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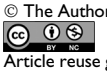

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Trips to the Grocery Store and Online Grocery Shopping: A Comparison of Individual Behaviors before and during the First Wave of the COVID-19 Pandemic

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Abstract

This study examines changes in online and in-store grocery shopping in California during the COVID-19 pandemic. We analyzed survey data from before the pandemic (pre-February 2020) and during the first wave (March-June 2020). Our findings indicate an increase in online grocery purchases among consumerist individuals, while financially conservative individuals and those facing financial struggles showed a decrease. People bought more items per purchase in stores, visited stores less frequently, and transitioned from dining out to cooking at home. Those who enjoy driving and being physically active continued visiting stores more often. Social media use and health concerns influenced shopping patterns. Sociodemographic factors such as household income and race also impacted these changes.

Keywords

COVID-19, in-store grocery shopping, online grocery shopping, revealed preference survey, travel behavior

The COVID-19 pandemic has changed lives in many ways around the world. To react to and contain the spread of the virus, by mid-March 2020, most U.S. states implemented shelter-in-place orders to practice social distancing (*1*). On March 19, 2020, Governor G. Newsom issued an executive order for the State of California (*2*), which requested that all individuals had to stay at their place of residence to disrupt the spread of the novel COVID-19 virus, the only exceptions being for those activities that were considered essential and necessary, for example, buying food and accessing health care.

Although, in general, travel was not allowed, visiting the grocery store is considered an essential need, and recent studies, such as the one from Rieger and Wang (*3*) that looked at several countries around the world, suggest that food purchasing was the most frequently mentioned reason for going out during the pandemic. Others found that consumers overreacted and panic buying was the initial response to the health crisis (*4*), reporting that the need for food supplies increased compared with normal conditions (*5*, *6*). Grashuis et al. (*7*) found that when the virus spread at an increasing rate, many consumers were less likely to do their grocery shopping in person. Although a major transition from in-store shopping to online shopping was observed (*8*), research in the U.S. showed that some people still preferred in-store shopping (*9*).

In this study, we are interested in analyzing the change in grocery shopping behavior before and during the pandemic, focusing on both in-store and online

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grocery shopping. This study investigates the factors that influenced this change, for example, buying more items per visit might lead to a reduction in the number of in-store visits, or visiting only one store that offers everything as opposed to a variety of stores (e.g., visit one store for produce and another one for baked goods) might also lead to fewer in-store visits. We study the causal effect of the change in various activities during the pandemic, personal attitudes with regard to lifestyle, mobility, and the environment, and sociodemographic characteristics. Although it is unclear what long-term impact the pandemic will have on people's habits, some customers may become accustomed to e-shopping and do less in-store shopping in the future (*10*). With this hypothesis in mind, we explore the factors that influenced the change in behavior with regard to in-store and online grocery shopping using data collected from a behavioral survey looking at the situation before the pandemic (February 2020 or earlier) and during its first phase (March–June 2020) in the state of California. Findings from this investigation may be timely and crucial in providing public authorities and regulators with insights to improve the preparedness of society to respond to situations of great sudden stress (e.g., a pandemic), and in providing market research teams with a better understanding of their customers' needs and changing habits, some of which might extend beyond the end of the COVID-19 pandemic.

The paper is structured as follows. The next section provides a review of the literature. Then, we describe the data collection and available sample, and the methodology that is adopted. This is followed by the results of the model and an accompanying discussion. The final section summarizes our conclusions from the study.

Literature Review

The COVID-19 pandemic was not the first outbreak of a contagious disease in the modern era. In the U.S.A., from cholera in the 1990s to coronavirus in 2019, we have learned the commonalities and differences between various health crises in relation to their causes and consequences. The following four factors are known to influence the spread of disease: characteristics of the pathogen (*11*, *12*); human mobility patterns (*13*, *14*); social networking among the population (*15*, *16*); and quarantine strategies (*17*, *18*). We describe these below.

Adalja et al. (*19*) identified that biological agents with specific characteristics are those that constitute a global catastrophic biological risk. These traits include "efficient human-to-human transmissibility, an appreciable case fatality rate, the absence of an effective or widely available medical countermeasure, an immunologically naïve population, virulence factors enabling immune system evasion, and respiratory mode of spread. Additionally, the ability to transmit during incubation periods and/or the occurrence of mild illnesses would further augment spread" (*19*). The identification of such attributes provides a valid framework for refining pandemic preparedness. COVID-19 has such characteristics; indeed, millions of Americans, led by the State of California (*20*), were asked to stay at home as much as possible in a desperate race to control the virus.

Mobility can especially influence the dynamics of a highly transmissive virus, either via intercommunity or intracommunity travel (*21*); the epicenters of huge infection and mortality tend to be in communities that are close to trade hubs and transportation routes (*22*). Although reducing travel rates has proved to be effective in interrupting disease transmission (*23*, *24*), it is worth noting that quarantine rules may be more or less strict depending on individual local authorities. In such cases, individual spontaneous behavioral changes are more likely to be determined by a person's own perceived risk of infection (*25*), which can play a crucial role in the timing and course of a pandemic (*26*).

Social networks also forge people's perception of a pandemic (*4*, *27*). Sahni and Sharma (*28*) found they played a key role in changing people's behavior in the context of COVID-19. False rumors are associated with misinformation that can have a negative effect on the spread of the virus; however, building public awareness based on experts' advice can correct misconceptions and lead to safe behavior. Yum (*29*) adds that in social networks, key players (e.g., political figures) carried a great deal of responsibility for the progress of COVID-19.

Quarantine strategies during a pandemic can have side effects on the economy and other aspects of daily life. For instance, the advantages of e-commerce platforms are amplified, because of expanded purchasing options with 24/7 availability, as well as perceived safety with a low risk of infection and easy home delivery (*30*, *31*). Fan (*32*) found that the 2003 SARS crisis in Hong Kong contributed to a rise in online shopping as an alternative to in-store shopping. Likewise, because of widespread stay-at-home restrictions during the COVID-19 pandemic, a significant shift toward online shopping has been witnessed in many countries as consumers admitted they felt stressed by in-store shopping (*33–38*). This shift was also confirmed by our collected data as explained later in the Results and Discussion section of this paper.

