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Boon or Bane? Urban Food Security and Online Food Purchasing during the COVID-19 Epidemic in Nanjing, China

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Abstract: This paper examines the relationship between the rapid growth of online food purchasing and household food security during the first wave of the COVID-19 pandemic in China using the city of Nanjing as a case study. The paper presents the results of an online survey of 968 households in Nanjing in March 2020 focused on their food purchasing behavior and levels of food security during the early weeks of the pandemic. While online food purchasing has increased rapidly in many countries during the COVID-19 pandemic, little research attention has been paid to the relationship between online food purchasing and household food security. This paper provides detailed insights into this relationship in China. The medium- and longer-term food security and other consequences of the pandemic pivot to online food purchasing are a fertile area for future research in China and elsewhere.

Keywords: online food purchase; food security; dietary quality; COVID-19; wet markets; Nanjing

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1. Introduction

Over the last decade, e-commerce and online food purchasing have undergone sustained though geographically uneven growth [1–4]. Prior to the COVID-19 pandemic, online food purchasers in most countries were largely drawn from specific socioeconomic and demographic groups, especially young adults, more affluent households, and those with health-related mobility challenges. In Italy, for example, online purchasers were most likely to be young, well educated, females, living in small families, and well-off [5]. Situational factors affecting the probability of online food purchase included working hours and having health problems. In Australia, consumers ordering meals online were more likely to be younger, with a higher body mass index, more educated, and with greater income levels and more likely to consume sugary drinks and patronize fast-food restaurants [6]. In the UK, adults with the highest education, younger adults, those living with children, and females were most likely to purchase food online [7].

Prior to the COVID-19 pandemic in China, there was evidence of dramatic growth in the online food retail market due to a large population base, low delivery cost, weak offline retail market, and major investments to improve the online retail environment [8]. However, food purchasing on e-commerce platforms was far from universal. One study, for example, identified what they call "online-food-pioneer" consumers who were more likely to have a medium or high income, be married, have a high-level job or be self-employed, and/or be 31 to 40 years of age [9]. Another study found that the likelihood of shopping for fresh produce online was directly related to perceptions and beliefs about the freshness of the produce [10]. For all its efficiency and convenience for the consumer, online food shopping, like fast food, might also be playing a role in the increasingly well-documented prevalence of diet-related noncommunicable disease in China [11].

As human-to-human transmission is one of the main mechanisms of the SARS-CoV-2 spread, lockdown measures, stay-at-home and shelter-in-place orders, and movement restrictions were enacted in many countries to control the rapid spread of the virus and to ease the burden on overstretched health facilities and personnel [12,13]. In addition, particularly when COVID-19 science was in its infancy and before the advent of vaccines, many consumers changed their food shopping behavior to reduce their own risk of infection. Increasingly well-documented responses of consumers to these COVID-19 public health restrictions have been changed in the food purchasing and consumption preferences and habits of urban consumers [14–18]. A range of case studies have demonstrated that there was a significant pandemic-related increase in online food purchasing and delivery in countries and cities in different parts of the world [19–22].

In part, the COVID-related global shift to online food purchasing has been driven by disruptions to global and national food supply chains, which have increased food prices and narrowed the range of foods on store shelves [23,24]. In the early weeks of the pandemic, shortages were also exacerbated by panic buying and the stockpiling behavior of households [25,26]. In some countries, changes in food sourcing patterns were necessitated by public health measures, which shuttered food retail spaces and operators deemed to be high risk [27–29]. The first, but far from the only example, was the closure of wet markets in Wuhan during the lockdown of the city [30]. The closure of food markets and restrictions on informal food retailing in some countries had an extremely negative impact on incomes and food accessibility for the urban poor [27,31,32]. All of these factors combined to a greater or lesser extent to create unprecedented pivoting opportunities for e-commerce, online food platforms, and food delivery services [33].

The onset of COVID-19 precipitated a major shift in food purchasing behavior across China [34]. There was a rapid increase in online food purchasing involving the expansion of e-commerce food ordering platforms and food delivery services, massive growth in the number of consumers involved and in the volume and range of products purchased, and participation in online buying by a much more representative demographic [35–39]. Even with COVID-19 under control, online food purchasing appears to have remained higher than at pre-pandemic levels. To reduce the spread of COVID-19 and increase access to foods, the central, provincial, and municipal governments urged citizens to utilize technology and contactless methods to obtain groceries and foods. The demand-side drivers of online food purchasing included complete and partial residential lockdowns; the closure of food outlets, such as wet markets and street vending; restrictions on people's everyday mobility and ability to buy fresh produce on a daily basis; and the need to reduce the risk of personal and household infection.

One survey conducted by researchers at Hunan University in China in April 2020 found that there had been a 70% increase in the numbers shopping online and that those who were more anxious about COVID-19 were more likely to shop online during the pandemic [38]. Local private e-commerce platforms were the most efficient at delivering produce to residential complexes as the number of customers and orders surged in the cities [40,41]. Food e-commerce companies launched contactless delivery in late January in many cities, aimed at maximizing the safety of users and couriers in the food receiving process. Online ordering and contactless delivery were then rolled out and promoted in the national logistics and e-commerce industry. According to the "Contactless Delivery Report" issued by Meituan, one of the giants in the online food delivery industry in China, some e-commerce platforms' contactless delivery orders accounted for more than 80% of their total number of orders from 26 January to 8 February 2020 [42]. In addition, supermarkets, hotels, and restaurants developed contactless delivery channels to reduce economic losses [43].

While research on the COVID-related boom in online food purchasing is growing, few studies have paid attention to whether or not this trend led to greater food security among participating households. This is the first study we are aware of to systematically examine the relationship between online food purchase and food security in urban China during the pandemic. Using survey data from an online survey of the impact of the pandemic on household food insecurity among 968 households in the city of Nanjing, the paper examines the complex relationship between online food purchasing and household food insecurity during the early weeks of the pandemic. Section 2 of the paper discusses the study site, methodology, and variables and models used in the data analysis. Section 3 presents the results of the modelling with particular focus on the nexus between online food purchasing and household food security. Section 4 discusses the implications of the findings and why online food purchase was both a boon and a bane for households. Finally, in Section 5, the paper discusses the implications for emergency preparedness planning and key questions for future research.

2. Materials and Methods

2.1. COVID-19, Household Food Insecurity, and Online Food Purchasing

The initial outbreak of COVID-19 in Chinese cities increased the risk of household food insecurity (Figure 1). Control and mitigation strategies included a series of movement restrictions, such as stay-at-home orders and constraints on food transportation to and within cities. On the one hand, urban residents were required to reduce the frequency of going out to purchase food and other necessities in person, which increased the challenge of physical access to food. On the other hand, households faced a reduction in economic access to food because of income loss and soaring food prices in the face of sudden shortages. As companies and factories were unable to operate normally, the lack of work and employment income made it hard to maintain household food security.

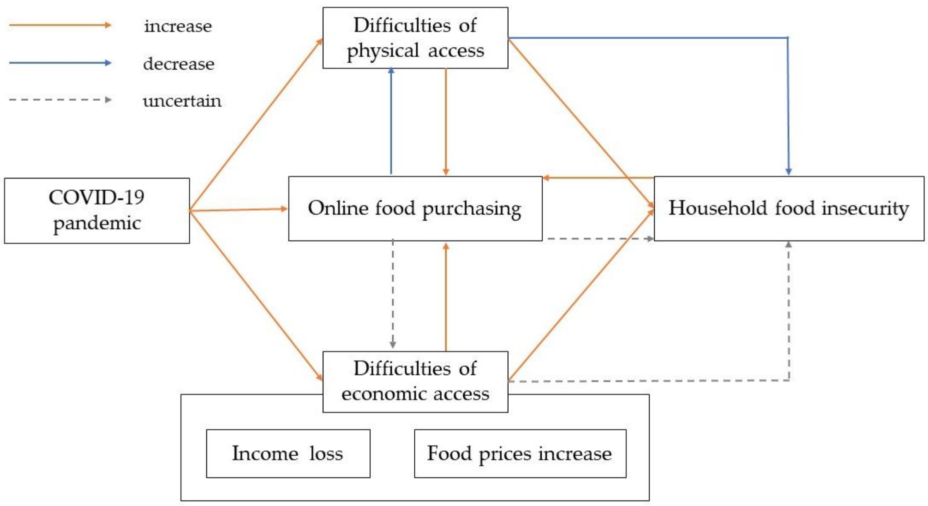


Figure 1. Relationship between COVID-19, household food insecurity, and online food purchasing. Source: Authors' own compilation.

