PNAS NEXUS

PNAS Nexus, 2025, **4**, pgaf124
https://doi.org/10.1093/pnasnexus/pgaf124
Advance access publication 24 April 2025
Research Report

Air pollutions affect restaurant and foodservice industry in China

Xu Tian[a,1], Shi Min[b,1], Jiexi Shen[c], Qianqian Hong[d], Derek Headey[e], Fangxiao Zhao[d] and Xiaobing Wang[d,*]

[a]Academy of Global Food Economics and Policy, College of Economics and Management, China Agricultural University, Beijing 100083, China
[b]College of Economics and Management, Huazhong Agricultural University, Shizishan Street 1, Hongshan District, Wuhan 430070, Hubei, China
[c]Business School, Jinling Institute of Technology, Nanjing 211169, China
[d]China Center for Agricultural Policy, School of Advanced Agricultural Sciences, Peking University, Yiheyuan Road 5, Haidian District, Beijing 100871, China
[e]Development Strategies and Governance Unit, International Food Policy Research Institute, I Street, NW, Washington, DC 1201, USA
*To whom correspondence should be addressed: Email: xbwang.ccap@pku.edu.cn
[1]X.T. and S.M. contributed equally to this manuscript.
Edited By Rebecca Seguin-Fowler

Abstract

This study examines the impact of air pollution on food away from home (FAFH) consumption in 52 cities across 20 provinces of China, focusing on expenditures for online food delivery (online FAFH) and dine-in restaurants (offline FAFH). Using unique daily aggregated city-level consumption data linked with hourly air quality data, we employ both semiparametric and parametric models to uncover a positive relationship between PM2.5 levels and online FAFH, contrasted by a significantly negative relationship with offline FAFH. Our analysis reveals that shifts in consumer demand for food services on polluted days, coupled with changes in urban mobility patterns, contribute to these outcomes. We also detect temporal variations based on meal type, enhancing our understanding of how air pollution influences food consumption behavior. The findings indicate that increased PM2.5 levels lead to a net loss in restaurant revenue, a reduction in greenhouse gas emissions, and an increase in plastic waste. These findings contribute to a deeper understanding of the multifaceted impacts of air pollution on FAFH and corresponding economy and environmental implications.

Keywords: air pollution, food away from home, dine-in restaurant, online food delivery, rebound effect

Significance Statement

Air pollution in developing countries is a growing concern, prompting precautionary behaviors to minimize exposure. Using high-frequency air quality and food consumption data in urban China, we find that air pollution significantly negatively affects offline food away from home (FAFH), with a positive but insignificant impact on online FAFH. Changes in FAFH can lead to unintended environmental impacts. The decrease in offline FAFH is mainly due to changes in consumer demand, as indicated by the change in orders per restaurant. Heterogeneous analyses show that air pollution has a more significant negative impact on offline FAFH during breakfast, dinner, and working days.

Introduction

Air pollution in developing countries is a widespread concern. Air pollution is primarily caused by ambient particulates (1, 2). Poor air quality often results in visible haze or smog (3), and through smartphones, consumers are increasingly aware of local air quality, including air quality warnings, with a high degree of precision. According to a recent report, the top 10 countries with the most severe air pollution in 2022 were all developing countries, mostly in South Asia (4). China, however, stands out as one of the few developing countries where air quality has been improving in recent decades. Major cities in China have seen a decline of over 50% in annual mean of particulate matter with a diameter of <2.5 μm (PM2.5) since 2015 (4). As of 2023, only two Chinese cities are in the top 50 IQAir list of most polluted cities (40 of the 50 are in India alone). Nevertheless, the annual mean PM2.5 declined sharply from 61.1 to 30.6 $\mu m/m^3$ from 2007 to 2022 in urban China, which is around six times higher than the guideline set by the World Health Organization (4). In addition, there were still 40.1% of prefecture and above cities that did not meet the ambient air quality standards in 2023, and the primary pollutant was PM2.5 (5).

Air pollution seriously harms people's physical and mental health (6–9) and leads to a wide range of adverse welfare consequences (10, 11). Air pollution has become the fourth leading cause of deaths and was associated with 6.67 million deaths worldwide in 2019 (7). Between 1990 and 2017, particular matter pollution in China became the fourth leading risk factor for deaths and disability-adjusted life-years (9). Given China's population—as well as the importance of air pollution in populous India—air

Competing Interest: The authors declare no competing interests.
Received: November 18, 2024. **Accepted:** April 4, 2025

pollution was estimated to account for 11.62% of deaths worldwide (12). Moreover, air pollution can reduce labor productivity of workers (13–15), affecting both manual and cognitive tasks (16, 17), and likewise affects students' cognitive ability and academic performance (10, 18, 19). Air pollution also increases the probability of dementia diagnoses (20), adversely affects mood, mental health, social engagement, and subjective well-being (21), and can increase preferences for unhealthy foods (22). Poor air quality can also lead to an increase in urban violent crime incidents (23).

In response to air pollution, people in China and other affected countries have increasingly adopted precautionary behaviors, particularly spending less time outside. First, consumers know that exposure to air pollution is linked to respiratory symptoms, leading to impaired exercise capacity (24). Second, the appearance of visible haze may discourage people going outside (25) or even affected decisions to migrate (26). Third, a recent natural laboratory experiment conducted in China revealed that air pollution (increased haze) makes individuals more risk-averse and affects their decision-making process, leading to a decreased demand for prosocial activities such as recreational and entertainment pursuits (27, 28). Finally, media warnings and reminders about poor air quality—including air quality apps on smart phones—can change people's decision on spending time outdoors (29, 30). For example, the Canadian government developed a risk communication tool, the Air Quality Health Index (AQHI), which uses a scale to show the health risk associated with the air pollution we breathe. Now widely adopted globally, the AQHI recommends to "reduce or reschedule strenuous activities outdoors" to mitigate the health risks of high levels of air pollution. Various air quality apps such as the MoJi Weather and AirVisual are also widely used in China, providing real-time air quality information.

Given the availability of real-time air pollution information, residents may shift from dinning out at restaurants to alternative dining methods, such as cooking at home or ordering food online. This precautionary behavior warrants investigation for two key reasons. First, dine-in restaurants with friends or business partners have become an important means of building social network in urban (25, 27, 28, 31). Thus, the shift in dinning habits represents not just a change in food consumption, but also a potential loss of social and cultural amenities within the city. Second, the catering industry is a major contributor of urban economy (11). A reduction in dine-in restaurants visits could lead to significant revenue losses.

However, empirical evidence on the impact of air pollution on residents' food consumption behavior is limited. For instance, Sun et al. (11) showed that a rise in PM2.5 from the 25th to 75th percentile was associated with 1.6% decline in dining in restaurants in Beijing. Similarly, Xi et al. (32) reported that air pollution reduced visits to a restaurant chain, resulting in a total loss of 307 million Chinese yuan (RMB) in Beijing. On the contrary, Chu et al. (25) found that a 100-μg/m^3 increase in PM2.5 raised the likelihood of ordering online food delivery by 40%. Other studies suggest that air pollution indirectly influences food consumption in different countries. Pandey et al. (33) evaluated the economic impact of ozone pollution in India and proposed that it affects wheat prices, impacting consumers. Andrei et al. (34), based on data from 15 European capitals, also found that PM2.5 pollution affects restaurant food prices and economic consumption. While these studies indicate a shift from dining out to online food delivery due to air pollution (11, 25, 32), the representativeness of data used in these studies is limited. For example, the studies conducted by Sun et al. (11) and Chu et al. (25) rely solely on data collected from several cities in northern China, while the data analyzed by Xi et al. (32) exclusively originate from only a single restaurant chain. Hence, while existing studies usefully indicate some effect of air pollution on food consumption behaviors, more representative empirical evidence on these associations is needed.

