Willingness to Pay for Clean Air:

Evidence from Air Purifier Markets in China

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Abstract

We develop a framework to estimate willingness to pay (WTP) for clean air from defensive investment. Applying this framework to product-by-store level scanner data on air purifier sales in China, we provide among the first revealed preference estimates of WTP for clean air in developing countries. A spatial discontinuity in air pollution created by the Huai River heating policy enables us to analyze household responses to long-run exposure to pollution. Our model allows heterogeneity in preference parameters to investigate potential heterogeneity in WTP among households. We show that our estimates provide important policy implications for optimal environmental regulation.

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1 Introduction

Air quality is remarkably poor in developing countries, and severe air pollution is imposing a substantial health and economic burden on billions of people. For example, the annual average exposure to fine particulate matter in China was more than five times higher than that of the US 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 to economic development.

However, a large economic burden of air pollution does not necessarily imply that existing environmental regulations are not optimal. Optimal environmental regulation depends on the extent to which individuals value air quality improvements—that is, their 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 social planners prioritize economic growth over environmental regulation. On the other hand, if WTP is high, the current stringency of regulations can be far from optimal. Therefore, WTP for clean air is a key parameter when considering the 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 because of limited availability of high quality data and a 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 for the estimation of 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 attributes—high-efficiency particulate arrestance (HEPA)—informs both consumers and econometricians of the purifier's effectiveness 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 improvement.

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 effectiveness to reduce indoor air pollution. Our data cover January 2006 through December 2012. The dataset provides comprehensive transaction records of 395 air purifier products for some of 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' WTP 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 heating policy provided city-wide coal-based heating for cities north of the river, which generated substantially higher pollution levels in the northern cities (Almond et al., 2009; Chen et al., 2013). The advantage of this spatial RD approach is twofold. First, it allows us to exploit plausibly exogenous policy-induced variation in air pollution. Second, the policy-induced variation in air pollution has existed since the 1950s. This natural experiment provides long-run variation in air pollution, which enables us to examine how households respond to long-lasting, not transitory, variation in pollution.

To address the endogeneity of prices, we combine two approaches. First, we observe data from many markets (cities) in China, and therefore we are able to include both product fixed effects and city fixed effects. These fixed effects absorb product-level unobserved demand factors and city-level demand shocks. The remaining potential concern is product-city level unobserved factors that are correlated with prices by product and city. We construct an instrumental variable, which measures the distance from each product's manufacturing plant (or its port if the product is imported) to each market, with the aim of capturing variation in transportation cost, which is a supply-side cost shifter.

We first present visual and statistical evidence that the level of air pollution (PM_{10}) is discontinuously higher in cities 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 in cities 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 USD 190. Third, we estimate that the marginal WTP for removing 1 ug/m^3 of PM_{10} for five years is USD 4.40. We show that our RD estimates are robust to using a range of different bandwidths and local quadratic estimation. Fourth, to learn about the distribution of WTP, we relax a few assumptions on standard logit demand estimation and estimate a random-coefficient logit model. The 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 the marginal WTP ranges from USD 0 to over USD 15 among households in our sample and that higher-income households have significantly higher marginal WTP for clean air compared to lower-income households.

This study provides three primary contributions to the literature and ongoing policy discussions. First, we develop a framework to estimate WTP for clean air based on defensive investment on market products. Earlier studies on avoidance behavior on pollution examine whether individuals take avoidance behavior in response to pollution exposure.[1] A key question in the recent literature is whether researchers can obtain monetized WTP for environmental quality from observing defensive behavior. Earlier theoretical work in environmental economics emphasizes that defensive investment on market products can be useful to learn about the preferences for environmental quality (Braden et al., 1991). However, few existing studies attempt to provide a framework to connect this economic theory with market data for empirical analysis.[2] Our paper compliments the literature by providing

[1]Earlier studies on avoidance behavior against pollution find that people do engage in defensive investment against pollution. For evidence in the US, 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). A key question in the recent literature is whether researchers can estimate WTP for improvements in environmental quality from observing defensive investment in markets.

[2]There are two recent papers that are most relevant to our study in the sense that our approach and the approaches taken by the following papers are broadly categorized by the household production approach. Kremer et al. (2011) uses a randomized control trial (RCT) in Kenya to estimate the WTP for water quality. Deschenes et al. (2012) use medical expenditure data in the United Sates to learn about the cost of air pollution and the benefit of air quality

a framework that can be applicable to market-level sales and price data, which are available in a variety of product markets in many countries through scanner data from manufacturers and retailers.[3]

The second contribution is that our analysis provides empirical evidence of an important "missing piece" in the literature on air pollution in developing countries. Greenstone and Jack (2013) suggest 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 among developed and developing countries. We fill this gap by providing revealed preference estimates of WTP for air quality in China. Our estimates are particularly useful because the identification comes from long-run exposure to air pollution induced by the Huai River policy. This is informative for WTP in the developing world where a large part of pollution is not presented as "on-and-off shocks".

Finally, our findings provide important policy implications for ongoing discussions in energy and environmental regulation in developing countries. Developing country governments recently proposed and implemented interventions to combat air pollution problems. For example, Chinese Premier Li Keqiang declared "War Against Pollution" to reduce emissions of PM_{10} and $PM_{2.5}$ and has proposed various reforms in energy and environmental policies (Zhu, 2014). China has also made a commitment to address global climate change, as featured by the *New York Times* in April 2016 (Davenport, 2016). For example, policies include reforming the Huai River heating policy and the launch of a national cap-and-trade program on carbon emissions in 2017. A key question is whether implementing such policies enhances welfare. 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 the welfare implications of energy and environmental policies.

regulation.

[3] 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 particulate matter has most consistently shown an adverse effect on human health in recent medical research (Dockery et al. 1993, Pope et al. 2009 and Correia et al. 2013). Additionally, particulate matter is mostly concentrated in developing countries. According to a global map of satellite-derived $PM_{2.5}$ (particulate matter with a 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 the main air pollutant in Chinese cities. Since 2000, the Chinese Ministry of Environmental Protection (MEP) has released a daily air pollution index (API) for 120 cities. In each city, a number of monitors record hourly concentration measures of three air pollutants: PM_{10} (particulate matter with a diameter of 10 micrometers or less), SO_2 and NO_2. Daily API is converted from the pollutant with 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, an API value of 0 to 50 represents excellent air while an API value over 300 represents heavily polluted air. When the API is above 50, the MEP reports the specific type of pollutant from which the API was converted. During 2006-2012, the main pollutant was PM10, followed by SO2 and NO2 with respective shares of 91%, 8.9%, and 0.15% of the total days in our sample of cities The official API, based on ambient PM_{10} for most days, is the only accessible pollution information for Chinese citizens during our sample period.[4] Both daily API level and the main pollutant type are reported to local residents by city weather channels, radio and newspapers.

2.2 Air Purifiers

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

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

rifier's effectiveness to reduce indoor particulate matter. According to the US Department of Energy, a HEPA air purifier removes at least 99.97% of particles of 0.3 micrometer or larger in diameter (DOE, 2005). It is even 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 symptoms and asthma-related health visits among children, lower marker levels of 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 US Department of Energy standards, 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 approximately 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 a 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. Because of budget constraints, the government provided city-wide centralized heating to northern cities only (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 is not a border for other administrative purposes (Chen et al., 2013). Cities to the north of the river boundary have received centralized heating in every winter. In contrast, cities in the south have not had a 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 remaining one-third is generated by combined heat and power generators for the larger areas of each city. This system is 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, particularly particulate matter. Because most heat is generated by boilers within an apartment complex, the pollution from coal-based heating remains largely local. Almond et al. (2009) find that the Huai River policy led to higher total suspended particulate (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 expectancy in the north.

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

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

Our analysis focuses on to period from 2006 to 2012, after the 2003 reform on heating billing.

We summarize the comparison of winter heating between the north and the south. First, winter heating is provided in the same way 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 methods of staying warm in winter, including using the heating function of air conditioners, space heaters, heated blankets, etc. Second, heating costs in the north have changed since the 2003 reform. Northern households no longer enjoy free heating and instead have to pay a substantial proportion of their heating bills from the centralized heating while households in the south continue to pay for the heating methods of their choice. We collected heating costs in 20 cities within three 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.[5]

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 2005 Chinese census micro data. 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 account for over 80% of all in-store sales. During the period 2006 to 2012, in-store sales consisted of over 95% of overall purifier sales. The

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

marketing firm provided 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 to 2012.

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 in 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 can remove.

Finally, to address the endogeneity of prices in our empirical analysis, we construct an instrumental variable, which measures the distance from each product's manufacturing plant (or its port if the product is imported) to each market. The distance measure captures the variation in the transportation cost, which is a supply-side price shifter. 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 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 the API was taken from on days when the air quality is not excellent (API is above 50). This information is also disclosed to the public. 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 nonlinear function. For the 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 the 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 late November and turned off at the end of March.

We are cautious in using the API data because recent studies find evidence of 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 an API below 100 as a blue sky day and links 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 API level for cities for the period 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 potential manipulation changes the city-level average API for our sample period by a negligible amount. This is because the manipulation occurs only at the margin of 100 and therefore, it has a minimal effect on the average API over a long trem.

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 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 the percentage of individuals who have 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. Of the 395 products, 206 products, or 52% of all products, have a HEPA filter. 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 filter replacement. In contrast, the difference is statistically significant for the price of purifiers and the price of replacement filters. On average, HEPA purifiers are USD 112 more expensive than non-HEPA purifiers, and the difference is statistically significant at the 10% level. HEPA replacement filters are also USD 20 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, a population of 2.5 million. The average GDP per capita is USD 8,277. The average years of schooling is 8.36 years, and the percentage of individuals who have completed college is, on average, 3.6%.

