Final Project Report

Access to Food in a Severe Prolonged Disruption: The Case of Grocery and Meal Shopping During the COVID-19 Pandemic

Prepared for **Teaching Old Models New Tricks (TOMNET) Transportation Center**

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The COVID-19 pandemic has revealed the fault lines in society. Whether it be remote work, remote learning, online shopping, grocery and meal deliveries, or medical care, there are disparities and inequities among socio-economic and demographic groups that leave some segments of society more vulnerable and less adaptable. This project aims to identify vulnerable and less adaptable groups in the context of access to food. Using a comprehensive behavioral survey data set collected during the height of the pandemic in 2020, this project aims to provide insights on the groups that may have experienced food access vulnerability during the disruption when businesses and establishments were restricted, the risk of contagion was high, and accessing online platforms required technology-savviness and the ability to afford delivery charges. The project proposes and presents estimation results for a simultaneous equations model of six endogenous choice variables defined by a combination of two food types (groceries and meals) and three access modalities (in-person, online with in-person pickup, and online with delivery). The model estimation results show that attitudes and perceptions play a significant role in shaping pandemic-era access modalities. The model revealed that, even after controlling for a host of attitudinal indicators, minorities, low-income individuals, and individuals residing in rural low-density areas are particularly vulnerable to being left behind and experiencing challenges in accessing food during a severe and prolonged disruption. Social programs should aim to provide these vulnerable groups with tools and financial resources to leverage online activity engagement and access modalities.</td></tr>
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EXECUTIVE SUMMARY

The COVID-19 pandemic has revealed the fault lines in society. Whether it be remote work, remote learning, online shopping, grocery and meal deliveries, or medical care, there are disparities and inequities among socio-economic and demographic groups that leave some segments of society more vulnerable and less adaptable. This report aims to identify vulnerable and less adaptable groups in the context of access to food. Using a comprehensive behavioral survey data set collected during the height of the pandemic in 2020, this project aims to provide insights on the groups that may have experienced food access vulnerability during the disruption when businesses and establishments were restricted, the risk of contagion was high, and accessing online platforms required technology-savviness and the ability to afford delivery charges. The project proposes and presents estimation results for a simultaneous equations model of six endogenous choice variables defined by a combination of two food types (groceries and meals) and three access modalities (in-person, online with in-person pickup, and online with delivery). The model estimation results show that attitudes and perceptions play a significant role in shaping pandemic-era access modalities. The model revealed that, even after controlling for a host of attitudinal indicators, minorities, low-income individuals, and individuals residing in rural low-density areas are particularly vulnerable to being left behind and experiencing challenges in accessing food during a severe and prolonged disruption. Social programs should aim to provide these vulnerable groups with tools and financial resources to leverage online activity engagement and access modalities.

1. INTRODUCTION

Access to good food is critically important to leading a healthy life. Even in a wealthy and well-developed nation such as the United States, 38 million people struggle with hunger (USDA, 2022) and 13.8 million households, which comprise 10.5 percent of all US households, were considered food insecure at some time during 2020 (USDA, 2022). The proportion of under-nourished people globally stands at about 10 percent (i.e., 828 million people) (WHO, 2022). These statistics suggest that, despite enormous progress in advancing food security, access to good food remains a challenge for many. Access to good food generally involves ensuring that a variety of healthy, wholesome food options are available within close proximity (for the household) and that the food options are affordable. In the United States, nearly 20 million people live in a food desert, which the US Department of Agriculture defines as a place where at least one-third of the population lives greater than one mile away from a supermarket for urban areas, or greater than 10 miles away for rural areas (USDA, 2021). In other words, the ability to access good food by traversing distances is critical to good health, thus implying that transportation plays a major role in enabling food security.

During a severe disruptive event, food security may come under threat (Mouloudj et al., 2020; Savary et al., 2020). This was seen during the height of the COVID-19 pandemic. Due to public health concerns, many jurisdictions ordered businesses to close, restaurants to cease operations, and grocery stores to limit hours and occupancy levels (Niles et al., 2020). Many individuals, especially those with immunocompromised systems and other underlying health conditions, feared going to stores or restaurants for fear of getting infected (Ahmed et al., 2021). Even individuals without such health conditions avoided going to food establishments to avoid taking any risks (Jacobsen and Jacobsen, 2020). However, in response to the COVID-19 disruption, many grocery stores and restaurants quickly ramped up their virtual options. Grocery stores enabled systems allowing people to order groceries online and then travel to the store to pick them up (in a reasonably touchless transaction system) or have them delivered to the home. Similarly, restaurants also pivoted rapidly, implementing systems that made it easy to order freshly prepared meals over the phone or online. The consumer could travel to the restaurant to pick up the meal or use a delivery service to deliver the food to the doorstep. All of these virtual options (online grocery with pickup/delivery; online restaurant with pickup/delivery) provided many with the ability to access food during the height of the pandemic while minimizing exposure and risk of contagion. This represents a high degree of adaptability, with systems rapidly adjusting to circumstances to retain access to goods and services.

The extent to which such services and options were utilized by different socio-economic and demographic groups is worthy of exploration. Many pickup and delivery services charge an additional fee, possibly rendering such services unaffordable for low-income households (Rummo et al., 2020). Some households may be on the wrong side of the digital divide or not have the technology-savviness to use virtual platforms for ordering groceries and fresh meals (Ali et al., 2021). Individuals in these households may feel compelled to go in-person (to avoid paying a fee), even though they may be concerned about their safety in the midst of a pandemic. Individuals who are unable or unwilling to travel (due to health risks) and unable to take advantage of virtual platforms (due to affordability or technology constraints) may end up experiencing food insecurity (Ahmed et al., 2021; Ali et al., 2021).

