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Research Note

Preferences for online grocery shopping during the COVID-19 pandemic — the role of fear-related attitudes[☆]

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ABSTRACT

In this study, we employ a choice experiment to analyze New York City residents' preferences for online grocery shopping at the beginning of the COVID-19 pandemic. We employ a latent class specification to identify three market segments and estimate consumers' willingness to pay for a variety of attributes of online grocery services related to the quality of the stock, delivery characteristics, and the cost of the online order. We characterize consumers in each segment by their observed characteristics as well as fear-related latent variables. On the one hand, we find that individuals who are actively protecting themselves against COVID-19 have a higher willingness to pay for almost all attributes. On the other hand, consumers who avoid crowds have a lower willingness to pay, but they assign relatively higher importance to no-contact delivery.

1. Introduction

The new coronavirus COVID-19, first identified at the end of 2019, quickly became a major challenge to the modern world. A subsequent global health crisis was officially acknowledged by WHO on March 11, 2020, when COVID-19 was declared a pandemic. Since then, COVID-19 has affected the lives of people all around the world, forcing them to change their daily habits and behaviors in a rapid fashion. Suddenly, individuals needed to adjust to a new reality of social distancing, wearing masks, and often also remote working or schooling. The growing number of COVID-19 cases caused panic (Depoux et al., 2020) as well as affected individuals' well-being and mental health (Zhang et al., 2020; O'Connor et al., 2021). To limit the spread of the virus multiple public policies were introduced, including restricting social life to decrease physical interactions between individuals. For instance, the "New York State on PAUSE" executive order was introduced on March 22, 2020, closing all non-essential businesses in the state, including restaurants and retail shops. As a consequence of increased health risk of social interactions and mobility-restricting public policies, individuals turned towards digital media, such as gaming, streaming services, social media, and online shopping (Eger et al., 2021; Lemenager et al., 2021; Tsao et al., 2021). In this paper, we focus on online shopping. Specifically, we analyze New York City (NYC) residents' preferences for online grocery shopping at the beginning of the COVID-19 pandemic. To this end, we exploit choice microdata from an online survey conducted at the beginning of May of 2020 in NYC when the "New York State on PAUSE" order was still in place.

The online grocery shopping sector has been steadily growing throughout the last decade (Anesbury et al., 2016), making it an important field of study within consumer research. This growth has been rapidly hastened by the pandemic. Although some of the

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interest in online grocery is likely to fall after the pandemic, some habits developed during this period are likely to continue (Sheth, 2020). Furthermore, multiple large retailers invested in online grocery technology, and continue to do so, even after the number of COVID-19 cases dropped and government restrictions were lifted (Arcieri, 2021). The contribution of the current study is twofold. First, we contribute to the literature regarding online groceries by developing a choice experiment (CE) in which characteristics of the online grocery service related to delivery, quality of stock, and additional costs are each described by several attributes and therefore recognize the multidimensional nature of online purchasing decisions. Second, we study consumers' behavior during the pandemic. Because of the surrounding global health crisis, there are emergent socio-psychological factors that are likely to affect individuals' propensity to shop for groceries online, which were not considered before the outbreak. Recent studies analyzing such factors consider constructs such as perceived vulnerability and risk of infection (Moon et al., 2021), fear of the health-related and economic consequences of the pandemic (Eger et al., 2021), general uncertainty caused by the pandemic, attitudes towards social distancing guidelines (Moon et al., 2021), and the perceived risk of formal penalties (e.g., fines) for not complying with the governmental restrictions (Alhaimer, 2021). With the pandemic still active, and having in mind possible future pandemics (Halabowski and Rzymski, 2021), it is important to understand how these factors affect individuals' behavior. In this study, we focus on the effect of fear and anxiety that the pandemic has induced (O'Connor et al., 2021). Conceptually, we link individuals' stated grocery choices in the CE with individuals' responses to the pandemic. Specifically, we operationalize a choice model that integrates two attitudinal constructs. The first attitude measures individuals' propensity to employ some active protection against COVID-19, such as wearing a mask outdoors or using disinfecting wipes. We hypothesize that individuals who take active actions against COVID-19 will be more likely to use online grocery services, as another measure to limit their exposure to the virus. With the second attitude, we measure individuals' avoidance of crowds. One of the most direct responses to fear and anxiety is escape or avoidance (So et al., 2016). As social distancing is probably one of the most common non-pharmaceutical interventions introduced by the governments around the world (Ferguson et al., 2020; Greenstone and Nigam, 2020), the avoidance of crowds is probably the most straightforward reaction to the pandemic-induced fear. At the same time, offline shopping is often connected to crowding, as one of the main advantages of large retail shops is that they can process a large number of customers in a short time (Li et al., 2020). As during the pandemic crowding had basically become a health hazard, we argue that a negative attitude towards crowding may act as a significant factor pulling individuals from offline shopping to online shopping. To combine CE data with measures of attitudes and socio-demographic variables we implement a hybrid choice model (Ben-Akiva et al., 2002). In fact, we exploit a latent class logit kernel to account for unobserved preference heterogeneity in a way that is more easily interpretable than when working with continuous heterogeneity distributions.

The rest of the paper is structured as follows. In Section 2 we present a literature review regarding online grocery shopping and coping with fear and anxiety in the context of consumer behavior. We also postulate the hypotheses that will be investigated in the current study. Section 3 provides details about the survey and CE that we use. In Section 4, we describe the hybrid choice model used for the econometric analysis of the data. Section 5 presents the results of the analysis. The last section provides the discussion of the results and their implication for retailers as well as for public policy.

2. Literature review

2.1. Online grocery shopping

Starting in the early 2000s, online grocery became a subject of studies from the perspective of the consumer (Verhoef and Langerak, 2001; Hansen et al., 2004) as well as the retailer (Anckar et al., 2002). Darley et al. (2010) provide a review of early research as well as a conceptual framework for a consumer's decision process when shopping online. Studies conducted to date have analyzed how consumers behave when shopping online (Anesbury et al., 2016), situational factors that make individuals start or stop using online services (Hand et al., 2009), and compared attitudes between traditional and online shopping (Kacen et al., 2013). Nonetheless, as argued by Bauerová (2018) limited research investigated the effects of delivery conditions and services offered on consumers' preferences. Frank and Peschel (2020) show that not only delivery conditions are important for the consumer, but also that there exists significant preference heterogeneity with respect to attributes' importance. In the current study, we expand on this research by considering the multidimensional nature of online purchasing decisions and investigating consumers' preferences towards delivery conditions, quality of the stock, and associated costs. In order to elicit consumers' preferences for this wide variety of attributes and account for possible preference heterogeneity, we employ a choice experiment method.

