From Fog to Smog: The Value of Pollution Information*

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First version: February 2019
This version: August 2019

Abstract

This paper presents the first empirical analysis of the impact of a large-scale pollution monitoring and disclosure program on a range of household behavior and health outcomes. During 2013-2014, China launched a nation-wide, real-time air quality monitoring and disclosure program, the first-of-its-kind in its history. Exploiting this natural experiment and its staggered introduction across cities, we show that pollution information is a key determinant of pollution avoidance and associated health impacts. Household activities such as online searches, day-to-day shopping, and housing demand are much more responsive to pollution when information becomes widely available. The information program reduces air pollution's mortality cost by nearly 7%, amounting to an annual benefit of RMB 120 Billion, an order of magnitude larger than the cost of the program itself and avoidance behavior. Our findings highlight large benefits from improving access to pollution information in developing countries that are experiencing the world's worst air pollution but lack basic information infrastructure.

JEL Classification: D80, Q53, Q58
Keywords: Pollution monitoring, Information disclosure, Smog, Avoidance

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1 Introduction

Economists have long emphasized the importance of information in decision making. In almost any decision environment, perfect information is necessary to ensure individually optimal choices and general market efficiency (e.g., Stigler, 1961; Hirshleifer, 1971; Grossman and Stiglitz, 1976). However, information as an input to decision making is often imperfect in real-world settings. Sellers of private goods may have incentives to conceal certain product attributes, leading to information asymmetry (Akerlof, 1970). Forecasts on weather, disease prevention, and pollution exhibit strong public good properties and are rarely provided by private parties. The difficulties in appropriating returns for this type of information provide room for government intervention. Therefore, understanding the associated value has important implications for the optimal level of government investment in information gathering and reporting (Nelson and Winter, 1964; Craft, 1998).

Obtaining information on air pollution can be costly, as most air pollutants are odorless, invisible, and vary substantially from day to day even within a small geographic area. This is particularly challenging in developing countries, where pollution information is not collected or deliberately withheld by the government and public access is often hindered by a lack of infrastructure to disseminate information.[1] Consequently, questions like whether citizens can engage in effective pollution avoidance, what is the value of information, and how much public support is optimal remain largely unanswered. These issues are particularly acute in developing countries since public funding for improving information infrastructure often competes with meeting basic needs in health care, nutrition, and education for the poor.

China provides a unique setting for studying the role of pollution information. The daily average concentration of fine particulate matter ($PM_{2.5}$) since the early 2000s has been over 50 ug/m^3, or about five times of the World Health Organization guideline. Despite the hazardous level of exposure, comprehensive monitoring network was non-existent. Dissemination of the scant data that were collected was politically controlled and, in many cases, forbidden. As a result, citizens had limited access to pollution information. In 2013, amid the social outcry on the lack of transparency and a dramatic shift in government position on air pollution, China launched a nation-wide, real-time air quality monitoring and disclosure program (henceforth, the information program), with a staggered introduction across cities. The social impacts of this program are far-reaching and range from a greater awareness of the health impact of $PM_{2.5}$ to a better understanding of the science of air pollution, from immediate short-term avoidance and defensive behavior to changes in long-run decisions that

[1] Among the 20 countries with the worst $PM_{2.5}$ level (annual median $>$ 46 ug/m^3), only four (Nepal, Saudi Arabia, India, and China) have installed a pollution monitoring system.

take into account the consequences of pollution. $PM_{2.5}$ is now a household word. The term "smog" ("wu mai" in Chinese) became for the first time a buzzword in social media in China in 2013 and has remained a popular search phrase since then.

The emergence of the monitoring and disclosure program provides a unique opportunity to study changes in behavior upon a sharp and permanent increase in the availability of pollution information. We compile a rich database on information availability and awareness, local air pollution levels, economic activities, and health outcomes in China that covers the period both before and after the program. We begin by presenting strong evidence that the information program substantially advances public access to pollution information and raises households' awareness about pollution issues. The frequency of articles on air pollution related topics in *People's Daily*, the government's official newspaper, rises from less than once-per-week to daily. The number of mobile phone applications ("apps") that stream air pollution data to users increases disproportionately more than other apps. Searches on "smog" jump by 75% and sales of air purifiers more than double one year after the program is implemented in a city.

We then examine how both short- and long-run avoidance behavior responds to pollution disclosure. To overcome the challenge that reliable pollution monitoring data are only available after the disclosure, we draw air pollution measures from satellite data. Thus, our estimation framework allows us to isolate changes in the outcome-pollution relationships due to improved information provision.

In our short-run avoidance analysis, we exploit the universe of credit and debit card transactions in China from 2011 to 2015 to build a measure of outdoor purchase trips. Linking purchase activities to ambient air pollution, we show that the information program boosts pollution avoidance by triggering a negative purchase-pollution elasticity of about 2%. As expected, avoidance concentrates in plausibly "deferrable" consumption categories, such as supermarket shopping, dining out, and entertainment, rather than in "scheduled" trips such as bill-pays, business-to-business wholesales, and cancer treatment sessions.

Our long-run avoidance analysis focuses on the housing market. Leveraging geo-location information from the near-universe of new home sales in Beijing during 2006-2014, we examine changes in the relationship between housing values and pollution levels induced by the information program using two different research designs, corresponding to two different scenarios in terms of the types of pollution information used in consumer decisions. First, we assume that consumers make decisions based on fine-scale pollution information. To obtain localized pollution information, we employ pixel-averaging technique ("oversampling") to enhance the original satellite data's spatial resolution from 10-by-10 km to 1-by-1 km (e.g., Fioletov et al., 2011; Streets et al., 2013). The high-resolution pollution measure allows us

to conduct cross-sectional comparison of home values within fine geographic regions, such as zip codes. We estimate a home value-pollution elasticity of -0.6 to -0.8 post disclosure. In contrast, for periods before the information program, the elasticity is small and statistically insignificant (-0.10 to 0.09).

Second, we assume that consumers make decisions based on heuristic pollution information rather than precise pollution levels. We link China's emission inventory database with business registries to identify locations of major polluters in Beijing: the 10% of facilities that account for 90% of total industrial air emissions. These big polluters tend to be visible and well known landmarks in the city. This allows us to estimate separate "distance gradient" curves (e.g., Currie et al., 2015) that express the home value as a function of proximity to the nearest major polluter before and after pollution disclosure. While there is no correlation between housing prices and proximity to polluters prior to the monitoring and disclosure program, housing values are 27% lower within 3 km of a major polluter afterwards, which corresponds to 42% of the interquartile range of the housing price dispersion. Thus, the information program facilitates the capitalization of air quality in the housing market, with a potential to improve residential sorting and social welfare.

Our last set of empirical analyses examine changes in the mortality-pollution relationship as access to information improves. Using nationally representative mortality data from the Chinese Center for Disease Control and Prevention (CDC), we find a 5 percentage-point reduction in the mortality-pollution elasticity (especially for cardio-respiratory causes) post monitoring. Assuming a linear dose-response function and combining our findings with existing estimate on the causal effect of pollution on mortality in China (e.g., Ebenstein et al., 2017), access to pollution information has reduced premature deaths attributable to air pollution exposure by nearly 7%. It generates a health benefit that is equivalent to 10 ug/m^3 reduction in PM_{10}, with an associated social Willingness-to-Pay in the order of RMB 120 billion annually based on recent estimates in the literature (Ito and Zhang, 2018).

We make three main contributions to the literature. First, our study provides to our knowledge the first empirical estimate of the value of information provision through a nationwide program on pollution monitoring and disclosure.[2] Our empirical findings highlight the potentially large benefit in improving pollution information infrastructure in developing and especially fast-growing countries, many of which are experiencing the worst mortality damage from pollution exposure in the world (Landrigan et al., 2018). The success of China's program provides a benchmark for policy discussions (e.g., the cost-benefit analysis) on

[2]A similar literature quantifies the value of weather forecasts, another type of government-provided information, as an important input to production decisions (Lave, 1963; Craft, 1998; Shrader, 2018; Jagnani et al., 2018).

building information infrastructure in these countries.

Second, our study shows that information is a key determinant of avoidance behavior and defensive spending. Consumer activities (online searches, day-to-day shopping, and housing demand) exhibit little response to pollution until such information becomes widely available. This contrasts with the implicit assumption of perfect information on pollution exposure in the existing literature that uses revealed-preference to estimate the value of non-marketed environmental goods. To the extent that access to information is often lacking especially in developing countries, this assumption underestimates consumers' true willingness-to-pay for environmental goods. Our findings provide a potential explanation for why environmental quality is severely undervalued in developing countries (Greenstone and Jack, 2015) and why the dose relationship between pollution and mortality can be different across developed and developing countries (Arceo, Hanna and Oliva, 2015).

Third, this study contributes to the broad empirical literature on the role of information in consumer choices. Growing evidence suggests that consumers misperceive product attributes in a wide range of context such as food nutritional contents (Bollinger, Leslie and Sorensen, 2011), insurance policy costs (Kling et al., 2012), vehicle fuel economy (Allcott, 2013), retirement savings (Bernheim, Fradkin and Popov, 2015), taxation (Chetty, Looney and Kroft, 2009), and energy prices (Shin, 1985; Ito, 2014). Information provision programs can improve consumers' perception of product attributes (Smith and Johnson, 1988; Oberholzer-Gee and Mitsunari, 2006), change consumer choices (Hastings and Weinstein, 2008; Dranove and Jin, 2010; Jessoe and Rapson, 2014; Wichman, 2017), and drive up average product quality (Jin and Leslie, 2003; Bai, 2018). In the context of environmental quality, recent studies have documented behavioral responses to pollution information in both the short- and long-terms. Our analysis shows that these behavioral responses could lead to improvement in health conditions, through which the value of pollution information is quantified.[3]

The rest of this paper is organized as follows. Section 2 reviews institutional details on the pollution information program and describes data sources. Section 3 presents the theoretical framework. Section 4 documents the dramatic changes in pollution information access and awareness after the program. Section 5 employs a unified framework to examine the effect of the program on short- and long-term avoidance behavior, and mortality effects. Section 6 provides a calculation of the value of information. Section 7 concludes.

[3] Cutter and Neidell (2009); Graff Zivin and Neidell (2009); Sun, Kahn and Zheng (2017); Zhang and Mu (2018) document changes in short-run avoidance and defensive spending while Chay and Greenstone (2005); Banzhaf and Walsh (2008); Bayer, Keohane and Timmins (2009); Mastromonaco (2015); Chen, Oliva and Zhang (2017); Freeman et al. (2019) show housing and migration decisions in the long-term in response to pollution information.

2 Institutional Background and Data

2.1 Environmental Regulations

The real-time $PM_{2.5}$ monitoring and disclosure program started in 2013 is a watershed moment in the history of China's environmental regulations. The program brought about a sharp and sudden change in the access of pollution information for the average residents and the awareness of the health impact of $PM_{2.5}$. To help understand this change, we provide a brief history of China's environmental regulations.

Environmental Regulations Prior to 2012 China established its first national ambient air quality standards (NAAQS) in 1982 which set limits for six air pollutants including Total Suspended Particulate (TSP), coarse particulate matter (PM_{10}), sulfur dioxide (SO_2), nitrogen oxides (NO_x), carbon monoxide (CO), and ozone (O_3). The standards were subsequently amended in 1996, 2000, and 2012. The 1996 amendment strengthened and expanded the standards to reflect the improvement in abatement capabilities while the 2000 amendment removed NO_x from the list and relaxed the standards for NO_2 and O_3 in response to non-compliance due to the increase in automobile usage.

Throughout much of the 1980's to early 2000's, the major threat of air quality was considered to be SO_2 due to coal burning being the major source of air pollution. As acid rain caused widespread and visible damages to crops, forest, and the aquatic environments, the control of acid rain and SO_2 emissions was the focus of the environmental regulations (Yi, Hao and Tang, 2007). The prominent regulation is the two-control zone policy (TCZ) implemented from 1998 where prefectures with high PH value of precipitation or SO_2 concentration were designated as either the acid rain control zone (located in the south) or the SO_2 control zone (mostly in the north). A series of measures were imposed in these zones such as mandating the installation of flue gas desulfurization in coal-fired power plants and closing down the small coal-fired power plants (Tanaka, 2015). As a result of aggressive emissions control and clean energy measures, the average SO_2 concentration was reduced by nearly 45% from 1990 to 2002, with the majority of the cities achieving the national standard by 1998 (Hao and Wang, 2005).[4]

Starting from early 2000, the source of air pollution shifted from coal burning being the dominant one to mixed sources, and particulate matter (PM) rather than SO_2 became the major pollutant. This shift was driven by the fact that while the emissions from coal-fired power plants have reduced significantly, the emissions from automobiles, industrial

[4]The fraction of the acid rain zone in China's total terrain has decreased from the peak level of about 30% to 8.8% in 2015.

facilities, and construction have increased due to the dramatic growth in vehicle ownership, industrial activities (after China's WTO accession in 2001) and rapid urbanization. The regulatory focus was shifted to reducing urban air pollution through city-level efforts such as ranking cities based on the number of "blue sky days" in a year or rewarding cities with good environmental performance (Ghanem and Zhang, 2014).

The city-level efforts proved to be ineffective in reducing urban air pollution in the presence of the strong competing incentives for economic growth at the local level together with the weak monitoring and enforcement from the central government. Episodes of extreme and regional-wide air pollution were common especially during winters in many urban centers. U.S. Embassy in Beijing and consulates in Guangzhou and Shanghai started to report hourly $PM_{2.5}$ in 2008 based on monitoring stations installed on site. The $PM_{2.5}$ readings from these sites were often inconsistent with the official pollution reports and became sources of diplomatic tensions.[5]

Limited Pollution Awareness Prior to 2013 While air pollution has been a long-standing issue, public access to the level of pollution exposure, i.e. daily fluctuations, is almost absent prior to 2013. Although the Ministry of Environmental Protection (MEP) publishes daily Air Pollution Index (API) data for major cities starting from 2000, the information was not well incorporated into the mass media publications or broadcasts prior to the information program.[6] In addition, the reported API prior to the information program only partially reflected true air quality because it did not incorporate $PM_{2.5}$, which turns out to be the major air pollutant in many Chinese cities. More importantly, the API data was gathered and reported by local environmental bureaus which is part of the local governments and whose leaders were appointment by the local governments. The MEP does not control the monitoring stations and has limited ability to monitor the data quality. Recent research has found evidence of widespread manipulation of the API data (Andrews, 2008; Chen et al., 2012; Ghanem and Zhang, 2014; Greenstone et al., 2019).

As the dominant pollutant shifted from SO_2 to particulate matter in early 2000's, there was no systematic collection of $PM_{2.5}$ data and consumer awareness of $PM_{2.5}$ is very limited prior to 2013. Poor visibility due to high levels of $PM_{2.5}$ was often characterized as fog rather

[5]The then-vice minister of the Ministry of Environmental Protection (MEP), Wu, Xiaoqing, openly requested U.S. embassy and consulates to stop releasing $PM_{2.5}$ data from their monitoring stations during the press conference on the World Environment Day in 2012 (June 5th). He stated the public release of air-quality data by the consulates "not only doesn't abide by the spirits of the Vienna Convention on Diplomatic Relations and Vienna Convention on Consular Relations, but also violates relevant provisions of environmental protection." (New York Times, June 5, 2012).

[6]API coverts the concentration of PM_{10}, SO_2, and NO_2 into a single index through a set of piece-wise linear transformations and the dominant pollutant on each day determines of the level of API.

than smog by both government agencies and the media. For example, newspaper headlines as well as China Meteorological Administration characterized flight delays and cancellations as being caused by widespread and dense fog in Beijing and Northern China in November 27, 2011. In fact, this was a major pollution event from NASA satellite views of China and the high AOD measure from NASA MODIS algorithm as shown in Figure 1. A similar pollution event occurred in December 4-6, in 2011 where news media including CCTV and popular website such as sina.com covered this event again as dense fog.

The lack of awareness of $PM_{2.5}$ and fog-smog confusion among the public and the media were reflected upon by the prominent journalist-turned-environmentalist Chai Jing in her high-profile documentary on China's air pollution titled Under the Dome released in February 2015: "... I go back and check the headline from that day's newspaper (on December 1st, 2004): 'Fog at Beijing Capital Airport Causes Worst Flight Delays in Recent Years'. We all believed that was fog back then. That's what we called it.... as a former journalist, I started to blame myself because for all those years I had been reporting stories on pollution all across the country, I always thought pollution is about mining sites and those places near factories spewing smoke plumes. I never thought the skies that we see every day could be polluted."[7]

$PM_{2.5}$ Information Program and Regulation Post 2012 In 2012, the MEP revised the NAAQS which for the first time in China's history sets the national standard for $PM_{2.5}$. The new standards were slated to take effect nationwide in 2016 but some key cities and regions were required to implement the standards earlier.[8] To help achieve the standards, China's State Council released the Action Plan on Air Pollution Prevention and Control in September 2013, which set specific target for $PM_{2.5}$ reduction from 2013 to 2017 and provided 10 specific measures such as promoting the role of market-based mechanisms and establishing monitoring and warning systems to cope with severe air pollution events.[9] In addition to this action plan, for the first time in the history of national five-year plans, the 13th Five-year Plan sets a target of 18% $PM_{2.5}$ reduction by 2020 relative to 2015 in prefectural-level cities or higher.

[7]The documentary has been compared with Al Gore's *An Inconvenient Truth* in terms of its style and impact. The film was viewed over 150 million times on popular website tencent.com within three days of its release, and viewed a further 150 million times by the time it was taken offline by the government four days later.

[8]The cities in Beijing-Tianjin-Hebei region, Yangtze River Delta, and Pearl River Delta as well as provincial capitals are required to implement the standards in 2012 while all prefecture-level cities are required to implement the standards by 2015.

[9]The plan may have been China's most influential and successful environmental policy during the past decade. Under this plan, $PM_{2.5}$ reduced by over 37% in Beijing-Tianjin-Hebin Region, 35% in Yangtze River Delta and 26% in Pearl River Delta, and over 30% on average in over 70 key cities (Huang et al., 2018).

This sharp and sudden shift in government's recognition of $PM_{2.5}$ as a major pollutant marked an important transition of the China's long-standing strategy of prioritizing economic growth over environmental concerns and happened under the backdrop of China's 12th and 13th Five-Year Plans that set pollution reduction as one of the bureaucratic hard targets in the cadre evaluation system (Wang, 2017).[10] To effectively monitor local air pollution levels and to address the pitfalls of the previous reporting system of API (Greenstone et al., 2019), the MEP implemented the nationwide monitoring and disclosure program starting from 2013 with the focus of building a scientific system of air quality monitoring system and publicly disclosing the real-time data.

The program contained two major provisions. First, it initiated continuous monitoring of major air pollutants, including $PM_{2.5}$, PM_{10}, O_3, CO, NO_2, and SO_2. This led to the installation of a comprehensive network of monitors which were built in three waves. Different from early monitoring stations used by the local environmental bureaus to report API, these monitors are under the direct control of the MEP and the data are directly transmitted to MEP's information center in real-time to avoid the potential manipulation by the local government. In the first wave, monitoring networks were built between May and December 2012 in 74 cities that represented the country's key population and economic centers such as the provincial capital cities. Real-time readings on all major air pollutants were posted online and ready for streaming by December 31, 2012. By October 31, 2013, the second wave was completed, adding an additional 116 cities. In the final wave, achieved by November 20, 2014, the program reached the remaining 177 cities. Roll-out of the program is plotted in Figure 2. By the end of the third wave, the program had built more than 1,400 monitoring stations in 337 cities covering an estimated 98% of the country's population.[11]

Second, the information program established a pollution data dissemination system to report a real-time Air Quality Index (AQI) that incorporates multiple pollutants' concentrations and translates them from units of measurement (such as ug/m^3 for $PM_{2.5}$) to a single scale of 0-500. Monitoring results are displayed in real-time on MEP's website. Both hourly and daily AQIs, as well as concentration of $PM_{2.5}$, PM_{10}, O_3, CO, NO_2, and SO_2,

[10]The mandate to reduce air pollution comes from the highest level of government officials. Premier Li, Keqiang described smog as "nature's red-light warning against inefficient and blind development" and declared war against pollution as they fought the war against poverty at the opening of annual meeting of People's congress in March 2014. The phrase, war on pollution, has been quoted by President Xi, Jinping in national meetings since then.

[11]In Appendix Table D.1 we document that earlier-wave cities tend to have larger population size, higher GDP per capita, higher levels of air pollution and industrial emissions, etc. On the other hand, in Appendix Table D.2 we show that these economic and environmental conditions do not shift systematically after information roll-out. Together, these evidence suggest that cities sort into different roll-out waves based on permanent differences in city characteristics, rather than based on unobservables that correlate with the timing of information roll-out.

are available at individual station and city levels, with an interactive map showing locations of monitoring stations. We provide a screen-shot of the website interface in the Appendix (Appendix Figure D.1). Importantly, the government allows private parties to access and stream data directly from the web. This functionality spurs a surge in private websites and mobile phone applications that report real-time air quality information. We provide more details on how awareness on $PM_{2.5}$ and smog was affected by the program in section 4.

2.2 Data

This section documents the primary data sources for the main analysis of the paper.

Mass Media, Phone Apps, and Web Search We draw on several digital sources to illustrate the evolution of access to pollution information. First, we look at publication trends by *People's Daily*, the government's official newspaper, and pull articles whose title or content contain the word "smog" from *People's Daily*'s digital archive. For each article that mentions "smog", we also identify which cities are mentioned.

Second, we measure availability of Chinese mobile apps that contain air pollution information. We apply keyword search (including "air pollution", "atmospheric pollution", or "smog") using Apple's App Store API to obtain apps' initial release information. The API returns the 200 most relevant apps for a given keyword. These apps typically contain a chart that displays the evolution of hourly pollution levels in the past. Some apps also provide general health behavior guidelines (e.g., avoid outdoor activities) when pollution levels are high. In Appendix Figure D.2, we provide an example screenshot from a typical pollution app. We also obtain release information for other major categories such as gaming, reading, and shopping as a control group.

Third, the most widely used search engine in China, Baidu, provides a search index since 2011 that summarizes number of queries for certain words in a city and day among both desktop and mobile users. We focus on the search index for "smog", the buzzword for air pollution. The mapping between the index and the underlying raw search traffic is based on a similar algorithm for Google Trends and reflects search intensity, e.g., total number of searches of the topic relative to all other topics in a city and day.

We note that the rising Internet and mobile phone usage among the Chinese population provides a unique opportunity to investigate pollution awareness. Data from the China Internet Network Information Center (CINIC) show that, by the end of 2012, China had about 0.56 billion (or about 40% of population) Internet users, more than 80% of whom

were active search engine users.[12] Mobile phone prevalence rose from 73.5 per 100 people in 2011 to 95.6 per 100 people in 2016 (National Bureau of Statistics), with a smart-phone penetration rate of 72% in 2013 (Nielsen). We take advantage of China's high internet and mobile phone penetration and collect data on mass media coverage, mobile apps, and internet queries on air pollution. In addition, we compile a rich set of data on air purifier sales, bank card transactions, housing transactions, mortality rates, as well as location of major polluters in Beijing and satellite measures of air pollution concentration.