The objective of this study was to explore the impact of air pollution on residents' consumption of food away from home (FAFH) by using more comprehensive and representative data from China. China is an important case to study because of its booming catering industry and the huge urban population as well as the severity of its air pollution. To achieve this objective, we employed a comprehensive hourly air quality dataset and two high-frequency datasets on FAFH in China. In this study, FAFH is further divided into two parts: offline FAFH and online FAFH. Offline FAFH refers to the consumption of meals outside the home in traditional dining establishments such as restaurants, cafes, and dining halls. Online FAFH pertains to the purchase and consumption of meals provided outside the home through online food delivery platforms. And it involves ordering food from restaurants or food vendors via Apps or websites, with the meals delivered directly to the consumer's doorstep. The first one contains daily data on eating at restaurants (offline FAFH) obtained from Keruyun, which is one of the largest platforms in China for providing restaurants with smart cash register systems and records restaurants' sales data for more than 200 out of the 339 cities. The second one is daily online food delivery data (online FAFH) provided by one of the major online food delivery platforms -the Ele.me platform in China. Ele.me has covered more than 300 cities nationwide and accounted for 35.5% market share of online food delivery in China in 2022. To identify the impact of PM2.5 pollutions on total sales and orders of offline FAFH and online FAFH, an instrumental variable (IV) semiparametric model is employed as the main estimation strategy. In addition, an instrumental variable two-way fixed-effects (IVTWFE) model is employed to estimate the marginal effect and test the robustness of results from semiparametric models. Moreover, we also examine potential pathways to further explain the changes in total sales and orders. Finally, we conduct several heterogeneity analyses and robustness tests to confirm our main findings.

The study contributes to better understanding consumer behavior in response to air pollution. First, by analyzing how consumers' dining choices adapt to air pollution, we gain insights into their preferences and behaviors, such as a shift towards online food delivery rather than dining out on days with visible air pollution. This shift reveals how consumers adapt their behavior to protect their health and well-being. Second, examining the impact of air pollution on consumers' food consumption behavior helps us extend our understanding of the broader social and environmental costs associated with air pollution. While direct costs, such as medical expenses due to health risk and effects, are well known, this study highlights additional indirect costs linked to changes in consumer behavior. This broader perspective contributes to a more accurate estimation of the total cost of air pollution, providing policymakers with comprehensive information in designing policy portfolios to mitigate the adverse impacts of air pollution on the catering industry and social welfare. Third, our study builds upon previous research by incorporating data from a relatively large number of cities, which offers a somewhat more comprehensive perspective across different geographic and demographic contexts. Moreover, the use of high-frequency data enables a finer-grained analysis, allowing us to detect short-term fluctuations and immediate responses to air pollution. Finally, our study incorporates data from both dining establishments and online food delivery services. This unique combination of datasets enables us to examine the shifting consumer behavior between dining out and opting for online food delivery. This granularity enhances the precision of our estimates and offers valuable insights into the temporal dynamics of consumer behavior, including the occurrence of rebound effects.

Results

Spatial distribution of FAFH and PM2.5 in China

Figure 1 illustrates the percentage of polluted days (with PM2.5 levels exceeding 75) and the daily average PM2.5 concentrations across 52 sampled cities[a] during the study period. The mean proportion of polluted days stood at 12.4%, while the average daily PM2.5 concentration was 44.4 μg/m³. Considerable variability was observed across the representative sampled cities, with the percentage of polluted days ranging from 0% in Haikou to 29.0% in Linyi and daily PM2.5 averages fluctuating from 19.4 μg/m³ in Haikou to 66.1 μg/m³ in Jining.

In Fig. 2, the frequency and value of FAFH orders per 1,000 residents are presented. The results highlight significant variation across cities. Inhabitants of larger cities tended to consume FAFH more often and spend more on such orders compared with those in smaller cities. For example, the number of online and offline FAFH orders per 1,000 residents reached 14.1 and 4.4, respectively, in Shanghai—the most populous city in the study—while in Ezhou—the smallest city by population—these figures were just 1.29 and 0.65, respectively. Similarly, the daily expenditure on online and offline FAFH per 1,000 residents in Shanghai (amounting to 926.7 RMB for online and 329.9 RMB for offline FAFH) was more than 10-fold higher than that in Ezhou (52.8 RMB for online and 29.4 RMB for offline FAFH).

Air pollution differently affects offline and online FAFH

We initially assessed the influence of PM2.5 on both offline and online FAFH consumption using a partial linear semiparametric model. The association between PM2.5 levels and FAFH is depicted in Fig. 3, with detailed results of the parametric portion given in Table S1. We observed a general upward trend in two aggregate indicators for offline FAFH: total transaction value and the overall number of orders. Conversely, a positive correlation was noted between the value of transactions and the volume of online FAFH orders as a function of increasing PM2.5 levels.

To further quantify the marginal impact of PM2.5 on offline and online FAFH, we employed the IV technique with IVTWFE to estimate Eq. 2 in Supplementary Material. Consistent with the trends identified in the semiparametric model, higher air pollution correlates with a rise in online FAFH and a decline in offline FAFH (Table S2). Specifically, a 1% increase in PM2.5 is associated with a 0.8% reduction in the total value of offline FAFH transactions (95% CI: −1.4%, −0.1%) and a 0.5% decrease in the number of offline FAFH orders (95% CI: −0.9%, −0.1%). However, air pollution does not appear to have a statistically significant effect on online FAFH, as evidenced by the CIs (95% CI for transaction value: −0.2%, 0.3% and for the number of orders: −0.1%, 0.4%).

The semiparametric model sheds light on the general trend of increased online FAFH, while the IVTWFE model offers insight into the marginal effects and adds further nuance to the analysis. The differences in results estimated by these two models are discussed in the Discussion section.

Air pollution decreases demand for offline FAFH

Given that the total transaction value and the overall number of orders are measured at the city-aggregated level, the decrease in

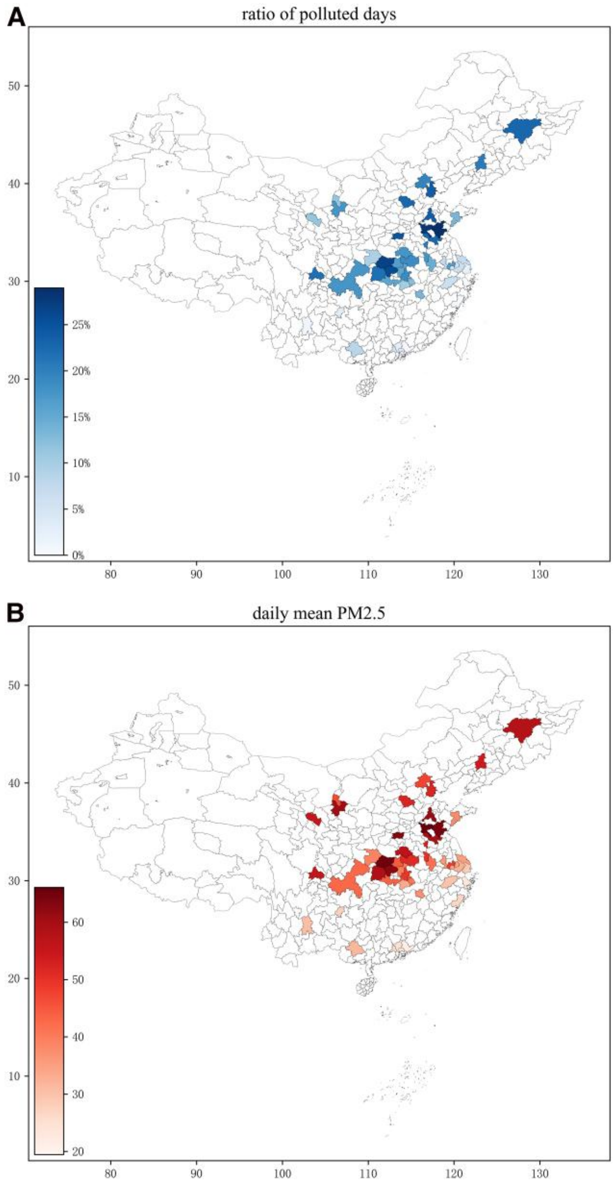

Fig. 1. Air pollution in sample cities (Panel A: Ratio of polluted days; Panel B: Daily mean PM2.5). Ratio of polluted days (Panel A) is defined as the ratio of days with PM2.5 >75 (threshold of light pollution) in the total study period. Daily mean PM2.5 (Panel B) is the mean daily PM2.5 value during the whole study period.

spending could be influenced by either the intensive margin, which refers to a reduction in consumer demand (few orders per restaurant), or the extensive margin, which refers to a decrease in the number of restaurants offering offline dining services. To gain deeper insight into how air pollution influences online and offline FAFH, we examined the effects of PM2.5 levels on the number of operating restaurants and the average transaction per restaurant. This was done using the described semiparametric and parametric models. Our analysis identified a positive relationship between PM2.5 concentrations and both the number of operating restaurants and the average transaction value for online FAFH. Conversely, a negative relationship was observed for offline FAFH (Fig. 4; detailed results of the parametric portion are given in Table S3).

