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Public health shocks, learning and diet improvement☆

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ARTICLE INFO

Keywords:
Health behavior
COVID-19
Nutrition
Diet quality
Learning

ABSTRACT

Many governments aim to mitigate health risks by attacking nutritional failures. In this article, we exploit a unique natural experiment, the COVID-19 pandemic as an exogenous public health shock, to estimate the learning effects of intensive health information campaigns on nutrient intake during the pandemic. Using data from nearly-one million food purchases in China, our empirical findings strongly support the learning effect in explaining improvements in nutrient intake in the post-COVID-19 period. We conclude that when public health shocks occur, policy makers can boost relevant learning mechanisms by promoting information and education to improve individuals’ awareness of preventive health behaviors of a more permanent nature, which can lead to health improvements in a society.

1. Introduction

Many governments aim to mitigate health risks by attacking nutritional failures. To achieve such a goal, economists have often advocated the use of pricing mechanisms, such as obesity and junk food taxes or subsidies for healthy foods, but the effectiveness of these policies in promoting health outcomes remains controversial (see Alston et al., 2016, for a review). Alternatively, non-price policies, such as health information provision, including nutrition education programs; effective nutrition labeling on food packages; and health campaigns, have shown great potential to encourage improved nutrient intake through learning effects. Although the impact of health information provision on inattentive individuals is shown to be limited because of its salient features (e.g., Cawley and Ruhm, 2012), these findings shed light on when health information provision could effectively trigger a learning mechanism. For example, Agüero and Beleche (2017) show that the H1N1 pandemic, rather than seasonal flu, significantly altered long-run health behaviors in Mexico.

In this article, we use food purchases in China to illustrate the learning effect on health behaviors, specifically improvement in nutrient intake, during the COVID-19 pandemic and after if came under control. When the nation announced the first large-scale outbreak of COVID-19 on January 23, 2020 (the date of the Wuhan lockdown), the government and society experienced great pressures from the pandemic due to limited knowledge about the new virus. Chinese health authorities’ first response was to start intensive, nationwide information campaigns about adopting health behaviors to limit the spread of the virus, such as handwashing, wearing masks, sanitizing, and following a healthier diet to build strong immune systems. The novel virus was soon discovered to be highly transmittable and lethal, providing surprising changes in the state of nature that may effectively have triggered learning mechanisms to improve health behaviors.

Although we find a deterioration of nutrient intake during the active periods of COVID-19 infections, when we extend our analysis to the period when infections were under control, we observe a sharp increase in the consumption of good nutrients and a decrease in bad nutrients relative to before or during the COVID-19 active period. Specifically, COVID-19 infections increased the daily consumption of “bad” nutrients...
proprietary dataset from a restaurant conglomerate in China. In 2019, we utilize the transaction data for food delivery from 72 restaurant locations in its largest chain, which potentially covers 138 million people.

2. Data on food purchases

This article contributes to the growing body of research on the importance of behavioral mechanisms when individuals make decisions about nutrient intake. For instance, Smith (2012) and Staudigel (2016) document emotional eating behaviors stemming from adverse economic conditions. Salience is also broadly discussed for other health issues, ranging from hospital rankings (Cutler et al., 2004; Pope, 2009) to restaurant hygiene alerts (Jin and Leslie, 2003; Dai and Luca, 2020). Similar to our work, Bennett et al. (2015) and Agüero and Beleche (2017) discuss the learning effect from public health shocks such as SARSs and H1N1.

Finally, this article also contributes to the handful of economic studies using a detailed account of nutrition information to capture the healthfulness of meals (i.e., Anderson et al., 2018; Zhu et al., 2016), in contrast to most studies, which use dummy variables like nutrition program enrollment (Belot and James, 2011; Chakraborty and Jayaraman, 2019) or indirect measures such as children’s heights (Thomsen et al., 2016), or that classify products into broad food groups (Oster, 2018).

2. Data and empirical strategy

2.1. Data on food purchases

The two main datasets used consists of: (1) daily COVID-19 case counts collected from local city and national health committee websites; and (2) 966,193 transactions for food delivery drawn from a confidential proprietary dataset from a restaurant conglomerate in China. In 2019, the conglomerate’s total food delivery sales reached 154 million RMB (around 18 million U.S. dollars), or 2.4 percent of China’s food delivery market in the restaurant industry. To meet the 30- to 60-minute time requirement for delivery and to minimize transportation costs, dishes in delivery transactions are usually prepared at the restaurants instead of centralized factories. The conglomerate owns four different chains, and we utilize the transaction data for food delivery from 72 restaurant locations in its largest chain, which potentially covers 138 million people in 10 cities across China. In 2019, the total market size for food deliveries in China reached 603.5 billion RMB (around 86 billion USD).

Most food delivery transactions are submitted through the two largest online delivery platforms, Meituan-Dianping and Ele.me (like Yelp and TripAdvisor). To strip out the impact of COVID-19 from other factors, we truncate the sample from January 1 through May 31, 2020, because the second outbreak in China occurred in early June 2020.

2.2. Measurements of nutrient intake

The dependent variable used in the empirical models is the average nutritional content per transaction. To construct the nutrition measure, we first use the chain’s recipe data to collect the names and amounts of ingredients used for all dishes and then convert the ingredient amounts to nutrients using the China Food Composition Tables (Chinese Center for Disease Control and Prevention, 2019). We then calculate the average nutritional content per transaction by dividing the sum of the nutrients scaled by the energy content, adjusting for portion sizes. The nutrients included in the analysis are both nutrients-to-limit or “bad” nutrients (fat, sugar, and sodium) and nutrients-to-encourage or “good” nutrients (fiber and protein). In total, we utilize nine nutrients. The food is prepared following standard recipes and any changes are recorded. Updates of recipes are not frequent, and most updates only focus on one dish.

In addition to individual nutrients, we also utilize two summary indices of nutrition. To this end, we calculate Nutrient Rich Food (NRF) scores using individual nutrient information per transaction. NRF scores have been compared extensively to other methods and have been validated with respect to measuring a healthy diet. Finally, we explore the robustness of our results by utilizing the Nutrient Profiling Index (NPI) system developed by the Food Standards Agency of the U.K. Department of Health in 2004–2005. NPI uses a scoring system to balance the contribution made by beneficial nutrients with nutrients that should be eaten less (U.K. Department of Health, 2011). We normalize NPI to range between 0 and 100, with higher values representing healthier nutritional choices.

One potential issue is an individual’s lack of knowledge of the nutrient content of the various dishes. This is unlikely to occur in our study because customers are mainly from the middle-income population in China, which have relative high levels of educational attainment. In addition, in China there is also common about the nutritional characteristics of different cooking methods. For example, steamed dishes are healthier than deep-fried ones. Consider four popular dishes in our sample, which are displayed in Fig. 2. Fried noodles contain more oil and saturated fat than noodle soup, and sweet and sour pork ribs are less healthy than lotus root pork ribs soup because of more added sugars. In addition, healthfulness of animal protein dishes is familiar to most people through traditional Chinese wisdom, such as “no-legged meat

5 In the China Food Composition Tables, because there is no information about sugar content for each food, we use the carbohydrate content to proxy sugar in each food. The total sugar content used in the analysis includes the carbohydrates in each food as well as sugar added during cooking. Also note that although vitamins, calcium, and iron are included in the calculations of nutrition indexes, they are not included in the tables of results for individual nutrients.

6 The restaurants occasionally update their recipes in their computer system. In our sample, we account for sporadic changes in recipes by updating the nutrition information in real time.

7 The basic idea of the NRF scores is to define nutrient-rich foods rather than energy-dense ones, as encouraged by the 2005 Dietary Guidelines for Americans (U.S. Department of Health and Human Services, 2005). Following standard procedure, NRFs are computed as the sum of the percentage of daily values of nutrients-to-encourage minus the sum of the percentage of maximum recommended values of nutrients-to-limit. The formula for calculating the nutrition indexes is in Appendix B.

8 NRFs are used internationally to identify healthier foods via scores based on energy and individual nutrients, as well as amounts of healthy foods such as fruit and vegetables (U.K. Department of Health, 2011).
infection counts, and (2) daily national-level infection counts, both of which are higher than four-legged [pork]. Fish is healthier than two-legged meat [chicken]; two-legged is healthier than four-legged [pork].

All values reported are means of transaction-level observations for both periods from January 1-May 31 for the years 2019 and 2020. The number of observations is 398,094 in the 2019 sample and 578,099 in the 2020 sample. Instead of reporting all dummy variables, we report only city-month interactions. In total, we have 18 interactions after multiplying nine city dummies by month dummies. Other fixed effects included in the regressions are restaurant dummies, city dummies, day-of-week dummies, hour dummies (which hour in a day that the transaction happens), and month dummies.

