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Self-Protection Investment Exacerbates Air Pollution Exposure Inequality in China

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Abstract
Income inequality is rising in China at the same time that urban air pollution remains high. Households can purchase market products such as masks and air filters to protect themselves from pollution. Using a unique data set of Internet purchases, we document that households invest more in such products when ambient pollution levels exceed key alert thresholds. Richer people are more likely to invest in these products. By combining several existing pieces of research, we provide an estimate of the differential exposure to pollution between rich and poor people in urban China. This differential has implications for life expectancy across groups and suggests that quality of life inequality exceeds cross-sectional measures of income inequality.

Significance Statement
Urban air pollution remains high in China. During hazy days, Chinese urbanites wear masks outdoors and use air filters indoors to protect themselves against the dirty air. Using a unique data set of Internet purchases, we find that people buy more masks and filters when local air pollution is higher. Richer people are more likely to invest in such self-protection products. By combining several pieces of information, we estimate that the poor inhale more $PM_{2.5}$, and this shortens their life expectancy relative to richer individuals. This differential is due to differential self-protection investments. We conclude that in China's cities today that quality of life inequality exceeds income inequality.

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Text

Introduction

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Income inequality has been rising sharply in China. The Gini coefficient reached 0.491 in 2008 (National Bureau of Statistics of China, thereafter NBSC). Xie and Zhou (2014) estimate that China's Gini was 0.50 in the year 2010. At a time when there is renewed interest in the causes of income inequality (Piketty 2014), it is equally important to examine the consequences of this trend and its implications for trends in quality of life inequality. National income accounts that measure a nation's per-capita Gross National Product do not reflect broader measures of well being such as the damage to health and quality of life caused by local pollution (Stiglitz, Sen and Fitoussi 2010, Smith 2012).

This study measures pollution exposure inequality in urban China across income groups. China's urban air pollution challenges have been well documented. The Asian Development Bank reports that less 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). In 2013, about half of China suffered from the heavy haze in December (http://usa.chinadaily.com.cn/china/2013-12/09/content_17160658.htm). Pollution exposure impacts both the quantity and quality of life. 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).

There are two strategies for reducing the social costs of air pollution. First, government can introduce regulations to reduce emissions from various polluting sectors such as industry, transportation, and construction. Second, private individuals can invest in avoidance behavior to reduce their pollution exposure. While investments in public goods (the first strategy) broadly benefit everyone, investments in private self protection may be mainly an option for richer households.

In reviewing long run United States health trends over the last 150 years, Costa (2014) argues that health inequality declined when public investments such as sewage treatment plants were built and that health inequality rose when the main source of health progress was private household investments in customized health care. In the past two decades, China's central government focused on economic growth with an emphasis on GDP as the key evaluation criteria of local officials' performance. Facing these incentives, local officials invested little in environmental protection (Zheng and Kahn 2013; Wu et al. 2014). The central government has recently prioritized making environmental progress but China's ongoing coal reliance, industrial production, and increased vehicle use suggest that tangible environmental progress will only be observed in the medium term. As Chinese urbanites become richer and more highly educated, they have strong incentives to invest more in avoidance behavior.

The objectives of this research are two-folds. First, we test whether Chinese urbanites respond to high levels of outdoor air pollution by buying masks for outdoor use and investing in indoor air filters. Second, we investigate whether richer people are more likely to engage in this defensive expenditure. We use estimates from the literature and input from experts to quantify the expected life expectancy inequality across Chinese urban income groups caused by differential exposure to air pollution.

Self-Protecting Against Air Pollution in 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 the most polluted cities and the dirtier areas within a city. Several studies have documented that real estate prices are higher and that 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 exogenous improvements in air pollution trigger a migration by richer people into the community. Cross-county migration research documents that households reveal a high willingness to pay for clean air (Bayer, Keohane and Timmins 2009). Using cross-sectional data on real estate prices across Beijing, Zheng and Kahn (2008) find that a home's price is 4.1% higher at the location with a 10μg/m^3 lower average PM_{10} concentration. Zheng et al. (2014) 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.

