	1.36

	2018 & 2020 parameters		2020 COVID-19 subsample parameters	
	Parameter	Std. error	Parameter	Std. error
HH Income < 50k - Both in-person and online	0.87	0.73	-0.88	0.94
HH Income 75 - 100k - No shopping	0.93	1.09	-1.80	1.77
HH Income 75 - 100k - Online only			0.08	1.19
HH Income 75 - 100k - Both in-person and online	-0.81	1.15	0.76	1.26
HH Income 100k+ - No shopping	0.97	1.08	**-3.04***	**1.72**
HH Income 100k+ - Online only			0.86	0.92
HH Income 100k+ - Both in-person and online	**1.05***	**0.60**	-0.70	0.71

	2018 & 2020 parameters		2020 COVID-19 subsample parameters	
	Parameter	**Std. error**	**Parameter**	**Std. error**
COVID related HH income reduction - No shopping			0.87	1.18
COVID related HH income reduction - Online only			0.76	0.79
COVID related HH income reduction - Both in-person and online			0.27	0.36
At least 85th percentile population density - No shopping	0.27	0.94	0.00	1.39
At least 85th percentile population density - Online only			0.57	0.68
At least 85th percentile population density - Both in-person and online	0.12	0.52	-0.06	0.62
Apartment - No shopping	-0.25	0.89	0.51	1.48
Apartment - Online only			0.42	0.80
Apartment - Both in-person and online	0.09	0.57	-0.13	0.68
Female-identifying - No shopping	0.71	0.86	0.32	1.43
Female-identifying - Online only			1.75**	0.85
Female-identifying - Both in-person and online	0.76*	0.43	-0.83	0.51
Respondent had a travel disability - No shopping	2.00**	1.00	-1.85	1.47
Respondent had a travel disability - Online only			0.05	0.84
Respondent had a travel disability - Both in-person and online	1.21*	0.73	-1.22	0.87
Unknown disability status - No shopping			-2.24**	1.09

	2018 & 2020 parameters		2020 COVID-19 subsample parameters	
	Parameter	Std. error	Parameter	Std. error
Unknown disability status - Online only			-0.99	0.71
Unknown disability status - Both in-person and online			-0.18	0.34
Amazon Prime: member since at least 2018 - No shopping	0.71	0.86	-1.28	1.23
Amazon Prime: member since at least 2018 - Online only			0.99	0.67
Amazon Prime: member since at least 2018 - Both in-person and online	-0.64	0.42	1.57***	0.50
Grocery Delivery: COVID signup - No shopping			3.06*	1.63
Grocery Delivery: COVID signup - Online only			2.66**	1.08
Grocery Delivery: COVID signup - Both in-person and online			0.57	0.89
Shared burden for all shopping needs - No shopping			2.11*	1.15
Shared burden for all shopping needs - Online only			-2.02*	1.10
Shared burden for all shopping needs - Both in-person and online			-0.10	0.31
Shopping on behalf of immediate family members only - No shopping			0.03	0.95
Shopping on behalf of immediate family members only - Online only			-0.24	0.68
Shopping on behalf of immediate family members only - Both in-person and online			0.04	0.29
COVID related reduction in employment - No shopping			-0.28	1.56

	2018 & 2020 parameters		2020 COVID-19 subsample parameters	
	Parameter	Std. error	Parameter	Std. error
COVID related reduction in employment - Online only			0.80	0.89
COVID related reduction in employment - Both in-person and online			0.09	0.51
Female-identifying respondents living with children - No shopping			0.20	1.36
Female-identifying respondents living with children - Online only			-0.71	0.85
Female-identifying respondents living with children - Both in-person and online			0.36	0.44

Shopping in person only

According to the model results in-person only shopping is the predominant alternative before and after the onset of the pandemic. However, the pandemic did push households to be more likely to shop *both* in-person and online. These results make sense as food is a necessary household item and some people would not have been as able to get to the grocery store. The results are also consistent with observed reduction in the number grocery and pharmacy trips in the region during the observation week (Google, 2020).

Both in-person and online

In both 2018 and 2020, households earning above $100,000 per year, female-identifying respondents, and respondents with travel disabilities were more likely to shop *both* in-person and online for food, compared to households earning the median income, men, and respondents without travel disabilities though all these groups are still more likely to only shop for food in person. during both years. Single-person households are the least likely to shop *both* in-person and online during but they too were more likely do so as a result of the pandemic.

