Air Pollution, Outdoor Activities, and Small Business*

Xiaoou Liu[†] Tauhidur Rahman[‡] Xiangrui Wang[§]

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Abstract

The social cost of pollution avoidance behavior has received less attention. We attempt to shed light on the effect of a particular pollution avoidance behavior, reducing outdoor activities, on small businesses that rely on the customers visiting their premises. We estimate the causal effect of air pollution on business performance of ninety-six restaurants from three groups of chain restaurants in Beijing that have similar characteristics but experience varying levels of air pollution due to their different location. We show that air pollution has an adverse effect on their business performance especially on the weekends, when most people can choose to stay indoors to avoid air pollution since they do not have outside obligations (e.g., work or school). In comparison, the adverse effect on the weekdays, when the opportunity cost of failing to meet outside obligations is high, is relatively weaker and less robust.

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[†]Liu: Renmin University of China. Email: xiaoou.liu@ruc.edu.cn

[‡]Rahman: University of Arizona, USA. Email: tauhid@email.arizona.edu

[§]Wang (Corresponding Author): Renmin University of China. Email: wangxr1020@ruc.edu.cn

1 Introduction

Efforts to mitigate pollution and address environmental challenges often encounter implementation obstacles. Policymakers have to weigh the benefits of a clean environment against the potential costs imposed on polluting industries which often results in economic losses (e.g., reduced output and jobs). However, this may not hold true in all cases. Recent studies provide evidence on adverse effects of air pollution on labor market outcomes, including worker absenteeism and productivity (Hanna and Oliva, 2015; Graff Zivin and Neidell, 2012; Aragón and Rud, 2016; Chang et al., 2016, 2019; He et al., 2019; Hanlon, 2020; Fu et al., 2021), suggesting that some industries may actually economically benefit from pollution control efforts. Small businesses in retail and service sector are a group of stakeholders that have not received due attention in the context of pollution policy debate. Small businesses, especially those that mainly rely on the customers visiting their premises, may draw reduced numbers of customers if there is a pollution-induced decrease in outdoor human activities. Consequently, air pollution can harm their business performance. In this study, we examine it empirically by investigating the effect of air pollution on a particular type of small business: restaurants. We show that air pollution adversely affects the business performance of restaurants. In doing so, we contribute to the growing body of evidence on the benefits of pollution control measures to traditional industries and local economies.

Restaurants make for an ideal focus in our study for several reasons. They are typical a retail and service business, and small-scale enterprises, which are vital to the local economies. Among their other contributions to the local economies, they provide job opportunities to workers especially from poor socioeconomic background, which further underscores the distributional consequences of air pollution. However, they are particularly vulnerable to negative shocks such as reduced customer traffic due to air pollution. Furthermore, restaurant business is undergoing a technological shift with increased integration of gig-economy elements into the traditional business models. For example, home-delivery service is increasingly becoming a vital component of their business[1], providing some business resilience against negative external shocks, which we also examine in this study. Home-delivery service is also becoming important to other businesses in the service and retail businesses (e.g., grocery stores, coffee shops). Thus, our study also sheds lights on the effects of air pollution on other businesses in the service and retail sectors.

Our empirical approach exploits the high-frequency contemporaneous variations in air pollution and business performance of restaurants in the inner city of Beijing. In a sprawling metropolis like Beijing, spatial variations in air pollution exist, primarily driven by mobile sources such as vehicles. We calculate air pollution levels in the vicinity of each restaurant in our sample. Restaurants within a chain share many similarities (e.g., similar business model, management practices, menu of foods, pricing strategies) but experience varying levels of air pollution due to their different locations. To establish a causal link between business performance of restaurants and air pollution, we employ an instrumental variable approach that relies on air pollution originating from neighboring cities carried into Beijing by wind.

We also investigate outdoor human activities as a mechanism of the pollution avoidance behavior that helps in explaining the adverse effect of air pollution on business performance of the restaurants. For this, we introduce local traffic speed as a proxy for local outdoor activities into the estimation of causal effect of air pollution on business performance of the restaurants.[2] Our exploration of this mechanism is motivated by the fact that pollution-induced reduced outdoor human activities may arguably affect other businesses in the retail and service sectors. We analyze the business performance of restaurants separately on the weekends and weekdays. Since most people on the weekends do not have outside obligations (e.g., work or schools), they have more autonomy to decide whether to stay indoors to avoid

[1]There are establishments known as "ghost kitchens" that exclusively cater to home-delivery of food orders. That said, for most restaurants, dining-in service still contributes most revenue. As discussed later, home-delivery account for approximately 15% of revenue in our sample.

[2]Here also we utilize an instrumental variable approach to account for the potential reverse causality between local traffic speed and air pollution. We discuss this in Section 4.2.

air pollution, resulting in a stronger pollution avoidance behavior (i.e., reduced outdoor activities). Consequently, the effect of air pollution on business performance of the restaurants on the weekends is expected to be stronger. In comparison, on the weekdays, most people have outside obligations and not meeting those obligations have higher opportunity costs. Therefore, pollution avoidance behavior is expected to be relatively weaker on the weekdays, resulting in a weaker effect on business performance of restaurants.[3]

Our study yields several key findings. First, we demonstrate that air pollution has a detrimental impact on restaurant revenue during the weekends. Specifically, a one-standard deviation increase in the Air Quality Index (AQI) results in a 2.5% reduction in half-hourly revenue for the sample chain restaurants. Second, we validate avoidance behavior, characterized by reduced outdoor activities, as one of the potential mechanisms driving this adverse effect, although it is not the sole factor. Notably, a one-kilometer-per-hour increase in traffic speed (meaning reduced local outdoor activities), induced by air pollution, leads to an approximately 2.7% revenue loss for the sample restaurant chains during weekends. Third, we find that home-delivery services, powered by the gig economy, do not provide restaurants with a new revenue stream when air quality deteriorates during weekends. Instead, air pollution contributes to a decrease in revenue from home-delivery services. Fourth, when we replicate our empirical analysis using the weekday subsample, we observe that air pollution no longer significantly reduces restaurant business. Reduced outdoor activities are replaced by defensive investments during weekdays, alleviating the negative impact on sample restaurants. Moreover, home-delivery revenue experiences an upswing when air quality declines on weekdays, which can be attributed to time constraints faced by customers.

Our study offers two notable contributions to the existing literature. First, we present the first empirical evidence demonstrating the adverse effects of air pollution on both traditional and emerging business models, particularly those powered by the gig economy, within

[3]We note that on the weekdays, when outdoor activities is deemed to be too costly to forgo, people may opt for defensive investments such as masks and air purifiers.

the small business sector. While recent literature has documented the detrimental impact of air pollution on conventional businesses such as movie theaters, restaurant visits (proxied by online review counts), and grocery shopping (He et al., 2022; Sun et al., 2019; Barwick et al., 2018), the gig economy remains relatively unexplored in this context.[4] The gig economy has become an indispensable component of the contemporary retail and service industry, providing potential alternative revenue streams when traditional business models are negatively affected by air pollution. Moreover, we employ detailed business transaction data, enabling a more comprehensive assessment of business performance. We consider not only revenue but also various other facets, including the number of customers and orders, as well as the intensive margin of business, such as dishes per order and revenue per order, which has not been extensively explored in related literature. Moreover, we employ high-frequency business transaction and air pollution data, allowing us to estimate contemporaneous effect of air pollution on restaurant revenue with a different empirical design.

Additionally, our paper aligns with the stream of literature focused on avoidance behavior in response to air pollution. Since Neidell (2009) first demonstrated that smoke alerts significantly reduce daily attendance at outdoor facilities, recent research has documented passive avoidance behaviors, such as the purchase of masks and air purifiers, particularly when the opportunity cost of outdoor activities is high (Zhang and Mu, 2018; Ito and Zhang, 2020). Recent evidence also suggests that individuals tend to travel or migrate to cleaner areas to evade air pollution (Cui et al., 2019; Chen et al., 2022). In our study, we illuminate how opportunity costs and time constraints influence avoidance behavior by comparing weekends and weekdays. Furthermore, we explore whether the gig economy serves as an additional form of avoidance behavior, enabling consumers to enjoy restaurant food without exposure to air pollution.

[4]There is a growing literature on gig economies such as Uber, Yelp.com, and Airbnb (Luca and Zervas, 2016; Edelman et al., 2017; Cook et al., 2020). Our sample restaurants use online food delivery service providers such as Meituan and Ele.me. The former is listed on Nasdaq, while the latter is a subsidiary of Alibaba Group.

2 Background: Air Pollution, Outdoor Activities, and Restaurant Business

A substantial body of literature in epidemiology and toxicology documents the adverse health effects of air pollution, including respiratory and cardiovascular diseases (Ghio et al., 2000). Children, pregnant women, seniors, and individuals with pre-existing heart and lung conditions are particularly susceptible to these health risks. Not surprisingy, air pollution is increasingly being recognized as a serious public health concern in developing countries, while continues to be a concern in developed countries. The twenty-second annual report of the American Lung Association, "State of the Air", using data from 2017 to 2019, shows that approximately four in every ten Americans breath unhealthy air. Moreover, environmental justice concerns are well-documented. For instance, Tessum et al. (2019) finds that while PM2.5 in the United States results mainly from the consumption of goods and services by the non-Hispanic white populations, it is disproportionately inhaled by black and Hispanic populations.

Pollution avoidance behaviors can generate social costs, beyond adversely affecting labor market outcomes (e.g., labor supply and productivity) and other aspects of life (e.g., school attendance), accruing from defensive investments, temporary and long-term out-migration, and reduced outdoor activities. When reducing outdoor activities have high opportunity costs (e.g., work or school obligations), people may resort to defensive investments (e.g., purchasing facial masks). Zhang et al. (2018) finds that a 100-point increase in the AQI leads to a 70.6% increase in the consumption of anti-PM2.5 masks. Air purifier is another common defensive investment that helps maintain indoor air quality. Ito and Zhang (2020) finds that households are willing to pay $13.4 per year to remove 10 $\mu g/m^3$ of PM10. Some people undertake temporary intercity trips from polluted cities to cleaner ones to avoid air pollution. Using smart-phone location data, Cui et al. (2019) finds that a 10 $\mu g/m^3$

increase in PM2.5 can lead to a 4.7% population flow. Pollution avoidance behavior can also manifest into long-term migration. In a given county, a 10% increase in air pollution can reduce population through net out-migration by approximately 2.8% (Chen et al. (2022)).

In addition to defensive investments and temporary/long-term migrations, reducing outdoor activity is another pollution avoidance behavior. Neidell (2009) provided the initial evidence on reduced outdoor activities as a response to air pollution by showing a negative effect of smoke alerts on daily attendance at outdoor facilities. Reduced outdoor activities can harm businesses that rely especially on the customers visiting their premises. Restaurants are one such business. Reduced outdoor activities can affect both extensive and intensive margins of their business performance. The volume of orders and customers may decrease if potential customers stay indoors to avoid air pollution. Furthermore, group size of restaurant customers may become smaller, which may reduce the economy of scale for ordering larger or more expensive dishes. Thus, a more comprehensive understanding of the social costs of air pollution and pollution avoidance behaviors is important for appropriate and effective pollution control measures.

The impact of air pollution on restaurant industry is expected to vary across its different segments. Restaurants are priced at different levels, offering food and services ranging from necessities to luxury experiences. During periods of elevated air pollution, restaurants that cater to social gatherings and provide medium to high-priced dining experiences can be affected through at least two potential channels. First, reduced number of customers can decrease both the counts of orders and dishes, and the likelihood of ordering expensive items. Second, despite air pollution if some customers choose to dine at restaurants, they may seek better dining experiences to compensate for the unpleasantness of pollution. On other hand, fast-food restaurants that offer low-priced options may attract more customers due to air pollution, including some who may have switched from high-priced restaurants.

The linkage between air pollution, outdoor activities, and business performance of restaurants is expected to be stronger when individual outdoor activity decision is not constrained by outdoor obligations (e.g., work or school), which is more applicable to non-working days (i.e., weekends). In comparison, since most people have outside obligations on the weekdays, the linkage is expected to be relatively weaker. This is because on the weekdays, given outside obligations, the opportunity cost of not meeting them is higher. Therefore, we expect that the effect of pollution-induced decrease in the outdoor activities on business performance of restaurants on the weekdays will be relatively weaker compared to the corresponding effects on the weekends.

Home-delivery services, powered by the gig economy, provide customers an alternative to visiting restaurants to enjoy restaurant food at home. This, in turn, gives restaurants another source of revenue especially during the elevated levels of air pollution. The aggregate effect of pollution avoidance behavior on business performance of restaurants will depend on the dominance of their two components of revenue (in-house dining and home-delivery demands). We note, however, that home-delivery revenue typically accounts for a small proportion of the total revenue, except for “ghost kitchens” that exclusively offer home-delivery services. Furthermore, the profit margin of home-delivery service is lower than that of in-house dining service, as the platforms organizing home-delivery charge a fee.[5]

Last but not least, discouraging outdoor activities is not the only potential mechanism through which air pollution can affect businesses that rely mainly on customers visiting their premises. Air pollution can also lead to anxiety, depression, and loss of appetite (Power et al., 2015; Simmons et al., 2016; Pun et al., 2017; Simmons et al., 2020), which can adversely affect business performance of restaurants. However, we do not explore these mechanisms due to data limitations.

[5]In addition, the quality of food delivered at home may not match the quality of food served at restaurants (e.g., freshness of food). Also, food delivery riders may experience productivity loss especially during elevated levels of air pollution (Wang et al., 2022).

3 Data

We utilize data from multiple sources. It includes data on 96 restaurants from three restaurant chains (Chain A (18 stores), B (24 stores), and C (54 stores)) in Beijing; local traffic, air pollution, and weather in the surroundings of the restaurants; and air pollution in the neighboring cities of Beijing that we utilize to construct an instrument variable for local air pollution in Beijing. We combine them to construct a comprehensive high-frequency dataset at the restaurant level.

3.1 Restaurant Data

Our sample of 96 restaurants are from three restaurant chains (A, B, C).[6] The average price per customer at Chain A, B, and C is 94, 129, and 40 CNY (equivalent to 13, 18, and 6 U.S. Dollars), respectively. Chain A serves traditional Chinese food, priced at medium level. Chain B serves more expensive fish and seafood. Chain C mainly serves fast food, such as noodles, fried rice, and porridge. The average number of customers per order are 2.2, 3.9, and 1.2 for the three chains, respectively. Chain A and B are open for approximately 11 hours a day, focusing on both lunch and dinner. Chain C serves breakfast as well. Therefore, it is open for more than 11 hours a day. Our sample of restaurants are located in the inner city of Beijing (Figure 1), which is an important consideration for our empirical strategy (see Section 4). Data from Chain A covers the period of 2017 to 2019, whereas data from Chain B and C covers the period of 2018 to 2019.

