Ecological Economics 131 (2017) 468–474

Contents lists available at ScienceDirect

Ecological Economics

journal homepage: www.elsevier.com/locate/ecolecon

Analysis

Self-protection investment exacerbates air pollution exposure inequality in urban China

Cong Sun [b,c], Matthew E. Kahn [a,*], Siqi Zheng [c]

[a] Department of Economics, University of South California, Los Angeles, CA 90089, United States
[b] School of Urban and Regional Science, Shanghai University of Finance and Economics, Shanghai 200433, People's Republic of China
[c] Hang Lung Center for Real Estate, and Department of Construction Management, Tsinghua University, Beijing 100084, People's Republic of China

ARTICLE INFO

Article history:
Received 10 July 2015
Received in revised form 18 May 2016
Accepted 5 June 2016
Available online xxxx

ABSTRACT

Urban China's high level of ambient air pollution lowers quality of life and raises mortality risk. China's wealthy can purchase private products such as portable room air filters that offset some of their pollution exposure risk. Using a unique data set of Internet purchases, we document that households invest more in masks and air filter products when ambient pollution levels exceed key alert thresholds. Richer people are more likely to invest in air filters, which are much more expensive and more effective than masks. Our findings have implications for trends in quality of life inequality in urban China.

1. Introduction

Income inequality has been rising sharply in China. The Gini coefficient peaked at 0.491 in 2008, which was much higher than the recognized level of 0.4 (National Bureau of Statistics of China, thereafter NBSC).[1] Xie and Zhou (2014) estimate that China's Gini even reached 0.50 in the year 2010. At a time when there is great interest in the causes of income inequality (Piketty, 2014), it is important to examine the quality of life consequences of this trend. We study how private markets help richer people to protect themselves from China's high levels of urban air pollution. We document that richer people invest more in self protection than poorer people. Such differentials in private precautionary investments means that inequality in air pollution exposure rises as income inequality increases.

China's urban air pollution challenges have been well documented (Zheng and Kahn, 2013). At the beginning of the economic reform in the 1980s, Chinese cities suffered from black smoke produced by heavy industry, high levels of coal burning by power plants and winter heating units. This activity created extremely high levels of acid rain pollution in southern cities (He et al., 2002). In recent years, the major air pollutant has been PM_{10} and $PM_{2.5}$ (particles with an aerodynamic diameter < 10 μm or 2.5 μm) which is largely produced as a byproduct of manufacturing production, car driving and coal burning. The Asian Development Bank reports that fewer than 1% of the 500 cities in China meet the air quality standards recommended by the World Health Organization, and seven of these cities are ranked among the top ten polluted cities in the world (Asian Development Bank, 2012).

Pollution exposure impacts both the quantity and quality of life (MacKerron and Mourato, 2009; Hall et al., 2010). Breathing polluted air as measured by particulate matter (PM) raises one's risk of heart and lung disease (Chay and Greenstone, 2003; Evans and Smith, 2005; Moretti and Neidell, 2011; Pope et al., 2011). Chen et al. (2013) use the Huai River winter heating policy as a natural experiment to examine the impact of air pollution on life expectancy reduction in China. They find that the higher particulate matter concentrations in the north, caused by subsidized coal based winter heating, led to a reduction of 5.5 years in people's life expectancy relative to the south.[2] Ebenstein et al. (2015) document that life expectancy in China has increased by less than what would be predicted given its per-capita income growth. They argue that rising air pollution levels is a key explanation for this life expectancy gap.

Pollution exposure also has direct impacts on human capital accumulation and utilization. James Heckman's research posits a dynamic complementarity effect such that young children learn more in school if they are healthier (Heckman, 2007). Children in worse health learn less in school and this compounds over time so that these children are less likely to achieve their full potential. Pollution exposure increases school absences and lowers test performance (see Currie et al., 2009, 2014; Zweig et al., 2014). Human capital attainment is negatively affected by life time pollution exposure (Graff Zivin and Neidell, 2013). Given

* Corresponding author.
E-mail addresses: sun.cong@mail.shufe.edu.cn (C. Sun), kahnme@usc.edu (M.E. Kahn), zhengsiqi@tsinghua.edu.cn (S. Zheng).

[1] According to United Nation's standard, Gini index above 0.4 signals a large income inequality.

[2] In China, cities north to the Huai River and Qinling Mountain receive subsidized coal-based heating in winter months, while cities south to this Huai River line are not entitled to this subsidized heating.

http://dx.doi.org/10.1016/j.ecolecon.2016.06.030
0921-8009/

China's one child policy, parents have strong incentives to invest in a variety of strategies to protect their only child's health in the face of very high levels of local pollution.