Choice experiments (CE) allow researchers to investigate consumers' preferences for the set of attributes of a given good and study the trade-offs that individuals make between them. It is a popular method of eliciting preferences used in consumer research, environmental economics, transportation, and health economics. Surprisingly, the use of CE to study online shopping behavior is rather sparse (Martín et al., 2019). The advantage of CE is that a researcher can exogenously vary the levels of considered attributes, and, therefore, gain an insight into the effect of a change in the quality of a given attribute on a consumer's choice. In the online grocery context, CE can therefore help retailers to identify the attributes of the service that consumers consider to be important as well as identify other factors that drive their behavior. Furthermore, as CEs constitute a rich data source, they can be used to investigate preference heterogeneity and market segmentation.

Most of the studies employing CEs in the online shopping context use a labeled format, where the choice is either between online-grocery shopping and in-store shopping, or between different methods of delivery of online groceries. Schmid and Axhausen (2019) focus on the former, with separate CEs for the shopping of groceries and electronics (durable goods). The survey was conducted in Zurich, Switzerland between 2015 and 2016. They find that the disutility related to the delivery time and delivery cost is much greater in the case of groceries (when compared to electronics), making it much more likely that consumers will prefer to simply buy groceries in the store. Milioti et al. (2021) use CE to analyze consumers' preferences for e-groceries in the UK and Greece in 2016. They focus on the mode of delivery (home vs. pick-up) and time window in which the product will become available, by additionally considering the urgency of the purchase. They find that consumers consistently prefer home delivery over pick-up, although this difference diminishes if the purchase is urgent. Magalhães (2021) also focus on the mode of delivery (home vs. automatic delivery stations), with the additional analysis of the effects of elapsed time from order to delivery, and the order fill rate (the percentage of products ordered by the customer that can be met from stock). The study is based on a 2012 choice experiment survey conducted in Brazil. Marcucci et al. (2021) consider a CE in which consumers choose between in-store shopping and two modes of online-grocery delivery. The study was conducted in 2018 in Norway. They find considerable market segmentation, with one consumer segment vastly preferring in-store shopping, while the other preferring e-groceries with home delivery.

We are aware of only two online grocery-related CEs conducted during the pandemic. Grashuis et al. (2020), similarly to Milioti et al. (2021), focus on the method of delivery and time window, but they additionally account for the minimum order requirement. Furthermore, they exogenously vary pandemic conditions, by informing respondents whether the number of COVID-19 cases is currently increasing or not. They find that the intensity of infections affects consumers' preferences for different methods of delivery. Meister et al. (2023) consider a similar setting to Schmid and Axhausen (2019) at the beginning of the pandemic in Switzerland. They introduce two CEs: the first describing a choice situation before the pandemic, and the second describing a choice situation during the pandemic. They estimate that the pandemic may have increased the probability of using online-grocery shopping by about 13%-points.

Several other studies employ the CE method within the online shopping context, although they do not specifically consider purchasing groceries (Gawor and Hoberg, 2019; Nguyen et al., 2019). The subject of these studies is often the method of delivery, usually comparing house delivery with some pick-up points (Collins, 2015; Oliveira et al., 2017).

2.2. Fear as a driver of behavior

Our study is driven by the theoretical literature regarding individuals' coping with fear and anxiety (Lazarus, 1991; So et al., 2016). In consumer research, there is a long-time interest in this topic, mainly concerning the so-called fear appeals and related models. Fear appeal denotes a strategy to motivate individuals to certain actions by arousing fear. It is often used by marketing companies, especially for health-related products. In the context of the COVID-19 pandemic, fear appeals were often used by governments to encourage compliance with governmental restrictions, vaccination, etc. (Biana and Joaquin, 2020). Although using fear appeals as a part of social campaigns is a controversial topic (Stolow et al., 2020), the rich literature on their effects provides a conceptual framework for the current study.

It is generally acknowledged that individuals can deal with fear and anxiety in two ways, namely: (i) by taking a proactive action (problem-focused coping), or (ii) by trying to manage their emotions (emotion-focused coping) (So et al., 2016). The former usually means taking actions that limit exposure to a given threat, whereas the latter involves some coping mechanisms such as reframing or denial to manage the fear itself. As postulated by the extended parallel process model (Witte, 1992), whether an individual will use (i) or (ii) depends on the perception of the efficiency of the available actions. If they are perceived as highly effective, then the individual will try to manage the given threat by taking the necessary actions, whereas if they are deemed as ineffective, the individual will try to manage his fears, for example by engaging in denial. Nonetheless, as argued by So et al. (2016) most studies utilizing the extended parallel process model put too much emphasis on emotion-focused coping, which is not consistent with the functional theories of emotion. Indeed, as stated by Lazarus (1991), "acting against danger, even when there is little or nothing effective to be done, is more reassuring than uncertainty and inactivity". In the current study, we, therefore, focus on problem-focused coping.

The emergence of COVID-19 has led to worldwide fear and anxiety (Ahorsu et al., 2020), especially in the early months of the pandemic. In the face of the crisis, individuals had to cope with the fear they were experiencing. The main two types of problem-focused coping are protection and avoidance (So et al., 2016). Protection could include taking preventive measures such as wearing masks, frequently washing hands, or using disinfecting wipes. (In the later stage of the pandemic, vaccination has become the main protective measure.) Avoidance is not straightforward in the case of the virus, as it is an invisible threat and therefore cannot be easily avoided. Nonetheless, individuals could still be avoiding COVID-19 by avoiding other people. As the spread of the virus accelerates with the number of individuals, we specifically focus on the avoidance of crowds. Social distancing could be considered to be both, a protective measure as well as an avoidance behavior. Nonetheless, in the current study, we argue that these attitudes are distinct, as formulated in our first hypothesis.

$\boldsymbol{H_1}$: Individuals have distinct attitudes towards active protection against COVID-19 and avoiding crowds.

In this study, we link individuals' attitude towards active protection against COVID-19 with their preferences for online-grocery shopping. Shopping for groceries online is associated with a lower risk of infection, as users are not exposed to the virus in the same way as they could be in a regular retail environment. Therefore, we expect that individuals who are likely to employ protective measures will be more likely to use online grocery services. This constitutes our second hypothesis.

$\boldsymbol{H_2}$: Individuals with a high attitude towards active protection against COVID-19 are more likely to opt-in for online-grocery shopping.

There is considerable literature on the effect of perceived crowding on retail behavior (Blut and Iyer, 2020). Findings from marketing studies indicate that crowding has a significant effect on in-store shopping behavior and related outcomes. Often studies distinguish between human and spatial crowding (Kim et al., 2016). The former refers simply to the number of individuals in the

given venue, whereas the latter refers more to the limited space of the retail environment, which may induce individuals to feel like their movement is restricted. Spatial crowding is usually associated with a negative effect, whereas human crowding may actually lead to positive effects (e.g., higher satisfaction). The positive effect may be caused by individuals treating the number of individuals (human crowding) as a proxy for the quality of a given shop. Nonetheless, as argued by Eroglu et al. (2022), because of the pandemic we entered the "new normal", and therefore the effect of human crowding should be reexamined. Indeed, their findings suggest that during the pandemic perceived human crowding has a negative effect on shopping satisfaction. In the current study, we built upon this research by considering the effect of crowding on online grocery shopping. Of course, there is no crowding when shopping online. Nonetheless, online grocery shopping is a substitute for in-person shopping, which is often connected with heavy crowding. As during the pandemic human crowding had basically become a health hazard, we argue that crowding avoidance attitude may act as a significant factor pulling individuals from offline shopping to online shopping. This constitutes the base of our third hypothesis.
$\boldsymbol{H_3}$: Individuals with high crowds avoidance attitudes are more likely to opt-in for online-grocery shopping.