We chose to analyze the business performance of chain restaurants for several important

[6]Our sample of restaurants account for account for 0.2% of the restaurants in Beijing. Chain A, B, and C are much smaller compared to other restaurant chains. For example, KFC, McDonald's, and Pizza Hut have 325, 284, and 197 stores in Beijing, respectively. Our sample chains are also small compare to chain restaurants serve similar Chinese cuisine such as "沙县小吃"(394), "呷哺呷哺"(292), "张亮麻辣烫"(221), "田老师红烧肉"(193), just to name a few. Our sample of restaurants are very similar to other non-chain restaurants, which is an important consideration for the external validity of our study.

empirical considerations. First, with chain restaurants, we mitigate potential confounding factors related to differences in their business models, strategies, and management practices, which are almost identical across restaurants within a chain. This helps in more clearly isolating the effect of air pollution from other factors. Second, given that the three chains differ in their characteristics, we estimate the effect of air pollution on their business performance separately after estimating the aggregate effect. This provides insights into external validity of our findings and the heterogeneous effects of air pollution on different segments of the dining industry.[7]

We use three distinct but related measures of the business performance of the restaurants (Table 1). The first one is half-an-hourly revenue. The average half-an-hourly revenue is 1789.5, 2419.7, and 634.5 CNY, respectively for the three chains. A change in revenue of a restaurant is a good approximation of a change in its profit, which is a welfare measure. The difference between revenue and profit includes fixed cost (e.g., rent), quasi-fixed cost (e.g., utility bills and salaries of employees who are normally under monthly contracts), and variable cost (food ingredients). Given our half-hour data structure, we can control restaurant and time fixed effects at a high frequency, which can absorb the fixed costs. Regarding the variable cost, we can reasonably assume that a large share of it is for perishable ingredients that must be used in any given day, otherwise they will be wasted.

The second measure of the business performance is the extensive margin, captured by order and customer counts. The average half-an-hourly order count is 8.5, 4.8, and 13.4 for the three chains, respectively. The average half-an-hourly customer count is 19.05, 18.73, and 15.95, respectively. Our third measure of the business performance is the intensive margin, captured by revenue per order, revenue per dish, dishes per order, and dishes per customer. These provide insights into potential economies of scale. For instance, a large customer group can share more, larger, and more expensive dishes. The effect of air pollution on

[7] From the box-cox plots of the main measures of the business performance of restaurants, we observe distinct patterns (Appendix Figure A1).

the intensive margin is theoretically ambiguous and it is, therefore, an empirical question, depending on customer behavior in response to pollution-related discomforts.

3.2 Pollution

We obtained our air pollution data from the China National Environmental Monitoring Center, which is affiliated with The Ministry of Ecology and Environment of the People's Republic of China (中华人民共和国生态环境部). This data includes information on several air quality parameters, including the Air Quality Index (AQI), fine particulate matter (PM2.5), particulate matter (PM10), nitrogen dioxide (NO2), ozone (O3), sulfur dioxide (SO2), and carbon monoxide (CO). Descriptive statistics for these air pollution measures are presented in Table 2.

To calculate the half-hourly air pollution in the surroundings of the restaurants, we match their locations to the air pollution readings from nearby monitoring sites. To minimize measurement errors, we compute distance-weighted pollutant readings from the three nearest pollution monitoring sites (Figure 2). The average distances between a restaurant and its three closest pollution monitors are 3.2, 5.3, and 6.8 kilometers, respectively. We also construct two alternative measures of air pollution in the surroundings of the restaurants using the reading from the closest monitor, and averaging the readings from the three closest monitors, respectively. Our results are robust to these alternative measures of air pollution(Appendix Table A2). Therefore, we discuss the results using the distance-weighted air pollution, since it is our preferred measure of air pollution surrounding a restaurant.

AQI is a composite measure of air pollution that takes into account PM2.5, PM10, NO2, O3, SO2, and CO. While PM2.5, PM10, NO2, and O3 are more visible pollutants than SO2 and CO, AQI is more appropriate for our analysis given that it is a composite measure and has widespread accessibility. For instance, AQI is accompanied with colored grades that indicate levels of air quality.[8] In contrast, interpreting specific pollutants is challenging for people if they are not familiar with them and their different threshold levels. Therefore, we discuss the results using AQI.[9] However, we also separately estimate the effects of specific pollutants to gain further insights into the effects of air pollution on local traffic speed and business performance of restaurants. The results using the visible pollutants are consistent with those obtained using AQI (Appendix Table A3), which is expected since the visible pollutants are more strongly correlated with AQI.

Figure 3 shows the distribution of AQI in Beijing. We plot the kernel density of hourly AQI for the years 2017, 2018, and 2019.[10] The AQI is rated on a scale: 0 to 50 (Excellent), 51-100 (Good), 100-150 (Unhealthy for sensitive individuals), 151-200 (Moderately polluted), 200-300 (Heavily polluted), and above 300 (Severely polluted). The distributions are positively skewed, meaning that the mean AQI is higher than the median AQI. Approximately 15% of the distributions fall into the "Unhealthy for sensitive individuals" category, even though air quality improved between 2017 and 2019.

Figure 4 provides a closer look at the distribution of AQI in the inner city of Beijing. Panel (a) shows the contour of average AQI, while panel (b) displays the contour of the number of unhealthy days (AQI $\geq$ 150) between 2017 and 2019. The southern and eastern parts of the city experienced more severe air pollution, possibly due to the presence of the airport and railway stations, as well as the prevailing wind direction (from the north and northwest). More importantly, our sample of restaurants are located in the areas with the varying levels of air pollution.

[8]The 2014 revision of the Environmental Protection Law of China required central, provincial, and local governments to disclose ambient air quality data.

[9]Studies on health effects of air pollution have analyzed the effects of the pollutants separately since they represent different types of health risks and consequences.

[10]Distributions of the six pollutants are reported in Figure A2, which are similar to the distribution of AQI.

3.3 Traffic

We obtained traffic data for 2017-2019 from the Beijing Municipal Commission of Transport (BMCT). This dataset contains high-frequency information on average real-time traffic speed (in kilometers per hour), categorized by administrative districts and road rings. The data is collected using sensors installed on passenger cars, primarily taxis, registered with the municipal service. These sensors monitor traffic conditions and send real-time information on vehicle speed and geographic location to the BMCT. We aggregated this data by administrative districts and road rings to calculate the average speed at 30-minute intervals. This restaurant-level measure of traffic speed serves as a proxy for local outdoor activities and captures customer traffic to the corresponding restaurants.

Figure 5 shows the traffic speed data by districts and road rings. The average speed is approximately 35.7 kilometers per hour. On weekdays, traffic peaks during two periods: 8:00-9:00 AM and 6:00-7:00 PM, with speeds dropping to around 22.8 kilometers per hour during these peak hours, which is about 63.9% of the average speed. In contrast, traffic on weekends follows a smoother pattern, with the slowest speeds recorded during 5:30-6:30 PM. The traffic patterns by road rings and administrative districts exhibit striking similarities. We provide additional descriptive statistics in Table 2.

There are significant variations in traffic speeds across districts and road rings. This suggests that the restaurants in our sample experience varying levels of customer traffic depending on their locations. For instance, the Dongcheng and Xicheng districts, situated in the city center, have the slowest speeds but relatively stable traffic, indicating consistently high customer traffic. In contrast, Chaoyang district exhibits the largest speed variance, likely due to its extensive coverage, spanning from the 2nd to the 6th road ring and encompassing Beijing Capital Airport (PEK). Regarding speed variance across road rings, the outermost road ring, farther from the city center, generally has the fastest speeds, implying lower customer traffic levels. However, the difference in traffic speeds between road rings decreases as the day progresses from morning to night.

Since early 2000s when air pollution worsened, Beijing has implemented comprehensive traffic regulations aimed at reducing congestion and pollution. These measures, especially those enacted after 2011, are of particular relevance to our study as they imposed restrictions on vehicles entering the inner city of Beijing.[11] Non-local vehicles are required to obtain a temporary certificate (进京证) with validity ranging from seven days to six months to drive within the 6th road ring of the city, and they are prohibited during peak traffic hours (7:00-9:00 AM and 5:00-8:00 PM). Violating these restrictions results in monetary penalties and a 3-point deduction from a driver's 12-point license. Non-local vehicles also have to adhere to rules designed for local vehicles. These regulations became even stricter in 2014, with the validity of temporary certificates reduced to seven days, with the possibility of a five-day extension. These measures were in effect during the period of our study (2017-2019). These contributed to variations in traffic speed and air pollution in the inner city of Beijing. We exploit these variations to identify and estimate the causal effects, using the instrumental variable (IV) approach, of air pollution on business performance of restaurants (Section 4).

3.4 Weather

We obtained weather data from the National Oceanic and Atmospheric Administration (NOAA) of the United States, which includes information on temperature, precipitation, wind speed, and wind direction. Weather conditions are known to influence individual decisions regarding outdoor activities. Therefore, in our estimation of the effect of air pollution on business performance of restaurants, we control for weather effects. Descriptive statistics of the weather variables are in Table 2.

We utilize data on wind direction and speed, in conjunction with air pollution levels

[11] Beijing also introduced regulations limiting the registration of vehicles within the city. For additional details, please refer to Wang et al. (2014) and Viard and Fu (2015).

in neighboring cities of Beijing, to construct an instrumental variable (IV) for air pollution in the surroundings of the restaurants (see Section 4). Wind direction is divided into 16 sectors, with each sector representing a 22.5-degree angle (Figure 6, (a)). The prevailing wind direction in Beijing is north, accounting for approximately 14.5% of the observations. The average wind speed is 2.69 meters per second, equivalent to 232.4 kilometers per day. Using this average wind speed, we establish a buffer zone (Figure 6, (b)) to determine the list of nearby cities to be employed in the construction of the IV.

4 Empirical Methodology

Our empirical methodology consists of two main components. First, we specify a reduced-form model to estimate the contemporaneous effects of air pollution on business performance of restaurants. Second, we specifically examine pollution-induced change in local outdoor activities as the mechanism linking air pollution with business performance of restaurants.

4.1 Air Pollution and Business Performance of Restaurants

We specify a reduced-form regression to estimate the contemporaneous effect of local air pollution on business performance of restaurants. Our regression takes the form of an additive linear regression equation:

$$Y_{rt} = \eta_1 \cdot [LP_{rt}] + \underbrace{W_{rt} \cdot \Phi + \mu_r + \delta_t}_{Q_{rt}\Xi} + \xi_{rt} \tag{1}$$

where r and t denote restaurants and time (at a half-an-hour interval), respectively. Y_{rt} is business performance of restaurants (i.e., revenue, extensive margin, and intensive margin).

LP_{rt} is local air pollution. W_{rt} is weather variables.[12] μ_r is restaurant fixed effects. δ_t is a set of date and time fixed effects: year, month, day of week, and half-an-hour time interval. The high-frequency fixed effects allow η_1 to capture the effect of contemporaneous local air pollution on business performance of restaurants.[13]

There are potentially several challenges to identification of η_1 in equation (1) as the causal effect of air pollution on business performance of restaurants. First, if there is potential "sorting" problem, when restaurants select into locations based on air pollution, then the air pollution in the surroundings of the restaurants can be nonrandom. However, we believe this is not a concern in our context. Because a restaurant location is a long-term decision, determined by considerations including potential demand, competition, availability of space, and rent. Therefore, the influence of air pollution on a restaurant location decision is unlikely to be substantial, unlike its well-documented roles in household decisions (e.g., residential sorting). In addition, our sample of restaurants are from three chains, which have well-defined protocol for location choice that each store must follow.[14]

Second, if there is measurement errors in the local air pollution, it can lead to attenuation bias in the estimation of equation (1). However, air pollution typically suffers from such errors if it is measured at larger units of analysis (e.g., counties in the US) and when

[12]Conceptually, weather variables should be a restaurant level, but weather data at restaurant level, measured half-an-hourly interval, is not available. Therefore, in empirical estimation of the model, we include weather variables that measured at city level measured at every 1 hour. We believe this is not a serious limitation for the following reasons.First, given that our sample of restaurants are located in the inner city of Beijing, meteorological variation across them is expected to be small. Second, potential weather variation at restaurant level is absorbed by the restaurant fixed effects that we include in our model.

[13]Restaurant fixed effects control for fixed cost (e.g., rent) and other unobserved time-consistent factors that may affect the traffic speeds surrounding restaurants and business performance of restaurants. Variation in semi-fixed cost across restaurants (e.g., utilities and salaries paid for chefs, waiter, and waitress) is controlled by a combination of restaurant and time fixed effects. We assume that restaurants do not save on utility expenses due to air pollution. We also assume that restaurants do not lay off employees due to contemporaneous change in customer traffic, which holds given that employees are under monthly contract. Regarding variable costs, especially the cost of ingredients, we note that most fresh ingredients are perishable and cannot be reused again.

[14]From a microeconomics prospective, food supply decision of a restaurant is not affected by variation in air pollution in its surroundings. Restaurants must plan for the food that they serve so that the ingredients can be prepared. Therefore, food supply decision of a restaurant is mainly driven by expected customer traffic and holiday shocks, among demand-supply factors.

pollution monitors are sparsely distributed. As a result, attributing a monitor reading to an exact location is challenging (Deryugina et al., 2019). Also, frequent changes in wind direction and speed can lead to measurement errors. In our case, this is less of a concern because each restaurant is paired with pollution monitors in its close proximity (Section 3.2). Nevertheless, we utilize an IV design, which further minimizes the potential measurement error concerns. Another potential measurement error can occur in the calculation of AQI, which is a composite index of major pollutants. Therefore, we estimate also the effects of each pollutant on the business performance of restaurants, serving as a robustness check for the results obtained from using AQI.

Third, potential reverse causality between the business performance of restaurants and air pollution in their surroundings can also bias our estimates. For example, restaurants can emit pollutants because of cooking, especially those cooked on outdoor grills. But the restaurants in our sample mainly serve stir-fry, soup, seafood, and cooking is done indoors, where emission is not intense. More importantly, in the densely populated inner city of Beijing, emission from a restaurant is unlikely to make much difference to air pollution in its surrounding, given other major pollution emitting activities. A restaurant can also attract customers traveling by personal vehicles, which can add to local air pollution. But, again, the share of local air pollution that can be attributed to vehicles drawn by a restaurant is likely marginal, especially given other major factors of local traffic. It is possible that an individual "star" restaurant can make a difference to air pollution in its surrounding by virtue of being a star attraction. While the restaurants in our sample are popular, they are not "star", vintage restaurants that can drive local traffic. That said, the results from Chain A are further validated by the results from Chain B and C.

Fourth, if there are restaurant-level time-variant unobservable factors, they can bias our estimates. For example, it is possible that market condition can change sharply for only a subset of the restaurants in our sample. However, this is unlikely given the maturity of the business environment in the inner city of Beijing. In addition, there are occasional events in the restaurant industry such as successful promotions or notorious customer complaints that may affect individual restaurants. But, such events, due to media coverage, turn a restaurant-level time-variant unobservable into a common time trend for the entire restaurant chain.

