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Social distancing and store choice in times of a pandemic

Tomás Rossetti [a,*], So-Yeon Yoon [b], Ricardo A. Daziano [c]

[a] Systems Science and Engineering, Cornell University, Ithaca, NY, 14 853, USA
[b] Design and Environmental Analysis, College of Human Ecology, Cornell University, USA
[c] School of Civil and Environmental Engineering, Cornell University, USA

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ABSTRACT

Public health officials enforced several measures to contain the COVID-19 pandemic that affected grocery stores, such as limits on store capacities and enforcement of masks and physical distancing among customers. Nevertheless, these measures can provoke queues, which could drive customers away from stores. In this study, we investigate how customers trade off between social distancing measures and increased waiting times during the peak of the COVID-19 pandemic. Our data comes from an online survey applied in New York City in May 2020. This survey included a set of discrete choice experiments framed in virtual stores, as well as a set of psychometric indicators regarding the pandemic. With this data, we estimated a latent class conditional logit model where assignment to classes is correlated with COVID-19 latent variables. We identified three latent classes with preference structures that valued social distancing to varying degrees. In spite of this heterogeneity in preferences, we found that customers were willing to wait longer to access stores with better social distancing measures. This result suggests that stores could increase, rather than decrease, their sales if they enforce public health measures at the expense of longer waiting times.

1. Introduction

Public health restrictions imposed as a consequence of the COVID-19 pandemic have provoked mixed reactions in the United States. Whereas these restrictions have been necessary to contain the spread of the virus, and have had generally good public approval (Reed et al., 2020), some business leaders have argued that measures such as reduced indoor capacities do not adequately weigh health outcomes against their economic consequences (see, for example, Barrett, 2020; Fung, 2020; Haddon and Wernau, 2020; Haddon and Nassauer, 2020; Haddon, 2021; Ip, 2020; The Wall Street Journal Editorial Board, 2020).

It is unclear whether more relaxed safety measures would attract more customers. Economic theory predicts two conflicting directions. Consumers could, understandably, be weary of becoming infected and prefer to patronize stores that have better safety measures at the cost of incurring in longer waiting times. On the other hand, customers may seek stores with more relaxed safety measures to make shopping faster and easier. Since the cost of the latter alternative is a likely higher exposure to the virus, the trade-off between both directions is mediated, in part, by the value consumers put on their time and health.

Scientific literature on the subject up to the moment has been scant. Most studies in the realm of retail and consumption have focused on the effect of the pandemic on actual visits to stores (Cronin and Evans, 2020) or the shift toward online shopping (Chenarides et al., 2020; Grashuis et al., 2020). A micro-level analysis of store choice as a function of safety measures has yet to be done.

In this study, we carry out such an analysis using grocery shopping as a case study. Such establishments are, arguably, more relevant than others during a pandemic. Many people depend on in-person shopping because of time, cost, or technological barriers. Moreover, access to food or cleaning supplies is vital during lockdowns, whereas access to products such as clothing or entertainment is secondary. Finally, consumers usually have more than one choice for grocery shopping, which makes competitive advantages important.

Using data from a survey applied in New York City during May 2020, we estimate a latent class choice model to understand how customers trade off such attributes as social distancing and walking or waiting times. To account for the fact that different attitudes toward the pandemic may define the value put on health and time, We used latent variables to inform class assignment. These latent variables are outputs of a structural equation model that assesses customers' pandemic-induced reactions and attitudes.

* Corresponding author.
E-mail address: ter58@cornell.edu (T. Rossetti).

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Results show that there is substantial preference heterogeneity among customers, and that attitudes such as distaste for crowds or the degree to which respondents have reduced their daily activities away from home mediate this process. We also find significant evidence that support public health measures aimed at reducing crowding at the cost of increased queues and waiting times.

Our study provides information to back arguments in favor of better safety measures in the context of the current and future pandemics. Since most customers prefer safer shopping environments, retail owners will be better off in the long run by adapting to a pandemic reality and ensuring that their customers feel comfortable and safe.

This study makes two methodological contributions. First, it operationalizes in the retail context a blend of structural equation models and discrete choice models into a tractable and statistically sound framework. Second, this study also shows how conflicting preferences (the desires to shop in safer environments and spend less time in line) can be quantified.

The remainder of this manuscript is organized as follows: Section 2 briefly reviews the literature on crowding in retail, as well as recent literature on crowding during the pandemic. Section 3 details how data was collected and the methods used for analyses. Then, Section 4 shows the results, including the structural equation model and the latent class choice model. Finally, Section 5 concludes with some analyses, implications, and a brief summary.

2. Literature review

The retail literature has extensively studied the effect of crowding on customers. Results have been mixed and there is still no widespread consensus on when and in what contexts crowding affects businesses.

As Blut and Iyer (2020) point out, crowding has been understood in the retail literature as either physical crowding, which is related to the physical features of a store, or human crowding, which is solely related to the number of customers present and their interactions. Since the work of Harrell and Hurt (1976), the marketing literature has found that crowding impacts consumer outcomes such as behaviors, attitudes, and cognition. Human and physical crowding does not necessarily have the same impact on consumer satisfaction and must be analyzed independently (e.g., Machleit et al., 1994; Li et al., 2009). Finally, an objective measure of crowding is not perceived the same across all individuals, so perceptions must be taken into account when analyzing these effects (Machleit et al., 2000).

In general, the evidence has found that crowding negatively impacts consumer outcomes. Nevertheless, the direction and magnitude of this effect is uneven across settings and types of crowding. For example, Blut and Iyer (2020) found in a meta-analysis that physical crowding was negatively correlated with consumer outcomes, whereas human crowding was positively so. However, the authors did not find a positive relation between consumer outcomes and human crowding in utilitarian settings such as grocery stores. This result shows that, whereas crowding may be desirable in such places as restaurants or concerts, it is much less so when consumers have to carry out a given task.

Another meta-analysis carried out by Santini et al. (2020) found that, whereas crowding does produce both positive and negative emotions among customers, important business variables such as purchase intention, satisfaction, and loyalty are negatively correlated with crowding. This correlation does have exceptions in the literature. For example, Katakam et al. (2021) found more impulse buying in more crowded stores, and Calvo-Porral and Lévy-Mangin (2021) found no influence of store crowding on satisfaction in hedonic and utilitarian shopping environments. In a similar note, Aydinli et al. (2021) found that crowding was correlated with more "hedonic" purchases and more national brands in a large-scale study in the Netherlands, which in many cases translate into a higher total purchase cost.

A literature review carried out by Mehta (2013) found similar results. In most of the papers reviewed by the author, crowding and waiting time negatively affected retail outcomes such as consumer satisfaction and attitudes toward stores. The general consensus is that this effect is more marked in utilitarian stores such as supermarkets, although results are, once again, mixed. For example, Aylott and Mitchell (1998) found that crowding and queuing were the two major sources of stress for grocery shoppers. Eroglu and Machleit (1990) found that the negative effects of crowding on consumer reactions were strongest in "task-oriented shoppers," a kind of customer that is more prevalent in grocery stores than in other kinds of retail. Some previous studies have found positive relations, although not in grocery stores. For example, Uhrich (2011) found that, in some cases, a medium level of crowding may provide the best consumer responses in a bookstore. Giebelhausen et al. (2011) found that higher waiting times are sometimes linked to higher perceived quality in the case of restaurants.

