Two Hearts Tugging at One Load: Air Pollution, Sympathy and Online Charitable Giving

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Abstract

We investigate the relationship between sympathy and charitable giving in a natural setting with an unconventional context: exposure to air pollution that elicits sympathy and promotes donations for its victims - respiratory disease patients. Leveraging detailed visit data from a major online medical crowdfunding platform in China, we show air pollution affects charitable giving in two ways: 1) through a mood effect that reduces giving and 2) by evoking sympathy, drawing donors' attention to environmental-related features, particularly respiratory diseases, and increasing donations. A one-standard-deviation increase in ambient $PM_{2.5}$ experienced by a visitor leads to a significant 21.5% rise in donations towards respiratory disease patients compared to non-respiratory disease patients. We find that air pollution predominantly influences charitable giving through direct physical exposure to local air pollution rather than by disseminating information about pollution. The charitable contributions induced by air pollution towards respiratory diseases is quantitatively comparable to the additional medical expenses caused by air pollution, offering a silver lining amidst the challenges posed by air pollution.

Keywords: Sympathy, Charitable Giving, Air Pollution, Online Medical Crowdfunding

1 Introduction

Helping is increased through sympathy. Existing studies, grounded in experiments, have demonstrated that prosocial behavior is significantly influenced by evoking sympathy (e.g., Andreoni and Rao, 2011; Coke et al., 1978), an emotional response typically triggered by understanding another person's misfortune. However, it is worth noting that in controlled laboratory settings, participants are often provided with specific instructions to generate feelings of sympathy, while there is also a lack of evidence from field experiments. This gap in existing studies raises important questions about the extent to which sympathetic feelings effectively translate into real-world motivation to help.

In this study, we investigate the relationship between sympathy and charitable giving in a natural setting with an unconventional context: exposure to air pollution that elicits sympathy and promotes donations for its victims - respiratory disease patients. As an environmental hazard, air pollution has long been recognized for its adverse health effects, including heightening the risk of respiratory disease.[1] Therefore, visiting a campaign about a respiratory disease patient amidst severe air pollution serve as a quasi-experimental way to evoke sympathy. Leveraging detailed visit data from a major online medical crowdfunding platform in China, we document the sympathy effect of air pollution on charitable donations and explore the conditions and mechanisms that underlie the triggering of sympathy towards patients.

Online medical crowdfunding platforms play a vital role in helping the low-income group of patients diagnosed with critical illnesses in China. The public health insurance generally only covers about half of medical costs, with the proportion lower for serious or chronic illnesses. Medical crowdfunding platforms were launched to bring together individuals in need of financial support and those willing to donate through social media campaigns, essentially serving as a form of social insurance.

Our study is based on unique individual visit data from a major online crowdfunding platform[2], which serves the entire Chinese market, and is considered a reliable source for understanding online charitable giving practices in China. This peer-to-peer fundraising platform allows patients and their families facing financial difficulties to launch verified medical crowdfunding campaigns. These fundraisers typically have critical illnesses, such as cancer, severe injury due to accidents, and require organ transplants, among others. The primary distribution method for fundraising campaigns is through social media platforms where users share posts to promote the campaigns. For our study, we collect

[1] For discussion about particle pollution and its respiratory effects, please see the symposium by the United States Environmental Protection Agency (EPA). Source: https://www.epa.gov/pmcourse/particle-pollution-and-respiratory-effects.

[2] We refer to the platform as "A" in order to maintain data confidentiality and adhere to usage guidelines.

detailed records of visits and donations to 90 campaigns from Fall 2018, and match these individual visit records with hourly air pollution data. Our identification hinges on the fact that the precise timing of patient visits, down to the hour, is likely exogenous to potential confounding factors, which allows us to identify the causal relationship between air pollution and charitable givings.

Our initial analysis using a simple OLS framework suggests an insignificant and negative relationship between donation amount and air pollution, as shown in Figure 1. However, underlying this seemingly null effect lie two competing channels: the mood effect and the sympathy effect. On one hand, existing studies have shown that a pleasant ambient environment tends to induce positive moods and fosters greater prosocial behavior (Cunningham, 1979; Guéguen and Lamy, 2013; Rind and Strohmetz, 2001). Consequently, the presence of poor air quality acts as a dampening factor on donations due to its adverse psychological and mood effects. On the other hand, the pervasive issue of air pollution has garnered increased public awareness, catalyzed by governmental initiatives and social media platforms. Consequently, environmental-related features have gained prominence in the collective consciousness, triggering not only defensive behaviors (Chang et al., 2018) but also evoking feelings of sympathy towards individuals afflicted by diseases attributed to the detrimental effects of air pollution.

To empirically distinguish between these two opposing channels, we use a difference-in-difference approach to investigate the effect of air pollution on charitable giving. Specifically, we first compare visitors who were exposed to high versus low levels of ambient air pollutants, then compare visitors contributing to campaigns of respiratory diseases versus other types of diseases. In our context, campaign visitors who are exposed to poor air quality are more likely to be connected to the patients who have respiratory diseases and to elicit feelings of sympathy. We find a one-standard-deviation increase in a visitor's ambient $PM_{2.5}$ increases donations towards respiratory diseases by 21.5%, relative to donations towards non-respiratory diseases. Amongst the group of donors, the effect is slightly more pronounced: a one-standard-deviation increase in $PM_{2.5}$ leads to 22.9% more donations towards fundraisers with respiratory diseases.

We then investigate the mechanisms that trigger sympathy towards patients with respiratory diseases. The exposure to ambient air pollution can occur through either perception or information channels. In the perception channel, visitors are physically exposed to local air pollution. In contrast, the information channel involves visitors being informed about air pollution through sources such as local news or social media. We differentiate these two channels leveraging the features of the Chinese pollution alert system and online search index as potential sources of information exposure. Our findings suggest limited evidence supporting the information exposure as the primary channel, indirectly supporting the perception channel as the primary mechanism instead.

This paper contributes to the literature in several significant ways. Firstly, we explore the impact of air pollution on a relatively understudied aspect of human behavior – charitable giving. While previous studies have identified several behavioral consequences of poor air quality, such as decreased labor productivity (Graff Zivin and Neidell, 2012), worsened school performance (Lavy et al., 2014), increased purchase of health insurance (Chang et al., 2018), and rising violent crimes (Herrnstadt et al., 2021), our study documents that air pollution can also increase people's willingness to help those suffering from respiratory diseases. Further, the use of fine-scaled data on air pollution and donations (individual visit data identified at city-hour level) largely mitigates bias in estimation due to measurement errors and endogeneity issues that have been present in prior air pollution impact studies.

Second, we provide novel empirical evidence on how feelings of sympathy arise from a deepening connection, and subsequently promote prosocial behavior in a large natural experiment setting. Prior studies examining the sympathy effect on prosocial behavior have primarily been conducted in laboratory settings (Andreoni and Rao, 2011; Batson et al., 1991; Underwood and Moore, 1982). However, these laboratory experiments typically measure or trigger feelings of sympathy through information channel such as video watching (Dovidio et al., 1990), listening to an audio recording (Batson et al., 1997; Galinsky et al., 2008), or writing a short narrative essay (Galinsky et al., 2008; Mazzocco et al., 2012). It is unclear whether these findings can be replicated in natural settings where subjects are not given explicit instructions. While few existing studies manage to demonstrate the sympathy effect in a natural setting without providing information or instructions, we show in section 4.1 that supplying subjects with deliberately crafted information might not effectively stimulate feelings of sympathy.

Next, this paper also contributes to the literature on the private provision of green public goods (Bergstrom et al., 1986; Kotchen, 2009; Kotchen and Wagner, 2023). Existing studies offer comprehensive theoretical discussions on the mechanisms and welfare effects of private volunteer provision of public goods to address environmental externalities, such as carbon offsets, ecological protection, and cleaner energy. We present a new perspective: a negative externality, typically associated with unfavorable outcomes, can paradoxically act as a driving force behind voluntary contributions aimed at remedying its consequences. Our back-of-the-envelope calculation demonstrates that the air pollution-induced donations to respiratory diseases hold considerable quantitative significance compared to the impact of air pollution on increased medical expenses. Therefore, the private provision of medical donations for respiratory diseases acts as a form of social insurance to mitigate environmental damage. Consequently, our paper carries a clear policy implication, advocating for the establishment of a green market (Kotchen, 2006) and emphasizing the salience of environmental damage in encouraging the voluntary provision of public goods.

The rest of the paper is structured as follows. In section 2, we provide some background information on China's online crowdfunding platforms, the public's awareness of the air quality problems and our data sources. Section 3 presents empirical evidence on the impact of air pollution on charitable giving. Section 4 discusses the conditions and mechanisms underlying our main findings. Finally, Section 5 concludes with implications for future research.

2 Background and Data

2.1 Online Medical Fundraising Platform in China

According to the National Healthcare Security Administration, basic government-sponsored health insurance covers at least 95% of China's 1.4 billion people. Basic interventions are typically low-priced and covered by basic medical insurance, making them affordable even for low-income patients. However, more sophisticated interventions are priced above cost and not covered by basic medical insurance, with the expectation that health care providers will use these profits to cross-subsidize basic interventions. This pricing and insurance coverage structure has incentivized providers to offer sophisticated care wherever possible, increasing the risk of catastrophic spending for patients with critical illness. Additionally, commercial health insurance only accounts for less than 10% of coverage[3], and traditional charitable platforms have been slow and unresponsive due to the lengthy registration processes. On average, out-of-pocket spending accounts for 32% of China's total health expenditures, compared to only 9% in the United States.

Due to the absence of insurance coverage for critical illnesses and the rise of the social media market, online medical crowdfunding campaigns have become increasingly popular since 2015. As of 2021, the total amount of fundraising across all platforms had reached approximately 100 billion RMB. According to a recent survey conducted by the National Bureau of Statistics, 64% of the respondents are aware of medical crowdfunding platforms and among those who know about these platforms, 75.5% hold positive views.

[3]Source: *China Commercial Health Insurance Development Index Report 2018* by the China Insurance Association.

Our visit data is collected from a major online medical crowdfunding platform (Platform "A"), where patients and their families who face financial difficulties can create a verified crowdfunding campaign by providing evidence of the diagnosis, financial situation, and other verified documents. The majority of the fundraising campaigns on this platform are for critical illnesses, such as cancer, cardiovascular disease, severe injury, and organ transplants, among others.

A key feature of online medical fundraising in China is its heavy reliance on social media. Platform "A" does not provide a comprehensive list of ongoing fundraising campaigns for visitors to browse and support. Instead, the primary means of disseminating fundraising campaigns on platform "A" is through the two largest social media platforms in China: *Tencent WeChat* and *Sina Weibo*. *Tencent WeChat* is the most popular social networking space in China and functions as a comprehensive platform with services such as food delivery, messaging, mobile payment, ride-hailing. etc. By 2020, *WeChat* had over 1.2 billion monthly active users, with 78% of people in China aged 16-64 using the platform. *Sina Weibo* is the Chinese version of Twitter and is known for its use as a space for free speech. As of 2020, it had at least 500 million monthly active users. Due to their enormous user bases, marketing and e-commerce have thrived on these social media platforms.

