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. Our first approach exploits panel variation in air pollution in Chinese cities along with product-by-store level transaction data in air purifier markets. We first estimate the nationwide average of marginal willingness-to-pay (MWTP) for removing 1 ug/m^3 PM_{10} for a year, and WTP for removing the average level of PM_{10} (100 ug/m^3 of PM_{10}). Our second approach 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 local average of MWTP for removing 1 ug/m^3 PM_{10} that is generated by the Huai River policy. Combining our estimates on MWTP for clean air with estimates on the pollution-health relationship, we find that the lower bound of health valuation in China is substantially higher than previously understood for developing countries. 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 ($PM_{2.5}$) 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). Therefore, air pollution is one of the first-order problems 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 for economists and policymakers when considering tradeoffs between economics 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.

In this paper, we provide among the first revealed preference estimates of WTP for clean air in developing countries. Our idea is 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 attributes informs consumers and econometricians about the purifier's ability to reduce air pollution. We apply this framework to unique transaction data in air purifier markets in 82 Chinese cities. For each retail store in the 82 cities, we observe product-level information on monthly sales, monthly average price, and detailed product charac-

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

teristics. Our data cover January 2006 through December 2012. In this period, Chinese cities had substantially different cross-sectional and time-series variation in air pollution, which allows us to identify key parameters that are derived from our random utility model.

We use two empirical strategies. The first approach is a fixed effects (FE) approach, which exploits both cross-sectional and time-series variation in air pollution in the 82 cities. The panel structure of the data at the product-city-year-month level enables us to control for a series of fixed effects that capture unobserved confounding factors. Further, we address the potential concern of endogenous price by using an instrumental variable similar to Hausman (1997) and Nevo (2001). An advantage of the FE approach is that it estimates the nationwide average of marginal willingness-to-pay (MTWP) for indoor air quality improvements given the identification assumptions. We find that the nationwide average of MWTP for 1 ug/m^3 of PM_{10} reduction for a year is \$1.52, and the WTP for removing the average level of 100 ug/m^3 of PM_{10} for a year is \$152.

Our second strategy is a spatial regression discontinuity (RD) design, which exploits discontinuous valuation in air pollution created by a policy 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). An advantage of this RD approach is that it allows us to exploit plausibly exogenous variation in air pollution that was created by the policy. An disadvantage of this approach—relative to our FE approach—is that the RD design provides *local* average estimates of WTP and MWTP for indoor air quality improvements. We present visual and statistical evidence that, in winter months, 1) the PM_{10} level is significantly higher in the north of the Huai River, and 2) there is a discontinuous and substantial increase in the market share of air purifiers that remove particular matters just north to the river. Using estimates from the RD design, we find that the local average of MWTP for removing 1 ug/m^3 of PM_{10} for a year is \$2.46.[2] Our RD estimates are robust to using various functional forms of city latitude and also to using a subsample of cities closer to the Huai River boundary.

We also present a number of additional findings. First, because different products have different coverage of room size, we also estimate the MWTP for 1 unit of indoor pollution reduction per

[2]We provide evidence in Section 5.2 that the RD design is impervious to various potential threats to identification and inference.

square meter. Second, we examine heterogeneity in WTP for clean air by using city-year-month level demographic variables. We find that, as pollution levels increase, cities with higher average household income and more educated population respond more in the increase of demand for effective air purifiers. Third, we run a "horse race" between the official pollution information and the visibility measure, the latter of which proxies individuals' own eyeballing of pollution levels. Although people might have doubts on the official information, they still largely rely on it to make their self-protection decisions.

Finally, our estimates enable us to calculate a lower bound of health valuation—the extent to which consumers value additional years of life expectancy—under the assumption that consumers are aware of the relationship between PM_{10} and loss in life expectancy. We combine our estimates on MWTP for improvements in PM_{10} with estimates on the effect of PM_{10} on life expectancy in the literature. Ebenstein et al. (2015) finds that an increase of 100 ug/m^3 of PM_{10} is associated with 2.3 years loss of life expectancy at age 5. Using the nationwide average estimate of MWTP for PM_{10} reduction from our FE approach, the WTP for an additional year of life for one person is \$1,267, about 15% of average annual household income. Using the local average estimate of MWTP from the spatial RD design under the Huai River policy, the WTP for an additional life-year is \$2,050, roughly 25% of average annual household income. We find a higher health valuation using the Huai River policy because the estimated local average MWTP is higher than the estimated nationwide average MWTP using the FE approach. Our estimates from China are substantially higher than previously understood from design-based research in developing countries, for example, the valuation of one life-year based on WTP for clean water in Kenya is \$24 (5% of annual household income) (Kremer et al., 2011). Moreover, our estimates from China are lower than but not far below estimates from the US and other developed countries where environmental regulations are better established.[3]

Our study provides two primary contributions to the literature. 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

[3] In the US and other rich countries, estimated values of a statistical life (VSL) range from \$2 to \$7 million (Viscusi and Aldy (2003), Ashenfelter and Greenstone (2004), Hall and Jones (2007)). Using the life expectancy at birth of 78 years and the discount rate of 1%, the estimated value of a life-year ranges between \$37,000 and \$129,000, which is from 74% to 258% of average annual household income.

whether individuals take avoidance behavior in response to pollution exposure.[4] 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.[5]

The second contribution is that our analysis provides empirical evidence for an important "missing piece" in the literature on air pollution in developing countries, which offers important policy implications. Many recent studies show that severe air pollution in developing counties 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). However, as emphasized by Greenstone and Jack (2013), there is little evidence on revealed preference estimates of WTP for clean air. Our estimates provide a lower bound of MWTP for improvements in air quality, which is a key parameter for policymakers when considering tradeoffs between economic growth and environmental regulation. Specifically, in theory, more stringent environmental regulations can be justified if the marginal cost of regulation is below our MWTP estimate.

[4]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).

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

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

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).[6] Among 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 taken from the highest daily average value of these three pollutants. During 2006-2012, among the 78% of days when the MEP reported the specific type of pollutant from which API was taken from, 91.2% were from PM_{10}, 8.7% from SO_2 and 0.1% from NO_2.

The official API, mostly based on ambient PM_{10}, is the only accessible pollution information for Chinese citizens during the time period of this study.[7] 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_{10} and $PM_{2.5}$. 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, 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)).

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

[7] The Chinese government started to report $PM_{2.5}$ in a number of cities in 2013. We focus on 2006-2012 because of the availability and representativeness of our air purifier data in this time period.

On the Chinese market, other purification technologies either do not remove particulate matter, or they are less effective against particulate matter and generate other pollutants. Activated carbon absorbs volatile organic compounds (VOCs), but does not remove particles. A catalytic converter is effective in removing VOCs and formaldehyde. Finally, an air ioniser 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 ionisers, and they also produce ozone and other oxidants as by-products.

An air purifier can use multiple air purification technologies. For example, some air purifiers combine a HEPA filter with activated carbon to remove both particulate matter and VOC. As long as an air purifier uses a HEPA filter, a typical Chinese advertisement states that it 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. Heat is generated either by heat-only hot water boilers for one or several buildings, or by combined heat and power generators for larger areas. 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. 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.[8] 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).[9] Whether heat subsidy is provided by employers depends on the sector. In public sector, former in-kind transfer 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 82 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.[10]

Our analysis focuses on 2006-2012, after the 2003 reform. We summarize our comparison on

[8] `http://news.xinhuanet.com/zhengfu/2003-07/29/content_998737.htm`

[9] 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.

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

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 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 cost in 20 cities within 3 degrees of latitude relative to the Huai River boundary, household heating cost in the north could even be higher than that in the south.[11]

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-year-month level, which are usually hard to obtain in developing countries.

Air purifier data

We obtain monthly market transaction data of air purifiers in 82 cities in 2006-2012 from a top marketing consulting firm 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.[12] The sales and price data are at

[11] 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.

[12] The marketing consulting firm 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 firm 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.

the product-city-store-year-month level. Because the pollution information is recorded at the city level, we aggregate the transaction data to product-city-year-month level. There are 593 different products of 97 brands in our sample.

A unique feature of the data is that the type of filtration system that a product uses is included. Importantly, we observe whether a product uses a High Efficiency Particulate Arrestance (HEPA) filter, which enables us to quantify the amount of pollution reduction that a product brings. As discussed in Section 2.2, the HEPA filter is most effective against particulate matter. Based on the US standard for HEPA filters, air purifier advertisements in Chinese cities highlight that the 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 in two ways. First, if consumers think about API literally, the amount of pollution reduction that they think they will get from a HEPA purifier is equal to the API level, and 0 if they get a Non-HEPA purifier. Second, if instead consumers think about the underlying PM_{10} because it is the main pollutant in most days, the amount of pollution reduction that they think they will get from a HEPA purifier is equal to the PM_{10} level, and 0 if they get a Non-HEPA purifier.

We also observe a number of other product attributes, including Clean Air Delivery Rate (CADR) based on a particular pollutant that the product removes and maximum coverage area (square meter). The maximum coverage area is observed for two-thirds of all products in our sample, and the average is 41 square meters.

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 82 cities in our sample in 2006-2012 from Chinese Ministry of Environmental Protection (MEP). A network of air quality monitors throughout each city take hourly concentration measures of three air pollutants over a 24-hour period: For each monitor, the daily API is converted from the highest daily average value of these three pollutants. The city-level daily API reported to the public is the average API from these monitors. In addition to API level, the scale of the pollution level is also described to the public. An API level of 0-100 is excellent or good, 101-200 slightly or lightly polluted, 251-300 moderately or heavily polluted, and any API number larger than 300 is severely polluted.

The specific type of pollutant from which API was taken from is also disclosed to the public. During 2006-2012, among the 78% of days when the MEP reported the type of pollutant on which API was based, 91.2% were from PM_{10}, 8.7% from SO_2 and 0.1% 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 to convert daily API to daily PM_{10}. To match with the monthly market transaction data, we aggregate API and PM_{10} at the city-year-month 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 it to the performance evaluation of city governments. In the presence of underreporting, local residents may not be able to fully understand the actual pollution level and take self-protection behaviors efficiently.

To investigate to what extent the underreporting of API over 100 affects our empirical analysis, we perform McCrary density tests (McCrary (2008)) on daily API data for each of these 82 cities in 2006-2012. In Appendix Figure A.1a, at the city-year level, we find statistically significant discontinuity at 100 in the density of API in 25% of the city-year groups. Further, we use the distribution of API in the 75% non-manipulation city-years to plot a counterfactual distribution of the 25% manipulation city-years. See the original and counterfactual distributions of API in the manipulation sample in Appendix Figure A.1b. Two differences between these two distributions could affect our empirical analysis: 1) mean of API, if the relationship between API and the market share of air purifiers is linear, and 2) percentage of days above 100, if there is a threshold effect in self-protection behavior when API is beyond 100. We empirically test these concerns in the next section.

Although it is unlikely that local residents understand the density concept and realize the manipulation at a certain margin, anecdotally, people are skeptical about official pollution information in general. It is interesting to examine whether people respond to the official information or simply rely on their own eyeballing of the pollution level. We use visibility to proxy the direct observation of pollution levels among local residents. Visibility data are recorded by weather stations from the Global Surface Summary of Day data produced by the US's National Climate Data Center (NCDC). It is defined as the greatest distance at which an observer with normal eyesight can discern a dark object from the horizontal sky. Visibility data are not disclosed to the public and not used in the evaluation of government officials, and are therefore less subject to manipulation.

Weather and demographic controls

To help isolate the role of air pollution from that of weather conditions, we obtained daily mean temperature, mean dew point (measuring relative humidity), total precipitation and mean wind speed from weather stations from the Global Surface Summary of Day data produced by the US's National Climate Data Center (NCDC). Daily weather data are aggregated at the city-year-month level.

We compile demographic data from two sources. First, we obtain city-year measures on population, GDP per capita and share of GDP from manufacturing from *City Statistical Yearbooks* in 2006-2012. Second, we also use the microdata of 2005 population census to generate a number of aggregate measures at the city-level, including employment rate, annual household income, home price, percentage completed high school and college.

Descriptive statistics

Table 1 reports summary statistics for key variables in the whole sample and in a subsample in winter (December to March) separately. Average API in the whole sample is 69, and the mean PM_{10} is 101 ug/m^3. In winter, the mean PM_{10} is 115 ug/m^3. In the air purifier data, there are on average 7.2 sales per product per city in a year-month, and the mean market share in a city of a year-month is 7%. There are 58% of air purifiers have a HEPA filter. The mean clean air delivery rate (CADR) is 197. On average a purifier covers a room of maximum 41 square meters. The average price of a purifier is $390 (USD). All monetary terms are expressed in USD throughout the paper.

Figure 1 plots time-series patterns of monthly API and air purifier sales. Figure 1a focuses on HEPA purifiers. Clearly there is co-movement between API and HEPA purifier sales.Particularly, in winter months, when there is a spike of API, sales of HEPA purifiers also shows a spike. The co-movement is more pronounced in recent years. In contrast, the sales of Non-HEPA purifiers are less responsive to changes in API in Figure 1b.

