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Grocery Shopping Preferences during the COVID-19 Pandemic

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Abstract: Considering the temporary closure of many food-away-from-home establishments, consumer expenditure on groceries during the COVID-19 pandemic has increased. While grocery shopping is an essential activity, not much is known about the dynamic relationship of the COVID-19 pandemic to the behavior of grocery shoppers. With an objective to inform variability in the behavior of grocery shoppers under various scenarios of the COVID-19 pandemic, we conducted an online framed choice experiment to elicit preferences for purchasing methods, time windows, minimum order requirements, and fees. The manipulating factor relates to the trend in the COVID-19 pandemic, where we consider three scenarios: an increasing, decreasing, or constant number of new cases in the past two-week period. Using 32,400 choice decisions from a representative sample of 900 grocery shoppers in the United States, we conclude that the trend in the COVID-19 pandemic causes significant differences in grocery shopping preferences. In situations where COVID-19 is spreading at an increasing rate, consumers are generally less willing to shop inside the grocery store. When COVID-19 is spreading at a decreasing rate, the relative importance of the purchasing method attribute is lower in its entirety. We use our findings to inform recommendations for practitioners and policymakers.

Keywords: consumer behavior; coronavirus; COVID-19; food consumption; online shopping; choice experiment

1. Introduction

The novel coronavirus disease (COVID-19) has impacted the daily life of many people. In an attempt to limit the spread of COVID-19, individuals have changed how and how much they produce and consume. According to data on household consumption in the United States, expenses on air travel, grocery delivery, public transit, and other categories changed substantially from week to week during the early stage of the COVID-19 pandemic [1].

Next to the health care industry, the food industry is arguably the most affected by the pandemic [2]. In the United States, where 54% of food is consumed away from home under normal circumstances (U.S. Department of Agriculture-Economic Research Service), most eating establishments have been mandated by the government to close temporarily. However, even during the pandemic, groceries are still basic human necessities. In fact, consumer expenditure on groceries is on the rise in every type of grocery store [3]. By far the largest increase in consumer expenditure on groceries has been experienced by online retailers. In the United States, the usual market share of online retailers is about 3–4%, but has increased to 10–15% during the COVID-19 pandemic [4]. While grocery deliverers have also reported an increase in demand [5], supply and demand imbalances pose challenges to the sector [6].

Considering the foregoing, we conducted an online choice experiment to elicit grocery shopping preferences during the COVID-19 pandemic. Similar to Everett et al. [7] and Lunn et al. [8], we vary information of the COVID-19 pandemic to study dynamic consumer behavior. With a representative sample of 900 grocery shoppers from the United States, our objective is to elicit preferences for four grocery shopping attributes (i.e., purchasing methods, time windows, minimum order requirements, and fees) under various scenarios of the COVID-19 pandemic. We aim to answer the following research question: Are there significant differences in consumer preferences for grocery shopping attributes when the number of new COVID-19 cases is increasing, constant, or decreasing? The trend in the number of new COVID-19 cases may affect consumer behavior, as there is risk of contamination in case of physical proximity with other people. Consumers may use information on the number of new COVID-19 cases to help make decisions. Our study relates to the literature on online grocery shopping, which emerged in the late 1990s and early 2000s (e.g., [9]). More recent studies have explored the role of online grocery shopping attributes on purchasing behavior, including delivery costs [10–12], delivery times [13–15], and minimum order thresholds [16]. However, no empirical study has considered the four grocery shopping attributes at the same time. In addition, to our knowledge, the literature on the impact of an epidemic outbreak on grocery shopping preferences is limited to two relevant publications, one relating to the Middle East respiratory syndrome (MERS) in South Korea [17], and the other to COVID-19 [18]. While finding a significant impact of the two outbreaks on consumer behavior and expenditure, neither study considered the roles of purchasing methods, time windows, minimum order requirements, and fees. We thus contribute to the scarce literature with evidence of consumer preferences for these grocery shopping attributes under various scenarios of the COVID-19 pandemic. Our novel findings inform numerous recommendations for academics, practitioners, and policymakers during the COVID-19 pandemic.

2. Experimental Design and Procedure

The discrete choice experiment method is the go-to non-market valuation tool for food and drink product attributes [19]. The general objective of the choice experiment method is to elicit stated preferences for products with certain combinations of attributes. The method facilitates the ability to measure the willingness to substitute one attribute for another attribute. If price is included as an attribute in the choice design, it is possible to measure how much an attribute is worth (i.e., willingness to pay).