A number of studies have explored physical and virtual participation in activities, particularly in the wake of the pandemic. Virtual activity participation increased during the pandemic as people substituted in-person interactions for alternative modalities such as virtual socialization, online school, and telecommuting (Chakraborty et al., 2020; Javadinasr et al., 2021). Those who embrace virtual activity participation are more inclined to utilize online shopping services, including food pickup and delivery services (Akhter, 2015; Ali et al., 2021; Zhang et al., 2017). However, there is evidence that these virtual alternatives to in-person interactions were not viewed as equivalent substitutes by everyone during the pandemic or even available options for some (disadvantaged) subgroups. Individuals with higher social proclivities were found to be negatively associated with social distancing (Carvalho et al., 2020). Two of the largest barriers to following social distancing protocols included loneliness and the need to help others run errands (Coroui et al., 2020), illustrating how some chose to break health and safety protocols while others had no choice but to shop in-person. Virtual activity perspectives and social interaction propensity influence the choice to purchase food in-person or online for those who are capable of choosing. However, those in disadvantaged subgroups may have no option to purchase food online, potentially leading to food insecurity.

This project aims to explore and identify the market segments most at risk of food insecurity in the wake of a severe, prolonged disruption such as the COVID-19 pandemic. Subgroups capable of accessing food through virtual means may be considered *adaptable*, i.e., they have the ability to adapt to circumstances and not be compromised with respect to food and meals. On the other hand, subgroups of the population unable to travel and afford or use virtual platforms are left behind and *vulnerable*. These groups do not exhibit adaptability, and they need assistance through public services to ensure they do not lose access to healthy food and meals. Through a comprehensive modeling effort, this project aims to identify the subgroups who are adaptable and those who are vulnerable. Not only does the project seek to characterize the subgroups in terms of socio-economic and demographic attributes, but the project also seeks to characterize them in terms of their attitudes, perceptions, and risk averseness or tolerance. The project utilizes a rich data set collected through a survey administered across the United States. The data set, collected as part of the COVID Future Survey study, includes all respondent records for the first wave of the panel survey conducted at the height of the pandemic in 2020. The extensive survey is able to obtain a detailed picture of physical and virtual activity engagement during the pandemic.

The project considers two commodities: groceries and freshly prepared meals. There are three access modalities for each commodity type: in-person, online order + in-person pickup, and online order + delivery to home. Thus, there are a total of six possible options for accessing food and meals. In the survey data set, respondents have recorded the number of days they participated in each of these six modalities (in the past seven days). The six frequency variables constitute the project's endogenous (dependent) variables; they are all modeled jointly in a simultaneous equation modeling framework, thus enabling the consideration of all six dimensions as a lifestyle choice bundle, where decisions to participate in each of the modalities are made contemporaneously. As the frequency variables may be treated as ordered choices, the multivariate ordered probit modeling methodology is adopted in this project. The joint modeling framework explicitly accounts for error correlations across the six endogenous variables, thus capturing the potential effects/presence of correlated unobserved factors that simultaneously impact multiple endogenous variables. The Generalized Heterogeneous Data Model (GHDM) modeling methodology (Bhat, 2015) was adopted for model estimation.

The remainder of the project is organized as follows. The second section provides an overview of the data set used in the project. The third section presents an overview of the modeling methodology and framework, while the fourth section presents detailed model estimation results.

The fifth section offers concluding remarks.

2. DATA DESCRIPTION

This section presents a description of the data set used in the project and the survey that served as the data source. In addition, the section offers a detailed description of the sample, both in terms of socio-economic and demographic characteristics as well as the endogenous variables of interest in this project.

2.1. Overview of Survey and Sample Characteristics

The data set for this research is derived from the COVID Future Panel Survey (Chauhan et al., 2021). The survey was administered to a stratified random sample across the United States. The sampling strategy for the survey involved deploying multiple methods to recruit survey respondents and yield a large sample size. Multiple recruitment methods were used to enhance the sample size, including e-mail invitations sent to an extensive address database purchased from a commercial vendor, social media channels, an online Qualtrics survey panel, project website, and news stories in transportation-oriented and university websites. The survey collected detailed information about socio-economic and demographic attributes, mobility choices and activity-travel patterns, attitudes and perceptions towards mobility options and activity engagement modalities (physical or virtual), lifestyle and mobility preferences, and adaptation to the COVID-19 pandemic circumstances. The survey also elicited information about the degree to which individuals considered the COVID-19 virus a threat to themselves, family and friends, and society at large. The three waves of the survey were administered in April – October 2020, November 2020 – May 2021, and October – November 2021.

This project utilizes the subset of data from the first wave of the COVID Future Panel Survey. Wave 1 data, collected from April – October 2020, was used because this data was collected at the peak of the pandemic when there were significant health concerns, fear of the spread of the virus, and public and private entities that attempted to stem the spread through the implementation of limited business and restaurant operations. These restrictions may have differentially impacted various market segments. This project aims to identify the socio-economic and demographic groups that may have been more adversely affected by the pandemic regarding food access. A total of 9,912 responses were obtained in the first wave of the panel survey. After deleting these erroneous responses and filtering the data to remove records with substantial missing data, the final analysis sample includes 8,392 responses.

Table 1 presents an overview of sample socio-economic and demographic characteristics. The sample is large, covers the entire nation, and exhibits considerable variation for variables in the data set. It is found that 62.3 percent of the sample is female. The age distribution shows a reasonably even spread across the age groups, with about 15-20 percent of records in each group. About 43.2 percent of individuals are employed, while another 44.3 percent are neither workers nor students. About 30 percent of respondents have a Bachelor's degree, while another 21.6 percent have a graduate degree. About 80 percent of respondents are White, and nearly 10 percent are Black.