Finally, economic shocks that can affect the overall economic activity in Beijing is another potential concern for the identification of the causal effects. Such shocks may include major sporting, cultural, and educational (e.g., the beginning and closing of school terms) events that may cause abnormal surges in the demand for restaurants. Tourism can also create a surge in demand during holidays in Beijing since it is a tourist destination. Conversely, during Spring Break, roughly a 14-day traditional national holiday, families from Beijing leave for their original hometowns to reunite with relatives, resulting in an abnormal fall in demand for restaurants. We address these concerns by dropping national holidays from our data and analysis. Smaller unusual shocks can be absorbed by time fixed effects when restaurants in a chain are affected similarly. Moreover, our analysis of the business performance of three chains offers us the opportunity to test if unusual economic shocks affect the different segments of the dining industry differently.

4.1.1 IV Estimation

While we have reasoned that the preceding potential challenges are not serious concerns in our case, we estimate the equation (1) with the IV approach. To compare, we also present OLS results. Following the strategies employed by recent studies on social cost of air pollution (Schlenker and Walker, 2016; Deryugina et al., 2019; Herrnstadt et al., 2020), we construct an exclusive IV for local air pollution that captures the air pollution carried into Beijing by wind from its neighboring cities.[15] A valid IV must be strongly correlated with

[15] Another popular IV strategy to study the effects of air pollution is thermal inversion, which has most significant impacts on air pollution in urban valleys. Since Beijing is a windy city located at plain, we adopt a different IV strategy. Moreover, thermal inversion normally occurs during night when restaurants are closed. As a result, we may fail to capture the contemporaneous relationship between air pollution and business performance of restaurants.

LP_{rt} and it cannot directly affect business performance of restaurants, Y_{rt}. Pollution from the neighboring cities contributes to local air pollution in Beijing, which then has effects on business performance of restaurants. More specifically, our first stage regression model is as follows:

$$LP_{rt} = \beta_1 \cdot \frac{1}{\sum_{n=1}^{16} \mathcal{I}\{WD_{nt} = d_n\}} \cdot \sum_{n=1}^{16} \frac{WS_{nt} \cdot NP_{nt}}{D_{rn}} \cdot \mathcal{I}\{WD_{nt} = d_n\} + Q_{rt}\Xi + u_{rt} \qquad (2)$$

where n denotes 16 directions of neighboring cities and the other subscripts are the same as in equation (1). Figure 6 provides a graphic depiction of equation (2). When wind directions of the neighboring cities (WD_{nt}) are towards Beijing (d_n), their pollution (NP_{nt}) becomes a part of the exclusive IV. To construct the IV, we also use the wind speed at neighboring cities (WS_{nt}) and the distance between rth restaurant and nth neighboring cities (D_{rn}) as weights.

For a valid IV strategy, exogeneity restriction and relevance condition also must be met (Angrist et al., 1996). The exogeneity restriction is satisfied because the contemporaneous wind speed and direction are natural forces. Behind the relevance condition is the spatial exchange of pollutants, which captures both spatial and temporal serial correlations of pollution. We test the relevance condition and provide the result in Table 3. We also provide regression results of equation (2) for both AQI and various pollutants. Adjusted R^2 corresponding to different pollutants are greater than 0.15 and the p-values of joint F-tests are less than 0.01. We also check the Montiel Olea and Pflueger (2013) F-statistic for weak instrument (Andrews et al., 2018).

4.2 Mechanisms

Here we turn to exploring the mechanisms of air pollution's effect on the business performance of restaurants. In particular, we examine pollution-induced change in local traffic speed (our proxy for local outdoor activities) as a mechanism through which air pollution affects the business performance of restaurants. We conduct the analysis in two steps: we first estimate the causal effect of local air pollution on local traffic speed. Then we generate pollution-induced changes in local traffic speed to estimate its effects on the business performance of restaurants.[16]

4.2.1 Effect of Air Pollution on Outdoor Activities

Since air pollution discourages people's outdoor activities (see Section 2), during elevated levels of air pollution, there could be less people on the road and, as a result, less traffic congestion, which means relatively faster traffic speed. Conversely, local traffic congestion (meaning relatively slower traffic speed) can also contribute to local air pollution (Knittel et al., 2016). At any given time, a higher level of traffic congestion will be positively correlated with a higher number of vehicles on the road. This, in turn, means more fuel will be burnt and more tires will be on the road. Traffic congestion can also increase the amount of pollution added by individual cars, given that efficiency of an automobile is related to speed and continuity of driving (Davis and Diegel, 2007). Since traffic congestion leads to slower speed, meaning more time on the road to travel the same distance and, therefore, more fuel burned for each kilometer traveled. Thus, the identification of the causal effect of local air pollution on local traffic speed is not straightforward. It can get more complicated for the following two additional reasons. First, if unhindered traffic flow is moving at speeds above

[16] In Appendix 9.1, we also use regression to test whether reduced outdoor activities, induced by air pollution, is a mechanism underlying the adverse effect of air pollution on restaurant business. We confirm it is a mechanism, but not the unique one. Potential alternative mechanisms include but not limit to the anxiety, depression and loss of appetite caused by air pollution. We thank an anonymous referee for this comment.

the range of highest efficiency, mild amounts of traffic that slightly lower traveling speed can increase engine efficiency and decrease emissions (Davis and Diegel, 2007). Second, severe air pollution can reduce visibility, which can result in slower traffic speeds and more pollution.

To estimate the causal effect of local air pollution on local traffic speed, we adopt the following additive linear regression model and estimate it with an IV approach:

$$T_{rt} = \alpha_1 \cdot [LP_{rt}] + \underbrace{W_{rt} \cdot \Phi + \mu_r + \delta_t}_{Q_{rt}\Xi} + e_{rt} \tag{3}$$

where index r and t denote a restaurant and time, respectively. T_{rt} is traffic flow in the neighborhood of a restaurant r, measured by average traffic speed (kilometer/hour). LP_{rt}, W_{rt}, μ_r, and δ_t are same as in equation (1). e_{rt} is idiosyncratic errors. The parameter of interest is α_1, the effect of local air pollution on local traffic speed. The expected sign for α_1 is positive.

For the reasons highlighted above, it is possible that LP_{rt} in equation (3) is endogenous. Therefore, a panel fixed-effects estimation of the equation may produce a biased estimate of α_1. Thus, we need a valid IV that is strongly correlated with LP_{rt} without directly affecting T_{rt}. We use the IV described in equation (2).

The exclusion restriction condition can be violated if traffic is exchanged frequently between Beijing and its neighboring cities, because vehicle emission is an important source of air pollution. For instance, traffic from the neighboring cities that enter Beijing may be the factor behind potential correlation between the exclusive IV and local traffic in Beijing, primarily because it also contributes to air pollution. The reverse will be also valid if there are outflows of traffics from Beijing to its neighboring cities. To overcome these potential challenges, we adopt the following strategy. First, as described earlier, we take advantage of the fact that as a part of its pollution control plan, Beijing strictly controls traffics from the neighboring cities entering the inner city. Second, major traffic outflow from Beijing to the neighboring cities occurs during holidays. Therefore, we have excluded holidays data from our analysis. Our justification for the exogeneity and relevance conditions for the validity of IV has discussed in Section 4.1.

4.2.2 Effect of Pollution-Induced Outdoor Activities on Restaurants

We use the predicted values of LP_{rt} from equation (2) to estimate the effect of LP_{rt} on T_{rt} the pollution-induced change in local traffic speed, a proxy for outdoor activities. Then, to estimate the effect of pollution-induced change in local outdoor activities on the business performance of restaurants, we estimate the following regression equation:

$$Y_{rt} = \theta_1 \cdot \hat{T}_{rt} + W_{rt} \cdot \Psi + \mu_r + \delta_t + \epsilon_{rlt} \tag{4}$$

where Y_{rt} is business performance of restaurants, the same as in equation (1). $\hat{T}_{rt}$ is the predicted local traffic speed from two-stage estimation of equation (3). ϵ_{rt} is idiosyncratic error. The remaining notations are consistent with the preceding equations. Our parameter of interest is θ_1. Our reasoning for this effect is as follows. Air pollution discourages people from outdoor activities, which means less potential customers on the road. As a result, there will be less traffic congestion, which means an increase in traffic speed. Thus, we expect θ_1 to have negative sign on restaurant revenue on the weekends. On the weekdays, the negative effect is expected to be much smaller or insignificant, largely because most people have outside obligations. Therefore, the pollution-induced decrease in demand for restaurants is expected be smaller than what is expected on the weekends.

5 Results

We start by presenting the results on the effects of air pollution on the business performance of restaurants, from the estimation of the model in Section 4.1. Then we present the results from the core part of our analysis, the mechanism linking air pollution with the business performance of restaurants, from the estimation of the model in Section 4.2. This is followed by the results from the analysis using weekdays data, where we explore whether the mechanism, the pollution-induced change in local outdoor activities, works differently when most people have outdoor obligations.

Our analysis highlights an easy-to-overlook but persistent effect of air pollution. In Appendix Figure A3, we show the pattern between restaurant revenues and sharp changes in air pollution (i.e., AQI) occurred on the consecutive days. Panel (a) shows the pattern for the medium-priced restaurants, from Chain A, using the weekend data, in which two revenue bars are a matched pairs (dates on the horizontal axis) of two consecutive days. While the green bar corresponds to low AQI, the red bar to high AQI. When AQI increases sharply (shown by dashed plot along the right axis), the revenue drops in most cases, shown by the green bars that are taller than the red bars. In contrast, this pattern does not hold for the weekdays, shown in Panel (b), where it is more ambiguous. This suggests that the mechanism of air pollution's effects on the business performance of restaurants may differ from the weekends to the weekdays. In Appendix Figure A4, we compare restaurant revenues on severe air pollution days ($AQI > 300$) to those under excellent air quality ($AQI < 50$), where we plot the average half-an-hourly revenue of the restaurants from Chain A. It is clear that the revenue is lower under severe air pollution, particularly around dinner time. This result is strongly corroborated by our more rigorous analysis, discussed below.

5.1 The Effects of Air Pollution on Restaurant Business

Table 3 shows the effect of air pollution on revenue, measured at every half-an-hour, of 96 restaurants from three chains on the weekends.[17] From Column (1), we find that air pollution has a significant negative effect on restaurant revenue. More specifically, if AQI increases by 10 units, the half-hourly revenue declines by 2.51 CNY. In Column (2), we investigate nonlinear effect of air pollution, where we check for the effects of unhealthy levels of AQI.[18] The corresponding loss in half-hourly revenue are 41.55 CNY and 41.37 CNY (equivalent to 2.5% and 2.6% decline) compared to healthy level of AQI. However, the difference between the estimated effects of two unhealthy AQI levels is statistically insignificant. Column (4) presents the first-stage of the IV estimation, showing the statistical significance of our IV, where one unit increase in AQI of the neighboring cities of Beijing leads to 0.09 unit increase in local restaurant-level AQI in Beijing. Column (3) reports the IV estimate of the effect of air pollution on restaurant revenue. From it, we note that if AQI increases by 10 units, the half-hourly revenue decreases by 6.43 CNY, which is approximately 2.6 times of the corresponding OLS estimate.

[17] Appendix Table A1 - A3 show the results on model specification and alternative measurements of AQI. In Table A1, we check for the effects of different specifications of contemporaneous weather controls. Column (1) - (3), respectively, use linear, quadratic, and bins of temperature, precipitation, and wind speed. The results are robust across three specifications. Therefore, we use bins as our preferred specification, given its advantages for controlling nonlinear weather variation. In Table A2, we test the effects of alternative measurements of local AQI. In Column (1), we have our preferred measurement of AQI, where local AQI for each restaurant is calculated as a distance weighted average of the readings from the three nearest pollution monitors. In Column (2), local AQI is the simple average of the readings from the three nearest monitors. In Column (3), it local AQI is the AQI from the reading of the nearest monitor. As we can see, the results are robust across the three alternative measurements, with slight changes in the estimated magnitudes. In Table A3, we check for the effects of specific air pollutants on restaurant revenue. The effects of more visible pollutants (PM10 and PM2.5), in Column (2) and (3), are similar to the AQI results.

[18] We use AQI categories of bins as defined by Ministry of Ecology and Environment of the People's Republic of China (中华人民共和国生态环境部): 0 to 50 (Excellent), 51-100 (Good), 101-200 (Moderately Polluted), 201-300 (Heavily polluted), and above 300 (Severely polluted). The risks to health increases if AQI level is moderately polluted. If AQI is in the range of heavily to severely polluted, it risks respiratory symptoms even for healthy people, among other health risks. As a result, outdoor activities, including going out to restaurants. To test it, we replace the linear AQI variable in Equation (1) with three binary variables representing three different categories of AQI: "Healthy" ($AQI < 100$), "Unhealthy for Sensitive Individuals" ($100 <= AQI < 150$), and "Unhealthy" ($150 <= AQI$). The "Healthy" category serves as the comparison group.

In Table 4, we present and compare the effects of air pollution on business performance of restaurants on the weekends by chains. Column (1) shows the IV estimates of the effects of air pollution on their half-hourly revenue. Accordingly, if AQI increases by 10 units, the revenue declines by 11.57 (0.6% of the average) and 16.35 (0.7%), respectively, for Chain A and B. That is, one standard deviation of AQI (62.17 from Table 2) can lead to annual revenue loss on the weekends alone by 1.6 and 2.9 million CNY, respectively, for Chain A and B. In comparison, while the corresponding effect on Chain C is negative, it is statistically insignificant. Together, these results suggest that the adverse effect of air pollution is particularly significant for medium to high priced restaurants. An explanation is the possibility of substitution effects in the demands for the three chains since they are differently priced. In other words, it is likely that during elevated levels of air pollution, some customers cancel their plans for group gathering at the medium or high-priced restaurants (i.e., Chain A and B), but given that they need to eat, some of them may individually opt for low-priced restaurants (i.e., Chain C, which on average draws 1.2 people per order).[19]

Table 4 also shows the results on air pollution's effects on extensive and intensive margins. For Chain A and B, we find that the adverse effects of air pollution mainly pass through the extensive margin, captured by order (Column (2)) and customer (Column (3)) counts. More specifically, the marginal effects of 10 units increase in AQI for Chain A are -0.04 (0.5% of the average) on the order count and -0.14 (0.7% of the average) on the customer count. Similarly, the corresponding effects for Chain B are -0.04 (0.8% of the average) and -0.15 (0.8% of the average). The effects on intensive margin for Chain A and B, shown in Column (4)-(7), are either economically or statistically insignificant. For Chain C (low-priced restaurants), we find mixed results regarding extensive margin, where if AQI increases by 10 units, the order count increases by 0.05 (0.4% of the average), but it has no effect on the customer count. This suggests that customers may be going individually to Chain C, as opposed to group gathering, which is more common to Chain A and B. Regarding the effects

[19] We calculate average customers per order using count of daily orders and customers from Table 1.

on the intensive margin of Chain C, the results are mixed as well. Dish per order increases by 0.014 (0.3% of the average) if AQI increases by 10 units, but the corresponding effects on revenue per order and revenue per dish are -0.14 (0.2% of the average) and -0.06 (0.4% of the average), respectively. This further corroborates our reasoning that for Chain C the demand for food increases, though not necessarily the more profitable ones.