An Amazon Prime membership had a significant positive effect on *both* in-person and online shopping in 2020, although its effect is insignificant for 2018 and 2020 combined. This suggests that since the onset of the pandemic, households with Prime memberships are more likely to complement their in-person food purchases with an e-commerce purchase compared to non-Prime households, potentially because of their familiarity with online shopping in general, as well as Amazon's food delivery offerings through partnerships with Whole Foods.

Online only

Households who signed up for grocery delivery as a result of the pandemic, and female-identifying respondents, were more likely to shop *only* online than their comparison groups. Households sharing shopping responsibilities between two or more individuals were less likely to shop *only* online, suggesting that splitting the burden makes it easier for at least one of them to make a trip.

No shopping

In both observation years, respondents with a travel disability as well as single-person households were more likely than their comparison groups not to shop. However, the most likely alternative was still in-person shopping. Households earning over $100,000 were less likely suspend food shopping during the pandemic observation week, while those households who signed up for grocery delivery as a result of the pandemic or with shared shopping responsibilities were more likely to not shop during the observation week than they were to make an online order or shop in-person, suggesting that these groups were making food purchases less frequently during the pandemic than previously.

Other demographic variables

Similar to the non-food model, pandemic-related reductions to employment or income did not have significant effects on food shopping. Additionally, as with the non-food model, households earning below the area median income exhibited no significant differences compared to other income groups; nor did households earning $75,000 to $99,999. Population density and housing type were also not significant factors. While it is possible that female-identifying respondents are shopping more online due to increased household and/or familial responsibilities, the model found no significant differences between female-identifying respondents with children on food shopping behavior compared to those without children.

Summary

There are several key observations from the food model. Households that signed up for grocery delivery due to the pandemic *both* limited the frequency of their purchases and strongly shifting toward online only shopping, though this behavior may not outlast the pandemic, when individuals are no longer fearful of contracting COVID-19 from going to the grocery store or a restaurant. We cannot draw any conclusion about restaurant food delivery, as the incidences restaurant delivery signups and use before and after the onset of the pandemic were too few to include in the model.

The significance of an Amazon Prime membership—a predominantly non-food subscription—on food shopping suggests that non-food shopping behavior may be having an impact on online food shopping. More investigation is needed to confirm this trend and compare it to the findings of Dias et al. (2020), who suggest a complex and bi-directional relationship between different types of shopping.

2018 to 2020 changes: descriptively

We also examined changes in weekly household food shopping between 2018 and 2020 with descriptive statistics. We do this only for food shopping due to the tripmaking and exposure implications for those households continuing to shop for food (whereas households are more likely not to shop for non-food items in 2020). Figure 1 and Table 8 demonstrate a shift away from in-person shopping only toward complementing in-person food shopping with e-commerce. About two-thirds of those who did both in 2018 continued to do so but almost one quarter only shopped in person in 2020.

These results are consistent with the model results above and allow us to examine households who continued to shop in-person only for food) over time.

Table 8. Changes in food shopping from 2018 to 2020

2018 weekly behavior	2018 total	2020 weekly behavior (n=313)			
		In-person shopping only	Both in-person and online	Online shopping only	No shopping
In-person only	286 (87%)	41%	51%	5%	2%
Both	32 (10%)	22%	69%	3%	6%
No shopping	9 (3%)	56%	11%	22%	11%
2020 Total	327	130 (40%)	169 (52%)	18 (6%)	10 (3%)