We used a framed choice experiment to explore potential variability in grocery shopping behavior under various scenarios of the COVID-19 pandemic. The experiment consists of a between-subject design, where the trend in the number of new COVID-19 cases is the manipulating factor. Respondents were randomly assigned to one of three scenarios: (1) The average number of new cases of COVID-19 in the past 14 days has increased, (2) the average number of new cases of COVID-19 in the past 14 days has remained constant, or (3) the average number of new cases of COVID-19 in the past 14 days has decreased. Our framed approach is intended to reflect reality as the average number of new cases is increasing in 18 states, decreasing in 15 states, and more or less constant in the other 17 states at the moment of the study. In addition, the framed approach is intended to consider the dynamic character of the COVID-19 pandemic as the average number of new cases changes on a daily basis.

Considering the recent literature on online shopping [14,20,21], we include the following four product attributes with their levels:

- **Purchasing Method**. Generally, there are three substitutes to self-service grocery shopping inside the store. (*1*) In-store pick-up: The customer goes inside the store and collects the ordered groceries. (*2*) Curbside pick-up: The customer waits inside his/her vehicle outside the store and somebody else places the ordered groceries in the vehicle. (*3*) Home delivery: Somebody delivers the ordered groceries to the home of the customer.
- **Time Window**. When placing an online order, customers may pick or indicate a favored time window to either collect or receive the groceries. Based on information from such vendors as

Walmart, Instacart, and Shipt, we considered four levels: (*1*) Less than 4 h, (*2*) between 4 and 12 h, (*3*) between 12 and 24 h, and (*4*) more than 24 h.

- **Minimum order requirement**. Online customers may need to meet a minimum order requirement to make transactions. Again, based on information from such vendors as Walmart, Instacart, and Shipt, we considered five levels: (*1*) $10, (*2*) $20, (*3*) $30, (*4*) $40, and (*5*) $50.
- **Fee**. If the purchasing method is in-store pick-up or curbside pick-up, the four levels are: (*1*) $0.00, (*2*) $2.50, (*3*) $5.00, and (*4*) $7.50. If the purchasing method is home delivery, the four levels are: (*1*) $7.50, (*2*) $10.00, (*3*) $12.50, and (*4*) $15.00.

Considering all product attributes and attribute levels, the full factorial design is composed of 240 (3*4*5*4) unique product profiles. Following [22], we first built a fractional factorial design with 120 of the 240 unique product profiles. When including two product profiles per choice scenario, we had a design with 60 choice scenarios. The D-efficiency score is 99.57. A blocked design was implemented to avoid respondent fatigue while minimizing the loss of statistical power. We built 10 blocks of six choice scenarios each. We used randomization to assign respondents to two of the 10 blocks (i.e., 12 choice scenarios per respondent).

We recruited 900 respondents from Amazon's Mechanical Turk (MTurk). MTurk is an online platform where researchers and respondents come together. Across academic disciplines, MTurk samples are found to be robust alternatives to other common samples used by researchers [23–25]. To qualify for the study, subjects needed to be 18 years of age or above and identify themselves as the primary grocery shopper of their household. The experiment began with a brief introduction and explanation of the choice experiment. We followed the literature and included a cheap talk script to help mitigate hypothetical bias in our results by encouraging respondents to answer honestly to the choice scenarios [26]. After the cheap talk script, respondents received up-to-date information about the COVID-19 pandemic, including the treatment scenario in terms of the average number of new cases in their state (i.e., increasing, constant, decreasing). We then asked respondents to imagine the next time to get their groceries while responding to the twelve choice scenarios. In each choice scenario, we asked respondents to choose between three profiles with varying attributes (see Table 1). Following the choice experiment, we elicited socio-demographic characteristics through a self-reported survey.

Table 1. Example of a choice scenario.