Air Purifier Sales Air purifier sales data come from a leading market research firm. We observe the total units of air purifiers sold for both residential and institutional purposes at the monthly frequency for fifty cities from 2012-2015. Among the fifty cities, thirty-four, eleven, and five are in the first, second, and third roll-out waves, respectively.

Bank Card Transactions Data Households' shopping trips are constructed using the universe of debit and credit card transactions during 2011-2015 from Unionpay, the only inter-bank payment clearinghouse in China and the largest such network in the world. The database covers 59% of China's national consumption and 22% of its GDP and is the most comprehensive data with fine spatial and temporal resolution on consumption activities for China (Appendix Figures D.3, D.4, D.5 provide summary statistics). For each transaction, we observe the merchant name and location, transaction amount and time, currency, etc.

Our key outcome variable is *purchase rate*, defined as the ratio between (1) total number of transactions occurred in a city×week, and (2) total number of "active" cards with positive transactions in a city×year. We focus on all transactions of a 1% random sample of cards, with a total of 425 million transactions and an average of 18.3 million active cards at a given point in time.

Two features of the data worth mentioning. First, our data contains a small fraction (about 3%) of transactions that are made online. Online shopping took off in China in the second half of 2015 and varies substantially across cities. We drop online transactions and focus on transactions made through traditional point-of-sale (POS) venues. Second, we do not observe items purchased in each transaction. However, UnionPay provides a taxonomy of merchants across 300 plus categories, such as department stores, supermarkets, etc. We use merchant category information in some of our specifications below.

[12] CINIC's 2013 survey of more than 2,800 phone respondents shows more than 99% of Internet users have heard of the Baidu, the most popular search engine (seconded by Google, 87%), and 98% have used it in the past six months (seconded by 360, 43%).

Housing Transactions Data (Beijing) We observe a total of over 660,000 new home transactions in about 1,300 apartment-complexes in Beijing from January 2006 to April 2014, with a near-universe coverage. The dataset contains the transaction date and price, as well as characteristics of the housing unit, including geo-location of the apartment complex, floor, and size of the transacted unit. Beijing's housing market is fluid in general. Over 84% of transactions occur in complexes that are on the market for less than a year. Among all the 1,300 complexes, 64% are sold out in three years.

Polluter Data (Beijing) MEP conducts an annual survey of all major industrial polluters and compiles the Chinese Environmental Statistics (CES) database, the most comprehensive coverage of emission information in China (e.g., Liu, Shadbegian and Zhang, 2017; Zhang, Chen and Guo, 2018) and the source of the annual Environmental Yearbook. We have access to the 2007 CES, which contains information on a total of 587 polluters in Beijing, such as polluter's name and total industrial emissions across all pollutants. We obtain firm address and operation status by linking with registration records from Qixin (www.qixin.com) and geocode addresses using Baidu's Map API. Our study focuses on 407 polluters that operated throughout 2006-2014.

Mortality Data Chinese Center for Disease Control and Prevention (CDC) operates the Disease Surveillance Points (DSP) system that covers 161 counties and 73 million individuals during 2011-2016, a 5% representative sample of China's population. DSP's mortality database, drawn from hospital records and surveys of the deceased's household, is one of the highest-quality health databases that has been used in recent medical (e.g., Zhou et al., 2016) and economic research (e.g., Ebenstein et al., 2017). We observe the number of persons and total deaths for each county $\times$ week $\times$ sex $\times$ age-group, and separately for the following six groups: chronic obstructive pulmonary diseases, heart diseases, cerebrovascular diseases, respiratory infections, digestive diseases, and traffic accidents. The first four groups are closely related to cardiovascular diseases, which are affected by air pollution exposure, while the latter two causes serve as placebo-style outcomes.[13]

Satellite Data We measure ambient air quality using aerosol optical depth (AOD) from NASA's MODIS algorithm installed on satellite Terra's platform. The original data has a geographic resolution of 10 km $\times$ 10 km and a scanning frequency of 30 minutes, which we average to the city $\times$ day level from 2006-2015. MODIS records the degree to which sunlight

[13]The ideal data would of course contain a more comprehensive list of causes, but we are constrained by administrative complications of data extraction.

is scattered or absorbed in the entire atmospheric column corresponding to the overpassed area under cloud-clear condition. As such, AOD captures concentration of particle pollution such as sulfates, nitrates, black carbons, and sea salts, and serve as a proxy for outdoor particulate matter pollution (e.g., Van Donkelaar, Martin and Park, 2006). In the Appendix D, we document the strong correspondence between AOD and the PM2.5 monitoring data from China post the information program (Appendix Figure D.6).

We favor the MODIS AOD measurement over alternatives (such as satellite-based ground-level $PM_{2.5}$ predictions) for several reasons. First, MODIS data can be easily aggregated from daily to weekly or quarterly levels. This allows us to use the same pollution measure throughout our analysis. In contrast, processed satellite-based $PM_{2.5}$ data are distributed only at certain temporal interval (e.g., annual) and cannot be dis-aggregated in a straightforward manner. Second, MODIS AOD allows us to observe overlapping 10 km $\times$ 10 km grid cells it scans, which is essential for the oversampling exercise in Section 5.3. Finally, while MODIS AOD is a common input in predicted ground-level $PM_{2.5}$, there is no consensus on the precise relationship between AOD and PM2.5 in the atmospheric science literature.

3 Theoretical Model

Classical economic theory argues that the value of information stems from the fact that information as an input to the decision process can help economic agents make better-informed decisions, for example by resolving market uncertainty in demand and supply conditions (Stigler, 1961, 1962) or technology uncertainty in investment and production (Lave, 1963; Hirshleifer, 1971). Pollution information affects individual behavior in both the short- and long-term in that individuals who recognize the negative health impact of pollution could take measures to reduce the harm from pollution. In this section, we present a stylized model to illustrate how the information program affects individual behavior and utility by incorporating the elements of information economics (Hirshleifer, 1971; Hilton, 1981) into the classical model of health demand and production (Grossman, 1972).

3.1 Model Setup

Individuals derive utility from the consumption of a numeraire good x whose price is normalized to be one and health stock h: $U(x, h)$, where health stock depends on both the pollution level c and the extent of avoidance a (individuals' actions that mitigate the negative impact of pollution): $h = h(c, a)$.

The budget constraint is defined by: $I + w * g(h) \geq x + p_a * a$, where I is non-labor

income and w is the wage rate. Hours worked is denoted by $g(h)$ and is a function of the health stock. Individuals allocate their wage and non-wage income between consumption and engaging in the adaptation or avoidance behavior a, where p_a is the associated price (e.g., the cost of an air purifier or medication). We assume away dynamics and savings in this model to ease exposition. In addition, we use a to include a range of (costly) adaptation behavior.[14]

Under imperfect information on pollution, consumers may or may not know the real pollution level c. They maximize their utility by choosing the optimal consumption x and defensive investment a based on the perceived pollution level c_0:

$$\begin{aligned} &\max_{x,a} U(x,h) \\ \text{s.t. } &I + w * g(h) \geq x + p_a * a \\ &h = h(c_0, a) \end{aligned}$$

The health function $h = h(c_0, a)$ in the optimization can be viewed as an ex-ante health function which consumers relies on for decisions. It is different from the ex-post health condition $h = h(c, a)$ experienced by consumers. This difference gives rise to the discrepancy between the (ex-ante) decision utility and the (ex-post) experience utility as described in (Bernheim and Rangel, 2009; Allcott, 2013).

Let avoidance under perceived pollution c_0 be denoted by $a(c_0)$. Individuals' wage income is determined by the actual pollution level c and avoidance $a(c_0)$: $w * g[h(c, a(c_0))]$. The numeraire good consumption is denoted by:

$$x(c, c_0) = I + w * g[h(c, a(c_0))] - p_a * a(c_0)$$

which makes it explicit that x depends on the actual pollution c and perceived pollution c_0.[15] Individuals' (experience) utility based on the perceived pollution (e.g., prior to the information program) is:

$$U(X(c, c_0), h(c, a(c_0))) \equiv V(c, c_0)$$

where $V(\cdot, \cdot)$ denotes the indirect utility, with the first argument being the actual pollution

[14] These behavioral changes include reducing outdoor activities (Zivin and Neidell, 2009; Saberian, Heyes and Rivers, 2017), engaging in defensive spending (e.g., face masks and air purifiers) (Ito and Zhang, 2018; Zhang and Mu, 2018), and location choices and migration (Chay and Greenstone, 2005; Banzhaf and Walsh, 2008; Bayer, Keohane and Timmins, 2009; Chen, Oliva and Zhang, 2017).

[15] Individuals' perceived total income is $I + w * g[h(c_0, a(c_0))]$, but the actual total income is $I + w * g[h(c, a(c_0))]$. The actual consumption of the numeraire good is a residual of the budget constraint, after subtracting the cost of avoidance.

c and the second argument being the perceived pollution level. To examine the behavioral changes and the welfare impacts of the information program, we make the following assumptions:

Assumption (A1) Health stock is bounded and decreases in pollution and increases in avoidance: $\frac{\partial h}{\partial c} \leq 0$, and $\frac{\partial h}{\partial a} \geq 0$. In addition, the marginal health benefit of avoidance is decreasing: $\frac{\partial^2 h}{\partial a^2} \leq 0$. This assumption ensures that people don't engage in infinite amount of avoidance behavior. Finally, the worse the pollution, the larger the marginal health benefit of avoidance: $\frac{\partial^2 h}{\partial a \partial c} \geq 0$. The health benefit of avoidance is likely much higher when pollution is severe than when it is modest. Similarly, we assume that hours worked increases in health, but at a decreasing rate: $\frac{dg}{dh} \geq 0, \frac{d^2 g}{dh^2} \leq 0$.

We focus on interior solutions for the optimal level of avoidance behavior a. A necessary condition for an interior solution is $w * \frac{dg}{dh} * \frac{\partial h}{\partial a} \mid_{a=0} > p_a$. At low levels of avoidance, the marginal health benefit $\frac{\partial h}{\partial a}$ is likely to be large. In addition, there are many choices of different defensive mechanisms, some of which have low costs. For example, stay indoors at times of high $PM_{2.5}$, wearing facial masks, or purchasing air purifiers are all cheap and effective defensive mechanisms. When avoidance is cheap, individuals will engage in an appropriate amount of avoidance to increase wage income (via improved health stocks), relax the budget constraint, and enjoy a higher consumption of the numeraire good.

Assumption (A2) Utility is quasi-linear $U(x, h) = x + u(h)$ and increases in health at a decreasing rate: $\frac{\partial U}{\partial h} \geq 0, \frac{\partial^2 U}{\partial h^2} \leq 0$. Quasi-linear utility function is commonly used in the literature and helps ease the exposition.

Assumption (A3) Let c_0 denote individuals' perception of air pollution prior to the information program. We assume that $c_0 < c$, that is, perceived level of pollution before the program is lower than the actual level.[16] In addition, pollution concentration c is perfectly observed post the program.

Proposition 1. *Under assumptions (A1)-(A3), the information program is predicted to result in the following impacts:*

1. *Avoidance behavior increases:* $a(c) > a(c_0)$

[16] Another interpretation of Assumption 3 is that people underestimate the negative health impact of pollution.

2. *Health improves and the (downward slopping) health-pollution response curve flattens:*

$$h(c, a(c)) > h(c, a(c_0)), \frac{dh}{dc}|_{c_0=c} \geq \frac{dh}{dc}_{c_0<c}$$

3. *Individual utility increases:* $V(c, c) > V(c, c_0)$

The proof is provided in Appendix A. The theoretical model predicts that after the information program, individuals engage in more pollution avoidance, which in turn reduces the health damages from pollution and increases consumer welfare.[17] Our empirical analysis will provide empirical tests on the first two predictions and use the their prediction to quantify the value of pollution information.

3.2 Value of information

To derive the value of information (VIF), recall that:

$$V(c, c) = U[x, h(c, a(c))] + \lambda\{I + w * g\left[h(c, a(c))\right] - x - p_a(a(c))\}$$

where $V(c, c)$ denotes the indirect utility when individuals correctly perceive pollution and avoidance is chosen according to the optimal choice $a(c)$ given by the following condition:[18]

$$\left[U_h(c, a) + \lambda * w * g_h(h(c, a))\right] \frac{\partial h(c, a)}{\partial a} - \lambda p_a = 0$$

The indirect utility before the information program is::

$$V(c, c_0) = U[x, h(c, a(c_0))] + \lambda\{I + w * g\left[h(c, a(c_0))\right] - x - p_a(a(c_0)).\}$$

The key difference between $V(c, c)$ and $V(c, c_0)$ is the difference in the choice of avoidance: $a(c)$ is determined by equation 3.2 rather than equation A.1. To derive the value of information, we apply the Tailor's expansion to the indirect utility function $V(c, c)$ at the second argument $c = c_0$: $V(c, c) = V(c, c_0) + \frac{\partial V}{\partial c_0}(c - c_0) + Op(c - c_0)$. The value of information is therefore:

$$\begin{aligned} VIF &= V(c, c) - V(c, c_0) \\ &= \{U_h * \frac{\partial h}{\partial a} * \frac{\partial a}{\partial c_0} + \lambda * w * g_h * \frac{\partial h}{\partial a} * \frac{\partial a}{\partial c_0} - \lambda * p_a * \frac{\partial a}{\partial c_0}\}(c - c_0) + Op(c - c_0) \end{aligned}$$

[17] See Appendix B for a concrete example of the model assumptions and model predictions.

[18] x drops out from the indirect utility function since $U(x, h)$ is quasi-linear. In addition, $\lambda = 1$.

where $O_p(c - c_0)$ denotes higher order terms of $(c - c_0)$. There are three terms in the curly bracket. The first is changes in utility due to health changes from avoidance behavior and the second is the changes in wage income. The third term is changes in the avoidance cost. The benefit of the program, or the value of information, is bounded below by the first and third terms, which we measure in our empirical analysis.

4 The Sea Change in Information Access and Awareness

4.1 Information Access: News and Mobile Apps

We consider two venues through which the general public are most likely to access pollution information: newspapers and mobile phone apps. In Figure 3a, we count number of days in each month when *People's Daily*, the government's official newspaper, mention "smog" in any articles. "Smog" mention stays nearly zero before 2013. Almost immediately following the information program's initial roll-out, frequency of "smog" mention jumped to roughly 15 days per month.

While the sharp increase in "smog" mentions post 2013 is reassuring about the information sea change, it does not directly reveal the effect of the monitoring roll-out because many elements of the general environment could have also changed pre vs. post 2013. To examine changes in information access due to the monitoring policy, we test whether changes in pollution information at the city corresponds to the time when it began pollution monitoring. Ideally, this exercise would require data from every local news papers. Instead, we scan each smog article in *People's Daily* to determine which cities are mentioned. This allows us to construct a time series measure of "smog" for each city. Figure 3b plots standardized "smog" (mean 0, standard deviation 1) as a function of time since monitoring roll-out, spanning a year before and a year after monitoring. We estimate the event study controlling only for month-of-year dummies (12 indicators) and year dummies (5 indicators). In other words, we test for a differential change in "smog" mentions after a city began pollution monitoring, conditional on general within-year seasonality as well as year-by-year changes in mentions. We normalize the data to one month prior to the roll-out (event month t=-1).

The graphical pattern features a discrete increase exactly on the roll-out date (event month t=0). By one year after monitoring, "smog" mentions have increased by about 50% of a standard deviation. Intuitively, the pattern shows a rapid increase in the chance that a smog-related article *People's Daily* would mention a city after the city began pollution monitoring. Notice that the logic of this exercise is similar to an event study: assuming unobserved changes in the environment do not correlate exactly with the monitoring roll-

out, the difference between pre ($t < 0$) vs. post ($t \geq 0$) coefficients identifies the causal impact of monitoring.

We then examine availability of pollution-related mobile phone apps. Unlike newspapers which provide pollution information at a daily frequency, information from apps are more readily accessible in real time. Given the high mobile phone penetration in China, pollution apps may serve as a significant venue through which the public learn about their pollution exposure at the moment. As described in section 2.2, because for each category we only observe the 200 most relevant apps at a given point in time, the release time distribution likely contains a survivorship component: some oldest apps have lost popularity, while some newest apps might still take time to rise to the top. In other words, the release time distribution using the most relevant apps might contain too little mass in the tails than the distribution of all apps. To separate genuine changes in app availability over time from the survivorship component, we compare release time distribution of pollution apps with a "control" group of apps from various categories which we believe capture the majority of commonly-used apps. These categories are gaming, music, video, reading, finance, sports, education, shopping, and navigation.

Figure 4 presents the distribution of release time of apps. The graphical pattern shows a clear surge in the density of apps released after disclosure, relative to non-pollution apps. The largest jump in release risk occurs in the quarter following the initial monitoring roll-out. In total, about 82% of pollution apps are released post January 2013. This fraction is 62% for non-pollution apps.

4.2 Awareness: Web Searches and Air Purifier Sales

We examine changes in public awareness of air pollution issues in two ways.

First, we measure the demand for pollution-related information by internet searches of terms related to "smog". We use data from Baidu, the go-to search engine in China. The analysis is analogous to the "smog" news examination in section 4.1. We begin by documenting the national, overall trend of smog searches. Figure 5a plots raw search index time series. Our data suggests a sharp increase in smog searches starting January 2013, the month of initial roll-out. Post-2013 smog searches exhibit a strong secular pattern where the index is highest in winter seasons. This pattern coincides with the fact that smog is more severe in winter partly due to coal-fueled heating.

We also leverage the roll-out timing to test for changes in smog searches shortly before and after a city began monitoring. Here, we use city $\times$ daily search index, which breaks down the national time series by over 300 cities. Due to substantial differences in search activities

across cities and the frequent presence of days with zero search indexes for small cities, we present the results using a standardized (mean 0, standard deviation 1) scale. Figure 5b plots the mean of standardized search indexes in the year before and the year after monitoring roll-out. Similar to what we saw in "smog" news examination, smog searches show a flat and stable pre-trend in smog searches in the city, followed by a rapid rise when monitoring started. By one year after monitoring, smog searches have increased by about 75% of a standard deviation. In unreported analysis, we have also examined other pollution-related search terms such as "mask" and "air purifier", and the event studies show similar results.

Second, we examine shifts in the degree to which the public is actually willing to invest in defensive equipment. We repeat the exact same analysis using data on monthly air purifier sales for 50 cities. Figure 6a shows that air purifier sales more than doubles, rising from 11,000 units sold per month in 2012 to over 25,000 units per month after 2013. Similar to web searches, air purifier sales also exhibit strong seasonality where there are typically more sales in winter. Once again, Figure 6b suggests that the rise in sales increase coincides with the timing of monitoring roll-out at the city. For a typical city in our study sample, air purifier sales increase by over 100% after monitoring began.

4.3 Other Changes in Observables

To attribute to information changes, our research designs rely on the assumption that there are no confounding factors that systematically correlate with the timing of monitoring roll-out as we discuss in the next section. China is experiencing rapid social and economic changes during the study period, so one might be concerned to what degree does the no-confounder assumption hold. General trends are not necessarily problematic as our statistical analysis could control for general as well as city-specific time fixed effects. But one may still be concerned about differential trends that correlate systematically with the timing of monitoring roll-out.

Appendix Table D.2 presents a series of tests on differential shifts in city-level observables before vs. after the program. We examine four general classes of social and economic conditions that we can measure from various data sources. These include pollution levels (satellite-based AOD), political and regulatory environment (the number of downfall local officials during the anti-corruption campaign, demographics of local political leaders, news mention of regulation policies), healthcare access (the number of medical facilities), and consumption habit (the number of transactions made online). Overall, we find no evidence that the general social and economic conditions or the air quality shift in a way that correlates significantly with monitoring roll-out. One exception is for online transactions, where we

detect a small but statistically significant increase in the frequency of online purchases after monitoring roll-out. As will be discussed in more detail below, online transactions account for less than 3% of all transactions, and so they are unlikely to impact our main findings. In robustness checks, we have also confirmed that controlling for changes in online transactions has little effect on our findings.

5 Pollution Disclosure, Behavior, and Health

5.1 Empirical Framework

We examine the impact of the pollution monitoring and disclosure program on a set of outcomes including avoidance behavior, housing choice and prices, and health outcome. The increased access to pollution information and better consumer awareness under the program could induce a range of behavioral changes to mitigate pollution impacts, which in turn could lead to improvement in health. We use the following empirical framework to examine the change of the the relationship between pollution exposure and the outcomes (i.e. the "slope") before versus after the program:

$$\text{Outcome}_{ct} = \alpha \times \text{Pollution}_{ct} + \beta \times \text{Pollution}_{ct} \times \text{d}_{ct} + \text{x}'_{ct}\gamma + \varepsilon_{ct}, \tag{1}$$

where c denotes a city and t denotes time (e.g., day or week). Outcome_{ct} is the outcome variable and Pollution_{ct} measures the ambient air quality using AOD. d_{ct} represents the information treatment dummy and, for each city, it indicates time periods after monitoring began based on the staggered roll-out schedule. x_{ct} includes the information treatment dummy, weather conditions and rich spatial and temporal fixed effects such as city fixed effects and time fixed effects. ε_{ct} is the error term.

Equation 1 highlights the difference between our study's focus and the previous literature that estimates the causal effect of air pollution exposure. Conventionally, the key threat to identification arises because pollution exposure is likely to be correlated with the error term: $E\left(\text{Pollution}_{ct} \times \varepsilon_{ct}\right) \neq 0$. Such endogeneity could be due to unobservables (e.g., economic conditions, avoidance actions) that affect both the pollution level and outcomes. In addition, there could be errors in the measurement of pollution exposure.[19]Addressing endogeneity in air pollution is challenging and has been the subject of recent research on understanding the morbidity and mortality cost of air pollution (e.g., Bayer, Keohane and Timmins, 2009;

[19]For example, satellite-based AOD captures particulates concentration in the entire air column above a ground spot, which might differ from ground-level exposure; ambient pollution might differ from actual exposure due to outdoor-indoor difference in pollution level.

Chen et al., 2013; Arceo, Hanna and Oliva, 2015; Deschenes, Greenstone and Shapiro, 2017; Ito and Zhang, 2018; Barwick et al., 2018). In contrast, the scope of our empirical analysis differs in two ways. First, in most cases we are not interested in the causal effect of pollution *per se* (α), but rather in the *change* in the causal effect before vs after monitoring (β). Second, in our analysis, Pollution_{ct} is intended to be a direct measure of ambient pollution, rather than population pollution exposure which is determined by the ambient air quality, avoidance behavior, and population distribution. In fact, in the analysis below we directly examine how avoidance and residential sorting responds to ambient air pollution before vs after information availability.