We also use two maps to show the spatial distributions of the cities and manufacturing plants/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 North and South. Each dot represents a city in our sample. All cities in our sample are located east of 100 degrees of longitude. The river line east of 100 degrees of longitude ranges between 32.6 and 34.2 degrees of latitude. In our spatial RD approach using the Huai River policy, we define a city's relative latitude north of the river line. Because the river line has several different curved segments, we divide the river line into five segments. In each segment, we measure a city's relative latitude to the middle point of the river latitude range. For example, Beijing is located at 39.9 degrees of latitude and 116.3 degrees of longitude, and the corresponding middle point of the river latitude range is 33.4 degrees. Beijing's relative latitude north of the river line is 6.5 (39.9 to 33.4) degrees. Cities in our sample are located between -12.9 and 14.8 degrees north of the river line. In the appendix, we also show Figure A.1, which includes the 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 WTP for clean air by analyzing demand for air purifiers. Because air purifiers are differentiated products with multiple attributes, we start with a random utility model for differentiated products.[6] When a consumer purchases an air purifier, the consumer considers utility from the product attributes 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 of the purifier's effectiveness 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 on their WTP for indoor air quality improvements.

Consider that consumer i in city c has ambient air pollution x_c (particulate matter). The consumer can purchase air purifier j at price p_{jc} to reduce indoor air pollution by $x_{jc} = x_c \cdot e_j$. We denote purifier j's effectiveness 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:

$$u_{ijc} = \beta_i x_{jc} + \alpha_i p_{jc} + \eta_j + \lambda_c + \xi_{jc} + \epsilon_{ijc}, \tag{1}$$

where x_{jc} is the improvement in indoor air quality conditional on the purchase of product j, p_{jc} is the price of product j in market c, η_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 utility for clean air, and α_i indicates the marginal disutility of price. The functional form for the utility function assumes that each variable, including the error term, enter the utility function linearly.

Air purifiers usually run for five years and require filter replacement several times within five years. We assume that consumer i considers utility gains from purifier j for five years and p_{jc} as a total cost including the upfront and running cost.[7] This approach abstracts from the interesting

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

[7] This approach also implicitly assumes that consumers respond to the monetary value of an upfront cost and 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

possibility that consumers may consider the dynamics of product entries and make a dynamic decision. Unfortunately, it is not possible to examine such a dynamic decision in the context of 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 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 with instrumental variables for pollution and price. A random-coefficient logit model allows the preference parameters to vary by household 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. In this paper, we use both approaches to estimate WTP 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[8]

$$s_{jc} = \frac{\exp(\beta x_{jc} + \alpha p_{jc} + \eta_j + \lambda_c + \xi_{jc})}{\sum_{k=0}^{J} \exp(\beta x_{kc} + \alpha p_{kc} + \eta_k + \lambda_c + \xi_{kc})}. \tag{2}$$

The outside option ($j = 0$) is not to buy an 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

show empirically that consumers are not myopic concerning the running costs of durable goods (Busse et al., 2013). When calculating the total cost of a purifier, we do not consider future discount rates in its running cost. However, including discount rates changes the total cost only by a small amount and, therefore, we find that it does not have a significant effect on our empirical findings.

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

the total number of sales in city c. Our second assumption is that $x_{0c} = 0$. That is, if consumers do not buy an air purifier, they are exposed to indoor pollution that is equal to ambient air pollution. Note that for the standard logit estimation, the assumptions on the outside option are not required when we include city fixed effects. City fixed effects absorb observable and unobservable variation at the city level. For completeness, we include the log of market share for the outside option (s_{0c}) in the equation below, but the term will be absorbed by city fixed effects. The log market share for the outside options is $\ln s_{0c} = -\ln \left(\sum_{k=0}^{J} \exp(\beta x_{kc} + \alpha p_{kc} + \eta_k + \xi_{kc}) \right)$. The difference between the log market share for product j and the log market share for the outside options is,

$$\ln s_{jc} - \ln s_{0c} = \beta x_{jc} + \alpha p_{jc} + \eta_j + \lambda_c + \xi_{jc} \tag{3}$$

where 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 reduction. First, our approach assumes that indoor air pollution levels in the absence of air purifiers are equal to ambient pollution levels. Recent engineering studies show that, on average, indoor pollution levels are lower than outdoor pollution levels in China.[9] One approach we could take is to rely on an engineering estimate of the indoor-outdoor air pollution ratio, which would produce slightly larger estimates for MWTP. However, because we want to be as conservative 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 of the negative health effects of air pollution. Third, if the running costs of HEPA purifiers are higher because using HEPA filters costs more electricity, our MWTP estimate without accounting for the difference in the running costs could be underestimated.

An advantage of studying air purifier markets is that e_j (purifier j's effectiveness to reduce indoor particulate matters) is well-known for consumers. As we explained in Section 2.2, if a

[9] 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, April 23, 2015 (Zhang, 2015).

purifier has a HEPA filter, it can reduce 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 market, consumers are well-informed of the difference between HEPA purifiers and non-HEPA purifiers. Therefore, we define the pollution reduction by $x_{jc} = x_c \cdot HEPA_j$, which equals x_c if $HEPA_j = 1$ and equals zero if $HEPA_j = 0$. That is, 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 θ_j. Using $x_{jc} = x_c \cdot HEPA_j$, our random utility model leads to an estimation equation:

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

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 MWTP by $-\beta/\alpha$. 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 instrumental variables.

4.2 A Random-coefficient Logit Model

Our random-coefficient model relaxes some assumptions of the standard logit model. Since general discussions on random-coefficient models are provided extensively in the literature (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 $\beta_i = \beta_0 + \beta_1 y_i + u_i$ and $\alpha = \alpha_0 + \alpha_1 y_i + e_i$, where y_i is the log of household income for household i from the census micro data, $u_i \sim N(0, \sigma_\beta)$ and $e_i \sim N(0, \sigma_\alpha)$. Therefore, each of these two parameters depends on the mean coefficient, log of household-level income, and a normally distributed random unobserved heterogeneity. Denote the part of the utility function that does not depend on i (the mean utility level) by $\delta_{jc} = \beta_0 x_{jc} + \alpha_0 p_{jc} + \eta_j + \lambda_c + \xi_{jc}$ and the part that depends on i by $\mu_{jci} = (\beta_1 y_i + u_i)x_{jc} + (\alpha_1 y_i + e_i)p_{jc}$. 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:[10]

$$s_{jc} = \frac{1}{n_c}\sum_{i=1}^{n_c} s_{jci} = \frac{1}{n_c}\sum_{i=1}^{n_c} \frac{\exp(\delta_{jc} + \mu_{jci})}{\sum_{k=0}^{J}\exp(\delta_{kc} + \mu_{jki})}. \tag{5}$$

The important difference between equations (2) and (5) is that equation (5) now includes elements that vary by 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 $\xi_{jc} = \delta_{jc} - (\beta_0 x_{jc} + \alpha_0 p_{jc} + \eta_j + \lambda_c) \equiv \omega_{jc}$.

The idea behind the estimation is that if there is a set of instrumental variables that are uncorrelated with ω_{jc}, we can estimate the parameters by nonlinear GMM using the moment 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

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

in which Φ^{-1} is the optimal weight matrix for the GMM estimation. The GMM objective function is nonlinear in parameters. Therefore, it has to be evaluated numerically by nonlinear search algorithms. 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 WTP for clean air. We begin with standard logit estimation in section 5.1 followed by random-coefficient logit estimation in section 5.2.

[10]See Nevo (2001) for a more detailed explanation for how to derive this equation.

5.1 Logit Estimation

Our primary empirical challenge is that two variables in the 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 the 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 consider observed pollution levels across different cities exogenous variation because of potentially omitted variables. Air purifier prices are also unlikely to be determined exogenously because unobserved factors in demand are believed to be correlated with price. For example, suppose that some demand factors are unobservable to econometricians but observable to firms. If firms have the ability to set prices because of imperfect competition, we expect that they set prices in response to the unobserved demand factors, which creates correlation between the price and the error term in our demand estimation.

We address the endogeneity of air pollution by exploiting a regression discontinuity design at the spatial border of the Huai River as described in section 2.3. This approach provides us a useful research environment for two reasons. First, it allows us to exploit plausibly exogenous variation in air pollution created by the natural experiment—the Huai river heating policy. If households value air quality, our demand model in section 4 predicts that the market share for HEPA purifiers is discontinuously higher in cities north of the Huai River. Second, the discontinuous difference in air pollution created by the Huai River policy has existed since the 1950s. Therefore, the natural experiment provides long-run variation in air pollution, which enables us to examine how households respond to variation in pollution that is long-lasting rather than transitory.

We address the endogeneity of prices by combining two approaches. First, we use data from many markets (cities) in China, which allows us to include both product fixed effects and city fixed effects. These fixed effects absorb product-level and city-level unobserved demand factors. The remaining potential concern is product-city level unobserved factors that might be correlated with prices by product and city. To address this concern, we construct an instrumental variable that measures the distance from each product's manufacturing plant (or its port if the product is imported) to each market. This instrument provides variation at the city-product level because manufacturing locations or importing ports are different between products, and it captures transportation cost of the product, which is a supply-side cost shifter.

5.1.1 Empirical Strategy

First Stage on Air Pollution: We estimate the first stage on air pollution using a regression discontinuity design created by the Huai river heating policy. We denote air pollution (PM_{10}) for city c by x_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. Recent studies suggest that a local linear regression or quadratic polynomials with observations close to the cutoff provide more robust estimates for RD designs than those obtained by high order global polynomial controls with observations far from the cutoff (Imbens and Lemieux, 2008; Gelman and Imbens, 2014). 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,

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

The identification assumption is that the conditional expectation of the outcome variable (x_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 the percentage of individuals who have 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 x_c just north of the Huai River.