Figure 2 shows the location of the 82 cities on the China map in our analysis. The line of Huai

River/Qinling Mountains is the purple line on the map that divides China into its North and South. Each red dot represents a city in our sample. All cities in our sample are located east to 100 degree of longitude. The part of the river line east to 100 degree of longitude ranges between 32.4 and 34.6 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: 1) when the longitude is smaller than 103.7 degree, the latitude ranges between 33.5 and 34.6 degree; 2) when the longitude ranges between 103.7 and 107.7 degree, the latitude ranges between 32.9 and 33.7 degree; 3) when the longitude ranges between 107.7 and 115.7 degree, the latitude ranges between 32.5 and 33.2 degree; 4) when the longitude ranges between 115.7 and 118.7 degree, the latitude ranges between 33 and 33.8 degree; 5) when the longitude is larger than 118.7, the latitude ranges between 32.4 and 32.8 degree degree. In each segment, we measure a city's relative latitude to the middle point of the river latitude range. For example, Beijing locates at 116.3 degree of longitude and 39.9 degree of latitude, which falls into the longitude range between 115.7 and 118.7 degree, and the middle point of the river latitude range in this segment is 33.4 ((33+33.8)/2) 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.

4 A Random Utility Model for Air Purifier Demand

Our goal is to obtain a revealed preference estimate of WTP for indoor air quality improvements by analyzing demand for air purifiers. In a standard demand model for differentiated products, a consumer purchases an air purifier by considering utility from its product characteristics and disutility from its price. An advantage of analyzing air purifier markets is that one of the product characteristics called high-efficiency particulate arrestance (HEPA) indicates the purifier's ability to reduce indoor particulate matter. 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 standard random utility model similar to Berry (1994), Nevo (2001), and Kremer et al. (2011) to model demand for air purifiers. Consider that consumer i in city c at time

t has ambient air pollution z_{ct} (particular matters). The consumer can purchase air purifier j at price p_{cjt} to reduce indoor air pollution by $\Delta z_{cjt} = z_{ct} \cdot a_j$. We describe purifier j's ability to reduce indoor particulate matters by $a_{cj} \in [0, 1]$. We observe markets for $c = 1, ..., C$ cities and $t = 1, ..., T$ time periods, each with $i = 1, ..., I_{ct}$ consumers. In the estimation below, a market will be defined as a city-year-month combination. The conditional indirect utility of consumer i from purchasing air purifier j at market ct is:

$$u_{ijct} = \beta \Delta z_{jct} + \alpha p_{jct} + \theta_j + \xi_{jct} + \epsilon_{ijct}, \tag{1}$$

where Δz_{cjt} is the pollution reduction, p_{jct} is the price of product j in market ct, θ_j is a utility gain from unobserved and observed product characteristics for product j, ξ_{jct} is a city-product-time specific demand shock, and ϵ_{ijct} is a mean-zero stochastic term. Assuming the error term ϵ_{ijct} has an extreme value density function, the market share for product j in city c at time t is:

$$s_{jct} = \frac{\exp(\beta \Delta z_{jct} + \alpha p_{jct} + \theta_j + \xi_{jct})}{\sum_{j'=0}^{J} \exp(\beta \Delta z_{j'ct} + \alpha p_{j'ct} + \theta_{j'} + \xi_{j'ct})}. \tag{2}$$

For $j = 1, ..., J$, we observe product-level price and sales data in city c at year-month t, from which we construct the market share (s_{jct}). The outside option ($j = 0$) is not to buy any purifier. When we include city-time fixed effects in our estimation, the outside option does not matter to the estimation because the term will be absorbed by city-time fixed effects. When we cannot include city-time fixed effects, we need to make a few assumptions to construct he market share for outside options (s_{0ct}). We define s_{0ct} following Berry (1994); Nevo (2001). Assuming that the number of households in city c at year-month t are potential buyers and that each household purchases one or zero air purifier for a given month, s_{0ct} can be calculated by the difference of the number of households in city c at year-month t and the total number of sales in city c at year-month t. Then, we assume that $\Delta z_{c0t} = 0$ and $p_{c0t} = 0$. That is, the outside option is free and does not reduce indoor air pollution. This assumption can be violated when consumers can reduce indoor air pollution by purchasing some goods other than air purifiers. Again, our main specification of the fixed effect approach below controls for city-time fixed effects, which absorb all variation at the city-time level, including the outside option (s_{0ct}). The estimation is, therefore, unaffected by the assumption on outside options. For some of our estimation, we cannot include city-month fixed effects. For these regressions, we discuss how the assumption on outside options affects our estimates. Given these assumptions, we can construct the market share for outside options by $\ln s_{0ct} = 0 - \ln\left(\sum \exp(\beta \Delta z_{j'ct} + \alpha p_{j'ct} + \theta_{j'} + \xi_{j'ct})\right)$. Then, the difference between log market share for product j and log market share for outside options can be described by,

$$\ln s_{jct} - \ln s_{0ct} = \beta \Delta z_{jct} + \alpha p_{jct} + \theta_j + \xi_{jct}, \tag{3}$$

where β is the marginal utility from having one unit of pollution reductions and α is the marginal disutility from paying one more dollar for the purchase. Therefore, marginal willingness to pay (MWTP) for one unit of indoor air pollution reductions 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. Our approach assumes that indoor air pollution levels equal to ambient pollution levels ($z_{ct} = 0$). A recent engineering study shows that indoor pollution levels are lower than outdoor pollution levels in Beijing.[13] 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 *the lower bound* of MWTP.

An advantage of studying air purifier markets is that a_j (purifier j's ability to reduce indoor particulate matters) is straightforward, and consumers are well informed about it. As we explained in Section 3, if a purifier has a High Efficiency Particulate Arrestance (HEPA) filter, it reduces 99% of indoor particular matters. On the other hand, if a purifier does not have a HEPA filter, it does not reduce indoor particular matters. For our main estimation, we define the pollution reduction by:

$$\Delta z_{cjt} = z_{ct} \cdot HEPA_j = \begin{cases} z_{ct} & \text{if } HEPA_j = 1 \\ 0 & \text{if } HEPA_j = 0. \end{cases} \tag{4}$$

That is, air purifiers with a HEPA system reduce all indoor particular matters, while those without

[13] A study from Tsinghua University finds that, in Beijing, 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

a HEPA system does not reduce indoor particular matters.[14]

We consider two measures for z_{jct}. The first measure is API, which is the direct information that consumers can obtain. In this case, our estimate of $-\beta/\alpha$ indicates the MWTP for one unit of reduction in API. The second measure is PM10, which is converted from API using the official formula. For the estimation with PM10, our estimate of $-\beta/\alpha$ indicates the MWTP for one unit of reduction in PM10.

For the majority of air purifiers in our sample, we also know each purifier's maximum coverage of square meters. It is possible that customers value an air purifier that covers larger square meter. To test this possibility, our second approach defines Δz_{cjt} by $\Delta z_{cjt} = z_{ct} \cdot HEPA_j \cdot Coverage_j$. With this definition, our estimate of $-\beta/\alpha$ reveals MWTP for one unit of reduction in API or PM10 per square meter.

5 Empirical Analysis and Results

The goal of our empirical analysis is to obtain consistent estimates of $-\beta/\alpha$ in equation (3), which is MWTP for indoor air quality improvements. We use two empirical strategies. The first approach leverages the panel structure of our data at the product-city-year-month level by including a series of fixed effects at granular levels. The FE approach estimates the average of $-\beta/\alpha$ in all 82 cities in our sample. A potential concern is that unobserved demand shocks could bias the estimation. We use a second approach that takes advantage of a natural experiment at the spatial border of the Huai river, which is described in section 2.3. This approach allows us to exploit plausibly exogenous variation in air pollution created by the natural experiment to estimate local average estimates of $-\beta/\alpha$ in cities close to the Huai River boundary.

5.1 A Fixed Effect Approach

There are two potential sources of endogeneity in equation (3). The first concern is that unobservable demand shocks might be correlated with price. For example, if firms have ability to increase their product prices in response to demand shocks, there can be positive correlation between unob-

[14]Consumers and retail stores are well informed about the difference between HEPA purifiers and non-HEPA purifiers. However, there is possibility that a small fraction of consumers misunderstand the difference and purchase non-HEPA purifiers, hoping that it reduces indoor particular matters. This would make our estimation underestimate their MWTP.

servable demand shocks and price. To address this problem, Nevo (2001) uses data from multiple markets and includes product fixed effects. We take a similar approach. Recall that we have product-level data for city c and year-month t. This panel structure allows us to include product fixed effects (θ_j) to absorb observed and unobserved product-level characteristics. The second concern is that unobservable demand shocks might be correlated with pollution. For instance, city-level economic growth (e.g. GDP in city c at time t) could be a demand shock to overall air purifier sales, and it could be correlated with pollution levels in city c at time t. To address this concern, we include city-year-month fixed effects (θ_{ct}), which absorbs demand shocks to all air purifiers in a given city-year-month. We estimate equation (5) by OLS.

$$\text{ln}s_{jct} - \text{ln}s_{0ct} = \beta z_{ct} \cdot HEPA_j + \alpha p_{jct} + \theta_j + \theta_{ct} + \xi_{jct}, \tag{5}$$

where the ambient pollution measure z_{ct} is absorbed by the city-time fixed effects θ_{ct}. Note that the log market share of outside option lns_{0ct} is a constant when θ_{ct} is included. The identification assumption for this OLS estimation is that p_{jct} and $z_{ct} \cdot HEPA_j$ are uncorrelated with the error term.

There are two potential additional concerns for this estimation although they may not affect our estimates much in our context. First, even through we control for potential correlation between pollution levels and unobservable factors at the city-time level, Δz_{cjt} could be still correlated with ξ_{jct} if there are unobservable demand shocks that are correlated with pollution and that generate higher demand for HEPA purifiers than that for Non-HEPA purifiers. For example, if city-level GDP growth is correlated with pollution, and GDP growth leads to differential demand for HEPA purifiers and non-HEPA purifiers, we will have correlation between Δz_{cjt} and ξ_{jct}. It is difficult to think of channels other than particulate matter through which GDP growth affects the demand for the function of HEPA filter. Nevertheless, to address this potential concern on observed demand shocks, we also estimate the regression with an interaction term of z_{ct} and GDP at the city-time level. Furthermore, to address concerns about unobserved demand shock correlated with air pollution, we use the Huai River policy as a natural experiment that generates plausibly exogenous variation in air pollution in the next subsection.

Second, even though our product fixed effects absorb time-invariant unobservable factors at the product level, time-variant variation in product price can be correlated with unobserved demand shocks. Wholesale prices of air purifiers are determined at the national level and are therefore unlikely to respond to city-level changes in pollution levels month-by-month. However, one potential concern is that retail prices in city c at time t could respond to unobservable demand shocks in city c at time t. We test this concern in two ways. First, we use an instrumental variable that is similar to Hausman (1997) and Nevo (2001) in estimating equation (5). For product j in city c at time t, we calculate the product's average price in other cities by $\tilde{P}_{jct} = \frac{\sum_{k \neq c} p_{jkt}}{K}$. The idea behind this instrument is that it captures common cost shocks to product j and is uncorrelated with demand shocks specific to the city-time-product level. A limitation of this instrument is that it would be invalid if there is time-variant nationwide demand shocks at the year-month-product level that are correlated with the price for product j. For example, if firms change the nationwide wholesale price of product j in response to changes in national-level demand shocks that are correlated with changes in pollution levels, this instrumental variable estimation will be biased. In our second test, to examine if our estimation is affected by potential correlation between time-variant nationwide unobservable demand shocks and price for product j, we also estimate equation (6) by OLS with product-time fixed effects (θ_{jt}) and city fixed effect (θ_c).

$$\ln s_{jct} - \ln s_{0ct} = \beta z_{ct} \cdot HEPA_j + \alpha p_{jct} + \gamma z_{ct} + \theta_{jt} + \theta_c + \xi_{jct} \tag{6}$$

Do people buy the right purifiers?

In other words, do people value HEPA filter's unique feature to remove particulate matter, compared to other purification systems on the market? It is useful to empirically answer this question before we estimate equation (5) and (6) to obtain the MWTP for indoor air quality improvements.

In Table 2, API is interacted with each of these four purification systems in our sample, and the interaction of API and CADR is also included.[15] Column 1 includes product FE, and column 2 adds city FE, year-month FE and weather and socio-economic controls. Column 3 controls for product FE and city-year-month FE. Column 4 controls for city FE, product-year-month FE and weather and socio-economic controls. Across all specifications, when the API level increases, the market share of HEPA purifiers has a statistically significant increase. In contrast, none of Non-HEPA

[15] The omitted group is "other purification system".

purifiers shows increase in the market share. Moreover, there is a decline in the market share of catalytic converter purifiers, suggesting that HEPA purifiers might substitute Non-HEPA purifiers when API level goes up. These findings indicate that people do take self-protection against air pollution, and they take the right self-protection by purchasing the particular type of purifiers that effectively remove the main pollutant in Chinese cities.

MWTP for pollution reduction

We estimate equation (5) and (6) and report results in Table 3. In column (1)-(3), we use the pollution measure in the current month. In Panel A, we focus on API. Column 1 reports OLS estimates from estimating equation (5), including product FE and city-year-month FE. Also based on equation (5), column 2 reports 2SLS estimates with an instrumental variable for price.[16] Estimates for API*HEPA are the same in column (1) and (2), while the price coefficient becomes smaller after using an instrumental variable in column (2). Using estimates in column (2), MWTP for 1 unit reduction of API is 0.0032/0.0008=\$4. Column (3) reports OLS estimates from estimating equation (6), controlling for product-year-month FE, city FE and weather and socio-economic controls. Using estimates in column (3), MWTP for 1 unit reduction of API is 0.0046/0.0014=\$3.3. In column (1)-(3) of Panel B, we conduct the same exercise using PM_{10} of the current month. Using estimates in column 2, MWTP for 1 unit reduction of PM_{10} is 0.0017/0.0008=\$2.1. Using estimates in column 3, MWTP for 1 unit reduction of PM_{10} is 0.0025/0.0014=\$1.8.