In this paper, we test the general hypothesis that people reduced their number of visits to the grocery store and increased their online grocery shopping (*33–38*), and investigate the causal factors that might have led to this change. We developed various hypotheses to inform our research as follows:

Age factor: According to the World Health Organization (*39*), older people were challenged by

the "anxiety and fear of illness and death" caused by COVID-19; because of this, we hypothesize that older people would likely reduce their number of visits to the grocery store.

Financial situation: Various businesses were jeopardized by the pandemic (*40*, *41*). Consequently, some people faced a difficult financial situation (e.g., became unemployed, applied for unemployment benefits, or were just genuinely concerned about paying bills). We expect that these people would tend not to increase their online grocery shopping (*42*) because this is usually more expensive than shopping instores (*8*).

Reduction in travel: Martarelli and Wolff (*43*) pointed out that boredom is a motivator for behavioral change that might lead people to ignore social distancing regulations. Bearing this in mind, we believe that people who were used to traveling a lot (for work or other purposes) and were no longer able to do so during the pandemic, would probably not reduce their number of visits to the grocery store as an excuse to escape the stay-at-home boredom. We also hypothesize that people who kept traveling for work during the pandemic would probably keep visiting the grocery store, perhaps because they stop at the store on the way home.

Attitudes with regard to lifestyle, transportation, and the environment: We hypothesize that those who enjoy driving would probably not reduce their number of visits to the grocery store, because it is an excuse to drive. Similarly, we expect that people who like to have an active lifestyle, but who have been forced to be more sedentary during the pandemic, would still go to the grocery store as an excuse to move. Materialistic people, especially those who experience stress from a traumatic event such as COVID-19, are more likely to spend compulsively as a result (*44*); we expect that such people would tend to engage in more online shopping as well as increase their number of visits to the grocery store (purchase more). We also expect a positive correlation between an increase in online shopping of any kind and online grocery shopping. Furthermore, we expect that those who are environmentally conscious, who might be more respectful of rules and more mindful of the effect their behavior has on others, would also be likely to reduce the number of visits they make to the grocery store to help stop the spread of the virus.

Efficiency: Clark (*45*) found that saving time can be a major asset to a busy consumer; we expect that busy parents, whose children were forced to stay at home during the pandemic, would do more online grocery shopping to save time (deliveries are more time efficient).

Neighborhood type: Delivery services are more likely to be less available in rural areas (*46*). We hypothesize that people living in more remote locations would keep going to the grocery store because they do not have good online alternatives.

Health concerns: We expect that the fear of infection led people to reduce their number of visits to the grocery store. The hypothesis is supported by research undertaken by Shamim et al. (*47*), who found that the fear of getting infected by grocery workers and other shoppers at the store was one of the most prominent reasons behind the concerns about grocery shopping.

Grocery shopping habits: Data show that the number of trips to the grocery store went down, and the number of items purchased per visit went up (*35*) because people tended to buy more in bulk (*45*). We expect that during the pandemic people would develop the habit of visiting only one store that sold everything as opposed to a variety of stores (e.g., visit one store for produce and one for household supplies). We also expect they would buy more items per purchase.

Dining out habits: We hypothesize that a reduction in the number of times people dine out results in them eating more at home; thus, people purchase more grocery items (*4*, *27–29*).

Use of media: Studies suggest (*4*, *27–29*) that the use of media platforms has a powerful effect on public awareness and public health behavioral changes in relation to the COVID-19 pandemic. We expect that media might contribute to a reduction in the number of trips to the grocery store. Figure 1 illustrates the conceptual model of this study (where e represents the error term), and Table 1 summarizes its hypotheses.

Data Collection and Sample

We base this study on the analysis of data collected with a survey designed and administered by our research team at the Institute of Transportation Studies at the University of California, Davis to understand the changes in mobility before vs. during the COVID-19 pandemic. In the questionnaire we refer to "before the COVID-19 pandemic" as February 2020 or earlier, and "during the COVID-19 pandemic" as March 2020 or after. The data were collected from March to June 2020 (*48*). Although the full survey project covered 17 metropolitan areas in the U.S. and Canada, this study focuses on the state of California. Specifically, the data used for these analyses were collected in the counties of Alameda, Contra Costa, Marin, San Francisco, San Mateo, Santa Clara, El Dorado, Los Angeles, Orange, Placer, Sacramento, Yolo, and San Diego. Our data collection coincided with the stay-at-home executive order (*2*) for