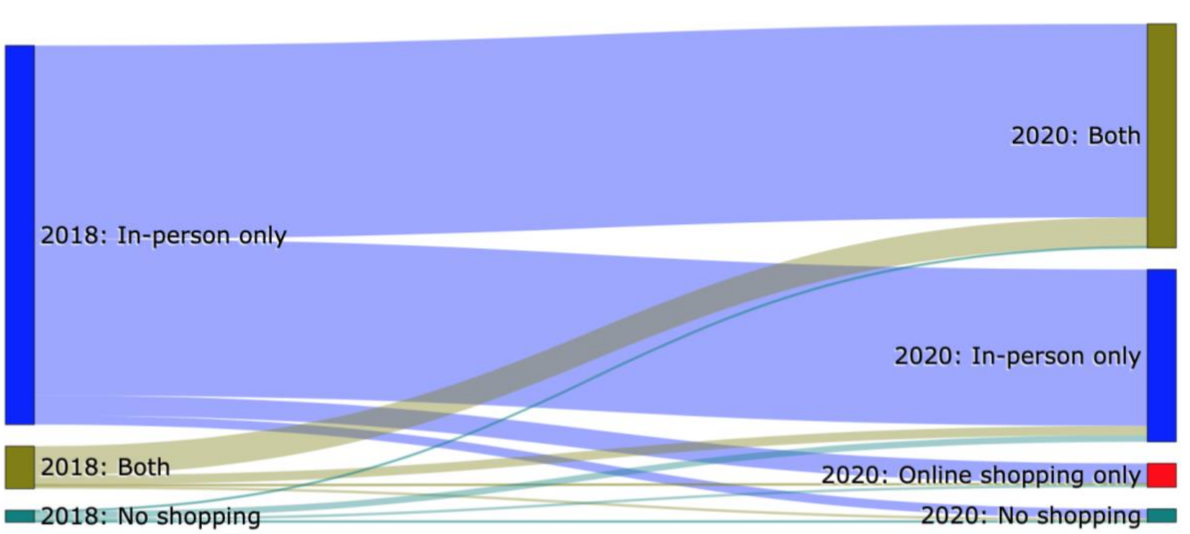

Figure 1. The majority of households added an e-commerce food purchase to their in-person behaviors in 2020

Given this large shift away from in-person shopping only, we looked further at: 1) those households that continue to shop *only* in-person between 2018 and 20, and 2) those households that shifted from in-person only to *both* in-person and online. We examine the demographic makeup of both groups to identify which segments of the population, if any, are subject to a greater risk of virus transmission by continuing to *only* shop in-person. While these are the largest subgroups, no significant results are obtained when using a difference of means test on the over- or under-representation comparing the percent of a demographic group following the pattern to the percent of the demographic group overall. This is the results are suggestive, but not statistically significant, likely due to the relatively small subsample sizes.

Households continuing to shop in-person *only* in 2020

Even amidst concerns over virus transmission from prolonged contact with others, particularly indoors, 41 percent of households that were shopping *only* in-person for food in 2018 (and 40% overall) continued to do so in 2020. This trend is important for two reasons: 1) these households may have been (and continue to be) at a higher risk compared to households not reducing their in-person shopping, and 2) these households may be the least likely to adopt e-commerce in the future.

Of the respondents continuing to shop *only* in-person, a disproportionately high number are from households earning under $50,000 per year, male-identifying survey respondents, and older survey respondents, particularly those over the age of 65. Conversely, households earning $100,000 per year are underrepresented in this subgroup, as are younger survey respondents, below the age of 35. This suggests that a higher risk of potential exposure among older and less affluent households, those with fewer means and those most vulnerable to serious complications from the disease. Older populations have been shown to have a lower rate of smartphone ownership and app use when compared with younger generations, and this aversion to using apps may directly translate into risk through the persistence of in-person shopping. While many grocery stores implemented senior and high-risk only shopping hours, it is unclear how much these programs actually reduce the risk of virus transmission. As for less affluent households, they may be avoiding the fees and product upcharges imposed by e-commerce restaurant food and grocery delivery services. Additionally, many e-commerce services do not accept Supplemental Nutrition Assistance Program (SNAP) benefits, making it more difficult for those receiving SNAP to engage in e-commerce. Amazon Fresh was at the forefront of opening its service to include SNAP payment; extending this and other payment options across the food delivery sector would reduce the concentration of risks on those specific populations.

Households complementing 2018 in-person shopping with e-commerce in 2020

A majority of households (51 percent) that shopped *only* in-person for food in 2018 complemented their in-person shopping with at least one e-commerce food purchase in 2020. These households may point toward future adoption among similar households, though this may not lead to reduced tripmaking or virus exposure.