The key insight of our empirical framework is that, under certain reasonable assumptions, one can consistently estimate the change in causal effects of pollution (β) simply using OLS, without having to consistently estimate the level of the effect itself (α). Intuitively, β measures the change in the slope of the pollution-outcome relationship before and after the treatment. If we were to estimate the slope separately for before and after the treatment, the endogeneity in pollution would lead to inconsistency in the estimates of both slopes. However, if the nature of the endogeneity in pollution is not affected by the treatment, the inconsistency in the slope estimates would exactly cancel out, leaving the OLS estimate of β to be consistent. The following two assumptions formalize this intuition:

Assumption (B1): $E\left(\varepsilon_{ct}|\mathrm{d}_{ct}, \mathrm{x}_{ct}\right) = 0$. This assumption implies that the treatment d_{ct} and other controls x_{ct} such as weather conditions are exogenous. As discussed in section 2.1, the information program was implemented against the backdrop of MEP's promulgation of the national $\mathrm{PM}_{2.5}$ standard, which marked a drastic change in the government's position regarding the balance between economic growth and environmental quality. The roll-out of the monitoring stations in three waves was based on the size and the administrative role of the cities, whereby the first wave covered the four directly administrated municipalities and provincial capital cities (Figure 2). That is, the program roll-out schedule is unlikely to be correlated with unobservables that affect outcomes including avoidance behavior and health outcomes. This exogeneity assumption of d_{ct} is further supported by evidence in Appendix Table D.2 that the pollution level and a host of other city-level characteristics do not exhibit significant changes along with the program roll-out.[20]

Assumption (B2): $\text{Pollution}_{ct} = \mathrm{x}_{ct}'\theta + \nu_{ct}$, where $E\left(\upsilon_{ct}|\mathrm{x}_{ct}\right) = 0$ and $E\left(\varepsilon_{ct} \times \nu_{ct}\right) = \sigma_{\varepsilon\nu}$. This assumption implies that the endogeneity of pollution arises only from the correlation of

[20]The exogeneity assumption of d_{ct} could be relaxed by adding d_{ct} in the regression to allow for the change in outcome variables before-after treatment. The consistency of OLS estimate of β can still be achieved with the assumption B2 below.

ν_{ct} and ε_{ct}, and that the correlation between Pollution_{ct} and the error term ε_{ct} is not affected by the treatment. In addition, this assumption implies that the treatment is random with respect to the pollution level conditional on x_{ct}: $E\left(\text{Pollution}_{ct}|\text{d}_{ct}, \text{x}_{ct}\right) = E\left(\text{Pollution}_{ct}|\text{x}_{ct}\right)$. Although the program was first rolled out in larger cities where the pollution tends to be worse on average than cities in the later waves, the exact roll-out time is likely to be exogenous conditional on the average level of pollution for a given city captured by city fixed effects.

Proposition 2. *Under assumptions (B1) and (B2), the OLS estimate of β in equation (1) is consistent.*

The proof is provided in Appendix C. There are two sources of inconsistency in the OLS estimate of β: one from the endogeneity of the interaction term $\text{d}_{ct}\text{p}_{ct}$, and the other from smearing due to the endogeneity of p_{ct}. The inconsistency from these two sources cancel out under the two assumptions. Based on this proposition, our subsequent analysis focuses on the OLS estimate of β. In the last analysis on the mortality outcome, we use both the regression discontinuity design and the IV strategy from the literature to address the endogeneity of p_{ct} in order to get the baseline impact of pollution on mortality α for comparison.

5.2 Pollution Disclosure and Avoidance

Our empirical analysis begins with the impact of pollution disclosure on avoidance behavior by conceptualizing purchase trips as a function of ambient pollution levels. We examine how such relationship changes as the information program is implemented in a city. Our estimation equation is as follows:

$$\text{PurchaseRate}_{ct} = \sum_{k=-24}^{15} \beta_k \times \ln \text{Pollution}_{ct} \times \mathbb{1}(t=k) + \sum_{k=-24}^{15} \eta_k \times \mathbb{1}(t=k) + \text{x}_{ct}'\gamma + \varepsilon_{ct} \quad (2)$$

The outcome variable "PurchaseRate_{ct}" is the number of card transactions in city c at week t per 10,000 active cards in the city in the corresponding year (section 2.2). The pollution measure "ln Pollution_{ct}" is logged average AOD in the city × week. The key parameters of interest are the β's, which represent changes in purchase rate per one percent increase in AOD. To examine changes in the purchase-pollution relationship before vs. after the program, we allow β's to vary by event month k relative to the roll-out time. Because roll-out time varies, cities do not have equal number of available pre and post periods. We look at an event window that spans 39 months (24 months before and 15 months after

disclosure). This event window is chosen so that there are nearly identical city × day observations underlying each event month. In other words, there is no composition change underlying the event study graph, and changes in the β_k coefficients do not reflect sample selection.

We identify β's using week-to-week variations in air pollution net of a flexible set of geographic and time controls (x_{ct}) that include city fixed effects, week-of-year fixed effects, and year fixed effects. As detailed below, we also experiment with increasingly stringent fixed effects to test the robustness of the estimates. In order for the β's estimates to be representative, we weight the regression using the number of active cards. ε_{ct} is an idiosyncratic error term. Standard errors are clustered at the city level. As we discuss further below, our estimation is robust to a range of econometric specification choices.

Figure 7 summarizes the estimates of β_k coefficients. We present binned β_k estimates that vary at the quarterly (3-month) level to aggregate out noises in time trends. Two patterns emerge. First, before the program, the β_k estimates remain flat and statistically indistinguishable from zero. This suggests that, conditional on the fixed effects controls, there is a stable and weak relationship between purchase and pollution before individuals have access to information. Second, β_k estimates exhibit a level-shift and become strongly negative following disclosure.

Table 1 provides point estimates counterpart of Figure 7. The econometric specifications in this table are modified from equation 2 in two ways. First, we include full interactions between the pollution term and the post-monitoring dummy variable, so that the coefficient on "Log(Pollution)" represents the OLS transaction-pollution gradient before the program, and the coefficient on "Log(Pollution) × 𝟙(after monitoring)" represents changes in the gradient after the program, as denoted by β in the empirical framework in Section 5.1. Second, we increasingly tighten the fixed effects strategy we use to exploit finer variation in the data. Column 1 uses simple city, week-of-year, and year fixed effects, which corresponds to the specification of Figure 7. Column 2 uses city and week-of-sample fixed effects. This is essentially a cross-sectional specification, exploiting variation in pollution in the same week-in-time, across cities with high vs. low pollution. Column 3 further adds region × year fixed effects to column 2's specification, allowing for potentially common trends in transactions and pollution that are specific to each region.[21] Column 4 is our most stringent specification, controlling for city and region × week-of-sample fixed effects. We obtain similar estimation results across the board.

Although we find that pollution information matters for short-term avoidance, the mag-

[21]"Region" is a conventional partition of cities by location: North (36 cities), Northeast (38 cities), East (105 cities), Centralsouth (81 cities), Southwest (54 cities), Northwest (52 cities).

nitude of the effect is modest. The average change-in-gradient estimate in Table 1, inversely weighted by the standard errors across columns 1-4, is 21.9 weekly transactions per 10,000 cards. This represents a 2.5% change relative to the mean of the dependent variable of 870.6.

In the Appendix D, we report three sets of additional analyses that support our main findings. First, we examine heterogeneity by the "deferrable" vs. "scheduled" nature of the consumption. We use POS merchant category information to look at changes in purchase-pollution gradient for several major categories including supermarkets, dining, and entertainment. These "deferrable" purchase trips are more likely subject to pollution avoidance. Appendix Table D.3 shows that over 75% of the change in overall purchase-pollution gradient is explained by transactions in these three categories. On the other hand, we conduct placebo-style tests looking at the impact of information roll-out on "scheduled" consumption including billings (bills in utilities, insurance, telecommunication, and cable services), government services (court costs, fines, taxes), business-to-business wholesales, as well as cancer treatment centers. Appendix Table D.4 shows that we find no statistical evidence that information availability changes "scheduled" consumption's responses to air pollution.

Second, we test the robustness of our results by varying a range of specification choices. Appendix Table D.5 details these tests. To highlight a few examples, we find that the inclusion of flexible weather controls are not consequential to our estimation, that increasing online transactions cannot explain away our findings, and that using neighboring cities (who have not yet experienced monitoring) as control units produce similar results in a triple difference research design.

Finally, we perform randomized inference to address the concern that we have a small number (three) of roll-out waves which is less than ideal for a staggered event study design. Appendix Figure D.7a compares our true t-test statistic with an "empirical null distribution" of test statistics obtained through 500 repetitions of random assignment of cities into monitoring roll-out waves. Tested against the empirical null (rather than the theoretical null of a t distribution), our effect estimate is statistically significant at the 5% level.

5.3 Pollution Disclosure and Housing Choices

We now turn to assess housing market responses to pollution disclosure using transaction-level data on the near-universe of new homes sold in Beijing from Jan. 2006 to April 2014. We rely on the following features of the data that we consistently observe for every unit sold: transaction price, transaction date, apartment complex name and address, floor level, and unit size. Analogous to the previous analysis in section 5.2, we focus on the degree to which the housing price-pollution relationship shifts before and after pollution disclosure.

We conduct two sets of analysis based on alternative measures of pollution at the sub-city level: fine-scale ambient air quality (AOD) at 1km-by-1km $\times$ year resolution, and distance to major polluters as a proxy for local pollution. The analysis based on the first measure has a strong assumption on information availability: air purifiers become common household appliance in highly polluted cities and they often provide real-time $PM_{2.5}$ readings. The analysis based on the distance to major polluters has a weaker information assumption and assumes that consumers use the distance to major polluters as a heuristic measure of local pollution levels.

Although we have housing data at the transaction level, we use pollution measures at a more aggregated level in both spatial and temporal dimensions (i.e., apartment-complex by year). In the temporal dimension, purchase decisions are more likely to be affected by the long-run pollution level rather than day-to-day variations. We use a two-step procedure to collapse the effective amount of information in the transaction data to match the granularity of the pollution data in both spatial and temporal dimensions. We take all transactions in our data and estimate the following equation:

$$\ln \text{TransactionPrice}_{ict} = \mathrm{w}'_{ict}\gamma + \eta_{cy} + \varepsilon_{ict}, \tag{3}$$

where $\ln \text{TransactionPrice}_{ict}$ is the log transaction price of unit i in apartment-complex c on date t. The vector of unit characteristics w_{ict} includes floor fixed effects, sale month-of-year fixed effects, and a quadratic term in unit size. The outcome variable of our hedonic price-pollution regression is therefore $\hat{\eta}_{cy}$, which are apartment-complex $\times$ year level, residualized averages of housing outcome after controlling for the observable aspects of the transaction. In this regression, the average apartment-complex $\times$ year cell contains 153 underlying transactions. The first step provides us $\hat{\eta}_{cy}$, the quality-adjusted price index at the apartment-complex $\times$year level.

The second step then takes $\hat{\eta}_{cy}$ as the dependent variable in a hedonic regression:

$$\hat{\eta}_{cy} = \alpha \cdot \ln \text{Pollution}_{cy} + \beta \cdot \ln \text{Pollution}_{cy} \times \mathbb{1}(\text{after monitoring}) + \mathrm{x}'_{cy}\gamma + \varepsilon_{cy} \tag{4}$$

where $\ln \text{Pollution}_{cy}$ is one of the two pollution measures. β captures the change in pollution-housing gradient before and after the program. Because we only have 14 months of post-disclosure housing market, we allow β, the housing-pollution elasticity estimate, to simply vary by pre- vs. post-program periods.

Fine-scale AOD and Housing Prices. To obtain a pollution measure with a high level of spatial resolution, we employ a frontier method in atmospheric science called "over-sampling" that re-processes the original AOD data to increase its spatial resolution from

10-by-10 km to 1-by-1 km, while sacrificing the temporal resolution from daily to annual. Oversampling takes advantage of the fact that MODIS scans a slightly different, but overlapping, set of pixels at a given location on each of the satellite's overpass. When the researcher is not interested in the high temporal dimension (such as in our case, where we only need annual information on pollution), it is possible to average across the overlapping overpasses to enhance the geo-spatial resolution of the AOD measure.[22] Figure 8 presents pre- and post-oversampling average AOD concentration in the city of Beijing. The pollution variable in the first set of analysis is therefore the oversampled AOD level in year y in the 1-by-1km region that contains the apartment-complex c.

We use two sources of variation in our regression analysis. The first source of variation comes from the fact that we often observe transactions in the same apartment-complex for a streak of years before all units are sold out. We can therefore use a standard panel fixed effects regression strategy to compare transaction prices within the same complex, but across different years with high versus low pollution levels. In the first type of specification, we include apartment-complex fixed effects, year fixed effects, and "year-on-market" fixed effects (9 indicators, each indicates if year y is the apartment-complex's r^{th} year on market).

The second source of variation comes from our ability to observe fine-grained, cross-sectional variations in air pollution even within small geographic area. We observe about 1,200 apartment-complexes scattered in 180 zip codes across 16 districts in Beijing. We compare transaction prices within the same district $\times$ year, but across apartment-complexes in areas with high versus low pollution levels, controlling for time-invariant differences in zip code-level characteristics. Hence in the second type of specification, we include district $\times$ year fixed effects, zip code fixed effects, and year-on-market fixed effects.

The two specifications therefore exploit rather different sources of pollution variation, with the former focusing more on year-to-year variation within the same location, the latter focusing more on cross-sectional variation at a given point in time. To flexibly account for potential autocorrelation in both housing price and pollution across time and over space, we two-way cluster standard errors at the zip code level and the district $\times$ year level. We report equation 4 results in Table 2. Column 1 shows that a doubling of annual pollution corresponds to an insignificant 9% increase in housing prices. After the program, the price elasticity becomes negative and the change in elasticity captured by the coefficient on the interaction term between pollution and the program dummy is -59 percentage points and significant at the 10% confidence level. The results suggest that housing prices do not respond to variation in pollution levels before the program, while after the program, air quality is

[22] In Appendix Figure D.8, we illustrate the oversampling idea using two consecutive days of MODIS AOD data for the city of Beijing.

capitalized in housing prices.

In column 2, we examine the effect of lagged pollution in addition to current year's pollution exposure. We obtain similar results: a marginally significant -73 percentage points change in elasticity on current pollution, but a noisy effect from lagged pollution. Columns 3 and 4 correspond to our cross-sectional specification estimates. These specification yields a similar reduction-in-elasticity estimates of -85 percentage points.

Our cross-sectional estimates of housing price-pollution elasticity for the post-monitoring period therefore ranges from -0.6 to -0.8. This is somewhat larger than those obtained in the U.S. setting. For example, Chay and Greenstone (2005) exploits permanent reduction in Total Suspended Particle pollution (TSP) due to the 1970s U.S. Clean Air Act. They estimate a price-pollution elasticity of -0.25. Taking into account moving costs and variation in air quality across U.S. metro areas, Bayer, Keohane and Timmins (2009) show a price-pollution elasticity of roughly -0.34 to -0.42. Our estimates are similar to those obtained in China settings. In a hedonic regression exercise using Beijing's housing transactions and land parcel data, Zheng and Kahn (2008) find a price-PM elasticity of -0.41. In a recent residential-sorting exercise, Freeman et al. (2019) use moving costs and housing value information from China Population Census micro-level data to estimate a price-PM2.5 elasticity of -0.71 to -1.10.

Proximity to Major Polluters and Housing Prices. As a robustness to using the fine-scale AOD as the pollution measure, we estimate a price hedonic with respect to the unit's distance to the nearest major pollution sources (e.g., Davis, 2011; Currie et al., 2015; Muehlenbachs, Spiller and Timmins, 2015). We then examine how does the distance gradient shifts before versus after pollution disclosure. Although residents may not know the variation in pollution across fine geographic areas with a city or a district, the large polluters tend to be visible and well known landmarks in the city. The pollution disclosure could raise the salience of the potential health impacts of these large polluters in residents' housing choice decisions.

As described in section 2.2, our distance-gradient analysis begins with a set of major polluters we identify as always-there in Beijing from 2007 – 2018. By using census emission measure from 2007, we find 41 top-decile polluters that account for nearly 90% of total emissions (Appendix Figure D.9). Using geo-locations of these major polluters, we construct a time-invariant "distance to major polluter" variable at the apartment-complex level, and we use this variable to replace the ln Pollution_{cy} term in equation 4. We use the cross-sectional-style specification (district by year fixed effects, zip code fixed effects, and year-on-market fixed effects). We cannot perform the time-series specification as the distance measure is time-invariant which perfectly colinears with apartment-complex fixed effects. We control

additionally for distance to non-top-decile polluters in the regression.

Figure 9 presents the results. Figure 9a shows the estimates of distance gradients separately for periods before and after the information program. We detect no statistically significant distance gradient curve before the program. The shape of the curve shifted substantially after the program, where a near-monotonic price-distance relationship emerges. In panel Figure 9b, we estimate the difference version of Figure 9a to test the statistical precision of the change in distance gradient. Results show a relative reduction of housing value of about 27% for transactions within 3 km to the nearest major polluter. The effect fades with distance, and no effect is detected for regions over 6 km.

5.4 Pollution Disclosure and Health

Our previous analysis has documented a range of behavioral responses to the information program. To quantify the value of pollution information, our endpoint analysis is to examine if the same amount of pollution exposure is associated with fewer deaths after information becomes widely available. We regress logged mortality rate in county c × quarter t on the corresponding logged pollution level, while allowing the coefficient to vary by event quarter k, i.e., the k^{th} quarter since pollution monitoring:

$$\ln \text{Mortality}_{ct} = \sum_{k=-10}^{6} \beta_k \times \ln \text{Pollution}_{ct} \times \mathbb{1}(t = k) + \sum_{k=-10}^{6} \eta_k \times \mathbb{1}(t = k) + \mathrm{x}_{ct}'\gamma + \varepsilon_{ct} \quad (5)$$

We made several specification choices based on the nature of our data. First, we aggregate weekly mortality rate to quarterly to average out noises. However, we have checked that the qualitative findings are the same whether we conduct our analysis at weekly, monthly, or quarterly level, with the β_k estimates being slightly smaller using the weekly and monthly data. Second, we allow the β_k coefficients to vary from 10 quarters before to 6 quarters after disclosure to ensure a roughly balanced number of underlying counties for each event quarter.

Figure 10 plots the β_k coefficient estimates. We find that mortality-pollution elasticity exhibits a roughly flat trend before the program, followed by a decline after the program. In the graphical analysis, we condition the regression on city, quarter-of-year, and year fixed effects. We examine robustness of the results in Table 3 where, analogous to Tables 1, we experiment with stringency of our fixed effects controls, e.g., by including quarter-of-sample, or region × quarter-of-sample fixed effects dummies. The coefficient estimate on the interaction term between pollution and the program dummy suggests a statistically significant 5

percentage point reduction in the mortality-pollution elasticity after the program. The results are similar across specifications and consistent with the graphical evidence from Figure 10.

We explore patterns in heterogeneity analysis to provide suggestive evidence of underlying mechanism behind the mortality effect. We split the sample into above vs. below average values of a series of city-level characteristics, including per capita income, shares of urban population, per capita number of hospitals, per capita residential electricity use, and shares of mobile phone users. Table 4 reports the results where we focus on the interaction between the change-in-gradient "Log(Pollution) $\times$ $\mathbb{1}$(after monitoring)" coefficient and city-level characteristics. Column 1 shows there is virtually no effect heterogeneity by city's average income. Interesting patterns emerge when we examine more specific dimensions of heterogeneity. Columns 2 through 5 suggest large reduction (about -8 percentage points) in mortality damage in cities that are more urban, having more hospitals, having higher rate of residential electricity use, and with higher mobile phone penetration. These findings are broadly consistent with our view that information as well as defensive activity can help counteract health damages of air pollution exposure.

In the Appendix D, we conduct a series of additional tests to examine the plausibility of the reduction in the mortality-pollution elasticity estimates. First, Appendix Figure D.10a examines age-specific mortality rates we construct from our DSP extract. We find that the effect is most precisely estimated among people aged over 40 who are presumably more vulnerable to pollution exposure than younger age groups. There is no change in the mortality-pollution relationship for infant (less than one-year old), which may seem counterintuitive. Pollution exposure among infants is low to begin with because they stay mostly indoors.[23] Next, in Appendix Figure D.10b, we find that changes in the mortality-pollution relationship concentrate in cardio-respiratory causes, such as COPD, heart diseases, and cerebrovascular diseases, which are widely considered as most relevant consequences of pollution exposure. The impact on mortality-pollution relationship from respiratory infection and digestive diseases is both small and insignificant. For traffic fatalities, the relationship post disclosure appears to become flatter though the change is not statistically significant.[24] Third, we have explored non-linear specification and found that the reduction in the mortality-pollution gradient is insignificantly convex in the level of pollution shock (Appendix Figure D.11). Finally, we repeat the same randomized inference exercise as discussed in section 5.2, where we compare the true effect size to a distribution of placebo effect size obtained from 500 rep-

[23]Traditional Chinese practice of caring for newborns is to keep them strictly indoors within the first month of their birth and minimize the outdoor exposure.

[24]Air pollution could affect visibility as well as cognitive function (Zhang, Chen and Zhang, 2018), both of which could result in increased risk from traffic accidents.

etitions of random city roll-out assignment. Appendix Figure D.7b shows our effect estimate is significant at the 5% level.

6 The Value of Pollution Information

The value of information (VOI) arises from the power of information in changing decisions. Our analysis shows that information on pollution disclosure affected a range of behavioral and market outcomes that reflect consumers' effort to mitigate the negative health consequences of air pollution. We can measure the VOI as the fraction of pollution-caused deaths that can be avoided by providing information access, holding pollution exposure constant.[25] In our study context, a measure for VOI can be expressed as:

$$\text{VOI} = \frac{\epsilon_1 - \epsilon_0}{\epsilon_0} \tag{6}$$

which is is the ratio between the *change* in the mortality-pollution elasticity due to the program ($\epsilon_1 - \epsilon_0$) and the *level* of the mortality-pollution elasticity prior to the program (ϵ_0). The change coefficient corresponds to the interaction coefficient in Table 3. While the coefficient estimate on the "Log(Pollution)" main effect term has a level-of-elasticity interpretation, it is likely to be endogenous. The estimate with a counter-intuitive sign is similar to the OLS estimates in the literature from on the correlation between PM exposure and mortality in China (e.g., Yin et al., 2017; Ebenstein et al., 2017). Studies based on quasi-experimental methods have yielded much larger effect sizes in the right direction (e.g., Chen et al., 2013; He, Fan and Zhou, 2016; Ebenstein et al., 2017).

To get at the true level of ϵ_0, we use the main finding of a recent paper by Ebenstein et al. (2017) that examines the long-term mortality effects of PM exposure. We favor this study because it is based on well-established quasi-experimental method, also uses DSP as their primary mortality measurement, and it is based on years 2004-2012, which is before pollution disclosure took place. Using a regression discontinuity (RD) design that leverages a free coal-based heating policy available only to cities to the north of the Huai River, the authors find that PM_{10} just to the north of the river is roughly 41.7 ug/m3 (about 35%) higher, while the corresponding difference in all-cause mortality rate is 26%, suggesting a mortality-PM_{10} elasticity of 0.70. Assuming a linear dosage-response function, our estimate of a 5 percentage point reduction in the mortality-pollution elasticity therefore indicates a

[25] Mitigation could be in the form of shift the timing of activities, wearing face masks, using air purifiers at home, and moving to a clearer neighborhood or city. The cost of mitigation could vary and should be taken into account in order to estimate the net value of pollution information. We do not attempt to do it here given the large set of possible mitigation choices.

roughly 7% reduction in deaths attributable to the same pollution exposure.