5.2 Mechanism

Here we present the results from the estimation of the model discussed in Section 4.2, in which local outdoor activities, proxied by local traffic speed, is explored as a mechanism of the effects of air pollution on the business performance of restaurants. More specifically, we first estimate the effect of local air pollution on local traffic speed. Then we generate pollution-induced change in local traffic speed to estimate its effect on the business performance of restaurants. In both steps, as discussed in Section 4.2, IV estimation approach is utilized.

Table 5 presents the results using data of the 96 restaurants from three chains. Column (1) has OLS result from the estimation of equation (3), which shows that local air pollution leads to faster local traffic speed which means reduced outdoor human activities. Column (2) shows the IV result, where we use an IV for local air pollution constructed as described in Section 4.2. The IV estimate (0.06) is slightly smaller than the OLS estimate (0.07). Accordingly, one standard deviation of local AQI (62.17 from Table 2) can lead to 1.2% increase of traffic speed. Column (3) and (4) compare the OLS and IV estimates of the effects of local traffic speed on revenue. The marginal effect of the pollution-induced increase traffic speed (i.e., decrease in local outdoor activities) on revenue is -44.4 CNY (2.7% of the average).

Table 6 reports the effects of pollution-induced change in local traffic speed on the business performance the restaurants by chains. From Column (1), we find that a 1 km/hour increase in pollution-induced local traffic speed (means reduced outdoor human activities and local customer flows to restaurants) reduces half-hourly restaurant revenues by 75.72 (4.2% of the average), 177.4 (7.3% of the average), and 9.03 (1.4% of the average) of Chain A, B, and C, respectively. To put these estimates into magnitudes, 1 km/hour increase in pollution-induced traffic speed (11.1% of standard deviation, which is 8.98 in Table 2) can lead to annual revenue loss during weekends alone of 1.9, 4.9, and 0.9 million CNY by Chain A, B, and C, respectively. There are concerns the fact that traffic speed is not a perfect measurement of customer flow, which can further complicate the interpretation. When traffic speed is high, it is easier for customers to reach restaurants during air pollution. This scenario should result in an underestimation of the adverse impact of reduced outdoor activities on restaurants.

Table 6 also presents the effects of pollution-induced change in traffic speed on the extensive and intensive margins of restaurant revenue. For Chain A (medium priced), the adverse effects of pollution-induced decrease in local traffic speed on two measures of the extensive margin (order and customer counts) are 0.28 (3% of the average) and 0.87 (4.5% of the average), respectively. The corresponding adverse effects for Chain B (High priced) are much larger at 0.41 (8.6% of the average) and 1.58 (8.4% of the average). The estimated effects on the measures of intensive margin are significant for Chain A and they are much smaller than the effects on extensive margin. Whereas the effects on the measures of intensive margin for Chain B are insignificant. For Chain C (low priced), the effect on the customer count is negative and significant, but there is no significant change in the order count. Also, when air pollution worsens, more dishes per order and per customer are placed, they tend to be less expensive ones, as reflected in the negative effects on revenue per order and per dish, respectively.

5.3 Effects of air pollution on restaurant business on the weekdays

To shed further light on pollution-induced decrease in outdoor activities as one of the mechanisms of the adverse effect of air pollution on business performance of restaurants on the weekends, we present the results the effects of air pollution on business performance of restaurants on the weekdays. As discussed in Section 2, the linkage between local outdoor activities and local air pollution is expected be stronger on the weekends when most people do not have outside obligations and are in a position to make voluntary decisions regarding outdoor activities. In contrast, on the weekdays, this linkage is not expected to be strong, given that most people have outside obligations. When people have outside obligations, they take alternative avoidance behaviors (e.g., wearing masks) to mitigate exposure to air pollution. Therefore, the effects of reduced outdoor activities due to air pollution on business performance of restaurants on the weekdays can be ambiguous, depending on the net effect of at least three sources of influences. First, during elevated level of air pollution, some people (e.g., elderly population who have no outside work-related obligations) may be discouraged from outdoor activities including going out to restaurants, which can adversely affect restaurant business. Second, people exposed to air pollution can reward themselves with better dining experience for comfort, in which case, restaurants will benefit. Third, it is possible that there will be substitution effects in the demands for restaurants priced at different levels.

Table 8 shows the results on the effects of pollution-induced change in local traffic speed on the business performance of restaurants on the weekdays.[20] The effect is negative in the pooled analysis including results from all chains. The significance level is weak statistically, which is largely driven by Chain C. For Chain A (medium-priced) and Chain B (high-priced), respectively, the effects on revenue are insignificant. However, for Chain A, the marginal

[20] Table 7 shows the effect of air pollution on business performance of restaurants on the weekdays by chains. The results remain consistent to Table 8, we therefore focus our discussion on the mechanism.

effects on intensive margin (i.e., dishes per order, revenue per order, and revenue per dish (Columns (4), (5), and (7)), are positive and significant, whereas the effects on extensive margin (i.e. order and customer counts) are insignificant. For Chain B, the corresponding effects on intensive margin (i.e., dishes per order and revenue per order) are negative and significant. The heterogeneous and moderate impacts on extensive and intensive margins are offsetting each other, resulting in unchanged revenue. In contrast to Chain A and B, on the weekdays, for Chain C (lowest-priced restaurants among the three chains), the effect of pollution-induced decline in local traffic speed on revenue is negative and significant, where the extent of decline in revenue is approximately 7% of the average. Also, the decline in revenue is driven by air pollution's adverse effects on both extensive (order and customer counts) and intensive (revenue per dish) margins. These results for Chain C suggest the possibility that on the weekdays when customers are exposed to air pollution, they may be treating themselves at relatively higher priced restaurants (e.g., Chain A and B) or home-cooking by switching from relatively low-priced Chain C.

6 Offsetting the Adverse Effect of Air Pollution on Restaurant Business

While for businesses physical traffic of customers to their locations remain the primary source of demand, for some businesses such as restaurants and grocery stores, the emergence of Gig-economy has made it possible and easier to deliver products to customers at their homes. Thus, especially during elevated levels of air pollution, home-delivery of food is an option both for the restaurant customers if they want to avoid exposure to pollution and for the restaurants to meet the home-delivery demands. Our chain of restaurants also offers home-delivery services. Therefore, in this section, we examine the effect of air pollution on the home-delivery component of restaurant business. Our purpose here is to explore whether the demand for home-delivery business increases if air pollution worsens. That is, we explore whether home-delivery of food is a viable option for the restaurants to offset some of the adverse effects of air pollution on their aggregate business performance.

From Table A4, we note that home-delivery accounts for 10.4%, 10.9%, and 19.4% of the revenues of Chain A, B, and C, respectively.[21] By comparison, home-delivery orders and margin per order are much lower. The average daily home-delivery order counts range from 32.98 for Chain B to 77.24 for Chain C. Likewise, the average revenues per order are much smaller than the corresponding dining-in revenues, which may be attributed to smaller and less expensive dishes being ordered for home-delivery, packaging cost of food, and fee payments to food delivery platforms, such as Meituan (美团) and Ele.me (饿了么), which are used by the restaurant chains to sell food online.[22]

Meituan charges between 15% and 25% of the value of an order for its home-delivery service, depending on distance to be covered, time of the day, and demand.[23] It charges between 3% and 15% of value of an order just for the use of its online ordering system.[24] The corresponding fees of Ele.me are very similar. While these third-party platforms expand the market radius of a restaurant, they also intensify competition with other restaurants. Therefore, aggressive pricing strategies (e.g., bundling and special menus) are often adopted by restaurants to compete for customers, resulting in even lower intensive margins.

Utilizing the empirical strategy described in Section 4.2, we investigate the effects of

[21]These percentages have been calculated using daily home-delivery revenue from Table A4 and daily dining-in revenue from Table 1.

[22]Most restaurants in China rely on third-party food delivery platforms for online food sale and delivery. There are two major platforms that compete horizontally in this market: Meituan (美团) backed by Tencent Group and Ele.me (饿了么) backed by Alibaba Group. There is another competitor Baidu Waimai (百度外卖), which was acquired by Ele.me in August 2017 and became a subsidiary, Ele.me Xingxuan (饿了么星选), but serves only highly ranked restaurants. Since Meituan entered the market in 2013, the food delivery platform in China took off quickly. According to Meituan's annual report, daily it delivered 11.2 million orders of food, with 308.5 million active daily users and 4.4 millions business users. These platform have contracted riders who typically deliver food using electronic bicycle within 10 kilometers areas of a restaurant.

[23]While this seems to be costly, it is the cheaper alternative to hiring own food-delivery team.

[24]A restaurant can rely on its own platform for receiving online orders, but its market reach will be very limited compared to Meituan and Ele.me.

air pollution on the home-delivery revenues of the three chains, separately on the weekends and the weekdays. The results are presented in Table 9. From Column (1), we find that pollution-induced decrease in local customer traffic speed adversely affect restaurant home-delivery revenue by 10.98 (4.7% of the average). Specifically, the adverse impact is significant for both Chain B and C, but not for Chain A. The marginal effects are -23.26 (6.7% of the average) and -15.54 (8.9% of the average) for chain B and C, respectively. These effects are consistent with the results for the dining-in revenues on the weekends. Although air pollution can induce an increase in the demand for home-delivery of food, it can also reduce the productivity of home-delivery riders, which can increase the time it takes to deliver food to a particular home. Also, the food delivery platforms may adopt surging pricing, making online order more expensive. Moreover, on the weekends, potential customers, discouraged by air pollution, may opt for home-cooking.

The corresponding results on weekdays, as presented in Column (2) of Table 9, reveal a positive and significant relationship between air pollution-induced changes in traffic speed and home-delivery revenue. Specifically, the estimated marginal effect suggests that for every 1 km/hour increase in speed due to air pollution, home-delivery revenue increases by 32.74 (equivalent to a 14% increase). Since cooking at home may be less convenient on weekdays when most people have outside obligations, the demand for home-delivery services may increase when air pollution levels rise. However, this increase in revenue is not substantial enough to offset the loss in dining-in revenue experienced on weekends. This pattern is observed for two out of the three restaurant chains (Chain B and C) but not for Chain A, which may be attributed to the unique cuisine it offers (regional cuisine), making it less affected by the observed trends. These findings shed light on how air pollution-induced changes in outdoor activities, specifically during weekdays, can influence consumer behavior and revenue patterns in the restaurant industry.

7 Conclusions and Policy Implications

We shed light on the effect of pollution-induced change in outdoor activities on business performance of small businesses that rely on the customers visiting their premises. To do so, we exploit high-frequency contemporaneous variations in business transactions of ninety-six restaurants from three groups of chain restaurants in the inner city of Beijing and local vehicular traffics and air pollution in their surroundings, and estimate the causal effect of air pollution on business performance of restaurants, including revenue and extensive and intensive margins. To account for potential challenges to identifying the effect of air pollution on business performance of the restaurants, we employ an IV approach. Our key findings reveal that reduced outdoor activities due to air pollution have a negative impact on restaurant revenues, particularly during weekends. This effect is less significant on weekdays when people are less likely to have outdoor obligations.

Our study carries important implications for the ongoing debates on air pollution regulation. Despite being a persistent environmental concern worldwide, efforts to mitigate air pollution often encounter various hurdles, including the need to balance the benefits of clean air against the compliance costs of pollution control measures. Our empirical evidence contributes to this dialogue by highlighting the economic benefits of pollution regulation efforts beyond their well-established health returns. Specifically, our findings underscore the adverse effects of air pollution on industries and businesses that rely on the physical presence of customers. These small businesses, often employing individuals from relatively weaker socioeconomic backgrounds, can benefit significantly from pollution control measures. This highlights the distributional impact of such policies and their importance in supporting the local economy.

Moreover, our study underscores the societal costs associated with avoidance behaviors resulting from air pollution, particularly the reduction in outdoor activities. Market activities are crucial for efficient resource allocation, and elevated air pollution discouraging outdoor activities can harm businesses, including those not limited to the restaurants we analyzed. This mechanism may potentially disrupt other public services as well, and it highlights a previously under-examined aspect of the social cost related to anti-pollution regulation.

We acknowledge three important caveats to our study. First, our analysis focuses on chain restaurants, which represent only a small proportion of the restaurant landscape in Beijing. Other types of restaurants, especially specialty ones catering to high-end customers with a focus on healthy food, may respond differently to elevated air pollution. Second, not all businesses are equally dependent on physical customer traffic, and our study primarily emphasizes businesses that rely on outdoor human activities. Finally, while we explore the deterrence effect of air pollution on outdoor activities as a mechanism influencing restaurant performance, we recognize that other mechanisms, such as psychological factors (e.g., pollution-induced changes in mental health), may also play a role. Further research in this area could provide valuable insights into these alternative mechanisms.