IVTWFE approach indicated that air pollution does not exert a significant impact on the quantity of operating restaurants that

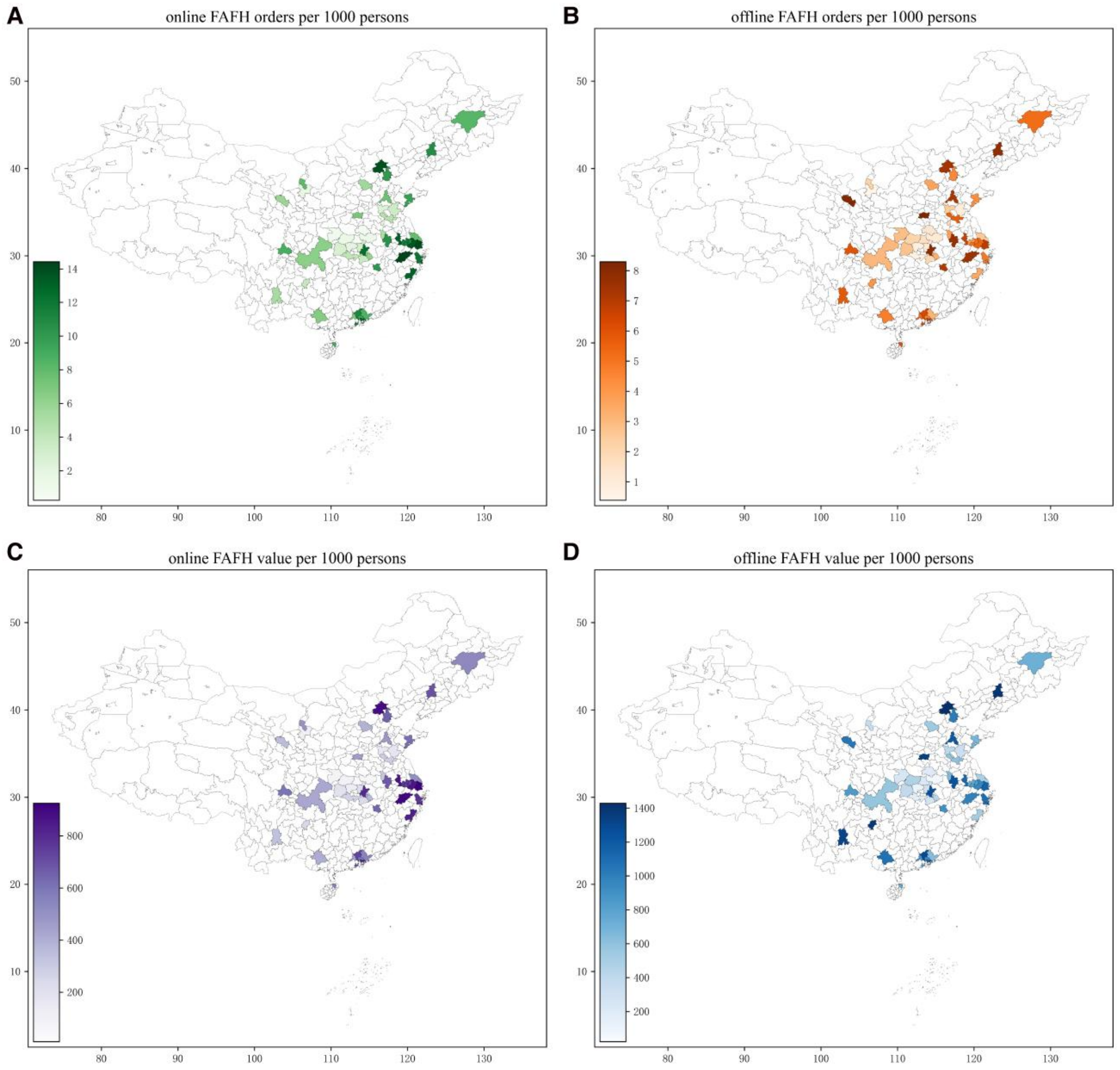

Fig. 2. Daily FAFH per 1,000 persons in sample cities (Panel A: Online FAFH orders; Panel B: Offline FAFH orders; Panel C: Online FAFH value; Panel D: Offline FAFH value). The FAFH indicators include online FAFH order (Panel A), offline FAFH order (Panel B), online FAFH value (Panel C), and offline FAFH value (Panel D), which refer to the transaction value of online FAFH (RMB), the total number of online orders, the transaction value of offline FAFH (RMB), and the total number of offline orders, respectively. All indicators are measured in per 1,000 persons.

provide either online FAFH (95% CI: −0.2%, 0.1%) or offline FAFH (95% CI: −0.3%, 0.0%). This indicates that air pollution has no significant impact on the supply of online or offline FAFH. In another word, the extensive margin is statistically insignificant for either online or offline FAFH. This implies that restaurant operators seem to more concerns for the economies of restaurant operations and tend to ignore air pollution.

However, air pollution significantly influences the average transaction volume, increasing the number of online food orders per restaurant and decreasing the number of offline food orders per restaurant. Specifically, a 1% rise in PM2.5 concentration leads to a 0.2% increase in the number of online food orders per restaurant (95% CI: 0.0%, 0.4%) and a 0.4% reduction in the number of offline food orders per restaurant (95% CI: −0.7%, −0.0%) (Table S4). Combining the above results regarding the impacts of air pollution on the number of offline and online FAFH orders and the number of operating restaurants, the significant positive impact of air pollution on the number of online food orders per restaurant is possible, while it also implies that the operating restaurants during air pollution days could gain more from online FAFH orders and compensate for offline losses. Furthermore, the negative effects of air pollution on the number of offline food orders per restaurant further highlight the decreased demand for offline FAFH. In fact, the decreased demand for offline FAFH could attribute to consumers' precautionary behaviors in response to air pollution, especially spending less time outside. With increasing health concerns, consumers tend to go out less to avoid air pollution and thereby have fewer demands for offline FAFH in air pollution days. Hence, the shifts in consumer demand (intensive margin) may serve as the mechanism by which air pollution impacts the dynamics of offline FAFH.

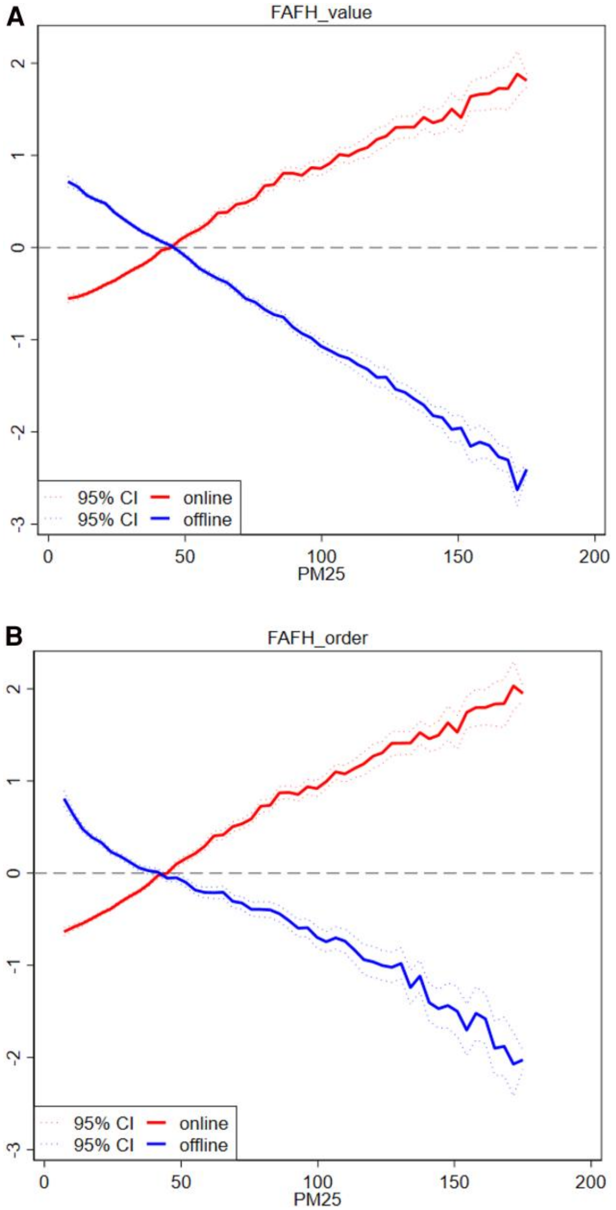

Fig. 3. Correlation between FAFH and air conditions estimated by using a semiparametric model (Panel A: FAFH value; Panel B: FAFH order). The solid line represents the estimated fitted values of various FAFH indicators using semiparametric regression. FAFH_value (Panel A) and FAFH_order (Panel B) refer to the transaction value and the total number of orders for online and offline FAFH, respectively. The dotted line represents the 95% CI. The semiparametric model was estimated using the method proposed by Baltagi and Li (35). The parametric part of the model includes control variables such as temperature, precipitation, centralized heating, and newly confirmed cases of COVID-19. Additionally, the regression controls for city fixed effects, day fixed effects, and meal fixed effects.

