Willingness to Pay for Clean Air: Evidence from Air Purifier Markets in China

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Abstract

This paper provides among the first revealed preference estimate of willingness to pay (WTP) for clean air in developing countries. We use product-by-store level transaction data on air purifier sales in Chinese cities and city-level air pollution data. Our empirical strategy leverages the Huai River heating policy, which created discontinuous quasi-experimental and long-lasting variation in air pollution between the north and south of the river. Using a spatial regression discontinuity design, we estimate the marginal willingness to pay for removing 1 ug/m^3 PM_{10}. Our findings provide important policy implications for optimal environmental regulation.

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1 Introduction

Air quality is remarkably worse in developing countries, and severe air pollution is imposing substantial health and economic burdens on billions of people. For example, the annual average exposure to fine particle pollution in China is more than five times higher than that in the United States in 2013 (Brauer et al., 2016). Such high levels of air pollution cause large negative impacts on a variety of economic outcomes, including infant mortality (Jayachandran, 2009; Arceo et al., 2012; Greenstone and Hanna, 2014), life expectancy (Chen et al., 2013) and labor supply (Hanna and Oliva, 2015). For this reason, policymakers and economists consider air pollution to be one of the first-order obstacles for economic development.

However, high economic burdens of air pollution do not necessarily imply that existing environmental regulations are not optimal. The optimal environmental regulation depends on the extent to which individuals value air quality improvements—that is, willingness to pay (WTP) for clean air (Greenstone and Jack, 2013). If WTP for clean air is low, the current level of air pollution can be optimal because the social planner prioritizes economic growth over environmental regulation. On the other hand, if WTP is high, the current stringency of regulation can be away from the optimum. Therefore, WTP for clean air is a key parameter to consider tradeoffs between economic growth and environmental regulation. Despite the importance of this question, the economics literature provides limited empirical evidence. This is primarily because obtaining a revealed preference estimate of WTP for clean air is particularly challenging in developing countries due to limited availability of high quality data and the lack of readily available exogenous variation in air quality that are necessary for empirical analysis.

In this paper, we provide among the first revealed preference estimates of WTP for clean air in developing countries. Our approach is based on the idea that demand for home-use air purifiers, a main defensive investment for reducing indoor air pollution, provides valuable information to estimating WTP for air quality improvements. We begin by developing a random utility model in which consumers purchase air purifiers to reduce indoor air pollution. A key advantage of analyzing air purifier markets is that one of the product attribute—high-efficiency particulate arrestance (HEPA)—informs both consumers and econometricians the purifier's ability to reduce indoor particulate matter. The extent to which consumers value this attribute, along with the price elasticity of demand, reveals their WTP for indoor air quality improvements.

We apply this framework to scanner data on market transactions in air purifier markets in Chinese cities. At the retail store level, we observe product-level information on monthly sales, monthly average price, and detailed product attributes. The product attributes include the information on each purifier's ability in reducing indoor air pollution. Our data cover January 2006 through December 2012. The dataset provides comprehensive transaction records of 395 air purifier products for among the most polluted cities in the world. To our knowledge, this paper is the first study to exploit these transaction data in the Chinese air purifier markets to examine consumers' willingness to pay for air quality. We also collect pollution data from air pollution monitors and micro data on demographics from the Chinese census to compile a dataset that consists of air purifier sales and prices, air pollution, and demographic characteristics.

The primary challenge for our empirical analysis is that two variables in the demand estimation—pollution and price—are likely to be endogenous. To address the endogeneity of air pollution, we use a spatial regression discontinuity (RD) design, which exploits discontinuous valuation in air pollution created by a policy-induced natural experiment at the Huai River boundary. The so-called Huai River policy provided city-wide coal-based heating for cities north to the river, which generated substantially higher pollution levels for the northern cities (Almond et al., 2009; Chen et al., 2013). The advantage of this spatial RD approach is twofolds. First, it allows us to exploit plausibly exogenous policy-induced variation in air pollution. Second, the policy-induced variation in air pollution has existed for a long time since the 1950s. Therefore, this natural experiment provides long-run variation in air pollution, which enables us to examine how households respond to variation in pollution that is not transitory but rather long-lasting.

To address the endogeneity of prices, we combine two approaches. First, using the fact that we observe data from many markets (cities) in China, we include product fixed effects and city fixed effects. With these fixed effects, we absorb product-level unobserved demand factors and city-level demand shocks. The remaining potential concern is product-city level unobserved factors that affect demand. We construct an instrument variable, which measures distance from each product's manufacturing plant (or its port if the product is imported) to each market, aiming to capture variation in transportation cost, which is a supply-side shifter for prices.

We first present visual and statistical evidence that the level of air pollution (PM_{10}) is discontinuously higher for cities in the north of the Huai River. A key prediction from our demand model is that if households value clean air, the market share for HEPA purifiers—that is, purifiers that can reduce indoor particular matter—should be higher for cities in the north of the river boundary. Our second empirical analysis shows that there is indeed a discontinuous and substantial increase in the market share of HEPA purifiers in the north. We estimate local linear regression for the RD design and find that the WTP for removing the amount of PM_{10} generated by the Huai river policy for five years is 53 dollars. Third, we estimate two stage least squares and present that the marginal WTP for removing 1 ug/m^3 of PM_{10} for five years is 1.6 dollars. We show that our RD estimates are robust to using a range of different bandwidths as well as local quadratic estimation. Fourth, we relax a few assumptions on standard logit demand estimation and estimate a random-coefficient logit model. Given a set of assumptions, our random-coefficient logit model allows us to estimate potentially heterogeneous preference parameters for pollution and price. We find substantial heterogeneity that can be explained by observed and unobserved factors. Our results indicate that higher-income households have significantly higher WTP for clean air compared to lower-income households.

This study provides three primary contributions to the literature and ongoing policy discussions. The first contribution is that we develop a framework to estimate WTP for improvements in environmental quality by estimating demand for defensive investment. Earlier studies on avoidance behavior against pollution examine whether individuals take avoidance behavior in response to pollution exposure.[1] A key question in the recent literature is whether researchers can estimate WTP for improvements in environmental quality from observing defensive investment in markets. To our knowledge, two recent papers ask this question. Kremer et al. (2011) uses a randomized control trial (RCT) for water pollution in Kenya. Our approach, a quasi-experimental experiment with non-experimental data, is closer to the approach taken by Deschenes et al. (2012), in which they use medical expenditure data in the United Sates. There is no doubt that RCT would be the ideal empirical strategy to answer the question for many reasons. However, a large-scale RCT on pollution is usually infeasible in most countries. Therefore, quasi-experimental approaches are important complements to address this question. We believe that our quasi-experimental framework

[1] For evidence in the United States, see Neidell (2009); Zivin and Neidell (2009); Zivin et al. (2011). For evidence in China, see Mu and Zhang (2014); Zheng et al. (2015). For evidence in other developing countries, see Madajewicz et al. (2007); Jalan and Somanathan (2008).

based on market data can be useful for other contexts because market-level sales and price data are most likely to exist in many countries because manufacturers or retail stores usually collect scanner data on product sales and price.[2]

The second contribution is that our analysis provides empirical evidence for an important "missing piece" in the literature on air pollution in developing countries. Greenstone and Jack (2013) describe that few studies have attempted to develop revealed preference estimates of WTP for environmental quality in developing countries despite the fact that recent pollution concentrations in these countries are far above those ever recorded in the US. The extrapolation of WTP estimators from studies in developed countries is unlikely to be valid because pollution and income levels are substantially different between developed and developing countries. We fill this gap by providing a revealed preference estimate of WTP for air quality in China. Our estimates are particularly useful for this question because the identification comes from long-run exposure to air pollution induced by the Huai River policy. This is particularly informative WTP in the developing world where large part of pollution does not come as "on-and-off shocks."

Finally, our findings provide important policy implications for ongoing discussions in energy and environmental regulation in developing countries. Governments in developing countries recently proposed and implemented interventions to their air pollution problems. For example, Chinese Premier Li, Keqiang declared "War Against Pollution" to reduce emission of PM_{10} and $PM_{2.5}$ and proposed various reforms in energy and environmental policies (Zhu, 2014). China has also made commitments to address global climate change, as featured by the *New York Times* April 2016 (Davenport, 2016). Reform policies, for example, include reforming the the Huai river heating policy and the launch of a national cap-and-trade program on carbon emission in 2017. A key question is whether implementing such policies enhances welfare or not. In the policy implication section of this paper, we provide an evaluation of the recent reform of the Huai River heating policy as an example to illustrate how estimates on the WTP for clean air can be used to examine welfare implications of energy and environmental policies.

[2] There are a few more related studies. Berry et al. (2012); Miller and Mobarak (2013) use randomized controlled trials to estimate WTP for water filters and cook stoves per se instead of WTP for improvements in environmental quality. Consumer behavior in housing markets is usually not considered to be "avoidance behavior", but Chay and Greenstone (2005) is related to our study in the sense that they provide a quasi-experimental approach to estimate WTP for clean air.

2 Air pollution, Air Purifiers and the Huai River Policy in China

In this section, we provide background information on air pollution in Chinese cities, air purifier markets in China, and the Huai River policy, which are key to our empirical analysis.

2.1 The Main Pollutant in Chinese Cities

Among ambient pollution measures, fine particle matter has shown most consistently an adverse effect on human health in recent medical research (Dockery et al. 1993, Pope et al. 2009 and Correia et al. 2013). Another fact about particle matter is that it is mostly concentrated in developing countries. According to a global map of satellite-derived $PM_{2.5}$ (particulate matter with diameter of 2.5 micrometers or less), northern and eastern China and northern India are the most polluted regions in the world (Van Donkelaar et al., 2010).

Particular matter is also the main air pollutant in Chinese cities. The Chinese Ministry of Environmental Protection (MEP) releases an daily air pollution index (API) in 120 cities since 2000. In each city, a number of monitors record hourly concentration measures of three air pollutants: PM_{10} (particulate matter with diameter of 10 micrometers or less), SO_2 and NO_2. Daily API is converted from one of these pollutants that has the highest daily average value. The API value scales from 0 to 500, the higher the value, the greater the level of air pollution. For example, API value in 0–50 represents excellent air, while an API value over 300 represents heavily polluted air. When API is above 50, the MEP reported the specific type of pollutant from which API was converted. During 2006–2012 in our sample of cities, the main pollutant was PM_{10} for 91%, SO_2 for 8.9%, and NO_2 for 0.15% of the days. The official API, based on ambient PM_{10} for most days, is the only accessible pollution information for Chinese citizens during our sample period.[3] Both daily API level and the main pollutant type are reported to local residents by city weather channel, radio and newspapers.

2.2 Air Purifiers

A key advantage of analyzing air purifier markets is that one of the product attribute—high-efficiency particulate arrestance (HEPA)—informs both consumers and econometricians the puri-

[3]The Chinese government started to report $PM_{2.5}$ in 2014. We focus on 2006-2012 because of the availability and representativeness of our air purifier data in this time period.

fier's ability to reduce indoor particulate matter. According to the US Department of Energy, a HEPA air purifier removes at least 99.97% of particles in 0.3 or larger micrometer in diameter (DOE, 2005). It is more effective for larger particles such as $PM_{2.5}$ and PM_{10}. Recent clinical studies find that the use of HEPA purifiers in various settings provides improvements in health, including reduced asthma visits and asthma symptoms among children, and lower levels of markers for inflammation and heart disease and reduced incidences of invasive aspergillosis among adults (Abdul Salam et al., 2010; Allen et al., 2011; Lanphear et al., 2011). In the Chinese air purifier markets, consistent with the standard by the US Department of Energy, air purifier manufacturers and retail stores explicitly advertise that a HEPA purifier can remove more than 99% of particle matter larger than 0.3 micrometers.

In Chinese cities, HEPA purifiers have about a half of the market share and non-HEPA purifiers have another half of the market share. Non-HEPA purification technologies are designed to remove other target pollutants, not particulate matter. Activated carbon absorbs volatile organic compounds (VOCs), but it does not remove particles. A catalytic converter is effective in removing VOCs and formaldehyde. An air ionizer generates electrically charged air or gas ions, which attach to airborne particles that are then attracted to a charged collector plate. However, there are no specific standards for air ionizers, and they also produce ozone and other oxidants as by-products. A study by Health Canada finds that residential ionizer only removes 4% of indoor $PM_{2.5}$ (Wallace, 2008).

2.3 The Huai River Policy and its Recent Reform

In 1958, the Chinese government decided to provide a centralized heating system. Due to budget constraint, the government provided city-wide centralized heating only to northern cities (Almond et al., 2009). Northern and Southern China are divided by a line formed by the Huai River and Qinling Mountains as shown in Figure 1. The government used this line because the average January temperature is roughly 0° Celsius along the line, and the line was not a border for other administrative purposes (Chen et al., 2013). Cities in the north of the boundary have received unlimited heating in winter every year until recent years. In contrast, cities in the south have not had centralized heating supply from the government.

The centralized heating supply in the north relies on coal-fired heating systems. Two-thirds of heat is generated by heat-only hot water boilers for one or several buildings in an apartment complex, and the other one-third is from combined heat and power generators for larger areas of each city. This system is known to be inflexible and energy inefficient. Consumers have no means to control their heat supply, and until recently there has been no measurement of heat consumption at the consumer level. The incomplete combustion of coal in the heat generation process leads to the release of air pollutants, especially particulate matter. Because most heat is generated by boilers within an apartment complex, the pollution from coal-based heating largely remains local. Almond et al. (2009) find that the Huai River policy led to higher total suspended particulates (TSP) levels in the north. Chen et al. (2013) further find that the higher pollution levels created by the policy led to a loss of 5.5 years of life expectancies in the north.

