The COVID-19 Pandemic and Consumption of Food away from Home: Evidence from High-frequency Restaurant Transaction Data

Chen Zhu, Rigoberto A. Lopez, Yuan Gao, Xiaoou Liu*

Abstract

This article investigates how the COVID-19 pandemic and related public health measures affected the consumption of food away from home (FAFH) among Chinese consumers. We obtained access to the complete sales records from a major restaurant chain in China, for 111 sites located in 12 cities, covering over 5.6 million high-frequency dining transactions made between 1 January 2019 and 31 December 2020. By applying a high-dimensional fixed-effects model, we found that, on average, consumers spent more and ordered more calories (as well as carbohydrates, protein, fat, and sodium) after the COVID-19 outbreak than in the pre-COVID-19 period. Our results do not support the hypothesis that COVID-19 led to healthier eating behaviors during and after the pandemic. Our results underline the importance of nutrition education and awareness programs to mitigate unhealthy eating habits generated by the pandemic and of the continued role of FAFH after the pandemic.

Keywords: COVID-19, food-away-from-home, food consumption, government stringency, nutritional intake

JEL codes: D12, H00, Q18

I. Introduction

According to the World Health Organization (2021), the COVID-19 pandemic has resulted in an excess of 119,000 confirmed cases of illness in China and over 241 million

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cases globally. In response to the rapid spread of COVID-19 across the country in early 2020, the Chinese government implemented a series of containment strategies, using the Emergency Response Law of the People’s Republic of China, and effectively mitigated the negative health effects of the pandemic (Liu et al., 2020). These prevention and control measures, which included lockdowns, travel restrictions, and shutdowns of nonessential businesses, in combination with the direct health impacts of coronavirus, have strongly affected not only the national and global economy but also people’s everyday lifestyles and habits (Chetty et al., 2020; Fezzi and Fanghella, 2020).

Regarding food systems, a growing body of literature has examined the immediate negative impacts of COVID-19 on the food supply and food security (Hobbs, 2020; Laborde et al., 2020; O’Hara and Toussaint, 2021) as the COVID-19 outbreak and economic shutdowns have greatly disrupted both agricultural production and logistics systems (Elleby et al., 2020; Singh et al., 2020). For example, Pu and Zhong (2020) show that COVID-19 has disrupted agricultural production and has undermined production capacity in China. On the food demand side, several studies have documented consumers’ panic buying and stockpiling behaviors, which occurred in many countries immediately after the COVID-19 outbreak (Martin-Neuninger and Ruby, 2020; Kassas and Nayga, 2021). However, given that the prevention and control of COVID-19 have become the new normal state that will persist for months, even years, there is a lack of knowledge of how COVID-19 and related public health measures affect consumers’ food consumption and dietary patterns, particularly with regard to food away from home (FAFH).

This study focuses on consumers, a crucial component and the end of the food supply chain, and investigates their food spending and consumption responses to the COVID-19 outbreak. Specifically, we examine the impact of the pandemic’s severity (measured by daily new confirmed COVID-19 cases) and government stringency (measured by different levels of public health emergency controls) on 5.6 million consumer food purchases at restaurants in 12 cities in China. Thus, the focus of this study is on urban settings, which account for an important share of total food expenditure in China (Liu et al., 2015). For example, in 2019, households in Beijing spent an average of 27.8 percent of their total food expenses on FAFH. In China, the pandemic came under control in March 2020, thus providing a useful case study of what to expect in countries that have not yet reached this phase.

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1 More than half of the global population resides in urban areas where FAFH is more prevalent.
2 See [http://m.cqn.com.cn/cj/content/2019-04/19/content_7026563.htm](http://m.cqn.com.cn/cj/content/2019-04/19/content_7026563.htm) (online; cited April 2020) and [http://beijing.qianlong.com/2019/0718/3366481.shtml](http://beijing.qianlong.com/2019/0718/3366481.shtml) (online; cited October 2020) for more details.
By investigating changes in consumption of individual nutrients, such as calories, protein, and fat, due to the COVID-19 crisis, our analysis also has implications for diet quality and human health. Although anecdotal evidence suggests that lockdowns may lead to a healthier diet in certain populations right after a COVID-19 outbreak (Di Renzo et al., 2020; Hassen et al., 2020; Snuggs and McGregor, 2021), scant evidence exists regarding the impact of COVID-19 on dietary patterns in the context of China. To the best of our knowledge, this is the first study that uses proprietary, nonpublic data to document the effects of COVID-19 and related control measures on food spending, consumption, and diet quality.

We consider FAFH consumption decisions as consisting of two strata of decision making. Consumers first decide whether to dine out and then make choices about how much to spend and what to eat (i.e. diet quality, including calories and nutrients to consume). Empirical results show that, at the restaurant level, COVID-19 is associated with declines in the daily total number of orders, customers, and total revenue. However, for people who chose to dine out, the average amount spent on food at restaurants on a per capita basis actually rose after the outbreak of COVID-19, driven by increases in food ordered rather than increases in food prices. Moreover, consumers were found consistently to order more calories, carbohydrates, protein, fat, and sodium after the shock of COVID-19, even when prevention and control measures became a new normal state. These findings suggest a potential overeating habit due to the shock of COVID-19 and a negative association between COVID-19 and diet quality in the urban Chinese population.

