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# FROM FOG TO SMOG:
# THE VALUE OF POLLUTION INFORMATION

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**ABSTRACT**

During 2013-2014, China launched a nationwide, real-time air quality monitoring and disclosure program, a watershed moment in the history of its environmental regulations. We present the first empirical analysis of this natural experiment by exploiting its staggered implementation across cities. The program has transformed the landscape of China's environmental protection, substantially expanded public access to pollution information, and dramatically increased households' awareness about pollution issues. These transformations, in turn, triggered a cascade of household behavioral changes, including increases in online searches for pollution-related topics, adjustments in day-to-day consumption patterns to avoid pollution exposure, and higher willingness to pay for housing in less polluted areas. As a result of both short- and long-term behavioral changes, the program significantly reduced the mortality impact of air pollution. Conservative estimates suggest that health benefits are at least one order of magnitude larger than the costs of the program and associated avoidance behaviors combined. Our findings highlight considerable benefits from improving access to pollution information in developing countries, many of which are experiencing the world's worst air pollution but do not systematically collect or disseminate pollution information.

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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 unavailable or underprovided in real-world settings, especially for information with public good properties (such as forecasts on weather, pollution, and disease prevention). The difficulties in appropriating private returns for this type of information call for government intervention. Understanding the value of providing such information is crucial for the optimal level of government investment in information gathering and reporting (Nelson and Winter, 1964; Craft, 1998).

There is very limited research on the value of gathering and providing pollution-related information in developing countries despite the fact that they experience the worst pollution in the world. This is because pollution information is either not collected or deliberately withheld by the government.[1] Consequently, key questions – such as what the benefits of information provision are and how much public support is optimal – remain mostly unanswered. These issues are pressing because public funding for improving information infrastructure competes with meeting basic needs in health care, nutrition, and education for the poor.

China provides a perfect setting for studying the role of pollution information. During the 2000s, its daily average concentration of fine particulate matter ($PM_{2.5}$) exceeded 50 ug/m$^3$, five times above the World Health Organization guideline. Despite the hazardous levels, a comprehensive monitoring network was nonexistent. Dissemination of the scant data that were collected was politically controlled and, in many cases, forbidden. In 2013, amid the social outcry over the lack of transparency and a dramatic shift in government position on air pollution, China launched a nationwide program that undertook real-time monitoring of air quality (henceforth, the information program). The program covers 98% of its population, a watershed moment in the history of China's environmental policies. The information program provides a unique opportunity to study changes in household behavior upon a sharp and permanent increase in the availability of pollution information.

We present the first empirical analysis of this natural experiment and provide the first estimate of the value of pollution information through this program. The basis of our identification strategy is the staggered introduction of the information program across three waves of cities and completed over the course of two years. The sequence of the staggered roll-out

[1] Among the 20 countries with the worst $PM_{2.5}$ level in 2018 (annual median $>$ 46 ug/m$^3$), only four (Nepal, Saudi Arabia, India, and China) installed a pollution monitoring system.

is based on cities' administrative hierarchy (e.g., provincial capitals) and pre-determined designations (e.g., environmental protection priority cities of 2007). The roll-out schedule of the program is a top-down decision driven by the physical constraints of installing monitoring stations, and it is thus uncorrelated with the day-to-day variation of local pollution levels as shown in our analysis. In addition, there were no other programs and regulations following a similar roll-out schedule during our sample period. To causally identify how information has altered consumer responses to (potentially endogenous) pollution, we formally derive two orthogonality conditions that allow our estimator to "difference out" the potential endogeneity of the pollution variable itself before and after the policy's introduction, thus isolating the causal effect of the policy. We show that these orthogonality assumptions pass two validity tests: (1) a pre-trend test analogous to the test for parallel trends assumption in the standard difference-in-differences setting, and (2) a balance test for the absence of *level* shifts in pollution before and after the policy. Our methodology allows us to estimate, using simple OLS, how information causes a "change in slope" – changes in how behavior and health outcomes respond to outdoor air quality.

We build the most comprehensive database ever compiled on a rich set of outcomes – including social awareness, air quality measures from satellites, short- and long-run economic activities, and health outcomes – that covers the period before and after the information program. We first document that the information program has profoundly transformed the landscape of public access to pollution information and dramatically increased households' awareness about pollution issues. The frequency of the publication of air pollution-related articles in *People's Daily*, the government's official newspaper, rises from less than once per week to almost daily. Immediately after the program is launched, the term "smog" ("wu mai" in Chinese) becomes, for the first time, a buzzword in social media. Within one year of the program implementation in a city, purchases of air purifiers almost double and become highly correlated with the local pollution level.

These changes in information access and public awareness triggered a cascade of short-run and long-run risk-compensating behavioral changes, such as day-to-day shopping and housing demand when pollution is elevated. In our short-run analysis, we exploit the universe of credit card and debit card transactions in China from 2011 to 2016 to build a measure of outdoor purchase trips for all cities in the country. Linking purchase activities to air pollution, we show that the information program boosted pollution avoidance by triggering a negative purchase-pollution elasticity of 3 percent, a pattern that is robust across a host of econometric specifications. As expected, the increase in avoidance concentrates in plausibly "deferrable" consumption categories, such as supermarket shopping, outdoor dining, and entertainment, rather than in "scheduled" trips such as paying bills, conducting business-to-business transactions, and attending cancer treatment sessions.

Our long-run analysis focuses on the capitalization of pollution information in the housing market. Leveraging geolocation information from the near-universe of new home sales in Beijing spanning 2006 to 2014, we examine the information-induced *changes* in the relationship between housing prices and local pollution levels using two different research designs. First, we employ the pixel-averaging technique ("oversampling") to enhance the original satellite pollution data's spatial resolution from 10-by-10 km to 1-by-1 km (Fioletov et al., 2011; Streets et al., 2013). The high-resolution measure allows us to conduct comparisons within fine geographic units, such as communities that are similar to census block groups in the United States. We estimate a home value-pollution elasticity of -0.6 post monitoring; one standard deviation increase in pollution is associated with a 4% decrease in housing prices. In contrast, the elasticity is small and statistically insignificant (about -0.01) before the information program. Second, we link China's emission inventory database with business registries to identify addresses of Beijing-area's mega polluters: the 10% facilities that account for 90% of total industrial air emissions. Following the literature (Currie et al., 2015), we estimate changes in the relationship between housing price and the proximity to these major polluters before and after the information program. While there is no correlation between housing prices and proximity to polluters prior to the program, home prices within 3 kilometers of a major polluter depreciate 9% afterward relative to homes that are farther away. This corresponds to 14% of the interquartile range of the housing price dispersion. While somewhat larger than the results of Currie et al. (2015), who find that properties within 1 kilometer of a toxic plant experience an 11% reduction in value, these estimates are plausible in light of Beijing's three-fold increase in housing prices over the sample period. Thus, the information program facilitates the capitalization of air quality in the housing market, potentially improving social welfare through residential sorting.

These behavior changes could significantly mitigate the devastating consequences of severe air pollution in China. Our last set of empirical analyses examines 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 2 percentage-point reduction in the mortality-pollution elasticity post monitoring that concentrates among individuals aged 60 and above. The impact is more pronounced in cities that have higher income per capita and a larger share of urban population, have more hospitals per capita, consume more electricity, and have a higher mobile phone penetration. These patterns are similar to heterogeneous short-term avoidance responses uncovered using the card spending data, suggesting a plausible pathway from effective avoidance to beneficial health outcomes.

Using the estimates of age-adjusted value of statistical life (VSL) and healthcare costs of air pollution in the literature (Ashenfelter and Greenstone, 2004; Murphy and Topel, 2006; Barwick et al., 2018), we calculate that risk-compensating behavioral changes from access to pollution information generate annual mortality and morbidity benefits of at least RMB 122 billion. Such social benefits outweigh the costs from defensive investments (such as air purifier purchases), avoidance behavior (such as foregone consumption), and program deployment and maintenance by at least one order of magnitude, making the information program among the most successful environmental policies in a developing country.

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

Second, our study shows that information is a crucial 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 estimates the value of non-marketed environmental goods via a revealed preference. To the extent that access to information is lacking in developing countries, the perfect-information assumption could underestimate 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-response relationship between pollution and mortality differs across developed and developing economies (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 contexts, 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;

[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).

Oberholzer-Gee and Mitsunari, 2006), change consumer choices (Hastings and Weinstein, 2008; Dranove and Jin, 2010; Jessoe and Rapson, 2014; Newell and Siikamäki, 2014; Mastromonaco, 2015; Wichman, 2017), and drive up average product quality (Jin and Leslie, 2003; Bai, 2018). In the context of air quality, recent studies have documented behavioral responses to pollution exposure over both the short and long terms. Our analysis shows that these behavioral responses could lead to improved health outcomes. We use the associated benefits in monetary terms to provide a lower-bound estimate of the value of pollution information.

The rest of this paper is organized as follows: Section 2 reviews institutional details on the information program and describes data sources. Section 3 presents the theoretical framework. Section 4 documents the dramatic changes in information access and awareness after the program. Section 5 describes the empirical framework. Section 6 presents the effect of the program on short- and long-term behavioral changes and on mortality. Section 7 calculates the value of information. Section 8 concludes.

# 2 Institutional Background and Data

## 2.1 Environmental Regulations

The real-time $PM_{2.5}$ monitoring-and-disclosure program started in 2013 was 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 drastically enhanced the public awareness of the health impact of $PM_{2.5}$. To help understand the significance of the change, we provide a brief history of China's environmental regulations.

**Environmental Regulations Prior to 2013** In 1982, China established its first national ambient air quality standards (NAAQS), which set limits for six air pollutants including total suspended particles (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. The 2000 amendment removed $NO_x$ from the list, and relaxed the standards for $NO_2$ and $O_3$ in response to noncompliance due to increased automobile usage.

Throughout much of the 1980s to the early 2000s, the primary threat of air quality was considered to be $SO_2$ due to coal burning. As acid rain caused widespread and visible damages to crops, forest, and the aquatic environment, environmental regulations focused on the control of acid rain and $SO_2$ emissions (Yi, Hao and Tang, 2007). The prominent regulation was the two-control zone policy (TCZ) implemented in 1998 where prefectures with high PH values of precipitation and $SO_2$ concentration were designated as either the acid rain control zone (located in the south) or the $SO_2$ control zone (mostly in the north). These zones imposed a series of measures, such as mandating the installation of flue gas desulfurization in coal-fired power plants and closing down small coal-fired power plants (Tanaka, 2015). These aggressive emissions control and clean energy policies reduced the average $SO_2$ concentration by nearly 45% from 1990 to 2002, with the majority of the cities achieving the national standard by 1998 (Hao and Wang, 2005).[3]

Starting from early 2000, the source of air pollution shifted from coal burning to mixed sources. Particulate matter (PM) rather than $SO_2$ became the primary pollutant. This shift was driven by the significant decline in emissions from coal-fired power plants, and by skyrocketing emissions from automobiles, manufacturing facilities, and construction linked to the dramatic growth in vehicle ownership, increased industrial activities (after China's World Trade Organization accession in 2001), and rapid urbanization. The regulatory focus shifted to reducing urban air pollution through city-level efforts (Ghanem and Zhang, 2014), which proved to be ineffective due to the strong competing incentives for economic growth at the local level, combined with weak monitoring and enforcement from the central government. Episodes of extreme air pollution became frequent, especially during winters in many urban centers. The U.S. Embassy in Beijing and U.S. consulates in Guangzhou and Shanghai started to report hourly $PM_{2.5}$ levels 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 they thus became sources of diplomatic tension.[4]

**Limited Pollution Awareness Prior to 2013** While air pollution has been a long-standing issue, public access to daily pollution measures was almost absent prior to 2013. Although the Ministry of Environmental Protection (MEP) began publishing the daily Air Pollution Index (API) for major cities in 2000, the reported API only partially reflected true air quality because it did not incorporate $PM_{2.5}$, which was the major air pollutant in

[3]The fraction of the acid rain zone in China's total terrain decreased from the peak level of about 30% in the mid-1990s to 8.8% in 2015.