The heating supply to the north has been consistent since the 1950s, while the payment system under the policy had an important reform in 2003. Prior to 2003, free heating was provided for residents in the north, and employers or local governments were responsible to pay for household heat bills (WorldBank, 2005). It was designed under the centrally planned economy, in which public sector employment dominated the labor market. However, during China's transition to a market economy, heat billing became a practical problem. The size of private sector has increased dramatically since the 1990s, and employers in private sector were not regulated to pay heat bills for their employees. Further, many public sector employees have moved out of public housing and purchased home in the private market, which made it difficult for employers to pay their heat bills in private homes.

In July 2003, the Chinese government issued a heat reform. The reform changed the payment system from free provision to a flat-rate billing (WorldBank, 2005). Individual households became responsible for paying their own heat bills each season, which is a fixed charge per square meter of floor area for the entire season regardless of actual heat usage. Whether heat subsidy is provided by employers varies by sector. In the public sector, former in-kind transfers were changed to a transparent payment for heat added to the wage. In contrast, private sector employers were not explicitly required to provide heat subsidy to their employees. In the 2005 census, 21% of labor force was in urban public sector in the 81 cities in our sample, suggesting that only a small percentage of employees get heat subsidy after the reform.

Our analysis focuses on 2006-2012, after the 2003 reform on heat billing. We summarize the comparison of winter heating between the north and the south. First, the way winter heating has been provided remains the same after the reform. The centralized city-wide heating supply in the north remains the same, where households have little option other than the centralized coal-based heating that generates higher pollution levels. In the south, households choose their own ways to stay warm in winter, including using air conditioners, space heaters, heated blankets, and etc. Second, heating cost in the north has changed since the 2003 reform. Northern households no longer enjoy free heating and instead have to pay a substantial proportion of their heat bills from the centralized heating, while households in the south remain to pay for heating methods of their choice. We collected heating costs in 20 cities within 3 degrees of latitude relative to the Huai River boundary and find that household heating costs in the north are comparable to, or could even be higher than, those in the south.[4]

3 Data and Descriptive Statistics

We compile a dataset from four data sources—air purifier market data, air pollution data, manufacturing/importing location data for each product, and demographic information from the Chinese census. In this section, we describe each data source and provide descriptive statistics.

3.1 Air Purifier Data

We use air purifier sales transaction data collected by a marketing firm in China from January 2006 through December 2012 for 81 cities. The company collected product-store-level scanner data on monthly sales, monthly average price, and product attributes. The data cover a network of major department stores and electrical appliance stores, which take up over 80% of all in-store sales. During 2006-2012, in-store sales consist of over 95% of overall purifier sales. The marketing firm provides us product-level data for in-store sales only. The share of online sales has started to increase significantly since 2013. Therefore, our empirical analysis focuses on data for 2006-2012.

[4]For example, in Xi'an, a city within 1 degree of latitude north to the Huai River, the price of heating per square meter per winter is 3.9USD. For an apartment of 100 square meters, the household pays 390USD. The average subsidy in public sector is 177USD per employee, and the number of public employee per household is 0.32 in the 2005 mini census. The average amount of subsidy per household is 57USD. Therefore, an average household's out-of-pocket payment is 333USD. In southern cities, space heater and heated blankets are the most common choices that could cost 150-200USD including purchasing these devices and the electricity bill in winter for a similar size of home. If a household choose a more expensive option, air conditioning, the electricity bill for three months in winter could be around 240-280USD, and their entire cost depends on the price of the air conditioners that varies to a large extent.

There are 395 products sold by 30 manufacturers in the dataset. The original sales and price data are at the product-city-store-year-month level. In our empirical analysis, the exogenous variation in pollution comes from cross-city variation. Therefore, we aggregate the transaction data to the product-city level. That is, the unit of observation is a product at a city, and the main variables of interest are the product's total sales and average price at the city level during 2006-2012. A unique feature of the dataset is that we observe detailed attributes for each product. The key attribute is a High Efficiency Particulate Arrestance (HEPA) filter, which enables us to quantify the amount of particulate matter that a product is able to remove.

Finally, to address the endogeneity of prices in our empirical analysis, we construct an instrument variable, which measures distance from each product's manufacturing plant (or its port if the product is imported) to each market, aiming to capture variation in transportation cost, which is a supply-side shifter for prices. For each product, we geo-coded the location of its manufacturing plant if it is domestically produced, or the location of the importing port if it is imported. Around 16% of products are imported. We then calculate the distance (km) from the city where the product is sold to its manufacturing plant for domestically produced products and to the importing port for imported products.

3.2 Pollution Data

The official air pollution index (API) is the only accessible air pollution information for Chinese citizens during the period of this study. We obtain daily API data for each city in our sample for 2006-2012 from the Chinese Ministry of Environmental Protection (MEP). In addition to the API level, the data source discloses the type of pollutant from which API was taken from is also disclosed to the public in days when the air quality is not excellent (API is above 50). During the sample period, the main pollutant was PM_{10} for 91% of the days.

The conversion from the concentration of each pollutant to API is based on a known non-linear function. For days that PM_{10} is reported as the main pollutant, we use the official formula from the Chinese MEP to convert daily API to daily PM_{10}. We then calculate the average daily PM_{10} for winter months (December to March) and non-winter months (April to November) at the city level. We calculate PM_{10} for these two seasons separately because the centralized heating in the north of the Huai river is turned on in the late November and turned off at the end of March.

We are cautious in using the API data because recent studies find evidence on underreporting of API at the margin of 100 (Chen et al. 2012, Ghanem and Zhang 2014). The manipulation is motivated by the blue-sky award, which defines a day with API below 100 as a blue sky day and link the number of annual blue sky days to the annual performance evaluation of city governments. For our analysis, we investigate the extent to which potential manipulation affects the average level of API at the city level for the period from 2006 to 2012. In the online appendix, we perform McCrary density tests (McCrary 2008) on daily API data to test potential manipulation and then estimate the effects of the manipulation on the average level of API at the city level. In Figure A.5 in the appendix, we find that the potential manipulation changes the city-level average API for our sample period by negligible amount. This is because the manipulation occurs only at the margin of 100, and therefore it affects the average API for a long time period minimally.

3.3 Demographic Data

We compile demographic data from two sources. First, we obtain city-year measures on population and GDP per capita from *City Statistical Yearbooks* in 2006-2012. Second, we obtain individual-level micro data from the 2005 population census. For each city, the dataset includes demographic variables for a random sample of individuals. We use household-level income data to create the empirical distribution of household annual income for each city, which we use in our empirical analysis. We also aggregate the census data to calculate some additional city-level demographic variables, including average years of schooling and percentage completed college.

3.4 Summary Statistics

Table 1 reports summary statistics. In Panel A, we show the summary statistics of our air purifier data at the product level. In our dataset, there are 395 products manufactured by 30 manufactures, including domestic and foreign companies. Out of the 395 products, 206 products have a HEPA filter, which are 52% of all products. We report product-level summary statistics for all products in column 1, HEPA purifiers in column 2 and non-HEPA purifiers in column 3. For each variable, we also calculate the difference in the means between HEPA purifiers and non-HEPA purifiers and the standard errors for the differences by clustering at the manufacturer level in column 4. Although we observe substantial heterogeneity for each variable at the product level, the difference in the means between HEPA and non-HEPA purifiers is statistically insignificant for sales, market share, other product attributes such as humidifying and room coverage, the distance to the factory or the port, and the frequency of replacing a filter. In contrast, the difference is statistically significant for the price of purifiers and the price of replacement filters. HEPA purifiers are 112 dollars more expensive than non-HEPA purifiers on average, and the difference is statistically significant at the 10% level. HEPA replacement filters are also 20 dollars more expensive than non-HEPA replacement filters, and the difference is statistically significant at the 10% level.

Panel B and C of Table 1 report summary statistics for our two datasets at the city level—pollution data and demographic data. The average PM_{10} in winter months is 115 ug/m^3, while it is 93 ug/m^3 in non-winter months. Cities in our dataset have on average 2.5 million population. The average GDP per capita is 8,277 USD. The average years of schooling is 8.36 years, and the fraction completed college is on average 3.6%.

We also use two maps to show spatial distributions of the cities and manufacturing plants/importing ports in our dataset. Figure 1 shows the location of the 81 cities on the China map in our analysis. The line of Huai River/Qinling Mountains divides China into its North and South. Each dot represents a city in our sample. All cities in our sample are located east to 100 degree of longitude. The river line east to 100 degree of longitude ranges between 32.6 and 34.2 degree of latitude. In our spatial RD approach using the Huai River policy, we define a city's relative latitude north to the river line. Because the river line has several different curved segments, we divide the river line to five segments. In each segment, we measure a city's relative latitude to the middle point of the river latitude range. For example, Beijing locates at 39.9 degree of latitude and 116.3 degree of longitude, and the corresponding middle point of the river latitude range is 33.4 degree. Beijing's relative latitude north to the river line is 6.5 (39.9-33.4) degree. Cities in our sample locate between -12.9 and 14.8 degree north to the river line. In the appendix, we also show Figure A.1, which includes locations of manufacturing plants of domestically produced products and ports of imported products on the map. Most manufacturing plants and ports are located on the east coast.

4 Demand for Air Purifiers

Our goal is to obtain a revealed preference estimate of willingness to pay for clean air by analyzing demand for air purifiers. Because air purifiers are differentiated products with multiple attributes, we start with a standard random utility model for differentiated products.[5] When a consumer purchases an air purifier, the consumer considers utility from the product characteristics and disutility from the price. For our objective, an advantage of analyzing air purifier markets is that one of the product characteristics—high-efficiency particulate arrestance (HEPA)—informs consumers and researchers the purifier's ability to reduce indoor particulate matter. The intuition behind our approach is that the extent to which consumers value this characteristic, along with the price elasticity of demand, provides useful information for their WTP for indoor air quality improvements.

Consider that consumer i in city c has ambient air pollution z_c (particulate matter). The consumer can purchase air purifier j in city c at price p_{jc} to reduce indoor air pollution. Indoor air pollution level conditional on purchasing product j in city c is $z_{jc} = z_c \cdot (1 - e_j)$. We denote purifier j's ability to reduce indoor particulate matters by $e_j \in [0, 1]$. We observe markets for $c = 1, ..., C$ cities with $i = 1, ..., I_c$ consumers. The conditional indirect utility of consumer i from purchasing air purifier j at city c is:

$$u_{ijc} = \beta_i' z_{jc} + \alpha_i p_{jc} + \theta_j + \lambda_c + \xi_{jc} + \epsilon_{ijc}, \tag{1}$$

where z_{jc} is the indoor air pollution for consumers in city c conditional on the purchase of product j, p_{jc} is the price of product j in market c, θ_j is product fixed effects that capture utility gains from unobserved and observed product characteristics, λ_c is city fixed effects, ξ_{jc} is a product-city specific demand shock, and ϵ_{ijc} is a mean-zero stochastic term. β_i' indicates the marginal disutility from indoor pollution, and α_i indicates the marginal disutility for price. The functional form for the utility function assumes that each variable, including the error terms, enter the utility function linearly.

Air purifiers usually run for five years and require replacement of filters several times within

[5] For more detailed discussion on a randomm utility models for differentiated products and its estimation, see Berry (1994); Berry et al. (1995); Goldberg (1995); Nevo (2001); Kremer et al. (2011); Knittel and Metaxoglou (2013).

five years. We consider that consumer i thinks of utility gains from purifier j for five years and p_{jc} as a total cost including the upfront and running cost.[6] This approach abstracts from interesting possibilities that consumers may consider dynamics of product entries and make a dynamic decision. Unfortunately, it is not possible to examine such a dynamic decision in our empirical setting. While we have monthly sales and price data, the exogenous variation in pollution comes from purely cross-sectional variation as opposed to time-series variation. Therefore, our empirical approach focuses on cross-sectional variation in pollution and purchasing behavior, which has to abstract from potential dynamic discrete choices.

We assume that the error term ϵ_{ijc} is distributed as a Type I extreme-value function. We then consider both of a standard logit model and a random-coefficient logit model. A standard logit model assumes that the preference parameters do not vary by i. The attractive feature of this approach is that the random utility model in equation (1) leads to a linear equation. The linear equation can be estimated by linear GMM estimation, which is equivalent to two-stage least squares. A random-coefficient logit model allows the preference parameters to vary by i through observable and unobservable factors. This feature comes at a cost—random-coefficient logit estimation involves nonlinear GMM estimation for a highly nonlinear objective function. We take both approaches to estimate willingness to pay for clean air.

4.1 A Logit Model

We begin with a standard logit model. Suppose that $\beta_i' = \beta'$ and $\alpha_i = \alpha$ for all consumer i and that the error term ϵ_{ijc} is distributed as a Type I extreme-value function. Consumer i purchases purifier j if $u_{ijc} > u_{ikc}$ for $\forall k \neq j$. Then, the market share for product j in city c can be characterized by[7]

$$s_{jc} = \frac{\exp(\beta' z_{jc} + \alpha p_{jc} + \theta_j + \lambda_c + \xi_{jc})}{1 + \sum_{k=1}^{J} \exp(\beta' z_{kc} + \alpha p_{kc} + \theta_k + \lambda_c + \xi_{kc})}. \tag{2}$$

[6] This approach also implicitly assumes that consumers respond to a monetary value of an upfront cost and that of running costs in the same way when they purchase air purifiers. For example, if consumers are myopic, they can be more responsive to an upfront cost than running costs. While we cannot rule out this possibility, recent studies show that empirically consumers are not myopic on the running costs of durable goods (Busse et al., 2013). When calculating the total cost of a purifier, we do not take into account future discount rates for its running cost. However, including discount rates change the total cost for only small amount, and therefore, we find that it does not have a significant change on our empirical findings.