With a slightly different sample period, we replicate the RD analysis in Ebenstein et al. (2017) and obtain very similar baseline mortality estimates as shown in Appendix Figure D.12 and Appendix Table D.6. Ebenstein et al. (2017) also report an OLS regression between logged cardio-respiratory mortality and logged PM_{10} exposure and yields an correlational elasticity estimate of 0.02, which is similar to our OLS estimate. In unreported analysis, we use the instrumental variable approach introduced in Barwick et al. (2018) that exploits long-range transport of pollution from upwind cities and obtain similar estimates on the baseline mortality impact.

To conceptualize the effect size, we note that under the assumption of linear mortality-pollution dose response function, the benefit of a 7% reduction in mortality-pollution elasticity is roughly the same with the benefit of a 7% reduction in pollution concentration. This corresponds to roughly 10 ug/m^3 reduction in PM_{10} or 5 ug/m^3 reduction in $PM_{2.5}$ in China. We perceive the effect size as moderate for several reasons. First, the effect size is moderate compared to the average cross-city variation in $PM_{2.5}$ after the program (SD = 20.4 ug/m^3, IQR = 25.2 ug/m^3). Second, the effect size is moderate compared several government programs that have been shown to shift pollution levels. For example, the winter heating policy implemented to the north of the Huai River is shown to increase PM_{10} by about 41.7 ug/m^3 (Ebenstein et al., 2017). Large-scale inspection and cleanup efforts across China since 2013 are associated with over 50 ug/m^3 reduction in $PM_{2.5}$ for some northern cities (Greenstone and Schwarz, 2018).

The information program brings meaningful economic and health benefits to the society. Using Ito and Zhang (2018)'s WTP estimate based on air purifier purchases in China, a 10 ug/m^3 reduction in PM_{10} is about RMB 90 ($13.4) per year, which aggregates to RMB 122 billion per year nationwide. In Barwick et al. (2018) , an individual saves RMB 38 ($5.7) in out-of-pocket health spending from a 5 ug/m^3 reduction in $PM_{2.5}$ exposure, aggregating to RMB 52 billion per year nationwide.

We then compare the benefits to financial costs associated with increased defensive and avoidance actions after the program. First, we observe that total sales of air purifiers ($PM_{2.5}$ masks) increased at a rate of RMB 7 (0.55) billion per year post 2013. Because many cities started the information program after 2013, we consider these numbers to be upper bounds on the costs of increased defensive investments due to the information program. Second, we consider forgone consumption due to pollution avoidance. From our bank-card analysis in section 5.2, we expect weekly purchase rate to reduce by about 20 purchases per 10,000 active cards post monitoring. In total, this translates into about 1.34 million fewer transactions per year. The average transaction in our data carries a value of about RMB 3,568. We therefore

estimate that the value of forgone transaction is about RMB 4.75 billion per year. Once again, we consider this number to be a likely upper bound on foregone consumption as some of these transactions are likely to be deferred rather than permanently foregone: as shown in section 5.2, the effect on bank-card use appears to concentrate on "deferrable" categories, many of which are highly temporally substitutable in nature (such as supermarkets trips). The cost of postponing/rescheduling of these (temporarily) foregone transactions is likely to be smaller than the value of these transactions. Summing up the costs numbers of defensive goods and forgone consumption, we conclude that the cost of the information program is around RMB 13 billion, which is an order of magnitude smaller than the health benefits.

7 Conclusion

This paper examines the role of pollution information in shaping how ambient air pollution affects household behavior and health outcomes. The focus is on a watershed policy change in China whereby air pollution monitoring stations are installed and real-time pollution information is made public by the government. Based on several rich and unique data sets, our analysis provides consistent evidence that the pollution monitoring and disclosure program led to a cascade of changes such as increased pollution access and awareness, more pronounced short- and long-term avoidance behavior, as well as muted pollution-health relationship. The findings suggest that the value of the program arising from improved health is an order of magnitude larger than its cost.

China's experience could offer an important lesson for other emerging and developing countries that are experiencing severe environmental challenges. The infrastructure for monitoring environmental quality and for information disclosure is often inadequate in those countries. As income rises, the demand for environmental quality increases in these countries and households are better able to adapt to the changing environment. Providing real-time pollution monitoring data, combined with effective dissemination infrastructure such as smartphones and internet that are now commonly available among developing countries, could prove to be a powerful tool to help households mitigate health damages from environmental pollution in other developing countries. In addition, while our study is in the context of environmental quality, the large-scale information program could offer guidance in better leveraging information provision to address issues related to food and nutrition, traffic safety, as well as risky health behaviors.

References

Akerlof, George A. 1970. "The Market for "Lemons": Quality Uncertainty and the Market Mechanism." *The Quarterly Journal of Economics*, 84(3): 488–500.

Allcott, Hunt. 2013. "The Welfare Effects of Misperceived Product Costs: Data and Calibrations from the Automobile Market." *American Economic Journal: Economic Policy*, 5(3): 30–66.

Andrews, Steven. 2008. "Inconsistencies in air quality metrics: 'Blue Sky' days and PM10 concentrations in Beijing." *Environmental Research Letters*, 034009(3).

Arceo, Eva, Rema Hanna, and Paulina Oliva. 2015. "Does the Effect of Pollution on Infant Mortality Differ Between Developing and Developed Countries? Evidence from Mexico City." *Economic Journal*, 126: 257–280.

Bai, Jie. 2018. "Melons as Lemons: Asymmetric Information, Consumer Learning and Quality Provision." Working Paper.

Banzhaf, H. Spencer, and Randall P. Walsh. 2008. "Do People Vote with Their Feet? An Empirical Test of Tiebout." *American Economic Review*, 98: 843–863.

Barwick, Panle Jia, Shanjun Li, Deyu Rao, and Nahim Bin Zahur. 2018. "The Morbidity Cost of Air Pollution: Evidence from the World's Largest Payment Network." NBER Working Paper.

Bayer, Patrick, Nate Keohane, and Christopher Timmins. 2009. "Migration and Hedonic Valuation: The Case of Air Quality." *Journal of Environmental Economics and Management*, 58: 1–14.

Bernheim, B. Douglas, and Antonio Rangel. 2009. "Beyond Revealed Preference: Choice-Theoretic Foundations for Behavioral Welfare Economics*." *The Quarterly Journal of Economics*, 124(1): 51–104.

Bernheim, B. Douglas, Andrey Fradkin, and Igor Popov. 2015. "The Welfare Economics of Default Options in 401(k) Plans." *American Economic Review*, 105(9): 2798–2837.

Bollinger, Bryan, Phillip Leslie, and Alan Sorensen. 2011. "Calorie posting in chain restaurants." *American Economic Journal: Economic Policy*, 3(1): 91–128.

Chay, Kenneth Y., and Michael Greenstone. 2005. "Does air quality matter? Evidence from the housing market." *Journal of political Economy*, 113(2): 376–424.

Chen, Shuai, Paulina Oliva, and Peng Zhang. 2017. "The Effect of Air Pollution on Migration: Evidence from China." NBER Working Paper No. 24036.

Chen, Yuyu, Avraham Ebenstein, Michael Greenstone, and Hongbin Li. 2013. "Evidence on the impact of sustained exposure to air pollution on life expectancy from China's Huai River policy." *Proceedings of the National Academy of Sciences*, 110: 12936–12941.

Chen, Yuyu, Ginger Jin, Naresh Kumar, and Guang Shi. 2012. "Gaming in Air Pollution Data? Lessons from China." *B.E. Journal of Economic Analysis Policy*, 3(12): e313 – e323.

Chetty, Raj, Adam Looney, and Kory Kroft. 2009. "Salience and Taxation: Theory and Evidence." *American Economic Review*, 99(4): 1145–77.

Craft, Erik D. 1998. "The Value of Weather Information Services for Nineteenth-Century Great Lakes Shipping." *American Economic Review*, 88(5): 1059–76.

Currie, Janet, Lucas Davis, Michael Greenstone, and Reed Walker. 2015. "Environmental Health Risks and Housing Values: Evidence from 1,600 Toxic Plant Openings and Closings." *American Economic Review*, 105(2): 678–709.

Cutter, W. Bowman, and Matthew Neidell. 2009. "Voluntary information programs and environmental regulation: Evidence from 'Spare the Air'." *Journal of Environmental Economics and Management*, 58(3): 253 – 265.

Davis, Lucas W. 2011. "The effect of power plants on local housing values and rents." *Review of Economics and Statistics*, 93(4): 1391–1402.

Deschenes, Olivier, Michael Greenstone, and Joseph Shapiro. 2017. "Defensive Investments and the Demand for Air Quality: Evidence from the NOx Budget Program." *American Economic Review*, 107(10): 2958–89.

Dranove, David, and Ginger Zhe Jin. 2010. "Quality Disclosure and Certification: Theory and Practice." *Journal of Economic Literature*, 48(4): 935–63.

Ebenstein, Avraham, Maoyong Fan, Michael Greenstone, Guojun He, and Maigeng Zhou. 2017. "New evidence on the impact of sustained exposure to air pollution on life expectancy from China's Huai River Policy." *Proceedings of the National Academy of Sciences*, 114: 10384–10389.

Fioletov, V. E., C. A. McLinden, N. Krotkov, M. D. Moran, and K. Yang. 2011. "Estimation of SO2 emissions using OMI retrievals." *Geophysical Research Letters*, 38(21).

Freeman, Richard, Wenquan Liang, Ran Song, and Christopher Timmins. 2019. "Willingness to pay for clean air in China." *Journal of Environmental Economics and Management*, 94: 188–216.

Ghanem, Dalia, and Junjie Zhang. 2014. "'Effortless Perfection:' Do Chinese cities manipulate air pollution data?" *Journal of Environmental Economics and Management*, 68(2): 203 – 225.

Graff Zivin, Joshua, and Matthew Neidell. 2009. "Days of haze: Environmental information disclosure and intertemporal avoidance behavior." *Journal of Environmental Economics and Management*, 58(2): 119–128.

Greenstone, Michael, and B. Kelsey Jack. 2015. "Envirodevonomics: A Research Agenda for an Emerging Field." *Journal of Economic Literature*, 53(1): 5–42.

Greenstone, Michael, and Patrick Schwarz. 2018. "Is China Winning its War on Pollution?" *Report from Energy Policy Institute at the University of Chicago*.

Greenstone, Michael, Guojun He, Ruixue Jia, and Tong Liu. 2019. "Can Technology Solve the Principal-Agent Problem? Evidence from Pollution Monitoring in China." Working Paper.

Grossman, Michael. 1972. "On the Concept of Health Capital and Demand for Health." *The Journal of Political Economy*, 80: 223–255.

Grossman, Sanford J., and Joseph E. Stiglitz. 1976. "Information and Competitive Price Systems." *The American Economic Review*, 66(2): 246–253.

Hao, Jiming, and Litao Wang. 2005. "Improving Urban Air Quality in China: Beijing Case Study." *Journal of the Air & Waste Management Association*, 55(9): 1298–1305.

Hastings, Justine S., and Jeffrey M. Weinstein. 2008. "Information, School Choice, and Academic Achievement: Evidence from Two Experiments*." *The Quarterly Journal of Economics*, 123(4): 1373–1414.

He, Guojun, Maoyong Fan, and Meigong Zhou. 2016. "The Effect of Air Pollution on Mortality in China: Evidence from the 2008 Beijing Olympic Games." *Journal of Environmental Economics and Management*. forthcoming.

Hilton, Ronald W. 1981. "The Determinants of Information Value: Synthesizing Some General Results." *Management Science*, 27(1): 57–64.

Hirshleifer, Jack. 1971. "The Private and Social Value of Information and the Reward to Inventive Activity." *The American Economic Review*, 61(4): 561–574.

Huang, Jing, Xiaochuan Pan, Xinbiao Guo, and Guoxing Li. 2018. "Health impact of China's Air Pollution Prevention and Control Action Plan: an analysis of national air quality monitoring and mortality data." *The Lancet Planetary Health*, 2(7): e313 – e323.

Ito, Koichiro. 2014. "Do Consumers Respond to Marginal or Average Price? Evidence from Nonlinear Electricity Pricing." *American Economic Review*, 104(2): 537–63.

Ito, Koichiro, and Shuang Zhang. 2018. "Willingness to Pay for Clean Air: Evidence from Air Purifier Markets in China." *Journal of Political Economcy*. forthcoming.

Jagnani, Maulik, Christopher Barrett, Yanyan Liu, and Liangzhi You. 2018. "Within-Season Producer Response to Warmer Temperatures: Defensive Investments by Kenyan Farmers." Working Paper.

Jessoe, Katrina, and David Rapson. 2014. "Knowledge Is (Less) Power: Experimental Evidence from Residential Energy Use." *American Economic Review*, 104(4): 1417–38.

Jin, Ginger Zhe, and Phillip Leslie. 2003. "The Effect of Information on Product Quality: Evidence from Restaurant Hygiene Grade Cards*." *The Quarterly Journal of Economics*, 118(2): 409–451.

Kling, Jeffrey R., Sendhil Mullainathan, Eldar Shafir, Lee C. Vermeulen, and Marian V. Wrobel. 2012. " Comparison Friction: Experimental Evidence from Medicare Drug Plans *." *The Quarterly Journal of Economics*, 127(1): 199–235.

Landrigan, Philip, Richard Fuller, Nereus J R Acosta, Olusoji Adeyi, Maureen Cropper, Alan Krupnick, Michael Greenstone, and et al. 2018. "The Lancet Commission on pollution and health." *The Lancet*, 391(10119): 462–512.

Lave, Lester B. 1963. "The Value of Better Weather Information to the Raisin Industry." *Econometrica*, 31(1/2): 151–164.

Liu, Mengdi, Ronald Shadbegian, and Bing Zhang. 2017. "Does environmental regulation affect labor demand in China? Evidence from the textile printing and dyeing industry." *Journal of Environmental Economics and Management*, 86: 277–294.

Mastromonaco, Ralph. 2015. "Do environmental right-to-know laws affect markets? Capitalization of information in the toxic release inventory." *Journal of Environmental Economics and Management*, 71: 54 – 70.

Muehlenbachs, Lucija, Elisheba Spiller, and Christopher Timmins. 2015. "The Housing Market Impacts of Shale Gas Development." *American Economic Review*, 105(12): 3633–59.

Nelson, Richard R., and Jr. Winter, Sidney G. 1964. "A Case Study in the Economics of Information and Coordination the Weather Forecasting System *." *The Quarterly Journal of Economics*, 78(3): 420–441.

Oberholzer-Gee, Felix, and Miki Mitsunari. 2006. "Information regulation: Do the victims of externalities pay attention?" *Journal of Regulatory Economics*, 30(2): 141–158.

Saberian, Soodeh, Anthony Heyes, and Nicholas Rivers. 2017. "Alerts work! Air quality warnings and cycling." *Resource and Energy Economics*, 49: 165 – 185.

Shin, Jeong-Shik. 1985. "Perception of Price When Price Information Is Costly: Evidence from Residential Electricity Demand." *The Review of Economics and Statistics*, 67(4): 591–598.

Shrader, Jeffrey. 2018. "Expectations and adaptation to environmental risks." Working Paper.

Smith, V. Kerry, and F. Reed Johnson. 1988. "How do Risk Perceptions Respond to Information? The Case of Radon." *The Review of Economics and Statistics*, 70(1): 1–8.

Stigler, George J. 1961. "The economics of information." *Journal of Political Economy*, 69(3): 213–225.

Stigler, George J. 1962. "Information in the Labor Market." *Journal of Political Economy*, 70(5): 94–105.

Streets, David G., Timothy Canty, Gregory R. Carmichael, Benjamin de Foy, Russell R. Dickerson, Bryan N. Duncan, David P. Edwards, John A. Haynes,

Daven K. Henze, Marc R. Houyoux, Daniel J. Jacob, Nickolay A. Krotkov, Lok N. Lamsal, Yang Liu, Zifeng Lu, Randall V. Martin, Gabriele G. Pfister, Robert W. Pinder, Ross J. Salawitch, and Kevin J. Wecht. 2013. "Emissions estimation from satellite retrievals: A review of current capability." *Atmospheric Environment*, 77: 1011 – 1042.

Sun, Cong, Matthew E. Kahn, and Siqi Zheng. 2017. "Self-protection investment exacerbates air pollution exposure inequality in urban China." *Ecological Economics*, 131: 468 – 474.

Tanaka, Shinsuke. 2015. "Environmental regulations on air pollution in China and their impact on infant mortality." *Journal of Health Economics*, 42: 90 – 103.

Van Donkelaar, Aaron, Randall V Martin, and Rokjin J Park. 2006. "Estimating ground-level PM2. 5 using aerosol optical depth determined from satellite remote sensing." *Journal of Geophysical Research: Atmospheres*, 111(D21).

Wang, Alex L. 2017. "Explaining environmental information disclosure in China." *Ecology LQ*, 44: 865.

Wichman, Casey J. 2017. "Information provision and consumer behavior: A natural experiment in billing frequency." *Journal of Public Economics*, 152: 13 – 33.

Yi, Honghong, Jiming Hao, and Xiaolong Tang. 2007. "Atmospheric environmental protection in China: Current status, developmental trend and research emphasis." *Energy Policy*, 35(2): 907 – 915.

Yin, Peng, Guojun He, Maoyong Fan, Kowk Yan Chiu, Maorong Fan, Chang Liu, An Xue, Tong Liu, Yuhang Pan, Quan Mu, et al. 2017. "Particulate air pollution and mortality in 38 of China's largest cities: time series analysis." *bmj*, 356: j667.

Zhang, Bing, Xiaolan Chen, and Huanxiu Guo. 2018. "Does central supervision enhance local environmental enforcement? Quasi-experimental evidence from China." *Journal of Public Economics*, 164: 70–90.

Zhang, Junjie, and Quan Mu. 2018. "Air pollution and defensive expenditures: Evidence from particulate-filtering facemasks." *Journal of Environmental Economics and Management*, 92: 517 – 536.

Zhang, Xin, Xi Chen, and Xiaobo Zhang. 2018. "The impact of exposure to air pollution on cognitive performance." *Proceedings of the National Academy of Sciences*, 115(37): 9193–9197.

Zheng, Siqi, and Matthew E Kahn. 2008. "Land and residential property markets in a booming economy: New evidence from Beijing." *Journal of Urban Economics*, 63(2): 743–757.

Zhou, Maigeng, Haidong Wang, Jun Zhu, Wanqing Chen, Linhong Wang, Shiwei Liu, Yichong Li, Lijun Wang, Yunning Liu, Peng Yin, et al. 2016. "Cause-specific mortality for 240 causes in China during 1990–2013: a systematic subnational analysis for

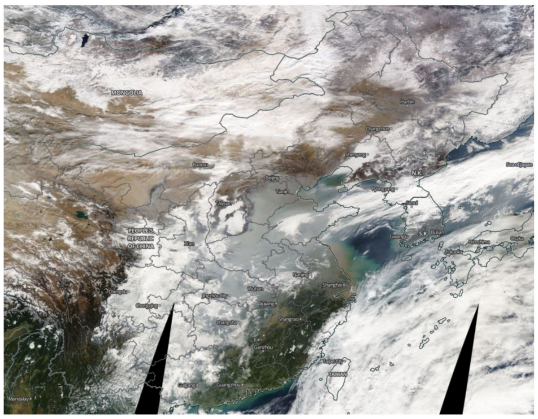
the Global Burden of Disease Study 2013." *The Lancet*, 387(10015): 251–272.

Zivin, Joshua Graff, and Matthew Neidell. 2009. "Days of haze: Environmental information disclosure and intertemporal avoidance behavior." *Journal of Environmental Economics and Management*, 58(2): 119 – 128.

