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In-person, pick up or delivery? Evolving patterns of household spending behavior through the early reopening phase of the COVID-19 pandemic

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ABSTRACT

Consumer reactions to COVID-19 pandemic disruptions have been varied, including modifications in spending frequency, amount, product categories and delivery channels. This study analyzes spending data from a sample of 720 U.S. households during the start of deconfinement and early vaccine rollout to understand changes in spending and behavior one year into the pandemic. This paper finds that overall spending is similar to pre-pandemic levels, except for a 28% decline in prepared food spending. More educated and higher income households with children have shifted away from in-person spending, whereas politically conservative respondents are more likely to shop in-person and via pickup.

1. Introduction

As the COVID-19 pandemic swept across the world, most countries implemented some form of lockdown and quarantine measures. In the United States (U.S.), by April 12, 2020, 43 of 50 states had issued stay-at-home orders, with the other seven states issuing some form of restrictions or mask mandates (Hauck et al., 2020; Mccannon and Hall, 2021). As a result of these orders and the ensuing restrictions on travel and human interaction, mobility in the U.S. was largely halted and businesses – specifically those that depend on the physical presence of patrons – were essentially paralyzed.

In parallel to changes in physical (im)mobility, consumer spending experienced major shifts throughout the pandemic. The changes include numerous new spending behaviors like panic buying and stockpiling at grocery stores as news about the severity of the COVID-19 virus started to surface (Ben Hassen et al., 2021; Islam et al., 2021; Sheth, 2020). New behaviors have emerged within product types, with a shift towards e-commerce and new channels of delivery, such as curbside pickup (Charlebois et al., 2021; Mohamad et al., 2020; Unnikrishnan and Figliozzi, 2021). Finally, during the evolving pandemic there has been a shift from in-person spending towards remote engagement, both within spending categories (from dining-in to take-out) as well as across spending categories (less money spent on restaurants and commuting coupled with a shift towards more spending on improving homes and investing in home-offices) (Ben Hassen et al., 2020; Chaudhary, 2020; Hong et al., 2021; Sherman and Huth, 2020).

While the most severe mobility restrictions may be behind us, analyzing household purchase behaviors during the evolving pandemic stages offers valuable insight as households navigate the extended and uncertain post-pandemic period (Shakibaei et al., 2021; Tran, 2021). It is hypothesized that changes in spending during the pandemic will experience some inertia as some of these changes may last beyond the pandemic, especially the shift to increased online shopping and delivery (Bezirgani and Lachapelle, 2021; Bian et al., 2021; Hamilton et al., 2019; Sheth, 2020). This inertia – or lack thereof – is important to understand as spending patterns through various channels are closely intertwined with the demand for travel. Thereby, these shifts in purchase behaviors and spending channels are posited to trigger changes in both travel and freight patterns for delivery (Figliozzi and Unnikrishnan, 2021a; Sevtsuk et al., 2021), highlighting the importance of understanding household

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expenditure for transportation planning and analysis. Indeed, as more customers shifted to conducting activities online and at home, including shopping, entertainment, and dining, demand for personal transport greatly decreased at least in the early stages of the pandemic, while goods movement associated with online purchase deliveries increased (Unnikrishnan and Figliozzi, 2021).

This paper analyzes the pandemic-related transformations in purchasing behavior of a representative U.S. sample of 720 respondents. The six-wave panel study covered a period of roughly-three months in the transitional phase of pandemic deconfinement in the U.S. characterized by the partial easing of restrictions and early vaccine rollout, between December 2020 and March 2021. In addition, the survey elicits pre-COVID spending levels to enable baseline comparison. Using hurdle regression models (Cameron and Trivedi, 2013; Cragg, 1971), the goal is to study both the discrete propensity to spend and the amount of spending in a range of categories, from food consumption to home-improvement. Specifically, we pinpoint the factors that drive variation in spending across categories and over time as we map out household patterns of spending channel engagement.

This study offers multiple contributions to the literature. This paper is one of the earliest longitudinal studies examining household spending and purchasing behavior during the evolving stages of the COVID-19 pandemic, providing insight regarding changes in spending over time and the main factors influencing these changes. In addition to analyzing expenditures across multiple delivery channels, the study also assesses expenditures across multiple spending categories, providing a more complete view of household spending and purchasing behavior shifts in the context of the pandemic (Figliozzi and Unnikrishnan, 2021a). Relevant practical implications for businesses, policy-makers and transport planners are also highlighted.

The remainder of this paper is organized as follows. The data collection and preparation processes are described in the following section along with sample statistics. Exploratory insights are presented next. The fourth section presents a hurdle model with time fixed-effects to assess the change in spending propensity and dollar value during the later stages of the pandemic compared to pre-pandemic. The fifth section expands the hurdle model to infer the effects of household and respondent attributes on the choice of spending channel (i.e., in-person, pickup, or delivery) and shifts in spending through each of these channels. Finally, the paper is concluded with a discussion and remarks on limitations and future research.

2. Survey design and data collection

The data collected for this study consists of a longitudinal online panel survey distributed to a representative U.S. sample, totaling six waves disseminated about every-two weeks between December 21, 2020 and March 8, 2021. More information on the survey is available in Tahlyan et al. (Tahlyan et al., 2022a, 2022b). The objective of this sequence of surveys is to collect information and data on facets of everyday life that have been largely affected by the pandemic. Specifically, the surveys inquire respondents about experiences in the following areas: (1) spending, (2) trip making, (3) mode choice, (4) employment and telework, (5) day-to-day activities and habits, (6) general sentiment and mental health during the pandemic, (7) direct impacts of COVID-19 such as job-loss or having to quarantine, along with (8) data on socioeconomics and demographics is also collected throughout the surveys.

The choice of disseminating the survey every 2 weeks strikes a balance between collecting data frequently enough to make nuanced observations on rapidly shifting behaviors during the pandemic while collecting data for a long enough period in the context of the pandemic (which had been declared a national emergency in the U.S. 9 months prior in March 2020). In the lead-up to the first wave of data collection, COVID-19 cases were on a record-breaking rise during November 2020, with over 100,000 new cases in a single day in the U.S. Indoor gatherings were heavily attributed to the rapid spread of the virus (Chang et al., 2021), especially with the colder weather during that period. December 2020 presented a period of positivity, with Pfizer and Moderna vaccines being granted Emergency Use Authorization from the FDA (U.S. Food and Drug Administration), with available vaccine doses being offered to healthcare workers, first respondents and other compromised groups. However, this was marred by the emergence of the Alpha variant of the COVID-19 virus.

During January 2021, the number of cases and deaths started dropping in the U.S. following another set of record-breaking numbers, with over 300,000 new daily cases (Johns Hopkins Coronavirus Resource Center, 2022). More variants of the virus start emerging, such as the Beta variant detected in the same month. In the following months, vaccines remained in short supply as doses were offered by age groups. At the time of the last wave in this study in March 2020, vaccines were still limited to only seniors over the age of 65 outside of the groups mentioned earlier and had not yet been mass adopted. Nonetheless, at this time, the number of cases was rather stable with roughly 50,000 new daily cases. In this period, Americans continued to see the pandemic as a pressing issue in the months to come but also expressed some optimism about the growing availability of vaccines (Deane et al., 2021).

2.1. Survey design

The 6-wave panel study consists of several independent blocks of questions that allow for modularity across waves. Each survey is kept to a length of about 10 min. Several questions on household spending are included in every survey wave, representing a *core block* of the survey. Other questions were only included in a subset of the six survey waves.

2.1.1. Weekly and monthly spending

This section queries respondents about their household spending in 3 different categories: (1a) weekly grocery spending, (1b) weekly prepared food spending, and (1c) weekly spending on items other than grocery or food. The questions are presented to respondents as follows:

a) In the past week, how much has your household spent on groceries […] (including uncooked meal kits and alcoholic beverages, in-store, online or otherwise)?
b) [response categories: $0; $1-$49; $50-$99; $100-$199; $200-$299; $300 or more]
c) In the past week, how much has your household spent on cooked meals (such as a cooked meal kit or food from a restaurant) […]?
d) [response categories: $0; $1-$49; $50-$99; $100-$199; $200-$299; $300 or more]
e) In the past week, how much has your household spent on purchases **other than groceries or cooked meals** (such as electronics, books, or clothing) […]?
f) [response categories: $0; $1-$99; $100-$249; $250-$499; $500-$999; $1000 or more]

Respondents are asked to answer the above questions for each of the following access channels: *in-person spending, ordered online for pick-up* and *ordered online and delivered*. Additionally, in the case of groceries, respondents are asked about their *total* weekly spending across all channels.

The second part of this section seeks responses about household spending on the following *miscellaneous items*: (1d) monthly spending on home improvement and electronics, (1e) monthly spending on clothing and apparel, and (1f) monthly spending on digital media and video games. The questions are presented below;

g) In the past 30 days, how much has your household spent on electronics, furniture, or other home improvement purchases in total?

h) [response categories: $0; $1-$249; $250-$499; $500-$999; $1000-$1499; $1500 or more]
i) In the past 30 days, how much has your household spent on clothing, shoes, or other fashion accessories in total?
j) [response categories: $0; $1-$49; $50-$99; $100-$199; $200-$299; $300 or more]
k) In the past 30 days, how much has your household spent on digital media (such as DVDs, Netflix, Spotify or Audible) and video games (such as disc purchases, digital purchases, or video game subscriptions) in total?
l) [response categories: $0; $1-$49; $50-$99; $100-$199; $200-$299; $300 or more]

The objective of these questions is to capture spending shifts for selected spending categories known to have been affected by the pandemic (Sherman and Huth, 2020). These questions are only presented to respondents once every-two waves (i.e., once a month) since it is expected that these expenses are not likely to occur at a similarly frequent cadence as spending on essential categories such as groceries or food. Furthermore, respondents are only asked to report their *total* spending for the latter three categories, unlike earlier weekly spending questions (1a-1c), mainly to avoid respondent fatigue.

