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How online food delivery platforms contributed to the resilience of the urban food system in China during the COVID-19 pandemic

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A R T I C L E I N F O

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A B S T R A C T

We use high-frequency data to quantify the nature and performance of online food delivery platforms during the COVID-19 pandemic in urban China, and to estimate the short- and long-term effects of lockdown and reopening measures. A staggered difference-in-differences (DID) estimation strategy and event study approach are used to identify the effects of lockdown and reopening measures on the performance of online food delivery platforms and restaurants. The results indicate that some restaurants continued to operate and offer online food delivery while lockdowns were in effect. Both the number of operating restaurants and their online food delivery services rebounded and experienced further growth after lockdowns were lifted. The adjustment path of the online food delivery business following the implementation of lockdowns differed from the adjustment path following the lifting of lockdowns. The lockdown and reopening measures did not affect all types of restaurant/cuisine equally. We also examine possible impact mechanisms of lockdown measures on online food delivery and restaurants, and conduct robustness checks to confirm the stability of the main findings. This study contributes to the existing literature by confirming the positive contribution of online food delivery to the resilience of urban food systems in response to unexpected external shocks. Our results have implications for the design of policies to guarantee food supply and help urban food systems adapt to unexpected shocks.

1. Introduction

The COVID-19 pandemic (hereafter 'the pandemic') poses a great threat to global and local food supply systems (Aday and Aday, 2020; Garnett et al., 2020; Lowe et al., 2021; Swinnen and Vos, 2021; McDermott and Swinnen, 2022). In response to the pandemic, most governments implemented (and continue to implement) various measures such as lockdowns, curfews, transport restrictions, social distancing, and market closures to delay and halt the spread of COVID-19 (Ali et al., 2020; Brodeur et al., 2021; Fan et al., 2021; Swinnen and McDermott, 2020). The pandemic and these prevention measures severely affected the restaurant business (Byrd et al., 2021; Neise et al., 2021; Freitas and Stedefeldt, 2020). On the demand side, many consumers reduced the frequency of restaurant visits to reduce the risk of contracting the disease (Goyal and Verma, 2021). On the supply side, many restaurants were not allowed to operate/open because of lockdowns or other restrictions designed to reduce social contacts. Consequently, most restaurants were closed during the lockdowns (Tucker and Yu, 2020; Filimonau et al., 2021; Garnett et al., 2020). The restaurants that remained open shifted their established food services to delivery, takeout, and outdoor dining options to fulfill consumers' demand and maintain operations through the crisis (Brizek et al., 2021; Freitas and Stedefeldt, 2020; Kim and Lee, 2020; Reardon et al., 2021; Yang et al., 2021).

The shifts in consumers' dining behavior and restaurants' operations emphasized the essential role of online food delivery platforms in urban

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food systems during the pandemic (Kumar and Shah, 2021). Online food delivery and takeaway platforms such as Ele.me, Meituan, Ubereats and Grubhub, acted as an interface between consumers and restaurants, and allowed consumers to order food via the Internet and have it either delivered to their home, or prepared and deposited for curbside pickup (Freitas and Stedefedt, 2020). This gave consumers access to food beyond their neighborhoods and workplaces via online food delivery apps (Maimaiti et al., 2018). Online food delivery platforms simultaneously expanded restaurants' market borders by collecting online orders from various consumers, and contracting delivery services to bring food to consumers (Maimaiti et al., 2018). These platforms thus provided restaurants with a means of offsetting the impact of the pandemic and reducing social contact (Freitas and Stedefedt, 2020), thereby enhancing the resilience of supply chains in urban food systems by improving food accessibility and availability (Maimaiti et al., 2018).[1] Contactless online food delivery platforms also minimized exposure to the COVID-19 virus, which might have helped to slow its transmission and protect at-risk consumers (Kumar and Shah, 2021).

Building on the penetration of information technology, online food delivery platforms have expanded in recent decades to improve food accessibility and availability in many countries (Kumar and Shah, 2021). China is the largest market for online food delivery and takeaway, which served 419 million customers with 17.12 billion orders in 2020.,[2],[3] Online food delivery platforms have developed rapidly with advances in app, smartphone and e-payment terminal technologies. The sales value of online takeaway platforms in China increased fourfold from 24.1 billion US$ in 2016 to 96.4 billion US$ in 2020 (Zhou et al., 2020).,[4],[5] In 2020, 380,000 new companies linked to food delivery services were registered in China (iiMedia, 2020).[6] However, to date, there is insufficient empirical evidence on the performance[7] of online food delivery during the pandemic. Previous studies have found that food supply chains in high, middle and low-income countries were temporally vulnerable following the onset of the pandemic (Carducci et al., 2021; Garnett et al., 2020). Furthermore, the disruptions in supply chains for fresh food, particularly perishable, nutrient-rich foods such as fruits and vegetables, increased price volatility and made healthy and nutritious diets less affordable (Laborde et al., 2021; Osendarp et al., 2021; Falkendal et al., 2021).

Against this background we analyze how the pandemic and related prevention measures affected online food delivery in China, where it has become an important food source especially for young urban residents. In addition, we study whether the pandemic temporarily or permanently shifted urban residents' food preferences. Investigating these questions can contribute to a better understanding of the importance of online food delivery in urban food systems, and guide the design of policies that enhance the resilience of these systems to external shocks. China is an interesting case to study because of its booming online food delivery market and the relatively strict lockdown measures that it implemented in response to the pandemic.

The aim of this paper is to address these research gaps by using a high-frequency dataset collected from the Ele.me platform (one of the major online food delivery platforms in China), which provides us with daily online food delivery orders for 57 cities in China from Dec. 1st, 2019 to May 01, 2020, and in 2021.,[8],[9] We first apply a staggered difference-in-difference (DID) estimation strategy and event study approach with daily city-level online food delivery data to identify the effects of lockdown and reopening measures on the online food delivery business. Second, we examine the effects of these measures on food consumption structures and residents' use of online food delivery and restaurants. Finally, we perform a set of robustness tests to confirm the stability of our empirical results.

The contributions of this study include but are not limited to the following points. First, this is the first study that sheds light on the performance and importance of online food delivery in response to the COVID-19 pandemic. Second, compared with previous descriptive studies based on macro-level data, this study provides evidence on the effects of the lockdown and reopening measures on the restaurant and online food delivery industries in urban food systems by employing rigorous empirical analyses with daily city-level food delivery data. Third, our study contributes to the existing literature by confirming the positive contribution of the online food delivery system to the resilience of urban food systems in response to unexpected external shocks. Rapidly expanding online food delivery platforms help to match the demand and supply of online food delivery by reducing the information asymmetry between consumers and restaurants; in addition, they can increase supply efficiency through intelligent order allocation systems. Fourth, our findings reveal some changes in consumers' preferences for different categories of food ordered online during and after the implementation of lockdown measures.

Of course, our results are only representative of China as a whole if the Ele.me online delivery platform that we study is representative. Developments on other platforms could cancel or otherwise modify the effects that we measure. However, the annual financial report of the largest online platform (Meituan, 2020) presents trends in transaction values that are similar to those that we find in the Ele.me data. Hence, we are confident that our main results can be generalized.

The paper is organized as follows. The following section 2 describes the data. The empirical estimation strategy is presented in Section 3. Empirical results are shown in Section 4, followed by a discussion. We close with concluding remarks in section 5.

2. Data

We obtained the data used in this study from different sources. Table B1 shows the sample cities and different lockdown and reopening measures that they implemented. Table B2 summarizes the definitions and mean values of all variables used in the empirical models. Table B3 presents comparisons of all independent variables' mean values in the pre-, during and post-lockdown phases. The significant differences in the mean values of all independent variables between the phases reflect the remarkable changes in these variables that took place as the lockdown and reopening measured were implemented.

2.1. Lockdown and reopening data

We followed previous literature and sampled cities from all three types of lockdown response: 15 cities under complete lockdown, 7 cities under partial lockdown and 35 no-lockdown cities (Table B1) (Fang et al., 2020). Figure B1 displays our sample cities on a map. Our sample includes all Chinese cities that implemented complete or partial lockdowns. We further selected 35 no-lockdown cities to represent the remaining 271 cities in China. In general, our sample cities are widely

[1] The restaurants deliver food ordered on online food delivery platforms directly to a consumer's home through a contactless express delivery service. Hence, the customer need not dine in the restaurant and can avoid direct contact with other customers.

[2] https://baijiahao.baidu.com/s?id=1708339591239907057&wfr=spider&for=pc.

[3] https://baijiahao.baidu.com/s?id=1690215312440154583&wfr=spider&for=pc.

[4] https://www.iimedia.cn/c460/77947.html.

[5] 1US$Dollar = 6.8974RMB in 2020.

[6] https://it.chinairn.com/news/20200622/174509209.html.

[7] In this study, the "performance" is defined as the number of orders and the transaction value.

[8] We describe these cities and the lockdown and reopening measures that they implemented in section 2.

[9] Under the terms of our agreement with the Ele.me platform, data are unavailable between May 02, 2020, and Dec. 18, 2020.

distributed throughout the country. China imposed a lockdown in Wuhan starting from 10 a.m. of January 23, 2020, and in all other cities in Hubei province one day later. These 15 cities in Hubei are defined as '*complete lockdown*', which means all public transport and private vehicles were banned in the city, all residential buildings were locked down, and residents were not allowed to leave the city. Residents living in these cities were not allowed to leave their homes (home confinement), which made shopping in supermarkets or food markets (which were closed anyhow) impossible. Food was supplied to residents either by the local community or on-line food delivery platforms on which some restaurants provided service. A further 7 cities implemented '*partial lockdown*', meaning that the majority of public transportation was temporarily locked down, checkpoints were set up to control the inflow of population, and surveillance and other controls were tightened in the neighborhoods. In all other cities (35 cities in our sample) public transport maintained normal operations, and only some checkpoints and quarantine zones were implemented. We define these cities as '*no-lockdown*' (Fang et al., 2020).

We base the dates of lockdown and reopening on official announcements collected from the websites of the local government for each city. Chinese Vice-Premier Sun Chunlan was sent to Wuhan in late January to manage Hubei's corona virus response, thus the reopening of Hubei province was managed by the central government and not by the local governments. By decision of the CPC Central Committee, Mrs. Sun stayed in Wuhan until April 27, 2020.[10] Detailed information on the exact dates on which different cities implemented lockdowns and reopened are presented in Appendix B of Table B1.

2.2. Online food delivery orders data

The data on online food delivery were obtained from the Ele.me platform, which is one of the two dominant online food delivery platforms in China.[11] Restaurants and food courts contract with Ele.me to be included on this platform. Each restaurant or food court provides an online menu and the customers can make online food orders via the platform. Delivery services are generally contracted between the restaurants or food courts and a delivery company. The platform records every online food delivery order for each restaurant within each city. Under our agreement with Ele.me platform, we were allowed to use the daily, city-level online food delivery order data from Dec. 1, 2019 to May 1, 2020, and from Dec. 19, 2020 to May 19, 2021. In total, we analyzed 17385 observations for 57 cities over 305 days.

The daily city-level food delivery data included i) total transaction value (both including and net of delivery fees), ii) the number of the online food delivery orders, iii) the number of restaurants offering online food deliveries, iv) the average transaction value (both including and net of delivery fees), v) the number of online food delivery orders per restaurant, and vi) the delivery fee per order. These are the outcome variables that will be analyzed in detail below. To investigate the effects of lockdowns and reopening on various categories of delivered foods, we divided all restaurants into four groups based on their main cuisines sold: Chinese style, western style, fresh food, and other.[12] Based on this division, we calculated the shares of each food category in the total number of orders and transaction values.

2.3. Covariates

The daily new COVID-19 cases in each Chinese city were collected from the Chinese Center for Disease Control and Prevention (http://2019ncov.chinacdc.cn/2019-nCoV/). We used cumulative new COVID-19 cases over the last 14 days to measure the spread of the pandemic in each city (Table B2).,[13],[14]

Daily temperature and precipitation in each city (Table B2) were obtained from the China Meteorological Data Service Center-National Meteorological Information Centre (http://data.cma.cn). These variables were used to control for the possible confounding effects of weather on online food delivery. Recent studies indicate that experiencing the bad weather such as extreme temperature and humidity, intense precipitation, and strong wind makes people less likely to go outside (He et al., 2022) and increases the demand for food delivery service, particularly in the young generation (Maimaiti et al., 2018). Chu et al. (2021) and Sun et al. (2019) concluded that individuals are more likely to order online food delivery services when their personal cost of exposure to the outdoor environment is high. Thus, the covariates of daily temperature and precipitation were used to control the possible confounding effects of weather on online food delivery.

3. Estimation strategy

3.1. Staggered difference-in-differences estimates

To examine the impact of lockdowns and reopening on food takeaway service through online food delivery platforms, we first used the staggered difference-in-differences (DID) estimation strategy. We used the following DID specification:

$$Y_{it} = \alpha + \beta_1 treat_i \times span_t + \gamma_1 COVID19_{it} + \gamma_2 tem_{it} + \gamma_3 prec_{it} + \delta_i + \tau_t + \varepsilon_{it} \quad (1)$$

In equation (1) Y_{it} is the outcome variable for city i at date t defined in subsection 2.2. The variable $treat_i$ equals 1 if the city belongs to the treatment group of cities in which complete or partial lockdown prevention measures were implemented, and equals 0 if the city belongs to the no-lockdown control group. The cumulative number of new reported COVID-19 infections in city i in the two weeks prior to t ($COVID19_{it}$), daily temperature (tem_{it}), and precipitation ($prec_{it}$) in each city were used to control for other factors that might affect online food delivery. δ_i and τ_t are city and time fixed effects, which were used to absorb city-specific heterogeneity and the time-specific effects that may contaminate the estimation of β_1, our coefficient of interest. ε_{it} is the idiosyncratic error. Standard errors were clustered at the city level.

To estimate the effects of the lockdowns on online food delivery, we coded $span_t$ to capture the lockdown and reopen scenarios. Three different coding strategies were used to define the variable $span_t$. In the first, $span_t$ equals 1 for city i in the treatment group from date t when it started to implement a lockdown until reopening, and 0 prior to t. The coefficient of interest β_1 in equation (1) therefore captures the average treatment effect (ATE) of the lockdown on the outcome variable of interest. Second, to estimate the effects of reopening on online food delivery compared with the lockdown, we coded $span_t$ to equal 1 for city i in the treatment group beginning from the date t on which it lifted its

[10] See for example "Efforts to contain the coronavirus outbreak a test of China's centralized control," Los Angeles Times, January 27, 2020, for news reporting about the central government's actions during this time.

[11] In September 2019, Ele.me platform ranked second of the food delivery platforms in China, and had a market share over 40% (https://baijiahao.baidu.com/s?id=1645628736727229724&wfr=spider&for=pc).

[12] For example, if the main cuisine sold in a restaurant was pizza, this restaurant was categorized as a western restaurant, and all online orders sold in this restaurant were categorized as western food.

[13] The reported official numbers of COVID-19 infections in Hubei province were adjusted after the Wuhan lockdown. We use the adjusted COVID-19 infection numbers in all of the sampled cities in Hubei province.

[14] COVID-19 prevention measures in China were adjusted by local communities based on the numbers of new COVID-19 infections over the past two weeks.

lockdown measures, and to equal 0 during the lockdown period. In this case, β_1 in equation (1) captures the ATE of reopening on the outcome variable.[15] Finally, to compare the performance of online food delivery after reopening with pre-lockdown levels, $span_t$ was coded to equal 1 if city i in the treatment group started to implement reopening from date t, and 0 for t prior to the implementation of lockdown. Thus, in this third case the coefficient β_1 captures whether the outcome variable of interest recovered to its pre-pandemic level in the short-term to May 1, 2020.

We also estimated the long-term effects of the lockdown and reopening measures using the DID model by supplementing the data from Dec. 19, 2020 to May 19, 2021. Here $span_t$ is coded to equal 1 for city i for t from Dec. 19, 2020 to May 19, 2021, and 0 for t prior to the implementation of the lockdown. Thus, in this case the coefficient β_1 in equation (1) measures whether the outcome variable of interest had recovered to its pre-pandemic level one year after the lockdown was lifted.

Finally, a set of robustness tests was conducted to confirm the stability of the empirical results. These included excluding observations during the spring festivals to control for possible effects of public holidays on the outcome variables, and coding $span_t$ using the exact dates on which restaurant operations were suspended and reopened rather than the dates on which lockdowns were implemented and lifted.

3.2. Event study

To better understand the adjustment paths of online food delivery outcome variables following lockdowns and reopening, we employed the event study approach to estimate effects on outcome variables at different times. We used the following event study specification:

$$Y_{it} = \alpha + \sum_{m=k, m\neq -1}^{M} \theta_k \times D_{itk} + \gamma_1 COVID19_{it} + \gamma_2 tem_{it} + \gamma_3 prec_{it} + \delta_i + \tau_t + \varepsilon_{it} \tag{2}$$

In equation (2), all variables are as defined above for equation (1). In addition, D_{itk} is a set of dummy variables indicating the lockdown status at different periods. We set one week (7 days) into one bin (bin $m \in M$), so that we can observe the unfolding effects of a lockdown on online food delivery over a sequence of weeks. m indices the m^{th} week related to the implementation of a city's lockdown. Hence, the dummy for $m = -2$ indicates two weeks before the lockdown in city i, $m = 0$ indicates the week in which the lockdown was implemented, and $m = 1$ indicates one week after the implementation of the lockdown. The dummy for $m = -1$ is omitted in equation (2) to represent the reference week.