There are two strategies for reducing the damage caused by air pollution. First, the government can introduce regulations to reduce emissions from various polluting sectors such as power generation, industry, transportation, and construction. Second, private individuals can invest in variety of environmental defensive strategies for reducing their exposure to current levels of outdoor pollution. While investments in public goods (the first strategy) broadly benefit everyone, investments in private self protection mainly benefit the individuals who choose this option (Antoci, 2009). Individuals gain private benefits from investing in self-protection and averting behavior (Smith et al., 1995; Graff Zivin and Neidell, 2009; Janke, 2014).

We use data from China to study private household investments to reduce their exposure to outdoor air pollution. To study private protective actions, we use a unique panel data base of online sales indices assembled by *Taobao.com* (see Section 3 for details). From *Taobao.com*, we obtained daily sales indices by city for all buyers, and also monthly sales indices by city for sub-groups of buyers (such as high-income, middle-income and low-income buyers). We use the city level data to study how household private investment in self protection varies as a function of government announcements concerning the severity of the level of air pollution. We also study how protection investments vary as a function of household income. We find that all groups respond to government announcements of severe pollution by investing more in self protection but that only the richest group increase their purchases of the most effective, and most expensive anti-pollution devices (portable room air filters) when local pollution levels are higher.

The rest of the paper is organized as follows: Section 2 reviews the empirical and theoretical studies on self-protection strategies and pollution exposure inequality. Section 3 describes the data and our empirical strategy. Section 4 presents the empirical results. Section 5 concludes.

2. Self-protection Strategies and Pollution Exposure Inequality

2.1. Self-protection against Air Pollution

By choosing a city and a neighborhood within that city, urban residents have some control over their exposure to air pollution. Cross-county migration research documents that households reveal a high willingness to pay for clean air in the United States (Bayer et al., 2009; Chay and Greenstone, 2005). Using data from within the Los Angeles metro region, Sieg et al. (2004) document that when the Clean Air Act's successful implementation reduced smog levels in specific communities that this attracted richer people to move to such communities.

China's central government has been reforming the *hukou* registration system in the past three decades, and the restriction on labor mobility has been largely relaxed. People are free to choose which city and which location within a city to live. Job opportunity and quality of life are two major attractions a city can provide. Local public services (such as schools, healthcare facilities) and environmental quality are key determinants of local quality of life. Zheng et al. (2014) study standardized home prices across China's major cities and find that, all else equal, a 10% decrease in imported neighbor pollution is associated with a 0.76% increase in local home prices. They also report that the marginal valuation for clean air is larger in richer Chinese cities. Within Beijing, people have a higher willingness to pay for those locations with better air quality, such as the northwest part in Beijing. Using cross-sectional data on real estate prices across Beijing, Zheng and Kahn (2008) find that, all else equal, a home's price is 4.1% higher at the location with a 10 μg/m^3 lower average PM_{10} concentration.

One's residential location alone is not sufficient for describing one's pollution exposure. When the outdoor air is polluted, people will prefer to drive private cars (rather than walking on the street), and they will also decrease their time spent outdoors (Neidell, 2009). Based on the estimate in Chen and Zhao (2011), the indoor particulate matter concentration is on average about 80% of the outdoor concentration in Chinese cities, so people can breathe less polluted air when they are indoors on polluted days. Moreover, modern buildings in Chinese cities have HVAC air conditioning systems with air filtering which further improves the indoor air quality.

China's nascent market economy offers households a growing array of products intended to improve day to day quality of life. In the case of avoiding air pollution, masks and air filters represent key examples of such market products. During a hazy week at the end of 2013, mask and portable room air filter sales reached 760,000 and 140,000 respectively. Sales that week of masks and room air filters rose by 52.35% and 74.1%, respectively, relative to the previous week. Air filters are more effective than masks in protecting people against air pollution. Research conducted by the Department of Building Science at Tsinghua University, and tests conducted by China Consumer Association show that the mean effectiveness of masks and air filters is 33.0% and 92.0% respectively. That is, people with masks or air filters are exposed to 67.0% or 8.0% of the original $PM_{2.5}$ concentration, respectively.[3]

2.2. Pollution Exposure Inequality Due to Differences in Self Protection

Differential purchases of these items between the rich and poor will exacerbate pollution exposure differences and hence increase health inequality. As shown in the cross-city and within-city compensation differentials studies in Chinese cities discussed above (Zheng et al., 2014; Zheng and Kahn, 2008), real estate prices are higher and housing demand is higher in less polluted geographic areas. Thus, the poor live in dirtier areas within a city.