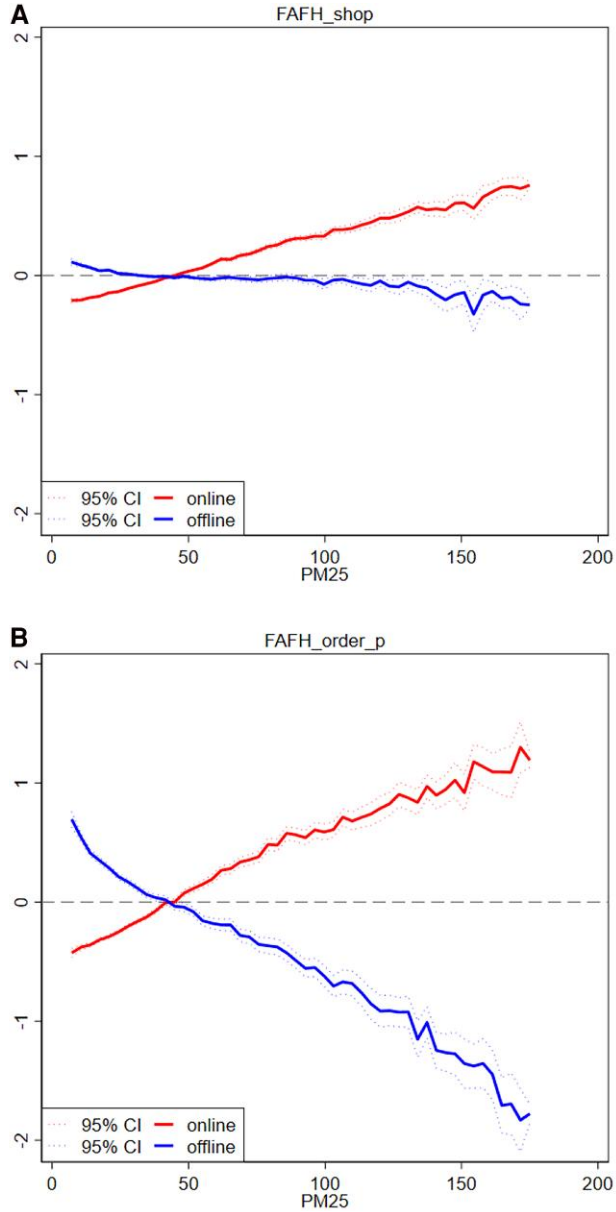

Fig. 4. Impact of air conditions on demand and supply using a semiparametric model (Panel A: FAFH shop; Panel B: FAFH order per shop). The solid line represents the estimated fitted values of various FAFH indicators using semiparametric regression. The dotted line represents the 95% CI. FAFH_shop (Panel A) and FAFH_order_p (Panel B) refer the number of restaurants and the average number of orders per restaurant, respectively. The semiparametric model was estimated using the method proposed by Baltagi and Li (35). The parametric part of the model includes control variables such as temperature, precipitation, centralized heating, and newly confirmed cases of COVID-19. Additionally, the regression controls for city fixed effects, day fixed effects, and meal fixed effects.

The demand for online FAFH decreases, while the demand for offline FAFH increases after polluted days

There may exist a rebound effect in consumer behavior of FAFH after air pollution in short periods due to consumers' compensation psychology or social networking needs (36). Here, we explored the possibility of a "rebound effect" in FAFH, i.e. the hypothesis that after several polluted days, residents may be more inclined to dine out, thus reducing the demand for online food deliveries when air quality clears up (11). To investigate this, we utilized a dummy variable that assumes the value of 1 if the PM2.5 concentration decreased from above 75 to below 75 from one day to the next. The results are presented in Table 1.

Our findings confirmed a decrease in the demand for online FAFH, alongside an increased demand for offline FAFH after significant improvements in air quality relative to the previous pollution-heavy day. The transaction value for online FAFH dropped by 37.1% (95% CI: −71.9%, −2.4%), and the total number

Table 1. Testing for postpollution rebound effects on FAFH consumption using IVTWFE.

	Online FAFH		Offline FAFH		Online FAFH		Offline FAFH	
	Total transaction value (ln)	Online orders (ln)	Total transaction value (ln)	Online orders (ln)	Number of restaurants (ln)	Orders per restaurant (ln)	Number of restaurants (ln)	Orders per restaurant (ln)
Rebound	−0.371**	−0.329*	0.469	0.637**	−0.120	−0.139*	0.100	−0.488**
	(0.177)	(0.170)	(0.456)	(0.271)	(0.089)	(0.084)	(0.101)	(0.196)
Temperature (°C)	−0.002*	0.000	0.012***	0.013***	−0.000	0.001**	0.004***	0.008***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Precipitation (mm)	0.003***	0.003***	−0.001**	−0.003***	0.001***	0.002***	−0.001***	−0.002***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
COVID19 (cases)	−0.026***	−0.029***	−0.028***	−0.028***	−0.029***	−0.001	−0.029***	0.002**
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.001)	(0.003)	(0.001)
Heating (1 = yes)	−0.014	−0.020*	−0.044	0.026	−0.005	−0.015***	0.005	0.018
	(0.012)	(0.011)	(0.031)	(0.018)	(0.006)	(0.005)	(0.007)	(0.013)
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Meal fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
S^2	0.130	0.225	0.139	−0.073	0.583	0.082	0.550	−0.082
Observations	7,124	7,124	7,124	7,124	7,124	7,124	7,124	7,124

The asterisks indicate a statistical significance level: ***$P < 0.01$; **$P < 0.05$; *$P < 0.1$. An IVTWFE estimation strategy, along with day city-level data, is employed to analyze the effects of PM2.5 on various FAFH indicators. All outcome variables are measured in logarithm. Rebound is a dummy variable that equals 1 if the PM2.5 concentration decreased from above 75 in the previous day to below 75 in the current time. The *F* test of the excluded IV is 7.55.

of online FAFH orders fell by 32.9% (95% CI: −66.2%, 0.3%). Conversely, the total number of offline orders rose by 63.7% (95% CI: 10.6%, 116.8%). However, the growth in the total transaction value for offline FAFH was not statistically significant (95% CI: −42.5%, 136.2%), as indicated in Table 2. Further analysis showed that the rebound was mainly caused by the change in demand. In particular, after a polluted day, residents tended to increase offline FAFH by 48.8% (95% CI: 10.4%, 87.2%) but decrease online FAFH by 13.9% (95% CI: 2.6%, 30.4%). These results support the existence of a rebound effect in consumer behavior with respect to the FAFH sector following short-term fluctuations in air quality.

Further evidence from inner-city mobility

The demand for FAFH is closely related to the mobility patterns within a city since urban residents who move around more are likely to dine out. To mitigate exposure to air pollution, individuals might prefer to remain indoors, particularly on days with high pollution levels, resulting in reduced mobility. Consequently, on days with higher air pollution, we expect to see a decline in inner-city mobility. To quantitatively assess this, we used the Baidu inner-city mobility index, which evaluates the intensity of urban movement. This index is derived from the proportion of people moving around within the city relative to the resident population (37).

