Pushing or clicking the grocery cart?
Health and economic concerns during the COVID-19 pandemic

Yilan Xu1 | Wookjae Heo2 | Diane Elizabeth Kiss3 | Soo Hyun Cho4 | Michael S. Gutter5

1Department of Agricultural and Consumer Economics, University of Illinois at Urbana-Champaign, Urbana, Illinois, USA
2Division of Consumer Sciences, Purdue University, West Lafayette, Indiana, USA
3Department of Personal Financial Planning, Kansas State University, Manhattan, Kansas, USA
4Department of Family and Consumer Sciences, California State University Long Beach, Long Beach, California, USA
5Institute of Food & Agricultural Sciences, University of Florida, Gainesville, Florida, USA

Abstract
Online Grocery Shopping (OGS) has grown dramatically during the COVID-19 pandemic. It is unknown, however, how consumers weighed pandemic situational factors versus household production considerations of timesaving and cost. We collect and analyze survey data from a nationally representative sample to examine how consumers with different health and socio-demographic profiles consider these factors for OGS choices and how their choices changed in the first seven months of the pandemic. We find that consumers with moderate-to-high income, white, having insurance, and not in the labor force value the timesaving and convenience of OGS more than pandemic situational factors. Still, some consumers with health risks choose to shop in person because of the cost of OGS. Lung disease, diabetes, mental health conditions, age, income, and college degree explain the dynamics of OGS choice as the pandemic evolved. Our findings shed light on the development of technology-assisted adaptation to future public health emergencies.

KEYWORDS
health, household production, online grocery shopping, pandemic, risk perception
1 | INTRODUCTION

Online shopping has experienced rapid growth in the United States since the debuts of Amazon and eBay in the mid-1990’s. Online grocery shopping (“OGS”), however, is relatively new and less utilized. A series of Gallup surveys suggested that the usage has been limited and growth has been slow. In 2017, only 16% of Americans reported having used the service, and this number only grew to 18% in 2019 (Jones & Kashanchi, 2019; Newport & Brenan, 2017; Saad, 2018). The novel-coronavirus (COVID-19) pandemic brought opportunities for growth in OGS. A September 2020 Oracle Grocery Retail survey reported that 53% of survey respondents shopped for their groceries online during the pandemic (Redman, 2020). It is unknown, however, how consumers weighed situational factors related to the pandemic versus the usual household production considerations of timesaving and expenses of the service. This study utilizes a unique set of survey data to examine how consumers with different health and socio-demographic profiles weighed these factors and changed their choice in the first seven months of the pandemic.

Previous literature has explored facilitators and barriers of OGS but lacked a theoretical framework for empirical analysis of OGS behavior. A US study documented that convenience and saving time were the primary reasons for buying groceries online in the early 2000’s, followed by physical constraints (Morganosky & Cude, 2000). A UK study found that situational factors such as living with elderly parents, limited mobility, or lifestyle changes drove the adoption of OGS (Hand et al., 2009). However, the authors also noted that the adoption of OGS can be easily reversed if negative experiences or dissatisfaction with service occurs. A systematic literature review reported inconvenience, impulse buying, concern with the freshness of the products, and distrust in the security of the payment systems as barriers to OGS (Klepek & Bauerova, 2020). Empirical analysis of data collected in the Czech Republic also found that the most common reason for not using OGS is the preference for hands-on grocery shopping, followed by distrust of e-merchants, and the notion that online shopping takes more time and effort than in-store shopping (Klepek & Bauerova, 2020).

In this article, we developed a household production model to describe consumers’ choice of in-store versus online grocery shopping. In-store store grocery shopping is considered a household-produced service whereas OGS is considered a market-produced service. In addition to the usual considerations in the household production theory, that is, the value of time and cost of OGS, we factored in the major situational factors of the pandemic, that is, the perceived risk of COVID-19 infection from in-store shopping and perceived treatment costs resulting from it. The model predicts that as the perceived infection risk and perceived treatment costs increase, consumers tend to decrease in-store shopping but increase online shopping. Based on this prediction, we design an empirical approach to study the dynamics of consumers’ OGS choices as the pandemic developed in the first seven months. Specifically, we examined how various proxies of risk perception and other sociodemographic factors predicted the reasons for and timing of OGS adoption.

We developed a survey included in the RAND American life panel (ALP) Omnibus Survey [2300 wave 7] in October 2020 to collect data from a nationally representative sample (RAND ALP, 2022a). The outcomes of interests are the primary reason for adopting or not adopting OGS at the time of the survey and the dynamics of the OGS choice prior to the survey. In a survey question, we allowed consumers to choose COVID-19 specific considerations in addition to the usual household production considerations of timesaving and affordability as the primary reason driving their decision for using or not using OGS. These alternative considerations included shoppers’ perceptions about the COVID-19 exposure level in their community, their
health, comfort with outdoor trips, accessibility of service, their support for local business, and their face mask preference. Another survey question explicitly captured the time of consumers’ adoption of OGS prior to the survey so that we can examine the consumer decision as a dynamic process. We did five one-on-one comparisons between four types of consumers: always users, later users, discontinued users, and never users. In our analyses, we explicitly controlled for proxies of perceived infection risk and perceived treatment costs. These proxies were consumers’ physical and mental health status, medical conditions identified by the U.S. Centers for Disease Control and Prevention (CDC) as putting adults of any age at increased risk for severe illness from the COVID-19 virus (CDC, 2021), and health insurance coverage. We examined whether these proxies of risk perception and other sociodemographic factors predicted the reasoning and timing of OGS adoption.

Our study contributes to the consumer economics literature by examining household production of grocery shopping services in the context of technological development and the public health crisis of a pandemic. Our analysis factored in health and economic concerns, two important elements of family resources, into a household’s allocation of time and money within the framework of household production theory. We expanded the growing literature that studies changing consumer behaviors during the pandemic by creating a theoretical framework to examine the dynamics of consumer choices so that our empirical analysis can shed light on the marketing strategies of OGS and the technology-assisted adaptation to future public health crises. Our survey question design had advantages over snapshot surveys by collecting recalled timing of OGS adoption and the primary reason for consumers’ OGS choice, which are critical to understanding the consumer profiles that drove the dynamics of OGS in the first seven months of the pandemic.

2 | GROCERY SHOPPING DURING THE PANDEMIC

The COVID-19 pandemic, declared by the World Health Organization (WHO) on March 12, 2020, led many countries and local jurisdictions to declare partial or complete lockdowns due to the highly contagious nature of the disease. At the time of data collection, in the United States, 47 states had implemented emergency orders and 27 states mandated face masks because of the pandemic (NASHP, 2020). Under such circumstances, many households switched their grocery shopping routines from brick-and-mortar retail stores to online apps. A May 2020 survey of consumers in Detroit, Michigan, and Phoenix, Arizona found that 66% of respondents had “gone to the food store less often,” and the participation in grocery delivery increased from 9% before the pandemic to 15% during the pandemic (Chenarides et al., 2020). A September 2020 Oracle grocery retail survey showed that more than half (53%) of US consumers shopped for groceries online during the pandemic by September 2020 (Redman, 2020). The majority (72%) of the online grocery purchases were delivered to consumers’ homes. Of the slightly fewer than 30% of consumers who reported using “click-and-collect” services, 15% picked up curbside while 13% went inside the store to pick up their orders. The same survey also found that 93% reported plans to continue shopping online after the pandemic (Redman, 2020).

It has been documented in the literature that perceived risk impacted consumers’ online shopping intention (e.g., Kim & Forsythe, 2010; Amirtha et al., 2020; Habib & Hamadneh, 2021). Existing studies focus on the perceived risk of negative online shopping experiences. Consumers’ intentions to shop online were negatively impacted by performance, social, time-loss, psychological, source, security, and after-sale service risks (Amirtha et al., 2020). Evidence from India suggested...
that perceived risk associated with online purchases continued to influence consumers’ intention to do OGS during the pandemic (Habib & Hamadneh, 2021). Examples of such perceived risk included concerns over personal information disclosure and banking information breach, and concerns about the fulfillment of an order, reasonable price, and timely delivery.