[4]The then-vice minister of the Ministry of Environmental Protection (MEP), Wu Xiaoqing, openly requested the 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. He stated that the public release of air-quality data by the consulates "not only does not 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).

many Chinese cities since the 2000s and onward.[5] In addition, mass media and broadcasts did not report the API index. Furthermore, the API data were gathered and reported by local environmental bureaus whose leaders were appointed by local governments. The MEP did not control the monitoring stations, and it had limited ability to monitor 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).

Though the dominant pollutant had shifted from $SO_2$ to particulate matter in the 2000s, there was no systematic collection of $PM_{2.5}$ measures. As a result, consumer awareness of $PM_{2.5}$ concentration was extremely limited prior to 2013. Both government agencies and the media often characterized poor visibility due to high levels of $PM_{2.5}$ as *fog* rather than *smog*. For example, on November 27, 2011, newspaper headlines, as well as the China Meteorological Administration, attributed dense fog in Beijing and northern cities as the reason for widespread flight delays and cancellations. In fact, extreme pollution caused the low visibility, as shown in Figure 1 that displays the U.S. National Aeronautics and Space Administration (NASA) satellite view of China and the aerosol optical depth (AOD) reading of 4.5 or higher for many northern cities.[6] A similar pollution event that occurred on December 4-6, in 2011 was again reported to be dense fog by major news media including China Central Television, the predominant state television broadcaster in Mainland China, and popular websites such as sina.com.

The lack of awareness of $PM_{2.5}$ and the "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 it was fog back then. That's what we called it.... as a former journalist, I started to blame myself because for all these years I had been reporting stories on pollution all across the country, I always thought pollution was about mining sites and those places near factories spewing smoke plumes. I never thought the skies that we saw every day could be polluted."[7]

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

[6] The AOD measure is usually between 0.1 to 0.15 in the United States. For China, the average is about 0.5.

[7] The documentary has been compared with Al Gore's *An Inconvenient Truth* in terms of its style and impact. The film had been viewed over 150 million times on the popular website tencent.com within three days of its release, before the government took it offline. Tu et al. (2020) show that household willingness to pay for clean air increased among those who had viewed the documentary; the findings are based on a longitudinal survey conducted in the city of Nanjing, and a regression discontinuity (in time) design.

**The Information Program and Environmental Regulation Post 2013** In 2012, China's MEP revised the NAAQS and for the first time in history set the national standards for $PM_{2.5}$. The new standards were slated to take effect nationwide in 2016, but some 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 targets for $PM_{2.5}$ reduction from 2013 to 2017 and outlined 10 concrete policies 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 required cities at prefecture level or higher to reduce $PM_{2.5}$ concentrations by 18% from 2015 to 2020 (Wang, 2017).[10]

The recognition of $PM_{2.5}$ as a primary pollutant, and the aggressive policies to reduce $PM_{2.5}$ concentrations marked a significant shift of the China's long-standing strategy of prioritizing economic growth over environmental concerns. 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 a nationwide monitoring-and-disclosure program starting in 2013. The focus was to build an efficient, scientific system to monitor air quality, and to publicly disclose data in real time.

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 that were built in three waves. In the first wave, monitoring networks were built between May and December 2012 in 74 major cities that represented the country's key population and economic centers (the Beijing-Tianjin-Hebei Metropolitan Region, the Yangtze River Delta, the Pearl River Delta, direct-administered municipalities, and provincial capitals). Real-time readings on all major air pollutants were posted online, and they were ready for streaming by December 31, 2012. By October 31, 2013, the second wave was completed, adding 116 cities from the list of the Environmental Improvement Priority Cities and the National Environmental Protection Exemplary Cities.[11]

[8]The cities in the Beijing-Tianjin-Hebei region, the Yangtze River Delta, and the 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 environmental policy during the past decade. Under this plan, $PM_{2.5}$ fell by over 37% in the Beijing-Tianjin-Hebei Region, 35% in the Yangtze River Delta, 26% in the Pearl River Delta, and over 30% on average in more than 70 major cities (Huang et al., 2018).

[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." He declared a war on pollution at the opening of the 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]The Environmental Improvement Priority Cities were designated in 2007 during the Eleventh-Five-Year

In the final wave, achieved by November 20, 2014, the program reached the remaining 177 cities. Figure 2 plots the roll-out of the program. 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.

Second, and more importantly, the information program established a dissemination system to report a real-time Air Quality Index (AQI) that is on a single scale of 0 to 500. Monitoring results are displayed in real time on MEP's website. In contrast to the previous API reporting system, the MEP directly controls the new monitors, and data are directly transmitted to MEP's information center in real time to avoid manipulation by the local government. Both hourly and daily AQIs, as well as concentrations of $PM_{2.5}$, $PM_{10}$, $O_3$, CO, $NO_2$, and $SO_2$, are available at individual station and city levels, with an interactive map showing the location of each monitoring station. Appendix Figure C.2 provides a screenshot of the website interface. Importantly, the government allows private parties to access and stream data directly from the web. This has spurred a surge in private websites and mobile phone applications that report real-time air quality information. Section 4 provides more detail on the program's effects on information access and public awareness about $PM_{2.5}$ and related health consequences.

**Concurrent Government Policies and Potential Confounders** A key feature of the information program's roll-out is that it is based on cities' administrative hierarchies and well-known groupings that were designated long before the initiation of the information program. The pre-determined nature of these groupings indicates that there is little likelihood of selecting cities into different roll-out waves based on unobservable characteristics or future projections of outcome variables. In addition, the date of program implementation across cities is a top-down decision driven by the physical constraints of installing monitoring stations, and, thus, uncorrelated with *day-to-day* variation in local pollution, as shown in our balance tests.[12]

We are unaware of any other concurrent government policies that coincide with the geography and the timeline of the information program's roll-out during our study period.

period and contain important regional economic centers and cities face significant environmental challenges. The National Environmental Protection Exemplary Cities program was created during the Ninth Five-Year Plan; 68 cites were awarded the title from 1997 to 2007 based on a host of environmental quality criteria. Appendix Figure C.1 tabulates cities by waves and their associated city clusters.

[12] Appendix Table C.1 tabulates economics attributes for cities in each wave. Cities in earlier waves tend to have a larger population, higher GDP per capita, and higher levels of air pollution and industrial emissions. On the other hand, as shown in balance tests in Appendix Table C.2, these economic and environmental conditions do not change systematically before and after the program roll-out. Together, the nature of the program and the evidence suggest that the choice of cities and the timing of the program roll-out are unlikely to be based on city-level unobservables.

Nevertheless, several major environmental and energy programs are worth noting. First, China rolled out pilot $CO_2$ cap-and-trade programs targeted at heavily polluting industries in two provinces (Guangdong in December 2013 and Hubei in April 2014) and five individual cities (Shenzhen in June 2013, Beijing and Shanghai in November 2013, Tianjin in December 2013, and Chongqing in June 2014).[13] The second policy is the energy reduction plan among over 16,000 of the largest energy users that collectively accounted for over 60% of total energy consumption in 2010. The policy, started in 2012, aimed to reduce energy intensity and carbon intensity as outlined in the 12th Five-Year Plan. The third policy is fuel switching from coal to natural gas for winter heating in northern China from the winter season of 2013 as part of the *Action Plan on Air Pollution Prevention and Control.*

To the extent that there is no significant overlap in the geography or timeline of implementation of these policies with the monitoring roll-out schedule, we expect the impact of these policies to be picked up by the rich set of spatial and temporal controls we use in our econometric models (e.g., city fixed effects and region-by-week-of-sample fixed effects). Consistent with this view, a series of tests (reported in Appendix Table C.2) shows that the information roll-out is not associated with any significant changes in the *level* of pollution in the treated city conditional on the fixed effect controls, while the spatial and time fixed effects pick up a substantial reduction of *overall* pollution levels since 2014.

## 2.2 Data

We compile multiple data sets to allow for a comprehensive study of the impacts of the information disclosure program on a variety of outcomes. The data sets include data on consumer awareness and online search behavior, air purifier sales, bank card transactions, housing transactions, mortality rates, and air quality measures from satellites. Table 1 shows city and time coverage as well as the mean and standard deviation of the primary variables used in our analysis. Our housing transactions data are from the city of Beijing, the capital city with nearly 20 million residents; air purifier sales data cover 50 cities, or about 28% of national population. All the other data sets are national or nationally representative in scope, and are available at the city-weekly level from January 2011 to April 2016, with mortality data available through December 2016. Below we provide more details on each individual data source.

[13] These seven regional pilots were a proof of concept for the national $CO_2$ cap-and-trade program slated to come online in 2020. However, the program had limited impact on carbon emission and air quality given the generous allocation and the lack of strong punishment mechanism for noncompliance (Zhang, Wang and Du, 2017).

**Mass Media, Phone Apps, and Web Searches** The high Internet and mobile phone penetration among the Chinese population provides a unique opportunity to investigate pollution awareness using digital sources.[14] We draw on several digital sources to illustrate the evolution of public access to pollution information. First, we look at the publication trends in the *People's Daily*, the government's official newspaper. We pull articles that contain the word "smog" (or "air pollution", or "atmospheric pollution") from the *People's Daily*'s digital archive, and we also identify a list of relevant cities mentioned in each of these articles.

Second, we scrape Apple's App Store to obtain release information on Chinese mobile apps that contain air pollution information, using keywords including "smog," "air pollution," or "atmospheric pollution."[15] These apps typically display current hourly pollution levels; some also provide health-related guidelines (e.g., avoiding outdoor activities) when pollution levels are high. Appendix Figure C.3 is a screenshot from a typical pollution app. We also scrape information on Apps in other major categories – such as gaming, reading, and shopping – which serve as a control group.

Third, the most widely used search engine in China, Baidu, publishes a search intensity index that summarizes the number of queries for certain words in a given city and on a given day among both desktop and mobile users since 2011. We focus on the search index for "smog," the buzzword for air pollution. The search index is generated using an algorithm similar to Google Trends.

**Air Purifier Sales** Air purifier sales data come from a leading market research firm, and report the total units of air purifiers sold for both residential and institutional purposes at monthly frequencies for 50 cities from 2012-2016.[16] Among these 50 cities, 34, 11, and 5 are in the first, second, and third waves of the information program roll-out, respectively.

