Economic Value of Restaurant Safety Measures and Propensity to Dine during the COVID-19 Pandemic

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Abstract

The COVID-19 pandemic presented a particularly challenging situation for restaurants and their management and innovation of the servicescape; a novel airborne virus that spreads easily among asymptomatic patrons created significant fear, risk, and uncertainty. This paper attempts too empirically study consumers' preferences for COVID-19 safety measures in the dining servicescape. We contribute to the emerging literature that explores individual subjective beliefs about health risk (pre- and post-COVID-19), evaluates risk perceptions, and assesses Willingness to Pay (WTP) for safety measures. Our survey data represent household/individual level information for Georgia, Florida, South Carolina, North Carolina, Virginia, and Maryland (providing variation in public policy response to the pandemic); we design a choice experiment to assess preferences for dining safety protocol measures and estimate a series of Random Utility Maximization (RUM) models of dining choice (including opt-out/no dine) as a function of COVID mitigation measures and price. Dining utility is specified as a function of features like outdoor tables, social-distancing indoors, masks on servers, masks on patrons (when not eating or drinking), permitting us to assess preferences and WTP for such mitigation measures. We explore standard conditional logit models, mixed logit, as well as generalized logit models that permit scale heterogeneity.

JEL Codes: D12, D81, D91, Q18

Keywords: COVID-19, dining, safety, WTP, choice experiment

1 Introduction

The hospitality industry (restaurants, in particular) is an important economic sector, providing significant business revenue and employment. The disruptive impacts of COVID-19 left indelible marks on the hospitality industry, including cancelled events, hotel and restaurant closures, lost revenue, and shuttered tourist attractions across the country(Baum and Hai (2020)). In the United States prior to the COVID-19 pandemic, the restaurant industry was expected to reach about $899 billion in sales revenue in 2020 (National Restaurant Association (2021)). The public health emergency associated with the pandemic, however, lead to lock-downs and stay-at-home orders that severely limited the industry. Restrictions were imposed on public and private establishments, with virtually all restaurants being forced to suspend dine-in-services. Many restaurants struggled to understand how to maintain safe food preparation conditions and provide provisions for take-out, while some consumers were leery of interacting with food establishments in any way. The US restaurant industry suffered significant losses, estimated to be $120 billion between March and May 2020 (Harris et al. (2020)). These impacts did not discriminate across types, as per NPR's Yuki Noguchi, nationwide every restaurant ranging from fast casual to luxury dining was severely and adversely affecting, making the COVID-19 pandemic an extremely unique challenge (Noguchi (2020)).

By December 2020, 110,000 restaurants and bars had been shuttered permanently and there were 2.5 million fewer jobs in the restaurant sector (Association (2021)). On the demand side, consumers worried that COVID-19 could be food-borne and might spread through take-out if prepared by someone who was infected by the disease (Datassential (2020a); IFIC (2020); Wadyka (2020); Whitworth (2020)). Despite eventual confirmation from the U.S. Centers for Disease Control and Prevention (CDC) that food was not a source of COVID-19 transmission, misperceptions about contracting COVID-19 from restaurant food remained within some socio-demographic groups (CDC (2020)). In general, there was desire to return to restaurants among many baby boomers, while there appeared to be much more reluctance on the part of Gen Z and Millennials (Murell (2021)).

In responding to changes in food safety protocol, consumer tastes, and other factors, a restauranteur needs to understand the complexity of dining attribute perceptions and their impact on customers' purchase decisions, dining experience, and satisfaction (Stierand and Wood (2012a);Nemeschansky (2017); Stierand and Wood (2012b)). The concept of servicescape, defined as the physical environment where a service transaction takes place, captures many important elements of the consumer's dining experience. Servicescape facilitates customer experience and can augment dining through ambience, comfort, and "feel" of a restaurant. Visible aspects of servicescale influence customer's first impressions of a restaurant, often before entering or interacting with staff. Restaurant servicescape has been evolving over the last several decades, while restaurants have also witnessed increased diversity in menu design, use of non-processed and local food ingredients, vegetable-based menu options (vegetarian and vegan), improvements in waste management, and increased crowd-sourcing of information through online reviews and aggregator websites (Suhartanto et al. (2019); Bristow and Jenkins (2018); Canny (2014); Higgins-Desbiolles et al. (2019); Kwok et al. (2016); Wen et al. (2020); Zanella (2020)). The COVID-19 pandemic presented a particularly challenging situation for restaurants and their management and innovation of the servicescape; a novel airborne virus that spreads easily among asymptomatic patrons created significant fear, risk, and uncertainty that could not easily be addressed through changes in food preparation and service provisions.

As understanding of COVID-19 risks and their mitigation and management has improved, restaurants witnessed an opportunity to modify their business operations and maintain some level of service, by offering outside dining, observing social distancing, and requiring masks indoors. Some consumers have embraced such provisions, while others continue to harbor concerns over social distancing and hygiene, and thus have been reluctant to return to restaurants and other places where people congregate (Sung et al. (2021)). Still others appear to have not desire for safety precautions and re-engaged in dining as soon as lock-down restrictions eased. Previous research has shown that consumer assessment of sanitation and food safety affect dining decisions (Jin et al. (2012)), while visible elements, social context, food presentation, and restaurant image are important criteria for customer satisfaction, and these factors influence restaurant choice (Ponnam and Balaji (2014)). A recent survey by the National Restaurant Association Association (2021) indicates that the majority of consumers in the U.S are more likely to dine in restaurants that have immediate implementation of COVID-19 prevention measures. Restaurant guidelines for improved safety during the pandemic include sanitizing and disinfecting all surfaces, utensils, menus, and hands; providing improved ventilation; reducing the number of patrons to permit social distancing; and wearing face coverings to prevent spreading of potentially infected moisture droplets (CDC (2020)). While the pandemic waxes and wanes, we still know little about the value of servicescape features that can address consumer safety concerns. Forward looking recovery strategies like operational stabilization, financial re-emergence, revenue enhancement, and coping mechanism of employment structure also need to be assessed (Campiranon and Scott (2014)).

We contribute to the literature on consumer perceptions of the restaurant servicescape in the context of the COVID-19 pandemic. Employing a random sample of households in the US southeast, we analyze dining behavior (pre- and post-COVID-19), risk perceptions, and willingness-to-pay (WTP) for safety measures (such as masks, outdoor dining, social distance, and plexiglass barriers) in the servicescape.

2 Background

Food Away from Home in the US

The food service industry comprises operations that cater meals/snacks for immediate consumption on site, also known as "food-away-from-home" (FAFH) in the food research literature ((2020)). The restaurant industry recognizes three segments: quick service, fast-casual and full service. Restaurants are the largest source of FAFH expenditure in the United States. While budget shares allocated to food generally fall as income increases, dining-out expenditures increase more than proportional to income changes (luxury good). With households becoming more time-constrained due educational attainment and increased participation of women in the labor force, at-home meal preparation has become less attractive for many households. The practice of eating out at a restaurant, be it fast-casual or up-scale, is well ingrained across many cultures and many segments of society. Given the diverse assemblage of restaurants establishments, ranging from local “mom and pop” establishments to global chains, the restaurant sector is linked to the overall economy in complex and multi-faceted ways.

Despite strong demand, the restaurant industry remains potentially perilous for entrants. Given the competitive nature of the food service industry, several studies have demonstrated that approximately 30% of restaurants fail during their first year of operation (Parsa et al. (2005)). While food service provides significant employment benefits, many of of the entry-level employees are part-time workers, students, and undocumented immigrants (Edwards (2013)). The industry is marked by long working hours, low employee pay, and a high turnover rate (Edwards (2013)).

