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Asymmetric effects of air pollution on online food delivery before and after COVID-19

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ABSTRACT

This study examines the asymmetric effects of air pollution on residents' consumption of online food delivery (OFD) before and after COVID-19 lockdown measures. Using daily high-frequency OFD data from 54 cities collected between 1 December 2019 and 1 May 2020, an instrumental variable two-way fixed effect model is employed to estimate the interaction effects of air pollution and lockdown measures on OFD. The results indicate significant and positive effects of air pollution on OFD before the lockdown and after reopening, compared to the lockdown stage. Note that, the impact magnitude of air pollution on OFD after reopening is comparatively greater than that before lockdown. The mechanisms explaining the effects of air pollution on OFD before and after the lockdown include inner-city mobility on the demand side and the number of operating restaurants, the average price of OFD per order, the average discount per order, and the average delivery fee per order on the supply side. The results remain robust across various specifications, including alternative measures of air pollution like $PM_{2.5}$, alternative samples, and alternative controls for fixed effects. Furthermore, the effects of air pollution on OFD are heterogeneous by various types of food, distinct degrees of air pollution, cities with different locations and sizes, and three meals a day. This study contributes to the literature on OFD, COVID-19, and air pollution, shedding light on the understanding of human consumption behavior associated with air pollution before and after the pandemic.

1. Introduction

Air pollution has a widespread impact on human behavior. When faced with air pollution, people usually take various avoidance behaviors, such as staying indoors to reduce personal exposure to harmful air contaminants (Graff Zivin & Neidell, 2009), purchasing particulate-filtering facemasks on a highly polluted day (Neidell, 2009; Zhang & Mu, 2018), reducing their labor productivity (He et al., 2019), short-term travel and migration (Chen et al., 2021, 2022). To avoid exposure to air pollution, people's consumption behavior of food away from home also changes on polluted days, tending to order online food delivery (OFD) (Chu et al., 2021) instead of going out and dining in restaurants (Sun et al., 2019), and air pollution also increases the purchase of unhealthy food (Liu et al., 2022).

The COVID-19 pandemic might distort the impact of air pollution on people's consumption behavior of OFD. First, the lockdown and reopening measures during the COVID-19 have affected people's behavior of staying at home and going out. During the lockdown, there was a significant decrease in people's mobility (Fang et al., 2020; Li et al., 2022), whereas, after the reopening, there was a surge in demand for outdoor activities surpassing pre-lockdown levels within a short span of time (Fisman et al., 2021). Secondly, air pollution has significantly reduced in some regions including China, where strict preventive measures (e.g., lockdowns, curfews, transport restrictions, etc.) in coping with COVID-19 were implemented (Cooper et al., 2022; Dang & Trinh, 2021; He et al., 2020; Kahn et al., 2022; Li et al., 2022; Qi et al., 2021). Thirdly, previous studies found a significant impact of the lockdown and reopening measures during COVID-19 on people's consumption behavior of OFD (Das & Ramalingam, 2022; Gao et al., 2020; Wang et al., 2022). Intuitively, the impact of air pollution on OFD may be affected by the lockdown and reopening measures due to COVID-19. Yet, it remains implicit whether the impact of air pollution on residents'

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consumption behavior of OFD may change at different stages of COVID-19 including before the lockdown, during the lockdown, and after the reopening. Answering the question requires more empirical evidence.

The objective of this study is to examine the impacts of air pollution on OFD before and after COVID-19 lockdown measures. We take China as a case by considering the following reasons. First, OFD is booming in China. From 2018 to 2022, the proportion of China's OFD revenue in the total revenue of the national catering industry increased from 10.9 % to 25.4 %, and China's OFD market will continue to expand (SIC, 2023). Second, China has suffered from air pollution over the past decades (Chen et al., 2022; Ebenstein et al., 2017). It's estimated that air quality in only less than one-third of China's cities met the air quality standards by 2017 (MEE, 2017). Third, China was severely affected at the beginning of COVID-19 and, meanwhile, has implemented strict preventive measures such as the lockdown in coping with COVID-19 (Fang et al., 2020). Although air pollution in China appears to be mitigated since the COVID-19 pandemic (He et al., 2020; Venter et al., 2020), it is widely believed that air pollution would soon resurge with increased industrial production and scale as economic activity recovers post COVID-19 (Bhatti et al., 2022).

To achieve the objective, an instrumental variable two-way fixed effect (IVTWFE) model and an event study approach are applied to the daily high-frequency data of OFD between 1 December 2019 and 1 May 2020 in 54 cities in China. The daily aggregated consumption data of OFD at the city level are obtained from Ele.me platform.[1] These data are combined with the maximum daily readings of air pollution from all monitoring stations in these 54 cities. We divide the sample stage into three different stages according to the lockdown and reopening time of each city, which were defined as before lockdown, lockdown stage, and reopening/after reopening. Air pollution before the lockdown and after reopening are designed to capture the changes in the impact of air pollution on OFD, referring to the lockdown stage.

The main findings of this study are summarized as follows. First, when compared to the days of air pollution during the lockdown stage, there are significant and positive effects of air pollution on OFD both before and after the reopening. In addition, the magnitude of the coefficients of air pollution on OFD after the reopening is larger than that before the lockdown. Second, inner-city mobility,[2] the number of operating restaurants, the average price of OFD per order, the average discount per order, and the average delivery fee per order were found to be possible mechanisms through which air pollution asymmetrically affects OFD before and after the lockdown from the demand and supply sides. Third, the findings remain consistent when using different measures of air pollution such as a dummy variable according to the maximum value of $PM_{2.5}$, different samples, and different controls for fixed effects. Fourth, the results of the placebo test show that our findings are not affected by other confounding factors, such as other policies or shocks during the same period. Lastly, there are heterogeneous interaction effects of air pollution on OFD before the lockdown and after the reopening for various types of food, different degrees of air pollution, cities with different locations and sizes, and across three meals a day.

This study expands the existing literature in the following ways. First, this study supplements the literature on the impacts of air pollution on human behavior, with a particular highlight on the changes in the impacts under an external shock. Existing literature mainly focuses on avoidance behaviors in response to air pollution such as staying indoors (Graff Zivin & Neidell, 2009), purchasing facemasks (Neidell, 2009; Zhang & Mu, 2018), or short-term travel and migration (Chen et al., 2021, 2022), while this study emphasizes the effects of air pollution on residents' OFD consumption (Chu et al., 2021). Especially, we have noticed the changes in the impacts of air pollution on residents' OFD under the shock of COVID-19 and revealed the asymmetric effects of air pollution on OFD before and after the COVID-19 pandemic.

Secondly, this study broadens the analysis of the factors affecting OFD from the view of air quality. The majority of research on OFD concentrates on the impact of service quality (Saad, 2020; Shankar et al., 2022), food environment (Kong et al., 2024), and availability (Gunden et al., 2020b; Saad, 2020), while few studies analyze OFD from an interdisciplinary perspective, such as the impact of air pollution on OFD (Chu et al., 2021). This study supplements existing studies by investigating the interaction effects of air pollution and COVID-19 on OFD.

Finally, this study enhances the research on the impact of COVID-19 on residents' behavior of food consumption. Previous studies have widely investigated the direct effects of COVID-19 on residents' food consumption behavior (e.g. Chenarides et al., 2021; Hirvonen et al., 2021). This study further found that COVID-19 has an indirect effect on OFD by mediating the impact of air pollution on residents' consumption behavior of OFD. Also, this study empirically tested the underlying mechanisms through which air pollution impacts OFD before and after COVID-19 lockdown measures from both the demand and supply sides.

The rest of the paper is organized as follows: Section 2 provides a brief introduction to the context of China's OFD. Section 3 introduces empirical models and identification strategies. Section 4 presents a series of data sources and data descriptive statistics. Section 5 reports the estimation results of the interaction impact of air pollution and COVID-19 on OFD, explores the potential impact mechanisms, and conducts a series of heterogeneous analyses. Section 6 concludes.

2. The context of China's online food delivery

Online food delivery (OFD) refers to food ordered and delivered using online platforms such as food delivery apps and websites (Shankar et al., 2022). The popularity of OFD has surged due to the advancement of the app, smartphone, and e-payment terminal technologies (Gunden et al., 2020a; Maimaiti et al., 2018). The value of OFD sales in China has kept fourfold growth from 24.1 billion US$ in 2016 to 96.4 billion US$ in 2020 (Zhou et al., 2020). OFD primarily saves time and serves as a strategy for adapting to inclement weather shocks, such as cold and rainy weather, so it is a preferred option for residents who don't tend to cook or choose to eat at restaurants during poor weather conditions (Chu et al., 2021; Liu & Chen, 2021). The existing research on OFD has mainly focused on the factors that affect OFD, such as the service quality of OFD delivery platforms (Saad, 2020; Shankar et al., 2022), the food price (Gunden et al., 2020b), and delivery time (Saad, 2020).

With the increasing concerns about air pollution in China, some studies paid attention to assessing its impact on residents' OFD behavior (Chu et al., 2021; Zhang et al., 2017). Existing studies focusing on OFD have reached a unanimous conclusion that air pollution increases the demand for OFD, as OFD allows residents to stay indoors and avoid the impact of air pollution. Zhang et al. (2017) suggested that a 100-point increase in AQI leads to a 5 % increase in online food sales in China, revealing residents' tendency to adopt alternative consumption behavior to avoid pollution. Chu et al. (2021) investigated the effects of $PM_{2.5}$ on consumers' OFD and identified that an increase in matter pollution would increase consumers' tendency to order OFD.

COVID-19 and the strict prevention measures such as lockdown and isolation have also seriously shocked the restaurant and food supply sector (Aday & Aday, 2020; Garnett et al., 2020; Lowe et al., 2021; McDermott & Swinnen, 2022; Swinnen & Vos, 2021). Firstly, the COVID-19 pandemic has directly led to a decrease in OFD (Zhu et al., 2021). Secondly, there may be also an indirect impact of the COVID-19 pandemic on OFD. Lockdown measures implemented during the pandemic significantly changed people's behavior (Fang et al., 2020;

[1] Ele.me platform is affiliated with Alibaba Group Holding Ltd. (China's largest mobile payment and e-commerce platform). Ele.me is one of the major OFD platforms in China.

[2] This index is established by Baidu to measure the intensity of mobility within a city, calculated as the ratio of the number of people traveling in a city to the city's resident population.

Fisman et al., 2021; O'Garra & Fouquet, 2022), which may in turn enhance or weaken their reactions towards air pollution, thereby further affecting consumption of OFD. However, there is a lack of studies taking people's changes in consumption behavior before and after COVID-19 into account. It remains unclear whether the effect of air pollution on OFD has changed during different stages of lockdown measures during COVID-19, and how large the corresponding impact is.

3. Empirical models

In order to test whether and to what extent COVID-19 changes the impact of air pollution on residents' consumption of OFD, first, we develop an instrumental variable two-way fixed effect (IVTWFE) model to estimate the interaction effect of air pollution and the lockdown and reopening measures on OFD. Secondly, an event study is used to rule out any pre-existing trend in residents' consumption of OFD and observe how the effects of air pollution on OFD vary across different weeks. In addition, we employ the IVTWFE model to explore the underlying mechanism by which air pollution and COVID-19 collectively impact OFD.

