Willingness to Pay for Clean Air:

Evidence from Air Purifier Markets in China

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Abstract

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

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1 Introduction

Air quality is remarkably worse in developing countries, and severe air pollution causes substantial health and economic burdens for billions of people. For example, the annual average exposure to fine particle pollution in China is six times higher than that in the United States in 2010.[1] 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 that air pollution is one of the first-order obstacles for economic development for many countries.

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

The goal of this paper is to 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 estimating a *lower bound* 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 characteristics—high-efficiency particulate arrestance (HEPA)—informs consumers and econometricians the purifier's ability to reduce indoor particulate matter. The extent to which consumers value this characteristic, along

[1] http://data.worldbank.org/indicator/EN.ATM.PM25.MC.M3/countries?display=default

with the price elasticity of demand, reveals their WTP for indoor air quality improvements.

We apply this framework to unique transaction data in air purifier markets in 81 Chinese cities. For each retail store in these 81 cities, we observe product-level information on monthly sales, monthly average price, and detailed product characteristics. Importantly, the dataset includes detailed information about product attributes, including the information about each purifier's ability in reducing indoor air pollution. Our data cover January 2006 through December 2012. We also collect data on air pollution and demographic characteristics to construct a dataset that includes air purifier sales and prices, air pollution, and demographic characteristics.

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

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

We first present visual and statistical evidence that the level of air pollution (PM_{10}) is discontinuously higher for cities in the north of the Huai River compared to cities in the south. A key prediction of our demand model is that if households value clean air, the market share for HEPA purifiers should be higher for cities in the north of the river boundary. Our second empirical anal-

ysis provides evidence that there is in fact 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 is 53 dollars. Third, we estimate two stage least squares and find that the marginal WTP for removing 1 ug/m^3 of PM_{10} is 1.6 dollars. We show that our RD estimates are robust to using a range of different bandwidths as well as local quadratic estimation. Fourth, we relax a few assumptions behind standard logit demand estimation by estimating a random-coefficient logit model. Given a set of assumptions, our random-coefficient logit model allows us to estimate potentially heterogeneous preference parameters for pollution and prices. We find substantial heterogeneity that can be explained both by observed and unobserved factors. Our results indicate that higher-income households have significantly higher WTP for clean air compared to lower-income households.

Our study provides three primary contributions to the literature and ongoing policy discussions. The first contribution is that we develop a framework to estimate WTP for improvements in environmental quality by estimating demand for defensive investment. Earlier studies on avoidance behavior against pollution examine whether individuals take avoidance behavior in response to pollution exposure.[2] A key question in recent studies is whether researchers can estimate WTP for improvements in environmental quality from observing defensive investment in markets. To our knowledge, two recent papers ask this question. Kremer et al. (2011) uses a randomized control trial (RCT) for water pollution in Kenya. Our approach, a quasi-experimental experiment with non-experimental data, is closer to the approach by Deschenes et al. (2012), in which they use medical expenditure data in the United Sates at the individual level. There is no doubt that RCT would be the ideal empirical strategy to answer the question. However, a large-scale RCT on pollution is not always feasible in many countries. Therefore, quasi-experimental approaches are also important complements to address this question. We believe that our quasi-experimental framework can be useful for other contexts because our method relies on market-level sales and price data, which are more likely to exist in most countries because manufacturers and retail stores usually collect scanner data on product sales and price.[3]

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

[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

The second contribution is that our analysis provides empirical evidence for an important "missing piece" in the literature on air pollution in developing countries, where pollution concentrations are far above those ever recorded in the US and most other countries and incomes are lower. As emphasized by Greenstone and Jack (2013), few studies have attempted to develop revealed preference estimates of WTP for environmental quality in developing countries. On the other hand, extrapolation of WTP estimators from studies in developed countries is unlikely to be valid because of the relatively low pollution level and high incomes. We fill in this gap by providing a revealed preference estimate of WTP for air quality in China. Our estimates are particularly useful for this question because our identification comes from long-run exposure to air pollution induced by the Huai River policy, which is more informative of WTP in the developing world setting where environmental quality has remained low and pollution does not come as "on-and-off shocks".

Finally, our findings provide important policy implications for ongoing discussions in energy and environmental regulation in developing countries. Governments in developing countries are starting to propose interventions to the air pollution problems. China's official news agency *Xinhua News* reported in 2014 that Chinese Premier Li, Keqiang declared "War Against Pollution" to reduce emission of PM_{10} and $PM_{2.5}$ (Zhu, 2014). China has also made commitments to address global climate change, as featured by the *New York Times* April 2016 (Davenport, 2016). Reform policies, for example, include reforming the the Huai river heating policy, and the launch of a national cap-and-trade program on carbon emission in 2017. Our results provide quantitative evidence for one of the benefits from such policies, which is a useful parameter for policy-makers in deciding optimal environmental regulation.

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

2.1 The main pollutant in Chinese cities

Northern and eastern China has perhaps the most polluted cities in the world according to NASA's global map on $PM_{2.5}$ (particulate matter with diameter of 2.5 micrometers or less).[4] Among

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.

[4] http://www.nasa.gov/topics/earth/features/health-sapping.html

ambient pollution measures, $PM_{2.5}$ has shown most consistently an adverse effect on human health (Dockery et al. (1993), Pope et al. (2009) and Correia et al. (2013)).

The main pollutant in Chinese cities is particulate matter. The Chinese Ministry of Environmental Protection (MEP) releases an daily air pollution index (API) in 120 cities since 2000. In each city, a number of monitors take hourly concentration measures of three air pollutants: PM_{10} (particulate matter with diameter of 10 micrometers or less), SO_2 and NO_2. Daily API is converted from one of these pollutants that has the highest daily average value. The API value scales from 0 to 500, the higher the value, the greater the level of air pollution. For example, API value in 0-50 represents excellent air, while an API value over 300 represents heavily polluted air. In days when API is above 50, the MEP reported the specific type of pollutant from which API was taken from. In our sample of cities, during 2006-2012, in 79% of days when the type of pollutant is reported (API>50), 91% were from PM_{10}, 8.9% from SO_2 and 0.15% from NO_2.

The official API, based on ambient PM_{10} in most days, is the only accessible pollution information for Chinese citizens during the time period of this study.[5] Both daily API level and the main pollutant type are reported to local residents by city weather channel, radio and newspapers.

2.2 Air purifiers

Among already known air purification technologies, the High Efficiency Particulate Arrestance (HEPA) filter is most effective against particulate matter. According to the US Department of Energy, a HEPA filter must remove (from the air that passes through) at least 99.97% of particles in 0.3 micrometer in diameter (DOE (2005)). It is more effective for particles which are larger, for example, $PM_{2.5}$ and PM_{10}. Recent clinical studies find that the uses of HEPA purifiers in various settings are associated with improvements in health, including reduced asthma visits and asthma symptoms among children, and lower levels of markers for inflammation and heart disease and reduced incidences of invasive aspergillosis among adults (Abdul Salam et al. (2010); Allen et al. (2011); Lanphear et al. (2011)).

On the Chinese market, other available Non-HEPA purification technologies are designed for removing other target pollutants, not particulate matter. Activated carbon absorbs volatile organic

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

compounds (VOCs), but it does not remove particles. A catalytic converter is effective in removing VOCs and formaldehyde. An air ionizer generates electrically charged air or gas ions, which attach to airborne particles that are then attracted to a charged collector plate. However, there are no specific standards for air ionizers, and they also produce ozone and other oxidants as by-products. A study by Health Canada finds that residential ionizer only removes 4% of indoor $PM_{2.5}$ (Wallace, 2008).

An air purifier can use multiple air purification technologies, which must pass quality testing by a certified testing center before entering the market. Air purifier companies are required to make their product testing results available. To learn more about the function of air purifier products, we compiled testing certificates for products in our sample from company websites. Air purifiers with a HEPA filter report testing results on the percentage of indoor $PM_{2.5}$ it removes, and Non-HEPA air purifiers that use activated carbon report testing results on the effectiveness in removing VOCs. Testings on $PM_{2.5}$ are not conducted if a product does not have a HEPA filter. Air purifiers that combine a HEPA filter with activated carbon to remove both particulate matter and VOC report testing results on both.