The pandemic brought in another perspective of perceived risk to consumers’ decision about OGS—the perceived risk of COVID-19 infection associated with in-store shopping. The May 2020 survey in Detroit and Phoenix documented that “scared of COVID-19” and “feeling unsafe” were the top-rated reasons for participating in grocery pickup or delivery programs, 74.9% and 66.3% of survey respondents chose these two reasons, respectively (Chenarides et al., 2020). In an online choice experiment of a sample of 900 grocery shoppers, Grashuis et al. (2020) found that a hypothetical scenario of increased new COVID-19 cases raised the demand for home delivery service whereas a scenario of decreasing new cases lowered the demand (Grashuis et al., 2020). In the Netherlands, an additional COVID-19 hospital admission at the municipal level between the end of February 2020 and August 2020 increased OGS app traffic by 7.3% and OGS sales by 0.31%. At the same time, a one-unit increase in the national index of Google keyword searches related to pandemic information increased OGS app traffic by 0.76% (Baarsma & Groenewegen, 2021). In Taiwan, an additional confirmed COVID-19 case between January 21, 2020, and April 6, 2020, increased OGS app traffic by 4.9% and sales by 5.7% (Chang & Meyerhoefer, 2021).

The studies reviewed above relied on snapshot surveys or experiments conducted in the very early stage of the pandemic. As such, they are incapable of capturing the dynamic nature of the shopping decision. Although a short panel survey such as the four-wave panel between Mid-March and late April 2020 in Ellison et al. (2021) showed increasing use of OGS, consumer decisions continued to evolve with the development of the pandemic. Without a theoretical framework and observations further into the pandemic, it is challenging to infer the implications of the observed consumer patterns. Our paper fills the gap in the literature by leveraging data collected in October 2020 by asking consumers to recall their OGS decisions in the first seven months of the pandemic. Our survey design captured the dynamics of consumer choice during this period. More importantly, we developed a household production model to differentiate situational factors from household production factors that influence OGS decisions.

3 | CONCEPTUAL FRAMEWORK AND SURVEY DESIGN

3.1 | Theoretical model

Grocery shopping has traditionally been an activity undertaken by households. Thus, it can be considered as a household-produced service. The productive role of the household was first recognized by the pioneering work of Becker (1965), in which households produce goods or services using market-produced inputs, their own time, and their skills. Examples of household production are homemade meals, childcare, and housework. According to Gronau (1977, 1986), home-produced goods and market-produced goods are perfectly substitutable. Thus, in his framework, households can outsource household production to the market. For example, households can eat out, hire a child sitter, and hire a domestic helper. Similarly, OGS is a way of outsourcing shopping activities.

We propose the following household production model to describe households’ grocery shopping decisions during the pandemic. In our context, in-store grocery shopping, denoted as
$X_i$, is the amount of home-produced service, and OGS, denoted as $X_o$, is the amount of purchased service. The two forms of service are assumed to be perfect substitutes so that a household only values the total amount of service,

$$X = X_i + X_o.$$ 

The household has a strictly concave and increasing utility function:

$$U = U(L, X; \tau),$$

where $L$ is leisure, $X$ is total service consumed, and $\tau$ is a preference parameter. The household allocates their total time $T$, between leisure $L$, housework $h$, and market labor work $l$ with a time constraint

$$T = L + h + l.$$ 

The production function of $X_i$ is assumed to be strictly concave in its input, housework $h$:

$$X_i = G(h; \varphi),$$

where $\varphi$ is a parameter for household production technology.

During the pandemic, there has been an additional cost associated with the production of $X_i$, that is, the potential cost if the home producer of in-store shopping service gets infected with COVID-19 due to the in-store shopping. The infection cost can take the form of medical treatment expenses and/or forgone opportunity cost due to quarantine or sick leave. The household perceives the infection cost to occur at a probability $\rho$, and the infection cost is $C$ for each unit of $X_i$. If a household produces zero unit of $X_i$, then there is no infection cost.

The household earns wage income at the rate of $W$ per unit of labor and receives nonlabor income $V$. The total infection cost $\rho CX_i$ enters the households’ budget constraint in the theoretical model as a contingent cost. $Z$ is the total cost of all other household activities. The disposable income, $I$, can be spent to purchase market-produced shopping services. Thus, the budget constraint is

$$I = W \cdot l + V - \rho CX_i - Z \geq PX_o,$$

where $P$ is the per-unit price of online shopping service $X_o$. The potential total income, $F$, from household’s total time and asset is

$$F = W \cdot T + V.$$ 

Combining the time constraint with the budget constraint, it becomes

$$F = W \cdot T + V = WL + Wh + PX_o + \rho CX_i.$$ 

From first-order conditions, the optimal housework time $h^*$ solves the following:
\[ \frac{G_h}{\rho C} = \frac{U_X W}{P(U_X - \rho C)}. \]

Without the pandemic, \( \rho = 0 \) and \( C = 0 \), and this condition reduces to

\[ G_h = \frac{W}{P}. \]

This equation is the standard one-variable input profit-maximizing condition in Gronau's model, that is, a household allocates housework time \( h^* \) so that the marginal productivity in home production equals the real wage rate. In this case, \( h^* \) would increase with \( P \) but decreases with \( W \). In our model, the two conclusions still hold. In addition, \( h^* \) decreases with both the perceived infection risk \( \rho \) and the treatment cost \( C \). As a result, \( X_i \) also increases with \( P \) but decreases with \( W, \rho, \) and \( C \). In other words, all else being equal, the household will increase in-store shopping if OGS gets more expensive but will decrease in-store shopping if the value of time increases, or the perceived infection risk or infection cost increases.

3.2 | Research questions

From the theoretical model, we can see that the value of time and the cost of purchased services are two universal considerations for the allocation between household production and market purchase of grocery shopping service regardless of the pandemic. Meanwhile, the perceived infection risk and the COVID-19 infection costs are situational factors that affect the allocation during the pandemic. Thus, it is important to know to what extent OGS during the pandemic is driven by situational factors as opposed to time and cost. We designed a survey with recall questions that asked consumers about their OGS choice during the first seven months of the COVID-19 pandemic and the reasoning for their choice. In particular, we distinguished the timing of OGS adoption which helps shed light on the dynamic choice of OGS as the pandemic evolved.

This research is the first of its kind to explore the driving forces of the booming use of OGS during the pandemic, thus, we did not form hypotheses regarding who would choose what. Rather, the following research questions have guided our analysis:

1. How do consumers weigh different factors when making the OGS decision?
2. What explains the dynamics of the OGS decision during the pandemic?

To address research question 1, we asked consumers to select the primary reason for their OGS choice from a set of designed alternatives. Considering the theoretical model, we factored in the value of timesaving as the baseline reason for currently using OGS and the cost of OGS as the baseline reason for not currently using OGS. We considered alternative reasons that reflect consumers’ perceived infection risks as well as other preferences. Specifically, we allowed health conditions and perceived community exposure to COVID-19 to be potential reasons for currently using or not using the service. Meanwhile, other COVID-19-specific factors can affect consumer choice. Some consumers may find it mentally stressful to go out in public during the pandemic, whereas others may find it mentally healthy to have some out-of-home activities.
Consumers' preference to avoid face masks, their willingness to shop locally and support local business during the pandemic, and the preference to handpick their own groceries could also influence their tendency to shop online versus in person. Finally, inaccessibility to OGS service can prevent some consumers from using the service. If consumers chose COVID-19-specific factors as their primary reason for their OGS choice, then their behavior is likely to change as the pandemic ends. If they choose more universal reasons such as time, costs, accessibility, preference to handpick their groceries, then these factors are likely to pertain to OGS in the post-pandemic era.

The theoretical model guides our selection of relevant explanatory variables in addition to frequently used control variables. We proxied the perceived infection risk $\rho$ with underlying medical conditions that put consumers at increased risk for severe illness from COVID-19 (CDC, 2021), as well as subjective health status. We proxied the treatment cost $C$ with at-risk medical conditions, subjective health status, and health insurance coverage. We also controlled for demographic variables including income, gender, race, college degree, homeownership, marital status, rural status, and labor force participation. Gallup surveys suggest that those 65 years old and older were least likely to shop online while those aged 18–29 years old are most likely to do so and that consumers with children younger than 18, ages 35–54, employed, and with household incomes of $75,000 or higher were more likely to order groceries online (Newport & Brenan, 2017; Saad, 2018). A September 2020 Oracle grocery retail survey (Redman, 2020) confirmed that parents were more likely to make online purchases than those without children (82% compared to 36%). It also found that 72% of those aged 40–54, 61% of those aged 18–24, and 60% of those aged 25–39 bought groceries online during the pandemic. Among the oldest age group, 55 years old and older, 30% shopped online for groceries, a 173% increase compared to before the pandemic.