In addition to measuring spending throughout the pandemic, respondents are asked to recall their spending prior to the pandemic to establish a *pre-COVID baseline*. Pre-COVID spending questions are only presented to respondents once across six waves and mirror the latter spending questions in terms of categories, channels and wording. Using *total weekly grocery spending* as an example, the pre-COVID baseline question is;

Before the COVID-19 pandemic, in a **typical week**, how much did your household spend on **groceries** in total (including uncooked meal kits and alcoholic beverages, in-store, online or otherwise)?

To avoid erroneous responses and to facilitate visual differentiation, *pre-COVID baseline* questions have been presented to respondents in a consistently different color (green) across waves. This information was collected in waves 3 and 4 as per Table 1. While the authors acknowledge the potential bias inherent in asking respondents to recall past spending, the responses still offer valuable insight into the impact of the pandemic on spending behavior, especially in the absence of a practical alternative approach to obtain this information.

2.1.2. Direct impacts of COVID-19 pandemic

The goal of this section is to query respondents about major events or disruptions that may have occurred due to the pandemic, as it is hypothesized that such major changes are likely to affect habits and spending. Respondents are asked every-two waves if in the prior month they or their household members (7a) have lost a job due to the pandemic, (7b) have received a pay cut due to the pandemic, (7c) have been tested for COVID-19 and the result of the test. They are also asked individually if they (7d) have taken the COVID-19 antibody test and the result of the test, and (7e) have taken at least one dose of a COVID-19 vaccine.

2.1.3. Socioeconomics and demographics

Finally, respondents are presented with questions related to their socioeconomic status and demographics. Respondents are asked about (8a) gender, (8b) age, (8c) education, (8d) employment status, (8e) ethnicity, (8f) household size, (8g) number of children under 12 years old in household, (8h) number of household vehicles, (8i) number of household bicycles, (8j) location of residence, (8k) political views, and (8l) household income.

Questions for some of the above attributes are repeated across waves to monitor possible adjustments, mainly (8d) employment status, (8f) household size, (8j) location of residence, and (8k) political views. Other questions are not repeated as they are assumed to be fixed within the timeframe of the data collection (such as age or number of children in the household) or to avoid respondent fatigue (such as household income). Additionally, respondents are asked about their pre-COVID baselines for several socioeconomic and demographic variables, specifically (8d) employment status, (8f) household size, (8h) number of household vehicles, (8j) location of residence, and (8l) household income.

Table 1
Overview of longitudinal survey design and respondent recruitment.

Wave	Date*	Data Collected	New Respondents	Returning Respondents	Total Responses	Cumulative Unique Respondents
1	Dec 21	- weekly spending categories - socioeconomics & demographics	457	–	457	457
2	Jan 11	- weekly spending categories - monthly spending categories - impacts of COVID-19 - socioeconomics & demographics	107	372	479	564
3	Jan 25	- weekly spending categories - *pre-COVID baseline* - socioeconomics & demographics - *pre-COVID baseline*	103	421	524	667
4	Feb 08	- weekly spending categories - monthly spending categories - *pre-COVID baseline* - impacts of COVID-19 - socioeconomics & demographics	101	466	567	768
5	Feb 22	- weekly spending categories - socioeconomics & demographics	103	485	588	871
6	Mar 08	- weekly spending categories - monthly spending categories - impacts of COVID-19 - socioeconomics & demographics	101	516	617	972

* Wave 1 was disseminated in the year 2020; all other waves were disseminated in 2021.

2.2. Sample description and statistics

Data was collected using a longitudinal web survey designed on Qualtrics and disseminated through the Prolific platform (Palan and Schitter, 2018) to 720 unique U.S. respondents across 6 waves, resulting in 450 responses per wave when accounting for attrition (drop-out) and panel refreshment (top-up) sampling. The number of responses and respondents across waves is shown in Table 1. These responses already exclude 25 responses that had quality issues such as being largely incomplete or exhibiting straight lining (17 responses) or failing attention checks or excessive rushing (8 responses). The 450 responses per wave are selected to be representative of the U.S. population across **gender**, **age,** and **race**.

A summary of the sample statistics of all six waves, the average statistics across the waves and population data is provided in Table 2. Responses have been collected from 47 of the 50 states (missing Montana, Vermont, and Wyoming) and from Washington, D.C. The number of responses from the four most represented states are shown in Table 2.

Looking at the age distributions, the sample is slightly younger than the U.S. adult population with a sample mean age of 42.7 years compared to 48.0 for the adult population. In terms of race and ethnicity, 70.2 % of the sample identify as White, 13.0 % are Black, 8.8 % are Asian and 5.0 % are Hispanic or Latino. Politically, the sample is *liberal-leaning*. Excluding respondents who preferred not to answer, 57.2 % of the sample consider themselves as *liberal*, 25.2 % as *conservative* and 17.7 % as *moderate*. This bias is likely the result of self-selection in online surveys (Heen et al., 2014; Huff and Tingley, 2015; Zhang and Gearhart, 2020). Finally, the average and median income for the sample are $80,800 and $62,500 annually, compared to $88,600 and $62,800 in the 2019 5-year American Community Survey (U.S. Census Bureau, 2019).

3. Exploratory analysis

As discussed in the previous section, household spending data has been collected for three different buying *channels* (in-person, pickup, and delivery) for different product *categories* (groceries, prepared food, and items other than grocery or food). For simplicity, the remainder of the paper will refer to items other than groceries or food as *other spending*. Additionally, spending data have been collected on three further areas of spending (referred to as *miscellaneous*), particularly relevant in the work-from-home and social distancing period, namely home improvement and electronics, clothing and apparel, and digital media and video games.

The average spending for the latter categories and items across different channels is shown in Fig. 1. The average percent change in spending during the pandemic compared to pre-COVID is presented in Fig. 2a-c as a function of different household and respondent attributes. Average values are calculated by using the midpoint values for each spending category. Responses from Latino/a respondents have been

Table 2
Sample statistics.

Statistics[†]	Wave 1	Wave 2	Wave 3	Wave 4	Wave 5	Wave 6	Sample Average	U.S. population/other sources[*] (%)
State								
California	10.5 %	10.5 %	11.4 %	10.5 %	12.5 %	11.6 %	11.2 %	12.0 %
Florida	8.7 %	7.8 %	8.3 %	9.1 %	7.6 %	7.6 %	8.2 %	6.7 %
New York	8.0 %	8.5 %	8.3 %	8.2 %	8.0 %	7.6 %	8.1 %	6.2 %
Texas	6.7 %	7.6 %	6.7 %	6.9 %	7.6 %	8.5 %	7.3 %	8.3 %
Gender								
Male	48.7 %	48.7 %	48.0 %	48.0 %	48.4 %	48.8 %	48.4 %	49.2 %
Female	50.0 %	50.2 %	50.4 %	50.2 %	50.0 %	50.6 %	50.2 %	50.8 %
Non-Binary	1.3 %	1.1 %	1.6 %	1.8 %	1.6 %	0.7 %	1.4 %	–
Age								
18– 24 years	10.9 %	12.9 %	12.0 %	11.1 %	11.1 %	11.1 %	11.5 %	11.9 %
25– 34 years	19.3 %	20.4 %	21.3 %	20.0 %	20.2 %	19.6 %	20.1 %	17.9 %
35–44 years	19.1 %	18.2 %	18.4 %	18.9 %	19.6 %	19.3 %	18.9 %	16.4 %
45–54 years	16.7 %	15.3 %	14.4 %	15.8 %	15.6 %	16.7 %	15.8 %	16.0 %
55–64 years	19.6 %	19.6 %	19.8 %	20.0 %	19.6 %	19.6 %	19.7 %	16.6 %
65 years or older	14.4 %	13.6 %	14.0 %	14.2 %	14.0 %	13.8 %	14.0 %	21.2 %
Race & Ethnicity								
White	70.2 %	69.6 %	70.2 %	69.8 %	70.2 %	70.9 %	70.2 %	74.1 %
Black	14.4 %	12.9 %	12.7 %	13.3 %	12.7 %	12.2 %	13.0 %	12.3 %
Asian	8.0 %	9.8 %	8.7 %	8.9 %	8.7 %	8.7 %	8.8 %	5.7 %
Hispanic or Latino[‡]	4.4 %	4.9 %	5.6 %	5.3 %	5.1 %	4.7 %	5.0 %	–
Other	2.9 %	2.9 %	2.9 %	2.7 %	3.3 %	3.6 %	3.0 %	7.8 %
Political Leaning								
Liberal	53.6 %	56.3 %	56.0 %	57.9 %	60.4 %	58.8 %	57.2 %	26.0 %
Moderate	19.2 %	18.2 %	18.7 %	16.7 %	16.6 %	16.6 %	17.7 %	36.5 %
Conservative	27.1 %	25.5 %	25.3 %	25.5 %	23.1 %	24.6 %	25.2 %	37.5 %
Income								
< $25,000	14.4 %	15.5 %	16.1 %	16.5 %	16.2 %	16.4 %	15.8 %	14.9 %
$25,000– $49,999	25.6 %	26.9 %	26.6 %	25.2 %	26.3 %	24.9 %	25.9 %	19.1 %
$50,000–$99,999	22.4 %	22.3 %	22.9 %	23.8 %	21.9 %	22.1 %	22.6 %	32.0 %
$100,000–$149,999	16.0 %	14.1 %	14.9 %	14.2 %	14.2 %	13.7 %	14.5 %	17.3 %
≥ $150,000	13.2 %	10.7 %	10.8 %	10.1 %	10.7 %	11.9 %	11.2 %	16.7 %

[†] Non-responses per category (out of 720 respondents): state = 3, gender = 1, age = 0, ethnicity = 0, political leaning = 12, income = 21.
[‡] Survey inquired about race and ethnicity as a single category, whereas the census inquires about Latin/Hispanic origins separately (18.4% of the population).
[*] Sources: U.S. Census (U.S. Census Bureau, 2019): state, gender, age, race, ethnicity, and income. *Gallup 2020 Sample (Saad, 2021): political leaning.*