**Bank Card Transactions Data** Households' shopping trips are constructed using the universe of credit card and debit card transactions 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 in 2015 as shown in

[14] Data from the China Internet Network Information Center show that, by the end of 2012, China had about 0.56 billion internet users (or 40% of its population). More than 99% of Internet users have heard of Baidu, the most popular search engine (seconded by Google, 87%), and 98% have used it in the past six months (seconded by 360.cn, 43%). 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).

[15] The API returns the 200 most relevant apps for a given keyword as of December 2015.

[16] The firm name is withheld per our data use agreement.

Appendix Figure C.4. For each transaction, we observe the merchant name and location, and transaction amount and time. Appendix Figure C.5 shows the spatial pattern of cards and transactions. Credit and debit cards are widely adopted across the country as the most commonly used transaction method, especially in urban areas (Barwick et al., 2018).[17] To the best of our knowledge, the fine degree of spatial and temporal resolution provided by this data set represents the most comprehensive data available on consumption activities for China.

Two features of the data are worth mentioning. First, the Point-of-Sale information in the UnionPay data allows us to distinguish between online and offline transactions. Our data contain a small fraction of transactions that are made online, which we drop because tracing these buyers' physical locations is difficult.[18] We focus on the vast majority of the transactions that are made offline to measure *outdoor* purchase trips. Second, we do not observe specific items purchased in each transaction. Instead, UnionPay classifies merchants into over 300 categories, such as department stores and supermarkets. We use the category information in our analysis to measure the general purpose of each trip.

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

**Housing Transactions Data (Beijing)** Our housing data contain a total of over 660,000 new home purchases in Beijing from January 2006 to April 2014, with a nearly universal coverage. The Metropolitan Beijing area is divided into 16 districts, which are further divided into 180 communities ('jiedao' in Chinese). A community (henceforth "ZIP Code") is comparable to a U.S. ZIP Code in terms of geographical coverage and consists of apartment complexes. An apartment-complex is similar to a U.S. census block group in size. We aggregate individual transaction records to the apartment-complex level which is the finest level at which we observe geo-location information. Our data contain new home transactions in about 1,300 different apartment-complexes. Among these apartment-complexes, 64% are sold out within three years. Housing variables recorded include the transaction date and price, housing unit characteristics (floor, size of the unit, etc.), as well as attributes and the exact geolocation of the apartment-complex. Beijing features an extraordinarily dynamic housing market, with a 262% growth in the average price during our study period.

[17] Since 2016, mobile payment apps including Alipay and Wechat have become popular, but cards transactions still account for more than 50% of national consumption.

[18] Online transactions accounted for 5.1% of total transaction volume and 3.6% by transaction value between 2013 and 2015. The shares were smaller in earlier years.

**Polluter Data (Beijing)** The MEP conducts an annual survey of all major industrial polluters, and compiles the Chinese Environmental Statistics database (CES), the most comprehensive coverage of firm emissions in China.[19]. We have access to the 2007 CES, which reports total industrial emissions across all pollutants for 587 polluters in Beijing. We obtain the address and operation status of each firm by linking CES data with firm registration records from Qixin (www.qixin.com) and geocode addresses using Baidu's Map API. Our study focuses on 407 polluters that operated throughout the 2006-2014 period, the sample period of our housing transactions.

**Mortality Data** The Chinese Center for Disease Control and Prevention (CDC) operates a Disease Surveillance Points (DSP) system that covers 73 million individuals in 131 cities, a 5% representative sample of China's population over the 2011-2016 period. Among these 131 cities, 38 implemented the information program in the first wave, 38 in the second wave, and 55 in the last wave.[20] The DSP mortality database, drawn from hospital records and surveys of the deceased's household, is one of the highest-quality health databases used in recent medical and economic research (Zhou et al., 2016; Ebenstein et al., 2017). We observe the number of persons and total deaths by each city-week-age group, and separately by causes of death.

**Satellite Data** To overcome the challenge that reliable pollution data are only available post the information program, we obtain ambient air quality measures from AOD via the Moderate Resolution Imaging Spectroradiometer (MODIS) algorithm, operated by NASA and installed on the platform of the research satellite Terra. The original data have a geographic resolution of 10-by-10 km and a scanning frequency of 30 minutes, which we average to the city-week level from 2006 to 2016. MODIS records the degree to which sunlight is scattered or absorbed in the entire atmospheric column corresponding to the overpassed area under cloud-clear condition. As such, AOD captures concentration of particles such as sulfates, nitrates, black carbons, and sea salts, and serve as a proxy for outdoor particulate matter pollution (Van Donkelaar, Martin and Park, 2006). Appendix Figure C.6 documents a strong correspondence between AOD and $PM_{2.5}$ after the implementation of the information program.

We favor the MODIS AOD measure over alternatives (such as satellite-based $PM_{2.5}$ pre-

[19]CES is also the source of China's annual Environmental Yearbook (Liu, Shadbegian and Zhang, 2017; Zhang, Chen and Guo, 2018)

[20]The original DSP data report information for 161 counties and city districts which are smaller geo-units than cities. To use the same geographic unit of analysis throughout the paper, we aggregate the county/city district level data to the city level.

dictions) for two main reasons. First, the MODIS data are available at high frequency (we use weekly data in our analysis), whereas processed satellite-based $PM_{2.5}$ data are often distributed at the annual intervals. Second, the polar-orbiting nature of MODIS allows us to observe AOD on *overlapping* 10-by-10 km grid cells. This feature is essential for the construction of high resolution, sub-city level pollution measure, as detailed in Section 6.2.

# 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 decisions – for example, by resolving market uncertainty in demand and supply conditions (Stigler, 1961, 1962) or technological uncertainty in investment and production decisions (Lave, 1963; Hirshleifer, 1971). Access to pollution information affects the behavior of informed individuals who 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 a classical model of health demand and production (Grossman, 1972; Deschenes, Greenstone and Shapiro, 2017). Readers not interested in theoretical predictions can jump to the empirical analysis in Section 4.

## 3.1 Model Setup

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

Individuals face a budget constraint that is given by: $I + w \cdot g(h) \geq x + p_a \cdot a$, 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.[21] Individuals allocate their wage and non-wage income between consumption and engaging in avoidance behavior $a$, where $p_a$ is the associated price (e.g., the cost of an air purifier or medication). We use $a$ to include broadly defined (costly) adaptation behavior.[22] Dynamics and savings are assumed away to ease exposition.

[21] The effect of health on wage income captures the impact of pollution on labor supply or productivity as documented in Graff Zivin and Neidell (2012); Hanna and Oliva (2015); Chang et al. (2019); He, Liu and Salvo (2019).

[22] Examples include reducing outdoor activities (Zivin and Neidell, 2009; Saberian, Heyes and Rivers, 2017), engaging in defensive spending (e.g., buying face masks and air purifiers) (Ito and Zhang, 2018; Zhang and Mu, 2018), and making choices to change residential locations or migrate (Chay and Greenstone,

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

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

The health function $h = h(c_0, a)$ in the optimization can be viewed as an ex ante health function upon which consumers rely for decisions before the health outcome is realized. It is different from the ex post health outcome $h = h(c, a)$ 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) and Allcott (2013).

Let avoidance under the perceived pollution $c_0$ be denoted by $a(c_0)$. Individuals' wage income is determined by the actual pollution level $c$ and avoidance $a(c_0)$: $w \cdot g[h(c, a(c_0))]$. Let $x(c, c_0)$ denote consumption of the numeraire good. The experience utility based on the perceived pollution 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: the first argument is the actual pollution $c$, and the second argument is the perceived pollution level $c_0$. To examine the behavioral changes associated with 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 do not engage in an unreasonable amount of avoidance behavior. Similarly, we assume that hours worked increases in health, but at a decreasing rate: $\frac{dg}{dh} \geq 0, \frac{d^2 g}{dh^2} \leq 0$. 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.

We focus on interior solutions for the optimal level of avoidance behavior $a$.[23] The assumption of $\frac{\partial^2 h}{\partial a \partial c} \geq 0$ is crucial in delivering "complementarity" between pollution and

2005; Banzhaf and Walsh, 2008; Bayer, Keohane and Timmins, 2009; Chen, Oliva and Zhang, 2017).

[23] A necessary condition for an interior solution is $w \cdot \frac{dg}{dh} \cdot \frac{\partial h}{\partial a} |_{a=0} > p_a$.

avoidance: the higher the pollution, the more intense avoidance is likely to be. At low levels of pollution, the marginal health benefit of avoidance $\frac{\partial h}{\partial a}$ is likely to be limited. As pollution elevates, higher marginal benefits induce individuals to engage in more avoidance to mitigate the health and wage impact of pollution. There are many low-cost defensive mechanisms. For example, avoiding outdoor activities at times of high $PM_{2.5}$, wearing facial masks, or purchasing air purifiers are all cheap and effective defensive mechanisms.

**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 functions are commonly used in the literature and help to simplify the exposition.

**Assumption A3** Let $c_0$ denote individuals' perception of air pollution before the information program. We assume that $c_0 < c$, that is, the perceived level of pollution is lower than the actual level. Another interpretation of Assumption 3 is that people underestimate the negative health impact of pollution. Pollution concentration $c$ is assumed to be perfectly observed following the implementation of the program.

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

1. *Avoidance behavior increases:* $a(c) > a(c_0)$
2. *Health improves and the (downward slopping) health-pollution response curve flattens:*

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

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

Appendix A provides the proof. The theoretical model predicts that following the implementation of the information program, individuals engage in more pollution avoidance, which, in turn, reduces the health damages from pollution and increases consumer welfare. Our empirical analysis provides empirical tests on the first two predictions, and uses the third prediction to quantify the value of the information program.

## 3.2 Value of Information

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

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

where $V(c, c)$ denotes the indirect utility when individuals correctly perceive pollution, and avoidance is chosen optimally according to the following condition:

$$[U_h(c, a) + \lambda \cdot w \cdot g_h(h(c, a))] \frac{\partial h(c, a)}{\partial a} - \lambda p_a = 0 \tag{1}$$

The indirect utility before the information program is:

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

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

$$\begin{aligned} VOI &= V(c, c) - V(c, c_0) \\ &= \{U_h \cdot \frac{\partial h}{\partial a} \cdot \frac{\partial a}{\partial c_0} + \lambda \cdot w \cdot g_h \cdot \frac{\partial h}{\partial a} \cdot \frac{\partial a}{\partial c_0} - \lambda \cdot p_a \cdot \frac{\partial a}{\partial c_0}\}(c - c_0) + o_p(c - c_0) \end{aligned} \tag{2}$$

There are three terms in the curly bracket. The first refers to changes in utility as health improves from the avoidance behavior. The second denotes changes in wage income due to pollution impact on effective work hours or productivity. The third term in the curly bracket captures the cost of taking additional avoidance measures such as buying air purifiers or changing outdoor activities. Our empirical analysis below quantifies the magnitude of the terms in the curly bracket.