To address research question 2, we examined which health and sociodemographic factors predict the dynamics of OGS adoption. The understanding of the driving forces of the changes in consumer behavior during the pandemic can have implications for OGS marketing strategies and technology-assisted adaptation for future public health emergencies. We had four types of consumers with different OGS choice dynamics: always users, later users, discontinued users, and never users. With four user types, we can have six combinations of pairs for comparison. We drop the always users and never users pair because they have nothing in common, whereas other pairs either have overlapped use of OGS at some point in time or both at least use OGS at one point in time. We did five one-on-one comparisons with the remaining pairs. First, among the users at the time of the survey, we compared the always users who had used the service since the outbreak with later users who only started using the service more recently. Thus, we can understand the factors associated with the early adoption of OGS. Second, among the users at the onset of the pandemic, we compared the always users with discontinued users who stopped using the service as the pandemic evolved. Thus, we can identify factors that explain the continued use of OGS beyond the first wave of the pandemic. Third, among the users at one point in time, we compared discontinued users with later users to study what distinguishes the timing of use. Fourth, among the nonusers at the time of the survey, we compared discontinued uses with never users to study what attracted early use among this group. Finally, among the nonusers at the onset of the pandemic, we compared later users with never users to see what motivated the use before the survey. In the analysis, we used the same set of proxies of risk perception and other sociodemographic factors as explained above as predictors.
3.3 Survey design and choice coding

We implemented our survey questions through the 2020 RAND ALP omnibus survey [2300 wave 7]. The RAND ALP is a nationally representative panel operating in its current form since 2003 (RAND ALP, 2022a). There are over 6000 panel members aged 18 and older (Pollard & Baird, 2017). The ALP provides the technological means for respondents to access and complete online surveys so that the panel is representative of all adults regardless of internet access. Panel members respond to quarterly household information survey update requests as well as periodic requests to participate in other survey modules throughout the year. The 2020 omnibus survey [2300 wave 7] is an example of a periodic survey module. It was in the field between October 5, 2020 and October 22, 2020. Data were available to researchers in November 2020. By collecting data through the omnibus survey, researchers could include several simple survey questions, link with current ALP demographic variables, and merge data with results from over 500 previously conducted ALP studies. It was an efficient and cost-effective way to collect nationally representative data. For example, recent omnibus surveys have been utilized by researchers to collect data on COVID-19 vaccine hesitancy (Bagasra et al., 2021), self-rated health and obesity (Bozick, 2021) and to experimentally assess how language impacts perceived mental health conditions (Breslau et al., 2020).

Given the cross-section constraint of our survey, we developed a recall question to capture how consumers’ OGS decisions evolved as the pandemic evolved, and we developed two questions to ask about the motivations of consumers’ decisions. Figure A1 shows the three survey questions, their answers, and the coding for statistical analysis. The first question (Q1) asked if the consumer or their family had ever used OGS services since the COVID-19 outbreak. Our survey did not capture whether the respondent is the primary shopper of the household. As pointed out by van Hove (2022), grocery shopping is a household activity allocated to a household member. Thus, we worded our survey questions to allow a non-primary shopper respondent to answer on behalf of their family. Given the pandemic situation, it is not unreasonable to assume the decision to shop in person or online has been discussed within the family factoring in all members’ risk factors, and the decision and reasoning become common knowledge to all adult family members. As a robustness check (results available upon request), we also restricted our sample to female respondents only, who historically, and even during the pandemic, have been the primary shopper of a household (van Droogenbroeck & van Hove, 2020). Our analyses show similar results to the full sample results, suggesting that the primary shopper role is less important during the pandemic due to the collective decision. In the first survey question, we provided examples of OGS services such as Walmart Grocery, Instacart, and Amazon Grocery as well as services offered through local grocers and paid grocery delivery services. Possible responses to the first question included: (a) having been using it since the outbreak, (b) only started using it recently, (c) used it earlier but have canceled it, and (d) have never used it.

The design of the four answers to the recall question captured the dynamic of OGS choice as the pandemic developed. For statistical analysis, among the current users, we defined the always users as those who had used the service since the outbreak (i.e., answered “a” to Q1) and the later users as those who only started using the service recently (i.e., answered “b” to Q1), we defined those who used the service at the outbreak but stopped using it later as discontinued users (i.e., answered “c” to Q1), and we defined those who never used the service by the time of survey as never users (i.e., answered “d” to Q1).
We followed up the recall question with two questions about the motivation of consumer choice. Depending on their answer to the first question, each survey respondent was directed to one of the two follow-up questions. If respondents answered (a) or (b) to Q1, they were directed to Q2a to select their most important reason for currently using the service. Possible responses included: to save time and/or for convenience (baseline); to reduce exposure to COVID-19, which is a problem in my community (“exposure”); do not feel comfortable shopping by myself/ourselves due to health conditions (“health”); to alleviate the stress of making outdoor trips (“outdoor stress”); to support business and create more job in my community (“pro-business”); and to avoid wearing a face mask (“no masks”). If respondents answered (c) or (d) to Q1, they were directed to Q2b to select their most important reason for not currently using the service. Possible responses included: too expensive (“baseline”); need to get out of the house anyway (“outdoor needs”); service not available in my region (“accessibility”); COVID-19 is not a problem in my community (“limited exposure”); feel comfortable shopping by myself/ourselves due to health conditions (“health”); and prefer to handpick the items by myself/ourselves (“handpick”).

4 | DATA AND EMPIRICAL METHOD

4.1 | The ALP omnibus survey data

The ALP Omnibus survey returned with 2310 observations that answered the designed survey questions. The observations were returned with pre-matched demographic information as collected by the most recent ALP survey before the 2020 October omnibus survey. The demographic information included age, gender, race/ethnicity, education, household size, family income, health insurance status, employment status, homeownership type, rural status, and general health. Using the unique ALP survey identifiers, we further matched the study sample to the most recent health and functional capacity survey (Ms522), which was in the field from April 4, 2019 to June 30, 2019. This survey collected information on respondents’ health, abilities, disability, functional capacity, and movement. A total of 2145 observations were matched, of which 2134 had complete information to be included in the data analysis. All our analyses included the sampling weights provided by the ALP (RAND ALP, 2022b).

We combined the general health status categories provided in the ALP omnibus survey as “poor/fair,” “good,” “very good,” and “excellent.” After matching the study sample to the health and functional capacity survey, we were able to extract the information about specific conditions that increase a person’s risk of severe COVID-19 illness per the Centers for Disease Control and Prevention (CDC) guideline (CDC, 2021). These conditions included chronic kidney disease; chronic obstructive pulmonary disease (COPD); obesity (BMI of 30 or higher); immunocompromised state (i.e., weakened immune system) from a solid organ transplant, serious heart conditions, such as heart failure, coronary artery disease, or cardiomyopathies; sickle cell disease; and Type 2 diabetes. In the health and functional capacity survey, these conditions corresponded to “Gastrointestinal and Kidney Problems” (Q1_gastro), “Lung Problems” (Q1_lung), “Immune Deficiency” (Q1_other_10), “Heart Problem” (Q1_heart), “Cancer” (Q1_other_1), “Diabetes” (Q1_other_2), and “Obesity” (Q1_other_3). We code mental health problems from “Mental” (Q1_mental).
4.2 | Empirical models

The goal of our analyses was to understand who chose what and why, that is, how perceived risks and sociodemographic factors relate to consumer preferences and OGS behavior. Consumers’ preferences are reflected by their reasoning for their current choice of OGS (survey Q2a and Q2b), and consumers’ OGS behavior is reflected by the timing of their adoption of OGS (survey Q1). In our empirical analysis, we use the former to address research question 1 regarding how consumers weigh different factors when making OGS decisions, and we used the latter to address research question 2 regarding what explains the early adoption and continued use of OGS.

We used multinomial logistic models to compare the likelihood of choosing different alternatives as coded in Figure A1 for the two research questions. The answers to the survey questions were coded such that the probabilities of choosing each alternative sum up to 1. The probability that respondent \( i \) chose an alternative reason \( l \) is modeled as the following:

\[
\text{Prob}(Y_i = l) = \frac{\exp(\alpha + X'_i \beta_l)}{\sum_{j=1}^{n} \exp(\alpha + X'_i \beta_j)},
\]

where \( Y_i \) is respondent \( i \)'s chosen alternative, and \( X_i \) is the vector of health risk factors and socio-demographic factors. The estimation will produce the coefficients that associate each sociodemographic factor to each of the alternatives, indicating the probability of choosing the alternative relative to the probability of choosing the baseline. For the multinomial analysis of the alternative reasons for using or not using OGS, if a sociodemographic factor has a positive and statistically significant coefficient for choosing a reason, then consumers with this sociodemographic factor value the reason more than the baseline reason (“saving time” for using OGS and “cost” for not using OGS).

