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

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We develop a framework to estimate willingness to pay for clean air from defensive investments on differentiated products. Applying this framework to scanner data on air purifier sales in China, we find that a household is willing to pay \$1.34 annually to remove 1 $\mu g/m^3$ of air pollution (PM_{10}) and \$32.7 annually to eliminate the pollution induced by the Huai River heating policy. Substantial heterogeneity is explained by income and exposure to information on air pollution. Using these estimates, we evaluate various environmental policies and quantify the value of recent air quality improvements since China declared a war on pollution in 2014.

I. Introduction

Air quality is remarkably poor in developing countries, and severe air pollution imposes a substantial health and economic burden on billions of people. For example, the annual average exposure to fine particulate

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matter in China was more than five times higher than that of the United States in 2013 (Brauer et al. 2016). Such severe air pollution causes great negative impacts on various economic outcomes, including infant mortality (Jayachandran 2009; Arceo, Hanna, and Oliva 2012; Greenstone and Hanna 2014), life expectancy (Chen et al. 2013; Ebenstein et al. 2017), and labor supply (Hanna and Oliva 2015). For this reason, policy makers and economists consider air pollution to be one of the first-order obstacles to economic development.

However, a great economic burden of air pollution does not necessarily imply that existing environmental regulations are not optimal. Optimal environmental regulation depends on the extent to which individuals value air quality improvements—that is, their willingness to pay (WTP) for clean air (Greenstone and Jack 2013). If WTP for clean air is low, the current level of air pollution could be optimal because a social planner should prioritize economic growth over environmental regulation. On the other hand, if WTP is high, the current stringency of regulations can be far from optimal. Therefore, WTP for clean air is a key parameter when considering the trade-offs between economic growth and environmental regulation. Despite the importance of this parameter, the economics literature provides limited empirical evidence. This is primarily because obtaining a revealed-preference estimate of WTP for clean air is challenging in developing countries because of limited availability of data and a lack of readily available exogenous variation in air quality for empirical analysis.

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

We apply this framework to scanner data on market transactions in air purifier markets in Chinese cities. At the retail store level, we observe product-level information on monthly sales, monthly average price, and detailed product attributes. The product attributes include the information on each purifier's effectiveness at reducing indoor air pollution. Our data cover January 2006 through December 2014. The data set provides comprehensive transaction records of 690 air purifier products for some of the most polluted cities in the world. To our knowledge, this paper is the first study to exploit these transaction data in the Chinese air purifier markets to examine consumers' WTP for air quality. We also collect pollution data from air pollution monitors and microdata on demographics from the Chinese census to compile a data set that consists of air purifier sales and prices, air pollution, and demographic characteristics.

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

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

We begin by presenting visual and statistical evidence that the level of air pollution (PM_{10}) is discontinuously higher in cities north of the Huai River by 24 $\mu g/m^3$ during our sample period. Using the theoretical prediction from our demand model, this discontinuity in air pollution implies that if households value air quality, the log market share of HEPA purifiers—purifiers that can reduce indoor particulate matter—should be discontinuously higher in cities north of the river boundary relative to non-HEPA purifiers. We show visual and statistical evidence that this theoretical prediction is consistent with the data. To estimate marginal WTP for air quality, we use standard logit estimation and random-coefficient logit estimation that allows for heterogeneity in preference parameters for pollution and price. We find that marginal WTP for removing 1 $\mu g/m^3$ of PM_{10} per year is \$1.34 and WTP for removing the amount of PM_{10} generated by the Huai River policy is \$32.7 per year. Our estimates are robust to using a range of different bandwidths and local linear and quadratic estimation. We find that substantial heterogeneity is explained by household income—higher-income households have significantly higher marginal WTP for clean air compared with lower-income households.

Our study provides three primary contributions to the literature. First, we develop a framework to estimate heterogeneity in WTP for environmental quality from defensive investment on the basis of market transaction data on differentiated products. Earlier studies on avoidance behavior examine whether individuals exhibit avoidance behavior in response to pollution exposure.[1] A key question in the recent literature is whether researchers can obtain monetized WTP for environmental quality from defensive behavior. For this question, theoretical work in environmental economics provides a useful insight; defensive investment on market products can be used to learn about the preference for environmental quality (Braden and Kolstad 1991). However, few existing studies attempt to develop a framework to connect this economic theory with market data.[2] Our idea is that this connection can be made by extending a random-utility framework that is commonly used for market share data analysis in industrial organization. Our model allows consumers to purchase differentiated products to improve their environmental quality. The model also allows for heterogeneous preferences for environmental quality and price elasticity. An attractive feature of this approach is that the conventional random-coefficient logit estimation (Berry, Levinsohn, and Pakes 1995; Nevo 2000) can be applied to investigate heterogeneity in WTP for environmental quality. We believe that our framework can be useful for many other settings because market transaction data are increasingly available for a variety of products in many countries, including developing countries, through store- and household-based scanner data.[3]

[1] Earlier studies on avoidance behavior against pollution find that people do engage in defensive investment against pollution. For evidence in the United States, see Neidell (2009), Zivin and Neidell (2009), and Zivin, Neidell, and Schlenker (2011). For evidence in China, see Mu and Zhang (2014) and Zheng, Sun, and Kahn (2015). For evidence in other developing countries, see Madajewicz et al. (2007) and Jalan and Somanathan (2008). A key question in the recent literature is whether researchers can estimate WTP for improvements in environmental quality from observing defensive investment in markets.

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

[3] There are a few more related studies. Berry, Fischer, and Guiteras (2012) and Miller and Mobarak (2013) use RCTs to estimate WTP for water filters and cookstoves 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 the authors provide a quasi-experimental approach to estimate WTP for clean air.

The second contribution is that we provide among the first revealed-preference estimates of WTP for clean air in developing countries. As emphasized by Greenstone and Jack (2013), WTP for environmental quality is a key parameter for policy design, but well-identified estimates of this parameter are barely available for air quality and, more generally, are quite scarce for any environmental quality in developing countries. An important exception is a seminal study by Kremer et al. (2011), which estimates WTP for water quality in Kenya by a randomized experiment. While experimental approaches provide many advantages, it is generally challenging to create long-run variation in pollution for a broad representation of the population in an experimental setting. Our quasi-experimental design provides variation in air pollution that lasted for an extended amount of time and affected heterogeneous households in many cities. This research design allows us to examine household responses to prolonged severe air pollution for a heterogeneous set of households. For this reason, we believe that our quasi-experimental approach is complementary to experimental approaches.[4]

Finally, our findings provide important policy implications for ongoing discussions on energy and environmental regulation in developing countries. For example, China declared a "war on pollution" in 2014 to reduce air pollution (Zhu 2014) and made a commitment to address global climate change in 2016, as featured by the *New York Times* (Davenport 2016). Because stringent environmental regulations are not costless, a key question is whether the benefit of a policy exceeds its cost. In the policy implication section, we use our estimate to evaluate existing and counterfactual environmental policies and quantify the value of the recent air quality improvements in China.

II. Air Pollution, Air Purifiers, and the Huai River Policy in China

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

A. *Air Purifiers*

A key advantage of analyzing air purifier markets is that one of the product attributes—HEPA—informs both consumers and econometricians about the purifier's effectiveness at reducing indoor particulate matter.

[4] In addition to our study, Freeman et al. (2017) and Barwick et al. (2018) are recent studies that use quasi-experimental research design to estimate WTP for clean air in China, although the focus of these papers is not long-run variation in air pollution.

According to the US Department of Energy, a HEPA air purifier removes at least 99.97% of particles that are 0.3 μm or larger in diameter (DOE 2005). It is even more effective for larger particles, such as $PM_{2.5}$ (particles with a diameter of 2.5 μm or smaller) and PM_{10} (particles with a diameter between 2.5 and 10 μm). Recent clinical studies find that the use of HEPA purifiers in various settings provides improvements in health, including reduced asthma symptoms and asthma-related health visits among children, lower marker levels of inflammation and heart disease, and reduced incidences of invasive aspergillosis among adults (Abdul Salam et al. 2010; Allen et al. 2011; Lanphear et al. 2011).

Consistent with the US Department of Energy standards, air purifier manufacturers and retail stores in China explicitly advertise that a HEPA purifier can remove more than 99% of particles that are 0.3 μm or larger. In contrast, non-HEPA purifiers are not effective at reducing small particles, such as $PM_{2.5}$ and PM_{10}. Yet non-HEPA purifiers provide consumers utility gains through attributes other than HEPA because these attributes are effective in removing other indoor pollutants. For example, many purifiers have a function called "activated carbon," which absorbs volatile organic compounds (VOCs)—one of the common indoor pollutants arising from house renovations, remodeling materials, and new furniture. Another example attribute is "catalytic converter," which is effective in removing formaldehyde as well as VOCs. Both HEPA and non-HEPA purifiers generally come with these functions, and HEPA purifiers provide an extra attribute that is specifically designed to reduce particulate matter.[5]

B. *Huai River Policy and Its Recent Reform*

In 1958, the Chinese government decided to provide a centralized heating system. Because of budget constraints, the government provided city-wide centralized heating to northern cities only (Almond et al. 2009). Northern and southern China are divided by a line formed by the Huai River and Qinling Mountains, as shown in figure 1. The government used this line because the average January temperature is roughly 0°C along the line and the line is not a border for other administrative purposes (Chen et al. 2013). Cities north of the river boundary have received centralized heating supply from the government during every winter, whereas cities in the south have not.

The centralized heating supply in the north relies on coal-fired heating systems. Two-thirds of heat is generated by heat-only hot water boilers for one or several buildings in an apartment complex, and the remaining

[5] One of the air purifier attributes, "air ionizer," is sometimes claimed to have some capacity to reduce small particles, but the effectiveness is usually quite limited. For example, a study by Health Canada finds that a residential ionizer removes only 4% of indoor $PM_{2.5}$ (Wallace 2008).

Fig. 1.—Huai River boundary and city locations. The line in the middle of the map shows the Huai River–Qinling Mountains boundary. A color version of this figure is available online.

one-third is generated by combined heat and power generators for the larger areas of each city. This system is inflexible and energy inefficient. Consumers have no means to control their heat supply, and until recently there has been no measurement of heat consumption at the consumer level. The incomplete combustion of coal in the heat-generation process leads to the release of air pollutants, particularly particulate matter. Because most heat is generated by boilers within an apartment complex, the pollution from coal-based heating remains largely local. Almond et al. (2009) find that the Huai River policy led to higher total suspended particulate (TSP) levels in the north. Ebenstein et al. (2017) further find that the higher pollution levels created by the policy led to a loss of 3 years of life expectancy in the north.

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

In July 2003, the Chinese government issued a heating reform. The reform changed the payment system from free provision to flat-rate billing (World Bank 2005). Individual households became responsible for the payment of their own heating bills for each season, which consisted of a fixed charge per square meter of floor area for the entire season, regardless of actual heating usage. Whether a heating subsidy is provided by employers varies by sector. In the public sector, former in-kind transfers were changed to a transparent payment for heating added to the wage. In contrast, private-sector employers were not explicitly required to provide a heating subsidy to their employees. In the 2005 census, 21% of the labor force was in the urban public sector in the 80 cities in our sample, suggesting that only a small percentage of employees receive a heating subsidy following the reform.