Our analysis demonstrated that a 1% increase in PM2.5 concentration leads to a substantial decrease in inner-city mobility by 1.6% (95% CI: −2.6%, −0.6%), as given in Table 2. This significant negative impact of air pollution on urban mobility suggests that on days with poor air quality, fewer people are choosing to dine outside, thus affecting the offline FAFH sector. This finding reveals the broader impact of environmental conditions on urban life and economic activities, such as dining patterns and the demand for food services. Thus, inner-city mobility could serve as additional evidence to confirm that air pollution affects offline FAFH.

Heterogeneous effects

The effects of air pollution on FAFH varied across different meal times. This variation was because residents generally had more time to prepare and consume breakfast and dinner at home, but often lacked the time and resources to do the same for lunch on weekdays (11, 25). Consequently, we assessed the impact of PM2.5 on FAFH separately for breakfast, lunch, and dinner. Our findings indicated a positive correlation between PM2.5 levels and both the number of operational restaurants and the average transaction value for online FAFH during dinner and breakfast times. In contrast, we observed a negative correlation for offline FAFH during breakfast and dinner (Fig. S1). However, the trends during lunchtime were inconsistent with those observed for breakfast and dinner, likely due to the limited time available on workdays. The IVTWFE model revealed that air pollution did not significantly affect online FAFH at any meal time but significantly decreased the total value of offline FAFH during breakfast by −0.6%, with a 95% CI of −1.1%, 0.0% (Table S5).

Table 2. Further evidence on the effect of air pollution on inner-city consumer mobility using IVTWFE.

	Baidu inner-city mobility index (ln)
Mean PM2.5 (ln)	−1.608***
	(0.505)
Temperature (°C)	0.063***
	(0.010)
Precipitation (mm)	−0.016***
	(0.004)
COVID19 (cases)	−0.070***
	(0.006)
Heating (1 = yes)	−0.024
	(0.033)
City fixed effects	Yes
Day fixed effects	Yes
Meal fixed effects	Yes
R^2	0.710
Observations	21,528

The asterisks indicate a statistical significance level: ***$P < 0.01$; **$P < 0.05$; *$P < 0.1$. The results were estimated using an IVTWFE regression. Mean PM2.5 and the outcome variable are measured in logarithm. The *F* test of the excluded IV is 11.88.

Moreover, urban residents' choices between FAFH on weekdays versus weekends appeared to differ. After segregating the data into weekdays and weekends, we found a positive correlation between PM2.5 levels and online FAFH, but a negative one for offline FAFH during weekdays, aligning with the findings presented in

Fig. 3. However, both online and offline FAFH experienced declines on polluted days during the weekends (Fig. S2), which may have been due to the reduced time constraints, allowing residents to cook at home. The IVTWFE model showed that a 1% increase in PM2.5 resulted in a 0.7% decrease in the total transaction value of offline FAFH (95% CI: −1.1%, −0.1%) and a 0.4% decrease in the total number of offline orders on weekdays (95% CI: −0.9%, −0.0%). Yet, it had no significant impact on either online or offline FAFH during weekends (Table S6).

Robustness tests

We also performed two robustness tests to check whether the main findings are not influenced by the forms of air pollution variables.

1. We calculated the mean values of PM2.5 for each day and used them to replace the meal-level PM2.5 data. Our results found a negative association between daily PM2.5 and offline FAFH, while the relationship between PM2.5 and online FAFH tended to follow a U shape (Fig. S3). The IVTWFE model showed that a 1% increase in daily mean PM2.5 resulted in an insignificant decrease in the total transaction value of offline FAFH (95% CI: −2.5%, −0.3%) and a significant 0.8% decrease in the total number of offline orders (95% CI: −1.6%, −0.1%). However, air pollution did not have a significant impact on online FAFH, with 95% CI ranging from −0.2 to 0.3% for the total transaction value and −0.1 to 0.6% for the total number of offline orders. Detailed results are given in Table S7.
2. We replaced PM2.5 with the air quality index and reconducted all regressions. Despite less statistical precision, we still found a positive impact on online FAFH and a negative impact on offline FAFH. Detailed results are given in Fig. S4 and Table S8.

Greenhouse gas footprint of online and offline FAFH

The dietary patterns differed between foods consumed at restaurants and those ordered via online food delivery platforms. Specifically, when dining at restaurants, individuals exhibited a tendency to consume greater quantities of cereals, legumes, vegetables, fruits, beef, mutton, aquatic products, eggs, sugar, and honey (Fig. 5). Furthermore, their intake of milk, beverages, and alcohol drinks was also notably higher in these settings. Conversely, the utilization of online food delivery services was associated with an increased consumption of pork, poultry, and starchy foods.

This disparity in dietary patterns also contributed to differences in greenhouse gas (GHG) emission between offline FAFH and online FAFH. For instance, an individual dinning at restaurants for an entire day generated a total GHG emission of 4,060.23 CO_{2e}, primarily attributed to elevated consumption of poultry (924.62 CO_{2e}), beef and mutton (720.63 CO_{2e}), cereals (633.34 CO_{2e}), and pork (503.11 CO_{2e}). In contrast, an individual consuming all meals via online FAFH over the same time frame produced total GHG emissions of 3,800.08 CO_{2e}, with more than 60% of these emissions stemming from increased consumption of poultry (1,270.30 CO_{2e}) and pork (1,059.85 CO_{2e}). We also assessed the GHG emissions for various food items using the Chinese Food Life Cycle Assessment Database (Tables S11 and S12).

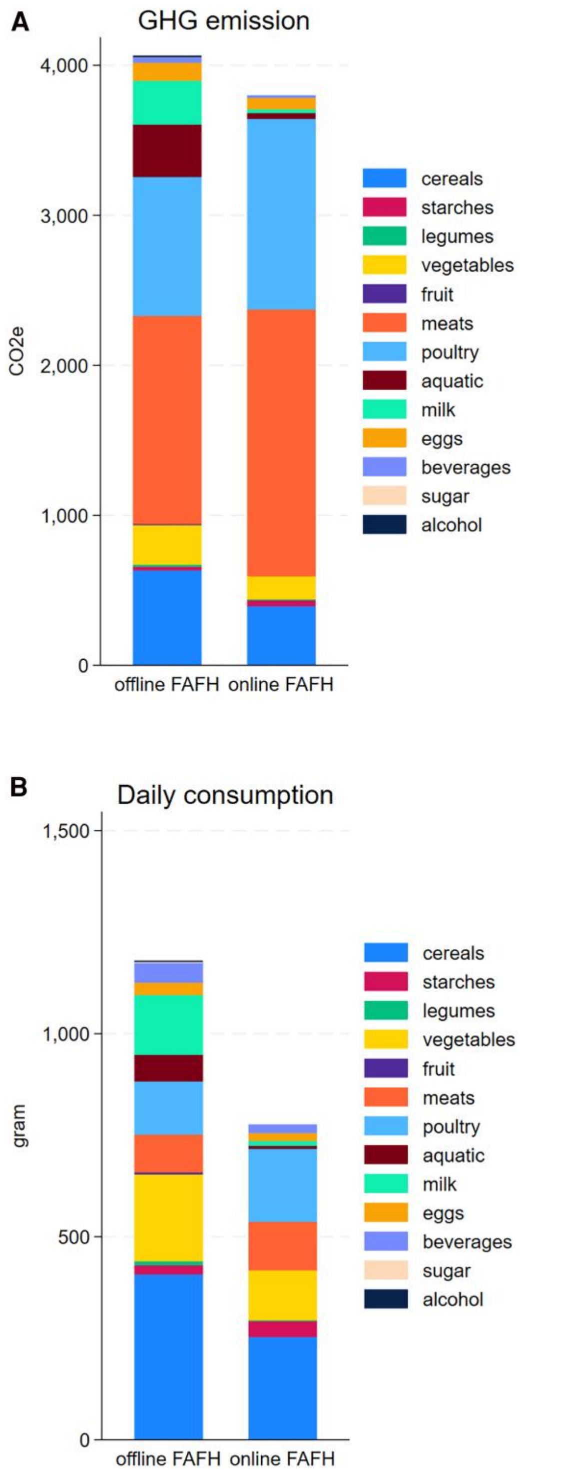

Fig. 5. GHG footprint and dietary pattern of online and offline FAFH (Panel A: GHS emission; Panel B: Daily consumption). Food consumption data were collected through an online survey collaborated with Sojump in 2022 and 2023. The survey adopted the 24-h recall method to collect data from 1,837 samples from 113 cities across nine provinces in China. Panel A refers to the total GHS emission of offline and online FAFH for an entire day; Panel B refers to the daily consumption pattern for offline and online FAFH.