TABLE 1 Sample Characteristics

Individual characteristics (N=8,392)		*Household characteristics (N=8,392)*	
Variable	**%**	**Variable**	**%**
Gender		**Household annual income**	
Female	62.3	Less than $25,000	16.4
Male	37.2	$25,000 to $49,999	21.5
Other	0.5	$50,000 to $99,999	31.7
Age category		$100,000 to $149,999	16.8
18-30 years	17.5	$150,000 to $199,999	6.7
31-40 years	16.9	$200,000 or more	6.9
41-50 years	14.0	**Household size**	
51-60 years	17.6	One	18.7
61-70 years	20.2	Two	38.0
71+ years	13.8	Three or more	43.3
Employment status		**Housing unit type**	
Student (part-time or full-time)	4.2	Stand-alone home	65.5
Worker (part-time or full-time)	43.2	Condo/apartment	19.7
Both worker and student	8.4	Other	14.7
Neither worker nor student	44.3	**Home ownership**	
Education attainment		Own	65.1
High school or less	17.4	Rent	30.0
Some college or technical school	31.2	Other	4.9
Bachelor's degree(s)	29.8	**Vehicle ownership**	
Graduate degree(s)	21.6	Zero	6.7
Race		One	37.7
Asian	4.6	Two	38.3
Black or African American	9.7	Three or more	17.4
Native American	1.3	**Presence of household children**	
White or Caucasian	79.9	Yes	26.7
Other	4.5	No	73.3
Main Outcome Variables (Number of Days in Past Week)			
Grocery in-store		**Meal in-store**	
Zero	19.8	Zero	71
One	46.7	One	17.9
Two or three	29.4	Two or three	9.4
Four or more	4.1	Four or more	1.7
Grocery pickup		**Meal pickup**	
Zero	81.4	Zero	49.1
One	12.2	One	31.7
Two or three	5.4	Two or three	17.0
Four or more	1.0	Four or more	2.3
Grocery delivery		**Meal delivery**	
Zero	80.3	Zero	67.4
One	12.0	One	19.4
Two or three	6.1	Two or three	11.0
Four or more	1.6	Four or more	2.2

Regarding household characteristics, the sample is skewed towards the lower income groups, with 16.4 percent in the less than $25,000 bracket and another 21.5 percent in the $25,000 - $49,999 bracket. Nearly 7 percent reside in households with an income greater than or equal to $200,000. About 43 percent of individuals reside in households with three or more members, nearly two-thirds live in a stand-alone home, and 65 percent own the home they reside in. Almost 7 percent of the respondents are in households with no vehicles, 38 percent are in households with two vehicles, and 17.4 percent are in households with three or more vehicles. Nearly three-quarters of the sample resides in households with no children. Overall, the sample characteristics reflect the variability needed for a modeling project of this nature.

2.2. Endogenous Variables and Attitudinal Indicators

Access to food is reflected through a focus on shopping for groceries and meals. The COVID Future Survey data set includes rich information about shopping modalities and frequencies, thus enabling a focus on these two commodities. Three different modalities are possible for each commodity (groceries or meals). Commodities may be purchased in-store; this may involve shopping in the grocery store in-person or dining in a restaurant in-person. Alternatively, food may be accessed through virtual means. Online platforms may be used to order groceries or meals, and the consumer may travel in-person to the establishment to pick up the items. The consumer would not need to spend any extended duration in the establishment and may even benefit from curbside pickup, enabling touchless transactions. Finally, the consumer may purchase food via online platforms and have the goods delivered to the home using any number of delivery services. Thus, there are a total of six possible outcome variables defined by two food commodity types and three modalities for each.

The distributions for these six endogenous choice variables are seen in Table 1. The survey asked respondents to report the number of days in the past week (past seven days) that the individual participated in each of the six activity modalities considered in this project. Thus, responses represent the number of *days* (not the number of *times*) an activity was undertaken in the past seven days. Nearly one-in-five respondents indicated that they did not engage in any in-store grocery shopping in the past week, while 46.7 percent stated that they shopped in-store for groceries one day. Only 4.1 percent shopped in-store four or more days. Even in the height of the pandemic, online modalities were employed by individuals at much lower frequency. For online ordering followed by customer pickup or home-delivery, it is found that about 80 percent did not engage in either type of grocery shopping modality in the previous seven days. About 12 percent participated in such a grocery modality on one day. It appears that many continued to shop for groceries in-store, possibly because grocery stores were largely open during the pandemic, and these locations served as places to connect with people (Palmer et al., 2021).

Shopping for meals, on the other hand, exhibits different patterns. At the height of the pandemic, many restaurants were closed or did not entertain in-person dining. As such, 71 percent of respondents did not engage in any in-person dining at restaurants in the prior week. About 18 percent did so on one day. However, a much larger percentage engaged in online ordering of meals followed by in-person pickup. About half of respondents ordered meals online and then picked them up in-person. With respect to delivery modality, about two-thirds indicate that they did not engage at all in the prior week. Nearly 20 percent engaged in the activity modality of ordering meals and having them delivered on one day, while another 11 percent engaged in such an activity modality on two or three days. It is likely that individuals engaged more in online + pickup as opposed to online + delivery because in-person pickup eliminates the need to pay for delivery fees, affords the ability to obtain the commodities at a time convenient to the customer, and provides an opportunity to get out of the home and interact with society. Overall, the six dependent variables exhibit distributions conducive to a joint econometric modeling effort capable of representing engagement in all six food access activities as a contemporaneous consumption choice bundle.

The survey included a rich set of attitudinal statements that captured respondent attitudes, values, perceptions, and preferences. To measure the effect of socio-economic and demographic attributes on frequency of participation in different activities and modalities, it is helpful to explicitly account for attitudes and preferences so that the magnitudes of coefficients associated with socio-economic and demographic explanatory variables are not confounded by the influence of attitudinal factors. In this project, three attitudinal factors are formulated and included in the model specification. They are *COVID-19 risk perception, virtual activity perspective,* and *social interaction propensity.* Three attitudinal statements comprise each factor; thus the three latent attitudinal constructs collectively account for nine attitudinal statements. Responses to the three statements that comprise a single factor are highly correlated with one another. The attitudinal statements associated with a latent factor were identified through a review of prior research and based on behavioral intuitiveness in terms of attitudes that are most likely to be influential in shaping food access activities and modalities. Figure 1 shows the latent factors, the attitudinal statements on which they are loaded, and the sample distribution for each attitudinal indicator (respondents indicated their level of agreement with each statement on a likert scale of *strongly disagree* to *strongly agree)*. The statement distributions considered in each latent variable show consistent and logical patterns. This signifies that they are reasonable as indicators of the selected latent variables.

Some patterns are noteworthy. For example, 47 percent of respondents strongly disagreed with the notion that society is over-reacting to the virus (recall that the data was collected at the height of the pandemic in spring/summer 2020). Respondents also expressed considerable concern that friends or family would have a severe reaction to the virus, with nearly three-quarters somewhat or strongly agreeing with that concern. Although there was only tepid enthusiasm for online learning (as a good alternative to classroom instruction), the enthusiasm for video calling as a good alternative to business meetings was quite substantial (79 percent somewhat agree or strongly agree that video calling is a good alternative). A vast majority of respondents (nearly 88 percent) indicated that they like being outside, which may explain (to some degree) why people engaged in grocery shopping in-person at a much higher rate than using virtual modalities. On the other hand, the eagerness for social interactions at the workplace is more measured, which is a likely explanation for why so many workers have embraced work-from-home and hybrid work modalities.