Attribute	Option 1	Option 2	Option 3
Purchasing Method	Home Delivery	In-Store Pick-Up	In-Store Purchase
Minimum Order	$40	$10	—
Time Window	12–24 h	4–12 h	—
Fee	$12.50	$5.00	—
Which option do you prefer?	○	○	○

3. Theoretical and Empirical Model

The theoretical framework of the choice experiment is random utility theory [27]. According to random utility theory, the utility associated with the consumption of a good is determined by its individual attributes $k = \{k_1, \ldots, k_j\}$. The utility function of a rational individual $i = \{i_1, \ldots, i_n\}$ is composed of a deterministic component V_{ijs} and a stochastic component ε_{ijs}, as in

$$U_{ijs} = V_{ijs} + \varepsilon_{ijs}. \quad (1)$$

Then, given a budget constraint, individual i is assumed to choose the set of attributes which maximizes his/her utility. Let

$$U_{ijs} = \sum_{s=1}^{S} \beta' x_{ijs} + \varepsilon_{ijs} \quad (2)$$

represent the utility derived by individual i from alternative j in choice scenario s, $xijs$ is the attribute of alternative j, β is the utility parameter associated with attribute k, and ε_{ijs} is the stochastic term, which is independently and identically distributed and follows a type I distribution to facilitate the derivation of a multinomial logit model. Rational individual i is expected to choose alternative j in choice scenario $S_i = \{s_1, \ldots, s_S\}$ as opposed to alternative m if $U_{ijs} > U_{ims}$, which, in terms of probability, is expressed as

$$P_{ijs} = \Pr(V_{ijs} + \varepsilon_{ijs} \geq V_{ims} + \varepsilon_{ims}; \forall j \neq k \in S_i. \quad (3)$$

The probability of individual i choosing alternative j in choice scenario s can be estimated by means of a conditional logit model [28], which is an extension of the multinomial logit model, as in

$$P_{ijs} = e\left[V_{ijs}\right] \Big/ \sum_{s\,=\,1}^{S} e[V_{ims}], \quad (4)$$

which is estimated using the maximum likelihood method.

While binary coding is the conventional approach with choice experiment data, we use effect coding to facilitate robust estimation and interpretation of all the attributes and their levels [29,30]. With binary coding, reference level l of attribute k is excluded in order to avoid perfect collinearity. By extension, the utility of reference level l of attribute k is captured intrinsically by the intercept term. It is therefore impossible to estimate the reference level or interpret the intercept term. Effect coding facilitates a solution by coding the reference level as −1 instead of 0. Non-reference level l of attribute k is coded as 1 if the level is present, as −1 if the reference level is present, and as 0 otherwise. Consequently, the sum of the coefficients across all levels of an attribute is zero. Thus, while the coefficient of the omitted reference level is constrained to zero with binary coding, with effect coding, it is recovered by calculating the negative of the sum of the coefficients of the non-omitted levels. Then, the intercept term only captures the utility associated with the opt-out alternative. In addition, with binary coding, the p-value indicates if the coefficient is significantly different from the reference level. With effect coding, however, the p-value indicates if the coefficient is significantly different from zero, which is the mean effect of each product attribute.

4. Sample Characteristics

A total of 900 consumers (52% male) participated in the online choice experiment. Table 2 shows a summary of the demographic characteristics of the participants along with a balance check across treatments. Participants ranged in age from 18 to 77, with an average age of 37 years and an average income of approximately $59,000. By comparison, the median age and income for the U.S. population are approximately 38 and $63,000, respectively (U.S. Census Bureau). Overall, the sample is highly educated, as 65% of the respondents possessed at least a four-year college degree. In spite of rising unemployment during the COVID-19 pandemic, only 8% of the respondents reported to have no employment. Approximately one third of our respondents identified as non-Caucasian. In terms of location, our respondents came from 48 of the 50 states in the United States and predominantly lived in urban environments. Altogether, the demographic characteristics of our respondents compare reasonably to the demographic characteristics of the overall U.S. population (U.S. Census Bureau). When comparing the demographic characteristics of the respondents across treatments, we find no significant differences in terms of gender, age, household size, geographic location, education, income, and employment ($p > 0.10$ in all X^2 tests). Due to proper randomization, the sample appears to be balanced across treatments, allowing us to compare the grocery shopping behavior of the respondents under the various scenarios of the COVID-19 pandemic.

Table 2. Demographic characteristics of sample respondents (mean values).