Richer people have a higher probability of owning cars, which protect them from the outdoor dirty air. Using micro-data from the 2006 Chinese Urban Household Survey conducted by NBSC, Zheng et al. (2011) estimate the income elasticity of car ownership is 0.81. Poorer people are more likely to commute to work by public transit or by motorbike and this requires them to stay outside for longer time. Low-skilled workers are also more likely to work in outdoor occupations such as construction, street cleaning and package delivery. In contrast, high-skilled workers work indoors. According to the Environmental Exposure Related Activity Patterns Survey in China, the ratio of office staff's average daily outdoor time to that for all workers is 0.64. Furthermore, richer people are more likely to have air conditioning, which means that windows can be closed on hot days with high pollution levels.

Air filters are more expensive than masks. An average portable room air filter costs $490 US dollars, while an average mask only costs and $0.9 US dollars. Consumers have to change the air filter's strainer once per year but a mask lasts for only ten days. Thus, the daily user cost (including electricity expenditure) of an air filter is more than ten times that of a mask. The sales data of masks and air filters on *Taobao.com* in 2013 reveals that the high-income group (the top 25% of total consumers) bought 31.9% of masks and 47.9% of air filters.

Recent research has studied the consequences of inequality for mitigating pollution exposure. Hotte and Winer (2012) model the optimal investment in private mitigation efforts to reduce pollution exposure. Their model yields the prediction that pollution mitigation efforts increase with the pollution level and with income. This means that poor people spend less to protect themselves. They present a general equilibrium model featuring both the production of pollution and the population's optimal response to exposure to this pollution. Antoci et al. (2012) also explicitly write out a general equilibrium model of pollution production and exposure. Bernard et al. (2014) model private self protection and environmental regulation as substitutes. In this case, effective regulation is likely to crowd out individual self protection.

[3] See: http://www.cca.org.cn/web/xfzd/newsShow.jsp?id=67720.

Each of these theoretical studies is relevant for our work. In our study, we adopt a partial equilibrium approach. The Chinese urbanites are exposed to a high level of air pollution. Holding government regulation constant, people choose how to self protect themselves. Given the extremely high levels of air pollution in Chinese cities, we do not believe that increased regulatory efforts to reduce urban air pollution will crowd out private self protection.

A novel feature of our study is explicitly introducing a spatial context where cities differ with respect to their pollution exposure and income. In this sense we exploit within nation variation, to test the self protection hypothesis.

3. Data and Models

3.1. Data

Many urban residents in China purchase products online. This fact allows us to build a novel data base. *Alibaba Group* is China's largest e-commerce company and it provides the largest online shopping platform *Taobao.com* (with hundreds of million online consumers) in China. *Taobao.com* accounts for about 90% of the online Consumer-to-Consumer sales and 57% of online Business-to-Consumer sales in China.[4] *iResearch* reports that *Taobao*'s gross sales volume exceeded 1 trillion RMB Yuan in the first eleven months in 2012, which accounted for about 5.4% of China's sales of retail consumer goods in that year.[5] Many daily consumption items are purchased on *Taobao.com* because of its low prices and low cost shipping. Our core data set for city level sales of self-protection products is based on data from *Taobao.com*. According to *Taobao*'s statistics, Chinese consumers spent 870 million yuan (US$143 million) on 4.5 million online transactions purchasing anti-smog products in 2013. While concerns about the "digital divide" raise the possibility that the poor are less likely to shop online, low income people in China prefer to use *Taobao* because its prices are lower than bricks and mortar stores. It is likely that some of the very poor people and the elderly may not use *Taobao* because they do not know how to use a computer or have access to the Internet.

Taobao.com provides daily and monthly sales indices of each market good covering the 34 major cities (all municipalities directly under the central government, provincial capital cities, and quasi provincial capital cities, excluding Lhasa in Tibet). By consulting the designers of this sales index at *Taobao.com*, we learned that the equation used to construct the sales index from the real sales volume is a linear function and the key parameters are constant for all income groups, all cities/regions and over the whole study period. We do not know the exact values of the parameters.[6] Therefore, we choose to directly use the sales indices in our regressions, and this will not affect the estimates of our key coefficients.