Both *Tencent WeChat* and *Sina Weibo* allow users to post, share, like, and comment on crowdfunding campaigns, which are spread through shared links. Users can access campaign postings through people they follow on social media (see Appendix Figure A.1 panel A). Therefore, visitors are not actively searching for medical fundraising campaigns but are instead passively receiving information about them. This feature is similar to that in laboratory experiments where agents are randomly assigned to various campaign information. One critical assumption required for our identification is that visitors to campaign sites should not be selected on unobservables that are correlated with air pollution, donation decisions and types of campaigns. This assumption is met in our setting because of the random assignment of fundraising campaigns to visitors.

Before clicking a campaign link, visitors are presented with only the title of the fundraising campaign, which may not necessarily reveal disease types. In Section 3.1, we show that the decision to visit a campaign website is not influenced by disease types (see Table 2). The actual campaign website, which can be accessed by clicking on the campaign link, provides visitors with more detailed information about the fundraiser, including photos, diagnosis, a description of the financial hardship, and donations made by others (see Appendix Figure A.1 panel B). During our study period, the profile pictures of recent donors were small and thus peer pressure and reputation concerns were not considered as confounding factors. Additionally, the campaign website features payment and sharing buttons, which enable visitors to make donations of any amount and share the campaign post on their own social media accounts. The payment process is straightforward and takes approximately thirty seconds. This feature enables visitors to donate quickly and conveniently.

The web cache archives every visit and records important information such as the time of the visit and visitor's IP address, used in our study to identify the visitor's city. We do not have access to visitor characteristics except for the gender of some visitors. However, aside from gender information for some visitors, we do not have access to other characteristics of the visitors. According to a recent survey conducted by the National Bureau of Statistics, the largest group of donors (33%) falls in the age range of 40-49, followed by the 20-29 age group (24%), the 30-39 age group (23%), and those over 50 (20%). Donors are mostly located in the central and eastern regions of the country, while fundraisers are more likely to be based in the northern and western regions. Our main findings are robust to controlling for the visitor characteristics, as shown in Appendix Table **??**.

2.2 Air Pollution and Public Awareness in China

Air pollution is a major environmental hazard to human health (Chay and Greenstone, 2003; Dockery et al., 1993; He et al., 2016; Tanaka, 2015). According to reports from the World Health Organization (WHO), air pollution can cause strokes, lung cancer, acute and chronic respiratory diseases, and other diseases. Exposure to ambient air pollution was estimated to cause 4.2 million premature deaths worldwide in 2016, with 91% of these deaths occurring in low- and middle-income countries. Over the past decade, managing air quality has become an increasingly important regulatory concern. China's central and municipal governments have implemented several large-scale and costly policies designed to control air pollution since the passage of the Air Pollution Prevention and Control Action Plan in 2013.

Meanwhile, government regulatory efforts have also raised public awareness of issues related to air pollution. In 2013, China launched a nationwide air quality monitoring program and disclosed real-time air quality data to the public for the first time. The public can easily access air quality information through government monitoring websites or mobile air quality apps. Moreover, air quality alerts are often issued through weather apps and social media, whenever local air quality reaches a certain cutoff. In section 4.1, we leverage this air pollution alert feature in a regression discontinuity design to study the effect of information about air pollution on donation.

In our setting, air pollution is considered as the trigger of sympathy towards patients with respiratory diseases. Therefore, it is important to know what the typical health consequences of exposure to air pollution are, as known by the public. Rajper et al. (2018) surveyed college students in China and found that 69.3% of their respondents were aware that air pollution causes cardiovascular and respiratory problems, and that air pollution was one of the major causes of mortality in China over the last two decades. Chang et al. (2018) showed that people are more willing to purchase health insurance when the ambient air pollution level is high.

By looking into the search results on major search engines, we also find supporting evidence that the Chinese public would associate air pollution with respiratory diseases. Figure 2 displays the number of related contents of searching "Air Pollution + Disease" in Chinese. We set the number of Google results on the keywords combination "Air Pollution + Respiratory Disease" to be 1. The numbers of search results on other keywords combos are all less than 10% of the results on "Air Pollution + Respiratory Disease". We find a similar effect on three representative Chinese websites as well, namely, *Baidu* (search engine), *Weibo* (social media) and *haodf* (medical advice platform). Both the survey study and our statistical analysis support that the majority of the public knows that air pollution mostly affects respiratory diseases. In Appendix Table A.2, we confirm that our main results are robust to if the public associates air pollution with both respiratory and cardiovascular diseases.

2.3 Data and Summary Statistics

Visit and donation records. We obtain detailed visit data for the one-month period from October 10th to November 9th in 2018 from a major online medical crowdfunding platform "A" via a restricted agreement. All of the campaigns were posted in the week of Oct 10th to Oct 16th, 2018. As described in Table 1 panel A, we have a complete dataset on 90 verified campaigns, including the age, gender, target fund, hometown, and disease type of each patient. The average age of the patients is 46.86 years old, with 58% being male. The average target fund is 198,890 RMB (∼\$30,000), which is 7 times the disposable income per capita as reported in 2018 by China's National Bureau of Statistics.

There are a total of 109,746 visit records for the 90 campaigns during our study period. Table 1 panel B describes the summary statistics of the visit records. The average donation per visit is 4.07 RMB (∼\$0.58) with 88.02% of the visits making no donation, and the largest amount of donation being 2,000 RMB (∼\$285). Donations to respiratory disease and non-respiratory diseases share a similar distribution (see Appendix Figure A.2). Unsurprisingly, most of the visits occur during periods when people have leisure time to scroll through posts on their social media (see Appendix Figure A.3). To alleviate the concern that our results might be driven by some outliers in donation, we show robustness using 95% and 99% winsorization sets in Appendix Table A.3. Out of the 90 campaigns, 14% are related to respiratory diseases. Our sample includes patients from 24 provinces across the country, with a relatively uniform distribution, except for certain western provinces like Xinjiang and Tibet, which have significantly lower population densities (see Appendix Figure A.4). Additionally, we do not find evidence that patients with respiratory diseases were more prevalent in regions with higher levels of pollution, such as northern China. Therefore, it can be inferred that the campaign disease types are not mechanically correlated with fundraiser's local air quality.

Table 1 panel C describes the summary statistics of the visitors who contribute to the campaigns. This sub-sample is about 11.98% of our entire sample. There are a total of 13,145 visitors who actually donate to a campaign, with the average donation amount being 33.98 RMB (∼$4.84) conditional on donating, and the probability of sharing the link rises to 20.76%. In addition, we also obtain information on how much time these donors spend on the campaign website (including reading about a campaign and making a payment). The average time donors spent on a campaign website is approximately 4.17 minutes, after removing obviously implausible records.

Air pollution, weather, and city characteristics. We take air pollution data from the National Urban Air Quality Real-time Publishing Platform and focus on $PM_{2.5}$, PM_{10}, SO_2 , NO_2 , Ozone , CO, and AQI. We calculate each city's hourly pollutant concentration according to the guideline provided by the Ministry of Ecology and Environment. There were about 400 active monitors during our study period for interpolation. The average hourly $PM_{2.5}$ is 37.93 $\mu g/m^3$ in the visitor sample, and 36.58 $\mu g/m^3$ in the donor sample.

We also collect hourly temperature, precipitation, wind, and cloud coverage data from the National Centers for Environmental Information (NCEI) Integrated Surface Database (ISD) from about 500 weather monitors in our study region. We use the weather monitor that is closest to each city's geographical centroid as weather proxies for each city.

Our city characteristics are drawn from *The China City Statistical Yearbook, 2018*. The city-level variables include total GDP, GDP per capita, public finance expenditure, average education level, and internet coverage, which are used to account for heterogeneity in economic growth across cities.

3 Method and Results

3.1 The Impact of Air Pollution on Visiting

We begin our analysis by showing that visitors to charitable campaigns are not selected on their personal or regional characteristics. One distinctive aspect of the crowdfunding platform "A" is that visitors are randomly exposed to campaigns posted by individuals they follow on social media. Prior to clicking on any campaign links, visitors do not possess comprehensive information about the campaign or the specific disease type (see Appendix Figure A.1).

Further, to address the concern that visitors from more industrialized cities tend to contribute more because of their higher income rather than sympathy effect, we examine if visitors are selected on ambient air pollution levels. Specifically, we aggregate our visit data to city-day level, and examine if visits to campaign websites are correlated with visitors' ambient air quality using equation (1):

$$Y_{ct} = \alpha_0 + \alpha_1 \, AQ_{ct} + \mathbf{W_{ct}\Gamma} + \epsilon_{ict} \tag{1}$$

where AQ_{ct} measures the ambient $PM_{2.5}$ concentration in city c, day t. Y_{ct} are aggregated outcomes of interest including the *log* of total visits, % visits to respiratory campaigns, % visits to campaigns with "respiratory" in the title, % visits from the same city as the fundraisers, and % male visitors. $\mathbf{W_{ict}}$ includes a set of weather controls, city, and day fixed effects. The coefficient of interest is α_1, which captures the correlation between air quality and the outcome variables of interest.

The result is reported in Table 2, suggesting that visitors who are exposed to higher levels of pollution are not more aware of the fundraising campaigns than those exposed to lower levels of pollution, regardless of the visitors' gender, location, and disease types of the campaign. Table 2 column (1) implies that the total number of visits are not correlated with air pollution level. Columns (2) and (3) show that higher levels of pollution do not result in more visits to respiratory campaigns, even when the campaign titles include the term "respiratory". Columns (4) and (5) show that neither the percentage of visits coming from the same cities as the fundraisers, nor the percentage of male visitors show any correlation with air quality. This suggests that visitor characteristics are evenly distributed across cities with varying pollution levels. Collectively, this empirical evidence indicates that the selection issue is not a concern in our study context, which is unsurprising given the unique nature of our setting, where social media users are unlikely to encounter information about the disease type before clicking on a campaign link.

3.2 Regression Framework

In section 3.1, we have established that social media users are not selected on visiting a campaign based on their ambient air quality. Leveraging this quasi-experimental context, our empirical study capitalizes on visitors being exposed to varying levels of air pollution and being randomly assigned to campaigns with or without respiratory diseases. This enables us to use a difference-in-difference(DiD) approach to identify the effects of sympathy on donation decisions. Specifically, we compare visits to respiratory campaigns with non-respiratory campaigns, as well as between exposure to high pollution with low pollution. The baseline DiD model is estimated using equation (2):

$$Y_{ict} = \beta_0 + \beta_1 AQ_{ct} + \beta_2 Res_{ict} + \beta_3 AQ_{ct} \times Res_{ict} + \mathbf{W_{ict}\Gamma} + \epsilon_{ict} \tag{2}$$

where Y_{ict} is the outcome variable related to the donation decisions for individual i, in city c, and visiting time t recorded at the hourly level. AQ_{ct} measures the ambient level of $\text{PM}_{2.5}$ concentration. Res_{ict} is a binary variable that equals one if a campaign is for patients with respiratory disease. The control variables $\mathbf{W_{ict}}$ include the campaign's characteristics (gender, age, age-squared, province, and target fund), weather controls (temperature, precipitation, and cloud coverage), and a set of fixed effects (FE) that include day-of-week, hour, and visitor's province FEs. We include the day-of-week and hour fixed effects to account for time-specific determinants of donation decisions. Visitor's province fixed effects are added to compare donations within each province. Standard errors are clustered to the visitors' city level.