We believe it is likely that this trend will hold in our data, and even more so in a context where health officials have warned citizens against crowding in indoor spaces. Therefore, we hypothesize that:

Hypothesis 1. *On average, customers dislike crowds and high waiting times.*

There is still not enough published evidence on the effect of the COVID-19 pandemic on crowding preferences in retail environments. Nevertheless, there are clear data points that indicate that customers' distaste for crowding has considerably increased.

For example, Cronin and Evans (2020) found that foot traffic to retail decreased considerably in a short period of time in the United States. Only 25 days after a state of emergency was declared at the state or county level, visits to nonessential retail declined, on average, by 60%, entertainment venues by 70%, and essential retail by 39%. They also found that around half of this decline can be explained by citizens' private response, and the rest of the decline can be explained by stay-at-home orders or other similar mandates.

Some studies have looked at the issue of crowding while shopping during the COVID-19 pandemic. Virtually all of these studies have done so indirectly, focusing on the choice between in-store or online shopping and the degree to which crowding weighs on this decision. One of the main findings is that there has been a marked shift away from in-store shopping that can be explained significantly by an aversion to crowds.

For example, a study carried out in Chicago showed that the percentage of respondents who "always" bought groceries from a physical store decreased from 45% before the pandemic to 17% after (Grashuis et al., 2020). Beckers et al. (2021) reported an increase in online food purchases during the pandemic in Belgium, especially among local stores. Two other studies showed that, all else equal, home delivery was the preferred method of getting groceries, and in-store purchase or pickup were the least preferred (Chenarides et al., 2020; Grashuis et al., 2020). Studies carried out before the pandemic did not show such marked preferences (e.g., Marcucci et al., 2021; Joewono et al., 2019; Schmid and Axhausen, 2019). Respondents for the study carried out by Shamshiripour et al. (2020) mentioned avoiding crowds as the most important reason for this shift.

These findings show that citizens are, in general, taking reasonable precautions to avoid contracting COVID-19 by staying at home. If they have to shop in person, it is reasonable to assume that they will keep safety measures like wearing a mask. This leads to our second hypothesis:

Hypothesis 2. *On average, customers value preventive measures such as mask-wearing or distancing.*

Some findings also show that health concerns were the main drivers of either the shift to online shopping or customer satisfaction in physical stores. Eroglu et al. (2022) found that the perceived risk of COVID-19 mediates the effect of safety measures on customer satisfaction in a retail setting. Similarly, in the case of Chenarides et al. (2020), respondents mentioned fear of COVID-19 and "feeling unsafe" as the two most important reasons for preferring online shopping or in-store

pick-up. Rather (2021) also found a negative effect of fear of COVID-19 on revisiting intentions to tourist sites. Finally, public acceptance of safety measures in the United States has been divided, which in turn have shaped how protective measures are valued (e.g., Armus and Hassan, 2020). This division is correlated with sociodemographic characteristics, such as political affiliation and geographic location, but is essentially driven by variables that are harder to measure like attitudes and perceptions. Therefore, a three-pronged hypothesis can be formulated:

Hypothesis 3a. *Pandemic-related attitudes segment the population into groups with distinct valuations of preventive measures.*

Hypothesis 3b. *Customers that more actively avoid crowds will value safety measures at a higher rate.*

Hypothesis 3c. *Customers that are staying home at a higher rate will value safety measures at a higher rate.*

Up to this moment, and to the best of our knowledge, there is a lack of studies focused on crowding and in-person grocery store choice. Crowd aversion for in-person grocery shopping is relevant to complement public health measures that have reduced store capacities in an uneven fashion around the world and across the United States, which is where we are focusing this study. In-person grocery shopping will hardly be replaced entirely by delivery because of time restrictions and costs, among other reasons. Therefore, it is important to understand how crowding affects consumers' behaviors to better tailor retail adjustment plans for the current pandemic and future ones.

3. Data and methods

The following subsections describe how data was collected and the methodology we used for analysis.

3.1. Data collection

We designed and applied a survey to assess how crowding, social distancing, and mask wearing affected store choice. The following paragraphs describe how and when participants were contacted, as well as some descriptive statistics of the sample.

The survey was deployed between May 5 and May 21 of 2020, targeting individuals over 18 years of age who lived in one of New York City's five boroughs. All respondents came from an online panel managed by Qualtrics and responded to this survey using the same platform.

At the time the survey was applied, the number of new COVID-19 cases in New York City was decreasing sharply, leaving the city's first deadly wave behind. The seven-day rolling average of new cases in this period went from 1624 to 833 (New York City Department of Health, 2021). Some emergency measures were being relaxed or dismissed during this period as well. For example, a field hospital built in Central Park to accommodate patient overflow closed the day before the survey's first response (Stack and Fink, 2020). Nevertheless, the city was still under a stay-at-home order which was relaxed only on June 8 (Goodman, 2020).

A total of 775 respondents successfully completed the survey (Table 1). This sample is not representative, nor was it designed to accurately represent the New York City population as a whole. There was a gender imbalance, as well as an over-representation of younger participants; whereas 2.6% of the sample was 65 years or older, 14.5% of the New York City population fell within this category in 2019. Participants were also more educated. Whereas 73.7% of the sample held at least a bachelor's degree, only 38.1% of the city's population holds such a degree. Even though a significant number of people of color completed the survey, there was a larger proportion of white individuals in the sample. For example, 24.3% of the city's population was Black or African American in 2019, whereas the sample contains only 11.5% of African Americans. Something similar happens with Hispanic and Asian individuals. Finally, the median yearly household income was higher than that of the city's population. The sample median income is between $100,000 and $125,000 per year, whereas the city's was around $64,000 in 2019 (United States Census Bureau, 2019). In the models, we controlled for all of these characteristics to address any biases that this imbalance may produce.

Table 1
Descriptive statistics of study participants.

Variable	Value	Number	Proportion
Gender	Female	309	39.9%
	Male	466	60.1%
Age	[18, 30)	181	23.4%
	[30, 40)	327	42.2%
	[40, 50)	180	23.2%
	[50, 60)	50	6.5%
	[60, 78]	37	4.8%
Education	High school or less	73	9.4%
	Some college	131	16.9%
	Bachelor's degree	235	30.3%
	Graduate degree	336	43.4%
Race or ethnicity	Asian	69	8.9%
	Black or African American	89	11.5%
	Hispanic	109	14.1%
	White	499	64.4%
	Other	9	1.2%
Yearly household income	Less than $20,000	65	8.4%
	[$20,000, $40,000)	75	9.7%
	[$40,000, $50,000)	39	5.0%
	[$50,000, $60,000)	45	5.8%
	[$60,000, $75,000)	54	7.0
	[$75,000, $100,000)	98	12.6%
	[$100,000, $125,000)	90	11.6%
	[$125,000, $150,000)	78	10.1%
	[$150,000, $200,000)	123	15.9%
	[$200,000, $250,000)	46	5.9%
	$250,000 or more	62	8.0%

The survey covered many aspects related to grocery shopping and the pandemic, as well as basic sociodemographic information. The main outcome variables of interest in this survey are several psychometric indicators, which are described in more detail in Section 4.1, and a set of discrete choice experiments.

The aim of the choice experiments was to assess how people trade off between different attributes when they decide where to go grocery shopping. Each individual faced nine binary experiments, such as the one shown in Fig. 1. The choice situations were designed using a D-efficient experimental design using Ngene (ChoiceMetrics, 2012). The attributes included are shown in Table 2.