Characteristic	Sample (N = 900)	Treatment 1 (N = 299)	Treatment 2 (N = 299)	Treatment 3 (N = 302)	*p*-Value *
Male	0.52	0.53	0.52	0.50	0.783
Age	37.49	37.61	38.21	36.67	0.240 †
Income (×1000)	59.12	56.89	61.27	59.19	0.294 †
Household Size	3.14	3.22	3.03	3.17	0.375 †
Geographic Region					
Northeast	0.20	0.19	0.17	0.22	0.322
South	0.34	0.35	0.36	0.30	0.265
West	0.29	0.27	0.30	0.32	0.396
Midwest	0.17	0.19	0.16	0.16	0.491
Residential Area					
Urban	0.85	0.85	0.85	0.86	0.901
Rural	0.15	0.15	0.15	0.14	0.210
Education					
High School	0.10	0.08	0.11	0.10	0.400
Some College	0.25	0.26	0.25	0.25	0.869
College or More	0.65	0.66	0.65	0.65	0.939
Employment					
Full-Time	0.70	0.71	0.70	0.70	0.963
Unemployed	0.08	0.07	0.07	0.09	0.644
Caucasian	0.68	0.70	0.66	0.68	0.521

* The *p*-values correspond to the outcomes of X^2 tests, unless otherwise indicated. † Scheffe test.

5. Results

We begin by reporting and discussing the results of the conditional logit model for the full sample (Table 3). In reference to the in-store pick-up method, both the curbside pick-up method and the home delivery method have positive marginal utilities. Respondents derive more utility when not entering the store to collect groceries, which corresponds to another study of grocery shopping preferences during the COVID-19 pandemic [18]. The curbside pick-up method and the home delivery method are more convenient to customers, who then need less time and effort to collect groceries. At the same time, the opportunity to maintain physical distance from other persons is also greater with both methods. The difference in the coefficients for the curbside pick-up method (β = 0.010) and the home delivery method (β = 0.430) is statistically significant (*Chi*2 = 57.92, p = 0.000). Our result is supported by [20], who reported a greater utility associated with the home delivery method as compared to the in-store pick-up method in a choice experiment with online consumers of electronics in the United States.

Table 3. Conditional logit model results †.

Attribute/Level	Full Sample	Treatment 1 Increasing	Treatment 2 Constant	Treatment 3 Decreasing
Purchasing Method				
In-Store Pick-Up	−0.440 *** (0.025)	−0.402 *** (0.043)	−0.490 *** (0.115)	−0.430 *** (0.044)
Curbside Pick-Up	0.010 (0.024)	−0.021 (0.042)	−0.049 (0.042)	0.102 ** (0.042)
Home Delivery	0.430 *** (0.035)	0.423 *** (0.061)	0.540 *** (0.062)	0.328 *** (0.062)

Table 3. *Cont.*

Attribute/Level	Full Sample	Treatment 1 Increasing	Treatment 2 Constant	Treatment 3 Decreasing
Minimum Order				
$10	0.126 *** (0.029)	0.056 (0.081)	0.187 ** (0.082)	0.135 ** (0.082)
$20	0.022 (0.029)	0.072 (0.049)	0.040 (0.050)	−0.041 (0.050)
$30	−0.027 (0.031)	−0.029 (0.053)	−0.034 (0.053)	−0.021 (0.053)
$40	−0.096 *** (0.031)	−0.092 * (0.054)	−0.164 *** (0.055)	−0.036 (0.054)
$50	−0.025 (0.031)	−0.008 (0.053)	−0.029 (0.054)	−0.037 (0.053)
Time Window				
Less Than 4 h	0.241 *** (0.025)	0.229 *** (0.044)	0.263 *** (0.044)	0.228 *** (0.044)
4–12 h	0.141 *** (0.026)	0.122 *** (0.046)	0.131 *** (0.046)	0.166 *** (0.045)
12–24 h	−0.091 *** (0.027)	−0.055 (0.046)	−0.071 (0.046)	−0.148 *** (0.046)
More Than 24 h	−0.290 *** (0.027)	−0.297 *** (0.047)	−0.323 *** (0.047)	−0.246 *** (0.047)
Price	−0.121 *** (0.005)	−0.131 *** (0.009)	−0.124 *** (0.009)	−0.110 *** (0.009)
Opt Out	−0.700 *** (0.038)	−0.832 *** (0.066)	−0.644 *** (0.066)	−0.625 *** (0.066)
N	32,400	32,400	32,400	32,400
Pseudo R2	0.042	0.045	0.043	0.044
Log Likelihood	−11,364.7	−3766.5	−3773.7	−3806.9

† Coefficients are marginal utilities. Parentheses contain standard errors. Statistical significance at $p = 0.10$, $p = 0.05$, and $p = 0.01$ levels is indicated by *, **, and ***, respectively.