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8 Figures and Tables

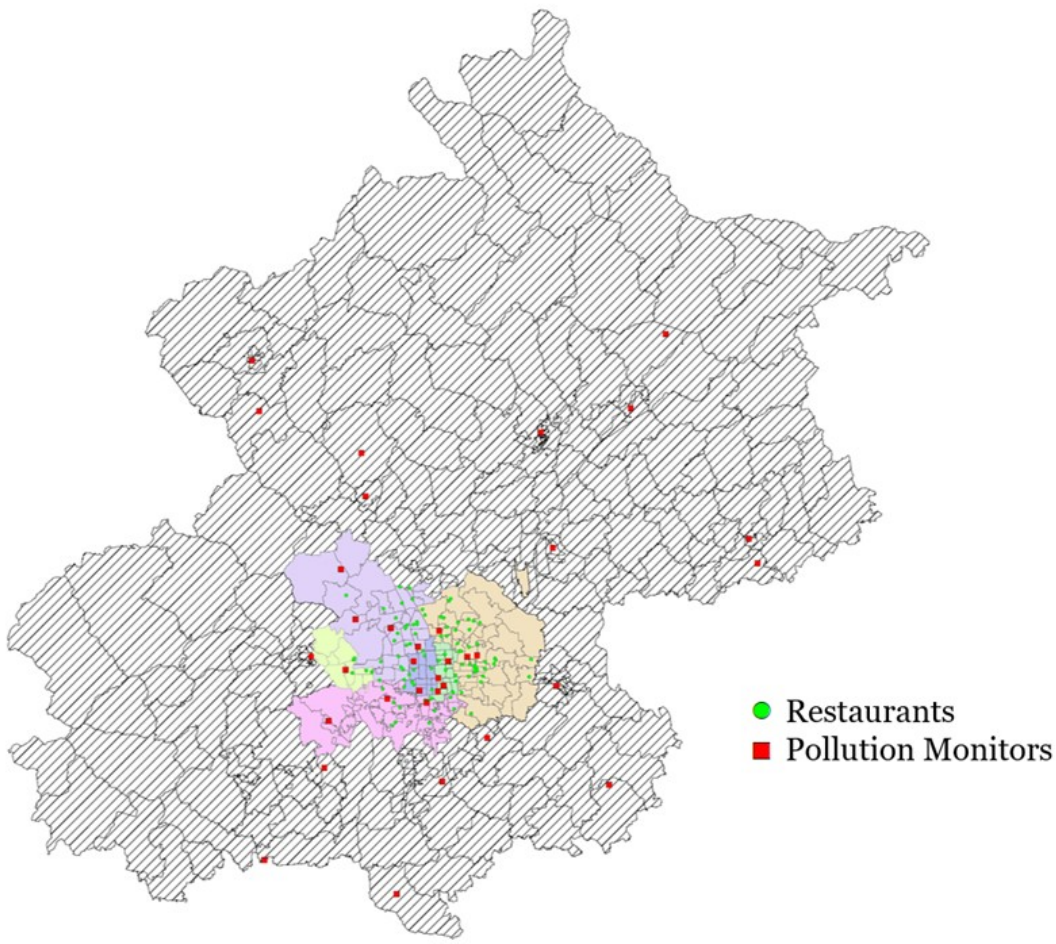
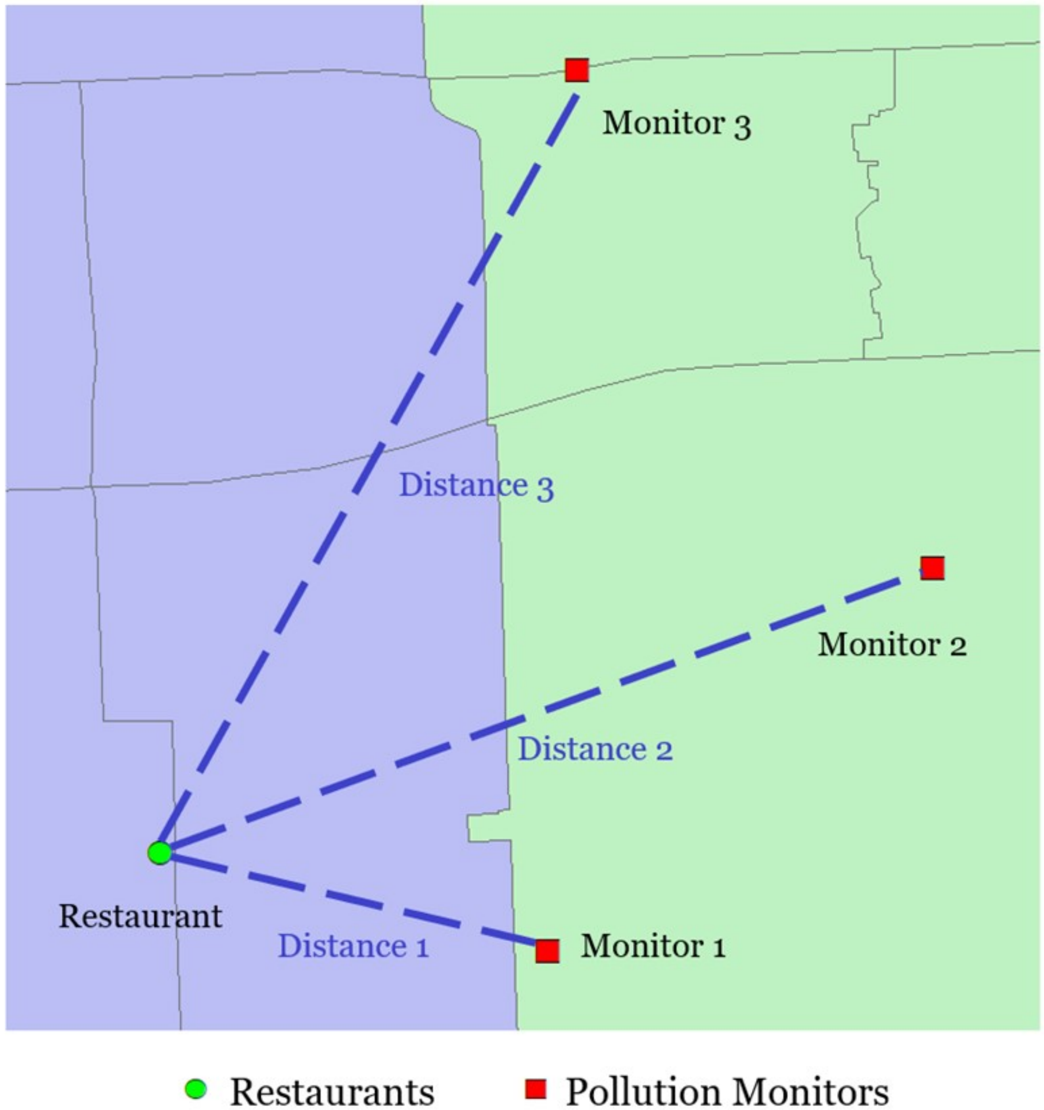


Fig. 1: Location of restaurants in our sample and air pollution monitors. The colored regions are the administrative districts located within the sixth rings of Beijing. The shaded areas are the suburb areas excluded from our analysis.



Notes: Our preferred measurement of air pollution at the restaurant-level is the inverse distance weighted (with the nearest 3 monitors), calculated as follows:

$$AQI_{Restaurant} = \sum_{i=1}^{3}(1 - \frac{Distance_i}{\sum_{k=1}^{3} Distance_k}) \times AQI^{i}_{Monitor}/2$$

For the 96 restaurants in our sample, the average distance to the 1st, 2nd, and 3rd nearest air pollution monitor are 3.2 km, 5.3 km, and 6.8 km, respectively. Alternative measurements of air pollution at the restaurant-level are average of the air pollution readings from the 3 nearest monitors, and the reading from the closest monitor. Results from using the alternative measures of air pollution at the restaurant-level are similar to the results from using our preferred measure.

Fig. 2: Calculation of the restaurant-level air pollution

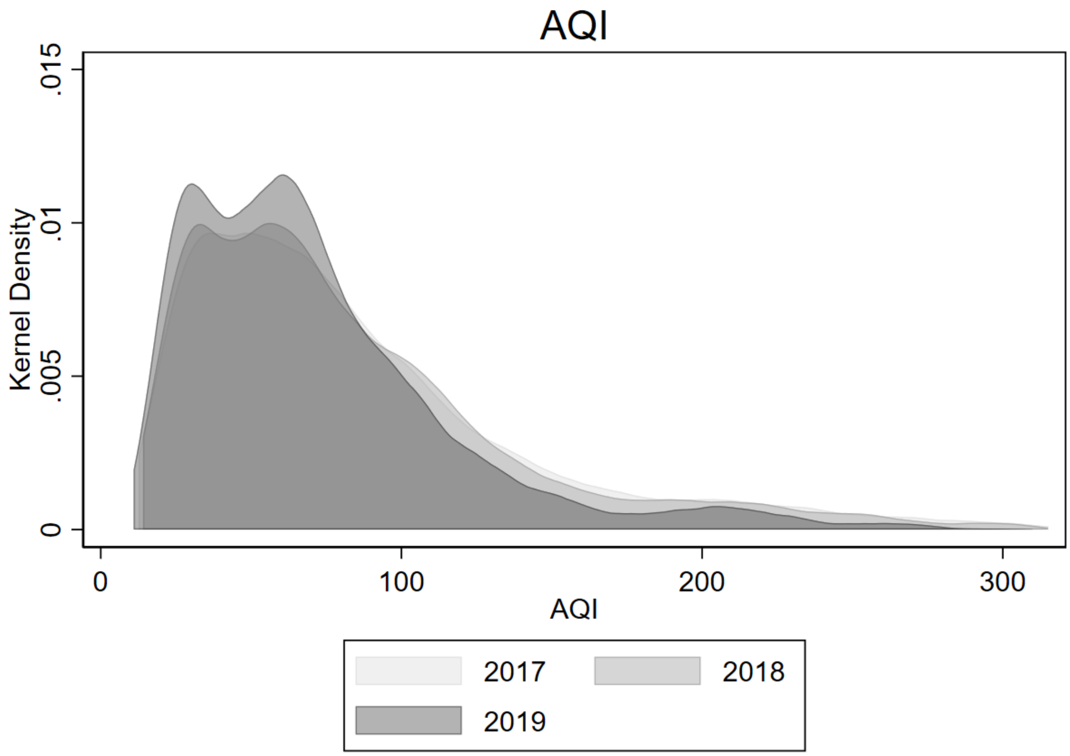


Fig. 3: Distribution of air pollution in Beijing. Kernel density of air pollution using daily average AQI.

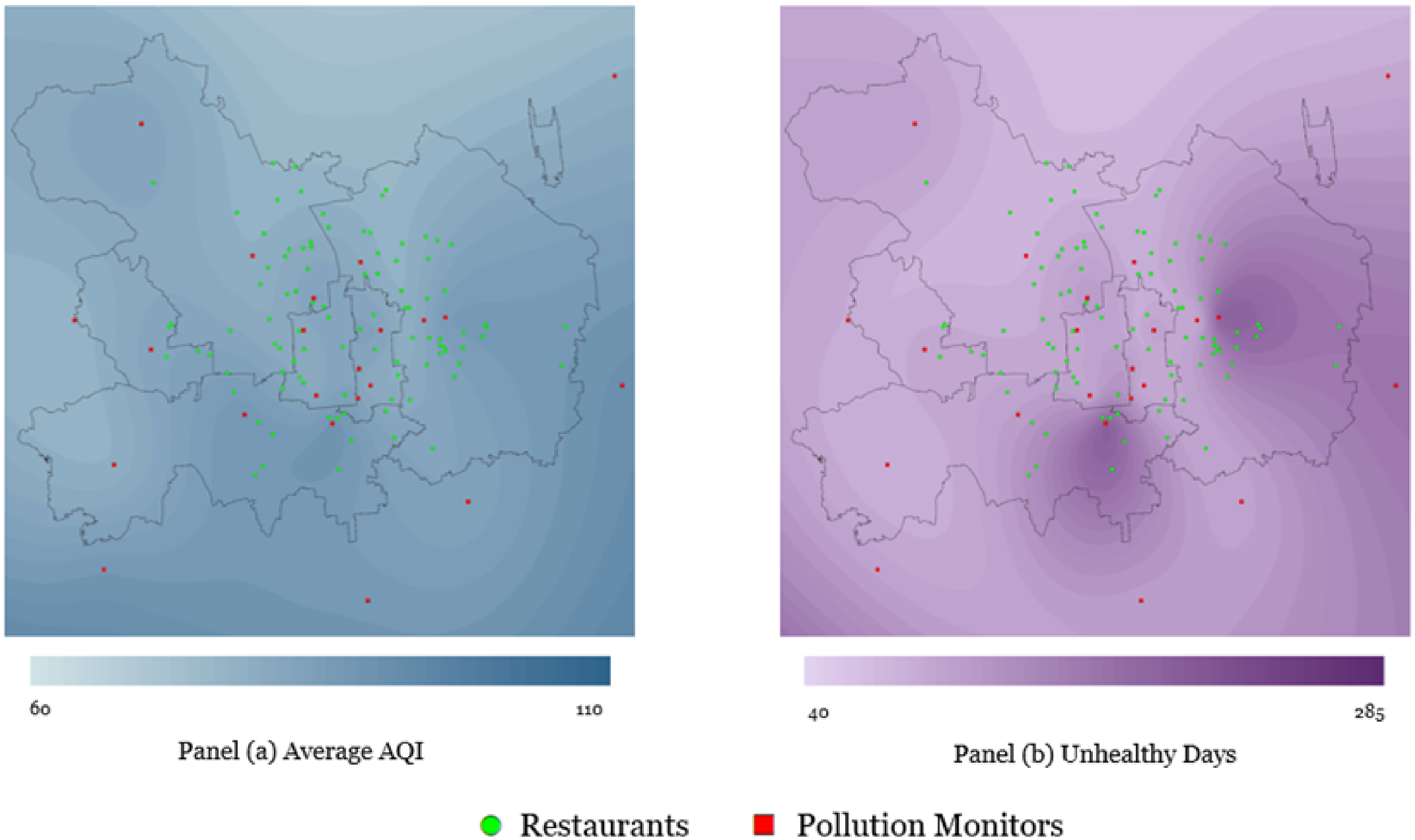
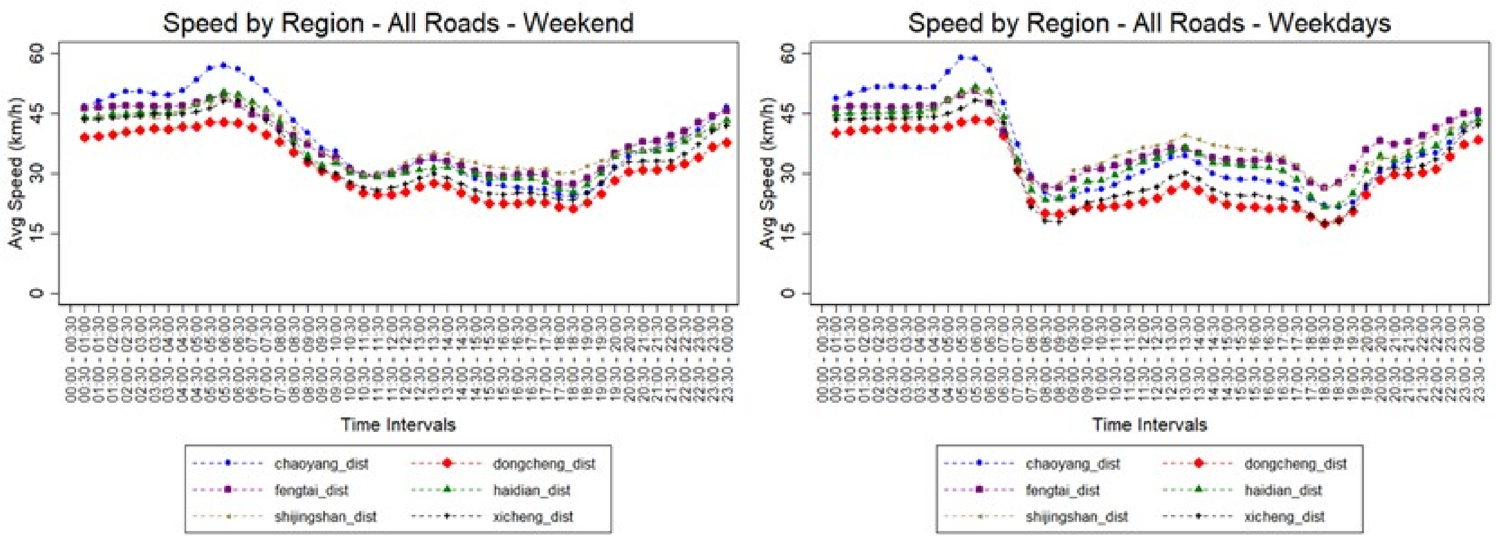
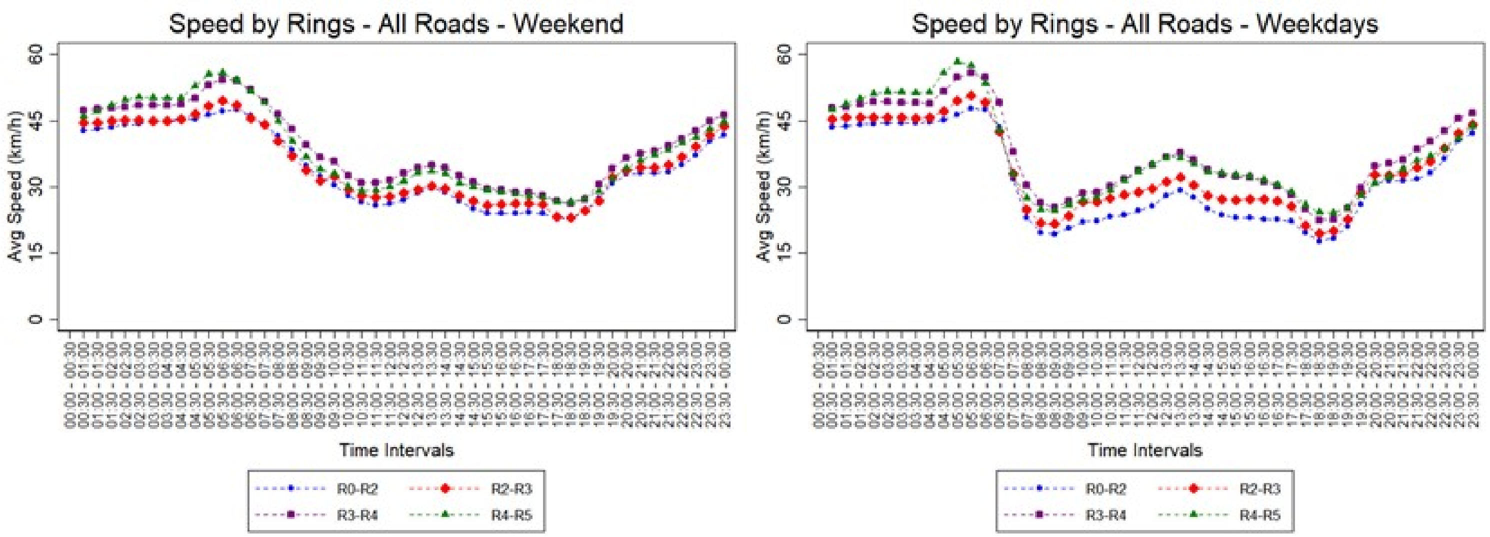