When estimating a regression discontinuity design, one needs to decide the bandwidth of the sample that is included in a local linear regression. We apply the algorithm developed by Imbens and Kalyanaraman (2012) to our data and find that the optimal bandwidth based on the algorithm is five latitude degrees. The general consensus in the recent literature is that researchers should report results with several sets of bandwidth choices to examine the robustness. Therefore, we use five latitude degrees for our main result but also report results with four, six, seven, and eight latitude degrees.

Finally, recent studies suggest that the local linear regressions should be run with kernel weights that assign more weights on observations near the cutoff (Imbens and Kalyanaraman, 2012; Calonico et al., 2014). For our main specification, we use a triangular kernel, which is most commonly used in recent studies. We also estimate our regressions without weights. Because we limit our sample to observation near the cutoff, we find that including or excluding weights does not substantially change the estimation results.

Reduced-form on Log Market Share: Suppose that our first stage on PM10 provides evidence of a discontinuous increase in PM10 at the Huai river boundary. Then, our demand model predicts that the market share for HEPA purifiers should be higher in cities north of the river if households value clean air. Our reduced-form estimation examines whether 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,

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

where η_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 ($\ln s_{0c}$) and a dummy variable for northern cities ($North_c$) are 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 $(\rho_1 L_c + \rho_2 L_c \cdot North_c) \cdot HEPA_j$.

As we described above, prices are likely to be endogenous in this equation. For instruments for prices, we measure the distance from each product's manufacturing plant (or its port if the product is imported) to each market to capture the city-product level variation in transportation cost. Our instruments are $distance$, $distance^2$, and $distance^3$, each of which is interacted with the dummy variables for the product's country of origin. In this way, we can allow flexible functional forms for the relationship between prices and the distance to the markets.

The reduced-form estimation itself provides policy-relevant parameters. From the estimates of ρ and α, we can calculate the WTP for removing the amount of pollution generated by the Huai River policy (γ in equation (7)) by $-\rho/\alpha$.

Second Stage on Log Market Share: We estimate the marginal willingness to pay (MWTP) for clean air by running the following second stage regression:

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

by using $North_c \cdot HEPA_j$ as the instrument for $x_c \cdot HEPA_j$ and the same set of instruments used in the reduced-form estimation as the instruments for p_{jc}. The identification assumption is that the instruments are uncorrelated with the error term given the control function and fixed effects. This estimation allows us to calculate the MWTP for removing one unit of PM10 by $-\beta/\alpha$.

5.1.2 Graphical Analysis

Huai River policy generates a natural experiment in air pollution in the 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 the winter months (December to March) during 2006-2012 by the running variable, which is the latitude of cities (L_t). Because few cities are located in the farthest north and the farthest south, the figure includes cities located within 10 degrees of latitude from the Huai River boundary. Each plot in the figure shows the average PM_{10} by 1.5 degrees 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 in cities 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 to 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 degrees of latitude. In the south, the market share of HEPA purifiers is 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. Additionally, the figure shows no strong trend in the outcome variable by 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 a substantial impact 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} of 37 to 39 units at the Huai River boundary. The magnitude of these estimates is 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 approximately 115 and jumps by approximately 30% just north of the river.

In Panel B of Table 2, we report the first stage estimation for prices. We include product fixed effects in all columns. The unit of the distance variable is in 1,000 kilometers (621 miles). The coefficient estimates for all columns imply that distance and prices have a nonlinear relationship, and it is monotonically increasing for the range of distance in the dataset. For example, the result in columns 1 implies that a hundred kilometer increase (a 62.1 mile increase) in the distance to the manufacturing plant or importing port is associated with an increase in price of approximately USD 12 $=136.14 \cdot (0.1) - 174.65 \cdot (0.1)^2 + 70.22 \cdot (0.1)^3$. Note that the 10th, 25th, 50th, 75th, and 90th percentiles of the distance variable in our data are 230 km, 550 km, 1,000 km, 1,400 km, and 1,700 km, and that the average price of air purifiers is USD 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 in these columns imply that the relationship between distance and price is robust to the inclusion of city fixed effects.

Table 3 shows the reduced-form results in Panel A and the second-stage results in Panel B.

We include product fixed effects and city fixed effects. Because we have more instruments than regressors (an over-identified case), the two-step GMM estimation with the optimal weight matrix provides a more efficient estimator than the two-stage least squares (Cameron and Trivedi, 2005). We use the orthogonality conditions of the instruments to implement the two-step linear GMM estimation and cluster the standard errors at the city level. Consistent with Figure 2b, the reduced-form results provide evidence that there is an economically and statistically significant discontinuous increase in the market share of HEPA purifiers in cities north of the river from both specifications. We calculate the WTP by $-\rho/\alpha$ and obtain 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 for five years is USD 190 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 second-stage results in Panel B of Table 3. 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} for five years. The results for the local linear regression indicate that the MWTP is about USD 4.4 per household.[11]

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 four and eight latitude degrees. We report the 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 Figures 2a and 2b.

A potential concern is that if high-income or better-educated households prefer HEPA purifiers

[11] 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 to November). This is consistent with the fact that the centralized heating in the north is provided in winter months only. Nevertheless, we consider the possibility that consumers could purchase air purifiers during an entire year including 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.4. The point estimates in the table suggest that demand for HEPA purifiers in all months has a moderate response to differences in winter PM_{10}, but the response is lower than in winter months.

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.

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 are smooth in the running variable across the river boundary. While potential outcomes are unobservable, we can examine whether observable variables 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 it 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 obtaining local social benefits and education opportunities, which makes migration a more costly decision than migration in countries without restrictions on mobility. The government started to relax the *Hukou* system by allowing a few types of migraiotn since the late 1990s, but the migration rate is still low. We look into migration in the micro-data of the two population census after the relaxation, the 2000 census and the 2005 census. Indeed, in the 2000 census micro-data, only 0.5 percent of the population in the city of origin within 1.5 latitude degrees north of the Huai river had migrated to the south. In the 2005 census micro-data, 1 percent of the population in the city of origin within 1.5 latitude degrees north of the Huai river had migrated to the south. Therefore, in our case, migration is unlikely to have a significant impact 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 to 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 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 the heating supply to the north a public welfare entitlement with subsidized heating costs for northern households, northern households might have a 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 flat-rate billing. Of critical importance is that northern households must pay a substantial proportion of the total heating bill since 2003. Therefore, in our analysis during the period 2006 to 2012, the heating subsidy has a minimal effect on households, although we cannot fully exclude the possibility that the subsidy before 2003 may have had 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 compared 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 degrees of latitude relative to the Huai River. We do not observe a discontinuous jump in the supply of HEPA purifiers just north of 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 a linear two-stage least squares or a linear GMM method, and therefore, 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 MWTP for clean air ($-\beta/\alpha$) is homogeneous across i.

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

5.2.1 Nonlinear optimization algorithms and starting values

Random-coefficient demand estimation requires nonlinear GMM estimation. 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 caution regarding such numerical optimization and provide guidelines in assessing robustness of estimation results. For example, Knittel and Metaxoglou (2013) suggest examining 1) conservative tolerance levels for nonlinear searches, 2) different sets of nonlinear search algorithms, and 3) many starting values, to analyze whether the estimated local optimum is indeed the global optimum of the GMM objective function.

We estimate our model with six nonlinear search algorithms (Conjugate gradient, SOLVOPT, quasi-Newton 1, and quasi-Newton 2, Simplex and Generalized pattern search), a hundred sets of starting values, and conservative tolerance levels for nonlinear searches. In total, we obtain 600 estimation results to test the robustness of our results. For starting values for nonlinear parameters, we generate random draws from a standard normal distribution. We set the tolerance level for the nested fixed-point iterations to 1E$-$14, and the tolerance level for changes in the parameter vector and objective function to 1E$-$04.

5.2.2 Estimation results

Figure 3 shows the box plot of the nonlinear GMM estimation results for each of the six nonlinear search algorithms with a hundred sets of starting values. The box plot shows the distribution of the final objective function value for each set of estimation. We use a conventional style of box plots—the thick vertical line indicates the median, the box shows the 25th and 75th percentiles, and the dots present outside values. Five of the six search algorithms produce the same minimum value of the objective function (48.723), which is the dashed vertical line in the figure. Only one of the algorithms—the conjugate gradient algorithm—does not reach that minimum value. Among the hundred set of starting values, 82% of them reach that minimum objective function value for Generalized pattern search, 81% for Simplex, 97% for Quasi-Newton 1, 95% for Quasi-Newton 2, and 92% for Solvopt. This result provides two key implications. First, it is important to test multiple search algorithms and starting values to ensure that the local minimum in a particular set of estimation is indeed the global minimum. This is consistent with the caution raised in recent studies. Second, the fact that the five nonlinear search algorithms reach the same minimum objective function value provides us strong evidence that the local minimum found at the function value of 48.723 is likely to be the global minimum of the GMM objective function. Therefore, we use the estimation result with this minimum objective function value to report the coefficient estimates.

Table 5 shows the coefficient estimates of the random coefficient model described in equation (6). As with our standard logit estimation, we use two sets of controls for latitude for our regression discontinuity design. Column1 uses linear and linear interacted with the indicator variable for cities in the north side of the Huai River, and column 2 uses quadratic controls for the latitude. The results provide several key findings for heterogeneity in preference parameters. First, the MWTP for the median and mean households are USD 5.13 and USD 5.46, which are slightly larger than but not far from the MWTP estimate obtained by the standard logit model in the previous section. Second, the positive and statistically significant coefficient β_1 implies that there is a positive relationship between the preference for clean air (β) and household income (y_i). We do not find statistically significant relationship between the sensitivity for price (α) and household income. Third, the coefficient estimate for σ_α indicates that there is statistically significant unobserved heterogeneity among households for the sensitivity for price.