3.1. Interaction impact of air pollution and COVID-19 lockdown measures on OFD

Our empirical strategy addresses standard concerns that can arise in estimating the causal effect of air pollution on OFD during COVID-19. First, air pollution is highly correlated with economic activities, and those cities with more transactions may also be cities with high air pollution, thus there may be endogeneity caused by reverse causality. Second, OFD consumption may be influenced by unobservable time-variant variables, such as other policies and shocks except COVID-19, which could drive part of the correlation between air pollution and the consumption of OFD and cause endogeneity bias. The combination of these two issues poses an important challenge in identifying the effect of air pollution on OFD.

To address these concerns, firstly, our baseline specification includes city fixed effects that absorb all time-invariant characteristics of the city that are associated with air pollution and COVID-19 lockdown measures and also affect the consumption of OFD. It also includes date fixed effects that account for any policies or shocks to the consumption of OFD, that coincide with the date but affect macroeconomic conditions beyond the level of a city. We also include date time trend and interactions between date time trend and city fixed effects in the robustness checks.

Secondly, we employ the instrumental variable (IV) approach to address endogeneity caused by reverse causality. Thermal inversions has been widely used as an instrument for air pollution to explore the effects of air pollution on human behavior (Chen et al., 2022; Chu et al., 2021; Fu et al., 2021; Xia et al., 2022). Thermal inversions is a common meteorological phenomenon that occurs when warmer air is suspended above cooler air. During these inversions, the ground-level air, which is cooler and often more polluted, is trapped beneath a layer of warmer air. Consequently, thermal inversions can lead to higher concentrations of pollutants near the ground. When examining the impact of air pollution on human behavior, thermal inversions can be used as an instrumental variable for air pollution, leveraging changes in atmospheric conditions as exogenous shocks to local pollution levels. In previous research on the impact of air pollution on OFD (Chu et al., 2021), thermal inversions was also used to construct instrumental variable. Hence, in this study, we similarly use thermal inversions as an instrument for air pollution to elucidate its impact on OFD.

The validity for our instrument variable requires that the thermal inversions is correlated with air pollution but uncorrelated with residents' OFD consumption. To test the relevance condition between the endogenous variable of air pollution and thermal inversions, Table A3 reports estimates from the first-stage regression, where air pollution is regressed on thermal inversions, conditional on a set of controls and city fixed effects. The first-stage coefficient of the interaction term is significantly positive at the 1 % level, and the F test of additional instruments is >10, which implies that thermal inversions is strongly correlated with air pollution. To obtain an asymptotically consistent estimator, it is critical to ensure that the instrument is orthogonal to unobservables correlated with changes in residents' OFD consumption behavior within cities. The process of thermal inversions is a natural phenomenon independent of economic activities (Chen et al., 2022), and it is unlikely to be directly observed by consumers. Thus, thermal inversions is unlikely to influence residents' OFD consumption directly, they can only affect OFD consumption through air pollution. The instrumental variable two-way fixed effect (IVTWFE) model is specified as follows:

$$lnY_{it} = \alpha + \beta Pollution_{it} + \gamma Z_{it} + \sigma_i + \delta_t + \varepsilon_{it} \tag{1}$$

$$Pollution_{it} = \alpha + \beta TI_{it} + \gamma Z_{it} + \sigma_i + \delta_t + \tag{2}$$

where lnY_{it} represents the logarithm form of OFD in the city i on date t. $Pollution_{it}$ is a dummy variable equal to 1 if the maximum value of AQI in city i is above 100 on date t, 0 otherwise,[3] and we treat it as endogenous. β, the coefficient of interest, captures the impact of air pollution on the outcome variables. β should be interpreted as the percentage change in transaction amount or orders of OFD (i.e., the relative impact of air pollution), holding other factors constant. The covariate vector Z_{it} consists weather factors, including daily average temperature, daily precipitation, and the cumulative new COVID-19 cases over the last 14 days in the city i on date t. The city fixed effects σ_i control for all time-invariant differences across the city and the date fixed effects δ_t control for all time-variant change that affect all cities simultaneously. Standard errors are clustered at the city level to solve the autocorrelation concerns at the city level.

Eq. (2) shows the first stage of our empirical strategy. We instrument air pollution with the average strength of thermal inversions on each date t of the city i, TI_{it}, conditional on covariate vector Z_{it}, city fixed effects σ_i, and date fixed effects δ_t. We define the strength of thermal inversions by the difference between the above-ground temperature and the ground temperature (Chen et al., 2022). A positive value in this difference signifies the presence of a thermal inversion, with the size of the value reflecting the strength of the inversion. Conversely, a negative value suggests the absence of a thermal inversion. In our approach, we retain the positive values and set any negative values to zero (Chen et al., 2022).

Furthermore, many cities have implemented lockdown measures during COVID-19, influencing both air pollution levels and the outdoor activities of residents (Fang et al., 2020; He et al., 2020). Consequently, these measures may have altered the impact of air pollution on OFD. To detect whether and to what extent the impact of air pollution on OFD changes with the implementation of lockdown measures, we construct interaction terms between air pollution and the lockdown measures. We divide the sample into three stages based on the different implementation stages of lockdown measures: (1) before lockdown, (2) lockdown stage, and (3) reopening (Fang et al., 2020). The specifications are as follows:

$$\begin{aligned} lnY_{it} = {} & \alpha + \beta_1 Pollution_{it} + \beta_2 Pollution_{it} \times Beforelockdown_{it} + \\ & \beta_3 Pollution_{it} \times Reoepn_{it} + \gamma Z_{it} + \sigma_i + \delta_t + \varepsilon_{it} \end{aligned} \tag{3}$$

$$\begin{aligned} Pollution_{it} = {} & \alpha + \beta_1 TI_{it} + \beta_2 TI_{it} \times Beforelockdown_{it} \\ & + \beta_3 TI_{it} \times Reoepn_{it} + \gamma Z_{it} + \sigma_i + \delta_t + \varepsilon_{it} \end{aligned} \tag{4}$$

[3] When the maximum value of AQI $>$ 100, it is defined as air pollution, according to the technical regulation on ambient air quality index by the Ministry of Ecology and Environment of the People's Republic of China (MEE, PRC). https://www.mee.gov.cn/ywgz/fgbz/bz/bzwb/jcffbz/201203/W020120410332725219541.pdf.

$$Pollution_{it} \times Beforelockdown_{it} = \alpha + \beta_1 TI_{it} + \beta_2 TI_{it} \times Beforelockdown_{it} + \beta_3 TI_{it} \times Reoepn_{it} + \gamma Z_{it} + \sigma_i + \delta_t + \varepsilon_{it} \tag{5}$$

$$Pollution_{it} \times Reoepn_{it} = +\beta_1 TI_{it} + \beta_2 TI_{it} \times Beforelockdown_{it} + \beta_3 TI_{it} \times Reoepn_{it} + \gamma Z_{it} + \sigma_i + \delta_t + \varepsilon_{it} \tag{6}$$

where $Beforelockdown_{it}$ as a measure time dummy variable, which equals 1 before the lockdown measure, and 0 otherwise; $Reopening_{it}$ is also a measure time dummy variable, which equals 1 after the reopening measure, and 0 otherwise. The interaction terms $Pollution_{it} \times Beforelockdown_{it}$ and $Pollution_{it} \times Reopening_t$ are used to examine whether the effects of air pollution on OFD changed before the lockdown and after the reopening measure of COVID-19, and $Pollution_{it} \times Lockdownperiod_{it}$ is omitted in the empirical estimation as the reference group. The setting of other variables is the same as those in model (1). The coefficients we focus on now are β_2 and β_3, which respectively reflect the impact of air pollution on OFD before and after the lockdown compared to the lockdown stage. Eqs. (4)–(6) shows the first stage of our empirical strategy.

Finally, the models using the city-date-meal level data are also constructed and presented in the appendix, while the corresponding regression results for meal heterogeneity are reported in Fig. 7.

3.2. The dynamic interaction impact of air pollution and COVID-19 lockdown measures on OFD

The event-study approach is further used to capture the stage-specific interaction effects of air pollution and reopening measures on residents' consumption of OFD. This approach serves two primary purposes: first, the event-study approach allows us to examine whether there is a pre-existing trend in OFD consumption among urban residents between cities that implemented lockdowns and those that did not. This test is crucial for validating the assumption of parallel trends. Second, the approach can comprehensively demonstrate the dynamic impact of air pollution on OFD over time, both before and after the implementation of reopening measures. The effects are measured relative to the week prior to the reopening measure, providing a clear temporal reference point. We put 7 days (one week) into one bin (bin $m\in M$), in order to observe how the effects of air pollution on OFD vary across different weeks and ensure that the event study is not impacted by the high volatility of daily air pollution. The event-study model is specified as follows:

$$lnY_{it} = \alpha + \beta_1 Pollution_{it} + \sum_{m=k, m\neq -1}^{M} \beta_2{}^k \times Pollution_{it} \times 1[Reopening]_{t,k} + \gamma Z_{it} + \sigma_i + \delta_t + \varepsilon_{it} \tag{7}$$

where m represents each week bin belongs to M, and $1[Reopening]_{t,k}$ are a set of dummy variables indicating the reopening measure status at different stages. So k shows the k^{th} week related to the implementation of the reopening measure. For example, $k = -2$ indicates two weeks before the reopening measure, and $k = 0$ indicates the week in which the reopening measure was implemented. The parameter of interest β^k estimates the interaction between air pollution and the effects of reopening measure m weeks after the implementation of reopening measure. Following the convention practice, $m = -1$ is excluded in Eq. (7) as the baseline week. The key coefficient β^k measures the difference in OFD between cities under air pollution and otherwise in stage k relative to the difference one week before the reopening measure. The settings of other variables are the same as those in models (1) and (3).

3.3. Identification strategy

Our empirical identification consists of several procedures. First, we utilize the instrumental variable two-way fixed effect (IVTWFE) model to estimate Eqs. (1) and (3), followed by an event study analysis to estimate Eq. (7). Second, we investigate the underlying mechanism through which air pollution and COVID-19 jointly influence OFD by employing Eq. (3) both from the demand and supply sides. Additionally, we conduct several robustness analyses by changing air pollution measures, altering samples, and controlling different fixed effects. Finally, heterogeneity analyses are used to study the interaction effects of air pollution and COVID-19 lockdown measures on OFD for preferences for Chinese food, Western food, fresh food, and other food, distinct levels of air pollution, across cities with different locations and population sizes, and three meals of the day.

4. Data source and descriptive statistics

The data used in this study are collected from a range of distinct sources, which are summarized as follows.

4.1. Online food delivery (OFD)

The data of OFD used in this study are obtained from Ele.me platforms, which is affiliated with Alibaba Group Holding Ltd. (China's largest mobile payment and e-commerce platform). Ele.me is one of the major OFD platforms in China.[4] Today, with improvements in app, smartphone, and e-payment terminal technologies, OFD platforms have grown rapidly. China has been the largest market for OFD and takeaway, which served 419 million customers with 17.12 billion orders in 2020. In 2020, 380,000 new companies linked to food delivery services were registered in China (iiMedia, 2020). OFD 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 (de Freitas & Stedefeldt, 2020).