The COVID-19 pandemic also furthered the development of a nascent online food purchase industry. Online food purchasing was extremely convenient as residents could purchase food using applications on smartphones and also reduced the risk of infection due to contactless delivery. In theory, the challenges of physical access to food were greatly reduced through online food purchasing. Our study hypothesized that all households had a higher probability of purchasing food online than normal, and that it was particularly attractive for households who faced difficulties in any aspect of food insecurity. Complicating the analysis is the fact that online platforms also experienced problems, such as increased prices and delayed delivery. Additionally, the development of fresh food delivery through online ordering in China was still very much in its infancy before the pandemic. As a result, the question of how online food purchasing affected household food insecurity can only be answered through detailed case study research in particular cities, in our case, Nanjing.

2.2. Case Study Site

Nanjing is the capital city of Jiangsu Province and is located in the southwest of Jiangsu with a total permanent population of 9.32 million and 11 districts (county-level administrative units). Its GDP reached CNY 148.18 billion in 2020 [44]. Nanjing was chosen as a case study for three reasons. First, online food ordering and delivery had achieved a relatively high penetration rate prior to the pandemic, notwithstanding the collapse of a major local company—CloudKitchens—in the months prior to COVID-19 [8]. In the first three quarters of 2019, for example, Nanjing's online food orders exceeded CNY 100 million in value [45].

Second, an earlier survey of food purchasing patterns in pre-pandemic Nanjing provided a baseline from which to assess the growth of online food commerce during the pandemic [46,47]. That study of cross-platform food shopping in Nanjing found a statistically significant correlation between the 17% of households that accessed food online and their patronage of fast-food outlets and restaurants. In addition, households that had accessed these food sources in the previous year tended to have heads who were younger and possessed postsecondary qualifications, although other household variables, such as income, were not significant. In Nanjing, the primary products sourced online were processed foods, including tinned meat and fruit, chips, candies, and other snacks [48].

Third, Nanjing's public health response to the COVID-19 pandemic resembled that of many other Chinese cities outside Wuhan with a relatively low case count because of mobility restrictions and only partial lockdown of many residential neighborhoods. The first confirmed case of COVID-19 was reported on 23 January 2020 in Nanjing, with a total of 93 cases reported on 18 February 2020 [49]. In Wuhan, the major sources of fresh produce (wet markets) were all closed for an extended period, whereas in Nanjing, they remained open, although the ability of households to access them was constrained by lockdown regulations [30].

2.3. Household Survey and Food Security Measurement

As residential neighborhoods were still under lockdown and had restricted access in March 2020, it was not possible to conduct a face-to-face survey. We therefore designed and implemented an online survey using the electronic questionnaire platform Wenjuanxing to distribute questionnaires. This platform has been widely used for online surveys in China, its main advantage being that we could ensure that the respondents were residing in Nanjing instead of other cities by limiting the IP addresses allowed to access the online survey. WeChat was used to distribute the questionnaire, which is the most popular social media application in China.

A total of 1445 responses to the survey were received from Nanjing residents. These were then screened based on two criteria. First, we eliminated cases with an answering time of less than 150 s as it would have been impossible to complete the questionnaire survey within that time. Second, cases were screened out if key information was missed or too many questions were not answered. The final tally was 968 validated questionnaires or 67% of the original sample.

Four main types of information were collected in the survey. One was basic information about the household, including household size, household structure, housing type, and housing property rights. The second was whether their neighborhood (residential community) was under closure or quarantine measures and if so, what type. Third, the survey collected detailed information about household food purchasing behavior including, but not limited to, the use of online purchasing to buy food, the foods purchased, the frequency of access, and the difficulties of buying food in the pandemic. This paper uses the commonly accepted FAO definition of food security as "a situation that exists when all people, at all times, have physical, [social] and economic access to sufficient, safe and nutritious food which meets their dietary needs and food preferences for an active and healthy life" [50,51]. To measure household-level food insecurity, we used two standardized and validated cross-cultural metrics to measure levels of household food insecurity during the 4 weeks prior to the survey: the Household Food Insecurity Access Scale (HFIAS) and the Household Food Insecurity Access Prevalence (HFIAP) classification [52]. Other studies have indicated that the HFIAS and HFIAP are also appropriate for monitoring and evaluating food security interventions since they provide for the design of appropriate mitigation measures [53,54].

Both metrics are based on nine frequency-of-occurrence questions addressing three different domains of household food insecurity in the 4 weeks prior to the survey: (1) feelings of uncertainty or anxiety about the household food supply (Q1); (2) food preferences and perceptions that food is of insufficient quality and variety (Q2–4); and (3) food quantity and intake being insufficient to meet household needs (Q5–9). The HFIAS allocates a score on a scale of 0 (completely food secure) to 27 (completely food insecure) to each household. An algorithm is then used to compute the HFIAP, which allocates each household to one of four categories: 1 (food secure), 2 (mildly food insecure), 3 (moderately food insecure), and 4 (severely food insecure) [52]. In this paper, we rely on four main measures of household food insecurity: the HFIAP plus three binary variables representing food anxiety, food quality, and food intake.

2.4. Simultaneous Equations Regression

Households that experienced food insecurity because their usual physical food outlets were closed or because of restrictions on their movement were more likely to obtain food through online food purchase. Because these constraints could affect both food security and household food purchasing behavior, any causal relationship between online food purchase and household food insecurity was unlikely to be unidirectional. Thus, an endogeneity problem might arise due to mutual impact. We therefore used a simultaneous equations framework to address the endogeneity issue of the mutual influence of the two dependent variables: food insecurity and online food purchasing behavior. However, both are finite variables, which means that their domains are not continuous or bounded and they do not obey the normal distribution, so conventional recursive methods, such as two-stage least squares (2SLS), are inappropriate.

Earlier studies formulated an alternative simultaneous equation model with both discrete and continuous endogenous variables and used a limited information maximum likelihood (LIML) or a full information maximum likelihood (FIML) as the estimation method. A more recent analysis developed a fully observed recursive mixed-process model, which can jointly estimate complex models, and created the command "cmp" that can be used on Stata [55]. We therefore estimated a two-equation system model by using this command in STATA. One equation is used to estimate the impact of online food purchase on the HFIAP, which is represented below as Equation (1) with HFIAP as the dependent variable in the system of equations. The other models the impact of the HFIAP and other indicators on the choice of online food purchase behavior, which is represented as Equation (2) with OFP as the dependent variable in the system of equations.

Because household online food purchase is a binary variable, the study used the probit model. As HFIAP is an ordered categorical variable, the bigger the number, the more severe the household food insecurity, so it is suitable for the ordered probit model. The simultaneous equation model is as follows:

$$\begin{cases} HFIAP_i{}^* = \beta OFP_i + \gamma K_i + \varepsilon_2 \\ OFP_i{}^* = \alpha HFIAP_i + \lambda J_i + \varepsilon_1 \end{cases} \tag{1}$$

For the ordered probit model, the observed HFIAP (represented as variable $HFIAP_i$) is related to its latent counterpart ($HFIAP_i^*$) as follows:

$$HFIAP_i = \begin{cases} 1 & if -\infty \leq HFIAP_i^* \leq \mu_1 \text{ (food secure)} \\ 2 & if\ \mu_1 < HFIAP_i^* \leq \mu_2 \text{ (mild food insecure)} \\ 3 & if\ \mu_2 < HFIAP_i^* \leq \mu_3 \text{ (moderately food insecure)} \\ 4 & if\ \mu_3 < HFIAP_i^* \leq +\infty \text{ (severe food insecure)} \end{cases} \quad (2)$$

where μ_1, μ_2, and μ_3 are unknown threshold (cut-off point) parameters to be estimated, and the model to analyze the influence of variables on the HFIAP is as follows:

$$P(HFIAP_i > j) = g(K_i\beta_j) = \frac{exp(\gamma_j + K_i\beta_j)}{1 + exp(\gamma_j + K_i\beta_j)}\ j = 1, 2, 3, 4 \quad (3)$$

where K_i is the vector of independent variables besides the variable *OFP* (representing the use of online food sources) for $HFIAP_i$, γ is a coefficient vector of K_i to be estimated, and β_j is a coefficient of the variable OFP_i estimated.

In the probit model, the variable *OFP* is a dependent variable, and the value of 1 is for household purchase online, while 0 is not. The probit model is estimated using the maximum likelihood estimation (MLE) technique [56,57]:

$$OFP_i = \begin{cases} 1,\ if\ OFP_i{}^* > 0 \\ 0,\ otherwise \end{cases} \quad (4)$$

where OFP_i^* denotes a latent continuous variable, control variables are represented by J_i, α and λ are those parameters needing to be estimated, and the error term is denoted by ε_j.

2.5. Dependent Variables

For the analysis, we selected two dependent variables: (a) household food insecurity (HFIAP) and (b) use of online food sources (*OFP*) (see Table 1). The variable HFIAP was used to measure the degree of household food insecurity. If a surveyed household was completely food secure, the variable HFIAP equals 1. If it was mildly food insecure, the HFIAP equals 2. If a household was moderately food insecure, the HFIAP equals 3. If a household was severely food insecure, the HFIAP equals 4.