# 4 The Sea Change in Information Access and Awareness

This paper examines a rich set of outcomes, including information access, awareness, short- and long-run behavior changes, and health responses. To facilitate the analysis across different outcomes, we use a unified empirical framework with all estimation equations closely mirror each other, subject to variations in data availability as we explain below.

In this section, we document how various measures of information access and awareness respond to the information program roll-out. Unless noted otherwise, for each outcome we report (1) a simple time series plot from January 2011 to April 2016, and (2) an event time plot from eight quarters before the information program reached the city, and five quarters after. In both plots we present the raw data patterns with no control variables included, though the patterns are essentially the same with spatial or temporal controls.[24] The coefficient for event quarter -1 (the quarter prior to the information program) is normalized to 0. We report the 95% confidence interval constructed from standard errors clustered at the city level.

In Sections 5 and 6, we adapt the same estimation framework to study how the information program altered the relationships between pollution and behavior changes, as well as health outcomes.

## 4.1 Information Access: News and Mobile Apps

The government's official newspaper, the *People's Daily*, and mobile phone apps are among the primary venues for the general public to access pollution information. In Figure 3a, we count the number of days in each month when the *People's Daily* mentions "smog" in any articles. "Smog" is rarely mentioned in the 1990s and 2000s. Almost immediately following the information program's initial roll-out, the frequency of "smog" appearing in the People's Daily jumped from two days per month in 2012 to sixteen days per month in 2013. It remained high for the rest of the sample period, hence is unlikely to be entirely driven by the coverage of the information program itself.[25]

The national trend in media smog mention may reflect changes in the general environment (e.g., shifts in government policies). To hone in on the impact of the information program, we scan each smog-containing article in the *People's Daily* to determine the list of cities mentioned. This allows us to construct a city panel data set and, combined with the staggered roll-out of the information program, conduct an event study for changes in smog mentions frequency before and after a city begins to monitor pollution. As we have data from 2011 through April 2016, we examine a balanced event time window between eight quarters before and five quarters after the information program roll-out in the city.

Figure 3b provides an event-time plot of smog mentions as a function of quarters relative to a local city's the information program roll-out, where smog mention is standardized to be zero mean with unit variance. The graphical pattern features a discrete increase exactly on the roll-out date (event quarter $t$=0). By one year after the roll-out, "smog" mentions in cities with the monitoring stations increased by 60% of a standard deviation ($p$-value = 0.038). We find very similar results when we repeat this analysis using other keywords, including "air pollution" and "atmospheric pollution."

We then examine the availability of pollution-related mobile phone apps. Unlike newspa-

[24]These results are available upon requests.

[25]There was a modest increase in the frequency of the term "smog" before 2013. A close read of the articles indicate that these phrases were mostly used to describe dense fog, and were rarely associated with pollution.

pers that provide pollution information at a daily frequency, information from apps is more readily accessible in real time. Given the high mobile phone penetration in China, pollution apps serve as a significant venue through which the public learns about its pollution exposure at the moment. We compare the distribution of the release times for pollution apps with the release times of apps from other popular categories – including gaming, music, video, reading, finance, sports, education, shopping, and navigation – that capture the majority of commonly used apps.

As shown in Figure 4, there is a clear surge in the density of pollution apps released after the information program, relative to non-pollution apps. The largest increase in pollution app releases occurs one quarter after the initial monitoring roll-out. In total, about 82% of pollution apps are released between 2013 and 2015, compared to 18% released between 2009 and 2013. In contrast, 38% and 62% of the apps in the control group are released during 2009-2013 and 2013-2015, respectively. The annual growth in pollution app is thus four times greater than the growth of other apps.[26]

## 4.2 Awareness: Web Searches and Air Purifier Sales

We examine changes in the public awareness of air pollution issues in two ways. First, we measure the demand for pollution-related information by Internet keyword searches on Baidu. This analysis is analogous to the examination of "smog" news in Section 4.1. Here we again focus on search queries for "smog," though the patterns for keywords "air pollution," "mask," and "air purifier" are very similar.

Figure 5 repeats the exercise in Figure 3, now using search index as the outcome variable. Figure 5a plots the time-series pattern of the search index for the keyword "smog" at the national level. The index varies between 0 and 200 for most of 2011 and 2012, and jumps overnight from 175 in December 2012 to 4,400 in January 2013, the month of the initial roll-out. This is a 25-fold increase. In addition to remaining at a high level post-2013, the search index exhibits a strong seasonal pattern and is highest in winter seasons, similar to that of smog which is more severe in winter partly due to coal-fueled heating. Not surprisingly, while the search index and AOD are essentially uncorrelated before 2013, they are strongly correlated afterward. The two outliers, 21,000 in December 2013 and 25,000 in January 2015, correspond to the two worst smog episodes in the country's recent history.

Leveraging disaggregated search indexes for over 300 cities, Figure 5b provides an event-

[26] A mass of pollution apps released before 2013 initially streamed weather information, and then incorporated air quality contents after the information program began. These apps were categorized as pollution apps since we lacked information on their historical content. Had we had such data and could correctly categorize these apps, the growth in pollution app would be even higher than that shown in Figure 4.

time plot of the standardized search indexes two years before and one year after the roll-out in a local city. Echoing results in Section 4.1, the index is flat and near zero before the information program, and rises rapidly when monitoring starts. Within one year after the roll-out, smog searches increase by 75% of a standard deviation.

Our second measure of awareness is public and private investments in specific type of defensive equipment: air purifiers. The air purifier sales data are available at the monthly frequency for 50 cities and became available in 2012, allowing us to examine one year of pre-treatment trend. We repeat the same exercise documenting national-level time series and city-level event-time trends for air purifier sales. Figure 6a shows that air purifier sales more than double, rising from 11,000 units per month in 2012 to over 25,000 units per month after 2013. Similar to web searches, air purifier sales are invariant to weather and pollution conditions prior to the launch of the information program, but after the launch, they exhibit a strong seasonality with more sales in winter. Finally, analogous to what we see in web search patterns, the increase in sales coincides with the timing of the information program roll-out, and doubles within four quarters of the roll-out (Figure 6b).

The surge in Internet searches and air purifier sales both nationally and locally and their strong correlation with air pollution after the start of the information program provide strong evidence that concepts such as "smog" and "air pollution," as well as related adverse health consequences, entered the public domain as a result of easy access to related information provided by the program. As forcefully put by Wainwright (2014) and quoted by Greenstone and Schwarz (2018), by 2014, the "daily talk of the AQI has become a national pastime amongst ex-pats and Chinese locals alike. Air-quality apps are the staple of every smartphone. Chinese micro blogs and parenting forums are monopolized by discussions about the best air filters (sales of the top brands have tripled over the last year alone) and chatter about holidays to 'clean-air destinations.' "

# 5 Empirical Framework

## 5.1 Econometric Specification

As shown above, the information program has substantially expanded public access to pollution information and dramatically increased households' awareness about pollution issues. In turn, these changes have triggered a cascade of short- and long-run behavioral changes in household activities, including avoidance behavior, housing demand and housing prices, and in health outcomes, including mortality. Throughout the regression analysis, we use the same unified empirical framework to examine these changes that are induced by the information program. We focus on the difference in the "slope," i.e., the relationship between pollution exposure and outcomes before and after the information program:

$$Outcome_{ct} = \alpha \cdot Pollution_{ct} + \beta \cdot Pollution_{ct} \times d(monitoring)_{ct} + x'_{ct}\gamma + \varepsilon_{ct}, \qquad (3)$$

where $c$ denotes a city and $t$ denotes week. $Pollution_{ct}$ is the (logged) AOD measure of the ambient air pollution. The dummy variable $d(monitoring)_{ct}$ represents the information treatment, and takes the value one for all periods after city $c$ implements the information program based on the staggered roll-out schedule. Vector $x_{ct}$ includes $d(monitoring)_{ct}$, city fixed effects, year fixed effects, and week-of-year fixed effects. The last term $\varepsilon_{ct}$ denotes remaining unexplained shocks. We cluster standard errors at the city level to allow for arbitrary serial correlations among the sample periods. Note that $\alpha$ represents the outcome-pollution gradient before the information program, and $\beta$ – the primary coefficient of interest – denotes changes in the gradient after the program. We defer the discussion on the identifying assumptions underlying the causal inference of $\beta$ to section 5.2.

For every outcome, we also implement an event study version of Equation (3) which replaces the $d(monitoring)_{ct}$ dummy with a series of quarter-since-monitoring indicators while using the same set of controls:

$$Outcome_{ct} = \alpha \cdot Pollution_{ct} + \sum_{q=-8}^{k} \beta_q \cdot Pollution_{ct} \times d(t \in q)_{ct} + x'_{ct}\gamma + \varepsilon_{ct}, \qquad (4)$$

where $d(t \in q)_{ct}$ indicates week $t$ being in the $q^{th}$ quarter since monitoring began in the city.[27] We plot $\beta_q$'s coefficients which provide a visual representation of how the relationship between pollution and outcome evolves as a function of time relative to monitoring roll-out. Cities in different waves have different numbers of pre- and post-periods. Our event studies trace out the evolution of $\beta_q$'s starting eight quarters before the monitoring roll-out. Depending on data availability (Table 1), we report post-monitoring $\beta_q$'s for five quarters in the analysis of purchase trips ($k = 5$), and eight quarters in the analysis of mortality ($k = 8$). These event time windows are chosen to ensure that the underlying sample for each $\beta_q$ coefficient is a balanced panel of cities. We dummy out the remaining sample periods.

We use the same estimation framework as described in Equations (3) and (4) throughout the regression analysis below, except for section 6.2 where we use annual variation instead of weekly variation to study the long-run impact of the information program on the housing market. In section 6.2, we explain in depth how we adapt the regression framework to the

[27] We report quarterly (rather than weekly) event study coefficients to average out noise in the trends. This does not affect the estimation of the average before/after program impact.

housing analysis.

## 5.2 Identification of the Change in the Outcome-Pollution Gradient

Equation (3) highlights the difference between our study 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: $E\left(Pollution_{ct} \times \varepsilon_{ct}\right) \neq 0$. Such endogeneity could be due to omitted variables or errors in the measurement of pollution exposure.[28] 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.[29] Critically, 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* (which is $\alpha$), but rather in the *change* in the causal effect that takes place after the information program (which is $\beta$). Second, in our analysis, $Pollution_{ct}$ is intended to be a direct measure of ambient pollution, rather than a measure of population exposure determined by the ambient air quality, avoidance behavior, and population distribution. In fact, in the analysis we directly compare how avoidance and residential sorting respond to ambient air pollution with and without readily available pollution information.

The key insight of our empirical framework is that, under reasonable assumptions, one can consistently estimate the change in pollution's causal effects ($\beta$) using OLS, without having to consistently estimate the level of the effect ($\alpha$). If we were to separately estimate the slope using data before and after the treatment, the endogeneity in pollution would lead to inconsistency in both estimates. However, if the nature of the endogeneity is not affected by the treatment, the inconsistency in the slope estimates could cancel out, leaving the OLS estimate of $\beta$ consistent. The following two assumptions formalize this intuition:

**Assumption B1:** $\varepsilon \perp d \mid x$. This assumption implies that conditioning on city attributes and other controls $x_{ct}$ (e.g., city and time fixed effects), the treatment $d(monitoring)_{ct}$ is exogenous.