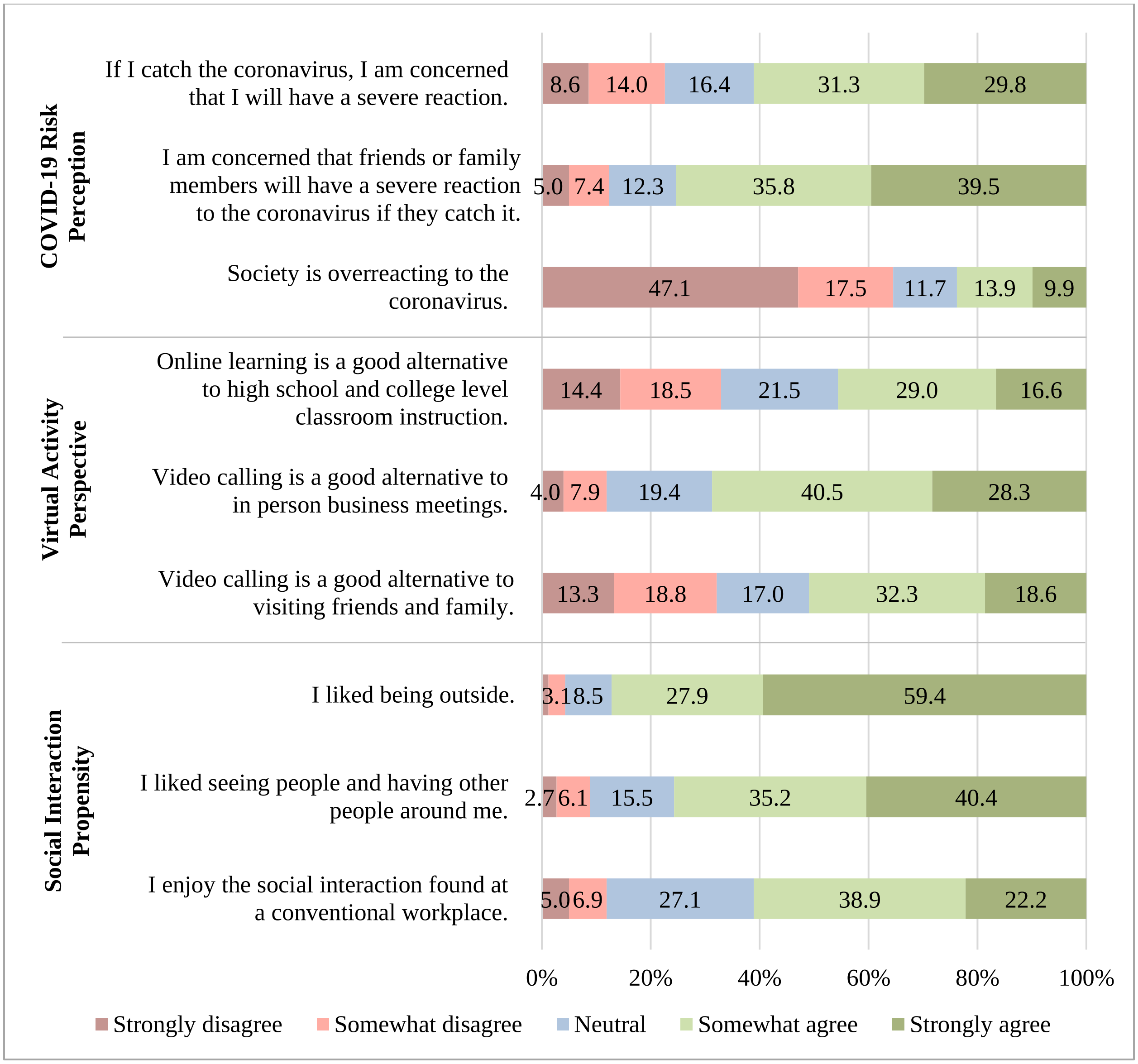

FIGURE 1 Response Distributions for Attitudinal Indicators of Latent Constructs (N=8,392)

The survey included two attitudinal statements that capture the degree to which respondents consider the virus to present a threat or risk. One statement captures degree of perceived risk to their own health, and the other statement captures degree of perceived risk for the health of family and friends. These two statements may be viewed as "COVID-19 risk perception" variables; likely, individual risk perceptions (in terms of potential effects on personal health or that of family or friends) are closely associated with the modality of choice in accessing food. An extensive analysis (not presented here in the interest of brevity) examining the relationship between grocery and meal shopping modality/frequency and COVID-19 risk perception variables showed that individuals perceiving COVID-19 as a greater threat engaged in in-person activities at a lower rate and vice versa.

3. MODELING FRAMEWORK

This section presents a brief overview of the modeling framework and methodology. The project aims to understand engagement in various activity modalities for accessing food (groceries and meals). The data set includes six endogenous variables stemming from two commodity types that can both be accessed via three modalities. While it is possible to model the six dependent variables independently, there is a high likelihood that there are correlated unobserved factors that simultaneously affect the six endogenous outcome variables of interest. Moreover, it is likely that decisions about participation in the respective activity modalities are not made in isolation from one another. Treating these six endogenous choice variables as representative of an overall integrated lifestyle approach (choice bundle) to accessing food would help in modeling the phenomenon in a comprehensive and holistic framework. For this reason, this project employs a simultaneous equation modeling framework capable of accounting for error correlations and endogeneity of attitudinal constructs.

In the interest of brevity, the modeling methodology is only qualitatively described in this manuscript. A detailed explanation of the model formulation and estimation methodology is provided elsewhere[1], which is not essential to understanding and interpreting the empirical findings that will later be presented. The formulation is quite lengthy and notation heavy. Interested readers are referred to Bhat (2015) for more information.