We focus on two outcome variables: (1) the amount donated, which defines the non-donors' amount as zero. This can be considered as capturing the effect on the "overall" donation amount. (2) conditional amount donated, the amount conditional on making a positive donation, namely, the "intensive" margin of the donation outcomes.

We are particularly interested in the signs of β_1, β_2 and β_3. Consider a simple case where there are four types of visits: exposed to low pollution and non-respiratory campaign (AQ = low, Res = 0), low pollution and respiratory (AQ = low, Res = 1), high pollution and non-respiratory (AQ = high, Res = 0), and high pollution and respiratory (AQ = high, Res = 1). The baseline group for comparison is the "low pollution and non-respiratory" group. β_1 estimates the difference between the baseline group and the "high pollution and non-respiratory" group. We conjecture that β_1 should be negative because being exposed to a more polluted environment should decrease the willingness to donate. β_2 estimates the difference between the baseline group and the "low pollution and respiratory" group. We expect that β_2 is close to zero since β_2 captures the effect of disease type on donation decisions. Given that the severity of the disease types is similar in our context, and that we have already controlled for the target fund of each campaign, β_2 should be close to zero. Finally, our main interest is in β_3, which estimates the sympathy effect. A positive β_3 implies that visitors are donating more to respiratory campaigns when visitors themselves are exposed to high levels of pollution. Specifically, such visitors are more likely to think in the shoes of a patient with respiratory disease and more likely to donate, which is the sympathy effect we are interested in capturing.

Recent studies have highlighted the potential endogeneity issues associated with air pollution due to unobservable factors, such as income and demographics, which may simultaneously correlate with the ambient air pollution and the outcomes of interest (Arceo et al., 2016). However, our study incorporates two crucial features in our specification that make it less vulnerable to the typical endogeneity concerns encountered in other papers examining the long-term impact of air pollution. First, air pollution exhibits greater stochasticity in the short run compared to the long run. Using the variation in air pollution concentrations at the hourly level, rather than daily or weekly averages, reduces the likelihood of confounding by other unobserved factors. This fine-scaled temporal resolution allows us to capture the immediate and transient effects of air pollution, enhancing the validity of our estimation.

Second, our main variable of interest is the interaction between air pollution and the indicator variable on respiratory campaigns. Consequently, even if there are confounding factors, such as traffic congestion, that are correlated with both air quality and visitors' donation decisions, any potential bias would need to substantially differ between respiratory and non-respiratory diseases to impact our causal estimation of the treatment effect. This design choice provides additional protection against endogeneity concerns. For these reasons, we stick with the difference-in-difference design as the main specification in our paper.

3.3 Main Results: The Sympathy Effect

The regression results are summarized in Table 3. Columns (1) and (2) report results across the entire sample, while columns (3) and (4) the donor sample. Columns (1) and (3) control for the weather variables and campaign characteristics. Columns (2) and (4) are estimated with our preferred specification using equation (2), in which we further include day-of-week, hour, and visitor's province fixed effects.

Three important empirical patterns emerge from our analysis. First, we find compelling evidence supporting the existence of the sympathy effect, which is captured by the coefficient on $\text{PM}_{2.5}\times\text{Res}$. In the overall sample (Table 3 column (2)), a one-standard-deviation increase in $\text{PM}_{2.5}$ leads to a 0.42 RMB ($\sim$\$0.06) increase in donations towards respiratory campaigns, relative to non-respiratory campaigns. In other words, individuals who are exposed to poor air quality tend to donate by 21.5% more when visiting a respiratory campaign, compared to when visiting a non-respiratory campaign.

The impact of the sympathy effect is slightly more pronounced when examining the subset of individuals who make a positive donation. This is evident from the results presented in Table 3 column (4). Here, we observe that a one-standard-deviation increase in $\text{PM}_{2.5}$ corresponds to a 7.66 RMB ($\sim$\$1.09) increase in the conditional amount donated towards respiratory campaigns, compared to other campaigns. Notably, this 7.66 RMB increase constitutes approximately 22.9% of the average donation amount. Thus the influence of sympathy, as captured by the association between air pollution and donations, becomes more evident and substantial when focusing on those who actively contribute to the cause.

Secondly, we confirm the presence of a mood effect resulting from poor air quality, whereby higher $\text{PM}_{2.5}$ concentrations lead to a decrease in the amount donated. This effect is statistically significant at a 10% level. In the case of visits to non-respiratory campaigns, a one-standard-deviation increase in the ambient $\text{PM}_{2.5}$ concentration results in a reduction of 0.05 RMB ($\sim$\$0.007) in the amount donated for the overall sample, and 2.10 RMB ($\sim$\$0.3) for the donor sample. Considering that the average amount donated and conditional amount donated are 4.07 RMB ($\sim$\$0.58) and 33.49 RMB ($\sim$\$4.77) respectively, the pure impact of air pollution on charitable giving holds significant magnitude. These findings align with previous research indicating that favorable weather conditions are associated with positive mood and increased prosocial behavior and vice versa (Cunningham, 1979; Guéguen and Lamy, 2013; Rind and Strohmetz, 2001).

Finally, as expected, our analysis reveals that visiting a respiratory campaign alone does not necessarily lead to more donations, after accounting for observable variables and fixed effects. The presence of a respiratory disease in the fundraiser's campaign is not sufficient to evoke sympathy or drive visitors' willingness to contribute.

Furthermore, our main findings remain robust when considering alternative specifications that incorporate additional control variables, as reported in Appendix Table **??**. These specifications include the inclusion of patient, province-by-hour, city, day fixed effects, as well as interactions between air pollution and other patient characteristics. The results from these alternative specifications reaffirm that the effects we have identified are not influenced by unobservable factors that are correlated with both pollution levels and donation decisions. To further enhance the robustness of our findings, we also construct a sample that is balanced on campaign characteristics using the Propensity Score Matching (PSM) method. Details and results of this analysis are presented in Appendix Table A.4. Notably, the main effects persist, although the standard errors tend to be larger due to the reduced sample size resulting from the matching process.

Avoidance Behavior. Our empirical findings have shown that increased air pollution leads to more contribution towards patients with respiratory diseases, which we attribute to the sympathy effect. One plausible counterargument is that during periods of high pollution, individuals may choose to stay indoors as a defensive measure, increasing social media usage, heightening attention to online medical campaigns, and consequently leading to a rise in donations. We show this is not the case. In Table 2 column (2), our analysis indicates that air pollution is not associated with a greater number of visits to respiratory campaigns. Moreover, even when considering the campaign titles that include disease names, air pollution still does not correlate with increased visits to respiratory campaigns (Table 2 column (3)). These findings do not support strong selection or avoidance behaviors in deciding whether to open the link.

Extensive Margin. Our analysis primarily focuses on the "intensive margin", specifically the impact of sympathy on the amount donated, conditional on donation. However, it is also worth exploring whether visitors have a higher probability of donating when exposed to higher levels of pollution and encountering information about a respiratory disease campaign. To address this question, we estimate equation (2) employing the "probability of giving" as the outcome variable. Table A.1 columns (1) and (2) report the results using the probability of giving as the outcome variable. Neither visiting a respiratory campaign, nor the level of ambient pollution has a significant impact on the probability of donation. The key variable of interest, $PM_{2.5} \times Res$, although positive, is also not statistically significant, indicating that no sympathy effect is found on the extensive margin. We also find a similar null effect using a conditional logit regression model, as shown in columns (3) and (4) in A.1.

A valid concern may arise regarding why we observe a null effect on the extensive margin (probability of giving), while still detecting a statistically significant impact on the amount donated. There are two reasons for this. Firstly, similar observations of differential effects on the extensive margin and the intensive margin are commonly reported in the existing literature on charitable giving in real-world contexts. Research has found that the manner in which donations are solicited can lead to varying effects on the probability of giving and the amount donated. For example, soliciting donations in person or via phone calls may primarily affect the probability of giving, without significantly influencing the amount donated (Meer and Rosen, 2011). Conversely, soliciting donations through mail or email may primarily impact the amount donated, while not significantly affecting the probability of giving (Eckel et al., 2017; Kessler et al., 2019). In our online solicitation setting, which is akin to the latter case, we find an effect solely on the amount donated but not on the probability of giving.

Furthermore, the observed pattern, where the majority of visitors do not respond to pollution levels and information about the disease type, is likely attributable to people's limited attention to social media (Qiu et al., 2017; Weng et al., 2012) and measurement error issues. Unlike controlled laboratory experiments where participants are explicitly instructed and provided sufficient time to read and process information, online visitors typically allocate limited attention to campaign details. Moreover, social media users may unintentionally click on links while casually scrolling through others' posts. Additionally, repetitive visits from the same visitor due to internet connection problems or other issues cannot be ruled out. All these factors contribute to potential measurement errors in the outcome variables. In the case of the donor sample, the average time spent on a campaign website is approximately 4.17 minutes, and there is a positive correlation between donation and the time spent on a campaign website. This serves as additional evidence that donors allocate more attention to the campaign characteristics compared to non-donors. Consequently, the results obtained on the intensive margin, i.e., the amount donated, are more reliable than those observed on the extensive margin — the probability of giving.

3.4 Placebo Test: No Sympathy Effect Found in Other Types of Diseases

We have demonstrated that sympathy is evoked when visitors exposed to high levels of ambient air pollution encounter respiratory campaign information. Furthermore, Figure 2 reveals a distinct public perception where air pollution is strongly associated with respiratory diseases, while not exhibiting the same level of association with other disease types. To address the concern of potential coincidental findings and to explore the unique nature of respiratory campaigns, we conduct a series of placebo-like tests in this section. We examine whether similar effects are observed on other disease types by utilizing alternative treatments based on the interactions between different diseases and air quality (AQ). Specifically, we substitute the respiratory disease binary variable in equation (2) with indicators representing other disease categories, namely, Brain-, Cancer-, Cardiology-, Kidney-, and Injury-related diseases. By doing so, we can assess whether there are comparative positive and significant effects for these alternative diseases. This analysis allows us to determine if the interaction term between disease and air pollution captures other compounding effects beyond the sympathy effect.

The results of the placebo tests are reported in Table 4, where Panel A and B correspond to the overall and donor sample respectively. For both groups, we find that none of the interaction terms are positively significant at the conventional level, indicating that as the concentration of ambient air pollution increases, visitors do not necessarily contribute more towards any of the five alternative diseases examined. While there is a statistically significant negative effect observed for "Kidney $\times$ $PM_{2.5}$" in the donor sample (column (10)), this effect does not persist when considering the larger sample (column (5)). Overall, the placebo check effectively alleviates the concerns of potential coincidental findings in our main results.