4. Results

4.1. The performance of online food delivery during the lockdown and reopening

Both the total and net (of delivery fees) transaction values of online food deliveries decreased following the imposition of lockdowns, by 78.4% and 77.4%, respectively (see Fig. 1a, Fig. 1b, Panel A of Fig. 2 and Table A1).[16] The number of online food delivery orders (Fig. 1c) and the number of restaurants offering online food delivery services (Fig. 1d) also decreased sharply by 85.7% and 90.0% of their pre-lockdown levels, respectively (Panel A of Fig. 2 and Table A1). However, in all 57 cities, some restaurants continued to operate and offer online food delivery while lockdowns were in effect (Fig. 1). Specifically, approximately 10% of all restaurants remained in operation during the lockdown period (Fig. 1d). Furthermore, the average transaction value (Fig. 3a-b) and the average number of online food delivery orders (Fig. 3c) per restaurant that remained open increased by 129.8% (139.6% net of delivery fees) and 40.1%, respectively (Panel A of Fig. 2 and Table A1).

Online food delivery sales rapidly returned to pre-lockdown levels following reopening of lockdown, especially in the complete lockdown cities (Fig. 1). This recovery was smaller in cities that had implemented partial lockdowns. The net transaction value of online food deliveries, the total number of online food delivery orders and the number of restaurants all recovered quickly after reopening (Fig. 1). However, the average transaction value (both including and net of delivery fees) and online food delivery orders per restaurant declined (Fig. 3). Nevertheless, compared with pre-lockdown levels, the net transaction value of online food deliveries increased by 9.4%, while the number of restaurants in operation was 13.2% lower (Panel C of Fig. 2 and Table A1). Meanwhile, the average transaction value and the average number of online food delivery orders per restaurant were higher by 24.5% (25.9% net of delivery fees) and 10.1%, respectively, than before the lockdown (Panel C of Fig. 2 and Table A1).

Both the number of operating restaurants and the numbers of online food delivery orders rebounded and experienced further growth one year after lockdowns were lifted (Fig. 1). However, significant growth was only observed in cities that had implemented complete lockdowns; the post-lockdown recovery was smaller in cities that had implemented partial lockdowns also in the longer term. In particular, the number of restaurants that offer online food delivery services increased (Fig. 1d), but not significantly (Fig. 4 and Table A2). The total and net (of delivery fees) transaction value of online food deliveries (8.5% and 8.0%), as well as the number of online food delivery orders (11.7%) (Fig. 1a-c), the average transaction value (both including and net of delivery fees) per restaurant (4.4% and 3.9%), and the average number of orders per restaurant (6.5%) (Fig. 3a-c) all increased (Fig. 4 and Table A2).

The adjustment path of online food delivery following the implementation of lockdowns differed from the adjustment path following the lifting of lockdowns. The results of event studies (equation (2)) indicate that 2–4 weeks after the lockdowns were implemented, the outcome variables of interest such as the total transaction value of online food delivery had reached their lowest levels (Fig. 5a-d). After reopening, it took longer, about 8 weeks, for these variables to return to their pre-lockdown levels. However, the average transaction value per restaurant (both including a net of delivery fees) and the average number of orders per restaurant peaked roughly 6–7 weeks after lockdowns were imposed, and took another 5–6 weeks after reopening to return to their pre-lockdown levels (Fig. 6a-c).[17]

[15] Due to the limited availability of data, we were only able to estimate the ATE of reopening using a comparatively short data period from Dec. 1, 2019 to May 1, 2020.

[16] Marginal effects are calculated using the coefficients estimated by equation (1). For example, the lockdown led to an estimated 78.4% reduction in the total transaction value of online food deliveries. This marginal effect is calculated by transforming the estimated coefficient (−1.531) into percentage terms ($e^{-1.531} - 1 = -0.784$).

[17] We also analyzed data on food eaten at the restaurants to complement the analysis of delivered online food orders. The event study results indicate that here the outcome variables of interest reached their lowest levels 4–6 weeks after the implementation of lockdown measures (Figures A1-A2). In addition, it took around 13–14 weeks after the lockdowns were lifted for food consumption at the restaurants to return to pre-lockdown levels. This suggests that customers' food away from home behavior responded to the implementation of lockdown measures differently depending on whether the food was eaten at the restaurant, or ordered online for delivery and consumption elsewhere. Compared with ordering food online for delivery, it took longer for customers to return to eating at restaurants. This is presumably due continued efforts to maintain social distance to reduce the risk of infection. More details about these data and results can be found in the Supplementary Information Materials (Figures A1-A2; Tables B2-B3).

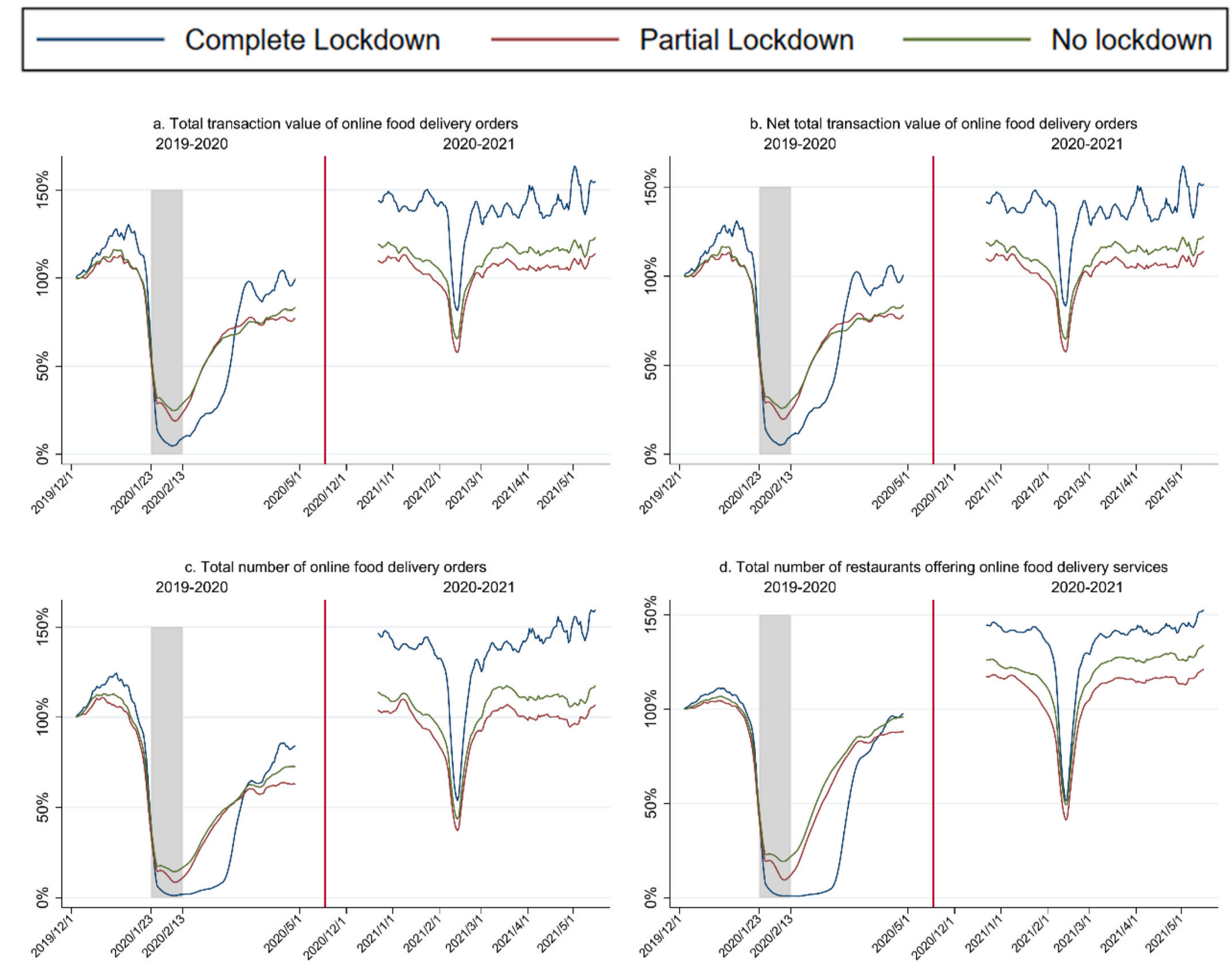

Fig. 1. Online food delivery consumption changes over time. Notes: [1.] All of the figures present 7-day moving averages, and the benchmark (100%) is the average of Dec. 1–7, 2019. Complete lockdown cities began to lockdown from Jan. 23, 2020; Partial lockdown cities began to lockdown from Feb. 2, 2020; Partial lockdown cities began to reopen from Feb. 13, 2020; Complete lockdown cities began to reopen from March 13, 2020; All of the partial lockdown cities had reopened by March 21, 2020; All of the complete lockdown cities had reopened by April 8, 2020; The shaded box represents the period from the beginning of the lockdown to the beginning of the reopening. [2.] The study duration is from Dec. 1, 2019 to May 1, 2020 and Dec. 19, 2020 to May 19, 2021; The solid vertical red line signifies an interruption of the time axis between May and December 2020. . (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

4.2. Heterogeneous effects on different categories of online food delivery

The lockdown and reopening measures did not affect all types of restaurant/cuisine equally (O'Connell et al., 2022). To explore this, we used the staggered DID approach mentioned above to estimate the effects of lockdown and reopening measures on each of the four food categories outlined above (Chinese, western, fresh and other).

During the lockdown, the shares (proportion of transaction value) of Chinese and western food in online food delivery fell by 16.2% and 9.2%, respectively, while the shares of fresh and other food increased by 14.1% and 9.6%, compared with before the lockdown (Panel A of Fig. 7 and Table A3).[18] After reopening, urban residents tended to buy less Chinese food (−3.8%) but more western food (2.9%) and other food (0.9%) through online food delivery platforms than they had before the lockdown (Panel C of Fig. 7 and Table A3). One year after the lockdown, the structure of ordered food changed again; consumers increased the consumption of fresh food by 0.1% but decreased the consumption of other food by 0.5% (Fig. 8 and Table A4).[19]

4.3. Mechanism analysis

We investigated three potential mechanisms that could explain the effects of lockdown measures on online food delivery. First, the Baidu search index, which is constructed based on the standardized search volume of specific keywords in a given period, can be considered a proxy for consumers' demand for online food delivery (Fisman et al., 2021). We used this index to measure the interest in specific keywords related to online food delivery and eating in restaurants in each of the cities in

[18] We have also calculated the share of food category structure by the amount of the orders. The results presented in Figure A3 are consistent with those reported here and in Fig. 7.

[19] We have also calculated the share of food category structure by the amount of the orders one year after the lockdown. The results presented in Figure A4 are consistent with those reported here and in Fig. 8.

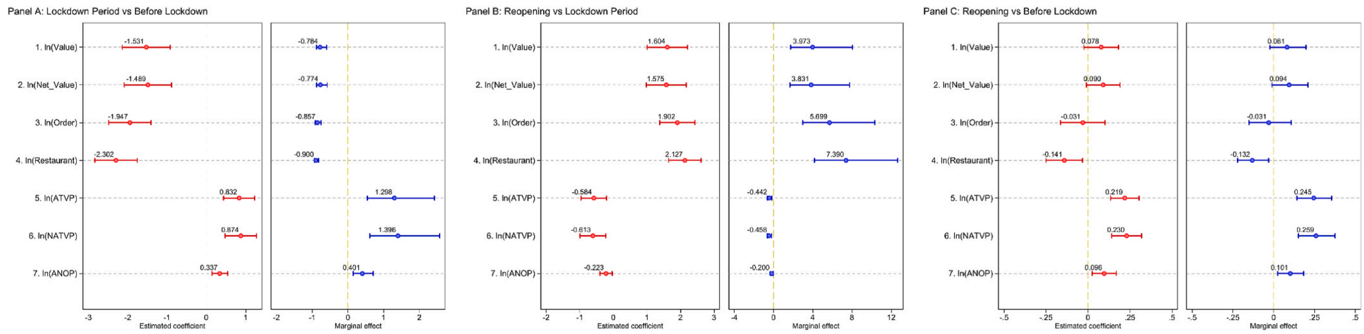

Fig. 2. The effects of lockdown and reopening measures on online food delivery consumption: Date fixed effects. Notes: [1.] The different color lines/marks represent the estimated coefficients and marginal effects for the effects of lockdown and reopening measures on online food delivery consumption. The specification controls for date and city fixed effects. [2.] The error bars represent the 95% confidence intervals for each coefficient estimated using city-level clustered standard errors. [3.] "ln (Value)" refers to the natural logarithm of the total transaction value of online food delivery orders paid by consumers (RMB); "ln(Net_Value)" refers to the natural logarithm of the total transaction value of online food delivery orders paid by consumers net of delivery costs (RMB); "ln(Order)" refers to the natural logarithm of the total number of online food delivery orders (number); "ln(Restaurant)" refers to the natural logarithm of the total number of restaurants offering online food delivery services (number); "ln(ATVP)" refers to the natural logarithm of the average transaction value of online food delivery orders per restaurant paid by consumers (RMB); "ln(NATVP)" refers to the natural logarithm of the average transaction value of online food delivery orders per restaurant paid by consumers net of delivery costs (RMB); "ln(ANOP)" refers to the natural logarithm of the average number of online food delivery orders per restaurant (number). [4.] Full results are presented in Table A1. . (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

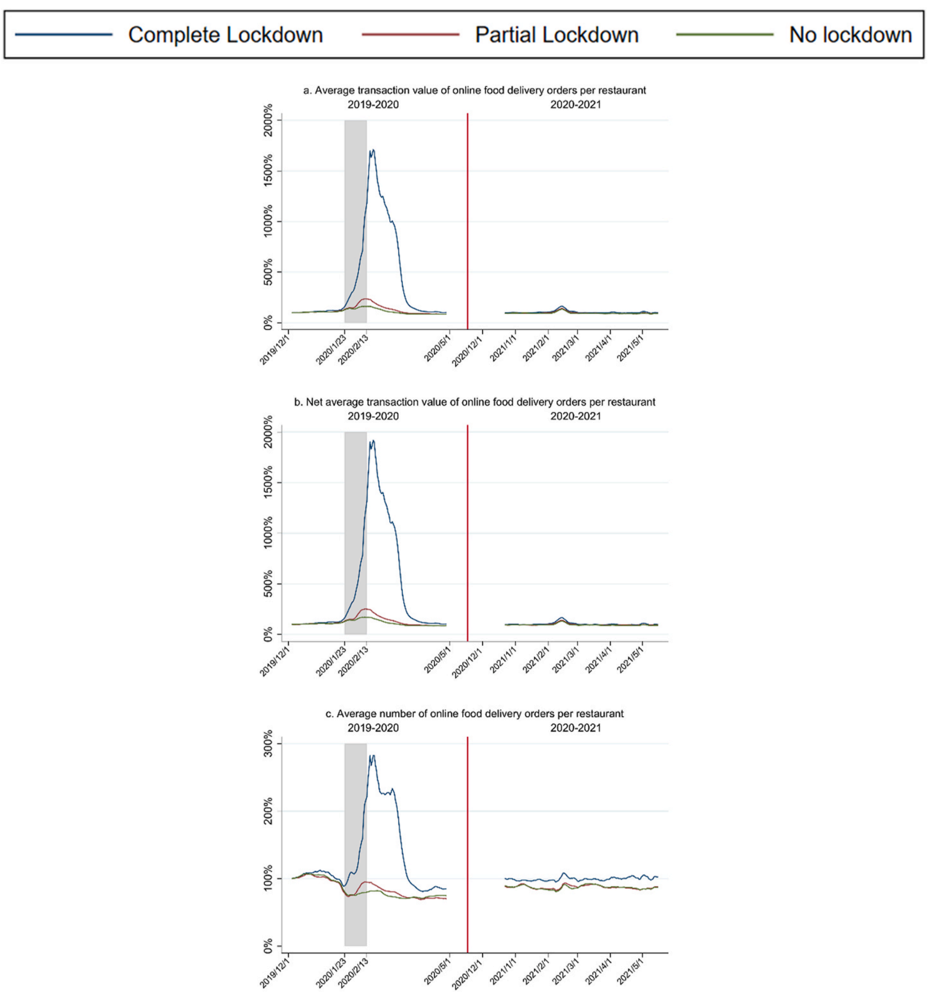

Fig. 3. The changes in online food delivery consumption per restaurant over time Notes: [1.] All of the figures present 7-day moving averages, and the benchmark (100%) is the average of Dec. 1–7, 2019. Complete lockdown cities began to lockdown from Jan. 23, 2020; Partial lockdown cities began to lockdown from Feb. 2, 2020; Partial lockdown cities began to reopen from Feb. 13, 2020; Complete lockdown cities began to reopen from March 13, 2020; All of the partial lockdown cities had reopened by March 21, 2020; All of the complete lockdown cities had reopened by April 8, 2020; The shaded box represents the period from the beginning of the lockdown to the beginning of the reopening. [2.] The study duration is from Dec. 1, 2019 to May 1, 2020 and Dec. 19, 2020 to May 19, 2021; The solid vertical red line signifies an interruption of the time axis between May and December 2020. . (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

our dataset (Fig. 9 and Table A5). Our list of keywords is as follows (Chinese pronunciation in parentheses): Online food delivery (WaiMai)+Catering (CanYin)+Restaurant (CanGuan); Online food delivery (WaiMai); Eat at restaurants (TangShi)+Catering (CanYin)+ Restaurant (CanGuan); and Eat at restaurants (TangShi).

