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Air pollution and defensive expenditures: Evidence from particulate-filtering facemasks☆

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ABSTRACT

Individuals take preventive measures to avoid costly air pollution exposure. This paper provides new empirical evidence of pollution avoidance that Chinese urban residents purchase particulate-filtering facemasks to protect against ambient air pollution. The analysis is conducted with detailed and comprehensive data available on daily facemask purchases and air quality that became available only very recently. We find that this transitory air pollution avoidance behavior exhibits dynamics and nonlinearities, with significant increases of facemask purchases during extreme pollution episodes. The daily model shows that a 100-point increase in Air Quality Index (AQI) increases the consumption of all masks by 54.5 percent and anti-$PM_{2.5}$ masks by 70.6 percent. The estimates from the aggregated model with flexible pollution levels are used to simulate the benefit of air quality improvement. If 10 percent of heavy pollution days (AQI $\geq$ 201) were eliminated, the total savings on facemasks alone would be approximately 187 million USD in China. This result suggests that reducing the occurrence of "airpocalypse" events represents a signifi1cant opportunity to improve social welfare. Nevertheless, our estimates are likely only a small part of the benefit of clean air because facemasks can only partially reduce the negative health effects of air pollution and the costs of other avoidance behaviors are not included.

Introduction

Air pollution is associated with negative health effects. In order to reduce costly pollution exposure, individuals take compensatory activities to create a better personal environment for themselves. Air pollution may be avoided in the first place. In the short run, individuals can adjust or cancel outdoor activities (Bresnahan et al., 1997; Neidell, 2009; Graff Zivin and Neidell, 2009). In the long run, urban residents can sort into places with better air quality, taking into account a large array of location attributes and individual preferences (Banzhaf and Walsh, 2008). If pollution exposure is inevitable, individuals can

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mitigate the negative health effects through pharmaceutical or medication usage (Deschenes et al., 2012). These deliberate pollution-averting activities reflect individuals' trade-offs between the cost of the preventive measures and the benefit of the reduced pollution exposure.[1] Therefore, studying defensive expenditures of consumers on pollution avoidance sheds light on the welfare implications of air pollution control policies.

This paper provides new empirical evidence of transitory avoidance behavior by investigating the relationship between **household** demand for particulate-filtering facemasks and ambient air pollution. Facepiece respirators remove particulate matter (PM) out of the air to protect the respiratory system.[2] If outdoor activities cannot be avoided, wearing facemasks with appropriate filters is arguably the most cost-effective way, and possibly the only way, to limit contact with harmful particulates. Existing studies on the use of facemasks against PM pollution are mostly related to occupational hazard, especially in developed countries, which has an inelastic demand due to mandatory workplace-related health and safety regulations (NIOSH, 1995; CDC, 1998). In comparison, the popularity of anti-PM facemasks among urban residents in developing countries to defend against airborne PM pollution, especially $PM_{2.5}$, is a recent phenomenon.

Our empirical study focuses on China because of the severity of air pollution and the popularity of facemask usage. The 2010 Global Burden of Disease Study reveals that air pollution is the 4th leading health risk factor for Chinese people (Yang et al., 2013). Air pollution is associated with elevated rates of mortality, which causes between 350,000 and 500,000 premature deaths each year in China (Chen et al., 2013b). The main driver of air pollution is particulate matter. A recent quasi-experimental study suggests that total suspended particulates (TSPs) reduce life expectancies of residents in North China by over five years (Chen et al., 2013a). To reduce air pollution exposure, the use of facemasks, especially those against $PM_{2.5}$, has gained popularity since a series of "airpocalypse" events in 2011.[3] Furthermore, the information disclosure of fine particulates since 2013 has incentivized urban residents to purchase anti-$PM_{2.5}$ facemasks. These particulate-filtering masks are more specialized and thus more expensive than those traditionally used by Chinese people for warmth in winter.

The analysis is conducted with detailed and comprehensive data available on daily facemask purchases, air quality, and weather at the city level across China. The facemask purchase data come from two e-commerce websites in the Alibaba Group: Taobao.com and Tmall.com. These two websites dominate China's online shopping activities and are the main retail channels for anti-$PM_{2.5}$ facemasks. The air pollution data, web-scraped from the Ministry of Environmental Protection (MEP), are the first batch of $PM_{2.5}$ pollution information disclosed since China enacted the new air quality standards in 2013. To address the concern that air pollution data may be manipulated by local authorities (Ghanem and Zhang, 2014), we obtained the $PM_{2.5}$ data from the US Embassy in five provincial capital cities for robustness checks. We also collected relevant weather variables at the station level from the National Climatic Data Center under the US National Oceanic and Atmospheric Administration (NOAA). Combining all of the above information, the final panel data set covers 190 cities at the daily level from January 2013 to April 2014, which contains a rich set of variables that allow us to apply flexible econometric specifications.

We use the day-to-day fluctuations in air quality to identify its marginal effect on facemask expenditures. We focus on particulate respirators that are mainly used to filter PM. These facemasks, especially those labeled as anti-$PM_{2.5}$, are less likely being used on a daily basis to keep warm or prevent spreading germs because of the high price and the special design. Nevertheless, one major concern is that some factors that are correlated with short-run air pollution—especially weather and epidemic—may also affect facemask purchases. Therefore, we include potentially confounding weather variables such as temperature, humidity, wind speed, or wind direction. Lack of epidemic data, various fixed effects to control for the impact of disease on mask use. In particular, our preferred specification uses the city-by-year-by-month-by-week fixed effect (City-Week FE), which allows us to flexibly control for unobservable shocks to facemask demand that varies across cities and over weeks. With these covariates and fixed effects, the high daily variation in air pollution provides a possible source of exogenous variation. We have also conducted extensive robustness checks to address some other potential threats to identification.

We find a statistically significant relationship between daily air quality and anti-PM facemask purchases. Individuals respond to the pollution information with lags up to four days; this lag is likely caused by dynamic avoidance behavior or due to the lags in the online transaction recording system. The preferred model shows that a 100-point increase in Air Quality Index (AQI) boosts total purchases of anti-$PM_{2.5}$ facemasks by 70.6 percent and total purchases of all facemasks by 50.4 percent. Furthermore, we use air quality levels to flexibly control for the nonlinear response to air pollution: the avoidance behavior is likely more pronounced during extreme pollution episodes. We aggregate the model to both the weekly and monthly level to cancel the dynamic avoidance behavior. Our preferred model shows that, relative to the days with excellent air quality ($AQI \leq 50$), one extra heavily polluted day ($201 \leq AQI \leq 300$) increases monthly anti-$PM_{2.5}$ facemask purchases by 11.1, and 7.6 percent on the purchases of all facemasks. When AQI rises to the severely polluted level ($AQI \geq 301$), the semi-elasticity jumps to 29.2 and 23.4 percent, respectively. These results are robust to wide a variety of specification tests.

[1] There has been a growing empirical literature on pollution avoidance besides air pollution. For water pollution, households install water filters or purchase bottled water in response to drinking water violations (Smith and Desvousges, 1986; Graff Zivin et al., 2011). Other notable examples of pollution avoidance includes reducing fish consumption in response to FDA mercury advisories (Shimshack et al., 2007) and adaptation to climate change by changing residential energy consumption (Deschenes and Greenstone, 2011).

[2] For example, N95, the most popular model approved by the National Institute for Occupational Safety and Health (NIOSH, 1995), filters at least 95 percent of particles.

[3] Airpocalypse is a newly coined term to informally describe a severely hazy day in China. In this paper, we use it to describe a day with Air Quality Index above 201.

Since facemasks protect against the effects of ambient air pollution, the value of marginal changes in air pollution can be measured by the increased expenditures on facemasks. Without a market price for air quality, defensive expenditures provide one way to bound the economic cost of air pollution (Courant and Porter, 1981; Harrington and Portney, 1987; Bartik, 1988). Using this approach, our model can quantify the cost of one-day air pollution in China. A back-of-the-envelope calculation shows that the cost of one severely polluted day (AQI $\geq$ 301) would be 610 thousand Yuan, or about 100 thousand USD, in China. Furthermore, we use the estimates from the monthly aggregated model to simulate the benefit of hypothetical air pollution control policies. If 10 percent of both these heavily and severely polluted days were eliminated by any mixture of air pollution control policies, the total savings for China would be 1.146 billion Yuan, or about 187 million USD.

This paper makes several contributions to the literature. First, to the best of our knowledge, this is the first empirical study that examines the household demand for facemasks in response to ambient air pollution. Second, this paper provides nationwide empirical evidence on defensive expenditures from China. In comparison, the previous literature has mostly focused on one area in the U.S. (Bresnahan et al., 1997; Neidell, 2009; Graff Zivin and Neidell, 2009). Third, this paper focuses on avoidance behavior related to fine particulates while other papers are mainly concerned with ground-level ozone pollution. PM is usually the principal pollutant in developing countries while ground-level ozone pollution is the main concern in developed countries. Fourth, we find that individuals take preventive measures in a dynamic and nonlinear manner, with most masks purchased during heavy pollution days. The empirical evidence is largely consistent with the findings from the previous literature on air pollution avoidance.[4]

The remainder of the paper is organized as follows. Section 2 introduces the empirical background to the analysis. Section 3 describes the data sources and summary statistics. Section 4 presents the empirical strategy of the paper. Section 5 reports empirical results and robustness checks. Section 6 discusses the policy implications from the results and caveats. Section 7 concludes the paper.

Empirical background

Efficacy of anti-PM facemasks

Particulate matter is the main driver of air pollution in China: PM_{10} and $PM_{2.5}$ caused 36% and 59% of pollution days in 2013, respectively.[5] Long et al. (2014) estimate that 1.322 billion people, or 98.6% of the total population, are exposed to $PM_{2.5}$ above the WHO's daily guideline for longer than half a year. Particulate matter (PM), especially fine particulate matter, has deleterious effects on health (Pope and Dockery, 2013; Dominici et al., 2014). Both short-run time series analysis and chronic exposure cohort studies have found strong correlation between PM levels and elevated morbidity and mortality (Brunekreef and Holgate, 2002; Englert, 2004; Pope and Dockery, 2006). Among the sub-indicators of PM ($PM_{2.5}$, PM_{10}, and TSP), $PM_{2.5}$ is of particular harm to public health in terms of both toxicity and duration. Fine particulates can reach deep into the body where it can cause harm to both respiratory and cardiovascular systems.