Table 1. Dependent and independent variables.

Variable	Definition	Mean	Standard Deviation
HFIAP	Household Food Insecurity Access Prevalence, food secure = 1, mildly food insecure = 2, moderately food insecure = 3, severely food insecure = 4	2.2	1.2
OFP	Online food purchase, *OFP* = 1 for households bought/purchased food online, otherwise, *OFP* = 0	0.8	0.4
PFGO	Purchase food through grassroots organizations, *PFGO* = 1 for households purchased food through grassroots organizations, otherwise, *PFGO* = 0	0.4	0.5
DPA	Difficulties of physical access, *DPA* = 1 for households had difficulties in physical access, otherwise, *DPA* = 0	0.7	0.5
DEA	Difficulties of economic access, *DEA* = 1 for households had difficulties in food affordability, otherwise, *DEA* = 0	0.4	0.5
HPR	Housing property rights, *HPR* = 1 for self-owned property, otherwise, *HPR* = 0	0.8	0.4
HT	Housing types, *HT* = 1 for households lived at urban run-down buildings, otherwise, *HT* = 0	0.0	0.2
HS	Household sizes, discrete values ranging from 1 to 10	3.5	1.5
NCC	Neighborhood with confirmed cases, *NCC* = 1 for a neighborhood with confirmed cases, otherwise, *NCC* = 0	0.0	0.2
HPI	Household with pregnant(s) or infant(s), *HPI*= 1 for household with pregnant(s) or infant(s), otherwise, *HPI* = 0	0.3	0.4
FSPS	Food shortage in physical stores, *FSPS* = 1 for shortage of food in physical stores, otherwise, *FSPS* = 0	0.3	0.4

Sources: calculated based on the data from online survey conducted in 2020.

In Nanjing, there are four online food purchase modes, including (a) online-to-offline in-store (O2O In-Store), (b) online-to-offline delivery (O2O Delivery), (c) business-to-consumer (B2C), and (d) new retail [26]. The first mode (O2O In-Store) was excluded from the study because it involves ordering local catering services online and consuming in offline premises, such as restaurants, which was not permitted in February 2020 [43]. The binary variable OFP was computed by answers to the question "Since January 23, how often (per week) has your household bought food using online stores and phone apps (such as Hema, Suning, and Meituan)?" If the interviewed household chose any of the frequency options, the value of *OFP* equals 1, 0 otherwise.

2.6. Independent Variables

Equation (1) explores the relationship between household food security and a set of independent variables. Where neighborhoods were subject to lockdown measures or a household was required to home quarantine, community-based "grassroots purchasing" became more common, as organizations made efforts to buy food for households with mobility restrictions or limited and insufficient access to food outlets. There are two kinds of grassroots organizations: property management agents and neighborhood committees. The former is usually a management company providing property management services for a neighborhood. The latter is an autonomous organization of urban residents in the Chinese administrative system responsible for the neighborhood's security, sanitation, welfare, and conflict resolution [58].

Purchasing food through grassroots organizations was an innovative response to the pandemic and included three steps. Households first submitted their food requests based on food supply lists released by the grassroots organization. Next, the organization's volunteers bought the food from a physical outlet, such as a supermarket or wet market. The final step involved delivery by the organization of the food to households or giving them notice to pick up their order from a designated spot within the neighborhood. Grassroots purchasing was generally a free service for residents. The binary variable *PFGO* was used to show whether households had obtained food by "grassroots purchasing" during the pandemic. If a household had purchased food through a grassroots organization, *PFGO* equals 1, 0 otherwise.

Access is one of four dimensions of food security, which means that people have physical, economic, and sociocultural access to adequate and nutritious food that meets dietary needs and food preferences [59]. As there is no guide on how best to bin the frequency indicators of Q1–9 into yes/no responses, we used two different kinds of coding method for *FA* (food anxiety, Q1), *FQ* (insufficient quality, Q2–4), and *FI* (inadequate food intake, Q5–9). The binary variable *DPA* was used to measure whether a household encountered problems or difficulties because of decreased physical access to food. The surveyed households were asked the question "Since 23 January, did you or any member of your household experience any of the following challenges? 'Restricted mobility to leave home', 'Restricted access to food markets and supermarkets', and 'Limited food availability and lack of food variety at wet markets or supermarkets'". If a household responded "yes" to any of these options, the value of the variable *DPA* equals 1, 0 otherwise.

The binary variable *DEA* was used to represent whether a household encountered problems or difficulties of decreased economic access to food. The surveyed households were asked the question "Since 23 January, did you or any member of your household experience any of the following challenges? 'Food price increased' and 'Loss of income due to the COVID-19 restriction'". If the answer was "yes" to either of these options, the value of the variable *DEA* equals 1, 0 otherwise.

The binary variable *HPR* was used to reflect whether the housing property of a household was self-owned. Self-owned housing tends to be associated with reduced food insecurity since the financial pressures are lower than that for renting a house [60]. Furthermore, self-owned housing suggests that households are more likely to have a stable economic situation and are more capable of coping with temporary economic crises than renters. If the housing unit was self-owned, *HPR* equals 1, 0 otherwise.

The related binary variable *HT* was used to indicate whether a household lived in run-down housing/buildings. Households in run-down urban housing/buildings or other places in a disadvantaged neighborhood condition are generally more likely to also have a higher level of food insecurity [61]. The economic situation of households living in these conditions is worse, and they are less able to deal with sudden crises [62,63]. In addition, their social capital is not as strong and interpersonal relationships are weak, so it is difficult to obtain food from other channels when physical stores are not open or accessible. In this analysis, the value of variable *HT* was dependent on the answer to the question "Which of the following best describes your place of residence?" If a surveyed household chose either "Greenhouse shed" or "Makeshift urban housing", the value of *HT* equals 1, 0 otherwise.

There are no definitive conclusions in the literature about the specific impact of household size on HFIAP. Some studies have observed that an initial increase in size has a strong negative effect on food insecurity, but that after a certain threshold is reached, further increases may boost household food security [64]. Although the more family members there are, the larger the demand and consumption of food, a big family also has a wider range of interpersonal relationships and potential wage earners, indicating that there are more sources of information and income to help obtain food. The discrete variable *HS* was used to measure household size, and ranges from 1 to 10.

Under the zero-COVID policies in China, neighborhoods with confirmed cases were subjected to stricter lockdown restrictions, which undoubtedly raised the difficulty for residents to purchase food. There were two kinds of lockdown measures, complete and partial lockdown. The complete lockdown measures imposed strict prohibitions on residents' access and outsiders' entry, and the township-level subdistrict (street) office arranged staff or volunteers to carry out the distribution of daily dietary materials. With partial lockdown measures, residents were able to personally access food retail outlets with limitations on times and frequency, and service providers were allowed to deliver food at the gate. The variable *NCC* was used to represent whether a neighborhood had confirmed cases of COVID-19. *NCC* equals 1 for yes, 0 for no.

Pregnant women and infants have specific food requirements, including fresh fruits, vegetables, and baby milk powder, and also need to avoid foods that would affect the health of the fetus [65]. Women with food insecurity are less able than women with food security to sustain exclusive breastfeeding. Therefore, for households with pregnant women or infants, the demand for food is stricter, and under the influence of the COVID-19 pandemic, not all special needs can be met. All other things being equal, households with pregnant women or infants are more likely to be food insecure. *HPI* was used to capture whether a household had pregnant women or infants. *HPI* equals 1 for yes, 0 for no.

Equation (2) investigates whether there was a relationship between food insecurity and online food purchase using the same independent variables and added a variable, *FSPS*, to measure whether households encountered food shortages in physical outlets. The assumption here is that when there are fewer types of food and insufficient amounts in physical stores, people are more likely to purchase food through online platforms. The variable is based on the question "Since 23 January, did you or any member of your household experience any of the following challenges?" If interviewed household chose the option of "Limited food availability and lack of food variety at wet markets or supermarkets", the value of *FSPS* equals 1, 0 otherwise.

Four sets of models were estimated in this study. Model I uses the HFIAP as a dependent variable in the Equation (1) system of equations. Models II, III, and IV include the variables *FA*, *FQ*, and *FI* as the dependent variables in Equation (1) to explore the relationships between three domains of household food security. The variable *FA* denotes whether the household had experienced anxiety about food in the previous 4 weeks; if the surveyed household answered that they never felt anxiety about food, *FA* equals 0, 1 otherwise. The variable *FQ* reflects whether the household experienced insufficient food quality. If the answers to Q2 to 4 (of the nine HFIAS questions) were "Rare", "Sometimes", or "Often", the value of *FQ* is 1, 0 otherwise ("Never"). The variable *FI* was used to represent whether the household experienced insufficient food intake. If a surveyed household answered "Rare", "Sometimes", or "Often" to Q5 to 9, the value of *FQL* is 1, 0 otherwise. Because *FA*, *FQ*, and, *FI* are binary variables, the two equations in Models II, III, and IV all use the probit model to estimate.