Overall, our study contributes to the growing literature about the effects of the COVID-19 pandemic on consumer behavior. Specifically, we expand on previous research that looked into the effect of fear (Al Amin et al., 2021; Eger et al., 2021; Eroglu et al., 2022) by focusing on the effect of attitudes related to problem-coping and using a choice experiment to measure individuals' preferences towards online grocery shopping.

3. Survey

3.1. Survey structure and data collection

Data used in this study come from an online survey conducted in May of 2020 in NYC. The aim of the survey was to measure the disruption of the daily lives of NYC residents caused by the COVID-19 outbreak. A large part of the questionnaire was concerned with grocery shopping behavior. Specifically, there were two CEs in the survey: one regarding in-person shopping during COVID-19 pandemic, and second, concerned with online groceries. In the current study we use data from the latter CE. Information about data collection, survey design, and modeling of the first CE can be found in Rossetti et al. (2022).

The survey consisted of six parts, with the median time to complete it of about 26 min. The survey started with some screening questions, after which respondents were asked to provide information regarding their daily life before COVID, for example, their daily commutes and sport activity. The next section was focused on grocery shopping. Respondents were interviewed about their habits before COVID as well as how their behavior had changed since the start of the pandemic. This part of the survey ended with a CE regarding in-person grocery shopping. After that, respondents were asked about their experience with online grocery shopping, which was followed by the second CE which is utilized in the current study. We describe the design of this CE in detail in the next subsection. The fifth part of the survey consisted of questions related to the COVID-19 pandemic. Specifically, individuals' concerns about the pandemic and how disruptive it has been for their daily lives. The questionnaire ended with standard socio-demographic questions. In total, 775 respondents completed the survey.

In Table 1 we report a brief summary of several variables from the survey that we later exploit in the econometric modeling of the data. For convenience, in the last column, we additionally provide data from the NYC census. In the first part of the table, we report basic socio-demographic covariates. Comparing the sample to the census data for NYC, we find that the sample has a lower share of older individuals, a lower share of females, a higher median income, and a higher education level. This difference in sampling is expected for a survey that was conducted online (Adriaan and Jacco, 2009; Szolnoki and Hoffmann, 2013). In the second part of the table, we report some statistics for individuals' grocery-related behavior. Specifically, the median respondent spends \$782 per month on groceries, and, on average, respondents have access to a grocery shop within a 1-mile radius. Furthermore, 20% of the sample never used any online grocery service. Table 1 is accompanied by Fig. 1 which provides more information regarding the grocery habits of respondents before the COVID-19 outbreak, as well as changes in their behavior due to the pandemic. From the upper plot in Fig. 1, we can distinguish three main types of consumers: those who shop for groceries in small quantities several times a week (36%), those who shop rarely but buy groceries in large quantities (46%), and those who do most of their grocery shopping online (10%). Furthermore, the lower plot reveals that only 12% of respondents stated that the pandemic did not affect their grocery shopping behavior. The three most often indicated changes are that individuals buy larger quantities (60%), buy products that last longer (48%), and buy online more often (41%). These results support the finding from the previous research that during the pandemic, stockpiling behavior is more prevalent (Hao et al., 2020) and that many individuals switched to online shopping (Baarsma and Groenewegen, 2021).

Additionally, in the last part of Table 1 we provide shares for the health-related variables used in this study. As poor health status can increase the risk of hospitalization and death from COVID-19, it is likely that these variables will affect individuals' behavior. We find that the share of overweight respondents (with Body Mass Index over 24.9) is 46%, whereas the share of respondents who reported their health status to be average or worse (on 5-point scale from excellent to very poor) is 17%.

3.2. Online grocery shopping choice experiment

The choice experiment elicited respondents' preferences for online grocery shopping. Each choice situation consisted of two alternatives, each of them representing different services for ordering groceries online. Additionally, respondents had an option to opt-out from the choice altogether in case they were not satisfied with any of the available options. Services differed in terms of several attributes which are listed in Table 2. Each service was described by the attributes in terms of the quality of the stock

Table 1
Basic socio-demographic, grocery-related and health-related characteristics of the respondents.

	Median (or share)	
	Sample	Census
Age: 20–39 (share)	0.64	0.39
Age: 40–64 (share)	0.33	0.42
Age: over 64 (share)	0.03	0.22
Female (share)	0.4	0.52
Education level: below high school (share)	0.01	0.16
Education level: high school or college without degree (share)	0.19	0.35
Education level: higher education (share)	0.8	0.49
Annual household income (before tax)	$87,500	$70,663
Number of children in household	2	
Number of elderly in household	1	
Grocery related variables		
Monthly grocery expenditures	$782	
Distance to grocery shop	1 mi	
Did not use any online grocery services (share)	0.2	
In the last month got online groceries once or never (share)	0.29	
Health related variables		
Overweight (share)	0.46	
Self reported health: Average or worse (share)	0.17	

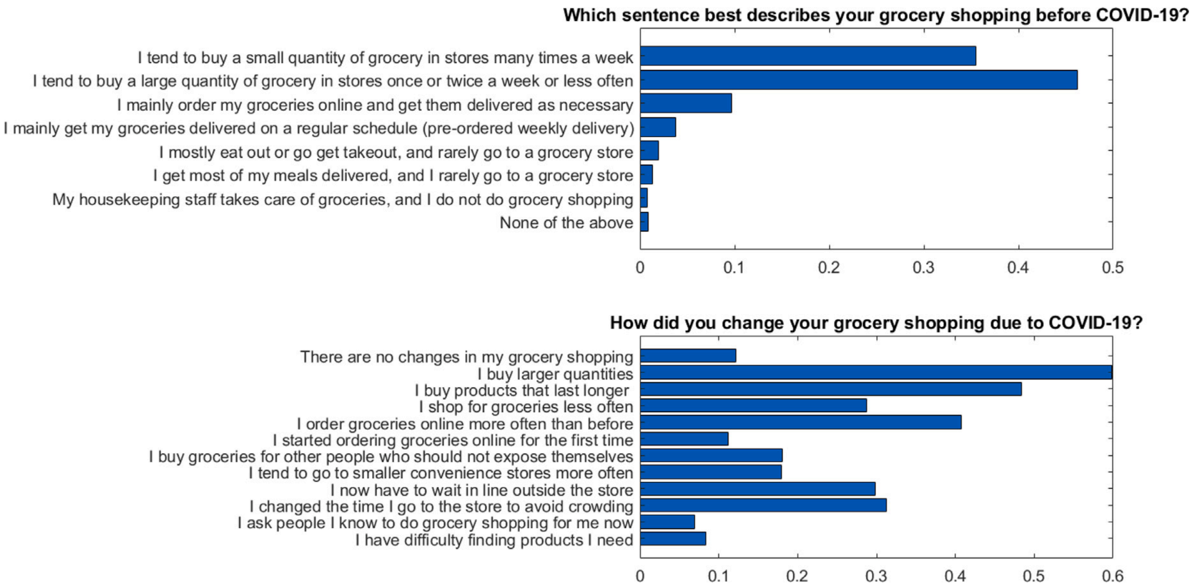

Fig. 1. Respondents' grocery-related habits and their change due to COVID-19 pandemic.