Air purifiers are durable goods, and people could use the pollution information over a longer time period for making their purchasing decisions. We also examine whether and to what extent pollution measures in the past few months affect the market share of HEPA purifiers. In Table A1, by estimating equation (6) including additional interactions of lagged API measures and HEPA indicator, we find that the market share of HEPA purifiers respond to changes in API up to the past six months. Thus, in column (4)-(6) in Table 3, we interact the average level of pollution measures in the past six months with the HEPA indicator. Using estimates from estimating equation (6) in column (6) of Panel A, MWTP for 1 unit reduction of API based on average API in the past

[16] The sample size in column (1)-(2) is smaller than that in column (3) because we use the sample with non-missing data of the instrumental variable in both column (1) and (2). In 6% of the data, a product is on the market in only one city in a certain year-month, from which we do not observe price in other cities of the same product and therefore do not have data for the instrument.

6 months is 0.007/0.0014=$5, larger than $3.3 from column (3) of Panel A. In column (6) of Panel B, MWTP for 1 unit reduction of PM_{10} based on average PM_{10} in the past 6 months is 0.0044/0.0014=$3.1, also larger than $1.8 from column (3) of Panel B.[17] To capture the demand for air purifiers as durable goods, we use the estimated MWTP of $3.1 as our main estimate from the FE approach.

Note that our estimates above do not include the replacement cost of HEPA filters because no data on replacement of filters or filter sales are available. To interpret the magnitude of the MWTP more precisely, we use additional information on the average replace cost. An air purifier machine depreciates in about 5 years. Consumers in China are advised by manufactures to replace the HEPA filter every 6 months, which costs on average $50 for each replacement. We assume that a household uses an air purifier for 5 years and commit to replace the filter every 6 months. Then the household's WTP to remove the average level of 100 ug/m^3 of PM_{10} for 5 years is $760 ($3.1*100+$50*9), and the MWTP for removing 1 ug/m^3 of PM_{10} for a year is $1.52 ($760/5/100). We also consider different assumptions on how many years household expect to use the air purifier and how frequent they replace filters. For example, some households may expect to use the purifier only for 3 years, or they replace filters more often than advised, especially in very polluted cities.[18] We calculate the implied MWTP for removing 1 ug/m^3 of PM_{10} for a year under various assumptions in Column (1) of Appendix Table A.7. Note that our main estimate of $1.52 is the lowest among estimates using various assumptions, suggesting that we present a lower bound of MWTP for PM_{10} reduction.

Finally, we examine whether the response of HEPA purifiers' market share to pollution information is non-linear in two ways. First, in column (1) and (2) of Table A3, we include quadratic and cubic trends of API separately. There is no evidence of non-linear relationship. Second, we test whether the response is different at critical thresholds of API. In column (3), we interact two indicators of API thresholds with HEPA and find larger response in market share at higher thresholds. However, when the API level interacted with HEPA is included in column (4), threshold effects are no longer statistically significant and positive. Column (4) suggests that the seemingly "threshold effects" in column (3) is mainly driven by higher API levels instead of particular thresholds. Overall,

[17] As discussed earlier, as a robustness check, we also estimate equation (5) and (6) including an interaction term of HEPA and GDP per capita at the city-time level and report results in Table A2. Results are very similar to those in Table 3.

[18] Anecdotal evidence shows that in Beijing, one of highly polluted cities, households replace the HEPA filter twice in winter and once in non-winter months, in total three times a year. `http://news.cheaa.com/2013/0305/358557.shtml`

these findings suggest a linear relationship between API and the demand for HEPA purifiers.

5.2 A Spatial Regression Discontinuity Design with Huai River Policy

Our second empirical strategy exploits a natural experiment that occurred at the spatial border of the Huai river. As described in section 2.3, the Huai river heating policy created substantially higher levels of pollution in the north of the river than the south of the river. If people value air quality, our demand model in section 4 predicts that the market shares for HEPA purifiers are higher in the north. Our RD design tests this hypothesis.

The first stage regression estimates a discontinuous increase in pollution at the border of the Huai river. For city c, we define a latitude north to the Huai River boundary by Lat_c and a dummy variable for cities north to the Huai River by $North_c = 1\{Lat_c \geq 0\}$. The first stage regression is,

$$z_{ct} = \gamma_0 + \gamma_1 North_c + f(Lat_c) + X_{ct}\lambda + Long_c + \theta_t + u_{ct}, \tag{7}$$

where z_{ct} is ambient pollution (e.g. PM10) in city c at year-month t and $f(.)$ is a smooth control function for latitude. Year-month fixed effects θ_t are controlled for. Lee and Lemieux (2010) note that geographical discontinuity designs should be used with careful investigation of omitted variables at the border. In our case, we are particularly concerned that the Huai river border is long distanced, and therefore, observable and unobservable characteristics can be different between cities in different parts of the Huai river. To address this concern, we compare observed socioeconomic characteristics of cities on either side of the Huai River and find little discrete changes at the river boundary. We include these city characteristics as covariates X_{ct}. Further, considering that cities around the Huai river span from the west to the east, we narrow the scope of unobserved differences on either side of the river by including fixed effects of longitude decile, $Long_c$. where Long is a decile of longitude with $Long = 1, ..., 10$.

Next, we estimate the reduced form at the product-city-year-month level using the following equation:

$$\ln s_{jct} - \ln s_{0ct} = \delta North_c * HEPA_j + \gamma North_c + f(Lat_c) + \alpha p_{jct} + X_{ct}\lambda + Long_c + \theta_{jt} + \epsilon_{jct} \tag{8}$$

where in addition to fixed effects and covariates in the first stage, we are also able to include product-time FE, θ_{jt}. Recall that we are interested to compare the relative market share of HEPA purifiers (to Non-HEPA purifiers) between the north and the south of the Huai River. Our coefficients of interests are δ and α. The WTP to remove the amount of pollution generated by the Huai River policy is measured by $-\delta/\alpha$.

Finally, for the second stage regression, we estimate two-stage least squares for,

$$\ln s_{jct} - \ln s_{0ct} = \beta z_{ct} * HEPA_j + \gamma z_{ct} + f(Lat_c) + \alpha p_{jct} + X_{ct}\lambda + Long_c + \theta_{jt} + \epsilon_{jct} \tag{9}$$

by using $North_c$ as the instrument for z_{ct}, and $North_c * HEPA_j$ as the instrument for $z_{ct} * HEPA_j$. Therefore, β is identified by the discontinuous cross-sectional variation in pollution between the north and the south of the Huai river. The identification assumption is that the instrument $North_c$ is uncorrelated with the error term given the smooth control function $f(Lat_c)$ and covariates. Intuitively, this condition means that potential confounding factors in the error term have to be smooth at the north-south cutoff point. We investigate whether observable variables such as demographic and economic variables at the city level are smooth at the cutoff point and find little significant differences. The MWTP to remove 1 unit of pollution generated by the Huai River policy is measured by $-\beta/\alpha$.

Visual presentation We begin by plotting PM_{10} and the market share of HEPA purifiers in winter months (December-March) during 2006-2012 by a city's latitude relative to the Huai River boundary. Because very few cities locate in the farthest north and the farthest south, we focus on cities located within 10.5 degree of latitude to the river line.[19] There are 74 cities in this range (out of 82 cities in our sample). In Figure 3a and Figure 3b, the vertical line at 0 indicates the location of the river. Each dot represents cities in 1.5 degree 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 degree of latitude north to the river line. The higher the degree, the further north relative to the river.

[19] All cities in our sample locate between -12.9 and 14.8 degree north to the river line.

Figure 3a plots the average monthly PM_{10} by 1.5 degree of latitude north to the river boundary. The y-axis indicates the average PM_{10} of cities within 1.5 degree of latitude. Consistent with findings on pollution in earlier studies (Almond et al. (2009), Chen et al. (2013)), in winter months, there is a discontinuous increase in PM_{10} just north to the Huai River, suggesting that the coal-based heating policy generates higher pollution levels in the north.[20] Turning to Figure 3b, it shows the monthly market share of HEPA purifiers by 1.5 degree of latitude north to the river line. In the south, the market share of HEPA purifiers are below 60%. A sharp jump to over 70% appears just north to the river, and the higher market share persists in the north. Moreover, the south and north trends are fairly smooth, suggesting that the choice of functional form would have little impact on the estimated difference of HEPA purifiers' market share at the river line. These sharp increases of both PM_{10} and the market share of HEPA purifiers right north to the river suggest that higher PM_{10} levels generated by the heating policy trigger higher demand for HEPA purifiers.

The visual presentation also provides useful guidance in choosing the functional form of latitude in our estimation below. We use quadratic trend in the main specification. For comparison, we also report results using linear trend, linear trend interacted with North, and quadratic trend interacted with North.

Estimation results

Table 4 presents our main estimates on the effects of the Huai River policy in 74 cities within 10.5 degree of latitude to the river boundary. Column (1) includes quadratic trend of latitude, and column (2) adds product FE. Column (3) adds year-month FE, and weather and socio-economic controls. Column (4) further controls for longitude decile FE. Column (5) is the most restrictive estimation in that product-year-month FE (instead of product FE and year-month FE) are controlled for.

The first stage on the effect of the Huai River polity on PM_{10} is reported in Panel A. To be consistent with the reduced form and 2SLS estimation, the first stage is estimated using data at the product-city-time level. In column (1), an increase of 21 units of PM_{10} is similar to the visual size of the change in Figure 3a. With richer sets of controls in column (2)-(5), estimates are robust,

[20] We also find that, in non-winter months (April-November), there is no discrete change in PM_{10} levels just north to the Huai River in Appendix Figure A2. Therefore, we focus our analysis on winter months.

and the magnitude becomes slightly larger. We focus on column (5) using the richest set of fixed effects and controls. There is an increase of 26 units of PM_{10} north to the Huai River. In Panel B, we present the reduced form results from estimating equation (8). Consistent with Figure 3b, there is an economically and statistically significant increase in HEPA's log(market share) in the north of the river across all specifications. Using estimates in column (5) with the richest specification, the reduced form estimate is 0.317/0.0014=$226. Finally, Panel C reports the 2SLS estimates from estimating equation (9). Based on estimates in column (5), the MWTP to reduce 1 unit of PM_{10} is 0.0109/0.0014=$7.8.

To interpret the magnitude, we also consider replacement cost of HEPA filters. We assume that a household uses an air purifier for 5 years and commit to replace the filter every 6 months. Then the household's WTP to remove 100 ug/m^3 of PM_{10} for 5 years is $1230 ($7.8*100+$50*9), and its average MWTP for removing 1 ug/m^3 of PM_{10} for a year over 5 years is $2.46 ($1230/5/100). We also consider different assumptions on how long households expect to use the air purifier and how frequent they replace filters. We calculate the implied MWTP for a year under various assumptions in Column (1) of Appendix Table A.8. Again, our main estimate of $2.46 is the lowest among estimates using various assumptions, suggesting that we present a lower bound of MWTP.

Note that estimates of MWTP using the spatial RD design with the Huai River policy are larger than those using the FE approach. The main difference between these two approaches is that, the estimate using the FE approach measures a national average of MWTP for pollution reduction, while the RD design with the Huai River policy provides the local average MWTP in cities close to the Huai River boundary.

We test the robustness of these results using different functional forms of latitude and the richest specification. In Table A.4, we use linear trend, linear trend interacted with North, quadratic trend, and quadratic trend interacted with North. In Panel A, estimates on PM_{10} are robust and precisely estimated. When the slope does not differ on either side of the river in column (1) and (3), the estimate using a quadratic trend is larger than that using a linear trend, consistent with the visual impression from Figure 3a. When we allow different slopes on either side of the river in column (2) and (4), estimates using linear and quadratic trends are similar. In Panel B, estimates using all functional forms are very similar, consistent with Figure 3b that the discontinuity just north to the river does not depend on the choice of functional form.

Imbens and Lemieux (2008) and Lee and Lemieux (2010) note that it is important to test whether RD estimates are robust to a selection of different bandwidths from the discontinuity cutoff. We also examine the robustness of our results using a narrower bandwidth in a 6-degree latitude window, where 52 cities locate. In Appendix Table A.5, we conduct the same exercise as that in the main table Table 4. In column (5) of Panel A, there is a 31 units increase in PM_{10}, slightly larger than that in the 10.5-degree latitude window. Estimates in Panel B and C are very similar to those in Table 4.

Comparison of covariates

A natural concern on the RD design is that if cities in the north are systematically different from cities in the south, higher demand for HEPA purifiers could be explained by north-south differences other than the Huai River policy. Particularly, if households have higher income or education level in cities just north to the river, these differences could contribute to the observed jump in HEPA purifiers' market share. Therefore, we compare observed socioeconomic characteristics of cities on either side of the Huai River.

In Appendix Figure A.3 and Figure A.4, we report the mean of covariates by 1.5 degree of latitude relative to the Huai River (in the 10.5-degree latitude window). Little discrete change is observed at the Huai River boundary on population, employment rate, percentage completed high school and college. There is an increase in the share of GDP from manufacturing in the first dot north to the river, but the increase does not persist in the north. Some decreases of GDP per capita, home price and annual household income appear just north to the river, which are in the opposite direction to the increase in air pollution and unlikely explain the increase in the demand for HEPA purifiers.