We use portion size to control the supply changes as well as the number of people who will share the dishes. One extension for this study is to control the supply changes as well and use a set of time fixed effects, including the time when the transaction was received, day of the week, and a month dummy, to account for seasonal changes.

We do not directly observe demographics associated with transactions, raising a concern is the potential for omitted variable bias on the demand side. To address this, we employ several data strategies. First, we use two proxies for income: daily automobile traffic (denoted as income1) and monthly foot traffic within a three-kilometer radius of each of the 72 restaurant locations in our sample (denoted as income2). Second, we also use city-month interactions to account for potential time-varying variations in demographics such as income. Third, we also utilize unsupervised machine learning techniques that have performed favorably in the estimation of demand without demographics and geographic variables (Blumberg and Thompson, 2021).

We also use a population mobility index to account for the impact of mobility restrictions implemented by China’s government during the pandemic. Mobility data tracks people’s movement between cities. Gaode offers location-based service (LBS), based on the global positioning system (GPS), IP addresses, locations of signaling towers, Wi-Fi for online searching and mapping, and a large variety of apps and software on mobile devices (Lai et al., 2020) to construct the mobility index. The index is classified as population inflows and outflows.

Table 1 presents a summary of the definitions and statistics of the variables used in the empirical analysis. Fig. 1 illustrates the trends in average NRF scores and the number of daily COVID-19 infections between January and June 2020. The upper panel shows that overall nutrition intake deteriorates up to March 2020, after which it appears to improve, reaching levels higher than those preceding the pandemic. The upper panel also suggests an inverse relationship between the number of infections and nutrient intake. To further illustrate this point, the lower panel shows that nutritional decision making deteriorates after March 2020, with a trend similar to that observed in the upper panel.

Table 1
Summary of Variable Definitions and Statistics.

| Category   | Variable Name | Variable Definition | Observations | Mean   | Std. Dev |
|------------|---------------|---------------------|--------------|--------|----------|
| Nutrition Measures | Fiber | Avg. fiber contents per transaction (grams) | 966,193 | 1.66  | 1.386  |
|             | Fat          | Avg. fat contents per transaction (grams) | 966,193 | 16.23 | 9.816   |
|             | Sugar        | Avg. sugar contents per transaction (grams) | 966,193 | 21.55 | 13.29   |
|             | Sodium       | Avg. sodium contents per transaction (mg) | 966,193 | 568.547 | 490.182 |
|             | Protein      | Avg. sodium contents per transaction (grams) | 966,193 | 8.504  | 4.453   |
|             | NRF          | Nutrition-Rich-Food score | 966,193 | 39.04 | 20.78   |
|             | NPI          | Nutrition Profile index | 966,193 | 41.57 | 12.92   |
| COVID-19   | National     | Daily number of infections at national level divided by 100 | 388,094 | 1.271 | 5.31    |
|             | Local        | Daily number of infections at local level | 388,094 | 0.721  | 3.19    |
| Income Proxies | Income1  | Daily traffic flow (restaurant-level) | 4,641 | 20.941 | 4.877   |
|             | Income2     | Monthly population flow (restaurant-level) | 4,641 | 0.257  | 0.246   |
| Baseline Controls | Price     | Average price per dish in a transaction | 966,193 | 23.02  | 12.331  |
|             | Discount    | Discount rate per transaction | 966,193 | 0.748  | 0.159   |
|             | Portion size| Total portion size per transaction (grams) | 966,193 | 688.932 | 600.065 |
|             | Number of transactions | Daily number of transactions in a restaurant | 966,193 | 81.16  | 55.913  |
|             | move_out    | Gaode Index for population move-out | 1,820 | 31.12  | 24.00   |
|             | move_in     | Gaode Index for population move-in | 1,820 | 33.99  | 22.81   |
|             | City-month  | Interaction term between city and month dummies | 966,193 | 0.033  | 0.180   |
|             | Post1       | Dummy = 1 for period Mar 19-May 31, 2020; =0 for Jan 1 to Jan 22, 2020 | 317,921 | 0.768  | 0.422   |
|             | Post2       | Dummy = 1 for period Mar 19-May 31, 2020; =0 for Jan 23 to Mar 18, 2020 | 314,223 | 0.777  | 0.416   |

| No. of Obs.: | 966,193 |

9 On February 12, 2020, the China National Health Committee switched the infection diagnosis procedure from molecular to clinical diagnosis, resulting in an abnormal—and the biggest—increase for that day, with 15,152 new cases. However, this spike was not observed again after February 20, 2020, when the government switched back to molecular diagnosis tests.

10 The price is usually determined by both demand and supply changes. One concern is the price may increase due to the supply constraints of the pandemic. In our data, we instead found the prices are declining. The trend of price changes would in principle reject the hypothesis of supply constraints or at least support the notion that declining demand forces were stronger than any supply constraints. One extension for this study is to control the supply changes as well and use a set of time fixed effects, including the time when the transaction was received, day of the week, and a month dummy, to account for seasonal changes.

12 We are indebted to a reviewer who pointed out and encouraged more discussion on the potential omitted variables/selection bias from missing demographics, particularly in the context of active food app users during the pandemic.

13 The data is provided by the GIS Daas Database at Tsinghua University. In general, restaurants deliver only to residents who live close by to ensure the guaranteed 30-minute delivery time. Cell phone data refers to the different cell phone number detected in the area per month.
panel plots the average NRF scores vs the number of infections regardless of dates, and it indicates a negative association between the two variables.

2.4. Estimation strategy

To investigate the impact of the COVID-19 pandemic more formally on nutrient intake, based on transaction-level food deliveries, we propose the following model:

\[ Nutrition_{ijct} = \alpha COVID\_Nat_t + \beta COVID\_Loc_t + \gamma X_{ijt} + \lambda_j + \mu_c + \nu_{month} + \delta \lambda_j \times \nu_{month} + \epsilon_{ijct} \]  

(1)

where Nutrition\_ijct is the individual nutrient content or nutrition index (NRF or NPI) contained in food delivery \( i \) from restaurant \( j \) in city \( c \) on day \( t \). COVID\_Loc\_t is the number of infections in city \( c \) on day \( t \), and COVID\_Nat\_t is the number of infections throughout China on day \( t \). Other control variables are denoted by \( X_{ijt} \). \( \lambda_j \), \( \mu_c \), and \( \nu_{month} \) denote restaurant, city, and month fixed effects. \( \epsilon_{ijct} \) is the unobserved term. We estimate equation (1) for the benchmark results using weighted least squares, with food delivery transactions in restaurant \( i \) on day \( t \) used as the weight.

Given that we do not observe individual household demographics, the main identification concern using equation (1) is the omitted demographic variables contained in the error term \( \epsilon_{ijct} \). That is,
\( \epsilon_{ijct} = D_{1ijc} + D_{2ct} + \epsilon_{ijct}, \) \hspace{1cm} (2)

where \( \epsilon_{ijct} \) is the i.i.d distributed error, \( D_{1ijc} \) are the time-invariant demographics, and \( D_{2ct} \) are the time-variant demographics. \( D_{1ijc} \) are likely to affect nutrient intake, but they are not correlated with the pandemic because they are time-invariant. \( D_{2ct} \) are the time-variant demographics that may affect diet choices and correlate with COVID-19 case counts. In this case, the estimates of COVID-19 may be biased by absorbing the impact of changes in unobserved demographics during the pandemic. We address this issue in the following ways.

First, \( D_{2ct} \) are unlikely to be substantial for an individual who orders deliveries from the restaurants in our sample. The restaurants are more frequently visited by middle- and high-income groups, given the average spending per transaction.\(^{14}\) As shown by Chetty et al. (2020), income variations led by the COVID-19 pandemic in the U.S. are mainly incurred by the low-income population, while income decreases modestly for the middle- and high-income populations. A similar trend is also found in China (Qian and Fan, 2020). If income variations for middle- and high-income groups remain, both correlate with COVID-19 and the nutrition variable in our sample, and we use a crude approach by including the restaurant fixed effects (\( \lambda_r \)) and city-month interactions (\( \mu_c \times v_{month} \)) as proxy variables for unobserved time-invariant and time-varying demographics in equation (1).