Wearing particulate-filtering facemasks is a popular transitory defensive activity against PM pollution. Particulate respirators have typically been used in polluted workplaces to protect the health of workers. After an intense and prolonged period of pollution in Beijing in October 2011, which was widely covered in national media, urban residents started to resort to anti-PM facemasks to protect themselves against the ambient air pollution in the city. Since this pollution event, the use of facemasks has increasingly gained popularity in Beijing and other heavily polluted cities.

Particulate-filtering facepiece respirators remove particles out of the air to protect the respiratory system. The regulation on the certification of the particulate filtering respirators was first promulgated by the NIOSH (1995). China established its own standards by the Standardization Administration in 2009.[6] Anti-PM facemasks are categorized by both the filtration efficiency and the types of particulate matter they can filter. According to standards in different countries, filtration efficiency ranges from over 80 percent to 100 percent. Individuals can choose the type of facemasks based on the source and level of pollution. For instance, the N95 respirator, which is the best-selling model in China, is designed to filter at least 95 percent of airborne particles but is not resistant to oil.

It is also noteworthy that the performance of air-purifying facemasks hinges on various environmental and behavioral factors. For example, inappropriate fitting of facemasks can lead to poor filtration performance (CDC, 1998). Therefore, field experiments are required to measure the actual effect of facemasks on protecting health. There is only one known experiment that studied the daily use facemasks against the ambient air pollution. This experiment in Beijing found that wearing a typical anti-PM facemask reduced personal exposure to particulate matter by 96.6 percent.[7] As a result, in this experiment,

[4] Using the panel data with 226 residents in the Los Angeles area during 1985-1986, Bresnahan et al. (1997) found that people with smog-related symptoms spent less time outdoors when confronted with high-level ozone concentrations. Using the forecasted ozone data and the data on attendance at two outdoor facilities in Southern California, Neidell (2009) found that smog alerts reduced daily attendance at zoo and observatory by about 13% and 6% respectively; Graff Zivin and Neidell (2009) showed dynamic avoidance behavior that individuals disregarded the second day warning.

[5] A pollution day refers to a day with Air Quality Index above 100.

[6] The existing technical standard is designed for filtering respirators at workplace. Up till now, the new standards for daily facemask usage still at the drawing-board stage.

[7] The anti-PM facemask used in this experiment is 3M Dust Respirator 8812.

facemasks were found to diminish the adverse effects of air pollution on blood pressure and heart rate variability (Langrish et al., 2009).

Anti-PM facemask market

We study online purchases of anti-PM facemasks mainly because the online shopping data are available with a fine spatial and temporal resolution. The data are obtained from the dominant e-commerce websites in China: Taobao.com and Tmall.com, both under the Alibaba Group.[8] According to the China Internet Network Information Center (CINIC), about 75 percent of Chinese Internet users, or 474 million, visit Taobao.com on a daily basis and 50 percent, or 316 million, visit Tmall.com. Taobao.com is a monopoly in the consumer-to-consumer (C2C) e-commerce space in China with a market share of approximately 97 percent; it also boasts nearly a billion items for sale while being one top 20 most-visited websites globally. Tmall.com is the largest player in the business-to-consumer (B2C) e-commerce in China, accounting for about 50 percent of the market share.[9]

It is a natural concern that the unobservable facemask purchases from the brick-and-mortar businesses (B&M) might impact the external validity of this study. We argue that e-commerce might prevail over B&M in the anti-PM facemask market for the following reasons. First, online prices are normally identical with that of local stores, but online retailers sometimes offer discounts and purchase with gifts. In addition, online shopping has access to a wider variety of facemasks and therefore meets the heterogeneous demand better.

Second, shipping and handling of online orders is both cheap and fast. Many online stores offer free shipping and handling for certain number of purchases; otherwise they charge an additional fee of about 5-12 Yuan, or 1-2 USD.[10] The shipping and handling time is between zero to four days due to efficient levels of logistics in China. In particular, in many big cities, which tend to be both population and pollution centers, a buyer can receive their order on the same day. Therefore, shipping and handling is not an obstacle of online shopping.

Third, online shopping will reduce searching costs and the associated pollution exposure. Offline purchases are more desirable if a bricks-and-mortar store is around the corner. If a local store is not conveniently available, the searching for a drug store will increase pollution exposure. Since most people do not wear masks indoor, many would prefer online shopping and waiting for the orders to be delivered to home or office.

Fourth, the major manufacturer of anti-PM facemasks relies on e-commerce as their main retail channel. The 3M Company has the largest market share for anti-$PM_{2.5}$ facemasks.[11] The 3M Company does not have stand-alone B&M retail stores in China. Instead, it has two official flagship stores with thousands of third-party distributors on Tmall.com and JD.com.

Fifth, Internet users are likely to be the majority of consumers, and online shoppers, for anti-PM facemasks. Although these people account for about half of the Chinese population in 2013, or 618 million[12], they live in the major cities with both high Internet penetration and AQI information disclosure. Since major cities are the most likely to have high levels of pollution, these consumers are the most likely to seek out particulate filtering masks. Those who have no access to the Internet access tend to live in remote areas without AQI information. Since remote areas usually have better air quality and lower income, these consumers are less likely purchase facemasks. Furthermore, pollution information is mainly distributed online and concern about fine particulates initially spread on the Internet before it became a national issue.

Air pollution information

Air pollution is a critical public health concern in Chinese cities. To reduce the negative health impacts of air pollution, the Chinese government discloses air quality information to encourage pollution avoidance. The Ministry of Environmental Protection of China (MEP) enacted the new Ambient Air Quality Standard (GB3095-2012) and AQI Guidelines on February 29, 2012. The switch from Air Pollution Index (API) to Air Quality Index (AQI) reflected two major revisions: (1) $PM_{2.5}$ and ozone were included as new criteria pollutants; and (2) the frequency of reporting pollution increased from daily to hourly. In accordance with the new rules, to date, 190 cities have been required to report hourly concentrations of six criteria pollutants: NO_2, SO_2, PM_{10}, $PM_{2.5}$, CO, and O_3. This real-time pollution information is then submitted to the MEP's National Environmental Monitoring Center (CNEMC) and where it is disclosed to the public on its official website.

The MEP uses daily AQI, which is a normalized index transformed from the pollutant concentrations, to represent the overall air quality in a city. AQI ranges from 0 to 500, with a larger number indicating poorer air quality. It is classified into six levels of air quality: excellent for $AQI \leq 50$, good for $51 \leq AQI \leq 100$, lightly polluted for $101 \leq AQI \leq 150$, moderately polluted for $151 \leq AQI \leq 200$, heavily polluted for $201 \leq AQI \leq 300$, and severely polluted for $301 \leq AQI \leq 500$. In addition,

[8] Alibaba Group is a publicly traded company listed on the New York Stock Exchange (NYSE). Its initial public offering (IPO) on September 19, 2014 is the largest in history.

[9] All the daily visits and market share data are calculated based on the data from CINIC.

[10] The exchange rate of USD/RMB was 6.3125 in 2013 according to the China Statistical Yearbook.

[11] Based on the data from JD.com, the second largest e-commerce company in China, 3M had a market share of 67.8% in 2012-13.

[12] Source: China Internet Network Information Center. 2014. China Internet Development Report 32:5–7

the AQI reporting also includes the primary pollutant, color codes, potential health effects, and a cautionary statement for specific sensitive groups of people. Please see Figure A1 in the Appendix for more details.

These air pollution reports are available from various channels. In addition to traditional media sources such as newspaper, TV, or radio, the Internet has become a major source of information. First, the MEP has disclosed pollution information on its official website since 2000. Second, real-time air quality information is also disseminated by all Internet portals, major websites, smart phone apps, and social networks.[13] These emerging new media sources cover about half of the Chinese population with Internet access: one seventh of the population have smart phones, over one third have Weibo accounts, and half have Wechat accounts.

Besides the official pollution reports, residents in five capital cities—Beijing, Shanghai, Guangzhou, Chengdu, and Shenyang—have access to the air quality information disclosed by the US Embassy in these cities. The US Embassy reports real-time AQI following the Air Quality Guidelines of the US Environmental Protection Agency (US EPA). Please see Figure A1 in the Appendix for the levels of US AQI. Both hourly $PM_{2.5}$ concentrations and the corresponding US AQI are reported on Twitter.[14] Although Twitter is blocked in China, many third-party websites and smart phone apps provide side-by-side comparisons of the MEP AQI and the US AQI. Therefore, the US AQI has become a well-known alternative to the official air quality information.

Data

Data sources

We have assembled a unique data set that includes air pollution, facemask purchases, and weather from various sources. The data set is aggregated to the city and daily level. The final data set covers 190 cities from January 2013 to April 2014.

Facemask purchases. The data of daily facemask purchases, in the form of a normalized index, come from Taobao.com and Tmall.com. The data include two mask indices: total mask index and anti-$PM_{2.5}$ mask index. A record of a purchase enters the index system only when the transaction is complete, which is the time at which a consumer receives the package. The facemask data set covers the period from January 2013 to April 2014 for 316 cities on a daily basis. Only several prefectures in Tibet and some cities with small populations have no data. We also collected original anti-$PM_{2.5}$ facemask transaction records from 176 online stores on Taobao.com and Tmall.com. These online stores are required to disclose transaction records of the most recent month on their own home pages. Due to resource constraints, we only examine the sales data from late September 2013 to October 2013. Although 4400 online stores sold anti-$PM_{2.5}$ facemasks during that month, our sample accounted for 70 percent of the total completed transactions. We aggregate the actual sales data from the store level to the national level.

AQI. The station-level air pollution data were obtained from web-scraping the website of the Ministry of Environment Protection (MEP) of China.[15] MEP has established a national environmental monitoring network that covers 988 ground-based monitoring stations in 190 cities by the end of 2013, increasing from 74 cities at the beginning of the year. The data that we are using are from January 2013 to April 2014. The data set provides hourly concentrations of six criteria pollutants: NO_2, SO_2, PM_{10}, $PM_{2.5}$, CO, and O_3. Since most people pay attention to AQI instead of individual pollutant concentrations, we also generate daily AQI for each city from the hourly station-level data.

Weather. The weather data come from the National Climatic Data Center under the National Oceanic and Atmospheric Administration (NOAA) of the United States. The data set for our analysis covers 499 weather stations, using measurements every three hour from 2013 to 2014. Weather variables are potentially confounding factors for anti-PM facemask purchases. The variables used in this paper include visibility (in statute miles), temperature (in Fahrenheit), dew point (in Fahrenheit), wind speed (in miles per hour), and wind direction (in compass degrees). All of these weather variables are daily averages at the city level, which matches the temporal and spatial resolution of the mask indices.