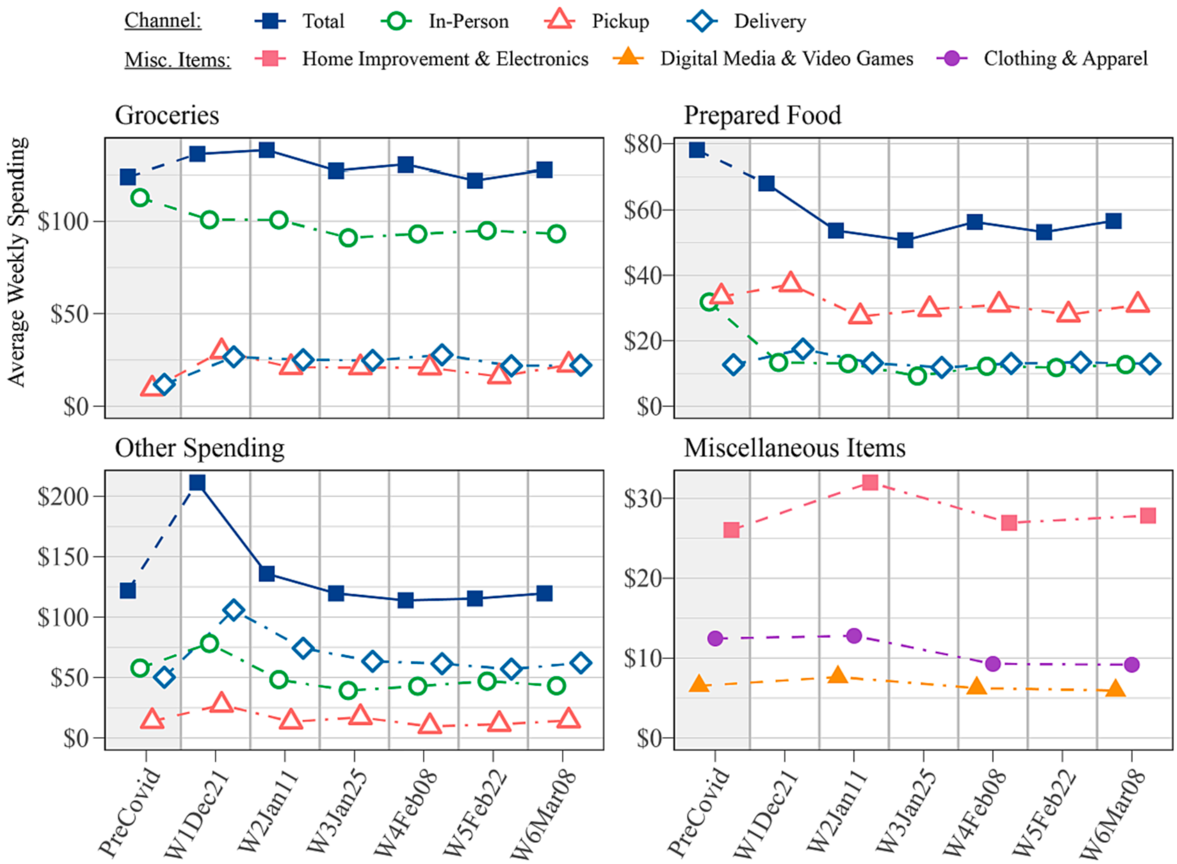

Fig. 1. Weekly spending by item category by acquisition channel at different time points.

grouped with the *other* ethnicity category due to insufficient responses for the pre-COVID baseline (12 responses).

The data show that grocery and other spending are the most sizeable categories of weekly household spending, mostly in the range of $100 and $150 per week on average. Total grocery spending is generally stable over time, with a slight increase around the holidays (Probasco, 2021). Instead, on the side of delivery channel preference, we observe adaptations with grocery spending shifting from in-person spending to pickup and delivery. This reflects a tendency to prefer acquisition of groceries through channels that do not require in-store presence. Looking more closely at household factors, several trends are noted. Fig. 2a-c shows both item and channel type broken down by the most impactful household characteristics.

Households with more vehicles have a greater uptick in expenditure on grocery delivery and pickup. Food spending, however, decreased noticeably during the pandemic, from $78/week pre-COVID to $56/week on average during the pandemic. This shift is mainly the result of decreased spending at restaurants in person, which has not been offset via increased pickup or delivery orders. Households with higher income and higher education have a larger percentage decrease in spending on dining out, in part due to their higher spending on dining out pre-pandemic. Liberal-leaning respondents more significantly decreased in-person spending on prepared food and dining during the pandemic. Similarly, older respondents' households had a larger decrease in in-person spending on prepared food and dining out.

For items other than groceries or food, a significant increase in spending of about 1.7 times is observed during the holidays (wave 2) compared to other waves and pre-pandemic, likely the result of holiday shopping (Probasco, 2021). The largest increase is for delivery orders, in line with the popularity of e-commerce during the pandemic (Fareeha, 2021; Food, 2020). Excluding the holidays, however, there is a slight decrease in in-person spending, as also observed in (Ben Hassen et al., 2021). Unlike that work, we observe an increase in delivery channel spending compared to pre-COVID, suggesting a moderate substitution also for non-food spending.

Overall, a decrease in in-person spending is observed across all categories, in line with other observations and reports regarding the shift in spending channels during the pandemic (Popper, 2021). Whether due to lingering fear towards COVID-19 (Grashuis et al., 2020; Harper et al., 2021) or due to mobility restrictions, in-person spending remains lower than pre-COVID even a year into the pandemic. Excluding the holiday period of data collection, spending is mostly stable across the three months during which data was collected. This stability may be an indicator of adaptation and normalization during the pandemic (Hamilton et al., 2019) and is in line with recent work by Mishra et al. (2021). Earlier research has suggested that periods of restriction caused by disruptions can, over time, lead consumption behaviors to become less reactive and more resilient (Hamilton et al., 2019).

Looking at the *miscellaneous* items, the category with the highest spending is home improvement and electronics. A small increase in holiday spending is observed for this category from roughly $112/month pre-pandemic to $137/month on average, attributed to holiday spending on gifts, home decorations, and other household items (Probasco, 2021). Nonetheless, spending in waves 4 and 6 ($117/month) is similar to pre-pandemic levels. This observation is contrary to reports early in the pandemic which showed a noticeable increase in average home improvement expenditure (Sherman and Huth, 2020). Alternatively, the data from waves 4 and 6 seem to suggest that the surge in home improvement expenditure has been limited to the early months of the pandemic. As discussed in the next section, this discrepancy is the result of fewer households spending on home improvement and electronics, while those households that still spend on home improvement spend almost 1.7 times as much during the pandemic compared to pre-pandemic.

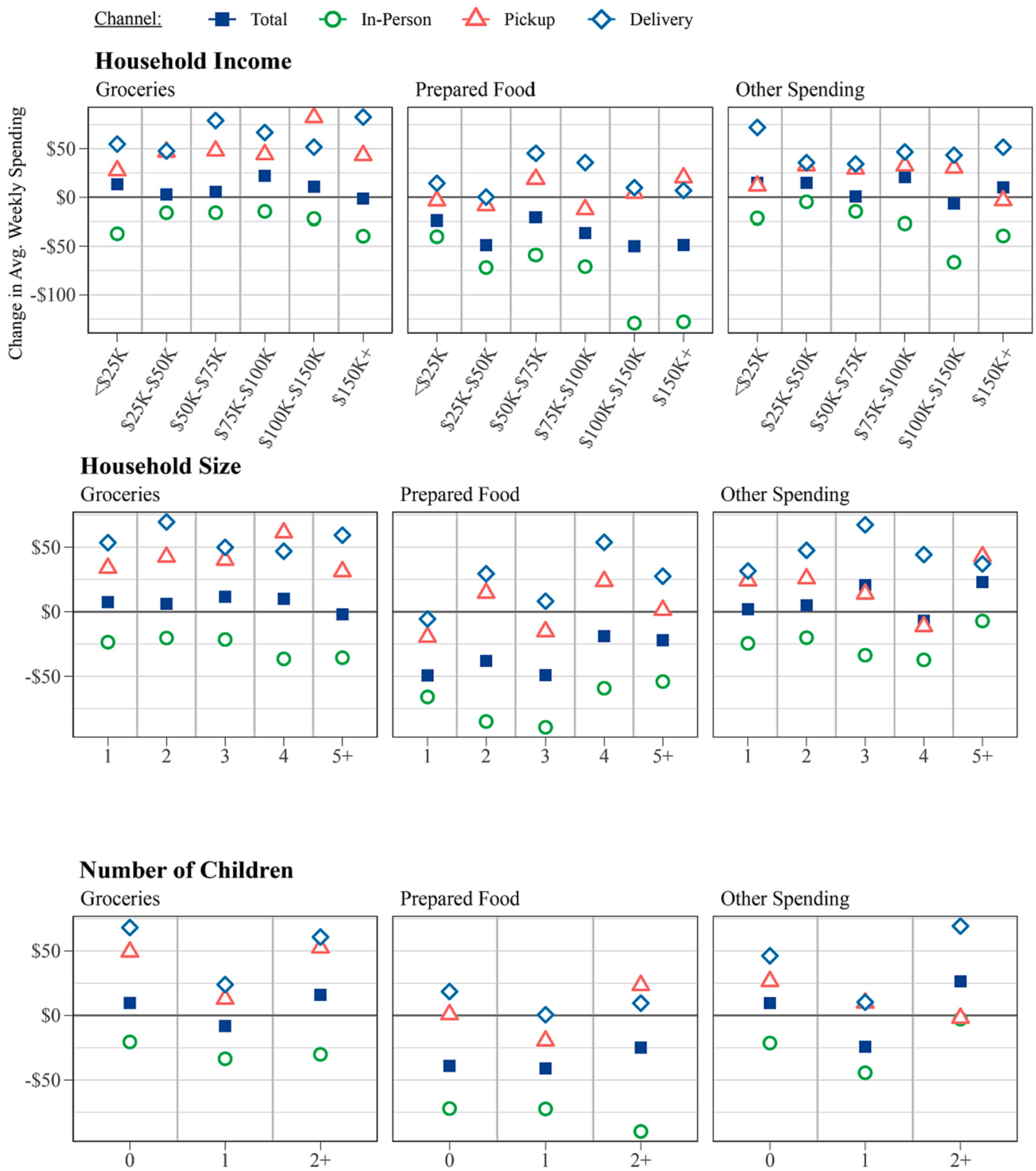

Fig. 2. A change in weekly spending by item category and acquisition channel during the pandemic compared to pre-covid2b change in weekly spending by item category and acquisition channel during the pandemic compared to pre-covid2c change in weekly spending by item category and acquisition channel during the pandemic compared to pre-COVID.