This article provides a useful case study of how COVID-19 affects consumer decisions about FAFH consumption. In China, as in the US and other countries, FAFH has become an important component of food consumption. In 2019, Chinese consumer restaurant spending grew at the rate of 10 percent and reached over 55 percent of total food spending (China Catering Industry Association, 2019; China National Bureau of Statistics, 2019). Since the beginning of 2020, the catering industry has been experiencing unprecedented challenges from the COVID-19 pandemic. In the first quarter of 2020, the revenue of the catering industry in China dropped by RMB602 billion – about 44.3 percent of revenues received during the same period in 2019. The China National Bureau of Statistics (2020) showed that the total revenue of the catering industry was around RMB3.9 trillion in 2020, only 83.4 percent of the 2019 revenue. Estimating the impact of COVID-19 on FAFH consumption provides an insight into the overall impact of COVID-19 on food markets.

The remainder of this article is organized as follows. Section II presents an intertemporal model to explain consumers’ food consumption behavior under various
scenarios of public health shocks that may trigger food consumption changes. Section III summarizes the data and provides descriptive analyses of dining-out activities before and after the COVID-19 outbreak. Section IV details our empirical methods and discusses potential sources of selection bias. Section V presents the estimation results and discusses possible explanations. Section VI concludes with important results, policy implications, limitations, and suggestions for further research.

II. Conceptual analysis

In this section, we provide a conceptual analysis of changes in consumer behavior concerning food consumption and nutrition quality under an external shock induced by the pandemic, which increased fear and anxiety. This analysis leads to some hypotheses that will be tested empirically in the following sections.

Why might people eat more and unhealthier after the COVID-19 outbreak? The work of Davis et al. (2004) provides an explanation for the increased consumption of food and overeating behavior after the outbreak of COVID-19, based on the brain mechanism of the reward system. Eating, like many pleasurable activities, can trigger the release of dopamine, a feel-good transmitter, in the brain. This internal chemical reward, in turn, increases the likelihood that the associated action will eventually become a habit through positive re-enforcement conditioning. As COVID-19 brings about fear and uncertainty, consumers may choose to overeat, exceeding their basic energy requirements to alleviate their stress.

To link consumers’ diet healthfulness to pandemic-initiated stress and fear more effectively, we built a formal intertemporal model consisting of four parts: hedonic utility, health-related expected utility, a time preference parameter weighting hedonic utility and health-related expected utility, and a subjective probability of individuals’ belief about the true relation between health-related utility and diet (Gao et al., 2021). Consider individuals who decide what to eat. Let \( x \) denote the healthiness of their diet, which reflects the nutritional contents from eating. Assume that \( x > x' \), which indicates \( x \) being “healthier” than \( x' \).

Suppose the individual decides over two time stages, 0 and 1. At time 0, consumers obtain an experienced utility \( v(x) \) from consuming the nutritional intake \( x \). The experienced utility \( v(x) \) measures the hedonic quality gained from eating. The choice of \( x \) at time 0 will also influence the individual’s health-related utility, \( u(x) \), at time 1. Assume that the individual shows two kinds of subjective beliefs about the true relationship between health-related utility and nutrition intake: (1) health-related utility is equal to \( u_1(x) \) and not correlated with nutrient intake; and (2) health-related utility
The optimal choices of nutrition intake are given by maximizing the following equation:

$$\max \ v(x) + \delta \mathbb{E}_p u(x),$$

(1)

$\mathbb{E}_p u(x)$ is the individual’s expected health-related utility and can be rewritten as:

$$\mathbb{E}_p u(x) = (1 - p)u_1(x) + pu_2(x),$$

(2)

$\delta \in [0,1]$ is the individual’s time preferences about discounting the future health-related utility. When $\delta$ becomes larger, it means that the individual gives more weight to the health-related utility $u(x)$ in the future. Combining Equations (1) and (2), the optimization problem can be rewritten as:

$$\max \ v(x) + \delta(1 - p)u_1(x) + \delta pu_2(x),$$

(3)

The solution to Equation (3) is based on the two assumptions. First, the hedonic utility from eating, $v(x)$, is assumed to be a decreasing function with nutrition intake $x$, because the literature of diet and health economics has shown that “unhealthy” food with higher levels of sugar and fat can increase the hedonic experience for consumers. To be a valid utility function, we further assume that $v' < 0$ and $v'' > 0$. The second assumption states that when $x$ approaches the left boundary of its domain – that is, when the diet becomes extremely unhealthy, the individuals will benefit significantly if they eat more healthily. That is, when the individual eats extremely unhealthily, the increase in marginal health-related utility of $u(x)$ is greater than marginal hedonic utility $v(x)$ if the individuals choose to eat healthier, and vice versa. Based on the two assumptions, we can derive the first order condition of Equation (3) as

$$v'(x^*) + \delta pu'_2(x^*) = 0,$$

(4)

with $x^*$ being the optimal nutrient intake level.

The comparative static analysis for the first order conditions in Equation (4) shows that when $\delta$ becomes smaller, the individual places more weight on the hedonic utility rather than the future health-related utility. In this way, the individuals’ optimal choice of nutrition intake $x^*$ becomes smaller because $-v'$ increases more quickly than $\delta pu'_2$.

During the COVID-19 pandemic, the pandemic-initiated stress and fear of being infected could affect individuals’ time preference, as studies in both psychology and behavioral economics have shown that individuals experiencing stress and fear tend to value an immediately realized utility more than a later one. It has also been reported in
health economics that stress induced by economic insecurity triggers unhealthy eating behavior, such as increasing sugar intake. These facts suggest that the COVID-19 outbreak could have caused a negative shock on the individuals’ time preferences, and shifted $\delta$ to a smaller $\tilde{\delta}$, indicating that individuals become more focused on immediate hedonic utility rather than health-related utility in the future, implying that the pandemic contributed to the observed trend of unhealthier eating.