3.1. Model Structure

A simplified representation of the model structure is shown in Figure 2. The analytical framework aims to provide the ability to specify and estimate a joint model that considers six main outcome variables associated with people's in-store shopping and online purchase frequencies of groceries and meals. Note that the indicators for each latent construct are not shown for ease of representation. Each latent construct is formulated based on three attitudinal statements, as depicted in Figure 1.

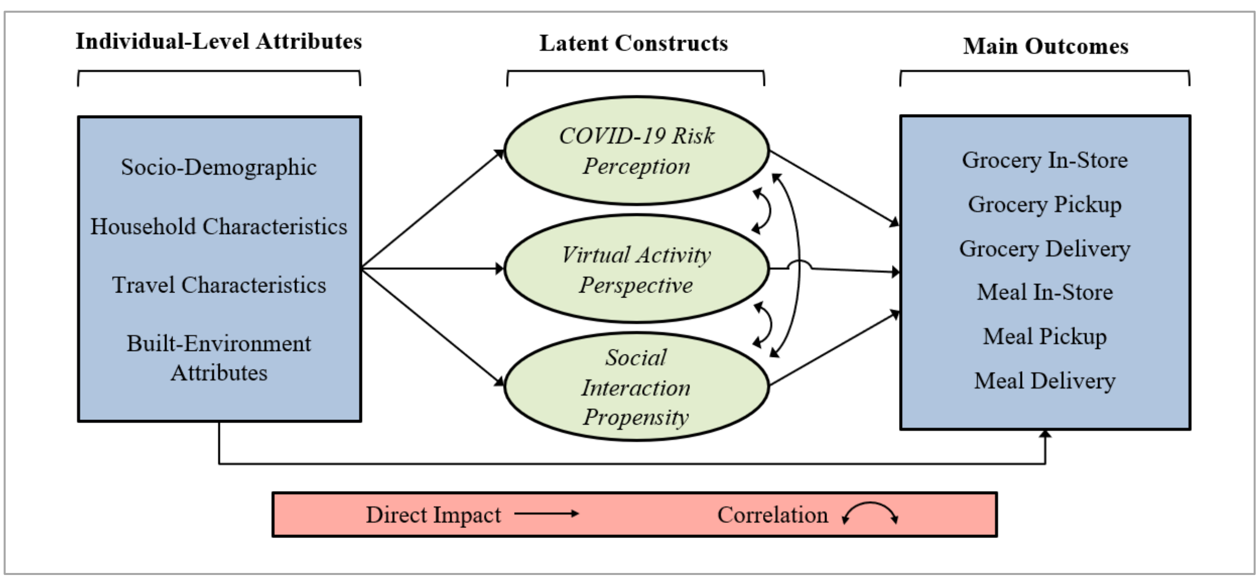

FIGURE 2 Modeling Framework

[1] https://live-tomnet-utc.pantheonsite.io/wp-content/uploads/2022/08/Covid19_Shopping_Methodology.pdf

The right-hand side of the figure shows the six endogenous variables of interest. Each variable is treated as an ordered choice, with the frequency (represented by number of days within the past week that grocery or meal purchase activities were pursued for each in-person or virtual modality) serving as an ordered response. Thus, the model is formulated as a multivariate ordered response model system with error correlations engendered through the recognition that the latent constructs themselves are stochastic variables with error components. By accounting for error correlations between the three latent constructs, error correlations between the endogenous choice dimensions can be inferred and computed. The three latent constructs are themselves endogenous variables (influenced by socio-economic and demographic attributes), and they in turn influence the outcome variables of interest. Socio-economic and demographic variables (exogenous attributes) may directly affect the outcome variables (frequency of grocery and meal activities by various modalities) and/or affect them indirectly through the latent factors (which serve as mediating variables). Factor scores are continuous variables, while the six endogenous variables represent ordered discrete outcomes. The entire model structure can be estimated in an integrated econometric framework using the Generalized Heterogenous Data Model (Bhat, 2015). The latent constructs are modeled through a structural equations model (SEM) component and measurement equations model (MEM) component of the GHDM; the latent constructs appear as exogenous variables in the multivariate ordered-response probit (MORP) model of the six main outcomes. However, the entire model system is estimated in one step through the GHDM approach.

4. RESULTS

This section presents a detailed description of the model estimation results. First, the latent construct structural equation model (SEM) component is presented together with the measurement equation model (MEM) model component depicting factor loadings. Second, results are presented for the multivariate ordered probit (MORP) model of endogenous outcomes of interest.

4.1. Latent Constructs Model Component

Results of the latent constructs model components are shown in Table 2. The top half of the table shows the structural equation model component, depicting the influence of socio-economic and demographic variables on the three latent constructs. This component is estimated as a multivariate regression incorporating error correlations.

The interpretation of the model coefficients is behaviorally intuitive and consistent with expectations. Women view virtual activity modalities more positively than men and exhibit a higher social interaction propensity. Men exhibit a lower level of COVID-19 risk perception. Given the extensive media coverage that older individuals were more susceptible to severe reactions to COVID-19, it is not surprising to see younger individuals exhibit a lower risk perception. They also exhibit a lower social interaction propensity, suggesting that younger individuals do not feel as much of a need to interact in person. Older individuals are less likely to embrace virtual activity platforms, consistent with the technology-savvy nature of younger generations. Those with a higher educational attainment exhibit higher levels of COVID-19 risk perception, presumably due to their greater awareness and trust in official sources of information. Those with a lower educational attainment exhibit a lower social interaction propensity. The results show differences among races, with Whites less enamored with virtual activity platforms and Blacks more enthusiastic about such technologies. Blacks and Asians depict a higher level of COVID-19 risk perception, which may affect their proclivity to engage in out-of-home activities. Non-Whites exhibit a lower social interaction propensity.