[7] See Berry (1994) for the proof and more detailed discussions.

The outside option ($j = 0$) is not to buy any air purifier. We make a few assumptions to construct the market share for the outside option (s_{0c}). We assume that the number of households in city c are potential buyers and that each household purchases one or zero air purifier during our sample period. Then, s_{0c} can be calculated by the difference between the number of households in city c and the total number of sales in city c. Our second assumption is that $z_{c0} = z_c$. That is, if consumers do not buy any air purifier, they are exposed to indoor pollution that is equal to ambient air pollution. This assumption is one of the reasons why we consider our estimate to be a *lower bound* estimate for the WTP for clean air. Indoor air pollution could be equal to or lower than outside air pollution. The difference between the two pollution levels depends on each household's building structure, air flow, etc., which are unknown to us. Therefore, we take a conservative assumption—indoor pollution in the absence of air purifiers is equal to ambient air pollution. If indoor air pollution is lower than ambient air pollution ($z_0 < z_c$), our estimate of β is underestimated.

Note that the assumptions on the outside option are not required when we include city fixed effects for the standard logit estimation. City fixed effects absorb observable and unobservable variation at the city level. For completeness, we calculate and include the log of market share for the outside option (s_{0c}) in the equation below, but one can see that the term will be absorbed by city fixed effects. The market share for outside options is $\ln s_{0c} = \beta' z_0 - \ln\left(\sum_{k=1}^{J} \exp(\beta' z_{kc} + \alpha p_{kc} + \theta_k + \xi_{kc})\right)$. The difference between log market share for product j and log market share for outside options is,

$$\begin{aligned} \ln s_{jc} - \ln s_{0c} &= \beta'(z_{jc} - z_0) + \alpha p_{jc} + \theta_j + \lambda_c + \xi_{jc} \\ &= \beta \Delta z_{jc} + \alpha p_{jc} + \theta_j + \lambda_c + \xi_{jc}, \end{aligned} \tag{3}$$

where $\Delta z_{jc} \equiv (z_0 - z_{jc})$ is the reduction in indoor air pollution conditional on purifier j, β is the marginal utility for clean air, and α is the marginal disutility from price. The marginal willingness to pay (MWTP) for one unit of indoor air pollution reduction can be obtained by $-\beta/\alpha$.

We interpret that our estimate of $-\beta/\alpha$ provides a *lower bound* of MWTP for one unit of indoor pollution reductions. First, our approach assumes that indoor air pollution levels in the absence of air purifiers equal to ambient pollution levels (z_c). Recent engineering studies show that, on average, indoor pollution levels are lower than outdoor pollution levels in China.[8] One

[8] A study from Tsinghua University finds that, in Beijing, on average, the indoor concentration of $PM_{2.5}$ is 67% of the outdoor concentration of $PM_{2.5}$. See The People's Daily on April 23rd 2015 (Zhang, 2015).

approach we could take is to rely on an engineering estimate of indoor-outdoor air pollution ratio, which would produce slightly larger estimates for the MWTP. However, because we want to be conservative as much as possible, we assume that indoor air pollution levels are equal to outdoor pollution levels, which is likely to underestimate the MWTP. Second, households may have limited information on the negative health effects of air pollution and therefore are likely to underestimate the health risk. If this is the case, our MWTP estimate can be underestimated compared to the case in which consumers are well-informed about the negative health effects of air pollution.

An advantage of studying air purifier markets is that e_j (purifier j's ability to reduce indoor particulate matters) is well-known for consumers. As we explained in Section 2.2, if a purifier has an attribute, High Efficiency Particulate Arrestance (HEPA), it reduces 99% of indoor particular matter. On the other hand, if a purifier does not have HEPA, it does not reduce indoor particular matter. In advertisements and product descriptions of air purifier products in the Chinese markets, consumers are well-informed about the difference between HEPA purifiers and non-HEPA purifiers. Therefore, we define the pollution reduction by $\Delta z_{jc} = z_c \cdot HEPA_j$, which equals z_c if $HEPA_j = 1$ and equals 0 if $HEPA_j = 0$. It implies that conditional on the purchase of a HEPA purifier, consumers can reduce indoor air pollution by z_c. Otherwise, the reduction in indoor air pollution is zero. Note that non-HEPA purifiers do not provide reductions in particular matter but provide other utility gains, including reductions in VOCs and odors. These utility gains are captured by the product fixed effects. Using $\Delta z_{jc} = z_c \cdot HEPA_j$, our random utility model finally leads to an estimation equation:

$$\ln s_{jc} - \ln s_{0c} = \beta z_c \cdot HEPA_j + \alpha p_{jc} + \theta_j + \lambda_c + \xi_{jc}. \tag{4}$$

As we explained above, the log market share of the outside option ($\ln s_{0c}$) will be absorbed by city fixed effects (λ_c). From this equation, we can calculate a *lower bound* of the marginal willingness to pay by $-\beta/\alpha$ if we can obtain consistent estimates of β and α. The empirical challenge is that pollution and price are likely to be endogenous even if we include product fixed effects and city fixed effects. In our empirical strategy section, we explain how we address these endogeneity problems by using instrumental variables.

4.2 A Random-Coefficient Logit Model

In this section, we describe a random-coefficient model, which relaxes some assumptions in the standard logit model. Because general discussions about random-coefficient models are provided extensively in previous studies (Berry et al., 1995; Nevo, 2001; Knittel and Metaxoglou, 2013), we provide a brief description, focusing on key parts for our empirical analysis.

We begin with the same random utility model described in equation (1) but relax the assumptions on β_i' and α_i by allowing the two parameters to vary by consumer i through observable and unobservable factors. We model the two parameters by $\beta_i' = \beta_0' + \beta_1' D_i + u_i$ and $\alpha = \alpha_0 + \alpha_1 D_i + e_i$, where D_i is the log of household-level income from the census data, $u_i \sim N(0, \sigma_\beta)$, and $e_i \sim N(0, \sigma_\alpha)$. That is, each parameter depends on the mean coefficient, log of household-level income, and a normally distributed random error. Denote the part of the utility function that does not depend on i (the mean utility level) by $\delta_{jc} = \beta_0' z_{jc} + \alpha_0 p_{jc} + \theta_j + \lambda_c + \xi_{jc}$, and the part that depends on i by $\mu_{jci} = (\beta_1 D_i + u_i) z_{jc} + (\alpha_1 D_i + e_i) p_{jc}$. Then, the market share for product j in city c can be evaluated using Monte Carlo integration assuming a number n_c of individuals for city c by:[9]

$$s_{jc} = \frac{1}{n_c} \sum_{i=1}^{n_c} s_{jci} = \frac{1}{n_c} \sum_{i=1}^{n_c} \frac{\exp(\delta_{jc} + \mu_{jci})}{1 + \sum_{k=1}^{J} \exp(\delta_{kc} + \mu_{jki})}. \tag{5}$$

The important difference between equations (2) and (5) is that equation (5) now includes elements that depend on i. Therefore, the market share and δ_{jc} has to be calculated numerically by the fixed point iterations: $\delta_{.c}^{h+1} = \delta_{.c}^{h} + \ln S_{.c} - \ln s_{.c}$ for $h = 0, ..., H$, in which $s_{.c}$ is the predicted market share by equation (5) and $S_{.c}$ is the observed market share from the data. Once δ is obtained, ξ_{jc} can be written by $\xi_{jc} = \delta_{jc} - (\beta_0' z_{jc} + \alpha_0 p_{jc} + \theta_j + \lambda_c) \equiv \omega_{jc}$.

The idea behind the estimation is that if there is a set of instrumental variables that are orthogonal to ω_{jc}, the parameters can be estimated by nonlinear GMM using the orthogonality conditions of the instruments and ω_{jc}. Denote the vector of the parameters by θ, and a set of instruments by $\mathbf{Z_{jc}}$. Then, the GMM estimate is

$$\hat{\theta} = \text{argmin} \;\; \omega_{jc}(\theta)'(Z_{jc})\Phi^{-1}(Z_{jc}')\omega_{jc}(\theta), \tag{6}$$

[9] See Nevo (2001) for more detailed discussions.

in which Φ^{-1} is the weight matrix for the GMM estimation. As one can see, the GMM objective function is nonlinear in parameters and does not have a closed form solution. Therefore, the objective function has to be evaluated numerically, and nonlinear-search algorithms are required to find the optimum. In the empirical strategy section below, we describe details about the estimation.

5 Empirical Analysis and Results

In this section, we provide empirical analysis based on the estimating equations derived in the previous section. Our primary goal is to obtain consistent estimates of the preference parameters for pollution (β') and price (α) to calculate the willingness to pay for clean air. We begin with logit estimation in section 5.1 followed by random-coefficient logit estimation in section 5.2.

5.1 Logit Estimation

Our primary empirical challenge is that two variables in our demand estimation—pollution and price—are likely to be endogenous. In an ideal controlled experiment, one would expose different consumers to randomly assigned pollution levels and purifier prices to estimate demand for air purifiers in relation to variation in air pollution. In reality, these two variables are unlikely to be randomly assigned. Air pollution is determined by both observable and unobservable factors. Therefore, we cannot think of observed pollution levels across different cities as exogenous variation because of potential omitted variables. Air purifier prices are also unlikely to be determined exogenously because unobserved factors in demand estimation is believed to be correlated with prices. For example, suppose that some demand factors are unobserved to econometricians but observable to firms, who have the ability to set prices because of imperfect competition. Then, we expect that firms set prices in response to the unobserved demand factors, which creates correlation between prices and the error term in our demand estimation.

To address the endogeneity of air pollution, we exploit a regression discontinuity in air pollution at the spatial border of the Huai river as described in section 2.3. This approach provides us a nearly ideal research environment to answer our research questions for two reasons. First, it allows us to exploit plausibly exogenous variation in air pollution created by the natural experiment. If people value air quality, our demand model in section 4 predicts that the market shares for

HEPA purifiers are discontinuously higher in the cities in the north of Huai river. Second, the discontinuous difference in air pollution created by the Huai River policy has existed for a long time since the 1950s. Therefore, the experiment provides long-run variation in air pollution, which enables us to examine how households respond to variation in pollution that is not transitory but rather long-lasting.

To address the endogeneity of prices, we combine two approaches. First, using the fact that we observe data from many markets (cities) in China, we include product fixed effects and city fixed effects. With these fixed effects, we can absorb product-level unobserved demand factors and city-level demand shocks. Then, the remaining potential concern is product-city level unobserved factors that might affect demand. We construct an instrument variable by measuring distance from each product's manufacturing plant (or its port if the product is imported) to each market, aiming to capture variation in transportation cost, which is a supply-side shifter for prices.

5.1.1 Empirical Strategy

First Stage on Air Pollution: We estimate the first stage on air pollution using a regression discontinuity design in air pollution (PM_{10}) at the border of the Huai river. We denote air pollution (PM_{10}) for city c by z_c, the latitude relative to the Huai River boundary by L_c, a dummy variable for cities north of the Huai River by $North_c = 1\{L_c > 0\}$, and demographic control variables by X_c. For regression discontinuity designs, recent studies suggest that a local linear regression or quadratic polynomials that use observations close to the cutoff provide more robust results than those obtained by high order global polynomial controls for observations far from the cutoff (Imbens and Lemieux, 2008; Gelman and Imbens, 2014). Therefore, we estimate a local linear regression and a local quadratic regression for observations near the cutoff of $North_c = 1$. Our local linear regression is,

$$z_c = \gamma North_c + \gamma_1 L_c + \gamma_2 L_c \cdot North_c + \gamma_3 X_c + \epsilon_c. \tag{7}$$

The identification assumption is that the conditional expectation of the outcome variable (z_c) is smooth at the cutoff. One way to examine the validity of the RD design is to investigate observed variables on either side of the Huai River. In the appendix, we show that there are no significant discrete changes in population, GDP per capita, average years of schooling and fraction completed college at the cutoff (Figure A.3). Nevertheless, we test the robustness of our estimate by including these city demographics as covariates in X_c. Our coefficient of interest, γ, measures the discontinuous increase in z_c just north of the Huai river.

When estimating a regression discontinuity design, one needs to decide the bandwidth of sample that is included in a local linear regression. General consensus in the recent literature is that researchers should report results with several sets of bandwidth choices to examine the robustness, although recent studies provide a few methods to calculate the optimal bandwidth. We estimate the optimal bandwidth for our sample by using methods proposed by Ludwig and Miller (2007), Imbens and Kalyanaraman (2012), and Calonico et al. (2014). A range of bandwidths between 4 and 8 latitude degrees are suggested by these methods. Therefore, we use 6 latitude degrees for our main results and also report all results using bandwidths from 4 to 8 latitude degrees.