Discussion

Offline and online FAFH may play distinct roles in strengthening the resilience of urban food systems, particularly during air pollution episodes. While both types of FAFH are crucial, air pollution affects them differently (37). Offline FAFH suffers due to reduced demand, as air pollution discourages dinning out. This poses a threat to urban food systems, especially in large cities where residents often live in small apartments, households rely less on household food preparation and more on frequent restaurant dining for eating. In contrast, online food delivery remains resilient to pollution and has grown significantly, particularly during weather extremes and the COVID-19 pandemic (37). Ordering food online has become exceedingly popular in urban China, especially among office workers who have limited time for cooking at home (11, 25). Delivery services offer a convenient and efficient way to access food, particularly for individuals living alone or those with busy schedules, including working women.

We find that air pollution significantly reduces offline FAFH transaction values and orders, but it does not significantly impact online food delivery. The contrasts with previous studies, such as Chu et al. (25), which found a significantly positive impact of air pollution on online food delivery. This discrepancy could be attributed to two reasons. First, the previous study only surveyed office workers in three major northern cities in China, namely Beijing, Shijiazhuang, and Shenyang, while our sample included 52 cities across China, varying in scale and location. The varying impacts observed in different regions could contribute to the inconsistency between our study and the previous one (refer to Tables S2, S3, and S5). Second, the previous study focused solely on lunchtime consumption and relied on respondents' self-recorded data, whereas our study utilized data collected from both offline and online transaction platforms, providing macro-level aggregated data. This approach helps minimize sample selection biases and allows for a more precise estimation of the actual transaction values. Third, the previous study was conducted in 2018, before the COVID-19 pandemic. In contract, our study uses data collected after the outbreak of COVID19. Consumer preferences for online and offline FAFH may have changed as a result of the pandemic (37).

One interesting point worth of discussion is that the semiparametric model reveals a significant impact of air pollution on online FAFH, while the IVTWFE model suggests only a weak positive association between air pollution and online FAFH. These two models complement each other to reveal how consumers' FAFH behavior changes on days with high air pollution. With the increase in air pollution, more consumers tend to reduce offline FAFH. While online FAFH may increase as air pollution increases, the changes are not statistically significant. In practice, in air pollution days, consumers could choose online FAFH or home cooking as alternatives to decreased offline FAFH. Therefore, it is reasonable to observe a positive relation between air pollution and online FAFH. However, the insignificant impact of air pollution on online FAFH by the IVTWFE model further implies that consumers primarily turn to home cooking rather than online FAFH as a substitute for diminished offline FAFH opportunities. In our analysis, we observe that air pollution leads to a decreased demand for offline FAFH, which we attribute to consumers' precautionary psychologies and behaviors. Particularly, during periods of poor air quality, individuals may choose to spend less time outdoors to minimize their exposure to pollutants (38), thereby opting for online food ordering as a more convenient and safer alternative. This behavioral adaptation can be seen as a protective measure to safeguard their health. Moreover, the "rebound effect" observed in our data, where there are a decrease in online FAFH and an increase in offline FAFH after polluted days, might be attributable to compensation psychology or social networking needs (36). After being confined indoors during polluted days, consumers may feel a need to compensate for the time spent indoors by engaging more in outdoor activities, including dining out, once the air quality improves. Additionally, the desire for social interaction and networking could drive consumers to resume offline dining as the air quality becomes more favorable (11).

Analyzing the impact of air pollution on the catering industry, particularly FAFH, is significant for several reasons. First, it sheds light on the socioeconomic effects of air pollution, particularly in local economies. The industry is evolving with technological advancements, such as online food delivery, which not only creates job opportunities in the gig economy (e.g. online food delivery services), but also enhances resilience against external shocks like COVID-19 (39). Examining how air pollution influences this shift between food delivery and dining in can reveal labor distribution impacts. Second, it provides a lens through which to explore health and environmental consequences. Restaurant and delivery meals often contain higher levels of salt, sugar, and fat compared with home-cooked meals, leading to deviations from dietary guidelines and posing significant health risks (40). Additionally, food delivery contributes significantly to carbon emissions—Chinese cities generated 1.67 MtCO2e from 13.07 billion deliveries in 2019—and plastic waste, with 7.3 billion single-use plastic tableware sets used annually (25, 41). Third, it highlights social equity issues. Spatial disparities in air pollution affect access to and quality of FAFH, revealing inequities in the catering industry (42, 43).

Air pollution poses significant challenges to the catering industry, a key economic sector in rapidly urbanizing countries like China (37). Since the implementation of the reform and opening-up policy initiated in the late 1970s, China's catering industry has experienced exponential growth. In 2021, the total revenue of the industry reached 4.7 trillion RMB, over 800 times more than in 1978, and the total number of employees increased from 1 million to ~30 million (44). Additionally, China has become the largest market for online food delivery and takeaway, serving over 544 million consumers, with total sales exceeding 900 billion RMB (about 125 billion US dollar) in 2022 (45). However, according to our findings, the decline in demand for dine-in restaurants caused by air pollution results in significant losses for the catering industry, and online food delivery does not fully offset this decline.

Air pollution affects social interactions and may have various subtle and indirect costs. The availability of well-developed public transit and access to social media platforms further facilitate meeting friends at various restaurants and building up social connections. A recent survey conducted in 114 Chinese cities between 2022 and 2023 revealed that urban residents visited restaurants an average of seven times per month, spending an average of 372 RMB, or approximately one-third of their total food expenditure (46). Obviously, dine-in restaurants have also become important social spaces for individuals to socialize with friends and build social capital (11). However, during polluted days, urban residents tend to stay at home and reduce their outdoor activities. Adversely, this could have an impact on the social capital that is formed through interactions in restaurants, as well as their mental health (25, 27, 31). But at a more aggregate level, the decline in inner-city mobility can also harm the economic and social vitality of cities (11). Therefore, it is also essential to address the indirect costs of air pollution, which have not been thoroughly examined in previous studies and merit further investigation, including through economy wide modeling studies.

Furthermore, the shift from offline to online FAFH during periods of air pollution has mixed environmental impacts. In recent years, Chinese consumers have increasingly turned to dining out, with notable rise in the consumption of beef, mutton, aquatic products, milk, and cereals (47). Those foods, particularly ruminant meats, are associated with significantly higher GHG emissions compared with plant-based alternatives—~250 times per gram of protein and 160 times per serving (48, 49). Consequently, online FAFH generally results in lower GHG emissions compared with offline FAFH. However, the increase in plastic waste from online food delivery partially offsets this reduction in GHG emissions (50, 51). On average, plastic packaging used for online FAFH per meal is approximately nine times greater than that used for offline FAFH (53.95 versus 6.64 g) (25). Moreover, a 100-μg/m^3 increase in PM2.5 leads to a 1.37% reduction in offline FAFH, translating to an estimated loss of 1.25 RMB, a decrease of 22.25 CO_{2e} in GHG emission, and an additional 0.09 g of plastic waste per meal. Conversely, this same increase results in a 0.39% rise in online FAFH, corresponding to an estimated additional revenue of 0.20 RMB, an increase of 14.82 CO_{2e} in GHG emissions, and an extra 0.21 g of plastic waste per meal. Aggregating these factors, a 100-μg/m^3 increase in PM2.5 results in a net loss of 1.05 RMB in restaurant revenue, a reduction in 7.43 CO_{2e} in GHG emissions, and an increase of 0.13 g in plastic waste per meal. Although air pollution in China has been improved in recent years, it remains sever in certain cities (52), particularly in provinces such as Shanxi, Shaanxi, and Hena. This situation has likely hindered the development of the restaurant industry in these areas, resulting in potential economic loss and higher plastic waste generation. It is important to note that this analysis is a rough estimation, and a more precise evaluation would require a general equilibrium analysis integrating both economic and environmental models.