Households earning above the area median income are overrepresented in this subgroup, as are younger respondents (i.e., under the age of 35), male-identifying respondents, and older respondents over the age of 65. Households earning the area median income and/or below are underrepresented, as are middle-age groups (35-64 years old) and female-identifying respondents. Similar to the model results, this shows that more affluent households are better able to adopt e-commerce to meet their food shopping needs when compared with their less affluent neighbors. Younger age groups may be more familiar with e-commerce and mobile apps and thus more willing to adopt online shopping when needed, even if it is not their default choice. Older populations are overrepresented in those who adopt e-commerce as well as those who continue to shop *only* in-person, signaling a split between those who may not want to change their behavior and thus accept the risk and those who are acting cautiously. The digital divide may not be insurmountable for older populations; respondents over the age of 65 were also overrepresented (although statistically insignificantly) among those who signed up for grocery delivery and restaurant delivery services in response to the pandemic. This indicates that older populations are willing to use e-commerce, although they may require a triggering event to do so.

Changes in tripmaking patterns in response to COVID-19

In addition to examining demographic-level behavioral differences, we investigated subsample-wide changes to tripmaking in order to observe the effects, if any, on pandemic-related shopping trips and e-commerce purchases in the region. In line with general observed travel trends for the SACOG region during the pandemic, Table 9 shows a decrease in 2020 for all trip types. With many dining and non-food retail establishments closed in accordance with Stay at Home orders during the second stage of California's re-opening plan, the 70 percent reduction in average weekly household meal trips and 54 percent reduction non-food shopping trips are not unsurprising and may be confounded by latent shopping demand that cannot be fulfilled at closed stores. Weekly average grocery trips only went down by 13 percent, consistent with the fact that many households still need to visit grocery stores in-person to purchase food, and individuals are eating a higher-than-normal number of meals at home during the pandemic. Table 10 implies online food ordering substituted for in-person dining with over a 375 percent increase in weekly deliveries. On the other hand, Table 11 reveals that online ordering for prepared food tended to replace dining out, whereas online purchases for groceries tended to complement other trips. Non-food e-commerce shopping also appears to be substituting for in-person trips, as the number of orders remain flat compared with 2018, while tripmaking rates plummeted.

Table 9. Post-pandemic dips in meal and non-food shopping trips while groceries hold steadier

April/May 2018	May 2020	April/May 2018	May 2020	April/May 2018	May 2020
Average HH Grocery trips per Week	**Average HH Grocery trips per Week**	**Average HH Meal trips per Week**	**Average HH Meal trips per Week**	**Average HH Non-Food Shopping Trips per week**	**Average HH Non-Food Shopping Trips per week**
3.21	2.80	5.85	1.73	3.20	1.46

Table 10. A pandemic-induced spike in food e-commerce use

April/May 2018	May 2020	April/May 2018	May 2020
Average HH Days/Week with Non-food Home Deliveries	**Average Household Non-food E-commerce deliveries/week**	**Average HH Days/Week with Food Home Deliveries**	**Average Household Food E-commerce deliveries/week**
1.61	1.59	0.13	.62

We compare weekly average tripmaking and purchase frequencies in 2018 to the comparable ones in 2020 by demographics using a t-test on the difference of means. The significant variables in the MNL model: gender, household size, household income, and disability status, do not yield significant results when comparing 2018 to 2020 nor when comparing 2020 values to one another. This—in addition to the lack of model significance of other thought-to-be important explanatory variables in the models—implies decisions driving tripmaking and online purchasing behavior under the pandemic conditions are systematically different than prior to the SaH orders. It is also possible that this lack of significance is due to a small sample size.

While demographic analyses in the model do not yield telling results regarding the driving forces behind behavior changes, examining the directions and magnitudes of consumption trends by commodity and by channel provide insights that can help inform how and for what consumers were shopping and how these changes play out in the short term on roads and at curbsides. As noted above, interesting patterns are found related to *only* in-person shopping among households earning under $50,000 per year, male-identifying respondents, and older survey respondents, particularly those over the age of 65. Households earning $100,000 per year are underrepresented in this subgroup as are younger survey respondents.

Taken together, Table 9, Table 10, and Table 11 demonstrate that e-commerce purchases show a strong complementary effect to in-person shopping for food items (particularly for groceries) and a weaker but still complementary effect for essential non-food items. Not surprisingly, e-commerce for non-essential food items substitute tripmaking for non-essential items. While households are still willing to travel for the items they need, they are foregoing trips for less needed items that they would normally make during non-pandemic times. There could be some confusion with these results, as many retail stores were closed at the time of the survey, limiting available purchase options.

