

# **Self-Protection Investment Exacerbates Air Pollution Exposure Inequality in Urban China**

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## **Abstract**

Urban China's high levels of ambient air pollution both lowers quality of life and raises mortality risk. China's wealthy have the purchasing power to purchase private products such as air filters that allows them to offset some of the 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 than masks. Our findings have implications for trends in inequality in human capital accumulation and 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).<sup>1</sup> 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 consequences of this trend. The wealthy have greater consumption opportunities than poorer people. In this paper, 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.

China's urban air pollution challenges have been well documented. 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, Huo and Zhang 2002). In recent years, the major air pollutant has been PM<sub>2.5</sub> (particles with an aerodynamic diameter < 2.5 μm) which is largely produced as a byproduct of manufacturing production, car driving and coal burning. The Beijing Environmental Protection Bureau has issued a local PM<sub>2.5</sub> inventory. In the year 2014, 30% of emissions was produced by vehicles, 22.4% from coal combustion, 18.1% from industrial production, 14.3% from dust, and 14.1% from other sources such as cooking<sup>2</sup> The Asian Development Bank reports that fewer than 1% of the 500 largest 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). PM<sub>2.5</sub> concentrations in China's eastern region are significantly higher than those in other regions (Zhao et al. 2013).

Pollution exposure impacts both the quantity and quality of life (MacKerron and Mourato 2009, Hall et. al 2010). Breathing polluted air as measured by particular 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, and find that the higher PM

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<sup>1</sup> According to United Nation's standard, Gini index above 0.4 signals a large income inequality.

<sup>2</sup> <http://cleanairasia.org/portal/node/12353>

concentrations in the north caused by winter heating lower 5.5 years of life expectancy.<sup>3</sup>

Pollution exposure also has direct impacts on human capital accumulation and utilization. Outdoor workers are less productive on more polluted days (Graff Zivin and Neidell 2012). James Heckman's research posits a dynamic complementarity effect such that young children learn more in school if they are healthier (Heckman, 2007). According to his model, children with 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, Zweig et. al. 2009, Currie et. al 2014). Human capital attainment is negatively affected by life time pollution exposure (Graff Zivin and Neidell, 2013). Given 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 different strategies for reducing their exposure to current levels of outdoor pollution. For evidence on such investments based on data from England see Janke (2014). 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).

We use data from China to study private household investments to reduce their exposure to outdoor air pollution. Such investments offer direct amenity benefits to households through lowering pollution exposure and they also embody an investment dimension through the human capital channel as adult workers will be more productive at work and children in the household will learn more in school and be more likely to grow up healthy. To study private protective actions, we use a unique panel data base of sales indices assembled by *Taobao.com*, which is the largest online shopping platform owned by *Alibaba Group* (China's largest e-commerce company) with hundreds of million online consumers in China, similar to eBay and Amazon. . 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

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<sup>3</sup> 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.

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 and to study how these consumption dynamics differ between rich, middle class, and poorer Chinese urbanites. 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 (air filters) when local pollution levels are higher. Our study contributes to a recent literature studying pollution exposure inequality between urban and rural residents in China (see Schoolman and Ma 2012) and highlight an issue that China will face increasing demands to address (Zhao, Zhang and Fan 2014).

## **2. Self-Protecting Against Air Pollution in Urban China**

By choosing a city and a neighborhood within that city, urban residents have some control over their exposure to air pollution. The poor, with their limited budget, are more likely to live in the dirtier areas within a city. Real estate prices are higher and housing demand is higher in less polluted geographic areas (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. Cross-county migration research documents that households reveal a high willingness to pay for clean air (Bayer et al., 2009). 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 can 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 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. Sometimes people have to sacrifice environmental quality in order to gain other advantages a city offers. As China's capital city, Beijing faces a high pollution level, but it continues to be a highly attractive destination for urbanites, due to the high density clusters of great universities, high-quality hospitals and valuable political resources. 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  $10\mu\text{g}/\text{m}^3$  lower average  $\text{PM}_{10}$  concentration. These hedonic researches suggest that poor children will be more likely to grow up in more polluted cities and live in more polluted areas within those cities. Previous U.S based research has measured the differential health impacts borne by the poor when they are exposed to urban air pollution (Neidell 2004).