Our daily sales index data covers the time period November 1, 2013 to January 31, 2014. This three-month time period covers a large number of foggy and hazy days, including the severe haze at the end of 2013. In December 2013, the Pearl River Delta, where Shanghai and Nanjing are located, suffered from the most severe haze event of the past ten years. Beijing and Shijiazhuang also experienced terrible days of haze in December 2013 and January 2014. We also collect monthly sales indices from April 2013 to April 2014 for each of the three income groups (high-income, middle-income and low-income). These categories correspond to consumers within the 75%–100% percentile ("high-income"), 25%–75% percentile ("middle-income") and 0%–25% percentile ("low-income") in the distribution of the overall distribution of consumers' purchase expenditures. Unfortunately we are unable to access daily index data by income group.

The air pollution data and the daily pollution alerts are obtained from China's Ministry of Environmental Protection (MEP). Daily and monthly $PM_{2.5}$ concentrations are calculated from the MEP's official hourly real-time data. According to China's new Ambient Air Quality Standards (GB3095-2012) released by the MEP, there are six levels of pollution alerts: excellent, good, lightly polluted, moderately polluted, heavily polluted and severely polluted. The thresholds of those alerts are based on the air quality index constructed by the MEP. Fu et al. (2014) list the detailed thresholds of the air quality index for each alert. MEP releases hourly air pollution alert for these cities on its website.[7] Each city's Bureau of Environmental Protection releases its city's alert on its own website. People can also access this information through several mobile phone apps. We obtained city level historical weather record such as daily temperature, humidity, wind speed and presences of rain, snow and fog from the website TuTiempo.net.[8]

The recent public campaign in China has urged the state to create a nationwide $PM_{2.5}$ monitoring network. The recent MEP official $PM_{2.5}$ data and the US embassy $PM_{2.5}$ data provide consistent readings. For instance, the mean value of the US Embassy $PM_{2.5}$ reading in 2013 is 87.4 $\mu g/m^3$, and that for the MEP official $PM_{2.5}$ reading at the air quality monitor near the US Embassy in Beijing is 90 $\mu g/m^3$. Therefore Chinese urbanites have been gaining confidence in the MEP's air pollution alerts. In the case of the United States, information disclosure regulation has been documented to have success in increasing household self protection investment (Neidell, 2004, 2009).

Variable definitions and summary statistics are listed in Table 1. Summary statistics of the control variables, such as weather attributes and national holidays, are not listed but are available upon request.

3.2. Hypotheses and Econometric Models

The online purchase data allow us to test the following two hypotheses.

Hypothesis #1. People respond to higher levels of air pollution by buying more masks and filters. They respond to both government's pollution alerts (determined by $PM_{2.5}$ exceeding key thresholds) and to the level of outdoor $PM_{2.5}$. Market Internet purchases of other goods (socks and towels) are not correlated with pollution alerts and the level of outdoor $PM_{2.5}$.

Hypothesis #2. Compared to poorer people, richer people invest more in self-protection products when air pollution is higher.

To test Hypothesis #1, we estimate the model presented in Eq. (1):

$$Q_{it} = \alpha_0 + \alpha_1 \cdot \ln(PM_{it}) + \alpha_2 \cdot A_{it} + \alpha_3 \cdot X_{it} + \alpha_4 \cdot T_t + \alpha_5 \cdot C_i + \varepsilon_{it} \quad (1)$$

The unit of analysis for Eq. (1) is city/day. Q_{it} is the sales index of each market product (masks or air filters) in city i in day t. Here we use the daily sales index data which is available for the short three-month period (from November 1, 2013 to January 31, 2014). PM_{it} is the daily $PM_{2.5}$ concentration in city i in day t. Four pollution alert dummies are included as A_{it}. ("blue sky" days, with the alert being either "excellent" or "good", as the default). X_{it} is a vector of weather attributes and control variables such as China's national holidays. Weather attributes include daily mean temperature, humidity, wind speed and several dummies like rainfall, snow and fog. The two variable T_t and C_i represent time trend and city-fixed effects, to control for the time trend in sales and unobserved city attributes, respectively. ε_{it} is a disturbance term. We cluster the standard errors by city.

4 http://dealbook.nytimes.com/2013/09/25/alibaba-said-to-shift-target-from-hong-kong-to-u-s-for-i-p-o/.

5 http://www.iresearchchina.com/views/4730.html.