Two other provisos are necessary concerning the representativeness of the data and generalizability of the findings given the restrictions on in-person surveys brought about by the pandemic itself. First, the online survey recruitment method meant that respondents self-selected rather than being randomly sampled. Certain population groups, such as the elderly, the more marginalized, and those with limited online experience, may therefore be under-represented. Second, the study collected cross-sectional rather than panel data, although many questions adopted 1-month recall period. This makes it difficult to make definitive comparisons with the prepandemic situation.

3. Results

3.1. Food Insecurity and Food Purchasing Behavior

A 2015 citywide survey in Nanjing found that 79% of households in the city were completely food secure, 14% were mildly food insecure, 5% were moderately food insecure, and only 2% were severely food insecure [48]. Of the 968 households interviewed in this online survey, only 37% were completely food secure, while 24% were mildly food insecure, 19% moderately food insecure, and 20% severely food insecure (Table 2, top row). Thus, the proportion of households experiencing a degree of food insecurity was 21% overall in 2015 and 63% of households surveyed online. While the two samples are not strictly comparable, they suggest that COVID-19 had a significant negative impact on household food security in Nanjing.

Table 2. Characteristics of food purchasing behaviours by food security categories.

% of Households	Food Secure (*n* = 362)	Mildly Food Insecure (*n* = 232)	Moderately Food Insecure (*n* = 181)	Severely Food Insecure (*n* = 193)	% of Total Households
HFIAP distribution	37.4	24.0	18.7	19.9	100.0
Physical food purchase	93.4	97.0	95.6	95.9	95.1
Online food purchase	64.4	76.1	81.5	78.0	80.4
Food from grassroots organizations	60.7	58.6	66.9	61.7	61.6
Difficulty with physical access to food	51.4	68.5	85.6	84.5	68.5
Difficulties with economic access to food	28. 5	50.0	56.9	38.9	41.0

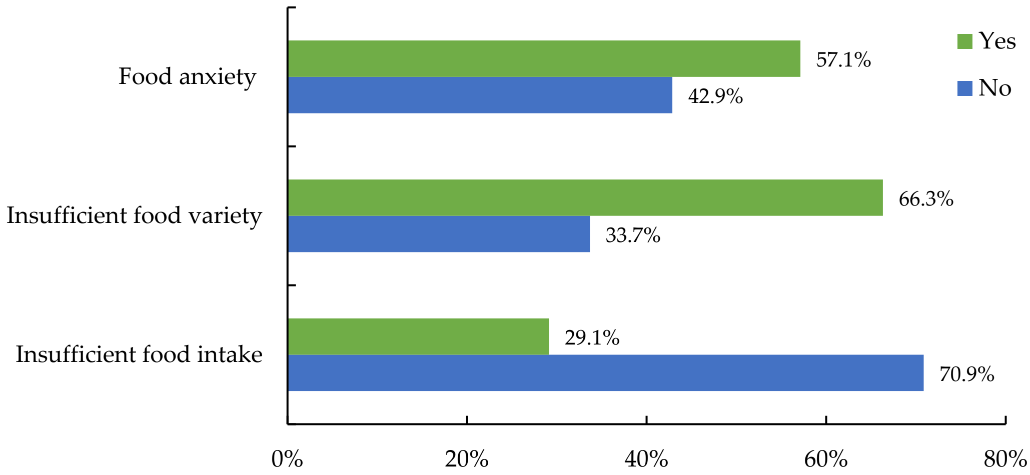
Source: Authors' own compilation from 2020 online survey.

Table 2 (final column) provides the food sources of all surveyed households and shows that 80% of households had purchased food online in the previous month and only 20% had not. While over 90% of the households had purchased food at a physical outlet (such as a supermarket or wet market), the frequency with which they were able to leave their residences and shop in person declined [39]. Over two-thirds of households (62%) had also obtained food via grassroots organizations in their neighborhood.

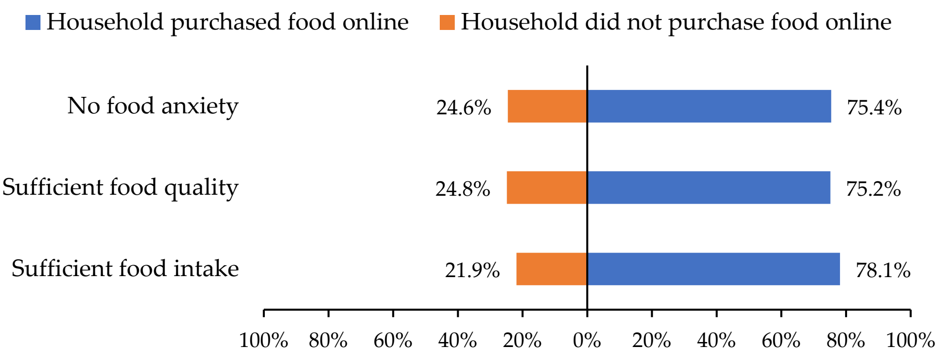
Table 2 also provides a breakdown of food sources by the four HFIAP categories. When it came to online food purchasing, there was a difference between food-secure households (of whom 64% had bought food online) and households in the three food-insecure categories of mildly food insecure (76%), moderately food insecure (81%), and severely food insecure (78%). In contrast, a similar proportion of households in each of the four food security categories bought food at physical outlets and through neighborhood grassroots organizations.

The final column of Table 2 also shows the proportion of households that experienced problems and challenges with physical and economic access to food. In total, 68% of households said they had difficulties of physical food accessibility and 41% had difficulties of economic food accessibility. In both cases, the proportion of food-secure households who experienced both physical and economic problems was lower than for the three food-insecure categories. For example, 84% of severely food-insecure households experienced physical challenges and 39% experienced economic difficulties, compared with 52% and 29% of food-secure households, respectively. At the descriptive level, we can hypothesize that one reason for the greater online patronage by food-insecure households was physical or economic food accessibility challenges or some combination of the two.

Figure 2 breaks down the relationship between online food purchasing and food security by showing the extent of online use by the three broad categories of food insecurity: anxiety about the household food supply, insufficient food quality, and insufficient food intake. Figure 2a shows that the impacts of the pandemic response on household food insecurity were greatest in relation to the impact on food quality (experienced by 66% of households), followed by anxiety about the household food supply (57% of households). Only 30% of households reported to have suffered from insufficient food intake.

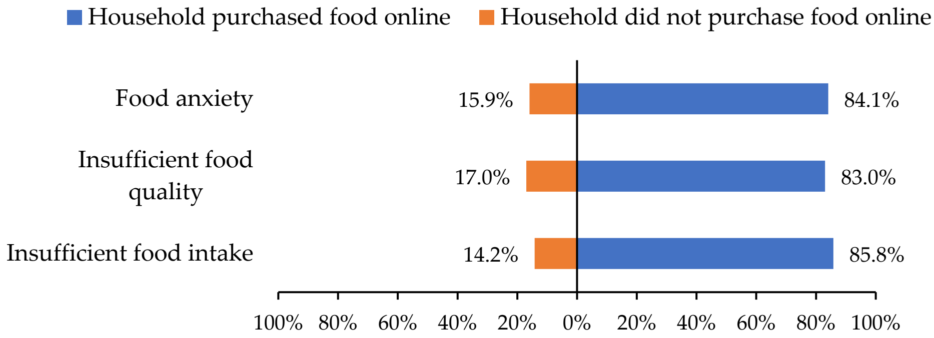


(**a**)



(**b**)

Figure 2. *Cont.*



(**c**)

Figure 2. Distribution of online food purchase in relation to three different aspects of household food insecurity: (**a**) prevalence of household food anxiety, food quality, and food intake; (**b**) online food purchase by households with adequate food quality and intake and no anxiety about food supply; and (**c**) online food purchase by households with insufficient food quality and intake and with anxiety about food supply. Source: Authors' own compilation.

Figure 2b,c suggests that the proportion of food-insecure households purchasing food online was higher than that of food-secure households across all three dimensions of food insecurity. The highest online patronage was among food-insecure households who experienced insufficient food intake (86%), followed by those with anxiety about their food supply (84%) and those with concerns about the quality of their food (83%).

3.2. Model Estimation Results

The results of the simultaneous equations of model I are shown in Table 3. Equation (1) estimates the strength of the relationship between the independent variables and food insecurity (*HFIAP* as dependent variable), while Equation (2) is the estimation of the strength of the relationship between the various independent variables and online food purchasing (*OFP* as dependent variable).