To further address this issue, we also estimate alternative models using income proxy variables for \( D_{2ct} \) in equation (2). Given limited access to income data in China, Data for the U.S. from Chetty et. al (2020) indicate that business activities are more closely related to income variations than to the COVID-19 pandemic in the U.S, as shown in Fig. 3. To examine whether the above relationships also apply to China, we collected yearly household income and business revenue for China from 2008 to 2018. Panel C in Fig. 3 shows that he 11-year trend of household income is significantly and positively correlated with business activities in China. Based on this, we propose two proxy variables for business activity in our sample: daily automobile traffic flow at the restaurant-level (income1) and monthly foot traffic (income2), both within a three-kilometer radius of each of the 72 restaurant locations. The data are provided by the GIS DaaS Database from Tsinghua University.

However, demographic variables may not be good proxies to control for consumer heterogeneity in taste when consumers who fall into the same income category have different taste in dishes.\(^{15}\) As capturing variations in taste is equivalent to segmenting consumers with different

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\(^{14}\) The average expenditure per capita in the restaurants is around 89RMB (around 13USD) per transaction, and the total bill could be up to 400 RMB (around 57 USD) when four persons eat together (the normal size of groups that dine in the restaurants). Given that the average household yearly disposable income in China was around 30,733 RMB (around 4,390 USD) in 2019, and the Chinese tradition that only one person pays the entire bill when dining in restaurants, low-income people are unlikely to frequently visit restaurants because one meal would cost more than their one-month income.

\(^{15}\) This was pointed out by one of the reviewers, which prompted further analysis reported below.
utility functions, we implement the Generalized Axiom of Revealed Preference (GARP) method and the K-means algorithm proposed by Blumberg and Thompson (2021), who conclude that both methods work better than demographics to describe differences in taste. The GARP algorithm needs to compare $\sum_{n=1}^{N} n!$ pairs of expenditure and quantity, which is computationally intensive given a standard personal computer without GPU. We solve this problem by using 1, 5, and 10 percent of the sample randomly drawn from the full sample, following the computer science literature for manipulating big data (for recent examples, see Danaf et. al 2019; Ruiz et. al 2020). Performing K-means is less intensive, so we clustered the whole sample according to the quantity and expenditure into 500, 1000 and 1500 clusters. We report the results of sampling GARP and K-means for 500 clusters in Tables 5 and 6.\textsuperscript{16}

To investigate the longer run effects of COVID-19 on nutrient intake, we split the sample into three periods: (1) January 1 through January 22, 2020, as the pre-pandemic period; (2) January 23 through March 18, 2020, as the middle-pandemic period; and (3) March 19 through May 31, 2020, as the post-COVID-19 period. January 23, 2020 is the date

\textsuperscript{16} We also conducted runs with 1,000 and 1,500 cluster fixed effects (reported in Appendix D), but the results were fundamentally like the ones reported in Tables 5 and 6 with 500 cluster fixed effects.
when the central government imposed a lockdown in Wuhan and other cities in Hubei province. March 18th is a critical date for the pandemic’s being well-controlled, as on that day new domestic infections in China reached zero for the first time and stayed at or nearly that level for the remaining period. We conduct pair-wise comparisons of model (1) using a dummy variable for the post-pandemic period (Post = 1; 0 for other periods), in lieu of COVID infections. We retain all other control variables of the baseline model (1). The parameter estimates for the baseline and alternative empirical models are presented below.

3. Empirical results

3.1. Impacts of COVID-19 on nutrient intakes

Table 2 presents parameter estimates for individual nutrient intakes.
increase in fat, sugar, and sodium consumption of 0.032–0.063 g, 0.03–0.16 g, and 1.2–2.2 mg per transaction. Using the mean of each nutrient intake in the 2020 sample, these results translate into a 0.1 to 0.7 percent increase in nutrients-to-limit and a 0.1 to 0.4 percent decrease in nutrients-to-encourage per transaction. The changes in nutrients stemming from local COVID-19 infections are more significant than those for an equivalent number of national infections. For every single increase in local infections, there were increases in fat, sugar, and sodium intake of about 0.032 g and 0.006 g per transaction. This accounts for a 0.4 to 1 percent increase in sodium, fat, and sugar (nutrients-to-limit) and a 0.1 to 0.6 percent decrease in fiber and protein (nutrients-to-encourage) per transaction.

Table 3 presents parameter estimates for equation (1) using NRF scores and NPI as dependent variables. These results corroborate the main finding of the results for individual nutrients: that is, nutrient intake. That is, although we control for city fixed effects, the impact of COVID-19 infections may spill over to other regions.

Table 3. Results for Nutrition Summary Indexes.

| Variable                | NRF         | NPI         |
|-------------------------|-------------|-------------|
|                         | (1)         | (2)         | (3)         | (4)         | (5)         | (6)         | (7)         | (8)         |
| National Cases          | -0.155**    | -0.280**    | -0.388**    | -0.013*     | -0.049***   | -0.073***   | -0.073***   | -0.073***   |
|                         | (0.072)     | (0.061)     | (0.042)     | (0.007)     | (0.008)     | (0.004)     | (0.007)     | (0.007)     |
| Local Cases             | -0.131**    | -0.249***   | -0.435***   | -0.017**    | -0.055***   | -0.088***   | -0.088***   |
|                         | (0.046)     | (0.060)     | (0.016)     | (0.006)     | (0.009)     | (0.007)     | (0.007)     |
| Other Control Variables | No          | Yes         | Yes         | Yes         | No          | Yes         | Yes         | Yes         |
| City-month              | Yes         | Yes         | Yes         | Yes         | Yes         | Yes         | Yes         | Yes         |
| Chain FE                | Yes         | Yes         | Yes         | Yes         | Yes         | Yes         | Yes         | Yes         |
| City FE                 | Yes         | Yes         | Yes         | Yes         | Yes         | Yes         | Yes         | Yes         |
| Day of the week FE      | Yes         | Yes         | Yes         | Yes         | Yes         | Yes         | Yes         | Yes         |
| Hour FE                 | Yes         | Yes         | Yes         | Yes         | Yes         | Yes         | Yes         | Yes         |
| Month FE                | Yes         | Yes         | Yes         | Yes         | Yes         | Yes         | Yes         | Yes         |
| Observations            | 144,044     | 144,044     | 144,044     | 144,044     | 144,044     | 144,044     | 144,044     | 144,044     |
| R-squared               | 0.030       | 0.121       | 0.121       | 0.120       | 0.042       | 0.206       | 0.206       | 0.206       |

Model specification follows equation (1) using transaction-level data from January 1-March 18, 2020, using nutrition summary metrics (NRF and NPI) as dependent variables. The estimations are estimated using weighted least squares, using as weight the daily number of transactions in each restaurant. Note that *, **, *** indicate 90%, 95%, and 99% confidence intervals. All errors are clustered at the city level.

We conduct several additional robustness checks. First, we check for controlling tastes. Table 5 shows that the impact of national and local cases on the nutrition index are not just significantly negative for 1%, 5% and 10% samples to perform GARP, but also more significant than without controlling the tastes. The results for Table 6 show a similar pattern as those in the baseline results.

The second set of robustness checks focuses on the potentially unobserved regional effects that are correlated with COVID-19 and nutrient intake. That is, although we control for city fixed effects, the impact of COVID-19 infections may spill over to other regions. Following Chang et al. (2018), we use COVID-19 case counts from other cities to proxy unobserved local factors that may correlate with a particular city’s COVID-19 prevalence and nutrition decisions and then rerun the regression including COVID-19 infections in the nearest city. The results, presented in Table 7, show that the COVID-19 infections in neighboring cities did not have a discernable impact on nutrient intake in our baseline results and that their omission likely did not significantly bias the results.

The third set of robustness checks focused on whether the impacts are driven in part by pre-pandemic trends that may arise with seasonal or other time-dependent effects or by other effects that cause spurious correlation with 2020 COVID impacts, that is, in terms of our sample, by a similar trend for the same period in 2019. To this end, we run the baseline model with the same dates (January 1 through March 18) and the same control variables and restaurant orders for 2019. Columns (5)-(8) of Table 5 report the results for the two nutrition summary indexes. None of the estimates are significantly different from zero, showing no similar trend in nutrition decisions in our 2019 sample. Thus, no discernable pre-pandemic city or time differences are evident in our sample.

### 3.2. Robustness checks

We use the average of the results of specifications (1), (2), and (3), which include national infections. Note that the impact of national infections is not significant for sugar and protein under model specification (3) in Table 2, which excludes control variables.

Note from Table 1 that national infections were measured in the one-hundreds while local infections are reported in actual numbers.

The impact of local infections is not significant for protein in the first model specification, which excludes all other control variables.

17 We use the average of the results of specifications (1), (2), and (3), which include national infections. Note that the impact of national infections is not significant for sugar and protein under model specification (3) in Table 2, which excludes control variables.

18 Note from Table 1 that national infections were measured in the one-hundreds while local infections are reported in actual numbers.

19 The impact of local infections is not significant for protein in the first model specification, which excludes all other control variables.