Our analysis focuses on the period from 2006 to 2014, after the 2003 reform on heating billing. We now summarize the comparison of winter heating between the north and the south. First, winter heating is provided in the same way after the reform. The centralized citywide heating supply in the north remains the same, where households have little option other than the centralized coal-based heating that generates higher pollution levels. In the south, households choose their own methods of staying warm during the winter, which could include using the heating function of air conditioners, space heaters, and heated blankets, among a myriad of other options. Second, heating costs in the north have changed since the 2003 reform. Northern households no longer enjoy free heating and instead have to pay (in the absence of subsidy) all of their compulsory centralized heating bills. On the other hand, households in the south continue to pay for the heating methods of their choice. We collected heating costs in 20 cities just north and just south of the Huai River boundary and find that household heating costs in the north are comparable to—or could even be higher than—those in the south.[6]

[6] For example, in Xi'an, a city just north of the Huai River, the price of heating per square meter in the winter is \$3.90. For an apartment of 100 m^2, the household pays \$390. The average subsidy in the public sector is \$177 per employee, and the number of public employees per household is 0.32 according to the 2005 population census. The average amount of subsidy per household is \$57. Therefore, an average household's out-of-pocket payment is \$333. In southern cities, space heaters and heated blankets are the most

III. Data and Descriptive Statistics

We compile a data set from five data sources—air purifier market data, air pollution data, manufacturing or importing location data for each product, city-by-year demographic information from *City Statistical Yearbooks*, and individual-level demographic variables from the 2005 Chinese census microdata. In this section, we describe each data source and provide descriptive statistics.

A. Air Purifier Data

We use air purifier sales transaction data collected by a marketing firm in China from January 2006 through December 2014 for 80 cities. The company collected transaction-level scanner data from each major retail store in these cities. We are provided with monthly sales and monthly average price for each product by store, along with information on product attributes. The data we analyze are in-store transactions and primarily from individual purchases.[7] The data set covers in-store transactions in major department stores and electrical appliance stores, which account for over 80% of all in-store sales. During the period 2006–14, in-store sales made up 72% of overall purifier sales (including in-store and online sales).

Because our data set does not cover 100% of purifier sales, we take two approaches to defining sales volume for our estimation. In the first approach, we simply ignore transactions outside our data set. Although this procedure provides transparency and conservative estimates, it underestimates each product's sales volume. In the second approach, we adjust sales volume proportionally to address this limitation. Specifically, we multiply the sales volume of each product by 1.73 $(=1/(0.8 \cdot 0.72))$. Since both approaches have their advantages and disadvantages, we report empirical results with both approaches—the latter as main results and the former in table A.8 (tables A.1–A.8 are available online). As we describe in section IV, the two approaches produce exactly the same results for standard logit estimation because the proportional multipliers will be fully absorbed by city fixed effects. While this is not the case for

common choices, which could cost \$150–\$200 including the purchasing of these devices and the electricity bill in winter for a similar-sized home. If a household chooses a more expensive option—air conditioning—the electricity bill for 3 months in winter could be approximately \$240–\$280, and the entire cost depends on the price of the air conditioners, which varies to a great extent.

[7] The raw scanner data include both individual and corporate purchases in retail stores, and the data indicate whether an official invoice is issued for each transaction. In China, for a government or corporate purchase to be reimbursed, an official invoice issued by the Chinese Tax Bureau (but provided by the seller), called a *fapiao*, is required. The invoice is addressed to the government or the corporate office. To generate the data for our analysis, the marketing company first includes individual purchases without official invoices in the raw transaction-level data and then generates monthly sales and prices data by store and product.

random-coefficient logit estimation due to its nonlinearity, we show that results for random-coefficient estimation are also very similar between the two approaches because city fixed effects absorb most of the differential variation.

There are 690 products sold by 45 manufacturers, including domestic and foreign companies. The raw sales and price data are at the product-city-store-year-month level. In our empirical analysis, the exogenous variation in pollution comes from city-level variation. Therefore, we aggregate the transaction data to the product-city level. A unique feature of the data set is that we observe detailed attributes for each product. The key attribute for our study is the HEPA filter, which allows us to quantify the amount of particulate matter that a product can remove.

B. *Air Pollution Data*

For air pollution data, we use city-level annual average PM_{10} from 2006 to 2014, which was collected by Ebenstein et al. (2017). The raw data come from two publications in Chinese, *China's Environmental Yearbooks* and *China's Environmental Quality Annual Reports*.

C. *Demographic Data*

We compile demographic data from two sources. First, we obtain city-year measures on population, urban population, and GDP per capita from *City Statistical Yearbooks* in 2006–14. Second, we obtain individual-level microdata from the 2005 census. For each city, the data set includes demographic variables for a random sample of individuals. We use household-level income data to create the empirical distribution of each city's household annual income, which we use in our empirical analysis. We also aggregate the census microdata to calculate a rich set of city-level socioeconomic measures, including average years of schooling, illiteracy rate, high school completion rate, college completion rate, average household income per capita, home size (in m^2), and measures of housing quality.

D. *Geographic Information System (GIS) Data and Map*

In figure 1, we present the city centroids of the 80 cities that we use for our analysis. We obtain the latitudes and longitudes of the city centroids from the census data and plot them onto the map of China using ArcGIS. We also show the location of the Huai River–Qinling Mountains line, which divides China into north and south.[8]

[8] The original source of the Huai River–Qinling Mountains line is from the Harvard Map Collection at Lamont Library. This is the same source used in previous studies on the Huai River, such as Almond et al. (2009).

For our empirical analysis, we make two distance variables based on the city and river locations. The first variable is the distance between a city and the Huai River. For each city, we use ArcGIS to measure the shortest distance from the city centroids to the nearest point on the river. This distance ranges from 18 to 1,044 miles, and the median distance is 303 miles. The second distance variable is the road distance from a city's centroid to the factory or importing port locations of air purifiers. Figure A.1 (figs. A.1–A.6 are available online) shows the locations of manufacturing plants of domestically produced products and ports of imported products. We use GIS and Google Maps to measure the shortest road distances from city centroids to these locations.

E. Summary Statistics and Testing for Balance in Observables

Table 1 shows the summary statistics of the purifier data. In panel A, we report product-level summary statistics for all products in column 1, for HEPA purifiers in column 2, and for non-HEPA purifiers in column 3. In column 4, we calculate the difference in the means between HEPA and non-HEPA purifiers and the standard errors for the differences by clustering at the manufacturer level. Despite substantial heterogeneity across products, the difference in the means between HEPA and non-HEPA purifiers is statistically insignificant for many purifier attributes, such as humidifying function, distance to the factory or port, and frequency of filter replacement. We observe statistically significant differences between the two purifier types for three variables: price of purifiers, price of replacement filters, and room coverage, although the difference in room coverage is only marginally significant. On average, HEPA purifiers are $139 more expensive, cost $21 more when replacing a filter, and cover 8.4 more square meters.

In panel B, we show the number of purifier sales relative to the number of households as a percentage. For overall purifier sales, this statistic is higher for higher-income cities such as Beijing and Shanghai, implying that economic growth levels are likely to affect overall purifier sales. For our estimation, what matters is the relative sales share of HEPA purifiers to non-HEPA purifiers, as we explain in section IV. This statistic is presented in column 4. The ratio of HEPA purifier sales relative to non-HEPA purifier sales is approximately 1.2 for consumers located south of the Huai River and 2.0 for consumers located north of the Huai River. This statistic provides descriptive evidence that consumers north of the Huai River are more likely to buy purifiers with HEPA than consumers south of the river. We provide more formal RD analysis for this evidence in section V.[9]

[9] A potential approach to measuring the implied abatement cost of indoor air pollution is to calculate the air purifier price per a reduction in PM_{10}. For example, if we consider the

TABLE 1
Summary Statistics of Air Purifier Data

	All Purifiers (1)	HEPA Purifiers (2)	Non-HEPA Purifiers (3)	Difference in Means (4)
A. Air purifier attributes:				
Price of a purifier ($)	454.52	509.64	369.81	139.84***
	(383.81)	(404.24)	(333.45)	[52.14]
Humidifying (0 or 1)	.164	.177	.143	.034
	(.370)	(.382)	(.351)	[.070]
Room coverage (m^2)	41.85	44.97	36.50	8.47*
	(23.65)	(24.93)	(20.27)	[4.42]
Distance to factory or port (hundreds of miles)	7.48	7.32	7.72	−.39
	(2.87)	(2.69)	(3.12)	[.45]
Price of replacement filter ($)	46.38	56.39	34.92	21.47*
	(52.21)	(65.68)	(25.91)	[10.70]
Frequency of filter replacement (months)	9.03	10.08	7.92	2.17
	(5.93)	(6.55)	(4.97)	[1.37]
				HEPA/Non-HEPA (Ratio)
B. Number of purifier sales/number of households (%):				
Beijing (north)	17.82	12.10	5.72	2.12
Xi'an (north)	6.20	4.38	1.82	2.41
All northern cities	4.70	3.16	1.54	2.06
Shanghai (south)	8.89	5.08	3.81	1.33
Shenzhen (south)	8.35	4.39	3.96	1.11
All southern cities	3.47	1.94	1.53	1.27

Note.—The data set includes 690 air purifier products from 45 manufacturers; 418 products are HEPA purifiers, and 272 are non-HEPA purifiers. In panel A, standard deviations are reported in parentheses, and standard errors clustered at the manufacturer level are reported in brackets.
* Significant at the 10% level.
*** Significant at the 1% level.

Table 2 shows summary statistics of city-level observables. Columns 1 and 2 report the sample mean and standard deviation for the north and the south of the Huai River, respectively. Column 3 reports the raw

average price of HEPA purifiers with replacement filters for 5 years, the total average price is $846, which implies an annualized price of $169. If we consider a household that faces the average level of PM_{10} in our sample period (92 $\mu g/m^3$), then the implied average price per a reduction in PM_{10} is $1.83. However, this number may not properly reflect the implied abatement cost of indoor air pollution for two reasons. First, a HEPA purifier provides a positive utility gain not only from a reduction in PM_{10} but also from other attributes (or amenities) of the purifier. Thus, this simple calculation is likely to overstate the implied abatement cost of indoor air pollution. Second, this calculation implicitly assumes that air purifier prices are exogenous to demand. If sellers set prices in response to demand factors, prices reflect this endogenous relationship. This is why we need more formal demand estimation, as we describe in sec. IV, in which these two issues are addressed by the inclusion of product fixed effects and instrumental variables.

TABLE 2
Summary Statistics of Observables for North and South of the Huai River

	North (1)	South (2)	Differences in Means (3)	RD Estimates (Local Linear) (4)
Population (millions)	2.398	2.720	−.323	−.388
	(2.266)	(3.189)	[.625]	[1.411]
Urban population (millions)	1.773	1.974	−.200	−1.092
	(1.770)	(2.436)	[.480]	[1.151]
Years of schooling	9.30	8.64	.667***	−.101
	(.88)	(1.12)	[.227]	[.671]
Fraction illiterate	.052	.069	−.016**	.003
	(.022)	(.033)	(.006)	(.018)
Fraction completed high school	.338	.286	.051**	.018
	(.107)	(.112)	[.025]	[.074]
Fraction completed college	.052	.048	.004	−.019
	(.033)	(.031)	[.007]	[.021]
Per capita household income (in 2005 dollars)	527.52	698.10	−170.58**	−134.54
	(152.79)	(388.20)	[67.27]	[107.41]
House size (m^2)	75.24	92.04	−16.80***	−12.25
	(13.32)	(17.52)	[3.51]	[9.34]
Residence built after 1985	.691	.718	−.027	−.040
	(.083)	(.075)	[.018]	[.027]
Fraction of building materials include reinforced concrete (less insulated)	.668	.729	−.061	.010
	(.187)	(.147)	[.037]	[.107]
Fraction moved within city	.074	.065	.009	−.002
	(.030)	(.022)	[.006]	[.010]
Fraction of occupation involved with outdoor activities	.218	.208	.011	.032
	(.106)	(.099)	[.023]	[.074]

Note.—In cols. 1 and 2, standard deviations are reported in parentheses. In cols. 3 and 4, standard errors are reported in brackets.
** Significant at the 5% level.
*** Significant at the 1% level.

difference between these sample means. Note that this statistic shows a simple difference between all cities in the north and the south, which is not necessarily a discontinuous difference at the Huai River. In column 4, we investigate whether there is such a discontinuous difference. We use local linear regression—our main RD specification in the empirical analysis—to obtain RD estimates for the observables and report the standard errors in brackets.