Consistent with the standard from the US Department of Energy, Chinese market advertisements on air purifiers with a HEPA filter typically state explicitly that they can remove more than 99% of $PM_{2.5}$.

2.3 The Huai River policy and its recent reform

China has adopted the Soviet-era centralized heating system since 1958. Due to budget constraint, the Chinese government decided to provide city-wide centralized heating to cities in North China only (Almond et al. (2009)). North and South China are divided by the line formed by the Huai River and Qinling Mountains. This line was used to divide the country for heating policy because the average January temperature is roughly 0° Celsius along the line, and it is not a border used for administrative purposes (Chen et al. (2013)). Cities north to the line have received unlimited heating in winter every year. In contrast, cities south to the line have been denied centralized heating supply from the government. The heating policy is therefore called the Huai River policy. The heating supply to the north has been considered a public welfare entitlement, and it remains the same today.

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

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

In July 2003, the Chinese government issued a heat reform in northern cities. The reform changed the payment system from free provision to consumer-based billing (WorldBank (2005)). Individual households became responsible for paying their own heat bills each season, which is a flat rate per square meter of floor area (without changes in the metering method).[6] Whether heat subsidy is provided by employers depends on the sector. In public sector, former in-kind transfers

[6]The Chinese government has also been interested in introducing heat metering and consumption-based billing to improve the efficiency of heat utilization. To learn more about the progress of the reform, we recently had a conversation with the energy team of the World Bank about their collaboration with the Chinese government on the reform. According to their experiences in China, it has been difficult to switch to energy-saving construction technologies on a large scale. Little substantial progress along this dimension has been made so far. Thus, the consumer-based billing at a flat rate is not equivalent to consumption-based billing.

were changed to a transparent payment for heat added to the wage. In contrast, private sector employers were not explicitly required to provide heat subsidy to their employees. In the 2005 mini census, 21% of labor force was in urban public sector in the 81 cities in our sample, suggesting that only a small percentage of employees get heat subsidy after the reform. Anecdotally, from an online survey on heat bills among more than 800 individuals in Qingdao (a northern city) in 2012, 78% do not receive any heat subsidy, 12% think that the amount of heat subsidy is very small, and only 10% think that they get a reasonable subsidy for heat.[7]

Our analysis focuses on 2006-2012, after the 2003 reform on heat billing. We summarize our comparison on winter heating between the north and the south since the reform. First, the way winter heating has been provided remains the same after the reform. The centralized city-wide heating supply in the north remains the same, where households have little option other than the centralized coal-based heating that generates higher pollution levels. In the south, households choose their own ways to stay warm in winter, including using air conditioners, space heaters, heated blankets, and etc. Second, heating cost in the north has changed since the 2003 reform. Northern households no longer enjoy free heating and instead have to pay a substantial proportion of their heat bills from the centralized heating, while households in the south remain to pay for heating methods of their choice. According to our comprehensive search of heating costs in 20 cities within 3 degrees of latitude relative to the Huai River boundary, household heating costs in the north are comparable to, or could even be higher than, those in the south.[8]

3 Data and Descriptive Statistics

We compile comprehensive data from several sources. Our dataset is unique because it integrates air pollution data with detailed market transaction data at the product-city-store-year-month level, which are usually hard to obtain in developing countries.

[7] http://news.bandao.cn/news_html/201212/20121224/news_20121224_2048038.shtml

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

3.1 Data Sources

3.1.1 Air purifier data

We obtain monthly market transaction data of air purifiers in 81 cities in 2006-2012 from a top marketing consulting company in China. In each city, the transaction data are collected every month from a network of major department stores and electrical appliance stores, which take up on average more than 80% of all in-store sales in a city. During 2006-2012, in-store sales consist of on average over 95% of overall sales including in-store and online sales.[9] The original sales and price data are at the product-city-store-year-month level. Because our empirical strategy using the Huai River policy relies on cross-sectional variation, we aggregate the transaction data to the product-city level, for example, the total number of sales of a product during 2006-2012 by city, the average price of a product in 2006-2012 by city, etc. There are 395 products of 30 brands in our sample.

A unique feature of the data is that the type of filtration system that a product uses is observed. Importantly, we observe whether a product uses a High Efficiency Particulate Arrestance (HEPA) filter, which enables us to quantify the amount of particulate matter that a product is able to remove. As discussed in Section 2.2, the HEPA filter is most effective against particulate matter. Based on the US standard for HEPA filters, advertisements in Chinese cities highlight that air purifiers with a HEPA filter can remove more than 99% of $PM_{2.5}$. Combining the binary measure of having a HEPA filter with pollution levels, we measure the amount of pollution reduction as follows. Assuming that consumers are fully informed, the amount of pollution reduction that consumers think they will get from a HEPA purifier is equal to the level of PM_{10}, and 0 if they get a Non-HEPA purifier.

3.1.2 Pollution data

The official air pollution index (API) is the only accessible pollution information for Chinese citizens during the time period of this study. We obtain daily API data for 81 cities in our sample in 2006-2012 from Chinese Ministry of Environmental Protection (MEP). In addition to the API level, the

[9]The marketing consulting company provides detailed product-level data on in-store sales only. The share of online sales has increased dramatically since 2013, while the share of in-store sales has decreased. Data from the company suggest that online sales increased to 36% in 2013 and to 47% in 2014. Therefore, to use the data most representative of all sales, we focus our analysis on 2006-2012.

specific type of pollutant from which API was taken from is also disclosed to the public in days when the air quality is not excellent (API is above 50). In our sample of 81 cities, during 2006-2012, in 79% of days when the type of pollutant is reported, 91% were from PM_{10}, 8.9% from SO_2 and 0.15% from NO_2.

The conversion from the concentration of each pollutant to API is non-linear. For days that PM_{10} is reported as the main pollutant, we use the official formula used by Chinese MEP to convert daily API to daily PM_{10}. To match with the product-city level market transaction data, we aggregate the average PM_{10} in winter months and non-winter months respectively, at the city level.

We are cautious in using the API data because recent studies find evidence on underreporting of API at the margin of 100 (Chen et al. (2012), Ghanem and Zhang (2014)). The manipulation is motivated by the blue-sky award, which defines a day with API below 100 as a blue sky day and link the number of blue sky days in a year to the annual performance evaluation of city governments. For our analysis using the city-level pollution measure, we are concerned about the extent to which the manipulation affects the average level of API.

To investigate potential manipulation in our sample, we perform McCrary density tests (McCrary (2008)) on daily API data for each of these 81 cities in 2006-2012. In 75% of city-year observations, we find no statistically significant discontinuity in the density of daily API at 100 in Figure A.2a, while a statistically significant discontinuity at 100 is observed in 25% of city-year observations in Figure A.2b. To examine to what extent the manipulation 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 plot a counterfactual distribution in the 25% manipulation subsample. Figure A.2c shows the original distribution of API in the 25% subsample, where the mean of API is 147.90. Figure A.2d shows the the counterfactual distributions of API in the same 25% subsample, where the mean of API is 147.95. Thus, for our analysis, the similarity of these two mean values of API reduces the concern about the manipulation.

3.1.3 Measure of transportation costs

We are concerned that the price of air purifiers is likely correlated with unobserved demand shocks, particularly product-city level unobserved factors that generated cross-city variation within product.

We use a measure of transportation costs as a supply shifter as an instrument for price. For each product, we geo-coded the location of its manufacturing plant if it is domestically produced, or the location of the port if it is imported. Around 16% of products are imported. We then calculate the distance from the city a product sells to its manufacturing plant for domestically produced products, or to the port for imported products. We use this product-city level distance measure to capture transportation costs and use it as the instrument for price.