20 We deleted the number of infections for February 29, 2020, as that date did not apply in 2019.

21 We also conducted regressions aggregating observations to the restaurant level and adding the number of transactions as a proxy for active users (the results are reported in Appendix C). The key results for the impacts on COVID on diet quality were substantially the same.
protein intake in the sample. At the same time, the results show significant decreases in the amount of nutrients-to-limit: on average, a decrease of 1.628 g, 3.431 g, and 40.988 mg in fat, sugar, and sodium, respectively, accounting for 7 to 16 percent decreases relative to the sample means. The nutrient results are also supported by corresponding NRF scores and NPI increases of 11 and 1.4 percent, indicating an overall increase in the healthiness of the diet. Panel B that with the results for the middle v. the post-COVID-19 periods, shows that the impacts on nutrient intake are starker than those in Panel A. That is, we find even stronger evidence of nutritional improvement when the post-COVID period is compared to the most active period of the pandemic. Panel C simply compares the 2020 and the 2019 March 19-May 31 periods (post-COVID) and finds evidence of diet improvement in 2020 relative to the same period in 2019.

4. Potential mechanisms

4.1. An intertemporal model of nutrient intake

We develop a simple intertemporal choice model that focuses on the

| Variable | NRF | NPI |
|----------|-----|-----|
|          | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| National Cases | -0.388*** (0.042) | -0.397*** (0.040) | -0.388*** (0.042) | -0.396*** (0.040) | -0.435*** (0.016) | -0.470*** (0.021) | -0.434*** (0.015) | -0.470*** (0.020) |
| Local Cases | 0.218 (0.205) | 0.224 (0.190) | 0.453*** (0.220) | 0.460*** (0.203) |
| Income1 | 9.790 (5.491) | 9.837 (5.548) | 9.781 (5.420) | 9.873 (5.553) |
| Income2 | 0.073*** (0.004) | 0.067*** (0.005) | 0.073*** (0.004) | 0.067*** (0.005) |
| Other Control Variables | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| City-month | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Hour FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 144,044 | 144,044 | 144,044 | 144,044 | 144,044 | 144,044 | 144,044 | 144,044 |
| R-squared | 0.120 | 0.120 | 0.120 | 0.120 | 0.120 | 0.120 | 0.120 | 0.120 |

Results are at the transaction level from January 1-March 18, 2020. Note that the COVID-19 coefficients in columns (1a) and (1b) and (4a) and (4b) are from the same model, but the national and local COVID-19 coefficients are presented in different columns. Except where noted, all specifications are estimated with other control variables. Note that *, **, and *** indicate significance at the 90%, 95%, and 99% confidence intervals. All errors are clustered at the city level.
behavioral motivation aspects regarding the healthfulness of nutritional choices to link the COVID-19 pandemic to improvements in nutrient intake. Consider an individual who decides on the healthfulness of their diet at time 0. We summarize the healthfulness using a single quantity $u$. At time 0, the individual opts for nutrient intake $h_1 \leq h \leq h_2$ (Oliver and Wardle, 1999; Smith, 2012).

An individual chooses $h$ by maximizing their net expected utility:

$$\max_{h \in [h_1, h_2]} v(h) + \delta((1 - p)u_1 + p u_2(h))$$

(3)

The first order condition for the maximization of (1) yields.

$$v'(h^*) = \delta pu_2'(h^*) = 0.$$  

(4)

Equation (4) suggests that the degree of healthfulness of the diet is determined by an individual’s compounded valuation of experienced utility as well as their beliefs about the connection between nutrient intake and health.

4.2. Potential explanations of changes in nutrition

Following the behavioral economics literature, we explore three explanations of how COVID-19 works by affecting nutrient intake based on changes in $p$ and $\delta$ stemming from the shock of the COVID-19 pandemic. The details are shown in Appendix A.

4.2.1. Emotional eating

It is widely documented that health and economic insecurities cause stress and that individuals under stress tend to value an immediately realized utility more than an expected later one (Koppel et al., 2017; Delaney et al., 2014). For instance, stress induced by economic insecurity triggers unhealthy eating behavior by increasing sugar intake (Staudigel, 2016). By the same token, we expect that the COVID-19 pandemic causes stress and that individuals become more focused on their immediate experienced utility rather than a deliberation about a
nutrition-health utility in the future. Thus, this causes \( \delta \) to decrease, resulting in a lower \( h \) or nutrient intake relative to before the pandemic. Yet the impact of stress is temporary, as stress vanishes when the pandemic is well controlled.

4.2.2. Salience

Even if individuals were inattentive to the true relation between nutrition and health prior to the pandemic because the relationship nutrition-health was not salient, the pandemic could suddenly make this relationship salient by bringing about a greater focus on the expected utility of health rather than on experienced utility. In contrast to emotional eating, salience increases as an individual puts more weight on their expected health-related utility, resulting in a healthier diet during the COVID-19 period. Like emotional eating, salience is a temporary behavioral driving force, indicating that increases in \( \delta \) are temporary and that the impact of salience on nutrient intake vanishes in the post-pandemic period.

4.2.3. Learning

The pandemic stimulated a worldwide boom in health information provision from both public and private media. As an important component of the response to the pandemic, information about the relationship among eating a healthier diet, chronic diseases, and COVID-19-associated health risks can be found in the web pages of public health authorities and is widely discussed in social media. This fact may initiate extensive learning from health information as well as increases in an individual’s beliefs about \( u_2 \). That is, learning induces an increase in \( p \) and resulting in a higher \( h_2 \) or a healthier diet. Unlike the impacts of emotional eating and salience on \( \delta \), the learning effect on updating \( p \) is rational and lasts over the long run. That is, once an individual learns that \( u_2 \) is more likely to be true than they believed before, they will tend to hold that belief even in the post-COVID-19 period. In essence, the learning effect leads to a long-run improvement even after the pandemic.

In summary, our finding that nutrition deteriorates during the COVID-19 active period is more consistent with the explanation of emotional eating while learning is more consistent with the period when the COVID-19 pandemic came under control.

5. Policy implications

From a policy perspective, our results show that policy makers’ efforts to decrease overall stress and worries during health shocks are necessary but have limited and short-run effects. Instead, we suggest

---

Table 7

| Variables | Impact of Infected Cases from Neighboring Cities | Test for Pre-existing Trends from January 1–22, 2019 |
|-----------|-----------------------------------------------|--------------------------------------------------|
| NRF (1)   | (2)                                          | (3)                                             | (4)                                             |
| NPI (5)   | (6)                                          | (7)                                             | (8)                                             |
| National | −0.146*** (0.041) | −0.160*** (0.031) | −0.042*** (0.008) | −0.046*** (0.007) | −2.652 (1.768) | −1.636 (2.193) | −0.541 (0.447) | −0.156 (0.409) |
| Local    | −0.301*** (0.035) | −0.283*** (0.049) | −0.030*** (0.008) | −0.029*** (0.010) | 0.456 (0.483) | 0.374 (0.504) | 0.045 (0.107) | 0.021 (0.100) |
| Neighbor | −0.001 (0.106) | 0.024 (0.099) | −0.015 (0.037) | −0.013 (0.035) |
| K-means 500 | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Other Control Variables | No | Yes | No | Yes | Yes | Yes | Yes | Yes |
| City-month | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Restaurant FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| City FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Day of the week FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Hour FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 144,044 | 144,044 | 144,044 | 144,044 | 118,207 | 118,207 | 118,207 | 118,207 |
| R-squared | 0.030 | 0.121 | 0.042 | 0.207 | 0.022 | 0.057 | 0.036 | 0.229 |

The regressions are estimated using weighted least squares, using as weight the daily number of transactions in each restaurant. Note that * indicates 90%, ** 95%, and *** 99% levels of confidence. All errors are clustered at the city level.

22 As evidence for the demand for health information associated with the pandemic, using data from Baidu searches (China’s Google search engine) and internet searches between January 1 to May 31, 2020, we observe a more than a 10-fold increase of internet searches for four keywords after January 23, 2020: (1) mask, (2) sanitize, (3) immunity, and (4) handwashing.
that policy makers emphasize boosting learning mechanisms by promoting information and education to improve individuals’ awareness of preventive health behaviors of a more permanent nature, such as changes in nutrition and exercise behaviors. This, of course, is suggested in addition to encouraging such pandemic-specific behaviors as hand-washing, mask-wearing, and social distancing. The long-run positive health impacts of adopting preventive health behaviors may mitigate the negative impact of health shocks in a society and are likely to outlive the pandemic itself.