To help participants imagine how these stores would look and feel like, we developed virtual reality scenarios that depicted each experimental alternative. Respondents could imagine themselves within those scenarios more easily with this graphic representation, thus increasing the ecological validity of these choice experiments. The inclusion of images has been shown to better mimic what respondents would do in a real scenario (e.g., Higuera-Trujillo et al., 2017; Farooq et al., 2018).

3.2. Methodology

Customers trade off different attributes when they decide where to buy groceries, both in the discrete choice experiments described in the previous subsection and in reality. Even though there may be as many heuristics or decision rules as there are respondents, a reasonable and useful approach is to assume random utility maximization. Under this framework, it is assumed that customers perceive a certain utility when they choose an alternative, and that they will choose the alternative with the highest utility. Moreover, this framework assumes that at least part of this utility can be inferred, whereas the remaining portion is random to reflect any unobserved variables or preference shocks.

Fig. 1. Example of a discrete choice experiment.

Table 2
Attributes included in discrete choice experiments and their levels.

Attribute	Levels
Walk time	10, 20 min
Wait time	5, 15 min
Mask wearing	Yes, No
People outside	3, 7, 12
Distancing outside	1, 2, 4, 6 ft. (0.3, 0.6, 1.2, 1.8 m.)
People at check out	2, 4
Distancing at check out	2, 4, 6 ft. (0.6, 1.2, 1.8 m.)

Under this set of assumptions, utility can be decomposed into two elements, as is shown in (1). The first component is a deterministic utility that is made up of customer i's personal characteristics and attributes of alternative j, $\mathbf{X}_{ij}$, and a vector of preference parameters to be estimated, $\boldsymbol{\beta}$. Observed variables and parameters are related to one another through the index function V. The second element of utility U_{ij} is a random error term to account for any variables not included in $\mathbf{X}_{ij}$ and that represents a preference shock.

$$U_{ij} = V(\mathbf{X}_{ij};\boldsymbol{\beta}) + \epsilon_{ij} \tag{1}$$

If we assume that individuals select the alternative with the highest utility and that ϵ_{ij} are Type-I Extreme Value distributed, then the probability that i chooses j is given by the function shown in (2). This is called the conditional logit model in econometrics. Here, μ is the scale parameter of the distribution of the preference shock. If V is a linear function, then μ must be normalized to allow model estimation. This normalization does not affect probability or willingness to pay estimates.

$$P_i(j|\mathbf{X};\boldsymbol{\beta}) = \frac{\exp(\mu V(\mathbf{X}_{ij};\boldsymbol{\beta}))}{\sum_l \exp(\mu V(\mathbf{X}_{il};\boldsymbol{\beta}))} \tag{2}$$

This random utility maximization framework, proposed by McFadden (1974), is useful to analyze preferences and infer information such as willingness to pay for a given good. Nevertheless, the standard conditional logit model is limited since it assumes that individuals have preference parameters that are homogeneous and equal to the vector $\boldsymbol{\beta}$. This assumption is not realistic; different individuals probably value the same attribute differently. There are many ways this homogeneity assumption can be relaxed. We will use the latent class approach to allow for unobserved preference heterogeneity.

The latent class conditional logit (LCL) model (Kamakura and Russell, 1989) assumes that customers belong to certain unobservable categories or classes, and that each class has specific preference parameters. This model is made up of two components: one component relates individuals to latent (unobservable) classes, and the other component relates individuals to choices given their latent class.

The utility derived by individual i when they choose alternative j given that they belong to class s can be represented by (3). This utility function is equal to (1), but with class-specific values and specifications for $\boldsymbol{\beta}^s$, V^s and ϵ_{ij}^s.

$$U_{ij}^s = V^s(\mathbf{X}_{ij};\boldsymbol{\beta}^s) + \epsilon_{ij}^s \tag{3}$$

Under the same assumptions of the conditional logit model, the probability that customer i chooses alternative j given that they belong to class s is equal to the logit-type probability shown in (4).

$$P_i(j|s,\mathbf{X};\boldsymbol{\beta}^s) = \frac{\exp(\mu_s V^s(\mathbf{X}_{ij};\boldsymbol{\beta}^s))}{\sum_l \exp(\mu_s V^s(\mathbf{X}_{il};\boldsymbol{\beta}^s))} \tag{4}$$

Since class membership cannot be directly observed, a probabilistic measure relating individuals to classes must be constructed. Let W_{js} represent a class-membership function, as is shown in (5), that is proportional to the probability of i belonging to class s. In a very similar fashion to (1), $\boldsymbol{\gamma}^s$ is a vector of class-specific parameters relating observable consumer characteristics $\mathbf{X}_i$ to class s, and Z is a function defined by the modeler.

$$W_{is} = Z(\mathbf{X}_i;\boldsymbol{\gamma}^s) + \zeta_{is} \tag{5}$$

If we assume that $\boldsymbol{\zeta}$ are independent and identically distributed Type-I Extreme Value, the probability that i belongs to s is also given by a logit-type probability, as is shown in the multinomial logit specification (6). If Z has a linear specification, the scale parameter ς has to be once again normalized.

$$P_i(s|\mathbf{X}_i;\boldsymbol{\gamma}) = \frac{\exp(\varsigma \cdot Z(\mathbf{X}_i;\boldsymbol{\gamma}^s))}{\sum_{p=1}^{S} \exp(\varsigma \cdot Z(\mathbf{X}_i;\boldsymbol{\gamma}^p))} \tag{6}$$

To obtain the unconditional probability of i choosing j, we must marginalize $P_i(j|s)$ over $P_i(s)$, as shown in (7).

$$P_i\left(j|\mathbf{X}_{ij};\boldsymbol{\beta},\boldsymbol{\gamma}\right) = \sum_{s=1}^{S} P_i\left(j|s,\mathbf{X}_{ij};\boldsymbol{\beta}^s\right)\cdot P_i(s|\mathbf{X}_i;\boldsymbol{\gamma}^s) \tag{7}$$

With these probability measures, the likelihood of the model can be expressed by (8), and estimators for $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ can be obtained by likelihood maximization. The maximum likelihood estimator of the latent class logit model is implemented in existing statistical packages. In our case, we used the Apollo implementation, a package built for R (Hess and Palma, 2019).

$$\mathcal{L}(\boldsymbol{\beta},\boldsymbol{\gamma}|\mathbf{X}) = \prod_{i=1}^{I}\prod_{t=1}^{T_i}\sum_{s=1}^{S} P_i\left(j|s,\mathbf{X}_{ij};\boldsymbol{\beta}^s\right)\cdot P_i(s|\mathbf{X}_i;\boldsymbol{\gamma}^s) \tag{8}$$

One advantage of the LCL approach is that parameter interpretation is straightforward. Moreover, since classes are discrete categories, the marginalization of $P_i(j|s)$ does not require the computation of an integral, a complex computational procedure, unlike other choice models addressing unobserved preference heterogeneity. However, the LCL loglikelihood is a non-convex function, which still makes optimization difficult.

The LCL model has been applied in many settings. Some examples include preference for residential location (Walker and Li, 2007), medical procedures (Ho et al., 2020; Rozier et al., 2019), transportation mode (El Zarwi et al., 2017; Hurtubia et al., 2014; Shen, 2009; Bhat, 1997) vehicle ownership (Ferguson et al., 2018), and in the field of environmental economics (Araghi et al., 2016; Beharry-Borg and Scarpa, 2010).