Household food security *(HFIAP).* In Equation (1) of model I (Table 3), three independent variables had a significant relationship with household food insecurity: (i) Physical and economic access: the coefficient of *DPA* is 0.770 with a significance level of 1%, and the coefficient of *DEA* is 0.254 with a significance level of 1%. This indicates that households that experienced difficulties of physical or economic access to food were far more likely to be food insecure than those that did not experience such difficulties. Of the two, difficulties of physical accessibility had a greater impact on household food insecurity than economic accessibility. (ii) Housing property rights: the coefficient of *HPR* is −0.499, significant at the 1% level. This indicates that households that did not have a self-owned house were more likely to be food insecure, which suggests that having a stable residence and less of a negative income shock during the pandemic period was helpful to household food security. (iii) Housing type: the coefficient of *HT* is 0.309, significant at the 10% level, which implied that households that resided in run-down or makeshift accommodation were more likely to be food insecure than those who lived in commercial residential buildings.

Online food purchasing *(OFP).* In Equation (2) of model I, three independent variables had a significant relationship with online food purchasing behavior: (i) Household food insecurity: the coefficient of *HFIAP* is 0.138, significant at the 1% level, which indicates that households were more likely to obtain food by purchasing food online as the level of household food insecurity increased. (ii) Household size: the coefficient of *HS* is −0.061, significant at the 10% level, which indicates that the probability of purchasing food online was higher for smaller than larger households. (iii) Households with pregnant women and/or infants: the coefficient of *HPI* is 0.366, significant at the 1% level, which suggests that households with pregnant women or infants had a higher likelihood of purchasing food online.

Models II, III, and IV examine the relationship between online food purchase and the three dimensions of food security, using *FA* (food anxiety), *FQ* (food quality), and *FI* (food intake), respectively, as the dependent variables.

Food anxiety *(FA*). Equation (1) of model II (Table 4) shows that three independent variables had a significant relationship with household food anxiety: (i) Physical and economic access: the coefficient of *DPA* is 0.577 with a significance level of 1%, and the coefficient of *DEA* is 0.275 with a significance level of 1%. This indicates that households that experienced difficulties of physical or economic access to food had a higher probability of worrying about their food supply than those that did not. (ii) Housing property rights: the coefficient of *HPR* is −0.359, significant at the 1% level. This indicates that if a household had a self-owned house, they were much more likely not to be anxious about their food supply.

Online food purchasing *(OFP)*. Equation (2) of model II shows that three independent variables had a significant relationship with online food purchasing behavior: (i) Food anxiety: the coefficient of *FA* is 0.314, significant at the 1% level, which suggests that households who worried about their food supply were more likely to obtain food through purchasing food online than households who did not. (ii) Household size: the coefficient of *HS* is −0.059, significant at the 10% level, which indicates that the probability of purchasing food online was higher for smaller than larger households. (iii) Household with pregnant women or infants: the coefficient of *HPI* is 0.354, significant at the 1% level, which implies that households with pregnant women or infants had a higher likelihood of purchasing food online.

Insufficient food quality *(FQ).* In Equation (1) of model III (Table 5), four different independent variables had a significant relationship with household experiencing insufficient food quality: (i) Physical and economic access: the coefficient of the variable *DPA* is 0.692 with a 1% level of significance, and the coefficient of the variable *DEA* is 0.600, significant at the 1% level. This suggests that households that experienced difficulties of physical or economic access to food had a higher probability of experiencing insufficient food quality than those that did not. (ii) Household property rights: the coefficient of *HPR* is −0.385, significant at the 1% level, which implies that households who did not have a self-owned house were more likely to experience insufficient food quality. (iii) Pregnant women or infants: the coefficient of the variable *HPI* is 0.178, significant at the 10% level, meaning that households with pregnant women or infants had a higher likelihood of encountering insufficient food quality.

Online food purchasing (*OFP*). In Equation (2) of model III, four independent variables had a significant relationship with online food purchasing behavior: (i) Food quality: the coefficient of the variable *FQ* is 0.295, significant at the 1% level, which indicates that if a household encountered insufficient food quality, they were more likely to purchase food online. (ii) Economic access: households who had difficulties of economic access to food had a lower likelihood of purchasing food online than those that did not; the coefficient of the variable *DEA* is −0.171, significant at the 10% level. (iii) Household size: the coefficient of the variable *HS* is −0.060 with a 10% level of significance, which again suggests that smaller households were more likely to purchase food online, compared with larger households. (iv) Household with pregnant women or infants: also had a higher probability of online food purchase as the coefficient of the variable *HPI* is 0.355, significant at the 1% level.

Insufficient food intake *(FI*). Equation (1) of model IV (Table 6) shows that three different independent variables had a significant relationship with households experiencing insufficient food intake: (i) Physical food access: the coefficient of the variable *DPA* is 0.626 with a 1% level of significance, which indicates that households that experienced difficulties of physical access were far more likely to encounter insufficient food intake than those that did not. (ii) Household property rights: if a household had a self-owned house, they had higher probability of sufficient food intake as the coefficient of the variable *HPR* is −0.493, significant at the 1% level. (iii) Neighborhood with confirmed cases: the coefficient of the variable *NCC* is 0.389 with a 10% level of significance, which indicates that households who lived in a neighborhood with confirmed cases were far more likely to encounter insufficient food intake than those that did not.

Online food purchasing *(OFP).* In Equation (2) of model IV, three independent variables had a significant relationship with online food purchasing behavior: (i) Food intake: the coefficient of the variable *FI* is 0.304 with a 1% level of significance, which indicates that households who had inadequate food intake were more likely to obtain food by purchasing food online, compared with households who had sufficient food intake. (ii) Economic food access: the coefficient of the variable *DEA* is −0.124, significant at the 10% level, which implies that households that had difficulties of economic food access had a lower probability of obtaining food through online food purchase. (iii) Household size: the coefficient of the variable *HS* is −0.060 with a 5% level of significance, which again suggests that the probability of purchasing food online was higher for small households than large households.

3.3. Robustness Test

As noted above, there is no guide to binning the frequency indicators of Q1–9 into binary yes/no categories. This study recoded *FA*, *FQ*, and *FI* with the recoded variables labeled *FA2*, *FQ2*, and *FI2*, respectively. In other words, (a) when a household's answer to Q1 was "Sometimes" or "Often", the value of *FA2* equals 1, 0 otherwise (including "Never" or "Rarely"); (b) when the answer to Q2–4 was "Sometimes" or "Often", the value of *FQ2* is equal to 1, 0 otherwise (including "Never" or "Rarely"); and (c) when a household answered "Sometimes" or "Often" to Q5–9, the value of *FQ2* is equal to 1, 0 otherwise (including "Never" or "Rarely").

Models II-2, III-2, and IV-2 with the variables *FA2*, *FQ2*, and *FI2* as dependent variables, respectively, are shown in Tables 7–9. The estimated results were used as a robustness check in this study. The relationship between online food purchase and food anxiety and food intake are the same as in models II and IV (Tables 7 and 9). The *p*-value (representing the significance level) of online food purchase and food quality increased, indicating that the relationship between food quality and online food purchasing was not significant. This result demonstrated that household food quality is more sensitive to online food purchasing. Overall, the results support the conclusion that there is a significant relationship between online food purchase and household food insecurity.

Table 3. Estimated results of simultaneous equations: model I.

Equation (1): *HFIAP* as Dependent Variable					Equation (2): *OFP* as Dependent Variable				
Independent Variables	**Coefficient**	**Standard Errors**	**Z-Value**	**95% Confidence Interval**	**Independent Variables**	**Coefficient**	**Standard Errors**	**Z-Value**	**95% Confidence Interval**
OFP	0.284 ***	0.092	3.09	(0.104, 0.465)	*HFIAP*	0.138 ***	0.043	3.42	(0.064, 0.236)
PFGO	−0.038	0.074	−0.51	(−0.182, 0.107)	*DEA*	−0.152	0.098	−1.34	(−0.324, 0.061)
DPA	0.770 ***	0.081	9.56	(0.612, 0.928)	*HS*	−0.061 *	0.033	1.22	(−0.090, 0.387)
DEA	0.254 ***	0.073	3.50	(0.112, 0.397)	*NCC*	0.011	0.244	0.00	(−0.473, 0.475)
HPR	−0.499 ***	0.097	−5.15	(−0.689, −0.309)	*HPI*	0.366 ***	0.118	2.46	(0.056, 0.494)
HT	0.309 *	0.187	1.66	(−0.057, 0.676)	*FSPS*	0.034	0.113	0.26	(−0.191, 0.251)
HS	−0.020	0.027	−0.74	(−0.072, 0.032)					
NCC	0.256	0.181	1.41	(−0.100, 0.611)					
HPI	0.044	0.086	0.51	(−0.125, 0.213)					
Pseudo R^2	0.059				Pseudo R^2	0.024			
Log likelihood	−1225.039				Log likelihood	−468.003			
LR chi-square	154.280 (*p*-value = 0.000)				LR chi-square	20.770 (*p*-value = 0.002)			
Observations	968				Observations	968			

Note: *, **, and *** mean significant at the levels of 10%, 5%, and or 1%, respectively. Source: Authors' own compilation.