6 The algebra equation is: real sales volume$_{jt} = \theta_0 + \theta_1 \times$ Sales index$_{jt}$. Both θ_0 and θ_1 are constant for all income groups, all cities/regions and over the whole study period. The exact values of these two parameters are not released by *Taobao.com* due to confidential consideration. Mu and Zhang (2016) attempt to estimate that θ_1 is about 63 on average. Given that the two parameters are constant, we choose to directly use the sales index in our regressions, and this will not affect the estimates of our key coefficients.

7 http://113.108.142.147:20035/emcpublish/.

8 http://www.tutiempo.net/en/Climate/China/CN.html.

Table 1
Variable definitions and summary statistics.

Variable	Definition	Mean (std. dev.)	
		Daily	Monthly
PM2.5	$PM_{2.5}$ concentration (in μg/m^3)	96.34 (70.64)	66.22 (33.01)
Mask	Taobao.com sales index of "mask"	51.50 (223.8)	216.4 (869.3)
Filter	Taobao.com sales index of "air filter"	6.285 (20.66)	35.30 (85.82)
Sock	Taobao.com sales index of "sock"	77.71 (160.3)	621.0 (967.8)
Towel	Taobao.com sales index of "towel"	24.66 (52.09)	212.3 (300.2)
Six government pollution alerts:			
Excellent	1 = "excellent" level, 0 = otherwise	0.068 (0.252)	
Good	1 = "good" level, 0 = otherwise	0.366 (0.482)	
Lightly polluted	1 = "lightly polluted" level, 0 = otherwise	0.273 (0.445)	
Moderately polluted	1 = "moderately polluted" level, 0 = otherwise	0.139 (0.346)	
Heavily polluted	1 = "heavily polluted" level, 0 = otherwise	0.114 (0.318)	
Severely polluted	1 = "severely polluted" level, 0 = otherwise	0.040 (0.196)	
Income categories:			
Low income	1 = low-income group, 0 = otherwise		0.333 (0.472)
Middle income	1 = middle-income group, 0 = otherwise		0.333 (0.472)
High income	1 = high-income group, 0 = otherwise		0.333 (0.472)

The sales index is count data, so we estimate Eq. (1) using a count model. We will report estimates based on negative binomial and Poisson pseudo-maximum likelihood (PPML) models. Guimaraes et al. (2003 and 2004) show that the estimation based on PPML produces identical parameter estimates as a conditional logit model. In addition, this sales index contains some zero-value observations, because a city may have zero sales of air filters or masks on *Taobao.com* in a single day. To address this issue, we employ the zero-inflated versions of both count models (Lambert, 1992; Cameron and Englin, 1997; Sheu et al., 2004; Silva and Tenreyro, 2006; Helpman et al., 2008). The Vuong test is performed to test if zero-inflated models are more appropriate (Vuong, 1989; Greene, 1994).

We estimate Eq. (2) to test Hypothesis #2:

$$Q_{ijt} = \beta_0 + \beta_1 \cdot \ln(PM_{it}) + \beta_2 \cdot \ln(PM_{it}) \cdot middle\ income_i + \beta_3 \cdot \ln(PM_{it}) \cdot high\ income_i + \\ + \beta_4 \cdot middle\ income_{ij} + \beta_5 \cdot high\ income_{ij} + \beta_6 \cdot W_{it} + \beta_7 \cdot T_t + \beta_8 \cdot C_i + \nu_{ijt} \quad (2)$$

In Eq. (2), the unit of analysis is city/month/income group. Each city has three sales index series for low-income, middle-income and high-income buyers. Such income group specific sales indices are only available for monthly basis but for a longer time period (from April 2013 to April 2014). Q_{ijt} is income group j (1 = low-income, 2 = middle-income, 3 = high-income)'s sales index of each market product in city i in month t. $middle\ income_i$ and $high\ income_i$ are two income group dummies for city i (low-income group is the default category). W_{it} is a vector of monthly weather attributes, such as mean temperature, humidity, wind, and frequency of rainy day, snowy day and foggy day. The coefficient β_2 (or β_3) of the pollution-income interaction term measures the differential of the response gradient to pollution increases between the middle income group (or high-income group) and the omitted category low income group. The coefficient β_4 (or β_5) measures the "absolute" sales index gap between the middle-income group (or high-income group) and the low-income group. ν_{ijt} is a disturbance term. We will first report count model results, and then change the dependent variable to ln (*sales index* + 1) and run an OLS regression (we add 1 to the sales index to avoid the elimination of zero-value observations). We report OLS regressions here to ease the interpretation of the coefficients (β_2 or β_3) as the elasticities (% change in mask/filter sales with 1% increase in $PM_{2.5}$ concentration, for each of the three income groups).