To understand what sociodemographic factors explain the dynamics of OGS choice during the period, we ran a set of logit regressions for subsamples of respondents.

\[
\text{Prob}(Y_i = k) = \frac{\exp(\alpha + X'_i \beta)}{1 + \exp(\alpha + X'_i \beta)},
\]

where \( Y_i \) is respondent \( i \)'s OGS type, namely, always users, later users, discontinued users, or never users. We estimated five comparisons: comparisons between the always users and later users, between always users and discontinued users, between discontinued users and later users, between discontinued uses and never users, and between later users and never users.

5 | RESULTS

5.1 | Summary statistics

Table 1 reports the socio-demographic characteristics of the full sample, current users (including always users and later users), current nonusers (including discontinued users and never users), and the f-statistics for the null hypothesis that current users and nonusers have the same
characteristics. As shown in the first column, 1.02% of the full sample of respondents had an immune problem; 12.81% had lung issues; 1.55% had kidney disease; 2.22% had cancer; 12.06% had diabetes; 16.40% were obese; 30.87% had mental health problems. Over half of respondents (50.02%) reported that their health status was very good or excellent. In terms of socio-demographic factors, over 60% of respondents reported their income was higher than $50,000 per year. Slightly more than half of the respondents (52.75%) were female; 68.47% of respondents reported that they owned their home; over 75% of respondents were white; 37.21% of respondents had a college degree; around 60% of respondents were married; 21.6% were in rural areas; most respondents (94.57%) had health insurance coverage; and 34.33% of respondents were out of labor force. Finally, the average age of the total sample was 51.33 years old and household size averaged 2.78 individuals.

Comparing the current OGS users to current non-users, the former had higher chances of having health risk factors except for kidney diseases and diabetes, whereas significantly more of current nonusers reported excellent health (see the last column of Table 1). In terms of socio-demographic factors, current OGS users were younger (46 years old compared to 54 years old) and were more likely to have incomes of $75,000 and higher. They were less likely to be homeowners than non-users (59.70% compared to 73.10%), less likely to be White (73.97% compared to 77.98%) and had a larger household size (mean = 3.08 compared to 2.62).

5.2 How do consumers weigh different factors when making the OGS decision?

In this subsection, we examined potential reasons for consumers’ current choice of using and not using OGS service, respectively. Table 2 reports the estimation results for alternative reasons for using the service among the current user sample (n = 641). Table A1 in the Appendix provides a summary of the socio-demographic characteristics that positively or negatively contribute to a particular reason for using OGS. The baseline reason to compare with COVID-19-specific reason was “to save time and/or for convenience.” From the estimation results, we found certain health and socio-demographic characteristics were positively associated with selecting reasons other than timesaving and convenience when consumers explain why they use OGS. These findings revealed the consumers who valued COVID-19 specific factors more than timesaving and convenience. By the order of variables in Table 2, they were consumers with immune system problems who wanted to avoid masking; consumers with heart disease who wanted to protect their health; consumers with kidney disease, cancer, and diabetes who wanted to support local business; consumers with more than $125,000 income who wanted to avoid masks; female consumers who wanted to alleviate outdoor stress; homeowners who wanted to protect their health; college-educated consumers who wanted to minimize exposure, protect their health, and alleviate outdoor stress; married consumers who wanted to minimize exposure and support local business; rural consumers who wanted to avoid masking; and health insurance holders who wanted to alleviate outdoor stress and avoid masking. Meanwhile, some health and socio-demographic characteristics were negatively associated with reasons other than timesaving and convenience. These findings helped identify the consumers who weighed timesaving and convenience over COVID-19-specific reasons. They were consumers with immune system problems who valued timesaving more than health protection and alleviating outdoor stress; consumers with kidney disease, cancer, and diabetes who valued timesaving more than avoiding masking; consumers with better
| Binary variables | Freq. (%) | Freq. (%) | Freq. (%) | Freq. (%) | Freq. (%) | Freq. (%) | Freq. (%) | Freq. (%) | f     |
|------------------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-------|
| Risk factor      |           |           |           |           |           |           |           |           |       |
| Immune           | 21.20 (1.02) | 5.63 (0.96) | 2.51 (1.84) | 8.14 (1.13) | 5.20 (2.40) | 7.86 (0.68) | 13.06 (0.96) | 1.39***|
| Lung             | 267.33 (12.81) | 85.44 (14.63) | 23.52 (17.22) | 108.96 (15.12) | 41.45 (19.14) | 116.92 (10.18) | 158.37 (11.60) | 1.70***|
| Kidney           | 32.43 (1.55) | 7.47 (1.28) | 1.44 (1.05) | 8.91 (1.24) | 1.26 (0.58) | 22.26 (1.94) | 23.63 (1.72) | 0.52***|
| Cancer           | 46.37 (2.22) | 14.63 (2.51) | 5.10 (3.74) | 19.74 (2.74) | 4.34 (2.01) | 22.30 (1.94) | 26.64 (1.95) | 1.97***|
| Diabetes         | 251.53 (12.06) | 64.04 (10.96) | 19.22 (14.07) | 83.26 (11.55) | 12.41 (5.73) | 155.86 (13.57) | 168.27 (12.32) | 0.88   |
| Obesity          | 342.14 (16.40) | 107.70 (18.44) | 20.62 (15.09) | 128.32 (17.80) | 30.05 (13.88) | 183.77 (16.00) | 213.82 (15.66) | 1.29***|
| Mental           | 644.05 (30.87) | 207.12 (35.45) | 32.27 (23.62) | 239.39 (33.21) | 91.66 (42.33) | 313.00 (27.24) | 404.66 (29.64) | 1.26***|
| Health Status    |           |           |           |           |           |           |           |           |       |
| Poor/fair        | 300.70 (14.41) | 87.01 (14.89) | 21.10 (15.45) | 108.11 (15.00) | 27.51 (12.71) | 165.08 (14.37) | 192.59 (14.11) | 1.13   |
| Good             | 741.95 (35.57) | 209.29 (35.83) | 42.77 (31.31) | 252.06 (34.97) | 72.60 (33.53) | 417.29 (36.32) | 489.89 (35.88) | 0.95   |
| Very good        | 818.89 (39.25) | 242.41 (41.56) | 50.52 (36.98) | 293.29 (40.69) | 93.11 (43.00) | 432.48 (37.56) | 525.59 (38.49) | 1.12   |
| Excellent        | 224.61 (10.77) | 45.11 (7.72) | 22.21 (16.26) | 67.32 (9.34) | 23.31 (10.76) | 133.99 (11.66) | 157.29 (11.52) | 0.66***|
| Socio-demographic factor |           |           |           |           |           |           |           |           |       |
| Income           |           |           |           |           |           |           |           |           |       |
| Less than $29,999 | 417.71 (20.02) | 95.86 (16.41) | 39.05 (28.59) | 134.91 (18.72) | 40.45 (18.68) | 242.36 (21.10) | 282.80 (20.71) | 0.82**|
| $30,000–$49,999  | 382.91 (18.35) | 110.24 (18.87) | 14.07 (10.30) | 124.31 (17.25) | 26.49 (12.23) | 232.11 (20.20) | 258.60 (18.94) | 0.83**|
| $50,000–$74,999  | 435.15 (20.86) | 122.34 (20.94) | 21.91 (16.04) | 144.25 (20.01) | 40.53 (18.72) | 250.37 (21.79) | 290.90 (21.31) | 0.88   |
| $75,000–$124,999 | 453.77 (21.75) | 125.00 (21.40) | 41.71 (30.54) | 166.71 (23.13) | 63.85 (29.49) | 223.21 (19.43) | 287.06 (21.02) | 1.21**|
| Over $125,000    | 396.60 (19.01) | 130.74 (22.38) | 19.86 (14.54) | 150.60 (20.89) | 45.21 (20.88) | 200.79 (17.48) | 246.00 (18.02) | 1.34***|

**TABLE 1** Descriptive table for total and sub-samples (weighted)

Total (N = 2134)