The effects of lockdown and reopening measures on these search indices were estimated using the staggered DID approach (equation (1)). We find that the frequency of searches on keywords including "online food delivery" increased by more than 50% after lockdowns were implemented compared with before (Panel A of Fig. 9). After reopening,

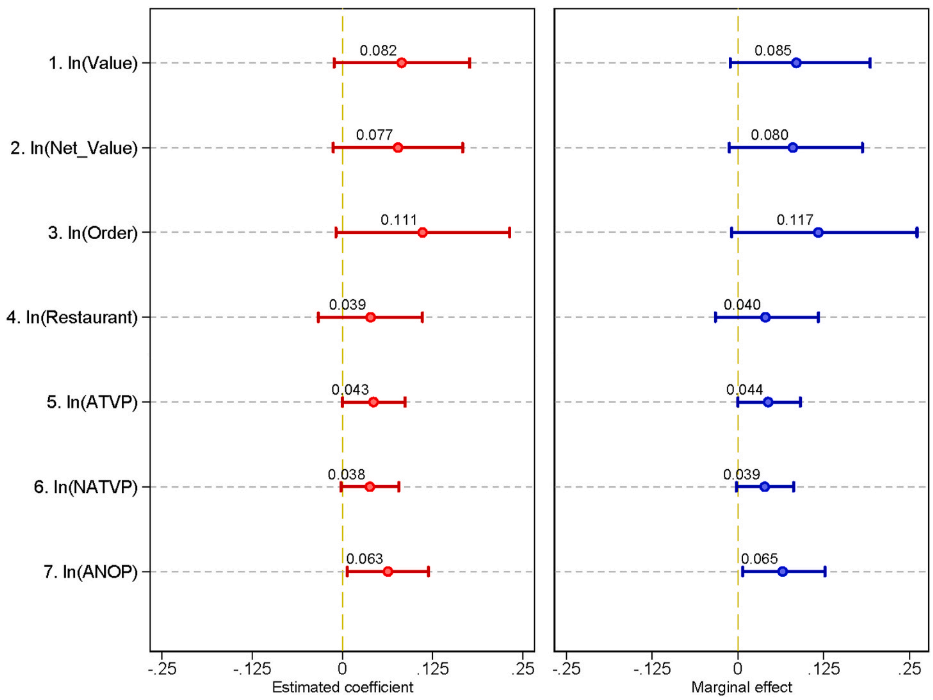

Fig. 4. The long-term effects of reopening measures on online food delivery consumption: Date fixed effects. Notes: [1.] The different color lines/marks represent the estimated coefficients and marginal effects for the long-term effects of reopening measures on online food delivery consumption. The specification controls for date and city fixed effects. [2.] The error bars represent the 95% confidence intervals for each coefficient estimated using city-level clustered standard errors. [3.] "ln(Value)" refers to the natural logarithm of the total transaction value of online food delivery orders paid by consumers (RMB); "ln(Net_Value)" refers to the natural logarithm of the total transaction value of online food delivery orders paid by consumers net of delivery costs (RMB); "ln(Order)" refers to the natural logarithm of the total number of online food delivery orders (number); "ln(Restaurant)" refers to the natural logarithm of the total number of restaurants offering online food delivery services (number); "ln(ATVP)" refers to the natural logarithm of the average transaction value of online food delivery orders per restaurant paid by consumers (RMB); "ln(NATVP)" refers to the natural logarithm of the average transaction value of online food delivery orders per restaurant paid by consumers net of delivery costs (RMB); "ln(ANOP)" refers to the natural logarithm of the average number of online food delivery orders per restaurant (number). [4.] Full results are presented in Table A2. . (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

the frequency of these searches fell again, but by less than they had increased during the lockdown (Panel B of Fig. 9). The result was a net increase from the pre-to the post-lockdown period (Panel C of Fig. 9). Conversely, the search frequency on keywords including "eat at restaurants" declined significantly during the lockdown (Panel A of Fig. 9) but increased significantly after reopening (Panel C of Fig. 9).[20] These results are presented in Table A5.

Second, the delivery fee per order is another factor that affects the demand and supply of online food delivery, and which might be also affected by the pandemic. We thus calculated the average delivery fee per order for each city in each day, and employed the staggered DID approach (equation (1)) to estimate the effects of lockdown and reopening, and the long-term effect of the pandemic on delivery fees. However, our results show that average delivery fees per order did not change significantly during or after the lockdown (Table 1). In addition, all of the important effects of lockdown measures are similar for both the total value of online food delivery transactions and the value net of delivery fees. This suggests that the supply and demand for the labor employed in the online food market (both production and delivery) adjusted quickly in response to the different phases of the lockdown. Hence, a flexible labor market with free entry and exit is also a key component of a resilient urban food system. Third, Baidu also generated an inner-city mobility index to capture the intensity of mobility within a city. This index equals the ratio of the number of people traveling in a city to the city's resident population. Since Baidu only provided inner-city mobility data during the Spring Festival each year before 2021, only data from Jan. 1, 2020 to May 1, 2020 were used in this part of the empirical analyses. Reductions in inner-city mobility during home confinement as a result of lockdowns might be a major reason for the increasing demand for online food delivery. To explore this possible mechanism, we estimated the links between lockdown measures and inner-city mobility again using the staggered DID strategy (equation (1)). This index decreased by 20.6% during the lockdown, but recovered quickly to the pre-lockdown level after reopening (Table 1).

4.4. Robustness check and placebo test

We conducted several robustness tests, including: dropping observations during the Spring Festival to remove the effects of public holidays in the short- and long-term, respectively (Figures A6-A7 and Tables A7-A8); using the alternative measures of lockdown measures and measures to suspend restaurant operation (Figures A8-A9 and Tables A9-A10); and trying a specification where complete lockdown cities and partial lockdown cities are separated out for the variable $treat_i$ in equation (1) (Tables A11-A12). In general, our main findings are robust.

Furthermore, we also conducted a placebo test to check whether the significant effects of lockdown and reopening measures occurred during the same period in different years. Results showed that most coefficients were insignificantly different from zero (Table A13). Because no lockdown and reopening measures were implemented in our sampled cities in 2021, the online food delivery orders and the number of restaurants in business did not display any systematic change.

5. Discussions

With the increasing consumption of food away from home (FAFH), online food delivery platforms have developed rapidly in China. Our results indicate that these platforms played an important role in enhancing the resilience of urban food systems by helping the restaurants that did remain open during the lockdown to serve food and meet residents' food demand.

In China, as in many high-income countries, FAFH has become a

[20] The long-term effects of reopening measures on the Baidu search index, reported in Figure A5 and TableA6, suggest that one year later the reopening measures had no statistically significant effects.

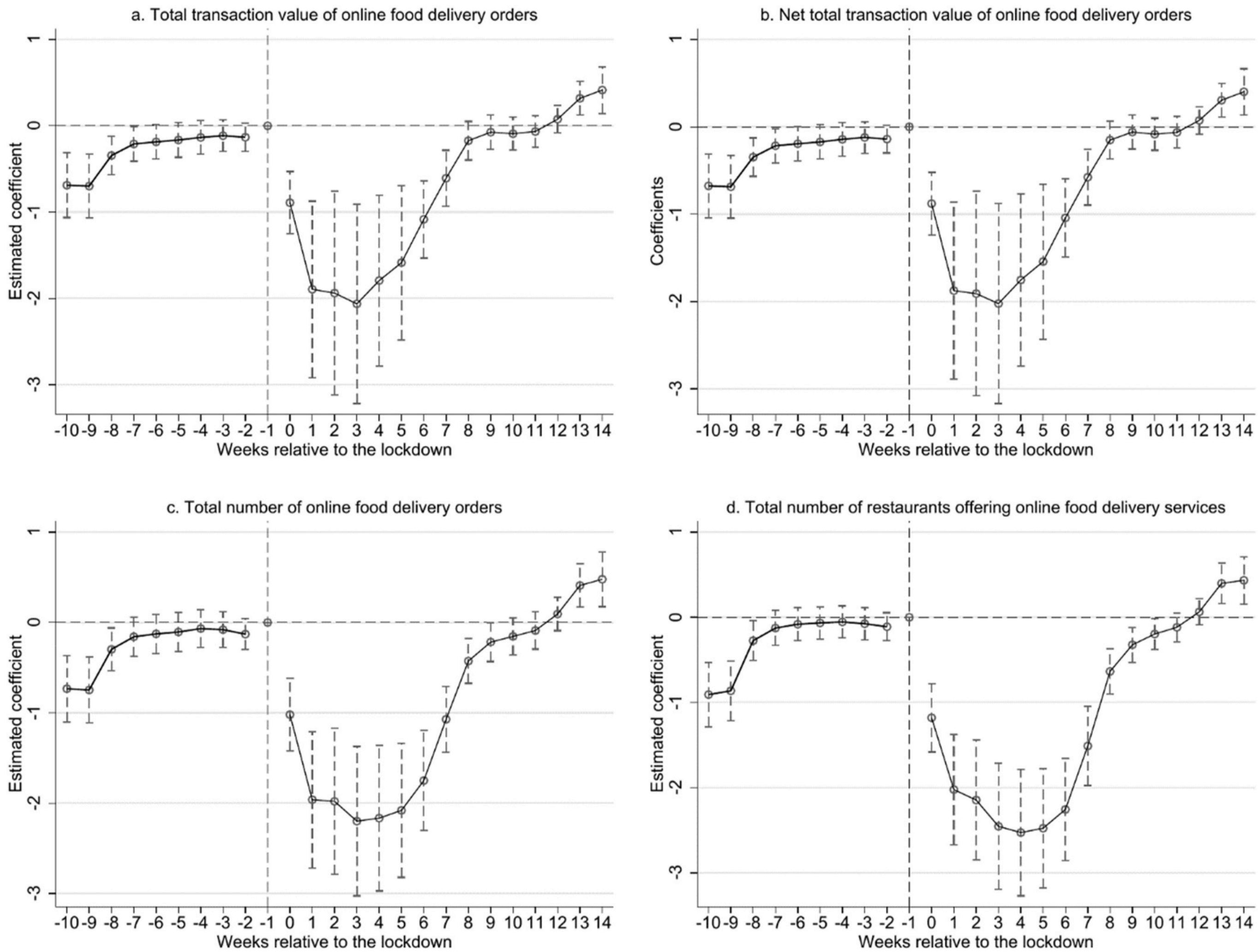

Fig. 5. Event study for the effects of lockdown measures on online food delivery. Notes: 1. The samples include both complete and partial lockdown cities. 2. The figure above shows the coefficients estimated using the event study method for the effects of lockdown measures on online food delivery over time. The specifications controls for date and city fixed effects. 3. The error bars represent the 95% confidence intervals for each coefficient estimated using city-level clustered standard errors.

major component of food consumption, particularly for young urban residents (Ma et al., 2006; Bai et al., 2010; Tian et al., 2016). Chinese consumers on average spent more than 55% of their total food expenditure on FAFH in 2019 (CCIA, 2019). As many members of younger generations do not know how to cook, or live in apartments without kitchens, online food delivery and takeaway, eating at restaurants, and processed food and snacks have become major sources of food. During the lockdown, online food delivery was essential to ensure the food security of these individuals (Reardon et al., 2021). In addition, online food delivery also provided an opportunity for small restaurants to survive during the lockdown, which supported employment in this sector and contributed to social stability (according to CCIA (2019), roughly 40 million people are employed in the catering industry).

However, online food delivery depends heavily on Online-To-Offline (OTO) platforms. Rapidly expanding OTO platforms help to match demand and supply for online food delivery by reducing the information asymmetry between consumers and restaurants; in addition, they can increase supply efficiency through intelligent order allocation systems. Therefore, although both the online food delivery platforms and restaurants were negatively affected by lockdowns in response to the pandemic, our results demonstrate that online food delivery platforms contribute to the resilience of urban food systems when such unexpected shocks occur (Reardon et al., 2021).

The changes in the shares of different categories of food that were ordered online during the lockdowns and following reopening, could have consequences for health. Previous studies from Greece (Morres et al., 2021), the UK (Robinson et al., 2020), and several other countries (Ammar et al., 2020) have found that people increased the consumption of unhealthy foods such as snacks, foods high in refined carbohydrates, salt, sugar and saturated fats during home confinement (NNEDPro, 2020). These changes in dietary behavior might be attributable to limited access to fresh food (WHO, 2020; Osendarp et al., 2021), to increased impulse-driven eating due to the anxiety and boredom evoked by quarantine (BDA, 2020), to having less time to plan healthy meals (Hawkes and Squires, 2021), and to a reduced motivation to maintain healthy eating (Gardner and Rebar, 2019). Poor nutrition combined with declining physical activity could lead to weight gain and thus negatively affect overall physical and mental health, and thus increased public health costs (WHO, 2020). Interestingly, our results show a decrease in the consumption of processed food (Chinese and western food) and an increase in the consumption of fresh food during the lockdown in China. This relatively healthy diet may be due to the availability of more labor and time for cooking at home, or perhaps a heightened awareness of health-related issues during the pandemic.

Another concern is that some large food companies saw the COVID-19 lockdowns as an opportunity to promote pre-packaged ‘ultra-

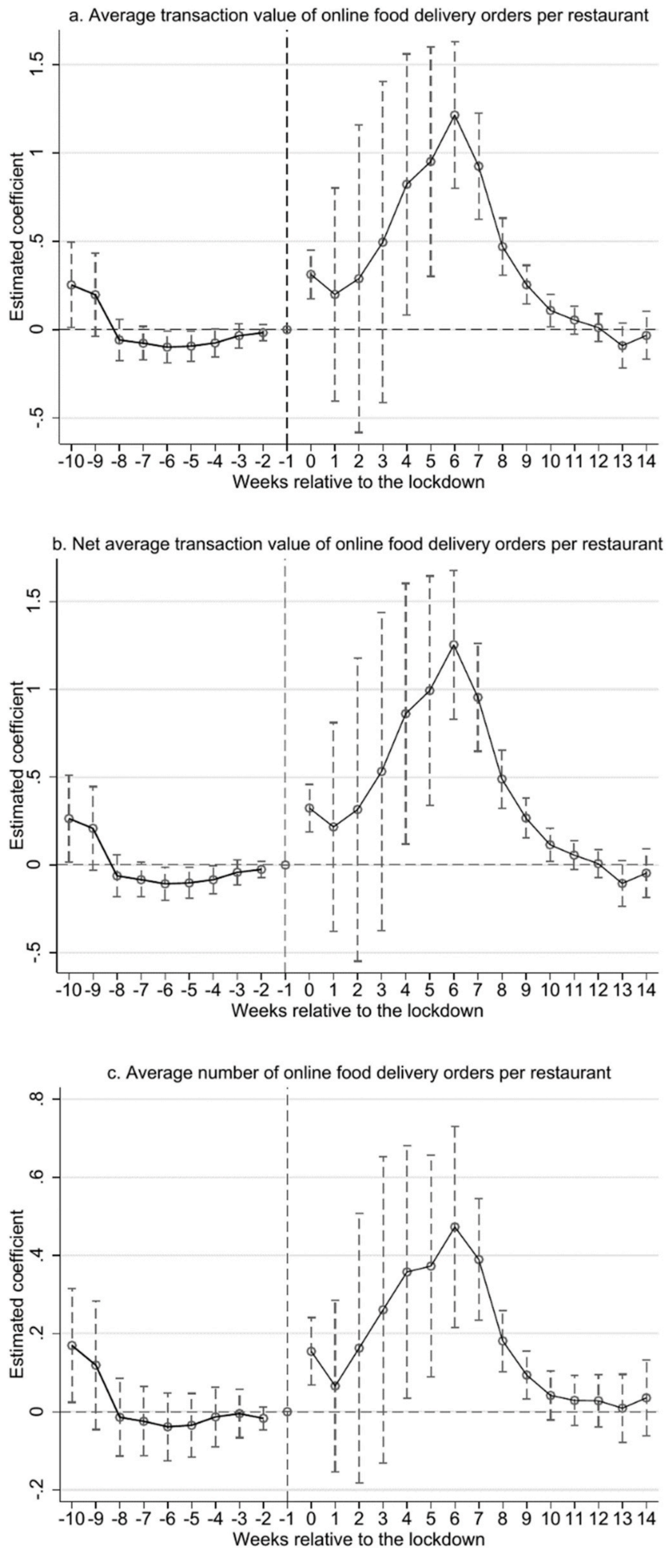

Fig. 6. Event study for the effects of lockdown measures on online food delivery per restaurant. Notes: [1.] The samples include both complete and partial lockdown cities. [2.] The figure above shows the coefficients estimated using the event study method for the effects of lockdown measures on online food delivery per restaurant over time. The specification controls for date and city fixed effects. [3.] The error bars represent the 95% confidence intervals for each coefficient estimated using city-level clustered standard errors.

processed' foods which are high in fats, sugars and salt (NCD Alliance and SPECTRUM, 2020). They donated food boxes containing ultra-processed foods to people in need, and promoted those foods with messages suggesting that they alleviate boredom (NCD Alliance and SPECTRUM, 2020; White et al., 2020). Any permanent increases in unhealthy eating due to these promotions would add to the health costs of the pandemic. Information and communications technology-based meal planning, and helping consumers control their food composition and calorie content via health and nutrition apps, could contribute to combating unhealthy eating habits acquired during lockdown (Ammar et al., 2020; BDA, 2020). For example, online food delivery platforms could calculate the content of main nutrients (e.g., calorie, sugar, salt, fat) in individual food orders and provide this information to consumers before payment. Similarly, online food delivery platforms could also provide a 'healthy diet' label to restaurants that offer low-fat, low-salt, and low-sugar foods. In addition, food vouchers and subsidies, which were issued in many Chinese cities to encourage consumers to eat at restaurants after reopening, could be directly linked to restaurants and other food supplies that provide nutritious foods, thus providing consumers with incentives to eat healthier foods, and encouraging restaurants to increase their supply of such foods (Hawkes and Squires, 2021; Carducci et al., 2021).