(brand variety, organic produce, reliability), delivery characteristics (no-contact, next available timeslot, likely delay) and a cost of the online order (markup, delivery cost). We note that due to increased demand at the time of data collection, consumers could face unprecedented delays in the availability of timeslots, which are reflected in the levels for that attribute. In contrast to the previous research we do not focus on the method of delivery (Milioti et al., 2021), and instead just consider home delivery. This is the most common delivery option in most countries (Hübner et al., 2016). The main disadvantage of home delivery is that individuals have to be at home to pick it up. We consider this to be less of a concern for the setting of the current study, as during pandemic and the "New York State on PAUSE" order, many individuals were working remotely from home, so this would be the most likely form of delivery. An example of the choice card is presented in Fig. 2. Whereas the first 30 respondents (pilot study) completed only 5 choice cards, the rest of the respondents completed 7 choice cards.

3.3. Attitudes

To control for respondents' attitudes, we use a hybrid choice model. In this framework, as described in detail in the next section, latent variables are identified by linking them with both, individuals' choices in CE, and individuals' answers to attitudinal questions.

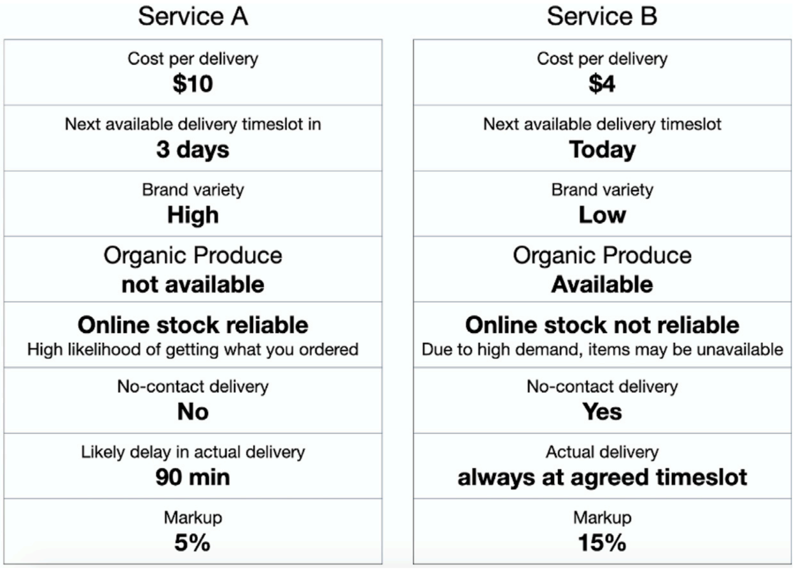

Fig. 2. Sample choice card.

Table 2
Choice experiment attributes and their levels.

Attribute name	Attribute levels
Cost per delivery	$4, $6, $10, $20
Next available delivery timeslot	Today, in 3 days, in 6 days, in 7 days
Brand variety	Low, Medium, High
Organic produce	Not available, available
Online stock reliable	No, Yes
No-contact delivery	No, Yes
Likely delay in actual delivery	On time, 45 min, 90 min
Markup	5%, 15%

In this study we focus on two attitudes: (i) active protection against COVID-19, and (ii) crowds avoidance. In Table 3 we list the indicator variables used in the hybrid choice model.

The first nine items refer to the actions that individuals can take to decrease the risk of infection and protect themselves against COVID-19. We find that practicing social distancing, wearing masks and washing hands are the most frequently employed measures. As practicing social distancing could be also related to the attitude towards crowding, we connect this indicator with both latent variables. Additionally, the first latent factor is also related to the question about the level of concern about COVID-19.

The next five items were used to identify a latent factor capturing individuals' attitude regarding crowds avoidance. We found that for these indicators the distribution of answers was much more uniform than in the case of the preceding questions. Nonetheless, a majority of respondents indicated that they are bothered by crowded places and prefer to avoid them. Furthermore, individuals reported that it is not worth dealing with a crowded store, even if it would lead to monetary savings or some other benefits. Similarly, as with the previous items, a vast majority of respondents stated that they practice social distancing. The last item was also connected with the other latent factor (active protection).

4. Modeling framework

To combine choice experiment data with attitudinal questions from the survey we use a hybrid choice modeling framework (Ben-Akiva et al., 2002). Hybrid choice models exploit a structural modeling approach to link latent factors with observed indicator variables as well as individuals' choices. The model used in this study consists of three components: (i) random utility-based choice model, (ii) structural equations, and (iii) measurement equations. We next describe each component in detail.

We employ a latent class specification for the choice model to account for unobserved preference heterogeneity. Latent class is useful in this context, as market segmentation is considered to be essential to better understand shopping behavior (Eger et al., 2021). A latent class model allows us to identify several segments of consumers with similar preferences. Instead of assigning individuals deterministically to a given segment, the latent class model treats assignment as an unobserved categorical variable. To get further insight into these segments we link probability of belonging to a given class with the observed characteristics of the individual as well as their unobserved attitudes.

Table 3
Indicator variables used in the hybrid choice models to identify latent factors.

Variable name						Active protection	Crowds avoidance
Since the lockdown (NYS on PAUSE) to contain COVID-19, how often do you?	Always (1)	Sometimes (2)	Rarely (3)	Never (4)			
Practice social distancing indoor	77.80%	17.90%	3.20%	1.00%		Yes	Yes
Practice social distancing outdoor	81.00%	16.90%	1.70%	0.40%		Yes	Yes
Use hand sanitizer	73.80%	19.60%	4.40%	2.20%		Yes	
Use disinfecting wipes	66.70%	21.20%	7.20%	4.90%		Yes	
Wear mask indoor	78.50%	16.30%	4.00%	1.30%		Yes	
Wear mask outdoor	81.80%	15.00%	1.90%	1.30%		Yes	
Minimize in-person contact	76.00%	21.30%	2.20%	0.50%		Yes	Yes
Wash your hands	80.80%	16.80%	1.90%	0.50%		Yes	
Tell others they should practice social distancing	50.70%	24.60%	9.70%	15.00%		Yes	
How concerned are you about the coronavirus outbreak?	Very concerned (1)	Somewhat concerned (2)	Not very concerned (3)	Not at all concerned (4)			
	78.30%	18.30%	2.30%	1.00%		Yes	
Please indicate your level of agreement with the following statements:	Strongly agree (1)	Somewhat agree (2)	Neither agree nor disagree (3)	Somewhat disagree (4)	Strongly disagree (5)		
I avoid crowded places whenever possible	79.60%	15.70%	2.50%	1.20%	1.00%		Yes
A crowded place doesn t really bother me	8.90%	10.80%	6.50%	19.70%	54.10%		Yes
It is worth having to deal with a crowded store if I can save money on the things I buy	12.30%	17.70%	14.60%	18.60%	36.90%		Yes
It is worth having to deal with a crowded store if I can find the things I need	12.80%	20.00%	17.30%	17.20%	32.80%		Yes
I respect social distancing guidelines	73.50%	18.70%	6.10%	1.00%	0.60%	Yes	Yes