Current users

- Always users (n = 528)
- Later users (n = 113)
- Sub-total 1 (n = 641)

Current nonusers

- Disc’d users (n = 206)
- Never users (n = 1287)
- Sub-total 2 (n = 1493)

Difference sub-total 1 = sub-total 2
TABLE 1 (Continued)

| Total | Current users | Current nonusers | Difference sub-total |
|-------|---------------|------------------|---------------------|
|       | Always users (n = 528) | Later users (n = 113) | Sub-total 1 (n = 641) | Disc’d users (n = 206) | Never users (n = 1287) | Sub-total 2 (n = 1493) | 1 = sub-total 2 |
| Female | 1100.35 (52.75) | 333.73 (57.13) | 73.72 (53.97) | 407.45 (56.53) | 134.16 (61.96) | 558.75 (48.64) | 692.90 (50.75) | 1.24** |
| House owner | 1428.42 (68.47) | 354.08 (60.61) | 76.26 (55.82) | 430.33 (59.70) | 142.66 (65.89) | 855.43 (74.46) | 998.09 (73.10) | 0.67*** |
| White | 1597.95 (76.60) | 437.31 (74.86) | 95.88 (70.19) | 533.19 (73.97) | 166.89 (77.08) | 897.87 (78.15) | 1064.76 (77.98) | 0.90 |
| College | 776.22 (37.21) | 271.29 (46.44) | 38.89 (28.47) | 310.19 (43.03) | 81.75 (37.76) | 384.28 (33.45) | 466.03 (34.13) | 1.59*** |
| Married | 1268.50 (60.81) | 353.23 (60.47) | 92.36 (67.62) | 445.59 (61.82) | 128.35 (59.74) | 693.55 (60.37) | 822.91 (60.27) | 1.05 |
| Rural | 452.50 (21.69) | 117.08 (20.04) | 18.25 (13.26) | 135.33 (18.78) | 46.37 (21.42) | 270.80 (23.57) | 317.17 (23.23) | 0.65*** |
| Have health insurance | 1972.87 (94.57) | 560.22 (95.90) | 124.47 (91.12) | 684.69 (94.99) | 208.92 (96.49) | 1079.25 (93.94) | 1288.18 (94.35) | 1.01 |
| Not in labor force | 716.17 (34.33) | 167.73 (28.71) | 47.38 (34.68) | 215.10 (29.84) | 58.65 (27.09) | 442.42 (38.51) | 501.07 (36.70) | 0.66*** |

**Continuous variables**

| Socio-demographic factor | Mean (SD) | Mean (SD) | Mean (SD) | Mean (SD) | Mean (SD) | Mean (SD) | Mean (SD) | t |
|--------------------------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|---|
| Age                      | 51.33 (15.70) | 46.12 (15.60) | 47.11 (13.01) | 46.30 (15.14) | 48.69 (15.87) | 54.98 (15.05) | 53.98 (15.35) | −10.64*** |
| Household size           | 2.78 (1.46) | 3.01 (1.53) | 3.39 (1.56) | 3.08 (1.55) | 2.69 (1.32) | 2.61 (1.40) | 2.62 (1.39) | 4.23*** |

Note: †p < 0.10; *p < 0.05; **p < 0.01; ***p < 0.001.
| Risk factor     | Exposure Coef. | S.E. | Health Coef. | S.E. | Outdoor stress Coef. | S.E. | Pro-business Coef. | S.E. | No mask Coef. | S.E. |
|----------------|---------------|------|--------------|------|----------------------|------|-------------------|------|---------------|------|
| Immune         | -0.05         | 1.34 | -17.84***    | 1.94 | -18.80***            | 1.38 | 2.18              | 2.20 | 3.84*         | 1.69 |
| Lung           | 0.44          | 0.39 | 0.90         | 0.59 | 0.01                 | 0.68 | -0.26             | 1.24 | -0.35         | 1.12 |
| Heart          | 0.67          | 0.44 | 1.42†        | 0.84 | -0.11                | 1.48 | 0.36              | 1.14 | 2.00          | 1.75 |
| Kidney         | -0.37         | 1.23 | 1.07         | 1.38 | 0.95                 | 1.50 | 4.16*             | 1.91 | -12.55***     | 3.04 |
| Cancer         | -0.15         | 0.61 | 1.24         | 0.79 | 0.63                 | 1.73 | 2.95**            | 0.91 | -29.61***     | 1.13 |
| Diabetes       | 0.58          | 0.44 | 0.43         | 0.67 | 0.35                 | 0.96 | 2.02†             | 1.08 | -12.07***     | 1.71 |
| Obesity        | -0.14         | 0.36 | 0.26         | 0.52 | -0.38                | 0.67 | -0.19             | 0.95 | -2.69         | 1.81 |
| Mental         | 0.28          | 0.31 | -0.51        | 0.61 | -0.56                | 0.63 | -0.27             | 0.67 | 0.31          | 0.68 |
| Health status  |              |      |              |      |                      |      |                   |      |               |      |
| Good           | -0.33         | 0.44 | -1.73**      | 0.55 | 0.92                 | 0.71 | -1.67             | 1.28 | -0.34         | 1.65 |
| Very good      | -0.92*        | 0.47 | -2.90***     | 0.75 | -1.13                | 0.94 | 1.07              | 0.98 | 0.65          | 1.53 |
| Excellent      | -0.97†        | 0.58 | -2.62**      | 0.97 | 0.35                 | 1.05 | -1.27             | 1.67 | 2.57          | 2.26 |
| Socio-demographic |          |      |              |      |                      |      |                   |      |               |      |
| Age            | -0.03         | 0.06 | -0.03        | 0.09 | -0.11                | 0.11 | -0.08             | 0.13 | -0.14         | 0.17 |
| Age²           | 0.00          | 0.00 | 0.00         | 0.00 | 0.00                 | 0.00 | 0.00              | 0.00 | 0.00          | 0.00 |
| Income         |              |      |              |      |                      |      |                   |      |               |      |
| $30 k–$49,999  | -0.63         | 0.47 | -0.25        | 0.99 | -2.40**              | 0.85 | 0.19              | 1.12 | 2.07          | 1.96 |
| $50 k–$74,999  | -1.43**       | 0.48 | -0.65        | 0.76 | -0.99                | 0.82 | -2.62†            | 1.34 | 2.23          | 1.98 |
| $75 k–$124,999 | -0.93†        | 0.52 | 0.30         | 0.74 | -0.06                | 0.91 | 0.29              | 1.21 | 2.49          | 1.64 |
| Over $125 k    | -1.63**       | 0.56 | 0.91         | 0.89 | -1.68                | 1.06 | -0.82             | 1.38 | 3.76†         | 2.01 |
| Female         | 0.45          | 0.29 | -0.14        | 0.52 | 1.37**               | 0.49 | 0.76              | 0.76 | 1.44          | 0.96 |
| House owner    | 0.12          | 0.35 | 0.93†        | 0.53 | -0.26                | 0.64 | -0.27             | 0.77 | 0.68          | 0.93 |
|                          | Exposure          | Health            | Outdoor stress | Pro-business | No mask |
|--------------------------|-------------------|-------------------|----------------|--------------|---------|
|                          | Coef.  | S.E.  | Coef.  | S.E.  | Coef.  | S.E.  | Coef.  | S.E.  | Coef.  | S.E.  |
| White                    | −0.84* | 0.37  | −0.86  | 0.60  | −1.49* | 0.67  | −0.76  | 0.78  | −0.97  | 1.19  |
| College                  | 1.11** | 0.34  | 1.22** | 0.47  | 1.25†  | 0.68  | −0.69  | 0.79  | −1.61  | 1.04  |
| Married                  | 1.37***| 0.35  | 0.28   | 0.50  | −0.12  | 0.78  | 2.84*  | 1.16  | −0.25  | 1.00  |
| Rural                    | −0.39  | 0.34  | −0.46  | 0.57  | 0.69   | 0.64  | −0.07  | 0.80  | 3.05***| 0.91  |
| Household size           | 0.08   | 0.10  | −0.05  | 0.16  | −0.13  | 0.19  | −0.51  | 0.33  | −0.17  | 0.55  |
| Have health ins.         | −1.65* | 0.75  | −2.45† | 1.41  | 2.53*  | 1.06  | −14.13***| 1.02 | 2.88*  | 1.14  |
| Not in labor force       | −0.56† | 0.33  | 0.67   | 0.53  | −0.26  | 0.60  | −2.41* | 0.96  | 0.18   | 0.78  |
| Constant                 | 0.09   | 1.69  | −1.34  | 2.88  | 1.50   | 3.06  | −2.39  | 2.80  | −2.45  | 4.46  |