3.2 Descriptive Statistics

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

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

We also use two maps to show spatial distributions of the cities and manufacturing plants/importing ports in our dataset. Figure 1 shows the location of the 81 cities on the China map in our analy-

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

4 Demand for Air Purifiers

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

We begin with a random utility framework similar to Berry (1994), Nevo (2001), and Kremer et al. (2011). Consider that consumer i in city c has ambient air pollution z_c (particular matters). The consumer can purchase air purifier j in city c at price p_{jc} to reduce indoor air pollution. Indoor air pollution level conditional on purchasing product j in city c is $z_{jc} = z_c \cdot (1 - e_j)$. We denote purifier j's ability to reduce indoor particulate matters by $e_j \in [0, 1]$. We observe markets for

$c = 1, ..., C$ cities with $i = 1, ..., I_c$ consumers. The conditional indirect utility of consumer i from purchasing air purifier j at city c is:

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

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

Air purifiers usually run for five years and require replacement of filters. We consider that consumer i thinks of utility gains from purifier j for five years and p_{jc} as a total cost including the upfront and running cost. This approach abstracts from interesting possibilities that consumers may consider dynamics of product entries and make a dynamic decision. Unfortunately, it is hard to examine such a dynamic decision in our empirical setting. While we have monthly sales and price data, the exogenous variation in pollution comes from purely cross-sectional variation. 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 and consider both of a standard logit model and a random-coefficient logit model. A standard logit model assumes that the preference parameters do not vary by i. The attractive feature of this approach is that the random utility model in equation (1) leads to a linear equation. The linear equation can be estimated by linear GMM estimation, which is equivalent to two-stage least squares. A random-coefficient logit model allows the preference parameters to vary by i through observable and unobservable factors. This feature comes at a cost—random-coefficient logit estimation involves nonlinear GMM estimation for highly a nonlinear objective function. In this paper, we take both approaches to estimate willingness to pay for clean air.

4.1 A Logit Model

We begin with a standard logit model. Suppose that $\beta_i' = \beta'$ and $\alpha_i = \alpha$ for all consumer i and that the error term ϵ_{ijc} is distributed as a Type I extreme-value function. Consumer i purchases purifier j if $u_{ijc} > u_{ikc}$ for $\forall k \neq j$. Then, the market share for product j in city c can be characterized by[10]

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

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

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

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

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

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

We interpret that our estimate of $-\beta/\alpha$ provides a *lower bound* of MWTP for one unit of indoor pollution reductions for the following reasons. First, our approach assumes that indoor air pollution levels equal to ambient pollution levels (z_c). A recent engineering study shows that, on average, indoor pollution levels are lower than outdoor pollution levels in Beijing.[11] If people understand that indoor air pollution level is lower than outdoor pollution level, our approach underestimates β. An alternative approach would be to rely on an engineering estimate of indoor-outdoor air pollution ratio, which would produce slightly larger values for the MWTP. However, we want to be conservative about our estimate as much as possible, and therefore, our estimation mostly focuses on estimating *a lower bound* of MWTP. Second, in the context of the Huai River policy, households have limited information on the negative health effects generated by the heating policy and likely underestimate the health effects. Consequently, our estimate of MWTP for clean air is also likely *a lower bound.*

An advantage of studying air purifier markets is that e_j (purifier j's ability to reduce indoor particulate matters) is straightforward, and consumers are well informed about it. As we explained in Section 2.2, if a purifier has High Efficiency Particulate Arrestance (HEPA) as an attribute, it reduces 99% of indoor particular matters. On the other hand, if a purifier does not have HEPA, it does not reduce indoor particular matters. In advertisements and product descriptions of air purifier products on the Chinese market, consumers are well informed about the difference between HEPA purifiers and non-HEPA purifiers. Therefore, we define the pollution reduction by $\Delta z_{jc} = z_c \cdot HEPA_j$, which equals to z_c if $HEPA_j = 1$ and equals to 0 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 matters but could provide reduction on other pollutants, for example, VOCs and odors. These potential utility gains are captured by the product fixed effects.

Then, our estimation equation, which is derived from the random utility model is:

[11] 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 http://news.tsinghua.edu.cn/publish/news/4204/2015/20150423100046963966000/20150423100046963966000_.html

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

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

4.2 A Random-Coefficient Logit Model

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

We begin with the same random utility model described in equation (1) but relax the assumptions on β_i' and α_i by allowing the two parameters to vary by consumer i through observable and unobservable factors. We model the two parameters by $\beta_i' = \beta_0' + \beta_1' D_i + u_i$ and $\alpha = \alpha_0 + \alpha_1 D_i + e_i$, where D_i is the log of household-level income from the census data, $u_i \sim N(0, \sigma_\beta)$, and $e_i \sim N(0, \sigma_\alpha)$. That is, each parameter depends on the mean coefficient, log of household-level income, and a normally distributed random error. Denote the part of the utility function that does not depend on i (the mean utility level) by $\delta_{jc} = \beta_0' z_{jc} + \alpha_0 p_{jc} + \theta_j + \lambda_c + \xi_{jc}$, and the part that depends on i by $\mu_{jci} = (\beta_1 D_i + u_i) z_{jc} + (\alpha_1 D_i + e_i) p_{jc}$. Then, the market share for product j in city c can be evaluated using Monte Carlo integration assuming a number n_c of individuals for city c by:[12]

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

The important difference between equations (2) and (5) is that equation (5) now includes elements that depend on i. Therefore, the market share and δ_{jc} has to be calculated numerically by the fixed point iterations: $\delta_{.c}^{h+1} = \delta_{.c}^{h} + \ln S_{.c} - \ln s_{.c}$ for $h = 0, ..., H$, in which $s_{.c}$ is the predicted market

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

share by equation (5) and $S_{.c}$ is the observed market share from the data. Once δ is obtained, ξ_{jc} can be written by $\xi_{jc} = \delta_{jc} - (\beta_0' z_{jc} + \alpha_0 p_{jc} + \theta_j + \lambda_c) \equiv \omega_{jc}$.

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

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

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

5 Empirical Analysis and Results

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

5.1 Logit Estimation

Our primary empirical challenge is that two variables in our demand estimation—pollution and price—are likely to be endogenous. In an ideal controlled experiment, one would expose different consumers to randomly assigned pollution levels and purifier prices to estimate demand for air purifiers in relation to variation in air pollution. In reality, these two variables are unlikely to be randomly assigned. Air pollution is determined by both observable and unobservable factors. Therefore, we cannot think of observed pollution levels across different cities as exogenous variation because of potential omitted variables. Air purifier prices are also unlikely to be determined exogenously because unobserved factors in demand estimation is believed to be correlated with prices.

For example, suppose that some demand factors are unobserved to econometricians but observable to firms, who have the ability to set prices because of imperfect competition. Then, we expect that firms set prices in response to the unobserved demand factors, which creates correlation between prices and the error term in our demand estimation.

To address the endogeneity of air pollution, we exploit a regression discontinuity in air pollution at the spatial border of the Huai river as described in section 2.3. This approach provides us a nearly ideal research environment to answer our research questions for two reasons. First, it allows us to exploit plausibly exogenous variation in air pollution created by the natural experiment. If people value air quality, our demand model in section 4 predicts that the market shares for HEPA purifiers are discontinuously higher in the cities in the north of Huai river. Second, the discontinuous difference in air pollution created by the Huai River policy has existed for a long time since the 1950s. Therefore, the experiment provides long-run variation in air pollution, which enables us to examine how households respond to variation in pollution that is not transitory but rather long-lasting.

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

5.1.1 Empirical Strategy

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

and Lemieux, 2008; Gelman and Imbens, 2014). Therefore, we estimate a local linear regression and a local quadratic regression for observations near the cutoff of $North_c = 1$. Our local linear regression is,

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

The identification assumption is that the conditional expectation of the outcome variable (z_c) is smooth at the cutoff. One way to examine the validity of the RD design is to investigate observed variables on either side of the Huai River. In the appendix, we show that there are no significant discrete changes in population, GDP per capita, average years of schooling and fraction completed college at the cutoff (Figure A.4). Nevertheless, we test the robustness of our estimate by including these city demographics as covariates in X_c. Our coefficient of interest, γ, measures the discontinuous increase in z_c just north of the Huai river.