We consider a wide range of socioeconomic variables that are relevant for our analysis, including population, urban population, illiteracy rate, high school completion rate, college completion rate, per capita household income, and home size (in m^2). Column 3 suggests that there are statistically significant differences in the sample means for several measures between the north and the south. However, the RD estimates in column 4 indicate that the differences are not statistically significant at the river boundary.

In addition, we also collect a number of other city-level measures to examine potential concerns regarding our identification strategy. The first concern is that the Huai River heating policy may have made demand for well-insulated homes lower in the northern cities. We test two measures of housing quality reported in the 2005 census data: the fraction of residency built after 1985, when China implemented the first regulation on insulation efficiency of home construction materials, and the fraction of building materials that include reinforced concrete (relatively less insulated).

The second concern is that if the Huai River policy produced worse air quality for the northern cities, it could possibly generate more within-city residential sorting for households in the north. Using the 2005 census data, we measure the fraction of individuals who have moved from another neighborhood in the same city in the past 5 years by city. Note that another related concern is residential sorting across cities. However, as we explain in appendix A (apps. A–F are available online), such sorting is unlikely to affect our analysis because of a strict immigration policy enforced by the Chinese government.

The third concern is that the Huai River heating policy may have made households spend more time indoors in the north, which would make the value of indoor air quality higher in the north. While we do not directly observe how much time individuals spend indoors, we can test whether people in the north are less likely to choose a job that involves substantial outdoor activities. Using the 2005 census data, we define a binary variable that is one if the occupation involves more outdoor activities (e.g., agriculture, construction, and transportation) and is zero otherwise. We test whether these measures differ between the north and the south. Neither the differences in the sample means in column 3 nor the RD estimates in column 4 show statistically significant differences.

IV. Demand for Air Purifiers

Our goal is to obtain a revealed-preference estimate of WTP for clean air by analyzing demand for air purifiers. Because air purifiers are differentiated products with multiple attributes, we start with a random-utility model for differentiated products.[10] When a consumer purchases an air purifier, the consumer considers utility from the product attributes and disutility from the price. For our objective, an advantage of analyzing air purifier markets is that one of the product characteristics—HEPA—informs consumers and researchers of the purifier's effectiveness at reducing

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

indoor particulate matter. The intuition behind our approach is that the extent to which consumers value this characteristic, along with the price elasticity of demand, provides useful information on their WTP for indoor air quality improvements.

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

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

where x_{jc} represents the improvements in indoor air quality conditional on the purchase of product j, p_{jc} represents the price of product j in market c, η_j represents product fixed effects that capture utility gains from unobserved and observed product characteristics, λ_c represents city fixed effects, ξ_{jc} represents a product-city specific demand shock, and ϵ_{ijc} represents a mean-zero stochastic term. The parameter β_i indicates the marginal utility for clean air, and α_i indicates the marginal disutility of price. The functional form for the utility function assumes that each variable, including the error term, enters the utility function linearly.

Air purifiers usually run for 5 years and require filter replacement several times within that period. We assume that consumer i considers utility gains from purifier j for 5 years and p_{jc} as a sum of up-front and running costs.[11] This approach abstracts from a potentially interesting dynamic decision, where consumers may consider the dynamics of product entries. Unfortunately, it is not possible to examine such a dynamic decision in the context of our empirical setting. While we have monthly sales and price data, the exogenous variation in pollution comes from purely cross-sectional variation as opposed to time series variation. Therefore, our empirical approach focuses on cross-sectional variation in pollution and purchasing behavior, which has to abstract from potential dynamic discrete choices.[12]

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

[12] For example, consumers may respond to intertemporal price variation. By aggregating the panel data to cross-sectional data, we abstract from this potential intertemporal response, which induces attenuation bias for the price elasticity. This is certainly a limitation of our empirical strategy.

We assume that the error term ϵ_{ijc} is distributed as a type I extreme-value function. We then consider both a standard logit model and a random-coefficient logit model. A standard logit model assumes that the preference parameters do not vary by i. The attractive feature of this approach is that the random-utility model in equation (1) leads to a linear equation. The linear equation can be estimated by linear generalized method of moments (GMM) estimation with instrumental variables for pollution and price. A random-coefficient logit model allows the preference parameters to vary by household i through observable and unobservable factors. This feature comes at a cost—random-coefficient logit estimation involves nonlinear GMM estimation for a highly nonlinear objective function. In this paper, we use both approaches to estimate WTP for clean air.

A. *Logit Model*

We begin with a standard logit model. Suppose that $\beta_i = \beta$ and $\alpha_i = \alpha$ for consumer i and that the error term ϵ_{ijc} is distributed as a type I extreme-value function. Consumer i purchases purifier j if $u_{ijc} > u_{ikc}$ for $\forall k \neq j$. The market share for product j in city c can then be characterized by[13]

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

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

Empirically, we construct the market shares for product j (s_{jc}) and the outside option (s_{0c}) as follows. We assume that the number of households in city c (I_c) represents potential buyers and that each household purchases one or zero air purifiers in 5 years. We use q_{jc} to denote the total sales volume for product j in city c during our sample period of 9 years. We then define the market share for product j by $s_{jc} = (q_{jc}/I_c) \cdot (5/9)$. The adjustment term (5/9) comes from the fact that the total sales volume is based on 9 years of data and a household uses air purifiers for 5 years. We define the market share of the outside option by $s_{0c} = 1 - \Sigma_{j=1}^{J} s_{jc}$. Note that both the adjustment term (5/9) and the outside option (s_{0c}) do not vary within city c. Therefore, as we show below, these two terms are fully absorbed by city fixed effects in the standard logit estimation and thus do not affect our estimates. We also show in table A.8 that this adjustment term does not substantially affect the random-coefficient logit estimation results in our context.

We assume that the reduction in indoor air pollution is zero when consumers do not purchase an air purifier (i.e., $x_{0c} = 0$). That is, if consumers do not buy an air purifier, they are exposed to indoor pollution that is

[13] See Berry (1994) for the proof and more detailed discussion.

equal to ambient air pollution. Importantly, this assumption does not affect our standard logit estimation because city fixed effects absorb x_{0c}. In random-coefficient logit estimation, city fixed effects absorb substantial variation in x_{0c} but do not completely do so because the model is nonlinear. By making this assumption, we are likely to underestimate WTP for clean air. This is because, in reality, x_{c0} (the improvements in indoor air quality when consumers do not buy air purifiers) is likely to be positive if consumers engage in other indoor avoidance behavior. This is one of the reasons why we interpret our WTP estimates as a lower bound. We explain this issue in detail in section IV.C.

Because $\ln s_{0c} = -\ln(\Sigma_{k=0}^{J} \exp(\beta x_{kc} + \alpha p_{kc} + \eta_k + \lambda_c + \xi_{kc}))$, the difference between the log market share for product j and the log market share for the outside options is $\ln s_{jc} - \ln s_{0c} = \beta x_{jc} + \alpha p_{jc} + \eta_j + \lambda_c + \xi_{jc}$, as shown by Berry (1994). Since $\ln s_{0c}$ is absorbed by city fixed effects, this equation is simplified to

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

where β represents the marginal utility for improvements in air quality and α represents the marginal disutility for price. The marginal willingness to pay (MWTP) for one unit of indoor air pollution reduction can be obtained by $-\beta/\alpha$.

An advantage of studying air purifier markets is that e_j (purifier j's effectiveness at reducing indoor particulate matter) is well known for consumers. As we explained in section II.A, if a purifier has a HEPA filter, it can reduce 99% of indoor particulate matter. On the other hand, if a purifier does not have HEPA, it does not reduce indoor particulate matter. In advertisements and product descriptions of air purifier products in the Chinese market, consumers are well informed of the difference between HEPA and non-HEPA purifiers. Therefore, we define the pollution reduction by $x_{jc} = x_c \cdot H_j$, where x_c represents ambient pollution and H_j is an indicator variable for HEPA purifiers. Then, x_{jc} equals x_c if $H_j = 1$ and equals zero if $H_j = 0$. That is, conditional on the purchase of a HEPA purifier, consumers can reduce indoor air pollution by x_c. Otherwise, the reduction in indoor air pollution is zero. Note that non-HEPA purifiers do not provide reductions in particulate matter but provide other utility gains, including reductions in VOCs and odors. These utility gains are captured by the product fixed effects η_j. Using $x_{jc} = x_c \cdot H_j$, our random-utility model results in an estimation equation:

$$\ln s_{jc} = \beta x_c H_j + \alpha p_{jc} + \eta_j + \lambda_c + \xi_{jc}. \tag{4}$$

Source of identifying variation.—It is worth clarifying the source of the identification variation in this equation. The product fixed effects (η_j) absorb all observed and unobserved product characteristics, and the city fixed effects (λ_c) absorb all city-level demand shocks. Even with these fixed effects, we can still identify β because ambient air pollution (x_c) varies by city and $x_c H_j$ has city-by-product variation. We can also identify α because we have city-by-product variation in p_{jc}. A key empirical question is whether there is exogenous variation in these two variables (x_c and p_{jc}). In "Empirical Strategy" (sec. V.A), we explain our instrumental variable strategy to exploit plausibly exogenous variation in these variables.

B. *Random-Coefficient Logit Model*

To relax some assumptions of the standard logit estimation, we also use random-coefficient estimation that allows for heterogeneity in the preference parameters. Because general discussions on random-coefficient estimation are well documented in the literature (Berry, Levinsohn, and Pakes 1995; Nevo 2001; Knittel and Metaxoglou 2013), we provide a brief description focusing on key issues for our empirical analysis.

We begin with the same random-utility model described in equation (1) but relax the assumptions on β_i and α_i by allowing the two parameters to vary by consumer i through observable and unobservable factors. We model the two parameters by $\beta_i = \beta_0 + \beta_1 y_i + u_i$ and $\alpha_i = \alpha_0 + \alpha_1 y_i + e_i$, where y_i is household i's income from the census microdata and u_i and e_i are lognormally distributed unobserved heterogeneity. That is, each of these two parameters depends on the mean coefficient, household-level income, and a random unobserved heterogeneity. We denote the part of the utility function that does not depend on i (the mean utility level) by $\delta_{jc} = \beta_0 x_{jc} + \alpha_0 p_{jc} + \eta_j + \lambda_c + \xi_{jc}$ and the part that depends on i by $\mu_{jci} = (\beta_1 y_i + u_i)x_{jc} + (\alpha_1 y_i + e_i)p_{jc}$. The market share for product j in city c can then be evaluated using Monte Carlo integration assuming a number of individuals n_c for city c by[14]

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

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

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

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

by nonlinear GMM using the moment conditions of the instruments and ω_{jc}. Denote the vector of the parameters by θ and a set of instruments by Z_{jc}. The GMM estimate is then

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

in which Φ^{-1} is the optimal weight matrix for the GMM estimation. The GMM objective function is nonlinear in parameters. Therefore, it has to be evaluated numerically by nonlinear search algorithms. In section V.A, we describe details about the estimation.