There are multiple variables that can be used in the class-membership function. In this study, we are interested in exploring how such variables as aversion to crowds or concern over the pandemic affect customers' shopping preferences. Since these variables are not directly measurable, we adopted the structural equation modeling (SEM) framework for latent variables. Then, we used these latent variables as inputs of the class-membership function Z in (5). Nevertheless, since there could be some unobserved biases in this sequential approach, we included an additional error component.

These modifications resulted in the class-membership probability shown in (9). Here, we assumed that Z is a linear function (which forces ς to be set to one to allow model identification), $\mathbf{X}_i^*$ is a vector of latent variables obtained from the SEM, and $\boldsymbol{\xi}$ is a vector of error terms for $\mathbf{X}_i^*$.

$$P_i(s|\mathbf{X}_i,\boldsymbol{\xi};\boldsymbol{\gamma}) = \frac{\exp\left(\left(\mathbf{X}_i^* + \boldsymbol{\xi}\right)\cdot\boldsymbol{\gamma}^s\right)}{\sum_{p=1}^{S}\exp\left(\left(\mathbf{X}_i^* + \boldsymbol{\xi}\right)\cdot\boldsymbol{\gamma}^p\right)} \tag{9}$$

The unconditional probability with respect to the error terms $\boldsymbol{\xi}$ can be obtained by marginalizing over them, as is shown in (10). Here, $f(\boldsymbol{\xi})$ is the multivariate probability density function of $\boldsymbol{\xi}$. This density function requires the modeler to assume a certain distribution for $\boldsymbol{\xi}$. In our case, we adopted a multivariate normal distribution.

$$P_i(s|\mathbf{X}_i;\boldsymbol{\gamma}) = \int \frac{\exp\left(\left(\mathbf{X}_i^* + \boldsymbol{\xi}\right)\cdot\boldsymbol{\gamma}^s\right)}{\sum_{p=1}^{S}\exp\left(\left(\mathbf{X}_i^* + \boldsymbol{\xi}\right)\cdot\boldsymbol{\gamma}^p\right)}\cdot f(\boldsymbol{\xi})\, d\boldsymbol{\xi} \tag{10}$$

This integral can be approximated using Monte Carlo integration. Under this numerical approximation, the likelihood can be approximated by (11), where $\boldsymbol{\xi}^{(d)}$ is the d-th draw for $\boldsymbol{\xi}$.

$$\mathcal{L}(\boldsymbol{\beta},\boldsymbol{\gamma}|\mathbf{X}) \approx \frac{1}{D}\sum_{d=1}^{D}\prod_{i=1}^{I}\prod_{t=1}^{T_i}\sum_{s=1}^{S} P_i\left(j|s,\mathbf{X}_{ij};\boldsymbol{\beta}^s\right)\cdot P_i\left(s|\mathbf{X}_i,\boldsymbol{\xi}^{(d)};\boldsymbol{\gamma}^s\right) \tag{11}$$

4. Results

The following subsections describe the results obtained from fitting the choice models with the collected data. First, the structural equation model is presented along with a discussion of behavioral implications. Then, a discrete choice model is presented that relates these latent constructs to grocery store preferences.

4.1. Structural equation model

One of the main questions of interest in this study is how attitudes of customers toward crowding shape shopping preferences in the context of the COVID-19 pandemic. Different aspects of the pandemic can potentially generate distinct attitudinal reactions, so we estimated a structural equation model (SEM) that can parse these pandemic-related attitudes.

We assumed that two pandemic attitudes could best explain store choice during the pandemic: distaste for crowds and the degree to which respondents have reduced their daily activities. We also assumed that other attitudes directly affect distaste for crowds and activity reduction, such as concern over the pandemic, degree of compliance with public health measures, and its economic impact.

With this framework in mind, we included several psychometric indicators in the survey that could be used to elicit these unobservable constructs. Most of the indicators were agreement statements on a Likert scale. We analyzed the existence of common method variance (Podsakoff et al., 2003) among all indicators using two methods: Harman's one-factor test and a confirmatory factor analysis model that controls for the effects of an unmeasured latent methods factor on all indicators considered. We did not find considerable prevalence of common factor variance using either (variance explained by Harman's one-factor test: 15.4%; variance explained by confirmatory factor analysis model: 18.8%).Whereas the majority of the indicators we collected were obviously associated to a specific attitude (e.g., "How concerned are you about the coronavirus outbreak" and concern about COVID-19), the ones related to crowds and social distancing guidelines were not as obvious. We therefore carried out exploratory factor analysis to identify the latent variables that could be derived from them.

The Kaiser-Meyer-Olkin measure of sampling adequacy for this subset of eight indicators was equal to 0.72, which is higher than the recommended value of 0.60. Bartlett's test of sphericity was also significant ($\chi^2 = 1752.39$, $p < 0.01$), which shows that a data compression strategy such as structural equation modeling can produce good results. Principal component analysis showed that the first, second, and third components explained 44%, 18%, and 12% of the variance respectively. Given the difference between the proportion of the variance explained by the first two components, we carried out factor analysis for only one factor using a promax rotation.

The results of the factor analysis showed one latent variable, "Crowd avoidance," that has a higher value for individuals with a higher agreement to statements such as "I avoid crowded places whenever possible" and a lower agreement to statements such as "A crowded place doesn't really bother me." We then used these results to construct the SEM. All indicators that were identified as significant in the factor analysis stage were included in the structural equation model. Then, those that were not significant at the $p = 0.01$ level were removed.

We used the lavaan package in R (Rosseel, 2012) to estimate the SEM parameters with the latent variable identified above and other latent variables whose indicators were more straightforward. The indicators used are shown in Table 3, and a path diagram of the adopted SEM is shown in Fig. 2. Multiple sociodemographic characteristics were tested, as well as covariance structures for the latent variables. We removed covariates if their p-value was below 0.10. Both reliability and validity were tested to reach a final model. Reliability was deemed appropriate since Cronbach's (1951) alpha was close to 0.75 for all latent variables except one, which had an alpha equal to 0.55. Discriminant validity was also deemed to be adequate since the correlation between the only two latent variables whose covariance was feasible, "Concern" and "Econ. impacts," was lower than 0.2. Convergent validity was also deemed adequate since Bartlett's test of sphericity was significant for all latent variables' indicators at the $p = 0.001$ level.

The SEM results are displayed in Table 4. The structural relations

Table 3
Psychometric indicators used in SEM model.