For clothing and apparel, a decrease in spending is observed in later waves (4 and 6), with spending outside of the holidays being lower than pre-pandemic spending – in line with other data (Ghosh, 2020; Sherman and Huth, 2020). This decrease is mainly due to a decline in the number of respondents who spent on clothing and apparel at the time of data collection. Prior to COVID-19, 83 % of respondents have spent some amount on clothing and apparel, compared to 56 % during the pandemic. This reduction is likely the result of limiting expenditures on non-essential services (Gu et al., 2021).

For digital media and videogames, while reports show increased spending in this category during the pandemic (Sherman and Huth, 2020), little variation in spending is observed in the data, even in comparison to pre-pandemic spending. Unlike the latter cases, spending in this category is accompanied by a smaller shift in the fraction of households that spend on media and gaming, with a change from 71 % pre-pandemic to 61 % during the pandemic and a 16 % increase in spending for households that still spend on this category.

All in all, average spending appears to have generally stabilized at this stage of the pandemic. Besides spending on dining out and prepared food, spending on most categories and items are relatively similar to pre-pandemic spending, albeit with some shift in spending from in-person shopping towards pickup and delivery.

4. Modeling shifts in spending over time

To analyze the drivers of spending behavior across time, a *hurdle regression* is estimated for each of the categories and channels discussed in the previous section. Given the nature of short-term spending data, it is not unexpected to find that a relatively significant fraction of households in any given week – or month – have had no spending for a specific category and/or channel. For example, in the case of in-person dining, 75 % of responses are $0/week. This creates a large number of zero-

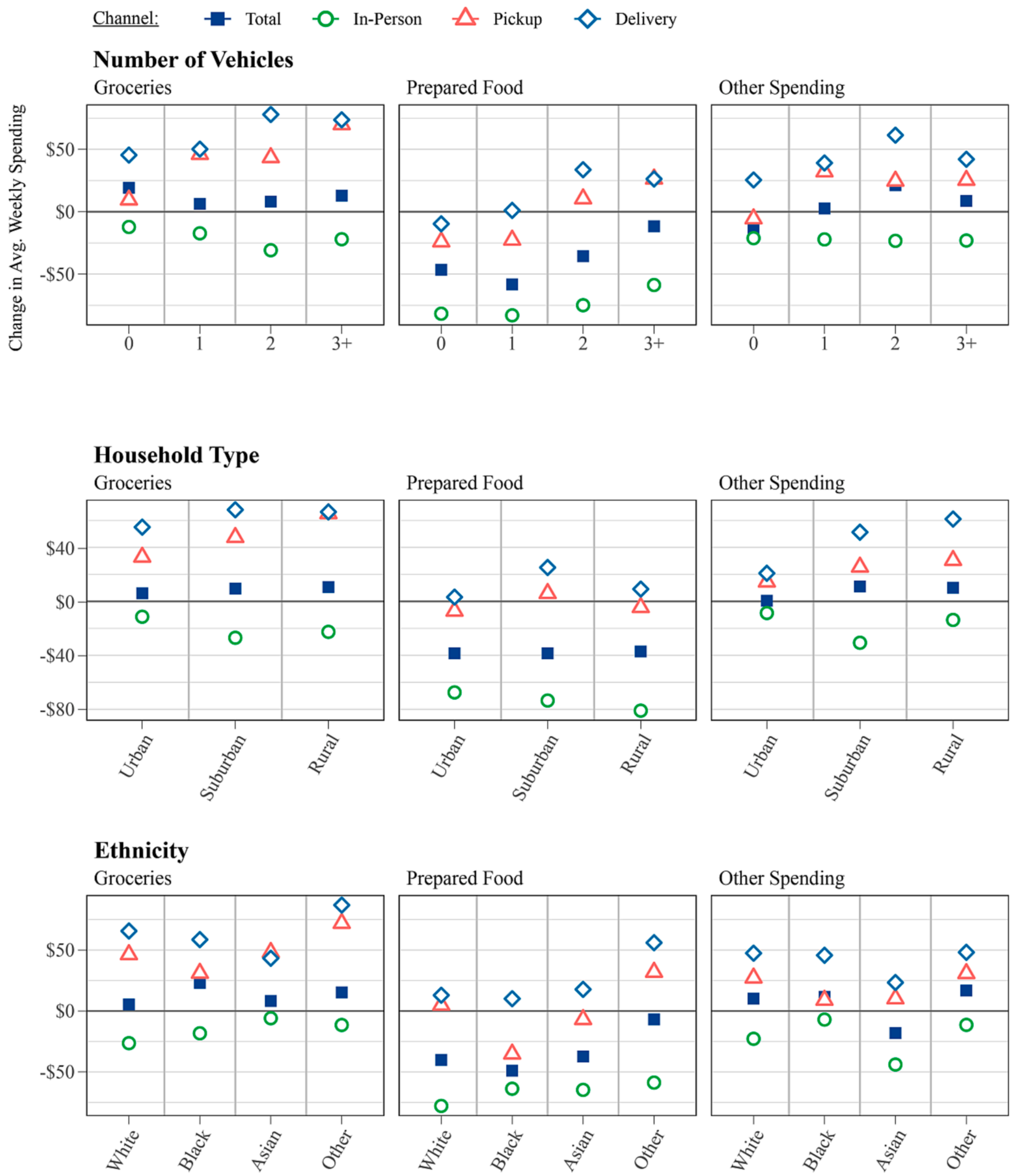

Fig. 2. (*continued*).

valued responses that tend to unduly influence a regular linear regression model and would violate typical distributional assumptions of the model.

To properly address this issue, *hurdle regression*, designed to account for excess zero-responses, can be used to reflect the zero-inflated nature of this data (Cragg, 1971). This is achieved by modeling the data in two stages: the first stage modeling whether a response is zero or not and the second stage modeling the value of non-zero responses.

Therefore, the goal of hurdle regression in the context of this study is to: (1) analyze the odds of making a purchase in the past week or month for a given spending category and channel, and (2) analyze the spending per week for those who do make a purchase. The first arm of the hurdle regression is a binary logit model formulated as a latent variable crossing a threshold, which governs the outcome of spending more than zero in a given category. The second arm is formulated as a linear regression that models the weekly spending dollar amount – using the midpoint of each spending category – conditional on non-zero spending taking place.

Modeling techniques other than hurdle regression were considered and tested during this study, such as *Tobit regression*, *zero-inflated Poisson regression,* and *multiple discrete–continuous extreme value model*. Whereas all options provided suitable tools for modeling the spending data collected in this study, hurdle regression models have been selected due to providing more intuitive results in terms of interpretability while remaining a powerful modeling tool.

Two specifications are presented in this paper. The first specification is intended to establish a reference for the model form and enable overall comparisons across spending categories; it models only the mean expenditure in each category for a given time period with no additional covariates. The second specification expands the former by including various covariates corresponding to individual and household attributes that influence those expenditures in each category and allows statistical testing of the significance of these factors. This section focuses on the first specification, while the second is addressed in the next section.

For both specifications, given the goal of observing change in spending as a function of time, the hurdle model is estimated by con-