Mask index

The actual sales data are not disclosed by the Alibaba Group, including Taobao.com and Tmall.com, in order to protect its trade secrets. Instead, only the Taobao Index is released, which is converted from actual sales, to facilitate its sellers and buyers to understand market trends. The mask index is a part of the broader Taobao Index that synthesizes the online shopping activities on Taobao.com and Tmall.com. The Taobao Index is arguably the most comprehensive indicator of China's e-commerce market. The data include two mask indices: total mask index and anti-$PM_{2.5}$ mask index. The total mask index

[13] To name a few, air pollution information is disseminated by popular websites such as Mojichina http://www.mojichina.com/, $PM_{2.5}$ in http://www.pm25.in/, and World's air quality http://aqicn.org/; well-known smart phone apps such as Moji, Tianqitong, and Weather forecasting; social media such as Weibo and Wechat.

[14] The official twitter account names are: @BeijingAir for Beijing, @CGChengduair for Chengdu, @CGShanghaiair for Shanghai, @CGGuangzhouair for Guangzhou, and @CGShenyangair for Shenyang.

[15] The MEP does not provide the compiled data of air pollution in 2013. Even the information released online will be retracted after a period of disclosure.

measures the aggregated purchases of all kinds of facemasks in a city during each day. The anti-$PM_{2.5}$ mask index only includes the purchase record of those facemasks labeled specifically as anti-$PM_{2.5}$.

The mask index is monotonically increasing in actual sales but the functional form is unknown. Therefore, we use the original sales records to recover this relationship. Because the transformation is deterministic, in theory we only need two-day sales data to estimate a linear function. Of course, with more data points, we can test for more specifications. Although we have only 14 days of actual sales data for anti-$PM_{2.5}$ facemasks, they are sufficient to estimate the functional relationship between actual sales and mask index.

The functional form is approximated by regressing overall sales on the mask index at the national level. The dependent variable is the quantity or total value of mask sales. We have tested various specifications of the relationship, and it turns out that the linear function has the best model fitting. Although our sample size is very small, the regression shows a strong relationship between facemask sales and the mask index. In the linear model, the mask index can explain 99 percent of variations of facemask sales. The regression result is reported in Table 2. It shows that a 1-unit mask index corresponds to 63 online orders or 566 Yuan expenditures on anti-$PM_{2.5}$ facemasks.

Summary statistics

The distribution of air pollution levels and primary pollutants for all cities in 2013 is illustrated in Fig. 1. On average, only 17 percent of days attained level-1 air quality, which is considered as “excellent” with an AQI below 50. In contrast, approximately 9 percent of days were categorized as “heavily polluted” or “severely polluted” with an AQI over 200. The annual average AQI for all Chinese cities was 98 in 2013, which falls in the domain of “good air quality” according to MEP’s definition. The air pollution was mainly caused by particulate matters; combined, PM_{10} and $PM_{2.5}$ were primary pollutants in 95 percent of pollution days.

The annual average concentration for PM_{10} was 108 $\mu g/m^3$ in 2013, which is over five times the guideline recommended by the World Health Organization (WHO). The annual average concentration for $PM_{2.5}$ was 68 $\mu g/m^3$, which is close to seven times the WHO guideline. The spatial distribution of particulate pollution is shown in Fig. 2. Because particulates with sizes are generated from different process, PM_{10} and $PM_{2.5}$ exhibit distinct spatial characteristics, and generally, PM_{10} pollution is worse in northern China, while $PM_{2.5}$ pollution is worse in the east.

The histogram of the mask index is illustrated in Fig. 3. It demonstrates that both mask indices are heavily skewed towards zero as the vast majority of observations are close to zero. However, the tail is very long because of the effect of extreme pollution episodes. The daily average mask index is 11 for all facemasks, and 4 for anti-$PM_{2.5}$ facemasks, which implies approximately 4,282 and 3,694 orders at the city level.

The spatial distribution of mask index at the prefecture level is depicted in Fig. 4. This figure shows that both the total mask index and anti-$PM_{2.5}$ mask index cover most prefectures across the 31 provinces of China. The demand for anti-PM facemasks is mainly from a number of larger cities and the spatial pattern of the mask index is quite close to that of the $PM_{2.5}$ distribution in Fig. 2, which suggests a link between fine-particulate pollution and mask purchases. The summary statistics of other variables used in the empirical analysis are reported in Table 1.

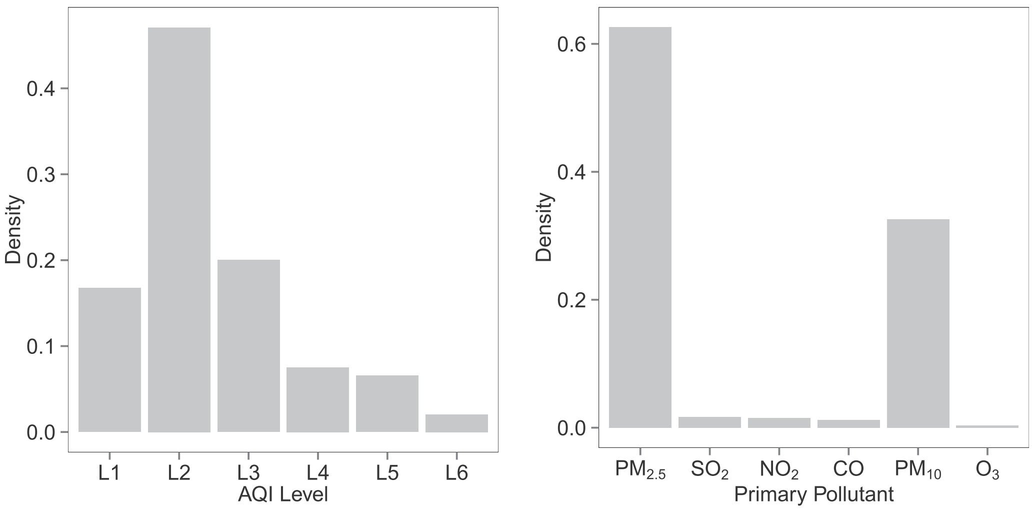

Fig. 1. AQI levels and primary pollutants. The left panel depicts the percentage of days falling into each category of air quality, with L1 being the best quality and L6 being the worst. The right panel shows the percentage of pollution days that is caused by each primary pollutant. The daily pollution data cover all cities that disclose AQI in 2013.

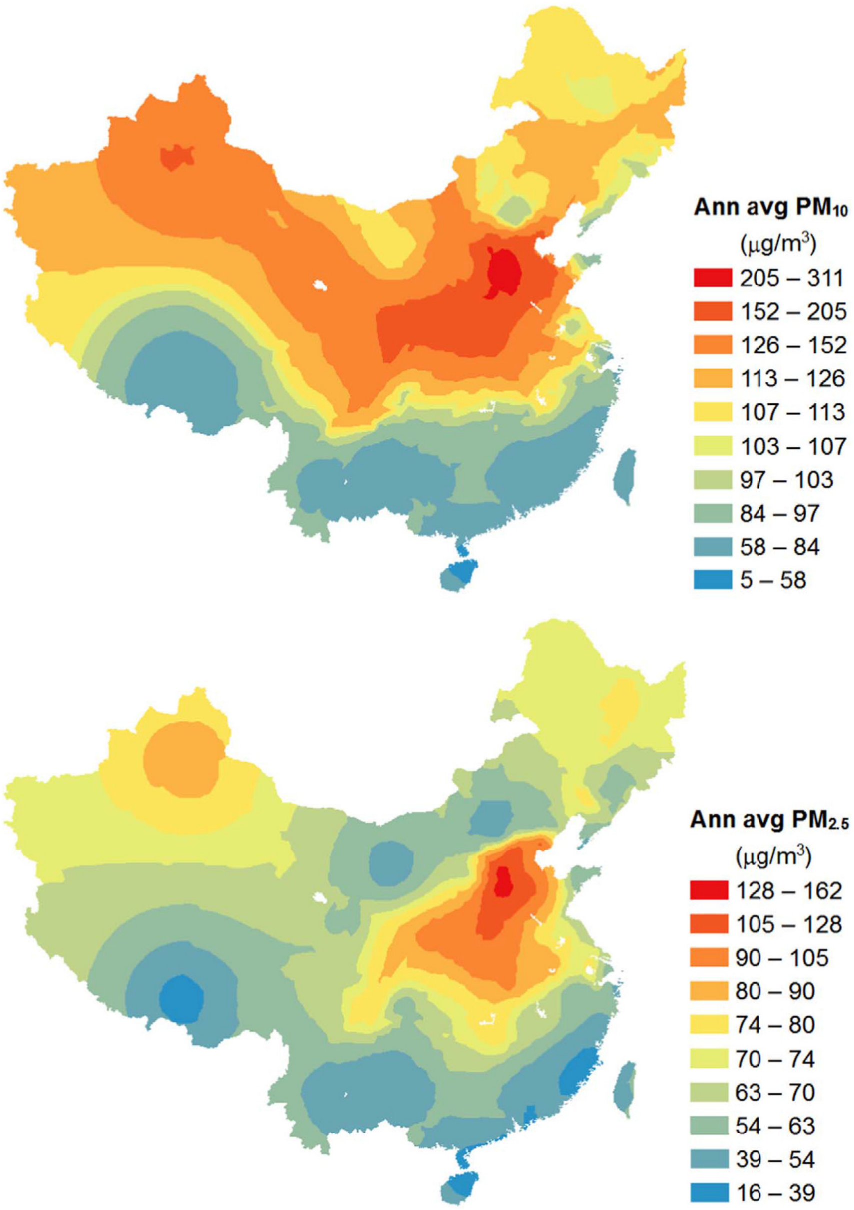

Fig. 2. Annual mean PM_{10} and $PM_{2.5}$ concentrations ($\mu g/m^3$) in 2013. The data are based on the annual mean concentrations of 532 monitoring stations. Spatial interpolation is implemented by means of kriging.