As placebo tests, we also report regression results based on Eqs. (1) and (2) where we replace the sales indices for air filters and masks with those for sales of socks and towels. We expect that there will be no causal relationship between the outdoor level of air pollution and the purchase of these products.

4. Empirical Results

4.1. Results Testing Hypothesis #1

We first study how the sales of masks and filters evolves as a function of a city's local daily $PM_{2.5}$ concentration level and the local government's alerts about the severity of air pollution on that day in Table 2 (Hypothesis #1).

In Table 2, the dependent variable reported in the odd columns is the daily sales of masks, and that in even columns is the daily sales of air filters. The omitted category for the government alert is a "blue sky" day. Columns (1) and (2) report the regression results based on a negative binomial model. We report PPML model results in columns (3) and (4), zero-inflated negative binomial model results in columns (5) and (6), and then zero-inflated Poisson model results in columns (7) and (8). The key results are stable across the different model specifications. Vuong statistics show that the zero-inflated models are the preferred specifications relative to the negative binomial model.

The results show that Chinese households respond to government's pollution alerts and also respond to the PM level. Note the monotonic relationship between the severity of the government alerts and the sales of masks and filters. There is a significant increase in mask and air filter sales when the pollution alert becomes "severely polluted". Based on the coefficients in columns (7) and (8), the daily sales of masks on the days when the government has issued a "heavily polluted" and "severely polluted" alert are 2.9 and 7.2 times those during a "blue sky" day. These two ratios are 1.6 and 3.0, respectively for air filter sales. This evidence suggests that the urbanites are responding to the government's pollution alerts.

Controlling for the government alerts, consumers also respond to the actual $PM_{2.5}$ concentration level by buying self-protection products, as indicated by the significant coefficients of ln($PM_{2.5}$). People can check their smartphones for real time updates about the reading of current $PM_{2.5}$ concentration, and they do so more frequently on the days when the government announces a "heavily polluted" or a "severely polluted" alert. This effect is larger for masks but weaker for air filters. This may be attributed to the cost differential between these two products. An air filter is much more expensive than a mask. Based on a similar *Taobao.com* transaction data set, in an independent work, Mu and Zhang (2016) find that a 100-point increase in Air Quality Index increases the consumption of all masks by 54.5% and anti-$PM_{2.5}$ masks by 70.6%. These results are consistent with our findings here.

Table 2
Daily Internet sales of self-protection products as a function of air pollution.

	Standard negative binomial model		Poisson pseudo-maximum likelihood (PPML)		Zero-inflated negative binomial model (ZINB)		Zero-inflated Poisson model (ZIP)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	Mask	Filter	Mask	Filter	Mask	Filter	Mask	Filter
Government alert dummies:								
Blue sky (*default*)								
Lightly polluted	0.0629	0.115**	−0.0478	0.00183	0.0906*	0.136***	−0.0471	0.0133
	(0.0592)	(0.0499)	(0.103)	(0.0905)	(0.0480)	(0.0387)	(0.103)	(0.0849)
Moderately polluted	0.224***	0.236***	0.259***	0.245***	0.256***	0.271***	0.252***	0.235***
	(0.0674)	(0.0737)	(0.0646)	(0.0503)	(0.0588)	(0.0521)	(0.0669)	(0.0479)
Heavily polluted	0.486***	0.405***	0.669***	0.479***	0.568***	0.457***	0.673***	0.459***
	(0.121)	(0.0915)	(0.162)	(0.125)	(0.102)	(0.0861)	(0.163)	(0.124)
Severely polluted	1.176***	0.936***	1.455***	1.272***	1.316***	1.057***	1.462***	1.245***
	(0.179)	(0.216)	(0.320)	(0.158)	(0.169)	(0.185)	(0.323)	(0.164)
ln(PM2.5)	0.306***	0.0972**	0.301*	0.0749	0.248***	0.0126	0.290	0.0445
	(0.0470)	(0.0473)	(0.171)	(0.101)	(0.0443)	(0.0444)	(0.177)	(0.117)
Weather attributes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Vuong test					10.21***	21.48***	7.01***	15.96***
Observations	3085	3085	3085	3085	3085	3085	3085	3085

Notes: The regression estimates are reported based on Eq. (1). In the zero-inflated count models (columns (3)–(6)), city dummies are used to model the probability that the dependent variable equals zero. Robust standard errors are reported in parentheses. Standard errors are clustered by city. Other control variables include; a constant, shopping festival dummies, national holiday dummies, city-fixed effects and a linear time trend.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