We use two figures to visually describe our estimation results. Figure 4 shows the distribution of estimated MWTP based on the estimation results from column 1 of Table 5. Recall that from the census data we have household-level income data for a random sample of households in each city. We use each household's log income y_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 coefficient estimates to calculate the household-level MWTP, $mwtp_i = -(\hat{\beta}_0 + \hat{\beta}_1 y_i + u_i)/(\hat{\alpha}_0 + \hat{\alpha}_1 y_i + e_i)$. 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. The heterogeneity is mainly driven by the two coefficients—observed heterogeneity $\beta_1 y_i$ and unobserved heterogeneity e_i.

In Figure 5, we show the relationship between the MWTP and household-level income in USD. The income distribution is based on household-level income data from the 2005 census. There is a long right tail in the distribution with a very small fraction of households with an income over USD 15,000. In the figure, we drop those with an income over USD 15,000 to better visualize the majority of the distribution. We present the fitted line of the MWTP estimate over income levels. It indicates that the MWTP is increasing in income, ranging from USD 0 to USD 9 for the range of income between USD 0 to USD 15,000.

Overall, the results of the random-coefficient model provide several key implications, under the assumptions required for the nonlinear GMM estimation. In our case, the results from the standard logit estimation are not far from the results from the random-coefficient estimation if our focus is to estimate the median or mean level of MWTP. However, the random-coefficient estimation highlights substantial heterogeneity in MWTP. In particular, the results indicate that higher-income and lower-income households have significantly different levels of MWTP for clean air.

6 Policy Implications

Our findings provide important policy implications for ongoing discussion in energy and environmental regulation in developing countries. Developing country governments recently proposed and implemented a variety of interventions to mitigate air pollution problems. For example, the 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 enhance welfare.

For example, in 2005, the Chinese government and the World Bank initiated 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 heating consumption and can control how much heating they consume.[12] Ten years after the start of the pilot reform, there is still ongoing debate

[12]As we describe in Section 2.3, the 2003 reform in all northern cities replaced a free heating provision with flat-rate billing. Households pay a fixed charge per square meter for heating for the entire winter, which does not depend on

about the reform—whether such a reform would improves welfare and whether similar reforms should be implemented in other northern cities in China. The main challenge is that the costs of installing individual meters and adopting consumption-based billing are high,[13] while the 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 the welfare implications of an environmental policy. Our analysis is based on a back-of-the-envelope calculation with a set of assumptions. This analysis can help shed light on the importance of WTP for clean air and policy discussion on optimal environmental regulation.

Our empirical findings inform us of how much a household is willingness to pay for a reduction in particulate matter that can be achieved by the reform. We use our random-coefficient logit estimation results to calculate the mean of $MWTP_i$ by $\frac{1}{N}\sum_{i=1}^{N}\Big(-(\hat{\beta}_0+\hat{\beta}_1\cdot y_i+u_i)/(\hat{\alpha}_0+\hat{\alpha}_1\cdot y_i+e_i)\Big)$, where the coefficient estimates come from column 1 of Table 5 and N is the number of households in the census micro data. The mean MWTP based on this calculation is USD 5.46. Because the amount of PM10 induced by the Huai river policy is 39, the estimate implies that a northern household is willing to pay USD 213 ($= 5.46 \cdot 39$) if the pollution generated by the Huai River policy can be mitigated. 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 USD 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 USD 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 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 household is willing to pay USD 213 to clean the air from heating-induced pollution for a period

the actual amount of usage. The flat-rate billing provides no incentives for households to respond to market-based energy costs.

[13] According to the People's Daily on October 23 2009 (People'sDaily, 2009), the Vice Minister of the Ministry of Housing and Urban-Rural Development summarized three obstacles to the implementation of 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, and 3) it is costly to build a new consumption-based billing system.

of five years. That is, the annualized WTP is USD 42.6 (= 213/5) 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 the reduction in PM_{10}, 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 USD 2.98 ($= 42.6 \cdot 0.07$) 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 WTP is USD 1.88 ($= 2.98 \cdot 0.63$) million per city per year. This estimate, measuring the total benefits of the heat reform for households, is larger than the abatement cost, which is USD 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.[14]

More broadly, our WTP estimate is useful for evaluating a series of new energy policies and environmental regulations that were recently implemented or announced to be introduced. For example, as featured by the *New York Times*, USD 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% by 2020 (Wong, 2015). More prominently, as the world's largest greenhouse gas polluter, China recently made a commitment 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 the welfare implications of the policy.

[14] This conclusion remains the same if we use the WTP estimate from the standard logit model. The standard logit estimation results imply that a northern household is willing to pay USD 190 if the pollution generated by the Huai River policy can be mitigated. If we use this number, the total WTP for the heating reform is USD 1.84 million per city per year. This estimate is larger than the abatement cost, which is USD 0.13 million per city per year.

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 improvement. 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 WTP for removing the amount of pollution generated by the Huai River policy and the MWTP for removing 1 ug/m^3 PM_{10}.

While we find a higher amount of WTP for environmental quality compared to previous studies in developing countries (Kremer et al., 2011), our estimate is still lower than similar estimates in the US (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 are more informed about the negative effects of air pollution on health and labor supply, do they have a higher WTP for clean air? Can policies be designed to provide information to the public on the pollution-health relationship to affect household responses to pollution? The answers to these questions are valuable to improve policy design to address pollution problems in many countries.

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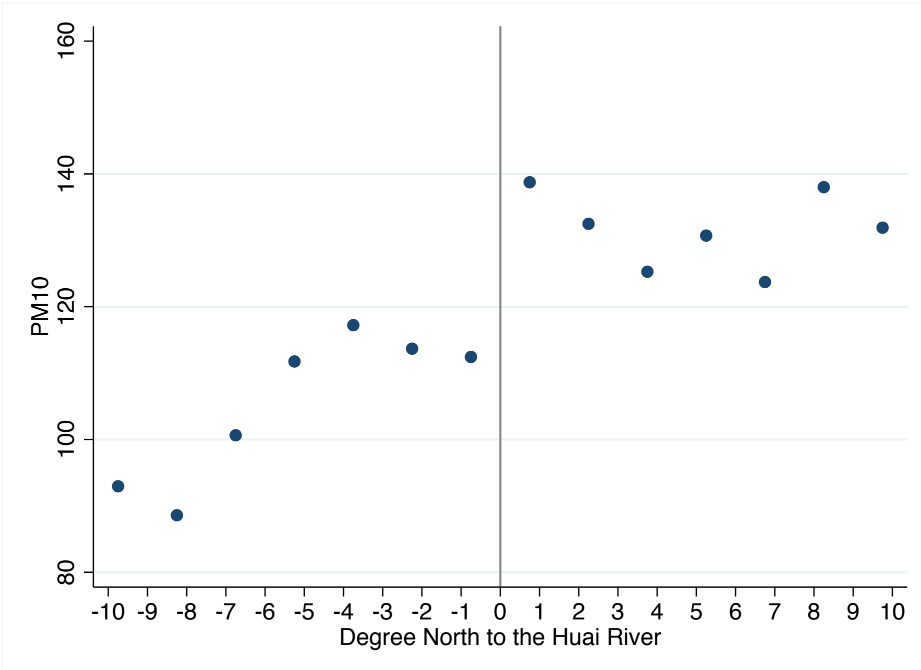
Figure 1: Huai River Boundary and City Locations

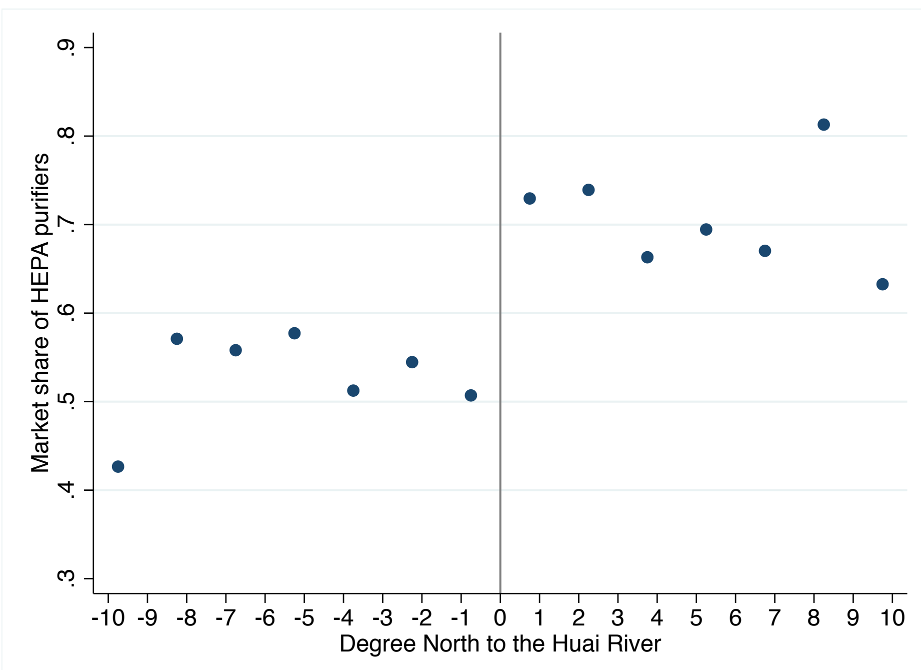
Notes: The line in the middle of the map is the Huai River-Qinling boundary. Each dot represents one city. There are 81 cities in our sample.