We assume that utility function of individual i, who belongs to class c, for the jth alternative in the tth choice task is given by

$$U_{ijt}^{c} = \beta_0^c ASC_{ijt}^{Opt-out} + \beta_2^c(\boldsymbol{\beta}_1^c \boldsymbol{X}_{ijt} - Cost_{ijt}) + \epsilon_{ijt} \tag{1}$$

In this setting, $ASC_{ijt}^{Opt-out}$ denotes an alternative specific constant for the opt-out alternative, $Cost_{ijt}$ denotes a delivery cost and $\boldsymbol{X}_{ijt}$ denotes a vector with all the other attributes used in the choice experiment, as described in the previous section. As usual, ϵ_{ijt} denotes a stochastic component, assumed to follow an i.i.d. type I extreme value distribution with constant variance. For convenience we specify the model in WTP-space (Train and Weeks, 2005), we note however that for the latent class model, preference- and WTP-space are equivalent. Nonetheless, the WTP-space specification allows us to easily interpret $\boldsymbol{\beta}_1^c$ coefficients in monetary terms. The probability of choosing alternative j, conditional on belonging to class c, is then given by the standard multinomial logit formula

$$P(y_{it} = j | C_i = c) = \frac{\exp(\beta_0^c ASC_{ijt}^{Opt-out} + \beta_2^c(\boldsymbol{\beta}_1^c \boldsymbol{X}_{ijt} - Cost_{ijt}))}{\sum_l \exp(\beta_0^c ASC_{ilt}^{Opt-out} + \beta_2^c(\boldsymbol{\beta}_1^c \boldsymbol{X}_{ilt} - Cost_{ilt}))} \tag{2}$$

In formula (2) we use C_i to denote an unobservable variable which indicates to which class a given individual belongs. As this covariate is latent, we need to specify its distribution. Specifically, we model it as a discrete random variable with probability described by the following multinomial logit formula

$$P(C_i = c | \boldsymbol{LV}_i) = \frac{\exp(\boldsymbol{\alpha}_1^c \boldsymbol{X}_i^{SD} + \boldsymbol{\alpha}_2^c \boldsymbol{LV}_i)}{\sum_s \exp(\boldsymbol{\alpha}_1^s \boldsymbol{X}_i^{SD} + \boldsymbol{\alpha}_2^s \boldsymbol{LV}_i)} \tag{3}$$

where $\boldsymbol{X}_i^{SD}$ denotes a vector of socio-demographic characteristics, whereas $\boldsymbol{LV}_i$ is a vector of unobservable latent factors. For identification we assume that for the last class $\boldsymbol{\alpha}_1^c$ and $\boldsymbol{\alpha}_2^c$ are equal to 0. Specification of (3) allows us to find the effect of analyzed latent factors on probability of belonging to a given segment.

The second component of the hybrid choice model consists of structural equations in which latent factors are explained by the socio-demographic variables. We assume that the kth latent factor is a linear function of the socio-demographic variables in the vector $\boldsymbol{X}_i^{SE}$ and an unobservable stochastic term, η_{ik}.

$$LV_{ik} = \frac{\boldsymbol{\gamma}_k \boldsymbol{X}_i^{SE} + \eta_{ik}}{\delta_k} \tag{4}$$

The error term η_{ik} is assumed to follow a standard normal distribution, where δ_k is a normalizing factor, which assures that the variance of LV_k is equal to 1.[1] This normalizing factor facilitates interpretation (e.g., the researcher can easily compare coefficients for different latent factors, as they have the same scale) and estimation (e.g., coefficients for the latent factors do not change much upon adding variables to $\boldsymbol{X}_i^{SE}$). Additionally, we estimate the correlation between the error terms, $corr(\eta_{i1}, \eta_{i2}) = \rho$.

The last component of the hybrid choice model consists of measurement equations which link answers to attitudinal questions with latent factors. The specific form of this part of the model depends on the distribution of the indicator variables. In the current study, all indicator variables are ordinal (e.g., measured on the Likert scale), and therefore an ordered probit specification was utilized. We denote individual i answer to the nth item on the m-point Likert scale by I_i^n. We then assume that there exist an unobserved variable, $\hat{I}_i^n$, such that

$$\hat{I}_i^n = \lambda_n \boldsymbol{LV}_i + \xi_i^n \tag{5}$$

and

$$\begin{aligned} I_i^n &= 1 \text{ if } \hat{I}_i^n \le \theta_1^n \\ I_i^n &= 2 \text{ if } \theta_1^n \le \hat{I}_i^n \le \theta_2^n \\ &\vdots \\ I_i^n &= m-1 \text{ if } \theta_{m-2}^n \le \hat{I}_i^n \le \theta_{m-1}^n \\ I_i^n &= m \text{ if } \theta_{m-1}^n \le \hat{I}_i^n \end{aligned} \tag{6}$$

In (5), ξ_i^n is a measurement error following a standard normal distribution, and λ_n is a vector of coefficients to be estimated, measuring how strongly the latent variables affect the answer to the given indicator question. θ's in (6) are the usual threshold parameters which translate the values of the continuous variable, $\hat{I}_i^n$, to the ordinal one. The probability of indicating in the survey that $I_i^n = k$ is then given by

$$P(\hat{I}_i^n = k | \boldsymbol{LV}_i) = \Phi(\theta_k^n - \lambda_n \boldsymbol{LV}_i) - \Phi(\theta_{k-1}^n - \lambda_n \boldsymbol{LV}_i) \tag{7}$$

where Φ is a cumulative distribution function of the normal distribution (we assume $\theta_0^n = -\infty$ and $\theta_m^n = \infty$). Combining (2), (3) and (7) leads to the following likelihood function

$$L_i = \int \prod_{t=1}^{T} \sum_{c=1}^{C} P(y_{it} = j | C_i) P(C_i = c | \boldsymbol{LV}_i) \prod_n P(\hat{I}_i^n = k | \boldsymbol{LV}_i) f(\boldsymbol{\eta}_i) d\boldsymbol{\eta}_i \tag{8}$$

The likelihood function above has a form of a multidimensional integral, as the error terms in structural equations, $\boldsymbol{\eta}_i$, are unobserved and therefore need to be integrated out. $f(\boldsymbol{\eta}_i)$ is the pdf function of these errors, which follow a standard multivariate normal distribution. As the integral in (8), does not have an analytical solution, we use the maximum simulated likelihood estimator to approximate it by using 2000 scrambled and shuffled Sobol draws (Czajkowski and Budziński, 2019).[2]

5. Results

In Table 4 we report the results for the latent class component of the estimated hybrid choice model. We employ a model specification with 3 distinct classes as it has a better fit to the data than models with 2 or 4 classes, as exhibited by the Bayesian Information Criteria reported at the bottom of the table. All attributes enter the model linearly with the exception of the *Likely delivery delay*, which was recoded as a binary variable equal to 1 if the delay is 45 min or longer. This was motivated by the improved model fit to data, which suggests that consumers are not sensitive to the change from a 45-min to a 90-min delay. We did not find evidence for any other nonlinear effects in the utility function.