C. *Interpretation of the Parameter Estimates*

For several reasons, our estimate of $-\beta/\alpha$ is likely to provide a lower bound estimate of MWTP for air quality. First, households in China may have limited information on the level of air pollution as well as the negative health effects of air pollution. As discussed in Greenstone and Jack (2013), the presence of such imperfect information is likely to make revealed-preference estimates of MWTP lower than the theoretical level of MWTP that would be observed when households have access to full information. In section V.D, we provide some empirical evidence on this point.

Second, our approach assumes that indoor air pollution levels in the absence of air purifiers are equal to ambient pollution levels. Recent engineering studies show that, on average, indoor pollution levels are lower than outdoor pollution levels in China.[15] One approach that we could take is to rely on engineering estimates of the indoor-outdoor air pollution ratio, which would make our MWTP estimates larger. However, because we want to report a conservative estimate, we keep the assumption that indoor air pollution levels are equal to outdoor pollution levels.

Third, our model assumes that the reduction in indoor air pollution is zero if households do not purchase a HEPA purifier, but there can be other avoidance methods that households can take to reduce indoor air pollution. For example, an individual can wear a mask, although it is uncommon for an individual in a Chinese household to wear a mask inside their home, and most masks do not provide a reduction in air pollution as comprehensively as air purifiers. Likewise, households can improve building insulation to reduce incoming flow of air pollution. Such unobserved avoidance behavior lowers the baseline indoor pollution level that would be obtained without buying an air purifier. That is, the reduction in indoor air pollution can be greater than zero even if households do not

[15] A study from Tsinghua University finds that in Beijing, on average, the indoor concentration of $PM_{2.5}$ is 67% of the outdoor concentration of $PM_{2.5}$. See Zhang (2015).

buy a purifier. This is another reason why our MWTP estimate is likely to be an underestimate.

Fourth, our model and empirical analysis incorporate running costs incurred by filter replacement but ignore electricity costs. According to information from air purifier manufacturers, the costs of running electricity for HEPA purifiers are slightly higher than for other air purifiers. This is another reason why our MWTP estimate is likely to be an underestimate.

V. Empirical Analysis and Results

We use the estimating equations derived from the random-utility model in the previous section to estimate the preference parameters for pollution (β) and price (α), which allows us to measure WTP for clean air. We begin by describing empirical challenges in estimating these parameters and how we address them. We then present graphical analysis of raw data, estimation results for the standard logit model, and estimation results for the random-coefficient logit model.

A. Empirical Strategy

The primary challenge for our empirical analysis is that two variables in the demand estimation—air pollution and air purifier prices—are likely to be endogenous in nonexperimental data. Air pollution is generated by observed and unobserved economic factors and can therefore be correlated with omitted variables in the demand equation. For this reason, it is generally hard to claim exogeneity for typical cross-sectional variation in air pollution. To address this problem, we exploit the RD design at the Huai River in section II.B. This approach provides us a useful research environment for two reasons. First, it allows us to exploit plausibly exogenous variation in air pollution created by the natural experiment—the Huai River heating policy. Second, the discontinuous difference in air pollution created by the policy has existed since the 1950s. Therefore, the natural experiment provides long-run variation in air pollution, which allows us to study how households respond to long-lasting variation in air pollution as opposed to transitory pollution shocks.

Another empirical challenge is that air purifier prices are also unlikely to be determined exogenously. For example, suppose that some demand factors are observable to firms but unobservable to econometricians. If firms have the ability to set prices because of imperfect competition, we expect that they set prices in response to the unobserved demand factors, which creates correlation between the price and the error term in the demand estimation. We address this problem by combining two approaches. First, we use data from many markets (cities) in China, which allows us to include both product and city fixed effects (Nevo 2000, 2001). These fixed effects absorb product- and city-level unobserved demand factors. The remaining concern is product-city-specific unobserved demand factors that are correlated with city-product-specific price variation. To address this issue, we construct instrumental variables that capture transportation cost between a product's manufacturing location and its market (city). These instruments provide variation at the city-by-product level because manufacturing locations are different between products. We provide a detailed description of these instruments below.

First stage on air pollution.—We estimate the first stage on air pollution using an RD design created by the Huai River heating policy. Consider that x_c is air pollution (PM_{10}) in city c and d_c is the distance between city c and the Huai River. We use positive values of d_c for distances north of the Huai River and negative values for distances south of the river. Additionally, a dummy variable for the north of the river can be denoted by $N_c = 1\{d_c > 0\}$.

We use the RD design to estimate a discontinuous change in air pollution (x_c) at the river border ($d_c = 0$) by controlling for the running variable (d_c). The recent literature suggests that a local linear regression based on data near the RD cutoff is likely to produce the most robust estimates (Imbens and Lemieux 2008; Gelman and Imbens 2014). Therefore, we use local linear regression as a main specification and also report results with quadratic controls for d_c. We use the algorithm developed by Imbens and Kalyanaraman (2012) to compute the optimal bandwidth but also report results with different choices of bandwidth to examine the robustness of our results. We also follow Imbens and Kalyanaraman (2012) and Calonico, Cattaneo, and Titiunik (2014) to use a triangular kernel weight to assign more weights on observations near the Huai River, although we find that such weighting does not substantially change our results.

Our baseline specification for the first stage on air pollution is the following local linear regression:

$$x_c = \gamma N_c + \phi_1 d_c + \phi_2 d_c N_c + \nu_l + \epsilon_c, \tag{7}$$

where x_c represents PM_{10} ($\mu g/m^3$) in city c, N_c is the dummy variable for the north, d_c represents the distance between city c and the Huai River, and ϵ_c is the error term. The coefficient of interest, γ, measures a discontinuous change in x_c at the Huai River border. A potential concern for spatial RD design like ours is that the spatial border is long from the west to the east of China and therefore unobserved factors in the west-east dimension could confound the RD estimate. To address this concern, we include longitude-quartile fixed effects (ν_l), which flexibly control for systematic differences in the west-east dimension.[16]

One way to investigate the validity of our RD designs is to test whether there are systematic differences in observable variables at the RD cutoff. In section III.E, we do not find a statistically significant discontinuity for a wide range of socioeconomic measures at the river boundary. Nevertheless, we examine the robustness of our results by including city demographics as additional covariates.

Reduced form of the RD design.—Suppose that our first stage on PM_{10} provides evidence of a discontinuous increase in PM_{10} at the Huai River boundary. Then, our demand model predicts that the log market share for HEPA purifiers relative to the log market share for other purifiers should be higher in cities north of the river if households value clean air. Our reduced-form estimation examines whether there is a discontinuous change in the market share for HEPA purifiers at the river boundary. We use our city-product-level data to estimate a reduced-form equation,

$$\ln s_{jc} = \rho N_c H_j + \alpha p_{jc} + (\psi_1 d_c + \psi_2 d_c N_c + \nu_l) H_j + \eta_j + \lambda_c + \epsilon_{jc}, \quad (8)$$

where s_{jc} and p_{jc} respectively represent the market share and the price of product j in city c, η_j represents product fixed effects, and λ_c represents city fixed effects. Because we include city fixed effects, the log market share for outside options ($\ln s_{0c}$) and a dummy variable for northern cities (N_c) are absorbed by λ_c.

We allow the control function for the running variable ($\psi_1 d_c + \psi_2 d_c N_c$) and the longitude-quartile fixed effects (ν_l) to differ between HEPA and non-HEPA purifiers by including $(\psi_1 d_c + \psi_2 d_c N_c) H_j$. Note that even without including these control variables, city- and product-level unobserved factors are already absorbed by city and product fixed effects. These HEPA-specific control variables allow us to further capture HEPA-specific potential confounding factors that may exist in the north-south and west-east dimensions.

Second stage of the RD design.—We estimate the MWTP for clean air by running the following second-stage regression,

$$\ln s_{jc} = \beta x_c H_j + \alpha p_{jc} + (\varphi_1 d_c + \varphi_2 d_c N_c + \nu_l) H_j + \eta_j + \lambda_c + \epsilon_{jc}, \quad (9)$$

by using $N_c H_j$ as the instrument for $x_c H_j$. The identification assumption is that the instruments are uncorrelated with the error term given the

[16] We make the longitude-quartile fixed effects by simply dividing our cities into quartiles on the basis of the longitudes of the city centroids. We also use longitude fixed effects based on the number of groups that are larger than four and find that our results do not change substantially.

control variables and fixed effects. The parameter of interest is $-\beta/\alpha$, which provides the MWTP for one unit of PM_{10} ($\mu g/m^3$).

Instruments for air purifier price.—In addition to the endogeneity of air pollution, we need to address the potential endogeneity of prices in equations (8) and (9). Before we explain our instruments, it is useful to describe the sources of endogeneity that are controlled by the product and city fixed effects and those that are not fully controlled by these fixed effects.

In the demand estimation of differentiated products, a major omitted-variable concern is unobserved product quality. A product with unobserved high quality is likely to have a high price and be preferred by consumers. Therefore, unobserved product quality can create correlation between prices and the error term. An advantage of our research design is that we have many markets (cities) so that we can include product fixed effects in the same way as Nevo (2000, 2001). Another omitted-variable concern is city-level unobservable economic factors that affect demand. If firms set higher prices in cities with greater economic development, this also creates correlation between prices and the error term. We include city fixed effects to control for this concern.

Thus, the remaining concern is unobserved demand factors at the product-by-city level that are correlated with product-by-city-specific price variation. For an unobserved reason, suppose that there is higher demand for a particular product than others in a city and also that this phenomena is specific to this city—otherwise, product fixed effects absorb this factor. In addition, suppose that firms know about these unobserved demand factors and are able to set a higher price for this product only in this city. In this case, our product fixed effect and city fixed effect cannot control for this endogeneity.

To address this concern, we need an instrument that varies at the product-by-city level. Any instrument that has only city- or product-level variation would be absorbed by product and city fixed effects. An ideal instrument is a supply-side cost shifter that does not directly affect demand. Our idea is that transportation costs from a product's manufacturing location to its market (city) has product-by-city variation and can be considered a supply-side cost shifter conditional on control variables in our estimation.

To make this instrument, we collect data on product-level factory locations (or port locations for imported products). We then use GIS to measure the shortest road distance from each product's factory (or port) location to each city. Because ground transportation is a primary shipping method for air purifiers in China, the road distance captures key variation in transportation costs. In the first-stage regression, we estimate the relationship between air purifier prices and the linear, quadratic, and cubic terms of the road distance. In addition, we also include the road distance variable interacted with manufacturer dummy variables to allow the price-distance relationship to be different among manufacturers.

The identification assumption is that the instrument (the road distance from a product's factory or port to each market) is uncorrelated with product-by-city unobserved demand factors. Note that either city- or product-level unobserved factors do not confound the instrument because of product and city fixed effects. For example, consider a concern that the distance from a city to a port can be correlated with city-level income because many coastal cities in China are high-income cities. This is not an issue in our estimation because this correlation is absorbed by city fixed effects. Thus, a threat to identification has to be unobservables that have product-by-city-level variation. In appendix A, we discuss potential threats to identification and provide several robustness checks.

B. *Graphical Analysis of the RD Design*

Before we proceed to formal regression analysis, we provide graphical analysis of the spatial RD design in figure 2. Figure 2*A* presents graphical analysis for the first stage of the RD design. The scatterplot shows the local means of PM_{10} during 2006–14 with a bin size of 50 miles. The horizontal axis is the running variable of the RD design (d_c), which is the distance between cities and the Huai River. The vertical line at $d_c = 0$ indicates the location of the Huai River. The northern cities are presented on the right-hand side of the river line, and the southern cities are presented on the left-hand side. We also include two sets of fitted regression lines. The solid line represents the regression fit with a linear control for the running variable and its interaction with the dummy variable for the northern cities. The dashed line represents the regression fit with linear and quadratic controls for the running variable.