Following the method of a previous study (Fang et al., 2020), we selected 54 cities as samples, including 19 cities that implemented lockdowns and 35 that did not. The 54 sample cities were selected through classified random sampling based on various control measures implemented during COVID-19. Fig. A1 displays the distribution of our 54 sample cities on a map. In general, our sample cities are widely distributed throughout the country and include the main economic development regions, all first-tier cities, as well as some second and third-tier cities. Due to data limitations, the sample period was chosen to reflect the time stages before, during, and after the COVID-19 lockdown measures as much as possible.

Under the agreement with the Ele.me platforms, we were allowed to use the high-frequency urban transaction data in 54 cities, from December 1, 2019 to May 1, 2020. Our original dataset includes the OFD transactional data for various cuisine categories during three meal times of the day (breakfast, lunch, and dinner) in 54 cities. Among them, the

[4] Ele.me platform holds a 43.9 % market share (Analysis, 2020), making it the second largest OFD platform in China. The annual financial report of the largest OFD platform Meituan presents trends that are similar to those that we find in the Ele.me data (Meituan, 2020).

cuisine categories are divided based on the main cuisine label of each restaurant. In our main analysis, we aggregate the raw data at the city-date level to obtain daily OFD transaction data for each city, resulting in a total of 8262 observations across 54 cities over a stage of 153 days.[5]

OFD data include transaction amount and the number of orders in each city. Specifically, we have two outcome variables: (1) the total transaction amount of OFD, and (2) the total number of OFD orders. The definitions of variables and descriptive statistics are shown in Table A1. The average daily transaction amount and average daily number of orders per city are 3,274,573 and 96,210, respectively. It is noted that due to the limitation of observation period of the OFD data, we can only consider the short-term impact of prevention measures of COVID-19 and air pollution on OFD.

4.2. Air pollution

Air quality data are obtained from the website of the China National Environmental Monitoring Center (CNEMC), the Ministry of Environmental Protection of China (MEP). The original dataset includes hourly readings of the Air Quality Index (AQI), $PM_{2.5}$, PM_{10}, SO_2, O_3, NO_2, and CO concentrations from 1605 air quality monitoring stations covering all of the prefectural cities in China. To construct the city-level daily air quality data, we first take the maximum value of the hourly data of each day to obtain the daily data.[6] Our research focuses on the daily maximum value of pollutants, which is the level of pollution that people are most concerned about and perceive. Second, following He et al. (2020), we calculated the distance from a city's population center to all monitoring stations within the corresponding city. Next, we aggregated station-level air quality data with city-level data using the inverse distance weights, which are inversely proportional to the square distance.[7] With this procedure, we acquired the daily air pollution dataset in each city.

The AQI is a comprehensive measure of air quality and reflects the overall air quality. In detail, the AQI index has been constructed using $PM_{2.5}$, PM_{10}, SO_2, CO, O_3, and NO_2 concentrations, which are derived from a piece-wise linear transformation of primary air pollutants. The AQI ranges from 0 to 500, where the larger number indicates a higher level of air pollution. Since people mainly perceive pollution alerts issued when AQI is above 100, we accordingly constructed a dummy variable of air pollution equals 1 if AQI is above 100 and 0 otherwise subject to the MEP's guideline of air quality (MEE, 2012).[8] $PM_{2.5}$ is also used in this study because it is the air quality indicator that people are most likely to perceive and pay attention to (Chen et al., 2022; Chu et al., 2021; Shi et al., 2017). Similarly, another dummy variable representing air pollution based on $PM_{2.5}$ is constructed. If $PM_{2.5}$ exceeds 75, it equals 1, 0 otherwise.[9] The mean values of dummy variables representing air pollution constructed by AQI and $PM_{2.5}$ in 54 cities are 0.366 and 0.334 during the sample stage. There is significant variation in air quality between cities. For example, Haikou only had 2 days classified as polluted, while Shijiazhuang had 104 days classified as polluted during the 153-day sample stage.

4.3. Thermal inversions

The thermal inverse is used as an instrumental variable (IV) to deal with potential endogenous bias. The data on thermal inversions were collected from the product M216NPANA version 5.12.4 from the Modern-Era Retrospective analysis for Research and Applications version 2 (MERRA-2) released by the National Aeronautics and Space Administration (NASA) of the U.S (Chen et al., 2022). The product divides the earth by 0.5 degrees $\times$ 0.625 degrees (around 50 km $\times$ 60 km) grid and records the six-hour air temperature at 42 layers, ranging from 110 m to 36,000 m. According to the latitude and longitude of the grid, we aggregate it to each city and calculate the average thermal inversions of each city (Chen et al., 2022).

In accordance with recent studies (Chen et al., 2022), the strength of thermal inversions is constructed. Within each 6-h stage, we calculate the temperature difference between the second layer (320 m) and the first layer (110 m). If the difference is positive, there exists a thermal inversion and the difference measures the inversion strength. If the difference is negative, we code it as zero. We then average the inversion strength across all six-hour lapses within each day to measure the strength of thermal inversions. The average strength during our study stage is 0.63 °C.

4.4. COVID-19 lockdown measures

Similar to the previous literature (Fang et al., 2020), the 54 sample cities are divided into two types: cities under lockdown during COVID-19, and cities not under lockdown during the pandemic. China implemented a lockdown in Wuhan starting from 10 a.m. on January 23, 2020, and in all other cities in Hubei province one day later. In lockdown cities, public transportation is prohibited and residents cannot leave the city. In no lockdown cities, public transport maintained normal operations, and only some checkpoints and quarantine zones were implemented (Fang et al., 2020). Fig. A1 shows the lockdown situation of our sample cities, including 19 lockdown cities and 35 no lockdown cities. The dates of lockdown and reopening on official announcements collected from the websites of the local government for each city are identified. Table A2 lists the specific dates of lockdown and reopening in each city.

4.5. Interaction term between air pollution and COVID-19 lockdown measures

According to the lockdown and reopening times of each city (Table A2), we construct interaction terms between air pollution and before lockdown, air pollution and reopening to explore the differential effects of air pollution on OFD at different lockdown stages, where the interaction term between air pollution and lockdown stage is omitted as a reference group. The lockdown and reopening time of each city is determined by the government and is not influenced by other factors except the pandemic situation (Fisman et al., 2021). Since the lockdown and reopening measure time is arguably orthogonal to economic shocks (such as trends of food consumption) that may affect OFD, it provides a compelling natural experiment to identify the interaction between different stages of lockdown and air pollution.

4.6. Mechanism variables

In this section, we test the following potential mechanisms through which air pollution may affect OFD from both the demand and supply

[5] In addition, we also aggregated the raw data at the city-date-meal level to obtain 153 days of breakfast, lunch, and dinner online food delivery consumption data for 54 cities. We present the model using the city-date-meal level data in the appendix and our regression results for meal heterogeneity in Fig. 7.

[6] Corresponding to online food delivery data, we also aggregate hourly pollution data at the city-date-meal level. We take the maximum value of pollutants during the three meals of each day (breakfast, lunch, and dinner) in each city, and construct dummy variables.

[7] For this process, stations closer to the population center are given higher weights so that city-level air pollution data can better represent the air pollution endured by residents in each city.

[8] The MEE defines six levels of AQI, with 0–50 for excellent air quality, 51–100 for good air quality, 101–150 for slightly polluted air, 151–200 for moderately polluted air, 201–300 for heavily polluted air, and above 300 for severely polluted air (MEE, 2012).

[9] When $PM_{2.5} > 75$, it is defined as air pollution, according to the technical regulation on the ambient air quality index by the Ministry of Ecology and Environment of the People's Republic of China (MEE, 2012). https://www.mee.gov.cn/ywgz/fgbz/bz/bzwb/jcffbz/201203/W020120410332725219541.pdf.

sides.

On the demand side, we use the Baidu 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.[10] Compared to the air pollution days during the lockdown stage, there may be more mobile people within the city before and after the lockdown stage, especially after the lockdown stage, where more people need to seek economic opportunities even during the air pollution days. This index can reflect the intensity of people's economic activities to some extent, which in turn reflects people's potential demand for OFD.

On the supply side, the restaurants and delivery services combined to influence the supply of OFD. Firstly, there may be more operating restaurants during air pollution days before lockdown and after reopening. Meanwhile, the operators of restaurants may lower prices and increase discounts to obtain more orders. So the data of the total number of operating restaurants, the average transaction amount per order, and the average discount per order collected from Ele.me are used to conduct mechanism analysis. Secondly, the delivery fee may drop on air pollution days before lockdown and after reopening, we also use the average delivery fee per order collected from Ele.me as a mechanism for air pollution affecting OFD.

4.7. Control variables

Weather factors are significant covariates that may also affect the OFD (Chu et al., 2021; Sun et al., 2019). Recent studies indicate that experiencing bad weather, such as extreme temperature and humidity, and intense precipitation, makes people less likely to go outside (He et al., 2022) and increases the demand for OFD. Chu et al. (2021) and Sun et al. (2019) reached a similar conclusion that individuals are more likely to order OFD services when their personal cost of exposure to the outdoor environment is high. The weather data in each city were obtained from the China Meteorological Data Service Center-National Meteorological Information Centre (http://data/cma.cn), which records daily average temperatures and precipitation for weather stations in 54 sample cities. Thus, the covariates of daily temperature and precipitation are used to control the possible confounding effects of weather on OFD.

The daily news of COVID-19 cases is also used to control the potential confounding impact of the COVID-19 pandemic on OFD (Beckman & Countryman, 2021). In the post-pandemic era, there were still sudden new cases in some cities, which may cause people to panic and correlate to the decision of the OFD. The daily news of COVID-19 cases in each Chinese city was collected from the Chinese Center for Disease Control and Prevention (http://2019ncov.chinacdc.cn/2019-nCoV/). We use cumulative new COVID-19 cases over the last 14 days to measure the spread of the pandemic in each city (WHO, 2020).

5. Empirical results

5.1. Main results

Columns (1)–(2) of Table 1 report the estimation results of the impact of air pollution on OFD based on an instrumental variable two-way fixed effect (IVTWFE) model (Eq. (1)). The variables of temperature, precipitation, and COVID-19 cases which may affect OFD are controlled. The city and date fixed effects are used to control for all time-invariant differences across the city and all time-variant changes that affect all cities simultaneously, respectively. Standard errors are clustered at the city level. The results in columns (1)–(2) of Table 1 indicate that air pollution has a negative and insignificant effect on OFD, inconsistent with previous studies that found air pollution positively affects OFD (Chu et al., 2021). This result is possible due to the differences in consumer behavior towards OFD before and after the COVID-19 lockdown measures (Wang et al., 2022), and thus further motivates us to study whether the impact of air pollution on OFD consumption behavior may change before and after the COVID-19 lockdown measures.

Columns (3)–(4) of Table 1 further present the interaction effects of air pollution and COVID-19 lockdown measures on OFD. The coefficients of the interaction terms in columns (3)–(4) are all positive and statistically significant. Compared to the pollution days during the lockdown stage, there is more OFD on the polluted days before lockdown and after reopening. Furthermore, after the reopening, the positive impact of air pollution on OFD is greater than before the lockdown stage. Specifically, the total transaction amount and the total number of orders of OFD for polluted days before the lockdown was 130.5 % and 204.5 % higher than the lockdown stage, respectively. Meanwhile, after the reopening, air pollution caused an increase of 384.9 % and 519.6 % of the total transaction amount and the total number of orders compared to the lockdown stage. These results imply that the impact of air pollution on OFD is indeed various at different stages of COVID-19.[11] There are asymmetric effects of air pollution on residents' consumption of OFD before and after COVID-19 lockdown measures.