One's residential location alone is not sufficient for describing one's pollution exposure. When the outdoor air is polluted, people decrease their time spent outdoors (Neidell 2009). 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 be outside more.

Low-skilled workers are more likely to work in outdoor occupations such as construction, street cleaning and delivering mail. In contrast, high-skilled workers work indoors in climate controlled buildings. According to the Environmental Exposure Related Activity Patterns Survey in China, the ratio of office staffs' average daily outdoor time to that for all workers is 0.64.

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 pollution filters represent key examples of such market products. Risk perception studies have documented that the population is aware of the risks they face from pollution. Such individuals gain private benefits from investing in self-protection and averting behavior (Smith et al., 1995; Graff Zivin and Neidell, 2009). Differential investments in these items between the rich and poor will exacerbate pollution exposure differences and hence increase health inequality.

Many urban residents in major cities 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 similar to eBay and Amazon. 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. During a hazy week at the end of 2013, mask and air filter sales reached 760,000 and 140,000 respectively, with

the weekly growth rates (compared to the previous week) of 52.35% and 74.1% respectively. While concerns about the “digital divide” raise the possibility that the poor are less likely to shop online, in China low income people 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.

An air filter is much more expensive than a mask. Their average prices are 490 and 0.9 US dollars, respectively. Consumers have to change the air filter’s strainer once per year but a mask only last for about ten days. Thus, the daily user cost (including electricity expenditure) of an air filter is more than ten times that of a mask. For both the mask and air filter transactions on *Taobao.com* in 2013, the high-income group (the top 25% of total consumers) bought 31.9% of masks and 47.9% of air filters.

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.<sup>4</sup>

To formalize this discussion, we present a simple Becker Household Production Function of household investment in health (Michael and Becker 1973). All households have the same utility function  $U(H, c)$  defined over health  $H(A)$  and private consumption,  $c$ . The only input in producing health is air quality,  $A$ . Increases in air quality ( $A$ ) increase one’s health ( $H$ ). A household purchases air quality by choosing to rent in a given location. By standard compensating differentials logic, areas with higher air quality feature higher equilibrium rents. In Figure 1, we graph the non-linear budget constraint for a rich person and a poor person. Given that a city such as Beijing has a bounded cleanest community (which still has a high level of air pollution) the budget constraint cuts off. Knowing a household’s indifference curves, we can immediately solve for the optimal location for a rich household and a poor household. With a strong taste for clean air, the rich person chooses the location with the best air quality  $A_r$  (or  $A_{max}$ ), and the poor person chooses the location with the air quality  $A_p$  worse than  $A_r$  ( $\Delta A = A_r - A_p > 0$ ).

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<sup>4</sup> See: <http://www.cca.org.cn/web/xfzd/newsShow.jsp?id=67720>.

In Figure 2, we now introduce the *Taobao* markets for masks and air filters. Note that both poor people and rich people can buy the masks at the same price. These masks change the budget constraint. We also introduce the option (only for the rich) to buy an air filter. We are assuming that the poor cannot afford it. The highest air quality households can achieve by living in the cleanest neighborhood and then buying masks is  $A_{mask}$ . Rich urbanites can also afford to purchase an expensive air filter to gain more protection. This means that they can achieve the consumption bundle associated with air quality of level  $A_{filter}$ . In Figure 3, we superimpose indifference curves and document that the introduction of private self protection markets exacerbates air pollution inequality between the rich and the poor. For the poor person, the utility maximizing point is where air quality equals  $A_p'$  (or  $A_{mask}$ , the highest air quality under mask protection). The rich live in cleaner neighborhoods, spend less time outside on dirty days and invest more in expensive self-protection products (air filters). The rich maximize their utility when air quality equals  $A_r'$ . Therefore, the inequality in air pollution exposure after introducing the provide self-protection products can be written as  $\Delta A' = A_r' - A_p'$ , which is larger than that before the mask and air filter markets are introduced ( $A_r' - A_p' > A_r - A_p$ ). Together this means that the children of the rich are exposed to less pollution. Such children will be less likely to suffer morbidity and mortality risk associated with pollution exposure and the absence of pollution will aid their human capital accumulation. This model highlights that the creation of private self protection markets exacerbates both quality of life differentials between rich and poor households and human capital differentials between their children.<sup>5</sup>