Economic downturns have a negative impact on households reducing their income and purchasing power.The Great Recession, from December 2007 to June 2009, spiked the rate of unemployment with over 8 million people losing their job by February 2010 and mean and median household income remained below pre-recession levels in 2014 (Kumcu and Kaufman (2011)). Dining-out at restaurants declined by 18% from 2006 to 2010 and this was largely manifested by decreased spending at full-service restaurants while spending at quick-service restaurants grew(Beatty and Senauer (2013)). Post-Great Recession, quick-service grew to about 15.8%, while fast casual restaurants (a hybrid between quick and full service restaurants) showed the speediest growth. Between 2004-2006, food spending at restaurants grew an average of about 7.3%, between 2007-2009, it was 3.1% and between 2010-2019 it was about 5.6 with a dip in 2020 due to the COVID-19 pandemic ((2020)).

The COVID-19 Pandemic

Most of the US entered a state of emergency during March of 2020, with restrictive (only essential businesses) shelter-in-place orders going into effect. Social gatherings with 10 or more people for non-essential purposes were generally restricted. With cases initially peaking in Spring 2020, there was limited evidence establishing correlation among containment strategies and COVID-19 case counts. Gradually, certain businesses (gyms, barbershops, movie theatres etc.) were granted permission to reopen with various levels of safety provisions, such as allowing take-out only, limiting indoor occupancy to 25% capacity, and encouraging social distancing of at least 6 feet, while symptomatic workers were restricted from reporting to work. Re-opening efforts, however, varied across US states.

Overall, Georgia, Florida, and South Carolina were slow to implement COVID-19 lockdown measures and early to re-open back their businesses and restaurants. On the other hand, North Carolina, Virginia and Maryland were quick to implement mitigation policies and adhered to more restrictive preventive measures. Reopening of businesses was slower in the these states as well. Lack of coherent and cohesive national response and sole delegation to a sub-national level i.e. the states to figure out mitigation policy by themselves has been a major problem in United States. The state governors shared details about plans to re-open the economy in three phases. Phase I involved opening more retail stores and permitting certain commercial activity, while still encouraging masks and restricting gatherings to 10 people; Phase II involved lifting the stay-at-home order and allowing a limited opening of restaurants, bars, personal care services, and fitness centers, and increasing the number of people allowed at gatherings; Phase III involved increased capacity at bars and restaurants, religious services, and entertainment venues.

As a result of the pandemic and accompanying safety restrictions, the restaurant industry suffered significant sales and job losses, with $240 billion loss of sales by the end of 2020; chances of survival for restaurants fell by 15% Association (2021). About 13.4 million restaurant jobs were affected in 2020, while in-person dining declined by 90% by October 2020 (Nhamo et al. (2020)), and 60% restaurants permanently closed (Croft (2020)). A survey conducted by National Restaurant Association stated that more than 6500 restaurant operators suffered a decrease in sales by 78% and sale loss being $30 billion in March and $50 billion in April.

With a decline in restaurant sales, operators were forced to cut on staffing levels and 701,000 American jobs were lost in March with major chunk coming from restaurants and bars (Ludlow (2020)). The food service sector took a major hit where about 417,000 Americans lost jobs and restaurants cut 83% off their total staff on pretext of furlough or lay-off (Ludlow (2020)). Around this same time, most states in the U.S. relaxed their stay-at-home orders after a slow downward trend of COVID-19 cases, and restaurants were allowed to reopen with preventive measures in place. Under CDC and NRA guidelines, food safety, cleaning and sanitizing, employee health and hygiene, and social distancing (Wei et al. (2021)) were of utmost importance to assist restaurants to reopen safely during COVID-19 recovery period. Additionally, the CDC divided restaurants into four risk-based groups, based on the level of interaction with the customers. For instance, drive-through and delivery services are regarded as the lowest risk, and restaurants without a six-foot social distancing layout were considered the highest risk (CDC (2020)).

Researchers have found that households tend to curtail their expenditure for non-essential goods and services in times of uncertainty or chaos (Yost et al. (2021)). In comparison to carry-out and delivery services, dine-in restaurants pose a higher risk of COVID-19 infections given that COVID-19 can spread through respiratory droplets as individuals interact face-to-face with each other and surface contamination can also cause potential threats (CDC (2020)). As many restaurants reopened at limited capacity, employment expanded for 13.49 million workers, and patrons began to come out of lock-down to enjoy dining and socializing (Arunan and Crawford (2021)). With the surge of COVID-19 cases, jurisdictions across United States have implemented varying degrees of safety protocol (like mask mandates).

3 Literature Review

Previous studies have indicated that food-away-from-home choices are influenced by restaurant attributes, such as perceived healthiness, assessment of value for food cost, overall food quality, social needs (food cravings, organizational behavioral needs), and destination atmosphere Anand (2011); Susskind et al. (2004)). There is a substantial literature focused on consumer perception of food quality and restaurant safety. The theory of reasoned actions and rational choice theory assumes that humans are primarily rational, seek full information, and weigh all aspects of choice (i.e. benefits and costs) through a systematic assimilation (Vallerand et al. (1992)), while other strands of social and behavioral sciences assert that much of consumer behavior is much more nuanced, bounded by rationality, limited or asymmetric information, prone to errors, and guided by inertia. Prior to the Covid-19 pandemic, Henson and Roberts (2006) analyzed how consumers formed perceptions of food safety in choosing a restaurant. Prior research shows that concerns about pesticides and chemicals being used in food at restaurants do affect purchase intention or consumption for some consumers (Byrne et al. (1994); Norris et al. (1991);Rimal (2001);Schafer et al. (1993); Wessells et al. (1996)). Furthermore, studies suggest that consumers are willing to pay more for products which are perceived to be safer or to be lower risk (Baker and Crosbie (1994)).Rimal (2001) argue that food safety and food consumption do not have direct correlation. Variables such as knowledge, trust and socio-demographics play an integral role in assessing risk. Experience influences risk perception which means if people perceive that they become ill because of food consumed at restaurants, their dining preference changes (Knight and Warland (2005)). A person who believes that restaurants perform their roles effectively will have lower concerns about food safety if there are higher levels of trust in food system and thereby will be less concerned with risk (Knight and Warland (2005)).

Due to Covid-19 pandemic, safety measures have become a critical factor along with visible and other aesthetic elements at any dining place. With this in mind, the literature has categorized two broad types of food-away-from-home consumers: the first type of consumer exhibits risk perceptions and risk tolerance towards safety issues that are well integrated within their cognitive abilities; the other type of consumer exhibits biased or skewed perceptions of safety risks that may be labile and easily affected by social interactions or the media (Frewer et al. (1996)). Previous literature has shown that many people exhibit an optimism bias when it comes to unfavorable outcomes. Scholars have distinguished among rational (thinking “slow”) and emotional/intuitive (thinking “fast”) decision modes (Bracha and Brown (2012)); competing mental models may be used in different domains and can be triggered by contextual factors (Schoemaker et al. (2013)). Mowen (2000) developed a meta-theoretic model of motivation, which seeks to account for how personality traits interact with different situations and parsimoniously illustrate risk perceptions based on this behavior. Mowen (2000) find that people substantially over-estimate the level of risk associated with engaging economic activity in the early stages of the pandemic. They are however more accurate about their relative risk measures and individual assessment of risk would expectedly vary across socio-economic and demographic groups as geographies in ways that are consistent with rational expectation behavior. Due to pandemic restrictions being different across US states, individual's elemental traits have been examined. Their unique coping strategies with unexpected risks and the compliance to restrictions can be assessed under this framework. Zajenkowski et al. (2020) find that people who tend to have a higher degree of agreeableness are more likely to comply with top-down restrictions; such actions can be helpful during a public health crisis, or other emergency situations that require voluntary compliance. Individuals with behavioral traits like conscientiousness and neuroticism are also more likely to adopt preventive measures like social distancing and mask-wearing, which can reduce the public health risk of Covid-19 infection (Abdelrahman (2020)).