The results of event studies in Fig. 1 indicate that there is almost no pre-trends before reopening, while compared to one week before the reopening measure, the significantly positive effects of air pollution on OFD may persist at least 1–3 weeks after the reopening measure. These results are consistent with the results of the baseline regression. Compared to the pollution days during the lockdown stage, air pollution has a positive impact on OFD after the reopening. Unfortunately, due to data limitations, we could not examine whether the effects of air pollution on OFD are permanently altered after the reopening measure.[12]

5.2. Mechanism analysis

To better understand the main channels through which air pollution and lockdown measures affect OFD, we conduct the mechanism analysis in this section. The equilibrium market of OFD is determined by the supply and demand of the OFD in the market. Any factors that could affect either the demand or supply would affect the OFD, so we investigate the mechanisms from the demand and supply side. Although the available cannot reveal all possible mechanisms, we attempt to use specific variables such as inner-city mobility, the number of operating restaurants, the average price of OFD per order, the average discount per order, and the average delivery fee per order to reveal the mechanisms as much as possible.

On the demand side, the Baidu inner-city mobility index is examined as a potential mechanism for the interaction impact of air pollution and COVID-19 lockdown measures on OFD. This index equals the ratio of the number of people traveling in a city to the city's resident population, which can reflect the intensity of people's economic activities and the potential demand for OFD. A higher Baidu inner-city mobility index indicates more mobile people in the cities and will result in a higher demand for OFD. Column (1) of Table 2 shows that as compared to the pollution days during the lockdown stage, the intensity of residents' mobility within the city on polluted days was 64.6 % higher before the lockdown and experienced an 89.8 % increase after the lockdown. The results reveal that there are more mobile people on air pollution days before and after lockdown compared to pollution days during lockdown. The increased mobility of people has generated a greater demand for

[10] Since Baidu only provided inner-city mobility data from Jan. 1, 2020 to May 1, 2020 were used in this part of the empirical analysis.

[11] The results of the first stage of the instrumental variable two-way fixed effect model are presented in Table A3.

[12] We also estimated the long-term interaction effects of air pollution and COVID-19 lockdown measures by supplementing the data from December 19, 2020 to May 19, 2021 (Table A4).

Table 1
The interaction effects of air pollution and COVID-19 lockdown measures on OFD.

Variables	(1)	(2)	(3)	(4)
	ln(Amount)	ln(Order)	ln(Amount)	ln(Order)
Pollution	−0.192	−0.998	−0.520	−1.149
	(0.864)	(1.202)	(0.690)	(0.818)
Pollution_Beforelockdown			1.305***	2.045***
			(0.322)	(0.397)
Pollution_Reopen			3.849***	5.196***
			(1.388)	(1.772)
Temperature	−0.014***	−0.017***	−0.024***	−0.029***
	(0.005)	(0.006)	(0.007)	(0.009)
Precipitation	0.002	−0.001	0.002	0.001
	(0.003)	(0.005)	(0.003)	(0.003)
COVID-19 cases	−4.832E-06	−2.304E-05	7.332E-06	−3.288E-06
	(0.000)	(0.000)	(0.000)	(0.000)
City FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
Observations	8262	8262	8262	8262
R-squared	0.908	0.887	0.881	0.862

Notes: 1. Air pollution dummy variables are constructed based on the maximum daily AQI levels in each city. According to MEE standards, if the maximum daily AQI level in a city exceeds 100, we classify that day as a day with air pollution in that city. 2. City-level clustered standard errors are presented in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. 3. The control variables include temperature, precipitation, and the number of COVID-19 cases over 14 days, as well as city and date fixed effects.

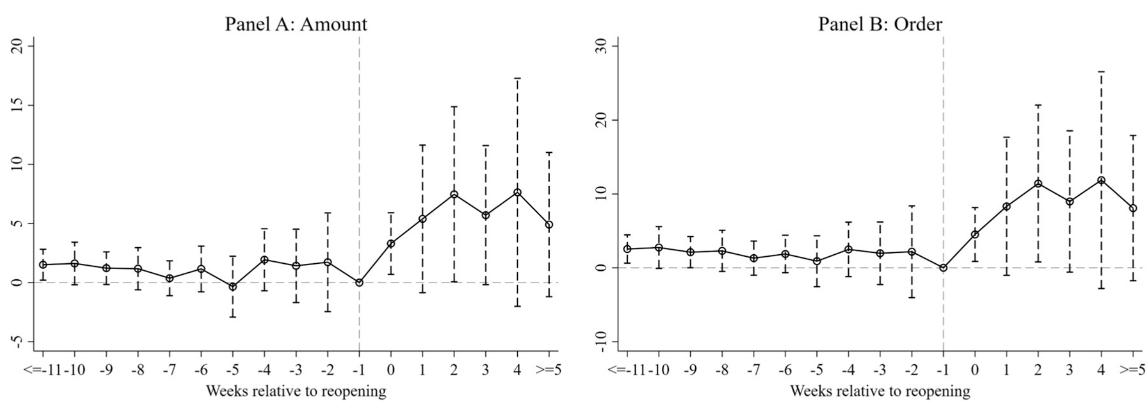

Fig. 1. Event study for the interaction effects of air pollution and COVID-19 on OFD.
Notes: 1. The figure above shows the coefficients estimated using the event study method for the effects of the interaction between air pollution and the reopening measure on OFD over time. 2. The specification controls for temperature, precipitation, and the number of COVID-19 cases over 14 days, as well as city and date fixed effects. 3. The error bars represent the 95 % confidence intervals for each coefficient estimated using city-level clustered standard errors.

Table 2
Mechanism analysis for the interaction effect of air pollution and COVID-19 lockdown measures on OFD.

Variables	(1)	(2)	(3)	(4)	(5)
	ln(Inner-city mobility)	ln(Restaurant)	ln(Price)	ln(Discount)	ln(Delivery)
Pollution	−0.586**	−1.590*	0.586**	−0.390	−0.004
	(0.243)	(0.959)	(0.299)	(0.285)	(0.123)
Pollution_Beforelockdown	0.646***	2.615***	−0.738***	0.455**	−0.117*
	(0.091)	(0.570)	(0.156)	(0.177)	(0.060)
Pollution_Reopen	0.898***	6.401***	−1.397***	0.992*	−0.298
	(0.325)	(2.092)	(0.518)	(0.517)	(0.197)
Control Variables	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes
Observations	6588	8262	8262	8262	8262
R-squared	0.721	0.784	0.415	0.571	0.557

Notes: 1. "Inner-city mobility" refers to the ratio of the number of people traveling in the city to the resident population of the city; "Restaurant" refers to the total number of restaurants offering OFD services (number); "Price" refers to the average transaction amount of OFD orders per order (RMB); "Discount" refers to the average discount per order (RMB); "Delivery" refers to the average delivery fee per order (RMB). 2. Since Baidu only provided inner-city mobility data from Jan. 1, 2020 to May 1, 2020, the observations of inner-city mobility is 6588. 3. Air pollution dummy variables are constructed based on the maximum daily AQI levels in each city. According to MEE standards, if the maximum daily AQI level in a city exceeds 100, we classify that day as a day with air pollution in that city. 4. City-level clustered standard errors are presented in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. 5. The control variables include temperature, precipitation, and the number of COVID-19 cases over 14 days, as well as city and date fixed effects.

dining out, and people are more likely to choose OFD to avoid exposure to air pollution (Chu et al., 2021). Consequently, this has resulted in a higher demand for OFD during air pollution days pre and post COVID-19.

In addition, Column (1) of Table 2 indicates the intensity of mobility on air pollution days after reopening is greater than before the lockdown stage. This is reasonable because the economy has deteriorated sharply after COVID-19 (IMF, 2020), prompting more people to go out in search of economic opportunities even on polluted days after reopening. Therefore, there were more mobile people inner-city on polluted days after reopening, while the demand for OFD on polluted days after reopening exceeded that before the lockdown. This results in an asymmetric impact of air pollution on OFD before and after the pandemic.

On the supply side, both the operation of restaurants and delivery services contribute to the supply of OFD. First, air pollution and COVID-19 lockdown measures may influence OFD by jointly affecting the number of restaurants that are open. COVID-19 brought a huge shock to the catering industry, the catering revenue decreased by 32.8 % in the first half of 2020 (NBSC, 2020), and 1.66 million restaurants were closed during COVID-19 (iiMedia, 2020). After reopening, to make up for the losses during COVID-19, restaurant operators are actively seeking more opportunities even on polluted days. The operators of restaurants take various actions to increase revenue and improve the profit of their restaurants. For example, restaurant operators will still open for business even on polluted days after reopening.[13] Therefore, the number of restaurants open on polluted days after COVID-19 was also likely to be higher than that on polluted days before COVID-19. Our empirical results confirm this hypothesis. Column (2) of Table 2 reflects that the number of operating restaurants on pollution days before the lockdown was 261.5 % higher than that during the lockdown stage. Furthermore, there was a significant increase of 640.1 % in the number of operating restaurants on pollution days after the lockdown compared to the lockdown stage. Additionally, restaurant operators may also attract a higher volume of orders by reducing prices and offering more discounts. The results in columns (3)–(4) of Table 2 suggest that compared to the pollution days during the lockdown stage, the average transaction amount per order on the pollution days before the lockdown was 73.8 % lower, while it was significantly reduced by 139.7 % on the pollution days after the lockdown. Meanwhile, on pollution days, the average discount per order was 45.5 % higher before the lockdown than that during the lockdown, and it increased by 99.2 % after the lockdown.

Secondly, air pollution and COVID-19 lockdown measures may have an interaction effect on delivery fee of OFD. The delivery fee reflects the supply of food delivery services; a lower delivery fee indicates a higher supply of food delivery services.[14] Delivery fee mainly depends on the delivery cost, with delivery cost declining before and after the pandemic compared to the pandemic period. Our results show that, relative to the days of pollution within the lockdown stage, the average delivery fee per order is significantly 11.7 % lower on pollution days before lockdown, while the average delivery fee per order is not significantly reduced by 29.8 % on pollution days after reopening. COVID-19 enhanced people's health awareness (Qi et al., 2021), and the delivery personnel will include the health cost caused by air pollution (Fu et al., 2021; Xia et al., 2022) in the delivery fee after reopening. Therefore, the non-significant drop in delivery fees may be due to the increased health cost on polluted days after COVID-19. Our results show that the lower delivery fees on polluted days before and after COVID-19 reflect the higher delivery services supply.

Table 3
Robustness checks 1: Alternative measures of air pollution.