Finally, the failure of food systems to ensure food security in some regions in the wake of the pandemic provided an opportunity to rethink the resilience of food systems (Swinnen and McDermott, 2020; Fan et al., 2021). A diverse set of food suppliers and sources is essential for resilience in food systems to cope with systemic shocks such as COVID-19 (Garnett et al., 2020). The evidence from China shows that online food delivery platforms, which provide various types of food from thousands of restaurants, food stalls, cafes, bakeries, and fruit stores, contribute to diversity in the food system and thus its ability to buffer supply disruptions.

6. Conclusion

Responses to the COVID-19 pandemic, such as lockdown, curfews, transport restrictions and social distancing, pose a great threat to global and local food supply systems. During the lockdown, most restaurants were closed. Those restaurants that remained open shifted their operations to delivery, takeout, and outdoor dining, which further boosted the online food delivery services. This study uses high-frequency data to quantify the nature and performance of online food delivery platforms during the pandemic in urban China, and to estimate the short- and long-term effects of lockdown and reopening measures on the performance of online food delivery platforms and restaurants. We found that some restaurants continued to operate and offer online food delivery during lockdowns, while both the number of operating restaurants and their online food delivery services rebounded and experienced further growth after lockdowns were lifted. In addition, the adjustment path of the online food delivery business following the implementation of lockdowns differed from its adjustment path following the lifting of lockdowns. Results also showed that the lockdown and reopening measures did not affect all types of restaurant/cuisine equally.

The findings of this study have implications for the design of policies to guarantee food supply and help urban food systems adapt to unexpected shocks. In the context of the pandemic, online food delivery platforms in China contributed to the resilience of urban food systems; thus, this model might be implemented in countries or regions which are similar to China. However, the success of online food delivery platforms in China has been aided by widespread, low-cost internet technology, relatively low labor costs, highly clustered populations in urban and/or suburban areas, and the increasing opportunity costs of cooking at home in China. The promotion of online food delivery platforms in other countries or regions might face several challenges. For instance, poor internet and other types of infrastructure are main constraints for the development of online food delivery platforms in many parts of Africa.

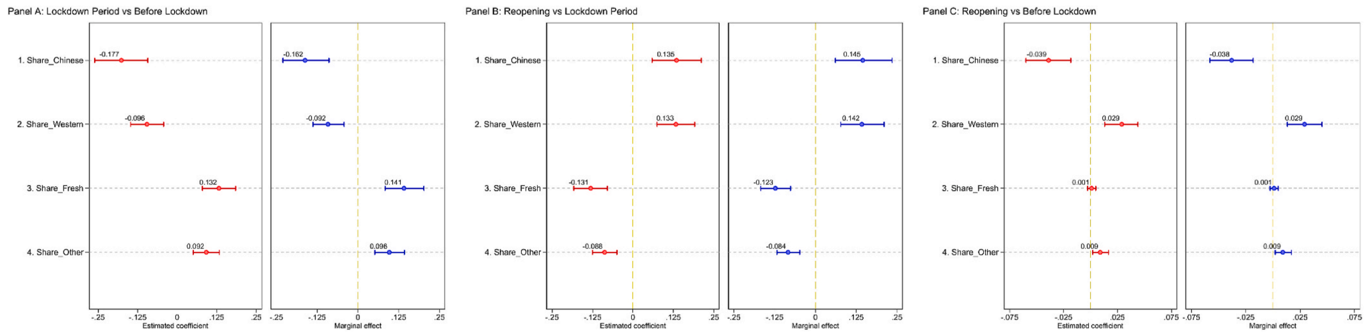

Fig. 7. The effects of lockdown and reopening measures on food consumption structure (Proportion of transaction value). Notes: 1. The different color lines/marks represent the estimated coefficients and marginal effects for the effects of lockdown and reopening measures on food consumption structure (Proportion of transaction value). The specification controls for date and city fixed effects. 2. The error bars represent the 95% confidence intervals for each coefficient estimated using city-level clustered standard errors. 3. "Share_Chinese" refers to the proportion of the transaction value of Chinese food to the total transaction value (%); "Share_Western" refers to the proportion of the transaction value of western food to total the transaction value (%); "Share_Fresh" refers to the proportion of the transaction value of fresh food to the total transaction value (%); "Share_Other" refers to the proportion of the transaction value of drinks and other food to the total transaction value (%). 4. Full results are presented in Table A3. . (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

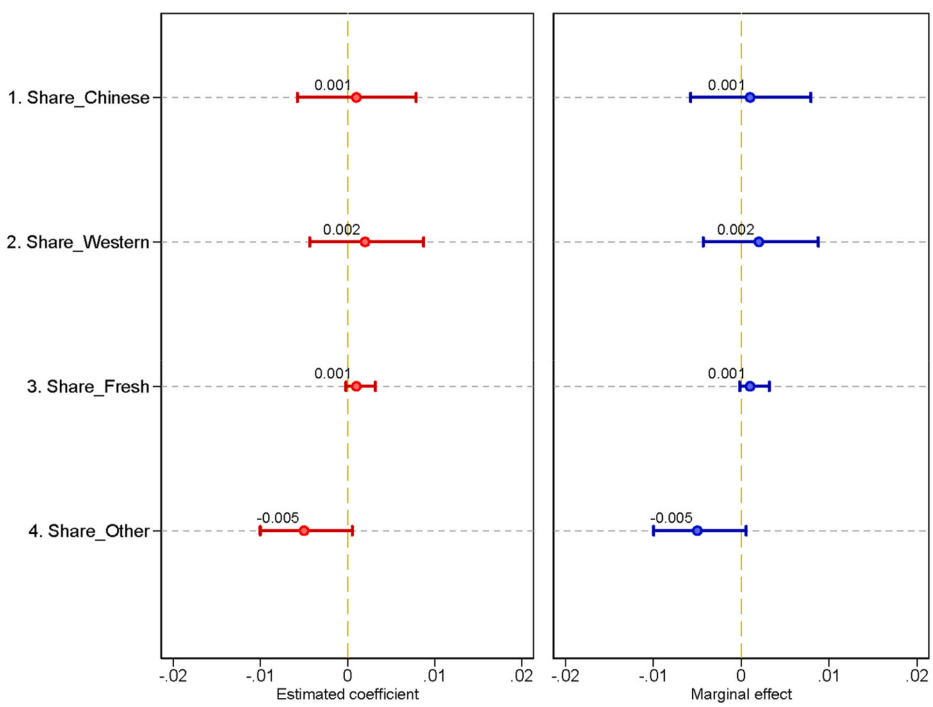

Fig. 8. The long-term effects of reopening measures on food consumption structure (Proportion of transaction value). Notes: 1. The different color lines/marks represent the estimated coefficients and marginal effects for the long-term effects of reopening measures on food consumption structure. The specification controls for date and city fixed effects. 2. The error bars represent the 95% confidence intervals for each coefficient estimated using city-level clustered standard errors. 3. "Share_Chinese" refers to the proportion of the transaction value of Chinese food to the total transaction value (%); "Share_Western" refers to the proportion of the transaction value of western food to the total transaction value (%); "Share_Fresh" refers to the proportion of the transaction value of fresh food to the total transaction value (%); "Share_Other" refers to the proportion of the transaction value of drinks and other food to the total transaction value (%). 4. Full results are presented in Table A4. . (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

In many industrialized countries, high labor cost might be a challenge. Nevertheless, in low- and middle-income countries that have a relatively high level of internet and other infrastructure, the promotion of online food delivery platforms could contribute to the resilience of urban food systems.

Significance statement

Responses to the COVID-19 pandemic, such as lockdowns and curfews, pose a great threat to global and local food supply systems. Using high-frequency data in urban China, we find that online food delivery played an important role in enhancing the resilience of urban food systems by helping the restaurants that did remain open during the lockdown to serve food and meet residents' food demand. We also find that consumers' preferences for online food delivery increased permanently in urban China. In addition, the consumption of relatively unhealthy food via online food delivery increased shortly after reopening, but one year later consumers had shifted to slightly healthier diets such as fresh food.

Code availability

All empirical analyses were conducted with Stata 17, and the code is available upon request.

Author contributions

Xiaobing Wang, Xu Tian, Shi Min conceived and designed the study, drafted the initial manuscript and revised it. Fangxiao Zhao analyzed the data. Stephan von Cramon-Taubadel comprehensively revised the manuscript and improved the study design. Jikun Huang and Shenggen Fan provided valuable comments on the study design and revised the manuscript.

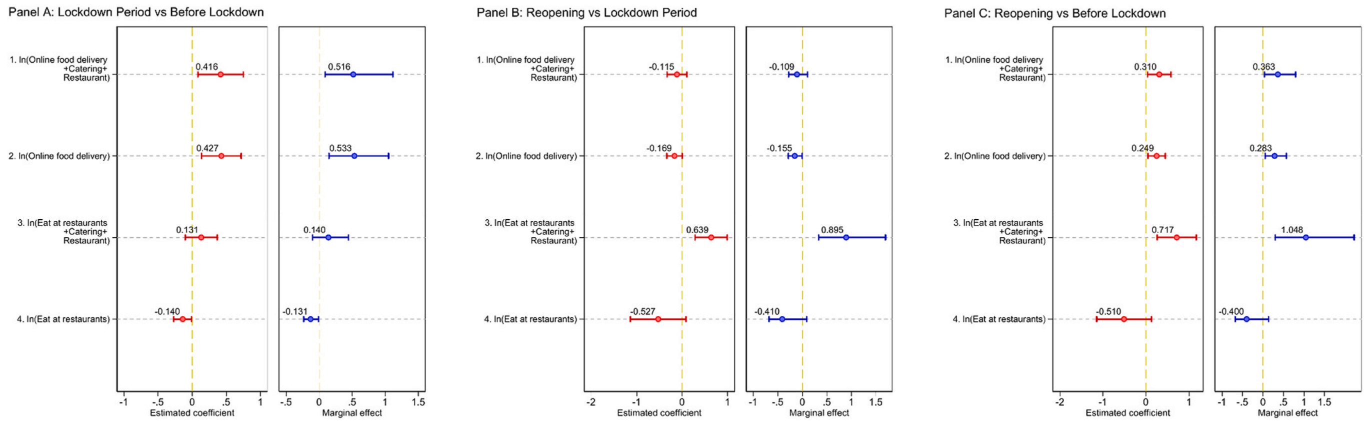

Fig. 9. The effects of lockdown and reopening measures on Baidu searching index. Notes: [1.] The different color lines/marks represent the estimated coefficients and marginal effects for the effects of lockdown and reopening measures on the Baidu search index. The specification controls for date and city fixed effects. [2.] The error bars represent the 95% confidence intervals for each coefficient estimated using city-level clustered standard errors. [3.] "ln(Online food delivery + Catering + Restaurant)" refers to the natural logarithm of the search volume for the keywords "Online food delivery (WaiMai)+Catering (CanYin)+Restaurant (CanGuan)"; "ln (Online food delivery)" refers to the natural logarithm of the search volume for the keywords "Online food delivery (WaiMai)"; "ln(Eat at restaurants + Catering + Restaurant)" refers to the natural logarithm of the search volume for the keywords "Eat at restaurants (TangShi)+Catering (CanYin)+Restaurant (CanGuan)"; "ln(Eat at restaurants)" refers to the natural logarithm of the search volume for the keywords "Eat at restaurants (TangShi)". [4.] Full results are presented in Table A5. . (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

Table 1
Mechanism analysis: Average delivery fee per order (unit: RMB) and the Baidu inner-city mobility index.

Variables	ln(Delivery)				ln(Inner-city mobility)		
Treat*Lockdown	0.057				-0.231***		
	(0.066)				(0.041)		
	[0.059]				[-0.206]		
Treat*Reopen1		-0.037				0.179***	
		(0.064)				(0.025)	
		[-0.036]				[0.196]	
Treat*Reopen2			0.021				-0.055
			(0.019)				(0.033)
			[0.021]				[-0.054]
Treat*Reopen3				0.002			
				(0.022)			
				[0.002]			
Control vars.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	1.793***	1.800***	1.788***	1.760***	1.885***	1.962***	1.065***
	(0.010)	(0.011)	(0.016)	(0.014)	(0.008)	(0.013)	(0.028)
Observations	7,609	7,456	7,732	11,685	5,842	6,371	5,965
R-squared	0.462	0.442	0.840	0.840	0.899	0.904	0.910

Notes: [1.] City-level clustered standard errors are presented in parentheses; ***p<0.01, **p<0.05, *p<0.1. A staggered DID estimation strategy and daily city-level data are used to identify the effects of lockdown and reopening measures on average delivery fee per order and on the Baidu inner-city movement index. The marginal effects calculated by transforming coefficients to percentage are presented in brackets.
[2.] The Baidu movement index is a measure of population flow between and within cities provided by Baidu Company based on Baidu Maps. It can be compared horizontally between different cities. The inner-city mobility index is the ratio of the number of people traveling in the city to the resident population of the city, reflecting the flow of population within the city. Since Baidu only provides movement data during the Spring Festival each year and it does not provide inner-city mobility data in 2021, the study duration for the Baidu movement index is from Jan. 1, 2020 to May 1, 2020, while the study duration for average delivery fee per order is from Dec. 1, 2019 to May 1, 2020 and Dec. 19, 2020 to May 19, 2021.

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.

Data availability

The authors do not have permission to share data.

Acknowledgements

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Appendix A. Empirical Results

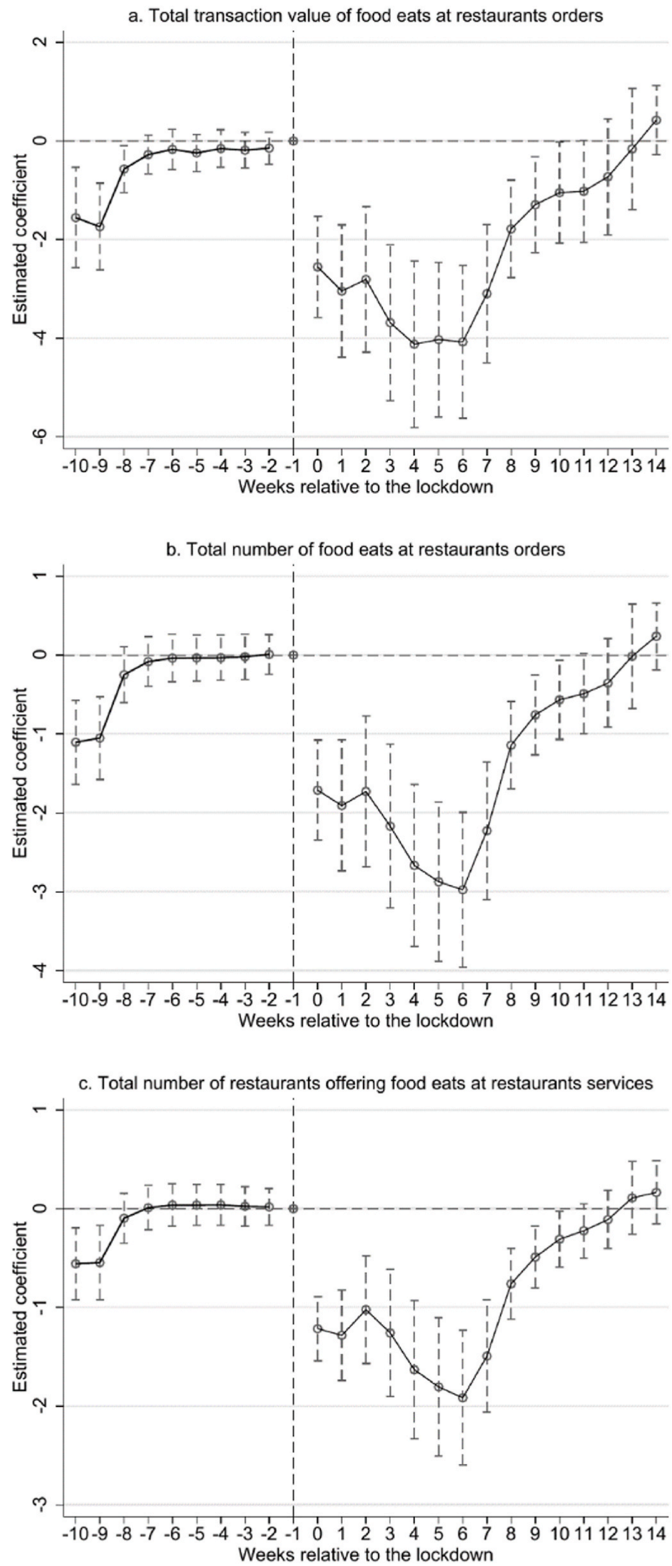

Fig. A1. Event Study for the effects of lockdown policies on food eats at restaurants. Notes:
[1.] The samples include both complete and partial lockdown cities. [2.] The figure above shows the coefficients estimated using the event study method for the effects of lockdown policies on food eats at restaurants over time. The specification controls for date and city fixed effects. [3.] The error bars represent the 95% confidence intervals for each coefficient estimated using city-level clustered standard errors.