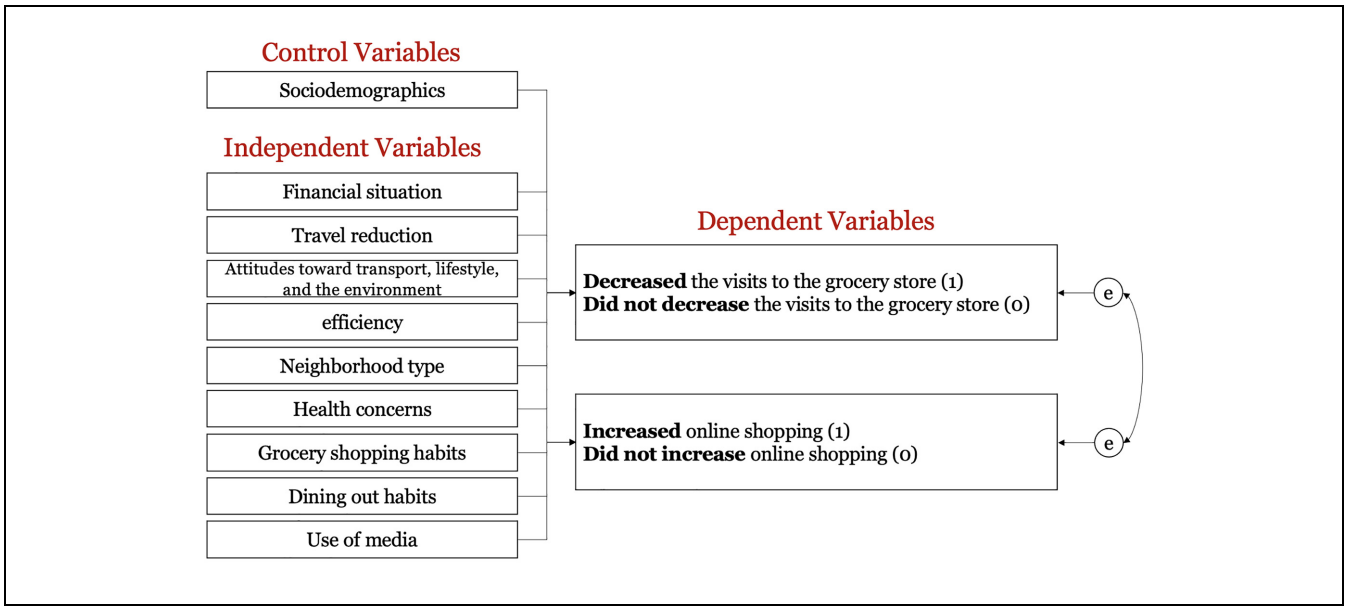

Figure 1. Conceptual model.

Table 1. Summary of Hypotheses

Variable	Hypothesis
Older people	Reduction in the number of in-store visits
Financial situation jeopardized by the pandemic	No increase in online grocery shopping
Having children in the household	Increase in online grocery shopping
Living in rural areas	No reduction in the number of in-store visits
Keep traveling to work during the pandemic	No reduction in the number of in-store visits
Long–distance travel (for work or leisure) reduced by the pandemic	No reduction in the number of in-store visits
Having a consumerist nature	No reduction in the number of in-store visits, and an increase in online grocery shopping
Buying more grocery items per purchase (bulk) as opposed to before the pandemic	Reduction in the number of in-store visits
Visiting fewer stores than before the pandemic (i.e., one single store that sells everything as opposed to a variety of stores [e.g., a store for produce, another one for meat])	Reduction in the number of in-store visits
Less dining out during the pandemic	No reduction in the number of in-store visits, and an increase in online grocery shopping
Enjoying an active lifestyle	No reduction in the number of in-store visits
Conforming to environmentally conscious behavior	Reduction in the number of in-store visits
Driving and car desirability	No reduction in the number of in-store visits
Media use	Reduction in the number of in-store visits, and an increase in online grocery shopping
Health concerns	Reduction in the number of in-store visits

the State of California signed by Governor G. Newsom on March 19, 2020, which stated that "all individuals have to stay at their place of residence in order to disrupt the spread of the novel COVID-19 virus, with the only exceptions for those activities that are considered essential and needed to maintain continuity, or necessities such as accessing food and health care." Indeed, the new registered daily cases in California grew from almost zero to more than 150 in the first 20 days of March 2020, and rapidly reached almost 8,000 new daily cases by the end of June (*49*).

Because of the need to conduct the survey in a relatively short window of time after the beginning of the pandemic, and the inability to recruit a true random sample of the California population through other channels, the online survey was administered through the Qualtrics online opinion panel platform, in addition to the recontact of respondents who already participated in

Table 2. Sociodemographic Characteristics of the Sample (n = 2,948)

	Sample	Population (from the 2019 5-Year American Community Survey Estimates)
Gender		
Female	1,732 (59.2%)	12,905,825 (50.5%)
Male	1,195 (40.8%)	12,670,689 (49.5%)
Race		
White/Caucasian	2,075 (70.4%)	15,154,197 (59.3%)
Non-white/Caucasian	873 (29.6%)	10,422,317 (40.7%)
Ethnicity		
Hispanic	635 (21.5%)	9,139,229 (35.7%)
Non-Hispanic	2,313 (78.5%)	16,437,285 (64.3%)
Age		
Youngest (18–34)	844 (28.6%)	6,357,097 (31.5%)
Middle (35–54)	999 (33.9%)	6,872,590 (34.1%)
Oldest (55 +)	1,105 (37.5%)	6,923,718 (34.4%)
2019 annual household income (before tax)		
Low (< $25,000–$49,999)	895 (30.8%)	2,543,648 (29.1%)
Medium ($50,000–$99,999)	864 (29.7%)	2,309,668 (26.5%)
High ($100,000 +)	1,147 (39.5%)	3,875,746 (44.4%)

previous data collections carried out by the reearch team. The survey contains questions that investigated two timeframes: before COVID-19 (February 2020 or before) and during COVID-19 (March–June 2020). A total of 2,961 respondents who lived in the study area completed the survey. The cleaning process left us with 2,948 complete cases. We acknowledge that the online nature of the survey excludes those who do not own any form of smart technology (phone, laptop, desktop computer, or tablet) and a internet connection to access the online survey. This may limit the representativeness of the analysis with regard to the segments of the population that were still not connected at the time of the data collection, or simply live without information and communication technology.

Table 2 shows the sociodemographic traits of the group of respondents who completed the survey.

Methods

In this study we jointly model the changes in visiting grocery stores and online grocery shopping before vs. during the COVID-19 pandemic as a function of various explanatory variables. The following paragraphs describe the dependent and independent variables used in the model, and the model specification.