### 3. Hypothesis Testing

The online Taobao purchase data allow us to test 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<sub>2.5</sub> exceeding key thresholds) and to the level of outdoor PM<sub>2.5</sub>. Market Internet purchases of other goods (socks and towels) are not correlated with pollution alerts and

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<sup>5</sup> We are assuming there are diminishing returns to the composite consumption good and that this good plays no role in child health and human development.

the level of outdoor PM<sub>2.5</sub>.

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

### 3.1 Data Construction

Our core data set for city level sales of self-protection products is based on data from *Taobao.com* which accounts for about 90% of the online Consumer-to-Consumer sales and 57% of online Business-to-Consumer sales in China<sup>6</sup>. *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 social retail goods in that year.<sup>7</sup> Many daily consumption items are purchased on *Taobao.com* because of its low prices and easy shipping. *Taobao.com* provides daily and monthly sales indices<sup>8</sup> of each market good covering the 34 major cities (all municipalities directly under the federal government, provincial capital cities, and quasi provincial capital cities, excluding Lhasa in Tibet). We collect the daily sales index data from 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 early 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 index 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. We are unable to access daily index data by income group.

The air pollution data and the daily pollution alerts are from China's Ministry of Environmental Protection (MEP). According to China's new Ambient Air Quality Standards (GB3095-2012), there are six levels of pollution alerts: excellent, good, lightly polluted, moderately polluted, heavily polluted and severely polluted. Each alert is based on the air quality index created by the MEP. Fu et al. (2014) list the detailed

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<sup>6</sup> <http://dealbook.nytimes.com/2013/09/25/alibaba-said-to-shift-target-from-hong-kong-to-u-s-for-i-p-o/>

<sup>7</sup> <http://www.iresearchchina.com/views/4730.html>

<sup>8</sup> The relationship between sales index and actual sales volume is linear. The algebra equation is: real sales volume<sub>*jt*</sub> =  $\theta_0$  +  $\theta_1 \times$  Sales index<sub>*jt*</sub>. According to technical personnel at *Taobao.com*, both  $\theta_0$  and  $\theta_1$  are constant for all income groups and over the whole study period. The exact values of these two parameters are not released by *Taobao.com* for confidential concern. However, given that the two parameters are constant, we can use the sales index to run our regressions and this will not affect the estimates of our key coefficients.



ranges of the air quality index for each alert. Daily and monthly PM<sub>2.5</sub> concentrations are calculated from the MEP's official hourly real-time data. MEP releases hourly air pollution alert of these cities on its website,<sup>9</sup> and 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.<sup>10</sup>

Chinese urbanites have been gaining confidence in the MEP's air pollution alerts. The recent public campaign in China has urged the state to create a nationwide PM<sub>2.5</sub> monitoring network which is supervised by the public. Information technology, public awareness of air quality's health impacts and the fact air quality information is an important public good are the major factors promoting public participation (Huang 2015). In fact, the recent MEP official PM<sub>2.5</sub> data and the US embassy PM<sub>2.5</sub> data provide consistent readings. For instance, the mean value of the US Embassy PM<sub>2.5</sub> reading in 2013 is 87.4 µg/m<sup>3</sup>, and that for the MEP official PM<sub>2.5</sub> reading at the air quality monitor near the US Embassy in Beijing is 90µg/m<sup>3</sup>. 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.

\*\*\* Insert Table 1 about here \*\*\*

### 3.2 Empirical Methods

To test Hypothesis #1, we estimate a negative binomial count model as presented in equation (1):

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

The unit of analysis for Equation (1) is city/day.  $Q_{it}$  is the sales index of each

<sup>9</sup> <http://113.108.142.147:20035/emcpublish/>

<sup>10</sup> <http://www.tutiempo.net/en/Climate/China/CN.html>

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<sub>2.5</sub> concentration in city  $i$  in day  $t$ . Five pollution alert dummies are included as  $A_{it}$ . (“excellent” as the default).  $X_{it}$  is a vector of weather attributes and control variables such as China’s national holidays. 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.  $\varepsilon_{it}$  is a disturbance term. We also report results based on equation (1) where we change the dependent variable to the sales index for sales of socks and towels. We chose these two products because we do not expect that there will be a relationship between the outdoor level of air pollution and the purchase of these products. In this sense, these regressions represent placebo tests.