Empirical model

Motivation

We use a random-utility model to describe an individual's decision as to whether to purchase anti-PM facemasks. We assume that individual i chooses alternative j (purchasing facemasks or outside good) at time t to maximize the following utility function:

$$u_{ijt} = v(x_{ijt};\theta) + \varepsilon_{ijt}. \tag{1}$$

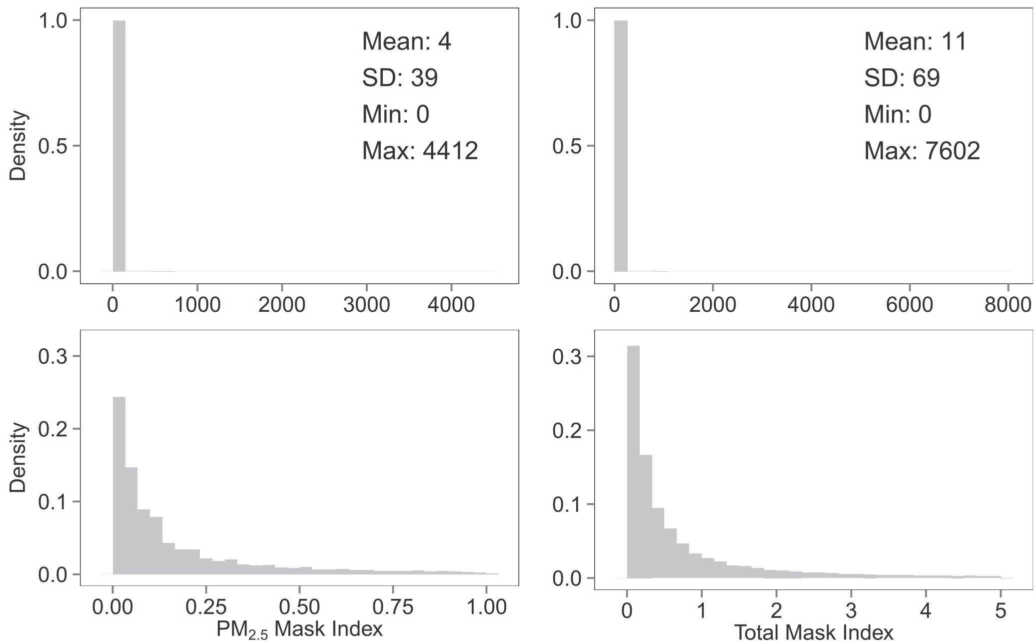

Fig. 3. Distribution of anti-$PM_{2.5}$ mask and all mask index in 2013. The left column illustrates the distribution over the whole support. The right panel zooms in the area for close to zero (1 for anti-$PM_{2.5}$ mask index and 5 for all mask index).

In this form, x_{ijt} is a collection of variables that determine mask purchases such as ambient air quality, facemask attributes, and individual characteristics. The unobservable error term is designated by ε_{ijt}. The deterministic part of the utility function is designated by $v()$ and parameterized by θ. It is specified as a linear function such that $v_{ijt} = x'_{ijt}\theta$.

Due to the fact that pollution avoidance behaviors other than purchasing facemasks are not observed in the data set, they are combined as the outside option and their utility is normalized to zero. It is worth noting that there are other avoidance behaviors beside anti-PM facemasks, such as canceling outdoor activities to reduce exposure to air pollution.

An individual chooses the alternative that maximizes her utility. Let d_{it} designate the binary choice variable with one indicating purchasing a facemask and zero indicating other behavior. The probability that individual i will choose option j is:

$$\Pr(d_{ijt} = 1) = \mathbb{E}_{\varepsilon} 1(u_{ijt} \geq u_{ikt},\ \forall k). \tag{2}$$

If ε has $i.i.d$ type-I extreme value distribution across i, j and t, the choice probability in Eq. (2) is represented by a multinomial logit model.

The random-utility model is used to motivate our empirical specification. Due to the fact that we lack individual-level purchase data, we aggregate this model to the city level. Another justification for aggregation is that the facemask data are characterized by extremely low frequency of purchases and the data are dominated by the records of zero purchases in many cities and days. Therefore, we aggregate the individual choice variable d to the city level y. Let m index city and N designate its population size, total facemask purchases in the city

$$y_{mt} = \sum_{i=1}^{N} d_{ijt}. \tag{3}$$

The “law of rare events” applies in this aggregation (Cameron and Trivedi, 1998). Since the population of a city is large, the total purchase of facemasks follows the Poisson distribution with the following probability density function:

$$f(y_{mt}|x_{mt}) = \frac{e^{-\mu_{mt}} \mu_{mt}^{y_{mt}}}{y_{mt}!}, \text{ where } \mu_{mt} = \exp(v(x_{mt};\theta)). \tag{4}$$

In this form, $\mu_{mt} = \mathbb{E}(y_{mt}|x_{mt})$ is the mean of the Poisson distribution. Model (4) reflects the fact that a Poisson model is consistent with the random-utility model in Eq. (1). In particular, a repeated logit model can be aggregated to a Poisson model, which is discussed by Hellerstein and Mendelsohn (1993) and was used in an empirical study by Zhang (2011).

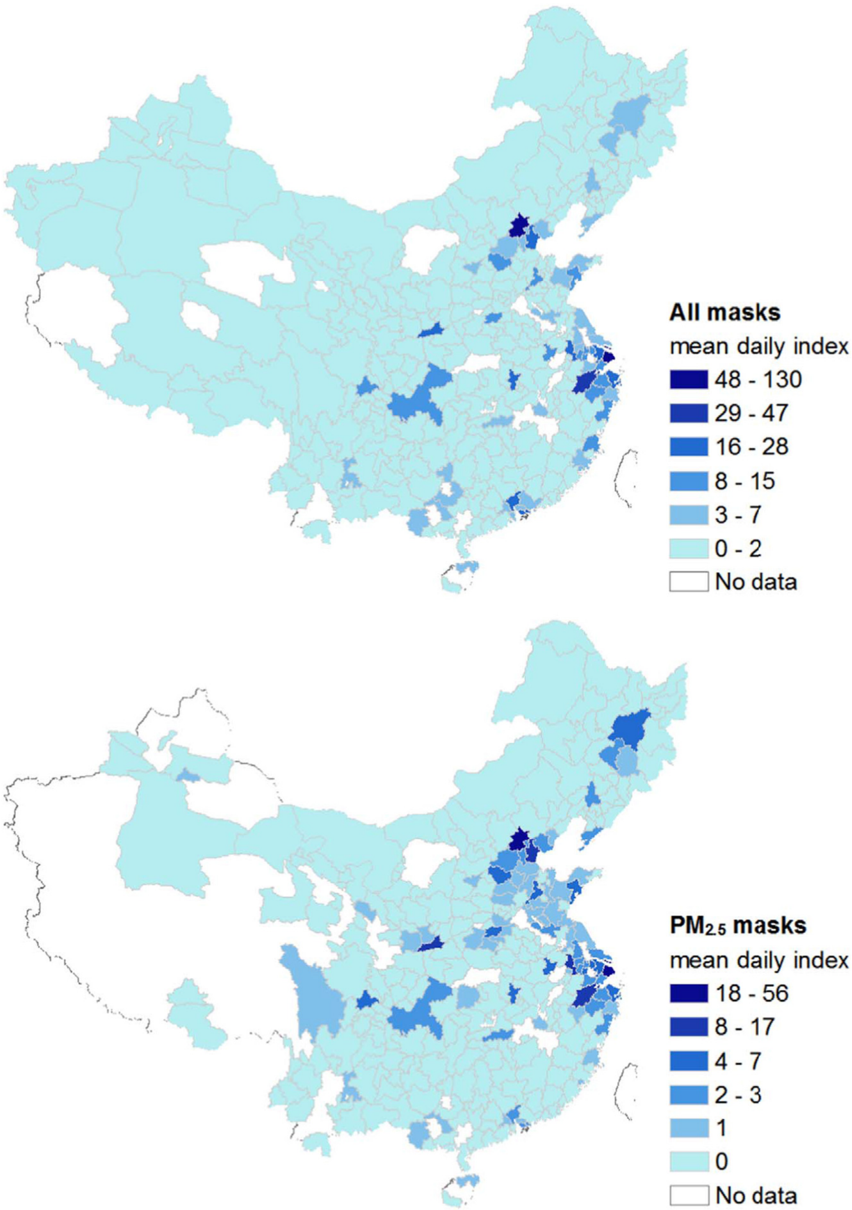

Fig. 4. Mean daily sales index for all masks and anti-$PM_{2.5}$ facemasks in 2013. The spatial resolution is prefecture.

Table 1
Summary statistic.

Variable	Label	N	Mean	SD	Min	Max
All Masks	Total mask index	40,584	10.901	69.156	0	7602.200
Anti-$PM_{2.5}$ Masks	Anti-$PM_{2.5}$ mask index	40,584	3.850	38.837	0	4412.090
AQI	Air Quality Index	40,584	104.991	69.407	0	500
DIR	Wind direction	40,584	245.880	139.347	20	888
SPD	Wind speed	40,584	5.876	3.264	0.250	35.571
TEMP	Temperature	40,584	53.617	19.011	−17.357	96
DEWP	Dew point	40,584	40.359	21.852	−28.429	82
VSB	Visibility	40,569	7.0665	4.196	0	18.800
HOL	Holiday	40,584	0.024	0.154	0	1

Empirical strategy

The baseline specification considers a daily market for anti-PM facemasks at the city level. Our goal is to estimate a demand function to evaluate the marginal effect of air pollution on mask purchases. Based on the intuition of the Poisson model, we use the following exponential conditional expectation function (CEF):

$$\ln\mathbb{E}(y_{mt}|x_{mt}) = \alpha a_{mt} + \beta' w_{mt} + \gamma' z_{mt} + \delta_m + \lambda_{mt}. \tag{5}$$

In this form, y_{mt} is the mask index for city m at day t, a_{mt} is the ambient air quality, w_{mt} is a vector of weather variables, z_{mt} includes other controls such as the day of week and whether it is holiday, δ_m is a city fixed effect, and λ_{mt} represents various types of time fixed effects.

We run the above regression separately for the total mask index and anti-$PM_{2.5}$ mask index. As for ambient air quality, we use mean AQI values and AQI bins in different specifications. Weather conditions can confound the relationship between air pollution and facemask purchases, so we control for wind direction (DIR), wind speed (SPD), temperature (TEMP), and dew point (DEWP). Dew point is mainly used as a proxy of humidity because the latter variable is not available in the NOAA weather data set.

We include a rich set of fixed effects to control for unobservable determinants for facemask purchases. We use city fixed effects (City FE) to control for city-level differences in facemask consumption. City FE absorbs all factors that do not change over time such as culture and geographic location. We also use three different time fixed effects to control for shocks that vary over time. The first one is date fixed effect (Date FE) that controls for unobservable facemask price and attributes that are common to all cities. Second, we use an interaction between province and date fixed effects (Province-Date FE) to control for regional time trends in facemask purchases. Third, we use the interaction of city and week fixed effects (City-Week FE) to control for time-varying local demand shifters such as media coverage, information disclosure, online shopping trends, or shipping costs. With City-Week FE, we also include day of week (DOW) and holiday (HOL) dummies to control for the vagaries of daily patterns of online shopping.