Consistent with findings in previous studies, such as Almond et al. (2009), Chen et al. (2013), and Ebenstein et al. (2017), the figure shows that there is a discontinuous increase in PM_{10} just north of the Huai River. This evidence suggests that the coal-based heating policy generated higher pollution levels in cities north of the river boundary.

Figure 2*B* shows graphical analysis for the reduced form of the RD design. Recall that the reduced-form equation (8) is $\ln s_{jc} = \rho N_c H_j + \alpha p_{jc} + (\psi_1 d_c + \psi_2 d_c N_c + \nu_l) H_j + \eta_j + \lambda_c + \epsilon_{jc}$. The coefficient of interest is ρ, which is the coefficient for the interaction term of the two dummy variables, north and HEPA. Econometrically, this coefficient shows how $E[\ln s_{jc} | H_j = 1] - E[\ln s_{jc} | H_j = 0]$ discontinuously changes at the Huai River boundary. To provide visual evidence, we calculate the sample analog of $E[\ln s_{jc} | H_j = 1] - E[\ln s_{jc} | H_j = 0]$ at the city level (the difference between the average log market share of HEPA purifiers in city c and the average log market share of non-HEPA purifiers in city c) and plot the local means and regression fits in figure 2*B*.

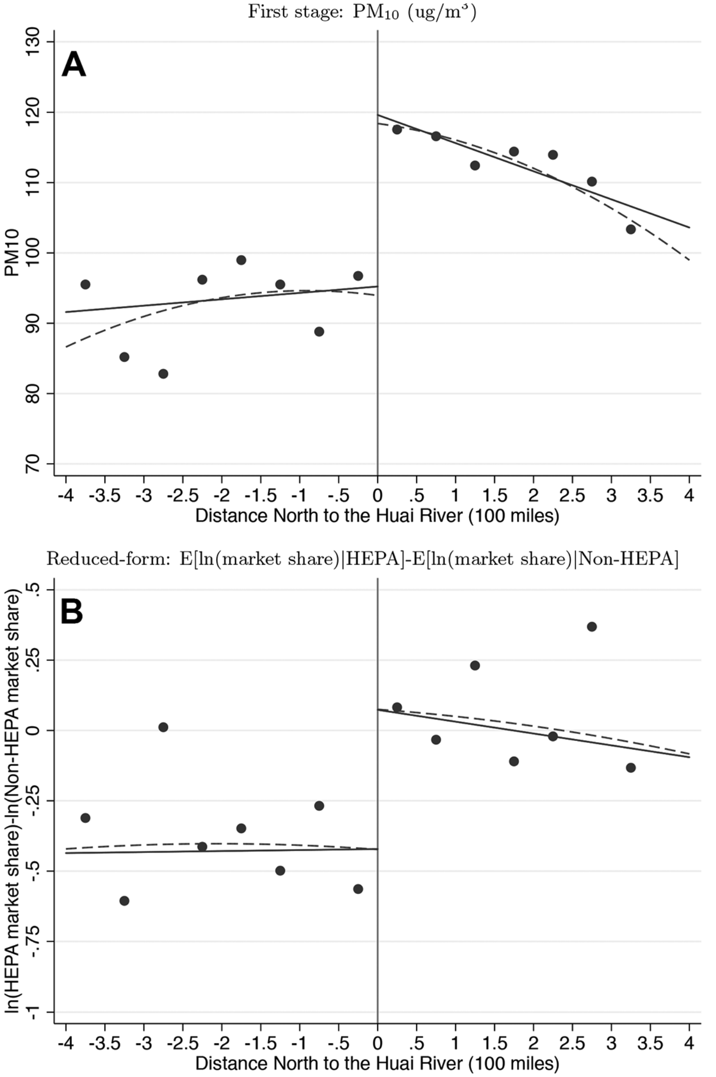

FIG. 2.—RD design at the Huai River boundary. The scatterplot in *A* shows the local means of PM_{10} during 2006–14 with a bin size of 50 miles. The horizontal axis is the distance to the Huai River—positive values are north of the river, and negative values are south of the river. The solid line is the regression fit with a linear control for the running variable and its interaction with the dummy variable for the northern cities. The dashed line is the regression fit with linear and quadratic controls for the running variable. The scatterplot in *B* shows the local means of $E[\ln(\text{market share})\,|\,\text{HEPA}] - E[\ln(\text{market share})\,|\,\text{non-HEPA}]$ along with two fitted regression lines. A color version of this figure is available online.

The figure indicates that there is a sharp increase in the log market share of HEPA purifiers relative to the log market share of non-HEPA purifiers at the river boundary. Visually, the discontinuous jump is approximately 0.4 log points, which is consistent with the reduced-form regression results that we present in the next section. Additionally, the figure shows no strong trend in the outcome variable over the running variable. The relatively flat relationship between the outcome variable and the running variable suggests that the choice of functional form for the running variable is unlikely to have a substantial impact on the RD estimates.[17]

C. *Baseline Results: Standard Logit Model*

Panel A of table 3 shows the first-stage estimation results for PM_{10}. Columns 1 and 2 are results without demographic controls and longitude-quartile fixed effects, and columns 3 and 4 are results with these controls. We report our estimates from local linear regression and local quadratic regression. The estimates are robust to the choice of control function for the running variable and the inclusion of demographic controls and longitude-quartile fixed effects. For example, column 3 suggests that there is a discontinuous change in PM_{10} at the Huai River by 24.38 $\mu g/m^3$. The magnitude is consistent with the visual evidence from figure 2*A*. Note that the mean PM_{10} is 92 $\mu g/m^3$ for cities just south of the Huai River. Thus, the RD estimate implies an approximate 26.5% increase in PM_{10}.

In panel B of table 3, we report the first-stage estimation result for air purifier prices. We include product fixed effects in all columns. The estimates imply that the distance to factory or port and prices are positively correlated. For example, the result in column 1 implies that the predicted effect of the road distance of 500 miles on price is \$46.46. This is an approximate 10% increase in price for the average purifier price of \$454.50. For each column, we report this calculation and associated standard errors. Note that the 10th, 25th, 50th, 75th, and 90th percentiles of the road distance are 211, 502, 801, 1,048, and 1,318 miles, respectively, in our data set. Thus, this result suggests that a considerable amount of variation in prices is explained by the road distance from manufacturing locations or importing ports to markets. In columns 3 and 4, we include city fixed effects to control for potentially confounding factors at the city level. For example, firms possibly set higher prices for cities with higher average

[17] We show this figure in terms of the log market shares to be consistent with the reduced-form regression eq. (8). Another form of outcome variable, which is not equivalent to the outcome variable in our regression analysis but can also be informative, is the nonlog version of the outcome variable, which is simply the fraction of HEPA purifier sales relative to all purifier sales at the city level. We include this figure in app. E (fig. A.2). The figure implies that the HEPA sales fraction is approximately 60% to the south of the Huai River and over 70% to the north of the river, with a discontinuous increase at the river boundary.

TABLE 3

First-Stage Estimation for PM_{10} and Air Purifier Price

	(1)	(2)	(3)	(4)
	Dependent Variable: PM_{10} ($\mu g/m^3$)			
A. First-stage estimation for PM_{10}:				
North	24.54***	24.55***	24.38***	24.19***
	(6.97)	(6.98)	(8.71)	(8.86)
Observations	49	49	49	49
R^2	.36	.36	.56	.57
Control function for running variable	Linear × north	Quadratic	Linear × north	Quadratic
Demographic controls			Yes	Yes
Longitude-quartile fixed effects			Yes	Yes
	Dependent Variable: Price ($)			
B. First-stage estimation for air purifier price:				
Distance to factory (hundreds of miles)	18.43***	18.39***	12.70**	12.67**
	(4.97)	(4.98)	(4.94)	(4.93)
Distance to factory^2 (hundreds of miles)	−2.32***	−2.33***	−1.49*	−1.49*
	(.72)	(.72)	(.77)	(.77)
Distance to factory^3 (hundreds of miles)	.10***	.10***	.06	.06
	(.03)	(.03)	(.04)	(.04)
Observations	7,359	7,359	7,359	7,359
R^2	.96	.96	.96	.96
Control function for running variable	Linear × north	Quadratic	Linear × north	Quadratic
Product fixed effects	Yes	Yes	Yes	Yes
City fixed effects			Yes	Yes
Longitude-quartile fixed effects × HEPA	Yes	Yes	Yes	Yes
Predicted effect of 500 miles on price	46.46***	46.30***	33.22***	33.16***
	(12.07)	(12.15)	(11.43)	(11.42)
Predicted effect as % of mean price	10.2	10.2	7.3	7.3

Note.—Observations in panel A are at the city level, and observations in panel B are at the product-by-city level. Demographic controls include population and GDP per capita from *City Statistical Yearbooks* (2006–14) and average years of schooling and the percentage of the population who have completed college from the 2005 census microdata. The distance variable in panel B measures each product's distances between the manufacturing factory or importing port to markets. We also include the interaction of the linear distance variable with manufacturer dummy variables to allow a flexible functional form for the relationship between prices and distance.

* Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.

TABLE 4
STANDARD LOGIT: REDUCED-FORM AND SECOND-STAGE ESTIMATION RESULTS

	DEPENDENT VARIABLE: ln(Market Share)	
	(1)	(2)
A. Reduced form of the RD design:		
North × HEPA (ρ)	.4275***	.4216***
	(.0329)	(.0320)
Price (α)	−.0052***	−.0052***
	(.0001)	(.0001)
Observations	7,359	7,359
First-stage *F*-statistic	870.29	1,115.94
Control function for running variable	Linear × north	Quadratic
B. Second stage of the RD design:		
PM_{10} × HEPA (β)	.0299***	.0302***
	(.0030)	(.0032)
Price (α)	−.0048***	−.0048***
	(.0001)	(.0001)
Observations	7,359	7,359
First-stage *F*-statistic	285.16	292.01
Control function for running variable	Linear × north	Quadratic
MWTP for 5 years ($-\beta/\alpha$)	6.2077***	6.3100***
	(.6649)	(.7130)
MWTP per year	1.2415***	1.2620***
	(.1330)	(.1426)

NOTE.—Panel A shows results for the reduced-form estimation in eq. (8). All regressions include product fixed effects, city fixed effects, and longitude-quartile fixed effects interacted with HEPA. Price is instrumented with the distance variables discussed in the main text. Panel B shows results for the second-stage estimation in eq. (9). PM_{10} × HEPA and price are instrumented with north × HEPA and the distance variables discussed in the main text. We use the two-step linear GMM estimation with the optimal weight matrix. Standard errors are clustered at the city level. We also report the Kleibergen-Paap *rk* Wald *F*-statistic. The Stock-Yogo weak identification test critical value for one endogenous variable (10% maximal instrumental variable size) is 16.38 and for two endogenous variables (10% maximal instrumental variable size) is 7.03.
*** Significant at the 1% level.

income. The results in these columns imply that the relationship between distance and price is robust to the inclusion of city fixed effects.

Table 4 shows the reduced-form and second-stage results of the RD design.[18] We include product and city fixed effects. Because we have more instruments than regressors (an overidentified case), the two-step GMM estimation with the optimal weight matrix provides a more efficient estimator than the two-stage least squares estimation (Cameron and Trivedi

[18] Note that the reduced-form result presented here is the reduced form of the RD design after we control for another endogenous variable (price) with its instruments. The purpose of this approach is to examine the reduced-form relationship between the outcome variable (log market share) and the variation created by the RD design (HEPA × north) by controlling for the effect of another endogenous variable (price) in a way that is consistent with the model described in sec. V. Because this is different from a conventional presentation of "reduced-form" estimation results, we use the terminology "the reduced form of the RD design" to make this point explicit.