We estimate equation (2) to test Hypothesis #2:

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

In equation (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 weather attributes. The coefficient  $\beta_2$  (or  $\beta_3$ ) 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 low income. The coefficient  $\beta_4$  (or  $\beta_5$ ) measures the “absolute” sales index gap between the middle-income group (or high-income group) and the low-income group, which does not change with pollution.  $v_{ijt}$  is a disturbance term.

### 3.3 Results testing Hypothesis #1

We seek to 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.

\*\*\* Insert Table 2 about here \*\*\*

Table 2 reports the regression results of equation (1). The dependent variable in columns (1) and (2) is the daily sales of masks and air filters, respectively. The omitted category is an “excellent” (blue skies) day. We find 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. The daily sales of masks on the days when the government has issued a “heavily polluted” and “severely polluted” alert are 2.5 and 11.2 times those during an “excellent” day. These two ratios are 1.3 and 4.9, respectively for air filter sales. This evidence suggests that the population trusts the government's pollution alerts.

Controlling for the discrete government alert, consumers also respond to the actual  $PM_{2.5}$  concentration level by buying more masks and air filters. On days when the government announces a “heavily polluted” or a “severely polluted” alert, people check their smartphones more often for real time updates about the reading of current  $PM_{2.5}$  concentration.

We report results from two additional regressions reported in columns (3) and (4). In these regressions, we switch the dependent variables to the Internet sales of socks and towels. These products do not offer self protection against outdoor air pollution. 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 positive  $PM_{2.5}$  coefficient, we do find that within pollution threshold categories that there is a positive correlation between  $PM_{2.5}$  concentrations and socks and towel sales. It is important to note that the economic magnitude of this effect is small. If  $PM_{2.5}$  is one standard deviation higher, the mean sock and towel sales increase by 7.8% and 6.9% respectively, but the mean mask sales increase by 19.7%.

Based on a similar *Taobao.com* transaction data set, in independent work, Mu and

Zhang (2014) find that a 100-point increase in Air Quality Index increases the consumption of all masks by 54.5 percent and anti-PM<sub>2.5</sub> masks by 70.6 percent. These results are consistent with our findings here but our emphasis is on cross income group exposure differences and hence on the role of income inequality, as we discuss in the subsection below.

### *3.4 Results Testing Hypothesis #2*

To test whether richer people invest more in self protection, we use the monthly Internet sales data stratified by the three income categories and test whether richer people are purchasing more masks and filters on more polluted days. The government alert variable is not available for this longer period, so the key independent variable is the monthly average PM<sub>2.5</sub> concentration data, and we interact this variable with income group dummies. Table 3 presents the regression results based on estimating equation (2).

\*\*\* Insert Table 3 about here \*\*\*

In the first column, a 1% increase in PM<sub>2.5</sub> concentration is associated with a statistically significant increase of 0.81% in mask purchases by the low-income group (the default category). We reject the hypothesis that the middle-income and high-income groups purchase more masks than the low-income group when PM<sub>2.5</sub> concentration rise. This finding may be due to the fact that masks are cheap so that even the poor can afford them. Also, recall that the rich can stay inside for longer time during the polluted days so they do not need to wear masks as intensively. 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. The low-income group has a nearly zero elasticity of air filter purchases with respect to PM<sub>2.5</sub> increases, while the middle-income and high-income groups have significantly positive elasticities of 0.23 and 0.27, respectively. The interaction terms in the placebo tests (using socks and towel purchases as the dependent variables) in columns (3) and (4) are all statistically insignificant.