Figure 2: Regression Discontinuity Design at the Huai River Boundary

(a) PM10 in Winter

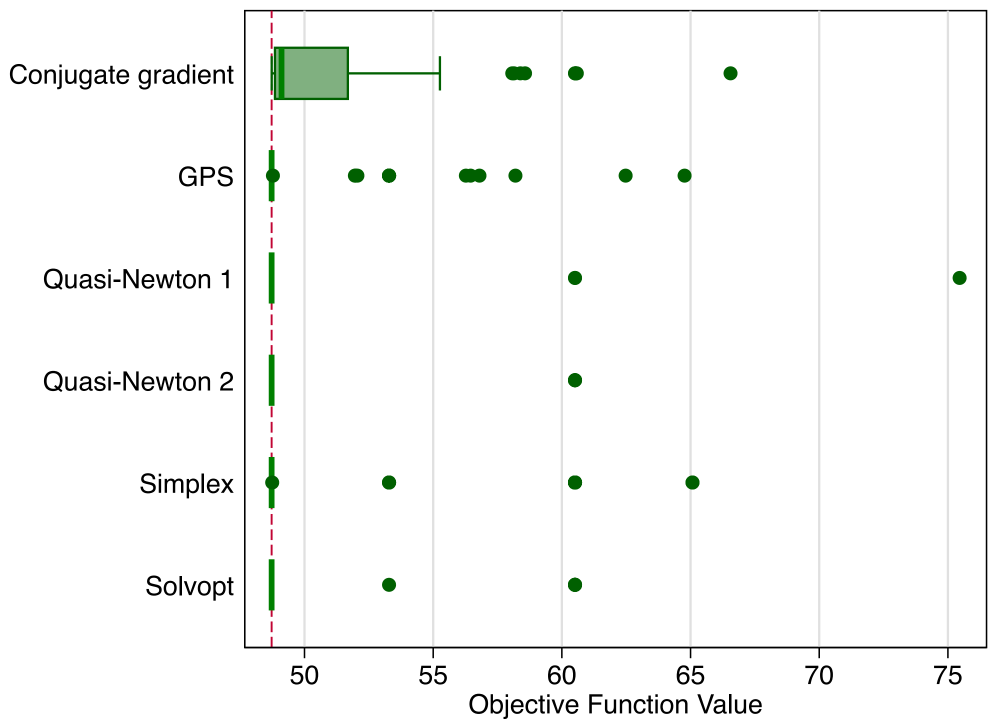


(b) Market Share of HEPA Purifiers in Winter



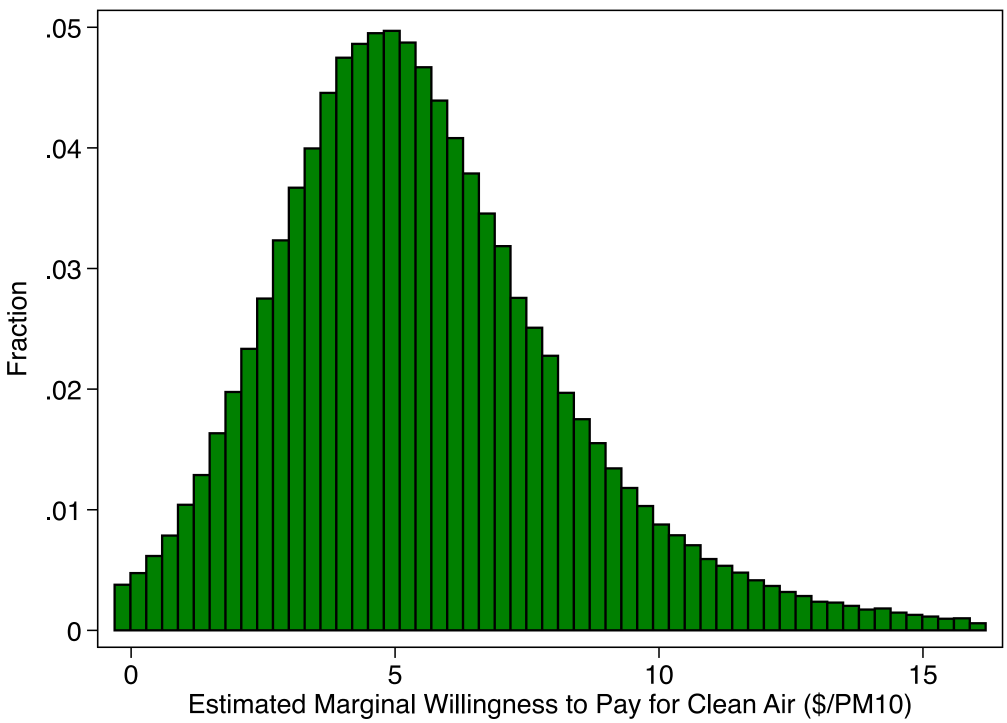
Note: Figure 2a plots the average PM_{10} during winter (December to March) in 2006 to 2012 by 1.5 degrees of latitude north of the Huai River boundary. The vertical line at 0 indicates the location of the Huai river. Each dot represents cities at 1.5 degrees of latitude and corresponds to the middle 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 of 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 by 1.5 degrees of latitude north of the Huai River line.

Figure 3: Box Plots of the Objective Function Value in the Nonlinear GMM estimation



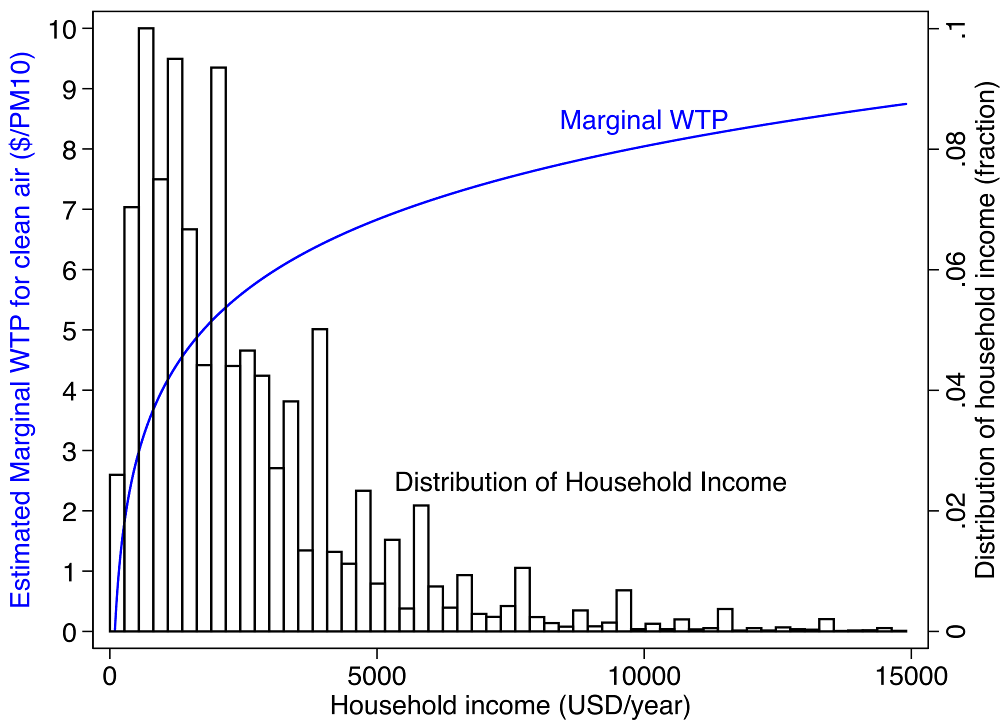
Note: For each of the six optimization algorithms listed in the vertical axis, we estimate the nonlinear GMM in equation (6) with a hundred sets of different starting values for the nonlinear parameters. The box plot shows the distribution of the final objective function value for each set of estimation. We use a conventional style of box plots—the thick vertical line indicates the median, the box shows the 25th and 75th percentiles, and the dots present outside values. We randomly draw starting values from a standard normal distribution. Among the hundred set of starting values, 82% of them reach the minimum objective function value for Generalized pattern search, 81% for Simplex, 97% for Quasi-Newton 1, 95% for Quasi-Newton 2, 92% for Solvopt, and 0% for Contingent gradient.

Figure 4: The Distribution of Marginal Willingness to Pay for Clean Air



Note: This histogram is based on the estimates of the random coefficient logit model in column 1 in Table 5 and household-level income from the 2005 census micro data.

Figure 5: Marginal Willingness to Pay for Clean Air and 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 data from the 2005 census micro data.