While in-person grocery tripmaking for in-store purchases is down 13%, after including the extra trips from grocery pickups tripmaking is down only 7% in 2020 in comparison to 2018. For prepared food purchases, even after including additional trips for food pickup, tripmaking is down 56% (and down 70% without such pickup trips). Overall, 85% of food e-commerce purchases lead to a trip, demonstrating a complementary effect between e-commerce and tripmaking. For essential non-food items, such as medications, cleaning supplies, and childcare necessities, respondents are more likely to pick an online purchase up than they are for non-essential items. This is most likely due to time sensitivity associated with such commodities. Non-essential non-food online purchases yield the lowest tripmaking rate, with only 11% of purchases leading to trips.

There also are a large proportion of new e-commerce users present in the 2020 COVID-19 subsample. Of the 71 households who made at least one grocery e-commerce purchase and the 147 who made at least one prepared food e-commerce purchase during the observation week, 18 (25%) and 22 (15%) are first time e-commerce users. A 10%-plus signup rate in roughly two months is a drastic and unexpected acceleration of e-commerce adoption, and industry experts have noted a five to ten-year acceleration in growth during the pandemic, which has the potential to re-make the retail landscape (Mahmassani et al., 2020). Additionally, the expectations and purchase behaviors of these new users differs from those who signed up for and used those services prior to the pandemic. The length of use of a service could be a significant variable in explaining behavior in future research. For clothing, a predominantly non-essential item and mature e-commerce good, none of the 81 e-commerce users were first-time online purchasers.

Table 11. e-commerce orders complement trips for non-essential items, supplement trips for essential items

Commodity:	Average HH weekly e-commerce Orders	Average HH weekly home deliveries	Average HH weekly curbside pick ups	Average HH weekly in-store pick ups	Percent e-commerce orders leading to trips	Average HH weekly in-store trips	Average HH weekly in-store trips (including e-commerce pickups)
All non-food	1.59	1.12	0.13	0.17	19%	1.46	1.77
Essential* non-food	0.58	0.35	0.05	0.12	29%	1.02	1.19
Non-essential** non-food	0.62	0.54	0.04	0.03	11%	0.15	0.22
Other non-food items	0.39	0.22	0.05	0.02	17%	0.30	0.37
All food	1.29	0.62	0.53	0.56	85%	4.78	5.87
Prepared food	0.80	0.27	0.40	0.44	105%***	1.73	2.57
Groceries	0.35	0.20	0.11	0.06	48%	2.80	2.97
Other food items	0.13	0.15	0.03	0.06	64%	0.24	0.33

*Essential non-food included paper products and cleaning supplies, medications, and childcare items

**Non-essential non-food included clothing and home office items

***This exceeds 100 percent possibly because a single order could lead to multiple pickups or reflect respondent error

Respondent Intentions Post-COVID

When asked about their future intentions as California moves into Stage 3 of its phased reopening (when retail establishments and restaurants are allowed to re-open for in-person and/or indoor use), we find that a majority of respondents indicate that they are likely to continue with in-store and curbside pickups, as well as contactless home deliveries as shown in Figure 2. These rapidly deployed services in response to the pandemic appear likely to stay, at least in the near term. Regarding in-person retail, we find that respondents indicate the strongest desire to return to non-food retail establishments, possibly because the majority of them were closed under Stage 2 restrictions at the time of the survey. Respondents show the strongest distaste for unfamiliar things such as automated vehicles, drones, and bundling online orders with their neighbors (a practice that was rolled out in some parts of Europe during the height of demand for grocery delivery in March and April 2020). Naturally, caution about new and unknown forms of mobility and delivery may be heightened during times of uncertainty.