## **4. 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, wearing an effective 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 investigate that households invest more in such two self-protection products when ambient pollution levels exceed key alert thresholds. According to our empirical estimation results, the daily sales of masks on the days when the government has issued a “heavily polluted” and “severely polluted” alert are 2.5 and 11.2 times those during an “excellent” day. These two ratios are 1.3 and 4.9 respectively for air filter sales. Controlling for the discrete government alert, 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 air filters, when air pollution is higher. The low-income group has a nearly a zero elasticity of air filter purchases with respect to  $PM_{2.5}$  increases, while the middle-income and high-income groups have elasticities of 0.23 and 0.27, respectively. Air filters are more effective than masks in protecting people from air pollution, therefore such differences in self-protection investment is likely to exacerbate air pollution exposure inequality in Chinese cities.

Given the investment differentials we have documented, 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 investment gap is due to information access versus price effects.

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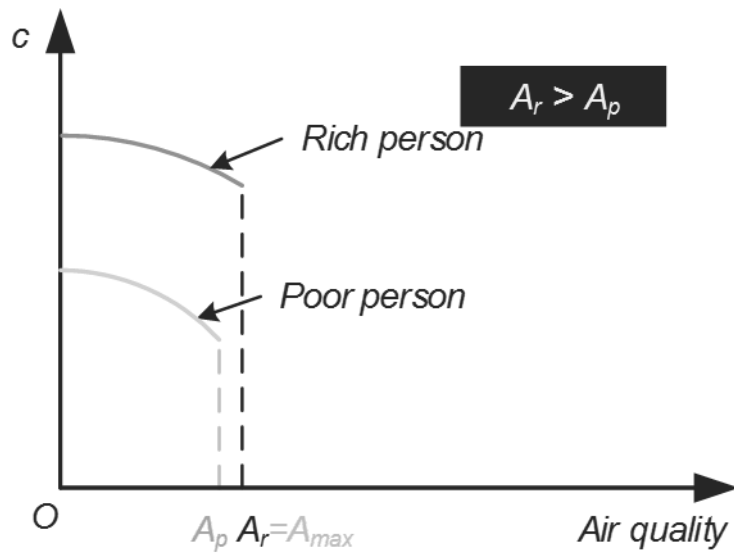


Figure 1. Two Budget Constraints in the Absence of Private Self Protection

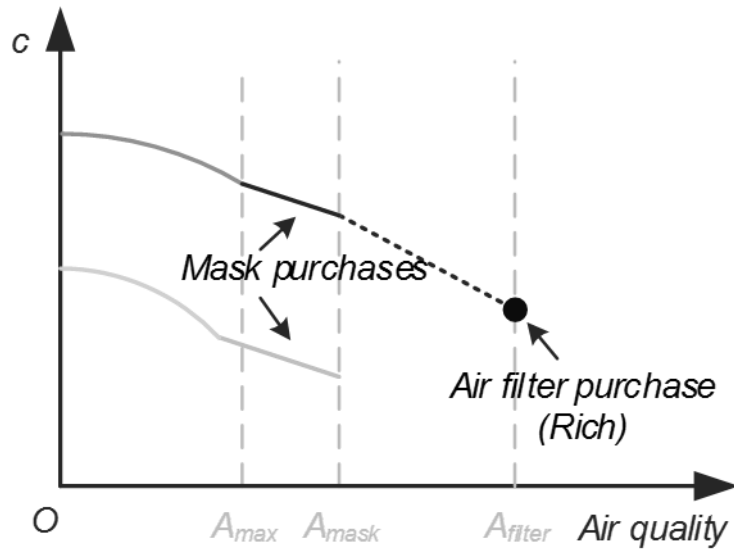


Figure 2. Two Budget Constraints in the Presence of Private Self Protection Markets