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 in 1000 km	0.901	0.899	0.904	-0.005
	(0.358)	(0.321)	(0.395)	[0.069]
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)			

Note: The product-level sample has 395 products of 30 brands. 206 products are HEPA purifiers and 189 are non-HEPA purifiers. In column (1) to (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	38.50***	36.94***	39.49***	39.84***
	(9.87)	(9.25)	(9.35)	(9.61)
Observations	45	45	45	45
R^2	0.28	0.28	0.53	0.53
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 in 1000 km	136.14***	136.24***	97.79**	98.02**
	(37.95)	(37.91)	(43.72)	(43.74)
(Distance in 1000 km)^2	-174.65***	-175.50***	-121.75*	-121.65*
	(54.30)	(53.59)	(64.72)	(64.76)
(Distance in 1000 km)^3	70.22***	70.73***	52.49*	52.38*
	(21.08)	(20.61)	(26.64)	(26.66)
Observations	3,046	3,046	3,046	3,046
R^2	0.97	0.97	0.97	0.97
Functional form	Linear*North	Quadratic	Linear*North	Quadratic
Product FE	Y	Y	Y	Y
City FE			Y	Y

Note: 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 the percentage of population that have completed college from the 2005 census microdata. In Table 2b, standard errors in parentheses are clustered at the city level. The distance variable measures each product's distance from a manufacturing factory/importing port to each market. In addition to *distance*, *distance*^{2}, and *distance*^{3}, we also include these three variables interacted with the dummy variables for the product's country of origin to allow a flexible functional form for the relationship between prices and distance. * significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Table 3: Reduced Form and Second Stage Estimation Results

	ln(market share)	
	(1)	(2)
Panel A: Reduced form		
North*HEPA (ρ)	0.886***	0.771***
	(0.099)	(0.082)
Price (α)	-0.0047***	-0.0047***
	(0.0004)	(0.0004)
WTP ($-\rho/\alpha$)	190.385***	165.179***
	(23.918)	(20.519)
Observations	3,046	3,046
First-Stage F-Stat	71.16	64.44
Panel B: Second-stage		
PM10*HEPA (β)	0.019***	0.017***
	(0.002)	(0.002)
Price (α)	-0.0044***	-0.0044***
	(0.0004)	(0.0004)
MWTP ($-\beta/\alpha$)	4.409***	3.899***
	(0.736)	(0.651)
Observations	3,046	3,046
First-Stage F-Stat	64.41	59.93
Functional form	Linear*North	Quadratic
Product FE	Y	Y
City FE	Y	Y

Note: Each observation represents a product-city. Panel A presents reduced-form estimates, where price is instrumented with the distance variables discussed in the text. Panel B presents the second stage results, where PM10*HEPA is instrumented with North*HEPA and price is instrumented with the distance variables discussed in the text. We estimate both of the reduced form and second stage regressions by the two-step linear GMM estimation with the optimal weight matrix. Standard errors in parentheses are clustered at the city level. * significant at 10% level; ** significant at 5% level; *** significant at 1% level. The Stock-Yogo weak identification test critical value for one endogenous variable (10% maximal IV size) is 16.38, and for two endogenous variables (10% maximal IV size) it is 7.03.

Table 4: Robustness Checks

	ln(market share)				
	(1) 4-degree	(2) 5-degree	(3) 6-degree	(4) 7-degree	(5) 8-degree
Panel A: Linear*North					
PM10*HEPA (β)	0.017***	0.019***	0.020***	0.025***	0.027***
	(0.002)	(0.002)	(0.003)	(0.005)	(0.007)
Price (α)	-0.0042***	-0.0044***	-0.0055***	-0.0056***	-0.0058***
	(0.0003)	(0.0004)	(0.0008)	(0.0008)	(0.0008)
MWTP (-β/α)	3.963***	4.409***	3.640***	4.439***	4.594***
	(0.622)	(0.736)	(0.919)	(1.180)	(1.537)
Observations	2,413	3,046	3,343	3,865	4,057
First-Stage F-Stat	131.20	64.41	46.83	33.45	54.70
Panel B: Quadratic					
PM10*HEPA (β)	0.016***	0.017***	0.018***	0.023***	0.025***
	(0.002)	(0.002)	(0.003)	(0.004)	(0.006)
Price (α)	-0.0042***	-0.0044***	-0.0055***	-0.0056***	-0.0058***
	(0.0003)	(0.0004)	(0.0008)	(0.0008)	(0.0008)
MWTP (-β/α)	3.742***	3.899***	3.313***	4.125***	4.429***
	(0.570)	(0.651)	(0.836)	(1.102)	(1.453)
Observations	2,413	3,046	3,343	3,865	4,057
First-Stage F-Stat	118.07	59.93	47.52	35.28	55.82
Product FE	Y	Y	Y	Y	Y
City FE	Y	Y	Y	Y	Y

Note: Each observation represents a product-city. This table shows the second stage regression results with different choices of bandwidth. See notes in Table 3. Standard errors in parentheses are clustered at the city level. * significant at 10% level; ** significant at 5% level; *** significant at 1% level. The Stock-Yogo weak identification test critical value for two endogenous variables (10% maximal IV size) is 7.03.

Table 5: Random-Coefficient Logit Estimation Results

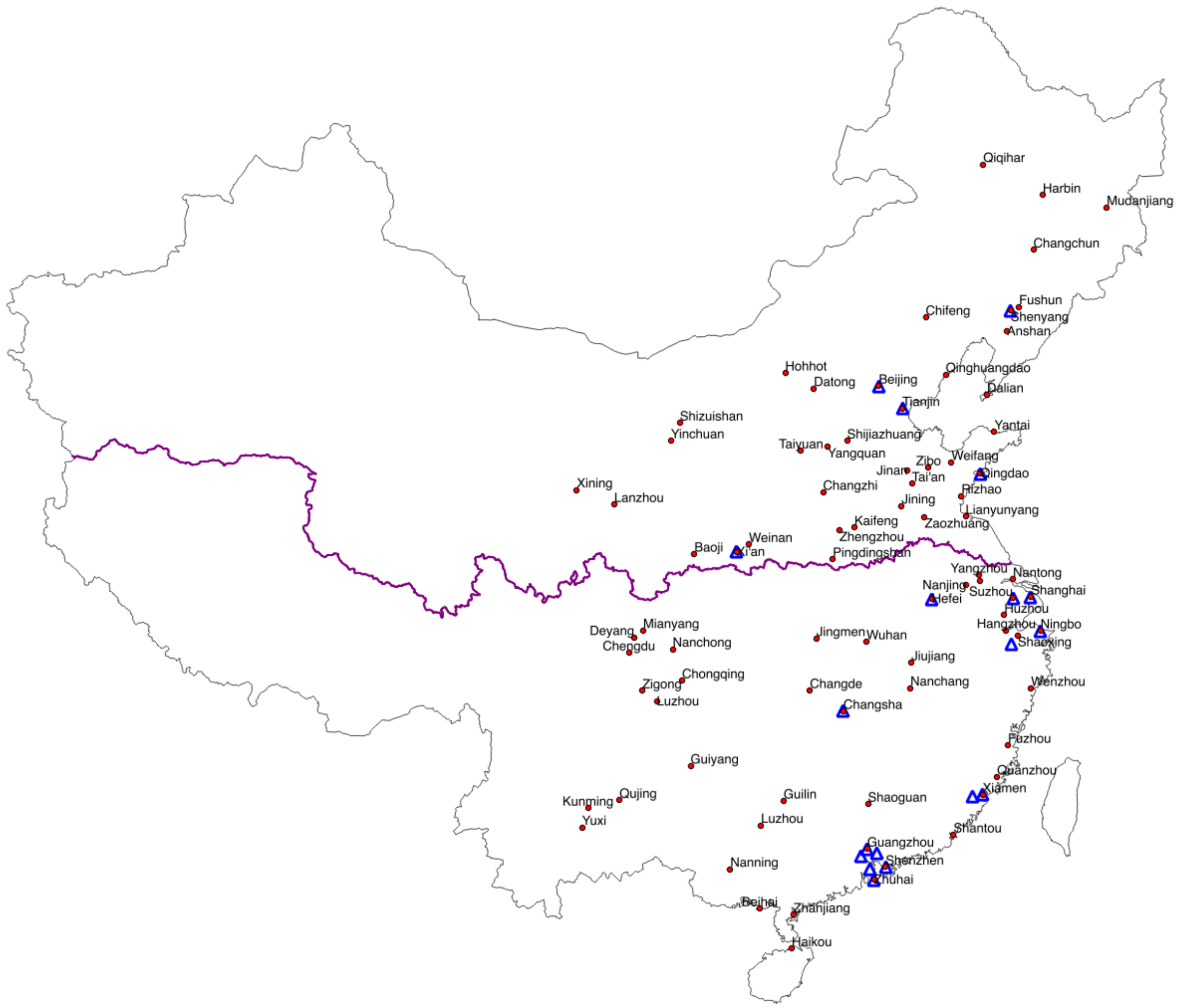
	(1)	(2)
PM10 · HEPA		
Mean coefficient (β_0)	0.0654	0.0659
	(0.0160)	(0.0172)
Interaction with log household income (β_1)	0.0221	0.0208
	(0.0079)	(0.0075)
Standard deviation (σ_β)	0.0002	0.0001
	(0.0098)	(0.0095)
Price		
Mean coefficient (α_0)	-0.0129	-0.0128
	(0.0037)	(0.0037)
Interaction with log household income (α_1)	0.0001	0.0001
	(0.0006)	(0.0006)
Standard deviation (σ_α)	0.0031	0.0030
	(0.0009)	(0.0010)
Observations	3,046	3,046
Control function for f(latitude)	Linear*North	Quadratic
Fixed effects	Product FE, City FE	Product FE, City FE
GMM objective function value	48.72	49.64
MWTP 5th percentile	2.18	2.37
MWTP 25th percentile	3.87	3.98
MWTP 50th percentile	5.13	5.19
MWTP mean	5.46	5.51
MWTP 75th percentile	6.61	6.64
MWTP 95th percentile	9.73	9.68

Note: This table shows the results of the random-coefficient logit estimation in equation (6). Column 1 uses a linear control for the latitude interacted with the North dummy variable, and column 2 uses a quadratic control for the latitude. Asymptotically robust standard errors are given in parentheses, which are corrected for the error due to the simulation process by taking account that the simulation draws are the same for all of the observations in a market. The household-level income data (in 2005 USD) come from the 2005 Chinese census. The distribution of the marginal willingness to pay for clean air is obtained by $mwtp_i = -(\hat{\beta}_0 + \hat{\beta}_1 y_i + u_i)/(\hat{\alpha}_0 + \hat{\alpha}_1 y_i + e_i)$ using the estimated coefficients, household-level income, and random draws from standard normal distributions.