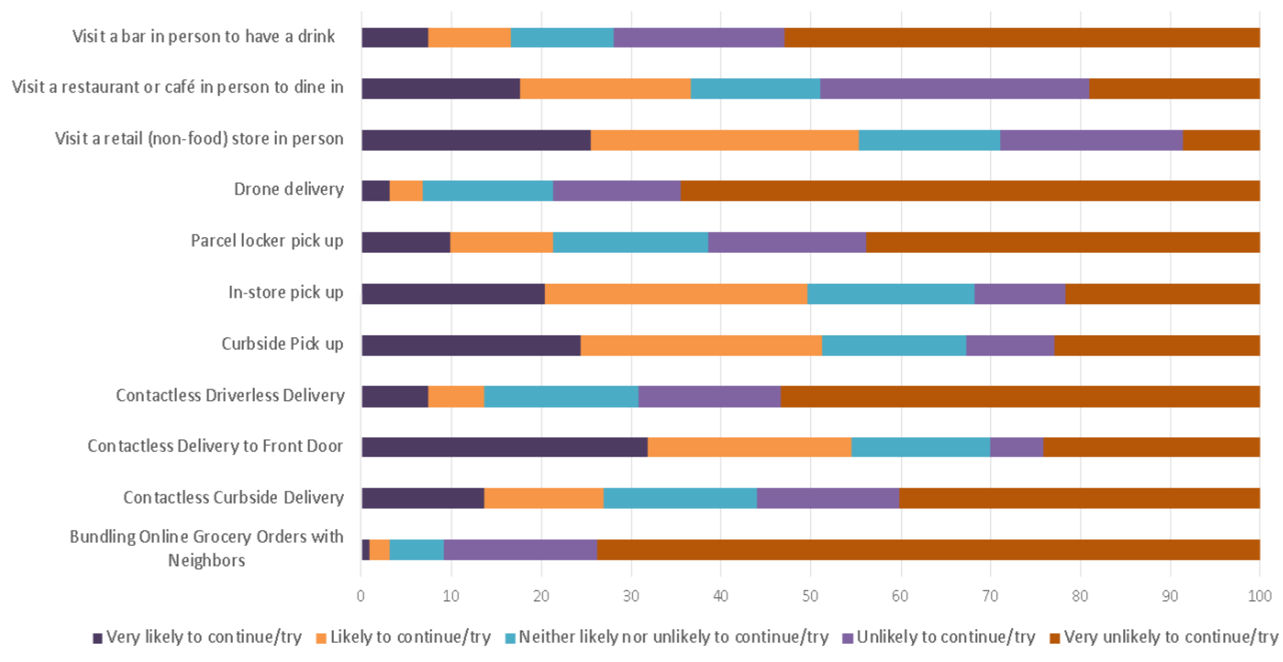

Figure 2. Respondent intent as California re-opens

Implications

By considering the model results, descriptive changes to shopping patterns, subsample-wide commodity-specific changes to tripmaking, and future intentions together, we reach the following conclusions on which demographic groups are more or less likely to change their behavior, the kinds of e-commerce purchases that lead to tripmaking, and the shifts in purchase channel (and thus curbside) use, along with what types of behaviors are likely to persist. This information can aid planners and policymakers in understanding both short- and long-term effects of pandemic-induced changes to shopping behavior in the SACOG region.

Shopping during the pandemic has not overwhelmed the curb in the SACOG region

Curbside implications from increasing use of e-commerce are a function of *both* mode choice and channel choice for in-person shopping and pickup. As we cover channel choice above, we look at mode choice for groceries and prepared food, the two commodities that resulted in the highest number of weekly pickups. Automobile use during the observation week use is shown below in Table 12. The relatively high drive-alone rates (all above 75 percent) in-store shopping trips or e-commerce pickups are well-above the reported 66 percent drive-alone rates for commuting among the subsample in 2018, but they are in line with the 75% drive-alone commute mode share in the region as of 2012—the most recent year for which statistics are available. However, even though a high incidence of auto use for in-store shopping and for e-commerce pickups makes curbside issues all the more important for planners to consider, representatives from the City of Sacramento indicated that curbside congestion around retail establishments was *not* a pressing issue during the early months of the pandemic (Confidential expert interview, unpublished 2020).

Table 12. High auto use for in-store trips and pickups

Commodity type	In-store shopping	E-commerce pick ups
Groceries	80% drive alone 94% auto mode w/parking needs (i.e., not transportation network company, such as Uber and Lyft, (TNC))	76% drive alone 100% auto mode w/parking needs (i.e., not TNC)
Prepared Food	75% drive alone 90% auto mode w/parking needs (i.e., not TNC)	77% drive alone 91% auto mode w/parking needs (i.e., not TNC)

Sub-sample-wide, the drop in tripmaking for in-person shopping and rise in e-commerce ordering indicate that curbside demand at and around restaurants is shifting from consumers parking for longer durations while they dined in to either gig-economy drivers or private individuals picking up take-out orders. This increase in the volume of shorter duration trips, in turn could overwhelm areas with a lack of loading/pickup zones; representatives from the City of Sacramento confirmed a higher-than-normal volume of applications for temporary loading zone permits during the first three months of the pandemic, particularly from restaurants (Confidential expert interview, unpublished 2020).