Although our specification is motivated by the Poisson model, the consistent estimation of the conditional mean parameters does not hinge on the Poisson distribution. As long as the exponential CEF in Eq. (5) is true, the Poisson pseudo-maximum likelihood (PML) estimator is robust to distributional misspecification (Cameron and Trivedi, 1998). Another advantage of this approach is that the fixed-effect Poisson PML estimator is not subject to the incidental parameter problem (Lancaster, 2002). This makes the nonlinear fixed effect model appealing to empirical researchers. Furthermore, the dependent variable does not have to be count variables. Therefore, although mask index is a continuous variable, it can be fully handled by PML. One concern of the Poisson model is its assumption of the equality of the conditional variance and mean. However, this concern can be mitigated by clustering standard errors.

We prefer the fixed-effect Poisson model because the dependent variable is significantly skewed towards zero (see Fig. 3), so the Poisson model fits the data very well. By comparison, the linear model fits poorly for the extremely skewed non-negative distribution and its estimation results are associated with large standard errors. Log-linear model is another alternative.[16] Because the facemask purchase data have a large number of zeros, log-linear model usually adopts the form of $\ln(y_{mt} + k)$, which might be sensitive to the choice of constant k in some cases. Therefore, we estimate both linear and log-linear models for robustness checks.

Threat to identification

Our empirical strategy is to use the day-to-day fluctuation in air quality to identify the causal effect of air pollution on defensive expenditures. To address the concern that the drivers of short-run air quality may also affect facemask purchases, we control for weather, day of week, holiday, city fixed effects, and various time fixed effects. After controlling for these important potentially confounding variables, the high frequency variation in air pollution provides a possible source of exogenous variations. However, there still remain some potential threats to identification.

First, facemask prices, including their shipping and handling costs, are not observable. If sellers raise their prices during heavy pollution days, omitting prices is likely to underestimate the marginal effect of air quality on facemask purchases. Since

[16] The alternative specification is motivated by the linear transformation of the multinomial logit model (Berry et al., 1995). Let s_{mj} designate the market share for facemask type j and s_{m0} as the share of the outside product:

$$\frac{s_{mjt}}{s_{m0t}} = \exp(\gamma a_{mt} + \beta' w_{mt} + \delta_m + \lambda_{mjt}).$$

The corresponding log-linear CEF is

$$\mathbb{E}\left(\ln\frac{s_{mjt}}{s_{m0t}}\middle|x_{mjt}\right) = \gamma a_{mt} + \beta' w_{mt} + \delta_m + \lambda_{mjt}. \tag{6}$$

Please note that the two CEFs in (5) and (6) have different specifications. However, their coefficients can be interpreted in a similar manner.

online stores set uniform prices nationwide, the unobservable prices can be controlled by the date fixed effect. Based on the limited price information that was collected from JD.com, we find that sellers adjust price infrequently. If price is not adjusted on a daily basis, using Date FE takes out too many variations. Therefore, we also test the week and month fixed effects. In case local discounts and promotions are offered, the Province-Date or City-Week FE is used to control for potential local price differences.

Second, facemask attributes—such as filtration efficiency, comfort of wearing, or appearance—affect facemask purchases but are not available. As air pollution gets worse, individuals are likely to choose more efficient (and more expensive) facemasks. Facemask attributes are also correlated with weather since facemasks can be used to defend against cold air besides pollution. The direction of the omitted variable bias (OVB) is unclear. Since our data only differentiate anti-$PM_{2.5}$ facemasks and all facemasks, our strategy is to run separate regressions for each of these facemask types. Through this method, we not only treat unobservable facemask attributes as a facemask-specific constant, but also allow for heterogeneous coefficients for different facemasks.

Third, the aggregated consumer attributes at the city level—such as income, population, health conditions, and culture—are either unobservable or, at best, available annually up until only 2012. These variables are correlated with both air quality and facemask purchases. For example, air quality affects the overall health conditions of the residents in a city, and the latter will also determine the demand for anti-PM facemasks. To address this concern, our preferred model controls for the unobservable city attributes by the city-by-year-by-month-by-week (City-Week) FE and it allows for the socioeconomic and demographic attributes to vary across cities and over weeks.

Fourth, defensive expenditures on facemasks produce joint benefits. Facemasks have been widely used among the residents in Chinese cities before air pollution was a major concern. These facemasks can be used to keep warm, prevent spreading germs, and even for fashion purpose. However, for the purposes of facemask use other than air pollution, the anti-$PM_{2.5}$ facemask is not the first choice because it is more expensive than other facemasks, and the City-Week fixed effect is able to control for the preference for facemask usage other than pollution avoidance for each city in a very fine time scale.

The fifth concern is caused by the presence of other avoidance behaviors. In the short run, individuals can cancel outdoor activities or change the location of activities to reduce pollution exposure. In the long run, air pollution can cause residential sorting. These alternative avoidance behaviors can be caused by air pollution and become substitutes for the purchases of anti-PM facemasks. However, these behaviors are unlikely to affect our estimation results for a number of reasons. First, our model measures the reduced-form effect of air pollution on facemask purchases, which has incorporated the impact of other avoidance activities. Second, since non-facemask defensive behavior is a consequence of air pollution, its inclusion would raise the concern of "bad control." Third, our paper focuses on the short-run pollution avoidance, residential sorting can be regarded as fixed especially as we include the City-Week FE. In addition, due to the tight system of household registration in China, moving between cities is rather restricted. Fourth, in order to cancel out the effect of rescheduling outdoor activities, we can aggregate the data to the weekly or monthly level, and we also include the dummy for day of week as a proxy for the difficulty of changing outdoor activities.

Finally, some argue that air quality varies within a city and using city average AQI will cause the concern of measurement error. We argue that this is a minor issue because of the following reasons. First, although air quality varies within a city and people move around during a day, the difference of air quality within a city is small. In particular, $PM_{2.5}$ is a diffusive pollutant and this reduces the concern of uneven distribution within a city. Second, this paper does not measure the health consequence of air pollution but measures the response to pollution information. The air pollution level, such as AQI, is usually reported at the city average level. Hence, the defensive behavior is mainly based on the average level of air quality information. Third, our empirical analysis is at the city level rather than the individual level. The marginal effect is the average effect within a city. Therefore, the individual heterogeneity has been averaged.

Results

Baseline model

Following the specification of the exponential CEF in Eq. (5), we regress daily facemask index on AQI, weather (WEA), holiday (HOL), day of week (DOW), and a set of city and time fixed effects. Weather includes temperature (TEMP), dew point (DEWP), wind speed (SPD), and wind direction (DIR). We test three combinations of fixed effects to control for city- and time-varying unobservable information that may affect facemask purchases. The first one uses city and date fixed effects. To allow for region-specific time trends, the second one uses city and province-by-date fixed effects. The last one uses city-by-year-by-month-by-week fixed effect to control for the unobservable information that varies across cities and over weeks.

We run separate regressions for the anti-$PM_{2.5}$ mask index and the total mask index. The model is estimated by means of the Poisson pseudo-maximum likelihood (PML) estimator. The standard errors are clustered at the city, province-date, and city-week levels, respectively . For the sake of brevity, we only report the estimate for AQI and suppress the others. The estimation results are presented in Table 3 and three models yield similar estimates. Since City-Week FE is the most flexible one, we use it in the following baseline specification for the daily model:

Table 2
Relationship between Anti-$PM_{2.5}$ mask index and sales.

	Quantity (1)	Value (2)
Mask Index	62.811***	565.610***
	(1.749)	(18.847)
t	35.920	30.010
p-value	0.000	0.000
Confidence Interval	[59.001, 66.621]	[524.547, 606.673]
N	13	13
R^2	0.991	0.987

Notes: Dependent variable is the quantity or value of anti-$PM_{2.5}$ mask sales at the national level. The only independent variable is anti-$PM_{2.5}$ mask index. The daily sales data span from late September 2013 to October 2013. $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$.

$$\begin{aligned}\ln\mathbb{E}(\text{Mask}_{mt}|x_{mt}) \quad = \quad & \alpha\text{AQI}_{mt} + \beta_1\text{TEMP}_{mt} + \beta_2\text{SPD}_{mt} + \beta_3\text{DIR}_{mt} + \beta_4\text{DEWP}_{mt} \\ & + \gamma_1\text{HOL}_t + \gamma_{2'}\text{DOW}_t + \text{City} - \text{WeekFE}_{mt}.\end{aligned}$$

The parameter of central interest is the coefficient for AQI, which is by divided by 100. With the exponential conditional expectation function, α measures the semi-elasticity of facemask purchases with respect to air quality:

$$\alpha = \frac{\partial\mathbb{E}(\text{Mask}_{mt}|x_{mt})}{\partial\text{AQI}_{mt}}\frac{1}{\mathbb{E}(\text{Mask}_{mt}|x_{mt})}. \tag{7}$$

Therefore, the interpretation of the Poisson model is analogous to the semi-log linear model that regresses the log of facemask purchases on air quality and other control variables.

The results of the preferred specification (columns (3) and (6) in Table 3) show that a 100-point increase in the AQI results in 23 percent growth in the anti-$PM_{2.5}$ mask index, and 21 percent in the total mask index.[17] Both estimates are statistically significant at 1 percent level. The results demonstrate unambiguous evidence that individuals respond to increased air pollution by purchasing more anti-PM facemasks. Specifically, the response is more pronounced for the facemasks that can filter fine particulates. This result is intuitive due to the fact that $PM_{2.5}$ is the main cause of air pollution and individuals take preventive measures against the most harmful pollutant.

Dynamic avoidance behavior

The baseline model assumes that individuals only respond to contemporaneous pollution information. However, it is likely that pollution information has a dynamic effect on avoidance behavior (Graff Zivin and Neidell, 2009). We probe the intertemporal issue by including four successive lags of AQI in the baseline model.[18] It results in the following distributed-lag model:

$$\ln\mathbb{E}(\text{Mask}_{mt}|x_{mt}) = \sum_{k=0}^{4}\alpha_k\text{AQI}_{mt-k} + \beta'\text{WEA}_{mt} + \gamma_1\text{HOL}_t + \gamma_2'\text{DOW}_t + \text{City} - \text{WeekFE}_{mt}.$$

The above model includes City-Week FE that corresponds to the preferred specification in the previous section. The estimation result of the dynamic model is reported in Table 4. We find that individuals respond to current and past pollution information with intertemporal effects up to four-day lags.