The findings of this study provide valuable insights for policymakers in designing strategies to assist the catering industry adapt their business approaches during air pollution episodes. In areas where air pollution has more pronounced detrimental effects on offline FAFH, local government should not only strive to improve air pollution control measures but also support restaurants in expanding their services to include online food delivery. This will enhance the resilience of local food systems as well as allow restaurants to compensate for offline losses by offering food delivery services or selling takeaway food through online platforms, especially in pollution-affected areas. Measures, such as catering vouchers and tax abatement, to stimulate consumers' demand for FAFH should be taken into account. Additionally, to address the plastic waste generated by online FAFH, particularly from disposable packaging, governments should consider implementing mitigation strategies such as promoting reusable containers, biodegradable packaging, and incentives for consumers to return packaging for recycling. Policymakers could also explore broader initiatives to reduce air pollution, such as stricter emissions regulations (53, 54), incentives for green transportation (55), and investments in renewable energy (56), which would address the root cause of the issue and benefit both public health and the economy (57, 58).

Further research could also study the impacts of air pollution on diets and diet-related health (e.g. intake of micronutrients, but also unhealthy foods). Since the evidence in this study suggests that air pollution increases food prepared at home, it is possible that air pollution has some dietary benefit if food prepared at home is healthier than FAFH. Previous studies claim that FAFH is a cause of the rising prevalence of obesity, as FAFH contains higher fat and energy but lower fiber and micronutrients (59, 60). However, the nutrition-related health influence of air pollution remains to be empirically demonstrated. A study conducted in Southern California found that childhood exposure to regional and traffic-related air pollutants was associated with increased consumption of trans fats and fast foods among adolescents, providing partial support for this concern (61). Government should implement specific policies to increase the availability of nutrition information of online and offline FAFH. For instance, Chinese consumers are increasingly seeking healthier and more sustainable dining options in recent years. This trend has been particularly evident in the rise of plant-based and organic food choices. In response to the shift in consumers' preference, Ele.me implemented the "Nutrition Labeling Program" in early 2023, which provides detailed ingredient and nutritional information, including calories, protein, fats, carbohydrates, and sodium on the ordering webpage. It also evaluates the nutrition value for each dish and offers a rating. Thus, consumers can easily understand the nutritional status of dishes when ordering food online. This nutrition labeling should be tested by a third-party organization and be made mandatory for both online and offline FAFH services.

Finally, it is important to note several limitations in our study. First, our analysis relies on data from just 52 out of China's 297 cities, as per an agreement with the Keruyun and Ele.me platforms. Given this limited sample, we cannot assert that the data comprehensively reflect all geographic and demographic situations. There may be unrepresented areas or population segments, which bounds our understanding of regional differences in consumer behavior, despite the potential for more in-depth exploration through broader comparisons. This constrained sample may not fully represent the 297-city population and could be influenced by the platforms' market strategies. Nevertheless, Fig. S1 shows the selected cities are widely distributed across China. If the heterogeneity between the selected and remaining cities is time-invariant, our empirical model can account for these differences. To improve the generalizability of the findings, future research should strive for including more capital cities and median and small cities. Second, the changes observed in the total transaction of FAFH could be attributed to both intensive margin and extensive margin. Due to insufficient data, we were unable to discern the specific effects caused by these two factors. Future research should focus on collecting more detailed transaction data to differentiate between these two margins. Potential methodologies include longitudinal studies that track individual customer behavior over time or surveys that gather comprehensive data on consumer preferences and transaction patterns. Third, our study primarily relies on secondary data from one online and one offline platforms, which may not capture the full spectrum of FAFH activities, including informal food services. This limitation could affect the accuracy of our estimates. To address this, future research should incorporate a combination of primary and secondary data sources, such as surveys of both online and offline customers, as well as data from local food service providers. By addressing these limitations and expanding the scope of data collection, future research could provide more comprehensive insights into the factors driving changes in FAFH transactions.

Note

[a] Figure S5 and Table S9 present details of the 52 sample cities, and Table S10 presents the definitions and summarizes the descriptive statistics of all variables used in the empirical analyses.

Acknowledgments

The authors highly appreciate two ele.me project coordinators, Ruidong Zhang and Yue Wang from Rajax Network Technology, for providing data as well as Yinze Zhang from Zhejiang University and Minghui Yao from China Agricultural University for their help in data processing. All errors are their own.

Supplementary Material

Supplementary material is available at *PNAS Nexus* online.

Funding

This study was supported by the National Social Science Foundation of China (22&ZD084), and the National Natural Sciences Foundation of China (72361147521, 72103072, and 72273002).

Author Contributions

X.T. was involved in the conceptualization, analyzed the data, drafted the initial manuscript, and revised it. S.M. was involved in the conceptualization, drafted the initial manuscript, and revised it. J.S. analyzed the data. Q.H. provided valuable comments on the study design and revised the manuscript. D.H. comprehensively revised the manuscript and improved the study design. F.Z. collected the data. X.W. was involved in the conceptualization, funding, and data curation and revised the manuscript.

Data Availability

The FAFH data including high-frequency transaction variables are not publicly available due to a confidentiality agreement with Ele.me. These data are available upon request from AliResearch directly at http://www.aliresearch.com/EN/index or by email from aileen.wl@alibaba-inc.com. The remaining data supporting the findings of this study can be accessed at Science Data Bank: https://doi.org/10.57760/sciencedb.23777, including the air quality dataset (comprising pollution, precipitation, temperature, thermal inversions, etc.), GHG emissions data for various food items, variables used for potential pathways and covariates, and the dietary pattern of FAFH. All empirical analyses were performed with Stata 17, and code for all figures and tables can be accessed at Science Data Bank: https://doi.org/10.57760/sciencedb.23777.

Declaration of Generative AI and AI-Assisted Technologies in the Writing Process

During the preparation of this work, the authors used ChatGPT4.0 in order to correct grammar mistakes and improve the readability of the paper. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

References

1 Lelieveld J, Evans JS, Fnais M, Giannadaki D, Pozzer A. 2015. The contribution of outdoor air pollution sources to premature mortality on a global scale. *Nature*. 525(7569):367–371.

2 Marlier ME, Jina AS, Kinney PL, DeFries RS. 2016. Extreme air pollution in global megacities. *Curr Clim Change Rep*. 2:15–27.

3 Zhang Q, *et al*. 2015. Effects of meteorology and secondary particle formation on visibility during heavy haze events in Beijing, China. *Sci Total Environ*. 502:578–584.

4 IQAir. World air quality report 2022: region & city PM2.5 ranking; [accessed 2023 Mar 14]. https://tech.china.com/article/20230314/032023_1238824.html.

5 Ministry of Ecology and Environment. 2023 China ecological environment status bulletin; [accessed 2023 Jun 5]. https://www.mee.gov.cn/hjzl/sthjzk/zghjzkgb/202406/P020240604551536165161.pdf.

6 Burnett R, *et al*. 2018. Global estimates of mortality associated with long-term exposure to outdoor fine particulate matter. *Proc Natl Acad Sci U S A*. 115(38):9592–9597.

7 Collaborators G, Ärnlöv J. 2020. Global burden of 87 risk factors in 204 countries and territories, 1990–2019: a systematic analysis for the Global Burden of Disease Study 2019. *Lancet*. 396(10258):1223–1249.

8 Landrigan PJ, *et al*. 2018. The lancet commission on pollution and health. *Lancet*. 391(10119):462–512.

9 Zhou M, *et al*. 2019. Mortality, morbidity, and risk factors in China and its provinces, 1990–2017: a systematic analysis for the global burden of disease study 2017. *Lancet*. 394(10204):1145–1158.

10 Ebenstein A, Lavy V, Roth S. 2016. The long-run economic consequences of high-stakes examinations: evidence from transitory variation in pollution. *Am Econ J Appl Econ*. 8(4):36–65.

11 Sun C, Zheng S, Wang J, Kahn ME. 2019. Does clean air increase the demand for the consumer city? Evidence from Beijing. *J Reg Sci*. 59(3):409–434.

12 Hu W, Fang L, Zhang H, Ni R, Pan G. 2023. Changing trends in the air pollution–related disease burden from 1990 to 2019 and its predicted level in 25 years. *Environ Sci Pollut Res Int*. 30(1):1761–1773.

13 Chang TY, Graff Zivin J, Gross T, Neidell M. 2019. The effect of pollution on worker productivity: evidence from call center workers in China. *Am Econ J Appl Econ*. 11(1):151–172.