As discussed in Section 2.1, the information program was implemented against the backdrop of the MEP's promulgation of the national $PM_{2.5}$ standard, which marked a sudden and drastic change in the government's stance regarding the importance of environmental quality. The roll-out schedule of the monitoring stations in three waves was primarily based

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

[29]See for example Bayer, Keohane and Timmins (2009); Chen et al. (2013); Arceo, Hanna and Oliva (2015); Deschenes, Greenstone and Shapiro (2017); Ito and Zhang (2018); Barwick et al. (2018).

on the pre-determined city designations (mostly administrative hierarchies, such as provincial capitals, and a list of environmental improvement priority cities designated in 2007), as shown in Figure 2 and Appendix Figure C.1. For a given city, the date of the roll-out is a top-down decision driven by the physical constraints of installing monitor stations, and uncorrelated with the day-to-day variation of local pollution levels as shown in our analysis.

One might be concerned about other contemporaneous regulations at both national and local levels to achieve the pollution-reduction goals set out in the 12th (2011-2015) and 13th (2016-2020) Five-Year Plans. As discussed in Section 2.1, other concurrent policies do not coincide with the information program in the roll-out schedule or the spatial coverage. In our regressions, we include a rich set of temporal and spatial fixed effects such as city fixed effects and region by week-of-sample fixed effects to control for unobserved policies and other confounders.

Nonetheless, one might still be concerned about differential trends. For example, the enforcement of the national $PM_{2.5}$ standards established in 2012 might be systematically correlated with the roll-out schedule. Or, there might be other confounding factors, in light of China's rapid social and economic changes. To examine these concerns, Appendix Table C.2 presents a series of balance tests on differential shifts in city-level observables before and after the program. We focus on three classes of social and economic conditions: pollution levels using satellite-based AOD (both the weekly average and the maximum pollution reading in a city-week), the political and regulatory environment (the number of local officials ousted during the anti-corruption campaign, demographics of local political leaders, news mentions of regulation policies), and healthcare access (the number of medical facilities). Each cell in Table C.2 is a regression of these observables on $d(monitoring)_{ct}$, controlling for the exact same suite of fixed effects controls we use in Equation (3). If changes in environmental regulations or other confounders are systematically correlated with the program roll-out, we should expect pollution levels as well as proxies for the regulatory environment to change before and after the program. Results for a rich set of pollution measures, economics, political, and social variables indicate no discernible differences before and after the program in any of these regressions, suggesting that the role of both observed and unobserved confounding factors is likely limited (Altonji, Elder and Taber, 2005).

Another direct evaluation of Assumption B1 is a pre-trend test in the same spirit as the test for parallel trends in a standard difference-in-differences setting. Patterns that are consistent with Assumption B1 would be stable estimates in event time, followed by a trend break that occurs exactly at the time of roll-out. This is indeed what we find in event studies below (e.g., Figure 5-9) , where the coefficient estimates are flat before and after the treatment, with a sizeable break that is both economically and statistically significant at the time of the information treatment. In addition, the estimate of the key parameter of interest $\beta$ is robust across specifications with different sets of fixed effects, suggesting limited effect by confounding factors and lending additional support to Assumption B1.

**Assumption B2:** $d \perp Pollution \quad | \quad x$. This assumption implies that conditioning on $x_{ct}$, the treatment is independent of the level of pollution.[30]

An intuitive way to conceptualize this assumption is to imagine a binary context in which *Pollution* indicates "high" vs. "low" pollution areas. Note that Equation (3) reduces to a difference-in-differences style setting that compares outcome in regions with high vs. low pollution, before vs. after policy introduction. The "slope", i.e., the outcome-pollution gradient, in this case is simply the difference in the outcomes experienced in areas with high and low pollution. Assumption B2 ensures that there are no compositional changes in regions that experience high or low levels of pollution after the policy introduction. In other words, the nature of the endogeneity in pollution does not change before and after the policy.

The balance checks in Appendix Table C.2 discussed above illustrate that, conditional on $x_{ct}$, the pollution level does not change after the policy introduction, consistent with Assumption B2. Note that these results are not inconsistent with recent evidence that China's air quality has improved in recent years, especially after 2015 (Huang et al., 2018; Greenstone and Schwarz, 2018). Regional and national improvement in air quality is absorbed by various trends in our empirical analysis. Rather, these balance tests indicate that during the months surrounding the local implementation of the information program, economic and environmental measures do not display noticeable differences.

**Proposition 2.** *Under Assumptions (B1) and (B2), the OLS estimate of $\beta$ in Equation* (3) *is consistent.*

The proof is provided in Appendix B. There are two sources of inconsistency in the OLS estimate of $\beta$: one from the endogeneity of the interaction term $Pollution_{ct} \times d(monitoring)_{ct}$, and the other from smearing due to the endogeneity of $Pollution_{ct}$. Under assumptions (B1) and (B2), the inconsistency from these two sources cancels out, leaving the OLS estimate of the difference (the change in slope that we are interested in) to be consistent. Based on Proposition 2, our subsequent analysis focuses on the OLS estimate of $\beta$.

[30] While we present Assumption B2 for ease of interpretation, the assumption is stronger than what we need to prove the consistency of $\beta$. As we show in Appendix B, a sufficient condition is $E[d|M_x \times Pollution] = c$, where $M_x$ is the projection matrix and $c$ is a constant.

# 6 Pollution Disclosure, Behavior, and Health

## 6.1 Pollution Disclosure and Avoidance

With access to reliable pollution information, households can take different measures to avoid or mitigate pollution exposure. Low-cost and effective solutions include staying indoors, wearing facial masks, or using air purifiers when pollution is elevated. We use outdoor purchase trips – defined as the number of bank card transactions in city $c$ at week $t$ per 10,000 active cards (Section 2.2) – as a proxy to evaluate short-run avoidance behavior, and we examine how the relationship between outdoor purchase trips and ambient pollution levels changes after the information program is implemented in a city. In order for the $\beta$ estimates to be representative of the population impact, we weight the regression using the number of active cards in a city and year to account for differences in bank card penetration rates across cities (Figure C.5).[31]

Figure 7 shows an event study graph for $\beta_q$'s – the purchase-pollution gradient as a function of quarters since pollution monitoring began – with the coefficient for the event quarter -1 ($\beta_{-1}$) normalized to zero. Two patterns emerge. First, before the program, the $\beta_q$'s estimates are flat and statistically indistinguishable from zero, suggesting a lack of pre-trends. Second, the purchase-pollution gradient exhibits a level shift of -20 trips on a weekly basis per 10,000 cards which occurred almost exactly upon the roll-out of the information program. To examine the statistical precision and the robustness of these patterns, we repeat the analysis across several specification choices in panel A of Table 2, with increasingly saturated fixed effects to exploit finer variation in the data. Column 1 uses city, week-of-year, and year fixed effects, which correspond to the specification of Figure 7. Column 2 uses city and week-of-sample fixed effects (fixed effects for all weeks during 2011-2016), exploiting variation in pollution across cities in the same week. Column 3 further adds region-by-year fixed effects, allowing for common trends in transactions and pollution that are specific to each region.[32] Column 4 is our most stringent specification, controlling for city and region-by-week-of-sample fixed effects. We obtain similar results across the board. Table 2 also suggests that purchase trips are invariant to pollution before the program. While our purchase-pollution slope estimate prior to the information program need not be causal (as previously discussed), it is consistent with the hypothesis that households are less likely to engage in any mitigating measures in the absence of information.

[31]The purchase rate is preferable to logs due to a non-trivial fraction of zero transactions in some categories in small cities from the 1% card sample. The patterns are very similar if we use inverse-hyperbolic-transformed transactions instead of the purchase rate.

[32]"Region" is a conventional partition of cities by location: north (36 cities), northeast (38 cities), east (105 cities), central south (81 cities), southwest (54 cities), and northwest (52 cities).

Our results suggest that purchase trips become more responsive to pollution levels after a city implements the monitoring program. The magnitude of the coefficient from our richest specification in Column 4 indicates that doubling the pollution level reduces purchase trips by about three percentage points (25.1 trips per week per 10,000 cards divided by the mean of the dependent variable which is 869.1). This is not a trivial change because our analysis covers *all* consumption categories, which constitute 59% of national consumption. Furthermore, the week-level analysis by construction has already incorporated within-week intertemporal substitution. The estimate could reflect to some extent permanently displaced consumption as households seek to mitigate pollution exposure. As a point of reference, Cutter and Neidell (2009) find that when a "Spare the Air" alert is issued in the San Francisco Bay Area, *daily* traffic falls by 2.5-3.5 percent with the largest effect during and just after the morning commuting period.[33] Graff Zivin and Neidell (2009) estimate that a *one-day* smog alert issued in Southern California leads to an 8-15% reduction in attendance at two major outdoor facilities (the Los Angeles Zoo and the Griffith Park Observatory) on the same day, though the effect dissipates quickly in consecutive days of such alerts. These two studies focus on immediate (daily) behavioral changes after government-issued air quality warnings while our estimates measure behavioral responses to air quality over the course of a week following the implementation of the information program.

In panels B and C of Table 2, we examine heterogeneity between "deferrable" and "non-deferrable" consumption. Deferrable categories include supermarkets, dining, and entertainment; non-deferrable consumption includes all other categories. We find that deferrable consumption experiences a 6 percentage points increase (in absolute value) in purchase-pollution gradient, and they explain about 80% of the change in overall purchase-pollution gradient.[34] The estimated effects on the rest of the consumption categories are negative but not statistically significant. In additional analysis, we conduct placebo-style tests looking at the impact of information roll-out on several specific types of "scheduled" consumption, including trips for paying bills (e.g., for utilities, insurance, telecommunication, and cable services), paying for government services (e.g., court costs, fines, and taxes), business-to-business transactions, as well as spending at cancer treatment centers. There is no statistical evidence that information availability changes the responses of scheduled consumption to air pollution.

We report two sets of additional analyses that support our main findings. First, we conduct a battery of robustness checks in Appendix Table C.3. To highlight a few examples,

[33] The "Spare the Air" (STA) advisories, designed to elicit voluntary reductions in vehicle usage and encourage the usage of public transit and carpooling, are issued on days when ground-level ozone is predicted to exceed National Ambient Air Quality Standards.

[34] The mean of the dependent variable in Panel B is 314.4. The coefficient in Column 4 translates to a 6 percentage points difference.

we find that the inclusion of flexible weather controls – including weekly temperature, precipitation, wind speed, barometric pressure – is not consequential to our estimation, that online transactions cannot explain away our findings, and that our conclusion holds for cities without the presence of a U.S. embassy or consulates.[35] In addition, our results are robust to excluding top 10% of the cities with the highest number of officials who were ousted as a result of China's sweeping anti-corruption campaign, which has been associated with a reduction in luxury consumption (Qian and Wen, 2015). Finally, results are similar when we use maximum pollution readings instead of average pollution readings.