3.5 Robustness Checks

We conduct a variety of robustness checks and discuss their implications in this section. Firstly, we relax the assumption of a linear response model and adopt a more flexible functional form. This allows us to examine if the impact of air pollution on donation decisions becomes more salient when air pollution concentration is high. Following the guideline of US Environmental Protection Agency (EPA), we categorize the $PM_{2.5}$ concentration observations into four groups: 0-34 $\mu g/m^3$ (good), 35-54 $\mu g/m^3$ (Moderate), 55-149 $\mu g/m^3$ (Unhealthy for sensitive groups), and over 150 $\mu g/m^3$ (Unhealthy). Our "Unhealthy" group combines the "Unhealthy", "Very unhealthy" and "Hazardous" categories specified by the EPA due to the limited number of observations in these tail categories. We estimate equation (2) by replacing the interaction term with a series of interactions between *Res* and binary variables for each pollution category.

In Figure 3, the effect of $PM_{2.5}$ on the amount donated becomes significant for the "Moderate" group. Moreover, as air pollution increases and moves into the "Unhealthy for sensitive groups" category, the effect further increases. Although the coefficient for the "Unhealthy" group is twice as large as the coefficient from the previous group, it is statistically insignificant at conventional levels due to the limited number of observations within this category. However, the trend suggests a potential intensification of the impact with higher air pollution levels.

Second, the measurement of stimulus variable, here, air pollution, poses a significant empirical challenge when estimating any dose-response function. Often, the constructed air pollution concentration serves as a proxy for a visitor's actual exposure to air pollution, rather than capturing the exposure comprehensively. This challenge is prevalent across existing studies that examine the acute impact of air quality on human behavior. Owing to the high temporal resolution in the visit data, we are able to take hourly air pollution concentration as the stimulus variable for evoking sympathy towards respiratory campaigns. We show in panels A and B of Table 5 that even when aggregating the air pollution variables to coarser resolutions, such as rush hour averages and daily averages, the impact estimates remain consistent. This provides assurance that our findings hold robustly across different temporal resolutions.

Third, while our analysis primarily focused on $PM_{2.5}$ as the air pollution variable, we also examine the robustness of our findings using other traffic-related air pollutants (TRAP) including PM_{10}, NO_2, and Air Quality Index (AQI). As shown in panels C and D in Table 5, the results confirm that our results hold true across various TRAP measures. We do not find a significant effect on the interaction between CO, Ozone, and SO2 and respiratory disease. This is likely due to the limited perceptibility of variations in these pollutants, which typically fall within the prescribed air quality standards.

Fourth, in our benchmark specification, we define our treatment as respiratory diseases, reflecting the association between air pollution and respiratory diseases suggested by web search frequency. However, from a scientific perspective, ambient air pollution can impact not only respiratory diseases but also cardiovascular diseases, as highlighted in the US Environmental Protection Agency (EPA)'s report. Therefore, we examine the robustness of our main results by extending the association of air pollution to both respiratory and cardiovascular diseases. Appendix Table A.2 confirms that our main results remain robust when considering the public's association of air pollution with both respiratory and cardiovascular diseases.

Fifth, to assess whether our findings are driven by a few extremely large donations to respiratory diseases made under high pollution conditions, we implemented winsorization by truncating the top 1% and top 5% of donations in our sample. Appendix Table A.3, columns (1) and (2) with the top 1% winsorization, and columns (3) and (4) with the top 5% winsorization demonstrate that after winsorization, the direction and significance of the main effect remain unchanged, though the initial magnitude of the estimated impact decreases.

Finally, to address the concern that our 90 campaigns were posted on different days within the first week of the sample period, potentially introducing bias into our estimates, we report in Appendix Table

A.5 our estimations using sample visits that occur within 7 days after a campaign has been posted. The findings from this restricted sample remain consistent with our main results.

4 Discussions

4.1 The Impact of Air Pollution Exposure on Prosocial Behavior: Perception vs. Information Channels

In our context, visitors to platform "A" were exposed to varying levels of air quality at the time of making donation decisions. We propose that exposure to high air pollution concentration would elicit feelings of sympathy, ultimately increasing their donations towards patients with respiratory diseases. On the other hand, visitors exposed to low air pollution concentration, may find it more challenging to generate such feelings of sympathy and are consequently donating less.

The exposure to air pollution can occur through two distinct channels: the perception channel and the information channel. In the perception channel, visitors are physically exposed to local air pollution. In the information channel, visitors are influenced by air pollution-related information obtained from sources such as local news or social media. Consequently, an intriguing question arises regarding which channel primarily triggers online visitors in our context to engage in donation behavior. Our empirical findings do not provide support for the information channel as the main driver of prosocial behavior. This indirectly implies that the perception channel, involving physical exposure to air pollution, is the principal means by which visitors are triggered to engage in prosocial behavior.

In the first empirical strategy, we exploit the unique feature of air pollution alerts system that categorizes air pollutants into six categories and individuals can check current air quality through channels such as weather apps. For instance, an AQI level below 100 is classified as as "Moderate", while a level above this cutoff is classified as "Unhealthy for Sensitive Groups"(see Appendix Figure A.5).

One distinctive aspect is that the physically perceived pollution concentration remains continuous around these cutoffs. This implies that the perceived difference between exposure to AQI of 99 versus 100 is minimal. However, once the threshold of 100 is surpassed, triggering the "unhealthy for sensitive group" alert, the air pollution issue becomes more salient to people. Therefore, if the information channel serves as the primary mechanism, we should expect to observe a "jump" in donation amount around these alert cutoffs. To this end, we employ the regression discontinuity (RD) design using equation (3):

$$Y_{ict} = \alpha_0 + \alpha_1 \mathbf{1}(AQ_{ct} - \text{cutoff} \geq 0) \times Res_{ict} + \alpha_2 f(AQ_{ict} - \text{cutoff}) \times Res_{ict} + \alpha_3 f(AQ_{ct} - \text{cutoff})$$
$$+ \alpha_4 \mathbf{1}(AQ_{ct} - \text{cutoff} \geq 0) + \mathbf{W_{ict}\Gamma} + \epsilon_{ict}, \qquad |AQ_{ct} - \text{cutoff}| < h \tag{3}$$

Where $\mathbf{1}(AQ - \text{cutoff} \geq 0)$ is an indicator that takes the value of 1 for visits that may receive alerts and 0 otherwise; $f(\cdot)$ is a flexible function in distance of pollution from to the cutoff points. The parameter of interest is α_1, which captures the differential impact of air pollution alerts on donations towards respiratory and non-respiratory campaigns. In other words, α_1 provides an estimate of the treatment effect, specifically, the impact of the information channel. We test the cutoff points between the categories "healthy" and "unhealthy for sensitive groups", as well as between "unhealthy for sensitive groups" and "Unhealthy". Our "Unhealthy" group combines the "Unhealthy", "Very unhealthy" and "Hazardous" categories due to the limited number of observations in these tail categories. The control variables and fixed effects are the same as in the main specification.

In Table 6 Panel A, we report the regression results using different bandwidth sizes of 5, 10 , and 20. Notably, none of the estimated α_1 coefficients are statistically different from 0, implying that the air pollution alerts do not affect the donations towards respiratory and non-respiratory campaigns differently, and that the potential sympathy effect observed in our study do not primarily manifest through the information channel.

Our second empirical strategy that differentiates between physical exposure and information channels is through leveraging online search intensity for pollution-related topics. *Baidu.com*, the most widely used search engine in China, publishes search indexes that quantify the number of searches for specific keywords on a daily basis at the city, province and national levels. These search indexes are generated using an algorithm similar to *Google Trends*. Specifically, we focus on search indexes related to air pollution keywords such as "air pollution", "air purifier", "$PM_{2.5}$" and "smog".

In our framework, if visitors indeed respond to information about air quality, we would anticipate similar findings when estimating a modified version of equation (2), where pollution concentration is replaced with air pollution-related daily search indexes for the visitor's city. Referring to Table 6 Panel B, an increased volume of online searches for air pollution-related buzzwords does not have any meaningful impact on donation behavior towards either respiratory or non-respiratory diseases. Therefore, based on these results, we conclude that information exposure is not the primary channel through which visitors' feelings of sympathy are triggered in our context.

4.2 Heterogeneity: Characteristics of Campaigns and Visitors

Numerous studies have established that individuals tend to exhibit preference towards members of their own social group over out-group members (Chen and Li, 2009; Stürmer et al., 2005; Turner et al., 1987). In a natural setting, two prominent social identities that significantly impact individuals are their location and gender. Given this, we seek to understand if identical social identities could enhance the sympathy effect triggered by air pollution. We divide the full sample into groups based on targeted characteristics such as gender, age and location, and run separate regressions within each group.

In Figure 4 panel A, the sympathy effect tends to be stronger when visitors share spatial similarities with the fundraisers, indicating that geographic proximity may contribute to a greater sense of empathy and understanding. In panel B, our analysis reveals an interesting pattern: the sympathy effects are more pronounced when visitors and fundraisers share the same gender. Notably, the sympathy effect is the strongest when both visitors and fundraisers are females, which aligns with the commonly held stereotype and research findings that women tend to be more empathetic than men. In Figure 4 panels C and D, we report the variation in sympathy effect based on other visitor and campaign characteristics.

4.3 Understanding the Extent of the Sympathy Effect

In this section, we investigate the magnitude of the sympathy effects by comparing them with medical expenditures incurred from air pollution. Recent studies have documented a causal relationship between air pollution and increased medical expenditures (Deryugina et al., 2019; Xia et al., 2022). Specifically, a 1 $\mu g/m^3$ increase in $PM_{2.5}$ is associated with approximately a 0.05% rise in medical costs both in the US (Deryugina et al., 2019) and China (Xia et al., 2022). Interestingly, our empirical analysis reveals an additional dimension to this complex relationship: beyond the financial burden imposed by air pollution, we find that air pollution also triggers a sympathy effect, leading individuals to contribute more to certain types of online medical campaigns. Essentially, donations to medical crowdfunding campaigns act as a "voluntary" form of social insurance. This raises an intriguing question: to what extent does this "voluntary" insurance provided through charitable giving effectively cover the medical expenses associated with air pollution?

To understand the extent of the incurred sympathy effect in relation to the additional medical costs associated with air pollution, we conduct a back-of-the-envelope calculation. In Table 7, panel A summarizes the amount donated associated with a 1 $\mu g/m^3$ increase in $PM_{2.5}$ estimated in this study while panel B outlines the increased medical cost associated with the same increase in $PM_{2.5}$, drawn from Deryugina et al. (2019) and Xia et al. (2022). Our estimations are drawn from Column (2) of Table 3. We standardize these coefficients to the percentage change in medical expenditures induced by a 1 $\mu g/m^3$ increase in the $PM_{2.5}$ level. A 1 $\mu g/m^3$ increase in $PM_{2.5}$ leads to a 0.52% increase in donations towards respiratory diseases, while a 0.30% decrease for non-respiratory diseases. In comparison, both Deryugina et al. (2019) and Xia et al. (2022) find the same increase in $PM_{2.5}$ raises medical expenses for respiratory and non-respiratory diseases by approximately 0.04-0.05%.