Other types of behavior traits can cause further difficulties during a public health emergency. For example, extroverted individuals tend to visit more places during a pandemic, as self-isolation is difficult for them. Such individuals are more likely to dine-out at a restaurant during a pandemic. Extroverted customers may utilize loyalty and trust as a primary reason for continuing to dine out during a pandemic. Those compelled to dine out will often search for information that can offer confirmation of the suitability of those decisions, whether that be approval from restaurateurs or presence of safety provisions that may ease concerns of health risks. Transparency can reduce customer information asymmetry and perceived risks if all details about service process and preventive measures are provided to the customers (Hustvedt and Bernard (2010)).

In the current paper, an investigation of these positive emotions under the willingness to pay framework would be assessed. How excitement and satisfaction would be perceived under a dining behavior by individuals under pre-Covid-19 and post-Covid-19 framework. Since every individual is genetically unique, the disposition of the behavior is more situational and would differ due to various factors like political autocracy, preventive measures by the State, lock-down restrictions, mandatory face-coverings etc. In the hospitality industry, increasing use of public information and social marketing campaigns, advertising controls, nutritional labeling, health mitigation measures also consumers to make better informed choices about dining choices. Disseminated information about segmented consumers' attitudes of food safety are an important indicator of their acceptance of food service practices to ensure safer environment during times of a pandemic (Vallerand et al. (1992); Bandura (1989); Kim and Hunter (1993)). With the Covid-19 pandemic, one would expect a higher willingness to pay due to concerns about food safety. Food establishments would be expected to share the safety cost with consumers and price elasticity would also be a contributing factor. As customers' WTP measures are important not only to restaurant managers but also price strategists to efficient pricing strategies are employed to capture the varying WTP during Covid-19. In a competitive market like that of the restaurant industry, "value for money", is crucial to experiential offer of a consumer which can prompt a consumer to pay more or even return back again for the dining experience (Teng and Chang (2013)). With Covid-19 mitigating measures of sanitation and hygiene, restaurants can allocate their resources at hand to increase profit and maximize return on investment (Bujisic et al. (2014)).

We build our empirical analysis on the theory of planned behavior and micro-econometric models of consumer decision-making, while accounting for complications that arise due to uncertainty, imperfect information, and behavioral anomalies. Our empirical methods can be categorized into three distinct parts. The first is a descriptive analysis comparing dining behaviors before and after the COVID-19 pandemic, exploring heterogeneity with regards to support for public health measures, subjective risk metrics, and other demographic factors. The second part of the analysis assesses determinants of consumer perceptions of risk and mitigation measures to understand how these factors vary in the population and across southeastern US states. Finally, we conclude our analysis by estimating a series of Random Utility Maximization (RUM) models to determine dining choice (including opt-out/no dine) as a function of COVID mitigation measures and price. Dining utility is specified as a function of features like outdoor tables, social-distancing indoors, masks on servers, masks on patrons (when not eating or drinking), permitting us to assess preferences and WTP for such mitigation measures. We explore standard conditional logit models, mixed logit, as well as generalized logit models that permit scale heterogeneity. Since we are applying stated preference methods to private goods, we also explore a new variant of consequentiality that seeks to attenuate hypothetical bias. Our approach differs from the typical consequential script employed in analysis of public goods (highlighting policy and payment consequences) by attempting to engaged other-regarding preferences in the script. In particular, the consequential script explains that COVID mitigation measures require costly investment on the part of restauranteurs and encourages respondents to respond truthfully so that business owners will not engage in unwise investments. To the extent that empathy, concern for others, or other forms of other-regarding preferences are operational and engaged by this script, we hypothesize a decrease in WTP for the sub-sample that received treatment. This would depend upon restaurant safety characteristics with individual specific parameters and the individual level cost of dining at restaurant.

Experimental & Survey Design

The survey was fielded in September of 2020 and was designed to measure dining behaviors before, immediately after the start, and in the depths of the COVID-19 pandemic. The data were collected by Qualtrics and focused on six southeastern US states: Florida, Georgia, and South Carolina (each with Republican Governors); and North Carolina, Virginia, and Maryland (each with Democratic Governors). This sampling frame was designed to permit comparative analysis across states with divergent COVID-19 responses. The survey instrument included attitudinal measures, knowledge, and beliefs about the pandemic and public health policy; mitigation behaviors in the immediate aftermath and during the depths of the pandemic; risk perceptions (subjective likelihood of contracting COVID and perceived health consequences); and a choice experiment designed to assess preferences for restaurant health safety protocol (e.g., outdoor dining, six-feet separation among tables; mask wearing). This paper focuses on the latter data.

The choice experiment initiated with the following preamble that describes the SP scenario: "Consider an opportunity to dine out at Upscale-casual or Casual establishment in the next week or two. Suppose your dining party is the usual size that you reported in Q26 (including adults and children). As you examine the list of dining options presented below, assume that all other characteristics (food quality, service quality, ambience, etc.) are the same. Please indicate which dining option you would choose, or whether you would choose not to dine out." Dining safety features considered in the experiment consist of 6 binary attributes: Outdoor seating; six-feet distant between tables; plexi-glass barriers shielding the host and carrier, and between tables; face masks and gloves for employees; face masks for patrons; and disposable menus and dinnerware. The cost attribute has four levels: (1) \$16 adult/ \$8 child; \$24 adult/ \$10 child; \$30 adult/ \$12 child; and \$40 adult/ \$15 child.

Each choice set was composed of two dining options (restaurant A, restaurant B) and a no-dine option. NGENE software efficient Bayesian experimental design protocol was used to create twenty-four restaurant safety profiles that we blocked into eight versions with three choices each. The algorithm used fairly uninformative priors (weakly positive expectations on outdoor seating, social distancing, plexi-glass barriers, and masks/ gloves on employees; strong negative prior on cost; no priors on patron masks and disposable menus/ dinnerware) and restricted dominated options from the output designs. Each choice set was followed by a 7-point Likert scale measuring respondent choice certainty.

Descriptive Statistics

The sampling frame was of households with heads at least 18 years of age residing in Georgia, Florida, South Carolina, North Carolina, Virginia and Maryland. In total 1,194 participants were surveyed, (roughly) equally split across the six states. Potential respondents were screened on the basis of whether they regularly eat-out at least once a month prior to the COVID-19 pandemic. Panel A in Table 1 presents descriptive statistics for demographic factors. Forty- six percent of respondents were male, and average age was almost 57 years. Twenty-nine percent were college graduates, while 26% had a graduate degree. At 86%, the majority of respondents identified as White, followed by Black/African American (almost 8%), and Asian (2.5%), with low representation among Native Americans (0.33%) and Pacific Islanders (0.08%). Four percent of respondents identified as Hispanic. Average household income was $101,000. Amongst the states analyzed, thirteen percent were from Maryland, seventeen percent were from North Carolina, sixteen percent were from Georgia, twenty-three percent were from Florida, eleven percent were from South Carolina and seventeen percent from Virginia. Panel B in Table 1 examines the attitudes about public health measures: 88.7% of respondents indicate support for initial shelter-in-place measures, while 70.2% support continued efforts to shelter in place (as much as possible) (as of fall 2020). Eighty-one percent agree that vulnerable individuals should continue to shelter-in-place, and 56.4% believe that vulnerable people should shelter-in-place until vaccinations are available (again, this was in fall of 2020). Only 30.2% believed it to be safe to gather in groups of 10 or more.