Second, we implement a "triple-difference" design to further tease out the effect of real-time monitoring *information*, as opposed to a salience effect related to news coverage or geographically correlated unobservables that may affect behavior even without the disclosure of pollution monitoring data. Specifically, for each wave of "treatment" cities, we introduce a group of "control" cities that share boarder with the treatment cities but have not yet experienced monitoring. These control cities are assigned the same roll-out time as their treated counterparts. We then estimate and compare *differential* change in the transaction-pollution gradient across the treatment and control cities.[36] Appendix Table C.4 summarizes the results. There are two key findings. First, the triple interaction term "Log(Pollution) × 1(after monitoring) × 1(Treated)" suggests a differential change in the transaction-pollution gradient in treatment cities relative to that of their neighbors by an amount similar to our main effect reported in Table 2. Second, the double interaction term "Log(Pollution) × 1(after monitoring) " shows that there are no detectable changes in the transaction-pollution gradient in neighboring cities at the time when the information program began in the treated cities. These findings suggest an isolated effect that occurs only in cities that actually experience monitoring.[37]

[35] The U.S. Embassy in Beijing started to report hourly $PM_{2.5}$ levels in 2008 based on monitoring stations installed on-site. U.S. consulates in Guangzhou, Shanghai, Chengdu and Shenyang followed the practice in 2011 and 2012. Residents in these cities might have had better information on air quality prior to 2013.

[36] This test compares purchase behavior before and after the information program, in treatment and control cities, on high and low pollution days. Cities in the last wave of the roll-out do not have control cities. We include them as treated units. Leaving out these cities leads to reduced power but qualitatively similar results.

[37] Our triple difference effect size and precision drop with the inclusion of region×week-of-sample fixed effects as shown in column 4 of Appendix Table C.4. This is largely due to the lack of independent variations among treated and neighboring areas within a region and week, especially for western China where cities are large in geographic area, as shown in Figure 2. In additional analysis, we restore both the effect size and precision if we group the northwest and southwest regions into one region.

## 6.2 Pollution Disclosure and Housing Choices

Our analysis so far suggests that the information program has resulted in short-term behavioral changes that reflect greater mitigation efforts in response to air pollution. To examine the long-run change in household response to pollution, we turn to the capitalization of air quality in the housing market before and after the program. The housing analysis is a canonical example to study household preference for non-marketed environmental goods (Oates, 1969; Chay and Greenstone, 2005; Banzhaf and Walsh, 2008; Bayer et al., 2016). The price gap among properties with similar attributes but different environmental qualities helps us infer preferences for environmental quality. Many studies have examined the impact of one of the most prominent U.S. pollution information programs, the Toxic Release Inventory (TRI), which publicizes toxic emissions reports from major emitters (Bui and Mayer, 2003; Oberholzer-Gee and Mitsunari, 2006; Konar and Cohen, 2001; Mastromonaco, 2015).

Our analysis focuses on Beijing for which we have access to nearly the universe of new home transactions from January 2006 to April 2014. Analogous to Section 6.1, we study the housing price-pollution relationship across neighborhoods with varying degrees of air pollution. Our parameter of interest is the extent to which this relationship shifts before and after the information program is implemented in Beijing in January 2013. As housing purchase decisions (and the capitalization of air quality) are likely affected by the long-run pollution level rather than week-to-week variation, we focus on *annual* changes in housing prices instead of *weekly* changes as in the other outcomes. We aggregate individual transaction records to the apartment-complex level, which is the finest level at which we observe geolocation information. Our data contain new home transactions in about 1,300 different apartment-complexes.

We obtain a complex-by-year housing price index through partialling out property attributes in a hedonic regression:

$$ln\ TransactionPrice_{ict} = \mathrm{w}'_{ict}\gamma + \eta_{cy} + \epsilon_{ict},$$

where the dependent variable is the log transaction price of unit $i$ in apartment-complex $c$ on date $t$. Property characteristics $\mathrm{w}_{ict}$ includes floor fixed effects, sale month-of-year fixed effects, unit size and its quadratic term. Our variable of interest is $\eta_{cy}$, which represents the average housing price for apartment-complex $c$ in year $t$. There are on average 153 underlying housing transactions for each apartment-complex and year. Note that we only observe prices in complex-years for which any housing units were sold, and thus the data is repeated cross-sectional in nature.

Next, we use the estimated quality-adjusted price index at the complex-year level as the dependent variable in Equation (3):

$$\hat{\eta}_{cy} = \alpha \cdot Pollution_{cy} + \beta \cdot Pollution_{cy} \times d(monitoring)_y + x'_{cy}\gamma + \varepsilon_{cy}.$$

The controls $x_{cy}$ in this equation include ZIP Code fixed effects, district-by-year year fixed effects, and fixed effects for the number of years on market since the complex first became available for sale.[38] This specification compares transaction prices within the same district and year, but across apartment-complexes with high and low pollution levels, controlling for ZIP Code level time-invariant characteristics.[39] To flexibly account for potential autocorrelation in both housing prices and pollution, we use two-way clustered standard errors at the ZIP Code level and the district-year level. The event study reports seven years of pre-trends (2006-2012) and "one" year of post-trends (2013 - April 2014).

Our housing transaction data contain rich spatial variation. Thus, we use two different measures of pollution at the sub-city level: a) logged high-resolution ambient air quality (AOD) at the 1km-by-1km-by-year resolution, and b) proximity to major polluting sources. We discuss each of these two sets of analysis below.

**Ambient Pollution and Housing Prices.** We begin by linking housing prices to *ambient* air pollution, analogous to what we have done in Section 6.1. To obtain a pollution measure with a high level of spatial resolution (i.e., at the apartment-complex level), we employ a frontier method in atmospheric science called "oversampling" that reprocesses the original AOD data to increase spatial resolution from 10-by-10 km to 1-by-1 km, while sacrificing the temporal resolution from daily to annual.[40] Appendix Figure C.8 presents Beijing's pre- and post-oversampling average AOD concentration. Our first pollution measure in the housing analysis is the annual AOD level in the 1-by-1 km region that contains the apartment-complex.

Table 3, panel A summarizes the change in price-pollution gradient before and after 2013 using Equation (3). Column 1 reports the specification with ZIP Code and district-by-year fixed effects. Column 2 adds the years-on-market fixed effects. Prior to the information

[38] Beijing is divided into 16 districts and 180 communities (analogous to ZIP Codes in U.S.) that consists of apartment complexes. Among the 1,300 apartment-complexes in our study sample, 64% are sold out within three years.

[39] We lack the power to implement an apartment-complex fixed effects specification as few complexes have observations both before and after the program. The point estimates for the change in the price-pollution gradient post the program are similar when we do control for apartment-complex fixed effects.

[40] Appendix Figure C.7 illustrates the oversampling idea using two consecutive days of MODIS AOD data. 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. We average the high-frequency temporal variation across the overlapping overpasses to enhance the geospatial resolution of the AOD measure.

program, doubling annual pollution leads to an insignificant 0.5-3% decrease in housing prices, indicating a lack of response to pollution. After the program, the price elasticity becomes significant at the 10% confidence level and is economically sizeable, varying from 0.54 (Column 1) to 0.62 (Column 2). Figure 8a plots the event study for Equation (4). The trends are remarkably flat before 2013, followed by a sharp change in magnitude after 2013 when the housing market begins to respond to pollution and capitalize air quality.

Our estimates of Beijing's housing price-pollution elasticity post monitoring is roughly -0.60. This is slightly larger than findings obtained in the U.S. setting, but comparable to those obtained in China's context. For example, by exploiting permanent reductions in total suspended particle (TSP) pollution in the wake of the U.S. Clean Air Act provisions undertaken in 1970 and 1977, Chay and Greenstone (2005) 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. In a hedonic price framework using Beijing's housing transactions and land parcel data, Zheng and Kahn (2008) find a price-$PM_{10}$ elasticity of -0.41. Using moving costs and housing value information from the China Population Census, Freeman et al. (2019) estimate a price-$PM_{2.5}$ elasticity of -0.71 to -1.10.

**Proximity to Major Polluters and Housing Prices.** One might be concerned about using the high-resolution AOD information given that there were fewer than 30 monitoring stations in the metropolitan area of Beijing. In practice, residents are likely to have more localized pollution information than that provided by monitoring stations. For example, air purifiers displaying real-time $PM_{2.5}$ readings have become a common household appliance in Beijing since 2013. Nearly a quarter of a million units of air purifiers were sold in Beijing in 2015 alone. In addition, portable $PM_{2.5}$ monitors are popular as well. Nevertheless, to address this concern, we next analyze the price-pollution relationship based on "coarser", but more salient, pollution information.

Following the literature (e.g., Davis, 2011; Currie et al., 2015; Muehlenbachs, Spiller and Timmins, 2015), we use proximity to the nearest major pollution source as our second pollution measure in Equation (3). While large polluters might be visible landmarks in a city, the information program could affect residents' housing choices through raising the salience of the health impacts of these large polluters in addition to providing real-time pollution information. The top 10% heavy polluters (a total of 41 firms) account for nearly 90% of total emissions in Beijing (Appendix Figure C.9). Using geolocations of all polluters, we compute each apartment-complex's (time-invariant) distance to the nearest major polluter. We then use a dummy variable for whether a complex is within 3 km of the nearest major polluter as our second pollution measure.[41] In addition to the set of controls as in Panel A of Table 3, we also control for distance to non-major polluters. We adapt the event study estimation equation analogously.

Panel B of Table 3 summarizes changes in the price-pollution gradient before and after 2013. Housing values for properties within 3 km of a major polluter do not appear to differ from other properties prior to the information program, but suffer from a significant reduction of -8.6% to -9.1% afterward. Echoing our findings using ambient air quality as the pollution measure, the capitalization of environmental amenities in housing values only emerged after the information program. Figure 8b plots the event study. The graphical pattern is remarkably similar to that in Figure 8a: there are no pre-trends in price-pollution gradient, until monitoring began in 2013.

To conceptualize our effect size, we note that Currie et al. (2015) estimate an 11% reduction in housing value for properties located within 1 km of a toxic plant in the United States. Gamper-Rabindran and Timmins (2013) show that the cleanup of Superfund sites leads to a 21% increase in the median housing price of census tracts within a 3-mile radius. Our estimate is within the range reported in the literature and appears reasonable in our context. During the sample period, Beijing experienced an unprecedented housing boom, and the average housing price grew by 262%. The effect size reported here corresponds to 14% of the interquartile range of the housing price dispersion.

Both sets of estimation find that after the information program, there is a stronger capitalization of air quality in housing prices in Beijing, implying that consumers are willing to pay for a higher premium for houses in cleaner locations. Interestingly, in the context of estimating Chinese residents' willingness to pay (WTP) for clean air based on demand for air purifiers, Ito and Zhang (2018) find that the WTP increased after 2013 at the national level, consistent with stronger consumer awareness of pollution. Overall, the change in the price-pollution gradient in the housing market corroborates the evidence on increased awareness of air pollution and short-term behavioral changes documented above, reflecting the sweeping changes that the information program has brought about.