Finally, one needs to decide if the regression is ran with kernel weights that assign larger weight on observations near the cutoff. For our main specification, we use a triangular kernel, which is most commonly used in recent studies (Imbens and Kalyanaraman, 2012; Calonico et al., 2014). We also estimate our regressions without weights (or equivalently with rectangular weights for observations within the bandwidth). Because we limit our sample to observation near the cutoff, we find that including or excluding weights does not make substantial changes in the estimation results.

Reduced Form on Log Market Share: Suppose that our first stage on PM10 provides evidence on a discontinuous increase in PM10 at the river boundary. Then, our demand model predicts that the market share for HEPA purifiers should be higher for cities in the north of the river if households value clean air. Our reduced form tests if there is a discontinuous change in the market share for HEPA purifiers at the river boundary. We use our city-product level data to estimate a reduced form equation,

$$\ln s_{jc} = \rho North_c \cdot HEPA_j + \alpha p_{jc} + (\rho_1 L_c + \rho_2 L_c \cdot North_c) \cdot HEPA_j + \theta_j + \lambda_c + \epsilon_{jc}, \tag{8}$$

where θ_j is product fixed effects and λ_c is city fixed effects. Because we include city fixed effects, the log market share for outside options ($\ln s_{0c}$) is dropped from the left hand side variable and $North_c$ is also absorbed by λ_c. We allow the control function for the running variable (latitude) to differ between HEPA purifiers and non-HEPA purifiers by including $(\rho_1 L_c + \rho_2 L_c \cdot North_c) \cdot HEPA_j$.

The reduce form estimation itself provides policy relevant parameters. If we obtain consistent estimates for ρ and α, we can calculate the willingness to pay for removing the amount of pollution generated by the Huai River policy (γ in equation (7)) by $-\rho/\alpha$. The reminding identification problem is that prices are endogenous in the equation. We construct an instrument variable by measuring distance from each product's manufacturing plant (or its port if the product is imported) to each market, aiming to capture variation in transportation cost, which is a supply-side shifter for prices. This instrument provides variation at the city-product level because manufacturing locations or importing ports are different between products. The identification assumption for the IV is that unobserved demand shocks are uncorrelated with the instrument given the fixed effects and control variables in the equation.

Second Stage on Log Market Share: For the second stage regression, we estimate two-stage least squares,

$$\ln s_{jc} = \beta z_c \cdot HEPA_j + \alpha p_{jc} + (\phi_1 L_c + \phi_2 L_c \cdot North_c) \cdot HEPA_j + \theta_j + \lambda_c + \epsilon_{jc}, \tag{9}$$

by using $North_c \cdot HEPA_j$ as the instrument for $z_c \cdot HEPA_j$, and distance as the instrument for p_{jc}. The identification assumption is that the two instruments are uncorrelated with the error term given the control function and fixed effects. The 2SLS provides the marginal willingness to pay for removing 1 unit of PM10 by $-\beta/\alpha$.

5.1.2 Graphical Analysis

Huai River policy generates a natural experiment in air pollution in winter months because the policy-induced pollution comes from centralized heating facilities operating in winter. In Figure 2a, we show the average PM_{10} in winter months (December-March) during 2006-2012 by the running variable, which is the latitudes of cities (L_t). Because very few cities locate in the farthest north and the farthest south, the figure includes cities located within 10 degrees of the latitude from the Huai river boundary. Each plot in the figure shows the average PM_{10} by 1.5 degree of latitude. The vertical line at $L_c = 0$ indicates the location of the Huai river. Consistent with findings in previous studies (Almond et al. (2009), Chen et al. (2013)), the figure suggests a discontinuous increase in PM_{10} just north of the Huai River. This evidence suggests that the coal-based heating policy generated higher pollution levels for cities in the north of the river boundary. We also investigate if a similar discontinuity in air pollution can be found for non-winter months, when the heating facilities do not operate. Figure A.2 in the appendix shows that there is no discontinuous change in PM_{10} levels at the boundary in non-winter months (April-November). This finding provides further support that the discontinuous increase in pollution presented in Figure 2a is likely generated by the Huai river policy.

In Figure 2b, we show an analogous RD figure for our outcome variable. That is, Figure 2b presents graphical analysis for the reduced form regression. We calculate the market share of HEPA purifiers by 1.5 degree of latitude. In the south, the market share of HEPA purifiers are below 60%. The figure indicates that there is a sharp increase in the market share of HEPA at the river boundary and that the share is over 70% in cities just north of the river. In addition, the figure shows that there does not exist strong trend in the outcome variable in latitude. The relatively flat relationship between the outcome variable and the running variable suggests that the choice of functional form for the running variable is unlikely to have substantial impacts on the reduced form estimation.

5.1.3 Estimation Results

Table 2 shows the results of the first stage estimation. We report the first stage estimation for PM_{10} in Panel A. The first two columns show results without demographic controls, and the last two columns show results with demographic controls. We report our estimates from local linear regression and local quadratic regression. Without demographic controls, our estimates imply that there is a discontinuous increase in PM_{10} by 32 to 33 units at the Huai river boundary. The magnitudes of these estimates are consistent with the visual evidence from Figure 2a. With demographic controls, the magnitude becomes slightly larger, but the estimates with and without demographic controls are statistically indifferent. Note that the mean PM_{10} for cities just south of the Huai river is about 115, and it jumped by about 30% just north of the river.

In Panel B of Table 2b, we report the first stage estimation for prices. We include product fixed effects in all columns. Results in columns 1 and 2 imply that one kilometer increase in the distance to the manufacturing plant or importing port is associated with an increase in price by around \$0.03 dollars. Note that the 10th, 25th, 50th, 75th, and 90th percentiles of the distance variable in our data are 230 km, 550 km, 1000 km, 1400 km, and 1700 km and that the average price of air purifiers is \$400. Therefore, the first stage estimates imply that a considerable amount of variation in prices can be explained by transportation costs to markets. In columns 3 and 4, we include city fixed effects to control for potentially confounding factors at the city level. For example, firms possibly set higher prices for cities with higher average income. The results imply that the relationship between distance and prices is robust to the inclusion of city fixed effects. The standard errors are clustered at the product level.

Table 3 shows the reduced form results in Panel A, and the 2SLS results in Panel B. We include product fixed effects and city fixed effects. Consistent with Figure 2b, the reduced form results provide evidence that there is an economically and statistically significant increase in the market share of HEPA purifiers in the north of the river. from both specifications. We calculate the measure of WTP by $-\rho/\alpha$ and calculate its standard error by the delta method. Using local linear regression, the estimates in column 1 imply that the WTP for reducing the amount of air pollution generated by the Huai river policy is \$53 for five years per household. With local quadratic regression in column 2, the magnitudes of the estimates change slightly, but the estimates from the two estimation methods are statistically indifferent.

Finally, we report the 2SLS results in Panel B of Table 3. Similar to the calculation of the WTP for the reduced form, we use the delta method to calculate the standard error for $-\beta/\alpha$, which tells us the marginal WTP for reducing one unit of PM_{10}. The results for the local linear regression indicate that the MWTP is about \$1.6 for five years per household.[10]

[10]Figure A.2 in the online appendix shows that we do not find a discontinuous change in PM_{10} at the river boundary for non-winter months (April-November). This is consistent with the fact that the Huai River policy affects only winter months through its centralized heating. Nevertheless, we consider the possibility that consumers could purchase air purifiers in non-winter months as a response to higher pollution levels in winter months because air purifiers are durable goods. In the online appendix, we test this possibility in Table A.5. The point estimates in the table suggest that demand for HEPA purifiers in non-winter months has a moderate response to differences in winter PM_{10}, but the response is much lower than that in winter months, and most estimates are statistically insignificant. Therefore, our analysis focuses on winter months, which provides variation in pollution from the natural experiment.

5.1.4 Robustness of the Estimates

We first test the robustness of our main results to bandwidth selection. For the second stage estimation in Table 4, we use a range of bandwidths between 4 and 8 latitude degrees. We report results using local linear regression in Panel A and local quadratic regression in Panel B. We use triangular kernel for both functional forms. The results imply that our estimates are stable to a choice of different bandwidths. We also report in Table A.2 and Table A.3 in the appendix that estimates of the first stage and reduced form are also robust, consistent with the visual evidence in Figure 2a and 2b.

One potential concern for our findings is that if high-income or better-educated households prefer HEPA purifiers over non-HEPA purifiers for reasons unrelated to air pollution, the interaction term of income and HEPA or that of education and HEPA can be omitted variables. In Table A.1 in the online appendix, we include the interaction of GDP per capita and HEPA and the interaction of average schooling and HEPA. We find that the results are similar to our main estimates in Table 3.

In terms of the standard errors, we also cluster the standard errors at the city level in 2SLS regressions. Table A.4 in the appendix reports that standard errors clustered at the city level are very similar to those clustered at the model level in the main results.

5.1.5 Potential Confounding Factors to the Estimation

In this section, we consider potential confounders that could bias our results. First, the RD design requires that the conditional expectation of potential outcomes for are smooth in the running variable across the river boundary. While potential outcomes are unobservable, we can examine whether observable variables do not have discontinuities at the river boundary. In Figure A.3 in the online appendix, we show that there are no discontinuous changes in demographic variables across the Huai River boundary.

The second possible concern is sorting of households because of air pollution—households in the north may migrate to the south to seek cleaner air. This sorting, if exists, could bias our estimates. In our case, however, sorting is unlikely to significantly affect our estimates because of strict migration policies enforced by the Chinese government. Internal migration in China is strictly constrained by the *Hukou* system. The *hukou,* obtained at one's city of birth, is crucial for getting local social benefits and education opportunities, which makes migration a more costly decision than that in countries without mobility restriction. Indeed, in the 2005 Census micro-data, only 1 percent of the population within 1.5 latitude degrees north of the Huai river migrated to the south. Therefore, in our case, migration is unlikely to have significant impacts on our estimation.

Third, if there are other policies that use the Huai River boundary, there can be differential impacts of such policies on households in the north and south of the river boundary. However, as described in Chen et al. (2013), this line was used to divide the country for heating policy because the average January temperature is roughly 0° Celsius along the line, and it has not been used for administrative purposes.

Fourth, we are concerned that the Huai River policy may affect purifier purchases for reasons unrelated to air pollution. For example, if we consider that the heating supply to the north has been a public welfare entitlement and subsidized heating cost of northern households, northern households might have higher income because of the heating subsidy. We cannot fully rule out this possibility, but our empirical strategy mitigates this concern for three reasons. First, our estimation includes city fixed effects. Therefore, if the subsidy for heating increases household wealth, which may increase demand for purifiers overall (i.e. both HEPA and non-HEPA purifiers), it does not bias our results. Second, in Table A.1, we find that including the interaction of GDP per capita and HEPA does not change our main estimate. Third, as we discussed in Section 2.3, the heat reform in 2003 changed the payment system from free provision to a flat-rate billing. Of critical importance is the change that northern households have to pay a substantial proportion of their heat bills from the centralized heating since 2003. Therefore, in our analysis during 2006–2012, heating subsidy has minimal effect on household, although we cannot fully exclude the possibility that the subsidy before 2003 may have long-run effects on households during 2006–2012.

A final note is on the availability of HEPA purifier products between the north and south of the river. If HEPA purifiers are more available in the north because appliance stores supply more of them relative to Non-HEPA purifiers, what we observe in Figure 2b might reflect the difference in supply. To directly test this concern, in Figure A.4, we plot the fraction of HEPA purifier products (out of all available purifier products on the market) by 1.5 degree of latitude relative to the Huai River. We do not observe a discontinuous jump on the supply of HEPA purifiers just north to the river boundary.

5.2 Random-Coefficient Logit Estimation

The advantage of the standard logit estimation presented in the previous section is that it can be estimated by conventional two-stage least squares. It does not involve nonlinear estimation. On the other hand, a key assumption in the standard logit model is that the preference parameters are homogeneous across individuals. That is, we implicitly assume that the preference for clean air (β) and price (α) are homogeneous, and hence, the marginal willingness to pay for clean air ($-\frac{\beta}{\alpha}$) is homogeneous across i.

In this section, we relax this assumption and estimate heterogeneity in β and α. We model these parameters by $\beta_i' = \beta_0' + \beta_1 D_i + u_i$ and $\alpha = \alpha_0 + \alpha_1 D_i + e_i$, where D_i is the log of household-level income, $u_i \sim N(0, \sigma_\beta)$, and $e_i \sim N(0, \sigma_\alpha)$. That is, we model that the preference parameters for consumer i depends on the mean coefficient, log of household-level income, and a normally distributed random error.

5.2.1 Nonlinear optimization methods and initial values

Random-coefficient demand estimation requires nonlinear GMM estimation for a nonlinear objective function that does not have a closed form solution. Because its nonlinear objective function most likely have multiple local optima, the estimation has to be based on a nonlinear-search algorithm with a set of starting values and stopping rules for termination. Recent studies show challenges and cautions regarding such numerical optimization and provide some guidelines for researchers to assess robustness of their estimation results. For example, Knittel and Metaxoglou (2013) show that it is important to estimate a random-coefficient demand model with different sets of 1) nonlinear-search algorithms and 2) starting values, with conservative stopping values (i.e. conservative tolerance levels for nonlinear searches) to investigate if the estimated local optimum is indeed the global optimum of the GMM objective function.