The marginal utilities for the levels of the minimum order requirement attribute are expected. Each $10 increase in the minimum order requirement is associated with negative marginal utilities as compared to the base category of $10. However, the coefficients are not all significantly different from the mean effect of zero and do not decrease in a linear fashion. In fact, the coefficient for the $50 minimum order value is lower compared to the coefficient for the $40 minimum order requirement. Jointly, the differences in the coefficients for the $20, $30, $40, and $50 minimum order requirements are not statistically significant (*Chi*2 = 6.12, $p = 0.110$). Thus, when going beyond the $10 minimum order requirement, utility decreases, but not linearly. We further explored the relationship of minimum order requirements to utility by replacing the four binary variables with a single continuous variable. When doing so, the coefficient is statistically significant but small in magnitude ($\beta = -0.004$, S.E. = 0.001, $p = 0.000$). Comparing and contrasting our results is difficult, as there appears to be no other applied research in which minimum order requirements have been related to the preferences of online grocery shoppers.

Based on the coefficients for the time window attribute, time is considered to be a valuable asset to the respondents. The longer or further the time window, the lower the marginal utility. In general, respondents prefer a time window closer to the present, perhaps in part because of the perishable nature of some groceries. Coefficients for the 4–12 h time window and the 12–24 h time window are significantly different (*Chi*2 = 27.16, p = 0.000), as are the coefficients for the 12–24 h time window and the more than 24 h time window (*Chi*2 = 19.27, p = 0.000). Our result is similar to those of other studies, which generally found a preference for shorter time windows [14,20,21].

The opt-out option, which, owing to effect coding, is uncorrelated with any of the product attributes, captures the disutility of shopping inside the grocery store. Assuming that the absolute difference in the coefficients of the most preferred level of an attribute and the least preferred level of the same attribute indicates its relative importance [30], the opt-out option is comparable in importance to the purchasing method attribute. Price appears to be the most important attribute, followed by the purchasing method, the time window, and then the minimum order requirement.

After estimating the same conditional logit model separately for respondents in each of the three treatments, we used the Z-score method to test for significant differences in the preferences for the various attributes [31]. Across the three treatments, there are six significant differences at the p = 0.05 significance level, and four more significant differences at the p = 0.10 significance level (see Table 4). As compared to respondents who assumed a decreasing number of new COVID-19 cases, respondents who assumed an increasing number of new cases indicated significantly stronger preferences for the $20 minimum order requirement (p = 0.054) and the 12–24 h time window (p = 0.076), yet significantly weaker preferences for the curbside pick-up method (p = 0.019) and the opt-out option (p = 0.013). Respondents facing an increasing number and respondents facing a constant number of new COVID-19 cases differed significantly in terms of the home delivery method (p = 0.089) and the opt-out option (p = 0.022). Compared to respondents who assumed a constant number of new COVID-19 cases, respondents who assumed a decreasing number of new COVID-19 cases revealed significantly stronger preferences for the curbside pick-up method (p = 0.006) and the $40 minimum order requirement (p = 0.047), and a significantly weaker preference for the home delivery method (p = 0.008). To test the robustness of our results, we ran a pooled regression with all 900 respondents and all 36,000 observations while interacting the three treatments with the attribute levels. We then conducted pairwise comparisons of coefficients by means of Wald tests with null hypotheses of no mean difference. While the test statistics and the p-values are different, the conclusions are almost identical. The results are available upon request.

Table 4. Equality of conditional logit model coefficients across treatments.

Attribute/Level	Increasing vs. Constant		Increasing vs. Decreasing		Constant vs. Decreasing	
	Z-Score	***p*-Value**	**Z-Score**	***p*-Value**	**Z-Score**	***p*-Value**
Purchasing Method						
In-Store Pick-Up	0.72	0.236	0.45	0.326	−0.49	0.312
Curbside Pick-Up	0.47	0.319	−2.08	0.019	−2.53	0.006
Home Delivery	−1.35	0.089	1.10	0.136	2.42	0.008
Minimum Order						
$10	−1.13	0.129	−0.68	0.248	0.45	0.326
$20	0.46	0.323	1.61	0.054	1.14	0.127
$30	0.07	0.472	−0.10	0.460	−0.18	0.429
$40	0.94	0.174	−0.74	0.230	−1.67	0.047
$50	0.28	0.390	0.40	0.345	0.11	0.456
Time Window						
Less Than 4 h	−0.55	0.291	0.01	0.496	0.56	0.288
4–12 h	−0.14	0.444	−0.67	0.251	−0.53	0.298
12–24 h	0.25	0.401	1.43	0.076	1.17	0.121
More Than 24 h	0.40	0.345	−0.77	0.221	−1.16	0.123
Price	−0.51	0.305	−1.62	0.053	−1.10	0.136
Opt Out	−2.01	0.022	−2.23	0.013	−0.21	0.417