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

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

Reduced Form on Log Market Share: Suppose that our first stage on PM10 provides evidence on a discontinuous increase in PM10 at the river boundary. Then, our demand model predicts that the market share for HEPA purifiers should be higher for cities in the north of the

river if households value clean air. Our reduced form tests if there is a discontinuous change in the market share for HEPA purifiers at the river boundary. We use our city-product level data to estimate a reduced form equation,

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

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

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

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

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

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

5.1.2 Graphical Analysis

Huai River policy generates a natural experiment in air pollution in winter months because the policy-induced pollution comes from centralized heating facilities operating in winter. In Figure 2a, we show the average PM_{10} in winter months (December-March) during 2006-2012 by the running variable, which is the latitudes of cities (L_t). Because very few cities locate in the farthest north and the farthest south, the figure includes cities located within 10 degrees of the latitude from the Huai river boundary. Each plot in the figure shows the average PM_{10} by 1.5 degree of latitude. The vertical line at $L_c = 0$ indicates the location of the Huai river. Consistent with findings in previous studies (Almond et al. (2009), Chen et al. (2013)), the figure suggests a discontinuous increase in PM_{10} just north of the Huai River. This evidence suggests that the coal-based heating policy generated higher pollution levels for cities in the north of the river boundary. We also investigate if a similar discontinuity in air pollution can be found for non-winter months, when the heating facilities do not operate. Figure A.3 in the appendix shows that there is no discontinuous change in PM_{10} levels at the boundary in non-winter months (April-November). This finding provides further support that the discontinuous increase in pollution presented in Figure 2a is likely generated by the Huai river policy.

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

5.1.3 Estimation Results

Table 2 shows the results of the first stage estimation. We report the first stage estimation for PM_{10} in Panel A. The first two columns show results without demographic controls, and the last

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

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

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

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

indicate that the MWTP is about $1.6 per household.

5.1.4 Robustness of the Estimates

Next, we test whether our main results are robust to using shorter or longer bandwidths. For the second stage estimation in Table 4, we use a range of bandwidths between 4 and 8 latitude degrees. We report results using local linear regression in Panel A and local quadratic regression in Panel B. Using both functional forms, we find that our estimates of MWTP are robust to using shorter and longer bandwidths. For further comparison, we also reports robustness results on the first stage on PM_{10} in Table A.2 and the reduced form in Table A.3. Consistent with Figure 2a, the magnitude of the first stage estimate on PM_{10} is slightly larger using shorter bandwidth. Also consistent with 2b, reduced form estimates on δ are similar using different bandwidths and functional forms.

A potential concern on the main specification is that, high income or better educated individuals might prefer HEPA purifiers over Non-HEPA purifiers for non-pollution reasons, and therefore interaction terms of income and HEPA or education and HEPA could be omitted variables. To directly test these possibilities, in Table A.1, we include the interaction of GDP per capita and HEPA and the interaction of average schooling and HEPA in both columns. Reduced form and 2SLS estimates are similar to our main estimates in Table 3, which reduces the concern on differential preferences on purifier types by income and education.

5.1.5 Interpretation of the Estimates

To interpret the higher demand for HEPA purifiers in the north as the consequence of the higher pollution levels generated by the heating policy, one should exclude other potential confounders. We do not observe discontinuous changes in observed demographics across the Huai River boundary in Figure A.4. Furthermore, our main specification includes city fixed effects that absorb all differences among cities across the river boundary. We discuss a number of other potential concerns below.

First, the Huai River boundary might affect air quality and the demand for HEPA purifiers in the north through other policies other than the heating policy. For example, if the Huai River boundary is used for making economic policies, for example, allocating heavy industries to the north which might also generate higher pollution level, we cannot attribute higher pollution and higher market share of HEPA purifiers solely to the heating policy. To incorporate such confounding

policies, we have conducted a comprehensive search for policies that are made differently on either side of the Huai River. We fail to find other policies using the Huai River to divide the country. This is consistent with the fact this line was used to divide the country for heating policy because the average January temperature is roughly 0° Celsius along the line, and it is not a border used for administrative purposes (Chen et al. (2013)).

Second, conceptually, one might still be concerned that the heating policy could lead to higher demand for HEPA purifiers in the north through channels other than higher pollution levels. Particularly, if the heating supply to the north has been a public welfare entitlement and subsidized heating cost of northern households, while households in cities just south to the river (with similar winter temperature) are responsible for paying their heating choice, northern households might have higher disposable income because of the heating subsidy. If this is the case, the heating policy might generate higher demand for HEPA purifiers through the subsidy channel instead of the pollution channel. However, as we discussed in Section 2.3, the heat reform in 2003 changed the payment system from free provision to consumer-based billing. Of critical importance is the change that northern households have to pay a substantial proportion of their heat bills from the centralized heating after 2003. From our comparison of heating costs in the north versus in the south in Section 2.3, household heating cost in the north could even be higher than that in the south. Therefore, in our analysis during 2006-2012, heating subsidy has minimal effect on household disposable income in the north.

The third possible concern is about migration for cleaner air. If some households migrated from the north to the south for cleaner air, our estimates on WTP from demand for air purifiers do not take into account of these households. Although we can not completely rule out migration for air quality, we do not find it a common reaction in China for the following reasons. First of all, internal migration in China is strictly constrained by the *Hukou* system. The *hukou,* obtained at one's city of birth, is crucial for getting local social benefits and education opportunities, which makes migration a more costly decision than that in countries without mobility restriction. Indeed, in the 2005 Census micro-data, only 1 percent of the population within 1.5 degrees north to the river migrated to the south. Furthermore, for households who migrate for clean air, we would expect that they are relatively wealthy. However, we find in the 2005 Census micro-data that the small number of northern migrants residing in the south are not among the top income percentiles

in their cities of origin, suggesting that clean air was less likely the main motive of the migration.

A final note is on the availability of HEPA purifier products between the north and south of the river. If HEPA purifiers are more available in the north because appliance stores supply more of them relative to Non-HEPA purifiers, what we observe in Figure 2b might reflect the difference in supply. To directly test this concern, in Figure A.5, we plot the fraction of HEPA purifier products (out of all available purifier products on the market) by 1.5 degree of latitude relative to the Huai River. We do not observe a discontinuous jump on the supply of HEPA purifiers just north to the river boundary.

5.2 Random-Coefficient Logit Estimation

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

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

5.2.1 Nonlinear optimization methods and initial values

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

algorithms and 2) starting values, with conservative stopping values (i.e. conservative tolerance levels for nonlinear searches) to investigate if the estimated local optimum is indeed the global optimum of the GMM objective function.

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

5.2.2 Estimation results

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

Table 5 shows the results. Same as our standard logit estimation, we use two sets of controls for latitude for our regression discontinuity design. Model 1 uses linear and linear interacted with the indicator variable for cities in the north side of the Huai river, and model 2 uses quadratic controls for the latitude. The results provide several key findings for heterogeneity in preference parameters. First, the mean marginal willingness to pay is \$1.6, similar to the estimate of the standard logit model in Table 3. Second, the standard deviations for marginal utility of clean air and price imply that there is unobserved heterogeneity among households. Third, we find that

the interaction with log household-level income is positive for both parameters. It implies that higher-income households have larger valuation for clean air, and they are less price-elastic than lower-income households.

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

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

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

6 Policy Implications

Our estimates on the WTP for clean air can be used as a key parameter to consider optimal environmental regulation. For example, the Chinese government and the world bank recently implemented reforms related to the Huai river policy. There is ongoing discussion about the reform—whether it is welfare enhancing or not, and whether similar reforms should be implemented to other regions in China. Our WTP estimate can be used to evaluate the cost-benefit of the reform. In 2005, in seven northern cities, the Ministry of Housing and Urban-Rural Development (MOHURD) collaborated with the World Bank on a pilot reform to improve energy efficiency in the heating sector. The primary goal of the reform is to save energy use by introducing household metering and consumption-based billing, under which consumers pay for actual heat consumption and are able to control how much heat they consume. Ten years after the start of the pilot reform, however, it is still under debate in the MOHURD on whether the reform should be scaled up to more northern cities. The main challenge is that costs of installing individual meters and adopting consumption-based billing are high, while benefits of the reform have not yet been examined.