4.2. Results Testing Hypothesis #2

We use the monthly Internet sales data stratified by the three income categories and test whether richer people are purchasing more masks and filters when monthly pollution levels are higher. The government alert variables are not available for this longer period, so the key independent variable is the monthly mean $PM_{2.5}$ concentration. We interact this variable with the income group dummies. We first estimate Eq. (2) using zero-inflated Poisson model (columns (1) and (2) in Table 3). We then switch to OLS regressions with $\ln(Q_{ijt}+1)$ as the dependent variable, in order to obtain the elasticity estimates (columns (3) and (4)). We also test if the results are robust if we do not add 1 to the sales index in the OLS regressions (columns (5) and (6)).

The estimates of the coefficient on ln(PM2.5) is statistically significant for the mask regressions (odd columns) but loses its significance in the air filter regressions (even columns). This indicates that, when the air becomes more polluted, that the low-income group buy more masks, but do not buy more air filters. This finding may be due to the fact that masks are cheap so that even the poor can afford them. Many of the poor work outside and thus have a greater incentive to invest in cheap masks.

In Table 3, we report results in which we interact the consumer's income category with the ambient air pollution level. Based on the results in column (1), we find that the high-income group buys more masks than the low-income group as the $PM_{2.5}$ concentration increases. The mask sales indices for the high-income and the low-income groups

Table 3
Internet sales as a function of air pollution and household income.

	Zero-inflated Poisson model (ZIP)		OLS			
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Mask	Filter	ln(mask + 1)	ln(filter + 1)	ln(mask)	ln(filter)
ln(PM2.5)	0.581**	0.0275	0.808***	−0.0556	0.926***	0.00429
	(0.279)	(0.0956)	(0.165)	(0.111)	(0.176)	(0.123)
ln(PM2.5) × middle income	0.0383	0.121***	0.00119	0.232***	−0.117*	0.151*
	(0.0268)	(0.0344)	(0.0617)	(0.0786)	(0.0631)	(0.0818)
ln(PM2.5) × high income	0.216***	0.103**	0.124	0.275***	0.0464	0.156**
	(0.0478)	(0.0446)	(0.0936)	(0.0747)	(0.102)	(0.0583)
Income category dummies	Yes	Yes	Yes	Yes	Yes	Yes
Weather attributes	Yes	Yes	Yes	Yes	Yes	Yes
Other control variables	Yes	Yes	Yes	Yes	Yes	Yes
Vuong test	2.76***	2.98***				
Observations	1326	1326	1326	1326	1264	1149
R-squared			0.843	0.888	0.820	0.882

Notes: The regression estimates are reported based on Eq. (2). In the zero-inflated count models (columns (1)–(2)), city dummies are used to model the probability that the dependent variable equals zero. Robust standard errors are reported in parentheses. Standard errors are clustered by city. Other control variables include; a constant, city-fixed effects and a linear time trend.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

rise by 1.3 and 0.4 in absolute value when the $PM_{2.5}$ concentration rises by 1% from its average value. This represents a 0.6% and 0.5% increase from their original sales indices, respectively. As shown in columns (3) and (5), we report pollution elasticities and the rich do not exhibit a significantly higher mask/pollution elasticity than the poor.

In contrast, the air filter is quite expensive and its main function is cleaning the indoor air. As expected, the income gradient for air filter purchases is statistically significant, in both the zero-inflated Poisson and OLS models. The low-income group has a nearly zero elasticity of air filter purchases with respect to $PM_{2.5}$ increases, while both the middle-income and high-income groups have a positive and statistically significant elasticity of roughly 0.2. The rich respond more when the air gets dirtier by buying more air filters which are expensive but effective in cleaning the indoor air.

4.3. Placebo Tests

Table 4 reports our placebo test results. In those regressions, we change the dependent variables to the Internet sales of socks and towels. These products do not offer self protection against outdoor air pollution. The model specifications in the first two columns are the same with columns (7) and (8) in Table 2, and those in the last four columns are the same with columns (1) to (4) in Table 3.

In the case of socks and towels, we find no evidence of increased sales as a function of government alerts of the severity of the pollution. In fact, we find that sales of these items decline on days when the pollution is especially severe. As shown by the ln($PM_{2.5}$) coefficients in columns (1) and (2), there is no positive correlation between $PM_{2.5}$ concentrations and socks and towel sales. In columns (3) to (6), the coefficients on the interaction terms are almost all statistically insignificant.