Item	ID	Statement	Response.
Crowd avoidance: "Please indicate your level of agreement with the following statements"			
	CA1	I avoid crowded places whenever possible	Strongly disagree to Strongly agree (five levels).
	CA2	A crowded place doesn't really bother me	
	CA4	It is worth having to deal with a crowded store if I can save money on the things I buy	
	CA5	It is worth having to deal with a crowded store if I can find the things I need	
	CA7	I respect social distancing guidelines	
Activity reduction: Inferred based on "Before the coronavirus outbreak, how often did you …" and "Since NYS on PAUSE started, how often do you …"			
	AR2	Go to the gym, yoga studio or practice sports indoors	Reduced, same, increased.
	AR3	Practice sports outdoors	
	AR4	Go eating out	
	AR6	Commute to work	
	AR8	Go to a pharmacy	
	AR9	Go out with friends	
Concern over COVID-19			
	CC1	How concerned are you about the coronavirus outbreak?	Not at all concerned to Very concerned (four levels).
	CC2	How supportive are you of the measures included in the NYS on PAUSE order?	Not supportive at all to Very supportive (four levels).
Compliance: "Since the lockdown (NYS on PAUSE) to contain COVID-19, how often do you …"			
	CM1	Practice social distancing of at least six feet from others at indoor public spaces	Never, Rarely, Sometimes, Always.
	CM2	Practice social distancing of at least six feet from others at outdoor public spaces	
	CM3	Use hand sanitizer when entering/ exiting a store	
	CM4	Use disinfecting wipes on groceries and packages	
	CM6	Wear a cloth face covering or mask in outdoor public spaces	
	CM7	Minimize in-person contact	
	CM8	Wash your hands for at least 20 s after being outside	
Economic impacts: "Have any of the following happened to you or someone in your household since March 1, 2020?"			
	E1	Been laid off or lost a job	To me or someone else in my household (binary).
	E2	Lost pay or income	
	E3	Put on temporary leave from a job	

found for each latent variable will be discussed in the following paragraphs. Latent variables will be referred to by their capitalized names for clarity.

Results show that, on average, millennials were less concerned over COVID-19. Concern also seemed to increase with household income. The former may be due to the fact that younger people are, on average, at a lower risk of serious disease or death due to COVID-19, which may lead to an (arguably false) sense of security among younger generations. Higher concern among higher-income individuals may be a result of their access to reliable information, among other factors.

Respondents from households with lower income, as well as men, stated they had suffered a greater economic impact. This impact has been reported previously: official US statistics show that people with lower income have had a steeper loss of jobs and a slower economic recovery (Long et al., 2020). Variables related to race or ethnicity were not significant in our results, contrary to evidence from other sources (Koeze, 2020). This may be due to size of the sample or to the moment in which the survey was applied.

On average, people with higher Concern about COVID-19 had a higher Compliance with public health regulations. This relation was expected because a higher degree of concern should translate into taking more steps to prevent spread of this disease. Hispanic individuals also showed a higher adherence to health mandates, although this relation was weak.

Reduction of activities was positively correlated with Compliance and negatively with Economic impact. The former relationship was expected, and the latter may have been due to the fact that people who are not working may need to go out to find a job or be in charge of more household chores outside the home. We also found a weak negative relationship between Concern and Activity Reduction. This could be due to a correction in the net effect of the former over the latter, since Concern also influenced Activity reduction through Compliance. We also found that, on average, African American respondents decreased their activities less than others, and that those with a bachelor's degree did so more.

Finally, we found that, on average, individuals with higher values for Concern, Compliance, and Activity reduction had higher values for Avoid Crowds as well. We expected more Concerned and Compliant individuals to avoid crowds to a higher degree, since this has been one of the main recommendations during the pandemic. Those that have reduced their activities more than others are, naturally, avoiding crowds, since both are highly interrelated. After controlling for these attitudes, and all else equal, we found that men, younger respondents, those from higher-income households, and those who politically identify as Republicans, had lower values for Avoid Crowds.

The effect of Concern, Activity Reduction, and Compliance on Avoid crowds shows that people who are more aware of the dangers of COVID-19 and those who can or are willing to adapt their lifestyles to the pandemic avoided crowds to a higher degree. This result sheds light on the motivations behind customer decisions while shopping during the pandemic. Whereas the effects of the sociodemographic variables may reflect a baseline aversion to crowds (for example, Tirachini et al. (2017) also found that men and younger individuals had a higher degree of tolerance to crowds in the context of a subway train), we also show that latent variables related to the pandemic significantly affect people's attitudes toward crowds.

4.2. Discrete choice model

The results of the structural equation model were used as inputs for a discrete choice model. Table 5 shows the results of a latent class conditional logit model that includes the latent variables described above in its class-membership component, as well as a baseline conditional logit model. The following paragraphs will discuss the main findings that can be derived from each.

The conditional logit model shows that, all else equal, respondents dislike walking, waiting, and queues. On the other hand, respondents show a (positive) preference for mask wearing and distancing. However, the difference between 4 and 6 ft distancing at the checkout was not significant ($t = 0.07, p = 0.94$), which means there is no much difference between these two levels when choosing where to shop. These results confirm Hypothesis 2.

The latent class conditional logit model displays that the average preference parameters estimated in the conditional logit model mask substantial heterogeneity. The different preference structures across classes, as well as the class-membership functions, show that three customer segments exist: one with cautious individuals who highly value social distancing measures (Class A), another one with unconcerned individuals that do not value these measures as highly (Class C), and an intermediate class that values these measures to a certain extent (Class B). The following paragraphs discuss the differences across these three classes, as well as what kind of customer falls within each category.

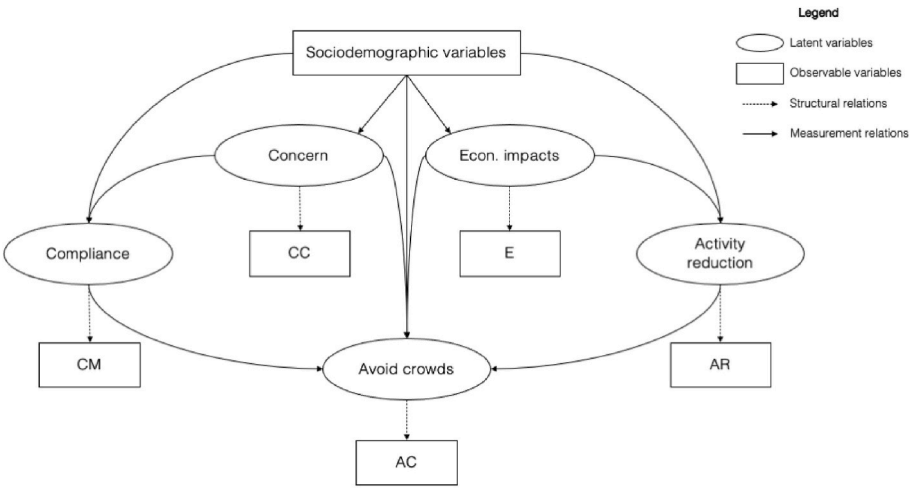


Fig. 2. Path diagram of SEM model associating Concern, Economic impacts of the pandemic, Compliance with pandemic rules, degree of Activity reduction, and degree of crowd avoidance.

Class membership is defined by two latent variables: Avoid Crowds and Activity Reduction. Respondents have a higher likelihood of belonging to the Cautious class if they have a higher value for the Activity reduction latent variable. Analogously, respondents have a higher likelihood of belonging to the Unconcerned class if they have a low value for Avoid Crowd. Since the latent variables significantly segmented the population, Hypothesis 3a is confirmed. Note that parameters for the class-membership function of the Intermediate class were kept fixed to allow model identification.

There are differences across classes in some key aspects. For example, whereas the Unconcerned class showed disutility for higher walking and waiting times, as we would expect in a non-pandemic scenario, the other two classes did not have significant walking time parameters. This result shows that people with higher likelihoods of belonging to the Cautious or Intermediate classes were willing to walk significantly longer to access a grocery store with better social distancing measures in place.

The Cautious or Intermediate classes also showed strong preference for shops where customers wore masks. Members of the Unconcerned class, on the other hand, did not display a significant preference for this attribute. This result may be explained by a more relaxed and irresponsible approach to existing measures to contain the pandemic, in combination with their higher tolerance to crowds. It is important to note that these data were collected before vaccines were available, after which mask-wearing rules were relaxed by public health officials.