Our WTP estimates provide an estimate that measures the value of the reform for households—a northern household is willing to pay 53 dollars if the pollution generated by the Huai river policy can be removed. This estimate enables us to provide back-of-the-envelope cost-benefit analysis on the heat reform. First, WorldBank (2014) estimates that the pilot heat reform in seven cities can generate a total reduction in coal usage by 51 million tons over a 20-year period at the total abatement cost of $18 million. Thus, over 20 years, the reduction in coal usage per city is 0.36 million tons per year at the abatement cost of $0.13 million per city per year. Second, the *China Daily* reports that all northern cities use over 700 million tons of coal at their centralized heating facilities alone per year (ChinaDaily, 2015), suggesting that an average northern city uses 5.3 million tons of coal for their centralized heating per year. If we consider the percentage of coal reductions from the pilot heat reform, it is 7% (=0.36/5.3) per city. Third, our WTP estimate suggests that a northern households is willing to pay $53 for cleaning up the air from heating-induced pollution for for a period of five years. That is, the annualized willingness to pay is $11 (=53/5) per year.

We make a simplifying assumption on the relationship between reductions in coal usage and reductions in PM10. We assume that a certain percent reduction in coal usage for heating leads

to the same percent reduction in PM10. This assumption can overestimate or underestimate it, depending on the actual relationship between the two variables. With this simple one-to-one assumption, we obtain that a household is willing to pay \$0.77 ($= 11 \cdot 0.07$) per for reductions in PM10 by 7%. Because the average number of households in a northern city is 0.63 million, the total willingness to pay is \$0.49 ($= 0.77 \cdot 0.63$) million per city per year.[13] This estimate, the total benefit of the reform for households, is larger than the abatement cost, which is \$0.13 million per city per year. Note that the benefits for households estimated here are lower bound estimates because our WTP estimate is a lower bound. Therefore, our analysis suggests that even if we consider the lower bound estimates of the benefits, the heat reform islikely to be cost-effective. Although we want to emphasize that this is back-of-envelop calculation based on a set of assumptions, our analysis suggests that the expansion of the reform to other northern cities could enhance the welfare.

More broadly, our WTP estimate could be used as a key parameter for policymakers when considering tradeoffs between economic growth and environmental regulation. China has recently announced a series of new energy policies and environmental regulations. For example, as featured by the *New York Times*, \$1.65 billion a year is offered to reward cities and regions that make "significant progress" in air pollution control (Wong, 2014a), tougher fines are enforced for polluters (Wong, 2014b), and coal-fired power plants will be upgraded to cut pollution from power plants by 60 percent by 2020 (Wong, 2015). More prominently, as the the world's largest greenhouse gas polluter, China recently made 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 policy.

7 Conclusion

This paper provides among the first revealed preference estimate of willingness to pay (WTP) for clean air in developing countries. We examine the demand for home-use air purifiers, a main defensive investment for reducing indoor air pollution, which provides valuable information for estimating a *lower bound* of WTP for air quality improvements. Our empirical strategy leverages the

[13] The average number of households in northern cities in our sample is 0.63 million.

Huai River heating policy, which created discontinuous quasi-experimental and long-run variation in air pollution between the north and south of the river. Using a spatial regression discontinuity design, we estimate that the willingness to pay for removing the amount of pollution generated by the Huai River policy is 53 dollars, and the marginal willingness to pay for removing 1 ug/m^3 PM_{10} is 1.6 dollars.

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

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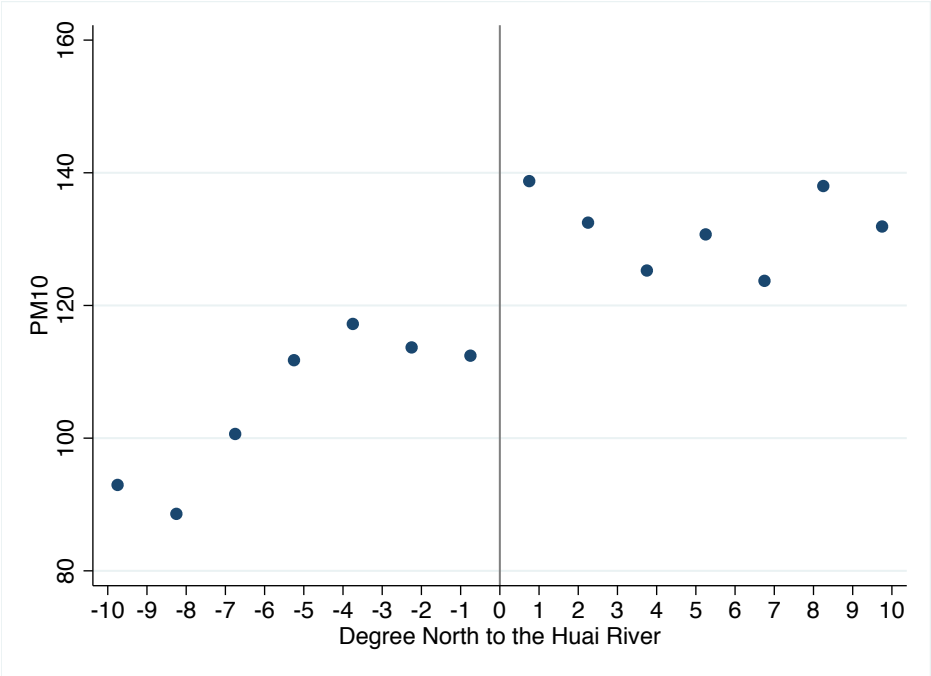
Figure 1: Huai River Boundary and City Locations



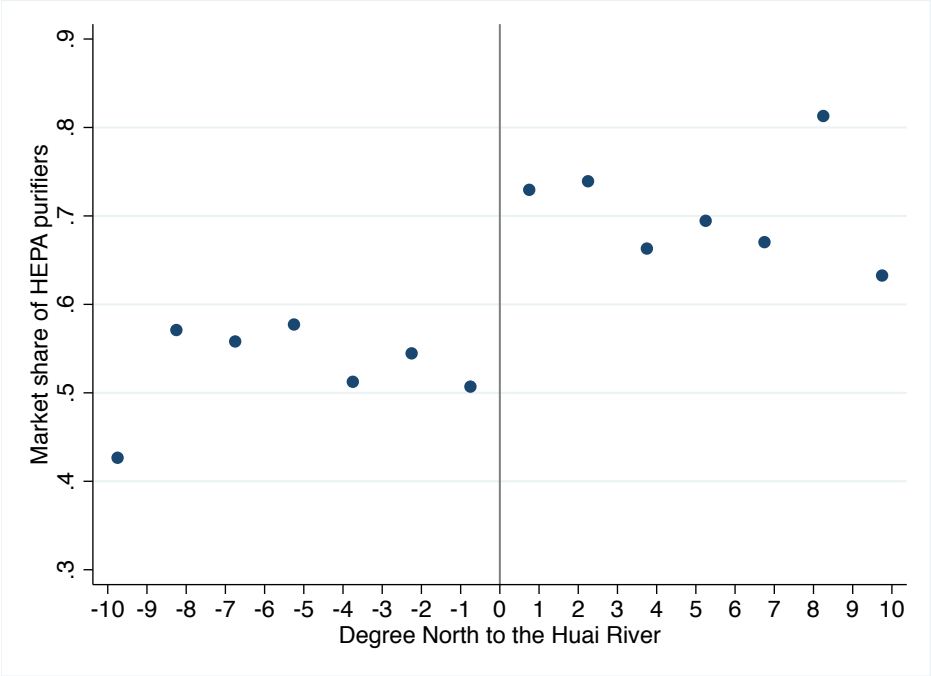
Notes: The line in the middle of the map is the Huai River-Qinling boundary. Each dot represents 1 city. There are 81 cities in our sample.