5. Conclusion

Chinese urbanites engage in self-protection against air pollution and richer individuals are more likely to make these investments. For a given level of outdoor air pollution, an individual can reduce her exposure by spending less time outside, and wearing a mask when one is outside. Such an individual can reduce her exposure to indoor air pollution by purchasing an effective filter. Based on a unique data set of Internet purchases, we study household investment in two different self protection products varies as a function of ambient city pollution levels exceeding key alert thresholds. The sales of masks on the days when the government has issued a “heavily polluted” and “severely polluted” alert are 2.9 and 7.2 times those during a “blue sky” day. These two ratios are 1.6 and 3.0 respectively for air filter sales. Controlling for government pollution announcement alerts, consumers also respond to the actual $PM_{2.5}$ concentration level by buying more masks and air filters.

We also find that richer people invest more in self protection products, especially the more expensive but more effective devices like air filters, when air pollution is higher. The low-income group exhibits a very flat air filter purchase propensity as a function of $PM_{2.5}$ concentration increases, while the middle-income and high-income groups have an elasticity of roughly 0.2. Air filters are more effective than masks in protecting people from air pollution. Differential investment in self protection means that air pollution exposure exacerbates quality of life inequality in Chinese cities.

Given widespread concerns about the consequences of income inequality in both the United States and China, it remains an important research topic to study how and why such income differentials translate into actual pollution exposure differentials. Future research could use a field experiment research design in which the urban poor are randomly selected to receive information about the day to day pollution exposure they face. A more expensive field experiment would subsidize the purchase price of masks and air filters. The research could then test whether mask and air filter purchases increase for the treatment group and by how much. Such research would be useful for judging how much of the rich/poor self protection investment gap is due to information access versus price effects.

Table 4
A placebo test.

	Zero-inflated Poisson model (ZIP)				OLS	
	Daily	Daily	Monthly	Monthly	Monthly	Monthly
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Sock	Towel	Sock	Towel	ln(sock + 1)	ln(towel + 1)
Government alert dummies:						
Blue sky (*default*)						
Lightly polluted	0.0249	−0.0158				
	(0.0299)	(0.0317)				
Moderately polluted	−0.00393	0.0000259				
	(0.0301)	(0.0408)				
Heavily polluted	−0.0327	0.0318				
	(0.0363)	(0.0517)				
Severely polluted	−0.00327	0.0693				
	(0.0667)	(0.0623)				
ln(PM2.5)	−0.0184	−0.0746**	0.201	−0.137**	0.455***	−0.107
	(0.0348)	(0.0309)	(0.167)	(0.0615)	(0.0929)	(0.0690)
ln(PM2.5) × middle income			0.0406**	0.0316	0.00295	0.0225
			(0.0192)	(0.0388)	(0.0417)	(0.0478)
ln(PM2.5) × high income			0.0591	0.103	0.0169	0.0940
			(0.0495)	(0.0723)	(0.0638)	(0.0854)
Weather attributes	Yes	Yes	Yes	Yes	Yes	Yes
Other control variables	Yes	Yes	Yes	Yes	Yes	Yes
Vuong test	8.05***	10.62***	0.89	2.29**		
Observations	3085	3085	1326	1326	1326	1326
R-squared					0.857	0.913

Notes: Four zero-inflated regression estimates and two OLS estimates are reported. Robust standard errors are reported in parentheses. In the zero-inflated count models (columns (1–4)), city dummies are used to model the probability that the dependent variable equals zero. Standard errors are clustered by city. Other control variables are same as the related columns in Tables 2 and 3.
** $p < 0.05$.
*** $p < 0.01$.

Acknowledgements

We thank two anonymous reviewers for extensive comments. The authors thank Professor Yinping Zhang and Professor Jinhan Mo in Department of Building Science in Tsinghua University, and Professor Xiaoli Duan in Chinese Research Academy of Environmental Sciences (CRAES) for their kind research supports. The authors thank Haishi Li for excellent research assistance. The authors also thank the National Natural Science Foundation of China (No. 71273154, No. 71322307 and No. 71603158), Social Science Foundation of China (No. 14AJY012), MOE (Ministry of Education in China) Project of Humanities and Social Sciences (No. 16YJC790090), Postdoctoral Science Foundation of China (No. 2016M591644) and University of California at Los Angeles Ziman Center for Real Estate for generous funding.

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