Fig. 4: Distribution of air pollution in Beijing and location of the restaurants in our sample. Panel (a) shows the contour of average AQI from 2017 to 2019. Panel (b) shows the contour for the number of unhealthy air pollution days (AQI $\geq$ 150) from 2017 to 2019.

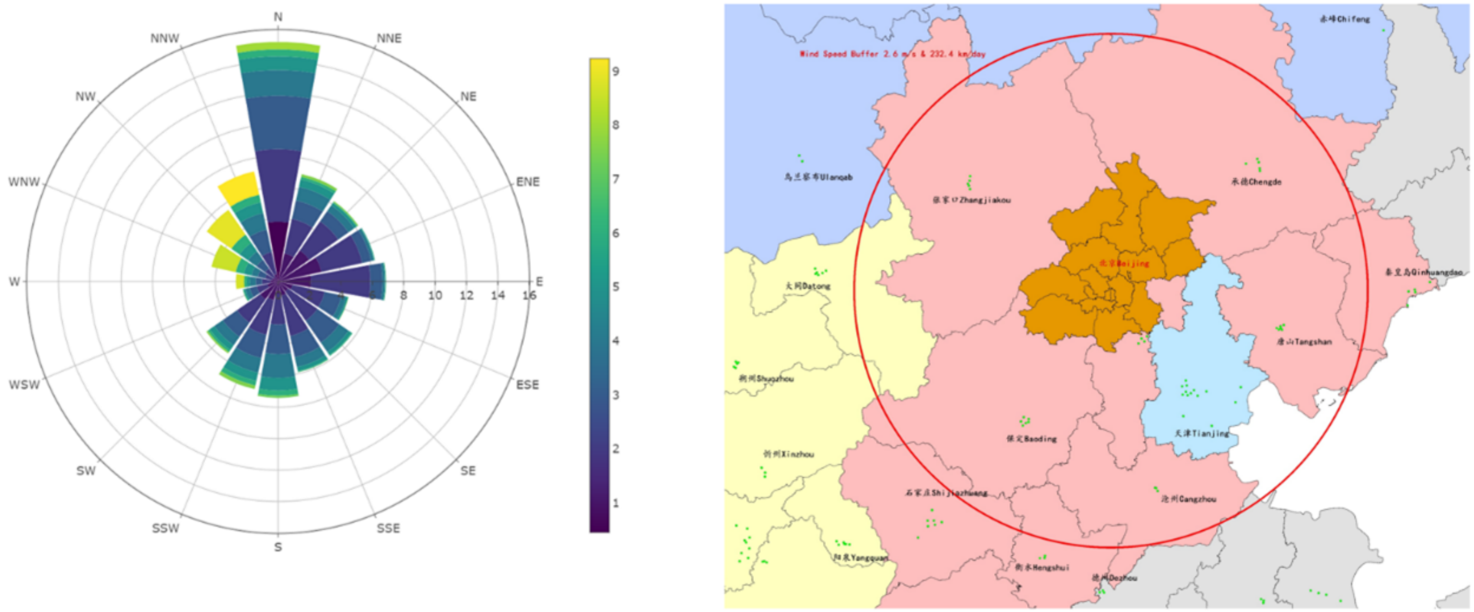


(a) By Administrative Districts



(b) By Ring Roads

Fig. 5: Half-hourly traffic speed in Beijing. Both panels plot half-hourly traffic speed during 2017-2019. Panel (a) is at the administrative district-level. Panel (b) is at the ring road-level.



Panel (a) Prevailing Wind Direction and Wind Speed (m/s)

Panel (b) Neighbor Cities

Fig. 6: Wind direction in Beijing and neighboring cities. Panel (a) shows the distribution of prevailing wind direction in Beijing during 2017-2019. Panel (b) shows the neighboring cities used to construct IV. We create a buffer (red) first using the average wind speed in Beijing (2017-2019). Then we select neighboring cities close to the buffer.

Table 1: Descriptive Statistics by Restaurant Chains

Variables	Chain A		Chain B		Chain C	
	Mean	SD	Mean	SD	Mean	SD
Daily Revenue (CNY)	23761.09	11165.79	27150.07	13874.62	11149.12	5574.50
Daily Orders (Count)	112.70	50.52	53.63	26.98	235.70	121.17
Daily Customers (Count)	253.02	120.92	210.66	117.03	281.04	132.20
Half-hourly Revenue (CNY)	1789.50	1407.03	2419.71	2063.61	634.54	504.58
Half-hourly Orders (Count)	8.49	6.19	4.78	3.75	13.40	10.12
Half-hourly Customers (Count)	19.05	14.99	18.73	16.79	15.95	11.75
Dishes Per Order (Count)	6.04	1.39	7.68	2.59	4.08	1.50
Revenue Per Order (CNY)	206.34	57.12	501.31	182.40	48.60	18.13
Dishes Per Customer (Count)	0.46	0.54	0.60	0.62	0.38	0.55
Revenue Per Dish (CNY)	34.98	7.15	68.88	18.14	13.48	4.67
N of Stores	18		24		54	
N of Observations	231,246		135,792		575,774	

Note: An observation is a restaurant at half-hour. Sample periods are Jan 1, 2017 to Dec 31, 2019 (Chain A), Mar 24, 2018 to Dec 31, 2019 (Chain B), and Jan 1, 2018 to Dec 31, 2019 (Chain C). National holidays are excluded.

Table 2: Descriptive Statistics of Pollutants, Weather, and Traffic Variables

Category	Variables	N. Obs	Mean	SD	Min	Max
Pollutants	AQI	25,127	83.15	62.17	10.94	506.88
	PM 2.5 ($\mu g/m^3$)	25,150	52.57	53.61	2.00	666.63
	PM 10 ($\mu g/m^3$)	24,798	87.13	78.52	2.00	1987.50
	NO_2 ($\mu g/m^3$)	25,149	48.90	26.33	3.93	197.81
	SO_2 ($\mu g/m^3$)	25,150	6.72	7.28	1.50	163.33
	CO (mg/m^3)	24,198	0.85	0.64	0.15	10.23
	O_3 ($\mu g/m^3$)	25,150	55.36	51.47	1.50	331.40
Traffic	Weekday Speed (km/hour)	33,475	35.37	9.83	12.80	58.30
	Weekend Speed (km/hour)	12,916	37.09	8.98	15.40	55.90
Weather	Temperature (Celsius)	25,847	13.59	12.22	-15.00	40.00
	Precipitation (mm)	25,848	0.06	1.08	0.00	66.00
	Wind Speed (Meters/Second)	25,847	2.70	2.02	0.00	17.00

Note: An observation is the city-level measurement. For our empirical analysis, we calculate restaurant-level measures of air pollution using nearby monitors based on each restaurant's location. Our preferred measure of air pollution is the distance weighted average of the readings from the 3 nearest monitors.

Table 3: The Effect of Air Pollution on Restaurant Revenue

Dependent variable is weekend revenue (Mean = 1,620.4 CNY)	OLS Revenue (1)	OLS categorical Revenue (2)	IV 2SLS Revenue (3)	IV 1st-stage AQI/10 (4)
AQI/10	-2.51***		-6.43***	
	(0.41)		(1.06)	
AQI Bin 2 (101-150)		-41.55***		
(Unhealthy for sensitive individuals)		(6.64)		
AQI Bin 3 (>150)		-41.37***		
(Unhealthy, unhealthy, and hazadous)		(6.82)		
Neighbor AQI/10				0.09***
				(0.003)
N. Obs	234,846	234,846	194,256	194,256
Adj. R^2	0.64	0.64	0.63	0.22
Montiel Olea and Pfueger F-statistics				4,992.29

Note: This shows the effect of air pollution on half-an-hourly revenue of restaurants for 98 stores on the weekends. In all specifications, we include bins of weather controls (results for alternative weather control is reported in Appendix Table A1), store fixed effects and time fixed effects (year, month, day of week, and half-hour). AQI/10 is our preferred measure is air pollution at the restaurant-level (results from using the alternative measures of air pollution are in Appendix Table A2). Neighbor AQI/10 is the exclusive instrumental variable constructed using air pollution in the neighboring cities of Beijing (results from using specific pollutants is in Appendix Table A3). Standard errors in parentheses are clustered at restaurant-level. * significant at 10%, ** at 5%, and *** significant at 1%.

Table 4: The Effects of Air Pollution on Business Performance of Restaurants on the Weekends (3 CHAINS)

2SLS IV Results		(1) Revenue	(2) N of Orders	(3) N of Cust.	(4) Dish Per Order	(5) Rev. Per Order	(6) Dish Per Cust.	(7) Rev Per Dish
Chain A	Mean	1789.50	8.49	19.05	6.04	206.34	0.46	34.98
AQI/10		-11.57***	-0.04***	-0.14***	-0.004*	-0.11	0.001***	-0.002
		(2.75)	(0.01)	(0.03)	(0.002)	(0.08)	(0.0005)	(0.011)
N. Obs		45,950	45,950	45,950	45,698	45,698	45,698	45,698
Adj. R^2		0.582	0.578	0.574	0.082	0.098	0.296	0.033
Chain B	Mean	2419.71	4.78	18.73	7.68	501.31	0.60	68.88
AQI/10		-16.35***	-0.04***	-0.15***	-0.0002	0.02	0.001	-0.00001
		(3.31)	(0.006)	(0.03)	(0.005)	(0.385)	(0.001)	(0.039)
N. Obs		29,348	29,348	29,348	28,619	28,619	28,619	28,619
Adj. R^2		0.456	0.506	0.472	0.191	0.175	0.301	0.075
Chain C	Mean	634.54	13.40	15.95	4.08	48.60	0.38	13.48
AQI/10		-0.19	0.05***	-0.02	0.014***	-0.14***	0.001	-0.06***
		(0.94)	(0.01)	(0.02)	(0.003)	(0.03)	(0.001)	(0.01)
N. Obs		118,958	118,958	118,958	118,061	118,061	118,061	118,061
Adj. R^2		0.454	0.467	0.444	0.279	0.254	0.237	0.318

Note: The results are from 21 regression equations. In all regressions, we include bins of weather controls, restaurant fixed effects and time fixed effects (year, month, day of week, and half-hour). Standard errors in parentheses are clustered at restaurant-level. * significant at 10%, ** at 5%, and *** significant at 1%.

Table 5: Mechanism of Air Pollution's Effect on the Weekends

	The Effect of Pollution on Traffic Speed		The Effect of Traffic Speed on Revenue	
	OLS	IV 2SLS	OLS	IV Induced Speed
	Traffic Speed (Mean = 30.9 km/hour)		Revenue (Mean = 1,620.4 CNY)	
	(1)	(2)	(3)	(4)
AQI/10	0.07***	0.06***		
	(0.002)	(0.003)		
Traffic Speed			-11.3***	
			(2.07)	
Predicted Traffic Speed				-44.4***
				(7.1)
N	232,001	191,885	264,411	234,846
Adj. R^2	0.81	0.82	0.64	0.63

Note: This table reports the result for 98 stores. Results for each chain are reported in Table 6. In all specifications, we include bins of weather controls, restaurant fixed effects and time fixed effects (year, month, day of week, and half-hour). The 1st-stage of IV results is identical to column (3) of Table 3. Standard errors in parentheses are clustered at the restaurant-level. * significant at 10%, ** at 5%, and *** significant at 1%.

Table 6: Mechanism of Air Pollution's Effects on the Weekends (3 CHAINS)

Traffic speed is predicted using IV (Weekend)		(1) Revenue	(2) N of Orders	(3) N of Cust.	(4) Dish Per Order	(5) Rev. Per Order	(6) Dish Per Cust.	(7) Rev Per Dish
Chain A	Mean	1789.50	8.49	19.05	6.04	206.34	0.46	34.98
Predicted Speed		-75.72***	-0.28***	-0.87***	-0.035**	-1.15*	0.013***	-0.015
		(17.73)	(0.08)	(0.19)	(0.014)	(0.61)	(0.004)	(0.07)
N. Obs		54,863	54,863	54,863	54,579	54,579	54,579	54,579
Adj. R^2		0.587	0.581	0.579	0.082	0.097	0.297	0.033
Chain B	Mean	2419.71	4.78	18.73	7.68	501.31	0.60	68.88
Predicted Speed		-177.4***	-0.41***	-1.58***	0.05	0.49	0.02	-0.71
		(54.72)	(0.09)	(0.51)	(0.09)	(5.84)	(0.013)	(0.53)
N. Obs		36,000	36,000	36,000	35,141	35,141	35,141	35,141
Adj. R^2		0.462	0.512	0.477	0.192	0.177	0.299	0.078
Chain C	Mean	634.54	13.40	15.95	4.08	48.60	0.38	13.48
Predicted Speed		-9.03**	-0.02	-0.22**	0.03***	-0.44***	0.02***	-0.18***
		(3.72)	(0.06)	(0.09)	(0.01)	(0.09)	(0.004)	(0.03)
N. Obs		143,983	143,983	143,983	142,926	142,926	142,926	142,926
Adj. R^2		0.464	0.481	0.454	0.282	0.256	0.240	0.321

Note: This table reports results from 21 regressions. In all regressions, we include bins of weather controls, restaurant fixed effects and time fixed effects (year, month, day of week, and half-hour). Standard errors in parentheses are clustered at restaurant-level. * significant at 10%, ** at 5%, and *** significant at 1%.