Figure 2: Regression Discontinuity Design at the Huai River Boundary

(a) PM10 in Winter

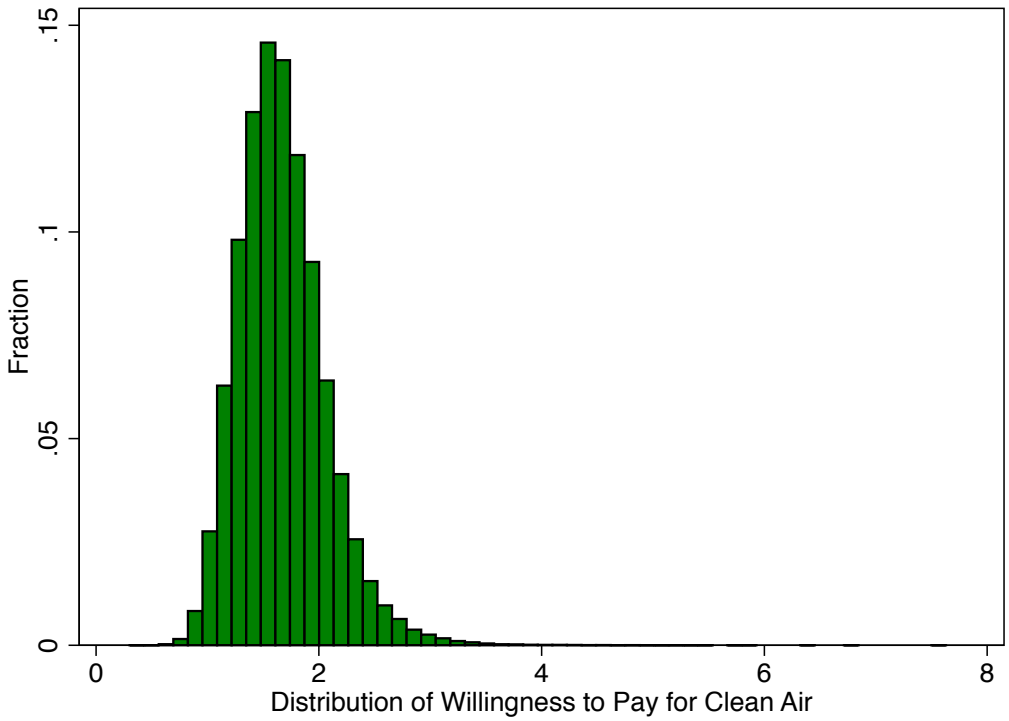


(b) Market Share of HEPA Purifiers in Winter



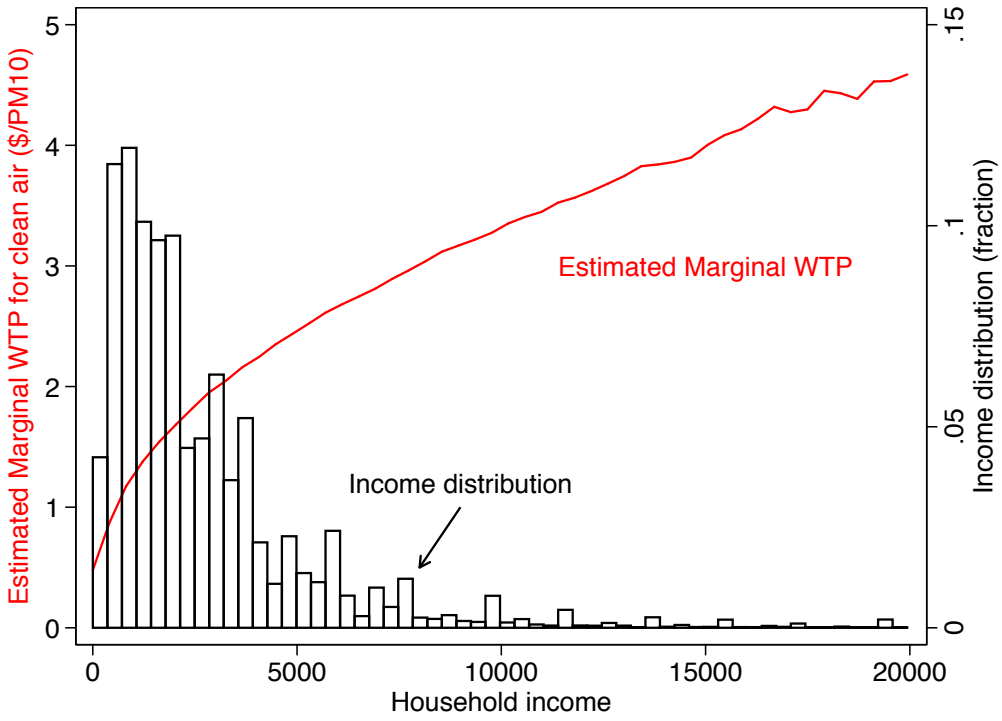
Notes: Figure 2a plots the average PM_{10} during winter (December-March) in 2006-2012 by 1.5 degrees of latitude north to the Huai River boundary. The vertical line at 0 indicates the location of the river. Each dot represents cities in 1.5 degrees of latitude and corresponds to the middle point of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

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



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

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



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

Table 1: Summary Statistics

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

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

Table 2: First Stage Estimation for PM10 and Prices

(a) First Stage Estimation for PM10

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

(b) First Stage Estimation for Air Purifier Prices

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

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

Table 3: Reduced Form and 2SLS Estimation Results

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

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

Table 4: Robustness Checks of 2SLS

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

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

Table 5: Random-Coefficient Logit Estimation Results

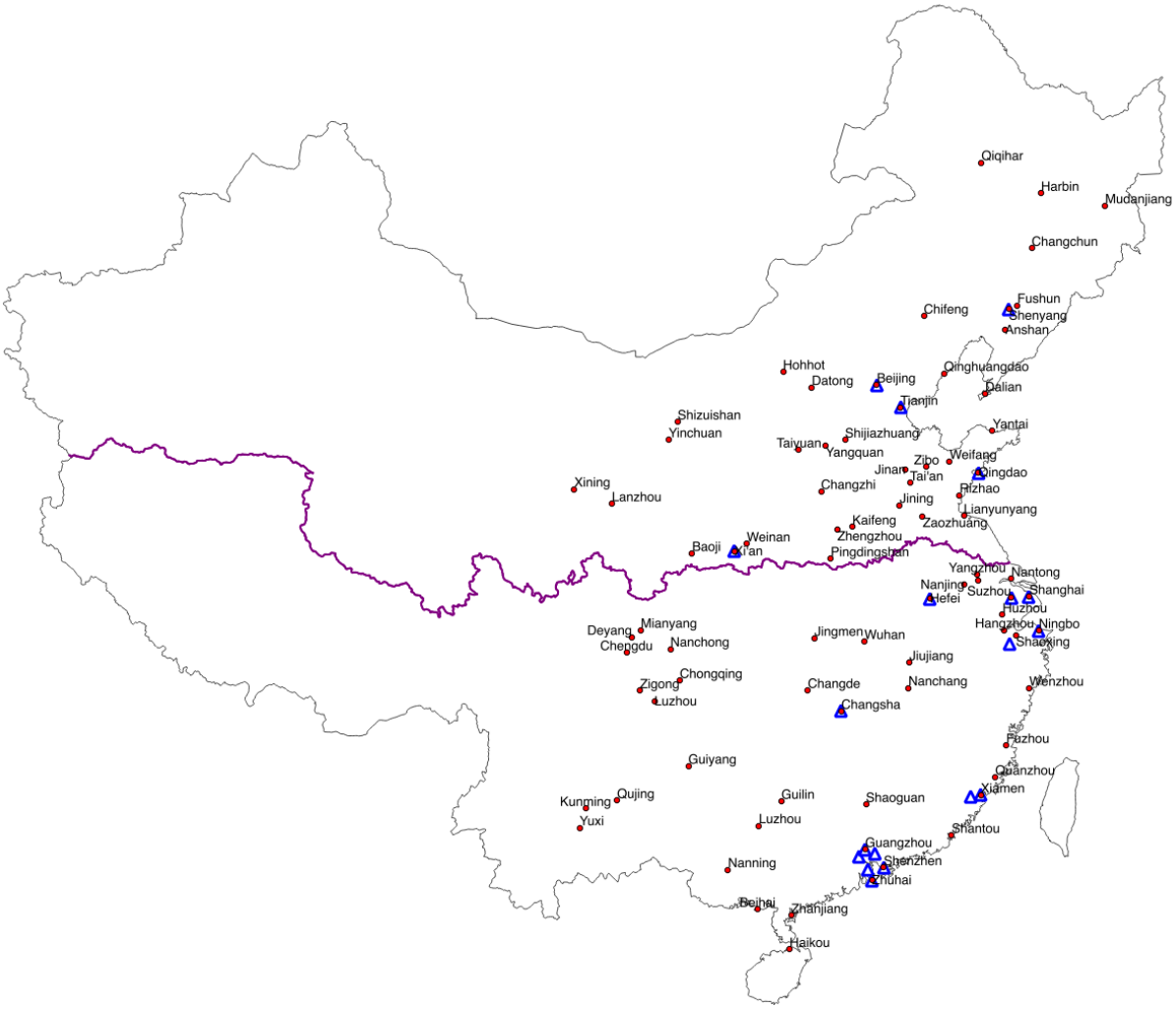
	Model 1			Model 2		
	Mean	Standard deviation	Interaction w. Log Income	Mean	Standard Deviation	Interaction w. Log Income
PM10 · HEPA	0.034	0.029	0.082	0.032	0.028	0.087
	(0.011)	(0.015)	(0.029)	(0.010)	(0.013)	(0.030)
Price	-0.021	0.015	0.041	-0.021	0.016	0.043
	(0.008)	(0.009)	(0.020)	(0.008)	(0.009)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