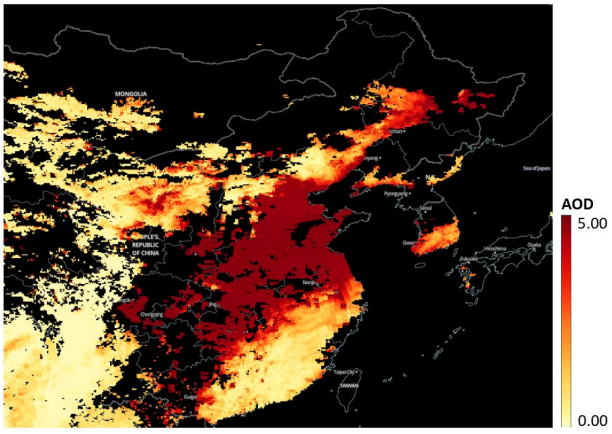
Figure 1: November 2011 "Widespread, Dense Fog Event"



(a) News coverage



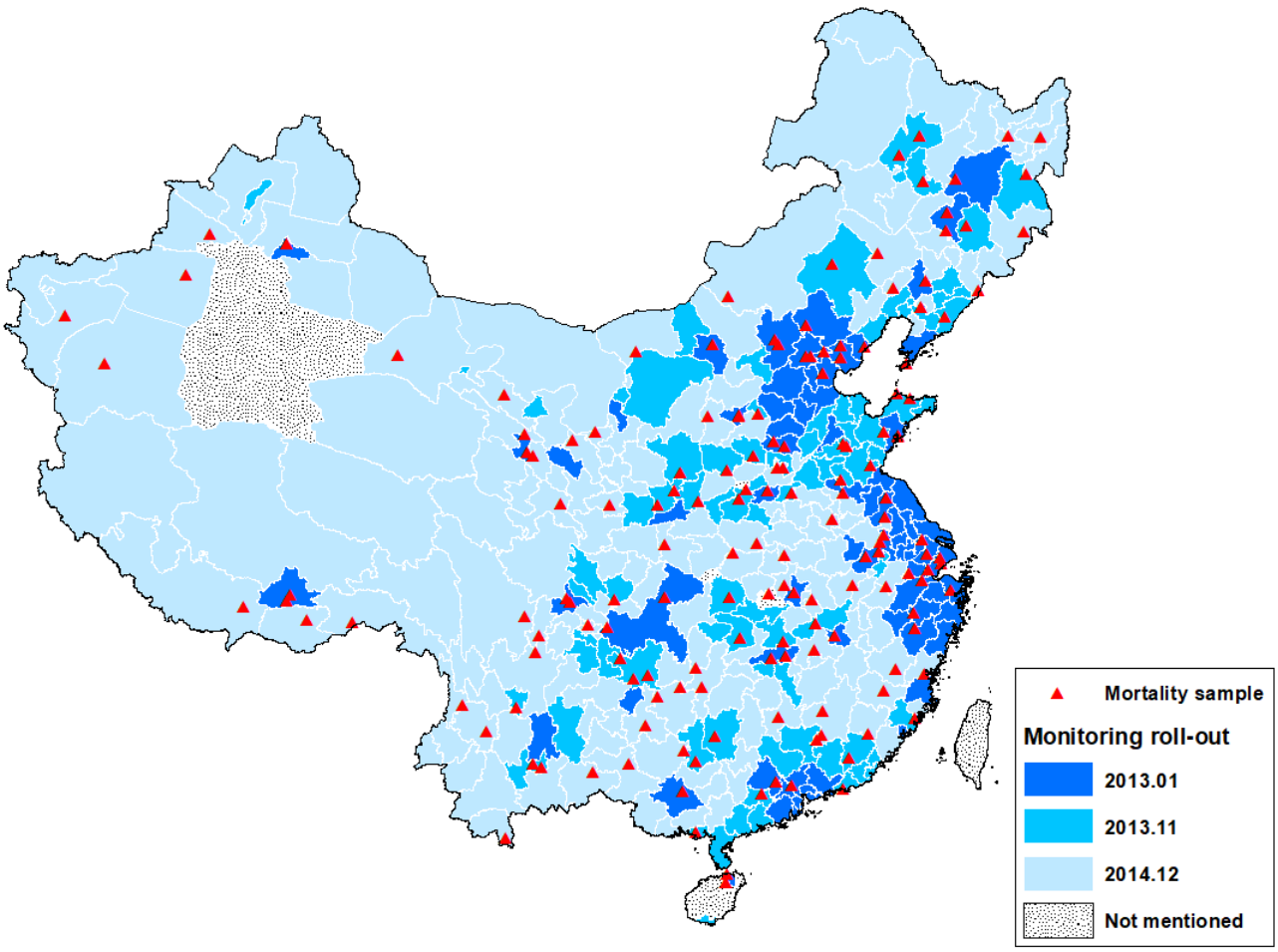
(b) Satellite picture of the event



(c) Satellite-retrieved pollution levels

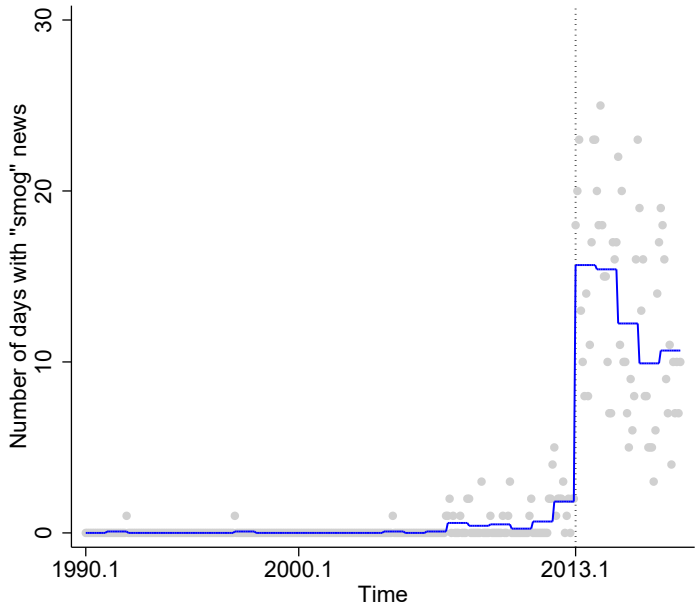
Notes: This figure illustrates a "widespread, dense fog event" around November 27, 2011 which is likely a major pollution event. Panel A, sourced from China Meteorological Administration, shows official news coverage of the event. Panel B, sourced from NASA, shows satellite views of China on the same day. Panel C, sourced from NASA MODIS algorithm, shows a measurement of satellite-based particulates pollution (aerosol optical depth) levels.

Figure 2: Air Pollution Monitoring Roll-out

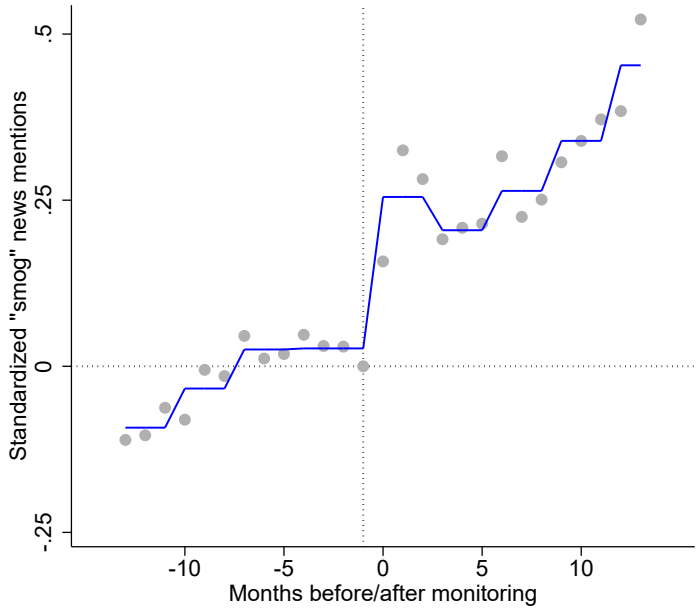


Notes: This map shows prefecture-city by the initiation date of real-time air pollution monitoring. "Not mentioned" are cities where the timing of monitoring is not mentioned in the government's policy notice. "Mortality sample" are centroids of counties included in the DSP mortality data.

Figure 3: Changes in Pollution Information Exposure: News



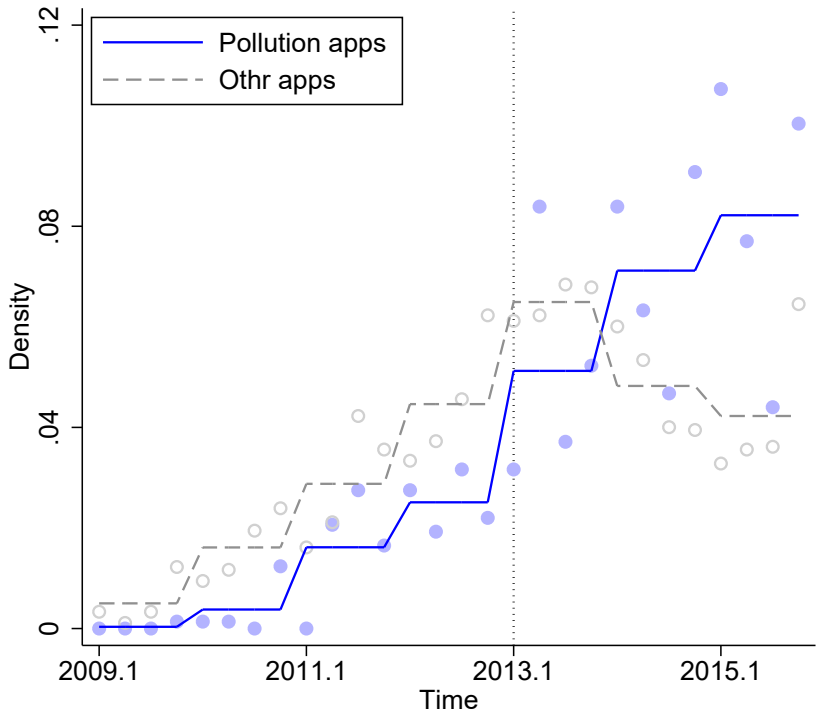
(a) *People's Daily* news "smog" mention



(b) "Smog" mentions before and after monitoring

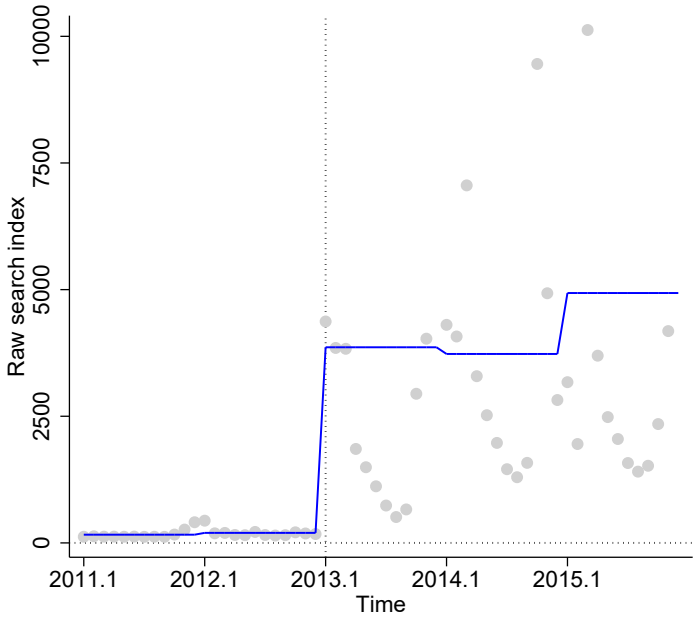
Notes: Panel A plots the number of days in each month when the *People's Daily* (official newspaper of the Chinese government) published articles containing "smog" in content. Each dot represents a month. Line shows annual averages. Panel B mean standardized "smog" mentions associated with the city, defined as news that mention both "smog" and the city name, as a function of month since monitoring initiation. Event month -1 is normalized to 0. The underlying regression controls for month-of-year and year indicators. Line shows quarterly averages.

Figure 4: Changes in Pollution Information Exposure: Mobile Phone Apps

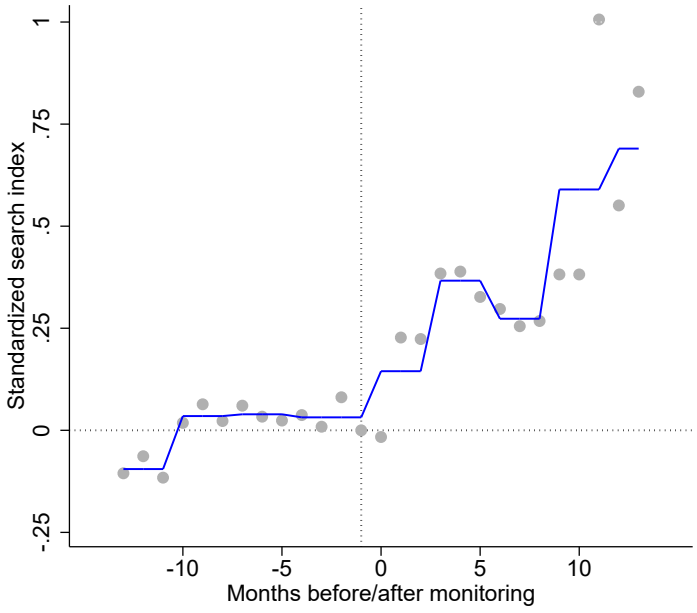


Notes: This chart shows release-date distribution of Apple App Store apps related to pollution (solid dots and line). Averaged release-time distribution for apps in other categories (dashed dots and line) includes game, music, video, reading, finance, sports, education, shopping, and navigation. For each category, sample is restricted to the first 200 apps returned by the Apple API given the search key. Data are accessed on December 27, 2015.

Figure 5: Changes in Pollution Awareness



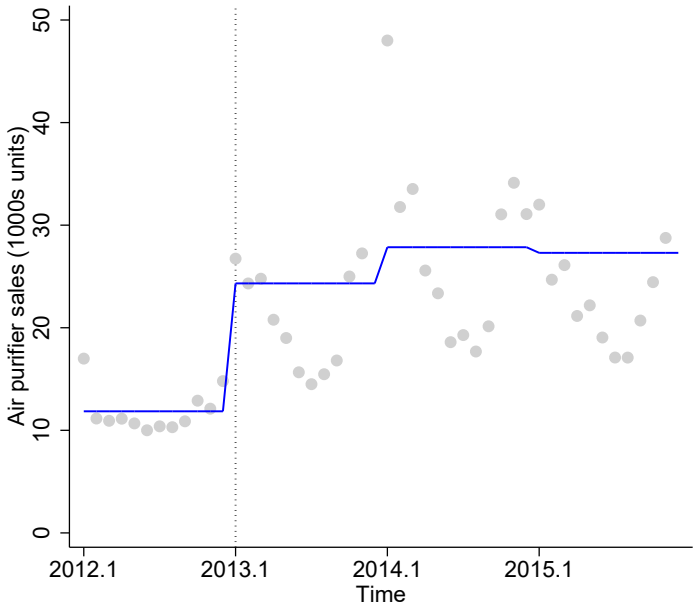
(a) Baidu search index for "smog"



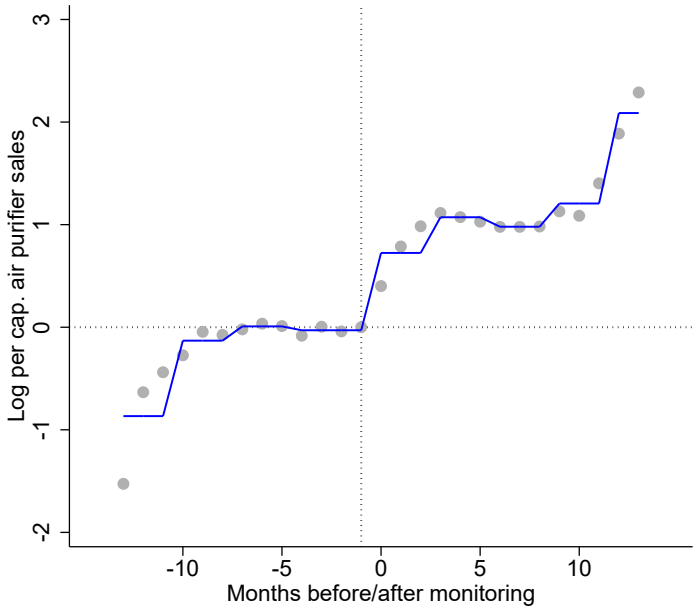
(b) "Smog" search index before and after monitoring

Notes: Panel A plots raw monthly trends in Baidu Search Index for the word "smog". The graph omits two dots with exceptionally high search index for readability purpose. These dots correspond to December 2013 (index = 20,942) and Decembet 2015 (index = 24,679). Line shows annual averages. Panel B plots mean standardized "smog" search index as a function of months since monitoring initiation. Event month -1 is normalized to 0. The underlying regression controls for month-of-year and year indicators. Line shows quarterly averages.

Figure 6: Changes in Air Purifier Sales (50 Cities)



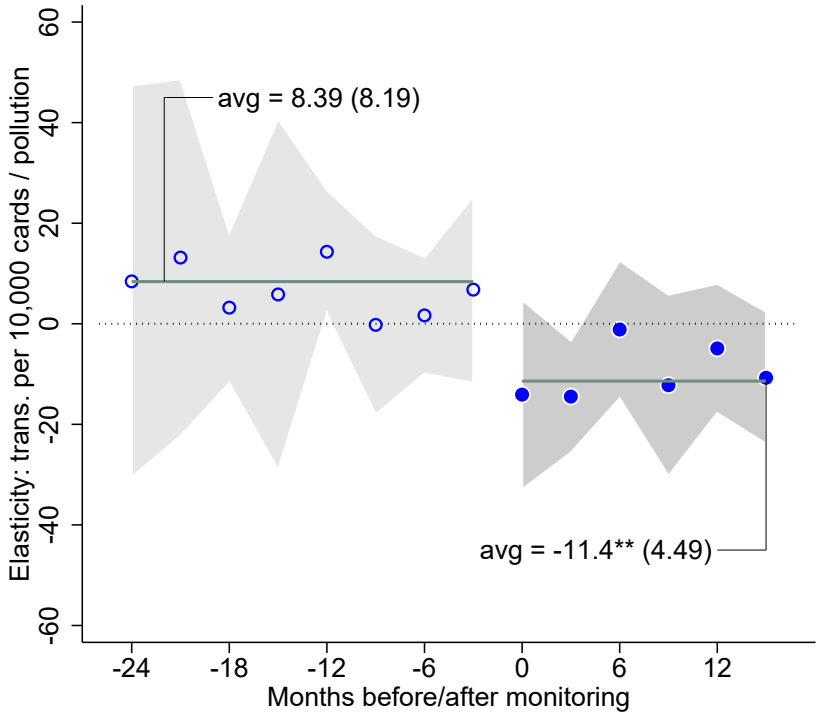
(a) Total air purifier sales



(b) Air purifier sales before and after monitoring

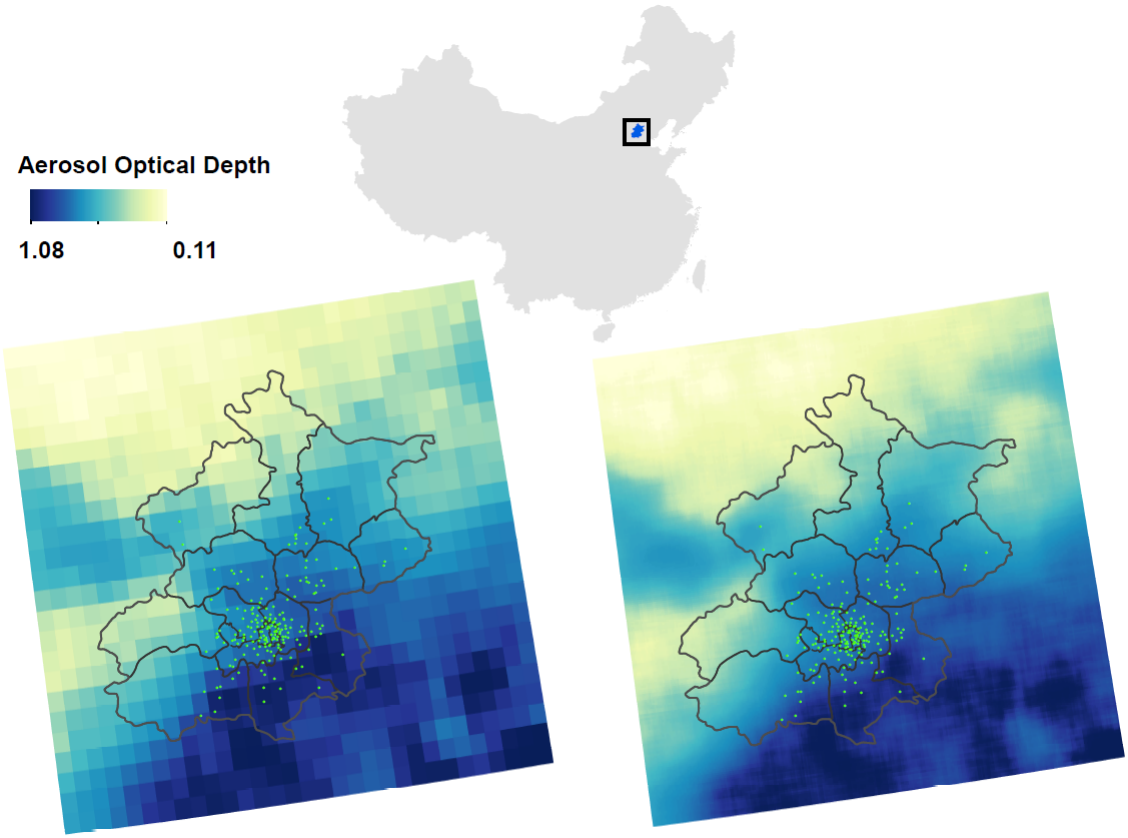
Notes: Panel A plots raw monthly trends in total air purifier sales from offline venues. The graph omits two dots with exceptionally high sales for readability purpose. These dots correspond to December 2013 (sales = 61,605 units) and Decembet 2015 (sales = 74,352 units). Line shows annual averages. Panel B plots log per capita air purifier sales as a function of months since monitoring initiation. Event month -1 is normalized to 0. The underlying regression controls for month-of-year and year indicators. Line shows quarterly averages.

Figure 7: Changes in Weekly Bank Card Transaction-Pollution Gradient



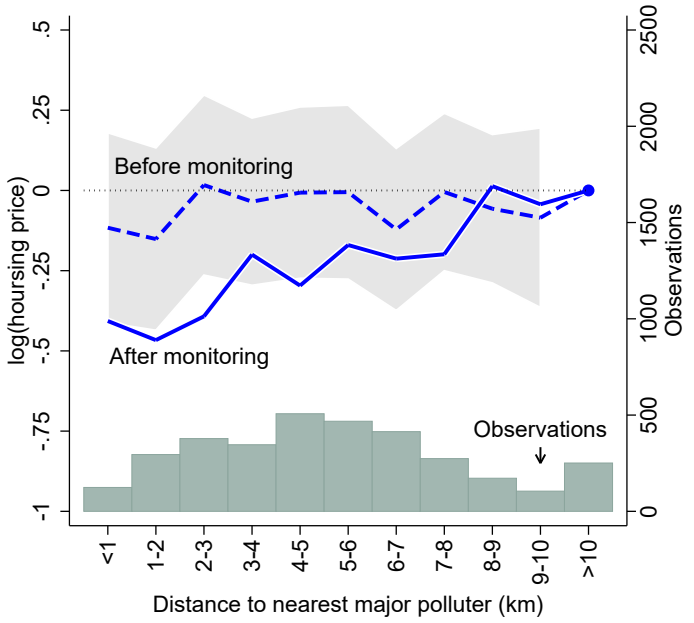
Notes: This graph shows the relationship between weekly bank card transcation rate and log satellite-based pollution as a function of time since monitoring initiation. The regression controls for prefectiry-city FEs, week-of-year FEs, and year FEs. "Avg" shows mean effect before and after monitoring began. Shaded region shows 95% confidence interval constructed from standard errors clustered at the prefecture-city level.

Figure 8: Original (10km) vs. Oversampled (1km) Aerosol Optical Depth, Beijing 2006-2014

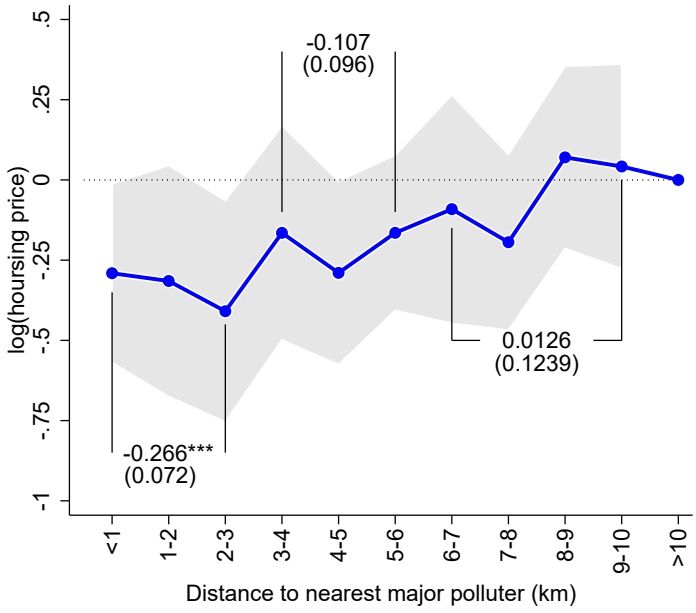


Notes: This map shows 2006-2014 average aerosol optical depth (AOD) level for the prefecture of Beijing. Left panel shows MODIS AOD at the original 10×10km resolution. Right panel shows AOD oversampled to 1×1km resolution. Dots show centroid locations of communities (i.e., "jiedao") in the housing transaction data.