In Appendix Table A.6, we formally test whether these covariates are different in the north of the river compared to the south. For each of these covariates, Column (1) reports the estimate of North with quadratic trend of latitude, and Column (2) adds longitude decile FE (and year FE for covariates at the city-year level). Most of these differences are not statistically significant. On GDP per capita and home price, consistent with figures, estimates in column (1) indicate lower levels in the North. However, after controlling for longitude decile FE in column (2), estimates are statistically insignificant and the magnitude becomes much smaller. All estimates controlling for longitude decile FE are statistically significant, which supports the use of longitude decile FE as controls in our main specification.

Interpretation

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 find that observed socioeconomic characteristics are not significantly different between the south and the north of the Huai River. Another possible concern is that 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)).

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.

6 Additional Results

6.1 MWTP for 1 unit pollution reduction per square meter

We propose an alternative way to define MWTP, which is the marginal willingness-to-pay for 1 unit of indoor pollution reduction per square meter, as discussed in Section 4. In Table 5, the regressors of interests are Pollution*HEPA*Area and Price. We conduct the same exercise as that in Table 3. In Panel A, column (6) suggests that the MWTP for 1 unit reduction in API per square meter is \$0.15. The average maximum coverage area in our data is 41 square meters. Therefore, the MWTP for 1 unit reduction in API in an average room of 41 square meters is \$6.6. In Panel B, column (6) suggests that the MWTP for 1 unit reduction in PM_{10} per square meter is \$0.09. The MWTP for 1 unit reduction in PM_{10} in an average room of 41 square meters is \$3.7. Using the estimate of \$3.7, we also consider replacement costs of HEPA filters. If a household uses an air purifier for 5 years and commit to replace the filter every 6 months, the household's WTP to remove 100 ug/m^3 of PM_{10} for 5 years is \$820 (\$3.7*100+\$50*9), and the MWTP for removing 1 ug/m^3 of PM_{10} for a year is \$1.64 (\$820/5/100), very close to our main estimate of \$1.52.

6.2 Heterogeneity in MWTP by socio-economic status

Does MWTP for pollution reduction differ by socio-economic status? Unfortunately, similar to most market transaction data, consumer characteristics are not observed in our data. Alternatively, we explore the heterogeneity in MWTP by socio-economic characteristics at the city-level. We focus on four measures of economic status and educational attainment: average household income, average home price, high school completion rate and college completion rate. Each variable is measured by decile. In column (1) of Table 6, PM10*HEPA is interacted with annual household income by decile, and price is also interacted with household income by decile. When PM_{10} level increases, cities with higher average household income have a larger increase in the relative market share of HEPA purifiers, and a larger change in a product's market share as response to price change. Similar results are found by home price, high school completion and college completion in column (2)-(4).

Using estimates in column (1) and (3), Figure 4 is a visual presentation of how MWTP changes in the distribution of average household income and education level (measured by high school completion rate). MWTP for 1 unit reduction in PM_{10} ranges from \$0.6 to \$4.2 by decile of average household income. At the median average household income, MWTP for unit reduction in PM_{10} is \$2.5. Similarly, there is a range of MWTP between \$0.6 and \$4.9 by decile of high school completion rate.

6.3 API *vs.* Visibility

If people are skeptical about the official pollution information, they could rely on their own eyeballing of the pollution level to make purchasing decisions. We run a "horse race" between the official API and visibility that measures the direct observation of pollution. In column (1) of Table 7, we compare API with visibility level. API has a statistically significant and robust association with the relative market share of HEPA purifiers, while the visibility level does not. In column (2), we measure very low visibility by a binary variable that is equal to 1 if visibility is less than 1 mile and 0 otherwise. There is suggestive evidence that very low level of visibility increases HEPA purifiers' relative market share, which, however, is not statistically significant. API "wins" over visibility again. Interestingly, although people might have doubts on the official pollution information, they still rely on it to make their self-protection decisions.

7 Health Valuation

Under the assumption that households are aware of the relationship between PM_{10} and loss in life expectancy, we provide implications for health valuation by combining our estimates on MWTP for PM_{10} reduction with estimates on the PM_{10} - life expectancy relationship from previous studies. We should note that our calculation of the WTP for an additional year of life possibly yields a *lower bound* of health valuation because our estimates of MWTP for one unit of indoor PM_{10} reduction provides a *lower bound*..

Using our estimates on the MWTP for PM_{10} reduction from the FE model, we calculate the WTP for an additional year of life. We use the MWTP for 1 unit reduction in PM_{10} for a year, \$1.52. Our evidence also suggests a linear relationship between PM_{10} and MWTP. Thus, the WTP for 100 units reduction in PM_{10} for a year is \$152. On the health effect of ambient PM_{10} in Chinese cities, Ebenstein et al. (2015) estimates that an increase of 100 units of PM_{10} is associated with 2.3 years loss of life expectancy at age 5. Assuming that the loss in life expectancy is evenly distributed in one's life cycle, for one person, we calculate that the loss in life expectancy from exposure to PM_{10} in 1 year is (2.3 years loss/70 years life expectancy at age 5)=0.03 years.[21] To combine our WTP for pollution reduction for a household with the health estimate at the individual level, we use the average number of household members in our sample, 4, from the 2005 population census. The WTP for an additional year of life for one person is (\$152/0.03 years)/4 persons=\$1,267, equivalent to 15% of average annual household income.[22] We provide additional estimates of health valuation under various assumption on household usage of the purifier and replacement of filters in Column (5) of Appendix Table A.7. Note that our main estimate of \$1,267 is a lower bound of health valuation.

Next, we combine our estimate on the MWTP for pollution reduction using the Huai River policy with the pollution-health estimate from Ebenstein et al. (2015). We find that the MWTP for 1 unit of PM_{10} reduction in a year is \$2.46, and thus the WTP for reducing 100 units of PM_{10} is \$246. Combing our WTP estimate of \$246 for a year and 0.03 years of loss in life expectancy from exposure to PM_{10} in 1 year, the WTP for an additional year of life for one person is (\$246/0.03 years)/4 persons=\$2,050, equivalent to 25% of average annual household income. We also provide additional estimates of health valuation under different assumptions in Column (5) of Appendix Table A.8. Our main estimate of \$2,050 is the lowest among all estimates.

The main difference between two health valuation estimates is from our two approaches for estimating the MWTP for PM_{10} reduction. The health valuation estimate using the Huai River policy is higher than that using the FE approach because we find a higher local average of MWTP for PM_{10} reduction using the spatial RD design than the nationwide average of MWTP using the FE approach.

The lower bound on the WTP for an additional year of life in China is substantially higher than previously understood for developing countries. Among limited design-based evidence on revealed preference in developing countries, the WTP for an additional year of life (disability adjusted) is \$24

[21] Average life expectancy at birth is 75 years Ebenstein et al. (2015).
[22] The average annual household income in our sample is 8332 USD (based on wage and employment data at the city-year level).

in Kenya (roughly 5% of annual household income) in Kremer et al. (2011). The estimated value in China is also much higher than the cost-effectiveness cutoffs used in analyzing health projects in developing countries. According to the 1993 World Development Report "Investing in Health", health interventions that cost less than $150 per disability adjusted life-year are very cost effective WorldBank (1993).

Our value of a life-year estimates are below estimated values in developed countries, consistent with models where health valuation is income elastic. However, they are not far below. In the US and other rich countries, estimated values of a statistical life (VSL) range from $2 to $7 million (Viscusi and Aldy (2003), Ashenfelter and Greenstone (2004), Hall and Jones (2007)). Using the life expectancy at birth of 78 years and the discount rate of 1%, we convert the VSL to the value of a statistical life-year (VSLY) based on Aldy and Viscusi (2007)'s method.[23] The estimated value of a life-year in developed countries ranges between $37,000 and $129,000, which is from 74% to 258% of average annual household income.[24] The comparison on health valuation between China and developed countries depends on which estimates we use. Nevertheless, our analysis reveals that Chinese households significantly value their health even compared to countries with well-established environmental regulations, which has not been found in previous studies or understood by policy makers in the tradeoff of China's economic development and environmental protection.

8 Conclusion

Despite higher pollution levels and mortality rates from pollution, limited design-based evidence shows very low WTP for environmental quality in developing countries. For example, the VSL based on WTP for environmental quality in Kenya is 10,000 times lower than that in US (Kremer et al. (2011)). Does the low WTP for environmental quality imply that the current level of environmental quality in developing countries is optimal? Or is WTP high, yet policy makers fail to express the preference of citizens in policy making and implementation? These questions remain poorly understood among economists and policy makers.

This paper provides new evidence on WTP for air quality from one of the most polluted countries in the world. Our estimates on the *lower bound* of WTP for improvements in air quality and

[23] According to Aldy and Viscusi (2007), $VSLY = (VLS * 0.01)/(1 - \frac{1}{(1+0.01)^{78}})$.

[24] We assume that the average annual household income is $50,000 in developed countries.

health valuation in China are substantially higher than previously understood for developing countries, which suggests that the current environmental regulations are not optimal and strengthening environmental regulations will largely improve human welfare.

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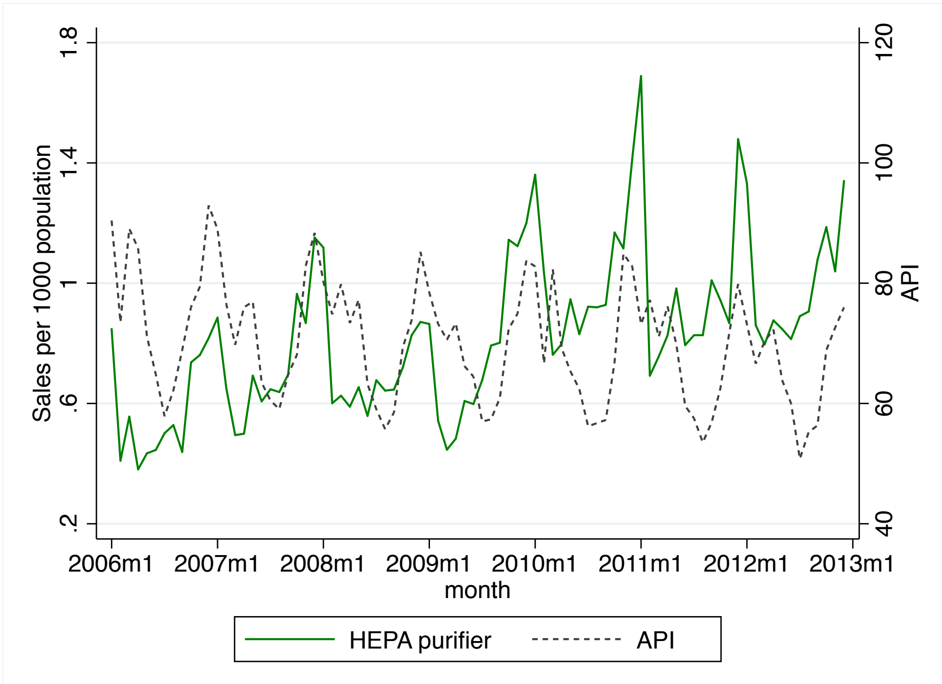
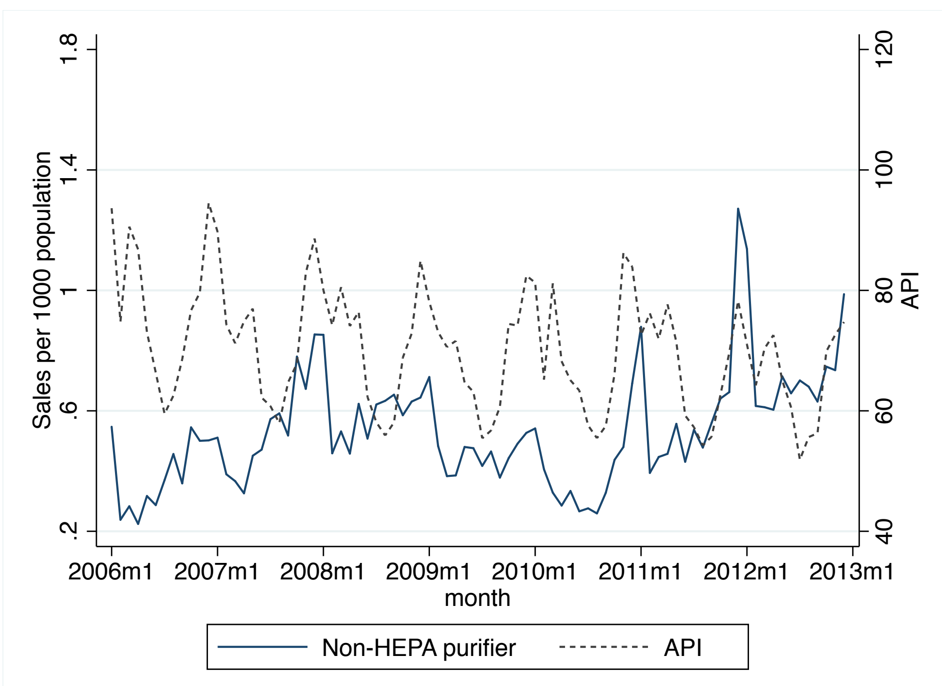
Figure 1: API and Air Purifier Sales