6. Discussion and Conclusions

The COVID-19 pandemic is changing life in many respects. Based on the results of our framed choice experiment, we conclude that the trend in the number of new COVID-19 cases also influences grocery shopping preferences. For instance, consumers in environments where COVID-19 is spreading at an increasing rate incur the most disutility of shopping inside the store. In environments where COVID-19 is spreading at a decreasing rate, consumer preferences for the home delivery method relative to the other methods are less strong, and the relative importance of the purchasing method attribute is lower in its entirety. Like [32], we hypothesize that the change in consumer behavior is driven partly by feelings of fear toward the virus. Overall, our study illustrates how grocery shoppers may behave as the world awaits the discovery of a COVID-19 vaccine.

Our findings have several implications for practitioners and policymakers. First, following the price and the purchasing method attributes, consumers also have relatively strong preferences for the time window attribute. Firm competitiveness may change according to the (in)ability to shorten time windows for the pick-up method and the delivery method. Food retailers and deliverers may consider increasing the capacity to handle temporary excess in demand by means of investments in capital and labor resources (e.g., personnel and machinery). In addition, considering the negative relationship of time to price, food retailers and deliverers may inversely relate the fee to the time window. Second, significant differences in the grocery shopping preferences of consumers who face increasing and decreasing rates of new COVID-19 cases indicate opportunities for food retailers and deliverers to tailor business strategies to both scenarios. The rate of new COVID-19 cases varies substantially on a daily basis across the United States, and states with a decreasing rate may once again experience an increasing rate in the future. Preferences for the curbside pick-up, home delivery, and in-store purchasing methods differ significantly across the scenarios. Food retailers and deliverers must be prepared to make proper strategic adjustments in response to the dynamic character of the COVID-19 pandemic. Third, policymakers may consider incentivizing the use of the curb-side pick-up method and the home delivery method to induce a positive change in consumer behavior if containing and mitigating the spread of the coronavirus is the objective. Even in times of an increasing number of new COVID-19 cases, many consumers still exhibit a preference for the in-store purchasing method. While grocery shopping is an essential activity, the in-store purchasing method should arguably be discouraged to help physical distancing. For example, at the moment, participants in the Supplemental Nutrition Assistance Program are not yet able to use their benefits in online transactions and must therefore use the in-store purchasing method by default, which speaks to the need of re-formulating food-related policy interventions that respond to the rapid changes of the pandemic while assuring food security to disadvantaged populations.

Academically, we demonstrated the usefulness of effect coding to facilitate interpretations of reference levels and intercepts. While binary coding is the norm with choice experiment data, the advantages of effect coding (i.e., interpretation of reference levels and intercepts) may outweigh the disadvantages (i.e., unconventional interpretation of coefficients). While effect coding enabled us to estimate preferences for purchasing methods, time windows, minimum order requirements, and fees, much more research is possible and necessary to shed light on the behavior of grocery shoppers as the pandemic continues to affect the global community. In the context of our study, there are multiple approaches to measuring or modeling the impact of the COVID-19 pandemic. While our analysis is limited by binary conceptualizations (i.e., increasing, constant, or decreasing number of new COVID-19 cases), it is possible to include the same data in the form of a continuous variable. Consumers may instead respond to the relative increase or decrease in the number of new COVID-19 cases. A similar limitation of our study is our strategy of relating variability in the preferences of grocery shoppers to an external manipulating factor. However, variability in grocery shopping preferences during the COVID-19 pandemic may also relate to demographic (e.g., age, income) and behavioral characteristics (e.g., risk aversion, health awareness). We look to future research endeavors to incorporate such ideas and thus improve our understanding of consumer behavior during periods of crisis.

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