Table 2 presents descriptive statistics for health status, risk perceptions, and risk attitudes. Four-point-six percent of individuals indicate that they had tested positive for COVID-19 (aas of fall 2020), and 14% of households have a family member that had tested positive. Respondents were asked to report the severity of illness they expect to experience

Table 1: Descriptive Statistics : Part I

Variable	Count	Mean	St. Dev.	Min	Max
Panel A: Demographics Measures					
Gender (Male)	1,194	0.465	0.499	0	1
Age	1,194	56.95142	17.13276	18	95
Education - Bachelor's Degree	10,746	0.291	0.455	0	1
Education - Graduate Degree	10,746	0.266	0.442	0	1
White	10,746	0.864	0.342	0	1
Black	10,746	0.080	0.271	0	1
Hispanic	10,746	0.419	0.200	0	1
Asian	10,746	0.025	.156	0	1
American Indian or Alaska Native	10,746	0.003	.0578	0	1
Native Hawaiian or Pacific Islander	10,746	0.000	.029	0	1
Income	1,194	101.571	102.499	7	354.733
Florida	1,194	0.232	0.422	0	1
Georgia	1,194	0.161	0.368	0	1
South Carolina	1,194	0.115	0.319	0	1
North Carolina	1,194	0.179	0.384	0	1
Virginia	1,194	0.179	0.384	0	1
Maryland	1,194	0.134	0.341	0	1
Panel B: Attitudes Toward Public Health Measures					
Supports Shelter-in-place	1,194	0.887	0.317	0	1
Supports Continued Shelter-in-place	1,194	0.702	0.457	0	1
Supports Continued Shelter-in-place	1,194	0.702	0.457	0	1
Support Shelter in place (vunerable people)	1,194	0.810	0.393	0	1
Support Shelter in place until vaccine	1,194	0.564	0.496	0	1
Mask in public places	1,194	0.871	0.335	0	1
Safe to gather in groups of 10 or more	1,194	0.301	0.459	0	1
Mask among restaurant employees	1,194	0.894	0.307	0	1

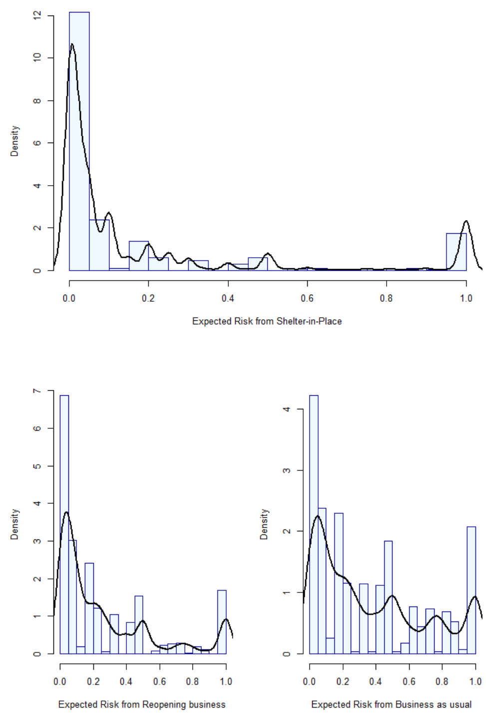
if they were to contract COVID-19; the response frequencies were: hospitalized with serious risk of death (16.5%); hospitalized without serious risk of death (7.8%); very ill, but not hospitalized (21.4%); minor illness (18.5%); and asymptomatic (5.8%) (the remaining 30% were unsure). Forty-nine percent of respondents perceived themselves or someone in their household having pre-existing conditions that would make them more vulnerable. Twenty-one percent believe exposure to COVID-19 would render immunity from future contraction of the disease. Panel F indicates that the average respondent expected a vaccine to be available in the next 11 months, whereas 2.7% felt vaccinations would never be available. Following recent developments in natural hazards (Landry and Turner (2020)), we use an expected relative frequency response to gauge subjective perceptions of risk within different contexts. The specific text for the first scenario (shelter-in-place) is presented in Figure 1. Similar queries follow shelter-in-place, focused on economic re-opening and return to

Table 2: Descriptive Statistics: Part II

Variable	Count	Mean	St. Dev.	Min	Max
Panel C: Covid-19 Health Status : Positive					
Individual	1,194	0.460	0.210	0	1
Household	1,194	0.141	0.348	0	1
Panel D: Subjective Risk Perceptions from Covid-19					
Death Risk	1,194	0.166	0.372	0	1
Serious Risk	1,194	0.078	0.268	0	1
Very Ill	1,194	0.214	0.410	0	1
Minor Ilness	1,194	0.185	0.389	0	1
Asymptomatic	1,194	0.058	0.233	0	1
Panel E: Pre-Existing vulnerabilities & Expected Immunity Exposure					
Pre-existing vulnerabilities	1,194	0.486	0.500	0	1
Immune	1,194	0.213	0.409	0	1
Panel F: Expected Months Until Vaccine Roll-out					
Expected Vaccine	1,162	11.707	6.840	5	28
Vaccine Never	1,194	0.027	0.162	0	1
Panel G:Subjective Risk Probability from Mitigation Measures (Business)					
Risk (shelter-in place)	1,194	0.170	0.293	0	1
Risk (Reopening businesses)	1,194	0.259	0.298	0	1
Risk (Business as usual)	1,194	0.370	0.330	0	1
Panel H: Risky Behavior (How willing are you to take risk?)					
Risky (Personal Health)	1,194	0.079	0.269	0	1
Averse (Personal Health)	1,194	0.293	0.456	0	1
Risky (Family Health)	1,194	0.069	0.254	0	1
Averse (Family Health)	1,194	0.399	0.490	0	1
Risk (Finance)	1,194	0.056	0.230	0	1
Averse (Finance)	1,194	0.190	0.392	0	1
Risk (Auto)	1,194	0.137	0.344	0	1
Averse (Auto)	1,194	0.183	0.386	0	1
Risk (Sports/Leisure)	1,194	0.055	0.229	0	1
Averse (Sports/Leisure)	1,194	0.281	0.449	0	1
Risk (Career)	1,194	0.066	0.249	0	1
Averse (Career)	1,194	0.163	0.370	0	1

business-as-usual. Interpreting the number of households as a relative frequency, the data suggest that the average respondent perceives 17% risk of contracting COVID-19 in the next 2 months while sheltering-in-place. This average risk perception elevates to 25.9% (37%) during re-opening (business-as-usual).

Figure 1: Subjective Risk of COVID-19 Infection



Theoretical Background

In the hospitality industry, increasing use of public information and social marketing campaigns, advertising efforts, nutritional labeling, and health mitigation measures aid consumers in making better informed choices about dining options. Little is known, however, about consumers' preferences for COVID-19 safety measures in the dining servicescape. In particular, what kinds of mitigation measures would induce restaurant patrons to dine out during COVID and how much are they willing to pay (WTP) for restaurant meals that include safety measures to limit spread of COVID. As mentioned above, to address this gap, we conduct a choice experiment to assess preferences for COVID mitigation measures in the restaurant servicescape.