Table 4. Estimated results of simultaneous equations: model II.

Equation (1): *FA* as Dependent Variable					Equation (2): *OFP* as Dependent Variable				
Independent Variables	**Coefficient**	**Standard Errors**	**Z-Value**	**95% Confidence Interval**	**Independent Variables**	**Coefficient**	**Standard Errors**	**Z-Value**	**95% Confidence Interval**
OFP	0.332 ***	0.105	3.15	(0.125, 0.538)	*FA*	0.314 ***	0.096	3.28	(0.126, 0.501)
PFGO	0.049	0.086	0.57	(−0.110, 0.216)	*DEA*	−0.146	0.098	−1.49	(−0.330, 0.045)
DPA	0.577 ***	0.089	6.45	(0.401, 0.751)	*HS*	−0.059 *	0.033	−1.78	(−0.120, 0.005)
DEA	0.275 ***	0.085	3.23	(0.108, 0.442)	*NCC*	0.071	0.244	0.29	(−0.400, 0.548)
HPR	−0.359 ***	0.116	−3.09	(−0.580, −0.130)	*HPI*	0.354 ***	0.118	2.99	(0.122, 0.585)
HT	0.260	0.225	1.15	(−0.180, 0.701)	*FSPS*	0.037	0.113	0.32	(−0.180, 0.257)
HS	−0.038	0.031	−1.23	(−0.090, 0.022)					
NCC	−0.197	0.211	−0.93	(−0.610, 0.216)					
HPI	0.162	0.101	1.60	(−0.030, 0.360)					
Pseudo R^2	0.063				Pseudo R^2	0.024			
Log likelihood	−619.274				Log likelihood	−467.798			
LR chi-square	83.6400 (*p*-value = 0.000)				LR chi-square	23.120 (*p*-value = 0.001)			
Observations	968				Observations	968			

Note: *, **, and *** mean significant at the levels of 10%, 5%, and or 1%, respectively. Source: Authors' own compilation.

Table 5. Estimated results of simultaneous equations: model III.

Equation (1): *FQ* as Dependent Variable					Equation (2): *OFP* as Dependent Variable				
Independent Variables	**Coefficient**	**Standard Errors**	**Z-Value**	**95% Confidence Interval**	**Independent Variables**	**Coefficient**	**Standard Errors**	**Z-Value**	**95% Confidence Interval**
OFP	0.297 ***	0.109	2.72	(0.083, 0.510)	*FQ*	0.295 ***	0.101	2.93	(0.097, 0.492)
PFGO	−0.019	0.090	−0.21	(−0.190, 0.157)	*DEA*	−0.171 *	0.100	−1.72	(−0.360, 0.024)
DPA	0.692 ***	0.092	7.53	(0.512, 0.872)	*HS*	−0.060 *	0.033	−1.81	(−0.120, 0.005)
DEA	0.600 ***	0.092	6.54	(0.419, 0.779)	*NCC*	0.030	0.244	0.12	(−0.440, 0.508)
HPR	−0.385 ***	0.125	−3.07	(−0.630, −0.130)	*HPI*	0.355 ***	0.118	3.01	(0.123, 0.586)
HT	0.336	0.247	1.36	(−0.140, 0.820)	*FSPS*	0.039	0.113	0.35	(−0.180, 0.261)
HS	−0.044	0.033	−1.36	(−0.100, 0.019)					
NCC	0.243	0.234	1.04	(−0.210, 0.701)					
HPI	0.178 *	0.108	1.65	(−0.030, 0.389)					
Pseudo R^2	0.107				Pseudo R^2	0.022			
Log likelihood	−552.043				Log likelihood	−468.903			
LR chi-square	132.770 (*p*-value = 0.000)				LR chi-square	20.910 (*p*-value = 0.002)			
Observations	968				Observations	968			

Note: *, **, and *** mean significant at the levels of 10%, 5%, and or 1%, respectively. Source: Authors' own compilation.

Table 6. Estimated results of simultaneous equations: model IV.

Equation (1): *FI* as Dependent Variable					Equation (2): *OFP* as Dependent Variable				
Independent Variables	**Coefficient**	**Standard Errors**	**Z-Value**	**95% Confidence Interval**	**Independent Variables**	**Coefficient**	**Standard Errors**	**Z-Value**	**95% Confidence Interval**
OFP	0.323 ***	0.118	2.74	(0.091, 0.553)	*FI*	0.304 ***	0.109	2.79	(0.090, 0.517)
PFGO	−0.066	0.091	−0.73	(−0.240, 0.112)	*DEA*	−0.124 *	0.097	−1.27	(−0.310, 0.067)
DPA	0.626 ***	0.102	6.15	(0.426, 0.826)	*HS*	−0.060 **	0.033	−1.81	(−0.120, 0.005)
DEA	0.060	0.089	0.68	(−0.110, 0.235)	*NCC*	−0.001	0.242	−0.01	(−0.470, 0.473)
HPR	−0.493 ***	0.114	−4.31	(−0.710, −0.260)	*HPI*	0.373	0.118	3.17	(0.142, 0.604)
HT	0.318	0.219	1.46	(−0.110, 0.747)	*FSPS*	0.070	0.112	0.62	(−0.140, 0.288)
HS	−0.040	0.033	−1.22	(−0.100, 0.024)					
NCC	0.389 *	0.212	1.83	(−0.020, 0.803)					
HPI	−0.035	0.107	−0.33	(−0.240, 0.174)					
Pseudo R^2	0.070				Pseudo R^2	0.021			
Log likelihood	−543.353				Log likelihood	−469.187			
LR chi-square	81.340 (*p*-value = 0.000)				LR chi-square	20.340 (*p*-value = 0.002)			
Observations	968				Observations	968			

Note: *, **, and *** mean significant at the levels of 10%, 5%, and or 1%, respectively. Source: Authors' own compilation.

Table 7. Results of robustness tests of model II.

Equation (1): *FA2* as Dependent Variable					Equation (2): *OFP* as Dependent Variable				
Independent Variables	**Coefficient**	**Standard Errors**	**Z-Value**	**95% Confidence Interval**	**Independent Variables**	**Coefficient**	**Standard Errors**	**Z-Value**	**95% Confidence Interval**
OFP	0.283 **	0.120	2.36	(0.047, 0.517)	*HFIAP*	0.281 **	0.114	2.48	(0.058, 0.503)
PFGO	−0.142	0.093	−1.52	(−0.320, 0.040)	*DEA*	−0.140	0.098	−1.43	(−0.330, 0.051)
DPA	0.671 ***	0.106	6.32	(0.463, 0.879)	*HS*	−0.065	0.033	−1.96	(−0.120, −0.000)
DEA	0.345 ***	0.090	3.81	(0.167, 0.522)	*NCC*	0.046	0.244	0.19	(−0.43, 0.524)
HPR	−0.238 **	0.118	−2.02	(−0.460, −0.000)	*HPI*	0.355 **	0.118	3.01	(0.123, 0.585)
HT	0.438 **	0.218	2.00	(0.009, 0.866)	*FSPS*	0.050 ***	0.113	0.45	(−0.170, 0.271)
HS	−0.009	0.033	−0.27	(−0.070, 0.056)					
NCC	0.074	0.224	0.33	(−0.360, 0.511)					
HPI	0.168	0.107	1.57	(−0.04, 0.377)					
Pseudo R^2		0.070			Pseudo R^2		0.020		
Log likelihood		−522.128			Log likelihood		−470.029		
LR chi-square		78.190 (*p*-value = 0.000)			LR chi-square		18.660 (*p*-value = 0.005)		
Observations		968			Observations		968		

Note: *, **, and *** mean significant at the levels of 10%, 5%, and or 1%, respectively. Source: Authors' own compilation.

Table 8. Results of robustness tests of model III.