Online Appendices Not For Publication

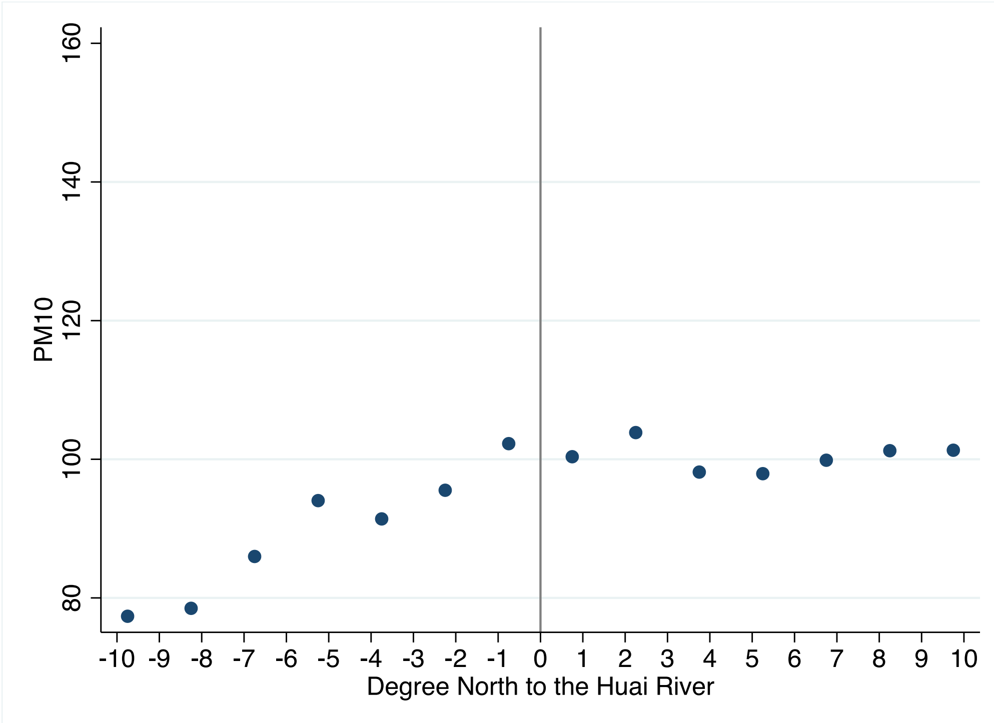
A Additional Figures

Figure A.1: Huai River Boundary and City Locations



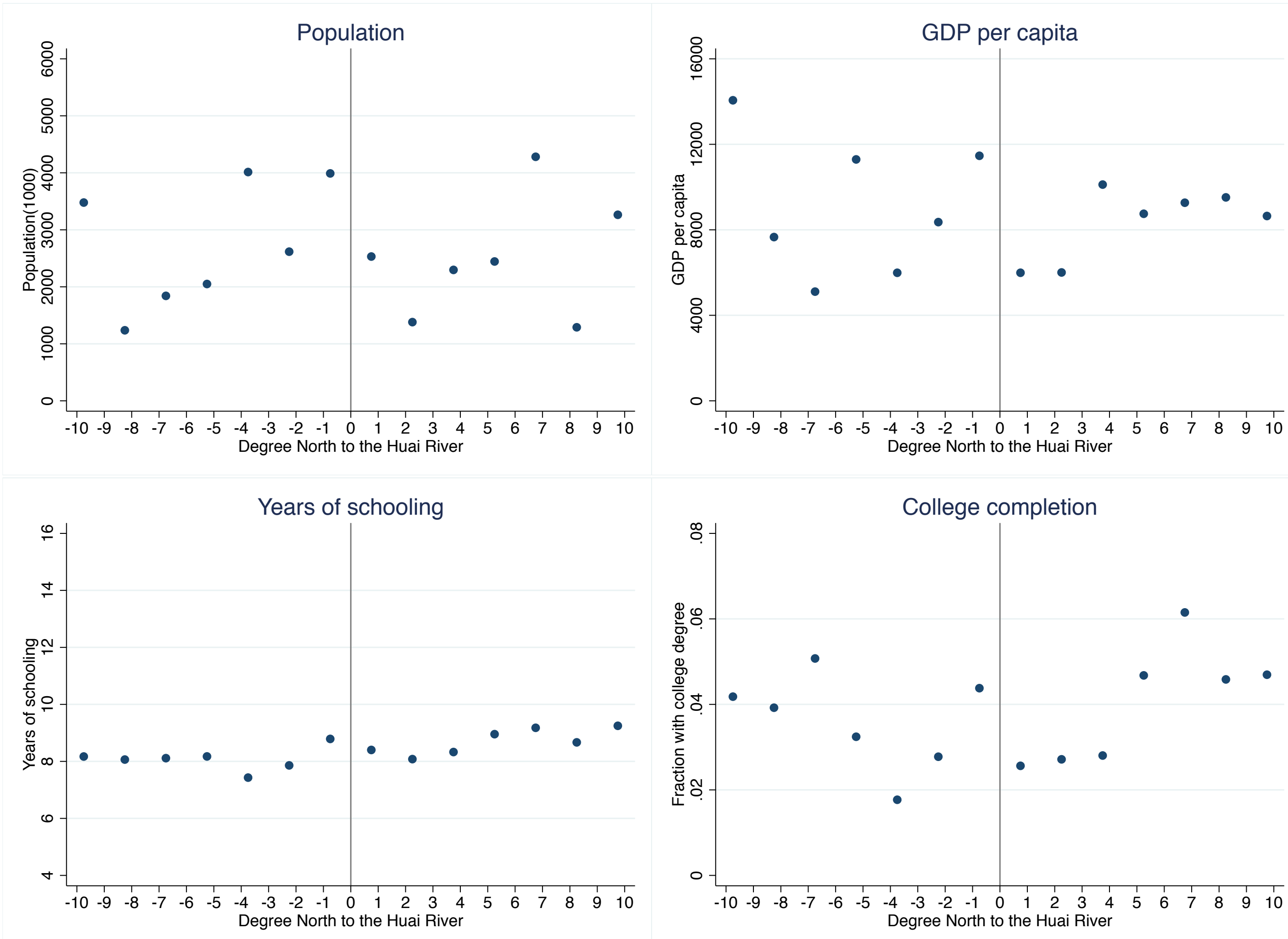
Note: The line in the middle of the map is the Huai River-Qinling boundary. Each dot represents one city. Each triangle represents a factory location or a port location.

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



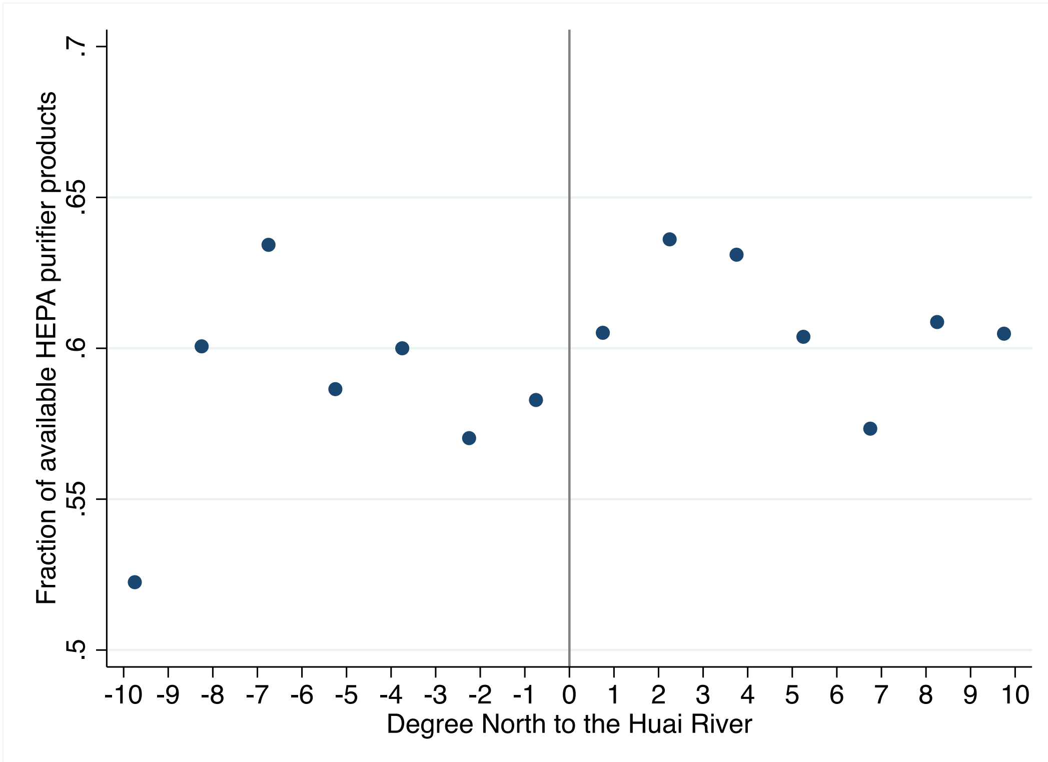
Note: This figure plots the average PM_{10} during non-winter months (April to November) in 2006-2012 by 1.5 degrees of latitude north of the Huai River boundary. The vertical line at 0 indicates the location of the river. Each dot represents cities at 1.5 degrees of latitude and corresponds to the middle 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 of 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



Note: These figures plot the mean of each demographic variable by 1.5 degrees of latitude north of the Huai River boundary. The vertical line at 0 indicates the location of the river. Each dot represents cities at 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 of the river line. The y-axis indicates the mean level of each variable in cities within 1.5 degrees of latitude.