[41] We also estimate a non-parametric version that traces out the impact of being close to major polluters for different distance bins, and do so separately for periods before and after the program (Appendix Figure C.10). Consistent with evidence in Panel A of Table 3, we detect no statistically significant price-distance curve before the program. The slope of the curve shifted substantially after the program, where a near-monotonic price-distance relationship emerges up to 6 km from major polluters. Prices for properties immediately next to major polluters reduce the most, and the effect tapers off with distance. Note that, relative to estimates reported in Table 3, the estimated impacts of the information program is larger and more precise when the pre versus post responses are estimated separately (i.e., allowing all right-hand side variables, including the fixed effects controls, to vary by pre and post periods). The main text focuses on more conservative estimates.

## 6.3 Pollution Disclosure and Health Benefit

Our previous analyses have documented a range of behavioral responses to the information program. To quantify the value of pollution information, our endpoint analysis examines whether the same amount of pollution exposure is associated with fewer deaths after pollution information becomes widely available. Our analysis uses weekly mortality data in 131 cities from 2011 to 2016.

Figure 9 plots the $\beta_q$ coefficient estimates for the event study (Equation (4)). The mortality-pollution elasticity exhibits a flat trend before the program, followed by a noticeable decline afterward, consistent with the event study analysis on short-term and long-term behavioral changes above. This decline appears to strengthen after a few quarters, suggesting that the mortality effect tends to manifest over time. Table 4 reports the mortality results using Equation (3), with the same specifications as in Table 2. Panel A suggests a statistically significant 2-3 percentage points reduction in the mortality-pollution elasticity after the program. Appendix Figure C.11 explores nonlinear specifications and shows that the reduction in the mortality-pollution gradient is moderately convex.

Next, we conduct a series of additional tests to examine the plausibility of the reduction in the mortality-pollution elasticity estimates. Panels B and C of Table 4 divide mortality by cause of death. Both the cardiorespiratory category (panel B) and non-cardiorespiratory category (panel C) register significant changes in the mortality-pollution gradient. Because cardiorespiratory deaths account for about half of total deaths, our estimates imply that over 50% of the reduction in mortality damage through information comes from cardiorespiratory causes – which are widely considered as the most direct consequences of pollution exposure. Panel D performs a placebo test that examines external injury mortality. The information program does not alter the relationship between pollution exposure and injury.

Table 5 reports an age-group decomposition of the mortality effect.[42] The effect of the information program concentrates among people aged over 60 who are more vulnerable to pollution exposure than younger age groups. For this age group, the reduction (e.g., flattening) of the mortality-pollution gradient is larger than the average impact shown in Table 4 and is significant at the 1% level across specifications. Interestingly, we find no change in the mortality-pollution relationship for infants under one year of age. This could be associated with the low pollution exposure among infants due to the traditional Chinese practice of keeping newborns indoors within the first few months of their birth to minimize the outdoor exposure.

[42] The low number of observations for the infant analysis (Panel A of Table 5) is due to city-weeks with zero infant deaths. Results are robust if we use the level of infant mortality rate or inverse-hyperbolic-transformed infant mortality rate as the outcome variable.

We further conduct heterogeneity analysis which provides suggestive evidence of the underlying mechanism behind the mortality effect. Specifically, we repeatedly split the sample into two using the average value of a series of city-level characteristics, including per capita income, share of the urban population, per capita number of hospitals, per capita residential electricity use, and share of mobile phone users. Panel A of Table 6 reports coefficients on the interaction between the change in the pollution gradient and each of five city-level characteristics. There exhibits a larger reduction in mortality damage in cities that have higher per capita income, are more urban, have more hospitals, consume a higher rate of residential electricity, and experience a higher mobile phone penetration. While the effect sizes for above-median cities are not statistically distinguishable from those for below-median cities, overall the findings are consistent with the observation that residents in these cities are more likely to benefit from pollution information and, at the same time, engage in defensive activities to reduce the health damage from air pollution exposure.

To better understand the pathway from pollution avoidance to health outcomes, we examine heterogeneity in short-run outdoor purchase trips across the same set of city attributes. Results in Panel B are consistent with the patterns in Panel A: residents in richer and more urban cities and cities that have more hospitals, great electricity use, and higher mobile phone penetration exhibit a stronger and more precisely estimated behavioral changes to elevated pollution. While there are many defensive mechanisms that could reduce the negative health impacts of air pollution, the evidence here suggests one plausible pathway from effective avoidance to improved health outcomes.

# 7 The Value of Pollution Information

As outlined in the theoretical model, the value of information (VOI) arises from the power of information in changing behaviors, which reduces the wedge between the experience utility and the decision utility. Our analyses illustrate that disclosing pollution information has affected a range of behavioral and market outcomes that reflect households' efforts to mitigate the negative health consequences of air pollution. In this section, we quantify the value of the information program by estimating the benefit and cost components outlined in equation (2) in the theory section.

A lower bound of the program benefit is based on the mortality impact of the program, which we quantify using age-adjusted value of statistical life (VSL). The VSL approach is commonly used by policymakers to evaluate the benefits of life-saving regulations. Due to the lack of reliable VSL estimates for the Chinese population, we use a benefit transfer method that infers the VSL for Chinese residents from U.S.-based VSL estimates and the income elasticity of VSL. The benefit-transfer method is commonly used for countries with insufficient or unreliable data (Viscusi and Masterman, 2017).

Ashenfelter and Greenstone (2004) estimate that the VSL in the U.S. is USD 2.3 million. Narain and Sall (2016) suggest a transfer elasticity of 1.2 for transferring the VSL from U.S. to a developing country. Combined with a one-to-nine income ratio between China and U.S., the VSL for population in China amounts to RMB 1.3 million (in 2015).[43] Based on the age adjustment suggested by Murphy and Topel (2006), the average age-adjusted VSL is estimated to be RMB 0.49 million for individuals 60 and above, among whom the mortality impact is concentrated. The estimates in Table 5 suggest that the program has reduced total mortality for this age group by 3 percentage points, amounting to a savings of 149,130 deaths per year.[44] Therefore, the mortality benefit of the program is RMB 73.3 billion (about USD 10 billion) annually.

The behavioral changes that reduce premature deaths could also lower morbidity. Relying on comprehensive data on health spending, recent studies such as Deschenes, Greenstone and Shapiro (2017) and Barwick et al. (2018) have shown that the healthcare cost alone, not accounting the quality of life impact, can be as high as two-thirds of the mortality cost in U.S. and China, respectively. This would imply a lower bound of the morbidity benefit of about RMB 48.8 billion (USD 7 billion) per year.

The combined mortality and morbidity benefits amount to at least RMB 122 billion (USD 17 billion) annually. This reflects a lower bound estimate of the program benefit for the following reasons. First, we use a conservative VSL estimate of USD 2.3 million for the U.S..[45] Second, the benefit calculation does not account for quality of life changes or productivity gains due to improved health. Third, to be consistent with the analysis on other outcomes, mortality-pollution relationship is estimated on weekly data, and hence short-run in nature. In unreported analysis, we find the longer-run reduction in the mortality-pollution gradient based on quarterly data is indeed slightly larger.

We now turn to the estimate of the costs of avoidance, which include increased defensive spending, the welfare loss from foregone consumption, and the cost of the program itself. First, total sales of air purifiers and $PM_{2.5}$ masks have increased at a rate of RMB 7 billion and RMB 0.55 billion per year post 2013, respectively. Because cities in waves two and three started the information program toward the end of 2013 and 2014, these numbers are upper bounds on the increased defensive investments. Second, to calculate the welfare loss

[43] VSL for China = USD 2.3/(1.2*9) mill = USD 0.21 mill, or RMB 1.3 mill.

[44] The number of total deaths among people 60 and above was 4,971,000 in 2012 according to China Statistical Yearbook 2013.

[45] US EPA recommends a central VSL estimate of USD 7.4 million in 2006 dollars, or USD 8.9 million in 2015 dollars based on a meta analysis of VSL studies.

from foregone consumption, we follow the literature and assume that the price elasticity for consumer goods varies from -1 to -1.5 (Deaton and Muellbauer, 1980; Blundell, Pashardes and Weber, 1993; Banks, Blundell and Lewbel, 1997), and use our estimates from Table 2 to calculate foregone consumption. The estimated deadweight loss from the foregone consumption ranges between RMB 3.5 and 5.3 billion. Third, the one-time cost to set up the monitoring stations and broadcast the pollution information online is estimated to be RMB 2-5 billion, and the annual operation cost (staff and maintenance) is about RMB 0.5 billion a year. Taken together, the upper bound of the total cost is RMB 18 billion in its first year (including the start-up costs) and RMB 13 billion annually thereafter.

The estimated annual benefit and cost of the program – at least RMB 122 billion health benefits relative to the associated costs of less than 12 billion – underscores the cost effectiveness of the information monitoring-and-disclosure program.[46] While this policy is not a substitute for other policies aimed at reducing pollution, the increased awareness about pollution among residents could put pressure on polluters, and could complement other environmental regulations in reducing pollution (Konar and Cohen, 1997). More importantly, empowering the public with real-time pollution information mobilizes individuals' ability to mitigate the adverse consequences of pollution. This, together with other environmental regulations, can more effectively reduce the societal cost of pollution.

# 8 Conclusion

This paper examines the role of pollution information in shaping how ambient air pollution affects household behavior and health outcomes. We focus on a watershed policy change in China that resulted in the installation of air pollution monitoring stations and provision of previously unavailable, real-time pollution information to the public. Based on several rich and unique data sets, our analysis provides strong evidence that the program led to cascading changes, including increased access to and awareness of information on pollution and its harm, more pronounced short- and long-term avoidance behaviors, and a reduction in the negative health effects. The findings suggest that the value of the information monitoring-and-disclosure program is at least one order of magnitude larger than its costs.

China's experience offers an important lesson for other developing countries that are experiencing severe environmental challenges. The infrastructure for monitoring environmental quality and disclosing information is often inadequate – or nonexistent – in many such coun-

[46]Successful environmental regulations such as the U.S. Acid Rain Program and the Clean Air Act have been shown to achieve benefit an order of magnitude larger than the cost (Krupnick and Morgenstern, 2002; Chestnut and Mills, 2005). Different from our context, these programs substantially reduced pollution levels. We are unaware of other studies that quantify the benefit and cost of pollution information programs.

tries. As income rises, the demand for environmental quality increases, and households are better able to adapt. Providing real-time pollution monitoring data, combined with effective dissemination infrastructure such as smartphones and the Internet, both of which are increasingly commonly available among developing countries, could be a powerful and cost-effective tool to help households themselves mitigate health damages from environmental pollution, and enhance the effectiveness of – and public demand for – other environmental regulations that go further in addressing pollution's health effects. Furthermore, optimal design of the monitoring system – which we hope will receive more attention in future research – should help provide more accurate air quality measurement and thus unleash the full health benefits of information.

Finally, while our study is in the context of environmental quality, lessons gleaned from this large-scale information program could offer important guidance on improving information gathering and transparency in other settings such as communicable diseases, food and nutritional guidance, and traffic safety. Well-designed information provision could mobilize household efforts and complement government regulations to help address market failures associated with information asymmetry and externalities, especially in developing countries.

# References


**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.

**Altonji, Joseph G., Todd E. Elder, and Christopher R. Taber.** 2005. "Selection on Observed and Unobserved Variables: Assessing the Effectiveness of Catholic Schools." *Journal of Political Economy*, 113(1): 151–184.