TABLE 2 Determinants of Latent Variables and Loading on Indicators (N=8,392)

Explanatory Variables (base category)		**Structural Equations Model Component**					
		COVID-19 Risk Perception		Virtual Activity Perspective		Social Interaction Propensity	
		Coef	t-stat	Coef	t-stat	Coef	t-stat
Individual characteristics							
Gender (*)	Female	na	na	0.22	8.06	0.14	4.45
	Male	-0.23	-8.68	na	na	na	na
Age (*)	18-40 years	-0.13	-5.20	na	na	-0.22	-6.92
	65 years or older	na	na	-0.25	-7.80	na	na
Education (*)	High school or less	na	na	na	na	-0.35	-8.21
	Bachelor’s degree(s)	0.17	6.08	na	na	na	na
	Graduate degree(s)	0.25	8.06	na	na	na	na
Race and ethnicity (*)	Non-White	na	na	na	na	-0.41	-10.76
	Non-Hispanic White	na	na	-0.24	-7.25	na	na
	Black	0.23	5.47	0.44	8.92	na	na
	Asian	0.20	3.54	na	na	na	na
Employment (non-worker)	Worker	-0.17	-6.56	na	na	na	na
Household characteristics							
Household income (*)	Up to $50,000	na	na	na	na	-0.39	-10.35
	$50,000 to $100,000	na	na	0.07	2.81	na	na
	$100,000 or more	na	na	na	na	0.19	4.76
Children in home (no children)	One or more	na	na	0.21	7.20	na	na
Correlations between latent constructs							
COVID-19 risk perception		1	—	0.43	8.45	0.06	3.32
Virtual activity perspective		na	na	1	—	0.01	0.99
Social interaction propensity		na	na	na	na	1	—
Attitudinal Indicators		**Loadings of Latent Variables on Indicators (Measurement Equations Model Component)**					
If I catch the coronavirus, I am concerned that I will have a severe reaction.		1.03	55.14	na	na	na	na
I am concerned that friends or family members will have a severe reaction to the coronavirus if they catch it.		0.77	47.17	na	na	na	na
Society is overreacting to the coronavirus.		-1.40	-52.66	na	na	na	na
Online learning is a good alternative to high school and college level classroom instruction.		na	na	0.68	42.90	na	na
Video calling is a good alternative to in person business meetings.		na	na	0.62	33.31	na	na
Video calling is a good alternative to visiting friends and family.		na	na	0.66	39.60	na	na
I liked being outside.		na	na	na	na	0.55	21.82
I liked seeing people and having other people around me.		na	na	na	na	0.60	20.19
I enjoy social interactions found at a conventional workplace.		na	na	na	na	0.49	24.54

Note: Coef = coefficient; na = not applicable; “—” = not statistically significantly different from zero at the 90% level of confidence and removed from the specification.
*Base category is not identical across the model equations and corresponds to all omitted categories.

Workers depict a lower COVID-19 risk perception, a finding that merits further investigation of underlying reasons. With respect to household characteristics, lower-income individuals exhibit a lower social interaction propensity, individuals residing in middle-income households are more likely to embrace virtual activity platforms, and the rich, making $100,000 or more, exhibit higher levels of social interaction propensity. Finally, the presence of children is associated with an elevated perspective of virtual activity platforms.

Two of the three error correlations are significant, thus supporting the use of a joint econometric model formulation for this project. All correlations are positive. This means that unobserved factors contributing to one attitudinal construct also elevate the level of other attitudinal constructs. The bottom half of Table 2 presents the factor loadings for the measurement equations model (MEM) component. All factor loadings are intuitive and statistically significant. All coefficients are positive, implying that the indicators lead to an elevation of the particular latent construct. The one exception is the loading of the statement on whether the individual feels society is overreacting to the virus. If an individual agrees with this statement, the person has a low COVID-19 risk perception (hence, believes that society is overreacting).

4.2. Bivariate Model of Behavioral Outcomes

Table 3 presents estimation results for the multivariate ordered probit (MORP) model of six endogenous outcomes representing food access modalities. A key finding is that attitudinal constructs significantly influence grocery and meal activity engagement. Higher COVID-19 risk perception is associated with a lower propensity to engage in in-store grocery shopping, eating meals in-store (restaurants), and picking up meals in-person. In other words, those who have a higher COVID-19 risk perception are less likely to engage in these activity modalities, potentially affecting their ability to access meals and food affordably (delivery fees can be cost prohibitive for many). Table 2 shows that minorities (Blacks and Asians) are more prone to having elevated COVID-19 risk perceptions. Elevated and more positive perspectives of virtual activity engagement platforms are associated with greater proclivity to engage in food access activities through virtual (online) means (food pickup or delivery). Those with a greater social interaction propensity are more likely to engage in in-person shopping and pickup. These findings are consistent with expectations and indicate that attitudes play a significant role in shaping disruption-era behaviors.

The rest of Table 3 provides all the coefficients associated with socio-economic and demographic attributes. Females are less likely to engage in all six activity modalities. This finding suggests that men were more likely to shop for groceries and meals both online and in-person during the pandemic. The age group of 51-60 is positively associated with in-store grocery shopping, while younger individuals are more likely to embrace virtual modalities, with the exception of buying meals in-store. They are also more technology-savvy and likely to engage in the use of virtual activity platforms to order goods and services. Middle-aged individuals tend to engage in more pickup and delivery modalities, presumably because of a higher presence of children and the need to juggle elevated household and childcare obligations and constraints during the pandemic.

TABLE 3 Estimation Results of Grocery Model Components (N=8,392)