III. Data

To operationalize some of the hypotheses raised in the preceding section, we used four main datasets. The first was the complete sales data of over 5.6 million observations made in 2019 and 2020 provided by a major restaurant chain in China. The second was the nutritional data for each dish, which could be merged with each transaction made in the restaurant. The third dataset was the publicly available number of newly confirmed COVID-19 cases at the city, province, and national levels. The fourth was the local-level public health emergencies data of each province (including cities) during the sample period.

1. Transaction data

The high-frequency dining transaction data we used was obtained from a major restaurant chain in China. The full dataset contained the complete sales records of 5.6 million orders from 111 sites, located in 12 cities, made from 1 January 2019 to 31 December 2020. On average, each restaurant had around 125 seats, with the average size of the dining area being around 3,837 square feet, and the locations of these restaurants reached a potential market of 140 million people. Table 1 lists the number of restaurant sites and the total number of orders in each city. The annual sales of the restaurant chain totaled RMB944 million in 2019 and RMB759 million in 2020, during which time the COVID-19 outbreak led to a reduction in annual revenue of around 19.6 percent.

For each order, we had a unique bill ID, the precise ordering/checkout time (year/month/day/hour/minute/second), the number of people in the dining group, the name and price of each dish ordered, and the total amount spent. The menus and dishes provided are identical across different cities and restaurant sites. The restaurant chain has received good ratings for taste (scoring about 4.6 out of 5.0 in Dianping, a leading lifestyle information app, for individual restaurants), is medium in price, and is popular mainly for leisure rather than business dining. Table 2 provides the basic descriptive statistics of the

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3The restaurant and city names are anonymous in this analysis due to restrictions on data use.
order data (mean values and standard deviations). From column (1), on average, the size of a dining party is 2.4 customers; they spend RMB100.3 per person and 55.3 minutes for a meal in the restaurant. Columns (3)–(6) of Table 2 further compare descriptive statistics between 2019 and 2020. Compared with 2019, the size of a dining party in 2020 remained stable, but customers, on average, spent 4.5 minutes less eating a meal in 2020.

Table 1. Distribution of sites and orders by city

| City (include provincial-level municipality) | Number of sites | Number of orders | Level I response execution date | Level II response execution date | Level III response execution date |
|---------------------------------------------|-----------------|------------------|---------------------------------|----------------------------------|----------------------------------|
| A Beijing                                   | 50              | 2,679,312        | 24 Jan 2020                     | 30 Apr 2020                      | 6 Jun 2020                       |
| B Shanghai                                  | 28              | 1,247,364        | 24 Jan 2020                     | 24 Mar 2020                      | 9 May 2020                       |
| C Guangdong                                 | 10              | 398,255          | 23 Jan 2020                     | 24 Feb 2020                      | 9 May 2020                       |
| D Hubei                                     | 4               | 256,663          | 24 Jan 2020                     | 2 May 2020                       | 13 Jun 2020                      |
| E Jiangsu                                   | 4               | 238,636          | 24 Jan 2020                     | 24 Feb 2020                      | 27 Mar 2020                      |
| F Sichuan                                   | 4               | 168,428          | 24 Jan 2020                     | 26 Feb 2020                      | 25 Mar 2020                      |
| G Shaanxi                                   | 2               | 126,902          | 24 Jan 2020                     | -                               | 28 Feb 2020                      |
| H Guangdong                                 | 2               | 118,300          | 23 Jan 2020                     | 24 Feb 2020                      | 9 May 2020                       |
| I Tianjin                                   | 2               | 99,338           | 24 Jan 2020                     | 30 Apr 2020                      | 6 Jun 2020                       |
| J Anhui                                     | 2               | 87,347           | 24 Jan 2020                     | 25 Feb 2020                      | 15 Mar 2020                      |
| K Zhejiang                                  | 2               | 84,052           | 23 Jan 2020                     | 2 Mar 2020                       | 23 Mar 2020                      |
| L Hebei                                     | 1               | 65,555           | 24 Jan 2020                     | 30 Apr 2020                      | 6 Jun 2020                       |
| **Total**                                   | **111**         | **5,570,152**    | -                               | -                               | -                                |

Source: Authors’ collection and calculation.

Table 2. Mean values and standard deviations of major order attributes

| Variable                                              | All 2019 | All 2020 |
|-------------------------------------------------------|----------|----------|
|                                                      | (1) Mean | (2) Standard deviation | (3) Mean | (4) Standard deviation | (5) Mean | (6) Standard deviation |
| Meal duration (in minute)                             | 55.3     | 36.4     | 57.1     | 37.5     | 52.6     | 34.6     |
| Size of party                                        | 2.4      | 1.2      | 2.4      | 1.2      | 2.4      | 1.2      |
| Per person spending (in RMB)                         | 100.3    | 67.1     | 99.8     | 73.6     | 100.7    | 62.2     |
| Per person calories ordered                          | 1,453.0  | 842.3    | 1,399.9  | 922.1    | 1,489.8  | 780.0    |
| Per person carbohydrate ordered (gram)              | 106.7    | 75.9     | 99.8     | 79.5     | 111.4    | 72.9     |
| Per person protein ordered (gram)                    | 84.1     | 59.9     | 82.9     | 64.1     | 84.8     | 56.9     |
| Per person fat ordered (gram)                        | 82.9     | 55.0     | 79.9     | 60.0     | 85.0     | 51.1     |
| Per person sodium ordered (milligram)                | 2,538.9  | 2,513.0  | 2.3      | 2.4      | 2.7      | 2.5      |
| City-level newly confirmed COVID-19 cases            | 0.5      | 2.4      | 0        | 0        | 1.3      | 3.7      |
| Country-level newly confirmed COVID-19 cases (exclude city-level case) | 34.4      | 123.8      | 0        | 0        | 84.1      | 182.4      |