Dependent Variables

To study the change in grocery shopping patterns before vs. during the pandemic, we looked at the difference between (a) the change in frequency of in-store trips and (b) the change in frequency of online grocery shopping. First, we converted the original ordinal variables, which measures the frequency of doing each of the two activities before and during the pandemic (i.e., never, less than once per month, …, five or more times a week type of scale), into continuous variables (*50*). The latter measure the approximate number and monthly visits to the grocery store and online grocery purchases, respectively. We then calculated the difference between the frequency (times per month) of visiting the grocery store (FS) and grocery shopping online (FO) during (T_2) and before (T_1) the pandemic. In the given case study, an individual's change in activities can take the following values:

$$\textit{Visiting grocery store} = \left\{ \begin{array}{c} 1\ (\textit{"Decreased"})\ \textit{if}\ FO_{T_2} - FO_{T_1} < 0 \\ 0\ (\textit{"Not decreased"})\ \textit{if}\ FO_{T_2} - FO_{T_1} \geqslant 0 \end{array} \right\}$$

$$\textit{Grocery shopping online} = \left\{ \begin{array}{c} 1\ (\textit{"Increased"})\ \textit{if}\ FS_{T_2} - FS_{T_1} > 0 \\ 0\ (\textit{"Not increased"})\ \textit{if}\ FS_{T_2} - FS_{T_1} \leqslant 0 \end{array} \right\}$$

Table 3 shows the counts and percentages of our response variables. About half of the respondents in our sample (52.7%) reduced the number of visits they made to the grocery store, whereas 30.80% increased their online grocery shopping.

Independent Variables

The study includes whether *having children*, who were forced to stay at home during the pandemic, leads busy

Table 3. Distribution of the Response Variables across the Sample (Count and % or Total) (n = 2,948)

			Grocery shopping online			
			Other (0)		Increased (1)	
	Decreased (1)	Decreased	Decreased 124 (4.2%)	Same 804 (27.3%)	Increased 627 (21.3%)	**Total** *1,555 (52.7%)*
Visiting grocery store	**Other (0)**	Same	79 (2.7%)	902 (30.6%)	235 (8%)	*1,216 (41.2%)*
		Increased	24 (0.8%)	107 (3.6%)	46 (1.6%)	*177 (6%)*
		Total	*227 (7.7%)*	*1,813 (61.5%)*	*908 (30.8%)*	*2,948 (100%)*

parents to change their grocery shopping activity. We investigate whether those who were affected by *unemployment*, applied for *unemployment benefits*, and were *concerned about paying bills* during the pandemic changed their grocery shopping activities. The model includes the *change in grocery shopping habits*, that is, visiting only one store as opposed to a variety of shops and purchasing more items per visit. We investigate whether a reduction in *dining out* had an impact on the style of grocery shopping. The model estimates the effect of *concerns about the health impact of the COVID-19 pandemic*. The study also models the association between the change in *long-distance travel* (for work or leisure) and the change in visiting grocery stores. Our expectation is that people who can no longer travel because of the pandemic would make more frequent trips to the grocery store as an excuse to get out of the house. Following the methodology developed by Makino et al. (*51*), the model includes the *long-distance travel for work or leisure* variables. We classified the sample into three subgroups: let the number of long-distance work and leisure trips (separately) that each respondent made during the whole of 2019 be L_1; and let those made in the first two months of the pandemic (March–April 2020) be L_2. Then, the classification for each respondent is as follows:

$$x = \left\{ \begin{array}{c} 1\ (''\text{Decreased}'')\ if\ L_2 = 0\ OR\ 0.5 < \frac{L_1}{6} - L_2 \\ 2\ (''\text{Same}'')\ if\ -0.5 \leqslant \frac{L_1}{6} - L_2 \leqslant 0.5 \\ 3\ (''\text{Increased}'')\ if\ \frac{L_1}{6} - L_2 < -0.5 \end{array} \right\}$$

Following this approach, we created six independent categorical variables that reflected the change in long-distance trips for work and leisure with three modes: car, air, and other. We also investigated whether *traveling to work during the pandemic* (both essential and non-essential workers) had an effect on visits to the grocery store. This variable was built in two steps: (a) we filtered those who still had a job during the pandemic; and (b) asked them the number of days they traveled to work during the week. We converted this variable into a binary situation in which 1 corresponds to those who (have a job and) travel to work at least once per week, and 0 otherwise. Furthermore, we control for *sociodemographics* such as family income, age, gender, and ethnicity, as well as the type of *neighborhood* respondents live in.

We rely on a contingency table and the Chi-square test to check the correlation of the aforementioned categorical independent variables with the changes in shopping activities (Table 4).

According to the cross-tabulation analysis, the majority of the categorical explanatory variables are significantly associated with at least one of the two change variables (i.e., the p-value of the Chi-square test is below the critical value of 0.05). Although several variables are not associated with the changes in activities according to the Chi-square test, we still tested their inclusion in the model because we are interested in investigating their relationship with the change variables in the context of a causal model.

More on Independent Variables

We also observe the relationship between continuous variables and the changes in grocery shopping activities. We study whether people who tended to do a lot of *online shopping in the past 30 days* (of various types, i.e., clothing, medicines, etc.) also tended to increase their online grocery shopping. We study the association between staying informed about COVID-19 updates through the *media* and the responses given. Several studies have shown the importance of individual attitudes in predicting behavior (*52*). Therefore, we included *individual attitudes*, performing a factor analysis on a set of indicators that measured respondents' agreement with various statements related to transportation, residential location, and lifestyles during the pandemic. We used oblique rotation because we observed that the variables' correlation exceeded 0.32 in the majority of cases, meaning there is a 10% (or more) overlap in variance among them, enough to justify oblique rotation. The correlated variables are found to be linearly related to a smaller number of unobservable (latent) factors that are reported in Table 5. Although Table 5 reports all the latent

Table 4. Relationship between the Changes in Shopping Activities and the Sociodemographic Characteristics and Other Independent Variables (n = 2,948)