Table 7: The Effect of Air Pollution on Business Performance of Restaurants on the Weekdays (3 CHAINS)

2SLS IV Results		(1) Revenue	(2) N of Orders	(3) N of Cust.	(4) Dish Per Order	(5) Rev. Per Order	(6) Dish Per Cust.	(7) Rev Per Dish
All 3 Chains	Mean	1082.1	10.67	16.13	4.98	149.16	0.43	26.42
AQI/10		-1.24*	-0.02***	-0.03***	0.001***	-0.03	0.001*	-0.01
		(0.71)	(0.005)	(0.01)	(0.001)	(0.06)	(0.0005)	(0.01)
N. Obs		472,730	472,730	472,730	462,754	462,754	462,754	462,754
Adj. R^2		0.531	0.488	0.423	0.501	0.815	0.251	0.838
Chain A	Mean	1587.74	7.62	16.84	5.95	204.18	0.51	35.05
AQI/10		-1.69	-0.01***	-0.03**	-0.0002	0.25	0.001	0.05
		(1.52)	(0.006)	(0.01)	(0.002)	(0.08)	(0.001)	(0.01)
N. Obs		117,703	117,703	117,703	114,698	114,698	114,698	114,698
Adj. R^2		0.545	0.568	0.548	0.052	0.057	0.292	0.021
Chain B	Mean	2125.33	4.16	15.98	7.68	501.28	0.64	68.47
AQI/10		-1.23	0.002	-0.02	-0.01**	-0.72	0.0006	0.04
		(3.37)	(0.004)	(0.03)	(0.005)	(0.433)	(0.001)	(0.051)
N. Obs		73,771	73,771	73,771	68,867	68,867	68,867	68,867
Adj. R^2		0.425	0.438	0.411	0.162	0.149	0.238	0.055
Chain C	Mean	623.79	13.50	15.87	3.98	47.26	0.36	13.42
AQI/10		-1.06**	-0.02***	-0.03***	0.008***	-0.01	0.001	-0.02***
		(0.42)	(0.01)	(0.01)	(0.002)	(0.016)	(0.001)	(0.005)
N. Obs		281,256	281,256	281,256	279,189	279,189	279,189	279,189
Adj. R^2		0.476	0.448	0.444	0.318	0.322	0.224	0.306

Note: This table reports the results from 28 regressions. In all regressions, we include bins of weather controls, restaurant fixed effects and time fixed effects (year, month, day of week, and half-hour). Standard errors in parentheses are clustered at restaurant-level. * significant at 10%, ** at 5%, and *** significant at 1%.

Table 8: Mechanism of Air Pollution's Effects on the Weekdays (3 CHAINS)

Traffic speed is predicted using IV (Weekdays)		(1) Revenue	(2) N of Orders	(3) N of Cust.	(4) Dish Per Order	(5) Rev. Per Order	(6) Dish Per Cust.	(7) Rev Per Dish
All 3 Chains	Mean	1082.1	10.67	16.13	4.98	149.16	0.43	26.42
Predicted Speed		-17.41*	-0.27***	-0.34***	0.05***	-0.55	0.004	-0.122
		(9.84)	(0.08)	(0.12)	(0.01)	(0.66)	(0.01)	(0.08)
N. Obs		562,640	562,640	562,640	550,937	550,937	550,937	550,937
Adj. R^2		0.532	0.491	0.424	0.505	0.816	0.254	0.838
Chain A	Mean	1587.74	7.62	16.84	5.95	204.18	0.51	35.05
Predicted Speed		1.81	-0.04	-0.09	0.05***	1.98**	0.01	0.18**
		(16.55)	(0.06)	(0.16)	(0.01)	(0.71)	(0.01)	(0.08)
N. Obs		137,815	137,815	137,815	134,339	134,339	134,339	134,339
Adj. R^2		0.546	0.568	0.548	0.054	0.059	0.294	0.022
Chain B	Mean	2125.33	4.16	15.98	7.68	501.28	0.64	68.47
Predicted Speed		18.51	0.08**	0.13	-0.07*	-6.23**	-0.02	-0.14
		(22.63)	(0.03)	(0.15)	(0.04)	(2.34)	(0.01)	(0.25)
N. Obs		88,963	88,963	88,963	83,150	83,150	83,150	83,150
Adj. R^2		0.427	0.439	0.412	0.162	0.150	0.242	0.056
Chain C	Mean	623.79	13.50	15.87	3.98	47.26	0.36	13.42
Predicted Speed		-44.40***	-0.86***	-0.91***	0.053**	-0.05	0.004	-0.21**
		(8.46)	(0.18)	(0.21)	(0.02)	(0.26)	(0.01)	(0.08)
N. Obs		335,862	335,862	335,862	333,448	333,448	333,448	333,448
Adj. R^2		0.483	0.457	0.451	0.324	0.326	0.227	0.306

Note: This table includes results from 28 regressions. In all regressions, we include bins of weather controls, store fixed effects and time fixed effects (year, month, day of week, and half-hour). Standard errors in parentheses are clustered at store. * significant at 10%, ** at 5%, and *** significant at 1%.

Table 9: Air Pollution's Effect on Home-Delivery Revenue (3 CHAINS)

Traffic speed is predicted using IV	Half-hourly Revenue (Weekend) (1)	Half-hourly Revenue (Weekdays) (2)
All 3 Chains (Mean = 231.36 CNY)		
Predicted Traffic Speed	-10.98***	32.74***
	(2.68)	(4.62)
N. Obs	184,172	464,587
Adj. R^2	0.397	0.364
Chain A (Mean = 335.87 CNY)		
Predicted Traffic Speed	4.39	2.64
	(7.55)	(5.89)
N. Obs	35,351	87,665
Adj. R^2	0.301	0.242
Chain B (Mean = 348.32 CNY)		
Predicted Traffic Speed	-23.26**	16.35***
	(11.16)	(4.15)
N. Obs	26,835	80,755
Adj. R^2	0.337	0.263
Chain C (Mean = 173.4 CNY)		
Predicted Traffic Speed	-15.54***	77.20***
	(2.49)	(8.25)
N. Obs	121,986	296,167
Adj. R^2	0.450	0.445

Note: This table reports the results from 8 regressions. In all regressions, we include bins of weather controls, restaurant fixed effects and time fixed effects (year, month, day of week, and half-hour). Standard errors in parentheses are clustered at restaurant-level.
* significant at 10%, ** at 5%, and *** significant at 1%.

9 Appendix

9.1 Testing Customer Flow as a Mechanism

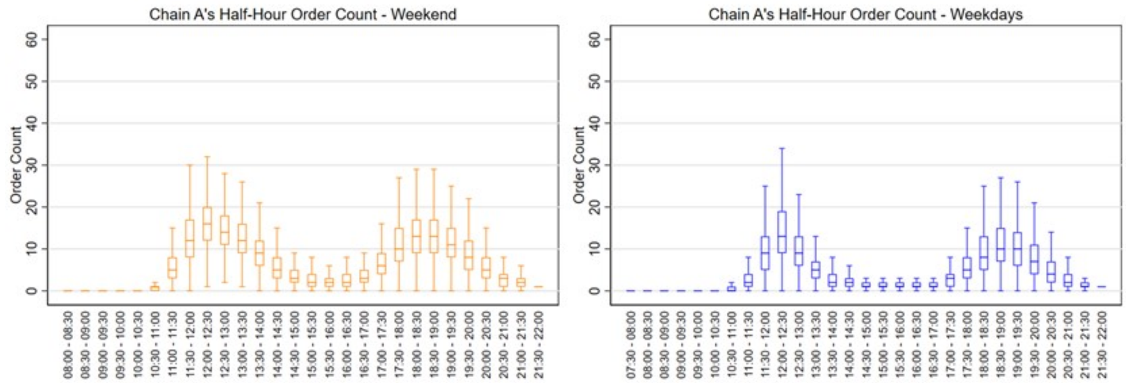
We can rewrite equation (1) to include local traffic flow as an explanatory variable:

$$Y_{rt} = \eta_1 \cdot [LP_{rt}] + \eta_2 \cdot T_{rt} + W_{rt} \cdot \Psi + \mu_r + \delta_t + \omega_{rt} \tag{5}$$

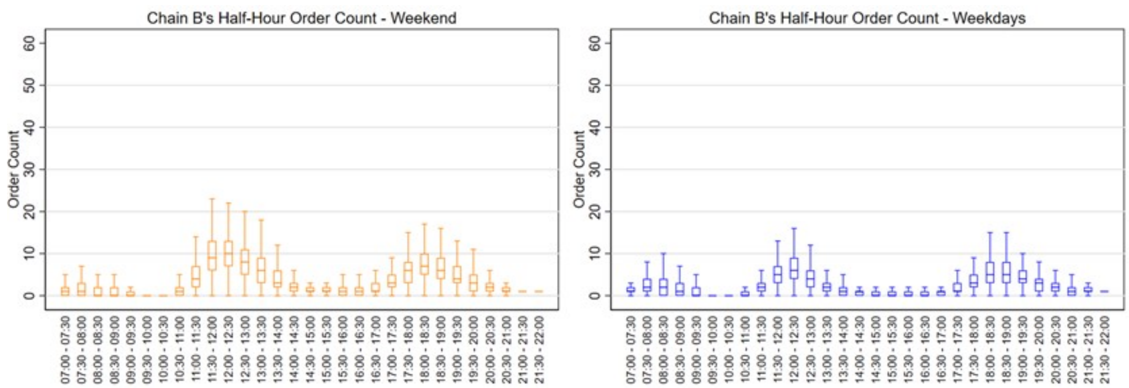
where T_{rt} is local traffic flow, a proxy for local customer flow to restaurants. The rest of indices and variables in equation (2) are same as in equation (1). Our parameters of interest are η_1 and η_2. If η_2 in Equation (2) is significant and η_1 is statistically different from its value in Equation (1), then we can infer that the local traffic flow is a mechanism of air pollution's effects on business performance of restaurants. If η_1 reduces to 0 or it is rendered insignificant, and η_2 is significant, then we have even stronger evidence for inferring local traffic flow as a clear mechanism of air pollution's effect on restaurant business. However, the possibility of other mechanisms remains. For example, studies have documented linkages between air pollution with psychological stress and loss of appetite, which may affect demand for restaurant food. Also, poor health, caused by severe air pollution, can affect appetite and demand for restaurant.[25] Results are presented in Table A5, which indicates that outdoor human activities (proxied by traffic) is a mechanism, but not the exclusive mechanism.

[25]We do not explore these potential mechanisms. Our focus has been on the role of pollution-induced decline in outdoor activities.

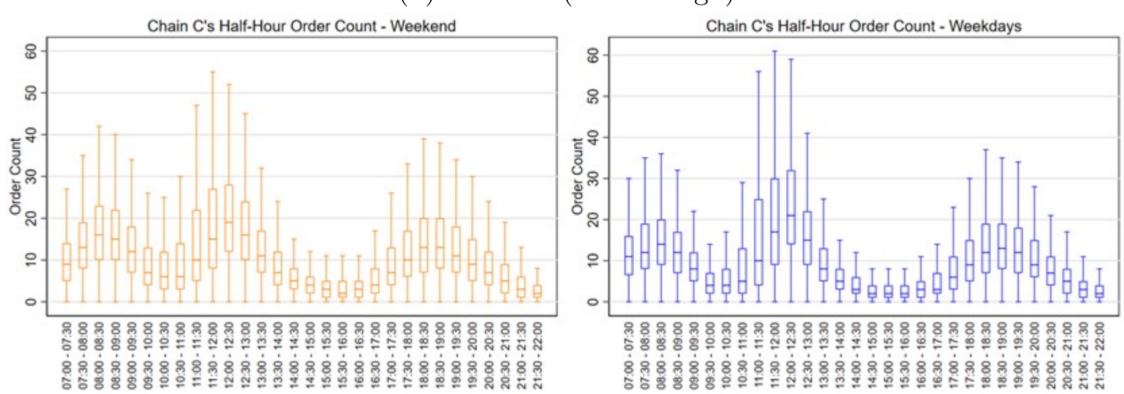
Tables and Figures for the Appendix



(a) Chain A (Priced Medium)



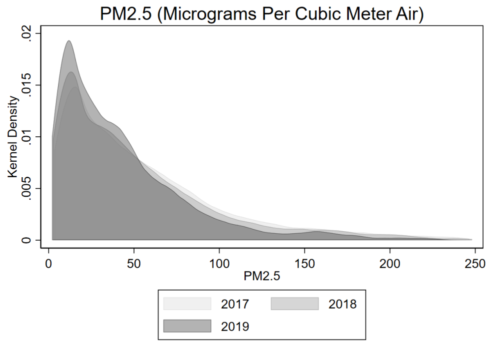
(b) Chain B (Priced High)



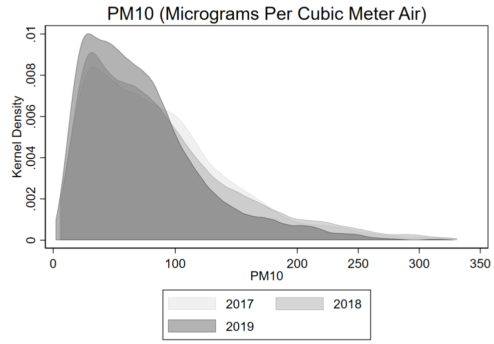
(c) Chain C (Priced Low)

Notes: The three panels plot the average half-hour order counts for each chain restaurants during sampling periods. Weekend and weekdays are plotted separately.