Source: Authors’ calculation.
2. Nutrition data
To understand better how individual food preferences and intake were affected by the pandemic, it is essential to acquire detailed nutritional information on each dish, which can then be summed up by meal. However, nutrition facts or calorie counts are normally not provided on the menu or in the restaurant, partially due to the complexity of authentic Chinese cuisine. Fortunately, we obtained detailed data on the ingredients and precise amounts used in each dish directly from the restaurant-chain administrator. This allowed us to match each ingredient with the nutritional data and compute the total calories as well as the carbohydrate/protein/fat/sodium ordered in each dish, and to sum these data by order. As reported in Table 2, an average customer ordered 1,453 calories, 107g of carbohydrate, 84g of protein, 83g of fat, and 2,539mg of sodium per meal. The 2016 Dietary Guidelines for Chinese Residents recommend that adults’ daily salt intake should not exceed 6g (≈ 2,362 mg of sodium), and daily cooking oil intake should be 25–30g (Wang et al., 2016). Table 2 reveals that the fat and sodium ordered per person in a meal exceeded the daily recommended values, suggesting an unhealthy eating pattern when dining out. Compared with 2019, customers on average ordered more calories, as well as more carbohydrate/protein/fat/sodium, in 2020.

3. COVID-19 data
We used the number of daily confirmed new infections to measure COVID-19 case counts at both the country and city levels, collected from the National Health Commission of the People’s Republic of China and the Chinese Center for Disease Control and Prevention websites. A positive COVID-19 case is defined as a patient who tested positive in nucleic acid tests and showed lung infection through computerized tomography scans the previous day. We exclude new infections among international travelers because our sampled city governments have required travelers to undergo centralized quarantine since early March of 2020, and these cases are unlikely to impact individuals’ diet decisions. Figure 1 provides a graph of the time trends of the country-level daily confirmed COVID-19 cases over the sample period. The time trend of newly confirmed cases shows that the major outbreak occurred at the end of January 2020, with a few minor local outbreaks in March and July 2020. New infections usually declined a few days after the outbreaks, reflecting the response of increased government stringency. In the estimates, we used both the city-level and country-level daily counts

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4 See http://2019ncov.chinacdc.cn/2019-nCoV/ (online; cited March 2020) and http://www.nhc.gov.cn/xcs/yqtb/list_gzbd.shtml (online; cited March 2020) for more details.
of newly confirmed cases to capture consumers’ reactions to the severity of COVID-19 at different scales.

Figure 1. Daily confirmed COVID-19 cases in China in 2020

Source: Restaurant transaction dataset.

4. Controls for levels of public health emergency

According to the Emergency Response Law of the People’s Republic of China and the Overall State Contingency Plans for Public Emergencies, the COVID-19 outbreak constituted a public health emergency.\(^5\) During the sample period, the response levels to COVID-19 ranged (with decreasing severity) from Level I to Level III, varying by area and time. The Level I response was organized and implemented by the State Council, and the people’s governments at the provincial level organized and coordinated emergency response work within the province under the unified leadership and command of the State Council. The Level II and Level III responses were organized and implemented by the provincial and municipal governments, respectively.

Since 24 January 2020, 31 provinces, autonomous regions, and municipalities nationwide in China have implemented Level I responses to the COVID-19 outbreak. On 30 January 2020, the World Health Organization declared that the COVID-19 outbreak posed a public health emergency of international concern (World Health Organization, 2020), and on 11 March 2020, it declared it a global pandemic. With prompt and prominent controls and prevention measures in place since 21 February

\(^5\)See http://www.china.org.cn/chinese/2020-08/06/content_76173252.htm (online; cited October 2020).
2020, several Chinese provinces and autonomous regions downgraded their emergency response to the COVID-19 epidemic to Level II or even Level III.

In general, all non-essential enterprises, including restaurants and fast-food restaurants, were closed during the Level I response (lockdown) and then gradually resumed business during the Level II and Level III responses. We therefore classify the data into four explicit periods to quantify the effects of emergency controls during the COVID-19 pandemic, namely (i) normal or pre-COVID-19 period, (ii) Level I response period, (iii) Level II response period, and (iv) Level III response period. Table 1 also lists detailed execution dates of Levels I/II/III emergency responses in each city. Cities C, H, and K were among the earliest to implement the highest response level of lockdown (23 January 2020), which was downgraded to Level II in late February and early March. City D, the city where the COVID-19 outbreak originated, downgraded to Level II on 2 May 2020, and to Level III on 13 June 2020. City A downgraded from Level II to III on 6 June 2020, but soon upgraded to Level II (16 June 2020) due to a local outbreak in an agricultural wholesale market.

Figure 2 shows the average daily total number of orders per restaurant during the sample period in four major cities in China. For each city, the dotted, unbroken, and dashed lines represent the dates when the Level I (highest severity), Level II, and Level III (lowest severity) responses were executed, respectively. It is not surprising that dining activity plunged to nearly zero immediately after the implementation of the Level I response in January 2020. In contrast, when the response level was downgraded to Level II or Level III, dining activity resumed and gradually recovered to the pre-COVID-19 level.

Figure 2. Daily total numbers of orders per restaurant and levels of response to the COVID-19 public health emergency in selected cities

a. City A
Source: Restaurant transaction dataset.