To assess the importance of medical donations to patients, we first examine the significance of these medical charitable donations in terms of their capacity to cover medical expenses. Using aggregated data on medical donations and expenditures drawn from the *2018 Annual Report on Charitable Donations in China* and *Statistical Bulletin on the Development of Health and Healthcare in China 2018*, our analysis reveals that the overall donations only account for approximately 1.78% of the total medical expenditures (see Table 7 Panel C). However, when focusing specifically on the low-income group of patients diagnosed with critical illnesses, the role of charitable giving takes on crucial importance. Through the analysis of our microdata, we find that the ratio of the total amount raised for each campaign to the initial target fund stands at 13.4%, which is eight times larger than the ratio estimated using the aggregated data. This highlights the significant impact of charitable donations, particularly for financially vulnerable individuals facing critical health conditions.

Next, we examine the size of the sympathy effect in comparison to additional medical costs induced by air pollution estimated from Xia et al. (2022). Specifically, we calculate the relative magnitude of the sympathy effect as $\frac{\partial \log(Donation)/\partial PM_{2.5}}{\partial \log(Expense)/\partial PM_{2.5}} \times \frac{Donation}{Expense}$, where the values are obtained from Table 7 Panels A through C. As shown in Panel D, the sympathy effect identified in this study accounts for 20% of the air pollution-induced medical expenditure. For low-income groups of patients diagnosed with critical respiratory disease, the sympathy effect accounts for 146% of the additional medical expenditure, suggesting that the social insurance triggered by the sympathy effect of air pollution can effectively cover the additional medical expenses associated with air pollution for the low-income patients.

Our back-of-the-envelope calculation shows that the air pollution-induced givings to respiratory diseases is quantitatively significant compared to the increased medical expenses caused by air pollution. Therefore, this private provision of medical donations for respiratory diseases essentially acts as a form of social insurance to mitigate environmental damage, presenting a silver lining amidst the challenges posed by air pollution. In this regard, we introduce a new perspective: a negative externality that leads to adverse outcomes can also serve as a driving force behind voluntary contributions aimed at remedying its consequences. As a result, this work carries a clear and important policy implication, advocating for the establishment of a green market (Kotchen, 2006) and emphasizing the role of salient environmental damage in encouraging voluntary provision of public goods.

5 Conclusion

In this paper, we examine the relationship between sympathy and charitable giving in a large-scale natural experiment with an unconventional context: exposure to air pollution that elicits sympathy and promotes donations for its victims - respiratory disease patients. Using detailed visit data from one of the largest Chinese online crowdfunding platforms, we document a one-standard-deviation increase in ambient $PM_{2.5}$ experienced by a visitor leads to a significant 21.5% rise in donations towards respiratory disease patients compared to non-respiratory disease patients. Amongst the group of donors, the effect is slightly more pronounced: a one-standard-deviation increase in $PM_{2.5}$ leads to 22.9% more donations towards fundraisers with respiratory diseases.

Our analysis also distinguishes between whether visitors are physically exposed to air pollution or influenced by air pollution-related information obtained from sources such as local news or social media. Taking two distinct approaches – exploiting the air pollution alerts mandate in a regression discontinuity design as well as using online search intensity for air pollution-related topics as proxy stimulus variables, we find physical exposure to air pollution is likely the principal means by which visitors are triggered to engage in prosocial behavior. Our finding suggests that at the operational level, fundraising campaigns can be more effective when targeting individuals who share similar life experiences to the fundraisers and can recall the difficult times they themselves have physically experienced.

The back-of-the-envelope calculation reveals that the charitable contributions induced by air pollution towards respiratory diseases are quantitatively comparable to the additional medical expenses caused by air pollution, especially for low-income patients diagnosed with critical diseases. Therefore, this private provision of donations for respiratory disease patients effectively functions as a form of social insurance to alleviate environmental damage, offering a silver lining amidst the adverse health impact posed by air pollution.

This paper provides a perspective on how adverse experiences can elicit feelings of sympathy toward those who have endured them. Sympathy has received relatively little attention in economics, yet it serves as a critical emotional stimulus for promoting prosocial behavior. Future research can expand and test our mechanisms in broader contexts, such as natural disasters, crime victims, and discrimination. Additionally, it is intriguing to investigate how the willingness to help others experiencing similar negative experiences changes over time. Moreover, it is important to quantify to what extent sympathy, as a personality trait, can predict prosocial behavior across various domains and contexts.

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Figures and Tables

Figures

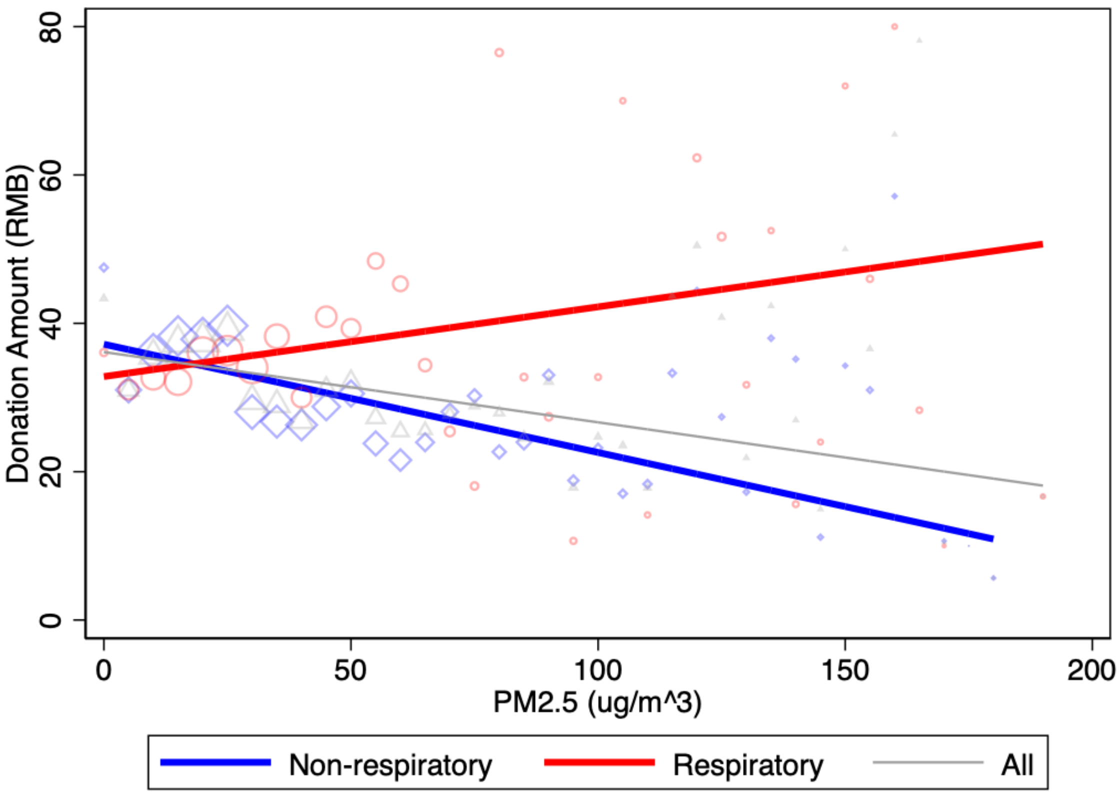


Figure 1: Relationship between donation amount and air pollution, by disease type

Notes: This figure shows the linear fit prediction for donation amount on air pollution by disease types. The red dots represent the binscatter plot for respiratory diseases and the blue ones for non-respiratory diseases. The bandwidth of each bin is 5. The size of dots denotes the sample size in that bin.

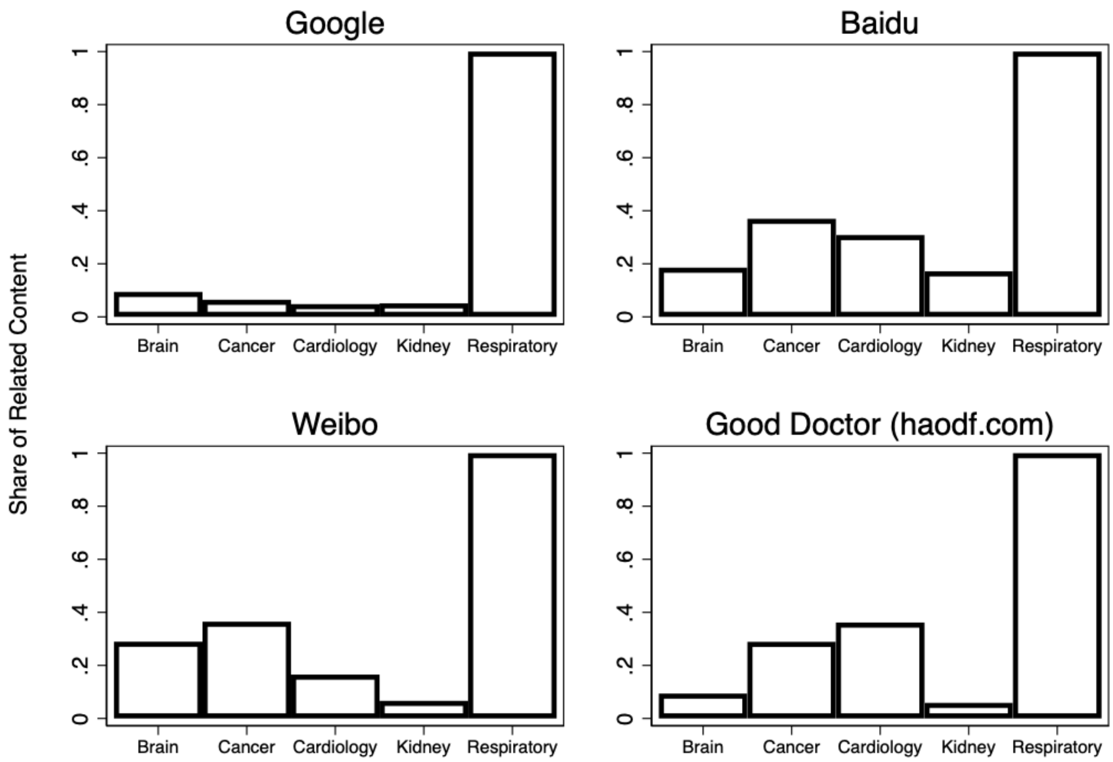


Figure 2: Number of Related Content for Keywords "Air pollution + Diseases"

Notes: This figure shows the number of search results for keywords "Air pollution + Diseases" on four platforms - *Google*, *Baidu* (search engine), *Weibo* (social media), and *Haodf.com* (medical advice platform). Data accessed 24 Oct 2022.