Variables	(1) ln (Amount)	(2) ln (Order)	(3) ln (Amount)	(4) ln (Order)
Pollution ($PM_{2.5}$)	−0.182	−0.944	−1.810	−2.967
	(0.812)	(1.099)	(1.367)	(1.846)
Pollution ($PM_{2.5}$) _Beforelockdown			1.961***	2.980***
			(0.733)	(0.996)
Pollution ($PM_{2.5}$)_Reopen			7.643*	10.642**
			(3.921)	(5.332)
Control Variables	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
Observations	8262	8262	8262	8262
R-squared	0.908	0.891	0.772	0.640

Notes: 1. Air pollution dummy variables are constructed based on the maximum daily $PM_{2.5}$ levels in each city. According to MEE standards, if the maximum daily $PM_{2.5}$ level in a city exceeds 75, we classify that day as a day with air pollution in that city. 2. City-level clustered standard errors are presented in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. 3. The control variables include temperature, precipitation, and the number of COVID-19 cases over 14 days, as well as city and date fixed effects.

5.3. Robustness checks and placebo tests

In this section, we conduct a variety of robustness checks and placebo tests to confirm the stability of our main findings.

First, in order to confirm that the main results are not affected by the measurement of air pollution, alternative measures of air pollution are used to check the robustness of the main findings. According to the air pollution standards released by MEE (2012), a dummy variable, which equals 1 if the daily maximum value of $PM_{2.5}$ exceeds 75, 0 otherwise. Table 3 exhibits similar patterns to those using AQI. We observe that on air pollution days, the transaction amount (196.1 %) and the number of orders (298.0 %) of OFD before the lockdown were higher compared to the lockdown stage. Similarly, the transaction amount (764.3 %) and the number of orders (1064.2 %) after the lockdown also increased compared to the lockdown stage. The positive interaction effects of $PM_{2.5}$ and the reopening measure on OFD are greater than the interaction effects of $PM_{2.5}$ and the before lockdown stage.[15]

Second, to mitigate the impact of outliers in the sample, which may be induced by extreme values, public holidays, and specific cities, robustness checks are carried out using different samples. a) The baseline results in Table 1 may be biased by the extreme values of the outcome variables and the lagged effects of air pollution. Thus, we conducted a 3-day moving average on the outcome variables to solve it, where the dependent variables are replaced with the 3-day moving average values of the current day, the previous day, and the previous two days. The estimation results in Panel A of Table 4 are similar to the baseline estimates, suggesting that the interaction effects of air pollution and lockdown measures on OFD are not remarkably affected by extreme values of OFD and lagged effects of air pollution. b) In addition, public holidays may change peoples' food consumption behavior, leading to an increase in food consumption among low-income individuals (Akbay & Jones, 2005), as well as a rise in nutrient-dense food intake (Schneider et al., 2023). As the most important national holiday in China, the Spring Festival could potentially confound the consumption of OFD. According

[13] Our data includes not only large chain restaurants but also small restaurants, roadside food stalls, and other types of restaurants that have OFD services, so restaurant operators may change their business status according to the weather conditions.

[14] The delivery services of OFD generally rely on third-party delivery companies rather than restaurant self-delivery in China, such as Meituan, Ele.me, etc. China's two major OFD platforms have 7.38 million delivery personnel (Ele.me, 2022; Meituan, 2022). These delivery personnel work in a flexible way, so they may adjust their working hours on pollution days.

[15] The results of the first stage of the instrumental variable two-way fixed effect model are presented in Table A5.

Table 4
Robustness checks 2: Alternative samples.

Variables	(1)	(2)	(3)	(4)
	ln(Amount)	ln(Order)	ln(Amount)	ln(Order)
Panel A: 3-day moving average				
Pollution	−0.424	−1.096	−0.690	−1.218
	(0.868)	(1.223)	(0.663)	(0.820)
Pollution_Beforelockdown			1.294***	1.996***
			(0.321)	(0.396)
Pollution_Reopen			3.668***	5.007***
			(1.356)	(1.729)
Observations	8154	8154	8154	8154
Panel B: Excluding Spring Festival				
Pollution	−0.492	−1.545	−0.772	−1.559
	(1.113)	(1.687)	(0.851)	(1.059)
Pollution_Beforelockdown			1.255***	2.067***
			(0.327)	(0.408)
Pollution_Reopen			3.422**	4.770**
			(1.409)	(1.894)
Observations	7830	7830	7830	7830
Panel C: Excluding first-tier cities				
Pollution	−0.190	−1.381	−0.572	−1.363
	(1.298)	(2.051)	(0.902)	(1.084)
Pollution_Beforelockdown			1.256***	1.976***
			(0.318)	(0.385)
Pollution_Reopen			3.645***	4.804***
			(1.368)	(1.772)
Observations	7650	7650	7650	7650
Control variables	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes

Notes: 1. Panel A displays the results using the 3-day moving average, where the dependent variables are replaced with the 3-day moving average values of the current day, the previous day, and the previous two days. Panel B shows the results of removing samples from the Spring Festival. According to the Chinese lunar calendar, we exclude the 8-day samples from New Year's Eve to the 7th day of the Spring Festival. Panel C shows the results of removing first-tier cities, and we excluded four sample cities: Beijing, Shanghai, Guangzhou, and Shenzhen from the sample. 2. Air pollution dummy variables are constructed based on the maximum daily AQI levels in each city. According to MEE standards, if the maximum daily AQI level in a city exceeds 100, we classify that day as a day with air pollution in that city. 3. City-level clustered standard errors are presented in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. 4. The control variables include temperature, precipitation, and the number of COVID-19 cases over 14 days, as well as city and date fixed effects.

to the Chinese lunar calendar, we exclude the 8-day samples from New Year's Eve to the 7th day of the Spring Festival. The results in Panel B of Table 4 indicate that excluding the Spring Festival holidays, the coefficients of the interaction terms remain positive and significant statistically, in line with our baseline results. c) To further test if the interaction effect of air pollution and lockdown measures on OFD exists in sub-samples, we remove four first-tier cities (Beijing, Shanghai, Guangzhou, and Shenzhen) from the whole sample. Accordingly, the estimation results in Panel C of Table 4 are consistent with our previous findings, further validating the robustness of our baseline results.

Third, we also assess the robustness of the baseline results by altering controls for fixed effects to validate that our main results are not influenced by model choices. We substitute date fixed effects in the baseline model with time trend and interactions between time trend and city fixed effects. The outcomes presented in Table 5 demonstrate the robustness of our results when changing the fixed effects of the model. The direction and significance of the estimated coefficients for the interaction terms are consistent with the main regression results in Table 1.

Finally, we conducted the placebo test. We have pushed forward the lockdown and reopening time of each city by 6 weeks and constructed placebo dummy variables "Beforelockdown" and "Reopen", and

Table 5
Robustness checks 3: Alternative controls for fixed effects.

Variables	(1)	(2)	(3)	(4)
	ln(Amount)	ln(Order)	ln(Amount)	ln(Order)
Pollution	0.313	0.770	−1.289	−1.744
	(0.543)	(0.682)	(0.979)	(1.461)
Pollution_Beforelockdown			2.112***	3.040***
			(0.467)	(0.593)
Pollution_Reopen			5.060***	7.114***
			(1.582)	(1.873)
Control Variables	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Time trend	Yes	Yes	Yes	Yes
City FE *Time trend	Yes	Yes	Yes	Yes
Observations	8262	8262	8262	8262

Notes:1. We include daily time trend and their interaction with city fixed effects. 2. Air pollution dummy variables are constructed based on the maximum daily AQI levels in each city. According to MEE standards, if the maximum daily AQI level in a city exceeds 100, we classify that day as a day with air pollution in that city. 3. City-level clustered standard errors are presented in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. 4. The control variables include temperature, precipitation, and the number of COVID-19 cases over 14 days, as well as city and date fixed effects.

Table 6
Placebo test: Move the lockdown and reopening times forward by 6 weeks.

Variables	(1)	(2)	(3)	(4)
	ln(Amount)	ln(Order)	ln(Amount)	ln(Order)
Pollution	−0.042	−0.034	−0.123	−0.381
	(0.033)	(0.038)	(0.627)	(0.690)
Pollution_Beforelockdown			0.670*	1.171**
			(0.393)	(0.503)
Pollution_Reopen			0.825	0.316
			(0.533)	(0.549)
Control Variables	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
Observations	8262	8262	8262	8262
R-squared	0.908	0.912	0.899	0.905

Notes: 1. We have pushed forward the lockdown and reopening times of each city by 6 weeks and construct placebo dummy variables "Beforelockdown" and "Reopen". 2. Air pollution dummy variables are constructed based on the maximum daily AQI levels in each city. According to MEE standards, if the maximum daily AQI level in a city exceeds 100, we classify that day as a day with air pollution in that city. 3. City-level clustered standard errors are presented in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. 4. The control variables include temperature, precipitation, and the number of COVID-19 cases over 14 days, as well as city and date fixed effects.

multiplied air pollution with two placebo dummy variables (Table 6). Results showed that coefficients of interaction terms were insignificantly different from zero (Table 6). The placebo results indicate that our results are indeed driven by the interaction effects of air pollution and lockdown measures, rather than other confounding factors.

5.4. Heterogeneity analysis

First, as the lockdown and reopening measures did not affect all types of restaurants/cuisines equally (O'Connell et al., 2022), the interaction effects of air pollution and the lockdown measures on OFD may also vary in types of food. Thus, we divide all OFD orders into four categories based on the main categories provided by Ele.me platform: Chinese food, Western food, fresh food, and other food (mainly drinks and

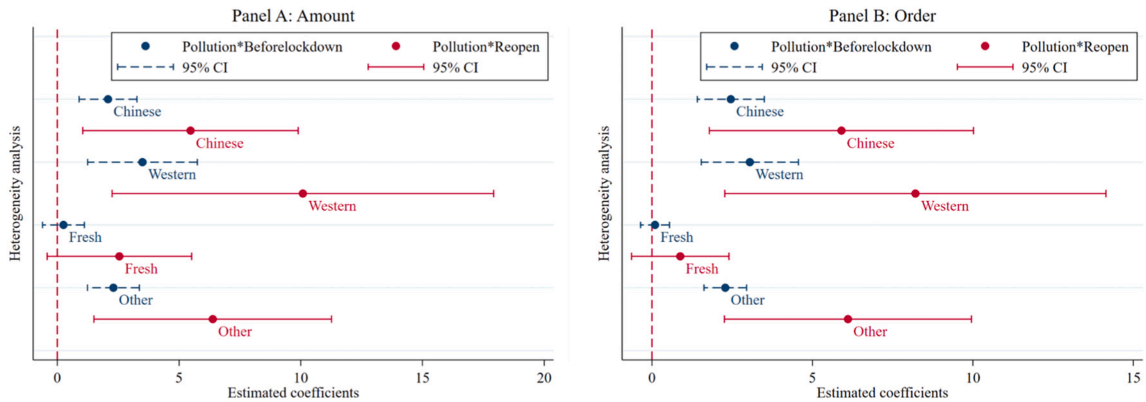

Fig. 2. Heterogeneous analyses on OFD consumption structure (according to the total transaction amount and the total number of orders for each food categories).
Notes: 1. The figure above shows the coefficients estimated for the heterogeneous effects of the interaction between air pollution and the lockdown and reopening measure on OFD of different food categories. 2. We divide all OFD orders into four categories based on the main categories provided by Ele.me platform: Chinese food, Western food, fresh food, and other food (mainly drinks and desserts). We calculate the total transaction amount and the total number of orders for each category as the dependent variables. 3. The specification controls for temperature, precipitation, and the number of COVID-19 cases over 14 days, as well as city and date fixed effects. 4. The error bars represent the 95 % confidence intervals for each coefficient estimated using city-level clustered standard errors.