Notes: In each city, the dotted line is the date that Level I response (highest severity) was executed, the unbroken line is the date that Level II response was executed, and the dashed line is the date that Level III response (lowest severity) was executed.
IV. Methodology

Our identification strategy relied on the variations in local severity of COVID-19 on the day and in the city of dining out transactions. One crucial concern in our analysis is the potential selection bias arising from the possibility that people may self-select into eating in a restaurant after the outbreak of COVID-19. For example, during days of Level II or Level III response periods, there may be a greater proportion of working professionals with stringent working schedules who visit restaurants, whereas children and seniors may not visit a restaurant at all during the pandemic. In such cases, the estimated impacts of COVID-19 on food spending and consumption may be driven by systematic differences among distinct customer groups rather than the pandemic per se. To address the potential self-selection issues, we adopted the high-dimensional fixed effects (HDFE) model proposed by Guimaraes and Portugal (2010), which enabled us to include thousands of fixed effects (FE), such as city FE, site FE, month FE, site-by-month FE, and monthly time trend, thereby partially alleviating the self-selection problem.

In particular, we examined the impact of COVID-19 on the decision-making of dining out in two steps. In the first step, before or after the outbreak of COVID-19, consumers decided whether to dine out, and we aggregated the data to the restaurant-day level to fit the following HDFE model:

$$ DailyResVar_{rt} = \alpha_0 + \sum_{k}^{3} \alpha_k Level_{ct}^k + \alpha_2 CityNewCase_{ct} + \alpha_3 CountryNewCase_{Spillover}_{ct} + \alpha_4 Weekend_{t} + \alpha_5 Restaurant + \alpha_6 City + \alpha_7 Month + \alpha_8 TimeTrend + \alpha_9 Restaurant \times Month + \epsilon_{rt}, $$

where $DailyResVar_{rt}$ denotes a specific restaurant-day-level outcome variable of restaurant site $r$ on day $t$. We used three daily restaurant outcomes to quantify the impact of COVID-19 on the overall decision to dine out, including the daily total number of orders, daily revenue, and daily total number of customers. $Level_{ct}^k$ is a set of dummy variables denoting the response level $k$ ($= 1, 2, 3$) to the COVID-19 public health emergency in city $c$ on day $t$, in which the pre-COVID-19 period is used as the baseline group. $CityNewCase_{ct}$ denotes the daily new confirmed COVID-19 infections in city $c$ on day $t$ and was used to capture the direct effect of local COVID-19 severity. $CountryNewCase_{Spillover}_{ct}$ is the difference between the country-level and city-level daily new confirmed cases of COVID-19 in city $c$ on day $t$, which can capture the spillover effect of the severity of COVID-19 nationwide. $Weekend_{t}$ denotes a dummy variable for weekends as an additional control. In all specifications, we include a total of 1,300 FEs, including 110 restaurant FEs ($\theta_1$), 11 city FEs ($\theta_2$), 11 month FEs ($\theta_3$), 23 monthly time trend FEs ($\theta_4$), and 1,145 site × month FEs ($\theta_5$). The inclusion of the large
number of FEs provides further control for the systematic differences among customer groups dining at a specific time or location.

In the second step, consumers decide how much to spend and what to order, and we examine the following HDFE model by using the order-level data without any aggregation:

\[
y_{irt} = \beta_0 + \sum_{k}^{1} \beta_{1k} \text{Level}_{ct}^k + \beta_2 \text{CityNewCase}_{ct} + \beta_3 \text{CountryNewCase}_c \text{Spillover}_{ct} + \beta_4 X_{irt} + \beta_5 \text{Restaurant} + \beta_6 \text{City} + \beta_7 \text{Month} + \beta_8 \text{TimeTrend} + \beta_9 \text{Restaurant} \times \text{Month} + \varepsilon_{irt},
\]

where \( y_{irt} \) denotes the per person spending and diet quality outcomes for order transaction \( i \) made at restaurant site \( r \) on day \( t \). For diet quality, we use multiple measures, including calories, carbohydrates, protein, fat, and sodium ordered per person for each order. \( \text{Level}_{ct}^k \), \( \text{CityNewCase}_{ct} \), and \( \text{CountryNewCase}_c \text{Spillover}_{ct} \) are defined as in Equation (5). The vector \( X_{irt} \) denotes a set of observable control variables, including the size of the party, meal duration, the dummy of dinner, the dummy of weekends, and the dummy of peak hours. We also employ a total of 1,300 fixed effects, as in Equation (5).

V. Results and discussion

1. Effects of COVID-19 on consumers’ dining out decisions and restaurant revenues

We first analyze how COVID-19 affects the daily total number of orders and customers and total revenue at the restaurant-site level to demonstrate consumer preferences in the first step of dining out decisions with respect to different levels of COVID-19 severity and government stringency. We aggregate the sample to the restaurant-day level and employ HDFE regression as specified in Equation (4).

Table 3 reports the parameter estimates for the HDFE models of the first step of the dining-out decision. Columns (1)–(3) report results from regressions that control for government stringency by using the set of response levels to the COVID-19 public health emergency at the city level. Compared with the pre-COVID-19 period, an average restaurant site during the most stringent Level I response period had a reduction of 78 orders (column (1)) and 184 customers (column (3)) each day, and they had a loss of daily revenue of about RMB18,252 (column (2)). The declines in the total number of orders, customers, and daily revenues are partially alleviated during the Level II and Level III periods, but the coefficients are still significant at the 1 percent level.