Figure 9: Changes in Annual Housing Prices-Distance to Polluter Gradient, Beijing



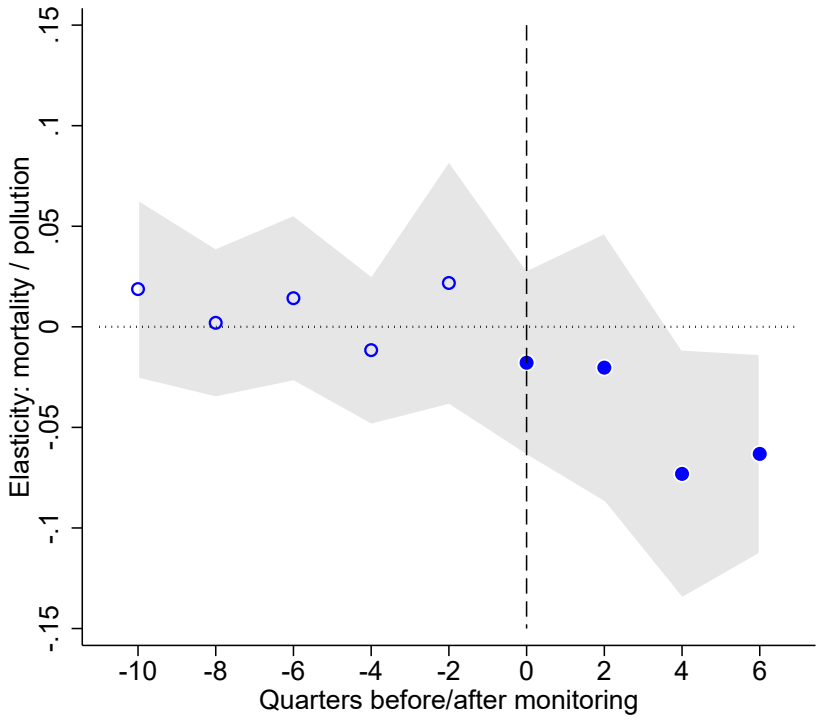
(a) Before vs. after monitoring



(b) Difference estimates

Notes: This graph shows coefficients from a regression of complex×annual log housing prices on distance (in 1-km bins) to nearest major polluter before and after January 2013 when Beijing initiated ambient pollution monitoring. In panel A, estimations are done separately for time before (dashed line) and after (solid line) monitoring began, with prices normalized to 0 for the >10-km bin. The histogram (right axis) plots total number of observations by distance bins. In panel B, the difference estimation pools before/after samples. All regressions control for district×year FEs, community FEs, and years-on-market FEs. Shaded region shows 95% confidence interval constructed from standard errors two-way clustered at the zip code level and the district×year level.

Figure 10: Changes in Quarterly Mortality-Pollution Gradient



Notes: This graph shows coefficients from a regression of log mortality rate on log satellite-based pollution as a function of quarters since monitoring initiation. The (-10 to 6) month event window is chosen so that the underlying sample is a balanced panel of cities. Coefficients are obtained from a single regression, controlling for prefectiry-city FEs, quarter-of-year FEs, and year FEs. Shaded region shows 95% confidence interval constructed from standard errors clustered at the prefecture-city level.

Table 1: Changes in Weekly Bank Card Transaction-Pollution Gradient

Dep. var.: Number of transactions per 10,000 active cards in a city×week				
	(1)	(2)	(3)	(4)
Log(Pollution)	8.39	6.07	7.96	10.3
	(8.19)	(8.78)	(5.75)	(7.20)
Log(Pollution) × 1(after monitoring)	-19.8**	-22.8**	-19.4**	-25.1**
	(8.67)	(10.8)	(7.77)	(10.1)
FEs: city	✓	✓	✓	✓
FEs: week-of-year	✓			
FEs: year	✓			
FEs: week-of-sample		✓	✓	
FEs: region×year			✓	
FEs: region×week-of-sample				✓
N	83,122	83,122	83,122	83,122

Notes: "Log(Pollution)" is logged AOD in the city×week. Mean of dependent variable is 869.1 transactions per week per 10,000 cards. "region" is a conventional partition of cities by location: North (36 cities), Northeast (38 cities), East (105 cities), Centralsouth (81 cities), Southwest (54 cities), Northwest (52 cities). Standard errors are clustered at the prefecture-city level. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Table 2: Changes in Beijing's Housing Price-Pollution Gradient

Dep. var.: Log housing price index in a complex×year				
	(1)	(2)	(3)	(4)
Identifying variation:	Within complex across years		Within district×year across communities	
Log(pollution)	0.090	0.063	0.009	-0.103
	(0.104)	(0.121)	(0.239)	(0.244)
Log(lagged pollution)		0.034		0.335
		(0.124)		(0.216)
Log(pollution)×1(after 2013)	-0.591*	-0.730*	-0.850*	-0.753*
	(0.299)	(0.434)	(0.436)	(0.432)
Log(lagged pollution)×1(after 2013)		-0.377		-0.216
		(0.490)		(0.754)
FEs: complex	✓	✓		
FEs: year	✓	✓		
FEs: years on-market	✓	✓	✓	✓
FEs: zip code			✓	✓
FEs: district×year			✓	✓
N	3,372	2,715	3,827	3,266
N (complex)	988	801	1,224	1,129
N (zip code)	179	167	180	172
N (district)	16	16	16	16

Notes: A complex is a real estate project site that often contains multiple buildings. The dependent variable is logged nominal housing price adjusted for quadratic floor size, floor indicators, and sale month-of-year indicators. "Log(pollution)" is logged AOD level at the (oversampled) 1km resolution corresponding to the complex's geographic coordinates. Standard errors are two-way clustered at the zip code (i.e., "jiedao") level and the district×year level. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Table 3: Changes in Quarterly Mortality-Pollution Gradient

Dep. var.: Log mortality rate in a city×quarter				
	(1)	(2)	(3)	(4)
Log(Pollution)	0.014	0.034	0.039*	0.041*
	(0.019)	(0.021)	(0.020)	(0.023)
Log(Pollution) × 1(after monitoring)	-0.048***	-0.055***	-0.055***	-0.046**
	(0.017)	(0.020)	(0.021)	(0.021)
FEs: city	✓	✓	✓	✓
FEs: quarter-of-year	✓			
FEs: year	✓			
FEs: quarter-of-sample		✓	✓	
FEs: region×year			✓	
FEs: region×quarter-of-sample				✓
N	2,620	2,620	2,620	2,620

Notes: "Log(Pollution)" is logged AOD in the city×quarter. "region" is a conventional partition of cities by location: North (36 cities), Northeast (38 cities), East (105 cities), Centralsouth (81 cities), Southwest (54 cities), Northwest (52 cities). Standard errors are clustered at the prefecture-city level. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Table 4: Changes in Mortality-Pollution Gradient: Heterogeneity by City Characteristics

Dep. var.: Log mortality rate in a city×quarter					
	(1)	(2)	(3)	(4)	(5)
City characteristics:	Per cap. income	Frac. urban	Per cap. hospitals	Per cap. residential electricity	Per cap. mobile phones
Log(Pollution) × 1(after monitoring)	-0.052**	-0.032	-0.036	-0.015	-0.025
× 1(below average)	(0.023)	(0.020)	(0.026)	(0.025)	(0.020)
Log(Pollution) × 1(after monitoring)	-0.046	-0.081***	-0.066***	-0.073*	-0.080**
× 1(above average)	(0.029)	(0.030)	(0.021)	(0.044)	(0.035)
Equality $p-$value	0.888	0.139	0.348	0.246	0.145
N	2,560	2,220	2,220	2,120	2,220

Notes: This table reports heterogeneous mortality-pollution gradient changes by above/below average city characteristics. Each column corresponds to a separate regression: column 1 = per capita personal dispensable income; column 2 = share of urban population; column 3 = per capita number of hospitals; column 4 = per capita residential electricity use; column 5 = share of mobile phone users. "Equality $p-$value" tests for equality across the above/below average coefficients. All regressions control for city, month-of-sample, and region-by-year fixed effects. All regressions include full sets of lower-order interaction terms which are not reported in the table in the interest of space. Standard errors are clustered at the prefecture-city level. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Appendices. For Online Publication Only

Appendix A: Proof of Proposition 1

Individuals choose optimal consumption x and defensive investment a to maximize utility under the perceived pollution level c_0 as described in Section 3.1. The Lagrangian equation is:

$$L = U(x, h(c_0, a)) + \lambda \left[I + w * g(h(c_0, a)) - x - p_a * a \right]$$

where λ is the Lagrange multiplier and denotes the marginal utility per dollar. The first order conditions are:

$$\begin{aligned} &\frac{\partial L}{\partial x} = 0 \Rightarrow U_x - \lambda = 0 \\ &\frac{\partial L}{\partial a} = 0 \Rightarrow (U_h + \lambda * w * g_h) \frac{\partial h(c_0, a)}{\partial a} - \lambda p_a = 0 \\ &\frac{\partial L}{\partial \lambda} = 0 \Rightarrow I + w * g(h) - x - p_a * a = 0 \end{aligned} \tag{A.1}$$

where U_x, U_h, and g_h denote partial derivatives. We first show that under Assumptions 1-3, optimal avoidance (weakly) increases in perceived pollution:

$$\frac{da}{dc} \geq 0.$$

Let f denote the first order condition w.r.t avoidance (equation A.1):

$$f = (U_h + \lambda * w * g_h) \frac{\partial h}{\partial a} - \lambda p_a = 0$$

Applying the implicit function theorem to f, we obtain:

$$\frac{da}{dc} = -\frac{\partial f/\partial c}{\partial f/\partial a} = -\frac{[U_{hh} + \lambda * w * g_{hh}] * \frac{\partial h}{\partial c} * \frac{\partial h}{\partial a} + (U_h + \lambda * w * g_h) * \frac{\partial^2 h}{\partial a \partial c}}{(U_{hh} + \lambda * w * g_{hh}) * \left(\frac{\partial h}{\partial a}\right)^2 + (U_h + \lambda * w * g_h) * \frac{\partial^2 h}{\partial a^2}}$$
$$= -\frac{A+B}{C+D}$$

where U_{hx}, U_{hh}, g_{hh} are second order derivatives. Under the assumption of diminishing marginal utility, decreasing marginal labor product of health, and decreasing health benefit of avoidance, $C + D \leq 0$.[26] Similarly, $A + B \geq 0$. Hence, avoidance increases weakly in (perceived) pollution. The key assumption for this result is $dh^2/dadc > 0$. When pollution deteriorates, avoidance restores health more effectively (that is, the marginal benefit of avoidance is large with bad pollution). After the information program, individuals observe the actual pollution c, which is higher than previously perceived level: c_0. The above analysis indicates that individuals would increase the level of avoidance post the policy intervention:

$$a(c) \geq a(c_0).$$

As the marginal health benefit of avoidance is positive from Assumption (A1) in Section 3.1, the health condition improves with avoidance:

$$h(c, a(c)) \geq h(c, a(c_0)).$$

Due to the lack of real-time information on pollution prior to the information program, perceived pollution c_0 is unlikely to respond to day-to-day changes in the actual pollution. Hence, the total derivative of health w.r.t. pollution is:

$$\frac{dh}{dc}\,|_{c_0} = \frac{\partial h}{\partial c} + \frac{\partial h}{\partial a} * \frac{da}{dc_0} * \frac{dc_0}{dc} = \frac{\partial h}{\partial c}$$

[26] At the optimal a and X, $U_h + \lambda * w * g(h) > 0$ by construction. In addition, $U_{hh}, g_{hh}, \partial^2 h/\partial a^2 < 0$. Another way to show $C + D \leq 0$ is that this is the second order condition for the optimal a.

where the second equation follows from the fact that $dc_0/dc = 0$. Post the information program, the perceived pollution is equal to the actual pollution and individuals can engage in effective avoidance to moderate the negative impact of pollution. The total derivative of health w.r.t. pollution is:

$$\frac{dh}{dc} \mid_c = \frac{\partial h}{\partial c} + \frac{\partial h}{\partial a} * \frac{da}{dc} \geq \frac{\partial h}{\partial c}$$

The second line follows from the fact that avoidance increases in (perceived) pollution and improves the health stock.

Lastly, let $V(c, c)$ denote the indirect utility when individuals accurately perceive pollution $c_0 = c$. In that case, the experience utility and decision utility coincides. $V(c, c_0)$ is the utility achieved by maximizing the decision utility under perceived pollution of c_0. Since utility is maximized under full information, we have:

$$V(c, c) \geq V(c, c_0).$$

Putting these together, we derive the following predictions of the information program:

- Avoidance behavior increases after the program: $a(c) > a(c_0)$
- Health improves and the (downward slopping) health-pollution response curve flattens:

$$h(c, a(c)) > h(c, a(c_0)), \frac{dh}{dc}|_{c_0=c} \geq \frac{dh}{dc}_{c_0<c}$$

- Individual utility increases: $V(c, c) > V(c, c_0)$

Appendix B: A Simple Example

Suppose the health production function is:

$$h(c,a) = \max\{0, h_0 - \frac{c}{a}\}, \quad h_c > 0, c > 0, a > 0$$

where h_0 is the initial health stock with zero pollution, c is pollution and a is avoidance. Assume that the labor production function is an identify function: $g(h) = h$. The budget constraint is:

$$I + w * h(c,a) \geq x + p_a * a$$

Suppose the utility function is:

$$U(x,h) = x$$

These functions satisfy Assumptions 1 and 2. In this simple example, maximizing utility subject to the budget constraint is equivalent to choosing a to maximize the amount of numeraire that can be afforded by the budget constraint:

$$\max_a I + w * h(c,a) - p_a * a$$

The optimal avoidance a satisfies:

$$a^* = \min\{\sqrt{\frac{w*c}{p_a}}, \frac{w*h_0}{p_a}\}$$

which (weakly) increases in c. Optimal health stock $h = \max\{0, h_0 - \sqrt{\frac{c*p_a}{w}}\}$ decreases in c and reaches the minimum of zero when pollution exceeds $\frac{w*h_0^2}{p_a}$. Consumption of the numeraire good and utility also decrease with c. When pollution exceeds $\frac{w*h_0^2}{p_a}$, the health stock is at the minimum, avoidance stops increasing in c and is kept at $\frac{w*h_0}{p_a}$. Consumption of the numeraire good also reaches the minimum level of $I - \sqrt{w*p_a}$. Finally, to ensure an interior solution, we need $I \geq \sqrt{w*p_a}$.

Appendix C: Identifying the Slope Change

To examine the impact of the information program om the pollution-outcome relationship, our analysis uses the following framework (simplifying notations in equation 1):

$$\mathrm{y}_{ct} = \alpha \times \mathrm{p}_{ct} + \beta \times \mathrm{p}_{ct} \times \mathrm{d}_{ct} + \mathrm{x}'_{ct}\gamma + \varepsilon_{ct}, \tag{C.2}$$

where c denotes a city and t denotes time (e.g., day or week). y_{ct} is the outcome variable. p_{ct} measures ambient air quality and could be correlated with the error term due to unobservables or measurement error as discussed in the main text. d_{ct} represents the treatment dummy and it turns to one in three waves across cities based on the staggered roll-out schedule. x_{ct} includes a set of controls including weather conditions and rich spatial and temporal fixed effects such as city fixed effects and time fixed effects. ε_{ct} is the error term. The key parameter of interest is β, the change in the slope of pollution-outcome relationship.

Although p_{ct} could be endogenous due to unobservables as discussed in the main text, the OLS estimate of β is consistent under the follow two assumptions.

Assumption (B1): $E\left(\varepsilon_{ct}|\mathrm{d}_{ct}, \mathrm{x}_{ct}\right) = 0.$

Assumption (B2): Pollution $\mathrm{p}_{ct} = \mathrm{x}'_{ct}\theta + \nu_{ct}$, where $E\left(v_{ct}|\mathrm{x}_{ct}\right) = 0$, and $E\left(\varepsilon_{ct}\nu_{ct}\right) = \sigma_{\varepsilon\nu}$.

Proof: We denote the set of regressors to be w'_{ct} as three blocks: $\left(\mathrm{x}'_{ct}, \mathrm{p}_{ct}, \mathrm{p}_{ct}\mathrm{d}_{ct}\right)$, where x_{ct} is a k by 1 vector of controls and w_{ct} is a (k+2) by 1 vector. Denote the vector of all parameters as η. For the OLS estimate $\hat{\eta}$: $\mathrm{plim}\hat{\eta} = \eta + [E(\mathrm{w}_{ct}\mathrm{w}'_{ct}]^{-1}[E(\mathrm{w}_{ct}\varepsilon_{ct})$.

The focus of our empirical analysis is β and in order to show that $\hat{\beta}$ is consistent, it suffices to show that the element in $[E(\mathrm{w}_{ct}\mathrm{w}'_{ct}]^{-1}[E(\mathrm{w}_{ct}\varepsilon_{ct})$ corresponding to the coefficient

for $d_i p_i$ is zero.

$$E(\mathrm{w}_{ct}\varepsilon_{ct}) = \begin{pmatrix} 0 \\ E\left(\mathrm{p}_{ct}\varepsilon_{ct}\right) \\ E\left(\mathrm{p}_{ct}\mathrm{d}_{ct}\varepsilon_{ct}\right) \end{pmatrix}, E(\mathrm{w}_{ct}\mathrm{w}'_{ct}) = \begin{pmatrix} E\left(\mathrm{x}_{ct}\mathrm{x}'_{ct}\right) & E\left(\mathrm{x}_{ct}\mathrm{p}_{ct}\right) & E\left(\mathrm{x}_{ct}\mathrm{p}_{ct}\mathrm{d}_{ct}\right) \\ E\left(\mathrm{p}_{ct}\mathrm{x}'_{ct}\right) & E\left(\mathrm{p}_{ct}^2\right) & E\left(\mathrm{p}_{ct}^2\mathrm{d}_{ct}\right) \\ E\left(\mathrm{p}_{ct}d_i\mathrm{x}'_{ct}\right) & E\left(\mathrm{p}_{ct}^2\mathrm{d}_{ct}\right) & E\left(\mathrm{p}_{ct}^2\mathrm{d}_{ct}^2\right) \end{pmatrix}.$$

$$E(\mathrm{w}_{ct}\mathrm{w}'_{ct})^{-1} = \frac{adj\left(E(\mathrm{w}_{ct}\mathrm{w}'_{ct})\right)}{\det(E(\mathrm{w}_{ct}\mathrm{w}'_{ct}))},$$

where $adj\left(E(\mathrm{w}_{ct}\mathrm{w}'_{ct})\right)$ is the transpose matrix of cofactors of $E(\mathrm{w}_{ct}\mathrm{w}'_{ct})$. To consider the OLS estimate of β, we only need to examine the cofactors corresponding to third column of the $E(\mathrm{w}_{ct}\mathrm{w}'_{ct})$. In particular,

$$\mathrm{plim}\beta - \beta = \frac{c_{23} * E\left(\mathrm{p}_{ct}\varepsilon_{ct}\right) + c_{33} * E\left(\mathrm{p}_{ct}\mathrm{d}_{ct}\varepsilon_{ct}\right)}{\det(E(\mathrm{w}_{ct}\mathrm{w}'_{ct}))}. \tag{C.3}$$

We now examine each component in the numerator of equation (C.3),

$$\begin{aligned} c_{23} &= -\det\begin{bmatrix} E\left(\mathrm{x}_{ct}\mathrm{x}'_{ct}\right)_{k\times k} & E\left(\mathrm{x}_{ct}\mathrm{p}_{ct}\mathrm{d}_{ct}\right)_{k\times 1} \\ E\left(\mathrm{p}_{ct}\mathrm{x}'_{ct}\right)_{1\times k} & E\left(\mathrm{p}_{ct}^2\mathrm{d}_{ct}\right)_{1\times 1} \end{bmatrix} \\ &= -\det\left(E\left(\mathrm{p}_{ct}^2\mathrm{d}_{ct}\right) - E\left(\mathrm{p}_{ct}\mathrm{x}'_{ct}\right)E\left(\mathrm{x}_{ct}\mathrm{x}'_{ct}\right)^{-1}E\left(\mathrm{x}_{ct}\mathrm{p}_{ct}\mathrm{d}_{ct}\right)\right)\det\left(E\left(\mathrm{x}_{ct}\mathrm{x}'_{ct}\right)\right) \\ c_{33} &= \det\begin{bmatrix} E\left(\mathrm{x}_{ct}\mathrm{x}'_{ct}\right)_{k\times k} & E\left(\mathrm{x}_{ct}\mathrm{p}_{ct}\right)_{k\times 1} \\ E\left(\mathrm{p}_{ct}\mathrm{x}'_{ct}\right)_{1\times k} & E\left(\mathrm{p}_{ct}^2\right)_{1\times 1} \end{bmatrix} \\ &= \det\left(E\left(\mathrm{p}_{ct}^2\right) - E\left(\mathrm{p}_{ct}\mathrm{x}'_{ct}\right)E\left(\mathrm{x}_{ct}\mathrm{x}'_{ct}\right)^{-1}E\left(\mathrm{x}_{ct}\mathrm{p}_{ct}\right)\right)\det\left(E\left(\mathrm{x}_{ct}\mathrm{x}'_{ct}\right)\right) \end{aligned}$$

$$
\begin{aligned}
E\left(\mathrm{x}_{ct}\mathrm{p}_{ct}\mathrm{d}_{ct}\right) &= E\left(\mathrm{x}_{ct}E\left(\mathrm{p}_{ct}\mathrm{d}_{ct}|\mathrm{x}_{ct}\right)\right) = E\left(\mathrm{x}_{ct}E\left(\mathrm{p}_{ct}|\mathrm{x}_{ct}\right)E\left(\mathrm{d}_{ct}|\mathrm{x}_{ct}\right)\right) = E\left(\mathrm{x}_{ct}\mathrm{x}_{ct}'E\left(\mathrm{d}_{ct}|\mathrm{x}_{ct}\right)\right)\theta \\
E\left(\mathrm{p}_{ct}\mathrm{x}_{ct}'\right) &= E\left(E\left(\mathrm{p}_{ct}|\mathrm{x}_{ct}\right)\mathrm{x}_{ct}'\right) = E\left(\theta'\mathrm{x}_{ct}\mathrm{x}_{ct}'\right) \\
E\left(\mathrm{x}_{ct}\mathrm{p}_{ct}\right) &= E\left(\mathrm{x}_{ct}E\left(\mathrm{p}_{ct}|\mathrm{x}_{ct}\right)\right) = E\left(\mathrm{x}_{ct}\mathrm{x}_{ct}'\theta\right) \\
E\left(\mathrm{p}_{ct}^2\mathrm{d}_{ct}\right) &= E\left(\left(\mathrm{x}_{ct}'\theta+\varepsilon_{ct}\right)^2\mathrm{d}_{ct}\right) = E\left(\mathrm{x}_{ct}'\theta\theta'\mathrm{x}_{ct}E\left(\mathrm{d}_{ct}|\mathrm{x}_{ct}\right)\right)+\sigma_\varepsilon^2E\left(\mathrm{d}_{ct}\right) \\
E\left(\mathrm{p}_{ct}^2\right) &= E\left(\left(\mathrm{x}_{ct}'\theta+\varepsilon_{ct}\right)^2\right) = E\left(\mathrm{x}_{ct}'\theta\theta'\mathrm{x}_{ct}\right)+\sigma_\varepsilon^2.
\end{aligned}
$$