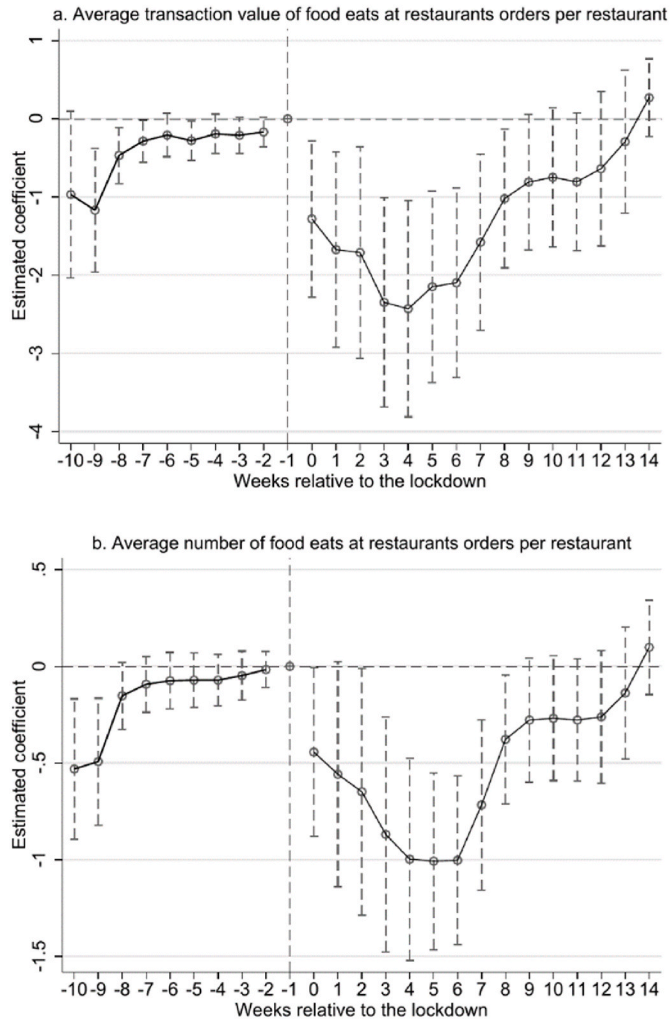

Fig. A2. Event Study for the effects of lockdown policies on food eats at restaurants per restaurant. Notes:
1. The samples include both complete and partial lockdown cities. 2. The figure above shows the coefficients estimated using the event study method for the effects of lockdown policies on food eats at restaurants per restaurant over time. The specification controls for date and city fixed effects. 3. The error bars represent the 95% confidence intervals for each coefficient estimated using city-level clustered standard errors.

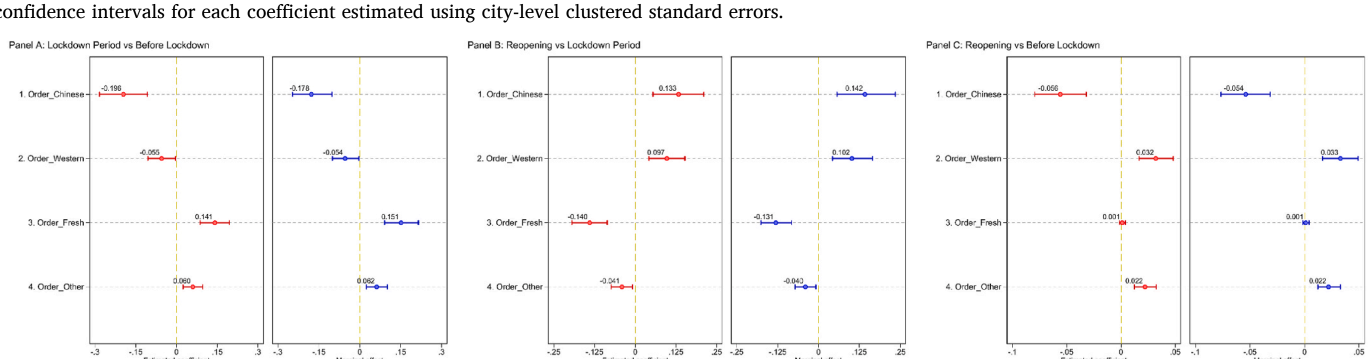

Fig. A3. The effects of lockdown and reopening policies on food consumption structure (Proportion of orders). Notes: 1. The different color lines/marks represent the estimated coefficients and marginal effects for the effects of lockdown and reopening policies on food consumption structure (Proportion of orders). The specification controls for date and city fixed effects. 2. The error bars represent the 95% confidence intervals for each coefficient estimated using city-level clustered standard errors. 3. "Order_Chinese" refers to the proportion of orders of Chinese food to total orders (%); "Order_Western" refers to the proportion of orders of western food to total orders (%); "Order_Fresh" refers to the proportion of orders of fresh food to total orders (%); "Order_Other" refers to the proportion of orders of drinks and other food to total orders (%). 4. Full results are presented in Table A3.

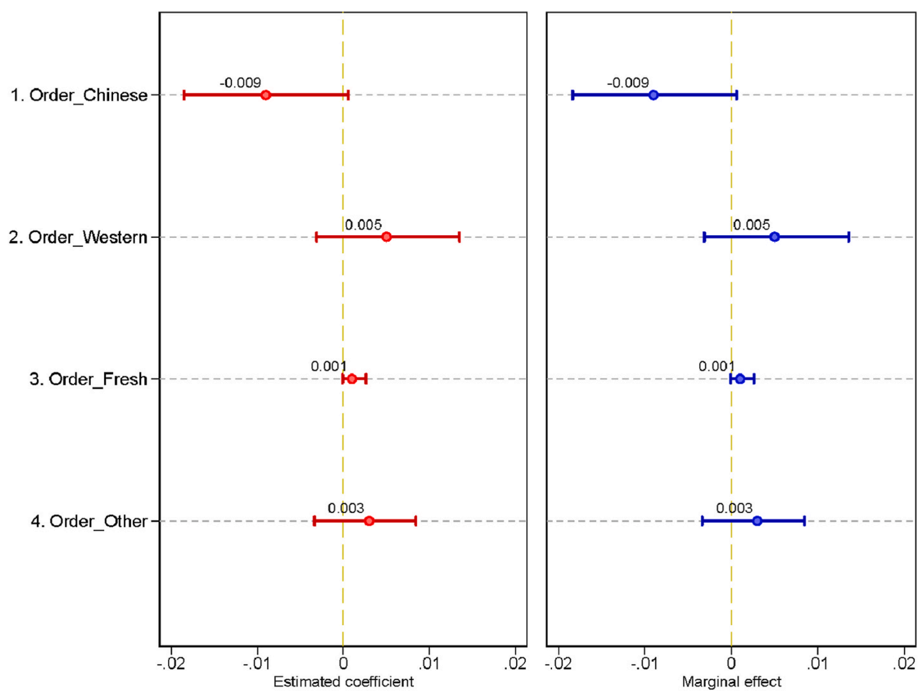

Fig. A4. The long-term effects of lockdown and reopening policies on food consumption structure (Proportion of orders). Notes: 1. The different color lines/marks represent the estimated coefficients and marginal effects for the long-term effects of lockdown and reopening policies on food consumption structure (Proportion of orders). The specification controls for date and city fixed effects. 2. The error bars represent the 95% confidence intervals for each coefficient estimated using city-level clustered standard errors. 3. "Order_Chinese" refers to the proportion of orders of Chinese food to total orders (%); "Order_Western" refers to the proportion of orders of western food to total orders (%); "Order_Fresh" refers to the proportion of orders of fresh food to total orders (%); "Order_Other" refers to the proportion of orders of drinks and other food to total orders (%). 4. Full results are presented in Table A4.

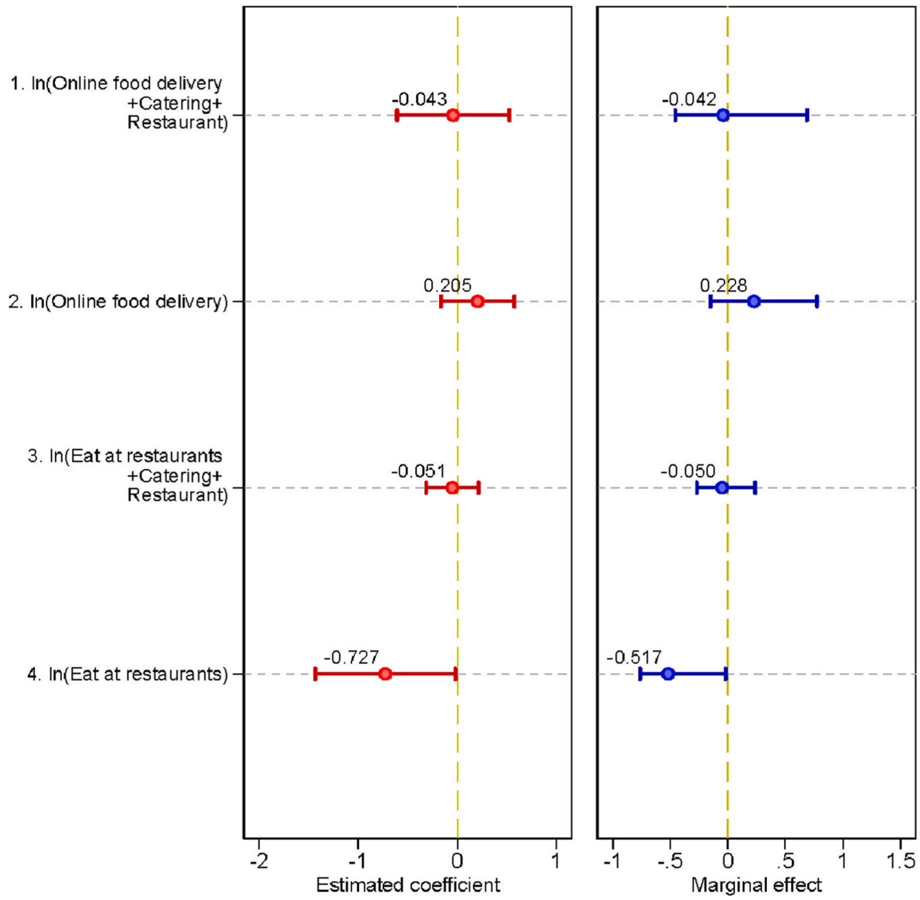

Fig. A5. The long-term effects of reopening policies on Baidu searching index. Notes: [1.] The different color lines/marks represent the estimated coefficients and marginal effects for the long-term effects of reopening policies on the Baidu search index. The specification controls for date and city fixed effects. [2.] The error bars represent the 95% confidence intervals for each coefficient estimated using city-level clustered standard errors. [3.] "ln(Online food delivery + Catering + Restaurant)" refers to the natural logarithm of the search volume for the keywords "Online food delivery (WaiMai)+Catering (CanYin)+Restaurant (CanGuan)"; "ln(Online food delivery)" refers to the natural logarithm of the search volume for the keywords "Online food delivery (WaiMai)"; "ln(Eat at restaurants + Catering + Restaurant)" refers to the natural logarithm of the search volume for the keywords "Eat at restaurants (TangShi)+Catering (CanYin)+Restaurant (CanGuan)"; "ln(Eat at restaurants)" refers to the natural logarithm of the search volume for the keywords "Eat at restaurants (TangShi)". [4.] Full results are presented in Table A6.

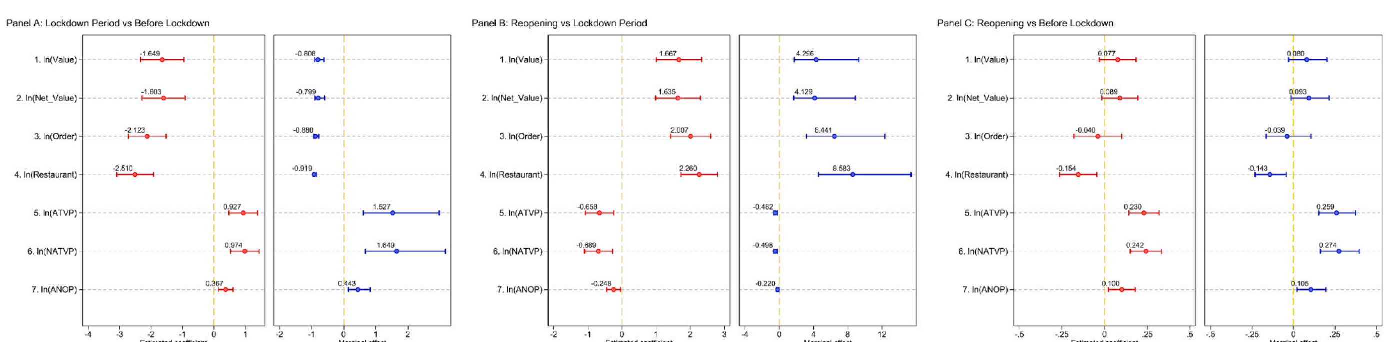

Fig. A6. The effects of lockdown and reopening policies on online food delivery consumption: Excluding Spring Festival. Notes: [1.] The different color lines/marks represent the estimated coefficients and marginal effects for the effects of lockdown and reopening policies on online food delivery consumption excluding Spring Festival. The specification controls for date and city fixed effects. [2.] The error bars represent the 95% confidence intervals for each coefficient estimated using city-level clustered standard errors. [3.] "ln(Value)" refers to the natural logarithm of the total transaction value of online food delivery orders paid by consumers (RMB); "ln (Net_Value)" refers to the natural logarithm of the total transaction value of online food delivery orders paid by consumers net of delivery costs (RMB); "ln(Order)" refers to the natural logarithm of the total number of online food delivery orders (number); "ln(Restaurant)" refers to the natural logarithm of the total number of restaurants offering online food delivery services (number); "ln(ATVP)" refers to the natural logarithm of the average transaction value of online food delivery orders per restaurant paid by consumers (RMB); "ln(NATVP)" refers to the natural logarithm of the average transaction value of online food delivery orders per restaurant paid by consumers net of delivery costs (RMB); "ln(ANOP)" refers to the natural logarithm of the average number of online food delivery orders per restaurant (number). [4.] Full results are presented in Table A7.

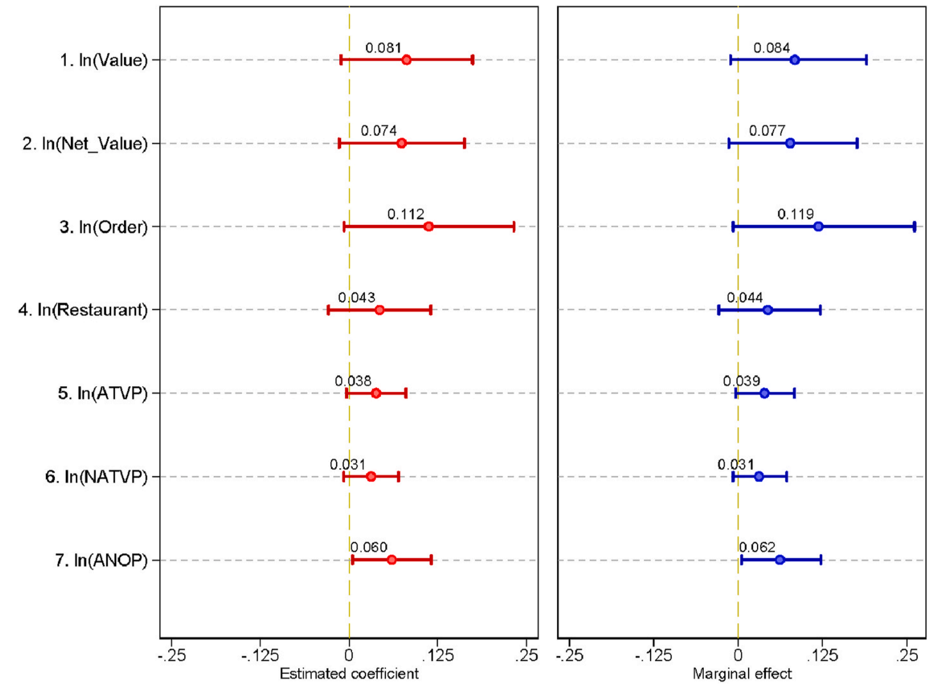

Fig. A7. The long-term effects of lockdown and reopening policies on online food delivery consumption: Excluding Spring Festival. Notes: 1. The different color lines/marks represent the estimated coefficients and marginal effects for the long-term effects of lockdown and reopening policies on online food delivery consumption excluding Spring Festival. The specification controls for date fixed effects as well as city fixed effects. 2. The error bars represent the 95% confidence intervals for each coefficient estimated using city-level clustered standard errors. 3. "ln(Value)" refers to the natural logarithm of the total transaction value of online food delivery orders paid by consumers (RMB); "ln(Net_Value)" refers to the natural logarithm of the total transaction value of online food delivery orders paid by consumers net of delivery costs (RMB); "ln(Order)" refers to the natural logarithm of the total number of online food delivery orders (number); "ln(Restaurant)" refers to the natural logarithm of the total number of restaurants offering online food delivery services (number); "ln(ATVP)" refers to the natural logarithm of the average transaction value of online food delivery orders per restaurant paid by consumers (RMB); "ln(NATVP)" refers to the natural logarithm of the average transaction value of online food delivery orders per restaurant paid by consumers net of delivery costs (RMB); "ln(ANOP)" refers to the natural logarithm of the average number of online food delivery orders per restaurant (number). 4. Full results are presented in Table A8.