(a) HEPA Purifiers

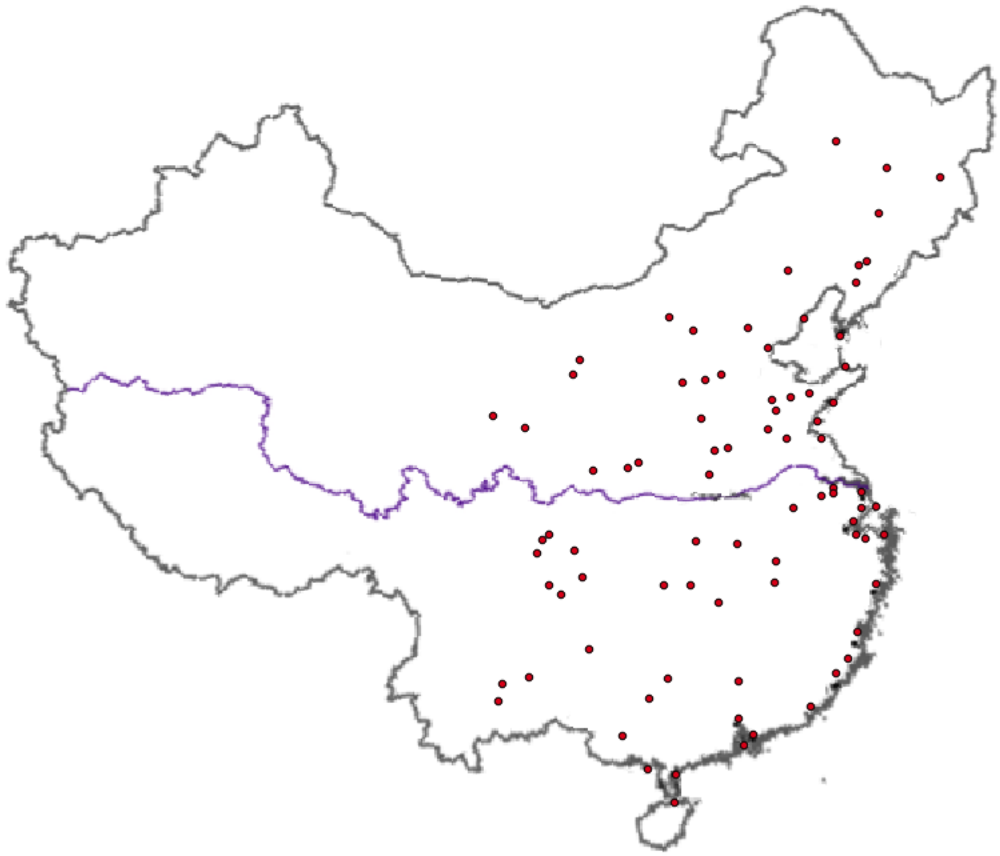


(b) Non-HEPA Purifiers



Notes: Figure 1a shows the national total sales per 1000 population of HEPA purifiers by year-month and national average API by year-month in 2006-2012. Figure 1b shows the national total sales per 1000 population of Non-HEPA purifiers by year-month and national average API by year-month in 2006-2012.

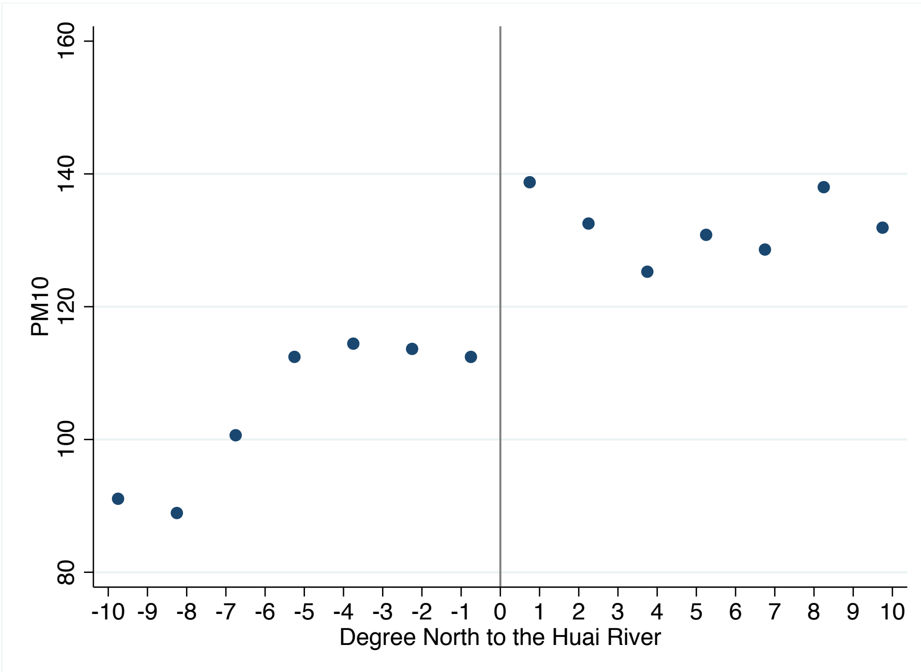
Figure 2: Huai River Boundary and City Locations



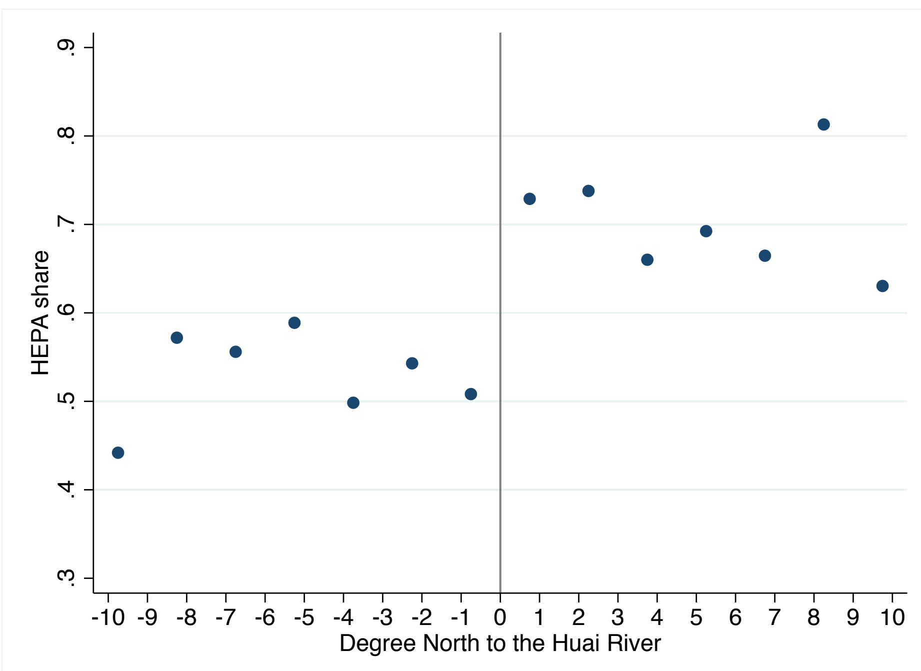
Notes: The line in the middle of the map is the Huai River-Qinling boundary. Each dot represents 1 city. There are 82 cities in our sample.

Figure 3: Regression Discontinuity Design at the Huai River Boundary

(a) PM10 in Winter

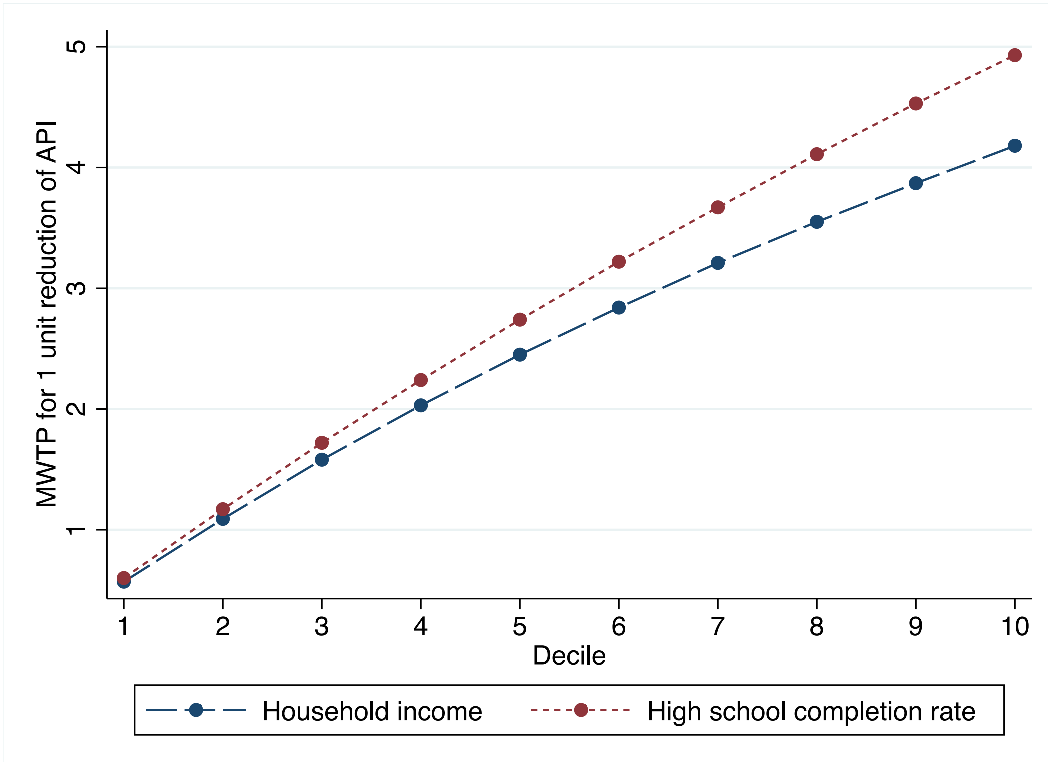


(b) Market Share of HEPA Purifiers in Winter



Notes: There are 72 cities within 10.5 degree of latitude relative to the river line. Figure 3a plots the average monthly PM_{10} during winter (December-March) in 2006-2012 by 1.5 degree 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 degree 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 degree of latitude north to the river line. The y-axis indicates the average PM_{10} level of cities within 1.5 degree of latitude. Figure 3b shows the monthly market share of HEPA purifiers in winter by 1.5 degree of latitude north to the Huai River line.

Figure 4: Heterogeneity in MWTP by city average income and education



Notes: We use estimates in column (1) and (3) of Table 6 to plot Figure 4. X-axis is MWTP for 1 unit reduction of PM10. Each dot connecting the long-dashed line represents 1 decile of city-level average household income. Each dot connecting the short-dashed line represents 1 decile of city-level high school completion rate. This figure shows changes in MWTP by decile of city-level household income and high school completion rate.

Table 1: Summary Statistics

	Whole sample		Winter (December-March)	
	Mean	Std. Dev.	Mean	Std. Dev.
Pollution (city-year-month)				
API	68.92	18.10	77.06	18.87
PM10 (ug/m3)	100.73	30.55	115.32	34.73
Air purifiers (product-city-year-month)				
Number of sales	7.21	21.78	7.81	24.26
Market share	0.07	0.12	0.07	0.12
Percentage HEPA purifiers	0.58	0.49	0.58	0.49
CADR	196.89	74.16	195.95	73.50
Maximum coverage area	41.26	16.89	41.01	16.67
Price (USD)	390.02	278.88	384.86	277.46
Weather (city-month)				
Temperature (degrees F)	59.29	18.71	40.74	14.83
Dew point (degrees F)	46.68	20.85	27.69	17.16
Wind speed (knots)	4.70	1.41	4.81	1.47
Precipitation (inches)	0.11	0.13	0.04	0.06
Visibility (miles)	7.58	3.13	6.91	3.06
City-year and city demographics				
1) City-year level (city statistical yearbooks)				
Population (1,000)	2476	2725	2476	2725
GDP per capita (USD)	8162	4284	8162	4284
Share of GDP from manufacturing	0.50	0.11	0.50	0.11
2) City level (2005 Census)				
Percentage employed	0.76	0.08	0.76	0.08
Annual household income (USD)	2070	1012	2070	1012
House purchase price (USD)	6493	3144	6493	3144
Percentage completed high school	0.24	0.10	0.24	0.10
Percentage completed college	0.04	0.03	0.04	0.03

Table 2: Fixed Effect Approach: Do people buy the right purifiers?

	Log(market share) - Log(outside option)			
	(1)	(2)	(3)	(4)
API*HEPA	0.0054***	0.0029***	0.0035***	0.0055***
	[0.0013]	[0.0011]	[0.0012]	[0.0017]
API*Active carbon	0.0003	0.0011	0.0005	0.0015
	[0.0015]	[0.0012]	[0.0013]	[0.0019]
API*Ion	0.0001	0.00002	0.0005	-0.0007
	[0.0012]	[0.0010]	[0.0011]	[0.0015]
API*Catalytic	-0.0127***	-0.0097***	-0.0095***	-0.0151***
	[0.0017]	[0.0012]	[0.0014]	[0.0020]
API*CADR	-0.000007	-0.000006	-0.000006	-0.000006
	[0.000007]	[0.000006]	[0.000006]	[0.000009]
Price	-0.0009***	-0.0011***	-0.0012***	-0.0015***
	[0.0001]	[0.0001]	[0.0001]	[0.0001]
API	-0.0029	0.0010		0.0003
	[0.0018]	[0.0015]		[0.0022]
Observations	63,479	63,479	63,479	63,479
R-squared	0.214	0.409	0.459	0.504
Product FE	Yes	Yes	Yes	
City FE		Yes		Yes
Year-month FE		Yes		
Product-year-month FE				Yes
City-year-month FE			Yes	
City-year-month weather controls		Yes		Yes
City-year socio-economic controls		Yes		Yes

Notes: Each observation represents a product-city-year-month. In all regressions, in addition to controls listed in the table, PM10 is also included. Weather controls include quadratic form of temperature, dew point, precipitation, wind speed and visibility. City-year socio-economic controls include city-year variables including population, GDP per capita, share of industrial GDP from City Statistical Yearbook and city-level variables including average household income, home price, percentage completed high school and percentage completed college from 2005 Census. The sample includes products with non-missing value on both filtration system and CADR. Standard errors in brackets are clustered at the product-city level.