	In-person visits to the grocery store			Online grocery shopping		
	Cross-tabulation (column-wise)		χ^2 test	Cross-tabulation (column-wise)		χ^2 test
	Decrease	No decrease	p-value*	Increase	No increase	p-value*
Gender			**0.000**			0.931
Female	964	768		531	1201	
Male	617	578		369	826	
Race			**0.019**			**0.017**
White/Caucasian	1,124	951		667	1,408	
Non-white/Caucasian	431	442		241	632	
Ethnicity			0.910			0.555
Hispanic	335	300		189	446	
Non-Hispanic	1,220	1,093		719	1,594	
Age			0.216			**0.008**
Youngest (18–34)	432	412		257	587	
Middle (35–54)	549	450		342	657	
Oldest (55 +)	574	531		309	796	
2019 annual household income (before tax)			0.055			**0.000**
Lower (< $25,000–$49,999)	443	452		218	677	
Middle ($50,000–$99,999)	466	398		307	557	
Higher ($100,000 +)	626	521		369	778	
Presence of children in the household			0.189			**0.000**
Do not have children	1,057	979		1,459	577	
Have children	498	414		331	581	
Neighborhood type			0.066			0.339
Urban part of a city/region	548	546		330	764	
Suburban part of a city/region	840	696		489	1,047	
Rural area and small town	167	151		89	229	
(Have a job and) travel to work status			**0.003**			**0.004**
Travel to work during the pandemic	795	788		524	1,059	
Do not travel to work during the pandemic	760	605		384	981	
Pandemic unemployment benefits			0.934			**0.004**
Applied	273	242		131	384	
Not applied	1,282	1,151		777	1,656	
No. of grocery stores visited during the pandemic			**0.000**			0.361
Fewer (only one grocery store as opposed to many)	677	454		360	771	
Other (no change or increase)	878	939		548	1,269	
No. of grocery items bought during the pandemic			**0.000**			**0.000**
More items per visit	945	608		552	1,001	
Other (no change or less)	610	785		356	1,039	
Dining out			**0.000**			**0.000**
Decreased	1,418	1,016		805	1,629	
Other (no change or increase)	137	377		103	411	
Concern about the health impact of the pandemic			**0.000**			**0.000**
Agree	1,413	1,141		830	1,724	
Neutral	78	125		40	163	
Disagree	64	127		38	153	
Long-distance trips by car: work/business			**0.005**			0.441
Fewer	1,457	1,263		834	1,886	
Other (no change or increase)	89	117		69	137	
Long-distance trips by air: work/business			0.306			0.986
Fewer	1,495	1,313		869	1,939	
Other (no change or increase)	45	50		30	65	
Long-distance trips by other: work/business			**0.001**			0.760
Fewer	1,507	1,303		867	1,943	
Other (no change or increase)	17	40		16	41	
Long-distance trips by car: leisure			0.069			0.064
Fewer	1,294	1,117		727	1,684	
Other (no change or increase)	248	257		174	331	
Long-distance trips by air: Leisure			**0.013**			0.491

(continued)

Table 4. (continued)

	In-person visits to the grocery store			Online grocery shopping		
	Cross-tabulation (column-wise)		χ^2 test	Cross-tabulation (column-wise)		χ^2 test
	Decrease	No decrease	*p*-value*	Increase	No increase	*p*-value*
Fewer	1,443	1,250		843	1,850	
Other (no change or increase)	70	92		46	116	
Long-distance trips by other: Leisure			**0.002**			0.473
Less	1,457	1,264		844	1,877	
Other (no change or increase)	28	51		21	58	
Concern about paying bills during the pandemic			0.918			0.400
Worried	639	572		387	824	
Not worried	872	782		503	1,151	
Lost job during the pandemic			0.274			0.510
Yes	139	108		71	176	
No	1,416	1,285		837	1,864	

*Values in bold are significant at 0.05 level.

factors, in the final model specification, we include only those that theoretically support our hypotheses of association of the changes in shopping activity with the following dimensions:

- Active lifestyle desirability: people who like to have an active lifestyle;
- Material and new things desirability: people who like to have the latest, new, and different things; and
- Environmental consciousness desirability: people who follow environmentally friendly rules.

Table 6 shows the association between the changes in shopping activity and the aforementioned continuous variables based on the analysis of variance (ANOVA) test. *Urban dense neighborhood desirability* and *driving desirability* are not statistically significantly correlated to any of the response variables.

We checked for potential multicollinearity between pairs of independent variables using the one-way ANOVA between continuous and categorical variables, the Chi-square test between categorical variables, and a Pearson correlation analysis between continuous variables. Although we found some dependencies across the explanatory variables, to ensure that potential multicollinearity issues do not affect the model coefficient estimates (the risk being they would change erratically in response to small changes in the model), we ran the model (described in the next section) with and without the correlated independent variables. We registered that these variables do not substantially affect (i.e. they do not cause instability in) the model's magnitude and sign of the coefficients.

Model Specification

We test the general hypothesis that (certain groups of) people reduced their number of visits to the grocery store and increased their online grocery shopping during the pandemic. Each of the dependent variables tests a dichotomous situation, that is, for the "physical visits to the grocery store" we are testing if the number of visits decreased (1) as opposed to did not decrease (0), and for "online grocery" we test if this type of shopping increased (1) as opposed to did not increase (0). We also select the binary form to define these variables as a simple way of measuring the "change" and to avoid having small group sizes for more disaggregate categories for the changes in the frequency with which people shop for groceries. We estimate the models jointly for the two outcomes because we hypothesize that they are correlated. Such a hypothesis may lead to endogeneity bias in a model, meaning that the unobserved factors affecting the visits to the grocery store may also affect the frequency with which online grocery shopping is carried out. This may lead to over/under estimation of our estimates. To address the endogeneity problem, we use a bivariate binary probit model, which is a joint model with two binary outcome variables that are interrelated, as opposed to independent.