One's location alone is not sufficient for describing one's pollution exposure. When the outdoor air is polluted, people decrease their outdoor activity (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. 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. The rich and poor have differential access to these goods. Risk perception studies have documented that the population is aware of the risks they face from pollution and the private benefits from investing in self-protection and averting behavior (Smith, Devousges and Payne 1995; Smith 2008; Zivin and Neidell 2009). Economists have posited that more educated people are more future focused and patient (Becker and Mulligan 1997) and these traits would further encourage richer (more educated) people to invest more in self protection to mitigate the pollution challenge. 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, especially those easy-shipping products. 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* (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 computer or access to the Internet.

Taobao divides all buyers into three groups based on the 25th and 75th percentile values of the overall distribution of buyers' purchase expenditures. These three groups are called "low-income" (0 – 25 percentile), "middle-income" (25 – 75 percentile) and "high-income" (75 – 100 percentile) groups in our study. For instance, a consumer who is in the 90^{th} percentile of total expenditure would be classified as "high income" (see the *Materials and Methods* section).

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% air filters.

These online purchase records 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 $PM_{2.5}$ 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.

Eq. 1 and Eq. 2 (described in detail in the *Materials and Methods* section) are estimated to test Hypothesis #1 and #2.

Results

Findings testing Hypothesis #1: As described in the *Materials and Methods section*, we have collected city level daily data from November 1, 2013 to January 31, 2014 on sales of masks, filters, socks and towels for 34 major cities. We seek to study how the sales of these products evolve 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 (see details in the *Materials and Methods* section). This three-month time period covers a large number of foggy and haze days in the past year, and the severe haze at the end of 2013.

Table 1. 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 (*default*)				
good	0.131**	-0.015	-0.060	-0.011
	(0.057)	(0.066)	(0.060)	(0.057)
lightly polluted	0.201**	0.100	-0.020	0.023
	(0.088)	(0.096)	(0.062)	(0.066)
moderately polluted	0.372***	0.219*	-0.084	-0.014
	(0.092)	(0.115)	(0.072)	(0.072)
heavily polluted	0.648***	0.386***	-0.165**	-0.138
	(0.129)	(0.131)	(0.071)	(0.087)
severely polluted	1.357***	0.915***	-0.237**	-0.246**
	(0.194)	(0.246)	(0.106)	(0.096)
ln(PM2.5)	0.268***	0.102*	0.091***	0.083***
	(0.052)	(0.054)	(0.024)	(0.032)
Control variables	YES	YES	YES	YES
Observations	3085	3085	3085	3085

Notes: Four negative binomial regression estimates are reported. Robust standard errors in parentheses. 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 1 reports the regression results of Eq. 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 PM2.5 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 PM2.5 is one standard deviation higher, the mean sock and towel sales increase 7.8% and 6.9% respectively, but the mean mask sales increase 19.7%.[2]

Findings 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 (details provided in *the Materials and Methods section*). The sample covers 34 cities for the period from April 2013 to April 2014. We use monthly data, instead of daily data, to test this hypothesis is because that no daily sales index stratified by income-group is available. The government alert variable is not available for this longer period, so the key independent variable is the monthly average PM2.5 concentration data, and we interact this variable with income group dummies. Table 2 presents the regression results based on estimating equation (2).

In the first column in Table 2, a 1% increase in $PM_{2.5}$ 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 $PM_{2.5}$ 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

[2] Based on a similar *taobao.com* transaction data set, an independent work by Mu and Zhang (2014) finds that a 100-point increase in Air Quality Index increases the consumption of all masks by 54.5 percent and anti-$PM_{2.5}$ 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.

can stay inside for longer time during the polluted days so they do not need to wear masks intensively. In contrast, the air filter is quite expensive (490 US dollars each on average) 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 a zero elasticity of air filter purchases with respect to PM2.5 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 in columns (3) and (4) are all statistically insignificant.

Table 2. 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***	-0.0556	0.4549***	-0.1075
	(0.165)	(0.111)	(0.093)	(0.069)
ln(PM2.5)*middle income	0.0012	0.2325***	0.0030	0.0225
	(0.062)	(0.079)	(0.042)	(0.048)
ln(PM2.5)*high income	0.1237	0.2746***	0.0169	0.0940
	(0.094)	(0.075)	(0.064)	(0.085)
Control variables	YES	YES	YES	YES
Observations	1326	1326	1326	1326
R-squared	0.843	0.888	0.857	0.913

Notes: Robust standard errors in parentheses; 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.