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

Online Appendices Not For Publication

A Additional Figures

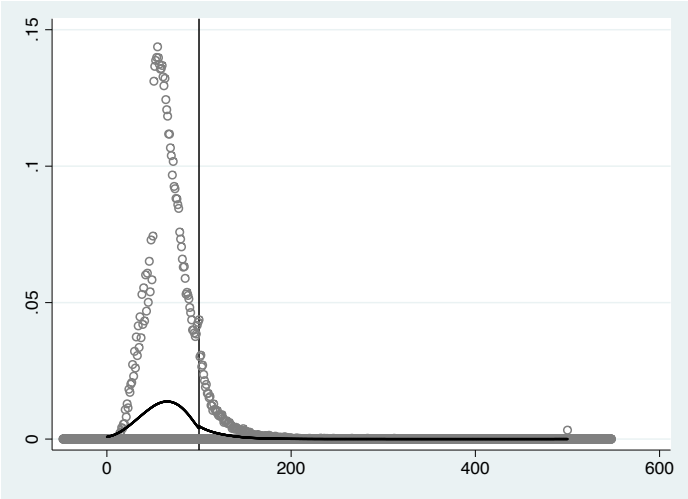
Figure A.1: Huai River Boundary and City Locations



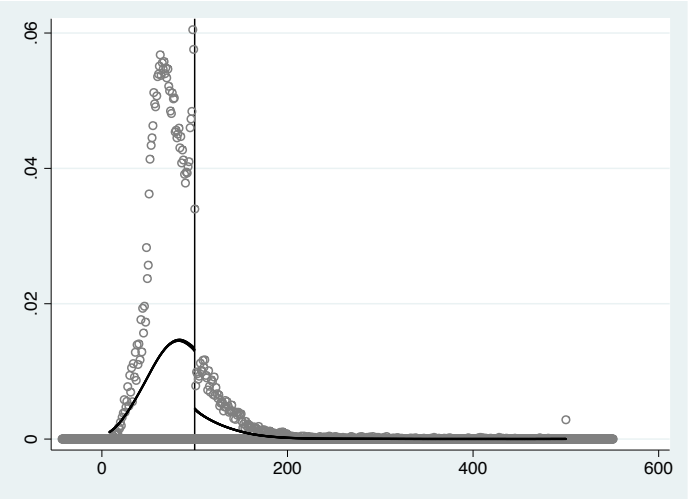
Notes: The line in the middle of the map is the Huai River-Qinling boundary. Each dot represents 1 city. Each triangle represents a factory location or a port location.

Figure A.2: API distribution

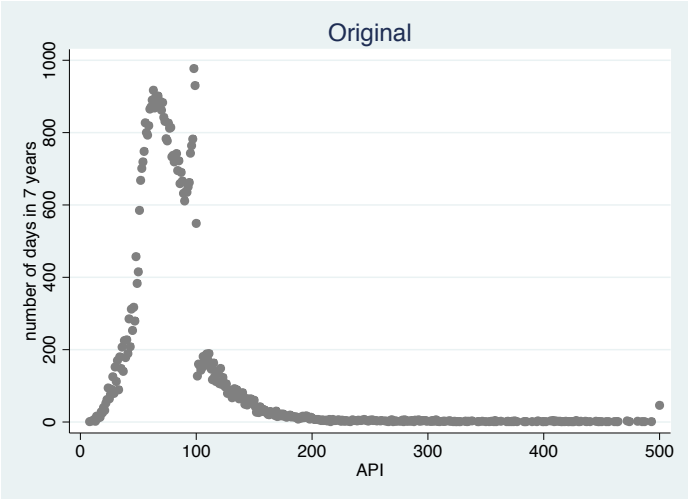
(a) McCrary density test (75% of sample)