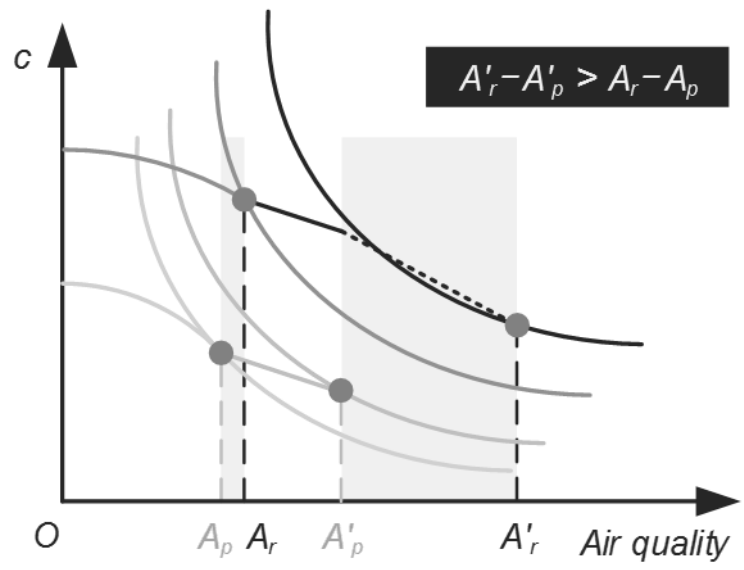


Figure 3. Optimal Consumption Choices in the Presence of Private Self Protection

Table 1. Variable Definitions and Summary Statistics

Variable	Definition	Mean (Std. Dev.)	
		Daily	Monthly
PM2.5	PM <sub>2.5</sub> concentration (in $\mu\text{g}/\text{m}^3$ )	96.34 (70.64)	66.22 (33.01)
Mask	<i>Taobao.com</i> sales index of “mask”	51.50 (223.8)	216.4 (869.3)
Filter	<i>Taobao.com</i> sales index of “air filter”	6.285 (20.66)	35.30 (85.82)
Sock	<i>Taobao.com</i> sales index of “sock”	77.71 (160.3)	621.0 (967.8)
Towel	<i>Taobao.com</i> 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)

Table 2. Daily Internet Sales by Product Category as a Function of Air Pollution

Variables	(1)	(2)	(3)	(4)
Dependent variable:	mask	filter	sock	towel
Six Government Alerts:				
excellent ( <i>default</i> )				
Good	0.131** (0.057)	-0.015 (0.066)	-0.060 (0.060)	-0.011 (0.057)
lightly polluted	0.201** (0.088)	0.100 (0.096)	-0.020 (0.062)	0.023 (0.066)
moderately polluted	0.372*** (0.092)	0.219* (0.115)	-0.084 (0.072)	-0.014 (0.072)
heavily polluted	0.648*** (0.129)	0.386*** (0.131)	-0.165** (0.071)	-0.138 (0.087)
severely polluted	1.357*** (0.194)	0.915*** (0.246)	-0.237** (0.106)	-0.246** (0.096)
ln(PM2.5)	0.268*** (0.052)	0.102* (0.054)	0.091*** (0.024)	0.083*** (0.032)
Control variables	YES	YES	YES	YES
Observations	3085	3085	3085	3085

*Notes:* Four negative binomial regression estimates are reported based on equation (1). Standard errors are reported in parentheses. Standard errors are clustered by city. The control variables include; a constant, shopping festival dummies, national holiday dummies, daily weather attributes, city-fixed effects and a linear time trend are included.

\*  $p < 0.10$ . \*\*  $p < 0.05$ . \*\*\*  $p < 0.01$ .

Table 3. Internet Sales as a Function of Air Pollution and Household Income

Variables	(1)	(2)	(3)	(4)
Dependent variable:	mask	filter	sock	towel
ln(PM2.5)	0.8078*** (0.165)	-0.0556 (0.111)	0.4549*** (0.093)	-0.1075 (0.069)
ln(PM2.5)*middle income	0.0012 (0.062)	0.2325*** (0.079)	0.0030 (0.042)	0.0225 (0.048)
ln(PM2.5)*high income	0.1237 (0.094)	0.2746*** (0.075)	0.0169 (0.064)	0.0940 (0.085)
Control variables	YES	YES	YES	YES
Observations	1326	1326	1326	1326
R-squared	0.843	0.888	0.857	0.913

Notes: Standard errors are reported in parentheses. Standard errors are clustered by city. The constant and the control variables for income categories, weather attributes, city-fixed effects and time trend are included but not reported. \*

$p < 0.10$ . \*\*  $p < 0.05$ . \*\*\*  $p < 0.01$ .