We build our empirical analysis on the theory of planned behavior and micro-econometric models of consumer decision-making, while accounting for complications that arise due to uncertainty, imperfect information, and behavioral anomalies. The basic framework of the Random Utility Maximization (RUM) model consists of a repeated, discrete choice logit model that links a deterministic model (based on observable factors) with a model of human behavior (that incorporates factors that the researcher cannot observe, but are known to the subject) (Sándor and Train (2004)). In our context, the utility (U_{nit}) of a respondent (n) derives from a choice (i) on occasion (t) is given by:

$$U_{nit} = V_{nit} + \epsilon_{nit} \tag{1}$$

where (V_{nit}) is the deterministic deterministic portion of utility that depends upon explanatory variables describing dining experience (X_{nit} - which may vary at the individual level), and ϵ_{nit} is a random variable following a type I extreme value distribution (McFadden (1974)). We use a use a mixed multinomial logit (MMNL) model, resulting in the following general utility structure:

$$U_{nit} = \begin{cases} V\,(\ z_{nit}, \alpha_n) + \varepsilon_{nit},\ \ i =)\ 0\ \ (status\ quo - no\ dine)\,; \\ V\,(x_{nit},\ \ c_{nit}, \beta_n, \gamma_n) + \varepsilon_{nit},\ \ i = A, B\ (trip\ to\ restaurant\ A, B) \end{cases} \tag{2}$$

where the observable utility, V, is an additive function that can depend upon household characteristics (Z_{nit}) with individual specific parameters (α_n) for the status quo option (not dining out on this occassion), dining utility (V) depends upon restaurant safety characteristics (x_{nit}) with individual specific parameters (β_n), and the individual level cost of dining at restaurant i (c_{nit}) with individual specific parameter (γ) (English et al. (2018)). The unobserved error term, (ϵ_{nit}), is assumed to be distributed type I extreme value with a cumulative distribution function (CDF):

$$F(\varepsilon) = exp\left(-\sum_k \left[\sum_{i\in S_k} e^{-\varepsilon_{nit}/\lambda_k}\right]^{\lambda_k}\right) \tag{3}$$

where k = restaurant (i = A,B), no-dine (i = 0), S_k is the restaurant-choice set, and γ_k is the inclusive value parameter that measures the degree of independence in unobserved utility among restaurants for the restaurant-choice nest (Sándor and Train (2004)). This formulation gives rise to the following choice probabilities:

$$P_{nit} = \frac{e^{V_{nit}/\lambda_k}\left[\sum_{i\in S_k} e^{V_{nit}/\lambda_k}\right]^{(\lambda_k-1)}}{e^{V_{n1t}} + \left[\sum_{i\in S_k} e^{V_{nit}/\lambda_k}\right]^{\lambda_k}} \tag{4}$$

The MMNL model implements a flexible specification that allows for the estimation of parameters for population moments of the sample, such that :

$$\beta_{nj} = \bar{\beta}_j \pm \psi_j q_n, \tag{5}$$

where $\bar{\beta}_j$ represents the mean parameter for site or household attribute j, ψ_j represents the spread of the distribution around the mean, and q_n represents random draws from a pre-determined distribution for each respondent n. When ψ_j is either not specified or not statistically significant, one interprets preferences as fixed parameters. Given the panel structure, log-likelihood function of the stated preference restaurant choice data is:

$$log\ E(L) = \sum_{n=1}^{N} logE(P_n^*) \tag{6}$$

with

$$P_n^* = \prod_{i \in 1}^{I} \prod_{t \in 1}^{T} (P_{nit})^{y_{nit}} \tag{7}$$

where P_nit is probability of individual n choosing restaurant n at time t (as in equation 4).

The model permits welfare analysis for restaurant dining under various safety conditions. Parameters can be interpreted as influencing the probability of dining at a particular restaurant establishment, and post-estimation calculations can assess the marginal effects of particular safety protocols (e.g. plexi-glass barriers), as well as marginal willingness to pay (WTP) for those features. Model parameters can also be used to assess total WTP for a particular array of safety protocols at a restaurant establishment. Following Williams et al. (1997), Small and Rosen (1981), and Sándor and Train (2004), the expected value of utility associated with restaurant choices for household i is given by:

$$E\left(MaxU_n\right) = \frac{1}{\bar{\gamma}} \ln \left(\sum_{i=1}^{I} \sum_{t=1}^{T} e^{V_{nit} + \ \varepsilon_{nit}} \right) + \ C \tag{8}$$

where $\bar{\gamma}$ is the mean of the (absolute value of) marginal utility of income (restaurant cost coefficient), the expectation is taken over the domain of $\epsilon_n it$, and C is a constant stemming from integration (reflecting the fact that the level of utility is relative). In this framework, household WTP to avoid loss of restaurant h is given by:

$$WTP_{hn} = -\left(E\left(MaxU_n\right) - E\left[\frac{1}{\bar{\gamma}} \ln \left(\sum_{i \neq h}^{I} \sum_{t=1}^{T} e^{V_{nit} + \ \varepsilon_{nit}} \right) + C \right] \right) \tag{9}$$

where the second summation excludes restaurant h from the choice set. (Confidence intervals for WTP can be generated by the delta method.) The expression in equation 9 is defined over all stated preference restaurant visits over all choice occasions for household n.

In addition to accounting for continuous heterogeneity with the MMNL model, we also explore discrete clusters of consumer "types" using the finite mixture multinomial logit model (FMML) approach. FMML permits unobserved heterogeneity by defining a finite number of latent classes that can vary in their choice parameters Smith and Landry (2021). The estimation follows closely to (Smith and Landry (2021); Orea and Kumbhakar (2004);Greene (2005)): we estimate the probability of group g membership π_g and the likelihood for each group.

$$lnL(\pi, \beta, \sigma_v, \sigma_u, \nu) = \sum_{i=1}^{N} ln(\sum_{g=1}^{G} \pi_g h_g(y_i - (x_i)'\beta | \sigma_v, \sigma_u, \nu)) \tag{10}$$

In the Equation 10, π_g follows a multinomial logistic specification with fixed parameter as the price and the exponential density function for h(.) is definded in (Smith and Landry (2021); Kumbhakar and Lovell (2003), page 81). THe FMM estimates G>1 frontiers using the EM step approach and the posterior probabilities of each Class is used as weights to estimate the class specific WTP measures. The E and M-steps are repeated until the likelihood improvement reached the maximum number of iterations for each compoenent in the model Muthén and Shedden (1999).

Empirical Results

The estimation results are shown in Tables **??** and **??**. Coefficients in Table **??**, column (1) are associated with the Conditional (fixed-effects) logistic regression. The model converged to a likelihood of −3,423.107 and has a pseudo R^2 of 0.519. The coefficients represent the average marginal utility, scaled by the error variance, across all observations with n= 10,746 and number of events= 3,582. The coefficient on price is negative, as expected, indicating higher meal prices are associated with a lower likelihood of being chosen (positive marginal utility of numeraire consumption). The No-Dine option is positive, indicating positive utility from averting risk associated with dining out during COVID-19. The remainder of the dining attribute coefficients are positive indicating that the presence of safety features increases dining utility. For example, diners indicate a preferences for the use of plexi-glass barriers, social distancing, outdoor seating, and face masks on both diners and employees. Disposable dinnerware and menus has no influence on dining choice. The relative magnitude of parameters indicates the relative influence on probability of choice. Thus, masks on employees is the most important safety factor in the conditional logit model, while masks on diners is the least important (of those that are statistically significant).