Table 3: Fixed Effect Approach: MWTP for Reduction in API and PM10

	Log(market share) - Log(outside option)					
	Pollution in current month			**Average pollution in the past 6 months**		
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	2SLS IV for price	OLS	OLS	2SLS IV for price	OLS
Panel A: API						
API*HEPA	0.0032***	0.0032***	0.0046***	0.0055***	0.0055***	0.0070***
	[0.0009]	[0.0009]	[0.0013]	[0.0015]	[0.0016]	[0.0019]
Price	-0.0011***	-0.0008***	-0.0014***	-0.0011***	-0.0008***	-0.0014***
	[0.0001]	[0.0003]	[0.0001]	[0.0001]	[0.0003]	[0.0001]
AP 1st stage F-stat		5021			5020	
Observations	68,775	68,775	73,390	68,746	68,746	73,360
R-squared	0.449	0.445	0.530	0.449	0.446	0.531
Panel B: PM10						
PM10*HEPA	0.0017***	0.0017***	0.0025***	0.0031***	0.0031***	0.0044***
	[0.0005]	[0.0005]	[0.0008]	[0.0010]	[0.0010]	[0.0013]
Price	-0.0011***	-0.0008***	-0.0014***	-0.0011***	-0.0008***	-0.0014***
	[0.0001]	[0.0003]	[0.0001]	[0.0001]	[0.0003]	[0.0001]
AP 1st stage F-stat		5005			5004	
Observations	68,557	68,557	73,160	68,528	68,528	73,130
R-squared	0.449	0.445	0.531	0.449	0.445	0.531
Product FE	Yes	Yes		Yes	Yes	
Product-year-month FE			Yes			Yes
City FE			Yes			Yes
City-year-month FE	Yes	Yes		Yes	Yes	
City-year-month weather controls			Yes			Yes
City-year socio-economic controls			Yes			Yes

Notes: Each observation represents a product-city-year-month. Column (1) reports OLS estimates from estimating equation (5). Column (2) reports 2SLS estimates with an instrumental variable for price using equation (5). Column (3) reports OLS estimates from estimating equation (6). Column (4) reports OLS estimates from estimating equation (5). Column (5) reports 2SLS estimates with an instrumental variable for price using equation (5). Column (6) reports OLS estimates from estimating equation (6). In all regressions, in addition to controls listed in the table, PM10 is also included. Weather controls include quadratic form of temperature, dew point, precipitation, wind speed and visibility. City-year socio-economic controls include city-year variables including population, GDP per capita, share of industrial GDP from City Statistical Yearbook and city-level variables including average household income, home price, percentage completed high school and percentage completed college from 2005 Census. Standard errors in brackets are clustered at the product-city level.

Table 4: Regression Discontinuity Estimates at the Huai River Boundary

	(1)	(2)	(3)	(4)	(5)
Panel A: First stage			**PM10**		
North	20.592***	20.660***	23.456***	26.124***	25.876***
	[1.569]	[1.526]	[1.342]	[1.447]	[1.627]
Observations	23,433	23,433	23,433	23,433	23,433
R-squared	0.271	0.316	0.614	0.649	0.689
Panel B: Reduced form			**Log(market share) - Log(outside option)**		
North*HEPA	0.285***	0.246***	0.253***	0.259***	0.317***
	[0.051]	[0.060]	[0.052]	[0.051]	[0.059]
Price	-0.0004***	-0.0010***	-0.0011***	-0.0011***	-0.0014***
	[0.0001]	[0.0001]	[0.0001]	[0.0001]	[0.0002]
Observations	23,442	23,442	23,442	23,442	23,442
R-squared	0.050	0.272	0.393	0.406	0.516
Panel C: 2SLS			**Log(market share) - Log(outside option)**		
PM10*HEPA (instrumented)	0.0027***	0.0087***	0.0086***	0.0087***	0.0109***
	[0.0005]	[0.0024]	[0.0017]	[0.0017]	[0.0020]
Price	-0.0001	-0.0009***	-0.0011***	-0.0011***	-0.0014***
	[0.0001]	[0.0002]	[0.0001]	[0.0001]	[0.0002]
Observations	23,433	23,433	23,433	23,433	23,442
Quadratic trend of latitude	Yes	Yes	Yes	Yes	Yes
Product FE		Yes	Yes	Yes	
Year-month FE			Yes	Yes	
Product-year-month FE					Yes
City-year-month weather controls			Yes	Yes	Yes
City-year socio-economic controls			Yes	Yes	Yes
Longitude decile FE				Yes	Yes

Notes: Each observation represents a product-city-year-month. The sample include 74 cities within 10.5 degree latitude relative to the Huai River and winter months (December to March). Panel A presents results of the first stage on PM10. Panel B presents reduced-form estimates from estimating equation (8), where North is also included in regressions. Panel C presents 2SLS results from estimating equation (9), where North*HEPA is the instrument for PM10*HEPA, and PM10 is also included in regressions (North is the instrument for PM10). Weather controls include quadratic form of temperature, dew point, precipitation, wind speed and visibility. City-year socio-economic controls include city-year variables including population, GDP per capita, share of industrial GDP from City Statistical Yearbook and city-level variables including average household income, home price, percentage completed high school and percentage completed college from 2005 Census. Standard errors in brackets are clustered at the product-city level.

Table 5: MWTP for Reduction in API and PM10 per Square Meter

	Log(market share) - Log(outside option)					
	Pollution in current month			**Average pollution in the past 6 months**		
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	2SLS IV for price	OLS	OLS	2SLS IV for price	OLS
Panel A: API						
API*HEPA*Area	0.00010***	0.00010***	0.00016***	0.00024***	0.00017***	0.00017***
	[0.00002]	[0.00002]	[0.00003]	[0.00005]	[0.00004]	[0.00004]
Price	-0.0012***	-0.0012**	-0.0013***	-0.0013***	-0.0012***	-0.0011**
	[0.0002]	[0.0005]	[0.0002]	[0.0002]	[0.0002]	[0.0005]
AP 1st stage F-stat		2116			2117	
Observations	47,349	47,349	49,681	49,671	47,339	47,339
R-squared	0.470	0.467	0.524	0.524	0.471	0.467
Panel B: PM10						
PM10*HEPA*Area	0.00008***	0.00005***	0.00005***	0.00014***	0.00010***	0.00010***
	[0.00002]	[0.00001]	[0.00001]	[0.00003]	[0.00003]	[0.00003]
Price	-0.0013***	-0.0012***	-0.0012**	-0.0013***	-0.0012***	-0.0011**
	[0.0002]	[0.0002]	[0.0005]	[0.0002]	[0.0002]	[0.0005]
AP 1st stage F-stat		2106			2018	
Observations	49,517	47,194	47,194	49,507	47,184	47,184
R-squared	0.523	0.470	0.467	0.525	0.470	0.467
Product FE	Yes	Yes		Yes	Yes	
Product-year-month FE			Yes			Yes
City FE			Yes			Yes
City-year-month FE	Yes	Yes		Yes	Yes	
City-year-month weather controls			Yes			Yes
City-year socio-economic controls			Yes			Yes

Notes: Each observation represents a product-city-year-month. In all regressions, in addition to controls listed in the table, PM10 is also included. Weather controls include quadratic form of temperature, dew point, precipitation, wind speed and visibility. City-year socio-economic controls include city-year variables including population, GDP per capita, share of industrial GDP from City Statistical Yearbook and city-level variables including average household income, home price, percentage completed high school and percentage completed college from 2005 Census. Standard errors in brackets are clustered at the product-city level.

Table 6: Heterogeneity in MWTP

	Log(market share) - Log(outside option)			
	(1)	(2)	(3)	(4)
PM10*HEPA*Household income decile	0.00071**			
	[0.00030]			
PM10*HEPA*Home price decile		0.00074**		
		[0.00029]		
PM10*HEPA*High school decile			0.00074***	
			[0.00028]	
PM10*HEPA*College decile				0.00066**
				[0.00028]
PM10*HEPA	-0.00044	-0.00062	-0.00118	-0.00050
	[0.00116]	[0.00111]	[0.00145]	[0.00139]
Price*Household income decile	-0.00005***			
	[0.00002]			
Price*Home price decile		-0.00004**		
		[0.00002]		
Price*High school decile			-0.00003**	
			[0.00002]	
Price*College decile				-0.00004**
				[0.00002]
Price	-0.0012***	-0.0013***	-0.0012***	-0.0012***
	[0.0002]	[0.0002]	[0.0002]	[0.0002]
Observations	73,130	73160	73160	73160
R-squared	0.532	0.532	0.531	0.531
City FE	Yes	Yes	Yes	Yes
Product-year-month FE	Yes	Yes	Yes	Yes
City-year-month weather controls	Yes	Yes	Yes	Yes
City-year socio-economic controls	Yes	Yes	Yes	Yes

Notes: Each observation represents a product-city-year-month. In all regressions, in addition to controls listed in the table, PM10 is also included. Weather controls include quadratic form of temperature, dew point, precipitation, wind speed and visibility. City-year socio-economic controls include city-year variables including population, GDP per capita, share of industrial GDP from City Statistical Yearbook and city-level variables including average household income, home price, percentage completed high school and percentage completed college from 2005 Census. Standard errors in brackets are clustered at the product-city level.

Table 7: API vs. Visibility

	Log(market share) - Log(outside option)			
	(1)	(2)	(3)	(4)
API*HEPA	0.0032***	0.0029***	0.0046***	0.0043***
	[0.0009]	[0.0009]	[0.0013]	[0.0014]
Visibility*HEPA	0.0023		-0.0006	
	[0.0073]		[0.0080]	
1{Visibility<1 mile}*HEPA		0.351		0.342
		[0.248]		[0.285]
Price	-0.0010***	-0.0010***	-0.0014***	-0.0014***
	[0.0001]	[0.0001]	[0.0001]	[0.0001]
Observations	73,390	73,390	73,390	73,390
R-squared	0.465	0.465	0.530	0.530
Product FE	Yes	Yes		
City FE			Yes	Yes
City-year-month FE	Yes	Yes		
Product-year-month FE			Yes	Yes
City-year-month weather controls			Yes	Yes
City-year socio-economic controls			Yes	Yes

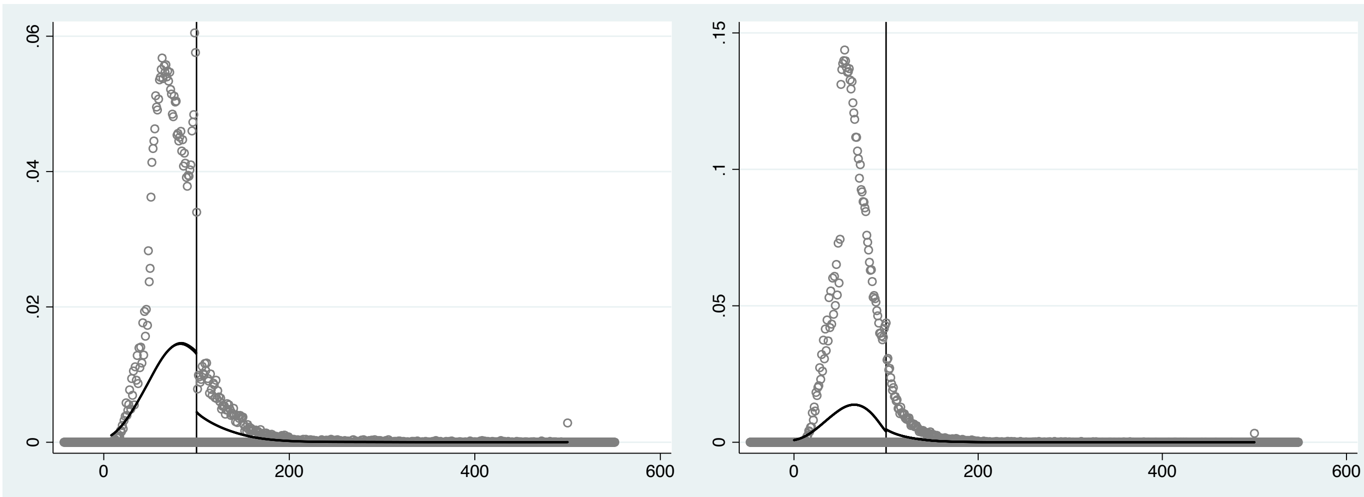
Notes: Each observation represents a product-city-year-month. In all regressions, in addition to controls listed in the table, API is also included. Weather controls include quadratic form of temperature, dew point, precipitation, wind speed and visibility. City-year socio-economic controls include city-year variables including population, GDP per capita, share of industrial GDP from City Statistical Yearbook and city-level variables including average household income, home price, percentage completed high school and percentage completed college from 2005 Census. Standard errors in brackets are clustered at the product-city level.