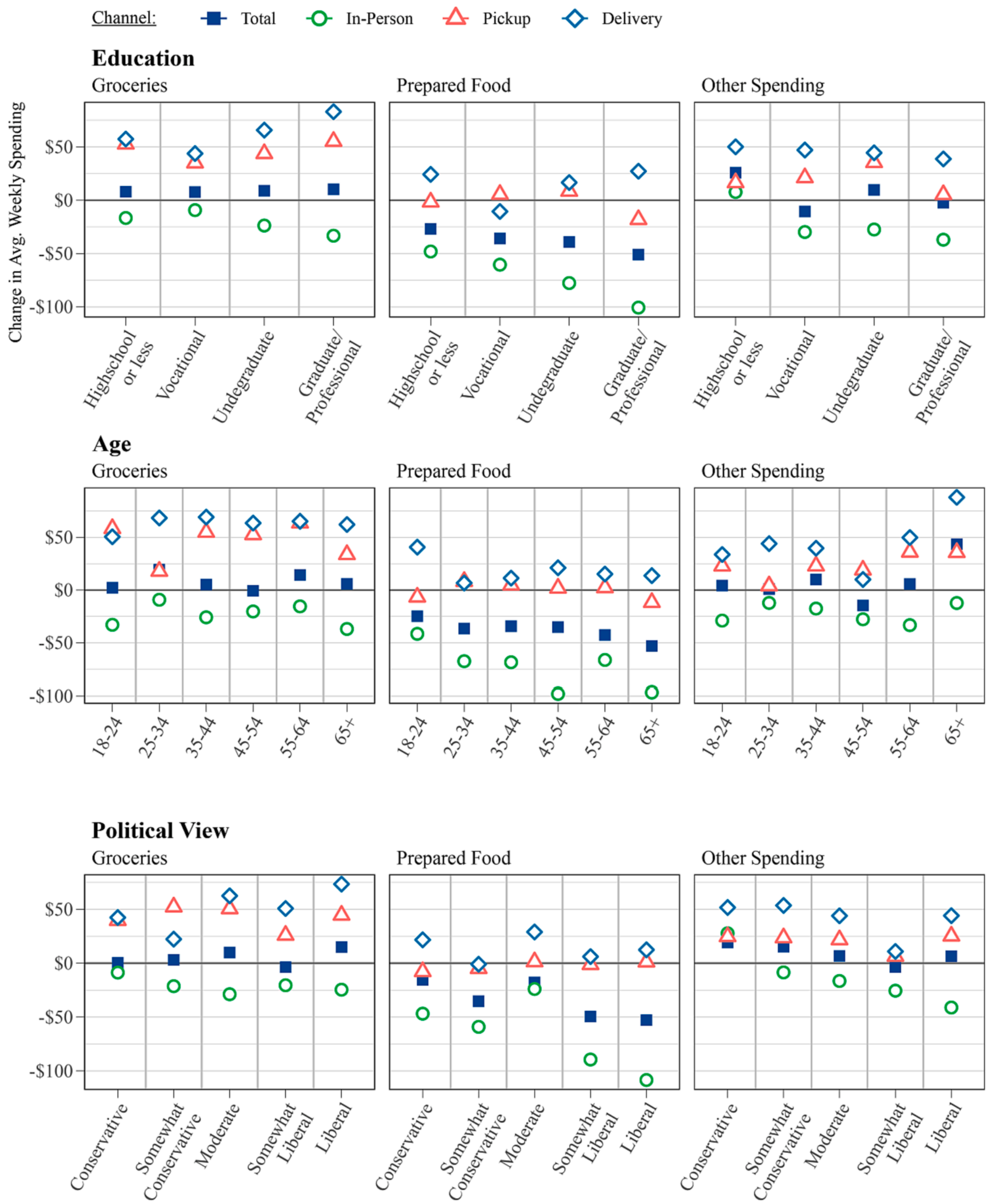

Fig. 2. (*continued*).

trolling for time fixed effects, which represent average spending or odds of spending at each respective time point. The time fixed-effects specification is motivated by the use of panel data taken at different time points, entailing the presence of unobservable effects prevailing at each particular period which will be captured by the fixed-effect coefficients.

Binary arm :

$$s_{itck} = \begin{cases} 0 if\ y_{itck} = \$0 \\ 1 if\ y_{itck} > \$0 \end{cases} logit(s_{itck}) = \alpha_{0,ck} + \alpha_{tck} \times wave_t + \epsilon_{ick} \quad (1)$$

Continuous arm :

$$if\ \ y_{itck} > \$0 : \ \ y_{itck} = \beta_{0,ck} + \beta_{tck} \times wave_t + u_{ick} \quad (2)$$

where y_{itck} is the weekly spending by individual i at time t in item category c through channel k, $wave_t$ is a dummy variable equal to 1 at time t and 0 otherwise, $\boldsymbol{\alpha}_{ck} = [\alpha_{0,ck}, \alpha_{tck}]$ and $\boldsymbol{\beta}_{ck} = [\beta_{0,ck}, \beta_{tck}]$ are the coefficients by spending category and channel for time t for each of the binary and continuous hurdle arms respectively. ϵ_{ick} and u_{ick} are logistic and normal error terms respectively. For more information on hurdle models, the reader is referred to Cameron and Trivedi (2013).

The model results are shown in Fig. 3a-b using robust standard errors clustered at the respondent level. The results from the binary arm are presented as the total log-odds of making a purchase at different time points, while the results of the continuous arm are presented as the percent change with respect to pre-COVID.

For groceries, a downward trend is observed for the total log-odds, but the decrease in probability is negligible compared to pre-COVID, from 0.99 probability of buying groceries in a week pre-COVID to 0.96 on average during the pandemic. Groceries typically include essential items; it is expected that most households still need to make frequent grocery purchases despite the pandemic. A decrease in the

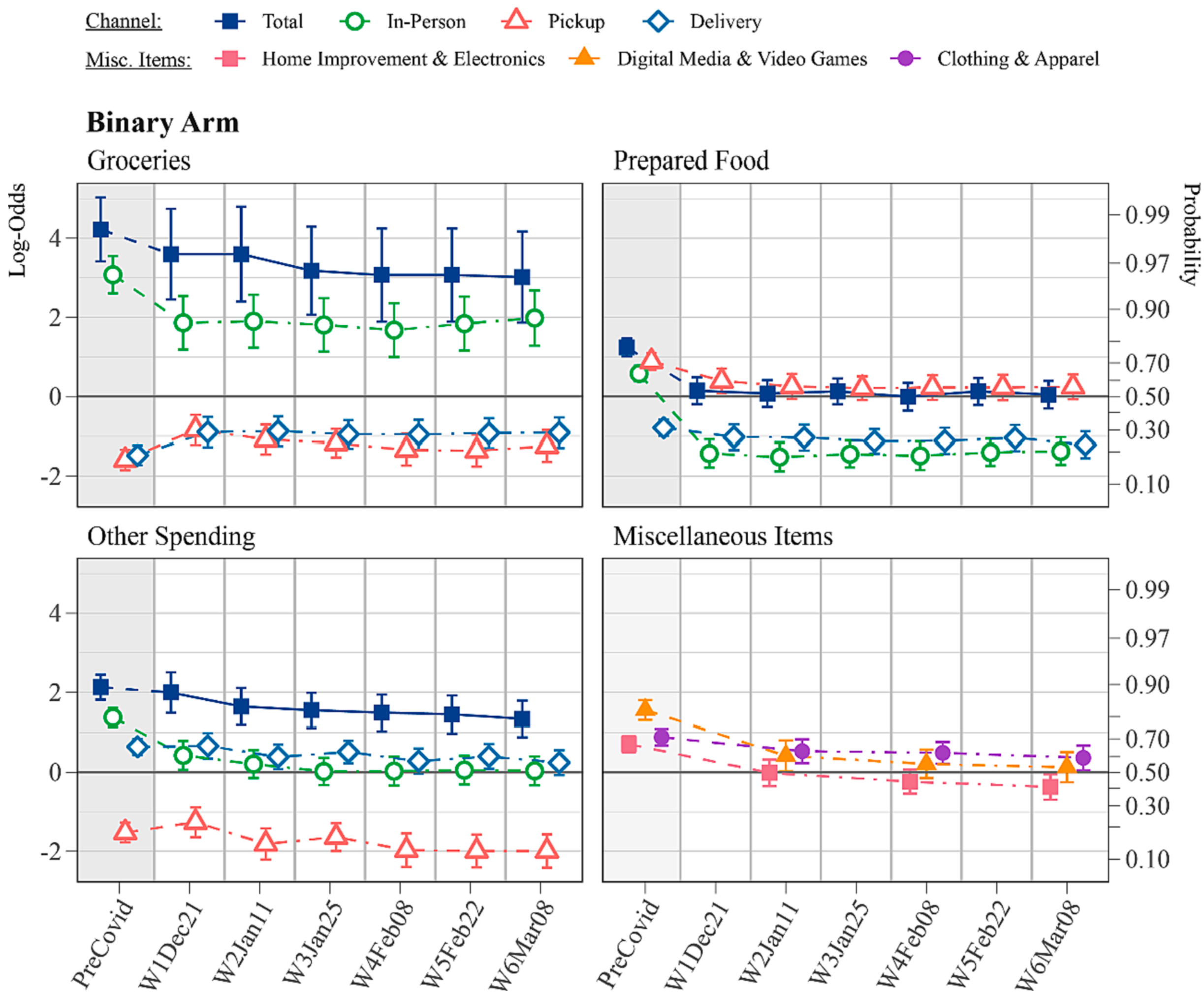

Fig. 3. a Results of binary arm of hurdle model with time fixed-effects with 95% confidence intervals: log-odds and probability of making a purchase within a specific category through a specific channel. b Results of continuous arm of hurdle model with time fixed-effects with 95% confidence intervals: percent spending change in spending for a specific channel and category with respect to pre-pandemic spending.

probability of making in-person grocery trips in the past week and an increase in the probability of shopping for groceries for pickup or delivery are noted, in line with earlier observations. A gradual decrease in pickup probability is observed, indicating a loss in momentum for this behavioral shift. This is not the case for delivery, however, which shows more stability. Finally, spending on groceries by mode of pickup and for delivery have increased by an average of 63.8 % and 37.6 % respectively, with an insignificant decrease for in-person spending.

In line with the previous section, the probability of dining out or ordering food in a specific week during the pandemic decreased from 0.78 to roughly 0.50, mostly as a result of the probability of in-person dining decreasing more than 3-fold during the pandemic. This is expected given persisting restrictions on in-person dining (Kim, 2021). The probability of ordering food for pickup or through delivery has decreased slightly on average by 0.14 and 0.06 respectively. While some increase in spending is observed across channels, total spending on prepared food and dining has been relatively stable.

As for other spending, the probability of ordering items other than food or groceries in-person has decreased from 0.80 pre-COVID to roughly 0.50 during the pandemic. The probability of pickup has also decreased, from 0.22 to 0.13. This change is similar to the decrease in probability of overall spending in this category, this observation is interesting given the push for curbside pickup by many retailers (Tyko, 2021). The probability of making orders for delivery is naturally high compared to other categories due to the popularity of e-commerce and relative stability over this phase of the pandemic, with values in the range of 0.66 and 0.56. While an increase in overall spending of roughly 75 % is observed for the week of December 14, preceding the holidays, this increase in spending is only maintained for delivery purchases in the following months.

For miscellaneous items, a noticeable decrease in the probability of buying clothing or apparel within a month is observed, from 0.83 to a low of 0.53 for February 2021. For home improvement and electronics, the probability to make a purchase decreased from 0.67 to 0.41. However, for those who do spend on home improvement and electronics, spending has increased by 66.4 % on average during the pandemic. This observation implies that the surge in home improvement during the pandemic may not have been due to an increased number of people spending on home improvement. Instead, people who have decided to invest in home improvement have significantly increased their spending in that category. With restrictions on in-person gatherings and events, the probability of spending on clothing and apparel has decreased, even though spending has not significantly changed. The probability of spending on digital media and videogames decreased from 0.71 to an average of 0.61. Outside of the holiday season, there is no significant change in spending on this category.