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



(c) Original distributions of the 25% sample



(d) Counterfactual distribution of the 25% sample

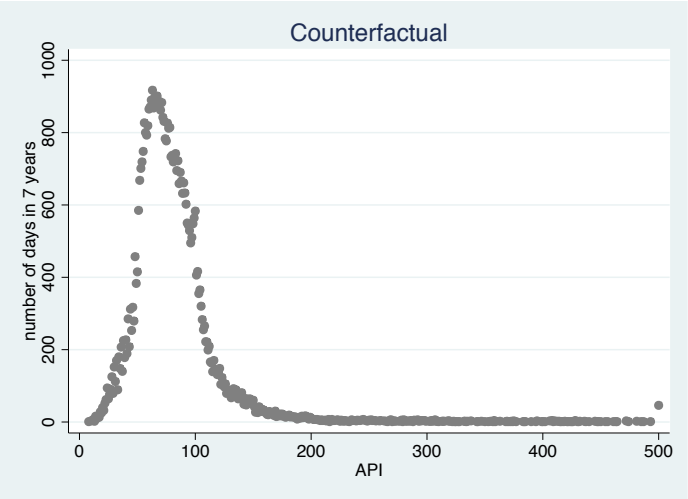
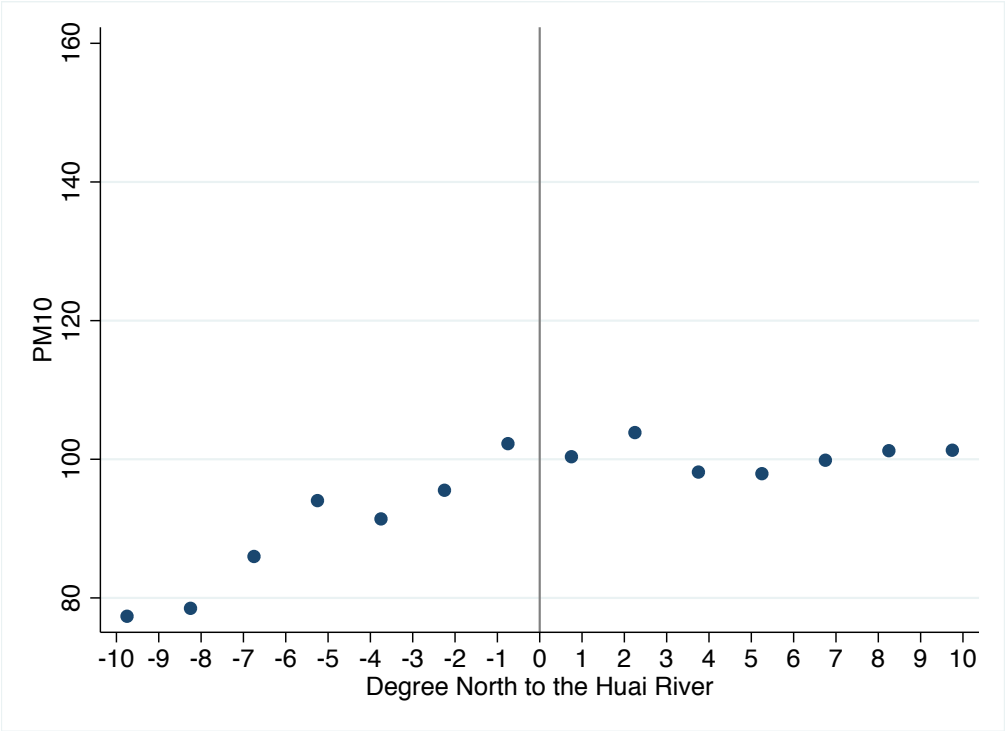
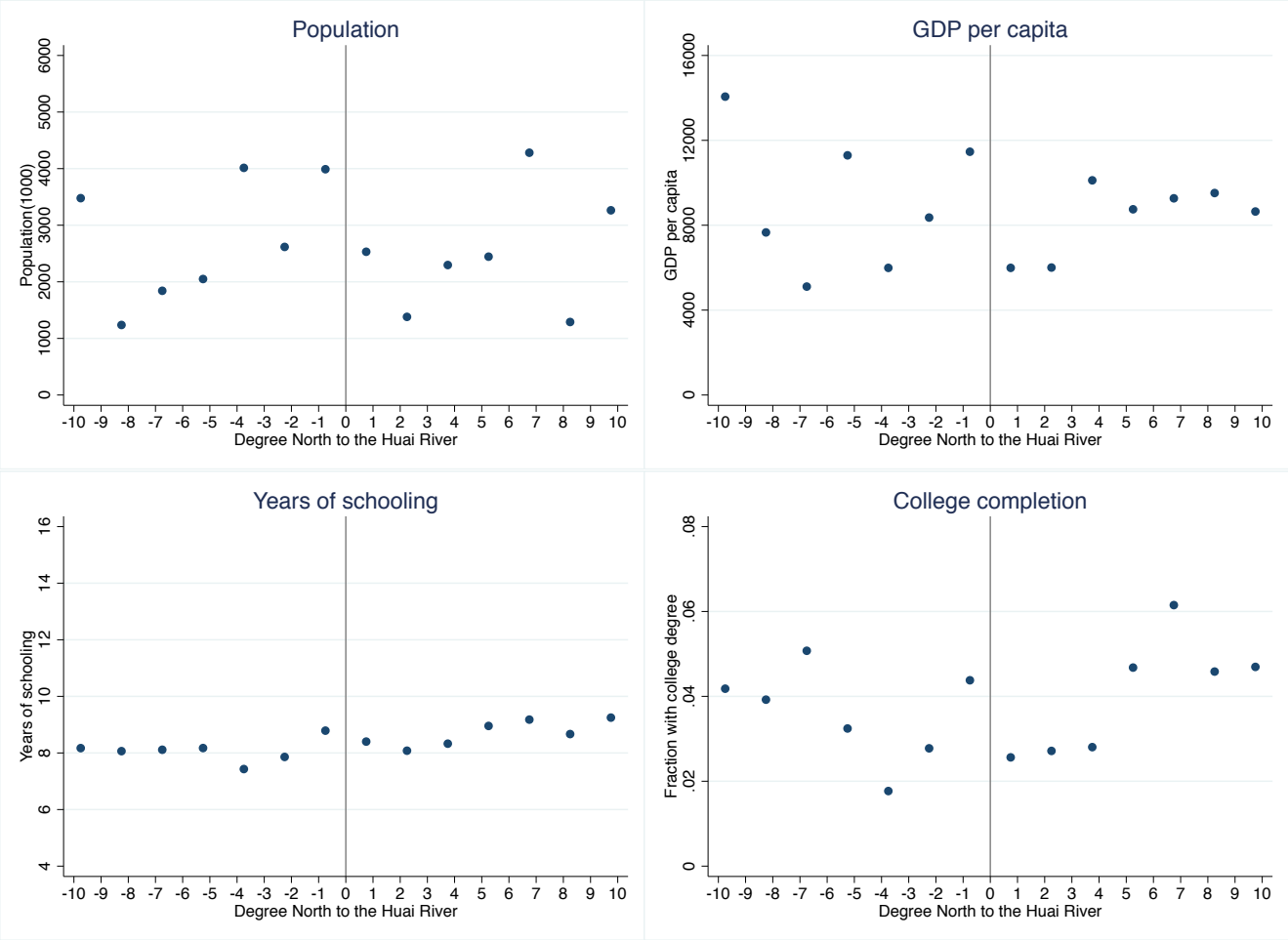


Figure A.3: Huai River: PM10 in non-winter months (April-November)



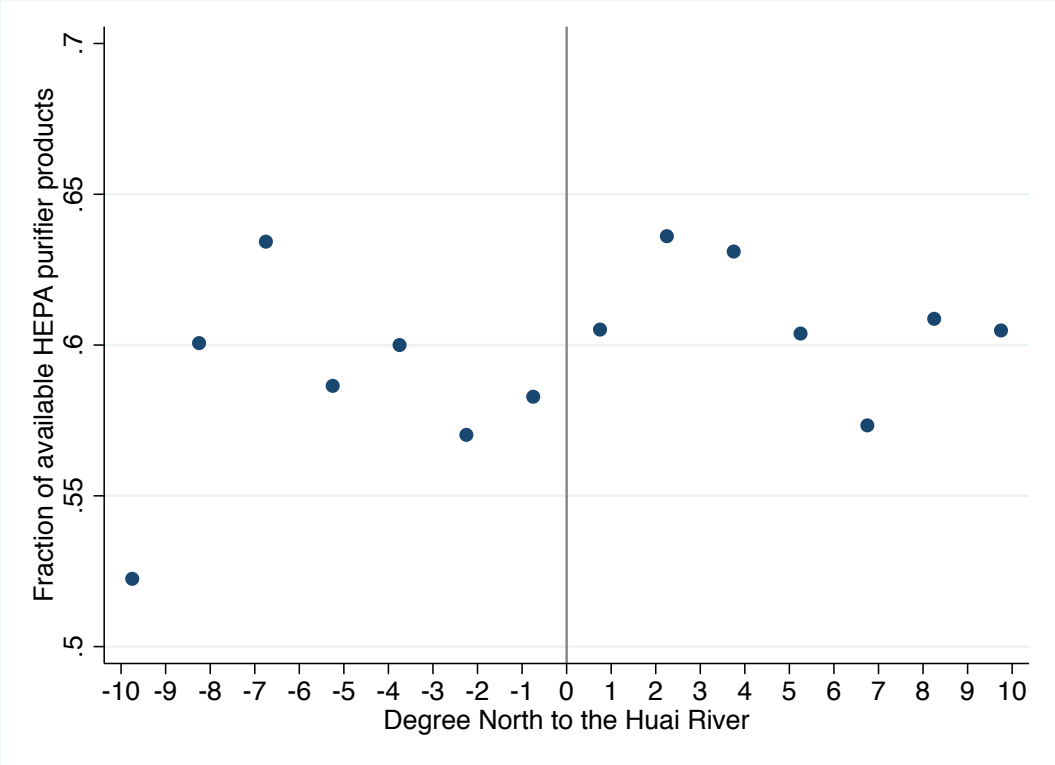
Notes: This figure plots the average PM_{10} during non-winter months (April-November) in 2006-2012 by 1.5 degrees of latitude north to the Huai River boundary. The vertical line at 0 indicates the location of the river. Each dot represents cities in 1.5 degrees of latitude and corresponds to the middle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

Figure A.4: Huai River and Demographics



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

Figure A.5: Fraction of available HEPA purifier products



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

B Additional Tables

Table A.1: Controlling for GDP*HEPA and Schooling*HEPA in 6 degrees

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

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

Table A.2: First Stage Robustness

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

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

Table A.3: Reduced-form Robustness

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

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