14 He J, Liu H, Salvo A. 2019. Severe air pollution and labor productivity: evidence from industrial towns in China. *Am Econ J Appl Econ*. 11(1):173–201.

15 Zivin JG, Neidell M. 2012. The impact of pollution on worker productivity. *Am Econ Rev*. 102(7):3652–3673.

16 Archsmith J, Heyes A, Saberian S. 2018. Air quality and error quantity: pollution and performance in a high-skilled, quality-focused occupation. *J Assoc Environ Resour Econ*. 5(4):827–863.

17 Chang T, Graff Zivin J, Gross T, Neidell M. 2016. Particulate pollution and the productivity of pear packers. *Am Econ J Econ Policy*. 8(3):141–169.

18 Chen X, Zhang X, Zhang X. 2017. Smog in our brains: Gender differences in the impact of exposure to air pollution on cognitive performance. IZA Discussion Paper No. 10628.

19 Stafford TM. 2015. Indoor air quality and academic performance. *J Environ Econ Manage*. 70:34–50.

20 Bishop KC, Ketcham JD, Kuminoff NV. 2023. Hazed and confused: the effect of air pollution on dementia. *Rev Econ Stud*. 90(5):2188–2214.

21 Xia X, Yu Y, Zou Y. 2022. Air pollution, social engagement and subjective well-being: evidence from the Gallup World Poll. *Environ Sci Pollut Res Int*. 29(34):52033–52056.

22 Liu J, Zou P, Ma Y. 2022. The effect of air pollution on food preferences. *J Acad Mark Sci*. 50:1–14.

23 Herrnstadt E, Heyes A, Muehlegger E, Saberian S. 2021. Air pollution and criminal activity: microgeographic evidence from Chicago. *Am Econ J Appl Econ*. 13(4):70–100.

24 Cakmak S, Dales R, Leech J, Liu L. 2011. The influence of air pollution on cardiovascular and pulmonary function and exercise capacity: Canadian Health Measures Survey (CHMS). *Environ Res*. 111(8):1309–1312.

25 Chu J, Liu H, Salvo A. 2021. Air pollution as a determinant of food delivery and related plastic waste. *Nat Hum Behav*. 5(2):212–220.

26 Gao X, Song R, Timmins C. 2023. Information, migration, and the value of clean air. *J Dev Econ*. 163:103079.

27 Chew SH, Huang W, Li X. 2021. Does haze cloud decision making? A natural laboratory experiment. *J Econ Behav Organ*. 182:132–161.

28 He X, Luo Z, Zhang J. 2022. The impact of air pollution on movie theater admissions. *J Environ Econ Manage*. 112:102626.
29 An R, *et al.* 2019. Impact of ambient air pollution on physical activity and sedentary behavior in China: a systematic review. *Environ Res*. 176:108545.
30 Saberian S, Heyes A, Rivers N. 2017. Alerts work! air quality warnings and cycling. *Resour Energy Econ*. 49:165–185.
31 Xi B, Dai J, Liu Y. 2022. Does environmental information disclosure affect the financial performance of commercial banks? Evidence from China. *Environ Sci Pollut Res Int*. 29(43):65826–65841.
32 Xi C, YX, Liu X, Zhu C. 2020. Food economy under smog: air pollution and residents' dining behavior. *World Econ Papers*. 6:16–36.
33 Pandey D, *et al.* 2023. Assessing the costs of ozone pollution in India for wheat producers, consumers, and government food welfare policies. *Proc Natl Acad Sci U S A*. 120(32):e2207081120.
34 Andrei JV, *et al.* 2024. Exploring the causal relationship between PM 2.5 air pollution and urban areas economic welfare and social-wellbeing: evidence form 15 European capitals. *Sustain Dev*. 32(5):4567–4592.
35 Baltagi BH, Li D. 2002. Series estimation of partially linear panel data models with fixed effects. *Annals Econ Finance*. 3(1):103–116.
36 Hellweg S, Benetto E, Huijbregts MA, Verones F, Wood R. 2023. Life-cycle assessment to guide solutions for the triple planetary crisis. *Nat Rev Earth Environ*. 4(7):471–486.
37 Wang X, *et al.* 2022. How online food delivery platforms contributed to the resilience of the urban food system in China during the COVID-19 pandemic. *Glob Food Sec*. 35:100658.
38 Zhao F, Wang X, Tian X, Min S. 2024. Asymmetric effects of air pollution on online food delivery before and after COVID-19. *Cities*. 155:105451.
39 Liu X, Rahman T, Wang X. 2024. The effect of urban air pollution on small businesses: evidence from Beijing. *Energy Econ*. 139:107863.
40 Meemken E-M, Bellemare MF, Reardon T, Vargas CM. 2022. Research and policy for the food-delivery revolution. *Science*. 377(6608):810–813.
41 Zhong Y, *et al.* 2024. Carbon emissions from urban takeaway delivery in China. *NPJ Urban Sustain*. 4(1):39.
42 Tessum CW, *et al.* 2019. Inequity in consumption of goods and services adds to racial–ethnic disparities in air pollution exposure. *Proc Natl Acad Sci U S A*. 116(13):6001–6006.
43 Zheng L, *et al.* 2024. Health burden from food systems is highly unequal across income groups. *Nat Food*. 5(3):251–261.
44 China Hospitality Association. 2022 National catering industry report; [accessed 2022 Sep 30]. https://www.toutiao.com/article/7154560222529487394/?\napp=news_article&timestamp=1665.
45 Huaxia Industrial Economy Research Institute. 2023. 2023-2029 China's online delivery industry development monitoring and market development forecast report.
46 Shang W, Yao M, Wang H, Tian X. 2025. A study on the dining out behavior and nutritional intake of adult urban residents in China. *Acta Nutrimenta Sinica*. 47(01):12–18.
47 Qiao C, Zhou Y, Tian X. 2024. Eating patterns and price sensitivity: estimating food demand elasticities for home and restaurant dining in urban China. *The 32nd International Conference of Agricultural Economists*; New Delhi City. IAAE. No. 21990.
48 Tilman D, Clark M. 2014. Global diets link environmental sustainability and human health. *Nature*. 515(7528):518–522.
49 Cai H, *et al.* 2022. Environmental footprints of Chinese foods and beverages: literature-based construction of a LCA database. *Data Brief*. 42:108244.
50 Allen J, *et al.* 2021. Understanding the transport and CO_2 impacts of on-demand meal deliveries: a London case study. *Cities*. 108: 102973.
51 Camps-Posino L, *et al.* 2021. Potential climate benefits of reusable packaging in food delivery services. A Chinese case study. *Sci Total Environ*. 794:148570.
52 Jiang H, Purohit P, Liang Q, Liu L, Zhang Y. 2023. Improving the regional deployment of carbon mitigation efforts by incorporating air-quality co-benefits: a multi-provincial analysis of China. *Ecol Econ*. 204:107675.
53 Tibrewal K, Venkataraman C. 2021. Climate co-benefits of air quality and clean energy policy in India. *Nat Sustain*. 4(4): 305–313.
54 He J, *et al.* 2024. COVID-19 perturbation on US air quality and human health impact assessment. *PNAS Nexus*. 3(1): pgad483.
55 Khomenko S, *et al.* 2021. Premature mortality due to air pollution in European cities: a health impact assessment. *Lancet Planet Health*. 5(3):e121–e134.
56 Shindell D, Smith CJ. 2019. Climate and air-quality benefits of a realistic phase-out of fossil fuels. *Nature*. 573(7774):408–411.
57 Shindell D, *et al.* 2017. A climate policy pathway for near-and long-term benefits. *Science*. 356(6337):493–494.
58 Tang R, *et al.* 2022. Air quality and health co-benefits of China's carbon dioxide emissions peaking before 2030. *Nat Commun*. 13(1):1008.
59 Lachat C, *et al.* 2012. Eating out of home and its association with dietary intake: a systematic review of the evidence. *Obes Rev*. 13(4):329–346.
60 Orfanos P, *et al.* 2009. Eating out of home: energy, macro-and micronutrient intakes in 10 European countries. The European Prospective Investigation into Cancer and Nutrition. *Eur J Clin Nutr*. 63(4):S239–S262.
61 Chen Z, *et al.* 2019. Regional and traffic-related air pollutants are associated with higher consumption of fast food and trans fat among adolescents. *Am J Clin Nutr*. 109(1):99–108.