The next section presents the results of the second specification which incorporates covariates to further explain the variation of

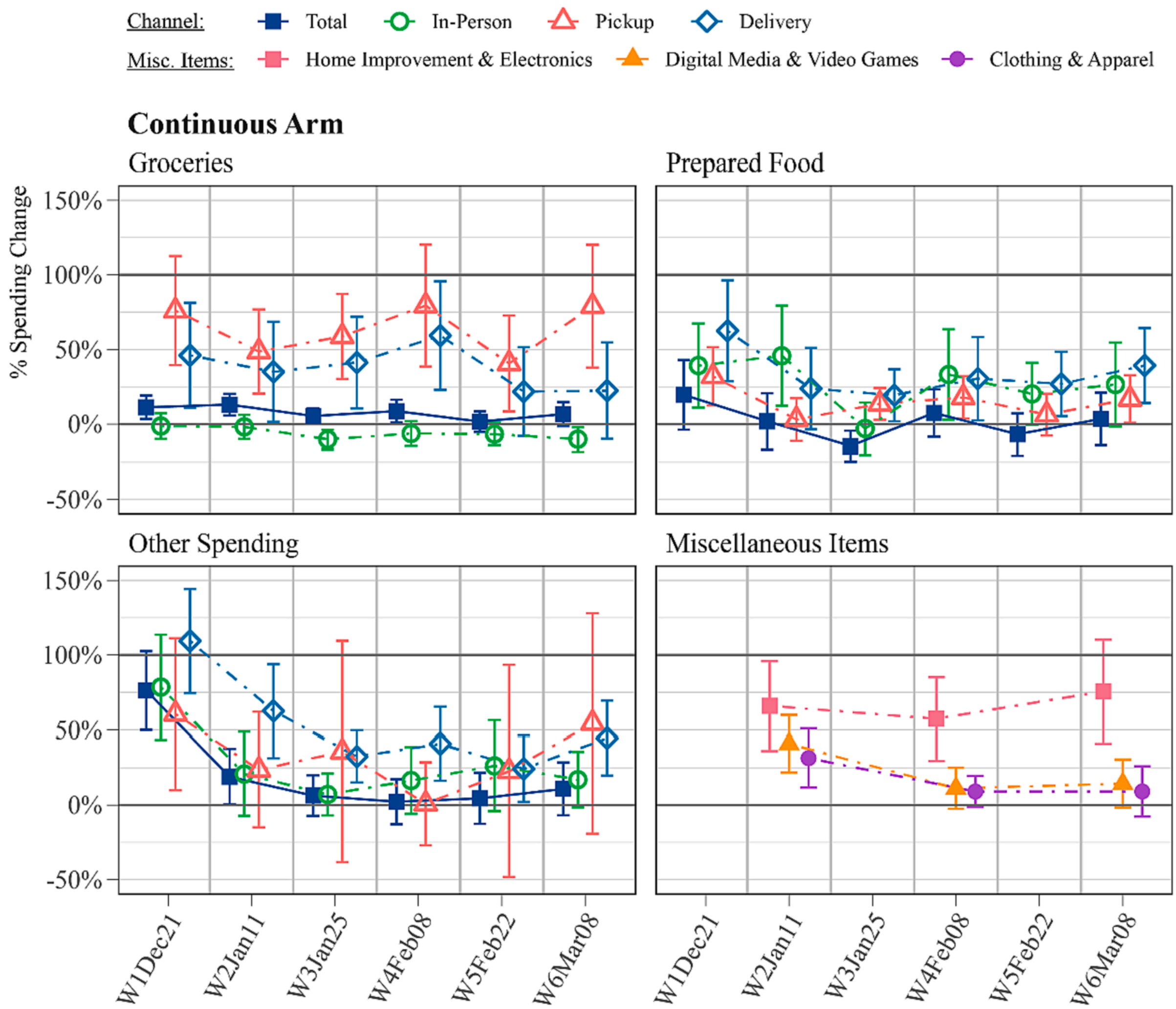

Fig. 3. (*continued*).

expenditures across individuals and households.

5. Household attributes and channel selection

In addition to observing the changes in spending over time, this paper also assesses how different household types change their spending behavior during the pandemic. Here, in addition to fixed-effect time controls, the models are constructed using household and respondent attributes as covariates to estimate their effect on spending. The models are constructed for each of the 3 spending channels, (1) in-person, (2) pickup, and (3) delivery. Another set of fixed-effect coefficients is added to the model to capture the spending category (i.e. grocery, food, or other).

Binary arm :

$$s_{itck} = \begin{cases} 0 if \ y_{itck} = \$0 \\ 1 if \ y_{itck} > \$0 \end{cases} logit(s_{itck})$$
$$= \alpha_{0,k} + \alpha_{tk} \times wave_t + \alpha_{ck} \times category_c + \sum_n \alpha_{n,ik,covid} \times covariate_{n,it}$$
$$\times covid_t + \sum_n \alpha_{n,ik,precovid} \times covariate_{n,it} \times (1 - covid_t) + \epsilon_{itck} \quad (3)$$

Continuous arm :

$$if \ y_{itck} > \$0 : y_{itck}$$
$$= \beta_{0,k} + \beta_{tk} \times wave_t + \beta_{ck} \times category_c + \sum_n \beta_{n,ik,covid} \times covariate_{n,it}$$
$$\times covid_t + \sum_n \beta_{n,ik,precovid} \times covariate_{n,it} \times (1 - covid_t) + u_{itck} \quad (4)$$

where y_{itck} is the weekly spending by individual i at time t in item category c through acquisition channel k, $wave_t$ is a dummy variable equal to 1 at time t and 0 otherwise, $category_c$ is a dummy variable equal to 1 for category c and 0 otherwise, $covariate_{n,it}$ is an attribute n for household or respondent i at time t, $covid_t$ is a dummy equal to 1 if time t is during the pandemic and 0 otherwise, and $\boldsymbol{\alpha}_k = [\alpha_{0,k}, \alpha_{tk}, \alpha_{n,ik,covid}, \alpha_{n,ik,precovid}]$ and $\boldsymbol{\beta}_k = [\beta_{0,k}, \beta_{tk}, \beta_{n,ik,covid}, \beta_{n,ik,precovid}]$ are the coefficients by acquisition channel for the binary and continuous hurdle arms respectively.

The covariates for household and respondent attributes are interacted with time binary indicators in order to disentangle the change in spending behavior due to these attributes during the pandemic compared to pre-pandemic. Results are shown in Fig. 4a-b (as well as in Table 3 in the Appendix). Respondents have not been asked about their political views or if they were an essential worker prior to the pandemic, therefore the coefficients for these covariates are only estimated for observations during the pandemic. Insignificant covariates ($p > 0.05$) have been systematically removed from the final models and are

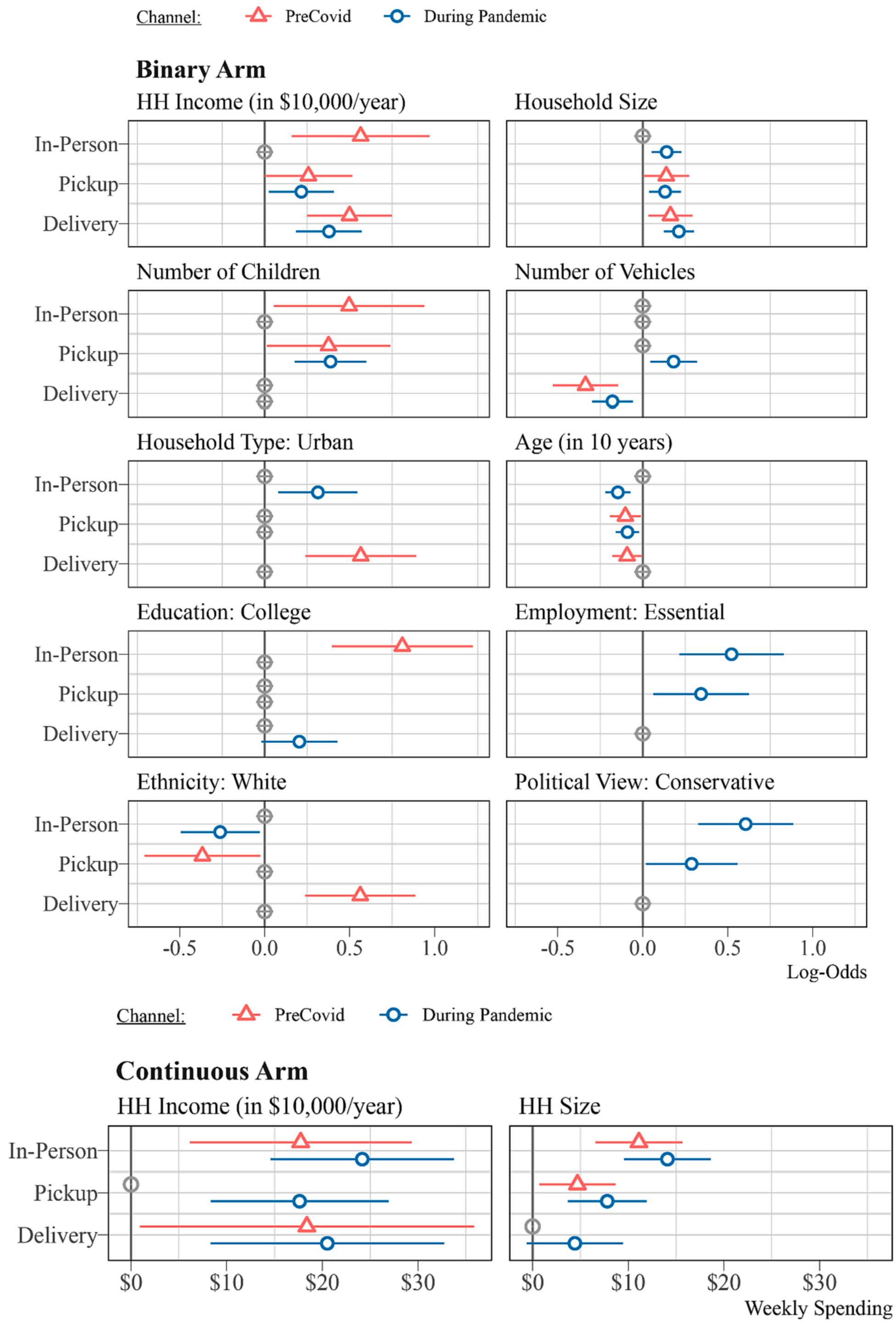

Fig. 4. a hurdle model binary arm coefficients for household and individual attributes by time with 95% confidence intervals (pre-pandemic vs during the pandemic) for three different acquisition channels: log odds of conducting a purchase within a week through a specific channel. b hurdle model continuous arm coefficients for household and individual attributes by time with 95% confidence intervals (pre-pandemic vs during the pandemic) for three different acquisition channels: spending amount within a week through a specific channel.

presented as gray in the figure.