Whereas the Intermediate and Unconcerned classes have negative preference parameters for people waiting in line both outside and inside, the Cautious class does not have significant parameters in either cases. This means that people who have reduced their activities to a greater degree did not mind long lines compared with other individuals. This attribute is independent of waiting time, so these parameters relate solely to the length of the line and not to waiting time as well.

Distancing outside and inside also showed significant variation across classes. Members from the Unconcerned class value distancing outside at the same rate as long as it is greater than 1 ft. They also do not value distancing inside as highly, perceiving a modest utility when it is 6 ft. At the other extreme, members from the Cautious class valued distancing highly, with significant increments outside (2–4 ft: $t = 4.16$, $p < 0.001$; 4–6 ft: $t = 4.44$, $p < 0.001$). Their preference for distancing inside is equal when it is 4 ft or 6 ft. Finally, the Intermediate class show preference for more separation, although it is more tepid than in the case of the Cautious class. For example, the Intermediate class values distancing outside at the same rate whether it is 2 or 4 ft, and they do not significantly value 4 ft distancing inside, just like the Unconcerned class.

In summary, individuals with a higher avoidance of crowds and those that stayed at home more often valued safety measures at a higher rate. Therefore, Hypotheses 3b and 3c are confirmed.

Fig. 3 shows the empirical density functions of the class-membership probabilities, together with their means. It can be observed that no individual has a class-membership probability close to or equal to 1. This means that respondents' actual preference structures are a combination of two or more classes, and cannot be accurately described by any class-specific set of parameters. Therefore, the segments can be interpreted as archetypes and not as descriptions of actual customers. The mean class-membership probabilities show that around 42% of the population have preferences that more closely resemble that of the Cautious class. The Intermediate and Unconcerned classes have virtually equal mean class-membership probabilities, close to 29%.

Class-membership probabilities are not entirely uncorrelated at the individual level. Fig. 4 shows that these probabilities are highly correlated in the case of the Unconcerned and Cautious classes. This was expected because preference parameters of these two classes were at odds in some key aspects, as discussed above. There is also a noticeable correlation between the probabilities of the Unconcerned and Intermediate classes, although it is weaker than the previous case.

One of the main advantages of discrete choice models is that marginal rates of substitution (MRS) can be easily derived, especially for the case of discrete heterogeneity distributions. Marginal rates of substitution indicate the change in one covariate that is required to offset a marginal change of another. The MRS is obtained by taking the ratio of two parameters when utility is assumed to be linear, as is the case in our specification. Given that the value of a parameter is stochastic in the case of a latent class conditional logit model, a distribution of MRS must be obtained instead of a single value. The following paragraphs describe some of the distributions that can be obtained from the model described above.

Fig. 5 shows the distribution of the MRS between waiting and walking times. The MRS is between 1 and 5, which means that a 1 min walking-time increase is equivalent to anything between 1.5 and 4.5 min of waiting time, with most individuals having an MRS between 2 and 4. Therefore, waiting is perceived as more taxing than walking. Moreover, we can conclude that a 1 min waiting-time reduction at a specific store would increase customers' willingness to walk to that store by 3 min on average.

Fig. 6 illustrates MRS estimates for all attributes with respect to waiting time. The estimates show, for example, that mask wearing inside and outside is equivalent to a decrease between 2 and 8 min of waiting time, with an average close to 6 min. Distancing outside is generally

Table 4
Results of structural equation model.

Variable	Estimate	z stat.	p-value
Factor Loadings			
Concern			
CC1	1.00	fixed	
CC2	0.72	9.16	0.00
Economic impacts			
E1	1.00	fixed	
E2	0.92	18.00	0.00
E3	0.85	19.17	0.00
Compliance			
CM2	1.00	fixed	
CM6	0.95	17.65	0.00
CM3	0.94	16.74	0.00
CM7	0.88	15.48	0.00
CM4	0.87	16.89	0.00
CM8	0.87	14.09	0.00
CM1	0.68	12.12	0.00
Activity reduction			
AR4	1.00	fixed	
AR6	0.97	13.34	0.00
AR9	0.94	15.07	0.00
AR2	0.94	14.75	0.00
AR3	0.86	14.01	0.00
AR8	0.86	13.51	0.00
Avoid crowds			
CA4	−1.00	fixed	
CA5	−0.99	−25.80	0.00
CA1	0.81	16.82	0.00
CA2	−0.78	−23.98	0.00
CA7	0.73	16.41	0.00
Regression Slopes			
Concern			
Millennial, 24–31 yrs.	−0.35	−3.06	0.00
Income: High	0.22	2.02	0.04
Income: Low	−0.26	−2.14	0.03
Economic impacts			
Female	−0.21	−2.38	0.02
Income: Low	0.38	3.68	0.00
Compliance			
Concern	0.64	8.23	0.00
Hispanic	0.23	1.99	0.05
Activity reduction			
Concern	−0.20	−1.84	0.07
Economic impacts	−0.16	−3.57	0.00
Compliance	0.44	4.64	0.00
Black	−0.23	−1.93	0.05
Educ.: Bachelor's	0.25	2.82	0.01
Avoid crowds			
Concern	0.42	4.55	0.00
Economic impacts	−0.05	−1.17	0.24
Activity reduction	0.33	5.68	0.00
Compliance	0.27	3.32	0.00
Female	0.24	3.08	0.00
Gen. Z, 18–23 yrs.	−0.34	−2.82	0.01
Income: High	−0.17	−2.09	0.04
Income: Low	0.17	1.95	0.05
Republican	−0.18	−2.37	0.02
N. of individuals	775		
N. of parameters	106		
χ^2	1096.56 ($p < 0.001$)		
RMSEA	0.046 ($p = 0.98$)		

viewed as more important than inside, and with high margins. For example, changing from 1 ft to 2 ft distancing is, on average, equivalent to a 7 min decrease in waiting time. The recommended 6 ft distancing, in turn, is equivalent to much higher decreases in waiting time, although the variance of this MRS estimate is high. On the other hand, the average valuation of distancing inside with respect to waiting time is small. For example, the MRS of 4 ft outside is smaller than 2 ft outside. Finally, the MRS estimate for the number of people inside and outside the store suggest that one extra individual is equivalent only to a very modest increase in waiting time, with an average of 1 min in both cases.

5. Discussion

5.1. Theoretical implications

The results we obtained using a latent class choice model that included latent variables suggest, first, that there are three distinct customer segments with varying degrees of preference for safety measures, and second, that on average such measures are highly valued.

Our study has theoretical implications that should be considered by researchers in the area of retail and consumer preferences. First, the differences between the latent class choice model and the conditional logit model highlight the fact that preference heterogeneity must be accounted for in discrete choice models. Heterogeneity is obscured when only average preferences are analyzed, and with them the nuances that can be derived from richer models. This is particularly true in settings where behaviors are not obvious, such as in disruptive contexts like a pandemic, or when social, political, or contextual schisms exist in the population. Interestingly, Eroglu et al. (2022) found a similar result using a different method (structural equation modeling) and a somewhat similar experiment.

Second, we found that attitudes are relevant variables to identify customer preference heterogeneity. Latent class choice models have traditionally been estimated as a function of sociodemographic variables. Such a specification produces interesting and useful results, but lack an adequate explanatory link between who belongs to a class and the reasons why their preference parameters differ from those of other classes. The implemented method is a modeling alternative for uncovering such heterogeneity using tractable and easily interpretable models.