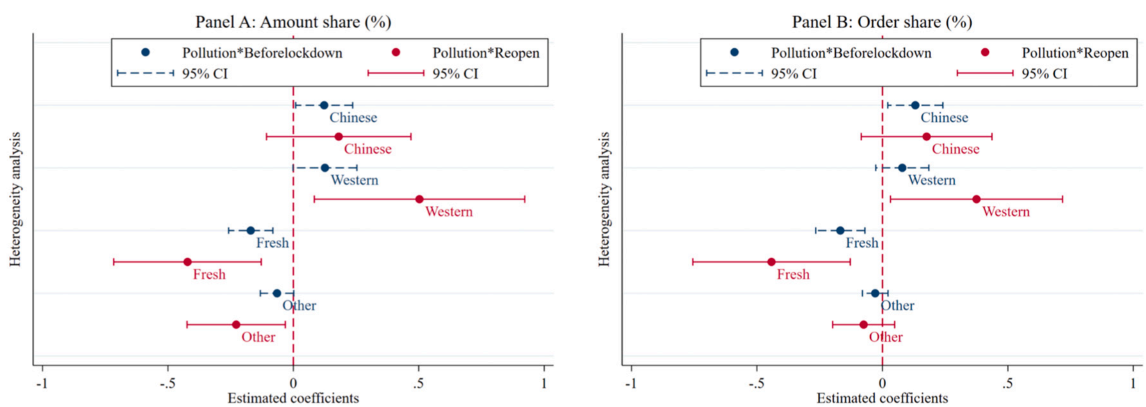

Fig. 3. Heterogeneous analyses on OFD consumption structure (according to the proportion of transaction amount and the proportion of the number of orders for four categories).
Notes: 1. The figure above shows the coefficients estimated for the heterogeneous effects of the interaction between air pollution and the lockdown and reopening measure on OFD of different food categories. 2. We divide all OFD orders into four categories based on the main categories provided by Ele.me platform: Chinese food, Western food, fresh food, and other food (mainly drinks and desserts). We calculate the proportion of transaction amount and the proportion of the number of orders for each category as the dependent variables. 3. The specification controls for temperature, precipitation, and the number of COVID-19 cases over 14 days, as well as city and date fixed effects. 4. The error bars represent the 95 % confidence intervals for each coefficient estimated using city-level clustered standard errors.

desserts).[16] We calculate the transaction amount and the number of orders for each category (Fig. 2), and the proportion of value and order for each category (Fig. 3). The estimation results regarding the interaction effects of air pollution and the lockdown measures on OFD by various types of food are reported in Figs. 2 and 3. Fig. 2 shows that on the pollution days, the transaction amount and the number of orders for the four types of food before the lockdown exceeded those during the lockdown, while there has been an increase after the pandemic, with particularly significant growth in Chinese food, Western food, and other food. Meanwhile, the proportion of Western food also increased significantly while the proportion of fresh food decreased significantly on the pollution days after the lockdown, compared to the lockdown stage (Fig. 3). This result is consistent with previous findings that air pollution significantly increases people's purchase of unhealthy foods and reduces the purchase of healthy foods by causing bad emotions in people (Liu et al., 2022). After reopening, air pollution has led to a significant increase in the purchase of unhealthy food compared to before the lockdown, while the purchase of healthy food has significantly decreased compared to before COVID-19.

Second, considering the potential cumulative effects of air pollution on OFD, we examine the differential interaction effect of varying air pollution levels and the lockdown measures on OFD. According to air pollution standards put forward by the MEE (2012) of PRC, we redefine the binary variables of pollution according to the different degrees of pollution: slight pollution ($100 < \text{maxAQI} \leq 150$), moderate pollution ($150 < \text{maxAQI} \leq 200$), and heavy pollution ($\text{maxAQI} > 200$). In our 8262 sample, there are 1840 observations for slight pollution, 576 observations for moderate pollution, and 608 observations for heavy pollution. Subsequently, the three dummy variables are multiplied by the lockdown and reopening measure dummy variable to create interaction terms. Fig. 4 shows that as the pollution level increases, the positive impact of air pollution on OFD first increases and then decreases on the pollution days before and after lockdown.

Third, considering that more southern cities are locked down and more severely affected by the pandemic than northern cities (Fang et al., 2020), we explore whether there exist heterogeneous effects of air pollution and lockdown measures on OFD between northern and

[16] In our data, Western food mainly includes fried chicken, hamburgers and other unhealthy foods.

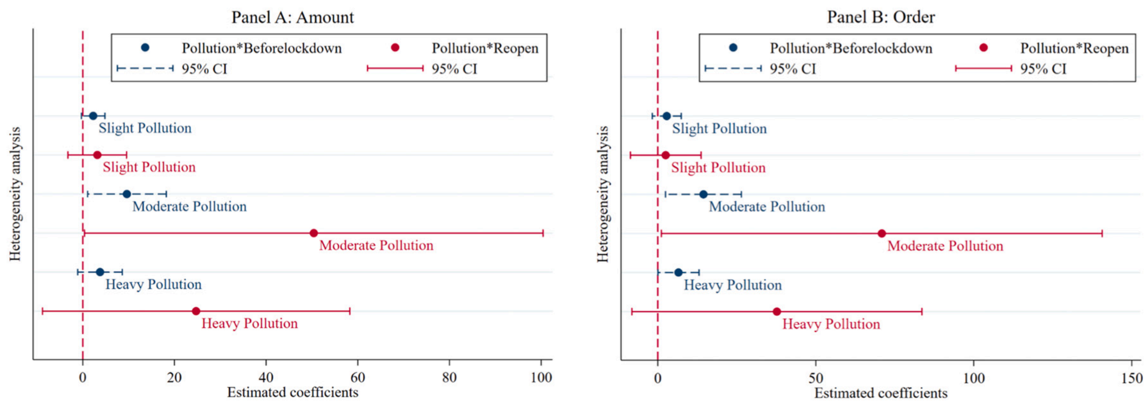

Fig. 4. Heterogeneous analyses by the different levels of air pollution.
Notes: 1. The figure above shows the coefficients estimated for the heterogeneous effects of the interaction between air pollution and the lockdown and reopening measure on OFD. 2. We redefine the binary variables of pollution according to the different degrees of pollution: slight pollution (100 < maxAQI ≤ 150), moderate pollution (150 < maxAQI ≤ 200), and heavy pollution (maxAQI > 200). In our 8262 sample, there are 1840 observations for slight pollution, 576 observations for moderate pollution, and 608 observations for heavy pollution. 3. The specification controls for temperature, precipitation, and the number of COVID-19 cases over 14 days, as well as city and date fixed effects. 4. The error bars represent the 95 % confidence intervals for each coefficient estimated using city-level clustered standard errors.

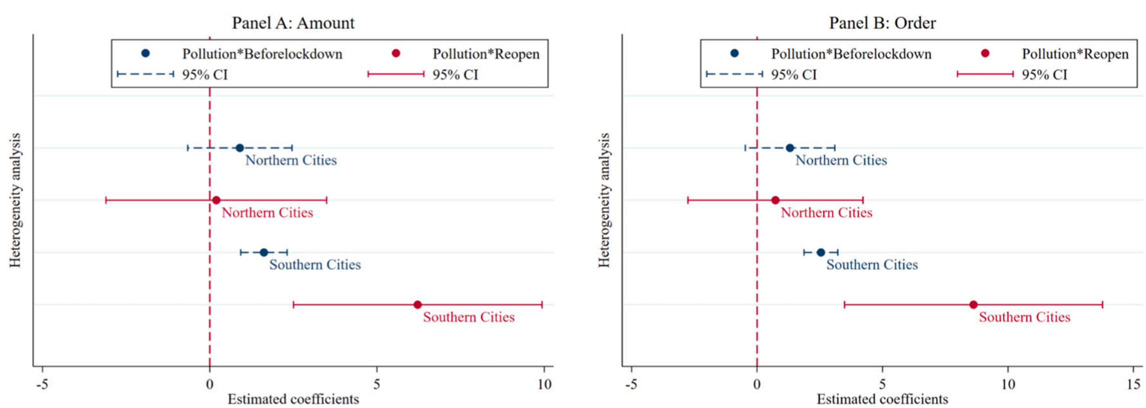

Fig. 5. Heterogeneous analyses for the samples of northern and southern cities.
Notes: 1. The figure above shows the coefficients estimated for the heterogeneous effects of the interaction between air pollution and the lockdown and reopening measure on OFD. 2. We divide our sample into northern cities and southern cities based on the Qinling-Huaihe Line. In our sample, there are 38 southern cities and 16 northern cities. 3. The specification controls for temperature, precipitation, and the number of COVID-19 cases over 14 days, as well as city and date fixed effects. 4. The error bars represent the 95 % confidence intervals for each coefficient estimated using city-level clustered standard errors.

southern cities. To address this, we divide our sample into northern cities and southern cities based on the Qinling-Huaihe Line. In our sample, there are 38 southern cities and 16 northern cities. Since southern cities were more severely affected by the pandemic, we speculate that the interaction effects between lockdown measures and air pollution are more pronounced in southern cities. The results in Fig. 5 confirm our conjecture: the interaction terms of air pollution and before the lockdown and the interaction terms of air pollution and reopening, lead to more OFD in the southern cities compared with the lockdown stage. While in the northern cities, the interaction terms have no significant effect. These findings imply that residents of southern cities are more susceptible to lockdown measures than those of northern cities, while these differences, in turn, result in the different choice behavior of residents' OFD between southern cities and northern cities on air pollution days.

Fourth, since economic development varies systematically across cities of distinct population sizes, residents' responses to air pollution may differ during different lockdown stages. We divided the sample cities into large cities and small cities based on the population of the city in 2020. Large cities are cities with a permanent population of over or equal to 10 million, while the rest are small cities. The population of each city is from the city statistical yearbook published by the National Bureau of Statistics. According to our definition, there are 38 large cities and 16 small cities in our sample. By estimating the effects of air pollution on the OFD in cities with different population sizes at different stages of lockdown (Fig. 6), we find that the significantly positive interaction effects of air pollution and before lockdown and air pollution and reopening measures on OFD are mainly reflected in small cities.

Furthermore, we also use the city-date-meal level data to explore the heterogeneous effects of air pollution on three meals a day at different lockdown stages. The results in Fig. 7 reveal that the interaction between air pollution and the stages before and after lockdown exerts a notably positive influence on all three meals, compared to the lockdown stage. Especially, this interaction effect is largest for breakfast, indicating a significant variation in the impact across different meals.