Household income and household size are the major attributes driving change in both the likelihood of spending through a specific channel and the dollar amount spent. For in-person spending, while households with higher income spend more on in-person purchases during the pandemic compared to lower-income households, their odds of conducting their purchases in-person diminish during the pandemic compared to pre-COVID. This could be an indicator of increased flexibility in lifestyle and remote work by higher-income households (Badger and Parlapiano, 2020; Brough et al., 2021). Higher-income households remain more likely to purchase items for pickup or delivery during the pandemic compared to lower-income households. The effect of household size is more prevalent on the amount spent, where larger households seem to have higher spending across all channels compared to pre-pandemic spending and to smaller households.

Compared to pre-COVID, households with more children have lower odds of shopping in person. Ecola et al. (2020) report similar results, stating that households with children are more likely to shop online. With requirements for social distancing, restrictions on the number of concurrent patrons at in-person stores, closure of daycare facilities, pivoting to online education and the ineligibility of children for the vaccine, it is hypothesized that households with children have less flexibility to conduct in-person shopping. On the other hand, owning a larger number of vehicles seems to facilitate shopping through the pickup, as indicated by the significant coefficient during the pandemic. Households with more vehicles are also more averse in general to shopping online for delivery, though this aversion is reduced during the pandemic.

Households in urban areas are more likely to conduct in-person shopping in comparison to households in suburban and rural areas compared to pre-COVID. While urban households were more likely to order items for delivery pre-COVID, this difference becomes insignificant during COVID as suburban and rural households spend more on delivery as observed earlier in Fig. 2. Older respondent households are less likely to purchase items in-person during the pandemic compared to younger respondents, but instead becoming equally likely to order items through delivery.

While only significant at the 0.10 level, being college educated entails living in a household with a higher likelihood of conducting purchases for delivery during the pandemic compared to other households. Prior to the pandemic, and controlling for all other covariates, being college educated is a determinant for in-person purchases. In terms of employment, essential worker households are more likely to conduct in-person and pick-up purchases during the pandemic compared to other respondents.

Households of White ethnicity respondents have lower odds of conducting a purchase in person during the pandemic compared to respondents from other ethnicities. While White respondents were more likely to order items for delivery prior to the pandemic, this gap becomes insignificant during the pandemic, with an equal propensity of ordering items for delivery across all ethnicities. It can also be observed that households of Asian ethnicity respondents tend to have lower odds of spending on for-delivery purchases during the pandemic compared to pre-COVID and to other respondents.

Finally, regarding political views, conservative respondent households exhibit a higher likelihood of using in-person and pickup channels during the pandemic compared to non-conservative respondents. Political orientation has been previously shown to affect pandemic behaviors (Bosman, 2020). Referring to Fig. 2, more liberal respondents have been more responsive to shifting away from in-person shopping.

In summary, more educated, higher income, White households and households with children have shifted away from in-person spending during the pandemic. More educated respondents also have a higher propensity toward using delivery services during the pandemic. On the other hand, respondents who are essential workers and those that identify as conservative have a higher propensity to conduct their purchases in-person or through pickup.

6. Conclusion

The COVID-19 crisis has induced substantial changes in global consumption patterns. Understanding the degree and nature of these shifts as economies recover from the pandemic remains a fundamental research challenge. Change in spending is a measure of behavior that reflects lifestyle changes and – more directly – shifts in preferences for different purchase channels. These changes in behavior have implications that extend beyond the domain of household spending, extending to the state of the economy, transportation systems, business operations and retail logistics strategies (Hendrickson and Rilett, 2020; Rutter et al., 2017; Toossi, 2002). Additionally, the shift to e-commerce and digitization during the pandemic has led to notable concerns regarding social equity, such as digital exclusion, affordability and livelihood issues (Alberti et al., 2020; Bastick and Mallet, 2021; Figliozzi and Unnikrishnan, 2021b; O'Donnel, 2021; Seifert et al., 2020; Tobin-Tyler, 2021; Villarosa, 2020).

Using a panel sample of 720 U.S. respondents, this study analyzes the changes in spending behavior in the United States during a transitional phase of the COVID-19 pandemic, from December 2020 to March 2021. Three different spending categories (*groceries*, *prepared food*, and *items other than groceries or food*), as well as break-down by 3 main spending channels: *in-person*, *pickup* and *delivery* are tracked bi-weekly. To also understand some more nuanced spending categories, 3 additional miscellaneous items are assessed monthly: *home improvement and electronics*, *digital media and video games*, and *clothing and apparel*.

This research has several contributions. First, this work collects and presents comprehensive self-reported spending data across a multitude of channels and spending categories during one of the earlier phases of the COVID-19 pandemic. Second, we systematically analyze shifts in expenditure to provide insight on factors affecting overall household spending, in addition to shifts across these channels and categories. In doing so, this study is one of the earliest longitudinal studies providing a holistic overview on household spending and behavior in the context of the pandemic, with several practical implications for businesses, policy makers, planners and supply-chain operators.

This study finds that, overall, average spending is not noticeably different from pre-COVID levels in the period of December 2020 to March 2021, except for prepared food expenditure which has decreased by roughly 28 %. This is despite of increased popularity of food delivery during the pandemic (Zhao and Bacao, 2020). Moreover, no major fluctuations in spending within the data collection period of roughly 3 months has been observed, apart from an increase in some categories of expenditure during the holiday period in December. Compared to the significant fluctuations in spending early on in the pandemic (Baker et al., 2020; Popper, 2021; Sherman and Huth, 2020), this stability appears to be an indicator of a *steady-state* developing for spending behavior (Salon et al., 2021). Although this *steady-state* is expected to be transitional as communities keep adjusting to COVID-19 rates and restrictions, based on the observations in this study, we hypothesize that future transitions will be slow and gradual, contrary to the abrupt behavioral shifts in the early months of the pandemic.

The data, however, does suggests a sustained shift in spending channels towards pickup and delivery modes. For example, respondents are almost 10 % less likely to buy groceries in-person in a given week, instead opting for pickup and delivery shopping. Simultaneously they are spending roughly 40 % to 60 % more through these channels compared to pre-pandemic baselines. This shift is a natural outcome as households work remotely and reduce – on average – their in-person activities in response to the pandemic, even in the case of essential activities. However, the stability across the three-month period for the chosen spending channel also indicates a sense of inertia. This implies that the pandemic-triggered experience with alternative delivery channels and the increased use of online platforms is likely to persist over time.

This study finds evidence for systematic differences in spending patterns according to sociodemographic and household factors. More educated and higher income households have shifted away from in-person spending during the pandemic (Figliozzi and Unnikrishnan, 2021b). As per Brough et al. (2021), this is also reflected in travel behavior. Travel intensity declined more among more educated and higher income individuals, highlighting a relationship between spending and travel behavior. White respondent households have tended to shift away from in-person spending compared to other races and ethnicities. Political views correlate with spending behavior adjustments, where self-reported conservative leaning respondents have a higher likelihood of carrying out purchases in-person and through pickup during the pandemic compared to non-conservative respondents. Given the rapid – and sometimes necessarily hastened – policy changes surrounding the COVID-19 pandemic, it is vital to understand these nuances in behaviors among different household types, across socioeconomic classes, and beliefs. While some groups are capable of readily adjusting to the shifting landscape of COVID-19 policies and restrictions, this is not true for others. For instance, higher income households have been more prone to adjust their spending during the pandemic (Badger and Parlapiano, 2020). Conversely, minorities have been disproportionality affected by the pandemic and are more likely to be frontline or essential workers, without the flexibility or option of working from home (Goldman et al., 2020; Tahlyan et al., 2022a; Tai et al., 2021). Conservative individuals have been observed to be less concerned about COVID-19's impact on public and personal health and to be less likely to embrace social distancing measures and restrictive measures surrounding the pandemic (Hsiehchen et al., 2020; Shao and Hao, 2021). Understanding this interaction between political views and behavior – including spending behavior – is important; whereas conservative individuals are more resistant to shifting behavior, this resistance has resulted in higher infection and fatality rates in conservative regions (Gollwitzer et al., 2020; Hsiehchen et al., 2020; Neelon et al., 2021).

Accordingly, this study has several practical implications. For transport planners, shifts in expenditure across different channels may act as precursors for shifts in derived traffic demand (Figliozzi and Unnikrishnan, 2021a). Earlier shifts in spending channels to delivery options has coincided with a reduction in overall traffic demand (Du et al., 2021; Federal Highway Administration, 2021; TomTom, 2021) and increased pressure on delivery services (Page and Stephens, 2020; Srivatsa Srinivas and Marathe, 2021; Suguna et al., 2021; Unnikrishnan and Figliozzi, 2021). At the time of this study, according to data from INRIX (Bureau of Transportation Statistics, 2021), the reduction and stability in spending is indeed accompanied by reduced yet relatively stable average VMT (vehicle miles traveled) at a national level. The mean VMT between December 14, 2020 and March 8, 2021 (excluding Christmas and New Year's weekends) is 88 % of pre-pandemic VMT with an average slope of 0.00 % per day.