For each individual i, the two dependent variables are the change in visits to the grocery store ($y_{i,1}$) and the change in online grocery shopping ($y_{i,2}$). For estimating the bivariate model, two latent variables are defined: y^*_{i1}, y^*_{i2}. The latent variables follow a bivariate normal distribution and are modeled as functions of sets of explanatory variables, which can vary across components and are modeled simultaneously (Equations 1 and 2). β_1 and β_2 are the set coefficients to be estimated, and the errors

Table 5. Factors and their Strongly Loading (> 0.30) Attitudinal Statements

Factors and strongly associated attitudinal statements	Loadings
Environmental consciousness desirability	
We should raise the price of gasoline to provide funding for better public transportation.	0.99
We should raise the price of gasoline to reduce the negative impact of transportation on the environment.	0.61
Active lifestyle desirability	
I like walking.	0.84
Getting regular exercise is very important to me.	0.74
I like riding a bike.	0.34
No alternative to car lifestyle	
My schedule makes it hard or impossible for me to use public transportation.	0.51
Most of the time, I have no reasonable alternative to driving.	0.81
I am too busy to do many things I would like to do.	0.41
Car and driving desirability	
I like driving a car.	0.99
I prefer to be a driver rather than a passenger.	0.54
I want to own a car.	0.35
Urban dense neighborhood desirability	
I like the idea of using public transit as transportation.	0.84
I prefer to live in a spacious home, even if it is farther from public transportation and many places I go to.	−0.30
I like the idea of having stores, restaurants, and offices mixed among the homes in my neighborhood.	0.37
Material and new things desirability	
I like to be among the first people to have the latest technology.	0.90
I will stretch my budget to buy something new and exciting.	0.56
I like trying things that are new and different.	0.35
Having Wi-Fi and/or good Internet access on my mobile phone everywhere I go is essential to me.	0.36
Utilitarian personality	
I always go for the low-priced options.	0.43
I am still trying to decide on my career (e.g., what I want to do, where I will end up).	0.73
I am generally satisfied with my life.	−0.31

terms , $\varepsilon_{i,1}$ and $\varepsilon_{i,2}$, are assumed to be correlated by ρ coefficient and to follow a normal distribution.

$$y^*_{i,1} = x_{i,1}'\beta_1 + \varepsilon_{i,1} \quad (1)$$

$$y^*_{i,2} = x_{i,2}'\beta_2 + \varepsilon_{i,2} \quad (2)$$

The bivariate probit model specifies the outcomes as in Equations 3 and 4, which show how the observed dependent variables are linked with the latent variables and take on the value 1 if the underlying latent variable takes on a value that is positive, and 0 otherwise:

$$y_{i,1} = \begin{cases} (1)\ \textit{"Decreased in store grocery shopping" if } y^*_{i,1} \geqslant 0, \\ (0)\ \textit{otherwise} \end{cases} \quad (3)$$

$$y_{i,2} = \begin{cases} (1)\ \textit{"Increased online grocery shopping" if } y^*_{i,2} \geqslant 0, \\ (0)\ \textit{otherwise} \end{cases} \quad (4)$$

To set up the bivariate probit model, based on Equations 1 to 4, we need to consider the following four joint probabilities (*53*):

$$\begin{aligned} P_{1,1} &= \Pr[y_{i1} = 1,\ y_{i2} = 1] = \int_{-\infty}^{x_{i1}'\beta_1}\int_{-\infty}^{x_{i2}'\beta_2} \phi_2(z_1, z_2, \rho)dz_1dz_2 \\ P_{1,0} &= \Pr[y_{i1} = 1,\ y_{i2} = 0] = \int_{-\infty}^{x_{i1}'\beta_1}\int_{x_{i2}'\beta_2}^{\infty} \phi_2(z_1, z_2, \rho)dz_1dz_2 \\ P_{0,1} &= \Pr[y_{i1} = 0,\ y_{i2} = 1] = \int_{x_{i1}'\beta_1}^{\infty}\int_{-\infty}^{x_{i2}'\beta_2} \phi_2(z_1, z_2, \rho)dz_1dz_2 \\ P_{0,0} &= \Pr[y_{i1} = 0,\ y_{i2} = 0] = \int_{x_{i1}'\beta_1}^{\infty}\int_{x_{i2}'\beta_2}^{\infty} \phi_2(z_1, z_2, \rho)dz_1dz_2 \end{aligned} \quad (5)$$

where the $\phi_2(z_1, z_2, \rho)$ is the bivariate normal density function. Then, fitting the bivariate probit model involves estimating the log-likelihood function as follows (Giles [*53*]):

$$\textit{Define}:\ q_{i1} = 2y_{i1} - 1 \text{ and } q_{i2} = 2y_{i2} - 1$$

$$\textit{Define}:\ z_{ij} = x_{ij}'\beta \text{ and } w_{ij} = q_{ij}z_{ij}; j = 1, 2$$

$$\textit{Define}:\ \rho^*_i = q_{i1}\ q_{i2}\rho$$

$$Pr[Y_1 = y_{i1};\ Y_2 = y_{i2}] = \phi_2\left(w_{i1}, w_{i2}, \rho^*_i\right) \quad (6)$$

$$logL = \sum\nolimits_{i=1}^{n} \log \phi_2\left(w_{i1}, w_{i2}, \rho^*_i\right) \quad (7)$$

We began our statistical modeling using all variables reported earlier in this section. Those variables that were not statistically significant at the 95% level or higher, or lacked practical implications and interpretability, were omitted from the final model, the latter to avoid including variables in the model specification that are only associated because of spurious correlations and do not have a true relationship with the dependent variables.

Results and Discussion

In this section we review the results from modeling the changes in grocery store trips and online grocery shopping according to the independent variables described above. The results are shown in Table 7, whose columns indicate the independent variables, estimated coefficient, and associated *p*-value.