Columns (4)–(6) report regressions that control for the severity of the epidemic by including the lagged values of the local newly confirmed COVID-19 cases as well as
the differences between the local- and country-level new cases, as discussed in Section IV. Parameter estimates of the Level I to III response periods have a similar negative association with the three measures of restaurant performance (columns (4)–(6)). When the local newly confirmed cases on the previous day increase by one, the daily total number of orders and customers in a typical restaurant site would decrease by 0.340 and 0.834, respectively, and the total daily revenue would reduce by RMB79.561. These findings indicate a general negative effect of COVID-19 on both consumers’ decisions to dine out and restaurant performance in terms of revenue. Interestingly, the difference between the lagged values of country-level and local new cases shows an opposite impact on the restaurant-level outcomes. In particular, a one-case increase in COVID-19 in other areas of the country is associated with 0.001 more daily orders, 0.004 more daily customers, and RMB0.283 more daily revenue at a local restaurant site, suggesting a positive spillover effect of the nationwide COVID-19 severity on local restaurant-level outcomes.

Table 3. Impacts of COVID-19 on daily restaurant orders and revenues

| Dependent variables | (1) Daily total number of orders | (2) Daily revenue | (3) Daily total number of customers | (4) Daily total number of orders | (5) Daily revenue | (6) Daily total number of customers |
|---------------------|--------------------------------|------------------|------------------------------------|--------------------------------|------------------|-----------------------------------|
| Level I response period | −77.715*** (2.002) | −18,251.585*** (474.990) | −184.082*** (5.176) | −77.704*** (2.001) | −18,249.124*** (474.539) | −184.055*** (5.171) |
| Level II response period | −58.597*** (2.278) | −15,464.723*** (540.295) | −158.514*** (5.887) | −58.094*** (2.276) | −15,348.377*** (539.976) | −157.195*** (5.884) |
| Level III response period | −36.219*** (2.378) | −10,555.360*** (564.147) | −107.278*** (6.147) | −36.367*** (2.376) | −10,590.979*** (563.678) | −107.592*** (6.142) |

| L1. city newly confirmed COVID-19 cases | | | | | | |
| L1. country newly Confirmed COVID-19 Cases (exclude city) | | | | | | |
| Weekend | 41.902*** (0.249) | 10,187.227*** (58.945) | 111.569*** (0.642) | 41.954*** (0.248) | 10,199.423*** (58.903) | 111.702*** (0.642) |
| Constant | 89.691*** (1.014) | 21,148.392*** (240.603) | 219.176*** (2.622) | 89.892*** (1.014) | 21,196.526*** (240.637) | 219.604*** (2.622) |

| Site-fixed effect | Yes | Yes | Yes | Yes | Yes | Yes |
| City-fixed effect | Yes | Yes | Yes | Yes | Yes | Yes |
| Month-fixed effect | Yes | Yes | Yes | Yes | Yes | Yes |
| Monthly time trend-fixed effect | Yes | Yes | Yes | Yes | Yes | Yes |
| Site × month-fixed effect | Yes | Yes | Yes | Yes | Yes | Yes |
| Total number of fixed effect | 1,300 | 1,300 | 1,300 | 1,300 | 1,300 | 1,300 |

| Observations | 69,165 | 69,165 | 69,165 | 69,164 | 69,164 | 69,164 |
| \(R^2\) | 0.683 | 0.682 | 0.673 | 0.684 | 0.683 | 0.673 |

Notes: *** represents significance at the 1 percent level. The pre-COVID-19 period is used as the baseline group in all models. L1 represents the lagged value of confirmed cases on the previous day. Standard errors are in parentheses.
2. Effects of COVID-19 on per capita food spending

We considered whether COVID-19 affected consumers’ second-step decision about how much to spend in the restaurant (after they had taken the first-step decision to dine out). As shown in column (1) of Table 4, the parameter estimates for the HDFE regression model using the disaggregate order-level data demonstrate that the Level I, II, and III response periods led to increases in average spending per customer of RMB7.3, RMB8.2, and RMB8.2, respectively, compared with the pre-COVID-19 period. On the other hand, the direct and spillover effects of COVID-19 severity are significantly associated with decreases in average spending of RMB0.072 and RMB0.002, although the magnitudes are small.