Discussion and 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 an effective mask when one is outside. Such an individual can reduce her exposure to indoor air pollution by purchasing an effective filter.

To provide a preliminary estimate of the total effect of these choices, on particulate matter exposure, we borrow several results from the literature. Based on equations (3) and (4) (see the *Materials and Methods* section), we calculate the average mean exposure to $PM_{2.5}$ by income group. On average, low-income urbanites inhale 28% more $PM_{2.5}$ than high-income urbanites. To translate differences in PM2.5 exposure concentrations into differences in life expectancy, we use estimates from Pope III et al. (2009). They find that an increase of 10μg/m^3 in the $PM_{2.5}$ concentration is associated with about a 0.61 year reduction in life expectancy.

In Table 3, we use this information to present three scenarios (A, B and C refer to the $PM_{2.5}$

concentration as the average value of the 35 major cities, that in the most polluted city, and that in the cleanest city, respectively. Details are reported in *Materials and Methods*). Table 3 shows that life expectancy inequality (the difference in life expectancy between the high-income group and the low-income group) is 8.49 months if everyone is exposed to the average $PM_{2.5}$ level across the 35 cities. This gap grows to 14.1 months if everyone is exposed to the Chinese city with the highest $PM_{2.5}$ level (Shijiazhuang City). As we discuss in the Materials and Methods section, it is important to note that these calculations are based on several assumptions that we explicitly state in that section.

Table 3. Life Expectancy Differentials across Income Groups in Different Types of Cities

Scenario	Life expectancy inequality
Scenario A (35 cities average, baseline)	8.49 months
Scenario B (most polluted city)	14.09 months
Scenario C (cleanest city)	3.64 months

Table 3 shows that public investment in pollution control and the resulting air pollution improvement will differentially improve the life expectancy of the Chinese urban poor.

Materials and Methods

Sample and Data. 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 (http://dealbook.nytimes.com/2013/09/25/alibaba-said-to-shift-target-from-hong-kong-to-u-s-for-i-p-o/). As *iResearch* reported, *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 (http://www.iresearchchina.com/views/4730.html). 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 (which bears a linear relationship with the real sales volume) 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 daily sales index from November 1, 2013 to January 31, 2014 to estimate equation (1). This time period covered several major pollution events; including in early December 2013, the Pearl River Delta where Shanghai and Nanjing locate suffered from the most severe haze event of the past ten years. Beijing and Shijiazhuang also experienced terrible haze days in December 2013 and January 2014.

To estimate the results reported in Table 2, we 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 buyers within the 75%-100%, 25%-75% and 0%-25% percentiles in the distribution of the online shopping expenditure per capita. No daily index stratified by income-group is available.

The air pollution data and the daily pollution alerts are from the 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 ranges of the air quality index for each alert. Daily and monthly $PM_{2.5}$ concentrations are calculated from the MEP's official hourly real-time data (http://113.108.142.147:20035/emcpublish/). 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 (http://www.tutiempo.net/en/Climate/China/CN.html).

The Econometric Model. To estimate the results reported in Table 1, we estimate the negative binomial count model presented in Eq.1:

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

Where Q_{it} is the sales index of each market product (masks or air filters) in city i in day t. PM_{it} is the daily $PM_{2.5}$ 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, respectively. ε_{it} is a disturbance term. We also run the placebo tests with the sales of socks and towels as the dependent variables in Eq. 1.

To estimate the results reported in Table 2, we estimate Eq. 2:

$$\ln(Q_{ijt}) = \beta_0 + \beta_1 \ln(PM_{it}) + \beta_2 \ln(PM_{it}) \cdot \textit{middle income}_i + \beta_3 \ln(PM_{it}) \cdot \textit{high income}_i + \beta_4 W_{it}$$
$$\beta_5 T_t + \beta_6 C_i + v_{ijt} \qquad [2]$$

Where Q_{ijt} is income group j (high-income, middle-income, low-income)'s sale index of each market product in city i in month t. *middle income* and *high income* are two dummy variables in city i. W_{it} is a vector of weather attributes. The coefficient β_2 (or β_3) of the pollution-income interaction term measures the differential of the respond gradient to pollution increase between the middle income group (or high income group) and the low income. v_{it} is a disturbance term.