We find that the contemporaneous AQI has the largest effect on facemask purchases. The impact of the lagged information is tapering except for the fourth-day lag. This is likely caused by the transaction recording system in the e-commerce sector. The shipping and handling time of online orders usually ranges from zero to four days, depending on the distance and the choice of parcel delivery company.[19] A transaction is regarded as complete only when the buyer receives the order. Therefore, the purchase record from online stores would enter the sales index four days later. This explains the reason that the coefficient of the fourth-day lag of AQI is larger than many other lags.

Accounting for the dynamics of avoidance behavior considerably increases the estimated semi-elasticity. Column (1) in Table 4 shows that a 100-point increase in AQI leads the anti-$PM_{2.5}$ mask index to grow by 19.5 percent in the same day, 17.3

[17] Please note AQI is scaled in hundreds of points for ease of interpretation.
[18] We also tested more lags of AQI, but they produce virtually identical estimates. Only up to four successive lags of AQI are significant.
[19] The shipping and handling time of online orders could be longer than four days for the remote areas. As Beijing accounts for 90 percent of facemask purchases and the majority of sellers are centered in the east or the north, the delivery time of most online orders is within four days. Although we do not have accurate data to show the distribution of delivery time, the promise of "zero to four days" is the common expectation of consumers.

Table 3
Fixed-effect Poisson model: daily mask index.

	Anti-$PM_{2.5}$ masks			All masks		
	(1)	(2)	(3)	(4)	(5)	(6)
AQI	0.279***	0.248***	0.227***	0.275***	0.244***	0.210***
	(0.062)	(0.052)	(0.040)	(0.048)	(0.054)	(0.033)
Weather	Yes	Yes	Yes	Yes	Yes	Yes
Holiday			Yes			Yes
Day of week			Yes			Yes
Date FE	Yes			Yes		
City FE	Yes	Yes		Yes	Yes	
Province-Date FE		Yes			Yes	
City-Week FE			Yes			Yes
N	40,584	33,283	40,327	40,584	33,285	40,351
Log Likelihood	−240602	−62245	−51438	−512345	−149482	−90164

Notes: Model is estimated by the Poisson pseudo-maximum likelihood (PML) estimator. Dependent variable is daily mask index. AQI is divided by 100. Weather includes temperature, dew point, wind speed, and wind direction. Holiday and day of week are dummy variables. The coefficient of AQI is interpreted as the percentage of change in mask index with respect to 100-point change in AQI. Standard errors in parenthesis clustered at the city, province-day, and city-week level respectively. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

percent in the second day, 9.7 percent in the third day, and 16.2 percent in the fourth day. The total semi-elasticity of anti-$PM_{2.5}$ facemask purchases with respect to AQI is 70.6 percent. For all facemasks, the total semi-elasticity is 54.5 percent as shown in column (2). These two effects are significantly larger than those estimated by the baseline model in Table 3, suggesting that intertemporal avoidance behavior and transaction recording system have non-trivial impacts on the results, though we are not able to identify the effect for each cause separately.

Comparing the results in Tables 3 and 4, the contemporaneous effect of the static model is only slightly higher than that of the dynamic model for both mask indices. This suggests that the past pollution information is not fully embedded into the current AQI, and the static model is likely to significantly underestimate individuals' response to air pollution. Therefore, we prefer the semi-elasticity estimated by the intertemporal model in Table 4 rather than the baseline result.

Temporal aggregation

A typical online order contains several facemasks that can last for multiple pollution days. An anti-PM mask can also be used multiple times as long as it is within its service time limits.[20] Therefore, forward-looking consumers are less likely to purchase facemasks for a single pollution day but for a certain period of pollution days. In addition, in anticipation of air pollution, individuals may store facemasks in advance because high-quality anti-PM facemasks sell out quickly during extreme pollution episodes. In these cases, consumers smooth facemask purchases over time. A daily model ignores the smoothing effect and it will under-estimate the effect of air quality on facemask purchases.

We aggregate mask index to the weekly or monthly level to address these concerns. Temporal aggregation also deals with the concern of dynamic avoidance behavior discussed in the previous subsection. Let τ index week or month and bar represents average. The aggregate model regresses weekly or monthly facemask index on average AQI, average weather, number of holidays (#HOLs), and city-by-year-by-month (City-Month FE) or city-by-year (City-Year FE) fixed effect such that:

$$\ln \mathbb{E}\left(\sum_{t \in \tau} \text{Mask}_{mt} | x_{m\tau}\right) = \gamma \overline{\text{AQI}}_{m\tau} + \beta' \overline{\text{WEA}}_{m\tau} + \gamma \#\text{HOLs}_{\tau} + \text{City} - \text{Month/YearFE}_{m\tau}.$$

The model is estimated by Poisson PML and the standard errors are clustered at the city-month or city-year level. We abuse notation for the parameters in the above equation. Additionally, it is noteworthy the parameters of the aggregate model are not directly comparable to those of the daily model because of the exponential CEF. To illustrate this point, $\mathbb{E}(\sum_t y_{mt} | x_{m\tau}) = \sum \exp(x'_{mt}\theta)$. Due to convexity, $\sum \exp(x'_{mt}\theta) \geq T\exp(\overline{x}'_{m\tau}\theta) = \exp(\overline{x}'_{m\tau}\theta + \ln T)$. The regression we are running is $\mathbb{E}(\sum_t y_{mt} | x_{m\tau}) = \exp(\overline{x}'_{m\tau}\pi)$. Therefore, even if without an intertemporal effect, the coefficients of AQI in the daily and aggregate models are different.

The estimation results, as shown in Table 5, demonstrate that the semi-elasticities are significantly larger than those of the baseline model. Specifically, the more aggregated the model is, the greater the estimate becomes. Notably, the estimated semi-elasticity of the monthly model is very close to that of the distributed-lag model in Table 4. This is not a pure coincidence; since pollution information has lags up to four days, the weekly model may not fully absorb the intertemporal effect; the monthly model can better capture the dynamics of pollution-facemask relationship.

[20] See NIOSH's recommendation on the use of particulate filter respirators: http://www.cdc.gov/niosh/npptl/topics/respirators/disp_part/RespSource3healthcare.html

Table 4
Dynamic effects of pollution information.

	Daily Mask Index	
	$PM_{2.5}$ (1)	All (2)
AQI_t	0.195^{***}	0.195^{***}
	(0.035)	(0.033)
AQI_{t-1}	0.173^{***}	0.095^{***}
	(0.025)	(0.021)
AQI_{t-2}	0.097^{***}	0.073^{***}
	(0.026)	(0.024)
AQI_{t-3}	0.079^{***}	0.059^{**}
	(0.026)	(0.024)
AQI_{t-4}	0.162^{***}	0.123^{***}
	(0.042)	(0.033)
Weather	Yes	Yes
Holiday	Yes	Yes
Day of week	Yes	Yes
City-Week FE	Yes	Yes
N	39,747	39,771
Log Likelihood	−47424	−85164

Notes: Specification is the fixed-effect Poisson model. Dependent variable is daily mask index. AQI is divided by 100. Weather includes temperature, dew point, wind speed, and wind direction. Holiday and day of week are dummy variables. The coefficient of AQI is interpreted as the percentage of change in mask index with respect to 100-point change in AQI. We tested various leads and lags; only the lags up to four days are significant. Standard errors clustered at the city-week level. $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$.

Table 5
Intertemporal smoothing: weekly and monthly aggregation.

	Weekly Mask Index		Monthly Mask Index	
	$PM_{2.5}$ (1)	All (2)	$PM_{2.5}$ (3)	All (4)
AQI	0.338^{***}	0.352^{***}	0.710^{**}	0.537^{**}
	(0.117)	(0.117)	(0.247)	(0.247)
Weather	Yes	Yes	Yes	Yes
City-Month FE	Yes	Yes		
City-Year FE			Yes	Yes
N	7,074	7,074	1,433	1,433
Log Likelihood	−91562	−91562	−82529	−82529

Notes: Specification is the fixed-effect Poisson model. Dependent variable is weekly or monthly mask index. AQI is divided by 100. Weather includes temperature, dew point, wind speed, and wind direction. Holiday and day of week are dummy variables. The coefficient of AQI is interpreted as the percentage of change in mask index with respect to 100-point change in AQI. Standard errors clustered at the city-month or city-year level. $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$.

Nonlinearity

Previously, we assumed that the semi-elasticity in Eq. (7) is a constant. However, since the majority of facemask purchases occurred during extreme pollution episodes, individuals' responses are more sensitive during highly polluted days. We therefore allow the semi-elasticity to be nonlinear in AQI. Instead of using polynomials of AQI, we use a more flexible specification that includes six pollution levels as dummy variables:

$$\ln\mathbb{E}(Mask_{mt}|x_{mt}) = \sum_{k=1}^{5}\alpha_k Level_{kmt} + \beta' WEA_{mt} + \gamma_1 HOL_t + \gamma_2' DOW_t + City - WeekFE_{mt}.$$

The dummy of AQI levels is aligned with the MEP AQI Guidelines on the classification of air quality. Level 1, or excellent air quality with AQI ≤ 50, is restricted as zero. The estimate of α is therefore compared with level-1 air quality. The above specification is consistent with the baseline model except for the semi-parametric specification of pollution levels.

The regression result of the flexible daily model is reported in columns (1)-(2) in Table 6. We find that individuals purchase anti-PM facemasks mainly during serious pollution days. Compared to the days with excellent air quality (AQI ≤ 50), a heavily polluted day ($201 \leq$ AQI ≤ 300) increases the anti-$PM_{2.5}$ mask index by 18, and 16 percent on the index of all facemasks. When AQI rises to the severely polluted level (AQI ≥ 300), the semi-elasticity jumps by 72 and 66 percent, respectively. Other lower pollution levels have statistically insignificant effect on facemask purchases compared to the level-1 air quality. Furthermore, the estimation results confirm that the purchases of anti-$PM_{2.5}$ facemasks are more responsive to AQI than other facemasks are.

Table 6
Flexible AQI levels.