6. Conclusion and policy implications

This study investigates the interaction effect of air pollution and COVID-19 lockdown measures on OFD. The results indicate that COVID-19 lockdown measures distorted the impact of air pollution on OFD, showing asymmetric effects of air pollution on OFD before and after

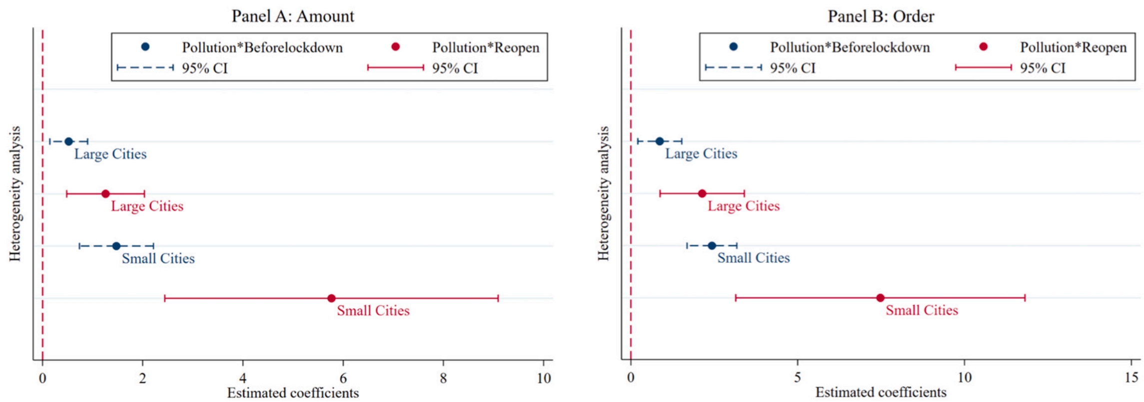

Fig. 6. Heterogeneous analyses by cities' population.
Notes: 1. The figure above shows the coefficients estimated for the heterogeneous effects of the interaction between air pollution and the lockdown and reopening measure on OFD. 2. We divide the sample cities into large cities and small cities based on the population of the city in 2020. Large cities are cities with a permanent population of over or equal to 10 million, while the rest are small cities. The population of each city is from the city statistical yearbook published by the National Bureau of Statistics. According to our definition, there are 38 large cities and 16 small cities in our sample. 3. The specification controls for temperature, precipitation, and the number of COVID-19 cases over 14 days, as well as city and date fixed effects. 4. The error bars represent the 95 % confidence intervals for each coefficient estimated using city-level clustered standard errors.

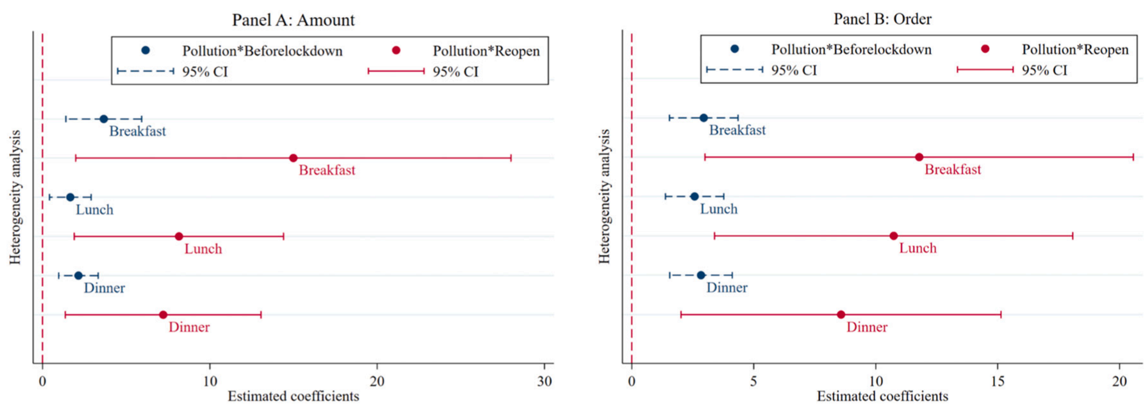

Fig. 7. Heterogeneous analyses by three meals.
Notes: 1. The figure above shows the coefficients estimated for the heterogeneous effects of the interaction between air pollution and the lockdown and reopening measure on OFD. 2. We take the maximum value of pollutants during the three meals of each day (breakfast, lunch and dinner) in each city, and construct corresponding dummy variables. 3. The specification controls for temperature, precipitation, and the number of COVID-19 cases over 14 days, as well as city and date fixed effects. 4. The error bars represent the 95 % confidence intervals for each coefficient estimated using city-level clustered standard errors.

COVID-19 lockdown measures. Compared to the lockdown stage, air pollution has a significant and positive impact on OFD before lockdown and after reopening. Meanwhile, the extent of the impact of air pollution on OFD is relatively greater after reopening than before the lockdown. Mechanism analyses reveal that the differences in the impact of air pollution on OFD at different stages of COVID-19 lockdown can be explained from the demand and supply sides by the inner-city mobility, the number of operating restaurants, the average price of OFD per order, the average discount per order, and the average delivery fee per order. A series of robustness checks confirm the reliability of the main findings of this study. Finally, we identify the heterogeneity in the interaction effects of air pollution and COVID-19 lockdown measures on OFD for various types of food, distinct levels of air pollution, in cities with different locations and sizes, and three meals a day.

The findings of this study have important policy implications. First, the findings of this study imply the necessity of re-evaluating residents' behavior under air pollution in the post-pandemic era. After experiencing intervention measures such as lockdowns due to the pandemic, various socio-economic situations have changed (Josephson et al., 2021), resulting in altered reactions of residents to air pollution. Compared to the stage before the COVID-19 lockdown, more people are going outside and more restaurants operating on polluted days after the COVID-19 lockdown lifting, contributing to the increase in OFD. Thus, when exploring people's behavior under air pollution, some empirical evidence before the pandemic may no longer be applicable, necessitating more empirical analysis of the behavior of residents after the pandemic. Second, the catering industry needs to seize the developing opportunity of OFD to offset the losses caused by air pollution and COVID-19. Air pollution and COVID-19 have brought serious losses and challenges to restaurants and the catering industry (Byrd et al., 2021; de Freitas & Stedefeldt, 2020; Sun et al., 2019), but also offer them a novel developing opportunity. Considering that air pollution and COVID-19 have increased OFD, expanding OFD business may be an effective response to recover losses in the catering industry. However, the government should also consider the potential negative impacts of Online Food Delivery (OFD). First, the monopoly of OFD platforms poses a threat to small restaurants and delivery personnel (Ji et al., 2024). Large platforms may exploit their market dominance to charge high commissions from small restaurants or impose unfair working conditions and compensation policies on delivery workers, thereby squeezing their survival space. Second, plastic waste from food packaging has a significant negative environmental impact (Chu et al., 2021; Molina-Besch, 2020). The extensive use of disposable food containers, utensils, and plastic bags exacerbates environmental pollution and puts enormous pressure on urban waste management systems. Third, OFD platforms often offer a wide range of unhealthy foods high in salt and fat, and excessive consumption of these foods can pose significant health risks to urban residents, increasing the incidence of chronic diseases such as obesity and cardiovascular problems (Liu et al., 2022).

To promote fair and inclusive development of the OFD industry, the government should take measures to strengthen the rights and welfare of small restaurants and delivery personnel, such as implementing policies to limit platform commission rates and ensuring delivery workers receive fair wages and social security. Simultaneously, the government should encourage the use of eco-friendly packaging, for instance, by offering tax incentives to restaurants using biodegradable materials or imposing additional fees on non-recyclable packaging to reduce plastic pollution. Furthermore, the government should take measures to guide residents towards healthier eating habits, including public health education campaigns to raise awareness about healthy eating, encouraging OFD platforms to provide more healthy food options, requiring OFD platforms to label nutritional content on menus to help consumers make informed choices, or providing incentives to restaurants offering healthy dishes to increase the supply of healthy foods. Through these measures, the government can promote more fair and inclusive development of the OFD industry while also considering public health, creating a healthier and more sustainable food delivery ecosystem.

This study does have some limitations due to data restrictions. First, the lack of micro-level data on individual consumers hinders the verification of consumer behavior mechanisms from the demand side. COVID-19 may lead to the formation of consumer habits. People who initially did not use OFD platforms may change their habits during the pandemic period, and they may continue to choose OFD after COVID-19, especially on pollution days. Second, the sample used in this study only covers a two-month stage after the reopening measure and the data one year later due to constraints in data accessibility, limiting our ability to assess the long-term changes in consumer behavior caused by COVID-19. It is worth further investigating how consumers' food consumption habits change over time when facing air pollution after the COVID-19 pandemic.

CRediT authorship contribution statement

Fangxiao Zhao: Methodology, Investigation, Data curation. **Xiaobing Wang:** Writing – review & editing, Writing – original draft, Methodology, Conceptualization. **Xu Tian:** Writing – review & editing. **Shi Min:** Writing – review & editing, Writing – original draft, Methodology.

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.

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Appendix A

Table A1
Definitions and descriptive statistics of variables.

Variables	Definitions	Mean (std. dev.)	Obs.
Dependent variables			
Amount	Total transaction amount of OFD orders paid by consumers (RMB)	3,274,573 (6,276,112)	8262
Order	Total number of OFD orders (number)	96,210.280 (162,021.900)	8262
Amount_Chinese	Total transaction amount of Chinese food orders paid by consumers (RMB)	2,093,862 (3,980,384)	8262
Amount_Western	Total transaction amount of Western food orders paid by consumers (RMB)	807,667.200 (1,579,856)	8262
Amount_Fresh	Total transaction amount of fresh food orders paid by consumers (RMB)	114,134.300 (228,943.100)	8262
Amount_Other	Total transaction amount of drinks and other food orders paid by consumers (RMB)	258,909.100 (590,936.5)	8262
Order_Chinese	Total number of Chinese food orders (number)	66,655.600 (112,895)	8262
Order_Western	Total number of Western food orders (number)	19,910.700 (32,984.100)	8262
Order_Fresh	Total number of fresh food orders (number)	2161.573 (4041.182)	8262
Order_Other	Total number of drinks and other food orders (number)	7482.408 (13,982.890)	8262
Amount share_Chinese	Proportion of transaction amount of Chinese food to total transaction amount (%)	0.609 (0.148)	8262
Amount share_Western	Proportion of transaction amount of Western food to total transaction amount (%)	0.252 (0.088)	8262
Amount share_Fresh	Proportion of transaction amount of fresh food to total transaction amount (%)	0.054 (0.112)	8262
Amount share_Other	Proportion of transaction amount of drinks and other food to total transaction amount (%)	0.083 (0.080)	8262
Order share_Chinese	Proportion of orders of Chinese food to total order (%)	0.649 (0.146)	8262
Order share_Western	Proportion of orders of Western food to total order (%)	0.219 (0.084)	8262
Order share_Fresh	Proportion of orders of fresh food to total order (%)	0.042 (0.107)	8262
Order share_Other	Proportion of orders of drinks and other food to total orders (%)	0.088 (0.070)	8262
Independent variables			
Pollution	Whether the city was polluted that day according to the maximum value of AQI (1 = Yes; 0 = No)	0.366 (0.482)	8262
Before lockdown	Whether the day was before the lockdown (1 = Before lockdown; 0 = Lockdown stage or reopen)	0.134 (0.340)	8262
Reopen	Whether the day has implemented the reopening measure (1 = Reopen; 0 = Not reopen)	0.117 (0.321)	8262
PM2.5	Whether the city was polluted that day according to the maximum value of $PM_{2.5}$ (1 = Yes; 0 = No)	0.334 (0.472)	8262
Mechanism variables			
Inner-city mobility	The ratio of the number of people traveling in the city to the resident population of the city	3.831 (1.568)	6588
Restaurant	Total number of restaurants offering OFD services (number)	12,761.870 (16,504.020)	8262

(*continued on next page*)

Table A1 (*continued*)

Variables	Definitions	Mean (std. dev.)	Obs.
Price	Average transaction amount of OFD orders per order (RMB)	38.645 (24.763)	8262
Discount	Average discount per order (RMB)	15.882 (5.305)	8262
Delivery	Average delivery fee per order (RMB)	3.999 (1.234)	8262
Control variables			
Temperature	Average temperature (°C)	10.187 (7.512)	8262
Precipitation	24-h precipitation (mm)	1.762 (5.469)	8262
COVID-19 cases	Cumulative new COVID-19 cases in the past 14 days	121.288 (1500.997)	8262

Notes: 1. This table summarizes the definitions and descriptive statistics of variables. 2. Since Baidu only provided inner-city mobility data from Jan. 1, 2020 to May 1, 2020, the observations of inner-city mobility is 6588.