Table 4. Effects of COVID-19 on per person food spending and nutrient content

| Dependent variables | (1) Food spending per person | (2) Calories ordered per person | (3) Carbohydrates ordered per person | (4) Protein ordered per person | (5) Fat ordered per person | (6) Sodium ordered per person |
|---------------------|-------------------------------|---------------------------------|-------------------------------------|-------------------------------|---------------------------|-------------------------------|
| Level I response period | 7.297*** (1.584) | 149.255*** (18.565) | 3.942** (1.689) | 8.570*** (1.411) | 11.970*** (1.225) | 488.246*** (58.812) |
| Level II response period | 8.182*** (1.632) | 157.859*** (19.130) | 9.471*** (1.740) | 7.372*** (1.454) | 10.899*** (1.262) | 469.046*** (60.601) |
| Level III response period | 8.210*** (1.642) | 145.504*** (19.244) | 10.655*** (1.751) | 6.561*** (1.462) | 9.288*** (1.270) | 451.751*** (60.962) |
| L1. city newly confirmed COVID-19 cases | −0.072*** (0.013) | 0.456*** (0.156) | 0.027* (0.014) | 0.012 (0.012) | 0.041*** (0.010) | 0.914* (0.495) |
| L1. country newly confirmed COVID-19 cases (exclude city) | −0.002*** (0.000) | −0.000 (0.004) | −0.001*** (0.000) | 0.000 (0.000) | 0.000* (0.000) | −0.015 (0.011) |
| Size of party | −8.444*** (0.023) | −145.235*** (0.267) | −13.125*** (0.024) | −7.407*** (0.020) | −7.471*** (0.018) | −228.464*** (0.846) |
| Duration | 0.184*** (0.001) | 2.550*** (0.009) | 0.135*** (0.001) | 0.205*** (0.001) | 0.146*** (0.001) | 5.621*** (0.029) |
| Weekend | 0.495*** (0.057) | 31.235*** (0.668) | 4.629*** (0.061) | 2.056*** (0.051) | 0.472*** (0.044) | 3.369 (2.116) |
| Dinner | 3.834*** (0.056) | 34.284*** (0.652) | −1.004*** (0.059) | 3.608*** (0.050) | 2.701*** (0.043) | 56.301*** (2.065) |
| Peak | −0.319*** (0.063) | 17.862*** (0.737) | 0.551*** (0.067) | 1.287*** (0.056) | 1.323*** (0.049) | 64.725*** (2.335) |
| Constant | 105.594*** (0.616) | 1,561.897*** (7.222) | 125.089*** (0.657) | 84.396*** (0.549) | 86.614*** (0.477) | 2,528.209*** (22.877) |
| Site-fixed effect | Yes | Yes | Yes | Yes | Yes | Yes |
| City-fixed effect | Yes | Yes | Yes | Yes | Yes | Yes |
| Month-fixed effect | Yes | Yes | Yes | Yes | Yes | Yes |
| Monthly time trend-fixed effect | Yes | Yes | Yes | Yes | Yes | Yes |
| Site × Month-fixed effect | Yes | Yes | Yes | Yes | Yes | Yes |
| Total number of fixed effect | 1,300 | 1,300 | 1,300 | 1,300 | 1,300 | 1,300 |
| Observations | 5,570,152 | 5,570,152 | 5,570,152 | 5,570,152 | 5,570,152 | 5,570,152 |
| $R^2$ | 0.046 | 0.096 | 0.101 | 0.059 | 0.065 | 0.042 |

Notes: ***, **, and * represent significance at the 1, 5, and 10 percent levels, respectively. The pre-COVID-19 period is used as the baseline group in all models. L1 represents the lagged value of confirmed cases on the previous day. Standard errors are in parentheses.
One possible explanation is that increases in per capita food spending might be due to increased prices after the outbreak of COVID-19. If this is the case, then the increases in average dining-out spending per customer during the Level I, II, and III response periods could be mainly driven by surges in the prices of dishes. We tested for changes in prices before and after the COVID-19 pandemic by using the dish-level selling price data and a fixed-effect model with an unbalanced panel. The results are presented in Table 5. We find that dish prices in 2020 did not significantly change relative to the previous year (column (1)). Thus, we did not find evidence that dish prices were significantly higher in any of the Level I, II, and III response periods compared with the pre-COVID-19 period (column (2)). Thus, these results suggest that changes in the number or combination of dishes may be the key reason for higher food spending after the COVID-19 outbreak. 

Table 5. Test for changes in price using fixed-effect models

| Variables                  | (1)          | (2)          |
|----------------------------|--------------|--------------|
| Year 2020                  | −3.898       |              |
|                            | (2.495)      |              |
| Level I response period    | 3.087        | 0.939        |
|                            | (4.008)      | (4.150)      |
| Level II response period   | −3.880       |              |
|                            | (3.770)      |              |
| Level III response period  |              |              |
|                            |              |              |
| Constant                   | 70.921***    | 68.956***    |
|                            | (1.768)      | (2.873)      |
| Number of dishes (fixed effect) | 1,734       | 1,734        |
| Observations               | 2,672        | 2,672        |
| \( R^2 \)                  | 0.003        | 0.005        |

Notes: *** represents significance at the 1 percent level. The year 2019 is used as the baseline group in model (1). The pre-COVID-19 period is used as the baseline group in model (2). Standard errors are in parentheses.

The nationwide lockdown policies and the overall severity of the pandemic (reflected in consumers’ fear of becoming infected) are two of the most plausible explanations for the declines in the number of orders and consumer visits (Goolsbee and Syverson, 2021). To explore the increases in per capita food spending, one possible explanation

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*Due to lack of data, we did not test for hoarding behavior such as consumers ordering extra food at restaurants to store at home. Such expenditure could explain some of the increased per capita spending at restaurants.*
is stockpiling behavior due to the pandemic (Wang et al., 2020; Lehberger et al., 2021; Micalizzi et al., 2021). When consumers have limited access to FAFH, they tend to order more than the amount of food that they could consume in one meal. This explanation is not testable in this research because the amount of plate leftovers is unobservable in our dataset. Another limitation of the empirical analysis is that we cannot exclude the impact of income fluctuations because the changes in consumption behavior led by COVID-19 could be short-term.

3. Effects of COVID-19 on calorie and nutrient intake
We explored the effects of COVID-19 on average per person intake of calories and specific nutrients embedded in food purchases, which are critically related to diet quality before and during the COVID-19 periods. As presented in column (2) of Table 4, consumers, on average, ordered 149 more calories per meal during the Level I response period, even more during the Level II response period (i.e. 158 more calories), and a little less during the Level III response period (i.e. 146 more calories). In addition, a 1 unit increase in confirmed COVID-19 cases in the local city is associated with 0.456 more calories ordered, whereas the spillover effect of country-level new cases is not statistically significant.