Variable definitions and summary statistics are listed in Table 4. Summary statistics of the control variables, such as weather attributes and national holidays, are not listed but are available upon request.

Table 4. 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)

Key parameters used in the life expectancy estimations. Eq. 3 shows how we quantify the $PM_{2.5}$ pollution exposure differential by income group.

$$exposure_i = PM2.5_{out} * share_{out,i} * prob_i(mask) * (1 - E(mask)) + PM2.5_{out} * share_{out,i} * (1 - prob_i(mask)) + PM2.5_{in} * share_{in,i} * prob_i(filter) * (1 - E(filter)) + PM2.5_{in} * share_{in,i} * (1 - prob_i(filter)) \quad [3]$$

In Eq. 3, *exposure* is daily $PM_{2.5}$ exposure; $PM2.5_{out}$ and $PM2.5_{in}$ is the outdoor and indoor $PM_{2.5}$ concentration, respectively; $share_{out}$ and $share_{in}$ is the share of time spent outside and inside, respectively; *prob* is self-protection product purchase probability and 1-*prob* is the probability of not buying a mask or filter. *E* is the effectiveness of the corresponding product as measured by what percent of the pollution it removes. The subscript *i* represents income group *i*.

We calculate equation (3) for each income group and then use the Pope III et. al. (2009) estimate to measure the life expectancy reduction. These inputs are used to create equation (4).

Life expectancy differential=Marginal life expectancy reduction*$PM_{2.5}$ exposure differential [4]

Four key parameters are needed to estimate Equations (3) and Equation (4). The first parameter is the $PM_{2.5}$ concentration. We present three scenarios. In Scenario A (the baseline), the outdoor $PM_{2.5}$ concentration is defined as the average value of 34 major cities in 2013 (67.32μg/m^3). In Scenario B (high case), outdoor $PM_{2.5}$ concentration is defined as the most polluted city's (Shijiazhuang City) annual mean concentration (111.67μg/m^3). Similarly, in Scenario C (low case), outdoor $PM_{2.5}$ concentration is defined as the cleanest city's (Haikou City) annual mean concentration (28.85μg/m^3). According to Chen and Zhao (2011), the indoor concentration is about 0.8 times of the outdoor concentration on average. We use this estimate to calculate the indoor $PM_{2.5}$ concentration in each of the three scenarios. We obtain an adult's daily outdoor and indoor time spent from the Environmental Exposure Related Activity Patterns Survey of Chinese Population. We calculate the usage probability of each self-protection product based on the *Taobao.com* sales index and a survey conducted by the National Bureau of Statistics of China. To measure the effectiveness of masks, we use research from the Department of Building Science at Tsinghua University. Professor Zhang, the director of Center for Building Environment Test and his research team have conducted experiments measuring mask effectiveness. Moreover, China Consumer Association provides test results to show the effectiveness of many air filters (http://www.cca.org.cn/web/xfzd/newsShow.jsp?id=67720). These studies indicate that the mean effectiveness of masks and air filters is 33.0% and 92.0% respectively. That is, we assume that mask and filter owning urbanites are exposed to 67.0% and 8.0% of the original $PM_{2.5}$ pollution.

Income groups differ with respect to their time spent outside and their probability of buying masks and filters. These differentials are presented in Table 5. In calculating this differential, we assume that for a given income group that a person's propensity to buy a mask or a filter is an additively separable function of the person's income and the local air pollution level. In this calculation we do not allow for the possibility that richer people may be even more likely to purchase self protection equipment in more polluted cities. Technically, we do not allow for an interaction effect between income and local air pollution. Such a positive interaction would only increase the inequality estimate.

Table 5. Parameters Used to Generate Table 3

Income group (quantiles)		Low-income	Middle-income	High-income
Time spending (minutes per day)	Outdoor (Indoor)	241.19 (1198.81)	227.36 (1212.64)	185.81 (1254.19)
Usage probability of self-protection (%)	Mask (Air filter)	13.51 (6.36)	15.11 (12.72)	16.97 (31.80)

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