Equation (1): *FQ2* as Dependent Variable					Equation (2): *OFP* as Dependent Variable				
Independent Variables	**Coefficient**	**Standard Errors**	**Z-Value**	**95% Confidence Interval**	**Independent Variables**	**Coefficient**	**Standard Errors**	**Z-Value**	**95% Confidence Interval**
OFP	0.068	0.112	0.61	(−0.15, 0.287)	*HFIAP*	0.084	0.103	0.82	(−0.11, 0.285)
PFGO	−0.036	0.089	−0.41	(−0.21, 0.138)	*DEA*	−0.127	0.099	−1.28	(−0.31, 0.066)
DPA	0.888 ***	0.102	8.7	(0.688, 1.088)	*HS*	−0.065 **	0.033	−1.99	(−0.13, −0.00)
DEA	0.487 ***	0.088	5.55	(0.315, 0.658)	*NCC*	0.040	0.243	0.16	(−0.43, 0.515)
HPR	−0.150	0.116	−1.29	(−0.37, 0.077)	*HPI*	0.364 ***	0.117	3.1	(0.133, 0.593)
HT	0.330	0.222	1.49	(−0.10, 0.764)	*FSPS*	0.072	0.113	0.64	(−0.14, 0.294)
HS	0.003	0.032	0.08	(−0.06, 0.065)					
NCC	0.282	0.212	1.33	(−0.13, 0.696)					
HPI	0.012	0.105	0.11	(−0.19, 0.217)					
Pseudo R^2		0.098			Pseudo R^2		0.014		
Log likelihood		−564.785			Log likelihood		−472.846		
LR chi-square		122.890 (*p*-value = 0.000)			LR chi-square		13.020 (*p*-value = 0.043)		
Observations		968			Observations		968		

Note: *, **, and *** mean significant at the levels of 10%, 5%, and or 1%, respectively. Source: Authors' own compilation.

Table 9. Results of robustness tests of model IV.

Equation (1): *FI2* as Dependent Variable					Equation (2): *OFP* as Dependent Variable				
Independent Variables	**Coefficient**	**Standard Errors**	**Z-Value**	**95% Confidence Interval**	**Independent Variables**	**Coefficient**	**Standard Errors**	**Z-Value**	**95% Confidence Interval**
OFP	0.448 ***	0.173	2.58	(0.107, 0.787)	*HFIAP*	0.482 ***	0.181	2.66	(0.127, 0.836)
PFGO	−0.107	0.120	−0.89	(−0.34, 0.128)	*DEA*	−0.110	0.098	−1.13	(−0.30, 0.081)
DPA	0.938 ***	0.172	5.44	(0.600, 1.276)	*HS*	−0.063 *	0.033	−1.9	(−0.12, 0.001)
DEA	−0.029	0.117	−0.25	(−0.25, 0.200)	*NCC*	0.019	0.244	0.08	(−0.45, 0.497)
HPR	−0.225	0.145	−1.55	(−0.50, 0.059)	*HPI*	0.375 ***	0.118	3.18	(0.143, 0.606)
HT	0.428	0.258	1.66	(−0.07, 0.933)	*FSPS*	0.065	0.112	0.57	(−0.15, 0.284)
HS	−0.023	0.041	−0.58	(−0.10, 0.056)					
NCC	0.315	0.253	1.25	(−0.17, 0.810)					
HPI	−0.124	0.142	−0.87	(0.107, 0.787)					
Pseudo R^2		0.090			Pseudo R^2		0.021		
Log likelihood		−294.675			Log likelihood		−469.284		
LR chi-square		58.270 (*p*-value = 0.000)			LR chi-square		20.150 (*p*-value = 0.021)		
Observations		968			Observations		968		

Note: *, **, and *** mean significant at the levels of 10%, 5%, and or 1%, respectively. Source: Authors' own compilation.

4. Discussion

Prior to the pandemic, around 20% of households in Nanjing shopped online for food. However, in the month prior to this survey, as many as 80% of households bought food online. Not only was this a dramatic increase in the overall use of online platforms, but also the types of foods purchased online diversified to include fresh produce, dairy, and processed foods other than junk food [66]. The technological preconditions for the surge in online purchasing were laid before the pandemic began and provided a good foundation for food e-commerce to dramatically grow and become highly popular [67]. When households had difficulties in obtaining food during the pandemic period, finding alternative options became the top priority. Online food purchase undoubtedly became the best alternative for ordinary households due to its convenience and widespread availability. Previous studies have also confirmed that the online ordering and delivery services guaranteed residents' demand for fruits and dairy products [66]. In this paper, we aimed to provide greater insights into the reasons for the surge in online food purchasing and its relationship with food insecurity in a city that did not experience a complete lockdown, such as in neighboring Wuhan, but still experienced major disruption of everyday life and food accessibility.

Online food purchase provided an alternative means for people to access food, and greatly reduced the impact of restrictions on physical food access caused by wet market closure and lockdown measures. New users included the middle-aged and elderly who had previously avoided online platforms [68]. Businesses offering e-commerce platforms grew quickly during the pandemic period as well. The year-on-year growth rate of fresh e-commerce in China was nearly 90% in January 2020 and increased quickly to 140% in April 2020 [68]. Not surprisingly, therefore, the growth of consumers buying online in Nanjing rose rapidly. In 2015, only 17% of households shopped for food online [48]. During the weeks of the COVID-19 pandemic, 80% of households surveyed had shopped online, a dramatic increase.

In view of the high transmission rates and susceptibility of humans to COVID-19, all levels of government in China, including central, provincial, prefectural, county, and township levels, enacted emergency responses. In a city region, such as Nanjing, there are municipal government (prefectural level), district governments (county level), and subdistrict offices (township level). The Nanjing municipal government took immediate emergency measures to reduce the spread of the virus by initially closing public places. Wet markets had to close and disinfect because they are confined indoor spaces with a large throughflow of people. On 30 January 2020, 159 wet markets were in operation, about half of the total number in the city [69]. By 12 February, only 10% of the wet markets were still closed [70]. The immediate closure and gradual reopening of wet markets reduced the high degree of access usually enjoyed by residents of the city and therefore threatened to temporarily increase food insecurity. While most households surveyed had been able to purchase food at physical outlets, such as wet markets, during the pandemic, restrictions on movement meant that they could no longer purchase fresh food at wet markets on a daily basis, a situation that encouraged online food purchase.

After the "stay at home" order was issued by the local government in Nanjing, some neighborhoods implemented partial lockdown measures, which only allowed residents to go out for purchasing essential needs. Others imposed complete lockdowns, and did not allow residents to exit or re-enter. Only 25% of surveyed households reported not experiencing any form of lockdown. Of the other three-quarters, 56% had experienced partial lockdown measures, 13% of households were completely locked down, and 6% of households experienced both complete and partial lockdown measures. Households under complete lockdown were more likely to buy online, but many partial lockdown households also did so, particularly as they were not permitted to go out and shop as they had been able to do prior to the order.

Due to the social distancing and lockdown measures, food access is one of the crucial factors affecting household food insecurity. Challenges related to physical access to food outlets led to increased household food insecurity during the COVID-19 epidemic period. Additionally, increased food insecurity raised the likelihood of online food purchase. Equation (1) of models I, II, III, and IV all provide confirmation of this observation. The estimated coefficients of the physical food access variable (*DPA*) demonstrated that the difficulties of physical access had a statistically significant relationship with household food insecurity, including all three food security domains. The coefficients of the HFIAP, food anxiety variable (*FA*), food quality variable (*FQ*), and food quantity variable (*FI*), are all significantly positive in Equation (2) of models I, II, III, and IV.

The number of people patronizing wet markets and supermarkets on a frequent basis dropped because of lockdown restrictions and also because of fear of infection. While these retail outlets instituted PPE, social distancing, and capacity limit requirements, customers still worried about long and dangerous queues and face-to-face contact in confined spaces. Meanwhile, the survey data showed that 96% of interviewees or their households had not had PCR tests. Insufficient capacity and limited testing in the early period of the COVID-19 outbreak of 2020 also discouraged people from leaving their residential neighborhoods. Online food purchasing and contactless delivery became popular because they greatly reduced the risk of infection through face-to-face contact.

Prior to COVID-19, Nanjing residents experienced a very high degree of food security. As our survey suggests, the levels of household food security dropped sharply during the pandemic. This was true on all dimensions of food security, including anxiety over the food supply, the quality and diversity of food, and the quantity of food consumed. The HFIAP metric allowed us to distinguish four different types of food security ranging from completely food secure to severely food insecure. One of the most unanticipated findings from the survey was that as the level of food insecurity increased, so did the prevalence of online food purchasing.

The analysis in this paper consistently identified household variables that had a strong relationship with online food purchasing. In addition to challenges with physical access to food outlets as discussed above, these included challenges with economic access to food, household size, and households with pregnant women and/or infants. Our expectation was that there would be a strong correlation between food security and online food purchasing. However, the reverse seems to have been the case. Equation (1) of models I, II, III, and IV demonstrate that the HFIAP, food anxiety, food quality, and food intake all had a statistically significant relationship with online food purchasing as the coefficients of the online food purchasing variable (*OFP)* are strongly positive. Although online food purchasing became an important alternative way to source food, it did not completely offset the insufficiency caused by decreased physical access to food and deteriorating food quality. While there are no grounds for positing a causal relationship that online purchasing increased food insecurity, more food-insecure households had higher levels of online patronage. This suggests that the levels of food insecurity might have been considerably higher, absent the option of online food purchasing. The fact that the levels of online food purchasing increased with increasing food insecurity is still something of a paradox.