It should be recalled that the model outcome variables are the change in the number of trips to the grocery store

Table 6. Relationships between the Changes in Shopping Activity and the Continuous Independent Variables (n = 2,948)

	In-person visits to the grocery store (ANOVA test *p-value)	Online grocery shopping (ANOVA test *p-value)
No. of online purchases in the past 30 days	0.089	**0.000**
Miles driven in a week	**0.000**	0.054
Urban dense neighborhood desirability	0.542	0.166
No alternative to car lifestyle	0.369	0.233
Material and new things desirability	0.665	**0.000**
Car and driving desirability	0.105	0.248
Active lifestyle desirability	0.105	**0.002**
Utilitarian personality	0.084	0.172
Environmental consciousness desirability	**0.000**	**0.002**
Staying updated with regard to COVID-19	**0.001**	**0.000**
Use of social media	**0.000**	**0.000**

Note: ANOVA = analysis of variance.
*p-values in bold are significant at 0.05 level.

(decreased or no decrease) and the change in online grocery shopping (increased and no increase). We used a no decrease (value of 0) in grocery store trips and a no increase (value of 0) in online grocery shopping as the base cases, and all coefficient estimates are compared with these. We started our modeling process with testing the inclusion of all the independent variables from Tables 4 and 6. We estimated several models, and the results in Table 7 indicate the independent variables that are significant for the change in number of trips to the grocery store and/or for the change in the frequency of online grocery shopping. The final model was estimated on 2,948 observations and has a McFadden's pseudo R^2 value of 0.078. The final model has a correlation coefficient (ρ) significantly different from zero, showing there is a correlation coefficient between the residuals of each of the two probit equations. The positive correlation suggests (and confirms our hypothesis) that the remaining impacts of the unobserved variables are associated with both a reduction in the frequency with which respondents shopped in stores and an increase in the frequency with which they shopped online.

In this section we interpret the results and relate them to our initial hypotheses. We also explain other findings from the final model. We found evidence to confirm the hypothesis that people who still traveled to work during the pandemic were less likely to reduce their number of visits to the grocery store. This is intuitive, because these people might be linking trips away from home in one chain that includes going to the grocery store. Therefore, if people kept traveling to work, this may also have caused them to stop at the grocery store on their way there or back. Similarly, we find that people who like to drive are associated with visiting the grocery store despite the pandemic. These findings are supported by the work of Martarelli and Wolff (*43*), who pointed out that boredom can be a motivator for people to keep visiting the grocery store as an escape from spending longer more time at home, and the trip to the shop provides an opportunity to ignore social distancing rules. Martarelli and Wolff's (*43*) point may support our other finding that people who enjoy an active lifestyle are less likely to reduce their number of trips to the grocery store. Perhaps this is a form of entertainment during lockdown and also a reaction to the travel restrictions imposed during the pandemic. We find an association between the inclination to do a lot of online shopping of various kinds (clothing, medicines, etc.) and an increase in online grocery shopping. As suggested by Ruvio and Somer (*44*), if individuals who have a consumerist nature experience stress from a traumatic event (e.g., a pandemic), they are more likely to spend compulsively as a result. Based on the work of several other authors (*4*, *27–29*), we found evidence to support our hypothesis that the use of media platforms has a powerful effect on awareness of the pandemic and the resulting public behavior; our data show that people who use media more frequently tend to reduce their number of visits to the grocery store and increase their online shopping. Those who made the transition are perhaps the most tech savvy. Our findings support the hypothesis that those who applied for unemployment benefits are less likely to increase their online grocery shopping. The reason for this could be that online shopping tends to be costlier, as also indicated by Shamshiripour et al. (*8*).

A study by Shamim et al. (*47*) found that people's perception of the risk of infection influences activities and the results support our similar hypothesis. Accordingly, in our model we find that people who reported they were concerned about the health impact of the pandemic were

Table 7. Bivariate Binary Probit Model Results (n = 2,948)

	Reduction in number of in-person visits to the grocery store		Increase in online grocery shopping	
	Coefficient	p-value*	Coefficient	p-value*
Sociodemographics				
Race (reference: White/Caucasian)				
Non-white/Caucasian	−0.147	**	−0.141	*
2019 annual household income (before tax) (reference: Higher)				
Low (< $25,000–$49,999)	—	—	−0.066	ns
Middle ($50,000–$99,999)	—	—	0.176	**
Individual specific variables				
(Have a job and) travel to work during pandemic (reference: No)				
Yes	−0.181	***	—	—
Applied for pandemic unemployment benefits (reference: Not applied)				
Applied	—	—	−0.227	***
Fewer grocery stores visited during the pandemic as opposed to during normal life (reference: Same or more)				
Fewer (tend to visit only one grocery store as opposed to many before the pandemic)	0.271	***	—	—
More grocery items bought per time during the pandemic as opposed to before the pandemic (reference: Same or fewer)				
More items per visit as opposed to before pandemic	0.337	***	0.212	***
Dining out before and during the pandemic (reference: No change or not increased)				
Decreased	0.770	***	0.324	***
Concern about the health impact of the pandemic (reference: Disagree)				
Agree	0.411	***	0.330	**
Neutral	0.253	ns	—	—
No. of online purchases (of any kind) in the past 30 days	—	—	0.009	***
Material and new things desirability	—	—	0.024	—
Car and driving desirability	−0.032	**	—	—
Active lifestyle desirability	−0.011	ns	—	—
Use of social media	0.014	***	0.014	***
Log-likelihood (null model)	−3787.846			
Log-likelihood (final model)	−3490.221			
ρ^2 (McFadden test)	0.0785			
ρ (correlation coefficient between the two equations)	0.29 (p-value = 0.000)			

— variables are not included in the final model specification.

*p-value critical level = 0.05.