Online Appendices Not For Publication

A Additional Figures

Figure A.1: API distribution

(a) McCrary density test



(b) Manipulation sample: original and counterfactual distributions

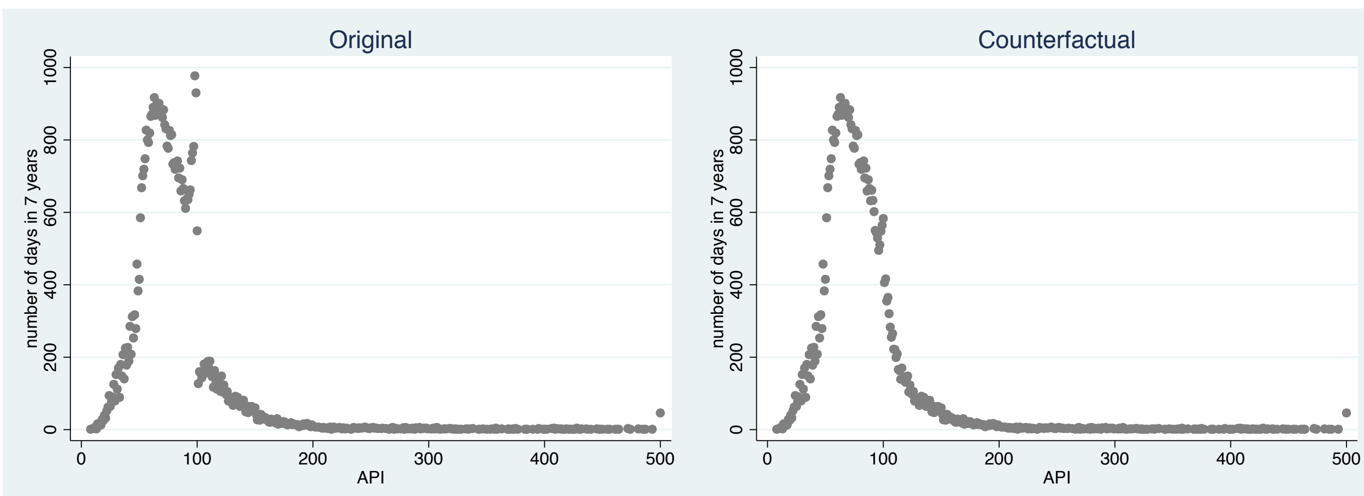
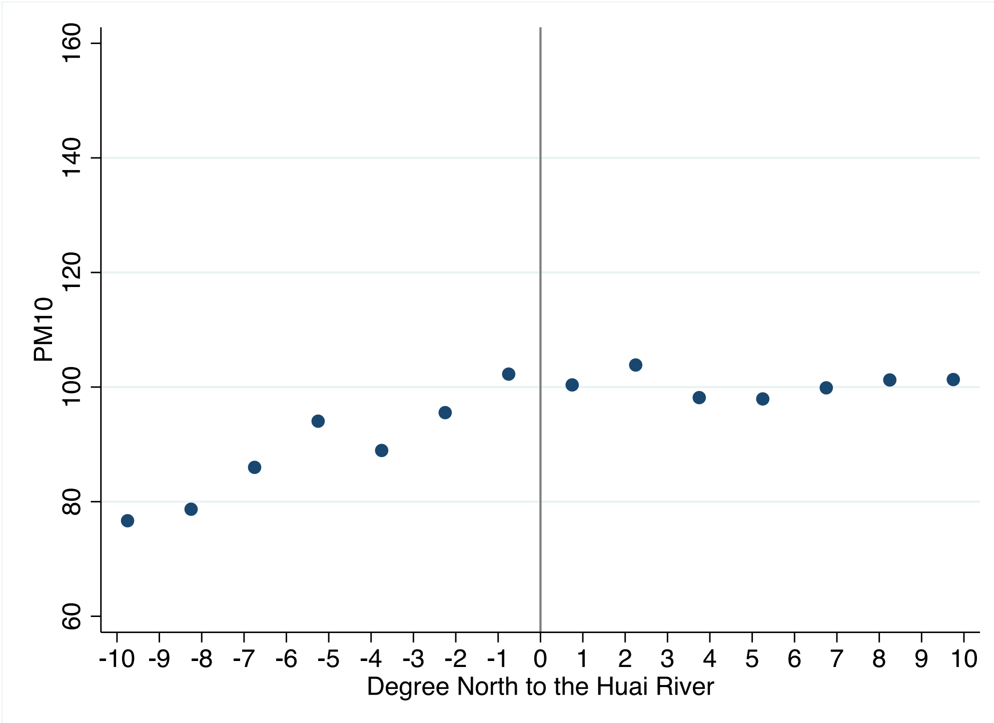
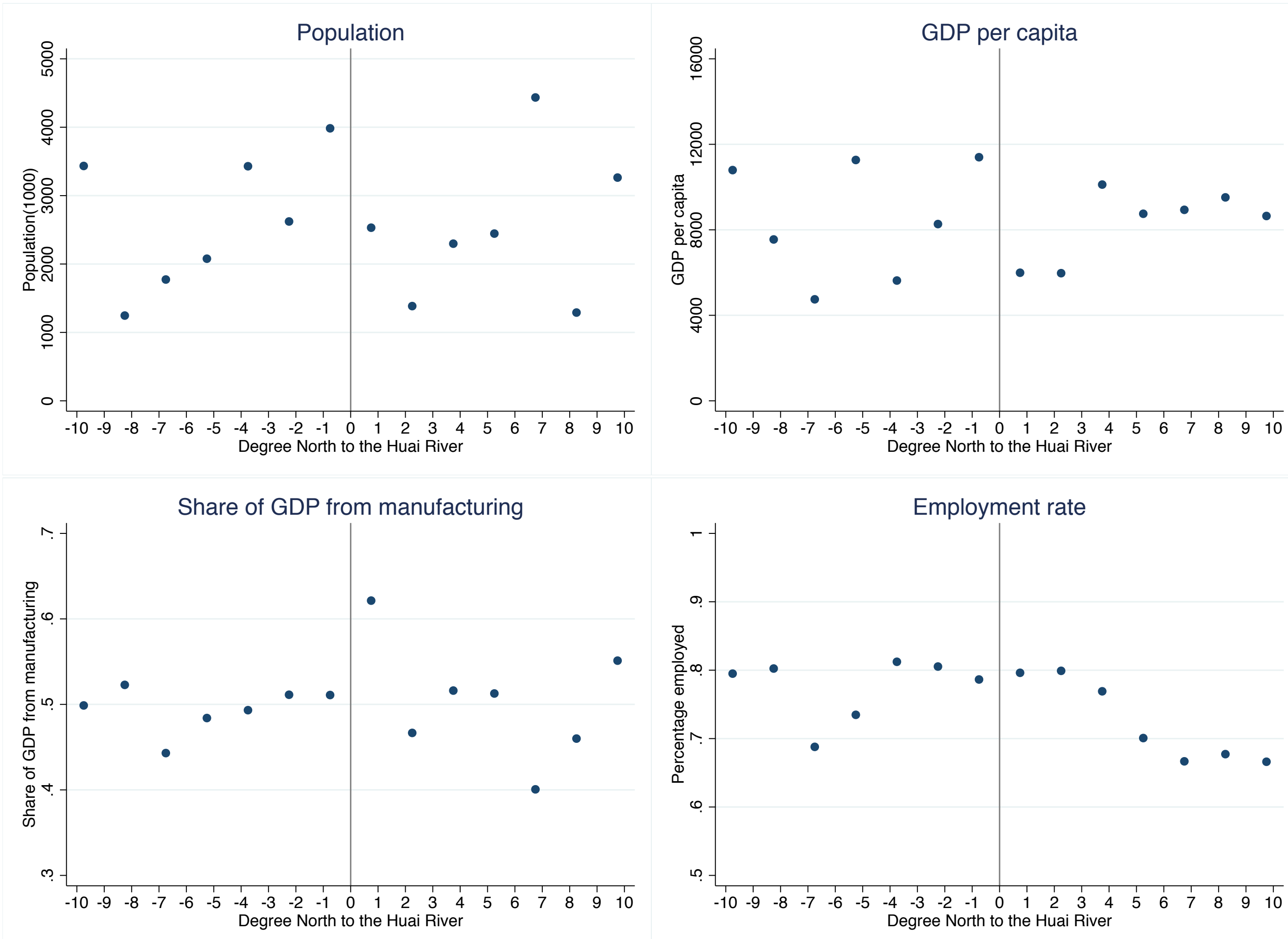


Figure A.2: Huai River: PM10 in non-winter months (April-November)



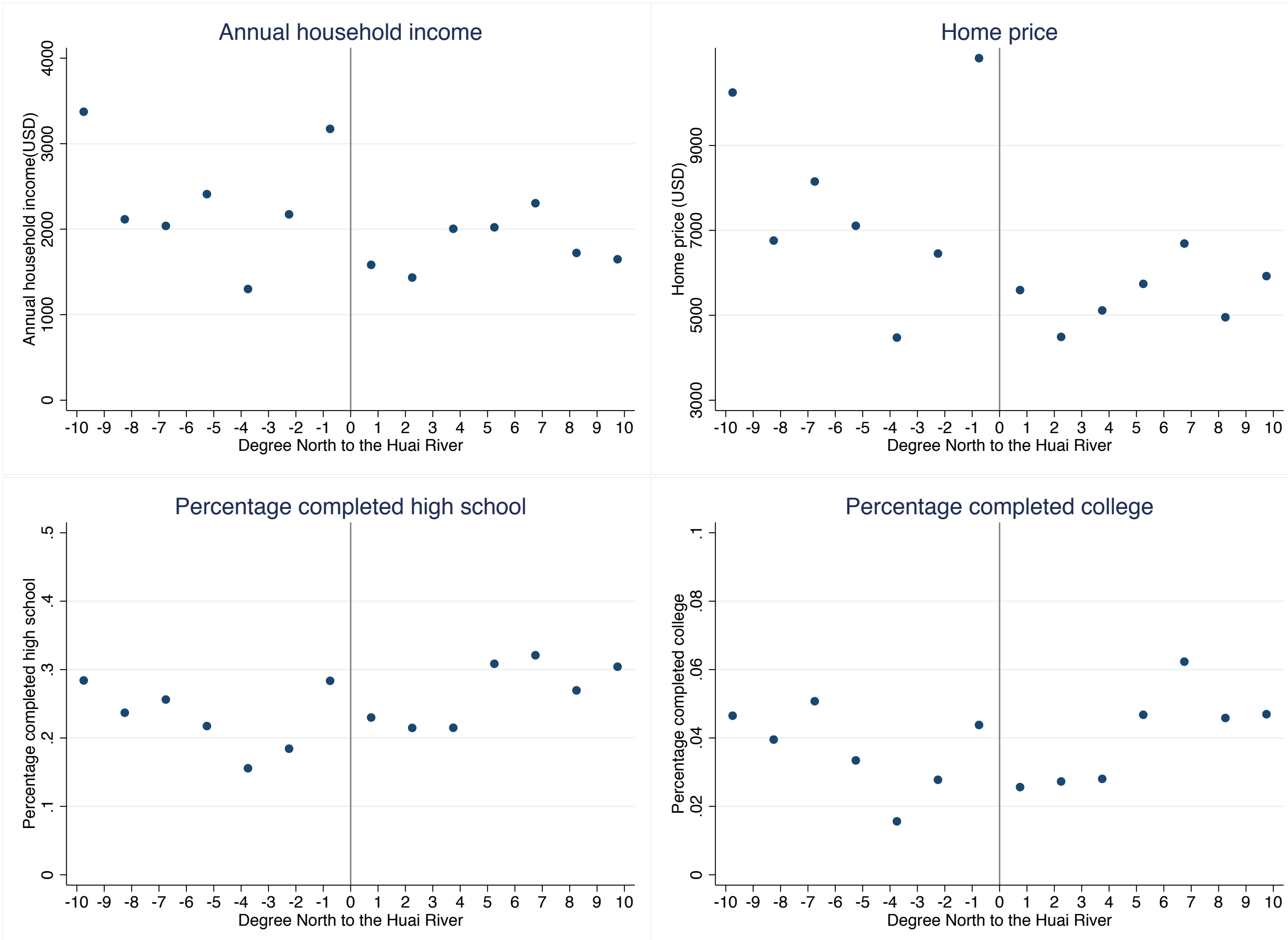
Notes: This figure plots the average monthly PM_{10} during non-winter months (April-November) in 2006-2012 by 1.5 degree of latitude north to the Huai River boundary. The vertical line at 0 indicates the location of the river. Each dot represents cities in 1.5 degree of latitude and corresponds to the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

Figure A.3: Huai River and Demographics (1)



Notes: These figures plot the mean of each demographic variable by 1.5 degree 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 degree 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 degree of latitude north to the river line. The y-axis indicates the mean level of each variable in cities within 1.5 degree of latitude.

Figure A.4: Huai River and Demographics (2)



Notes: These figures plot the mean of each demographic variable by 1.5 degree 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 degree 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 degree of latitude north to the river line. The y-axis indicates the mean level of each variable in cities within 1.5 degree of latitude.