Table A2
Various levels of prevention and control measures in sampled cities.

Types of lockdown	City	Province	Lockdown date	Reopen date
1	Wuhan	Hubei	2020/1/23	2020/4/8
1	Ezhou	Hubei	2020/1/23	2020/3/25
1	Xiaogan	Hubei	2020/1/24	2020/3/21
1	Jingzhou	Hubei	2020/1/24	2020/3/15
1	Suizhou	Hubei	2020/1/24	2020/3/17
1	Huangshi	Hubei	2020/1/24	2020/3/23
1	Yichang	Hubei	2020/1/24	2020/3/14
1	Jingmen	Hubei	2020/1/24	2020/3/17
1	Xianning	Hubei	2020/1/24	2020/3/15
1	Shiyan	Hubei	2020/1/24	2020/3/25
1	Enshi	Hubei	2020/1/24	2020/3/17
1	Xiangyang	Hubei	2020/1/28	2020/3/17
1	Wenzhou	Zhejiang	2020/2/2	2020/2/19
1	Harbin	Heilongjiang	2020/2/4	2020/3/9
1	Hangzhou	Zhejiang	2020/2/4	2020/3/21
1	Ningbo	Zhejiang	2020/2/4	2020/2/16
1	Zhengzhou	Henan	2020/2/4	2020/3/6
1	Zhumadian	Henan	2020/2/4	2020/2/21
1	Fuzhou	Fujian	2020/2/4	2020/2/13
2	Chongqing	Chongqing		
2	Yinchuan	Ningxia		
2	Wuzhong	Ningxia		
2	Huaian	Jiangsu		
2	Huaibei	Anhui		
2	Xinyang	Henan		
2	Nanjing	Jiangsu		
2	Xuzhou	Jiangsu		
2	Changzhou	Jiangsu		
2	Linyi	Shandong		
2	Nantong	Jiangsu		
2	Jining	Shandong		
2	Nanchang	Jiangxi		
2	Qingdao	Shandong		
2	Nanning	Guangxi		
2	Kunming	Yunnan		
2	Jinan	Shandong		
2	Haikou	Hainan		
2	Shijiazhuang	Hebei		
2	Zhuhai	Guangdong		
2	Suzhou	Jiangsu		
2	Shenyang	Liaoning		
2	Shenzhen	Guangdong		
2	Guangzhou	Guangdong		
2	Hefei	Anhui		
2	Chengdu	Sichuan		
2	Tianjin	Tianjin		
2	Lanzhou	Gansu		
2	Guiyang	Guizhou		
2	Foshan	Guangdong		
2	Dongguan	Guangdong		
2	Huizhou	Guangdong		
2	Wuxi	Jiangsu		
2	Beijing	Beijing		
2	Shanghai	Shanghai		

Notes: This table summarizes different levels of prevention and control measures across 54 cities. Panel A lists 19 cities with lockdown, which means public transport and private vehicles were banned in the city, and residents were not allowed to leave the city. 35 cities in Panel B did not implement lockdowns; in these cities public transport maintained normal operation.

Table A3
The effects of thermal inversions on air pollution (AQI first stage).

Variables	(1) Pollution	(2) Pollution_Beforelockdown	(3) Pollution_Reopen
Thermal inversions	−0.141***	−0.011**	−0.010***
	(0.010)	(0.005)	(0.003)
Thermal inversions_Beforelockdown	0.058***	0.252***	−0.024***
	(0.020)	(0.027)	(0.008)
Thermal inversions_Reopen	−0.054***	−0.071***	0.067***
	(0.016)	(0.009)	(0.141)
Control Variables	Yes	Yes	Yes
City FE	Yes	Yes	Yes
Date FE	Yes	Yes	Yes
Observations	8262	8262	8262
F-test	39.51***	7856.21***	3823.32***
R-squared	0.3724	0.4925	0.2129

Notes: 1. Air pollution dummy variables are constructed based on the maximum daily AQI levels in each city. According to MEE standards, if the maximum daily AQI level in a city exceeds 100, we classify that day as a day with air pollution in that city. 2. City-level clustered standard errors are presented in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. 3. The control variables include temperature, precipitation, and the number of COVID-19 cases over 14 days, as well as city and date fixed effects.

We estimated the long-term interaction effects of air pollution and COVID-19 lockdown measures on OFD using the IVTWFE model by supplementing the data from December 19, 2020, to May 19, 2021. The supplementary data includes 8208 observations across 54 cities over a period of 152 days. We merge this with data from December 1, 2019, to May 1, 2020 to jointly examine the long-term interaction effects of air pollution and COVID-19 on OFD.

Table A4
The long-term interaction effects of air pollution and COVID-19 lockdown measures on OFD.

Variables	(1) ln(Amount)	(2) ln(Order)	(3) ln(Amount)	(4) ln(Order)
Pollution	−1.004	−0.858	0.858	0.667
	(1.350)	(1.369)	(1.620)	(1.577)
Pollution_Beforelockdown			−1.164	−0.855
			(0.803)	(0.777)
Pollution_Reopen (2020 + 2021)			−2.226	−1.850
			(1.629)	(1.602)
Control Variables	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
Observations	16,470	16,470	16,470	16,470
R-squared	0.529	0.567	0.513	0.555

Notes: 1. Air pollution dummy variables are constructed based on the maximum daily AQI levels in each city. According to MEE standards, if the maximum daily AQI level in a city exceeds 100, we classify that day as a day with air pollution in that city. 2. City-level clustered standard errors are presented in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. 3. The control variables include temperature, precipitation, and the number of COVID-19 cases over 14 days, as well as city and date fixed effect.

Table A5
The effects of thermal inversions on air pollution ($PM_{2.5}$ first stage).

Variables	(1) Pollution ($PM_{2.5}$)	(2) Pollution ($PM_{2.5}$)_Beforelockdown	(3) Pollution ($PM_{2.5}$)_Reopen
Thermal inversions	−0.018	−0.011**	−0.007**
	(0.011)	(0.005)	(0.003)
Thermal inversions_Beforelockdown	0.058***	0.250***	−0.023***
	(0.019)	(0.027)	(0.006)
Thermal inversions_Reopen	−0.030*	−0.071***	0.036***
	(0.016)	(0.009)	(0.012)
Control Variables	Yes	Yes	Yes
City FE	Yes	Yes	Yes
Date FE	Yes	Yes	Yes
Observations	8262	8262	8262
F-test	34.78***	8034.33***	2441.70***
R-squared	0.3881	0.4895	0.1610

Notes: 1. Air pollution dummy variables are constructed based on the maximum daily $PM_{2.5}$ levels in each city. According to MEE standards, if the maximum daily $PM_{2.5}$ level in a city exceeds 75, we classify that day as a day with air pollution in that city. 2. City-level clustered standard errors are presented in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. 3. The control variables include temperature, precipitation, and the number of COVID-19 cases over 14 days, as well as city and date fixed effects.

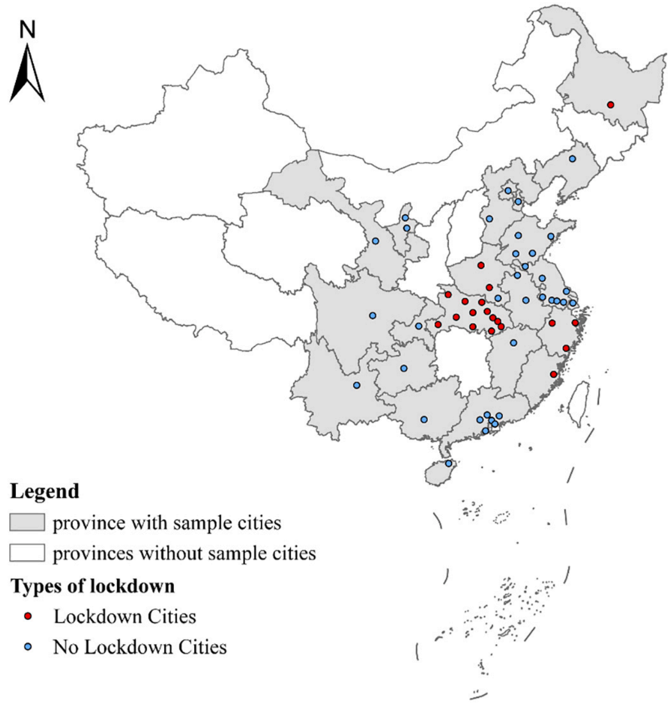

Fig. A1. Distribution of sample cities.
Notes: 1. The figure above shows the distribution of cities in our sample, with red dots representing 19 lockdown cities and blue dots representing 35 cities without lockdowns. 2. Provinces with sample cities and provinces without sample cities are represented by grey color blocks and white color blocks respectively.

Appendix B. The empirical models for the city-date-meal level data

In this section, we present the model using the city-date-meal level data, we adopt settings similar to Eqs. (1)–(6), and display our results in Fig. 7.

We first specify the instrumental variable two-way fixed effect (IVTWFE) model using the city-date-meal level data as follows:

$$lnY_{itj} = \alpha + \beta Pollution_{itj} + \gamma Z_{it} + \sigma_i + \delta_t + \tau_j + \varepsilon_{itj} \quad (8)$$

where lnY_{itj} represents the logarithm form of OFD in the city i on date t of meal stage j ($j = 1, 2, 3$, respectively representing breakfast, lunch, and dinner). $Pollution_{itj}$ is a dummy variable equal to 1 if the maximum value of AQI in city i of meal stage j is above 100 on date t, 0 otherwise. τ_j is the meal stage fixed effects control for all stage-variant change that affect all cities simultaneously. Standard errors are clustered at the city level to solve the autocorrelation concerns at the city level. The setting of other variables is the same as those in model (1), and the first stage of the empirical strategy is also the same as Eq. (2).

Furthermore, interaction terms between air pollution and the before-lockdown stage, as well as between air pollution and the reopening measure are constructed to detect whether and to what extent the impact of air pollution on OFD changes with the implementation of lockdown and reopening measures:

$$\begin{aligned} \ln Y_{itj} = {} & \alpha + \beta_1 Pollution_{itj} + \beta_2 Pollution_{itj} \times Beforelockdown_{it} + \\ & \beta_3 Pollution_{itj} \times Reoepn_{it} + \gamma Z_{it} + \sigma_i + \delta_t + \tau_j + \varepsilon_{itj} \end{aligned} \quad (9)$$

The setting of other variables is the same as those in model (3), and the first stage of the empirical strategy is also the same as Eqs. (4)–(6).

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