Finally, we showed how such models can be used to derive marginal rates of substitution between intangible products and money or time using indirect methods. We believe such indirect methods are more desirable than direct elicitation (as in contingent valuation) for such multidimensional concepts such as safety. Retail management is constantly in the need of improving qualitative business elements such store design and style, and customer-employee interactions. Discrete choice modeling provides an adequate method of quantifying the effect that such improvements will have on willingness to pay or the cost customers are willing to incur, including waiting and access time, to access a store.

5.2. Implications for retail management

The results we obtained suggest that imposing social distancing measures, limiting the number of customers inside stores, and requiring customers to wear masks is desirable in the context of the COVID-19 pandemic, even if this means waiting times will increase. Therefore, public health recommendations limiting the capacity of grocery stores might actually increase sales. This counter-intuitive result is the product of customers' desire to stay healthy and slow the transmission of COVID-19. Some individuals who could be described as Unconcerned do not show contempt for social distancing measures, but actually do not care about them (such as in the case of masks) or weakly prefer them (such as in the case of distancing). These findings are similar to the ones by Eroglu et al. (2022), and consistent with the drop of in-person shopping found by Cronin and Evans (2020), Grashuis et al. (2020)and Beckers

Table 5
Results of conditional logit (CL) latent class choice model.

Attribute	CL	Latent class choice model		
		Class A: Cautious	Class B: Intermediate	Class C: Unconcerned
Choice model				
LHS ASC	0 (fixed)		0 (fixed)	
RHS ASC	-0.0772** (-2.62)		-0.118** (-2.69)	
Walk	-0.0217*** (-4.23)	-0.0289 (-1.09)	-0.0215 (-1.60)	-0.0715*** (-5.69)
Wait	-0.0540*** (-4.48)	-0.174** (-3.11)	-0.102*** (-4.57)	-0.0925*** (-5.26)
Mask	0.373*** (7.83)	1.42*** (6.30)	1.06*** (4.17)	-0.0817 (-1.24)
People outside	-0.0711*** (-8.82)	-0.0619 (-1.66)	-0.227*** (-8.15)	-0.0503** (-2.91)
Dist. outside (1 ft.)	0 (fixed)		0 (fixed)	
Dist. outside (2 ft.)	0.339** (2.68)	1.16* (2.14)	1.11*** (4.43)	0.362** (2.88)
Dist. outside (4 ft.)	0.961*** (9.58)	2.29*** (6.01)	same as above	same as above
Dist. outside (6 ft.)	1.37*** (14.27)	5.51*** (7.05)	1.43*** (5.95)	same as above
People checkout	-0.0478* (-2.20)	0.0703 (0.87)	-0.237*** (-4.26)	-0.134** (-3.28)
Dist. checkout (2 ft.)	0 (fixed)		0 (fixed)	
Dist. checkout (4 ft.)	0.288*** (4.82)	1.40*** (4.72)	0.168 (1.00)	0.0867 (0.87)
Dist. checkout (6 ft.)	0.283*** (4.22)	same as above	0.593*** (4.08)	0.211* (2.27)
Latent class model				
Constant		0.329 (1.83)	0 (fixed)	-0.266 (-0.92)
Avoid crowd (LV)		0 (fixed)	0 (fixed)	-1.08*** (-6.56)
Activity reduction (LV)		0.693*** (4.42)	0 (fixed)	0 (fixed)
Avoid crowd (std. dev.)			0.0530 (0.50)	
Activity reduction (std. dev.)			0.134 (0.50)	
Mean membership prob.		0.418	0.291	0.291
N. of individuals	775	775		
N. of observations	6,945	6,945		
log-likelihood	-4,022.91	-3,420.48		

***p < 0.001, **p < 0.01, *p < 0.05.

et al. (2021).

Business leaders should embrace safety measures imposed by public health officials. If customers are willing to walk and wait more to access a safer store, then having better safety measures will attract more customers. Since these measures are valued, they should be communicated clearly in marketing messages. This is particularly important for safety measures that are not evident, such as HEPA air filters or enhanced cleaning practices. Even though we did not test vaccine mandates because vaccines were not available at the time data were collected, our results suggest that immunization could also attract customers.

Finally, businesses may want to understand their customer base to fine-tune their safety measures. If their most usual or valuable customers tend to be more averse to crowds, or in general be more concerned with the pandemic, then it might be important to increase safety measures beyond public health guidance.

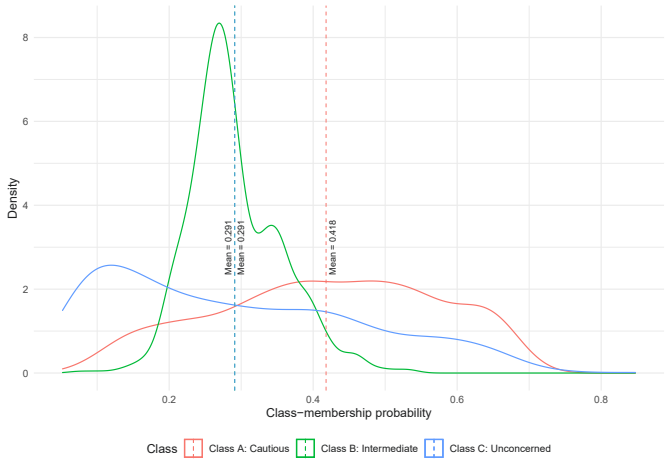


Fig. 3. Density of class-membership probabilities.

5.3. Limitations and future research

This study has several limitations that need to be acknowledged. First, data were collected during May 2020, when vaccines were not available and immediately after New York City's first deadly wave of COVID-19 infections. The preference structure we detected characterize customers during that place and point in time, and cannot be directly extrapolated to other moments. Elements such as disease prevalence, vaccine availability and adoption, and pandemic fatigue will likely change the preference structure identified in this work.

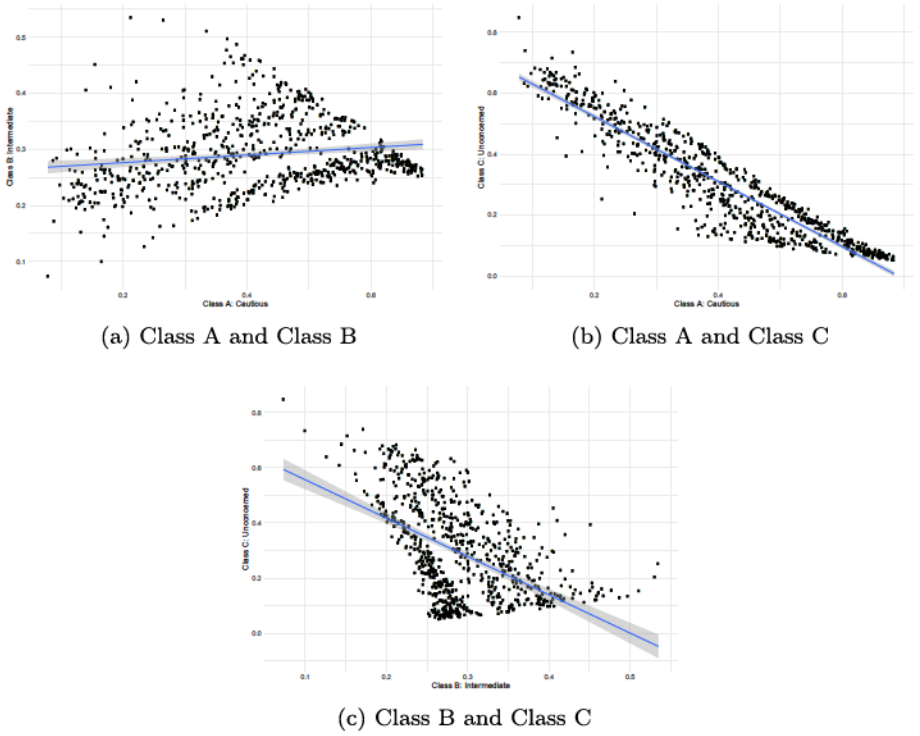
Second, we did not control for variables such as product quality or price. We set quality as homogeneous across stores to prioritize safety measures. Nevertheless, in situations where health measures are likely less valued, such attributes are more likely to be relevant.