We additionally provide information regarding the relative importance of each attribute (partworth analysis) in Table 5. Furthermore, Table 6 provides estimates of coefficients for the probability of belonging to a given class as described by Eq. (3). It is useful to interpret these tables jointly as it allows for a deeper understanding of the identified market segments. We note that several socio-demographic variables which were reported in Table 1 are not used in the presented model, as they occurred insignificant. For example, gender, education, income, and grocery expenditures were not significant predictors of individual's membership in a given class.

We start the interpretation with the second class, which describes the preferences of about 8% of the sample. Consumers belonging to this class have a very high probability of opting-out from choosing any of the available online grocery services. This

[1] Note that δ_k is not a coefficient to be estimated, but rather it is calculated from the data, $\delta_k = \sqrt{var(\boldsymbol{\gamma}_k \boldsymbol{X}^{SE}) + 1}$. At every step of the optimization algorithm the variance of the term $\boldsymbol{\gamma}_k \boldsymbol{X}^{SE}$ is obtained from the sample data.

[2] The model was estimated in MATLAB, using our own code based on https://github.com/czaj/DCE.

Table 4
Latent class model in WTP-space (except for the opt-out ASC). Standard errors are reported in [] brackets.

	Class 1		Class 2		Class 3		Mean	
Opt out ASC (in preference-space)	−3.32	***	−0.256		−1.366	***	−2.629	***
	[0.238]		[2.286]		[0.302]		[0.249]	
Next available delivery timeslot	−1.828	***	−0.976		−1.423	***	−1.667	***
	[0.306]		[0.855]		[0.288]		[0.217]	
Brand variety (medium)	6.584	**	−1.114		1.508		4.811	**
	[2.700]		[3.568]		[1.681]		[1.876]	
Brand variety (high)	11.581	***	8.765	**	5.246	***	9.931	***
	[2.137]		[3.548]		[1.583]		[1.406]	
Organic produce	8.529	***	2.292		3.503	***	6.888	***
	[1.551]		[2.299]		[1.135]		[1.055]	
Stock reliable	6.989	***	5.194		4.38	***	6.257	***
	[1.294]		[3.272]		[1.088]		[0.925]	
No contact delivery	5.647	***	−1.413		5.183	***	4.958	***
	[1.308]		[2.192]		[1.236]		[0.905]	
Likely delivery delay is 45 min. or greater	−4.199	***	−8.914	***	−4.177	***	−4.585	***
	[1.511]		[3.276]		[1.120]		[1.083]	
Mark up	−0.276	**	−0.756	**	−0.845	***	−0.443	***
	[0.120]		[0.352]		[0.140]		[0.089]	
(–) Delivery cost (in preference-space)	0.037	***	0.256	**	0.101	***	0.069	***
	[0.005]		[0.102]		[0.015]		[0.010]	
Average class probability	0.693	***	0.083	***	0.224	***		
	[0.023]		[0.011]		[0.023]			
BIC/N	5.179							
BIC/N (2 class model)	5.193							
BIC/N (4 class model)	5.180							

Table 5
Relative importance of the attributes (three highest values in each class are denoted in bold).

	Class 1	Class 2	Class 3
Next available delivery timeslot	**18.676%**	11.989%	**17.507%**
Brand variety	**16.906%**	**15.387%**	9.220%
Organic produce	12.450%	4.023%	6.156%
Stock reliable	10.203%	9.118%	7.698%
No contact delivery	8.243%	2.480%	9.109%
Likely delivery delay is 45 min. or greater	6.130%	**15.647%**	7.342%
Mark up	4.035%	13.268%	**14.847%**
(–) Delivery cost	**23.357%**	**28.087%**	**28.120%**

is caused by the highest estimate of the alternative specific constant (ASC) for the opt-out option as well as high coefficients for the delivery cost and mark up. Individuals in this class consider delivery cost, brand variety, and delivery delay to be the most important attributes.

As can be seen in Table 6, older individuals who have never used online grocery services are more likely to belong to this class. These results highlight the difficulty that retailers face when trying to convince new potential users to adopt e-grocery. The high sensitivity of these individuals to monetary attributes, such as delivery cost and mark-up, indicates that decreasing the additional cost of the first few deliveries (e.g. with a promotional discount), may increase the chances of individuals in this class to opt-in.

Class 1 represents the most common preference profile in the sample, as about 69% of respondents belong to this segment. This class is characterized by a very low probability of opting-out and the highest WTP for almost all attributes. Individuals in this class assign the highest importance to the delivery cost, next available delivery timeslot, and brand variety. Specifically, they are willing to pay $1.8 for decreasing delivery time by one day, and around a $11.6 premium for the high level of brand variety (relative to low variety). Furthermore, the mark-up is the least important attribute in this segment. Results in Table 6 reveal that individuals who have used online grocery services more than once in the past are more likely to belong to this class, whereas individuals who reported their health status to be average or worse are less likely to belong to this market segment.

Individuals who belong to class 3 constitute about 22% of the sample. The negative opt-out ASC indicates that these individuals are likely to use the online grocery service, although to a lesser extent than individuals from class 1. This is also caused by the higher sensitivity to cost, as indicated by the higher estimates for delivery cost and mark up. The increased income sensitivity is partially responsible for the lower WTP estimates for this class (when compared with class 1) for almost all attributes. Nonetheless, the preference profile of this class differs not only in the absolute values of WTP, but also in the relative importance of each attribute. Specifically, WTP for brand variety and organic produce is more than two times lower than in class 1. Consumers in this class are therefore more willing to sacrifice the quality of the available produce, in exchange for the cheaper service. Furthermore, no contact delivery and (avoidance of) delivery delay has similar importance as in class 1, with WTPs of about $5.18 and $4.18, respectively. This reveals the necessity for e-grocery retailers to adjust their services to the needs of different consumer segments.

Table 6
Model of class membership probability. Third class is considered to be a base level, for which all coefficients are equal to 0. Standard errors are reported in [] brackets.