Insights into this paradoxical relationship are provided by other household responses to the survey around online food shopping, including rising prices, insufficient variety, inadequate quantity, delayed delivery, and reduced freshness of food. The most significant problem with online food purchasing identified as a challenge by the greatest number of respondents was the increase in food prices that accompanied online shopping (cited by 33% of households). The pressure of rising prices was exacerbated by the impact on household income from stay-at-home orders and lockdowns, which prevented many people from getting to work. The increased financial burden of food shopping online was certainly not unique to Nanjing or China [71,72]. In addition, increased online food prices were more likely to more negatively impact lower-income households and increase their vulnerability to food insecurity.

Nearly 20% of online purchase consumers in Nanjing found that the variety and quantity of food in online stores were insufficient. Prior to the pandemic, the online food purchase system mainly focused on the supply of cooked food and snacks, but during the pandemic with reduced access to wet markets and supermarkets, the main demand was for fresh fruit and vegetables [20]. Food freshness is a primary concern of Chinese consumers when shopping for vegetables and meats, and buying food that is as fresh as possible is an everyday pursuit [73]. The supply of fresh fruits and vegetables to Nanjing was certainly disrupted by the initial closure of wet markets, transportation challenges, and labor shortages. These challenges also affected the freshness of food that did come into the city.

Online food supply and delivery platforms were faced with the challenge of quickly pivoting to meet the new online demand for fresh produce. Figure 3 suggests that they were relatively successful, although 15% of respondents complained that online produce was not fresh, which may have had as much to do with delivery challenges faced by the companies. Nearly 10% of online food purchasing households reported that they were dissatisfied with online food delivery, many of whom were the same households complaining about the lack of freshness.

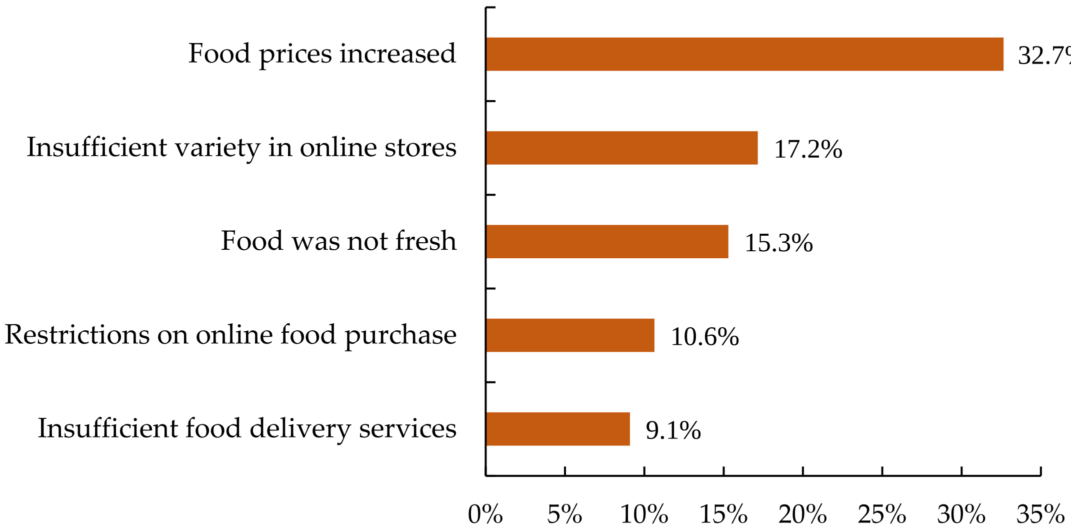


Figure 3. Problems of online food purchase during the pandemic period. Source: Authors' own compilation.

5. Conclusions

As a burgeoning method of purchasing food in China, online platforms were already starting to play a growing role in the daily lives of urban residents prior to COVID-19 particularly for ordering cooked and snack food. As a result, the IT infrastructure was in place for a rapid pivot by many consumers facing the disruption of their established food sourcing behaviors as a result of public health restrictions on their everyday mobility. Because online food purchasing could help people avoid large gatherings and reduce the risk of virus transmission by reducing contact, it became an attractive emergency pandemic response promoted by the government and e-commerce companies and adopted by many local consumers.

A number of studies examining the connections between pandemic restrictions and online food purchasing elsewhere have suggested that the pre-pandemic profile of consumers most likely to patronize online platforms quickly changed during the pandemic to include a sizable section of the population particularly in countries with high levels of digital literacy and ready access to the Internet [14,19,38,57]. This case study of changing patterns of online usage during the early months of the pandemic is the first to examine the shift to online food purchasing in the city of Nanjing. As we have shown, stay-at-home orders and partial and complete residential lockdowns, as well as the initial closure of wet markets, induced the vast majority of surveyed households to turn to online food purchase for their daily food needs. In turn, e-commerce platforms were quickly incentivized to greatly expand the range of foodstuffs that they offered including, for the first time, fresh produce.

This is the first study we know of to systematically examine the relationship between the dramatic escalation in online food purchasing and household food insecurity occasioned by sudden and dramatic restrictions on mobility, reduced access to physical outlets, and minimizing the risk of infection through personal contact [74]. Prior to the pandemic, the levels of food insecurity in Nanjing were low and a thing of the distant past for most households. The public–private city food system was functioning so effectively that food shortages and food insecurity were almost nonexistent. The sudden shock from COVID-19 public health mitigation measures threatened to precipitate an avalanche of daily hunger and food insecurity. Household anxiety about food supply reached unprecedented levels as they scrambled to access and stockpile food. Online ordering quickly became a vehicle for quick and easy stockpiling and a longer-term solution to meeting daily dietary needs especially for fresh produce and the special food needs of pregnant women and infants.

To examine the online food purchasing and food insecurity nexus with greater precision, our online survey of a large and diverse sample of Nanjing households conducted in February 2020 included questions on food sourcing behavior during the pandemic, as well as robust metrics for quantifying the experience of food insecurity and coping behaviors. These measures focus on three aspects of food insecurity: anxiety about the household food supply, decreased dietary quality, and changes in food intake as a result of absolute shortages. We found that all three had increased in intensity from a baseline established by a pre-pandemic survey but that the increase was uneven. For example, a decreased quality of food intake was the most seriously affected, while a negative change in the amount of food consumed was the least affected. Given that most households were restricted in accessing their normal sources—wet markets and supermarkets—and the fact that four in five households had ordered food online during the pandemic, it is reasonable to conclude that one of the primary reasons for the lower impact on dietary intake was the ability of many households to pivot to online ordering. At the same time, it is clear that online food purchase was especially important to certain households, including, somewhat paradoxically, those that were more food insecure.

To try to resolve this seeming contradiction, and the complex causal connections implied, the paper uses simultaneous equation models to solve the endogenous problem of the mutual effect between online food purchase and household food security. The analysis shows that despite their greater reliance on online purchasing, food-insecure households were primarily affected by negative experiences of dietary quality. This means, in effect, that online food purchase mainly played a role in reducing the decline in food intake caused by wet market closures and mobility restrictions, but the e-commerce platforms experienced problems in delivering a sufficient variety of food, containing rising food prices, and expanding delivery. While many providers did pivot to providing fresh produce, online food shopping provided only a partial fix and online food shopping was both a boon and a bane, better at addressing some dimensions of food insecurity than others.

The pandemic has focused attention on whether central and local emergency preparedness were adequate to deal with the shock of COVID-19 and how they should be refined going forward. In this context, the primary policy-related lesson to draw from the expansion in online food experience during COVID-19 is that it played a central role in ensuring that the population did not go hungry even if there were concerns about the quality of the food and the speed of delivery. This means that online food purchasing and delivery need to be integrated into the food emergency planning system. Specifically, this means developing contingency food transportation and distribution planning based on O2O food delivery networks in order to distribute food when physical stores are required to close. A second implication is that greater attention needs to be given to monitoring and improving the quality of food that is purchased online. Nanjing has rigorous food safety standards in its wholesale and wet markets, and attention needs to be given to ensuring that these are also applied to the online food industry to maintain consumer confidence and to ensure that the quality does not decline during emergencies. Finally, the government should consider subsidies for online food purchase during future emergencies to control food price increases and household expenditure on necessary food purchase, thereby reducing the threat to household food security.

The most important question for further research emerging from this study is whether the surge in online food purchasing during the pandemic was a temporary phenomenon or whether it has accelerated the growth trend of the online food market in Nanjing and China more generally. Even though China's zero-COVID policies allowed the population to return to a more normal existence much faster than in many other countries, vendors in wet markets and stores that sell fruits and vegetables have applied to participate in Meituan and Eleme, and the share of fresh food delivered to consumers has continued to increase. Taobao, Jingdong, and other mainstream e-commerce platforms have also launched food delivery platforms. The innovation and experimentation of these commercial giants in the online food ordering and delivery industry suggest that the market has huge development potential and is likely to challenge the traditional food retail market in the future.

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