	Daily Mask Index		Weekly Mask Index		Monthly Mask Index	
	$PM_{2.5}$ (1)	All (2)	$PM_{2.5}$ (3)	All (4)	$PM_{2.5}$ (5)	All (6)
Level 2	0.007	−0.012	0.180***	0.172***	0.074***	0.058***
(51–100)	(0.061)	(0.038)	(0.044)	(0.025)	(0.019)	(0.010)
Level 3	0.070	0.032	0.219***	0.174***	0.096***	0.078***
(101–150)	(0.083)	(0.048)	(0.035)	(0.015)	(0.013)	(0.011)
Level 4	0.065	−0.004	0.283***	0.208***	0.142***	0.077***
(151–200)	(0.080)	(0.052)	(0.052)	(0.028)	(0.022)	(0.015)
Level 5	0.176**	0.158***	0.359***	0.312***	0.111***	0.076***
(201–300)	(0.072)	(0.055)	(0.037)	(0.028)	(0.015)	(0.015)
Level 6	0.721***	0.661***	0.302***	0.304***	0.292***	0.234***
(301-500)	(0.111)	(0.103)	(0.062)	(0.063)	(0.039)	(0.036)
Weather	Yes	Yes	Yes	Yes	Yes	Yes
Holiday	Yes	Yes	Yes	Yes	Yes	Yes
Day of Week	Yes	Yes				
City-Week FE	Yes	Yes				
City-Month FE			Yes	Yes		
City-Year FE					Yes	Yes
N	40,327	40,351	7,074	7,074	1,433	1,433
Log Likelihood	−51322	−89995	−30965	−64925	−23355	−59378

Notes: Specification is the fixed-effect Poisson model. Dependent variable is daily, weekly, or monthly mask index. Weather includes temperature, dew point, wind speed, and wind direction. Holiday and day of week are dummy variables. For daily mask index, AQI levels are dummies. For weekly or monthly mask index, AQI levels are the number of days falling within each level. Standard errors clustered at the city-month or city-year level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

To account for the intertemporal dynamics, the daily model with flexible pollution levels is also aggregated to the weekly or monthly level. In the aggregated model, the key variable "Level" measures the number of days at each pollution level. The specification appears similar to the temporally aggregated model in the previous section except for flexible pollution levels. However, aggregation by the number of pollution days in each category is more reasonable. Because most facemasks are purchased during extreme pollution episodes, using average AQI in a period does not capture the particular pattern of demand.

Columns (3)-(6) in Table 6 present estimation results for the aggregated model with AQI levels. These results generally support the conclusion that the semi-elasticity of facemask purchases with respect to air pollution is increasing with the pollution level. However, compared to clean days (AQI $\leq$ 50), the aggregated model shows that individuals purchase more facemasks even when AQI is below 200. The semi-elasticity for the high pollution level in the aggregated model is significantly smaller than that of the daily model. The difference in the estimated semi-elasticities between the aggregated and daily models is likely due to the dynamic avoidance behavior that has been discussed in the previous section.

Heterogeneity

We consider several layers of heterogeneity in responses to air pollution. First of all, the avoidance behavior is affected by individuals' perceptions of air quality through visibility. When visibility declines markedly during hazy days, citizens would notice such changes more clearly and are likelier to buy anti-PM facemasks. To analyze the effect of visibility, we interact it with AQI and find statistically significant effects in the interaction term. The results are reported in columns (1)-(2) in Table 7. The estimated semi-elasticity is $(0.255 - 0.028 \times VSB)$ for anti-$PM_{2.5}$ facemasks and $(0.236 - 0.023 \times VSB)$ for all facemasks. It implies that 1-mile degradation in visibility reduces the semi-elasticity of anti-$PM_{2.5}$ mask index with respect to AQI by 2.8 percentage point, and 2.3 percentage point for the total mask index. This result suggests that observations of haze make individuals more responsive to formal pollution information.

Second, the semi-elasticity of facemask purchases is perhaps related to local provision of health care. One hypothesis is that better access to local medical services is likely to reduce the cost of treatment and make the defensive expenditures like facemasks less appealing. We consider three variables: number of hospitals, hospital beds, and doctors per capita. However, we find no statistically significant effect of heterogeneity related to any of these local medical conditions. These results are summarized in columns (3)-(4) in Table 7.

Third, we are concerned with the spatial heterogeneity of avoidance behavior. Although we have controlled for unobservable city attributes, the elasticity of defensive expenditure is common to all regions. We run the baseline regression separately for six traditional regions in China: north, northeast, east, south central, southwest, and northwest.[21] The

[21] North China includes Beijing, Tianjin, Hebei, Shanxi, and Inner Mongolia. Northeast China includes Liaoning, Jilin, and Heilongjiang. East China includes Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, and Shandong. South Central China includes Henan, Hubei, Hunan, Guangdong, Guangxi, Hainan. Southwest China includes Chongqing, Sichuan, Guizhou, Yunnan, Tibet. Northwest China includes Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang.

Table 7
Heterogeneity of response to air pollution.

	Daily Mask Index		Daily Mask Index	
	$PM_{2.5}$ (1)	All (2)	$PM_{2.5}$ (3)	All (4)
AQI	0.255***	0.236***	0.142	0.224***
	(0.041)	(0.034)	(0.119)	(0.085)
AQI×VSB	−0.028***	−0.023**		
	(0.009)	(0.009)		
AQI×Hospitals			−0.090	−0.073
			(0.086)	(0.051)
AQI×Beds			0.001	0.001
			(0.002)	(0.002)
AQI×Doctors			0.000	−0.001
			(0.004)	(0.003)
Weather	Yes	Yes	Yes	Yes
Holiday	Yes	Yes	Yes	Yes
Day of Week	Yes	Yes	Yes	Yes
City-Week FE	Yes	Yes	Yes	Yes
N	40,310	40,334	39,752	39,776
Log Likelihood	−51221	−89799	−50627	−88070

Notes: Specification is the fixed-effect Poisson model. Dependent variable is daily mask index. AQI is divided by 100. VSB is visibility measured in statute miles. Weather includes temperature, dew point, wind speed, and wind direction. Holiday and day of week are dummy variables. Hospitals, beds and doctors are measured in per capita. The coefficient of AQI is interpreted as the percentage of change in mask index with respect to 100-point change in AQI. We tested various leads and lags; only the lags up to four days are significant. Standard errors clustered at the city-week level. $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$.

estimated semi-elasticities are illustrated in Fig. 5. The result reveals that all regions have similar semi-elasticities (around 20 percent) except for Southwest China, where AQI has an insignificant effect on facemask purchases.

Robustness checks

The credibility of air pollution data in China has been a major concern. Ghanem and Zhang (2014) find suggestive evidence that a large number of Chinese cities manipulated Air Pollution Index (API) during 2001-2010 in order to achieve a certain number of "blue-sky days." In particular, about half of the cities are likely to under-report PM_{10} levels. If air quality data are misreported, it introduces measurement errors and attenuates the parameter of AQI in the demand function for anti-PM facemasks. The quality of air pollution data has been improved significantly since 2010, partly thanks to the direct reporting system established by MEP. Nevertheless, we still conducted several robustness checks on the data quality.

In order to assess the potential data quality problem, we use the US Embassy data in five cities—Beijing, Shanghai, Guangzhou, Chengdu, and Shenyang—as the robustness checks. These estimation results are reported in Table 8. Columns (1) and (4) use MEP AQI in the five cities, while columns (2) and (5) use station AQI-$PM_{2.5}$, which is the daily averaged individual pollutant AQI of $PM_{2.5}$ at the monitoring station level.[22] Columns (3) and (6) use US AQI reported by the US Embassy. The sample is restricted to the five cities with US Embassy or Consulates.

The models that use city-level MEP AQI have significantly smaller estimates than the models that use US AQI. The difference is attributed to the fact that MEP AQI includes 6 criteria pollutants while US AQI only includes $PM_{2.5}$. In addition, MEP AQI averages readings from all stations in a city, including downtown and suburban locations, while the US Embassy is normally located in downtown. For this reason, we use the $PM_{2.5}$-specific AQI from the monitoring station that is closest to the US Embassy or Consulate. We find the estimated semi-elasticities by two air pollution measures are reasonably close, which suggests that the recent MEP AQI is reliable.

We also test for the robustness of our model specification. Specifically, we estimate the baseline model by linear and semi-log specifications. In each model, we include three combinations of fixed effects: City FE plus Date FE, City FE plus Province-Date FE, and City-Week FE. The linear model's estimation result, reported in Table A1 in the online Appendix, shows that a 100-point increase in AQI boosts the anti-$PM_{2.5}$ mask index by 3.54 points, or 89 percent more facemask purchases. Correspondingly, it increases the total mask index by 51 percent higher levels of facemask purchases. These estimates are significantly higher than those of the Poisson model. In contrast, the elasticities estimated by the semi-log model, reported in Table A2 in the online Appendix, are close to our preferred estimates in the fixed-effect Poisson model.

An alternative specification is lagged dependent variables model. Because a package of facemasks typically includes several masks, the order on one day might affect purchases in subsequent days. In this case, we run a set of regressions with lagged facemask purchases and the results are reported in Table A3. Compared with FE model results in Table 3, the dynamic model has much higher estimates for the coefficient of AQI. We cannot include both lagged dependent variables and unobserved individual effects. This is because the differenced residual is necessarily correlated with the lagged dependent

[22] The stations with distance to the US Embassy/Consulates: Beijing Nongzhanguan(1.8 km), Shanghai Jingan (4.3 km), Guangzhou Tianhezhiyou(2.2 km), Chengdu Sanwayao (4.3 km), Shenyang Wenyilu(2.7 km).

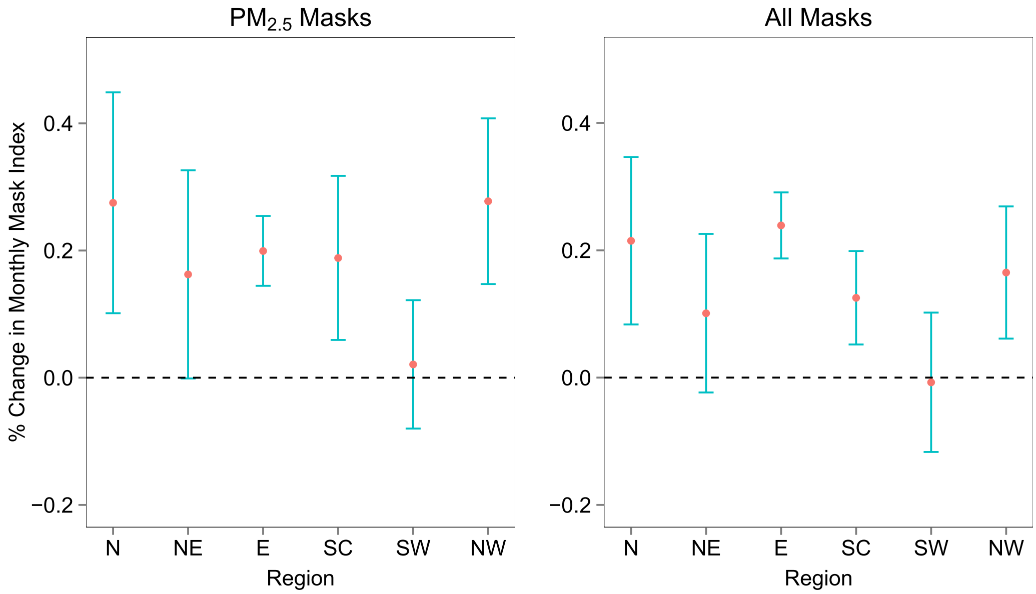

Fig. 5. Mask purchases in six Chinese regions respond heterogeneously to air pollution. The graph illustrates the parameter estimate (±1.96 SE) of AQI in model (3) in Table 3. The regression is run separately for each region and each mask type ($PM_{2.5}$ and all). Six traditional regions are: North China (N), Northeast China (NE), East China (E), South Central China (SC), Southwest China (SW), and Northwest China (NW).