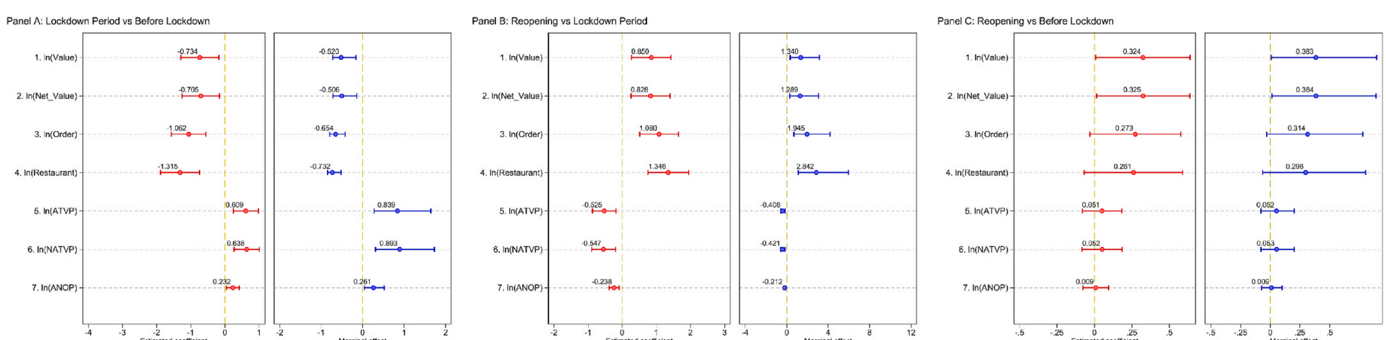

Fig. A8. The effects of restaurants suspension and recovery policies on online food delivery consumption. Notes: 1. The different color lines/marks represent the estimated coefficients and marginal effects for the effects of restaurants suspension and recovery policies on online food delivery consumption. The specification controls for date fixed effects as well as city fixed effects. 2. The error bars represent the 95% confidence intervals for each coefficient estimated using city-level clustered standard errors. 3. "ln(Value)" refers to the natural logarithm of the total transaction value of online food delivery orders paid by consumers (RMB); "ln (Net_Value)" refers to the natural logarithm of the total transaction value of online food delivery orders paid by consumers net of delivery costs (RMB); "ln(Order)" refers to the natural logarithm of the total number of online food delivery orders (number); "ln(Restaurant)" refers to the natural logarithm of the total number of restaurants offering online food delivery services (number); "ln(ATVP)" refers to the natural logarithm of the average transaction value of online food delivery orders per restaurant paid by consumers (RMB); "ln(NATVP)" refers to the natural logarithm of the average transaction value of online food delivery orders per restaurant paid by consumers net of delivery costs (RMB); "ln(ANOP)" refers to the natural logarithm of the average number of online food delivery orders per restaurant (number). 4. Full results are presented in Table A9.

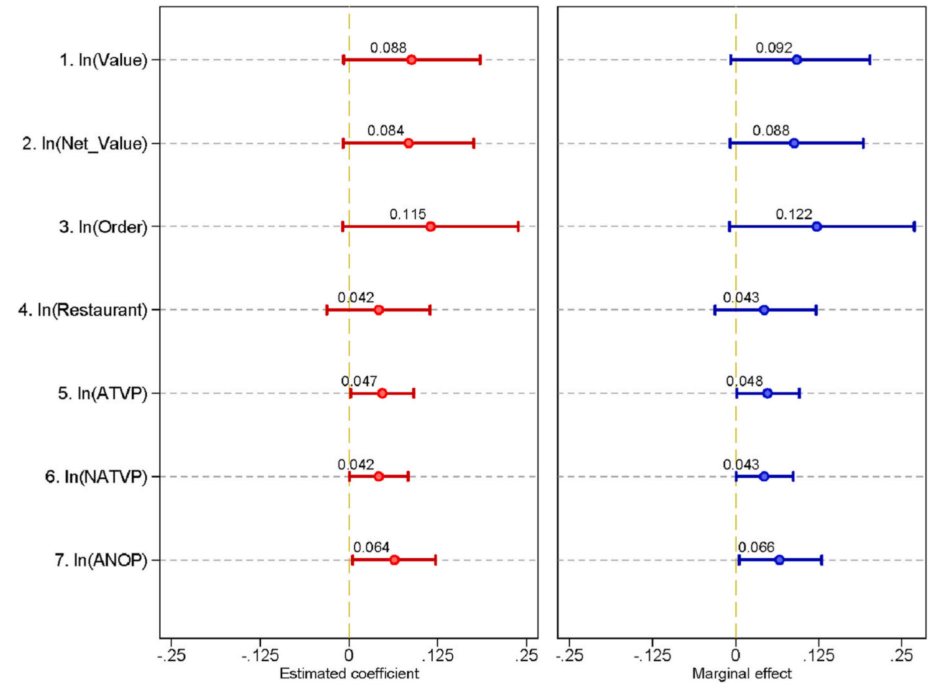

Fig. A9. The long-term effects of restaurants suspension and recovery policies on online food delivery consumption. Notes: [1.] The different color lines/marks represent the estimated coefficients and marginal effects for the long-term effects of restaurants suspension and recovery policies on online food delivery consumption. The specification controls for date fixed effects as well as city fixed effects. [2.] The error bars represent the 95% confidence intervals for each coefficient estimated using city-level clustered standard errors. [3.] "ln(Value)" refers to the natural logarithm of the total transaction value of online food delivery orders paid by consumers (RMB); "ln(Net_Value)" refers to the natural logarithm of the total transaction value of online food delivery orders paid by consumers net of delivery costs (RMB); "ln(Order)" refers to the natural logarithm of the total number of online food delivery orders (number); "ln(Restaurant)" refers to the natural logarithm of the total number of restaurants offering online food delivery services (number); "ln(ATVP)" refers to the natural logarithm of the average transaction value of online food delivery orders per restaurant paid by consumers (RMB); "ln(NATVP)" refers to the natural logarithm of the average transaction value of online food delivery orders per restaurant paid by consumers net of delivery costs (RMB); "ln(ANOP)" refers to the natural logarithm of the average number of online food delivery orders per restaurant (number). [4.] Full results are presented in Table A10.

Table A1
The effects of lockdown and reopening policies on online food delivery consumption: Date fixed effects

Variables	ln(Value)	ln(Net_Value)	ln(Order)	ln(Restaurant)	ln(ATVP)	ln(NATVP)	ln(ANOP)
Panel A: Lockdown Period vs Before Lockdown							
Treat*Lockdown	-1.531***	-1.489***	-1.947***	-2.302***	0.832***	0.874***	0.337***
	(0.305)	(0.301)	(0.269)	(0.269)	(0.199)	(0.199)	(0.099)
	[-0.784]	[-0.774]	[-0.857]	[-0.900]	[1.298]	[1.396]	[0.401]
Control vars.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	17.884***	17.746***	14.242***	11.770***	6.113***	5.976***	2.540***
	(0.032)	(0.032)	(0.040)	(0.038)	(0.021)	(0.022)	(0.015)
Observations	7,609	7,609	7,609	7,609	7,609	7,609	7,609
R-squared	0.894	0.895	0.940	0.945	0.441	0.457	0.547
Panel B: Reopening vs Lockdown Period							
Treat*Reopen1	1.604***	1.575***	1.902***	2.127***	-0.584***	-0.613***	-0.223**
	(0.300)	(0.297)	(0.262)	(0.243)	(0.189)	(0.190)	(0.091)
	[3.973]	[3.831]	[5.699]	[7.390]	[-0.442]	[-0.458]	[-0.200]
Control vars.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	17.891***	17.755***	14.228***	11.744***	6.147***	6.011***	2.550***
	(0.032)	(0.032)	(0.041)	(0.037)	(0.021)	(0.022)	(0.017)
Observations	7,456	7,456	7,456	7,456	7,456	7,456	7,456
R-squared	0.895	0.895	0.941	0.947	0.439	0.454	0.551
Panel C: Reopening vs Before Lockdown							
Treat*Reopen2	0.078	0.090*	-0.031	-0.141**	0.219***	0.230***	0.096***
	(0.051)	(0.050)	(0.066)	(0.054)	(0.043)	(0.044)	(0.036)
	[0.081]	[0.094]	[-0.031]	[-0.132]	[0.245]	[0.259]	[0.101]
Control vars.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	17.864***	17.727***	14.222***	11.727***	6.140***	6.003***	2.561***

(continued on next page)

Table A1 (*continued*)

Variables	ln(Value)	ln(Net_Value)	ln(Order)	ln(Restaurant)	ln(ATVP)	ln(NATVP)	ln(ANOP)
	(0.054)	(0.053)	(0.080)	(0.073)	(0.030)	(0.031)	(0.019)
Observations	7,732	7,732	7,732	7,732	7,732	7,732	7,732
R-squared	0.975	0.976	0.963	0.954	0.869	0.866	0.880

Notes: City-level clustered standard errors are presented in parentheses; ***p<0.01, **p<0.05, *p<0.1. A staggered DID estimation strategy and daily city-level data are used to identify the effects of lockdown and reopening policies on online food delivery consumption. The marginal effects calculated by transforming coefficients to percentage (e.g. $e^{-1.531} - 1 = -0.784$) are presented in brackets.

Table A2
The long-term effects of lockdown and reopening policies on online food delivery consumption: Date fixed effects

Variables	ln(Value)	ln(Net_Value)	ln(Order)	ln(Restaurant)	ln(ATVP)	ln(NATVP)	ln(ANOP)
Treat*Reopen3	0.082*	0.077*	0.111*	0.039	0.043**	0.038*	0.063**
	(0.047)	(0.045)	(0.060)	(0.036)	(0.022)	(0.020)	(0.028)
	[0.085]	[0.080]	[0.117]	[0.040]	[0.044]	[0.039]	[0.065]
Control vars.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	17.825***	17.695***	14.162***	11.650***	6.176***	6.046***	2.581***
	(0.025)	(0.025)	(0.030)	(0.021)	(0.014)	(0.014)	(0.014)
Observations	11,685	11,685	11,685	11,685	11,685	11,685	11,685
R-squared	0.995	0.995	0.992	0.995	0.978	0.978	0.943

Notes: City-level clustered standard errors are presented in parentheses; ***p<0.01, **p<0.05, *p<0.1. A staggered DID estimation strategy and daily city-level data are used to identify the long-term effects of lockdown and reopening policies on online food delivery consumption. The marginal effects calculated by transforming coefficients to percentage are presented in brackets.

Table A3
The effects of lockdown and reopening policies on food consumption structure

Variables	Share_Chinese	Share_Western	Share_Fresh	Share_Other	Order_Chinese	Order_Western	Order_Fresh	Order_Other
Panel A: Lockdown Period vs Before Lockdown								
Treat*Lockdown	-0.177***	-0.096***	0.132***	0.092***	-0.196***	-0.055**	0.141***	0.060***
	(0.042)	(0.026)	(0.026)	(0.021)	(0.044)	(0.026)	(0.027)	(0.018)
	[-0.162]	[-0.092]	[0.141]	[0.096]	[-0.178]	[-0.054]	[0.151]	[0.062]
Control vars.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.644***	0.244***	0.020***	0.093***	0.683***	0.203***	0.018***	0.097***
	(0.006)	(0.003)	(0.003)	(0.003)	(0.006)	(0.003)	(0.003)	(0.002)
Observations	7,609	7,609	7,609	7,609	7,609	7,609	7,609	7,609
R-squared	0.640	0.408	0.420	0.328	0.616	0.368	0.383	0.311
Panel B: Reopening vs Lockdown Period								
Treat*Reopen1	0.135***	0.133***	-0.131***	-0.088***	0.133***	0.097***	-0.140***	-0.041**
	(0.038)	(0.029)	(0.026)	(0.019)	(0.039)	(0.028)	(0.027)	(0.016)
	[0.145]	[0.142]	[-0.123]	[-0.084]	[0.142]	[0.102]	[-0.131]	[-0.040]
Control vars.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.632***	0.245***	0.022***	0.100***	0.670***	0.207***	0.020***	0.103***
	(0.005)	(0.003)	(0.003)	(0.002)	(0.006)	(0.003)	(0.003)	(0.002)
Observations	7,456	7,456	7,456	7,456	7,456	7,456	7,456	7,456
R-squared	0.637	0.384	0.422	0.345	0.617	0.353	0.386	0.336
Panel C: Reopening vs Before Lockdown								
Treat*Reopen2	-0.039***	0.029***	0.001	0.009**	-0.056***	0.032***	0.001	0.022***
	(0.010)	(0.008)	(0.002)	(0.004)	(0.012)	(0.008)	(0.001)	(0.005)
	[-0.038]	[0.029]	[0.001]	[0.009]	[-0.054]	[0.033]	[0.001]	[0.022]
Control vars.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.631***	0.250***	0.021**	0.098***	0.670***	0.207***	0.022***	0.101***
	(0.008)	(0.003)	(0.009)	(0.002)	(0.009)	(0.003)	(0.007)	(0.002)
Observations	7,732	7,732	7,732	7,732	7,732	7,732	7,732	7,732
R-squared	0.733	0.698	0.488	0.588	0.690	0.652	0.351	0.675

Notes: City-level clustered standard errors are presented in parentheses; ***p<0.01, **p<0.05, *p<0.1. A staggered DID estimation strategy and daily city-level data are used to identify the effects of lockdown and reopening policies on food consumption structure. The marginal effects calculated by transforming coefficients to percentage are presented in brackets.

Table A4
The long-term effects of lockdown and reopening policies on food consumption structure

Variables	Share_Chinese	Share_Western	Share_Fresh	Share_Other	Order_Chinese	Order_Western	Order_Fresh	Order_Other
Treat*Reopen3	0.001	0.002	0.001*	-0.005*	-0.009*	0.005	0.001*	0.003
	(0.003)	(0.003)	(0.001)	(0.003)	(0.005)	(0.004)	(0.001)	(0.003)
	[0.001]	[0.002]	[0.001]	[-0.005]	[-0.009]	[0.005]	[0.001]	[0.003]
			]p					
			]					
Control vars.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.641***	0.248***	0.019***	0.092***	0.688***	0.202***	0.020***	0.090***
	(0.003)	(0.002)	(0.001)	(0.002)	(0.004)	(0.002)	(0.001)	(0.002)
Observations	11,685	11,685	11,685	11,685	11,685	11,685	11,685	11,685
R-squared	0.887	0.831	0.739	0.773	0.894	0.794	0.757	0.837

Notes: City-level clustered standard errors are presented in parentheses; ***p<0.01, **p<0.05, *p<0.1. A staggered DID estimation strategy and daily city-level data are used to identify the long-term effects of lockdown and reopening policies on food consumption structure. The marginal effects calculated by transforming coefficients to percentage are presented in brackets.

Table A5
The effects of lockdown and reopening policies on Baidu searching index

Variables	ln(Online food delivery + Catering + Restaurant)	ln(Online food delivery)	ln(Eat at restaurants + Catering + Restaurant)	ln(Eat at restaurants)
Panel A: Lockdown Period vs Before Lockdown				
Treat*Lockdown	0.416**	0.427***	0.131	-0.140**
	(0.166)	(0.145)	(0.117)	(0.065)
	[0.516]	[0.533]	[0.140]	[-0.131]
Control vars.	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes
Constant	6.041***	5.360***	5.018***	0.272***
	(0.173)	(0.147)	(0.195)	(0.060)
Observations	7,609	7,609	7,609	7,609
R-squared	0.722	0.682	0.689	0.859
Panel B: Reopening vs Lockdown Period				
Treat*Reopen1	-0.115	-0.169**	0.639***	-0.527*
	(0.108)	(0.084)	(0.176)	(0.306)
	[-0.109]	[-0.155]	[0.895]	[-0.410]
Control vars.	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes
Constant	5.943***	5.365***	4.829***	0.281***
	(0.166)	(0.163)	(0.228)	(0.061)
Observations	7,456	7,456	7,456	7,456
R-squared	0.689	0.642	0.642	0.807
Panel C: Reopening vs Before Lockdown				
Treat*Reopen2	0.310**	0.249**	0.717***	-0.510
	(0.138)	(0.101)	(0.227)	(0.318)
	[0.363]	[0.283]	[1.048]	[-0.400]
Control vars.	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes
Constant	6.058***	5.358***	5.022***	0.332***
	(0.175)	(0.147)	(0.197)	(0.074)
Observations	7,732	7,732	7,732	7,732
R-squared	0.727	0.696	0.649	0.814

Notes: City-level clustered standard errors are presented in parentheses; ***p<0.01, **p<0.05, *p<0.1. A staggered DID estimation strategy and daily city-level data are used to identify the effects of lockdown and reopening policies on Baidu searching index. The marginal effects calculated by transforming coefficients to percentage are presented in brackets.