	Class 1		Class 2	
Const.	1.944	***	−3.801	***
	[0.555]		[0.701]	
Age	−0.008		0.055	***
	[0.013]		[0.015]	
Did not use any online services	−0.929	***	1.777	***
	[0.348]		[0.604]	
How often have you gotten groceries online (Once or Never)	−0.866	***	−0.723	
	[0.302]		[0.555]	
Distance to grocery shop	0.081	*	−0.021	*
	[0.042]		[0.011]	
Self reported health: Average or worse	−1.039	***	0.284	
	[0.297]		[0.435]	
Overweight	0.051		−0.736	
	[0.248]		[0.472]	
LV_1 - Active protection	0.367	**	−0.338	
	[0.184]		[0.274]	
LV_2 - Crowds avoidance	−0.651	***	−0.259	
	[0.166]		[0.267]	

We next analyze the results for the two latent variables that we incorporate in the model. We start with the results for the measurement equations (as described by Eqs. (5)–(7)), which are reported in Table 7, to provide the reasoning for the interpretation of these factors. Both latent variables are significant and have expected effects on each indicator variable. We denote the first latent factor as *Active protection* as all coefficients next to it are negative, which means that individuals with a high value of this LV have a higher probability of answering "*Always*" to the attitudinal questions regarding using protective measures against COVID-19. At the same time, we denote the second latent factor as *Crowds avoidance*, as it has negative coefficients for items like "*I avoid crowded places whenever possible*", which corresponds to a higher probability of answering "*Strongly agree*", and negative coefficients to items like "*A crowded place does not really bother me*", which corresponds to a higher probability of answering "*Strongly disagree*".

It may seem that the two latent variables have very similar effects on the indicator variables in Table 7. In the hybrid choice model that we utilize, latent variables also affect individuals' choices through the class membership probability (Table 6). When looking at these effects, it occurs that they are actually opposite to each other. Specifically, *Active protection* attitude increases the probability of belonging to the first class, whereas *Crowds avoidance* decreases this probability. (Both variables are not significant for the probability of belonging to the second class.) The auxiliary analysis revealed that the current model has a better fit to data than an analogous specification, which utilizes only one latent factor instead of two. This suggests that these attitudes are actually distinct.[3] This finding confirms our first research hypothesis.

In Fig. 3 we simulate the average probability of opting out as a function of the given latent factor. Specifically, we calculate the probability of opting out for each respondent, choice task, and class, utilizing Eq. (2). This is then averaged over the respondents and choice tasks to obtain the mean probability in each class. Finally, these values are averaged over classes using class membership probabilities (Eq. (3)) calculated for the mean values of the socio-demographic variables, and a given value of the latent factor.[4]

The effect of the *Active protection* latent factor is in line with our second research hypothesis. As illustrated in Fig. 3, individuals who are employing measures to protect themselves against COVID-19 are more likely to opt-in for the grocery choice to avoid additional exposure risk related to in-person shopping. Furthermore, they will be less bothered by the cost of such service, leading to a lower cost sensitivity and higher WTP for the attributes. On the other hand, results for the *Crowds avoidance* go against our third hypothesis. Specifically, individuals who have a strong need to avoid crowds are more likely to belong to the third class, and therefore are less likely to opt-in (cf. Fig. 3). This is surprising, especially since consumers in the third class are also more sensitive to the cost (when compared with the first class), which corresponds to lower WTPs for such a service. We would expect individuals who dislike crowding to be willing to pay more for the possibility of avoiding it during grocery shopping. However, individuals in the third class also assign relatively larger importance to the no-contact delivery. Indeed, no-contact delivery is one of the two attributes for which WTP is not much smaller than in the first class.[5] It seems then, that even though individuals who avoid crowds have lower WTP in general, their priorities for the online grocery shopping services are different from individuals who do not exhibit such avoidance behavior.

Even though both latent factors affect the probability of opting-in, we note that these effects are not very strong. As can be seen in Fig. 3, the change in probability is from about 0.8 to 0.94. This is because the latent variables affect mostly the probabilities of belonging to classes 1 and 3, and do not affect the probability of belonging to the second class.

[3] This is further confirmed by analyzing the correlation between the latent factors, which is significantly lower than 1 (see Table 8 below).

[4] The other latent factor is integrated out using its conditional distribution, similarly as in (8).

[5] The other attribute is avoiding delivery delay. In Table 5 they both have slightly higher relative importance in the third class when compared with the first class.

Table 7
Estimates of coefficient for measurement equations (ordered probits). Standard errors are reported in [] brackets.

	LV_1 - Active protection		LV_2 - Crowds avoidance		CutOff 1		CutOff 2		CutOff 3		CutOff 4	
	Since the lockdown (NYS on PAUSE) to contain COVID-19, how often do you?											
Practice social distancing indoor	−0.675	***	−0.044		0.951	***	2.079	***	2.702	***		
	[0.097]		[0.072]		[0.073]		[0.318]		[0.335]			
Practice social distancing outdoor	−0.979	***	−0.206	**	1.281	***	2.956	***	3.855	***		
	[0.128]		[0.093]		[0.107]		[0.149]		[0.146]			
Use hand sanitizer	−1.347	***			1.074	***	2.538	***	3.354	***		
	[0.159]				[0.111]		[0.510]		[0.445]			
Use disinfecting wipes	−1.199	***			0.683	***	1.809	***	2.563	***		
	[0.133]				[0.081]		[0.304]		[0.338]			
Wear mask indoor	−0.524	***			0.899	***	1.819	***	2.474	***		
	[0.085]				[0.064]		[0.619]		[0.601]			
Wear mask outdoor	−0.923	***			1.229	***	2.513	***	3.049	***		
	[0.116]				[0.093]		[0.557]		[0.500]			
Minimize in-person contact	−0.62	***	−0.299	***	0.898	***	2.412	***	3.17	***		
	[0.103]		[0.073]		[0.071]		[0.084]		[0.091]			
Wash your hands	−0.768	***			1.098	***	2.463	***	3.24	***		
	[0.102]				[0.079]		[0.091]		[0.094]			
Tell others they should practice social distancing	−0.624	***			0.03		0.813	***	1.218	***		
	[0.079]				[0.052]		[0.032]		[0.035]			
How concerned are you about the coronavirus outbreak?	−0.726	***			0.963	***	2.265	**	2.886	***		
	[0.099]				[0.073]		[1.068]		[1.030]			
	Please indicate your level of agreement with the following statements:											
I avoid crowded places whenever possible			−0.489	***	0.926	***	1.851	***	2.216	***	2.548	***
			[0.070]		[0.060]		[0.064]		[0.065]		[0.065]	
A crowded place doesn t really bother me			0.886	***	−1.798	***	−1.149	***	−0.856	***	−0.149	
			[0.083]		[0.103]		[0.157]		[0.147]		[0.192]	
It is worth having to deal with a crowded store if I can save money on the things I buy			2.334	***	−2.891	***	−1.539	***	−0.533	**	0.779	**
			[0.260]		[0.301]		[0.222]		[0.241]		[0.365]	
It is worth having to deal with a crowded store if I can find the things I need			2.113	***	−2.604	***	−1.197	***	−0.155		0.992	**
			[0.209]		[0.231]		[0.306]		[0.345]		[0.461]	
I respect social distancing guidelines	−0.611	***	−0.34	***	0.815	***	1.805	***	2.65	***	3.069	***
	[0.083]		[0.070]		[0.068]		[0.224]		[0.278]		[0.289]	