Dropping the subscript for simplicity,

$$
\begin{aligned}
&E\left(\mathrm{p}^2\mathrm{d}\right)-E\left(\mathrm{px}'\right)E\left(\mathrm{xx}'\right)^{-1}E\left(\mathrm{xpd}\right) = E\left(\mathrm{x}'\theta\theta'\mathrm{x}E\left(\mathrm{d}|\mathrm{x}\right)\right)+\sigma_\varepsilon^2E\left(\mathrm{d}\right) \\
&-\theta'E\left(\mathrm{xx}'\right)E\left(\mathrm{xx}'\right)^{-1}E\left(\mathrm{xx}'E\left(\mathrm{d}|\mathrm{x}\right)\right)\theta = \sigma_\varepsilon^2E\left(\mathrm{d}\right).
\end{aligned}
$$

The last equality follows from the fact that $\mathrm{x}'\theta\theta'x$ is a scalar and equal to $\theta'\mathrm{xx}'\theta$.

$$
\begin{aligned}
E\left(\mathrm{p}^2\right)-E\left(\mathrm{px}'\right)E\left(\mathrm{xx}'\right)^{-1}E\left(\mathrm{xp}\right) &= E\left(\mathrm{x}'\theta\theta'\mathrm{x}\right)+\sigma_\varepsilon^2-\theta'E\left(\mathrm{xx}'\right)E\left(\mathrm{xx}'\right)^{-1}E\left(\mathrm{xx}'\right)\theta \\
&= \sigma_\varepsilon^2.
\end{aligned}
$$

Therefore, $c_{23} = -E\left(\mathrm{d}\right)\sigma_\varepsilon^2\det\left(E\left(\mathrm{xx}'\right)\right)$, and $c_{33} = \sigma_\varepsilon^2\det\left(E\left(\mathrm{xx}'\right)\right)$.

$$
\begin{aligned}
E\left(\mathrm{p}\varepsilon\right) &= E\left(\left(\mathrm{x}'\theta+v\right)\varepsilon\right) = \sigma_{ve} \\
E\left(\mathrm{pd}\varepsilon\right) &= E\left(\left(\mathrm{x}'\theta+v\right)\mathrm{d}\varepsilon\right) = E\left(\mathrm{x}'\mathrm{d}\varepsilon\right)\theta+E\left(v\mathrm{d}\varepsilon\right) \\
&= E\left[\mathrm{x}'\mathrm{d}E\left(\varepsilon|\mathrm{x},\mathrm{d}\right)\right]\theta+E\left[\mathrm{d}E\left(v\varepsilon|\mathrm{d}\right)\right] = \sigma_{ve}E\left(\mathrm{d}\right).
\end{aligned}
$$

Collecting terms, the consistency of OLS estimate of β follows:

$$
\mathrm{plim}\hat{\beta}-\beta = c_{23}E\left(\mathrm{p}\varepsilon\right)+c_{33}E\left(\mathrm{pd}\varepsilon\right) = \sigma_{ve}\left(c_{23}+c_{33}E\left(\mathrm{d}\right)\right) = 0.
$$

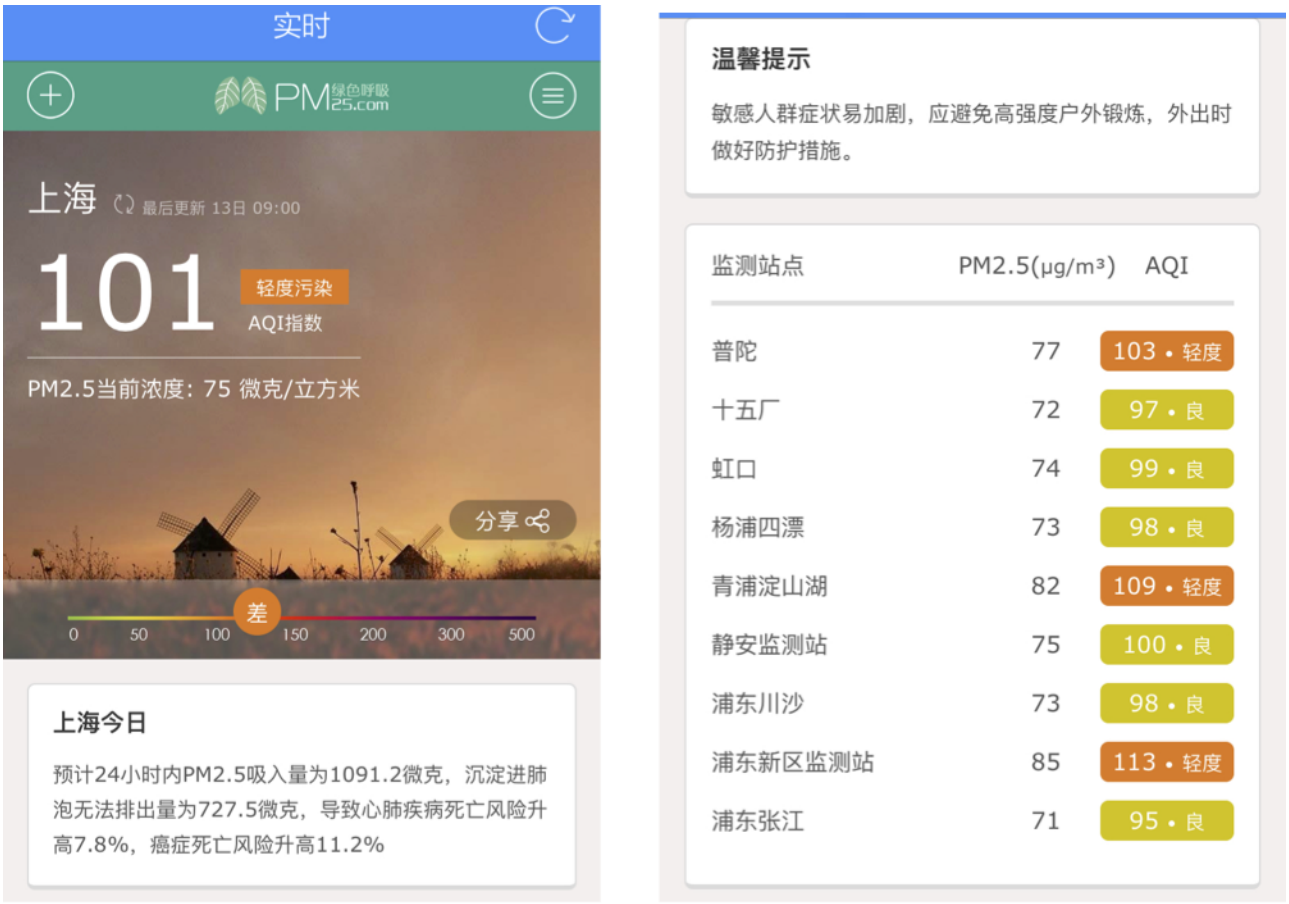
Appendix D: Figures and Tables

Figure D.1: Screenshot of the Government's Air Quality Disclosure Platform



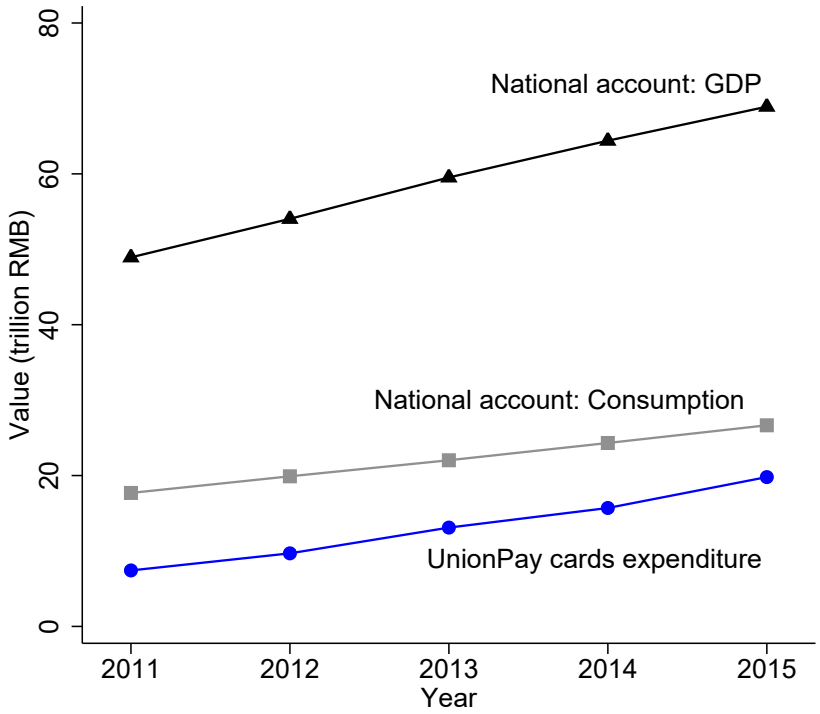
Notes: This figure shows a screenshot of the Ministry of Environmental Protection's real time air quality disclosure platform as of September 25, 2016.

Figure D.2: Screenshot of an Air Quality App



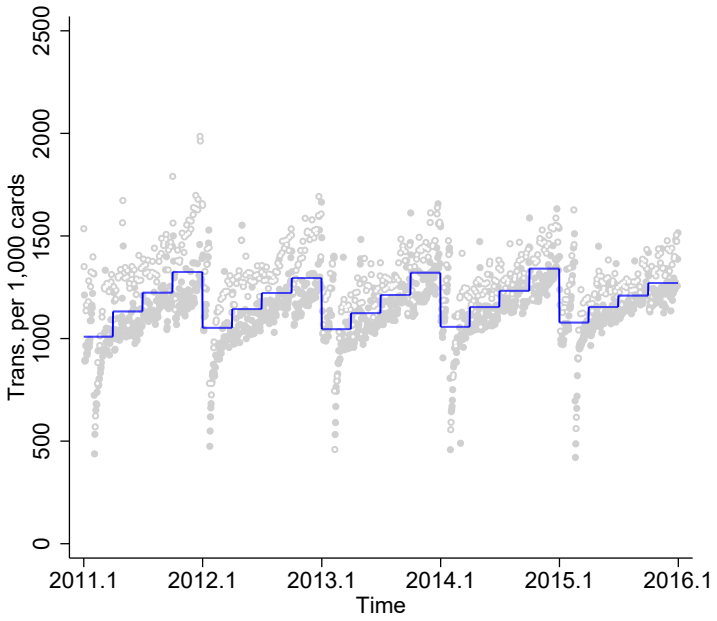
Notes: This figure shows a screenshot of a typical air quality app. The left panel shows the AQI in the city of Shanghai for that hour is 101 ($PM_{2.5}$=75 ug/m3). The right panel shows air quality readings at different locations within Shanghai.

Figure D.3: Consumption Trends: UnionPay vs. National Accounts

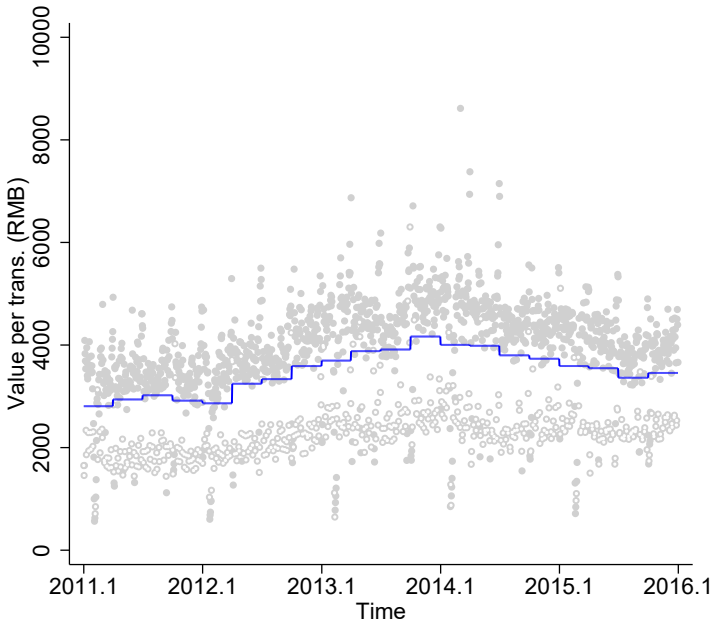


Notes: This figure plots annual GDP (triangles), consumption (squares) reported by the National Bureau of Statistics of China (NBS), and total bank card spendings $\times 100$ (circles) aggregated from the UnionPay 1% bank card data. UnionPay data excludes transactions in the business wholesale categories.

Figure D.4: UnionPay Bank Card Transaction Trends



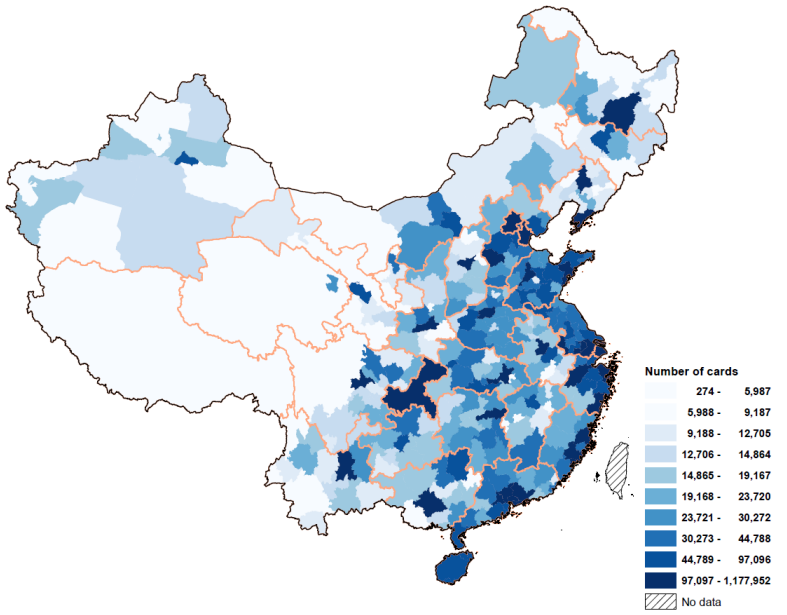
(a) Number of transactions per 100,000 cards



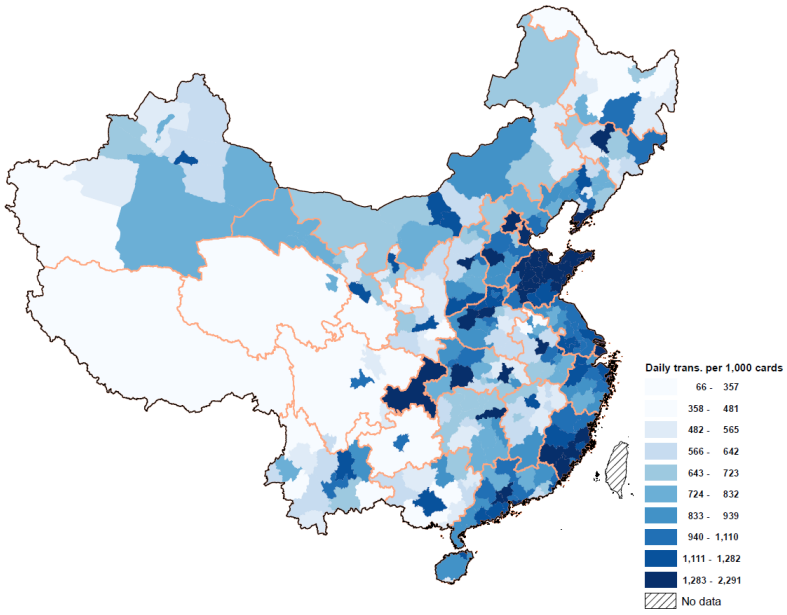
(b) Spending per transaction

Notes: Each dot represents transaction rate (panel A) and spending per transaction (panel B) on a day. Solid dots show weekdays and hollow dots show weekends. Lines show quarterly averages.

Figure D.5: UnionPay Bank Card Transaction by Prefecture-City, 2011-2015 Average



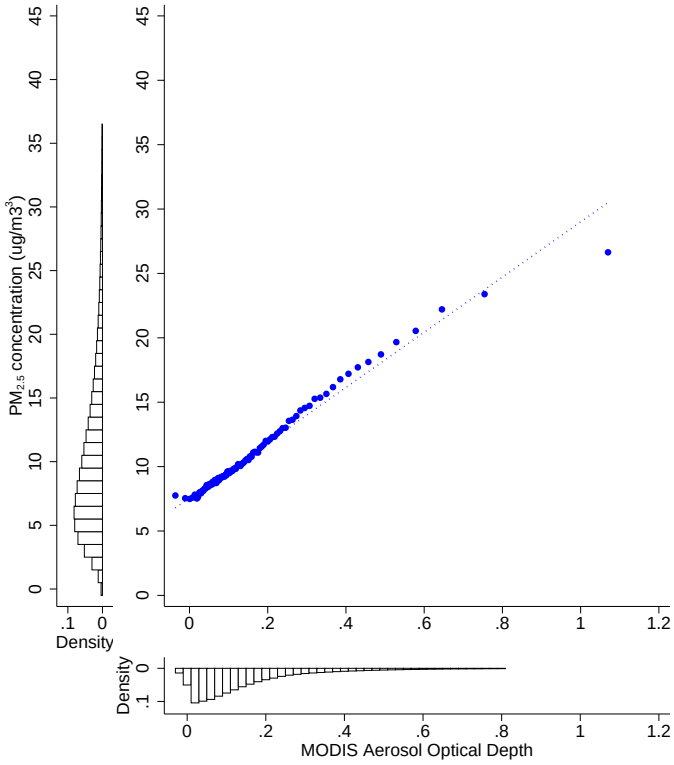
(a) Number of active cards



(b) Number of transactions per 100,000 cards

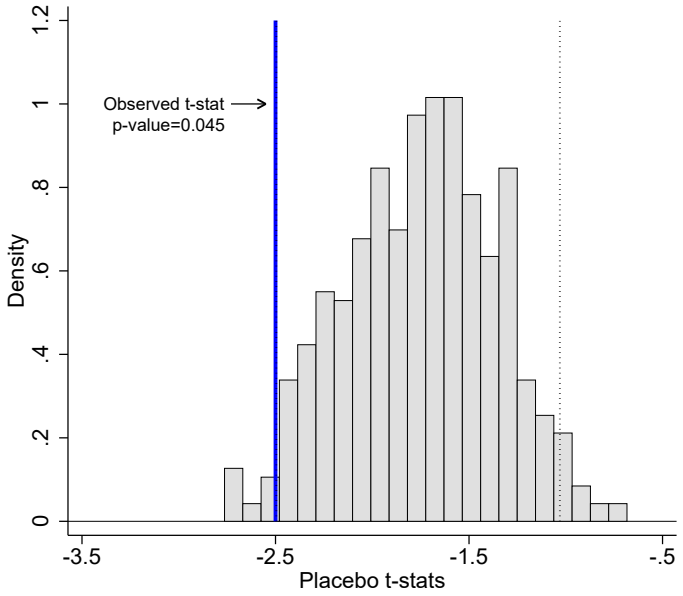
Notes: The maps show 2011-2015 average number of active UnionPay bank cards (panel A) and transactions per 1,000 cards (panel B) at the prefecture-city level. Orange lines show inter-provincial borders.

Figure D.6: Correlation between $PM_{2.5}$ and AOD

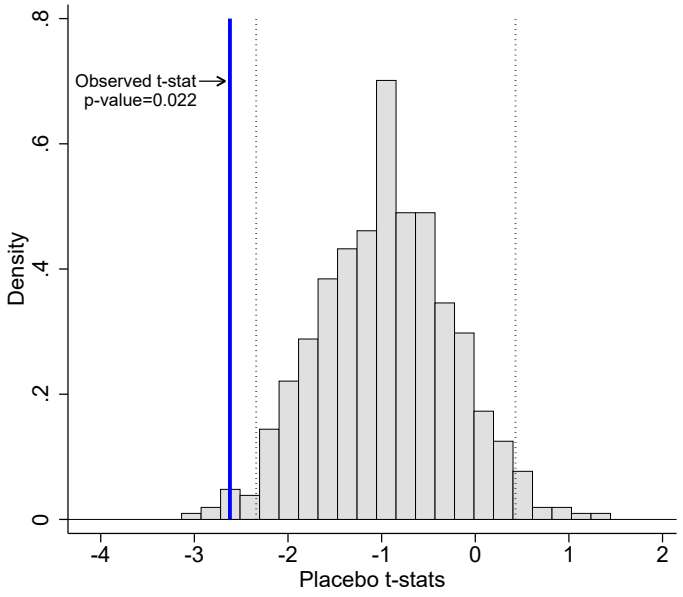


Notes: This graph shows city×day level average $PM_{2.5}$ concentratoin (y-axis) by 100 equal bins of AOD (x-axis), for time periods after monitoring began. Histograms show distribution of the two variables.