Besides general public-health concerns for the entire population, a more specific but important policy implication concerns children’s health during COVID-19, as early-life exposure to malnutrition has long-term consequences for adult health, education, and labor market outcomes (Almond and Currie, 2011). Like the negative findings reported in Baron et al. (2020) for school closures during the pandemic, our findings imply that school closure may also have a negative nutritional impact on children who are eating at home during the period of an active pandemic when diet follows emotional eating. Thus, nutrition guidelines and health education should be provided to parents and students to mitigate negative effects of potential health shocks during the pandemic.

### Table 8

Results at Different Stages of the Pandemic.

| Variable | PANEL A: Post – 1 for Post-COVID period (March 19-May 31, 2020) vs Pre-COVID Period (January 1-22, 2020) | Fat | Sugar | Sodium | Protein | Fiber | NRF | NPI |
|----------|---------------------------------------------------------------------------------|-----|-------|--------|---------|-------|-----|-----|
| Post     | (1.628*** (0.378)) – 3.431*** (0.121) – 40.98*** (12.260) 0.080*** (0.004) 0.135*** (0.031) 4.413*** (1.436) 0.602* (0.326) | (1) | (2)   | (3)    | (4)     | (5)   | (6) | (7) |
| K-means 500 | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Other Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| City-month | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Chain FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| City FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Day of the week | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Hour FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Day FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 317,921 | 317,921 | 317,921 | 317,921 | 317,921 | 317,921 | 317,921 | 317,921 |
| R-squared | 0.141 | 0.298 | 0.032 | 0.139 | 0.103 | 0.105 | 0.212 | 0.212 |

| Variable | PANEL B: Post – 1 for Post-COVID Period (March 19-May 31, 2020) vs COVID Period (January 23-March 18, 2020) | Fat | Sugar | Sodium | Protein | Fiber | NRF | NPI |
|----------|---------------------------------------------------------------------------------------------------|-----|-------|--------|---------|-------|-----|-----|
| Post     | (0.763*** (0.261) – 5.755*** (0.355) – 75.491*** (16.528) 0.739*** (0.243) 0.727*** (0.055) 5.619*** (0.949) 3.909*** (0.558) | (8) | (9)   | (10)   | (11)    | (12)  | (13) | (14) |
| K-means 500 | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Other Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| City-month | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Chain FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| City FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Day of the week | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Hour FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Day FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 314,223 | 314,223 | 314,223 | 314,223 | 314,223 | 314,223 | 314,223 | 314,223 |
| R-squared | 0.129 | 0.299 | 0.060 | 0.150 | 0.141 | 0.095 | 0.239 | 0.239 |

| Variable | PANEL C: Post – 1 for Post-Covid Period (March 19-May 31, 2020) vs year 2019 (March 19-May 31, 2019) | Fat | Sugar | Sodium | Protein | Fiber | NRF | NPI |
|----------|-------------------------------------------------------------------------------------------------|-----|-------|--------|---------|-------|-----|-----|
| Post     | (3.155*** (0.294) – 1.891** (0.582) – 32.654*** (2.176) 1.581*** (0.228) 0.136*** (0.015) 5.607*** (1.617) 1.094* (0.500) | (8) | (9)   | (10)   | (11)    | (12)  | (13) | (14) |
| K-means 500 | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Other Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| City-month | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Chain FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| City FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Day of the week | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Hour FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Day FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 515,691 | 515,691 | 515,691 | 515,691 | 515,691 | 515,691 | 515,691 | 515,691 |
| R-squared | 0.239 | 0.370 | 0.168 | 0.263 | 0.130 | 0.187 | 0.282 | 0.282 | 0.282 |

The regressions are estimated using weighted least squares. The dependent variable is the weighted daily number of transactions in each restaurant. Note that *, **, *** indicate 90%, 95%, and 99% confidence intervals. All errors are clustered at the city level.

### 6. Conclusion

In this article, we examine the potential effects of the COVID-19 pandemic on nutrient intake, using this pandemic as a case study of a public health shock. The theoretical analysis proposes that emotional eating or salience temporarily induces negative changes in nutrient intake, while learning can improve it in the long run. To empirically test these effects, we utilize data from approximately-one million restaurant transactions in 10 cities in China, and a battery of model specifications and robustness checks to identify the effects. To account for possible selection bias, even though we empirically use proxies for income that may well be valid instruments for income, there may be other consumer characteristics that may bias the results. One would be the selection of active users of food delivery apps during the pandemic. As noted by Statista (2022), in June 2020, about 31 % of the Chinese respondents ordered more from food delivery apps during the COVID-19 pandemic. However, 33 % ordered less through food apps, 19 % did not change their food-ordering habits, and 16 % stopped using apps. Given this mixed picture, it is not possible to speculate on the direction of the likely bias in our sample. In addition, we used city and restaurant fixed effects to capture fixed unobservable variables that could include the nature of...
the neighborhoods each restaurant is located. We also applied GARP and K-means to control for potential heterogeneities in Taste. Finally, we provide a conceptual analysis for potential behavioral mechanisms that can explain the outcomes observed, including learning.

Overall, we find that individuals eat less healthily as the number of COVID-19 infections increases. However, once the pandemic comes under control, the healthfulness of their nutrition improves significantly relative to the middle, early, and pre-pandemic periods, as indicated by changes in intake of individual nutrients as well as changes in Nutrient Rich Food (NRF) scores and the Nutrition Profile indexes. These findings are robust, and they empirically support our theoretical predictions for learning as a driving mechanism for nutrient-intake improvement stemming from the pandemic health shock. Thus, learning eventually not only overcomes the negative impact of emotional eating and economic insecurity on nutrient intake, but it also overcomes the negative forces on diet after the pandemic comes under control providing a silver lining. By utilizing the COVID-19 pandemic as a natural experiment of a public health shock, the findings fill a gap in the health policy literature concerning how and to what extent the learning effect from health shocks can lead to changes in nutritional choices. The pandemic not only generates a widespread and substantial learning effect that could be detected empirically, but it also allows us to distinguish the learning effects from other effects.

**Declaration of Competing Interest**

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

**Appendix A. A choice model of nutrition intake**

We build an intertemporal choice model to study individuals’ behaviors in both the COVID period and the post-pandemic period. At time 0, individuals obtain a utility of \( u(h) \), which is considered to be an experienced utility that measures the hedonic quality gained from eating. Assume that \( u(h) \) reflects their utility gained from their future health outcomes, which are in turn dependent on nutrient intake at time 0. \( u(h) \) is defined as an individual’s health-related utility.

In the real world, individuals are likely to be aware that future health outcomes are to some degree connected to nutrient intake but unlikely to know the exact quantitative relationship. It is more natural to assume that individuals know that \( u(h) \) belongs to some subset of the set of all functions from \( H \) to \( \mathbb{R} \), and that they have some subjective belief about the likelihood of which \( u \) is true. Put formally, we assume \( u \in S \subseteq \mathbb{R}^H \) and, for the sake of simplicity, that \( S \) is finite. An individual’s subjective belief is denoted by \( f \in \Delta(S) \), where \( \Delta(S) \) is the set of all probability measures on \( S \). Suppose there is some \( u_t \in S \). We write \( h(u_t) = p_t \), where \( p_t \) is the individual’s subjective probability that \( u_t \) is the true health-related utility function.

Hence, individuals optimize the following problem:

\[
\max_{h \in H} v(h) + \delta E(r_u(u(h)).
\]

(A1)

where \( E(r_u) \) is their ex ante expected health-related utility, and \( \delta \in [0,1) \) is their time preferences about how they discount the future utility. A larger \( \delta \) means that the individuals weight the expected future utility more.

We introduce the following assumptions to make the analysis reasonable and tractable:

**Assumption 1.** \( v(\cdot) \) is continuous and twice differentiable, with \( \nu < 0 \) and \( \nu > 0 \).

We also require, out of technical consideration, that \( \nu > 0 \), in order to make the absolute value \( |\nu| \) a decreasing function and to simplify the mathematics.

**Assumption 2.** \( S = \{u_1, u_2\} \), where \( u_1 \) is a constant function on \( H \), and \( u_2 \) is continuous and twice differentiable, with \( u_2 > 0 \) and \( u_2 < 0 \).

Assumption 2 specifies individuals’ knowledge about the relationship between nutrient intake and health-related utility. Although we could encounter a spectrum of possible relations between health-related utility and nutrient intake, we only emphasize these two states as they are the most relevant to the considerations of this research.