We follow the approach taken by Knittel and Metaxoglou (2013), in which they estimate a model with different sets of search algorithms, starting values, and tolerance levels. For nonlinear-search algorithms, we use three derivative-based algorithms (SOLVOPT, quasi-Newton 1, and quasi-Newton 2) and a deterministic direct search algorithms (Simplex). For starting values for coefficients on nonlinear parts of our equation, we use 100 sets of draws from a standard normal distribution for each nonlinear-search algorithms. That is, for each algorithm, we run the estimation with 100 sets of starting values and make sure that we find the same optimum from different search algorithms. Recent studies show that the tolerance level should be set to a particularly conservative level for the nested fixed-point iterations that calculate market shares. We set the tolerance level for the nested fixed-point iterations to 1E−09, and the tolerance level for changes in the parameter vector and objective function to 1E−03.

5.2.2 Estimation results

We find that three search algorithms (SOLVOPT, quasi-Newton 2, and Simplex) lead to the same minimum value of the objective function. With our datasets, the Newton 1 search algorithm is sensitive to a set of initial values, and its minimum value of the objective function is larger than those obtained by the other three algorithms. This is consistent with the finding by Knittel and Metaxoglou (2013), in which they use the automobile datasets used by Berry et al. (1995), and ready-to-eat cereal datasets used by Nevo (2001). We report estimation results by using the minimum value of the objective function obtained by these three algorithms.

Table 5 shows the results. Same as our standard logit estimation, we use two sets of controls for latitude for our regression discontinuity design. Model 1 uses linear and linear interacted with the indicator variable for cities in the north side of the Huai river, and model 2 uses quadratic controls for the latitude. The results provide several key findings for heterogeneity in preference parameters. First, the mean marginal willingness to pay is \$1.6, similar to the estimate of the standard logit model in Table 3. Second, the standard deviations for marginal utility of clean air and price imply that there is unobserved heterogeneity among households. Third, we find that the interaction with log household-level income is positive for both parameters. It implies that higher-income households have larger valuation for clean air, and they are less price-elastic than lower-income households.

Figure 3 shows the distribution of estimated marginal willingness to pay for clean air based on the estimation results by Model 1. Note that we have household-level income data for a random sample of households in each city. We use each household's income D_i, two random errors from two standard normal distributions: $u_i \sim N(0, \hat{\sigma_\beta})$ and $e_i \sim N(0, \hat{\sigma_\alpha})$, and coefficients from the estimation to calculate the estimated household-level marginal willingness to pay. Note that the estimated marginal willingness to pay is based on a set of assumptions we make in the estimation, including the functional form of the utility function. With this caveat in mind, the histogram provides useful information for our estimates. First, the mean of the distribution is close to the mean of the marginal willingness to pay obtained by the estimates for ${\beta'}_0$ and α_0. Second, the distribution indicates that there is wide dispersion of marginal willingness to pay, and in particular, the distribution has a long tail to the right. That is, our estimates imply that there are a small set of households who have substantially larger marginal willingness to pay for clean air in China.

Figure 4 shows how the estimated marginal willingness to pay is related to log of household-level income. The income distribution is based on household-level income data from the 2005 Census. There is a long right tail in the distribution with small number of households whose income is larger than \$20,000. Our estimation is based on data including these households. In the figure, we drop data for income larger than \$20,000 to make it easy to visualize the majority of the distribution. The line shows a fitted line of our MWTP estimate by income levels. The figure indicates that the marginal willingness to pay is increasing in income, ranging from about \$1 to \$5 for the range of income between \$0 to \$20,000.

Overall, the results of the random-coefficient model provides a few key implications, given the assumptions required for the nonlinear GMM estimation. In our case, the results from the standard logit is not far from the ones obtained by the random-coefficient estimation if our focus is only on the mean of the marginal willingness to pay. However, the random-coefficient estimation highlights heterogeneity in the marginal willingness to pay. In particular, the results indicate that higher-income and lower-income households have significantly different levels of the marginal willingness to pay for clean air.

6 Policy Implications

Our findings provide important policy implications for ongoing discussions in energy and environmental regulation in developing countries. Governments in developing countries recently proposed and implemented a variety of interventions to their air pollution problems. For example, Chinese Premier Li, Keqiang declared "War Against Pollution" to reduce emission of PM_{10} and $PM_{2.5}$ (Zhu, 2014) and proposed various reforms in energy and environmental policies. A key question is whether implementing such policies enhances welfare or not.

For example, in 2005, the Chinese government and the World Bank started a pilot reform to improve the Huai river policy in seven northern cities. The primary goal of the reform is to save energy usage and reduce air pollution by introducing household metering and consumption-based billing, under which consumers pay for actual heat consumption and are able to control how much heat they consume.[11] Ten years after the start of the pilot reform, there is still ongoing debate about the reform—whether such a reform would improve welfare, and whether similar reforms should be implemented in other northern cities in China. The main challenge is that costs of installing individual meters and adopting consumption-based billing are high,[12] while benefits of the reform have not yet been systematically examined.

In this section, we provide an evaluation of this reform as an example to illustrate how our estimate on the WTP for clean air can be used to examine a welfare implication of an environmental policy. While we want to emphasize that our analysis is based on back-of-envelop calculation with a set of assumptions, this analysis can help shed light on the importance of WTP for clean air for policy discussion of optimal environmental regulation.

The WTP estimate in the previous sections informs us how much a household is willing to pay if the reform produces a reduction in particle matter. Our estimate implies that a northern household is willing to pay 53 dollars if the pollution generated by the Huai river policy can be removed. We use this estimate to provide a cost-benefit analysis of the heat reform. First, WorldBank (2014) estimates that the pilot heat reform in seven cities can generate a total reduction in coal usage by 51 million tons over a 20-year period at the total abatement cost of $18 million. Thus, over 20 years, the reduction in coal usage per city is 0.36 million tons per year at the abatement cost of $0.13 million per city per year. Second, the *China Daily* reports that all northern cities use over 700 million tons of coal at their centralized heating facilities alone per year (ChinaDaily, 2015), suggesting that an average northern city uses 5.3 million tons of coal for their centralized heating

[11] As we describe in Section 2.3, the 2003 reform in all northern cities replaced free heating provision with a flat-rate billing. Households pay a fixed charge per square meter for heating of the entire winter, which does not depend on the actual amount of usage. The flat-rate billing provides no incentives for households to respond to market-based energy costs.

[12] The People's Daily reported on October 23rd 2009 (People'sDaily, 2009) that, the vice minister of the Ministry of Housing and Urban-Rural Development summarized three obstacles of implementing the heat reform: 1) many new construction projects refuse to install household meters because they are expensive; 2) it is costly to remodel old buildings to accommodate the installation of household meters; 3) it is costly to build a new consumption-based billing system.

per year. If we consider the percentage of coal reductions from the pilot heat reform, it is 7% (= 0.36/5.3) per city. Third, our WTP estimate suggests that a northern households is willing to pay \$53 for cleaning up the air from heating-induced pollution for for a period of five years. That is, the annualized willingness to pay is \$11 (= 53/5) per year.

We make a simplifying assumption on the relationship between reductions in coal usage and reductions in PM_{10}. We assume that a certain percent reduction in coal usage for heating leads to the same percent reduction in PM_{10}. This assumption can overestimate or underestimate it, depending on the actual relationship between the two variables. With this simple one-to-one assumption, we obtain that a household is willing to pay \$0.77 ($= 11 \cdot 0.07$) per year for a 7% reduction in PM_{10}. Because the average number of households in a northern city is 0.63 million, the total willingness to pay is \$0.49 ($= 0.77 \cdot 0.63$) million per city per year. This estimate, the total benefits of the reform for households, is larger than the abatement cost, which is \$0.13 million per city per year. Note that this benefit estimate is a *lower bound* estimate because our WTP estimate is a lower bound. Therefore, our analysis suggests that even if we consider the lower bound estimate of the benefits, the heat reform is likely to be cost-effective. Our analysis suggests that the expansion of the heat reform to other northern cities could enhance household welfare.

More broadly, our WTP estimate is useful for evaluating a series of new energy policies and environmental regulations that were recently announced. For example, as featured by the *New York Times*, \$1.65 billion a year is offered to reward cities and regions that make “significant progress” in air pollution control (Wong, 2014a), tougher fines are enforced for polluters (Wong, 2014b), and coal-fired power plants will be upgraded to cut pollution from power plants by 60 percent by 2020 (Wong, 2015). More prominently, as the the world’s largest greenhouse gas polluter, China recently made commitments to address global climate change by launching a national cap-and-trade program in 2017, when the government will set a cap on total carbon emissions and firms can buy and sell emission permits (Davenport and Hirschfeld, 2015). For these policies, policymakers could compare the abatement costs to our WTP estimate to assess welfare implications of the policy.

7 Conclusion

In this paper, we provide among the first revealed preference estimate of willingness to pay (WTP) for clean air in developing countries. We examine the demand for home-use air purifiers, a main defensive investment for reducing indoor air pollution, which provides valuable information for estimating a *lower bound* of WTP for air quality improvements. Our empirical strategy leverages the Huai River heating policy, which created discontinuous quasi-experimental and long-run variation in air pollution between the north and south of the river. Using a spatial regression discontinuity design, we estimate that the willingness to pay for removing the amount of pollution generated by the Huai River policy is 53 dollars, and the marginal willingness to pay for removing 1 ug/m^3 PM_{10} is 1.6 dollars.

While we find higher amount of WTP for environmental quality compared to previous studies in developing countries (Kremer et al., 2011), our estimate is still low if we compare it to similar estimates in the United States (Chay and Greenstone, 2005; Deschenes et al., 2012). An important direction for future research is to understand the reasons for this difference. For example, if households fully understand the negative effects of air pollution on health and labor supply, do they have higher willingness-to-pay for clean air? Can policies be designed to provide information to the public on the pollution-health relationship to affect household responses to pollution? Answers to these questions are expected to advance the economics literature on environmental regulation and improve policy design to address pollution problems in many countries.

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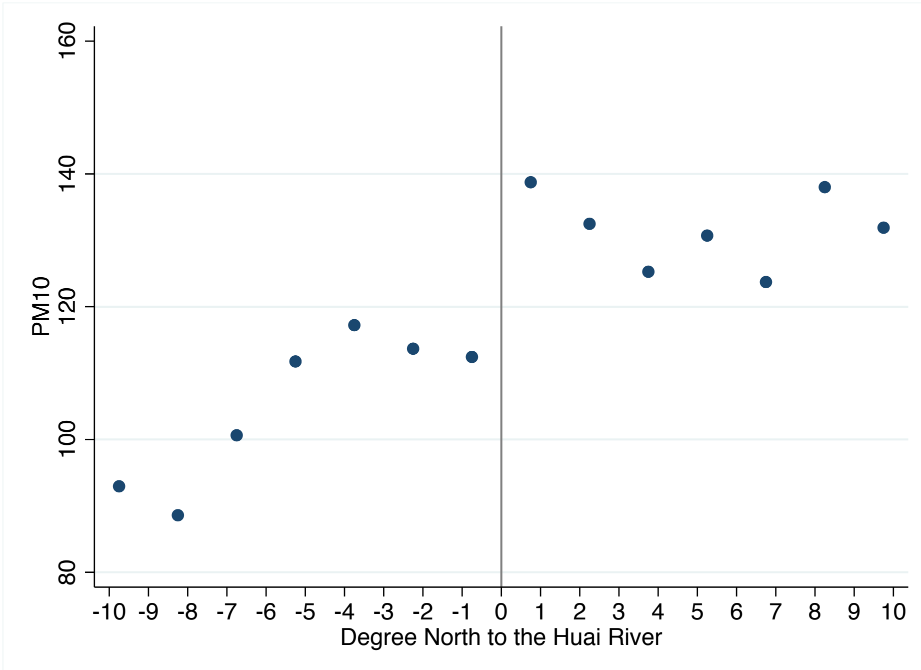
Figure 1: Huai River Boundary and City Locations

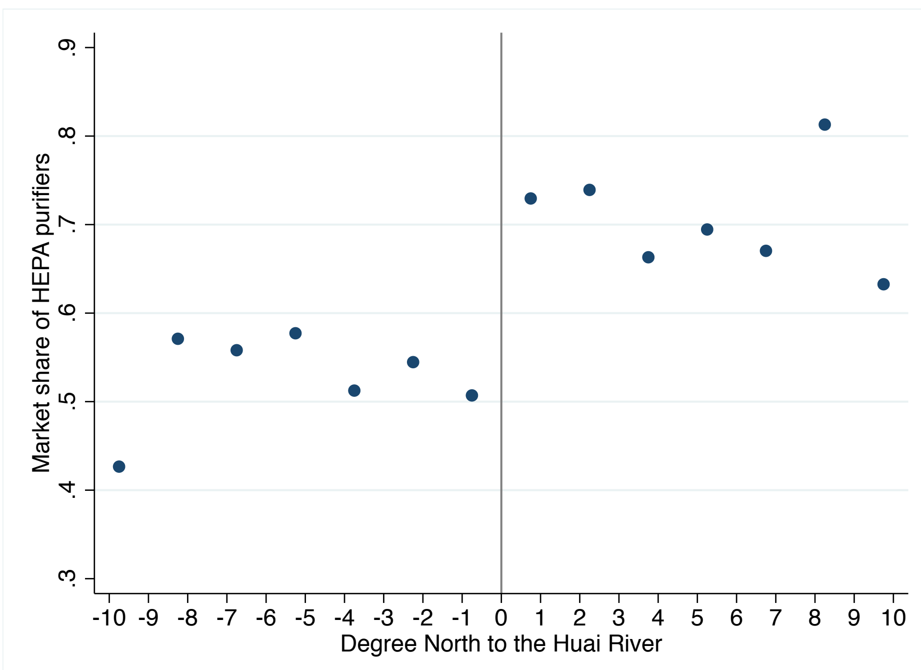
Notes: The line in the middle of the map is the Huai River-Qinling boundary. Each dot represents 1 city. There are 81 cities in our sample.