Finally, the population we targeted lives within New York City. New Yorkers tend to be more liberal, prefer urban environments, and be more used to crowding in general. The city also experienced one of the worst COVID-19 outbreaks in the country. Thus, our results may not be easily translated into contexts that are rural or suburban, in low density areas, or where the prevalence of COVID-19 did not reach such a critical point.

6. Conclusions

The COVID-19 pandemic has significantly disrupted people's lives and businesses, including grocery stores. Customer capacities were capped in most cities and states across the US, which meant that customers had to wait longer to buy essential goods. Some customers migrated to online shopping to avoid queues and crowded spaces, but switching to online shopping is simply not possible for many individuals.

With these retail behavior changes in mind, we decided to research how the pandemic affected customers' choices of grocery stores, especially considering crowds and social distancing measures. The retail literature has extensively demonstrated that customers dislike crowds and long waiting times. Nevertheless, we were interested in exploring to what extent these distastes had changed, and to what extent people were



(a) Class A and Class B

(b) Class A and Class C

(c) Class B and Class C

Fig. 4. Relation between the three class-membership probabilities at the individual level and best-fit linear relation.

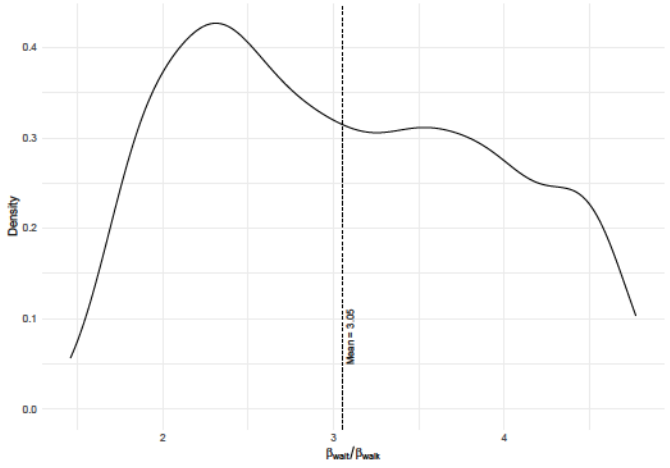


Fig. 5. Distribution of the marginal rate of substitution (MRS) between waiting and walking times.

willing to trade higher waiting times in exchange for better social distancing measures. We also hypothesized that these preferences were likely mediated by attitudes toward the pandemic. In this study, we fitted a latent class conditional logit model that included these attitudes as latent variables that informed class membership. Data for this model came from an online survey applied in New York City during May 2020 that was specifically designed for this study.

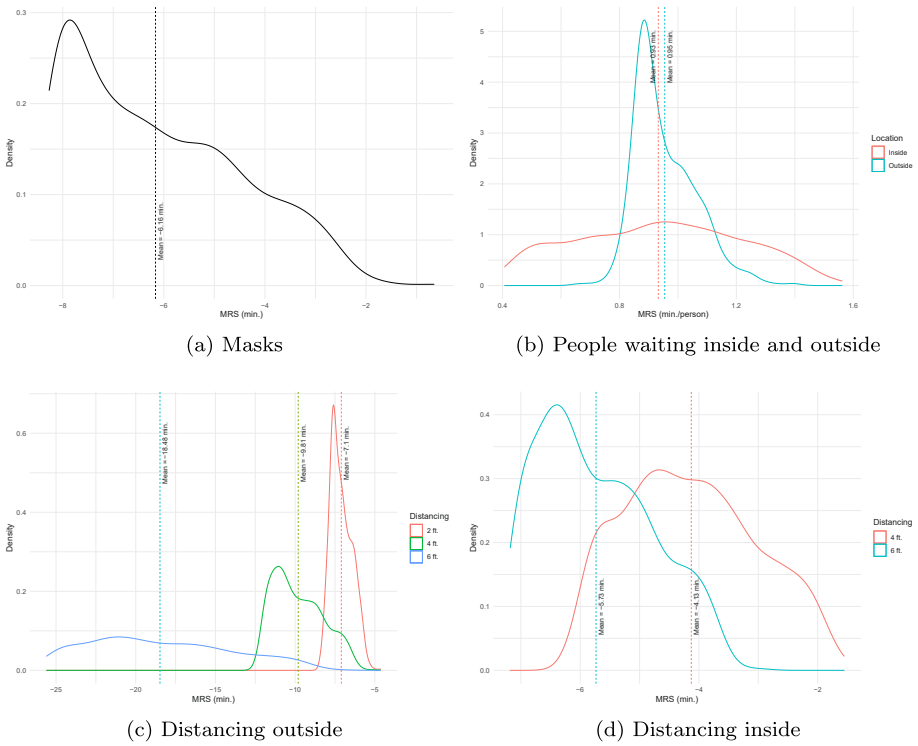
Our analyses demonstrated that, in the first place, concern for COVID-19 varied across age and income groups. Second, we also found that this concern was the main factor driving compliance with preventive measures such as wearing masks and keeping a distance of 6 feet away from other people. Third, we found that the degree to which people reduced their daily activities was positively correlated with compliance and negatively correlated with the economic damage caused by the pandemic. Finally, concern, compliance, and the degree of activity reduction all had a significant impact on aversion to crowds.

A subset of the identified latent variables was used to explain how preferences for grocery stores vary across the population. We found three clusters of individuals with distinct preference structures. We called one group "Cautious" due to of its high preference for social distancing measures, another "Unconcerned" due to its apathy toward these measures, and the third class was labeled "Intermediate" because of its tepid taste for distancing and mask wearing.

An analysis of marginal rates of substitution provides evidence that people were willing to wait longer to access a store with better social distancing measures in place. Although there certainly was heterogeneity in the trade-offs, we did not find evidence of people unwilling to exchange waiting time for access to a store with extra safety precautions.

These results suggest that measures imposed by public health officials on grocery stores actually attract rather than deter customers willing to buy in person. Given this observation, we believe that stores could in some cases reduce their capacity further, at the cost of extra waiting times, without actually damaging sales. This is good news for stores and the public in general, because the goals of businesses and public health officials are aligned to a certain extent.

Further research should look into how these preferences have evolved since May 2020, and especially after a significant portion of the population has been vaccinated. In fact, it would be informative to analyze this evolution as a function of the percentage of people who have taken a COVID-19 vaccine, as well as the prevalence of new, more contagious variants. If and how customer preferences change under this scenario is still an open question.



(a) Masks (b) People waiting inside and outside

(c) Distancing outside (d) Distancing inside

Fig. 6. Marginal rates of substitution of all parameters with respect to waiting time.

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