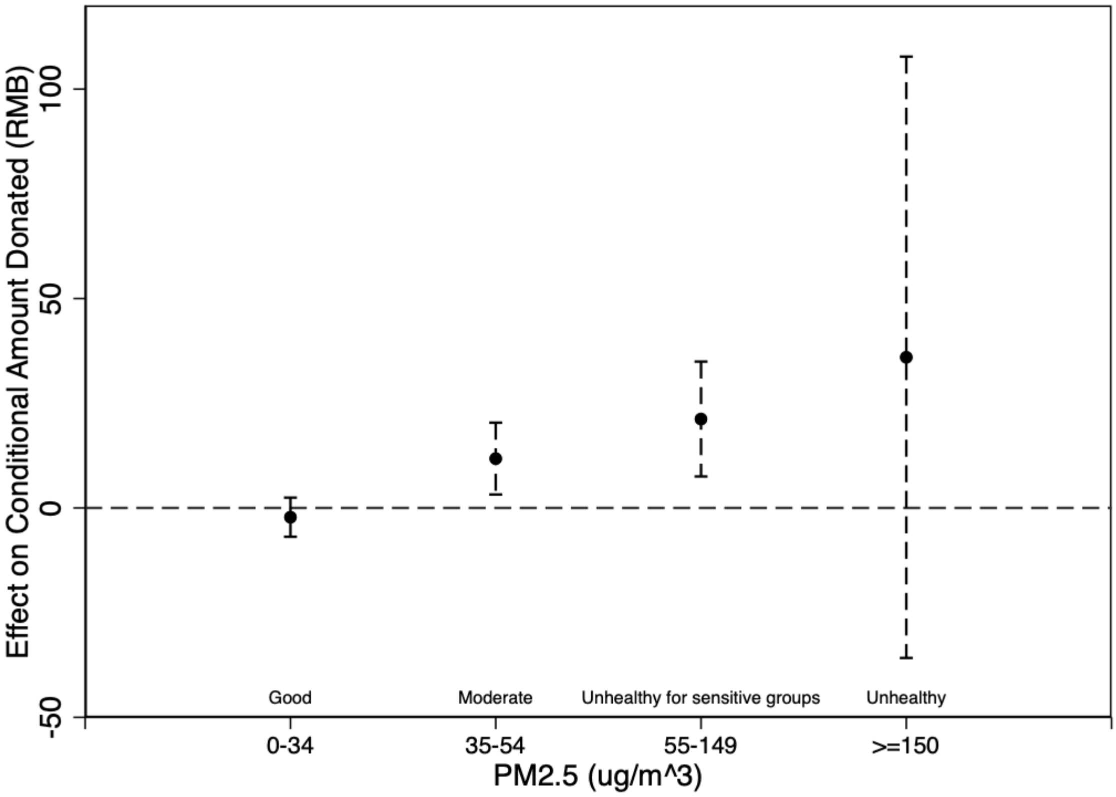


Figure 3: Nonlinear effect by pollution exposure level: intensive margin

Notes: This figure presents the estimated coefficients and associated 95% confidence intervals on four different levels of air quality in the donor sample by replacing the interaction term in equation (2) with a series of interactions between *Res* and binary variables for each pollution category.

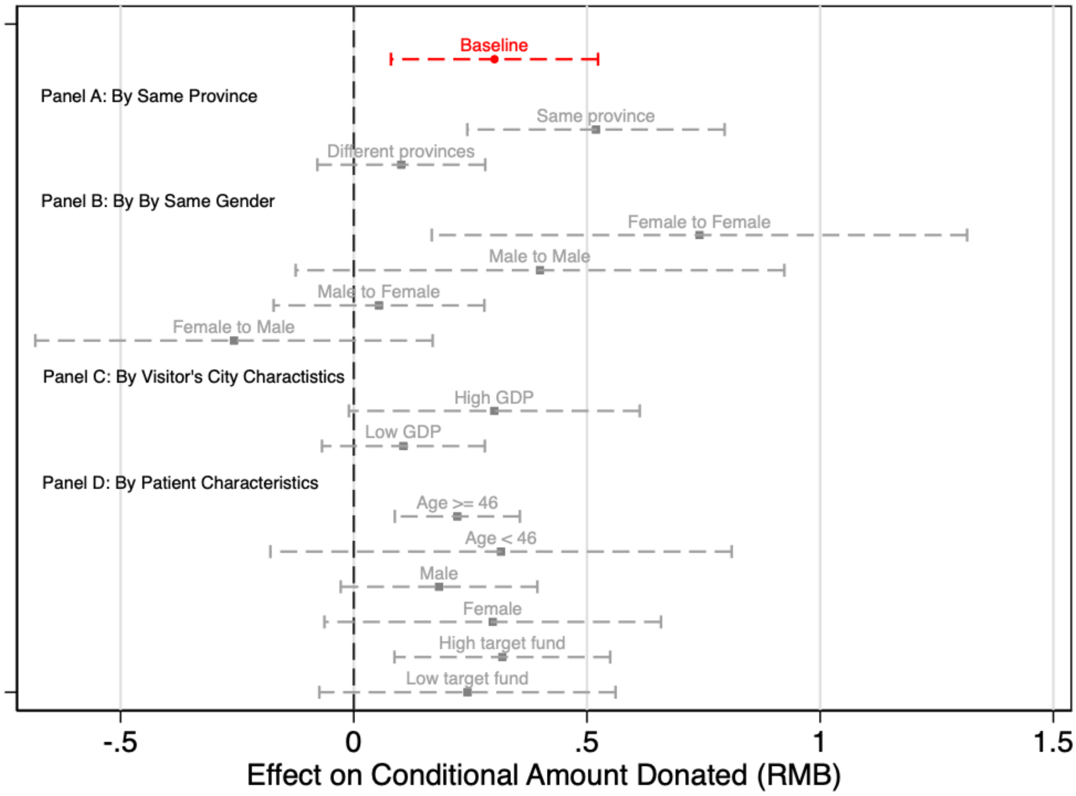


Figure 4: Heterogeneous effects of air pollution on donation amount

Notes: This figure displays the estimated coefficients and associated 95% confidence intervals on different subsets of donors using equation (2). The estimated coefficient and 95% confidence interval from the entire donor sample is labeled in red for comparison.

Tables

Table 1: Summary Statistics

Variable	Mean	Std. dev.	Min	Max
Panel A. Campaign Characteristics (N=90)				
Patient Age	46.86	14.85	3	73
% Male	0.58	0.50	0	1
Target Fund (1,000 RMB)	198.89	158.39	20	1,000
Illness Type				
Respiratory	0.14	0.35	0	1
Cardiology	0.03	0.18	0	1
Brain	0.16	0.36	0	1
Kidney	0.08	0.27	0	1
Cancer	0.44	0.50	0	1
Injury	0.16	0.36	0	1
Panel B. Full Sample (N=109,746)				
Amount Donated	4.07	24.03	0	2,000
Prob. of Donation	11.98	32.47	0	100
Prob. of Sharing	3.73	18.96	0	100
$PM_{2.5}$	37.93	26.48	1	402
% Male	0.64	0.48	0	1
GDP per cap (1,000 RMB)	78.51	45.24	12.66	191.94
Panel C. Donor Sample (N=13,145)				
Amount Donated	33.49	60.84	1	2,000
Prob. of Sharing	20.76	40.56	0	100
$PM_{2.5}$	36.58	25.36	1	244
% Male	0.60	0.49	0	1
GDP per cap (1,000 RMB)	86.48	47.65	12.66	191.94
Visit Duration	250.37	322.46	9	2,172

Table 2: Visit and Visitor Characteristics

	(1) All visits	(2) % Respiratory	(3) % Respiratory in Title	(4) % Same City	(5) % Male
$PM_{2.5}$	0.0610	0.0107	-0.0116	-0.0006	0.0226
	(0.370)	(0.067)	(0.011)	(0.036)	(0.027)
Weather Ctrls	Y	Y	Y	Y	Y
City FE	Y	Y	Y	Y	Y
Date FE	Y	Y	Y	Y	Y
Adjusted R^2	0.612	0.656	0.637	0.857	0.234
N	5,284	5,284	5,284	5,284	3,367

Notes: This table displays the correlation between $PM_{2.5}$ and visit data aggregated to city-day level using equation (1). The dependent variables are (1) log of total visits; (2) % visits to respiratory campaigns; (3) % visits to campaigns with "respiratory" in the title; (4) % visits from the same city as the fundraisers and (5) % male visitors. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Effect of Air Pollution on Donations to Respiratory Campaigns

	All Visitors		Donors Only	
	(1)	(2)	(3)	(4)
$PM_{2.5}$	-0.012**	-0.012*	-0.090*	-0.083*
	(0.006)	(0.006)	(0.049)	(0.046)
Res	-0.674	-0.692	-4.793	-5.893
	(0.505)	(0.490)	(4.560)	(4.540)
$PM_{2.5} \times$ Res	0.033***	0.032***	0.300***	0.302***
	(0.009)	(0.010)	(0.109)	(0.113)
Weather Ctrls	Y	Y	Y	Y
Campaign Ctrls	Y	Y	Y	Y
DOW FE	N	Y	N	Y
Hour FE	N	Y	N	Y
Province FE	N	Y	N	Y
Adjusted R^2	0.01	0.01	0.02	0.03
N	109,746	109,746	13,145	13,145

Notes: The dependent variable in column (1) and (2) are the donation amount (RMB), assuming visitors who do not donate essentially makes a donation of 0. The dependent variable in columns (3) and (4) are the donation amount based on samples that make a positive donation. Each model includes the following fixed effects: day-of-week, hour, and visitor's province. Standard errors are clustered to city level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Placebo Test - Effect of Air Pollution on Donations to Other Diseases' Campaigns

Panel A. All Visitors

	(1) Brain	(2) Cancer	(3) Cardiology	(4) Injury	(5) Kidney
Disease × $PM_{2.5}$	0.016	-0.005	-0.007	0.015	-0.017
	(0.010)	(0.010)	(0.013)	(0.013)	(0.014)
$PM_{2.5}$	-0.006	-0.002	-0.004	-0.004	-0.001
	(0.005)	(0.008)	(0.006)	(0.006)	(0.005)
Disease	-0.626	1.447**	-1.311*	-0.065	-1.220
	(0.548)	(0.566)	(0.687)	(1.087)	(1.079)
Adjusted R^2	0.008	0.008	0.008	0.008	0.008
N	109,746	109,746	109,746	109,746	109,746

Panel B. Donors Only

	(6) Brain	(7) Cancer	(8) Cardiology	(9) Injury	(10) Kidney
Disease × $PM_{2.5}$	0.101	0.045	-0.064	0.046	-0.173**
	(0.076)	(0.079)	(0.174)	(0.076)	(0.085)
$PM_{2.5}$	-0.033	-0.034	-0.019	-0.021	0.013
	(0.042)	(0.060)	(0.046)	(0.046)	(0.039)
Disease	-8.085**	6.395*	-3.349	1.893	-4.052
	(3.871)	(3.430)	(8.741)	(5.764)	(4.224)
Adjusted R^2	0.029	0.031	0.029	0.029	0.031
N	13,145	13,145	13,145	13,145	13,145

Notes: The dependent variables in panel A are the donation amount (RMB), assuming visitors who do not donate essentially makes a donation of 0. The dependent variable in panel B are the donation amount based on samples that make a positive donation. All models are estimated using equation (2) with "Res" being replaced with five other types of diseases respectively. Each model includes the day-of-week, hour, and visitor's province FE. Standard errors are clustered to city level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Measures of Air Pollution and Their Effects