Figure 2: Regression Discontinuity Design at the Huai River Boundary

(a) PM10 in Winter

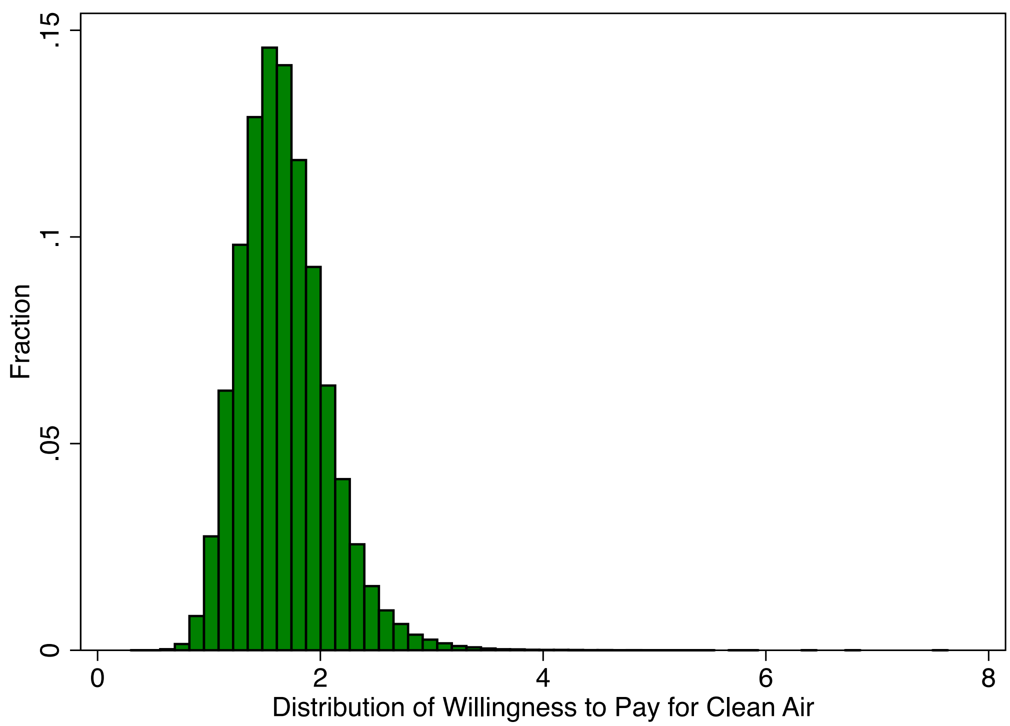


(b) Market Share of HEPA Purifiers in Winter



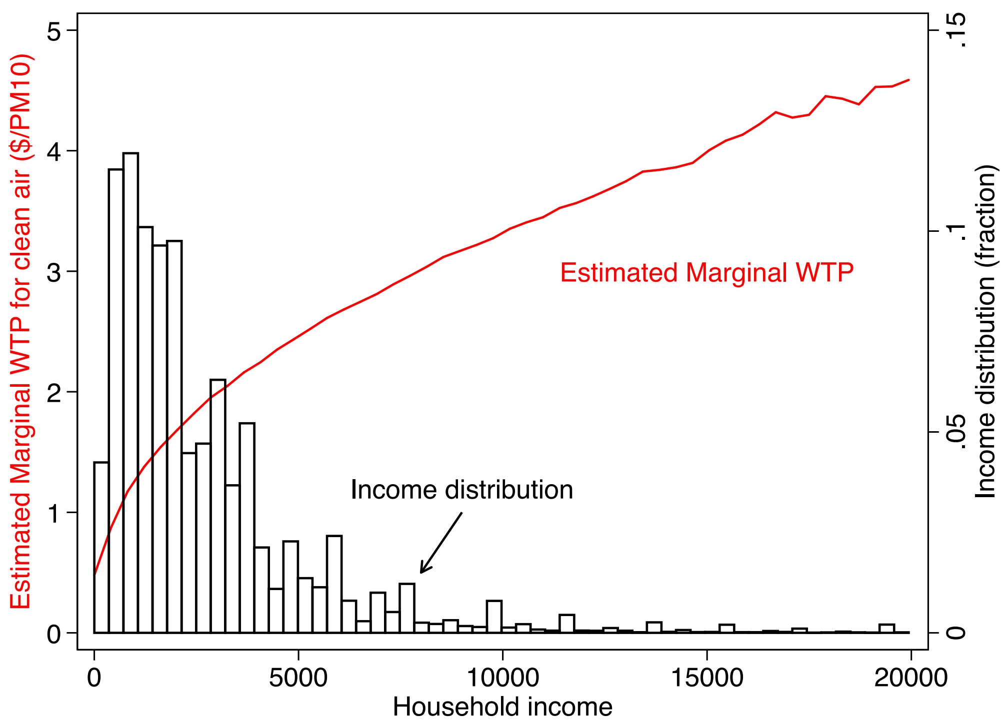
Notes: Figure 2a plots the average PM_{10} during winter (December-March) in 2006-2012 by 1.5 degrees of latitude north to the Huai River boundary. The vertical line at 0 indicates the location of the river. Each dot represents cities in 1.5 degrees of latitude and corresponds to the middle point of the range on the x-axis. For example, the dot at 0.75 on the x-axis represents cities between 0 and 1.5 degrees of latitude north to the river line. The y-axis indicates the average PM_{10} level of cities within 1.5 degrees of latitude. Figure 2b shows the market share of HEPA purifiers in winter by 1.5 degrees of latitude north to the Huai River line.

Figure 3: The Distribution of Estimated Marginal Willingness to Pay for Clean Air



Note: The histogram is based on the estimates of the random coefficient logit model in Table 5 and household-level income from the census.

Figure 4: Estimated Marginal Willingness to Pay for Clean Air over Household Income



Note: This figures plots the estimated marginal willingness to pay over household income based on the estimates of the random coefficient logit model in Table 5 and household-level income from the census.

Table 1: Summary Statistics

	(1) Whole sample	(2) HEPA purifiers	(3) Non-HEPA purifiers	(4) Difference in means
Panel A: Air purifier data (product level)				
Percentage of HEPA purifiers	0.52			
	(0.50)			
Number of sales	495.96	570.18	415.07	155.11
	(1285.791)	(1525.62)	(956.14)	[259.27]
Market share	0.0025	0.0029	0.0021	0.0008
	(0.0066)	(0.0078)	(0.0049)	[0.0013]
Price of a purifier (USD)	411.12	464.54	352.56	111.65*
	(350.28)	(358.89)	(331.90)	[54.70]
Humidifing	0.134	0.136	0.132	0.004
	(0.341)	(0.344)	(0.340)	[0.069]
Room coverage (square meter)	41.87	44.00	38.89	5.11
	(22.77)	(24.12)	(20.50)	[4.88]
Distance to factory or port (km)	901.21	898.66	903.99	-5.34
	(358.29)	(321.28)	(395.56)	[68.62]
Price of a replacement filter (USD)	45.46	54.72	35.04	19.68*
	(48.08)	(59.78)	(26.43)	[9.65]
Replacement frequency (in months)	9.04	10.02	8.02	2.01
	(6.05)	(6.71)	(5.08)	[1.47]
Panel B: Pollution data (city level)				
PM10 in Winter (ug/m3)	114.85			
	(24.63)			
PM10 in Non-winter (ug/m3)	92.97			
	(14.93)			
Panel C: Demographics data (city level)				
Population (1,000)	2497.70			
	(2719.96)			
GDP per capita (USD)	8276.97			
	(3405.99)			
Annual household income in 2005 (USD)	2253.5			
	(1212.4)			
Years of schooling in 2005	8.36			
	(0.89)			
Fraction completed college in 2005	0.036			
	(0.027)			

Notes: The product-level sample has 395 products of 30 brands. 206 products are HEPA purifiers and 189 are Non-HEPA purifiers. In column (1)-(3), standard deviations are reported in parentheses. In column (4), standard errors clustered at the brand level are reported in brackets. * significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Table 2: First Stage Estimation for PM10 and Prices

(a) First Stage Estimation for PM10

	PM10			
	(1)	(2)	(3)	(4)
North	33.36***	31.81***	36.75***	36.58***
	(9.43)	(9.02)	(9.18)	(9.29)
Observations	50	50	50	50
R^2	0.24	0.24	0.51	0.51
Functional form	Linear*North	Quadratic	Linear*North	Quadratic
Demographic controls			Y	Y

(b) First Stage Estimation for Air Purifier Prices

	Price			
	(1)	(2)	(3)	(4)
Distance (to factory or port)	0.029***	0.030***	0.034***	0.034***
	(0.006)	(0.006)	(0.007)	(0.007)
Observations	3,343	3,343	3,343	3,343
R^2	0.96	0.96	0.96	0.96
Functional form	Linear*North	Quadratic	Linear*North	Quadratic
Product FE	Y	Y	Y	Y
City FE			Y	Y

Notes: In Table 2a, each observation represents a city. In Table 2b, each observation presents a product-city. City-level demographic controls include population and GDP per capita from City Statistical Yearbook (2006-2012), and average years of schooling and fraction completed college from the 2005 Census microdata. In Table 2b, standard errors in parentheses are clustered at the model level. * significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Table 3: Reduced Form and 2SLS Estimation Results

	ln(market share)	
	(1)	(2)
Panel A: Reduced form		
North*HEPA	0.717***	0.640**
	(0.268)	(0.258)
Price	-0.013***	-0.013***
	(0.004)	(0.004)
WTP	53.344**	47.575**
	(24.458)	(23.324)
Observations	3,343	3,343
First-Stage F-Stat	22.68	22.72
Panel B: 2SLS		
PM10*HEPA	0.022**	0.020**
	(0.009)	(0.008)
Price	-0.014***	-0.014***
	(0.004)	(0.004)
MWTP	1.587**	1.435**
	(0.713)	(0.688)
Observations	3,343	3,343
First-Stage F-Stat	11.46	11.54
Functional form	Linear*North	Quadratic
Product FE	Y	Y
City FE	Y	Y

Notes: Each observation represents a product-city. Panel A presents reduced-form estimates, where price is instrumented with distance to factory/port. Panel B presents 2SLS results, where PM10*HEPA is instrumented with North*HEPA and price is instrumented with distance to factory/port. Standard errors in parentheses are clustered at the model level. * significant at 10% level; ** significant at 5% level; *** significant at 1% level. Stock-Yogo weak identification test critical value for for one endogenous variable (10% maximal IV size) is 16.38 and for two endogenous variables (10% maximal IV size) is 7.03.

Table 4: Robustness Checks of 2SLS

	ln(market share)				
	(1) 4-degree	(2) 5-degree	(3) 6-degree	(4) 7-degree	(5) 8-degree
Panel A: Linear*North					
PM10*HEPA	0.016**	0.018**	0.022**	0.028***	0.032***
	(0.008)	(0.007)	(0.009)	(0.011)	(0.012)
Price	-0.011***	-0.012***	-0.014***	-0.017***	-0.019***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
MWTP	1.475*	1.544**	1.587**	1.679**	1.670**
	(0.869)	(0.780)	(0.713)	(0.707)	(0.697)
Observations	2,413	3,046	3,343	3,865	4,057
First-Stage F-Stat	8.45	9.45	11.46	11.79	11.69
Panel B: Quadratic					
PM10*HEPA	0.017**	0.017**	0.020**	0.026**	0.030**
	(0.008)	(0.007)	(0.008)	(0.010)	(0.012)
Price	-0.011***	-0.012***	-0.014***	-0.017***	-0.019***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
MWTP	1.511*	1.460*	1.435**	1.519**	1.539**
	(0.858)	(0.746)	(0.688)	(0.683)	(0.679)
Observations	2,413	3,046	3,343	3,865	4,057
First-Stage F-Stat	8.39	9.47	11.54	11.89	11.80
Product FE	Y	Y	Y	Y	Y
City FE	Y	Y	Y	Y	Y

Notes: Each observation represents a product-city. This table presents 2SLS results, where PM10*HEPA is instrumented with North*HEPA and price is instrumented with distance to factory/port. Standard errors in parentheses are clustered at the model level. * significant at 10% level; ** significant at 5% level; *** significant at 1% level. Stock-Yogo weak identification test critical value for two endogenous variables (10% maximal IV size): 7.03.