Explanatory Variables (base category)		Main Outcome Variables (*4-level: zero to four or more times per week*)											
		Grocery in-store		Grocery pickup		Grocery delivery		Meal in-store		Meal pickup		Meal delivery	
		Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
Latent constructs													
COVID-19 risk perception		-0.40	-40.04	—	—	0.03	2.33	-0.38	-32.45	-0.04	-2.42	—	—
Virtual activity participation		na	na	0.36	23.10	0.53	39.98	0.03	1.68	0.15	9.29	0.43	40.10
Social interaction propensity		0.08	4.98	na	na	na	na	0.11	5.57	0.08	4.63	—	—
Individual characteristics													
Gender (not female)	Female	-0.09	-3.61	-0.24	-6.24	-0.42	-10.98	-0.14	-4.70	-0.12	-4.40	-0.25	-8.15
Age (*)	18-30	na	na	0.49	9.44	0.34	6.49	0.15	4.65	na	na	0.75	18.42
	18-40	na	na	na	na	na	na	na	na	0.26	8.68	na	na
	31-40	na	na	0.53	10.26	0.41	7.42	na	na	na	na	0.62	14.43
	41-50	na	na	0.31	5.61	—	—	na	na	na	na	0.39	8.43
	51-60	0.11	3.26	na	na	na	na	na	na	na	na	na	na
Race and ethnicity (*)	Non-Hispanic White	-0.17	-5.02	na	na	na	na	na	na	-0.12	-3.84	na	na
	Non-Hispanic	na	na	—	—	na	na	na	na	na	na	na	na
	Non-White	na	na	na	na	-0.07	-1.72	na	na	na	na	—	—
	Asian	na	na	na	na	na	na	-0.16	-2.35	na	na	na	na
	Black	0.21	4.77	na	na	na	na	na	na	na	na	na	na
	Hispanic	na	na	na	na	na	na	0.08	1.67	na	na	na	na
Employment (*)	Worker	na	na	na	na	0.10	2.35	na	na	na	na	0.28	8.84
	Non-worker	—	—	-0.11	-2.78	na	na	-0.16	-5.03	-0.17	-6.11	na	na
Education (*)	High school or less	0.07	1.92	na	na	-0.14	-2.86	0.12	2.84	na	na	na	na
	Graduate degree(s)	na	na	0.22	5.38	na	na	na	na	na	na	na	na
COVID-19 test results (*)	Positive	na	na	0.42	3.22	0.25	1.93	na	na	0.22	2.25	0.41	3.92
	Negative	na	na	na	na	na	na	0.13	3.88	na	na	na	na
Household characteristics													
Household income (*)	Less than $25,000	na	na	na	na	-0.57	-9.36	na	na	na	na	na	na
	Less than $35,000	0.07	2.14	na	na	na	na	na	na	na	na	na	na
	Less than $50,000	na	na	na	na	na	na	na	na	-0.09	-2.74	—	—
	$25,000-$50,000	na	na	na	na	-0.45	-8.64	na	na	na	na	na	na
	$50,000-$100,000	na	na	na	na	-0.36	-8.16	na	na	na	na	na	na
	$100,000 or more	-0.10	-3.35	na	na	na	na	0.08	2.38	0.10	3.02	na	na
Household size (>1)	One	-0.09	-2.85	na	na	na	na	na	na	-0.22	-6.17	na	na
Household vehicles (*)	Zero	na	na	-0.42	-6.07	0.11	1.75	-0.21	-3.18	-0.37	-6.63	0.15	2.73
	Three or more	0.09	2.86	na	na	na	na	na	na	na	na	na	na

TABLE 3 CONTINUED Estimation Results of Grocery Model Components (N = 8,392)

Explanatory Variables (base category)		**Main Outcome Variables** (*4-level: zero to four or more times per week*)											
		Grocery in-store		Grocery pickup		Grocery delivery		Meal in-store		Meal pickup		Meal delivery	
		Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
Home type (*)	Stand-alone home	-0.11	-4.25	na	na	-0.26	-6.86	na	na	na	na	-0.10	-3.00
	Apartment	na	na	-0.15	-3.61	na	na	na	na	na	na	na	na
Household structure (*)	Children present	na	na	0.25	5.73	0.23	4.68	na	na	0.11	3.55	0.13	3.30
	Single parent	na	na	na	na	0.24	3.71	na	na	na	na	0.20	3.35
Built environment and travel characteristics													
Employment density (*)	<3000 jobs/km^2	na	na	-0.35	-4.78	na	na	na	na	na	na	na	na
Housing density (*)	<3000 housing units/km^2	na	na	na	na	na	na	-0.21	-3.67	-0.12	-2.29	na	na
Population density (*)	<3000 person/km^2	na	na	na	na	na	na	na	na	na	na	-0.22	-5.66
Retail jobs density (*)	<200 jobs/km^2	na	na	na	na	-0.33	-8.24	na	na	na	na	-0.10	-2.46
Commute distance (<40)	40 mi or more	na	na	0.30	3.27	na	na	na	na	na	na	na	na
Thresholds	1|2	-1.13	-24.45	0.73	7.57	0.27	4.20	0.35	5.30	-0.35	-5.62	0.55	10.52
	2|3	0.24	5.27	1.46	15.17	1.01	15.52	1.09	16.49	0.60	9.60	1.37	25.75
	3|4	1.71	34.58	2.36	22.67	1.97	27.11	2.07	28.53	1.79	26.23	2.48	40.64
Correlation	Grocery in-store	1.00		-0.05		-0.08		0.13		-0.01		-0.06	
	Grocery pickup	na		1.00		0.16		-0.03		0.05		0.13	
	Grocery delivery	na		na		1.00		-0.07		0.06		0.19	
	Meal in-store	na		na		na		1.00		0.00		-0.05	
	Meal pickup	na		na		na		na		1.00		0.05	
	Meal delivery	na		na		na		na		na		1.00	
Data Fit Measures		GHDM						Independent Model					
Log-likelihood at convergence		-41060.75						-42009.66					
Log-likelihood at constants		-44633.9											
Number of parameters		173						121					
Likelihood ratio test		0.080						0.059					
Average probability of correct prediction		0.0112						0.0109					

Note: Coef = coefficient; na = not applicable; "—" = not statistically significantly different from zero at the 90% level of confidence and removed from the specification.

*Base category is not identical across the model equations and corresponds to all omitted categories.

Built environment information is: Employment den at 95 percentile: 3000; Housing den at 95 percentile: 3000; Population density at 75 percentile: 3000

Retail jobs density at 75 percentile: 248

Non-Whites are less likely to order groceries for delivery. As mentioned earlier, minorities are also more likely to feel that COVID-19 presented a risk to their health. As a result, they are less likely to engage in in-person shopping activities. The race effect shows that minorities are also less likely to have groceries delivered. In other words, minority groups may experience diminished access to food during a public health pandemic by virtue of their reluctance to engage in in-person shopping activities and their lower levels of technology savviness/access and/or ability to pay for delivery.