Table **??**, column (2) presents estimates for the Mixed Logit Model using the Conditional Logit Model (1) estimates as starting values. Our fixed parameter was price and rest of the variables were normally distributed random parameters varying across individuals. For this model we followed 500 Halton draws to simulate the likelihood function, and our estimated pseudo-log-likelihood was -3414.5 with McFadden R^2 of 0.10. Unobserved heterogeneity is captured by the standard deviation parameters, which are statistically significant for no-dine option and mask worn by employees. Other attributes exhibit insignificant parametric variation in MMNL.

By permitting random parameters, the MMNL model provides much more flexible substitution patters in discrete choice (removing the typically restrictive Independence of Irrelevant Alternatives assumption). Thus, despite the lower McFadden R^2, MMNL will generally be preferred. The relative magnitude and direction of the impact of each of the explanatory variables on the probability of dining out can be directly interpreted, while marginal probability effects, marginal WTP for safety attributes, and total WTP for a particular safety profile require post-estimation calculations. It is observed in Table **??**, column (2) the sign pattern and levels of statistical significance are the same, but magnitudes vary. This will change marginal probabilities and WTP among the models.

From the estimates of MMNL (column 2), share of respondents choosing to not dine out was calculated to be 27.4% of the total population. Individuals choosing to not go out at restaurants to eat given employees are wearing mask are about 20.6% of the population estimated as shown in Figure 2. We also see that the distributions of social distancing and outdoor seating are completely or almost completely in the positive domain, indicating no respondents see these as undesirable (at least in a parametric sense), whereas other safety features may be viewed as desirable or undesirable by segments of the population. Understanding what drives these differences in preferences leads us to the FMML model.

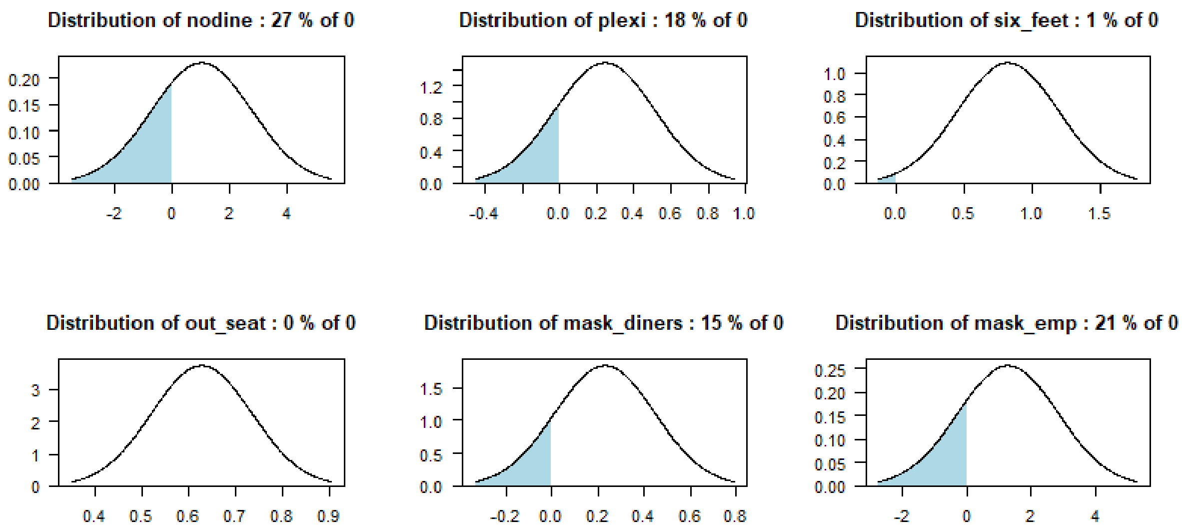


Figure 2: Conditional Distribution of Random Parameters of Mixed Logit Model

Table 3 estimates are the empirical model specified for the Finite Mixture Models, exploring heterogeneity in the choice alternative distribution due to differences in the underlying respondent's valuation towards different mitigation measures. The number of respondent classes, G, is variable and is chosen during the estimation of the model. Due to lack of theoretical guidance on the optimal number of mixture components, information criterion such as Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) and Integrated Completed Likelihood criterion (ICL), Bozdogan (1987) has been used to compare across g-components for appropriate model selection. The model is initially fitted to generalized linear response function using the expectation maximization algorithm with nrep = 3, which iteratively refines the starting value before maximizing the likelihood for the latent class indicator variable. Varying the component G = 1:10, we finalize the best fitting model with G = 3, for the model as shown in Figure 3.

The probability of belonging to each of the classes is calculated by taking the mean of the individual posterior probabilities, about 24.87% individuals being to Class 1, 46.17% individuals belong to Class 2, and 28.94% belong to the Class 3 and the predicted class probabilities are presented in Figure 4. Using the FMM Latent class allows flexibility with regards to heterogeneous nature of the sample population's preference. The marginal effects for Class 1, 2 and 3 from the finite mixture models are presented in **??**. As Class 2 represents about 46% of the population roughly and driving majority of the results in the general population from the previous models, we find all other coefficients except use of disposable dinner-wares and mask on diners highly significant and similar to MML in relative magnitudes. The no-dine coefficient is positive and highly significant for all classes, plexiglass is positive for Classes 1 and 2 but negative for Class 3. This suggest that these respondents attain negative utility from this feature in the context of dining out. Relative to Class 1 and 3, Class 2 respondents strongly prefer masks on employees. Marginal effects on 6-feet social distancing and outdoor seating are positive and significant for all Classes.

Table 3: Regression models for Conditional Logit, Mixed Logit and Finite Mixture Latent Class Models

	Logit Models		**Finite Mixture Latent Class Models**		
	(Conditional)	(Mixed)†	(Class 1)†	(Class 2)†	(Class 3)†
Price	−0.033***	−0.045***	−0.004***	−0.004***	−0.004***
	(0.003)	(0.006)	(0.000)	(0.000)	(0.000)
No-Dine-in	1.031***	1.049***	0.274***	0.338***	0.271***
	(0.130)	(0.182)	(0.036)	(0.034)	(0.057)
Disposable dinnerwares	0.082	0.121	−0.039	0.026	0.035
	(0.059)	(0.096)	0.034)	(0.024)	(0.019)
Plexi-glass barriers	0.207***	0.244***	0.118***	0.097***	−0.008
	(0.059)	(0.092)	(0.021)	(0.022)	(0.023)
6-feet Social Distancing	0.617***	0.818***	0.101**	0.090***	0.046*
	(0.058)	(0.118)	(0.032)	(0.021)	(0.019)
Outdoor-Seating	0.479***	0.628***	0.104***	0.075**	0.078**
	(0.061)	(0.108)	(0.025)	(0.025)	(0.025)
Mask on Diners	0.177**	0.229**	0.035	0.038	−0.000
	(0.069)	(0.108	(0.035)	(0.021)	(0.028))
Mask on Employees	1.106***	1.272***	0.242***	0.283***	0.131***
	(0.061)	(0.152)	(0.029)	(0.019)	(0.030)
SD:No-Dine-in		1.747***			
		(0.470)			
SD:Disposable dinnerwares		0.165			
		(0.988)			
SD:Plexi-glass barriers		0.270			
		(0.897)			
SD:6-feet Social Distancing		−0.368			
		(0.707)			
SD:Outdoor-Seating		0.107			
		(1.176)			
SD:Mask on Diners		−0.218			
		(0.931)			
SD:Mask on Employees		1.555***			
		(0.461)			
Intercept		−1.643***	0.151**	0.110**	0.239***
		(0.127)	(0.055)	(0.034)	(0.031)
Observations	10,746	3,582	2,673	4,962	3,111