Table A6
The long-term effects of lockdown and reopening policies on Baidu searching index

Variables	ln(Online food delivery + Catering + Restaurant)	ln(Online food delivery)	ln(Eat at restaurants + Catering + Restaurant)	ln(Eat at restaurants)
Treat*Reopen3	-0.043	0.205	-0.051	-0.727**
	(0.282)	(0.184)	(0.132)	(0.353)
	[-0.042]	[0.228]	[-0.050]	[-0.517]
Control vars.	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes
Constant	6.091***	5.500***	5.132***	0.758***
	(0.175)	(0.170)	(0.185)	(0.183)
Observations	11,685	11,685	11,685	11,685
R-squared	0.680	0.673	0.657	0.428

Notes: City-level clustered standard errors are presented in parentheses; ***p<0.01, **p<0.05, *p<0.1. A staggered DID estimation strategy and daily city-level data are used to identify the long-term effects of lockdown and reopening policies on Baidu searching index. The marginal effects calculated by transforming coefficients to percentage are presented in brackets.

Table A7
The effects of lockdown and reopening policies on online food delivery consumption: Excluding Spring Festival

Variables	ln(Value)	ln(Net_Value)	ln(Order)	ln(Restaurant)	ln(ATVP)	ln(NATVP)	ln(ANOP)
Panel A: Lockdown Period vs Before Lockdown							
Treat*Lockdown	-1.649***	-1.603***	-2.123***	-2.510***	0.927***	0.974***	0.367***
	(0.345)	(0.341)	(0.299)	(0.292)	(0.226)	(0.226)	(0.115)
	[-0.808]	[-0.799]	[-0.880]	[-0.919]	[1.527]	[1.649]	[0.443]
Control vars.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	17.856***	17.718***	14.211***	11.731***	6.126***	5.988***	2.547***
	(0.031)	(0.031)	(0.039)	(0.036)	(0.021)	(0.021)	(0.015)
Observations	7,039	7,039	7,039	7,039	7,039	7,039	7,039
R-squared	0.894	0.894	0.943	0.950	0.446	0.464	0.551
Panel B: Reopening vs Lockdown Period							
Treat*Reopen1	1.667***	1.635***	2.007***	2.260***	-0.658***	-0.689***	-0.248**
	(0.331)	(0.328)	(0.291)	(0.267)	(0.207)	(0.207)	(0.101)
	[4.296]	[4.129]	[6.441]	[8.583]	[-0.482]	[-0.498]	[-0.220]
Control vars.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	17.881***	17.744***	14.218***	11.729***	6.152***	6.015***	2.555***
	(0.031)	(0.031)	(0.041)	(0.037)	(0.021)	(0.021)	(0.016)
Observations	6,988	6,988	6,988	6,988	6,988	6,988	6,988
R-squared	0.895	0.895	0.943	0.951	0.446	0.462	0.559
Panel C: Reopening vs Before Lockdown							
Treat*Reopen2	0.077	0.089*	-0.040	-0.154***	0.230***	0.242***	0.100**
	(0.054)	(0.053)	(0.070)	(0.055)	(0.044)	(0.046)	(0.039)
	[0.080]	[0.093]	[-0.039]	[-0.143]	[0.259]	[0.274]	[0.105]
Control vars.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	17.855***	17.717***	14.211***	11.710***	6.147***	6.009***	2.567***
	(0.056)	(0.055)	(0.083)	(0.076)	(0.031)	(0.032)	(0.019)
Observations	7,280	7,280	7,280	7,280	7,280	7,280	7,280
R-squared	0.977	0.977	0.964	0.955	0.865	0.862	0.885

Notes: City-level clustered standard errors are presented in parentheses; ***p<0.01, **p<0.05, *p<0.1.A staggered DID estimation strategy and daily city-level data are used to identify the effects of lockdown and reopening policies on online food delivery consumption. The marginal effects calculated by transforming coefficients to percentage are presented in brackets.

Table A8
The long-term effects of lockdown and reopening policies on online food delivery consumption: Excluding Spring Festival

Variables	ln(Value)	ln(Net_Value)	ln(Order)	ln(Restaurant)	ln(ATVP)	ln(NATVP)	ln(ANOP)
Treat*Reopen3	0.081*	0.074*	0.112*	0.043	0.038*	0.031	0.060**
	(0.046)	(0.044)	(0.060)	(0.036)	(0.021)	(0.019)	(0.028)
	[0.084]	[0.077]	[0.119]	[0.044]	[0.039]	[0.031]	[0.062]
Control vars.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	17.815***	17.685***	14.150***	11.638***	6.178***	6.049***	2.582***
	(0.024)	(0.024)	(0.030)	(0.021)	(0.013)	(0.013)	(0.013)
Observations	11,115	11,115	11,115	11,115	11,115	11,115	11,115
R-squared	0.995	0.996	0.993	0.996	0.980	0.981	0.947

Notes: City-level clustered standard errors are presented in parentheses; ***p<0.01, **p<0.05, *p<0.1.A staggered DID estimation strategy and daily city-level data are used to identify the long-term effects of lockdown and reopening policies on online food delivery consumption. The marginal effects calculated by transforming coefficients to percentage are presented in brackets.

Table A9
The effects of restaurants suspension and recovery policies on online food delivery consumption

Variables	ln(Value)	ln(Net_Value)	ln(Order)	ln(Restaurant)	ln(ATVP)	ln(NATVP)	ln(ANOP)
Panel A: Suspension Period vs Before Suspension							
Treat*Suspension	-0.734**	-0.705**	-1.062***	-1.315***	0.609***	0.638***	0.232**
	(0.278)	(0.274)	(0.254)	(0.283)	(0.182)	(0.183)	(0.093)
	[-0.520]	[-0.506]	[-0.654]	[-0.732]	[0.839]	[0.893]	[0.261]
Control vars.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	17.950***	17.810***	14.313***	11.858***	6.089***	5.949***	2.523***
	(0.064)	(0.063)	(0.066)	(0.070)	(0.033)	(0.034)	(0.020)
Observations	7,878	7,878	7,878	7,878	7,878	7,878	7,878
R-squared	0.877	0.878	0.918	0.913	0.418	0.434	0.529
Panel B: Recovery vs Suspension Period							
Treat*Recover1	0.850***	0.828***	1.080***	1.346***	-0.525***	-0.547***	-0.238***
	(0.288)	(0.284)	(0.283)	(0.296)	(0.172)	(0.174)	(0.074)
	[1.340]	[1.289]	[1.945]	[2.842]	[-0.408]	[-0.421]	[-0.212]
Control vars.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	17.887***	17.751***	14.223***	11.739***	6.149***	6.013***	2.551***
	(0.032)	(0.032)	(0.042)	(0.038)	(0.021)	(0.022)	(0.016)
Observations	7,317	7,317	7,317	7,317	7,317	7,317	7,317
R-squared	0.895	0.896	0.927	0.927	0.487	0.501	0.608
Panel C: Recovery vs Before Suspension							
Treat*Recover2	0.324**	0.325**	0.273*	0.261	0.051	0.052	0.009
	(0.157)	(0.155)	(0.151)	(0.164)	(0.066)	(0.067)	(0.043)
	[0.383]	[0.384]	[0.314]	[0.298]	[0.052]	[0.053]	[0.009]
Control vars.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	17.966***	17.826***	14.326***	11.870***	6.093***	5.954***	2.526***
	(0.070)	(0.069)	(0.070)	(0.075)	(0.033)	(0.034)	(0.020)
Observations	7,602	7,602	7,602	7,602	7,602	7,602	7,602
R-squared	0.931	0.932	0.940	0.925	0.633	0.641	0.757

Notes: City-level clustered standard errors are presented in parentheses; ***p<0.01, **p<0.05, *p<0.1. A staggered DID estimation strategy and daily city-level data are used to identify the effects of restaurants suspension and recovery policies on online food delivery consumption. The marginal effects calculated by transforming coefficients to percentage are presented in brackets.

Table A10
The long-term effects of restaurants suspension and recovery policies on online food delivery consumption

Variables	ln(Value)	ln(Net_Value)	ln(Order)	ln(Restaurant)	ln(ATVP)	ln(NATVP)	ln(ANOP)
Treat*Recover3	0.088*	0.084*	0.115*	0.042	0.047**	0.042**	0.064**
	(0.048)	(0.046)	(0.062)	(0.036)	(0.022)	(0.021)	(0.029)
	[0.092]	[0.088]	[0.122]	[0.043]	[0.048]	[0.043]	[0.066]
Control vars.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	17.826***	17.696***	14.163***	11.653***	6.175***	6.045***	2.580***
	(0.025)	(0.024)	(0.030)	(0.020)	(0.013)	(0.013)	(0.014)
Observations	11,514	11,514	11,514	11,514	11,514	11,514	11,514
R-squared	0.995	0.995	0.992	0.995	0.978	0.978	0.943

Notes: City-level clustered standard errors are presented in parentheses; ***p<0.01, **p<0.05, *p<0.1. A staggered DID estimation strategy and daily city-level data are used to identify the long-term effects of restaurants suspension and recovery policies on online food delivery consumption. The marginal effects calculated by transforming coefficients to percentage are presented in brackets.

Table A11
The effects of lockdown and reopening policies on online food delivery consumption: Excluding partial lockdown cities

Variables	ln(Value)	ln(Net_Value)	ln(Order)	ln(Restaurant)	ln(ATVP)	ln(NATVP)	ln(ANOP)
Panel A: Lockdown Period vs Before Lockdown							
Treat*Lockdown	-1.964***	-1.911***	-2.439***	-2.869***	0.988***	1.041***	0.413***
	(0.349)	(0.346)	(0.244)	(0.196)	(0.258)	(0.257)	(0.128)
	[-0.860]	[-0.852]	[-0.913]	[-0.943]	[1.686]	[1.832]	[0.511]
Control vars.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	17.868***	17.730***	14.218***	11.741***	6.127***	5.989***	2.544***
	(0.032)	(0.032)	(0.040)	(0.038)	(0.021)	(0.022)	(0.016)
Observations	6,990	6,990	6,990	6,990	6,990	6,990	6,990
R-squared	0.896	0.896	0.947	0.958	0.427	0.445	0.515

(*continued on next page*)

Table A11 (*continued*)

Variables	ln(Value)	ln(Net_Value)	ln(Order)	ln(Restaurant)	ln(ATVP)	ln(NATVP)	ln(ANOP)
Panel B: Reopening vs Lockdown Period							
Treat*Reopen1	2.090***	2.053***	2.395***	2.650***	-0.644**	-0.681**	-0.256**
	(0.337)	(0.335)	(0.239)	(0.185)	(0.265)	(0.265)	(0.123)
	[7.085]	[6.791]	[9.968]	[13.154]	[-0.475]	[-0.494]	[-0.226]
Control vars.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	17.890***	17.754***	14.228***	11.744***	6.146***	6.010***	2.550***
	(0.032)	(0.032)	(0.042)	(0.038)	(0.022)	(0.022)	(0.017)
Observations	6,838	6,838	6,838	6,838	6,838	6,838	6,838
R-squared	0.898	0.898	0.947	0.957	0.421	0.436	0.527
Panel C: Reopening vs Before Lockdown							
Treat*Reopen2	0.106**	0.122**	-0.049	-0.214***	0.318***	0.334***	0.147***
	(0.049)	(0.048)	(0.071)	(0.041)	(0.031)	(0.034)	(0.036)
	[0.112]	[0.130]	[-0.048]	[-0.193]	[0.374]	[0.397]	[0.158]
Control vars.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	17.862***	17.724***	14.214***	11.717***	6.147***	6.010***	2.563***
	(0.056)	(0.055)	(0.083)	(0.076)	(0.031)	(0.032)	(0.020)
Observations	6,827	6,827	6,827	6,827	6,827	6,827	6,827
R-squared	0.973	0.974	0.960	0.952	0.863	0.860	0.873

Notes: City-level clustered standard errors are presented in parentheses; ***p<0.01, **p<0.05, *p<0.1.A staggered DID estimation strategy and daily city-level data are used to identify the effects of lockdown and reopening policies on online food delivery consumption. The marginal effects calculated by transforming coefficients to percentage are presented in brackets. The treatment group only includes complete lockdown cities, and the control group includes no-lockdown cities.

Table A12
The effects of lockdown and reopening policies on online food delivery consumption: Excluding complete lockdown cities

Variables	ln(Value)	ln(Net_Value)	ln(Order)	ln(Restaurant)	ln(ATVP)	ln(NATVP)	ln(ANOP)
Panel A: Lockdown Period vs Before Lockdown							
Treat*Lockdown	-0.264	-0.253	-0.491	-0.601	0.335***	0.345***	0.094
	(0.282)	(0.276)	(0.390)	(0.374)	(0.111)	(0.115)	(0.057)
	[-0.232]	[-0.224]	[-0.388]	[-0.452]	[0.398]	[0.412]	[0.099]
Control vars.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	17.883***	17.747***	14.225***	11.735***	6.150***	6.015***	2.557***
	(0.053)	(0.053)	(0.079)	(0.070)	(0.032)	(0.033)	(0.023)
Observations	5,974	5,974	5,974	5,974	5,974	5,974	5,974
R-squared	0.963	0.965	0.947	0.935	0.893	0.891	0.886
Panel B: Reopening vs Lockdown Period							
Treat*Reopen1	0.266	0.262	0.449	0.568*	-0.301***	-0.305***	-0.106*
	(0.230)	(0.224)	(0.317)	(0.292)	(0.109)	(0.110)	(0.063)
	[0.305]	[0.300]	[0.567]	[0.765]	[-0.260]	[-0.263]	[-0.101]
Control vars.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	17.893***	17.757***	14.232***	11.736***	6.160***	6.024***	2.562***
	(0.052)	(0.051)	(0.078)	(0.071)	(0.031)	(0.032)	(0.021)
Observations	5,973	5,973	5,973	5,973	5,973	5,973	5,973
R-squared	0.964	0.965	0.948	0.936	0.888	0.887	0.880
Panel C: Reopening vs Before Lockdown							
Treat*Reopen2	0.029	0.034	-0.014	-0.033	0.061	0.066	0.011
	(0.093)	(0.090)	(0.112)	(0.093)	(0.053)	(0.054)	(0.054)
	[0.029]	[0.035]	[-0.014]	[-0.032]	[0.063]	[0.068]	[0.011]
Control vars.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	17.891***	17.755***	14.236***	11.730***	6.164***	6.028***	2.571***
	(0.056)	(0.056)	(0.084)	(0.076)	(0.032)	(0.032)	(0.021)
Observations	6,260	6,260	6,260	6,260	6,260	6,260	6,260
R-squared	0.966	0.968	0.951	0.939	0.891	0.889	0.887

Notes: City-level clustered standard errors are presented in parentheses; ***p<0.01, **p<0.05, *p<0.1.A staggered DID estimation strategy and daily city-level data are used to identify the effects of lockdown and reopening policies on online food delivery consumption. The marginal effects calculated by transforming coefficients to percentage are presented in brackets. The treatment group only includes partial lockdown cities, and the control group includes the no-lockdown cities.