Table 5: Random-Coefficient Logit Estimation Results

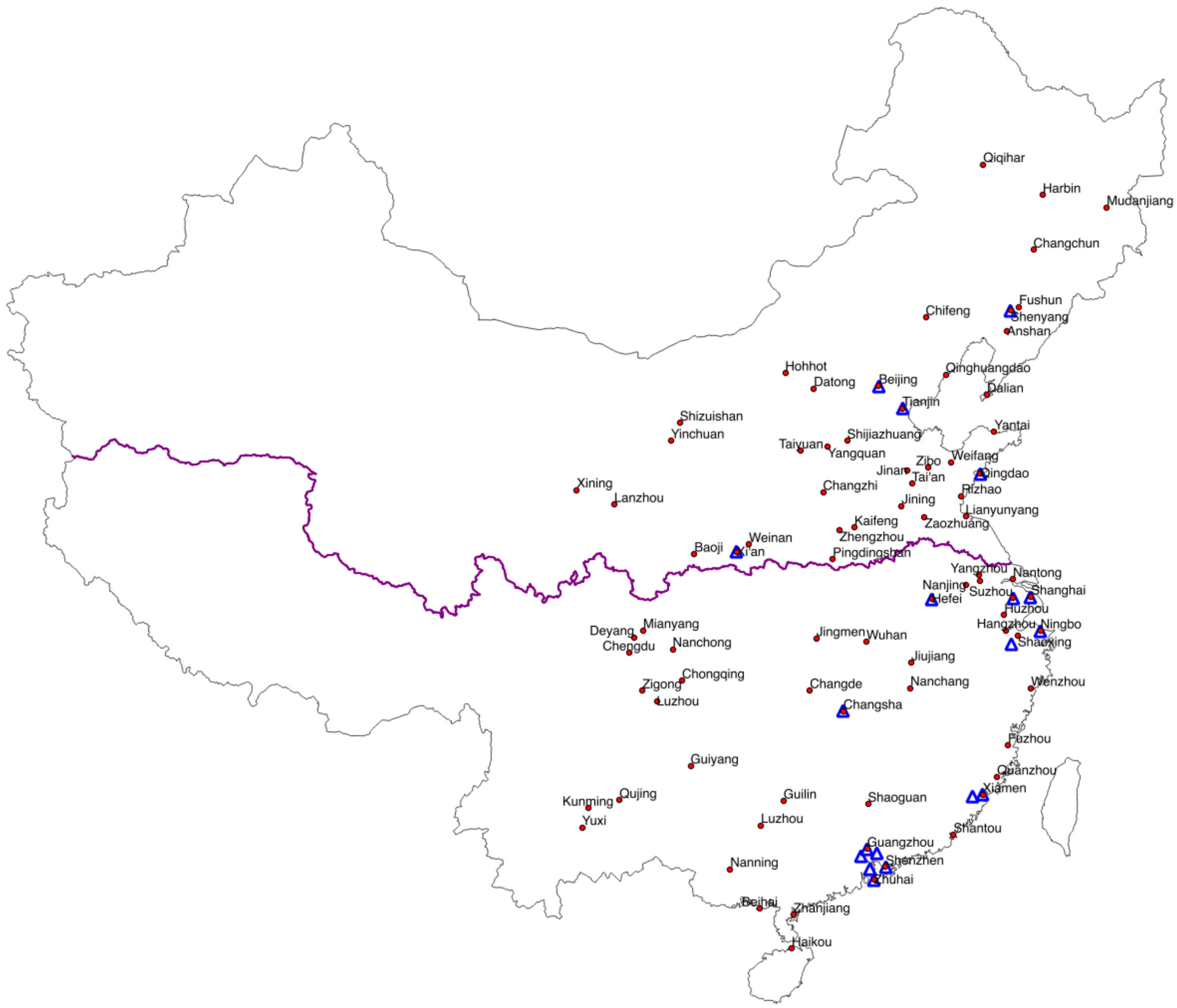
	Model 1			Model 2		
	Mean	Standard deviation	Interaction w. Log Income	Mean	Standard Deviation	Interaction w. Log Income
PM10 · HEPA	0.034	0.029	0.082	0.032	0.028	0.087
	(0.011)	(0.015)	(0.029)	(0.010)	(0.013)	(0.030)
Price	-0.021	0.015	0.041	-0.021	0.016	0.043
	(0.008)	(0.009)	(0.020)	(0.008)	(0.009)	(0.017)
Mean MWTP	1.619			1.524		
Observations	3,343			3,343		

Notes: This table shows the results of the random coefficient logit estimation in equation (6). Model 1 uses a linear control for the latitude interacted with the North dummy variable, and Model 2 uses a quadratic control for the latitude. Asymptotically robust standard errors are given in parentheses.

Online Appendices Not For Publication

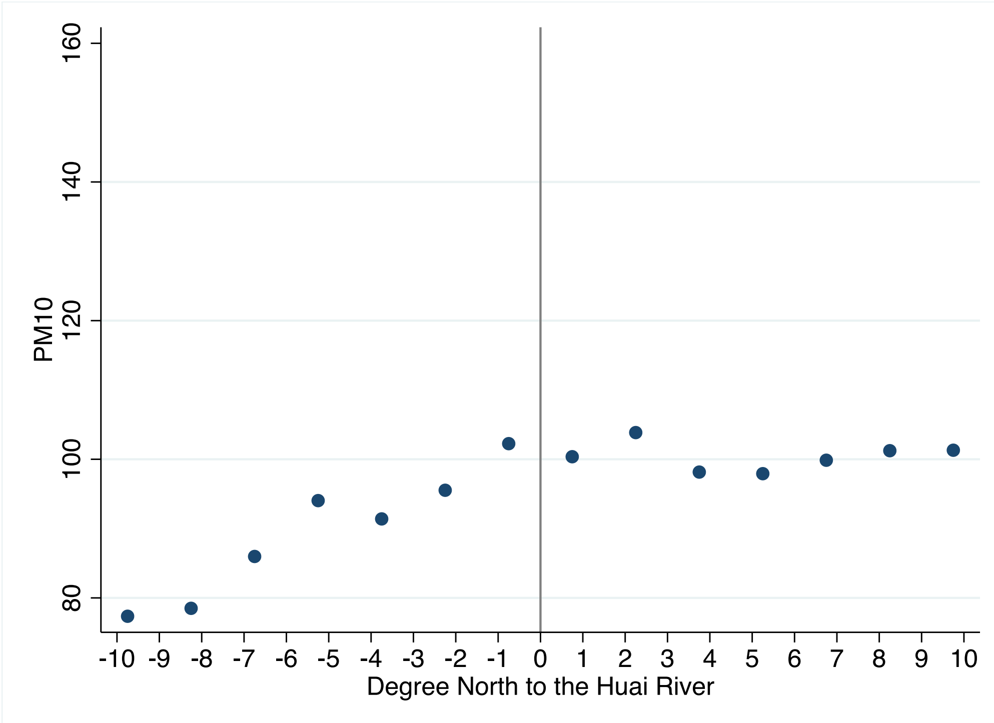
A Additional Figures

Figure A.1: Huai River Boundary and City Locations



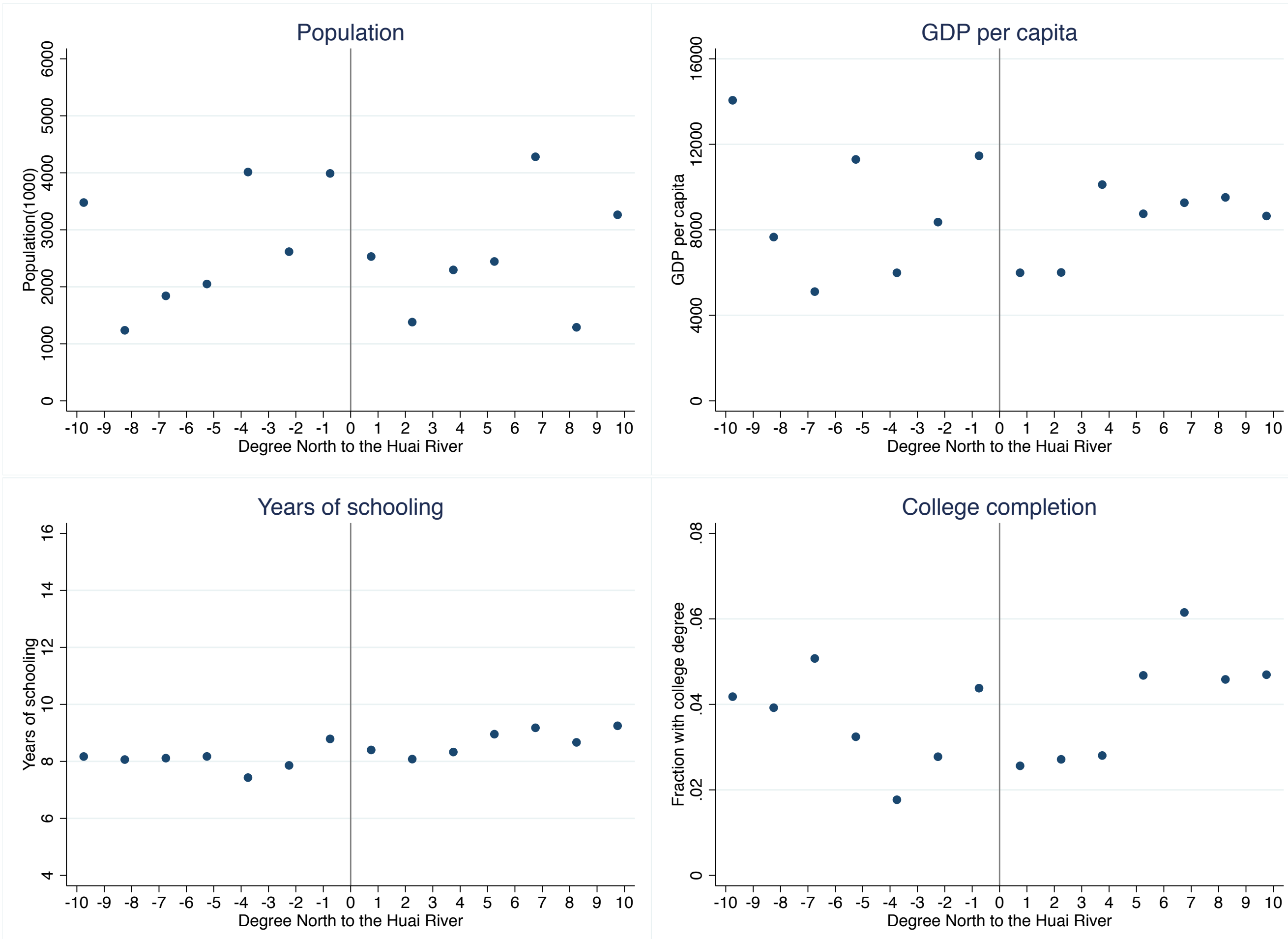
Notes: The line in the middle of the map is the Huai River-Qinling boundary. Each dot represents 1 city. Each triangle represents a factory location or a port location.

Figure A.2: Huai River: PM10 in non-winter months (April-November)



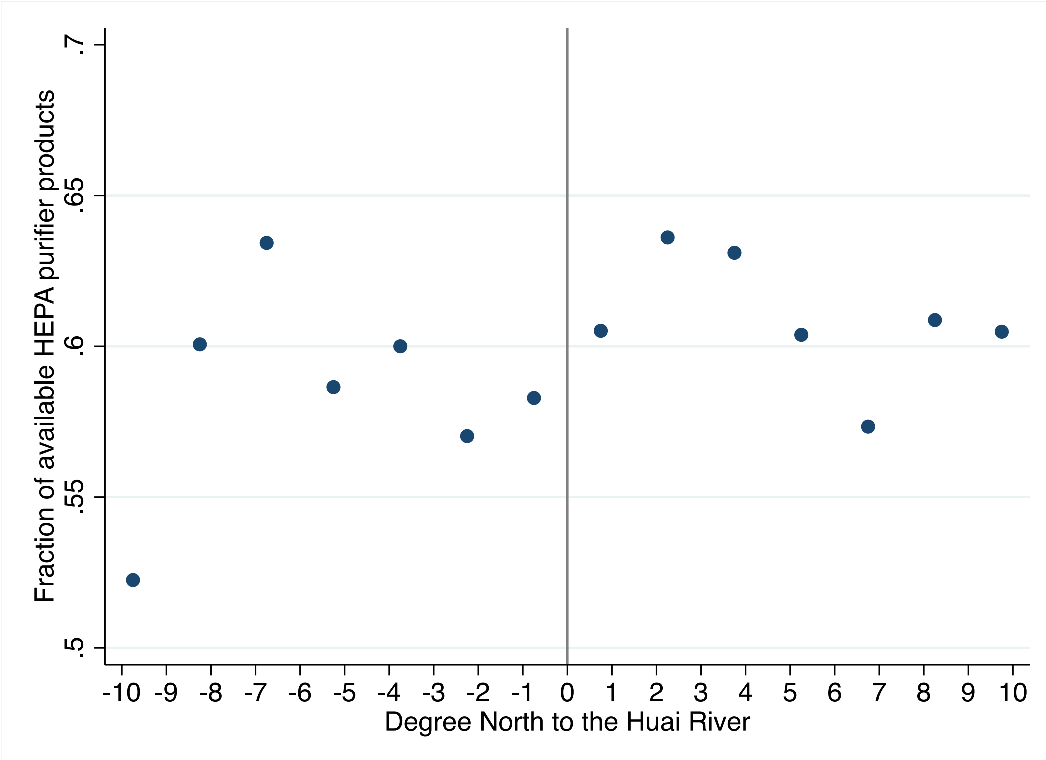
Notes: This figure plots the average PM_{10} during non-winter months (April-November) in 2006-2012 by 1.5 degrees of latitude north to the Huai River boundary. The vertical line at 0 indicates the location of the river. Each dot represents cities in 1.5 degrees of latitude and corresponds to the middle point of the range on the x-axis. For example, the dot at 0.75 on the x-axis represents cities between 0 and 1.5 degrees of latitude north to the river line. The y-axis indicates the average PM_{10} level of cities within 1.5 degrees of latitude.