Note: †p < 0.10; *p < 0.05; **p < 0.01; ***p < 0.001. The reference group for multinomial logistic was reason 1. Baseline reason is “to save time and/or for convenience.” The alternative reasons are the following: exposure means “to reduce exposure to COVID-19 which is a problem in my community”; health means “do not feel comfortable shopping by myself due to my health condition”; outdoor stress means “to alleviate stress of making outdoor trips”; pro-business means “to support business and jobs”; and no mask means “to avoid wearing a face mask.”
than good health who valued timesaving more than exposure; consumers with better than poor/fair health who valued timesaving more than health; consumers with income higher than $50,000 who valued timesaving more than exposure; consumers with income between $30,000 and $49,999 who valued timesaving more than alleviating outdoor stress; consumers with income between $50,000 and $74,999 who valued timesaving more than supporting local business; white consumers who valued timesaving more than exposure and alleviating outdoor stress; health insurance holders who valued timesaving more than exposure, health and supporting local business; and consumers not in the labor force who valued timesaving more than exposure and supporting local business.

Table 3 reports the estimation results for the reasons of not using OGS among the current nonuser sample ($n = 1493$). The baseline of these reasons was “too expensive.” From health and socio-demographic characteristics positively related to reasons other than the cost of OGS (i.e., the baseline), we learned who outweighed various COVID-19 specific factors. For instance, consumers with lung problems, consumers with better than poor health, and older consumers opted out of the service because they believed the exposure to COVID-19 is limited in their community. Moreover, older consumers and consumers in the highest income group opted out of the service because they liked to handpick groceries by themselves. This makes the older population target customers for possible online grocery service market expansion. Better service quality such as fresh produce and customizable services to address quality issues would likely help attract these consumers. Accessibility continues to be a reason for consumers with the highest income, those who are white, and those who live in rural areas to not use the service.

Some health and socio-demographic characteristics were negatively related to COVID-19 specific factors. These help us infer which consumers weigh affordability over COVID-19 specific factors. The findings imply that the price of the OGS is a prohibitive factor for consumers with immune deficiency, heart problems, kidney problems, cancer, and diabetes; consumers with income above $75,000; and consumers with college degrees. Table A1 summarizes the findings.

### 5.3 What explains the dynamics of OGS?

In this subsection, we estimated how perceived risk and socio-demographic characteristics explain the dynamics of consumers’ adoption of OGS. Table 4 reports the coefficients from five logistic estimations. In column 1 of Table 4, we first examined what drove the early adoption of OGS. Specifically, among the users at the time of the survey, we compared the always users who had used the service since the outbreak with later users who only started using the service more recently. Admittedly, some of the always users may have been using OGS prior to the pandemic, but the analysis identified what makes the always users different from the later users. We found the factors that distinguish first adopters from later users were: excellent health, age, age squared, income between $30,000 and $49,999, and a college degree. Specifically, excellent health and older age were barriers to the early adoption of OGS, whereas younger age, income between $30,000 and $49,999, and a college degree were drivers for early adoption of OGS.

In column 2 of Table 4, we examined what factors explain the continued use of OGS beyond the first peak of the pandemic. Among the users at the onset of the pandemic, we compared the always users with discontinued users who stopped using the service as the pandemic evolved. The drivers for continued use of OGS were diabetes and a college degree, and a barrier to continued use was mental health problems. In column 3 of Table 4, we examined consumers who
| Risk factor         | Outdoor need | Accessibility | Limited exposure | Health | Handpick |
|--------------------|--------------|---------------|------------------|--------|----------|
|                    | Coef. | S.E. | Coef. | S.E. | Coef. | S.E. | Coef. | S.E. | Coef. | S.E. |
| Immune             | $-18.44^{***}$ | 0.95 | $-17.12^{***}$ | 1.11 | $-14.63^{***}$ | 1.80 | $-0.37$ | 0.99 | 0.25 | 0.75 |
| Lung               | $-0.34$ | 0.56 | 0.46 | 0.75 | 3.02$^{***}$ | 0.68 | $-0.61$ | 0.51 | $-0.11$ | 0.46 |
| Heart              | 0.02 | 0.83 | $-0.82$ | 0.78 | $-14.08^{***}$ | 0.84 | 0.73 | 0.61 | 0.31 | 0.52 |
| Kidney             | $-0.19$ | 1.21 | $-0.53$ | 1.44 | $-11.70^{***}$ | 1.99 | $-1.73$ | 1.18 | $-0.57$ | 0.95 |
| Cancer             | $-0.81$ | 0.74 | $-1.33$ | 1.08 | $-15.60^{***}$ | 1.38 | $-0.46$ | 0.58 | $-0.82$ | 0.50 |
| Diabetes           | $-0.97$ | 0.64 | 0.08 | 0.87 | $-15.40^{***}$ | 1.02 | $-0.56$ | 0.61 | $-0.42$ | 0.48 |
| Obesity            | 0.05 | 0.55 | $-0.47$ | 0.62 | $-1.68$ | 1.29 | 0.23 | 0.50 | $-0.30$ | 0.41 |
| Mental             | $-0.31$ | 0.48 | $-0.86$ | 0.63 | 0.36 | 0.75 | $-0.32$ | 0.42 | $-0.22$ | 0.36 |

| Health status      | Outdoor need | Accessibility | Limited exposure | Health | Handpick |
|--------------------|--------------|---------------|------------------|--------|----------|
|                    | Coef. | S.E. | Coef. | S.E. | Coef. | S.E. | Coef. | S.E. | Coef. | S.E. |
| Good               | $-0.51$ | 0.64 | $-0.35$ | 0.80 | 2.95$^*$ | 1.31 | 0.17 | 0.64 | 0.30 | 0.49 |
| Very good          | 0.23 | 0.68 | $-0.33$ | 0.91 | 4.05$^*$ | 1.67 | 0.79 | 0.67 | 0.01 | 0.56 |
| Excellent          | $-0.22$ | 0.87 | $-1.67$ | 1.25 | 3.90$^*$ | 1.77 | 0.53 | 0.82 | $-0.04$ | 0.69 |

| Socio-demographic  | Outdoor need | Accessibility | Limited exposure | Health | Handpick |
|--------------------|--------------|---------------|------------------|--------|----------|
|                    | Coef. | S.E. | Coef. | S.E. | Coef. | S.E. | Coef. | S.E. | Coef. | S.E. |
| Age                | 0.16$^*$ | 0.09 | 0.12 | 0.12 | 0.32$^*$ | 0.17 | 0.08 | 0.08 | 0.18$^{**}$ | 0.07 |
| Age$^2$            | 0.00 | 0.00 | 0.00 | 0.00 | $-0.00^*$ | 0.00 | 0.00 | 0.00 | $-0.00^{*}$ | 0.00 |
| Income             | Outdoor need | Accessibility | Limited exposure | Health | Handpick |
|                    | Coef. | S.E. | Coef. | S.E. | Coef. | S.E. | Coef. | S.E. | Coef. | S.E. |
| $\leq 30k$         | $-0.57$ | 0.64 | 0.06 | 0.75 | $-0.92$ | 1.06 | $-0.04$ | 0.57 | 0.37 | 0.49 |
| $30k$–$49,999$     | $-0.95$ | 0.64 | $-0.76$ | 0.84 | $-0.78$ | 1.00 | 0.54 | 0.61 | 0.50 | 0.52 |
| $50k$–$74,999$     | $-0.12$ | 0.76 | 0.92 | 0.81 | $-2.04^*$ | 1.16 | 0.31 | 0.66 | 0.69 | 0.58 |
| Over $75k$         | 0.63 | 0.81 | $1.86^*$ | 0.84 | $-17.22^{***}$ | 2.01 | 1.19$^*$ | 0.70 | 1.53$^*$ | 0.62 |