Table A13
Placebo test: Excluding Spring Festival & According to the lunar calendar

Variables	ln(Value)	ln(Net_Value)	ln(Order)	ln(Restaurant)	ln(ATVP)	ln(NATVP)	ln(ANOP)
Panel A: Lockdown Period vs Before Lockdown							
Treat*Lockdown	-0.024	-0.022	-0.040	-0.032*	0.008	0.009	-0.007
	(0.022)	(0.022)	(0.031)	(0.017)	(0.009)	(0.009)	(0.014)
	[-0.024]	[-0.022]	[-0.039]	[-0.031]	[0.008]	[0.009]	[-0.007]
Control vars.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	17.938***	17.808***	14.253***	11.825***	6.114***	5.984***	2.506***
	(0.012)	(0.012)	(0.015)	(0.008)	(0.007)	(0.007)	(0.008)
Observations	7,004	7,004	7,004	7,004	7,004	7,004	7,004
R-squared	0.997	0.997	0.994	0.996	0.987	0.987	0.967
Panel B: Reopening vs Lockdown Period							
Treat*Reopen1	-0.011	-0.017	0.016	-0.005	-0.007	-0.013*	0.017
	(0.012)	(0.011)	(0.024)	(0.007)	(0.009)	(0.007)	(0.018)
	[-0.011]	[-0.017]	[0.016]	[-0.005]	[-0.007]	[-0.013]	[0.017]
Control vars.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	17.954***	17.826***	14.260***	11.832***	6.124***	5.996***	2.507***
	(0.016)	(0.016)	(0.022)	(0.012)	(0.007)	(0.007)	(0.010)
Observations	6,931	6,931	6,931	6,931	6,931	6,931	6,931
R-squared	0.997	0.997	0.994	0.996	0.988	0.988	0.965
Panel C: Reopening vs Before Lockdown							
Treat*Reopen2	-0.041	-0.045	-0.037	-0.040*	-0.001	-0.004	0.003
	(0.027)	(0.027)	(0.039)	(0.020)	(0.012)	(0.011)	(0.021)
	[-0.040]	[-0.044]	[-0.036]	[-0.039]	[-0.001]	[-0.004]	[0.003]
Control vars.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	17.935***	17.804***	14.249***	11.824***	6.112***	5.982***	2.503***
	(0.011)	(0.012)	(0.015)	(0.008)	(0.007)	(0.007)	(0.008)
Observations	7,223	7,223	7,223	7,223	7,223	7,223	7,223
R-squared	0.997	0.997	0.994	0.996	0.987	0.987	0.963

Notes: City-level clustered standard errors are presented in parentheses; ***p<0.01, **p<0.05, *p<0.1.A staggered DID estimation strategy and daily city-level data are used to identify the effects of lockdown and reopening policies on online food delivery consumption. The marginal effects calculated by transforming coefficients to percentage are presented in brackets.

Appendix B. Data Sources and Descriptive Statistics

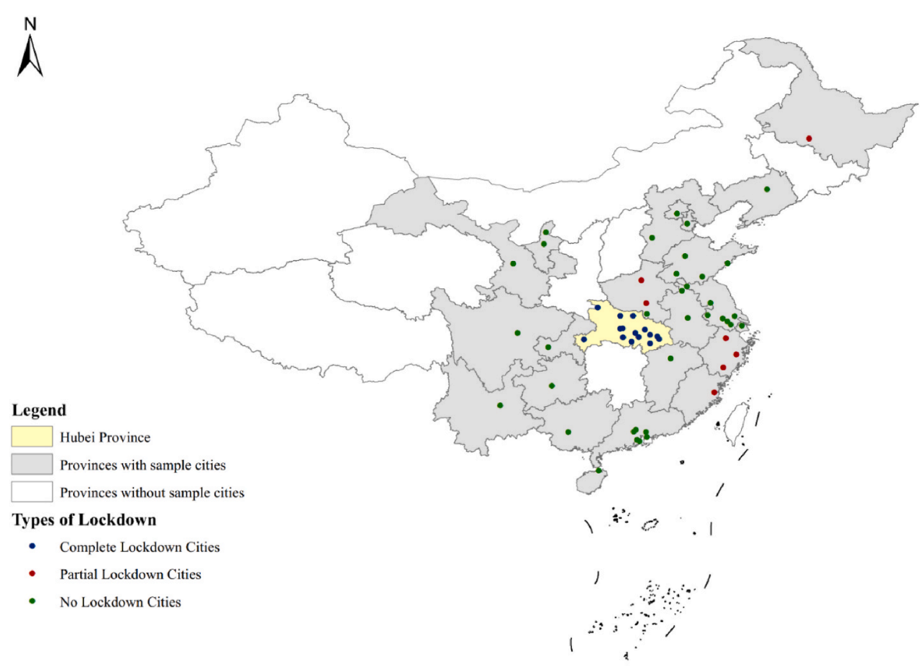

Fig. B1. Distribution of sample cities. Notes: [1.] The figure above shows the distribution of cities in our sample. [2.] Hubei and other sample provinces are represented by yellow and grey color blocks respectively. Provinces without sample cities are represented in white color. Dots of three colors show different types of lockdown cities. The blue, red and green dots represent complete lockdown, partial lockdown cities, and no lockdown cities respectively.

Table B1

Various levels of prevention and control measures in sampled cities

Types of Lockdown	City	Province	Lockdown Start Date	Cases as of Start Date	Lockdown End Date	Cases as of End Date	Cases as of May 1, 2020
Panel A. Complete Lockdown							
1	Wuhan	Hubei	2020/1/23	495	2020/4/8	50007	50333
1	Ezhou	Hubei	2020/1/23	0	2020/3/25	1394	1394
1	Xiaogan	Hubei	2020/1/24	26	2020/3/21	3518	3518
1	Jingzhou	Hubei	2020/1/24	10	2020/3/15	1580	1580
1	Suizhou	Hubei	2020/1/24	5	2020/3/17	1307	1307
1	Huangshi	Hubei	2020/1/24	0	2020/3/23	1015	1015
1	Yichang	Hubei	2020/1/24	1	2020/3/14	931	931
1	Jingmen	Hubei	2020/1/24	21	2020/3/17	928	928
1	Xianning	Hubei	2020/1/24	0	2020/3/15	836	836
1	Shiyan	Hubei	2020/1/24	5	2020/3/25	672	672
1	Xiantao	Hubei	2020/1/24	10	2020/3/13	575	575
1	Tianmen	Hubei	2020/1/24	3	2020/3/14	496	496
1	Enshi	Hubei	2020/1/24	11	2020/3/17	252	252
1	Qianjiang	Hubei	2020/1/24	0	2020/3/13	198	198
1	Xiangyang	Hubei	2020/1/28	131	2020/3/17	1175	1175
Panel B. Partial Lockdown							
2	Wenzhou	Zhejiang	2020/2/2	291	2020/2/19	504	504
2	Harbin	Heilongjiang	2020/2/4	73	2020/3/9	198	263
2	Hangzhou	Zhejiang	2020/2/4	141	2020/3/21	181	181
2	Ningbo	Zhejiang	2020/2/4	120	2020/2/16	156	157
2	Zhengzhou	Henan	2020/2/4	92	2020/3/6	157	157
2	Zhumadian	Henan	2020/2/4	82	2020/2/21	139	139
2	Fuzhou	Fujian	2020/2/4	55	2020/2/13	66	72
Panel C. No lockdown							
3	Chongqing	Chongqing					579
3	Yinchuan	Ningxia					36
3	Wuzhong	Ningxia					28
3	Huaian	Jiangsu					66
3	Huaibei	Anhui					27
3	Xinyang	Henan					274
3	Nanjing	Jiangsu					93
3	Xuzhou	Jiangsu					79
3	Changzhou	Jiangsu					51
3	Linyi	Shandong					49
3	Nantong	Jiangsu					40
3	Jining	Shandong					260
3	Nanchang	Jiangxi					230
3	Qingdao	Shandong					65
3	Nanning	Guangxi					55
3	Kunming	Yunnan					53
3	Jinan	Shandong					47
3	Haikou	Hainan					39
3	Shijiazhuang	Hebei					29
3	Zhuhai	Guangdong					103
3	Suzhou	Jiangsu					87
3	Shenyang	Liaoning					28
3	Shenzhen	Guangdong					462
3	Guangzhou	Guangdong					504
3	Hefei	Anhui					174
3	Chengdu	Sichuan					166
3	Tianjin	Tianjin					190
3	Lanzhou	Gansu					36
3	Guiyang	Guizhou					36
3	Foshan	Guangdong					100
3	Dongguan	Guangdong					100
3	Huizhou	Guangdong					62
3	Wuxi	Jiangsu					55
3	Beijing	Beijing					593
3	Shanghai	Shanghai					652

Notes: This table summarizes different levels of prevention and control measures across 57 cities. Panel A lists 15 cities with completed lockdown, which means all public transport and private vehicles were banned in the city, all residential buildings were locked down, and residents were not allowed to leave the city. 7 Cities in Panel B are under partial lockdown, the majority of the public transportation was temporarily locked down, checkpoints were set up to control the inflow of population, and surveillance and tighter controls were implemented in each neighborhood. 35 cities in Panel C did not implement lockdowns; in these cities public transport maintained normal operation.

Table B2
Definitions and descriptive statistics of variables

Variables	Definitions	2019–2020 Mean (Std. Dev.)	2020–2021 Mean (Std. Dev.)
Dependent variables			
Value	Total transaction value of online food delivery orders paid by consumers (RMB)	3104901 (6150980)	4342667 (7791635)
Net_Value	Total transaction value of online food delivery orders paid by consumers net of delivery costs (RMB)	2730509 (5378340)	3790569 (6840060)
Order	Total number of online food delivery orders (number)	91229.52 (159110)	140478.20 (207613.10)
Restaurant	Total number of restaurants offering online food delivery services (number)	12106.40 (16302.86)	18506.33 (21383.52)
ATVP	Average transaction value of online food delivery orders per restaurant paid by consumers (RMB)	268.49 (579.54)	161.25 (78.96)
NATVP	Average transaction value of online food delivery orders per restaurant paid by consumers net of delivery costs (RMB)	243.77 (561.13)	139.46 (70.28)
ANOP	Average number of online food delivery orders per restaurant (number)	5.97 (3.81)	5.76 (1.98)
Value_R	Total transaction value of food eats at restaurants orders paid by consumers (RMB)	3069781 (8625823)	9089393 (113000000)
Order_R	Total number of food eats at restaurants orders (number)	31881.13 (47366.83)	95384.03 (100316.50)
Restaurant_R	Total number of restaurants offering food eats at restaurants services (number)	1906.23 (2378.78)	4955.24 (4562.00)
ATVP_R	Average transaction value of food eats at restaurants order per restaurant paid by consumers (RMB)	1528.22 (9478.11)	1430.87 (7581.93)
ANOP_R	Average number of food eats at restaurants orders per restaurant (number)	14.42 (8.09)	17.70 (4.75)
Share_Chinese	Proportion of transaction value of Chinese food to total transaction value (%)	0.60 (0.16)	0.64 (0.06)
Share_Western	Proportion of transaction value of western food to total transaction value (%)	0.25 (0.09)	0.24 (0.04)
Share_Fresh	Proportion of transaction value of fresh food to total transaction value (%)	0.05 (0.12)	0.02 (0.01)
Share_Other	Proportion of transaction value of drinks and other food to total transaction value (%)	0.09 (0.09)	0.10 (0.03)
Order_Chinese	Proportion of orders of Chinese food to total orders (%)	0.64 (0.16)	0.66 (0.06)
Order_Western	Proportion of orders of western food to total orders (%)	0.22 (0.09)	0.22 (0.04)
Order_Fresh	Proportion of orders of fresh food to total orders (%)	0.04 (0.11)	0.01 (0.01)
Order_Other	Proportion of orders of drinks and other food to total orders (%)	0.09 (0.08)	0.11 (0.03)
Online food delivery + Cater-ing + Restaurant	Searching volumes of "Online food delivery (WaiMai)+Catering (CanYin)+Restaurant (CanGuan)" on Baidu (Index)	182.97 (136.73)	185.20 (138.40)
Online food delivery	Searching volumes of "Online food delivery (WaiMai)" on Baidu (Index)	94.35 (67.69)	91.13 (65.20)
Eat at restaurants + Catering + Restaurant	Searching volumes of "Eat at restaurants (TangShi)+Catering (CanYin)+Restaurant (CanGuan)" on Baidu (Index)	115.82 (115.62)	117.33 (107.81)
Eat at restaurants	Searching volumes of "Eat at restaurants (TangShi)" on Baidu (Index)	32.72 (61.59)	23.27 (37.54)
Delivery	Average delivery fee per order (RMB)	4.06 (1.48)	3.78 (0.66)
Inner-city mobility	The ratio of the number of people traveling in the city to the resident population of the city	3.80 (1.56)	
Independent variables			
Treat	Whether the city has implemented the lockdown policy (1 = Complete/Partial lockdown; 0 = No lockdown)	0.39 (0.49)	0.39 (0.49)
Lockdown	Whether the day has implemented the lockdown policy (1 = Lockdown period; 0 = Before lockdown or control group)	0.13 (0.34)	
Reopen1	Whether the day has implemented the reopening policy (1 = Reopen; 0 = Lockdown period or control group)	0.15 (0.36)	
Reopen2	Whether the day has implemented the reopening policy (1 = Reopen; 0 = Before lockdown or control group)	0.14 (0.35)	
Reopen3	Whether the day has implemented the reopening policy (1 = Reopen (long-term); 0 = Before lockdown or control group)		0.39 (0.49)
Control variables			
COVID-19 cases	Cumulative new COVID-19 cases in the past 14 days	116.97 (1461.23)	3.77 (29.17)
Temperature	Average temperature ($^{\circ}C$)	10.19 (7.42)	11.73 (8.41)
Precipitation	24-h precipitation (mm)	1.80 (5.53)	1.87 (6.36)
Observations		8721	8664

Table B3
Differences in mean value of dependent variables among different periods of COVID-19 pandemic

Variables	Control Group	Treatment Group			Difference#		
	Full sample	Before Lockdown (1)	Lockdown Period (2)	After lockdown (3)	Diff (2-1)	Diff (3-2)	Diff (3-1)
Value	3899121	2527302	781049.80	2004094	-1746252***	1223044***	-523208***
	(7257136)	(4166106)	(2112516)	(3161915)			
Net_Value	3423482	2207914	709312.40	1785525	-1498601***	1076212***	-422389***
	(6342899)	(3628350)	(1889197)	(2801308)			
Order	112375	91023.50	15498.80	56989	-75524***	41490***	-34034***
	(178737.80)	(150755.80)	(51488.86)	(89970.89)			
Restaurant	15230.91	9937.30	1799.59	8694.12	-8137.71***	6894.53***	-1243.18**
	(17904.85)	(13803.59)	(5831.58)	(11640.65)			
ATVP	190.36	168.42	923.37	176.19	754.95***	-747.18***	7.77**
	(89.85)	(84.98)	(1553.84)	(103.72)			
NATVP	167.92	146.16	876.52	157.29	730.36***	-719.23***	11.13***
	(80.74)	(75.24)	(1507.77)	(96.33)			
ANOP	5.77	5.95	8.42	4.78	2.47***	-3.64***	-1.17***
	(1.97)	(2.62)	(9.30)	(1.85)			
Value_R	3682578	3020221	155819.50	1868125	-2864401.50***	1712305.50***	-1152096**
	(8416669)	(8549137)	(658621.30)	(12300000)			
Order_R	37095.09	37024.84	2314.21	19482.51	-34710.63***	17168.30***	-17542.33***
	(46972.95)	(64119.58)	(7395.42)	(33912.01)			
Restaurant_R	2265.37	1762.21	180.80	1347.05	-1581.41***	1166.25***	-415.16***
	(2380.58)	(2743.17)	(589.24)	(2095.87)			
ATVP_R	1700.43	1609.10	664.21	1122.29	-944.89***	458.08*	-486.81*
	(11035.98)	(3724.95)	(933.36)	(7408.58)			
ANOP_R	14.70	18.09	10.27	12.11	-7.82***	1.84***	-5.98***
	(5.83)	(7.13)	(17.50)	(5.68)			
Share_Chinese	0.63	0.67	0.35	0.61	-0.32***	0.26***	-0.06***
	(0.11)	(0.07)	(0.27)	(0.09)			
Share_Western	0.26	0.24	0.20	0.28	-0.04***	0.08***	0.04***
	(0.06)	(0.06)	(0.20)	(0.06)			
Share_Fresh	0.04	0.02	0.22	0.02	0.2***	-0.2***	0
	(0.07)	(0.02)	(0.25)	(0.02)			
Share_Other	0.07	0.07	0.18	0.09	0.11***	-0.09***	0.02***
	(0.03)	(0.04)	(0.24)	(0.05)			
Order_Chinese	0.67	0.71	0.39	0.63	-0.32***	0.24***	-0.08***
	(0.10)	(0.07)	(0.28)	(0.09)			
Order_Western	0.22	0.20	0.20	0.24	0	0.04***	0.04***
	(0.06)	(0.05)	(0.21)	(0.06)			
Order_Fresh	0.03	0.01	0.20	0.01	0.19***	-0.19***	0*
	(0.06)	(0.01)	(0.25)	(0.01)			
Order_Other	0.08	0.07	0.16	0.11	0.09***	-0.05***	0.04***
	(0.04)	(0.03)	(0.21)	(0.05)			
Online food delivery + Catering + Restaurant	217.76	117.05	122.30	144.40	5.25	22.1***	27.35***
	(128.20)	(135.71)	(129.00)	(127.37)			
Online food delivery	114.53	57.39	62.44	67.60	5.05*	5.16*	10.21***
	(60.96)	(69.14)	(65.13)	(60.86)			
Eat at restaurants + Catering + Restaurant	138.64	45.26	55.36	139.93	10.10***	84.57***	94.67***
	(115.89)	(65.76)	(92.84)	(124.89)			
Eat at restaurants	35.41	0.00	13.96	73.68	13.96***	59.72***	73.68***
	(62.75)	(0.00)	(47.44)	(74.54)			
Delivery	3.87	3.83	5.56	3.94	1.73***	-1.62***	0.11***
	(0.92)	(0.96)	(3.27)	(0.53)			
Inner-city mobility	4.00	4.72	1.81	4.34	-2.91***	2.53***	-0.38***
	(1.50)	(1.31)	(0.90)	(0.83)			
Observations	5355	1265	989	1112			

Notes: #means comparison test; ***p<0.01, **p<0.05, *p<0.1.

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