**Assumption 3.** \( \sup\{|\nu(h)| : h \in H\} < \delta \sup\{u_1(h) : h \in H\}, \inf\{|\nu(h)| : h \in H\} > \inf\{u_2(h) : h \in H\}. \)

Assumption 3 indicates that when the diet becomes extremely unhealthy, that is, when \( h \) takes a small value in the domain \( H \), it is more beneficial for individuals to eat a little healthier. Since \( |\nu(h)| > \delta u_2(h) \) if \( h \) is small, the marginal health-related utility of eating a little healthier is larger than the marginal experienced utility of eating unhealthier if the diet is already extremely unhealthy. When the diet is already extremely healthy, i.e., when \( h \) takes a large value in the domain \( H \), it is more beneficial for individuals to eat a little unhealthier. Since \( |\nu(h)| > u_1(h) \) if \( h \) is large, the marginal experienced utility of eating a little unhealthier is larger than the marginal health-related utility of eating even healthier if the diet is already extremely healthy.

Note that, out of technical consideration (that is, to make the solution to the following first order condition (A.3) real, as will be shown below), we require \( \sup\{|\nu(h)| : h \in H\} < \delta \sup\{u_2(h) : h \in H\} \), which is stronger than \( \sup\{|\nu(h)| : h \in H\} < \sup\{u_2(h) : h \in H\} \), since \( 0 \leq \delta \leq 1 \).

As Assumption 2 specifies \( S \) to be a doubleton; we write \( f(u_1) = 1 - p \) and \( f(u_2) = p \), where \( p \in [0,1] \) is the subjective probability that individuals believe the true relation between health-related utility and nutrient intake to be \( u_2 \). Specifically, we can rewrite the optimization problem (A.opt01) as.

\[
\max_{h \in H} v(h) + \delta (1-p)u_1 + \delta p u_2(h).
\]

(A2)

The first order condition of equation (A.2) is.

\[
\nu (h^*) + \delta p u_2(h^*) = 0,
\]

(A3)

with \( h^* \) being the optimal nutrient intake level. The optimal solution exists and is unique, since the curves of \(-\nu(h) \) and \( \delta p u_2(h) \) intersect once and only once, according to Assumptions 1 to 3. See Fig. A1 for illustration.

(1) Stress and Time Preferences.

The first pathway through which COVID-19 affects diet is stress. For technical reasons we require that Assumption 3 still hold for \( \tilde{\delta} \).
Fig. A1. Optimal Nutrient Intake Given by Equation (A.3).

Fig. A2. The Effect of Stress on the Optimal Healthiness of Diet.

Fig. A3. The Effect of Salience on Diet.
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The Effect of Learning on Diet.

As $\delta < \delta$, we have $\delta \mu_u (h') < -v (h')$, and $h'$ is no longer the optimal choice of nutrient intake. The new optimal choice of nutrient intake $h_\cdot$ is smaller than $h'$, because both $-v$ and $\delta \mu_u$ increase when $h$ gets smaller, according to Assumptions 1 and 2, and $-v$ increases more quickly than $\delta \mu_u$, according to Assumption 3. Fig. A2 illustrates that by shifting $\delta$ to $\delta$, pandemic-caused stress moves the curve $\delta \mu_u (x)$ downward to $\delta \mu_u (x)$, giving rise to a smaller optimal solution $x_\cdot$. This shock is temporal, and its effect will start to vanish as the pandemic abates.

(2) Salience.

Like the stress-induced shocks, salience also brings about a shock to changes of time preferences $\delta$. But by shifting $\delta$ to a larger $\delta$, the shock of salience is positive, and it is reasonable to assume that the more salient the health considerations are, the larger is the weight that individuals put on their expected health-related utility. Contrary to the negative stressor shock (shifting $\delta$ to $\delta$), the positive shock of salience (shifting $\delta$ to $\delta$) drives the optimal choice of nutrient intake $h_\cdot$ higher than $h'$, indicating a healthier diet during the COVID period. As with stressor shock, the positive shock of salience will vanish in post-COVID-19 period. Fig. A3 illustrates that by shifting $\delta$ to $\delta$, salience moves the curve $\delta \mu_u (h)$ upward to $\delta \mu_u (h)$, giving rise to a larger optimal solution $x_\cdot$. This effect is temporary and will decrease as the pandemic abates.

(3) Learning.

In contrast to stress and salience, learning is a rational mechanism through which individuals update their beliefs about the diet-health link during the pandemic. Although social media and medical studies have long documented that healthy eating habits are crucial to individuals’ healthiness, it is likely that many individuals are not fully aware of this fact. This unawareness may be due to inattentiveness or lack of information, which is modeled in our framework by an individual’s uncertainty between $u_1$ and $u_2$. The outbreak of the COVID-19 pandemic stimulates information campaigns to provide enough medical information for individuals to learn more about the health behaviors, including eating a healthier diet, that could lead them to have more faith that $u_2$ is true.

Formally, the learning mechanism is captured by the positive impact on $p$, leading to a larger $\tilde{p}$ than $p$. Unlike the stress-caused shock on $\delta$, the learning effect lasts in the long run; that is, once individuals learn that $u_2$ is more likely to be true than they believed before, they will hold that belief even if the initial stimulus (e.g., the information campaign during the pandemic) has stopped. Similarly, we require that Assumption 3 still hold for $\tilde{p}$. Since $\tilde{p} > p$, we have $\delta \mu_u (h') > -v (h')$. This makes $h'$ no longer the optimal choice of nutrient intake. The new optimal choice of nutrient intake $h_\tilde{p}$ should be larger than $h'$, as both $-v$ and $\delta \mu_u$ decrease when $h$ gets larger, as implied in Assumptions 1 and 2, and $-v$ decreases more slowly than $\delta \mu_u$, according to Assumption 3. Fig. A4 illustrates that by shifting $p$ to $\tilde{p}$, learning moves the curve $\delta \mu_u (h)$ upward to $\delta \mu_u (h)$, giving rise to a larger optimal solution $x_\tilde{p}$. This learning effect will last even if the pandemic is under control.

Appendix B. Details on the calculations of nutrition scores

The basic idea of an NRF score is to define nutrient-rich foods rather than energy-dense ones, as encouraged by the 2005 Dietary Guidelines for Americans (U.S. Department of Health and Human Services, 2005). Following standard procedure, NRFs are computed as the sum of the percentage of daily values of nutrients-to-encourage minus the sum of the percentage of maximum recommended values of nutrients-to-limit (Drewnowski, 2009; Drewnowski and Fulgoni (2014)). In our analysis, we calculated NRF using the following formula:

$$
\text{NRF} = \left( \frac{\text{protein}/50 + \text{fiber}/25 - \text{saturated fat}/20 - \text{added sugars}/50 - \text{sodium}/2400}{100/\text{ED}} \cdot 100/\text{ED} \right)
$$

where the denominator in the parentheses is the reference daily values based on a 2000-kcal diet, the numerator is the nutritional contents per gram, and ED is energy density calculated as kcal/100 g. A negative NRF could be interpreted as the dish containing more nutrients-to-limit than nutrients-to-encourage.

For NPI, according to the U.K. Department of Health (https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/216094/dh_123492.pdf), the original NPI is calculated as:

$$
\text{NPI}_{\text{original}} = (\text{points for energy}) + (\text{points for saturated fat}) + (\text{points for sugars}) + (\text{points for sodium}) - (\text{points for % fruit, vegetable & nut content}) - (\text{points for fiber}) - (\text{points for protein})
$$

The relationship between points and nutrition contents is given by tables on page 5 of Nutrient Profiling Technical Guidance (U.K. Department of...
The larger original NPI scores indicate less healthy. To be comparable with NRF, we normalize NPI according to the following formula:

\[ \text{NPI} = \left( \frac{-\text{NPI}_{\text{original}} - \text{Min}(-\text{NPI}_{\text{original}})}{\text{Max}(-\text{NPI}_{\text{original}}) - \text{Min}(-\text{NPI}_{\text{original}})} \right) \times 100. \]

### Appendix C. Results for dish prices and Restaurant-Level Data.

See Fig. D1 and Tables C1 and C2.