Policy Implications and Conclusions

Here we present our study conclusions in four sections: 1) demographic effects on pandemic shopping behavior, 2) how near-term shopping behaviors might play out in the longer term, and 3) new opportunities for partnering between public and private stakeholders around the curb, 4) comments and recommendations on future data collection.

E-commerce during a pandemic: Who has access?

In this study, we observed a concentration of exposure among populations at higher risk for serious complications from the COVID-19 virus and populations with fewer means. Households should not have to weigh making a trip to the store to put food on the table with exposing themselves to a deadly virus; however, we see this behavior evident in the news and in our sample. This was a key takeaway from this study. Of the households continuing to shop *only* in-person, were overrepresented by those earning under $50,000 per year, male-identifying survey respondents, and older survey respondents, particularly those over the age of 65. Conversely, households earning $100,000 per year are underrepresented in this subgroup, as are younger survey respondents (i.e., below the age of 35). This points to a concentration of risk and potential exposure among older and less affluent households, who may be most vulnerable to serious complications from contracting COVID-19.

Due to the online nature of e-commerce—and a shift toward mobile apps over computer browsers—the digital divide appears to result in older individuals resisting the adoption of online ordering in favor of continuing to shop in stores. A similar trend is evident among households earning below the median income, likely a result of the layers of upcharges and fees associated with e-commerce use, particularly restaurant food and grocery e-commerce platforms. Challenges to more equitable e-commerce access are not insurmountable, and some strategies to address this exist already. For food, particularly grocery e-commerce, expanding SNAP acceptance through delivery platforms and participating grocery stores is a first step that some large platforms have already taken. Such programs would reduce the burden on eligible households even further by reducing fees and item markups specifically for SNAP users. Bridging the digital divide is a more difficult challenge, and more targeted research is needed to uncover the specific hurdles facing less technologically literate demographics. The use of order-by-phone might present an easier customer experience; however, the high costs associated with staffed phone lines and processing orders over the phone might make this service unprofitable for e-commerce platforms and stores. On a city- or state-scale, grants and funding for such a non-profit network can be successful, as shown by the continued operation of many such programs for restaurant food delivery in California.

On the other end of the spectrum, households earning above the median income (i.e., greater than $75,000 per year) are better able to insulate themselves from exposure by using e-commerce during the pandemic. This trend is evident both for food and non-food items. Model results indicate that prior to the pandemic, higher income households were less likely to shop *only* online for non-food items, whereas after the pandemic these same households began substituting in-person trips for online purchases. Higher income households use e-commerce to complement food shopping trips during the pandemic; this flexibility likely provides them access to a wider variety of items than other households in a time of shortages. E-commerce remains a viable option, especially for those who may have difficulty traveling.

E-commerce during a pandemic: How are services used?

Our week long 2020 survey data, displays trends that are in line with both regional and national statistics during the observation period. During the early months of the pandemic, many households were less focused on non-essential item purchases (e.g., clothing, electronics)—*both* in-person and online—while still making food purchases at nearly the same frequency prior to the pandemic. Not surprisingly, e-commerce purchases substituted for respondents' trips for the few non-food purchases made early on in the pandemic. On the other hand, an overwhelming share of e-commerce food purchases (85 percent) still led to a trip, with even higher numbers for restaurant food. This likely reflects the restrictions on indoor or outdoor dining during the observation period. We also observe a high incidence of new users for grocery e-commerce services (25 percent) and restaurant e-commerce platforms (15 percent). This is an indication that households are experimenting more with their shopping choices. The model results demonstrate that these new grocery e-commerce users are safety conscious, substituting e-commerce ordering for in-store shopping and even purchasing less frequently than prior to the pandemic.

As for new shopping behavior patterns emerging from the model results, we found: 1) an overall de-coupling of food and non-food shopping patterns and 2) an upsurge in e-commerce use food purchasing among those already enrolled in non-food subscription services on (suggesting that individuals or households familiar with online purchasing for one commodity type are more amenable to using it for other commodities). These results suggest that consumer shopping styles (e.g., Amazon Prime membership) may better predict behavior than demographic variables.

As e-commerce food shopping continues to grow and trips to the grocery store remain nearly flat, we also observe a flattening in non-food e-commerce purchases and a large drop-off in non-food shopping trips. This could mark a shift toward food purchasing as the high growth e-commerce sector, which had primarily handled non-food goods for a long time. Whether this trend will continue following the pandemic is an important future research question.