2005). We use the orthogonality conditions of the instruments to implement the two-step linear GMM estimation and cluster the standard errors at the city level. Consistent with figure 2*B*, the reduced-form results provide evidence that there is an economically and statistically significant discontinuous increase in the log market share of HEPA purifiers relative to the log market share of non-HEPA purifiers. In panel B of table 4, we report the second-stage results. As we described in section V, $-\beta/\alpha$ provides MWTP for 1 $\mu g/m^3$ reduction in PM_{10} for 5 years, and therefore $-(\beta/\alpha)/5$ provides MWTP per year. We provide both of these estimates in the table. The results for the local linear regression indicate that the MWTP per year is $1.34 per household.

In table 5, we test the robustness of the results to the selection of bandwidth and control functions for the running variable. We use a range of bandwidths that are narrower than the optimal bandwidth (400 miles) to examine how our RD estimate changes if we use cities farther from or closer to the Huai River. We report the results using local linear regression in panel A and the results using local quadratic regression in panel B. The results are robust to the bandwidth choice. In appendix F, we also report this robustness check for the first-stage estimation.

D. Role of Information in WTP for Clean Air

As we discussed in section IV, our MWTP estimate should be interpreted as MWTP given the information that was available to Chinese households in the sample period. For example, if households had limited information about air pollution because of imperfect information disclosed by the government as well as limited media coverage, our MWTP estimate can be lower than an MWTP estimate that would be obtained with perfect information.

With nonexperimental data, it is challenging to shed light on this point because the information-acquisition process itself is unlikely to be exogenous to a preference for clean air. A potential empirical strategy is to use a plausibly exogenous information shock and examine whether the MWTP estimate differs before and after the information shock. In our context, we consider that widespread media coverage on air pollution after January 2013—due to a sudden information disclosure by the US embassy in Beijing in January 2013—can be used as an information shock to explore the question.

In the beginning of 2013, there was a remarkable change in Chinese press coverage of air pollution. Before 2013, Chinese media rarely discussed air pollution and its associated health impacts. On January 12, 2013, the US embassy in Beijing posted an air quality index of 755, beyond the scale's maximum of 500, and deemed air quality "crazy bad" (Wong 2013). Immediate reactions and concerns among Chinese citizens

TABLE 5
Robustness Checks

	Dependent Variable: ln(Market Share)			
	250 Miles (1)	300 Miles (2)	350 Miles (3)	400 Miles (4)
A. Control function for the running variable—linear × north:				
PM_{10} × HEPA (β)	.0296***	.0322***	.0268***	.0299***
	(.0029)	(.0047)	(.0010)	(.0030)
Price (α)	−.0036***	−.0038***	−.0042***	−.0048***
	(.0002)	(.0002)	(.0001)	(.0001)
Observations	5,619	5,878	7,107	7,359
First-stage F-statistic	1,921.77	526.20	1,348.93	285.16
MWTP for 5 years ($-\beta/\alpha$)	8.2840***	8.4562***	6.3748***	6.2077***
	(1.0665)	(1.4798)	(.2764)	(.6649)
MWTP per year	1.6568***	1.6912***	1.2750***	1.2415***
	(.2133)	(.2960)	(.0553)	(.1330)
B. Control function for the running variable—quadratic:				
PM_{10} × HEPA (β)	.0298***	.0327***	.0265***	.0302***
	(.0028)	(.0046)	(.0010)	(.0032)
Price (α)	−.0035***	−.0037***	−.0042***	−.0048***
	(.0002)	(.0002)	(.0001)	(.0001)
Observations	5,619	5,878	7,107	7,359
First-stage F-statistic	2,122.08	467.03	1,399.44	292.01
MWTP for 5 years ($-\beta/\alpha$)	8.4464***	8.7436***	6.3470***	6.3100***
	(1.0758)	(1.5087)	(.3034)	(.7130)
MWTP per year	1.6893***	1.7487***	1.2694***	1.2620***
	(.2152)	(.3017)	(.0607)	(.1426)

Note.—This table shows results for the second-stage estimation in eq. (9) with alternative choices of bandwidth and control functions for the running variable. All regressions include product fixed effects, city fixed effects, and longitude-quartile fixed effects interacted with HEPA. See table 4's note. Standard errors are clustered at the city level. We also report the Kleibergen-Paap *rk* Wald F-statistic. The Stock-Yogo weak identification test critical value for two endogenous variables (10% maximal instrumental variable size) is 7.03.
*** Significant at the 1% level.

prompted widespread reporting of air pollution in state newspapers.[19] In figure A.4, we show that there were on average 158 headlines per year that mentioned air pollution in all Chinese newspapers from 2006 to 2012 and that this number increased dramatically to 1,327 in 2013 and 1,549 in 2014. Similarly, the number of newspaper headlines mentioning smog jumped from 12 per year during 2006–12 to over 1,000 per year in 2013 and 2014.

This sudden change in media coverage provides a useful research environment to examine the relationship between information and MWTP

[19] All Chinese newspapers are completely or primarily owned by the state (Qin, Strömberg, and Wu 2018).

estimates. For this analysis, we divide our data to create two cross-sectional data sets: one that includes data from 2006–12 and one that includes data from 2013–14. What we want to test is whether the preference for air quality (β in our model) changed in response to the change in media coverage in 2013. To test this prediction, we pool the two data sets and estimate the coefficient for the interaction term between $x_c H_j$ and post-2013, which is an indicator variable for years after 2013. We interact post-2013 with all of the control variables, such as city fixed effects, product fixed effects, and the running variables for the RD design.

Table 6 shows the results. The baseline result in column 1 implies that the preference for air quality (β) is higher in the post-2013 period than in the pre-2013 period, and the difference is statistically significant. The estimated per-year MWTP is \$0.53 in the pre-2013 period and \$1.44 in the post-2013 period. A potential concern in this regression is that time series variation in factors unrelated to media coverage may confound the estimate of the interaction term. For example, economic growth during

TABLE 6
Role of Information in WTP for Clean Air

	Dependent Variable: ln(Market Share)		
	(1)	(2)	(3)
PM_{10} × HEPA	.0192***	.0174***	.0193***
	(.0018)	(.0027)	(.0025)
PM_{10} × HEPA × post-2013	.0329***	.0307***	.0280***
	(.0076)	(.0079)	(.0090)
Price	−.0072***	−.0072***	−.0064***
	(.0001)	(.0002)	(.0002)
Observations	10,780	10,780	10,780
First-stage F-statistic	113.39	112.01	189.15
Control function for running variable	Linear × north	Linear × north	Linear × north
Product fixed effects × post-2013	Yes	Yes	Yes
City fixed effects × post-2013	Yes	Yes	Yes
Longitude-quartile fixed effects × HEPA × post-2013	Yes	Yes	Yes
Salary × HEPA		Yes	Yes
Salary × price			Yes
MWTP per year before 2013	.5313***	.4867***	.6001***
	(.0595)	(.0874)	(.0918)
MWTP per year after 2013	1.4438***	1.3458***	1.4707***
	(.1475)	(.1376)	(.2009)
Difference in MWTP per year	.9124***	.8591***	.8706***
	(.1961)	(.2040)	(.2647)

Note.—This table shows results for the second-stage estimation in eq. (9) but allows the preference for air quality (β) to be different before and after 2013. Observations are at the product-city-pre(-post)-2013 level. Standard errors are clustered at the city level. We also report the Kleibergen-Paap rk Wald F-statistic. The Stock-Yogo weak identification test critical value for one endogenous variable (10% maximal instrumental variable size) is 16.38 and for two endogenous variables (10% maximal instrumental variable size) is 7.03.
*** Significant at the 1% level.

the sample period could have made households wealthier in the post-2013 period. While it is challenging to completely address this issue, we can include additional controls to mitigate this concern. In column 2, we control for the interaction term between $x_c H_j$ and annual salary data.[20] In column 3, we also include the interaction term between p_{jc} and annual salary to control for the possibility that the price elasticity can be affected by a change in economic growth. Between the columns, the estimates change only slightly, indicating that the results are robust to these controls.

In figure A.5, we provide additional evidence that supports the findings in table 6. To investigate when the preference for air quality (β) changed in response to the information shock, we create a data set on purifier sales, prices, and air pollution at the city-year-month level. We then estimate β for each year-month before and after January 2013. We find that there is a discontinuous and persistent increase in the estimates of β immediately after January 2013, which suggests that the response to the information shock was immediate and long-lasting.

These results suggest an important role of information for MWTP. First, this finding provides empirical evidence for the point made by Greenstone and Jack (2013) that MWTP for environmental quality can be distorted by market failures—including imperfect information available to households in developing countries—and therefore estimated MWTP may be different from the theoretical MWTP with no market failures. Our empirical evidence suggests that the imperfect information on air pollution before 2013 was likely to create a downward bias for the revealed MWTP estimate relative to MWTP in the presence of more accessible information. Second, note that the information available to households in the post-2013 period may not be "full information" compared to information available to households in other countries, such as the United States. For this reason, we want to emphasize that our MWTP estimate should be interpreted as an MWTP estimate given the set of information available to households in our sample period. For instance, if households in our sample period have limited access to full information on air pollution even after 2013, our MWTP estimate should be considered a lower bound estimate of the theoretical MWTP under truly full information.

E. Heterogeneity in WTP for Clean Air

The advantage of the standard logit estimation in the previous section is that it can be estimated by a linear two-stage least squares or a linear GMM method and therefore does not involve nonlinear estimation. On the other hand, a key assumption in the standard logit model is that the

[20] While the household income data from the 2005 census do not provide panel variation, the annual salary data from the *Yearbook* give us panel variation.

preference parameters are homogeneous across individuals. We implicitly assume that the preference for clean air (β) and the sensitivity for price (α) are homogeneous across households, and hence the MWTP for clean air ($-\beta/\alpha$) is also homogeneous. In this section, we relax this assumption and estimate heterogeneity in β and α as we described in section IV.B.

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

We estimate our model with six nonlinear search algorithms (conjugate gradient, SOLVOPT, quasi-Newton 1 and quasi-Newton 2, simplex, and generalized pattern search), 100 sets of starting values, and conservative tolerance levels for nonlinear searches. In total, we obtain 600 estimation results to test the robustness of our results. For starting values for nonlinear parameters, we generate random draws from a standard normal distribution. We set the tolerance level for the nested fixed-point iterations to 1E–14 and the tolerance level for changes in the parameter vector and objective function to 1E–04.

Five of the six search algorithms produce the same minimum value of the objective function. Only one of the algorithms—conjugate gradient—does not reach that minimum value in our estimation. For the other five algorithms, we find that 81–97 of 100 sets of the starting values reach the same minimum value of the objective function. This result implies that it is important to test multiple search algorithms and starting values to ensure that the local minimum in a particular set of estimation is indeed likely to be the global minimum. The fact that the five nonlinear search algorithms reach the same minimum objective function value provides us strong evidence that the local minimum is likely to be the global minimum of the GMM objective function.

Table 7 shows the results of the random-coefficient model in equation (6). We provide results with two sets of controls for the running variable of the RD design. Column 1 uses a linear control for the latitude and its interaction with the indicator variable for cities on the north side of the Huai River. Column 2 uses linear and quadratic controls for the latitude. As with the results for the standard logit model in table 4, the two sets of controls provide nearly identical results.