† Marked Models were estimated against Dependent variable: Choice +p<0.1; *p<0.05; **p<0.01; ***p<0.001

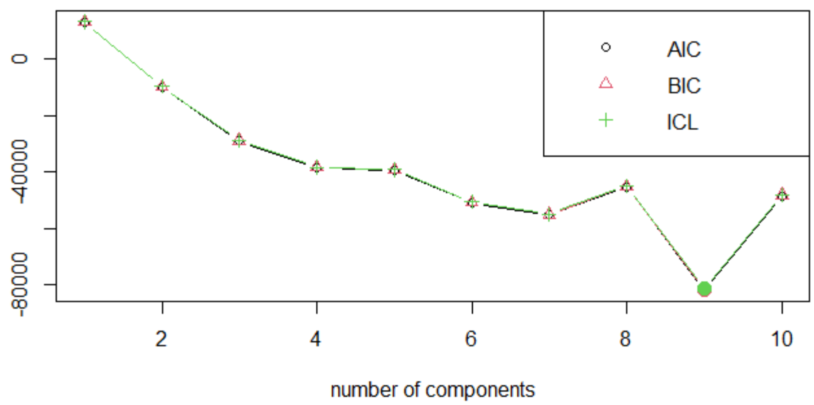


Figure 3: FMM Optimal Model Selection Criterion across 10 components

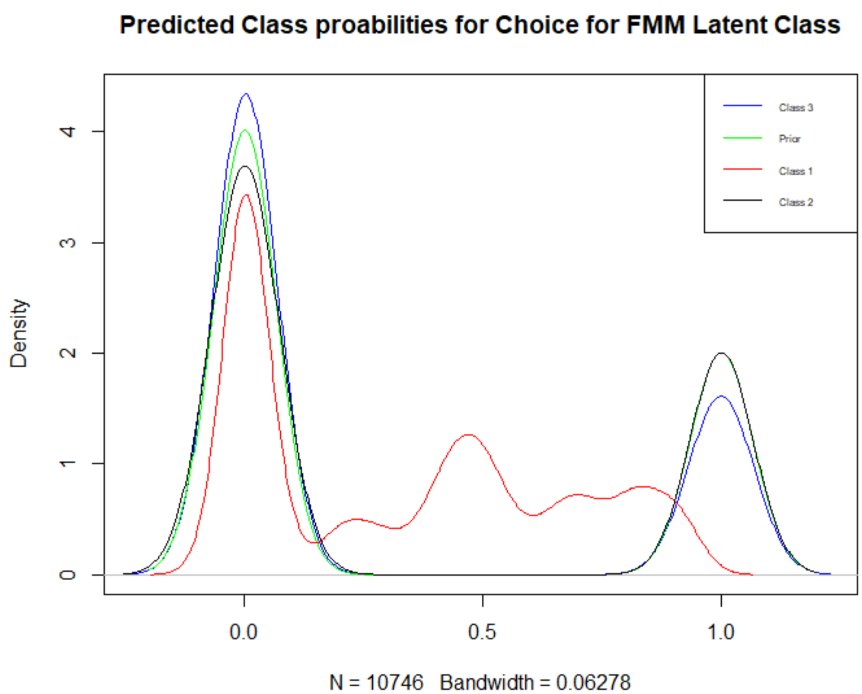


Figure 4: FMM Latent Class Predicted Probabilities

Welfare Estimates: Willingness to Pay Measures

The willingness to pay measures estimated using the Krinsky & Robb method presented in Figure 5, denote the premiums that respondents are willing to pay for a choice of going out to eat versus not during the pandemic at restaurants. Given a no-dining out option, respondents observe the one of the highest MWTP measure at $ 31.31 [$21.686 - $44.228]. With choice of going out, respondents elicit the highest MWTP for mask on employees at $ 33.59 [$28.124 - $40.815] and relatively low preference if there should be a mask on diners at $5.382 [$1.929 - $9.364]. Mitigation measures taken by the restaurants would be perceive a higher MTWP being observed like for outdoor seating options and Six-feet distance between tables would account respondents having a MWTP of $14.546 [$11.116 - $18.758] and 8.74 [$14.855 - $23.838] respectively.

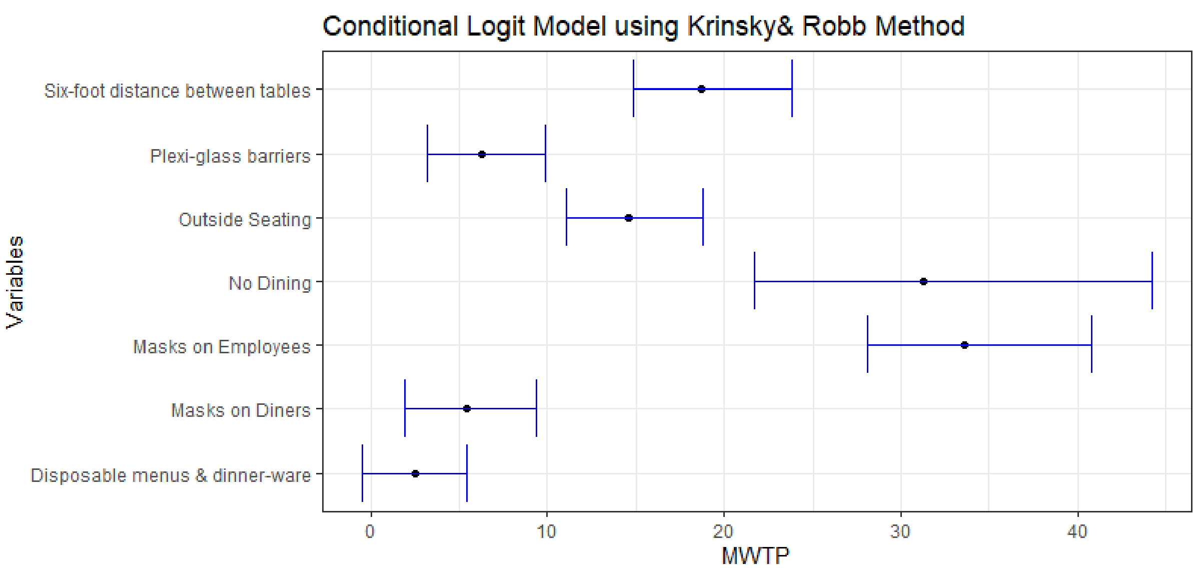


Figure 5: Marginal Willingnes to Pay for Conditional Logit Model

Table 4: Marginal Willingness to Pay Estimates for Conditional Logit Model

	MWTP	5%	95%
nodine	31.318	21.686	44.228
dispos	2.498	-0.474	5.450
plexi	6.298	3.192	9.884
six_feet	18.738	14.855	23.838
out_seat	14.546	11.116	18.758
mask_diners	5.382	1.929	9.364
mask_emp	33.598	28.124	40.815