Panel A. Alternative Measures of $PM_{2.5}$: All Visitors

	(1) Hourly	(2) Rush Hour Avg	(3) Daily Avg
$PM_{2.5}\times$ Res	0.032***	0.030***	0.030***
	(0.010)	(0.010)	(0.011)
$PM_{2.5}$	-0.012*	-0.017**	-0.019**
	(0.006)	(0.008)	(0.009)
Res	-0.692	-0.541	-0.648
	(0.490)	(0.517)	(0.522)
Adjusted R^2	0.01	0.01	0.01
N	109,746	109,746	109,746

Panel B. Alternative Measures of $PM_{2.5}$: Donors Only

	(1) Hourly	(2) Rush Hour Avg	(3) Daily Avg
$PM_{2.5}\times$ Res	0.302***	0.257***	0.272***
	(0.113)	(0.085)	(0.092)
$PM_{2.5}$	-0.083*	-0.104*	-0.124**
	(0.046)	(0.056)	(0.061)
Res	-5.893	-3.714	-5.021
	(4.540)	(3.845)	(4.140)
Adjusted R^2	0.03	0.03	0.03
N	13,145	13,145	13,145

Panel C. Other Air Pollutants: All Visitors

	(1) AQI	(2) CO	(3) NO_2	(4) Ozone	(5) PM_{10}	(6) SO_2
AQ$\times$ Res	0.023***	0.470	0.035***	-0.008	0.011*	-0.038*
	(0.008)	(0.750)	(0.012)	(0.008)	(0.006)	(0.023)
AQ	-0.005	-0.093	-0.003	0.002	-0.003	0.005
	(0.004)	(0.299)	(0.005)	(0.005)	(0.003)	(0.012)
Res	-0.899	0.209	-0.830	1.014	-0.176	1.019**
	(0.566)	(0.643)	(0.533)	(0.635)	(0.510)	(0.476)
Adjusted R^2	0.01	0.01	0.01	0.01	0.01	0.01
N	109,746	109,742	109,737	109,744	108,760	109,746

Panel D. Other Air Pollutants: Donors Only

	(1) AQI	(2) CO	(3) NO_2	(4) Ozone	(5) PM_{10}	(6) SO_2
AQ$\times$ Res	0.250***	3.174	0.286***	0.007	0.172**	-0.160
	(0.093)	(6.932)	(0.087)	(0.060)	(0.074)	(0.204)
AQ	-0.057	-1.085	-0.086**	0.000	-0.036	0.047
	(0.037)	(2.221)	(0.037)	(0.026)	(0.024)	(0.082)
Res	-9.966*	3.365	-5.524	5.544	-5.818	7.624**
	(5.815)	(5.696)	(3.874)	(4.068)	(4.935)	(3.364)
Adjusted R^2	0.03	0.03	0.03	0.03	0.03	0.03
N	13,145	13,145	13,145	13,145	13,008	13,145

Notes: The dependent variables in panels A and C are the donation amount (RMB), assuming visitors who do not donate essentially makes a donation of 0. The dependent variable in panels B and D are the donation amount based on samples that make a positive donation. All models are estimated using equation (2). Panels A and B measures air quality with rush hour average (column 2) and daily average (column 3). Panels C and D measures air quality using other air pollutants. Each model includes the day-of-week, hour, and visitor's province FE. Standard errors are clustered to city level. * p < 0.1, ** p < 0.05, *** p < 0.01.

Table 6: Distinguishing Perception vs. Information Channels

Panel A. Regression Discontinuity Using Air Pollution Alerts

	100 cutoff			150 cutoff		
	(1)	(2)	(3)	(4)	(5)	(6)
	5 bw	10 bw	20 bw	5 bw	10 bw	20 bw
$Res\times$ 1(AQI > cutoff)	-1.662*	-0.371	-0.729	1.863	-0.0165	1.392
	(0.912)	(0.722)	(0.820)	(3.036)	(2.621)	(1.533)
FE + Weather Ctrls	Y	Y	Y	Y	Y	Y
Adjusted R^2	0.007	0.007	0.015	-0.027	0.003	0.03
N	4,386	8,547	18,277	615	1,359	2,673

Panel B. Diff-in-Diff with City-level *Baidu Index*

	(1)	(2)	(3)	(4)	(5)
	$PM_{2.5}$	Air pollution	Haze	Air purifier	Lung cancer
$Res\times$ Baidu Index	0.115	3.373	-0.142	4.396	4.637**
	(0.137)	(4.351)	(0.368)	(3.291)	(2.340)
FE + Weather Ctrls	Y	Y	Y	Y	Y
Adjusted R^2	0.008	0.009	0.008	0.009	0.009
N	109,679	109,679	109,679	109,679	109,679

Notes: Panel A shows the effect of sympathy on donation using a regression discontinuity design, exploiting the feature of Air Pollution Alert System. Columns (1)-(3) uses AQI's "unhealthy for sensitive groups" cutoff at 100 and column (4)-(6) uses the "unhealthy" cutoff at 150. We display results at bandwidths of 5, 10 and 20. Panel B shows the effect of sympathy on donation using "Baidu Index" on city-level air quality-related keywords as measure of air pollution. Columns (1)-(5) corresponds to keywords "$PM_{2.5}$", "Air Pollution", "Haze", "Air purifier" and "Lung cancer" respectively. * p < 0.1, ** p < 0.05, *** p < 0.01.

Table 7: Understanding the Relative Magnitude of the Sympathy Effect

Disease type	Estimation	Sample	Source
Panel A. $\partial \log(\text{Donation})/\partial$ Pollution (% change, per $\mu g/m^3 \uparrow$)			
Respiratory diseases	0.516	China, hourly	This paper
Non-respiratory diseases	-0.295	China, hourly	This paper
Panel B. $\partial \log(\text{Expense})/\partial$ Pollution (% change, per $\mu g/m^3 \uparrow$)			
Respiratory diseases	0.0474	China, daily	Xia et al. (2022)
Non-respiratory diseases	0.0432	China, daily	Xia et al. (2022)
All diseases	0.0510	US, daily	Deryugina et al. (2019)
Panel C. Donation/Expense			
All patients	1.78%	China	Annual Report[a]
Low income group	13.4%	China	Author's calculation[b]
Panel D. Adjusted Donation/Expense			
All patients	19.4%	China	Author's calculation
Low income group	145.9%	China	Author's calculation

Notes: This table compares the relative magnitude of the sympathy effect to the effect of pollution on medical expenses. Panels A and B summarize the estimations in our paper and that of the two relevant studies respectively. Results are standardized to the % change in outcomes (measured in monetary value) induced by 1 $\mu g/m^3$ increase in the $PM_{2.5}$ level. Panel C shows the ratio of total medical donation to total medical expense and Panel D shows the ratio of marginal medical donation to marginal increase in medical expense, both of which are induced by air pollution. The marginal values are adjusted based on the proportion of medical donations to the overall medical expenses.

a. Source: *"2018 Annual Report on Charitable Donations in China"* and *"Statistical Bulletin on the Development of Health and Healthcare in China 2018"*

b. Author's calculation using donation campaign data.

Appendix A Appendix

A.1 Additional Figures

Panel A Panel B Panel C

Figure A.1: A Sample Campaign from *WeChat*

Notes: This figure shows a sample campaign posted on social media platform *WeChat*. Panel A displays the shared link as posted on "WeChat"; Panels B and C are screenshots of the campaign website which include the photos of the fundraiser, the diagnosis, and a description of the financial hardship.