B Additional Tables

Table A.1: FE Model: Lagged API

	Log(market share) - Log(outside option)					
	(1)	(2)	(3)	(4)	(5)	(6)
API*HEPA	0.0028***	0.0025**	0.0021**	0.0019**	0.0016*	0.0016*
	[0.0010]	[0.0010]	[0.0009]	[0.0009]	[0.0009]	[0.0009]
API 1-month lag*HEPA	0.0027***	0.0019***	0.0017**	0.0016**	0.0015**	0.0015**
	[0.0008]	[0.0007]	[0.0007]	[0.0007]	[0.0006]	[0.0006]
API 2-month lag*HEPA		0.0016**	0.0004	0.0003	0.0002	0.0002
		[0.0008]	[0.0007]	[0.0007]	[0.0007]	[0.0007]
API 3-month lag*HEPA			0.0023***	0.0014**	0.0013*	0.0012*
			[0.0008]	[0.0007]	[0.0007]	[0.0007]
API 4-month lag*HEPA				0.0016**	0.0005	0.0005
				[0.0007]	[0.0007]	[0.0006]
API 5-month lag*HEPA					0.0019***	0.0017**
					[0.0007]	[0.0007]
API 6-month lag*HEPA						0.0005
						[0.0007]
Price	-0.0014***	-0.0014***	-0.0014***	-0.0014***	-0.0014***	-0.0014***
	[0.0001]	[0.0001]	[0.0001]	[0.0001]	[0.0001]	[0.0001]
Observations	73,383	73,378	73,373	73,367	73,360	73,354
R-squared	0.531	0.531	0.531	0.531	0.531	0.531
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Product-year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
City-year-month weather controls	Yes	Yes	Yes	Yes	Yes	Yes
City-year socio-economic controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each observation represents a product-city-year-month. In all regressions, in addition to controls listed in the table, API is also included. Weather controls include quadratic form of temperature, dew point, precipitation, wind speed and visibility. City-year socio-economic controls include city-year variables including population, GDP per capita, share of industrial GDP from City Statistical Yearbook and city-level variables including average household income, home price, percentage completed high school and percentage completed college from 2005 Census. Standard errors in brackets are clustered at the product-city level.

Table A.2: FE model: include GDP per capita*HEPA

	Log(market share) - Log(outside option)					
	Pollution in current month			Average pollution in the past 6 months		
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	2SLS IV for price	OLS	OLS	2SLS IV for price	OLS
Panel A: API						
API*HEPA	0.0029***	0.0029***	0.0042***	0.0050***	0.0050***	0.0064***
	[0.0009]	[0.0009]	[0.0013]	[0.0015]	[0.0016]	[0.0019]
Price	-0.0011***	-0.0008***	-0.0014***	-0.0011***	-0.0008***	-0.0014***
	[0.0001]	[0.0003]	[0.0001]	[0.0001]	[0.0003]	[0.0001]
Observations	68,775	68,775	73,390	68,746	68,746	73,360
R-squared	0.449	0.446	0.531	0.449	0.446	0.531
Panel B: PM10						
PM10*HEPA	0.0016***	0.0016***	0.0024***	0.0029***	0.0030***	0.0041***
	[0.0005]	[0.0005]	[0.0008]	[0.0010]	[0.0010]	[0.0013]
Price	-0.0011***	-0.0008***	-0.0014***	-0.0011***	-0.0008***	-0.0014***
	[0.0001]	[0.0003]	[0.0001]	[0.0001]	[0.0003]	[0.0001]
Observations	68,557	68,557	73,160	68,528	68,528	73,130
R-squared	0.449	0.446	0.531	0.449	0.446	0.531
Product FE	Yes	Yes		Yes	Yes	
Product-year-month FE			Yes			Yes
City FE			Yes			Yes
City-year-month FE	Yes	Yes		Yes	Yes	
City-year-month weather controls			Yes			Yes
City-year socio-economic controls			Yes			Yes
GDP per capita*HEPA	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each observation represents a product-city-year-month. Column (1) reports OLS estimates from estimating equation (5). Column (2) reports 2SLS estimates with an instrumental variable for price using equation (5). Column (3) reports OLS estimates from estimating equation (6). Column (4) reports OLS estimates from estimating equation (5). Column (5) reports 2SLS estimates with an instrumental variable for price using equation (5). Column (6) reports OLS estimates from estimating equation (6). In all regressions, in addition to controls listed in the table, PM10 is also included. Weather controls include quadratic form of temperature, dew point, precipitation, wind speed and visibility. City-year socio-economic controls include city-year variables including population, GDP per capita, share of industrial GDP from City Statistical Yearbook and city-level variables including average household income, home price, percentage completed high school and percentage completed college from 2005 Census. Standard errors in brackets are clustered at the product-city level.

Table A.3: FE Model: Nonlinearity or threshold effects?

	Log (market share) - Log (outside option)			
	Nonlinearity		Thresholds	
	(1)	(2)	(3)	(4)
API*HEPA	0.0089**	0.0028		0.0057***
	[0.0036]	[0.0084]		[0.0018]
API^2*HEPA	-0.00003	0.00004		
	[0.00002]	[0.00008]		
API^3*HEPA		-0.00000		
		[0.00000]		
1{100<API<=200}*HEPA			0.416***	-0.077
			[0.141]	[0.160]
1{API>200}*HEPA			0.518	-1.090
			[0.614]	[0.775]
Price	-0.0014***	-0.0014***	-0.0014***	-0.0014***
	[0.0001]	[0.0001]	[0.0001]	[0.0001]
Observations	73,390	73,390	73,390	73,390
R-squared	0.530	0.530	0.530	0.530
City FE	Yes	Yes	Yes	Yes
Product-year-month FE	Yes	Yes	Yes	Yes
City-year-month weather controls	Yes	Yes	Yes	Yes
City-year socio-economic controls	Yes	Yes	Yes	Yes

Notes: Each observation represents a product-city-year-month. In all regressions, in addition to controls listed in the table, API is also included. Weather controls include quadratic form of temperature, dew point, precipitation, wind speed and visibility. City-year socio-economic controls include city-year variables including population, GDP per capita, share of industrial GDP from City Statistical Yearbook and city-level variables including average household income, home price, percentage completed high school and percentage completed college from 2005 Census. Standard errors in brackets are clustered at the product-city level.

Table A.4: The Huai River policy (various functional forms)

	(1) Linear	(2) Linear*North	(3) Quadratic	(4) Quadratic*North
Panel A: First Stage	**PM10**			
North	16.945***	28.850***	25.876***	23.458***
	[1.717]	[1.660]	[1.627]	[3.551]
Observations	23,433	23,433	23,433	23,433
R-squared	0.663	0.690	0.689	0.691
Panel B: Reduced form	**Log(market share) - Log(outside option)**			
North*HEPA	0.320***	0.316***	0.317***	0.314***
	[0.059]	[0.059]	[0.059]	[0.059]
Price	-0.0015***	-0.0014***	-0.0014***	-0.0014***
	[0.0002]	[0.0002]	[0.0002]	[0.0002]
Observations	23,442	23,442	23,442	23,442
R-squared	0.515	0.516	0.516	0.516
Polynomial in latitude	Yes	Yes	Yes	Yes
Product-year-month FE	Yes	Yes	Yes	Yes
City-year-month weather controls	Yes	Yes	Yes	Yes
City-year demographics controls	Yes	Yes	Yes	Yes
Longitude decile FE	Yes	Yes	Yes	Yes

Note: Each observation represents a product-city-year-month. The sample includes 74 cities within 10.5 degree latitude relative to the Huai River and winter months (December-March). Each column uses a different functional form of city latitude which is labeled as column title. Panel A presents results of the first stage on PM10. Panel B presents reduced-form estimates from estimating equation (8), where North is also included in regressions. Weather controls include quadratic form of temperature, dew point, precipitation, wind speed and visibility. City-year socio-economic controls include city-year variables including population, GDP per capita, share of industrial GDP from City Statistical Yearbook and city-level variables including average household income, home price, percentage completed high school and percentage completed college from 2005 Census. Standard errors in brackets are clustered at the product-city level.

Table A.5: The Huai River policy in 6 degree window

	(1)	(2)	(3)	(4)	(5)
Panel A: First stage	PM10				
North	31.316***	28.735***	19.954***	30.761***	30.977***
	[1.970]	[1.885]	[1.958]	[1.855]	[2.103]
Observations	15,250	15,250	15,250	15,250	15,250
R-squared	0.135	0.196	0.568	0.639	0.689
Panel B: Reduced form	Log(market share) - Log(outside option)				
North*HEPA	0.222***	0.242***	0.244***	0.261***	0.311***
	[0.053]	[0.074]	[0.059]	[0.058]	[0.068]
Price	-0.0003***	-0.0008***	-0.0010***	-0.0010***	-0.0014***
	[0.0001]	[0.0002]	[0.0001]	[0.0002]	[0.0002]
Observations	15,250	15,250	15,250	15,250	15,250
R-squared	0.052	0.277	0.422	0.435	0.555
Panel C: 2SLS	Log(market share) - Log(outside option)				
PM10*HEPA (instrumented)	0.0016***	0.0109***	0.0116***	0.0120***	0.0147***
	[0.0004]	[0.0035]	[0.0027]	[0.0026]	[0.0017]
Price	-0.0001	-0.0008***	-0.0010***	-0.0010***	-0.0014***
	[0.0001]	[0.0002]	[0.0001]	[0.0001]	[0.0001]
Observations	15250	15250	15250	15250	15250
Quadratic trend of latitude	Yes	Yes	Yes	Yes	Yes
Product FE		Yes	Yes	Yes	
Year-month FE			Yes	Yes	
Product-year-month FE					Yes
City-year-month weather controls			Yes	Yes	Yes
City-year socio-economic controls			Yes	Yes	Yes
Longitude decile FE				Yes	Yes

Notes: Each observation represents a product-city-year-month. The sample include 52 cities within 6 degree latitude relative to the Huai River and winter months (December to March). Panel A presents results of the first stage on PM10. Panel B presents reduced-form estimates from estimating equation (8), where North is also included in regressions. Panel C presents 2SLS results from estimating equation (9), where North*HEPA is the instrument for PM10*HEPA, and PM10 is also included in regressions (North is the instrument for PM10). Weather controls include quadratic form of temperature, dew point, precipitation, wind speed and visibility. City-year socio-economic controls include city-year variables including population, GDP per capita, share of industrial GDP from City Statistical Yearbook and city-level variables including average household income, home price, percentage completed high school and percentage completed college from 2005 Census. Standard errors in brackets are clustered at the product-city level.

Table A.6: Huai River and Demographics

	Population		GDP per capita		Share of GDP from manufacturing		Percentage employed	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
North	-1,535	-1,890	-2,711**	-301	0.019	0.062	0.029	0.043
	[1,118]	[1,169]	[1,357]	[1,442]	[0.046]	[0.045]	[0.029]	[0.033]
Observations	511	511	511	511	511	511	74	74
R-squared	0.021	0.137	0.037	0.405	0.006	0.197	0.292	0.382
Quadratic trend of latitude	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE		Yes		Yes		Yes		
Longitude decile FE		Yes		Yes		Yes		Yes
	Annual household income		**Home price**		**Percentage completed high school**		**Percentage completed college**	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
North	-672	-256	-2,634*	-953	0.006	-0.023	-0.005	-0.011
	[447]	[446]	[1,364]	[1,392]	[0.043]	[0.048]	[0.012]	[0.014]
Observations	74	74	74	74	74	74	74	74
R-squared	0.102	0.396	0.136	0.392	0.114	0.230	0.081	0.135
Quadratic trend of latitude	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Longitude decile FE		Yes		Yes		Yes		Yes

Notes: The sample includes 74 cities within 10.5 degree latitude relative to the Huai River. For population, GDP per capita, share of GDP from manufacturing, each observation represents a city-year. For percentage employed, annual household income, home price, percentage completed high school and percentage completed college, each observation represents a city. Quadratic trend of city latitude is included in all regressions. Standard errors in brackets are clustered at the city level.

Table A.7: MWTP and Health Valuation using estimates from FE model under various assumptions

	(1)	(2)	(3)	(4)	(5)
	MWTP for removing 1 units of PM10 for 1 year	WTP for removing 100 units of PM10 for 1 year	Loss of life expectancy at birth from 100 units of PM10	Loss of life expectancy from 100 units of PM10 in 1 year	WTP for an additional year of life for one person
	Panel A: Households replace filters twice a year				
use the air purifier for 1 year	3.6	360	2.3	0.03	3000
use the air purifier for 3 year	1.87	187	2.3	0.03	1556
use the air purifier for 5 year	**1.52**	**152**	**2.3**	**0.03**	**1267**
	Panel B: Households replace filters three times a year				
use the air purifier for 1 year	4.1	410	2.3	0.03	3417
use the air purifier for 3 year	2.37	237	2.3	0.03	1972
use the air purifier for 5 year	2.02	202	2.3	0.03	1683

Table A.8: MWTP and Health Valuation using estimates from the Huai River policy under various assumptions

	(1)	(2)	(3)	(4)	(5)
	MWTP for removing 1 units of PM10 for 1 year	WTP for removing 100 units of PM10 for 1 year	Loss of life expectancy at birth from 100 units of PM10	Loss of life expectancy from 100 units of PM10 in 1 year	WTP for an additional year of life for one person
	Panel A: Households replace filters twice a year				
use the air purifier for 1 year	8.3	830	2.3	0.03	6917
use the air purifier for 3 year	3.43	343	2.3	0.03	2861
use the air purifier for 5 year	**2.46**	**246**	**2.3**	**0.03**	**2050**
	Panel B: Households replace filters three times a year				
use the air purifier for 1 year	8.8	880	2.3	0.03	7333
use the air purifier for 3 year	3.93	393	2.3	0.03	3278
use the air purifier for 5 year	2.96	296	2.3	0.03	2467