***$p \leq 0.001$; **$p \leq 0.01$; *$p \leq 0.05$; '.'p=0.05; ns = significant.

more likely to reduce the number of in-person visits to the grocery store and more likely to increase their online grocery shopping than those who were not concerned. People who were worried might well have felt inhibited by stay-at-home orders and been very inclined to follow social distancing rules. Our findings confirm the hypothesis that people made fewer trips to the grocery store during the pandemic (*35*). We found that people who visited one store as opposed to a variety (i.e., visiting one store that sold everything rather than visiting one store for produce and another for household supplies, etc.) were more likely to reduce the number of in-person trips to the grocery store. Our research also highlighted that people who purchased more items per visit (as opposed to before the pandemic) were more likely to increase their online grocery shopping. It also confirms results from Severson (*35*) and Clark (*45*), who found that the number of items purchased per visit increased and people tended to buy more in bulk. During the pandemic many restaurants closed, so a lot of people who would normally have dined out at restaurants opted to eat at home and hone their culinary skills (although they might also have used take-away services). As supported by U.S. Department of Agriculture data (*54*), which indicate that consumers increased their expenditure on groceries while reducing the amount they spent on dining out, we found that those who dined out less during the pandemic were more likely to increase their online grocery shopping and reduce the number of visits they make to the grocery store, this latter perhaps in respect of stay-at-home rules.

In addition, we found some other correlations with our responses: non-white Caucasians, who represent the minority in our sample, were less likely to increase their online grocery shopping compared with white Caucasians. We found that although in absolute terms higher-income people increased their online shopping more than middle-income people, the latter group increased their shopping frequency (multiple times per week as opposed to monthly) more than the former. Thus, people in the middle income group are found to be more associated with online grocery shopping than people who have a higher income. On the contrary, lower-income people are found to be less associated with online shopping than higher-income people (although this was not statistically significant in the model).

To ensure we do not run into an endogeneity problem, we ran the model without three variables that might lead to some reversed causality issues: *Dine out; Fewer grocery stores visited during the pandemic*; and *More grocery items bought per visit during the pandemic*. Results did not show any noticeable differences (instability) in the other coefficients in terms of their magnitude and sign. We deduce that our model is not particularly affected by endogeneity issues and the presence of these variables in the model is not of great concern.

Conclusion

Delivery companies and grocery businesses have been affected in a very significant way since all of the lockdowns started and restrictions meant many consumers were forced to shop online. This study has investigated this topic through the analysis of survey data collected in California during the first wave of the pandemic in spring 2020. Our research, which estimates a bivariate model of changes in the frequency of physical trips to the grocery store and the frequency of online grocery shopping, provides an exploration of who adjusted their grocery shopping patterns during the early stage of the pandemic and what factors affected the changes in these habits.

One of the big questions associated with the impacts of the pandemic on society is whether new e-commerce habits that were established during the pandemic might carry on once life goes back to "normal." Some new e-customers could go back to shopping in person; others might prefer to continue shopping online. Although it is not for us to draw such conclusions based on data collected in the first phase of the pandemic, understanding the factors that affected the changes in grocery shopping behavior during the COVID-19 pandemic is crucial for business development and vital for public entities so they can better tackle crisis situations that cause high stress to large segments of the population.

We suggest that grocery stores pay attention to their distribution channels and stock levels, because people who developed the habit of purchasing in bulk and/or visiting one store that sold everything rather than go to multiple stores (e.g., visit one store for produce, one for meat) during the pandemic might not go back to their old routines. Market research could help investigate these aspects and address the problem of demand volatility. We found certain groups of people were more interested in switching to online grocery shopping, and these could be targeted to expand the online grocery marketplace. These groups include higher- and middle-income individuals and the segment of the population that tends to be more consumeristic, that is, people who are very active in purchasing any kind of goods online. It would probably be easy to interest such groups in newer forms of business or delivery apps because it is more likely they will end up shopping online.

Grocery stores should keep attracting commuters driving to and from work as well as those who will take any opportunity (including trips to buy groceries) to drive (because they love driving) or to be physically active, because these groups were found to be less likely to reduce the number of in-person visits to the grocery store. As society exits the pandemic, grocery stores should advertise among these groups to help shoppers who were found to reduce their number of in-person visits to the grocery store to regain confidence. On the other hand, those who were concerned about their health could also be the right people to target in marketing campaigns of online retailers to encourage people to stay with online grocery shopping. We also identified that people who frequently used media platforms to stay informed about the COVID-19 pandemic tended to reduce their number of visits to the grocery store and increase their online shopping. This finding can inform the work of public institutions so that in an eventual new state of emergency such as a pandemic they can establish rules that would make it mandatory for the media to raise public awareness based on experts' advice; as a result, misconceptions would be corrected, leading to safer public behaviors to help control the situation.

We acknowledge that this study has some limitations. For example, a tiny proportion of the individuals in our sample do not own a smart device such as a phone, laptop, desktop computer, or tablet. This may limit the representativeness of the analysis with regard to those who are were not "connected" at the time of data collection, or simply live without information and communication technology. Our model describes the change in grocery shopping habits in California; we acknowledge that the results may vary in other states that are different from a sociodemographic and economic perspective. We also recognize that this

study is based on the analysis of data collected during the first wave of the pandemic; the findings could be different if a similar analyses was replicated using data from later phases of the pandemic. Furthermore, the reader should bear in mind that knowledge about online grocery shopping has perhaps increased because of the circumstances of the pandemic and not necessarily because people prefer to shop for groceries online rather than visit stores in person. For this reason, it would be important for a future study to examine the effect of changes in grocery shopping habits based on longitudinal data collected in later phases of the pandemic to understand how consumer behaviors evolved (as we plan to do in later stages of related research). Such a longitudinal approach would create a stronger foundation on which to base a study of how consumers may behave in the future. The study could also be enriched with other data that have a more qualitative approach and collected, for example, through in-depth interviews or focus groups. These would allow us to shed more light on our findings. Such a project would help obtain a better understanding of human behavior during emergency situations such as a future pandemic that could lead to further lockdowns.

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Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: G. Circella, J. Compostella, K. Wang, X. Iogansen; data collection: G. Circella, J. Compostella, K. Wang, X. Iogansen; analysis and interpretation of results: J. Compostella, K. Wang, X. Iogansen; draft manuscript preparation: J. Compostella, K. Wang, X. Iogansen. All authors reviewed the results and approved the final version of the manuscript.

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