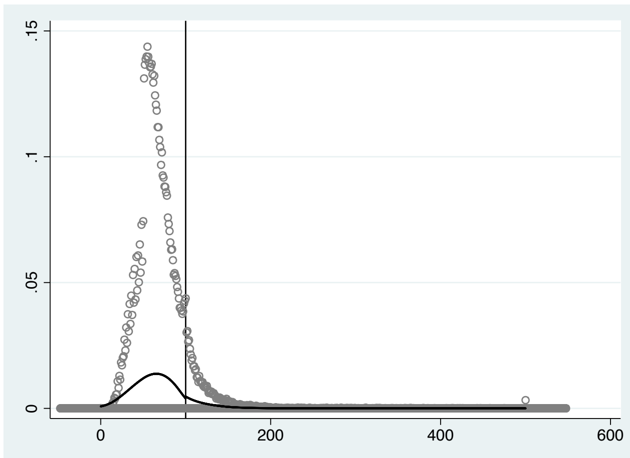
Figure A.4: Fraction of available HEPA purifier products



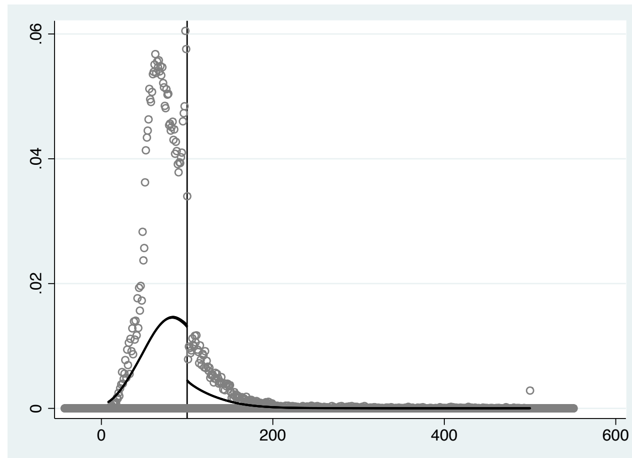
Note: This figure plots the fraction of available HEPA purifier products from all purifier products by 1.5 degrees of latitude north of the Huai River boundary. The vertical line at 0 indicates the location of the river. Each dot represents cities at 1.5 degrees of latitude and corresponds to the middle 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 of 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

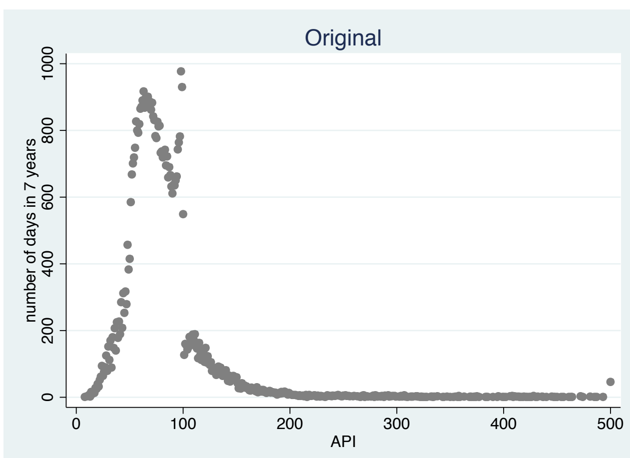
(a) McCrary density test (75% of sample)



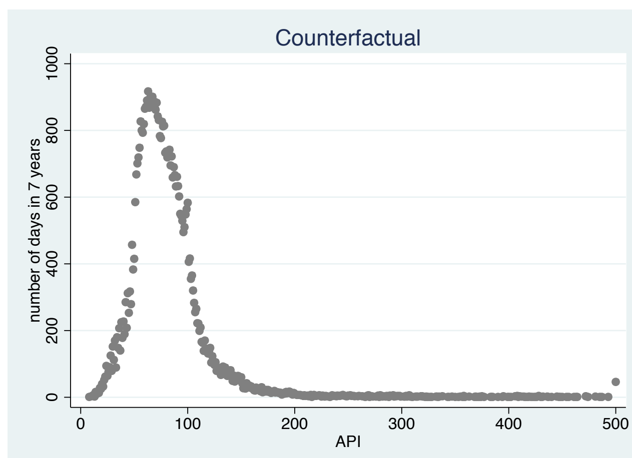
(b) McCrary density test (25% of sample)



(c) Original distributions of the 25% sample



(d) Counterfactual distribution of the 25% sample



Note: To investigate potential manipulation of the API data 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 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 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 a negligible amount. This is because the manipulation occurs only at the margin of 100 and, therefore, it affects the average API minimally over the long term.

B Additional Tables

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

	ln(market share)	
	(1)	(2)
Panel A: Reduced form		
North*HEPA (ρ)	0.931***	0.759***
	(0.143)	(0.106)
Price (α)	-0.0048***	-0.0048***
	(0.0004)	(0.0004)
WTP (-ρ/α)	194.8561***	158.0296***
	(33.0162)	(25.0110)
Observations	3,046	3,046
First-Stage F-Stat	45.10	46.59
Panel B: Second-stage		
PM10*HEPA (β)	0.019***	0.016***
	(0.004)	(0.003)
Price (α)	-0.0047***	-0.0047***
	(0.0004)	(0.0004)
MWTP (-β/α)	4.0631***	3.4114***
	(1.1245)	(0.7756)
Observations	3,046	3,046
First-Stage F-Stat	38.24	38.60
Functional form	Linear*North	Quadratic
Product FE	Y	Y
City FE	Y	Y
GDP*HEPA and Schooling*HEPA	Y	Y

Note: Each observation represents a product-city. Panel A presents reduced-form estimates, where price is instrumented with the distance variables discussed in the text. Panel B presents the second stage results, where PM10*HEPA is instrumented with North*HEPA and price is instrumented with the distance variables discussed in the text. We estimate both of the reduced form and second stage regressions by the two-step GMM estimation with the optimal weight matrix. Standard errors in parentheses are clustered at the city level. * significant at 10% level; ** significant at 5% level; *** significant at 1% level. The Stock-Yogo weak identification test critical value for one endogenous variable (10% maximal IV size) is 16.38, and for two endogenous variables (10% maximal IV size) it 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 to 2012), and average years of schooling and the percentage of population that have 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 (ρ)	0.871***	0.886***	0.709***	0.661***	0.605***
	(0.108)	(0.099)	(0.093)	(0.106)	(0.101)
Price (α)	-0.0045***	-0.0047***	-0.0053***	-0.0053***	-0.0054***
	(0.0003)	(0.0004)	(0.0008)	(0.0008)	(0.0008)
WTP ($-\rho/\alpha$)	193.444***	190.385***	134.087***	123.744***	113.148***
	(23.514)	(23.918)	(21.019)	(25.610)	(24.107)
Observations	2,413	3,046	3,343	3,865	4,057
First-Stage F-Stat	133.98	71.16	59.20	35.14	58.66
Panel B: Quadratic					
North*HEPA (ρ)	0.759***	0.771***	0.633***	0.610***	0.572***
	(0.086)	(0.082)	(0.085)	(0.099)	(0.099)
Price (α)	-0.0045***	-0.0047***	-0.0053***	-0.0054***	-0.0054***
	(0.0003)	(0.0004)	(0.0008)	(0.0008)	(0.0008)
WTP ($-\rho/\alpha$)	168.862***	165.179***	119.248***	113.870***	106.671***
	(20.105)	(20.519)	(18.940)	(23.942)	(23.386)
Observations	2,413	3,046	3,343	3,865	4,057
First-Stage F-Stat	140.49	64.44	58.94	35.12	58.16
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 the distance variables discussed in the text. Standard errors in parentheses are clustered at the city level. * significant at 10% level; ** significant at 5% level; *** significant at 1% level. The Stock-Yogo weak identification test critical value for one endogenous variable (10% maximal IV size) is 16.38.

Table A.4: PM10 in winter months and Market share in all months

	ln(market share)				
	(1) 4-degree	(2) 5-degree	(3) 6-degree	(4) 7-degree	(5) 8-degree
Panel A: Linear*North					
PM10*HEPA (β)	0.016***	0.016***	0.013***	0.016***	0.018***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)
Price (α)	-0.0070***	-0.0076***	-0.0087***	-0.0088***	-0.0089***
	(0.0005)	(0.0005)	(0.0005)	(0.0006)	(0.0008)
MWTP (-β/α)	2.315***	2.066***	1.480***	1.785***	1.968***
	(0.473)	(0.407)	(0.409)	(0.536)	(0.626)
Observations	3,118	3,889	4,289	4,892	5,152
First-Stage F-Stat	82.58	73.98	13.57	7.43	6.93
Panel B: Quadratic					
PM10*HEPA (β)	0.016***	0.014***	0.011***	0.014***	0.016***
	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)
Price (α)	-0.0070***	-0.0077***	-0.0087***	-0.0088***	-0.0089***
	(0.0005)	(0.0005)	(0.0005)	(0.0006)	(0.0008)
MWTP (-β/α)	2.268***	1.883***	1.283***	1.577***	1.757***
	(0.449)	(0.395)	(0.416)	(0.564)	(0.669)
Observations	3,118	3,889	4,289	4,892	5,152
First-Stage F-Stat	87.32	86.15	13.73	7.48	6.97
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 PM10*HEPA is instrumented with North*HEPA and price is instrumented with the distance variables discussed in the text. Note that we use PM10 in winter months as in all other tables, and we use market share in all months which is different from other tables where market share is from winter months. Standard errors in parentheses are clustered at the city level. * significant at 10% level; ** significant at 5% level; *** significant at 1% level. The Stock-Yogo weak identification test critical value for one endogenous variable (10% maximal IV size) is 16.38.