![Fig. D1. Average Dish Prices for 2019 and 2020.](image)

**Table C1**

COVID-19 Coefficients Under Alternative Income Proxies (Restaurant-Level Data).

| Variable                  | NRF         | (1)  | (2)  | (3)  | (4)  | (5)  | (6)  | (7)  | (8)  |
|---------------------------|-------------|------|------|------|------|------|------|------|------|
| National Cases            | -0.451***   | -0.409*** | -0.452**   | -0.411*** | -0.511*** | -0.455**   | -0.511*** | -0.458**  |
|                           | (0.089)     | (0.117) | (0.088) | (0.114) | (0.126) | (0.143) | (0.126) | (0.142)  |
| Local Cases               |             |       |       |       |       |       |       |       |       |
| Income1                   | -1.449      | -1.401 |       | -1.299 | -1.250 |       |       |       |       |
|                           | (0.997)     | (0.959) |       | (0.996) | (0.959) |       |       |       |       |
| Income2                   | 20.552      | 18.978 |       | 20.307 | 18.918 |       |       |       |       |
|                           | (16.330)    | (15.553) |       | (16.256) | (15.481) |       |       |       |       |
| Other Control Variables   | Yes         | Yes   | Yes   | Yes   | Yes   | Yes   | Yes   | Yes   | Yes   |
| City-month                | Yes         | Yes   | Yes   | Yes   | Yes   | Yes   | Yes   | Yes   | Yes   |
| Chain FE                  | Yes         | Yes   | Yes   | Yes   | Yes   | Yes   | Yes   | Yes   | Yes   |
| City FE                   | Yes         | Yes   | Yes   | Yes   | Yes   | Yes   | Yes   | Yes   | Yes   |
| Day of the week FE        | Yes         | Yes   | Yes   | Yes   | Yes   | Yes   | Yes   | Yes   | Yes   |
| Hour FE                   | Yes         | Yes   | Yes   | Yes   | Yes   | Yes   | Yes   | Yes   | Yes   |
| Month FE                  | Yes         | Yes   | Yes   | Yes   | Yes   | Yes   | Yes   | Yes   | Yes   |
| Observations              | 4.641       | 4.641 | 4.641 | 4.641 | 4.641 | 4.641 | 4.641 | 4.641 |       |
| R-squared                 | 0.267       | 0.271 | 0.269 | 0.272 | 0.268 | 0.271 | 0.270 | 0.272 |       |

| Variable                  | NPI         | (1)  | (2)  | (3)  | (4)  | (5)  | (6)  | (7)  | (8)  |
|---------------------------|-------------|------|------|------|------|------|------|------|------|
| National Cases            | -0.095***   | -0.090*** | -0.095**   | -0.091*** | -0.116**   | -0.110*** | -0.116** | -0.111***  |
|                           | (0.017)     | (0.014) | (0.017) | (0.014) | (0.037) | (0.029) | (0.037) | (0.029)  |
| Local Cases               |             |       |       |       |       |       |       |       |       |
| Income1                   | -0.176      | -0.164 |       | -0.130 | -0.118 |       |       |       |       |
|                           | (0.261)     | (0.262) |       | (0.242) | (0.243) |       |       |       |       |
| Income2                   | 4.793       | 4.608 |       | 4.744 | 4.612 |       |       |       |       |
|                           | (2.786)     | (3.009) |       | (2.807) | (3.000) |       |       |       |       |
| Other Control Variables   | Yes         | Yes   | Yes   | Yes   | Yes   | Yes   | Yes   | Yes   | Yes   |
| City-month                | Yes         | Yes   | Yes   | Yes   | Yes   | Yes   | Yes   | Yes   | Yes   |
| Chain FE                  | Yes         | Yes   | Yes   | Yes   | Yes   | Yes   | Yes   | Yes   | Yes   |
| City FE                   | Yes         | Yes   | Yes   | Yes   | Yes   | Yes   | Yes   | Yes   | Yes   |
| Day of the week FE        | Yes         | Yes   | Yes   | Yes   | Yes   | Yes   | Yes   | Yes   | Yes   |
| Hour FE                   | Yes         | Yes   | Yes   | Yes   | Yes   | Yes   | Yes   | Yes   | Yes   |
| Month FE                  | Yes         | Yes   | Yes   | Yes   | Yes   | Yes   | Yes   | Yes   | Yes   |
| Observations              | 4.641       | 4.641 | 4.641 | 4.641 | 4.641 | 4.641 | 4.641 | 4.641 |       |
| R-squared                 | 0.350       | 0.351 | 0.352 | 0.352 | 0.352 | 0.353 | 0.354 | 0.354 |       |
Appendix D. Results for revealed preference and K-Means
See Tables D1-D4.

Table D1
Robustness Check for Regional Spillovers and Pre-trends with 1000 Clusters.

| Variables            | Impact of Infections in Neighboring Cities | Test for Pre-existing Trends from January 1–22, 2019 |
|----------------------|-------------------------------------------|-----------------------------------------------|
|                      | NRF NPI                                   | NRF NPI                                        |
|                      | (1) (2) (3) (4) (5) (6) (7) (8)           | (5) (6) (7) (8)                                |
| National Cases       | −0.310** −0.311** −0.294** −0.061*** −0.060*** −0.962*** −0.966*** −0.606*** | −2.471 1.604 0.540 0.291 |
|                      | (0.102) (0.112) (0.114) (0.015) (0.015) (0.015) (0.015) (0.015) | (1.954 (2.221) (0.426) (0.459) |
| Local Cases          | −0.364** −0.330** −0.325** −0.087** −0.083** −0.087** −0.084** | 0.470 0.413 0.048 0.020 |
|                      | (0.146) (0.155) (0.155) (0.035) (0.035) (0.035) (0.035) | (0.456) (0.511) (0.101) (0.100) |
| Income1              | −1.156 −1.106 −1.101 −0.088 | 0.154 |
|                      | (1.045) (0.245) (0.245) (0.245) | (1.045) (0.245) (0.245) (0.245) |
| Income2              | 20.537 19.296 4.789 4.690 | 0.154 |
|                      | (16.232) (15.372) (2.752) (2.930) | (16.232) (15.372) (2.752) (2.930) |
| Other Control Variables | Yes Yes Yes Yes Yes Yes Yes Yes | Yes Yes Yes Yes Yes Yes Yes Yes |
| City-month | Yes Yes Yes Yes Yes Yes Yes Yes | Yes Yes Yes Yes Yes Yes Yes Yes |
| City FE               | Yes Yes Yes Yes Yes Yes Yes Yes | Yes Yes Yes Yes Yes Yes Yes Yes |
| Day of the week FE   | Yes Yes Yes Yes Yes Yes Yes Yes | Yes Yes Yes Yes Yes Yes Yes Yes |
| Hour FE               | Yes Yes Yes Yes Yes Yes Yes Yes | Yes Yes Yes Yes Yes Yes Yes Yes |
| Month FE              | Yes Yes Yes Yes Yes Yes Yes Yes | Yes Yes Yes Yes Yes Yes Yes Yes |
| Observations          | 4,641 4,641 4,641 4,641 4,641 4,641 4,641 4,641 | Yes Yes Yes Yes Yes Yes Yes Yes |
| R-squared             | 0.273 0.275 0.274 0.276 0.356 0.356 0.358 0.358 | Yes Yes Yes Yes Yes Yes Yes Yes |

Table D2
Changes in Vegetable, Fish and Other Meat (Pork and Beef) Dish Ratios.

| Variable              | Post = 1 for Post-COVID vs Pre-COVID | Post = 1 for Post-COVID vs COVID |
|-----------------------|-------------------------------------|----------------------------------|
|                      | Vegetable Fish Pork & Beef          | Vegetable Fish Pork & Beef       |
|                      | (1) (2) (3) (4) (5) (6)             | (4) (5) (6)                      |
| Post                  | −0.006 0.014 0.008*** 0.011*** −0.000 0.001 | 0.001                            |
|                      | (0.009) (0.012) (0.003) (0.002) (0.006) (0.002) | (0.006) (0.002) (0.002) |
| Other Controls        | Yes Yes Yes Yes Yes Yes Yes Yes | Yes Yes Yes Yes Yes Yes Yes Yes |
| City-month            | Yes Yes Yes Yes Yes Yes Yes Yes | Yes Yes Yes Yes Yes Yes Yes Yes |
| City FE               | Yes Yes Yes Yes Yes Yes Yes Yes | Yes Yes Yes Yes Yes Yes Yes Yes |
| Day of the week FE    | Yes Yes Yes Yes Yes Yes Yes Yes | Yes Yes Yes Yes Yes Yes Yes Yes |
| Hour FE               | Yes Yes Yes Yes Yes Yes Yes Yes | Yes Yes Yes Yes Yes Yes Yes Yes |
| Day FE                | Yes Yes Yes Yes Yes Yes Yes Yes | Yes Yes Yes Yes Yes Yes Yes Yes |
| Observations          | 317,921 317,921 317,921 314,223 314,223 314,223 | 314,223 314,223 314,223 314,223 |
| R-squared             | 0.055 0.294 0.182 0.050 0.290 0.154      | 0.154 |

The dependent variables are the ratios of vegetable, fish, and other meat (pork and beef) dishes to the total number of dishes ordered. Columns (1)-(3) report results by comparing changes during the post-COVID periods to pre-COVID periods. Columns (4)-(6) report results by comparing changes during the post-COVID periods to COVID periods. Note that *, **, and *** indicate significance at the 90%, 95%, and 99% confidence intervals. All errors are clustered at the city level.