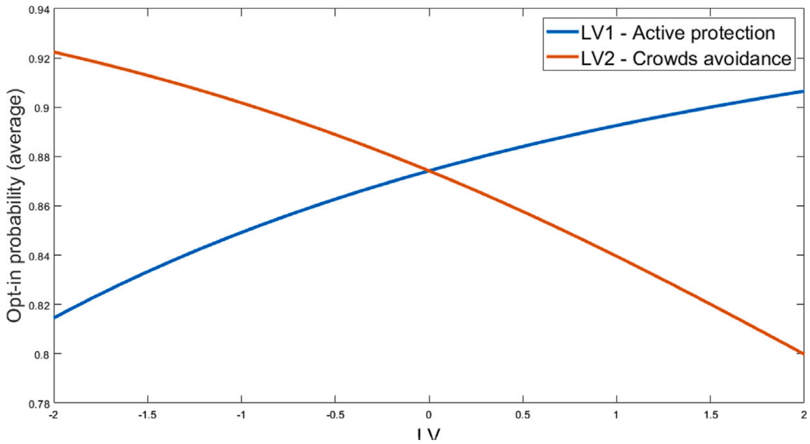

Fig. 3. Average probability of opting in to the online grocery choice as a function of the latent factors.

Lastly, in Table 8 we report estimates of structural equations for the two latent factors, which can deepen our understanding of these attitudes. We find that consumers who have fewer children and rarely use online grocery shopping services are less likely to actively protect themselves against COVID. Surprisingly, we find a similar effect for self-reported health, namely individuals in poor health are also less likely to take some protective measures.[6] As individuals in poor health are at higher health risk from COVID we would expect the opposite effect. Nonetheless, there is some evidence supporting such a relation, for example, Taylor et al. (2020)

[6] The effect is weakly significant with p-value of 0.06.

Table 8
Structural equations for the latent variables. Standard errors are reported in [] brackets.

	LV_1 - Active protection		LV_2 - Crowds avoidance	
Age	0.021		0.168	***
	[0.043]		[0.043]	
No. of children	0.137	***	−0.055	
	[0.052]		[0.040]	
No. of elderly	−0.018		−0.122	***
	[0.049]		[0.044]	
Did not use any online services	−0.094	*	0.004	
	[0.055]		[0.049]	
How often have you gotten groceries online (Once or Never)	−0.069		−0.024	
	[0.058]		[0.049]	
Distance to grocery shop	−0.01		−0.121	***
	[0.046]		[0.045]	
Self reported health: Average or worse	−0.09	*	0.06	
	[0.048]		[0.041]	
Overweight	0.007		−0.091	**
	[0.044]		[0.041]	
Correlation	0.367	***		
	[0.044]			

find that pre-existing general medical condition increases disregard for social distancing. With respect to the second latent factor, we find that older individuals are more crowd averse. On the other hand, individuals living with a higher number of elderly, living further away from the grocery shop, and being overweight, are less likely to avoid crowds. Finally, the correlation between the latent factors' error terms is 36.7%. Even though this value is significantly different from 0, it is much lower than 1, supporting our hypothesis that the two latent variables are indeed distinct.

6. Discussion

The current study contributes to the literature on consumers' preferences for online grocery shopping. We exploit CE data to estimate individuals' WTP for multiple characteristics of online grocery services. Using a latent class specification we account for preference heterogeneity and identify three market segments. We find that these three segments differ in terms of their likelihood to opt-out from online grocery shopping, how much consumers would be willing to pay for such a service, and the relative importance of the attributes. The probability of belonging to a given segment is not only dependent on the usual characteristics of the consumer, such as age and their previous experience with online grocery shopping, but also on the fear-related attitudes, such as active protection against COVID-19 and crowds avoidance. Contrary to the previous research (So et al., 2016), our study focuses on the attitudes related to problem-focused coping with fear, rather than emotion-focused coping. For future research, it would be interesting to see whether these consumers' characteristics stay relevant after the pandemic is over.

We find that fear-related attitudes are not likely to cause individuals to switch from the market segment which does not intend to use online-grocery shopping (Class 2 in Table 4) to a different class. Because of that, it is likely that the increased demand for online groceries during the pandemic was mostly caused by individuals who have already been consumers in this sector, rather than new customers entering the market.[7] Nonetheless, these factors affect consumers' WTP and the relative importance of the attributes. Specifically, individuals who are inclined to avoid crowds are more likely to belong to the segment with higher cost sensitivity, lower WTP, and higher importance of no-contact delivery (Class 3 in Table 4), whereas individuals who are prone to actively protect themselves against COVID-19 are more likely to belong to the segment with generally higher WTP, and higher importance of brand variety (Class 1 in Table 4). As attitude towards crowding is highly related to practicing social distancing, crowds avoidance can explain why such consumers assign a relatively higher weight to the no-contact delivery. Finally, consumers who actively try to limit their exposure to the virus have higher WTP for almost all attributes, which shows that they are willing to pay a premium in order to protect themselves against the virus. The significant effects of these constructs on individuals' choices highlight the importance of controlling for the attitudes related to problem-focused coping in consumer research.

Results provided by this study are relevant for the retail industry as well as policymakers who aim at limiting the spread of the virus. With respect to the former, we provide estimates of WTP for different attributes of online-grocery service as well as market segmentation of this sector. Quite importantly, we find that one segment (about 7% of the sample, consisting mostly of older respondents with no previous experience with online groceries), is unlikely to use any online grocery services. Still, we find that these consumers are sensitive to the monetary attributes, which suggests that decreasing the cost of these services may convince them to opt-in. With respect to COVID-related policies, we find that individuals who are the most vulnerable (i.e., in poor health and overweight) are less likely to use online grocery services, actively protect themselves against COVID-19, and avoid crowds. This

[7] As shown in Fig. 1, only about 10% of individuals started using online grocery shopping during the pandemic, but as much as 40% started using it more often than before the pandemic.

result suggests that a strategy of limited restrictions, in which individuals with the highest health risk are assumed to voluntarily take necessary precautions may prove unsuccessful.

We acknowledge that the limitation of the current study is that it was conducted in only a single city (NYC), and, therefore, it is not clear how generalizable our results are.

CRediT authorship contribution statement

Wiktor Budziński: Conceptualization, Methodology, Software, Formal analysis, Investigation, Writing – original draft. **Ricardo Daziano:** Conceptualization, Methodology, Investigation, Writing – original draft, Supervision, Funding acquisition.

Declaration of competing interest

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

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