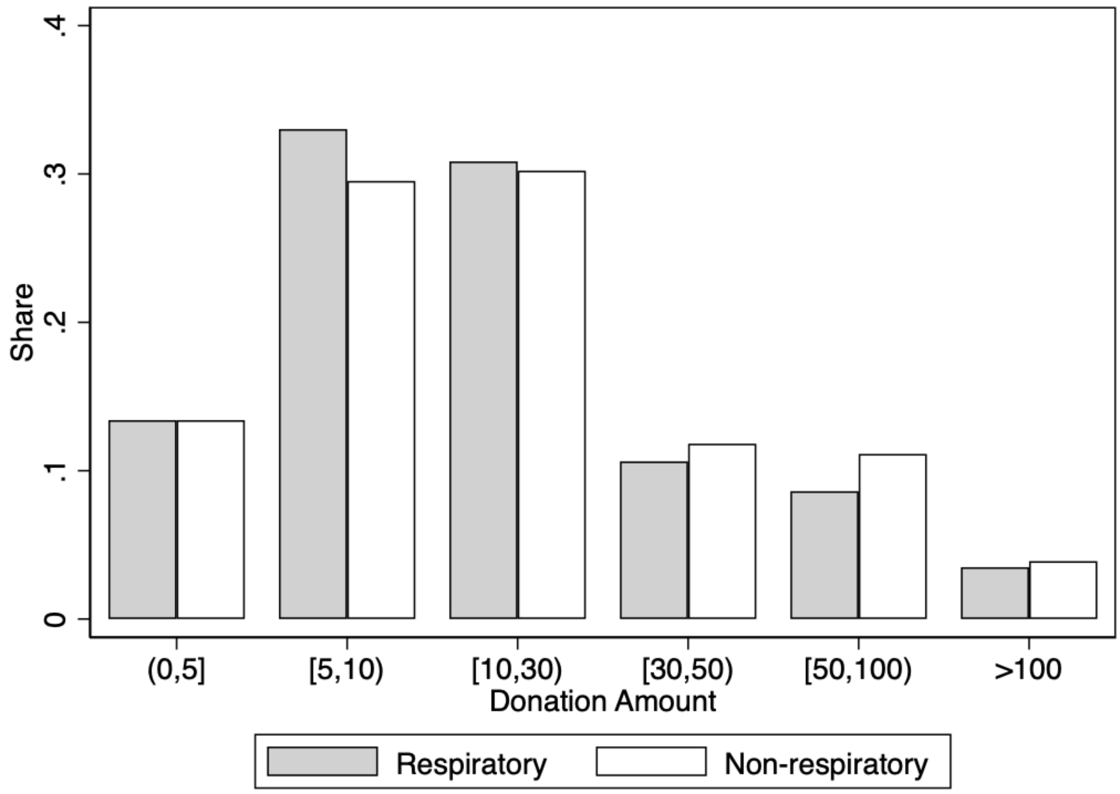


Figure A.2: Distribution of Donation Amount by Disease Type

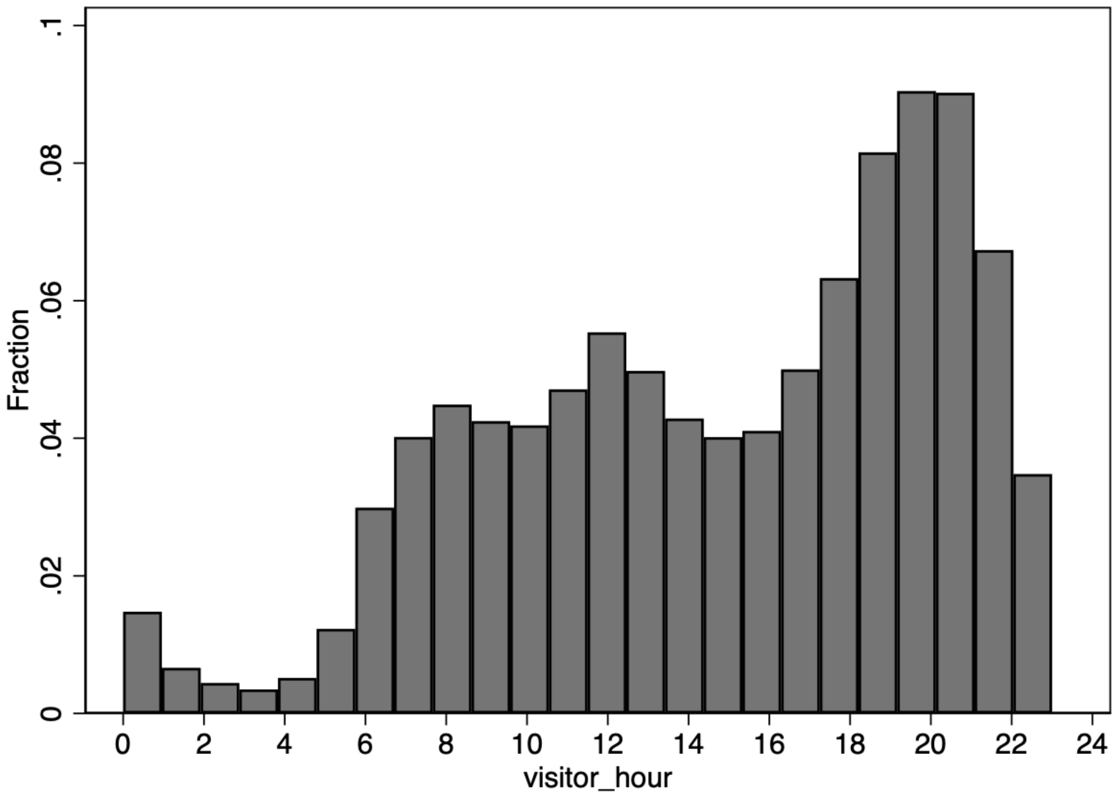
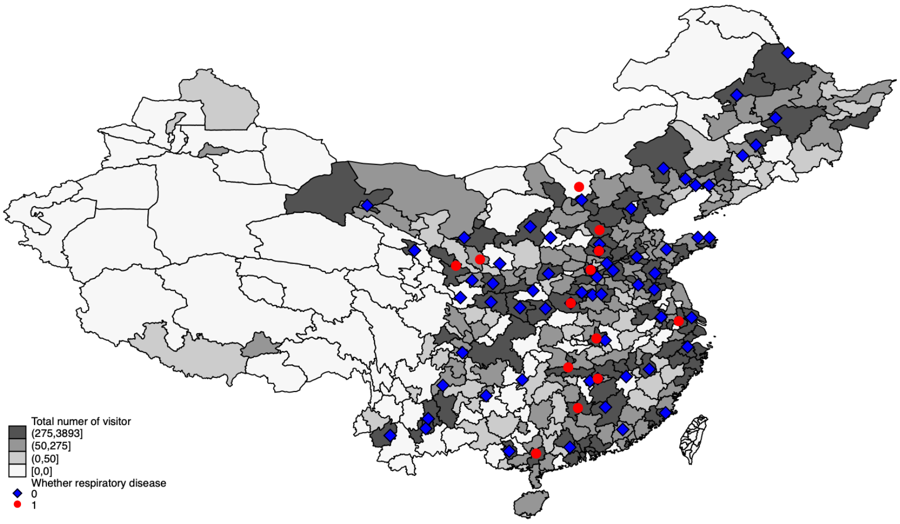
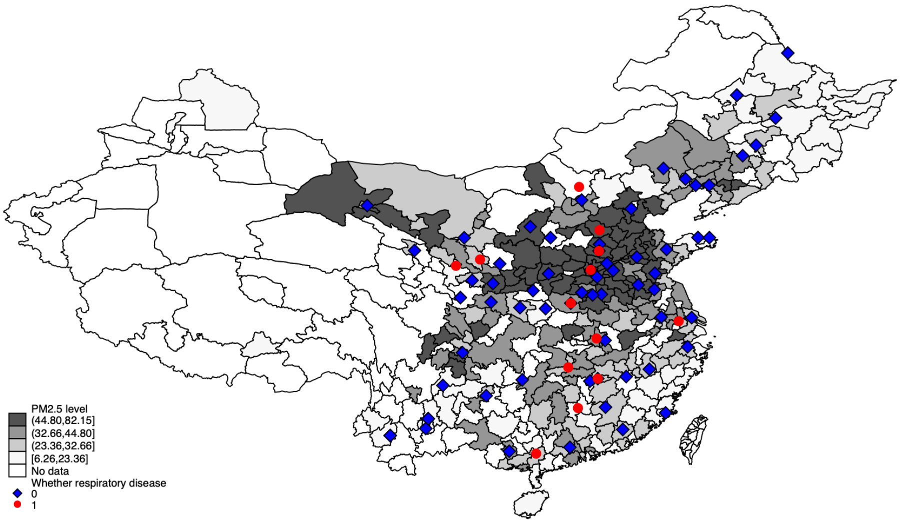


Figure A.3: Distribution of Visiting Time



(A)



(B)

Figure A.4: The Geographical Distribution of Campaigns and Visitors

Notes: These panels show the geographical distribution of our key variables. The red dots represent the location of respiratory-related disease campaigns; the blue dots the location of other disease campaigns. The shaded areas in panel A represent the number of visitors in each city; in panel B the $PM_{2.5}$ concentration level in each city.

AQI Basics for Ozone and Particle Pollution

Daily AQI Color	Levels of Concern	Values of Index	Description of Air Quality
Green	Good	0 to 50	Air quality is satisfactory, and air pollution poses little or no risk.
Yellow	Moderate	51 to 100	Air quality is acceptable. However, there may be a risk for some people, particularly those who are unusually sensitive to air pollution.
Orange	Unhealthy for Sensitive Groups	101 to 150	Members of sensitive groups may experience health effects. The general public is less likely to be affected.
Red	Unhealthy	151 to 200	Some members of the general public may experience health effects; members of sensitive groups may experience more serious health effects.
Purple	Very Unhealthy	201 to 300	Health alert: The risk of health effects is increased for everyone.
Maroon	Hazardous	301 and higher	Health warning of emergency conditions: everyone is more likely to be affected.

Figure A.5: The Air Quality Guide for Particle Pollution

Source: United States Environmental Protection Agency

A.2 Additional Tables

Table A.1: Effect of Air Pollution on the Probability of Giving to Respiratory Campaigns

	OLS		Logit	
	(1)	(2)	(3)	(4)
$PM_{2.5} \times$ Res	0.005	0.002	0.0003	0.0000
	(0.016)	(0.013)	(0.0018)	(0.0014)
$PM_{2.5}$	-0.006	-0.004	-0.0006	-0.0004
	(0.006)	(0.006)	(0.0006)	(0.0006)
Res	-0.508	-0.291	-0.0422	-0.0296
	(0.755)	(0.683)	(0.0791)	(0.0707)
Weather Ctrls	Y	Y	Y	Y
Patient Ctrls	Y	Y	Y	Y
DOW FE	N	Y	N	Y
Hours FE	N	Y	N	Y
Province FE	N	Y	N	Y
Adjusted R^2	0.01	0.01	0.01	0.02
N	109,746	109,746	109,746	109,746

Notes: The dependent variables are binary variables on whether a visitor donates to a campaign. Columns (1) and (2) are estimated with OLS while (3) and (4) with conditional logit model. All models assume visitors who do not donate essentially makes a donation of 0. Each model includes the following fixed effects: day-of-week, hour, province, campaign, and province-by-hour. We present cluster standard errors in parentheses. Standard errors are clustered to city level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.2: Adding Cardiovascular Diseases to the Treated Category

	(1) Prob. of Giving	(2) All Visitors	(3) Donors Only
$PM_{2.5} \times$ "Res+Cardio"	-0.007	0.025^{***}	0.264^{**}
	(0.013)	(0.010)	(0.105)
$PM_{2.5}$	-0.001	-0.011^{*}	-0.081^{*}
	(0.006)	(0.006)	(0.048)
"Res + Cardio"	-0.764	-0.821^{*}	-5.480
	(0.649)	(0.477)	(4.507)
Adjusted R^2	0.0143	0.0080	0.0309
N	109,746	109,746	13,145

Notes: Each model includes the following controls variables: weather controls, day-of-week FE, hour FE, and province FE. We present cluster standard errors in parentheses. Standard errors are clustered to city level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.3: Winsorizing the Top 1% and 5% Donors

	99th		95th	
	(1) All Visitors	(2) Donors Only	(3) All Visitors	(4) Donors Only
$PM_{2.5} \times$ Res	0.024***	0.216***	0.012**	0.122***
	(0.008)	(0.046)	(0.006)	(0.032)
$PM_{2.5}$	-0.011**	-0.082**	-0.005*	-0.042*
	(0.005)	(0.034)	(0.003)	(0.023)
Res	-0.944**	-7.431***	-0.193	-2.020
Adjusted R^2	0.012	0.045	0.014	0.043
N	109,646	13,045	109,277	12,676

Notes: Each model includes the following controls variables: weather controls, day-of-week FE, hour FE, and province FE. We present cluster standard errors in parentheses. Standard errors are clustered to city level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.4: Estimation with Propensity Score Matching Sample

	(1) Prob. of Giving	(2) All Visitors	(3) Donors Only
$PM_{2.5} \times$ Res	-0.017	0.014*	0.205**
	(0.017)	(0.008)	(0.081)
$PM_{2.5}$	0.011	-0.001	-0.038
	(0.010)	(0.006)	(0.052)
Res	0.358	-0.822	-9.765**
	(0.832)	(0.578)	(4.551)
Adjusted R^2	0.013	0.007	0.030
N	49,346	49,346	5,555

Notes: Each model includes the following controls variables: weather controls, day-of-week FE, hour FE, and province FE. We present cluster standard errors in parentheses. Standard errors are clustered to city level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.5: Donations Made Within 7 Days After Campaign Posting

	Full Sample		95th Winsorized Sample	
	(1) All Visitors	(2) Donors Only	(3) All Visitors	(4) Donors Only
$PM_{2.5}\times$ Res	0.031***	0.315***	0.010*	0.124***
	(0.009)	(0.121)	(0.005)	(0.033)
$PM_{2.5}$	-0.009*	-0.071	-0.004	-0.037*
	(0.006)	(0.046)	(0.003)	(0.022)
Res	-0.676	-6.507	-0.152	-2.344
	(0.507)	(4.810)	(0.277)	(1.584)
Weather Ctrls	Y	Y	Y	Y
Patient Ctrls	Y	Y	Y	Y
DOW FE	Y	Y	Y	Y
Hours FE	Y	Y	Y	Y
Province FE	Y	Y	Y	Y
Adjusted R^2	0.006	0.031	0.008	0.040
N	99,883	12,003	99,443	11,563

Notes: Each model includes the following controls variables: weather controls, day-of-week FE, hour FE, and province FE. We present cluster standard errors in parentheses. Standard errors are clustered to city level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.