As different future phases of the pandemic are encountered, changes in spending channel selection will become of increased relevance for transport planners as a potential indicator of traffic demand. This is especially important in the case of a reversal to in-person spending, which is expected to be accompanied by a respective reversal in derived travel demand. Indeed, following the final wave of this study, VMT seems to have started recovering towards pre-pandemic levels (Bureau of Transportation Statistics, 2021).

In terms of policy planning, in a period of uncertainty, the analysis provided here provides essential and detailed information on spending and behavior for appropriately supporting public welfare. Specifically, the findings of this study allow for targeted support to vulnerable households based on a number of sociodemographic household features.

These implications extend to businesses and operators as well, guiding their operations as spending shifts across channels and changes within categories. Within the timeframe of this study, spending has evidently shifted to online platforms, where increased spending is observed for pick-up and delivery purchases, increasing strain on inventory logistics, shipping services and last-mile operations – especially midst the current supply-chain crisis (Maiden, 2021; Ngo and Swanson, 2021). For smaller businesses, this study highlights the importance of having a notable online presence, especially in communities that have more readily shifted away from in-person spending. This more substantially applies to the food sector which has suffered most significantly during the pandemic and is required to meaningfully innovate amidst lower overall expenditure on prepared food and dining-out. With the pandemic accelerating the role of online interaction in the shopping process, from a retailing standpoint, customers now exhibit a wider range of behaviors in terms of pick-up and delivery. Whereas grocery expenditure remains resiliently in-person, this wider range of behaviors highlights the importance of multichannel operation, especially for other businesses and sectors.

6.1. Limitations and future work

Whereas the sample has been selected to be representative across gender, age and race, online samples may entail other biases not controlled for in this study, such as coverage bias and self-selection (Schaurer and Weiß, 2020; Sterrett et al., 2017). Nonetheless, recent research has shown that findings from online samples are consistent with traditional methods of data collection (Casler et al., 2013; Gosling et al., 2004; Smith et al., 2015). On the other hand, given the abrupt nature of the COVID-19 pandemic, survey respondents have been asked to recall past information regarding their spending and household attributes before the COVID-19 pandemic. While the authors acknowledge the biases inherent in asking respondents to recall their pre-pandemic spending, the data offers valuable insight into changes in behavior and spending during the pandemic. Although the study does not account for price inflation, inflation was essentially insignificant over the time-period of this study (U.S. Bureau of Labor Statistics, 2021).

A potential extension of this work is to collect data over a longer period of the pandemic, including the evolving phases, especially to observe the effects of changes in restrictive measures as vaccination rates increase in the United States and other COVID-19 variants emerge. Additionally, data measuring trip-making can be used to assess mobility during the pandemic in conjunction to household spending, to couple the analysis of travel and spending that is likely to be both substitutional and result in new types of trip chaining. Finally, augmenting the pre-pandemic spending baselines with revealed data would result in a more extensive analysis of shifts in household spending during the pandemic. These extensions would result in more comprehensive understanding of behavior within a global pandemic and better planning and policymaking in the current and future pandemics.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Author contributions

The authors confirm contribution to this paper as follows: study conception and design: MS, DT, AS, HM, JW, SS; data collection: MS, DT, AS, HM, JW, SS; analysis and interpretation: MS, DT, AS, HM, JW, SS; draft manuscript preparation and figures: MS; manuscript revision: MS, AS, DT, HM, SS. All authors reviewed the results and approved the final version of the manuscript.

Appendix

Table 3a
Hurdle regression model for household and individual attributes by time (pre-pandemic vs. during the pandemic) for different acquisition channels: binary logit arm for conducting a purchase within a week through a specific channel.

Binary Arm			
Model Statistics	**In-Person**	**Pickup**	**Delivery**
Number of Observations	*720*	*720*	*720*
Log-Likelihood at zero	*−6,405*	*−6,405*	*−6,405*
Constants-only Log-Lik.	*−4,786*	*−5,041*	*−5,634*
Final Log-Likelihood †	*−4,576*	*−4,773*	*−5,471*
Cragg-Uhler ρ^2	*0.424*	*0.280*	*0.183*
McFadden ρ^2	*0.278*	*0.178*	*0.109*
AIC	*9,191*	*9,592*	*10,982*
BIC	*9,334*	*9,756*	*11,125*

Parameter	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
Constants						
Intercept	0.838 ***	0.000	−1.481 ***	0.000	0.189	0.554
Date: W1Dec21	−0.379	0.192	−0.664 **	0.034	−0.224	0.494
Date: W2Jan11	−0.491 *	0.082	−0.951 ***	0.002	−0.325	0.335
Date: W3Jan25	−0.571 **	0.044	−0.926 ***	0.003	−0.314	0.334
Date: W4Feb08	−0.607 **	0.037	−1.062 ***	0.001	−0.422	0.204
Date: W5Feb22	−0.511 *	0.079	−1.054 ***	0.001	−0.335	0.306
Date: W6Mar08	−0.473	0.102	−1.006 ***	0.001	−0.436	0.181
Category: Groceries	1.806 ***	0.000	0.533 ***	0.000	−1.491 ***	0.000
Category: Prepared Food	−1.556 ***	0.000	2.213 ***	0.000	−1.548 ***	0.000
Pre-COVID Parameters						
HH Income (in $10,000/year)	0.565 ***	0.006	0.257 *	0.052	0.500 ***	0.000
Household Size	–	–	0.138 **	0.045	0.163 **	0.014
Number of Children	0.497 **	0.028	0.376 **	0.043	–	–
Number of Vehicles	–	–	–	–	−0.337 ***	0.001
Household Type: Urban	–	–	–	–	0.565 ***	0.001
Age (in 10 years)	–	–	−0.102 **	0.028	−0.092 **	0.036
Education: College	0.810 ***	0.000	–	–	–	–
Ethnicity: White	–	–	−0.367 **	0.035	0.563 ***	0.001

†Likelihood ratio tests of final model w.r.t. constants-only model (χ^2, df, p-value): in-person (419.6, 11, 0.000); pickup (535.5, 14, 0.000); delivery (304.9, 11, 0.000).
**** = significant at 0.01 level; ** = significant at 0.05 level; * = significant at 0.10 level*

Table 3b
Hurdle regression model for household and individual attributes by time (pre-pandemic vs. during the pandemic) for different acquisition channels: (cont'd) binary logit arm for conducting a purchase within a week through a specific channel.

Binary Arm						
	In-Person		**Pickup**		**Delivery**	
Parameter	**Coefficient**	**p-value**	**Coefficient**	**p-value**	**Coefficient**	**p-value**
COVID-Era Parameters						
HH Income (in $10,000/year)	–	–	0.216 **	0.026	0.379 ***	0.000
Household Size	0.141 ***	0.002	0.131 ***	0.006	0.213 ***	0.000
Number of Children	–	–	0.388 ***	0.000	–	–
Number of Vehicles	–	–	0.181 **	0.010	−0.178 ***	0.004
Household Type: Urban	0.313 ***	0.008	–	–	–	–
Age (in 10 years)	−0.147 ***	0.000	−0.0901**	0.010	–	–
Education: College	–	–	–	–	0.204 *	0.073
Employment: Essential	0.522 ***	0.001	0.343 **	0.017	–	–
Ethnicity: White	−0.262 **	0.027	–	–	–	–
Political View: Conservative	0.606 ***	0.000	0.287 **	0.037	–	–
Missing-Value Dummies						
HH Income	0.025	0.947	−0.285	0.366	0.389 *	0.095
Political View	−0.951 *	0.063	−0.773 *	0.073	–	–

**** = significant at 0.01 level; ** = significant at 0.05 level; * = significant at 0.10 level.*

Table 3c
Hurdle regression model for household and individual attributes by time (pre-pandemic vs. during the pandemic) for different acquisition channels: linear regression arm for spending amount per week.

Continuous Arm			
Mode Statistics	**In-Person**	**Pickup**	**Delivery**
Number of Observations	*692*	*624*	*659*
Log-Likelihood at zero	*−32,978*	*−18,269*	*−22,725*
Constants-only Log-Lik.	*−31,212*	*−17,479*	*−21,856*
Final Log-Likelihood	*−31,054*	*−17,431*	*−21,830*
Adjusted R^2	*0.095*	*0.084*	*0.067*

Parameter	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
Constants						
Intercept	44.5 ***	0.000	73.6 ***	0.000	69.6 ***	0.000
Date: W1Dec21	9.53	0.198	1.52	0.872	44.7 ***	0.000
Date: W2Jan11	−5.17	0.435	−14.7 **	0.034	19.8 *	0.057
Date: W3Jan25	−15.0 **	0.016	−8.11	0.327	8.84	0.348
Date: W4Feb08	−9.85	0.109	−9.70	0.193	15.6	0.153
Date: W5Feb22	−7.24	0.284	−15.5 **	0.036	3.28	0.739
Date: W6Mar08	−11.5 *	0.061	−3.50	0.546	12.1	0.257
Category: Groceries	23.9 ***	0.000	−12.1	0.157	−28.6 ***	0.000
Category: Prepared Food	−31.4 ***	0.000	−43.4 ***	0.000	−59.3 ***	0.000
Pre-COVID Parameters						
HH Income (in $10,000/year)	17.7 ***	0.003	–	–	18.4 **	0.039
Household Size	11.1 ***	0.000	4.69 **	0.021	–	–
COVID-Era Parameters						
HH Income (in $10,000/year)	24.2 ***	0.000	17.6 ***	0.000	20.5 ***	0.001
Household Size	14.1 ***	0.000	7.80 ***	0.000	4.42 *	0.085
Missing-Value Dummies						
Political View	3.25	0.755	3.11	0.635	30.4	0.265

[†]*Likelihood ratio tests of final model w.r.t. constants-only model (χ^2, df, p-value): in-person (316.1, 5, 0.000); pickup (94.8, 4, 0.000); delivery (52.6, 4,0.000).*
*[***] = significant at 0.01 level. [**] = significant at 0.05 level; * = significant at 0.10 level.*

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