Figure A.3: Huai River and Demographics



Notes: These figures plot the mean of each demographic variable by 1.5 degrees of latitude north to the Huai River boundary. The vertical line at 0 indicates the location of the river. Each dot represents cities in 1.5 degrees of latitude and corresponds to the middle point of the range on the x-axis. For example, the dot at 0.75 on the x-axis represents cities between 0 and 1.5 degrees of latitude north to the river line. The y-axis indicates the mean level of each variable in cities within 1.5 degrees of latitude.

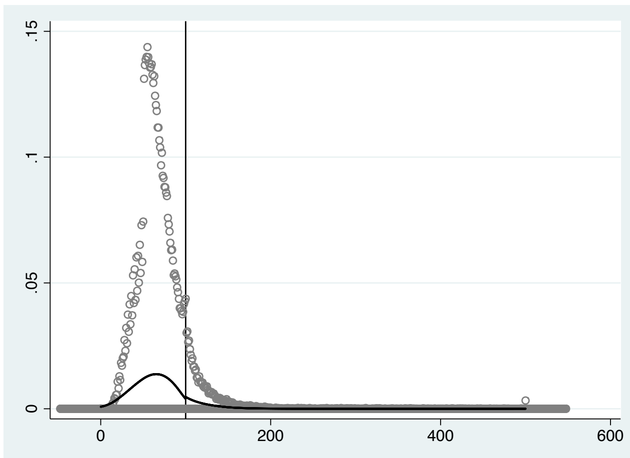
Figure A.4: Fraction of available HEPA purifier products



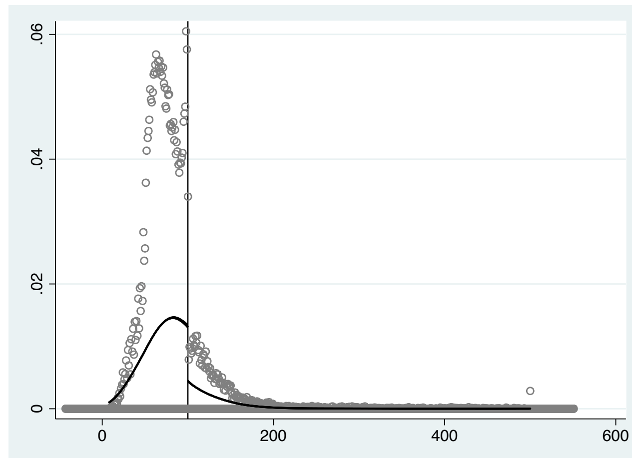
Notes: This figure plots the fraction of available HEPA purifier products out of all purifier products by 1.5 degrees of latitude north to the Huai River boundary. The vertical line at 0 indicates the location of the river. Each dot represents cities in 1.5 degrees of latitude and corresponds to the middle point of the range on the x-axis. For example, the dot at 0.75 on the x-axis represents cities between 0 and 1.5 degrees of latitude north to the river line. The y-axis indicates the mean level of each variable in cities within 1.5 degrees of latitude.

Figure A.5: API distribution

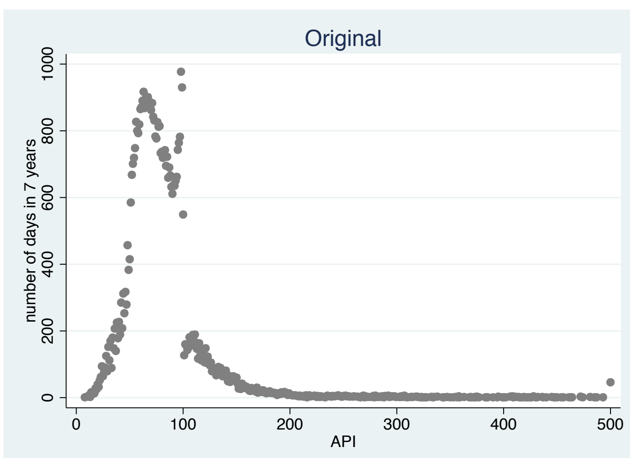
(a) McCrary density test (75% of sample)



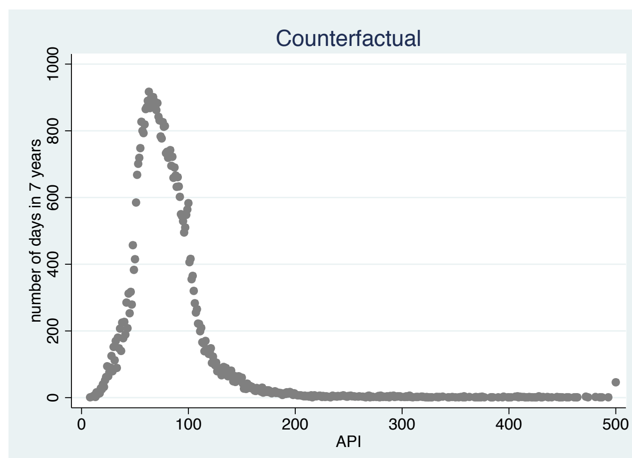
(b) McCrary density test (25% of sample)



(c) Original distributions of the 25% sample



(d) Counterfactual distribution of the 25% sample



Notes: To investigate potential manipulation in our sample, we perform McCrary density tests (McCrary 2008) on daily API data for each city during 2006–2012. We report the results in the online appendix. In 75% of city-year observations, we find no statistically significant bunching in the density of daily API at 100 in Figure A.5a. There is a statistically significant bunching at 100 in 25% of city-year observations in Figure A.5b. To examine to what extent the bunching in the 25% of city-year observations changes the average API, we use the distribution of API in the 75% non-manipulation city-year observations to estimate a counterfactual distribution for the 25% manipulation subsample. Figure A.5c shows the original distribution of API in the 25% subsample, where the mean of API is 147.90. Figure A.5d shows the the counterfactual distributions of API in the same 25% subsample, where the mean of API is 147.95. That is, the potential manipulation changes the city-level average API for our sample period by negligible amount. This is because the manipulation occurs only at the margin of 100, and therefore it affects the average API for a long time period minimally.

B Additional Tables

Table A.1: Controlling for GDP*HEPA and Schooling*HEPA

	ln(market share)	
	(1)	(2)
Panel A: Reduced form		
North*HEPA	0.702***	0.606**
	(0.264)	(0.251)
Price	-0.013***	-0.013***
	(0.003)	(0.003)
WTP	52.173**	45.012**
	(22.932)	(21.544)
Observations	3,343	3,343
Panel B: 2SLS		
PM10*HEPA	0.026**	0.021**
	(0.010)	(0.009)
Price	-0.014***	-0.014***
	(0.004)	(0.004)
MWTP	1.835**	1.490**
	(0.806)	(0.707)
Observations	3,343	3,343
First-Stage F-Stat	11.38	11.48
Functional form	Linear*North	Quadratic
Product FE	Y	Y
City FE	Y	Y
GDP*HEPA and Schooling*HEPA	Y	Y

Notes: Each observation represents a product-city. Panel A presents reduced-form estimates, where price is instrumented with distance to factory/port. Panel B presents 2SLS results, where PM10*HEPA is instrumented with North*HEPA and price is instrumented with distance to factory/port. Standard errors in parentheses are clustered at the model level. * significant at 10% level; ** significant at 5% level; *** significant at 1% level. Stock-Yogo weak identification test critical value for for one endogenous variable (10% maximal IV size) is 16.38 and for two endogenous variables (10% maximal IV size) is 7.03.

Table A.2: Robustness Checks of First Stage

	PM10				
	(1) 4-degree	(2) 5-degree	(3) 6-degree	(4) 7-degree	(5) 8-degree
Panel A: Linear*North					
North	41.22***	39.49***	36.75***	33.80***	30.24***
	(10.50)	(9.35)	(9.18)	(9.13)	(8.69)
Observations	38	45	50	54	59
R^2	0.59	0.53	0.51	0.49	0.47
Panel B: Quadratic					
North	41.94***	39.84***	36.58***	33.29***	29.33***
	(10.85)	(9.61)	(9.29)	(9.01)	(8.49)
Observations	38	45	50	54	59
R^2	0.59	0.53	0.51	0.49	0.47
Demographic controls	Y	Y	Y	Y	Y

Notes: Each observation represents a city. City-level demographic controls include population and GDP per capita from City Statistical Yearbook (2006-2012), and average years of schooling and fraction completed college from the 2005 Census microdata. * significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Table A.3: Robustness Checks of Reduced-form

	ln(market share)				
	(1) 4-degree	(2) 5-degree	(3) 6-degree	(4) 7-degree	(5) 8-degree
Panel A: Linear*North					
North*HEPA	0.683**	0.748**	0.717***	0.760***	0.768***
	(0.332)	(0.303)	(0.268)	(0.267)	(0.267)
Price	-0.011***	-0.011***	-0.013***	-0.016***	-0.018***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
WTP	64.796*	67.069*	53.344**	47.356**	42.185**
	(39.190)	(34.705)	(24.458)	(20.289)	(17.842)
Observations	2,413	3,046	3,343	3,865	4,057
First-Stage F-Stat	16.57	18.66	22.68	23.35	23.20
Panel B: Quadratic					
North*HEPA	0.659**	0.693**	0.640**	0.681***	0.697***
	(0.309)	(0.287)	(0.258)	(0.257)	(0.257)
Price	-0.011***	-0.011***	-0.013***	-0.016***	-0.018***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
WTP	62.778*	62.224*	47.575**	42.402**	38.221**
	(36.595)	(32.583)	(23.324)	(19.448)	(17.150)
Observations	2,413	3,046	3,343	3,865	4,057
First-Stage F-Stat	16.57	18.73	22.72	23.33	23.14
Product FE	Y	Y	Y	Y	Y
City FE	Y	Y	Y	Y	Y

Notes: Each observation represents a product-city. This table presents reduced-form estimates, where price is instrumented with distance to factory/port. Standard errors in parentheses are clustered at the model level. * significant at 10% level; ** significant at 5% level; *** significant at 1% level. Stock-Yogo weak identification test critical value for one endogenous variable (10% maximal IV size): 16.38.

Table A.4: 2SLS: Standard Errors Clustered at the City Level

	ln(market share)				
	(1) 4-degree	(2) 5-degree	(3) 6-degree	(4) 7-degree	(5) 8-degree
Panel A: Linear*North					
PM10*HEPA	0.016***	0.018***	0.022**	0.028*	0.032*
	(0.006)	(0.007)	(0.010)	(0.015)	(0.019)
Price	-0.011***	-0.012***	-0.014***	-0.017***	-0.019***
	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)
MWTP	1.475*	1.544**	1.587**	1.679*	1.670*
	(0.692)	(0.631)	(0.715)	(0.858)	(0.930)
Observations	2,413	3,046	3,343	3,865	4,057
First-Stage F-Stat	13.90	13.56	15.22	12.75	9.91
Panel B: Quadratic					
PM10*HEPA	0.017**	0.017***	0.020**	0.026*	0.030*
	(0.007)	(0.006)	(0.009)	(0.013)	(0.017)
Price	-0.011***	-0.012***	-0.014***	-0.017***	-0.019***
	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)
MWTP	1.511**	1.460**	1.435**	1.519**	1.539*
	(0.717)	(0.604)	(0.660)	(0.771)	(0.842)
Observations	2,413	3,046	3,343	3,865	4,057
First-Stage F-Stat	13.91	13.59	15.34	12.89	10.03
Product FE	Y	Y	Y	Y	Y
City FE	Y	Y	Y	Y	Y

Notes: Each observation represents a product-city. This table presents 2SLS results, where PM10*HEPA is instrumented with North*HEPA and price is instrumented with distance to factory/port. Standard errors in parentheses are clustered at the city level. * significant at 10% level; ** significant at 5% level; *** significant at 1% level. Stock-Yogo weak identification test critical value for two endogenous variables (10% maximal IV size): 7.03.

Table A.5: 2SLS in non-winter months (April-November)

	ln(market share)				
	(1) 4-degree	(2) 5-degree	(3) 6-degree	(4) 7-degree	(5) 8-degree
Panel A: Linear*North					
PM10*HEPA	0.016*	0.015*	0.012	0.015	0.018
	(0.009)	(0.008)	(0.009)	(0.011)	(0.013)
Price	-0.017***	-0.019***	-0.020***	-0.024***	-0.027***
	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)
MWTP	0.949	0.787	0.588	0.623	0.672
	(0.589)	(0.497)	(0.481)	(0.493)	(0.500)
Observations	2,803	3,489	3,851	4,402	4,627
First-Stage F-Stat	8.45	9.29	11.28	11.07	10.81
Panel B: Quadratic					
PM10*HEPA	0.014	0.012	0.010	0.013	0.016
	(0.009)	(0.008)	(0.009)	(0.011)	(0.013)
Price	-0.017***	-0.018***	-0.020***	-0.024***	-0.027***
	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)
MWTP	0.844	0.678	0.490	0.532	0.590
	(0.590)	(0.489)	(0.478)	(0.488)	(0.498)
Observations	2,803	3,489	3,851	4,402	4,627
First-Stage F-Stat	8.58	9.38	11.36	11.13	10.87
Product FE	Y	Y	Y	Y	Y
City FE	Y	Y	Y	Y	Y

Notes: Each observation represents a product-city. This table presents 2SLS results, where PM10*HEPA is instrumented with North*HEPA and price is instrumented with distance to factory/port. Standard errors in parentheses are clustered at the city level. * significant at 10% level; ** significant at 5% level; *** significant at 1% level. Stock-Yogo weak identification test critical value for two endogenous variables (10% maximal IV size): 7.03.