Figure D.7: Permutation Tests of the Effect of Monitoring



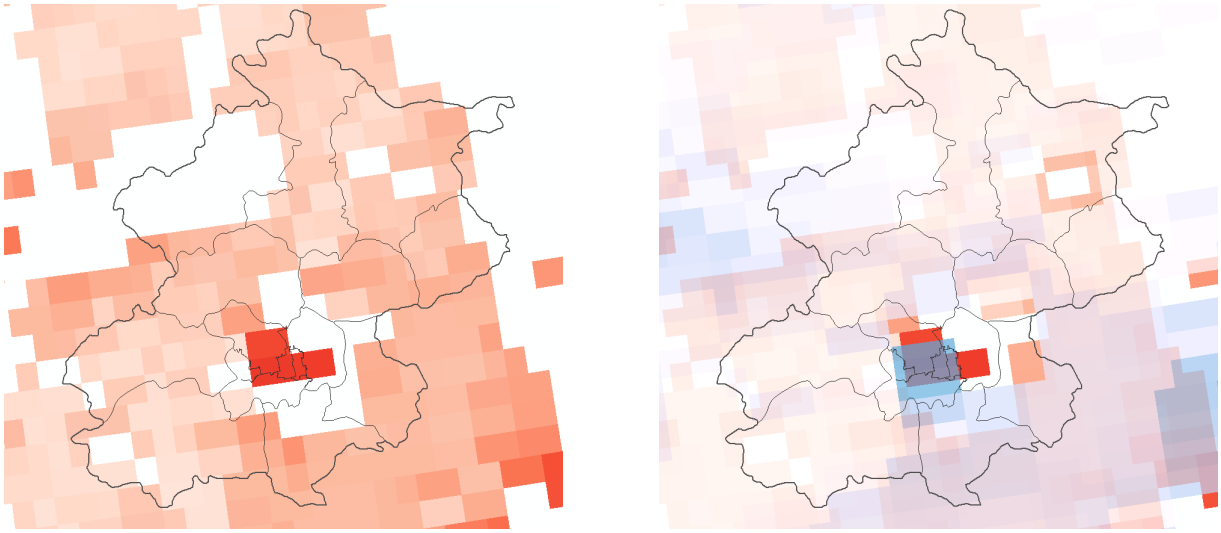
(a) Changes in bank card transaction-pollution gradient



(b) Changes in mortality-pollution gradient

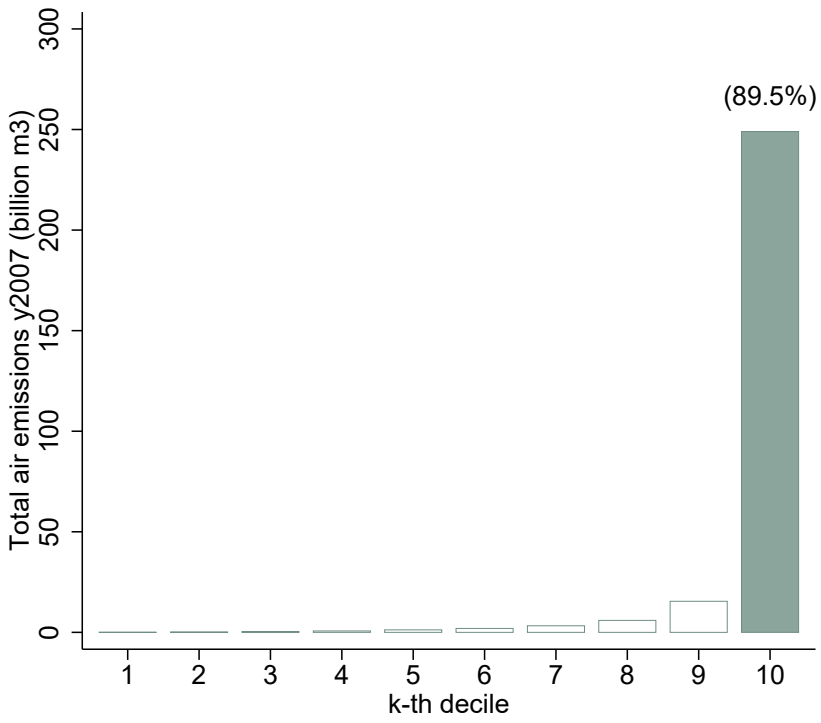
Notes: This plot shows the distribution of t-stats on the "Log(Pollution)$\times\mathbb{1}$(after monitoring)" term across 500 repetitions of random assignment of cities into information roll-out waves. Dashed vertical lines show 95% critical values of the distribution. Solid vertical line shows the observed t-stat from the true city assignment. The regression includes prefecture-city FEs, week(quarter)-of-sample FEs, and region$\times$year FEs. Standard errors are clustered at the city level.

Figure D.8: Illustration: Satellite AOD Oversampling



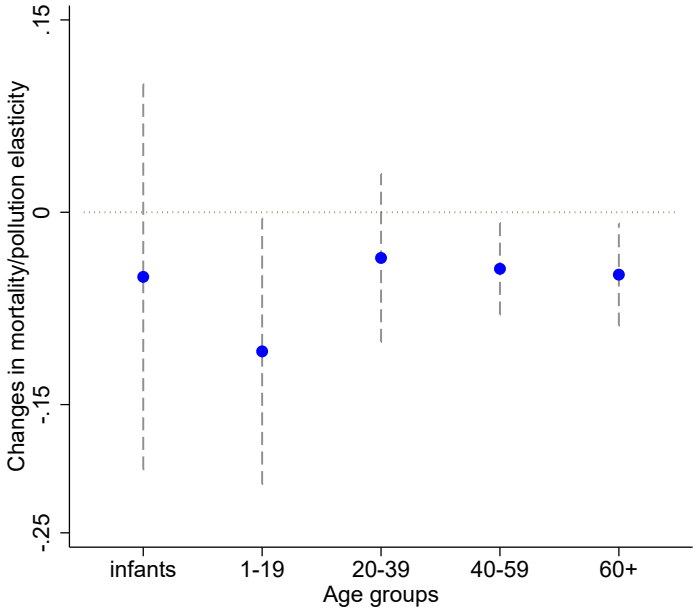
Notes: Left panel shows original MODIS AOD (10×10km) around Beijing on y2008 d243 (i.e., August 30, 2008). Right panel shows an overlay with data on y2008 d244. In both panels, darker colors indicate higher pollution levels.

Figure D.9: Total Air Emissions by Emission Deciles, Beijing Polluter Census 2007

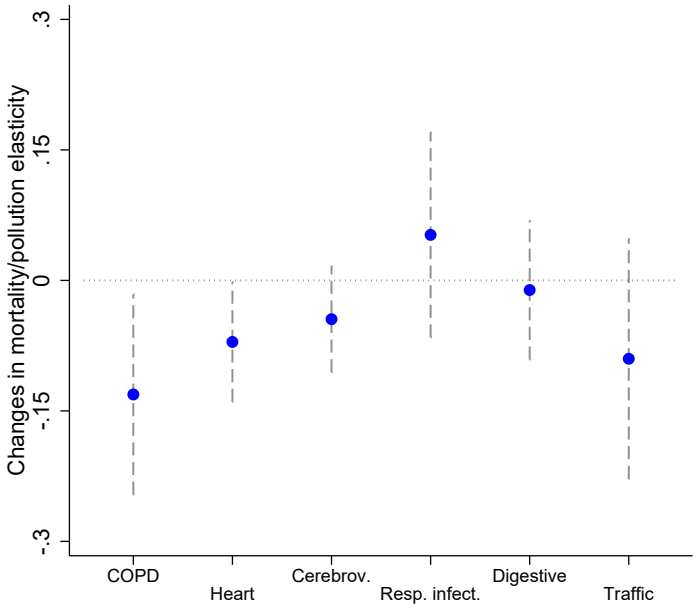


Notes: This graph shows total air emissions (in billion m^3) by Beijing polluters in the k-th decile of annual emission distribution according to the Polluter Census 2007. The sample includes about 440 polluters.

Figure D.10: Heterogeneous Changes in Quarterly Mortality-Pollution Gradient



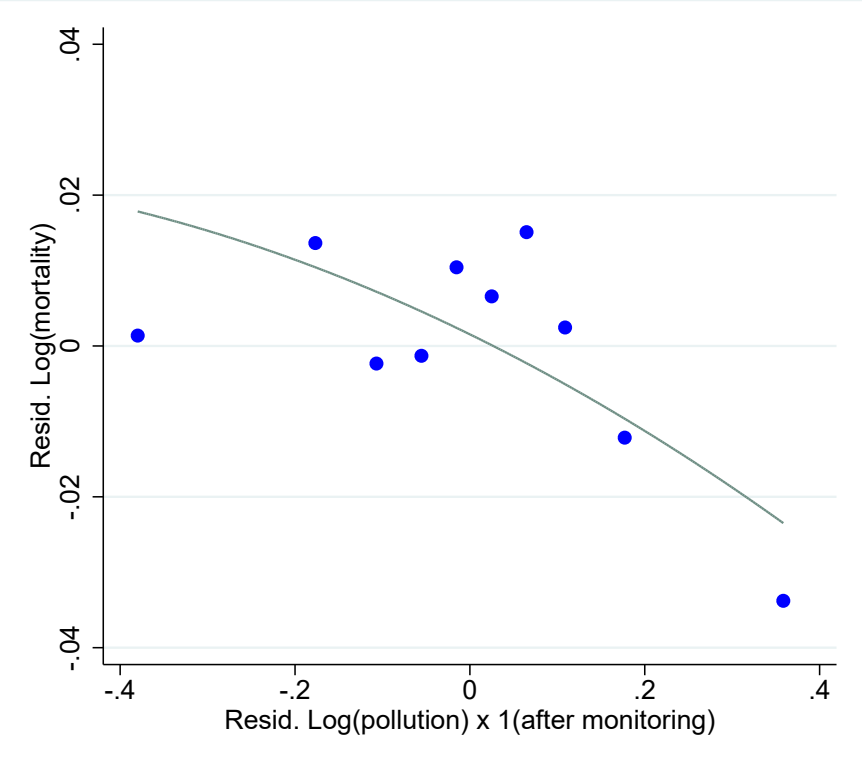
(a) Heterogeneity by age groups



(b) Heterogeneity by causes-of-death

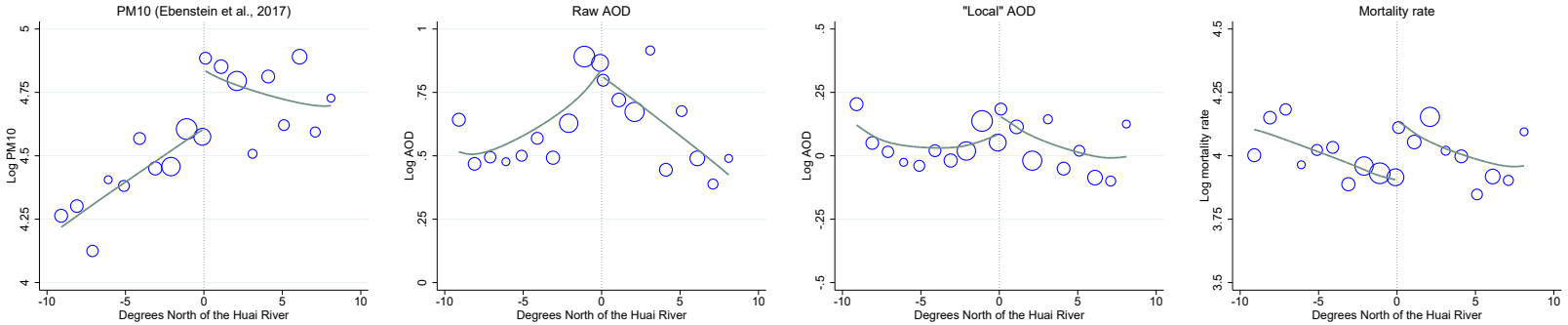
Notes: Each range plot item shows the mortality-pollution elasticity change coefficient (i.e., Log(Pollution)$\times\mathbb{1}$(after monitoring)) from a separate regression using sub-group log mortality rate as the outcome variable. All regressions control for prefectiry-city FEs and quarter-of-sample FEs. Range bars show 95% confidence interval constructed from standard errors clustered at the prefecture-city level.

Figure D.11: Changes in Weekly Bank Card Transaction-Pollution Gradient: Nonlinear Specification



Notes: This graph shows residualized plot between bankcard transaction rate by ten equal bins of residualized Log(Pollution) $\times$ $\mathbb{1}$(after monitoring). All regressions control for prefectiry-city FEs, week-of-year FEs, and year FEs.

Figure D.12: Regression Discontinuity at the Huai River (2011-2012 Sample)



Notes: Scatter plot in each panel shows the local means of the corresponding outcome variable with a bin size of 1 degree (Observations = 161). The horizontal axis is the distance (in degree) to the north of the Huai River, following Ebenstein et al. (2017). Solid lines are from local linear regressions estimated separately on each side of the river. Size of circles corresponds to total population in the distance bin. "Local" AOD = raw AOD residualized of inverse-distance weighted $PM_{2.5}$ from cities within 1,000 km radius.

Table D.1: Characteristics of Cities by Monitoring Rollout Waves

	(1)	(2)	(3)
	Wave 1	Wave 2	Wave 3
Number of cities	74	116	177
Population (million)	7.05	3.90	2.90
	(4.85)	(2.10)	(1.95)
GDP per capita (yuan)	69,836	42,881	27,400
	(27,627)	(23,110)	(13143)
AOD level	0.665	0.600	0.456
	(0.239)	(0.242)	(0.237)
$PM_{2.5}$ level (ug/m^3)	61.3	57.9	46.0
	(22.1)	(20.2)	(17.4)
Industrial SO_2 emissions (ton)	37,569	29,609	18,214
	(40,186)	(24,695)	(17,550)
Average temperature (F)	59.7	58.0	55.3
	(8.52)	(9.59)	(10.6)
Total precipitation (inches)	47.0	42.2	40.3
	(21.9)	(23.2)	(24.4)
Average wind speed (m/s)	1.94	1.71	1.47
	(0.63)	(0.62)	(0.68)

Notes: The underlying observations are at the city level. Standard deviations are in parentheses. All characteristics are measured by 2011-2015 average, except for $PM_{2.5}$ level (average of post-monitoring period) and Industrial SO_2 emissions (year 2006).

Table D.2: Changes in Environment After Monitoring

Indep. var.: 1(after monitoring)				
	(1)	(2)	(3)	(4)
Panel A. Pollution levels				
Log(Pollution)	0.0015	0.0003	-0.0011	-0.0062
	(0.0106)	(0.0097)	(0.0093)	(0.0093)
Log(max Pollution)	-0.0045	-0.0121	-0.0132	-0.0155
	(0.0148)	(0.0118)	(0.0107)	(0.0103)
Panel B. Political/regulatory environment				
[a]N(anti-corruption cases)	-0.037	-0.069	-0.032	-0.034
	(0.052)	(0.056)	(0.028)	(0.029)
[b]Age(mayor)	0.226	0.203	0.240	0.247
	(0.184)	(0.195)	(0.191)	(0.195)
[c]Likelihood(doc. mayor)	-0.013	-0.011	-0.018	-0.018
	(0.026)	(0.027)	(0.027)	(0.028)
[d]N("pollution regulation" news mention)	-0.0048	-0.0074	-0.0067	-0.0071
	(0.0064)	(0.0070)	(0.0072)	(0.0073)
Panel C. Healthcare access				
[e]Log N(hospitals per 1,000 people)	-0.044	-0.047	-0.042	-0.042
	(0.028)	(0.029)	(0.032)	(0.032)
Panel D. Bankcard spending style				
[f]Std Frac(online purchases)	0.057**	0.056*	0.059*	0.061*
	(0.027)	(0.029)	(0.033)	(0.035)
FEs: city	✓	✓	✓	✓
FEs: week-of-year	✓			
FEs: year	✓			
FEs: week-of-sample		✓	✓	
FEs: region×year			✓	
FEs: region×week-of-sample				✓
[a]N(anti-corruption cases)	mean = 0.24,		sd = 0.75	
[b]Age(mayor)	mean = 50.8,		sd = 3.63	
[c]Likelihood(doc. mayor)	mean = 0.234,		sd = 0.423	
[d]N("pollution regulation" news)	mean = 0.052,		sd = 0.45	
[e]N(hospitals per 1,000 people), annual frequency	mean = 1.61,		sd = 2.28	
[f]Frac(online purchases)	mean = 0.027,		sd = 0.058	

Notes: Row names show the dependent variable. "Log(Pollution)" is logged AOD in the city×week. "anti-corruption cases" are the number of downfall local officials during the anti-corruption campaign. "doc. mayor" indicates whether the current mayor of the city has a doctoral degree. "pollution regulation news" are the number of People's Daily news articles that mention both smog and the city name. "region" is a conventional partition of cities by location: North (36 cities), Northeast (38 cities), East (105 cities), Centralsouth (81 cities), Southwest (54 cities), Northwest (52 cities). Estimation data are at the city × weekly level, except for Panel C which uses city × annual observations of hospital counts. Standard errors are clustered at the prefecture-city level. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Table D.3: Changes in Weekly Bank Card Transaction-Pollution Gradient: "Deferrable" Consumptions

Dep. var.: Number of transactions per 10,000 active cards in a city×week				
	(1)	(2)	(3)	(4)
Panel A. Merchant type = supermarkets (mean = 257.9)				
Log(Pollution)	4.67	3.66	7.49***	8.19***
	(3.74)	(4.07)	(2.24)	(2.76)
Log(Pollution) × 1(after monitoring)	-11.3***	-11.3**	-14.4***	-17.5***
	(3.82)	(4.71)	(3.06)	(3.80)
Panel B. Merchant type = dining (mean = 46.7)				
Log(Pollution)	1.34*	1.62*	1.30**	1.59**
	(0.784)	(0.884)	(0.510)	(0.631)
Log(Pollution) × 1(after monitoring)	-2.84***	-3.35***	-2.22***	-2.54***
	(0.526)	(0.615)	(0.634)	(0.757)
Panel C. Merchant type = entertainment (mean = 9.70)				
Log(Pollution)	0.449	0.711*	0.409	0.498*
	(0.318)	(0.365)	(0.258)	(0.299)
Log(Pollution) × 1(after monitoring)	-0.667	-1.10**	-0.535	-0.686*
	(0.422)	(0.489)	(0.342)	(0.405)
FEs: city	✓	✓	✓	✓
FEs: week-of-year	✓			
FEs: year	✓			
FEs: week-of-sample		✓	✓	
FEs: region×year			✓	
FEs: region×week-of-sample				✓
N	83,122	83,122	83,122	83,122

Notes: "Log(Pollution)" is logged AOD in the city×week. "region" is a conventional partition of cities by location: North (36 cities), Northeast (38 cities), East (105 cities), Centralsouth (81 cities), Southwest (54 cities), Northwest (52 cities). Standard errors are clustered at the prefecture-city level. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Table D.4: Changes in Weekly Bank Card Transaction-Pollution Gradient: "Scheduled" Consumptions (Placebo Tests)

Dep. var.: Number of transactions per 10,000 active cards in a city×week				
	(1)	(2)	(3)	(4)
Panel A. Merchant type = billings (mean = 59.4)				
Log(Pollution)	0.252	0.725	2.64	3.51
	(2.32)	(2.70)	(1.80)	(2.16)
Log(Pollution) × 1(after monitoring)	1.04	-0.383	-3.74	-3.85
	(3.89)	(4.59)	(2.98)	(3.18)
Panel B. Merchant type = government services (mean = 12.4)				
Log(Pollution)	0.367	0.329	0.206	0.554
	(0.674)	(0.724)	(0.728)	(0.849)
Log(Pollution) × 1(after monitoring)	-0.565	-0.694	-0.541	-0.583
	(0.992)	(1.06)	(1.03)	(1.25)
Panel C. Merchant type = business-to-business wholesales (mean = 4.79)				
Log(Pollution)	-0.041	0.065	-0.050	-0.009
	(0.385)	(0.409)	(0.338)	(0.401)
Log(Pollution) × 1(after monitoring)	0.180	-0.119	0.071	0.068
	(0.571)	(0.600)	(0.475)	(0.559)
Panel D. Merchant type = cancer treatment centers (mean = 0.320)				
Log(Pollution)	0.009	0.011	0.016	0.014
	(0.012)	(0.013)	(0.011)	(0.013)
Log(Pollution) × 1(after monitoring)	-0.012	-0.017	-0.022	-0.022
	(0.016)	(0.018)	(0.016)	(0.018)
FEs: city	✓	✓	✓	✓
FEs: week-of-year	✓			
FEs: year	✓			
FEs: week-of-sample		✓	✓	
FEs: region×year			✓	
FEs: region×week-of-sample				✓
N	83,122	83,122	83,122	83,122

Notes: "Log(Pollution)" is logged AOD in the city×week. "billings" include transactions in utilities, insurance contribution, telecommunications and cable services. "government services" include transactions in political organizations, court costs, fines, taxes, and consulate charges. "region" is a conventional partition of cities by location: North (36 cities), Northeast (38 cities), East (105 cities), Centralsouth (81 cities), Southwest (54 cities), Northwest (52 cities). Standard errors are clustered at the prefecture-city level. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Table D.5: Changes in Weekly Bank Card Transaction-Pollution Gradient: Robustness Checks

Coef. of interest: Log(Pollution)×1(after monitoring)				
	(1)	(2)	(3)	(4)
Drop U.S. embassy/consulate cities	-14.1*	-16.6**	-16.9**	-21.0**
	(7.18)	(7.93)	(8.29)	(10.5)
Drop top 10% anti-corruption case cities	-16.3*	-18.8*	-18.0**	-23.4**
	(8.62)	(10.9)	(8.14)	(10.6)
Control for online shopping shares	-20.7**	-23.4**	-19.9***	-25.8***
	(8.43)	(10.4)	(7.63)	(9.91)
Control for weather elements	-22.3**	-25.8**	-24.3***	-30.6***
	(9.17)	(11.4)	(8.23)	(10.9)
Neighbors as control cities (triple diff.)	-27.4**	-26.4*	-23.1	10.1
	(13.5)	(14.5)	(14.3)	(20.5)
Use weekly max pollution level	-28.2***	-29.6***	-16.5**	-21.0**
	(9.76)	(10.4)	(7.33)	(9.08)
FEs: city	✓	✓	✓	✓
FEs: week-of-year	✓			
FEs: year	✓			
FEs: week-of-sample		✓	✓	
FEs: region×year			✓	
FEs: region×week-of-sample				✓

Notes: This table reports the changes in band card transactions - pollution gradient after monitoring. Each cell represents a separate regression. The main effect Log(Pollution) term is not reported in the interest of space. Embassy cities include Beijing, Chengdu, Guangzhou, and Shanghai where $PM_{2.5}$ monitoring data were available before 2013. Weather controls include linear terms of weekly temperature, precipitation, wind speed, barometric pressure, and their full interactions. "Neighbors" are neighboring cities in later roll-out waves. Standard errors are clustered at the prefecture-city level. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Table D.6: Regression Discontinuity at the Huai River (2011-2012 Sample)

Run. var.: Degrees north of the Huai River			
	(1)	(2)	(3)
Local polynomial:	Linear	Quadratic	Cubic
Panel A. RD estimates: Log(Outcome) $\sim$ 1(North)			
Log(Raw AOD)	-0.059	-0.059	0.348*
	(0.074)	(0.093)	(0.184)
Log("Local" AOD)	0.326***	0.351***	0.247***
	(0.157)	(0.064)	(0.096)
Log(PM_{10})	0.347***	0.440**	0.474**
	(0.130)	(0.219)	(0.239)
Log(Mortality rate)	0.219***	0.240**	0.083
	(0.072)	(0.101)	(0.173)
Panel B. IV estimates: Log(Mortality rate) $\sim$ $\hat{\text{L}}$og(Pollution)			
$\hat{\text{L}}$og("Local" AOD)	0.660*	0.591**	0.875
	(0.344)	(0.299)	(0.650)
$\hat{\text{L}}$og(PM_{10})	0.538	0.420	0.463
	(0.348)	(0.369)	(0.427)

Notes: In panel A, each row corresponds to an outcome variable, and each cell reports coefficient for a dummy indicating DSPs north of the Huai River in a separate regression (Observations = 161). "Local" AOD = raw AOD residualized of inverse-distance weighted $PM_{2.5}$ from cities within 1,000 km radius. PM_{10} data are from Ebenstein et al. (2017). Panel B reports fuzzy RD estimates of the effect of Log(Pollution) on Log(Mortality). Columns 1-3 show RD with locally linear, quadratic, and cubic control function for the running variable. All regressions use triangular kernel and Imbens and Kalyanaraman (2012) bandwidth selection. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.