(Continues)
|                  | Outdoor need | Accessibility | Limited exposure | Health    | Handpick  |
|------------------|--------------|---------------|------------------|-----------|-----------|
|                  | Coef.        | S.E.          | Coef.            | S.E.      | Coef.     | S.E.      | Coef.     | S.E.      | Coef.     | S.E.      |
| Female           | -0.23        | 0.43          | 0.59             | 0.48      | 0.35      | 1.06      | -0.09     | 0.36      | 0.13      | 0.31      |
| House owner      | -0.07        | 0.47          | 0.24             | 0.67      | 0.10      | 0.59      | -0.06     | 0.53      | 0.04      | 0.38      |
| White            | -0.64        | 0.47          | 2.31†            | 1.26      | 1.40      | 1.11      | 0.31      | 0.51      | -0.47     | 0.41      |
| College          | -0.59        | 0.42          | 0.48             | 0.45      | -3.03*    | 1.39      | -0.31     | 0.34      | -0.74*    | 0.31      |
| Married          | -0.37        | 0.49          | -0.11            | 0.55      | -1.20     | 0.79      | -0.08     | 0.39      | -0.25     | 0.39      |
| Rural            | 0.65         | 0.55          | 3.23***          | 0.56      | -0.74     | 0.97      | 0.33      | 0.55      | 0.50      | 0.41      |
| Household size   | -0.04        | 0.16          | 0.00             | 0.16      | 0.03      | 0.24      | -0.18     | 0.14      | -0.02     | 0.12      |
| Have health ins. | 0.39         | 0.84          | 0.14             | 1.25      | 0.82      | 1.26      | 0.58      | 0.76      | 0.91      | 0.70      |
| Not in labor force| 0.27       | 0.43          | -0.23            | 0.53      | -0.56     | 0.91      | -0.28     | 0.40      | -0.06     | 0.34      |
| Constant         | -4.23        | 2.58          | -9.32**          | 3.25      | -13.59*** | 4.03      | -2.59     | 2.30      | -3.80†    | 1.94      |

Note: †p < 0.10; *p < 0.05; **p < 0.01; ***p < 0.001. The reference group for multinomial logistic was reason 1. The baseline reason is “too expensive.” The alternative reasons are the following: outdoor need means “need to get out of the house anyway”; accessibility means “service not available in my region”; limited exposure means “COVID-19 is not a problem in my community”; health means “feel comfortable shopping by myself due to my health condition”; and handpick means “prefer to pick grocery items by myself.”
TABLE 4 Logit regressions for OGS decision dynamics

| Variables      | Always vs. later | Always vs. discontinued | Discontinued vs. later | Discontinued vs. never | Later vs. never |
|----------------|------------------|-------------------------|------------------------|------------------------|----------------|
| Risk factor    |                  |                         |                        |                        |                |
| Immune         | −0.42            | −0.79                   | −0.94                  | 1.05                   | 0.88           |
|                | (1.12)           | (0.81)                  | (1.07)                 | (0.70)                 | (1.01)         |
| Lung           | −0.16            | −0.25                   | −0.32                  | 0.68†                  | 0.93*          |
|                | (0.41)           | (0.41)                  | (0.47)                 | (0.38)                 | (0.41)         |
| Heart          | 0.43             | 0.01                    | 1.41                   | 0.21                   | 0.08           |
|                | (0.48)           | (0.37)                  | (0.89)                 | (0.35)                 | (0.51)         |
| Kidney         | −0.26            | 0.52                    | −1.14                  | −0.72                  | −0.39          |
|                | (0.97)           | (0.84)                  | (0.84)                 | (0.66)                 | (0.74)         |
| Cancer         | −0.89            | 0.51                    | −2.11†                 | 0.39                   | 1.21           |
|                | (0.94)           | (0.51)                  | (1.20)                 | (0.44)                 | (0.75)         |
| Diabetes       | −0.42            | 0.86†                   | −1.69**                | −0.75*                 | 0.33           |
|                | (0.44)           | (0.45)                  | (0.55)                 | (0.35)                 | (0.46)         |
| Obesity        | 0.39             | 0.35                    | 0.19                   | −0.23                  | −0.27          |
|                | (0.45)           | (0.33)                  | (0.48)                 | (0.32)                 | (0.43)         |
| Mental         | 0.44             | −0.52†                  | 1.02*                  | 0.44                   | −0.52          |
|                | (0.37)           | (0.29)                  | (0.41)                 | (0.29)                 | (0.38)         |
| Health status  |                  |                         |                        |                        |                |
| Good           | 0.14             | 0.17                    | −0.51                  | 0.04                   | −0.07          |
|                | (0.41)           | (0.46)                  | (0.61)                 | (0.45)                 | (0.40)         |
| Very good      | −0.16            | −0.10                   | −0.26                  | 0.13                   | 0.06           |
|                | (0.46)           | (0.46)                  | (0.64)                 | (0.46)                 | (0.50)         |
| Excellent      | −1.08†           | −0.45                   | −0.99                  | −0.23                  | 0.23           |
|                | (0.60)           | (0.59)                  | (0.75)                 | (0.53)                 | (0.62)         |
| Socio-demographic |               |                         |                        |                        |                |
| Age            | −0.19*           | −0.01                   | −0.20†                 | −0.10†                 | 0.001          |
|                | (0.08)           | (0.06)                  | (0.10)                 | (0.06)                 | (0.069)        |
| Age²           | 0.002*           | −0.00                   | 0.002*                 | 0.01                   | −0.00          |
|                | (0.001)          | (0.00)                  | (0.001)                | (0.00)                 | (0.00)         |
| Income         |                  |                         |                        |                        |                |
| $30 k–$49,999  | 1.01†            | 0.69                    | 0.69                   | −0.09                  | −0.77          |
|                | (0.52)           | (0.52)                  | (0.73)                 | (0.44)                 | (0.52)         |
| $50 k–$74,999  | 0.58             | −0.03                   | 1.11†                  | 0.37                   | −0.37          |
|                | (0.47)           | (0.54)                  | (0.66)                 | (0.48)                 | (0.56)         |
| $75 k–$124,999 | 0.12             | −0.48                   | 0.57                   | 1.12**                 | 0.64           |
|                | (0.56)           | (0.56)                  | (0.64)                 | (0.41)                 | (0.58)         |

(Continues)
Specifically, we compared discontinued users with later users to study what distinguishes the timing of use. We found that consumers with mental health problems, income between $50,000 and $75,000 and over $125,000 were more likely to use the service at the onset rather than later if they only used it at one point in time. Consumers with cancer, diabetes, older, having a larger household, and not in the labor force were more likely to use the service later. In column 4, we compared two types of nonusers at the time of the survey: discontinued users and never users. We found that conditional on not using the service at the time of the survey, consumers with lung disease, with income above $75,000, and female were more likely to have used it at the onset but discontinued, and those with diabetes and of older age were less likely to have used it at the onset. In column 5, we compared later users with never users, both of whom did not use

| Variables          | Always vs. later | Always vs. discontinued | Discontinued vs. later | Discontinued vs. never | Later vs. never |
|--------------------|------------------|-------------------------|------------------------|------------------------|-----------------|
| Over $125k         | 0.70             | −0.22                   | 1.35†                  | 0.81†                  | −0.18           |
|                    | (0.56)           | (0.54)                  | (0.70)                 | (0.45)                 | (0.61)          |
| Female             | 0.27             | −0.24                   | 0.26                   | 0.60*                  | 0.21            |
|                    | (0.33)           | (0.30)                  | (0.37)                 | (0.25)                 | (0.29)          |
| House owner        | 0.18             | −0.44                   | 0.22                   | −0.38                  | −0.72†          |
|                    | (0.40)           | (0.35)                  | (0.51)                 | (0.28)                 | (0.38)          |
| White              | 0.05             | 0.04                    | 0.33                   | −0.08                  | 0.02            |
|                    | (0.39)           | (0.37)                  | (0.43)                 | (0.35)                 | (0.36)          |
| College            | 0.76†            | 0.77*                   | −0.20                  | −0.16                  | −0.26           |
|                    | (0.40)           | (0.32)                  | (0.43)                 | (0.28)                 | (0.34)          |
| Married            | −0.31            | 0.18                    | −0.31                  | −0.03                  | 0.23            |
|                    | (0.37)           | (0.39)                  | (0.48)                 | (0.36)                 | (0.40)          |
| Rural              | 0.55             | 0.01                    | 0.70                   | −0.07                  | −0.56           |
|                    | (0.39)           | (0.35)                  | (0.43)                 | (0.30)                 | (0.37)          |
| Household size     | −0.10            | 0.16                    | −0.31*                 | −0.07                  | 0.20*           |
|                    | (0.11)           | (0.11)                  | (0.14)                 | (0.10)                 | (0.10)          |
| Have health insurance | 0.52            | −0.12                   | 0.90                   | 0.58                   | −0.03           |
|                    | (0.61)           | (0.71)                  | (0.68)                 | (0.57)                 | (0.63)          |
| Not in labor force | −0.52            | 0.44                    | −1.09*                 | −0.18                  | 0.69†           |
|                    | (0.40)           | (0.29)                  | (0.46)                 | (0.28)                 | (0.40)          |
| Constant           | 4.97*            | 1.25                    | 4.17                   | 0.30                   | −1.34           |
|                    | (2.07)           | (1.88)                  | (2.63)                 | (1.71)                 | (1.71)          |

Observations: 641, 734, 319, 1493, 1400

Note: †p < 0.10; *p < 0.05; **p < 0.01; ***p < 0.001. Estimates and robust standard errors from logit regressions are reported. Bolded types in the column title were coded as “1” and the alternative type as “0” for the dependent variable.
the service at the onset, but later users indicated they had recently begun using the service. We found that conditional on not using the service at the onset, consumers with lung disease, larger households, not in labor force were more likely and those who were homeowners were less likely to pick up the service before the survey.