Appendix D. Results for revealed preference and K-Means
See Tables D1-D4.
### Table D2

#### Results at Different Stages of the Pandemic with 1000 Clusters.

| Variable | PANEL A: Post = 1 for Post-COVID period (March 19-May 31, 2020) vs Pre-COVID Period (January 1–22, 2020) | PANEL B: Post = 1 for Post-COVID Period (March 19-May 31, 2020) vs COVID Period (January 23–March 18, 2020) | PANEL C: Post = 1 for Post-Covid Period (March 19-May 31, 2020) vs year 2019 (March 19-May 31, 2019) |
|----------|---------------------------------------------------------------|---------------------------------------------------------------|---------------------------------------------------------------|
|          | Fat (1) Sugar (2) Sodium (3) Protein (4) Fiber (5) NRF (6) NPI (7) | Fat (8) Sugar (9) Sodium (10) Protein (11) Fiber (12) NRF (13) NPI (14) | Fat (8) Sugar (9) Sodium (10) Protein (11) Fiber (12) NRF (13) NPI (14) |
| Post     | $-0.277^{***}$ (0.008) | $-2.038^{***}$ (0.344) | $-35.432^{**}$ (11.313) | $0.974^{***}$ (0.102) | $0.421^{***}$ (0.128) | $6.721^{***}$ (2.031) | $2.869^{**}$ (0.924) |
| K-means 1000 | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Other Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| City-month | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Chain FE | Yes | Yes | Yes | Yes | No | No | Yes |
| Day of the week FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Hour FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Day FE | Yes | Yes | Yes | No | No | No | Yes |
| Observations | 317,921 | 317,921 | 317,921 | 317,921 | 317,921 | 317,921 | 317,921 |
| R-squared | 0.238 | 0.359 | 0.143 | 0.233 | 0.209 | 0.178 | 0.274 |
|          | Fat (1) Sugar (2) Sodium (3) Protein (4) Fiber (5) NRF (6) NPI (7) | Fat (8) Sugar (9) Sodium (10) Protein (11) Fiber (12) NRF (13) NPI (14) | Fat (8) Sugar (9) Sodium (10) Protein (11) Fiber (12) NRF (13) NPI (14) |
| Post     | $-0.523^{***}$ (0.101) | $-5.617^{***}$ (0.304) | $-37.014^{***}$ (11.370) | $0.741^{***}$ (0.169) | $0.701^{***}$ (0.057) | $8.946^{***}$ (2.321) | $3.677^{***}$ (0.405) |
| K-means 1000 | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Other Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| City-month | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Chain FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Day of the week FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Hour FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Day FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 314,223 | 314,223 | 314,223 | 314,223 | 314,223 | 314,223 | 314,223 |
| R-squared | 0.221 | 0.348 | 0.152 | 0.229 | 0.207 | 0.160 | 0.292 |
|          | Fat (1) Sugar (2) Sodium (3) Protein (4) Fiber (5) NRF (6) NPI (7) | Fat (8) Sugar (9) Sodium (10) Protein (11) Fiber (12) NRF (13) NPI (14) | Fat (8) Sugar (9) Sodium (10) Protein (11) Fiber (12) NRF (13) NPI (14) |
| Post     | $-3.552^{***}$ (0.727) | $-1.853^{***}$ (0.409) | $-52.779^{**}$ (22.279) | $1.729^{***}$ (0.164) | $0.222^{*}$ (0.164) | $4.831^{***}$ (0.188) | $2.366^{***}$ (0.402) |
| K-means 1000 | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Other Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| City-month | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Chain FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Day of the week FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Hour FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Day FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 515,691 | 515,691 | 515,691 | 515,691 | 515,691 | 515,691 | 515,691 |
| R-squared | 0.257 | 0.384 | 0.192 | 0.266 | 0.158 | 0.206 | 0.298 |

The regressions are estimated using weighted least squares. The dependent variable is the weighted daily number of transactions in each restaurant. Note that *, **, *** indicate 90%, 95%, and 99% confidence intervals. All errors are clustered at the city level.
### Table D3
Robustness Check for Regional Spillovers and Pre-trends with 1500 Clusters.

| Variables | Impact of Infections in Neighboring Cities | Test for Pre-existing Trends from January 1–22, 2019 |
|-----------|------------------------------------------|------------------------------------------|
|           | NRF (1) | NRF (5) | NPI (2) | NPI (6) | NPI (3) | NPI (7) | NPI (4) | NPI (8) |
| National  |        |        |        |        |        |        |        |        |
|           | −0.017*** | −0.110*** | −0.039*** | −0.070*** | −2.330 | −1.428 | −0.172 | 0.151 |
|           | (0.003) | (0.001) | (0.009) | (0.018) | (1.716) | (2.050) | (0.409) | (0.461) |
| Local     | −0.332*** | −0.334*** | −0.022*** | −0.100*** | 0.492 | 0.491 | 0.019 | 0.006 |
|           | (0.064) | (0.049) | (0.003) | (0.002) | (0.432) | (0.491) | (0.098) | (0.098) |
| Neighbor  | 0.098 | 0.043 | 0.015 | −0.009 | 0.098 | 0.043 | 0.015 | −0.009 |
|           | (0.091) | (0.111) | (0.023) | (0.026) | (0.091) | (0.111) | (0.023) | (0.026) |

K-means 1500
Other Control Variables
City-month
Restaurant FE
City FE
Day of the week FE
Hour FE
Month FE
Observations

| NRF (1) | NRF (5) | NPI (2) | NPI (6) | NPI (3) | NPI (7) | NPI (4) | NPI (8) |
|---------|---------|---------|---------|---------|---------|---------|---------|
| National | −0.760 | −2.543 | 0.529 | 0.730 | −0.122 | −0.286 | 1.214 | 1.795 |
|          | (0.439) | (1.517) | (0.781) | (0.531) | (3.793) | (5.828) | (1.417) | (1.220) |
| Local    | 0.016 | 0.010 | 0.007 | −0.009 | 0.129 | 0.071 | 0.072 | 0.077 |
|          | (0.068) | (0.055) | (0.014) | (0.008) | (0.105) | (0.111) | (0.059) | (0.056) |
| K-means 1500 | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Other Control Variables | No | Yes | No | Yes | No | Yes | No | Yes |
| City-month | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Restaurant FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| City FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Day of the week FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Hour FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 188,251 | 188,251 | 188,251 | 188,251 | 271,641 | 271,641 | 271,641 | 271,641 |

R-squared

The regressions are estimated using weighted least squares, using as weight the daily number of transactions in each restaurant. Note that *, **, *** indicate 90%, 95%, and 99% levels of confidence. All errors are clustered at the city level.

### Table D4
Results at Different Stages of the Pandemic with 1500 Clusters.

| Variable | PANEL A: Post = 1 for Post-COVID period (March 19-May 31, 2020) vs Pre-COVID Period (January 1–22, 2020) | PANEL B: Post = 1 for Post-COVID Period (March 19-May 31, 2020) vs COVID Period (January 23-March 18, 2020) |
|----------|---------------------------------------------------------------|---------------------------------------------------------------|
|          | Fat (1) | Sugar (2) | Sodium (3) | Protein (4) | Fiber (5) | NRF (6) | NPI (7) | Fat (8) | Sugar (9) | Sodium (10) | Protein (11) | Fiber (12) | NRF (13) | NPI (14) |
| Post     | −0.946*** | −1.983*** | −34.660*** | 0.240* | 0.197* | 4.464*** | 1.497*** | −0.241*** | −5.382*** | −30.545*** | 0.710** | 0.713*** | 9.420*** | 3.396*** |
|          | (0.007) | (0.039) | (9.067) | (0.121) | (0.092) | (3.885) | (0.277) | (0.007) | (0.039) | (6.074) | (0.270) | (0.055) | (1.884) | (0.415) |
| K-means 1500 | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Other Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| City-month | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Restaurant FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| City FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Day of the week FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Hour FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Day FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 317,921 | 317,921 | 317,921 | 317,921 | 317,921 | 317,921 | 317,921 | 317,921 | 317,921 | 317,921 | 317,921 | 317,921 | 317,921 | 317,921 |

R-squared

The regressions are estimated using weighted least squares, using as weight the daily number of transactions in each restaurant. Note that *, **, *** indicate 90%, 95%, and 99% levels of confidence. All errors are clustered at the city level.
The regressions are estimated using weighted least squares. The dependent variable is the weighted daily number of transactions in each restaurant. Note that *, **, *** indicate 90%, 95%, and 99% confidence intervals. All errors are clustered at the city level.

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