Table 7 provides several key findings for heterogeneity in the preference parameters. First, the median and mean MWTP for a reduction of PM_{10} ($\mu g/m^3$) for 1 year are \$1.19 and \$1.34, respectively, which are

TABLE 7
Heterogeneity in WTP for Clean Air: Random-Coefficient Logit Estimation Results

	Dependent Variable: ln(Market Share)	
	(1)	(2)
PM_{10} × HEPA:		
Mean coefficient (β_0)	.0459***	.0498***
	(.0084)	(.0092)
Interaction household income (β_1)	.0924***	.0891***
	(.0224)	(.0253)
Standard deviation (σ_β)	.0056***	.0102***
	(.0020)	(.0021)
Price:		
Mean coefficient (α_0)	−.0069***	−.0071***
	(.0007)	(.0007)
Interaction with household income (α_1)	.0028**	.0028**
	(.0011)	(.0011)
Standard deviation (σ_α)	.0026	.0024
	(.0030)	(.0030)
Observations	7,359	7,359
Control function for running variable	Linear × north	Quadratic
GMM objective function value	375.05	378.93
MWTP per year: 5th percentile	.38	.07
MWTP per year: 10th percentile	.49	.20
MWTP per year: 25th percentile	.75	.53
MWTP per year: 50th percentile	1.19	1.10
MWTP per year: mean	1.34	1.41
MWTP per year: 75th percentile	1.90	2.04
MWTP per year: 90th percentile	2.92	3.45
MWTP per year: 95th percentile	3.86	4.69

Note.—This table shows the results of the random-coefficient logit estimation in eq. (6). All regressions include product fixed effects, city fixed effects, and longitude-quartile fixed effects interacted with HEPA. Column 1 uses a linear control for the running variable interacted with the north dummy variable, and col. 2 uses a quadratic control for the running variable. Asymptotically robust standard errors are given in parentheses, which are corrected for the error due to the simulation process by taking account that the simulation draws are the same for all of the observations in a market.

** Significant at the 5% level.

*** Significant at the 1% level.

not far from the MWTP estimate obtained by the standard logit model presented in table 4. These estimates imply that annual WTP for removing the amount of PM_{10} ($\mu g/m^3$) created by the Huai River heating policy (24.38 $\mu g/m^3$, taken from table 3) is \$32.70 for the average households in our sample. Second, the positive and statistically significant coefficient $\hat{\beta}_1$ implies that there is a positive relationship between the preference for clean air (β) and household income (y_i). Note that the unit for household income in this estimation is USD 10,000. Therefore, the coefficient ($\hat{\beta}_1 = 0.0924$) implies that an increase in household income by \$10,000 is associated with an increase in β by 0.0924. Third, the positive and statistically significant coefficient $\hat{\alpha}_1$ implies that

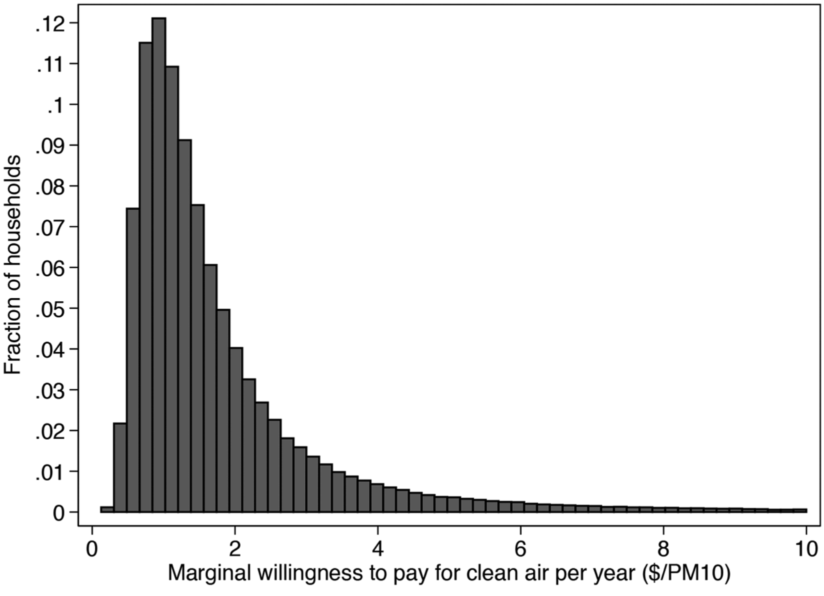

FIG. 3.—Distribution of marginal WTP for clean air. This histogram is based on the random-coefficient logit estimation results in column 1 of table 7 and household-level annual income from the 2005 census microdata. A color version of this figure is available online.

higher-income households are less price elastic than lower-income households. Fourth, the statistically significant estimate for σ_β suggests the existence of unobserved heterogeneity in the preference for air quality.[21]

We use two figures to visually describe the estimation results. Figure 3 shows the distribution of MWTP on the basis of the estimates in column 1 of table 7. The figure suggests that there is wide dispersion of MWTP per year, and the majority of the distribution is in the range between \$0.49 (10th percentile) and \$2.92 (90th percentile). We also show MWTP at several percentiles of the distribution at the bottom of table 7. In figure 4, we show the relationship between MWTP and household-level income. We present the fitted line of the MWTP estimate over income levels with

[21] Note that the analysis of heterogeneity on observables in general—including our analysis in this section—estimates how heterogeneity is associated with observables, which does not necessarily mean a causal relationship between heterogeneity and observables because observables are not randomly assigned. Using our census data, we find that other observables such as education do not provide a statistically significant relationship with heterogeneity once we control for heterogeneity with household income. While this result provides support that household income is an important factor for heterogeneity, it does not necessarily imply a causal relationship between heterogeneity in the preference parameters and household income, because there can be unobservables that are correlated with both income and heterogeneity. For example, home installation is an unobservable factor in our data, and it can be correlated with both income and heterogeneity.

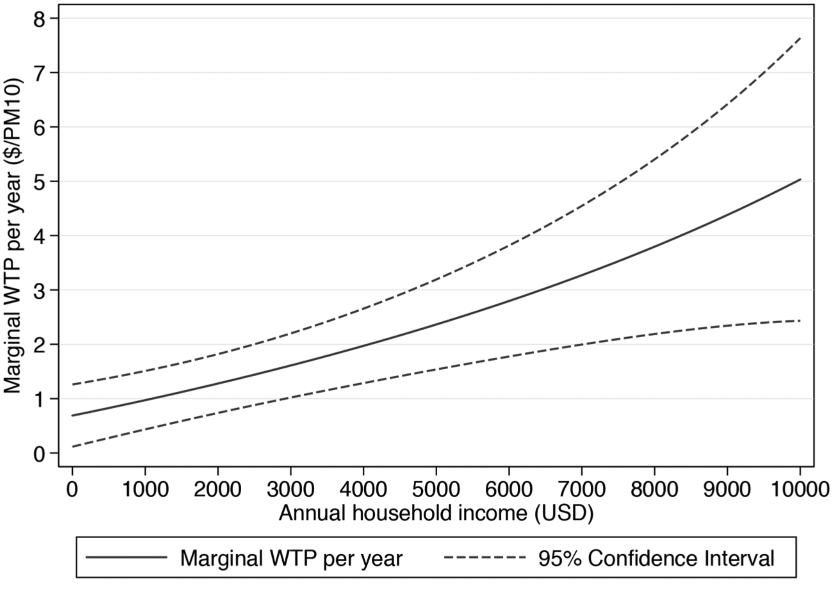

Fig. 4.—Marginal WTP for clean air and household income. This figure shows the relationship between the estimated marginal WTP for clean air and household-level income. A color version of this figure is available online.

95% confidence intervals. This indicates that the average MWTP given income is increasing in income, suggesting that higher-income households are willing to pay more for improvements in air quality.

Overall, the results of the random-coefficient model provide several key implications, under the assumptions required for the nonlinear GMM estimation. For the median and mean levels of MWTP, the estimates from the standard logit estimation are not far from those obtained by the random-coefficient estimation in our context. However, the random-coefficient estimation highlights substantial heterogeneity in MWTP and the positive relationship between MWTP and household income.

F. Additional Results

We provide additional results in the appendixes. First, we examine a number of potential threats to identification in appendix A. For example, we show that sorting is unlikely to confound our results because of restricted migration by the *Hukou* system. For instrumental variables for air purifier prices, we construct alternative instruments based on the theory of imperfect competition in differentiated products markets. We find that the results are robust to these alternative instruments.

Second, we explore the possibility that air pollution enters the WTP function nonlinearly. The challenge in estimating nonlinearity in WTP in our setting is that our instrument—the Huai River RD—provides only one discrete change in air pollution. Therefore, our main empirical strategy does not provide variation to estimate nonlinearity in WTP. To address this limitation, we divide our cities into four groups based on the quartiles of the longitude. Under a strong identification assumption—the variation across the four groups has to be exogenous conditional on our control variables—this approach creates more variation in the Huai River RD that allows us to estimate nonlinearity in WTP. We find evidence that MWTP is an increasing function of PM_{10} in the range of variation in PM_{10} in our data. We provide the details in appendix B.

VI. Policy Implications

Our findings provide important policy implications for ongoing discussion of energy and environmental regulation in developing countries. The governments of a number of developing countries recently proposed and implemented a variety of interventions to reduce air pollution. A key question is whether implementing such policies enhances welfare. Below, we use a few examples to illustrate that our WTP estimates can be used for the cost-benefit analysis of environmental policies.

A. Measuring Policy-Relevant MWTP for Clean Air

When it comes to policy discussions, policy makers often need an aggregate measure of MWTP, such as citywide or nationwide MWTP. Note that our estimation strategy has advantages and disadvantages in providing these measures. An advantage is that the random-coefficient estimation incorporates heterogeneity in MWTP. Because we have household-level income data for all cities from the census, we can calculate predicted MWTP for each city by incorporating heterogeneity in the distributions of household income. A disadvantage is that our estimation is based on the RD design at the Huai River. Therefore, unless we make additional assumptions, our estimates should be interpreted as the local average treatment effect (LATE) for cities near the river boundary. To make a prediction for other cities, we need to assume that the coefficients of the random-coefficient estimation can be extrapolated to out-of-sample prediction for cities away from the Huai River. Because this is an untestable assumption, we want to emphasize that the policy-relevant MWTP measures provided below should be interpreted with this assumption in mind.

In panel A of table 8, we use our random-coefficient estimation result to predict two policy-relevant measures of MWTP. The first is the household-level average and aggregate MWTP for seven northern cities (Tianjin,

TABLE 8
Policy Implications

	Household Level ($)	Aggregate ($)
A. Policy-relevant MWTP measures ($ per 1 $\mu g/m^3$ annual reduction in PM_{10}):		
In-sample estimate (from table 7)	1.34	
Seven northern cities	1.62	10.13 million
Nationwide	1.26	.45 billion
B. Cost-benefit analysis—heating reform in seven northern cities:		
Abatement cost ($)	2.25 million	
Estimated PM_{10} reduction ($\mu g/m^3$)	11.91	
Total WTP ($)	105.07 million	
Benefit-cost ratio	46.70	
	Wind	Natural Gas
C. Cost-benefit analysis—replacement of coal power plants by wind or natural gas:		
Estimated PM_{10} reduction ($\mu g/m^3$)	.56	.46
Total WTP ($)	.26 billion	.21 billion
MWTP for replacing coal-based electricity ($/MWh)	17.9	14.5

Note.—This table shows policy-relevant MWTP measures and the cost-benefit analysis of two policies discussed in sec. VI.