Table A1 summarizes the statistically significant differentiating factors. In sum, lung disease, diabetes, mental health problems, age, income over $125,000, and a college degree were major factors that explained the dynamics of OGS in the first 7 months of the pandemic. In general, those with lung disease, younger age, income over $125,000, and a college degree consistently favored the use of OGS.

6 CONCLUSION AND DISCUSSION

In this article, we studied consumers’ choice of OGS during the first seven months of the COVID-19 pandemic factoring in health and economic considerations. Our theoretical framework predicted that both situational factors related to the COVID-19 pandemic and household production factors should affect the choice between in-store and online grocery shopping. Specifically, consumers would decrease their in-store shopping and increase their online shopping as their time value, perceived infection risk, or perceived COVID-19 treatment costs increase, and they would do the opposite if the cost of OGS increases. Our unique survey design captured the reasoning behind and the dynamics of consumers’ OGS choices during the first seven months of the COVID-19 Pandemic. By studying the health and demographic profiles of consumers of different OGS choices and dynamics, we have gained insights into the future development of technology-assisted adaptation to a public health crisis.

Our empirical analyses reveal how perceived infection risks and perceived treatment costs of COVID-19 resulting from in-store shopping have played a role in the OGS choice. Our findings suggest that consumers with most COVID-19 risk conditions did not opt into OGS to limit exposure or protect their health, but they did so to support local businesses. Meanwhile, they were less likely to opt in because of their aversion to masking. When they have opted out of OGS to risk their exposure to COVID-19, they did so because OGS was too expensive for them. Consumers with better health opt into OGS because they valued their time; they would opt out if they perceived low exposure risk in their community. Older consumers would also opt out when they perceive low exposure risk. Health insurance holders seemed to worry less about exposure or protecting health, and they opted in for timesaving or aversion to masking.

Our findings provide insights into further avenues of development for the OGS market by linking consumers’ sociodemographic profiles to the reasons for their OGS choice. We find that consumers with moderate-to-high income, white consumers, and consumers not in the labor force value the timesaving and convenience of OGS more than various COVID-19 specific reasons even during the pandemic. The consumers who did opt out of OGS because of cost and accessibility are the potential market that the OGS industry can grow. Our study shows that higher-income (higher than $75,000) consumers would risk exposure because of costs. Consumers with the highest income (greater than >$125,000) and those who are white or reside in rural areas would opt out of OGS because of inaccessibility. Our findings also suggest how the OGS market can grow by improving the customer experience. We find that older consumers and the highest-income consumers indicated that they opt out of the service because they liked to handpick their grocery products.
Our analyses shed light on the development of technology-assisted adaptation to future emergency situations. We find that those with lung disease, younger age, income over $125,000, and a college degree consistently favored the use of OGS. These findings have important implications for the marketing strategy of providers of technology-assisted adaptation should another public health crisis or other emergencies emerge. They may want to direct their marketing efforts toward targeted populations who were not naturally early adopters of the service and who were less likely to stick to the service. The grocery industry may want to adjust its marketing strategy accordingly in preparation for future emergency situations.

The COVID-19 pandemic is unprecedented in any sense. The public, academia, and industry are making every effort to learn lessons from it. Technology-assisted adaptations such as OGS and remote working played a vital role in helping society resume its basic functions in the face of COVID-19 interruptions. Presumably, those who were able to take advantage of these options were better off in the pandemic. These technologies could have a profound impact on the social norms of how we conduct daily activities. Therefore, studying the initial adoption of the technologies is meaningful and will shed light on how to improve consumer wellbeing in general and especially in emergency situations. Our study provides insights into consumer decision-making and provides a framework for analyzing the adoption of new technologies that help outsource home production.

The timing of our survey is critical in interpreting our findings. The survey was conducted in October 2020, before the COVID-19 vaccine was available to the public. The findings thus were not confounded by the rollouts of the COVID-19 vaccination. It can be expected that as the vaccination rate increases, the population mobility and personal contact will increase, and the social distancing and face mask mandates will gradually be relaxed. In the interim between partial immunity and herd immunity, there exists a period of great uncertainty in exposure to the disease, which could also affect consumers’ willingness to shop in person. For instance, those who were doing OGS to minimize exposure to the disease may have a stronger motivation to do so when face masks are no longer expected yet herd immunity is not achieved. Future research should continue monitoring consumer decisions as the dynamics of the pandemic change, especially considering vaccine hesitancy and the emergence of new variants. Tracking a sample of consumers as the pandemic evolves would provide valuable information for data analysis. A mixed-method approach with a focus group interview could offer additional insights into more complex consumer motivations behind OGS decisions. Additional information about consumers’ work and life arrangements such as work-from-home and childcare would also further inform the analysis of OGS decisions.

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ORCID
Yilan Xu  https://orcid.org/0000-0003-3650-1416
Wookjae Heo  https://orcid.org/0000-0001-5807-9792
Soo Hyun Cho  https://orcid.org/0000-0002-8996-2489
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**APPENDIX A**

| Initial Question | Initial answers | RQ2 coding | Skip pattern | Following questions | Following answers | RQ1(a,b) coding |
|------------------|-----------------|------------|--------------|---------------------|------------------|-----------------|
| Q1. Have you or your family ever used online grocery shopping service (e.g., Walmart Grocery, Instacart, Amazon Grocery, or paid grocery delivery) since the COVID-19 outbreak? | a. Have been using it since the outbreak. | always users | Q2a. What is your most important reasons for using it? | a. To save time and/or for convenience. | baseline |
| | b. Only started using it recently. | later users | | b. To reduce exposure to COVID-19 which is problem in my community. | exposure |
| | c. Used it earlier but have canceled it. | discontinued users | Q2b. What is your most important reason for not using it now? | c. Do not feel comfortable shopping by myself/ourselves due to health conditions. | health |
| | d. Have never used it. | never users | | d. To alleviate stress of making outdoor trips. | outdoor stress |
| | | | | e. To support business and create more jobs in my community. | pro-business |
| | | | | f. To avoid wearing a face covering. | no masks |

**FIGURE A1** Survey questions and variable coding

**TABLE A1** Summary findings

| Variables | Exposure | Health | Outdoor stress | Proximity | No-travel | Outdoor need | Accounts try | Limited exposure | Health | Handpick | Always vs. More | Always vs. Less | Died by last | Died in last | Died in later | Ever | Ever vs. Never | Ever vs. Never | Ever vs. Never |
|-----------|----------|--------|----------------|-----------|-----------|--------------|--------------|-----------------|--------|-----------|----------------|----------------|--------------|-------------|---------------|-------|----------------|----------------|----------------|
| Baseline  |          |        |                |           |           |              |              |                 |        |           |                |                |              |             |               |       |                |                |                |
| Income    |          |        |                |           |           |              |              |                 |        |           |                |                |              |             |               |       |                |                |                |
|          |          |        |                |           |           |              |              |                 |        |           |                |                |              |             |               |       |                |                |                |
|          |          |        |                |           |           |              |              |                 |        |           |                |                |              |             |               |       |                |                |                |
|          |          |        |                |           |           |              |              |                 |        |           |                |                |              |             |               |       |                |                |                |
|          |          |        |                |           |           |              |              |                 |        |           |                |                |              |             |               |       |                |                |                |

1 p < .05; * p < .01; ** p < .001

Positive

Negative