Similar increases in the average intake of carbohydrates (column (3)), protein (column (4)), fat (column (5)), and sodium (column (6)) during the Levels I–III response periods are found by regressing the HDFE models on individual nutrients. In addition, a 1 unit increase in confirmed local COVID-19 cases is associated with 0.041g more of fat ordered (column (5)), whereas a 1 unit increase in confirmed country-level new cases (excluding the number of local cases) was associated with 0.001g less of carbohydrate ordered (column (3)).

Higher intakes of sodium and certain types of fat (e.g. saturated fat and trans fat) have been demonstrated to be risk factors for several nutrition-related non-communicable diseases (Yang et al., 2008; He et al., 2009). Thus, the results presented in this section reveal a negative impact of COVID-19 on diet quality. Moreover, increases in the average intake of calories and all individual nutrients suggest a positive association between COVID-19 and overeating behaviors, which may lead to overweight and obesity (Prentice, 2001).

VI. Conclusions
The COVID-19 pandemic has changed many aspects of people’s daily lives, including food consumption. In this study, we investigated the impacts of different levels of
COVID-19 severity and government stringency on urban Chinese consumers’ food-consumption behavior. Our results reveal several salient findings. First, although COVID-19 is associated with declines in the daily total number of orders and revenues at the restaurant-site level, for people who choose to dine out, the average spending per customer increased after the outbreak of COVID-19. We show that this result was not driven by prices but rather by increases in food and calories ordered. Second, consumers are found to order more calories, carbohydrates, protein, fat, and sodium in different periods of the COVID-19 pandemic. This suggests a potential positive association between COVID-19 and overeating behavior. Last, from a technical standpoint, our study demonstrates that the high-frequency restaurant transaction data can provide useful insights into consumer diet responses to the COVID-19 pandemic.

To explain the empirical findings, we developed an intertemporal choice model of diet healthiness consisting of four parts: hedonic utility, health-related expected utility, a time preference parameter weighting hedonic utility and health-related expected utility, and a subjective probability of individuals’ belief about the true relation between health-related utility and diet. The first-order condition of the utility maximization problem shows the optimal diet healthiness decreases with the time preference parameter. When COVID-19 causes individuals to experience the stress of health and economic insecurity, they increase the time preference parameter and weigh the experience utility more than health-related expected utility. The optimal healthiness of diet is lowered. Thus, the stress of being infected by COVID-19 triggers the behavioral mechanism by decreasing the time discount factor in the individuals’ decision problem and leads to a less healthy diet. The negative impact on the healthfulness of nutrition intake found in the empirical analysis is fully supported by the mechanism.

Our findings show that, during the COVID-19 pandemic period, the individuals’ decision-making problems underwent significant changes beyond the realm of reports in the popular media. It has become common knowledge in the academic literature that the severity of the COVID-19 pandemic and government policies that aim to reduce the spread of the virus are negatively related to the total number of orders, the total number of customers, and the total revenues of restaurants and other food outlets. But few studies show how eating behaviors are altered by the pandemic. Our findings suggest that the stress from the pandemic could significantly increase the intake of calories, carbohydrates, fat, and sodium. The increased intake of negative nutrients such as fat and sodium indicates that the negative health impact of COVID-19 is comprised by two parts. The first part is the more widely reported direct syndromes caused by the infections of the virus. The second part is the overeating behaviors the pandemic may
lead to among the rest of the population who are not infected by the virus but experience the stress and fear of being infected. We show that the pandemic-initiated stress and fears serve as a main contributor to the downward trend of healthfulness of the diet for the subpopulation, indicating a future risk of increasing incidence of chronic diseases for the group.

From a public policy perspective, our results point to the need to address unhealthy eating generated by the COVID-19 pandemic. To this end, information and nutrition education may be promoted during the pandemic period. In terms of the restaurant economy, which is a segment of the economy particularly sensitive to pandemics due to consumers’ fear of infection, the role of government, beyond controlling the pandemic, has been limited to restoring food traffic to restaurants, while the industry has responded by expanding online and pick-up food services.

Besides the general public health concerns, a more specific but important policy implication is about children’s health during COVID-19, as the literature has shown that early life exposure to malnutrition will have long-term consequences for adult health, education, and labor market outcomes. Like the negative findings studied in Baron et al. (2020) for school closures during the pandemic, our findings show that school closure may also contribute to a negative impact on the nutrition of children eating at home. Compared with the intensive policy attention to nutrition intervention with school meal programs before the pandemic, the current debates on school closure seem to miss the issue of nutrition and health education that children may receive at school. Our results have an important policy concern regarding this debate from the perspective of the nutrition. If the school continues to close due to the pandemic, potential nutrition guideline and health education should be provided to parents and students to mitigate the potential health shocks, say, obesity to the next generation and enhance their learning on the nutrition-health relationship.

This study has some limitations, which, however, provide opportunities for future research. First, our analysis was limited to a particular restaurant chain, which is not fully representative of the Chinese food market and may limit generalization to the broader population. Whether the results of this study can be extended to other populations beyond that in our sample is a question that awaits further empirical analysis. Expanding the study to food at home and other food delivery mechanisms will provide a more comprehensive picture of consumer behavior across these channels. Second, our data do not contain consumer demographics such as gender and income, as they are based on sales transactions. Demographic data could allow future studies to examine food consumption across consumer groups and explore the role of individual
characteristics in consumer behavior. Psychographic data could extend this view to include consumers’ attitudes and knowledge of health and nutrition. Third, follow-up studies would be useful to determine whether the decline in food ordering during the Level III phase persists after the pandemic abates. Finally, how our methods and results apply to other settings, such as urban consumers in other countries, is a question that awaits further empirical analysis.

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