Chengde, Tangshan, Dalian, Urumqi, Wuzhong, Datong) near the Huai River. We use this measure in the next subsection to evaluate a recently implemented heating reform in these cities. The second is the nationwide average and aggregate MWTP. This measure is useful when one evaluates the benefit of nationwide air quality improvements. For example, our data on PM_{10} indicate that since China declared a war on pollution in 2014, the national average PM_{10} decreased from 124 in 2013 to 72 in 2018. Our estimate suggests that a household is willing to pay at least \$65.52 ($=1.26 \cdot 52$) annually to have these air quality improvements.[22]

B. Cost-Benefit Analysis of Environmental Policies

1. Heating Policy Reform in Northern China

We first consider a policy that was recently implemented in China. In 2005, the Chinese government and the World Bank initiated a pilot reform to improve the Huai River heating policy in seven northern cities (Tianjin, Chengde, Tangshan, Dalian, Urumqi, Wuzhong, Datong). The goal of the reform is to save energy usage and reduce air pollution by

[22] Note that we do not claim this number as the benefit of the environmental policies implemented in this period because some of these pollution reductions can be due to reasons unrelated to policies. Our calculation simply provides WTP for the air quality improvements that occurred in this period.

introducing household metering and consumption-based billing.[23] Ten years after the start of the pilot reform, there is still ongoing debate—whether such a reform would improve welfare and whether similar reforms should be implemented in other cities. The main challenge is that the cost of installing individual meters and adopting consumption-based billing is not small, while the benefit of the reform has not been systematically examined.[24]

The abatement cost information is available in World Bank (2014)—this 8-year project cost \$18 million for the seven cities, suggesting that the abatement cost per year was \$2.25 million. The World Bank report also estimates that the project generated a reduction in annual coal consumption by 2.6 million tons, from a baseline level of 13.9 million tons, suggesting an 18.7% reduction in coal usage. To learn how much reduction in PM_{10} was associated with this change in coal usage, we need to know the elasticity of PM_{10} with respect to coal usage. In appendix C, we provide three methods to estimate the elasticity. For our analysis below, we use the implied elasticity (0.53) from one of our three methods.[25] With this elasticity, the 18.7% reduction in coal usage is associated with a 9.9% reduction in ambient PM_{10}, which implies an 11.91 $\mu g/m^3$ reduction in PM_{10} for the seven cities. We then multiply this number by the aggregate MWTP in the seven cities to obtain the total WTP for this policy, which is \$120.63 million.

Finally, we use this number as the benefit of the policy to calculate the benefit-cost ratio. Note that our MWTP estimate is likely to be a lower bound estimate for reasons described in section IV.C. Therefore, the benefit-cost ratio is also likely to be a lower bound estimate. Our result suggests that the heat reform policy is likely to be a welfare-improving environmental policy, even with our lower bound estimate of the policy's benefit.

2. Replacement of Coal Power Plants

Chinese electricity generation has heavily relied on coal, but policy makers recently started to consider whether some of the coal power plants

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

[24] According to the *People's Daily* (2009), the Vice Minister of the Ministry of Housing and Urban-Rural Development summarized three obstacles to the implementation of the heat reform: (1) many new construction projects refuse to install household meters because they are expensive, (2) it is costly to remodel old buildings to accommodate the installation of household meters, and (3) it is costly to build a new consumption-based billing system.

[25] Our result does not substantially change if we use estimates from the other two methods.

should be replaced by cleaner sources, such as natural gas or wind. We consider a counterfactual policy in which 10% of the existing coal power plants' electricity production is replaced by natural gas or wind. Because it is generally challenging to construct accurate emission inventory data in China, we want to emphasize that our calculation below should be interpreted as a back-of-the-envelope calculation. The emission inventory estimate in Ma et al. (2017) implies that 6% of PM_{10} in China is emitted from coal power plants.[26] Therefore, if 10% of the existing coal power plants' production is replaced by wind power, it would result in a 0.6% reduction in PM_{10}. Assuming that a 0.6% reduction in PM_{10} implies a 0.6% reduction in the average PM_{10} concentration, this implies a reduction in PM_{10} concentration by 0.56 μg/m^3 for the average nationwide level of PM_{10} concentration in our data (93 μg/m^3). We consider that the replaced power plants can operate for 30 years. Using these assumptions, the WTP for this replacement policy is \$7.67 billion ($=0.56 \cdot 0.45 \cdot 30$). EIA (2015) shows that the total electricity generation from coal power plants in China is 4.28 billion MWh. This implies that MWTP per megawatt hour is \$17.90 ($=7.67/(0.1 \cdot 4.28)$) to replace coal by wind.

We provide similar calculations for natural gas. Massetti et al. (2016) show that natural gas power plants produce 80.4% less PM_{10}/MWh relative to coal power plants. The 10% replacement with natural gas therefore implies a reduction in PM_{10} concentration by 0.49%—0.46 μg/m^3 for the average nationwide level of PM_{10} concentration in our data (93 μg/m^3). With the procedure presented in the previous paragraph, MWTP per megawatt hour is \$14.60 to replace coal by natural gas.

These numbers imply that the cost difference between coal power plants and wind farms (natural gas power plants) has to be less than \$17.90/MWh (\$14.60/MWh) to justify the cost-benefit of these replacement policies. It is difficult to obtain a reliable cost comparison between generation technologies in China because studies on the levelized cost of electricity (LCOE) provide a wide range of results depending on the assumptions behind the calculation (Borenstein 2012). China has potentially inexpensive sources of natural gas reserves, but given the current technology and infrastructures, at least for now the majority of studies suggest that the LCOE of coal power plants is substantially lower than that of natural gas power plants, most likely much more than \$14.60/MWh. Similarly, even though the cost of wind generation has been declining, most studies find that the difference in the LCOE between coal and wind is much larger than \$17.90/MWh in China. Therefore, WTP for a

[26] Note that this is about the emissions from coal-fired power plants and not overall coal usage. A substantial part of PM_{10} is due to coal, but coal-fired power plants are responsible for 6% of PM_{10} according to Ma et al. (2017).

reduction in PM_{10} per se is unlikely to justify the cost-benefit of these policies, at least for now.[27]

C. Avoidance Behavior and Implied VSL in Developing Countries

Finally, we compare our MWTP estimate with those estimated from other avoidance behavior in developing countries. A challenge in this exercise is that MWTP is not directly comparable across studies when it is estimated from different avoidance behavior. For example, Kremer et al. (2011) estimate MWTP for clean water on the basis of avoidance behavior on water pollution in Kenya. This MWTP is not directly comparable to our MWTP because the harmfulness of water pollution in Kenya is not necessarily comparable to that of air pollution in China. To make such comparison possible, one can calculate the implied value of statistical life (VSL) on the basis of the expected risk/damage of pollution and MWTP to avoid such pollution.

Before we show the comparison of the implied VSL, we emphasize two caveats required for this approach. First, this exercise requires the strong assumption that an individual's belief about the expected health damage of air pollution is equivalent to the information we use below. For example, one may have a biased belief if the person is not fully informed about the relationship between air pollution and health outcomes. Second, the implied VSL based on MWTP for air quality is likely to be an upper bound estimate of the true VSL. This is because MWTP for air quality could include not only health benefits but also other nonhealth amenities associated with air purification.

Given the assumption that households are aware of the relationship between PM_{10} and its health damage, we can calculate the implied VSL by the following procedure. The finding by Ebenstein et al. (2017) implies that a lifetime increase in PM_{10} by 1 $\mu g/m^3$ reduces life expectancy by 0.064 years. Our MWTP estimate implies that a household with the average life expectancy in China (76 years) is willing to pay \$101.84 ($=1.34 \cdot 76$) to avoid a lifetime increase in PM_{10} by 1 $\mu g/m^3$. Because the average household size is 3.5, the implied value of a statistical life year (VSLY) per person is \$455 ($=(101.84/0.064)/3.5$).

[27] There are two important notes on this calculation. First, this calculation does not include other benefits of cleaner power plants, including reductions in other pollutants, such as NO_x and SO_x. Second, the technological progress on natural gas and wind power plants may be reducing the cost advantage of coal power plants substantially in the near future. Therefore, this counterfactual policy could become relatively more cost effective in the near future when the cost difference between coal-based electricity and alternatives shrinks further.

TABLE 9
Comparison of Implied VSL

Study	Country (1)	Implied VSL ($/Year) (2)	Income ($/Year) (3)	Income Elasticity of VSL (4)
Kremer et al. 2011	Kenya	24	480	
This study	China	455	8,332	1.010
León and Miguel 2017	Sierra Leone (Africans)	13,500	62,360	1.012
León and Miguel 2017	Sierra Leone (Non-Africans)	23,232	99,000	1.008

Note.—This table compares the implied VSL between studies.

We compare this estimate with the implied VSLY in other studies. Kremer et al. (2011) find that the implied VSLY is $24 in Kenya. León and Miguel (2017) examine avoidance behavior on risky transportation in Sierra Leone and find that the implied VSLY is $13,500 for Africans and $23,232 for non-Africans. We show this comparison in the last two rows of table 9. Although the implied VSLY is different among the studies, income is also different in these countries. We investigate whether the difference in income can partly explain the difference in the VSLY. In column 4, we show the arc income elasticities of the implied VSLY, obtained from comparing each study to the study in the first row. We find that the constant income elasticity of one can consistently explain the difference in the implied VSLY between these studies.[28]

VII. Limitations and Directions for Further Research

In this paper, we provide among the first revealed-preference estimates of WTP for clean air in developing countries. In the paper and appendixes, we provide empirical evidence that supports our findings, but there are several key issues that were not fully addressed in our study.

First, a limitation of our data set is that we do not observe individual-level transactions. Therefore, we need to assume that a household can purchase at most one air purifier and uses it for 5 years on average—the average usage period of air purifiers according to manufacturers.

[28] Another useful comparison is to relate our MWTP estimate in China to the one in Chay and Greenstone (2005) in the United States. We describe details about the assumptions required for this comparison in app. D. Our calculation suggests that the estimated annual MWTP for a one-unit decrease in TSP is about $12 in the United States and $0.043 in China. This difference could come from various reasons, including (i) the methodological limitation in providing accurate comparison between the two studies, as we discuss in app. D; (ii) the difference in the LATE complier population between the two studies; (iii) the difference in the awareness for air pollution between the US and Chinese households; and (iv) the difference in income between the two countries.

For example, some households may purchase more than one air purifier to clean their homes. Some may use their air purifiers for shorter or longer than 5 years. With individual-level transaction data, these questions can be investigated. In addition, our data set does not include online sales. As we described in section III, the majority of sales were in-store sales in our sample period, 2006–14. However, online sales substantially increased after this period. Thus, online sales data would be particularly valuable information to understand the Chinese air purifier market for more recent years.

Second, we do not have information on indoor avoidance behavior besides air purifier purchases. For example, households may be able to mitigate indoor air pollution by installing better building materials or by closing windows on polluted days. While these avoidance methods do not provide as comprehensive reductions in indoor air pollution as air purifiers, they could be relatively less expensive options. Therefore, investing in such avoidance behavior is also an important research topic.

Third, we focus on a static demand model without exploiting time series variation in the data because the exogenous variation in air pollution comes from cross section. A downside of this approach is that the static demand model abstracts from a potentially important consumer's dynamic decision—consumers may consider intertemporal variation in prices, product availabilities, and air pollution when making their discrete choices. An important future research topic is to include such dynamic considerations within the framework presented in this paper.

Fourth, there needs to be more research on how market failures affect revealed-preference estimates of MWTP for environmental quality as emphasized by Greenstone and Jack (2013). In section V.D, we provide empirical evidence on how information available to households can be associated with MWTP estimates. However, there can be more market failures in developing countries that could make MWTP estimates deviate from the theoretical level of MWTP. Understanding this point is key to interpreting MWTP estimates and design policies that address relevant market failures.

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