Workers are more likely to have groceries and meals delivered, presumably because of their technology-savviness, constrained work schedules, and greater awareness of virtual platforms to access goods and services. Non-workers consistently depict a lower propensity to engage in in-store and pickup modalities, likely due to greater household obligations. Highly educated individuals exhibit a greater propensity to order groceries online for pickup, while those with lower educational attainment are more likely to shop in-store (increasing their risk exposure) and less likely to have groceries delivered (by virtue of income constraints). These findings suggest that individuals at the lower end of the educational spectrum may experience challenges accessing and affording virtual mechanisms for acquiring groceries. Those who experienced COVID-19 (indicated by positive test results) may be more cautious and hence show a greater proclivity for procuring groceries and meals online (both pickup and delivery) than in-person.

Household characteristics show a similar pattern of behaviorally intuitive results. The low-income groups are least likely to purchase groceries through online + delivery mechanisms. This suggests that low-income individuals face considerable technological and income barriers to taking advantage of virtual activity modalities for accessing food. The low-income group also exhibits a higher propensity to shop for groceries in-store, increasing their exposure to the virus. Middle-income groups also depict a lower propensity to shop for groceries online for delivery. Single adults are less likely to shop in-store and pickup meals, a finding meriting further investigation for underlying reasons.

From a *transportation* standpoint, access to vehicles matters. Individuals in households with zero vehicles exhibited a greater propensity to have groceries and meals delivered. They are less likely to engage in in-person pickup and in-store shopping/meals modalities, which is not surprising given their modal constraints. On the other hand, higher vehicle ownership is associated with a greater propensity to shop in-store. While virtual delivery-based activity modalities help individuals without a car access food through delivery services, affordability may be an issue – particularly during a prolonged disruption.

Households with children are more likely to purchase groceries for pickup and to purchase meals for pickup and delivery (Dias et al., 2020). This finding is likely due to the time pressures and constraints associated with the presence of children in homes. Single parents are more likely to engage in frequent grocery and meal deliveries, likely for similar reasons. Lower housing density is negatively associated with purchasing meals for pickup (Dias et al., 2020) or in-store dining, presumably because fewer restaurants are nearby. A lower population density is negatively associated with meal delivery. This finding may be explained by restaurants not serving low-density or rural areas far away from stores. Finally, retail job density is negatively associated with grocery delivery and meal delivery. In areas with high retail job density, grocery and meal establishments are likely to be in close proximity, thus enabling easy access for in-store or in-person pickup modalities. Finally, those commuting 40 miles or more are more likely to purchase groceries for pickup.

A number of error correlations are statistically significant, supporting the specification and estimation of a joint simultaneous equations model that considers all six endogenous outcomes as a bundle of choices. The correlations are behaviorally intuitive; generally, correlations between in-store modality on the one hand and pickup/delivery modalities on the other are negative, while correlations between pickup and delivery modalities are positive. This means that unobserved factors that elevate in-person in-store activity engagement are likely to be negatively correlated with unobserved factors that contribute to online activity engagement. On the other hand, unobserved factors that contribute to elevating one form of virtual activity engagement are also likely to elevate the other form. There are likely unobserved factors related to technology access and savviness, time pressure, and willingness to try new things that simultaneously impact alternative activity engagement modalities.

5. DISCUSSION AND CONCLUSIONS

The COVID-19 pandemic was a severe and long disruption leading to a public health crisis that impacted people's lives in many ways. During this disruption, many businesses and establishments restricted their operations, and policies were implemented to limit the virus's spread. This project focuses on studying access to food (groceries and meals) during the pandemic, with an emphasis on identifying segments of the population that may be particularly vulnerable and unable to sufficiently *adapt* to access food to the same degree as in a pre-pandemic era.

The project utilizes data collected in the first wave of a large national panel survey aimed at capturing behavioral changes over the course of the pandemic. The data set, derived from the COVID Future Panel Survey, includes more than 9,900 observations and contains detailed data about how frequently people engaged in various activities by different modalities (in-person and online) before and during the pandemic. This report defines food access as the ability to obtain groceries and meals. Both of these food types may be purchased in-store or ordered online for possible pickup in person or delivery to the consumer. Thus, there are two commodity types and three possible modalities, leading to six possible avenues for obtaining food. Engaging in any of these food access activity modalities constitutes a choice, and hence the six possible food access modalities may be treated as a bundle of choices that an individual exercises.

The project models the frequency with which individuals engage in each of the six possible modalities in a simultaneous equations modeling framework that accounts for error correlations across the dimensions of interest. The simultaneous equations model system incorporates a series of latent constructs that capture attitudes and perceptions, including COVID-19 risk perceptions, perceptions of the effectiveness of virtual activity platforms, and social interaction propensity. The model system showed that attitudes and perceptions, together with a host of socio-economic and demographic attributes, significantly affect participation in different activity modalities. Moreover, the presence of significant error correlations and the model goodness-of-fit measures show that the joint simultaneous equations modeling approach is warranted when considering a set of closely related endogenous variables.

The project findings show that critical inequities render certain population subgroups more vulnerable to food insecurity during a severe and prolonged disruption. Certain groups exhibited a greater proclivity to engage in in-store shopping even after accounting for the attitudinal proclivities and lifestyle preferences for social interactions. It appears that these groups continued to shop in-store and place themselves in harm's way because alternative online-based options were out of reach or unaffordable. Groups continuing to shop in-store during the pandemic included Hispanics and Blacks. These minority groups also experience a greater digital divide, rendering it difficult for them to access online platforms and utilize them effectively to access goods and services. In the case of food deliveries, the cost must be considered; the model showed that lower-income individuals are less likely to procure groceries via delivery mechanisms, presumably because of delivery fees. Older adults and those with lower educational attainment also exhibit lower levels of food access through virtual means, suggesting that they are particularly vulnerable should stores restrict operations for any prolonged time.

In conclusion, this project has shown that minorities, individuals residing in households with low income, and rural residents are prone to food insecurity and vulnerability in the wake of a COVID-19 pandemic type disruption. These groups need to be provided technological resources so they can participate in the online economy and leverage virtual platforms for procuring essential goods and services, including food. Providing assistance and training in the use of technology platforms would further assist in reducing vulnerability. Delivery fees can be quite substantial when ordering food and meals frequently, thus rendering the use of such services unaffordable for the income-constrained segments of society. Public subsidy programs (such as SNAP) need to be modified to cover delivery fees (perhaps up to a certain limit), thus enabling low-income individuals who depend on such programs for food to obtain groceries and meals without exposing themselves to risk.

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