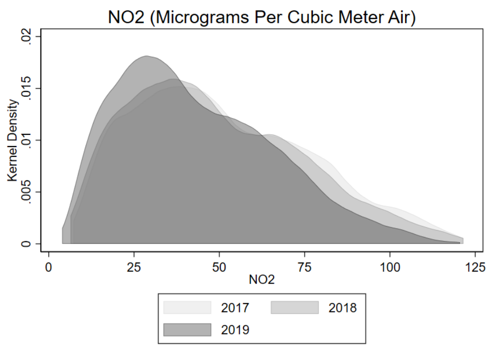
Fig. A1: Box Cox Plot of Half-hour Orders for 3 Chains



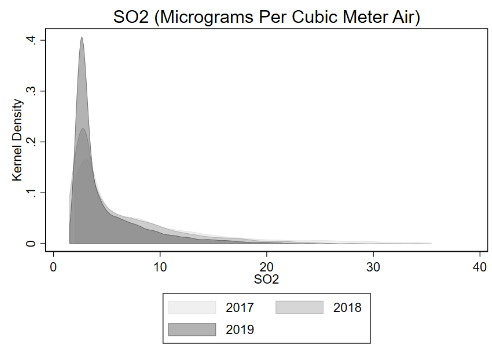
(a) PM2.5



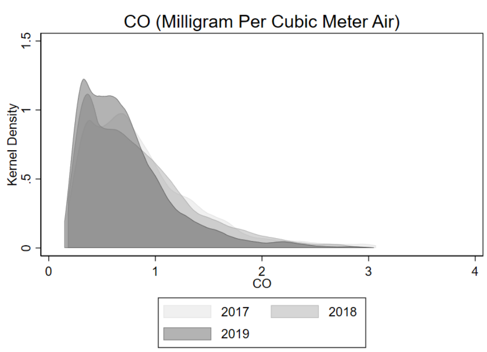
(b) PM10



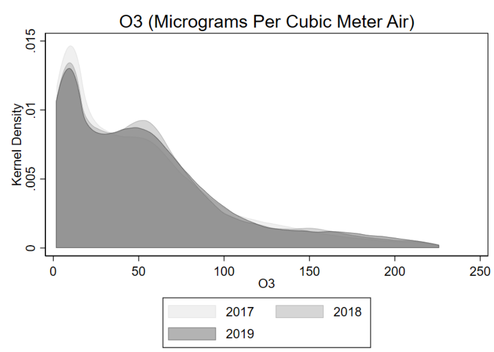
(c) NO2



(d) SO2



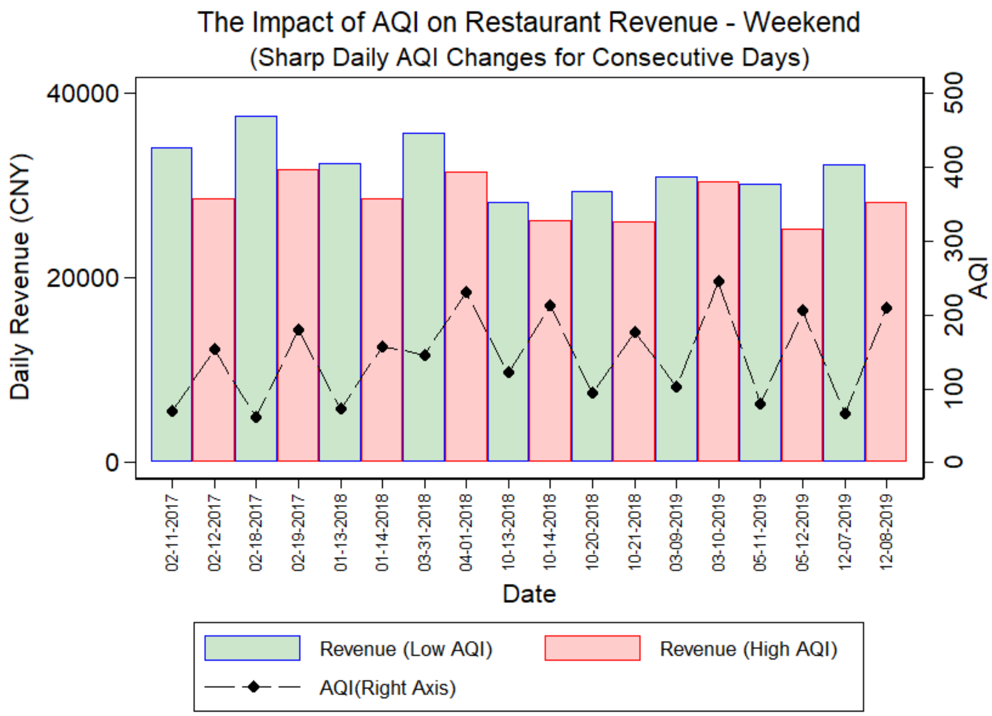
(e) CO



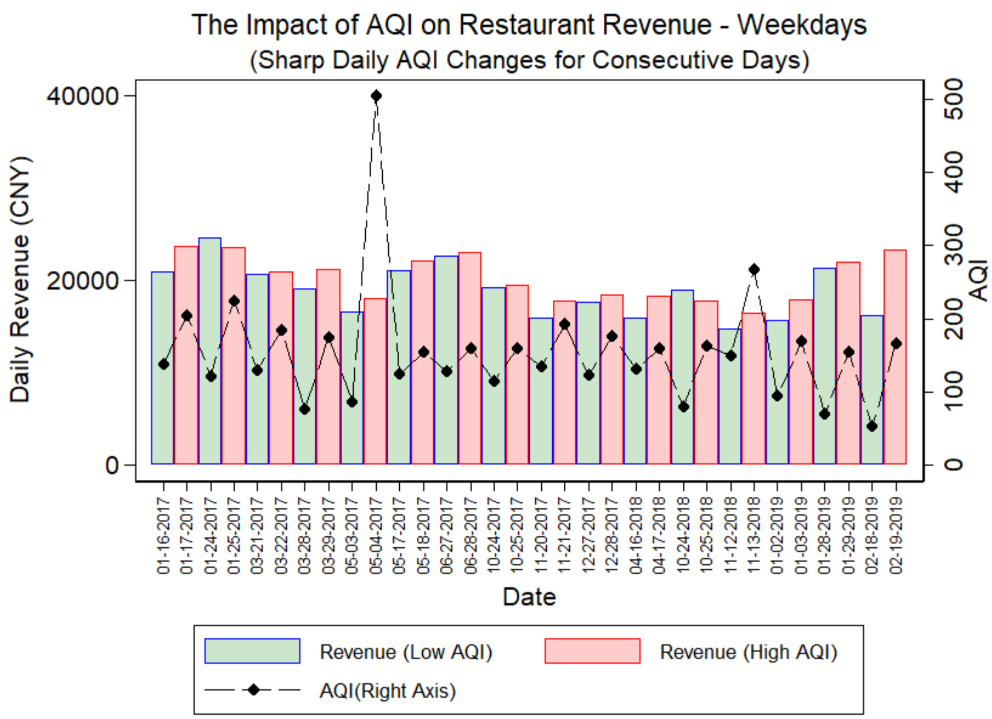
(f) O3

Notes: This figure plots the annual density of major pollutants in Beijing using daily average measurements.

Fig. A2: Distribution of Alternative Pollutants in Beijing



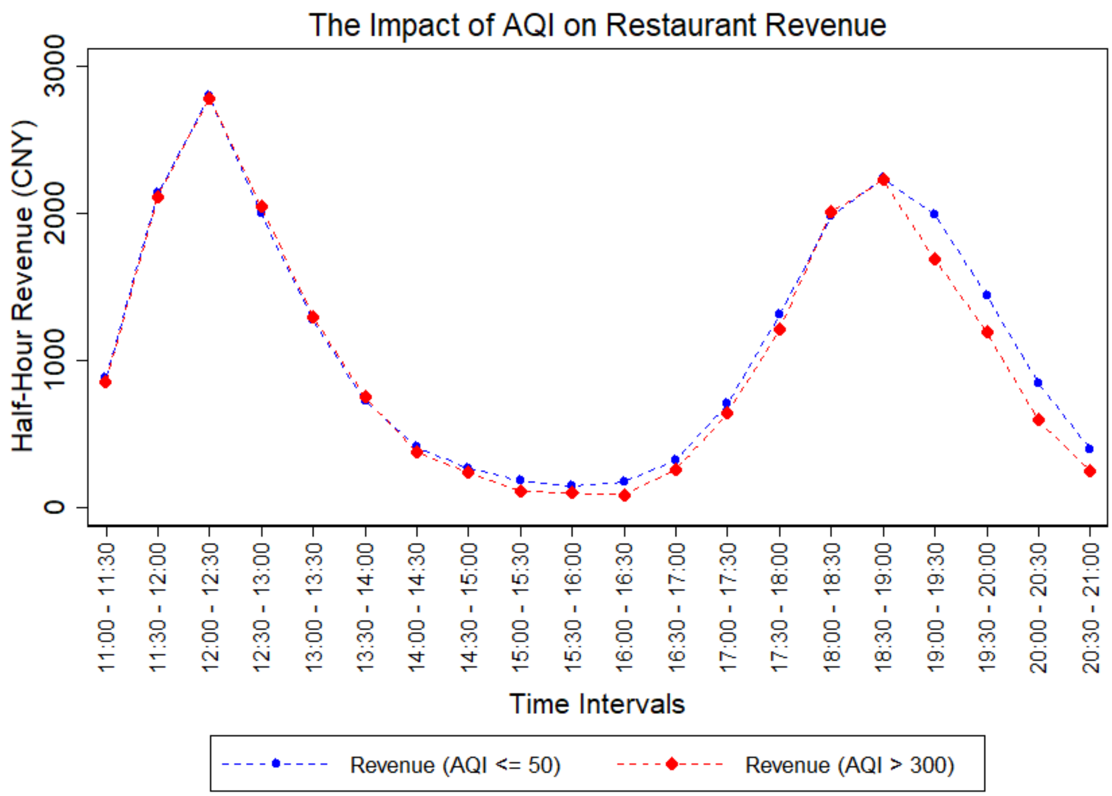
(a) Weekend



(b) Weekdays

Notes: Using average daily revenue of restaurants belong to Chain A as an example. We found pairs of consecutive days that daily AQI (bars) changed sharply during weekends (Panel a) and weekdays (Panel b). The revenues of these pairs were plot. We found that AQI lead to revenue loss for most matched pairs during weekends (Panel a). However, the impact is ambiguous for matched pairs during weekdays (Panel b).

Fig. A3: The Impact of Sharp AQI Change on Revenue



Notes: Using average hourly revenue of Chain A as an example. This figure compares the average hourly revenue of extremely low AQI days to extremely high AQI days.

Fig. A4: The Impact of Extreme AQI on Hourly Revenue

Table A1: Alternative Specifications of Weather Controls

Effect on weekend revenue	Half-Hour Revenue (Mean = 1,620.4 CNY) (1)	(2)	(3)
AQI/10	-2.44***	-2.48***	-2.52***
	(0.39)	(0.39)	(0.41)
Temperature (Celsius)	6.02***	5.98***	
	(0.67)	(1.29)	
Temperature Square		0.01	
		(0.04)	
Precipitation (mm)	0.23	-1.59	
	(1.46)	(4.14)	
Precipitation Square		0.04	
		(0.09)	
Wind Speed (km/day)	-0.05***	-0.15***	
	(0.01)	(0.03)	
Wind Speed Square		0.0001***	
		(0.00003)	
Weather Bin Controls	No	No	Yes
N. Obs	234,846	234,846	234,846
Adj. R^2	0.639	0.639	0.639

Note: This table reports the results for 98 stores' revenue on the weekends to test the specification of weather control. In all specifications, restaurant fixed effects and time fixed effects (year, month, day of week, and half-hour) are included. Standard errors in parentheses are clustered at restaurant-level. * significant at 10%, ** at 5%, and *** at 1%.

Table A2: Alternative Measures of Air Pollution at the Restaurant-Level

Effect on weekend revenue	Half-hourly Revenue (Mean = 1,620.4 CNY) (1)	(2)	(3)
AQI/10 (distance weighted average AQI from the 3 nearest monitors)	-2.52*** (0.41)		
AQI/10 Average (average AQI from the 3 nearest monitors)		-2.39*** (0.37)	
AQI/10 Nearest (AQI from the nearest monitor)			-2.38*** (0.38)
N. Obs	234,846	254,443	260,777
Adj. R^2	0.639	0.640	0.640

Note: This table reports the results on 98 stores' weekend revenue to test the specification of alternative measures of air pollution at the restaurant-level. In all specifications, weather bin controls, restaurant fixed effects and time fixed effects (year, month, day of week, and half-hour) are included. Standard errors in parentheses are clustered at the restaurant-level. * significant at 10%, ** at 5%, and *** at 1%.

Table A3: Effects of Specific Pollutants

Effect on weekend revenue	Half-Hour Revenue (Mean = 1,620.4 CNY)					
	(1)	(2)	(3)	(4)	(5)	(6)
PM10	-0.17***					
	(0.04)					
PM2.5		-0.24***				
		(0.04)				
CO			-29.83***			
			(5.83)			
NO2				-0.51***		
				(0.11)		
O3					-0.13**	
					(0.05)	
SO2						-2.18***
						(0.58)
N. Obs	234,654	260,775	253,907	260,777	260,777	260,761
Adj. R^2	0.63	0.64	0.64	0.64	0.64	0.64

Note: This table reports the results for 98 stores' weekend revenue to estimate the effects of specific pollutants. In all specifications, weather bin controls, restaurant fixed effects and time fixed effects (year, month, day of week, and half-hour) are included. Standard errors in parentheses are clustered at the restaurant-level. * significant at 10%, ** at 5%, and *** at 1%.

Table A4: Descriptive Statistics by Chain for Home-delivery Component

Variables	Chain A		Chain B		Chain C	
	Mean	SD	Mean	SD	Mean	SD
Daily Revenue (CNY)	2845.51	1798.00	3343.76	2048.23	2689.17	3268.89
Daily Orders (Count)	38.49	24.82	32.98	20.81	77.24	93.39
Half-hourly Revenue (CNY)	335.87	321.21	348.32	372.78	173.40	277.88
Half-hourly Orders (Count)	4.55	4.22	3.42	3.46	4.99	8.04
Dishes Per Order (Count)	5.48	1.09	6.08	2.24	5.29	1.14
Revenue Per Order (CNY)	75.99	36.04	108.72	79.33	34.96	10.73
Revenue Per Dish (CNY)	14.11	6.02	20.01	14.33	7.37	2.87
N of Stores	18		24		54	
N of Observations	147,535		116,978		502,027	

Note: An observation is a restaurant at half-hour. Sample periods are Jan 1, 2017 to Dec 31, 2019 (Chain A), Mar 24, 2018 to Dec 31, 2019 (Chain B), and Jan 1, 2018 to Dec 31, 2019 (Chain C). National holidays were excluded. Since home-delivery orders do not report number of customers, we do not report it.

Table A5: Testing Customer Flow as a Mechanism

Dependent Variable is Half-Hourly Revenue from All Stores (Mean = 1,620.4 CNY) During Weekend	Revenue (1)	Revenue (2)
AQI/10	-6.43***	-5.57***
	(1.29)	(1.29)
Traffic Speed		-9.48***
		(2.25)
N	194,256	191,885
Adj. R^2	0.63	0.64

Note: In all specifications, weather bin controls, restaurant fixed effects and time fixed effects (year, month, day of week, and half-hour) are included. Standard errors in parentheses are clustered at the restaurant-level. * significant at 10%, ** at 5%, and *** at 1%.