The willingness to pay measures shown in Figure 6 involves taking ratios of stocastic variables even for models with fixed coefficients like (price) Armstrong et al. (2001). The individual level WTP estimate proposed in Figure 6 for Mixed Logit Model are relatively lower than the other two models estimates as unobserved heterogeneity in the model has been taken into consideration. Individuals are willing to pay about 23$ for no dine in options at the restaurants and about 28$ at restaurants if employees were to wear mask at restaurants. Mixed Logit Model WTP estimates capture variation in respondent's attitude towards going out ot eat with a sizeable share of respondents prefering specific mitigation measure (mask on employees) over others , for example, mask on diners constitute about 15% of respondents at choice set (0) for a willingness to pay metric of only 5$. It means many respondents value mask on employees over diners as interaction would be significantly more with employees at the restaurants than with other diners if Covid-19 transmission were to happen. Additionally, smitigation measure of six feet distance has a MWTP of 18$ over having disposable dinner wares (MWTP of 2$) as respodents believe that in order to curb the spread of Covid-19 physical distancing measures would have more likely significant impact than having disposable dinnerwaress. Availability heuristics could potentially also play a role in detemining the preferences of individuals here as implied CDC guidelines seem to be more significantly positive than other measures to curb Covid-19.

Table 5: Individual-level Marginal Willingness to Pay Estimates for Multinomial Mixed Logit Model

	MWTP	5%	95%
nodine	23.133	15.376	34.204
dispos	2.670	-0.868	6.355
plexi	5.388	2.156	9.283
six_feet	18.040	13.984	23.320
out_seat	13.853	10.213	18.266
mask_diners	5.042	1.176	9.032
mask_emp	28.071	23.084	34.415

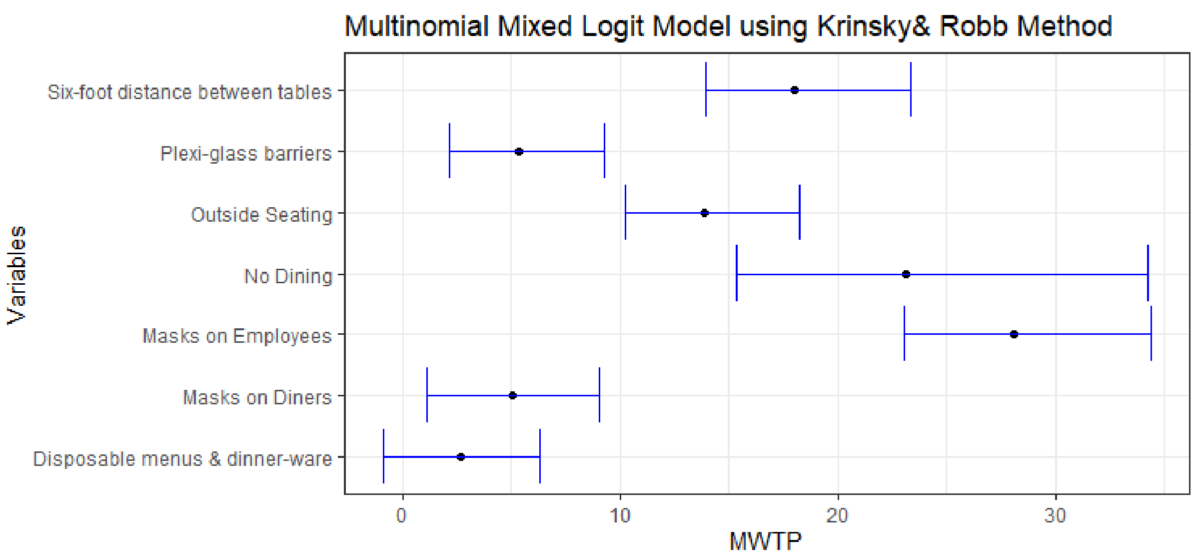


Figure 6: Marginal Willingnes to Pay for Multinomial Mixed Logit Model

The willingness to pay measures estimated presented in Table 6, since the coefficients of Class 2 is similar to the Logit models estimated, we find no similarities in the MWTP measures among the classes with the other models. Respondents belonging to Class 2 would be willing to pay $ 84.5 for a no dine in option and as much as $ 70.75 for mask on employees options. Class 3 is among the group the values the least the mitigation measures. The true preference of the respondents for the perceptions to eat out seem to be a mixture of Class 1 and Class 2, given the high probability of respondent's preference being dominated by class

2, this results is a positive valuation for restaurants to embark on a price journey which reflect the preferences of individual as properly captured by Class 2 using individual specific data.

Table 6: Marginal Willingness to Pay Estimates for Finite Mixture Models for Latent Class

MWTP	Class 1	Class 2	Class 3
nodine	68.5	84.5	67.75
dispos	−9.75	6.5	8.75
plexi	29.5	24.25	−2
six_feet	25.25	22.5	11.5
out_seat	26	18.75	19.5
mask_diners	8.75	9.5	0
mask_emp	60.5	70.75	32.75

Conclusions

To gain insight into the possible reasons for differing risk perceptions we find that diners were ambivalent about future viability of dining out. Despite the attempts by previous studies on how different consumers perceive and evaluate food information, none of them attempt to address the concerns that households have about COVID-19 related to hospitality sector, particularly dining out. What are the consumer attitudes towards these concerns and how has Covid-19 impacts on health and financial well being perpetuated over 2020? How have households changed their everyday eating out behavior in response to COVID-19, and how does this vary with personal protection versus pro-social versus discomfort dimensions? Addressing these questions in our research channelizes further avenues for future research. It leads to investigation of how differing subjective risk perceptions by a variety of individual and home characteristics could have systemic shocks across various segments of the servicescape. Summarizing all, our study is consistent with the literature of chaos theory and we predict a scenario of restoration of business mimicking the conventional ânormalâ and representing a turning point in the way restaurants operate which would be the “new normal”. (Murphy (1996)), introduced the chaos theory which aims to understand disorderly systems that do not behave in a linearly predictable way like the conventional cause and effect manner. (Lorenz (1972)), explained the Butterfly Effect which questioned whether a single flap of a butterflyâs wing could be instrumental in generating a tornado in Texas. If the theory persists, it could create instability which could present problems in predicting events under Covid-19 pandemic as well. Faulkner (2001) analyzed that once a system has been affected by some kind of crisis or distress, it may be destroyed as an entity and may also experience a return to a configuration towards the pre-crisis state arrangement in due time. As the restaurant industry would subsist after the Covid-19 pandemic, the Chaos theory proposed by (Seeger (2002)), predicts a scenario of restoration of business mimicking the conventional “normal” and representing a turning point in the way restaurants operate which is the “new normal”. For the restaurant industry along with preventive measures, cost effectiveness would also play an integral role in their survival. Effective food and beverage cost reduction strategy which would include menu-planning, purchasing practices, efficient storage solution and more proactive employee training approach. Another way of cutting costs would be to reduce the variable costs, achievable through negotiations with suppliers, support from staff for a reduction in pay or furloughs and controlling direct operational costs which can be critical in contribution towards financial recovery under crisis (Linassi et al. (2016)). Simultaneously with cost reduction, restaurants should also implement strategies to enhance revenue. To combat the pressures of mitigating covid-19, restaurants can increase its patronâs perceived value and reduce perceived risk of dining by adopting a marketing mix and a focus on sanitation and cleanliness. Capitalizing emphasis on health and immunity, restaurants can provide free delivery once a month for customers and additionally provide take-away and delivery services for customers who are afraid to dine out.

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