Table 8
Alternative pollution information from the US Embassy in 5 cities.

	Anti-$PM_{2.5}$ Masks			All Masks		
	(1)	(2)	(3)	(4)	(5)	(6)
AQI (City)	0.289^{***}			0.259^{***}		
	(0.061)			(0.050)		
AQI-$PM_{2.5}$ (Station)		0.368^{***}			0.312^{***}	
		(0.055)			(0.050)	
US AQI-$PM_{2.5}$ (Station)			0.371^{***}			0.303^{***}
			(0.084)			(0.086)
Weather	Yes	Yes	Yes	Yes	Yes	Yes
Holiday	Yes	Yes	Yes	Yes	Yes	Yes
Day of Week	Yes	Yes	Yes	Yes	Yes	Yes
City-Week FE	Yes	Yes	Yes	Yes	Yes	Yes
N	2,138	2,020	2,138	2,138	2,020	2,138
Log Likelihood	−14760	−12850	−14983	−20990	−28138	−21583

Notes: Specification is the fixed-effect Poisson model. Dependent variable is daily mask index. AQI is divided by 100. All models include weather(temperature, dew point, wind speed, and wind direction), holiday and day of week dummies, and city-week fixed effects. The coefficient of AQI is interpreted as the percentage of change in mask index with respect to 100-point change in AQI. The regression only uses 5 cities that have US Embassy/Consulates (Beijing, Shanghai, Guangzhou, Chengdu, and Shenyang). Station AQI-$PM_{2.5}$ is the daily averaged individual pollutant AQI of $PM_{2.5}$ at the monitoring station level. The stations with distance to the US Embassy/Consulates: Beijing Nongzhanguan(1.8 km), Shanghai Jingan (4.3 km), Guangzhou Tianhezhiyou (2.2 km), Chengdu Sanwayao (4.3 km), Shenyang Wenyilu (2.7 km). Standard errors clustered at the city-week level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

variable, which will make OLS estimates inconsistent (Nickell, 1981). The true estimates are likely bounded by the FE models and dynamic models (Guryan, 2004). We choose the FE model as the preferred specification mainly because their estimates are more conservative. The computational burden for the FE dynamic Poisson model is also a concern of model selection.

Individuals might use future pollution information to make decision on defensive expenditures since many cities report one-day-ahead pollution forecasts. However, the data of pollution forecasts are not available. To address this concern, we include four leads of AQI in the baseline model. The estimation results show that none of these leads are statistically significant. This might be explained by two reasons.[23] First, individuals only pay attention to existing information instead of

[23] This result is also found in the behavior of purchasing durable goods such as automobiles and houses. For example, Busse et al. (2015) shows that the choice to purchase a convertible depends on the weather at the time of purchase. Although the evidence is consistent with the classical utility theory, it can be explained by projection bias (an agents forecast of future emotional state is biased by the current mood) and salience (certain features of a product received disproportionally large attention of a consumer).

forecasts. Second, AQI forecasting is based on historic pollution levels and weather conditions. Since we have already controlled for these determinants in our model, pollution forecasts do not provide additional information to the regression.

Discussion

Policy implication

The substitutability between ambient air pollution and facemasks sheds new light on the value of air pollution control policies. Because facemask purchases signify the cost of air pollution, this defensive expenditures approach can be used to value the marginal benefit of air quality improvement (Courant and Porter, 1981). Specifically, the willingness to pay (WTP) for a marginal change in air quality is the marginal rate of substitution between facemasks and pollution, multiplied by the mask price. Because of the existence and use of other pollution-avoidance behaviors, the expenditure on masks can only measure a part of the air pollution cost.

Our preferred model estimates that a 100-point increase in the AQI leads to a 70.6 percent increase in expenditures on anti-$PM_{2.5}$ masks and a 54.4 percent increase for all types of masks. We aggregate the city-specific pollution costs to the national level. It shows that the cost of one-day of air pollution in China, with the AQI increasing from 105 to 205, is 80,247 USD, of which, 38,356 USD comes from anti-$PM_{2.5}$ masks. These estimates are very low because AQIs are still below the heavily polluted levels. Our previous results show that individuals purchase masks mainly during serious pollution days.

Concerning individuals' nonlinear responses to air quality, we also estimate the cost of extreme pollution episodes. Our preferred nonlinear model estimates that one extra severely polluted day ($AQI \geq 301$) within a month leads to 23.4 percent growth in the monthly total mask index, relative to a day with excellent air quality ($AQI \leq 50$). In comparison, the marginal effect of an extra heavily polluted day ($201 \leq AQI \leq 300$) on monthly mask purchases is 7.6 percent. Using the relationship between the mask index and actual sales of masks, a back-of-the-envelope calculation shows that the cost of one severely polluted day would be 610 thousand Yuan (about 100 thousand USD) in China. We also use these estimation results to simulate the benefit of hypothetical air pollution control policies. During our study period between January 2013-April 2014, there were 2934 heavily polluted city days and 933 severely polluted city days in China. If 10 percent of both these heavily and severely polluted days were eliminated by any mixture of air pollution control policies, the total savings for the society would be 1.146 billion Yuan (approximately 187 million USD) for China.

The estimated welfare impact of air pollution based on mask expenditures is very small compared with other estimates of the air pollution cost. For example, World Bank (2007) estimated that the health cost of air pollution in Chinese urban areas ranged from 157 to 520 billion Yuan in 2003. In an updated report, World Bank (2016) estimated that the welfare losses and forgone output in China due to air pollution in 2013 was about 1634 billion USD (2011 U.S. dollars, PPP-adjusted), or 10.09% of GDP. These estimates are significantly higher than the defensive expenditures on masks. We will further discuss this issue in the next section.

Caveat and discussion

The main caveat of this paper is to use mask purchase behavior to imply its use behavior. We only observe when consumers purchase a mask but have no information about when they use it. This results in a number of issues. First, we are unable to tell whether the purchase is for immediate consumption or for stock replenishment. Second, some consumers might order several masks on a low-pollution day but order none on subsequent high-pollution days. The existence of such behavior will likely cause underestimation of the marginal effect of AQI.

This paper cannot test whether or not consumers are rational due to the limitation of data and information. A significant number of consumers purchased wrong masks that have limited effect on PM2.5 pollution prevention. The vast majority of urbanites do not wear masks at all during pollution days. These behaviors might have rational explanations. This could be caused by the fact that consumers have incomplete knowledge about the functions of different masks. In addition, simply comparing the price of a mask and its health benefit likely leads to the conclusion that consumers are irrational. However, we might well underestimate the cost of a mask because of the disutility of wearing cannot be quantified.

Our analysis is also hampered by the unobservable offline shopping data. If offline purchases are more sensitive to daily pollution variations, the estimated marginal effect of AQI would understate the responsiveness of overall mask purchase. If offline purchases are less sensitive, this may cause our estimate to be overestimated. The sensitivity to pollution might be caused by different pricing strategy for online and offline retailers. If offline retailers behave the same way as online retailers, the price change can be controlled for by date fixed effect. However, if offline retailers behave differently, for example, increasing price more during heavy pollution days, our estimate is likely to be overstated. The direction of the bias is an empirical question. Unfortunately we cannot determine the bias unless we have information about the masks purchased offline.

The expenditure on facemasks can only quantify a small part of the cost of air pollution. First, our result cannot be simply interpreted as the lower bound of pollution cost, because the methodology proposed by Bartik (1988) assumes that "personal environmental quality" is held constant, a condition not true in the current empirical setting.[24] Second, we have no information about other defensive behaviors, therefore the total defensive expenditures in response to air pollution cannot be measured. Third, the price of a mask is only a part of the defensive cost; for example, the disutility of wearing a mask is not monetized. There are also joint benefits of masks, such as keeping warm and preventing spreading germs. These joint costs/benefits will further complicate the defensive expenditure approach.

Conclusion

In this paper, we document the relationship between anti-PM facemask purchases and ambient air pollution in Chinese cities. We not only provide new empirical evidence on pollution avoidance behavior, but we also use the estimated relationship to quantify the cost of air pollution. Our results suggest that the occurrence of "airpocalypse" events, which we define as AQI $\geq$ 200, will significantly increase expenditures from Chinese consumers on facemasks. These results complement the literature that estimate the welfare cost of air pollution using the "cost of illness" approach, and thus contribute to the current debate on the optimal pollution level in China.

The methodology developed in this paper is not only relevant in the Chinese setting, but also useful to study pollution avoidance in other developing countries. For example, some Indian cities are becoming the most polluted ones in the world, which has dramatically increased the demand for anti-pollution facemasks. In 2016, the masks sold by Amazon India was thirteen times of the sales in one year ago.[25] Because the average temperature in India is much higher than that of China, the disutility of wearing masks is also greater. Therefore, it is an interesting empirical question whether the Indian mask consumption is less elastic to air pollution.

This being said, our estimation results and policy simulation outcomes should be interpreted with caution. Using the expenditures on facemasks, we likely quantify only a small part of the cost of air pollution. Facemasks are not the only way to avert air pollution. Other defensive expenditures—such as indoor air purifiers and medication—are also a significant portion of pollution costs. Even for facemasks themselves, our data only cover the e-commerce market and the facemask purchases in the B&M business are not included. Therefore, the estimated cost in this paper is only a small part of the air pollution cost.

Appendix A. Supplementary data

Supplementary data associated with this article can be found in the online version at https://doi.org/10.1016/j.jeem.2017.07.006.

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