We also find a that an Amazon Prime membership increases the likelihood that a household uses e-commerce for non-food (prior to the pandemic) and food purchases (during the pandemic). This suggests that once an individual or household becomes used to a service for one type of item, it becomes easier to adopt it for other items.

What shopping behavior trends will persist and what are potential implications?

As noted earlier, many in the retail and e-commerce industries have noted the pandemic spurred a five to ten-year acceleration in growth. A question at the forefront of many of their minds is what will happen to this acceleration once the majority of the population is immunized: will it continue, slow, or perhaps reverse?

We shed light on this question, both by observing the trends during the pandemic, and through forward-looking hypothetical questions. Those who signed up for e-commerce services during the pandemic, particularly for grocery platforms, were the most likely to substitute online purchases for in-person trips, indicating a desire to limit exposure to the virus. However, it is unclear whether this safety-minded behavior will persist once the pandemic is over. The use of restaurant food e-commerce increased notably among our COVID-19 subsample, rising 375 percent from 2018 to 2020. Nevertheless, the pandemic is likely not responsible for all of this growth as other factors increased the use of food e-commerce in the intervening period, but this spike is still notable. The fact that these purchases tended to supplement trips to restaurants rather than replace them suggests that any longer-term preference for ordering in over in-person dining might be limited or negligible. Even with an e-commerce order-for-delivery model, the economies of scale for restaurant food or grocery delivery are much more limited than for non-perishable items.

Respondents indicated a strong desire to return to shopping in-person for non-food items, where e-commerce replace in-person shopping most strongly. From these results, VMT for non-food retail shopping is primed to rise when stores are fully open, which threatens to undercut reductions in car traffic achieved during the pandemic. In the longer term, although respondents' future behavior unpredictable, it will be important to track growth of the e-commerce industry to better understand if e-commerce will replace existing trips, complement them, or induce more new trips and to identify whether delivery drivers or individual customers will be maker greater use of the curb space in front of commercial businesses. Even though curb space issues have not been critical so far in the SACOG region, other denser areas may need to reallocate curb space to accommodate a sustained higher volume of short-duration parking, particularly as restaurants operate outdoors and restrictions on indoor dining are lifted and retail establishments resume in-person operations alongside curbside pickup. It will be key to balance the needs of all types of curb users and keep safety—both viral and traffic-related—a priority. At present, many COVID-19 testing facilities are currently using re-purposed surface parking lots, providing examples from which retail businesses and planners can learn. In the longer term, the re-purposing of parking lots to higher and better uses, such as housing, is warranted.

Keeping public sector data relevant in an e-commerce age

The most recent National Household Travel Survey (NHTS) updates provide more detailed insights into online shopping than any previously available public cross-sectional datasets. Nevertheless, improvements could be made to allow for comparisons from region to region, as well as interaction between e-commerce and tripmaking. All Metropolitan Planning Organizations and the agencies in charge of the NHTS should agree on consistent and comparable metrics and variable types. For online purchasing, it would be helpful to use numerical versus binary reporting for all categories of e-commerce purchases and the same number (and definitions) of categories for deliveries as for purchases, so orders and deliveries can be better compared (or even matched). Additionally, consistent definitions for groceries versus prepared food and non-food versus food items would greatly reduce the number of assumptions required for analysis and increase the interpretability of results. Although the vast majority of food ordering is done by calling a restaurant or employing a mobile app, many people receive food items through mail services, particularly non-perishable items or alcohol, which introduces ambiguity regarding commodities in the NHTS data. While providing greater specificity related to commodities would shed more light on purchasing behaviors, this could create added burdens for respondents. Allowing respondents to report multiple trip purposes would create more detailed information on multi-purpose trips. It would also be helpful to allow respondents to indicate an e-commerce pickup as a trip purpose. This would enable analysts to investigate patterns related to online shopping and trip- and tour-making at the individual and household level. Similarly, allowing respondents to indicate if they purchased anything on a shopping trip would provide valuable information not currently available. Collecting this type of information through NHTS efforts could increase our collective understanding of the complex interaction between traditional and new forms of shopping, yielding a better understanding of how behavior is changing and the implications for the management of public (and private) infrastructure to best facilitate consumer-facing retail operations.

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