**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.

**Ashenfelter, Orley, and Michael Greenstone.** 2004. "Estimating the Value of a Statistical Life: The Importance of Omitted Variables and Publication Bias." *American Economic Review*, 94(2): 454–460.

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

**Banks, James, Richard Blundell, and Arthur Lewbel.** 1997. "Quadratic Engel Curves and Consumer Demand." *The Review of Economics and Statistics*, 79(4): 527–539.

**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.

**Bayer, Patrick, Robert McMillan, Alvin Murphy, and Christopher Timmins.** 2016. "A Dynamic Model of Demand for Houses and Neighborhoods." *Econometrica*, 84(3): 893–942.

**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.

**Blundell, Richard, Panos Pashardes, and Guglielmo Weber.** 1993. "What do we

Learn About Consumer Demand Patterns from Micro Data?" *The American Economic Review*, 83(3): 570–597.

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

**Bui, Linda T. M., and Christopher J. Mayer.** 2003. "Regulation and Capitalization of Environmental Amenities: Evidence from the Toxic Release Inventory in Massachusetts." *The Review of Economics and Statistics*, 85(3): 693–708.

**Chang, Tom Y., Joshua Graff Zivin, Tal Gross, and Matthew Neidell.** 2019. "The Effect of Pollution on Worker Productivity: Evidence from Call Center Workers in China." *American Economic Journal: Applied Economics*, 11(1): 151–72.

**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.

**Chestnut, Lauraine G., and David M. Mills.** 2005. "A fresh look at the benefits and costs of the US acid rain program." *Journal of Environmental Management*, 77(3): 252 – 266.

**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.

**Deaton, Angus, and John Muellbauer.** 1980. "An Almost Ideal Demand System." *The*

*American Economic Review*, 70(3): 312–326.

**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.

**Gamper-Rabindran, Shanti, and Christopher Timmins.** 2013. "Does cleanup of hazardous waste sites raise housing values? Evidence of spatially localized benefits." *Journal of Environmental Economics and Management*, 65(3): 345 – 360.

**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.

**Graff Zivin, Joshua, and Matthew Neidell.** 2012. "The Impact of Pollution on Worker Productivity." *American Economic Review*, 102(7): 3652–73.

**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.

**Hanna, Rema, and Paulina Oliva.** 2015. "The effect of pollution on labor supply: Evidence from a natural experiment in Mexico City." *Journal of Public Economics*, 122: 68 – 79.

**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, Jiaxiu, Haoming Liu, and Alberto Salvo.** 2019. "Severe Air Pollution and Labor Productivity: Evidence from Industrial Towns in China." *American Economic Journal: Applied Economics*, 11(1): 173–201.

**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 Economy*. 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.

**Konar, Shameek, and Mark A. Cohen.** 1997. "Information As Regulation: The Effect of Community Right to Know Laws on Toxic Emissions." *Journal of Environmental Economics and Management*, 32(1): 109 – 124.

**Konar, Shameek, and Mark A. Cohen.** 2001. "Does the Market Value Environmental

Performance?" *The Review of Economics and Statistics*, 83(2): 281–289.

**Krupnick, Alan, and Richard Morgenstern.** 2002. "The Future of Benefit-Cost Analyses of the Clean Air Act." *Annual Review of Public Health*, 23(1): 427–448.

**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.

**Murphy, Kevin M., and Robert H. Topel.** 2006. "The Value of Health and Longevity." *Journal of Political Economy*, 114(5): 871–904.

**Narain, Urvashi, and Chris Sall.** 2016. *Methodology for Valuing the Health Impacts of Air Pollution: Discussion of Challenges and Proposed Solutions.* The World Bank.

**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.

**Newell, Richard G., and Juha Siikamäki.** 2014. "Nudging Energy Efficiency Behavior: The Role of Information Labels." *Journal of the Association of Environmental and Resource Economists*, 1(4): 555–598.

**Oates, Wallace E.** 1969. "The Effects of Property Taxes and Local Public Spending on Property Values: An Empirical Study of Tax Capitalization and the Tiebout Hypothesis." *Journal of Political Economy*, 77(6): 957–971.

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

**Qian, Nancy, and Jaya Wen.** 2015. "The Impact of Xi Jinping's Anti-Corruption Campaign on Luxury Imports in China." *Northwestern Working Paper.*

**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.

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

**Tu, Meng, Bing Zhang, Jianhua Xu, and Fangwen Lu.** 2020. "Mass media, information and demand for environmental quality: Evidence from the "Under the Dome"." *Journal of Development Economics*, 143: 102402.

**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).

**Viscusi, W. Kip, and Clayton J. Masterman.** 2017. "Income Elasticities and Global Values of a Statistical Life." *Journal of Benefit-Cost Analysis*, 8(2): 226–250.

**Wainwright, Oliver.** 2014. "Inside Beijing's airpocalypse – a city made 'almost uninhabitable' by pollution." *The Guardian*.

**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.

**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, Junjie, Zhenxuan Wang, and Xinming Du.** 2017. "Lessons learned from China's regional carbon market pilots." *Economics of Energy & Environmental Policy*, 0(Number 2).

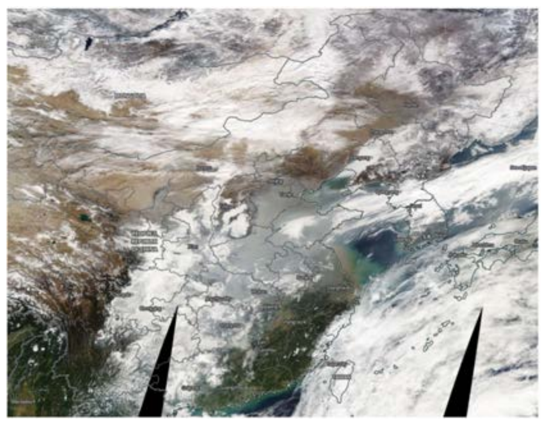
**Zheng, Siqi, and Matthew E Kahn.** 2008. "Land and residential property markets in a booming economy: New evidence from Beijing." *Journal of Urban Economics*, 63(2): 743–757.

**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.

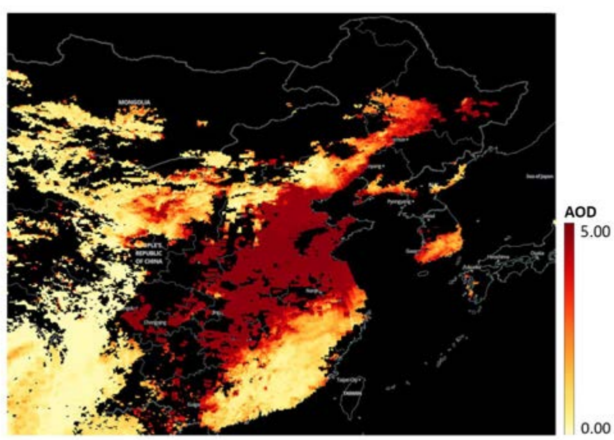
**Zivin, Joshua Graff, and Matthew Neidell.** 2009. "Days of haze: Environmental information disclosure and intertemporal avoidance behavior." *Journal of Environmental Economics and Management*, 58(2): 119 – 128.

Figure 1: November 2011 “Widespread, Dense Fog Event”


(a) News coverage



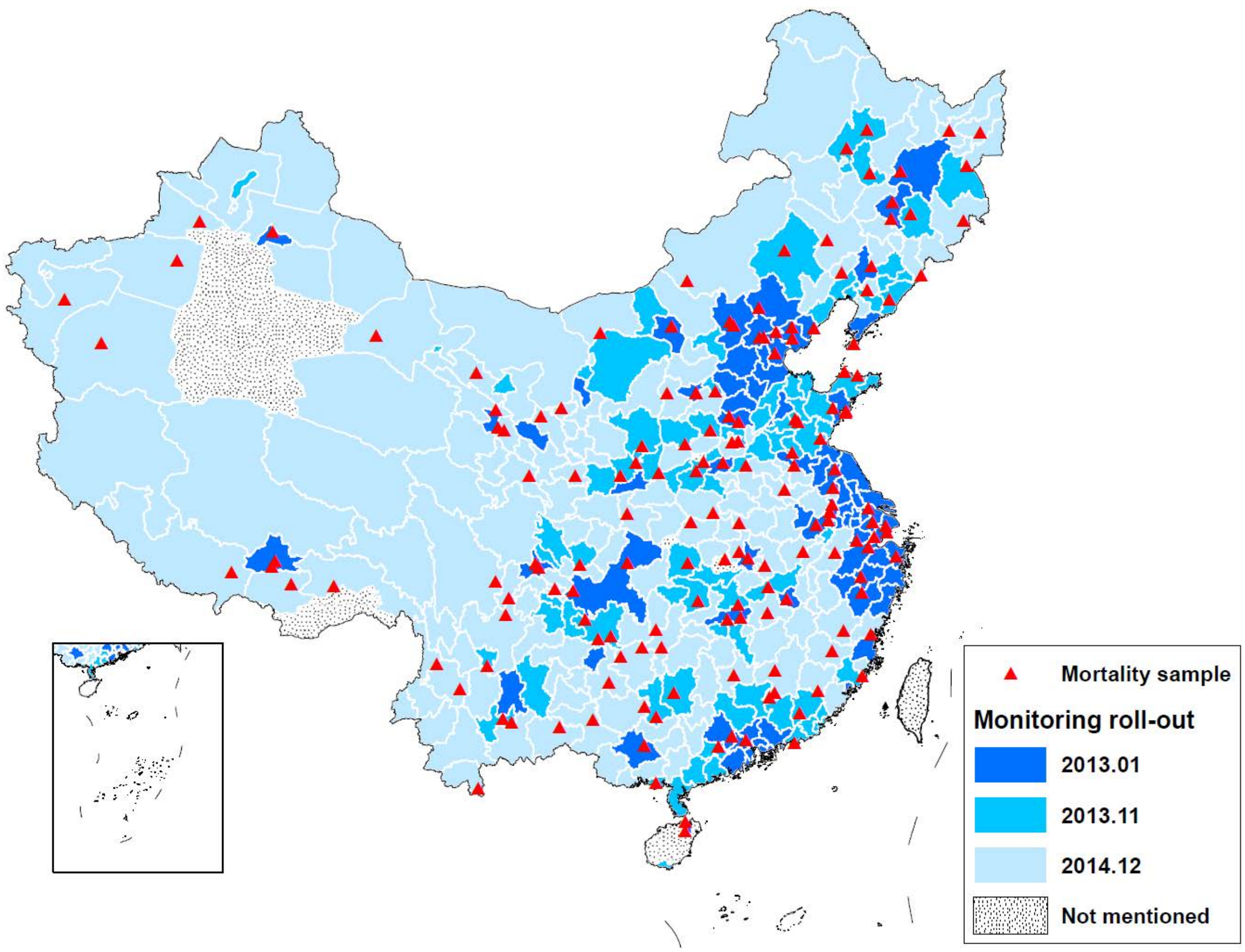
(b) Satellite picture of the event




(c) Satellite-retrieved pollution levels

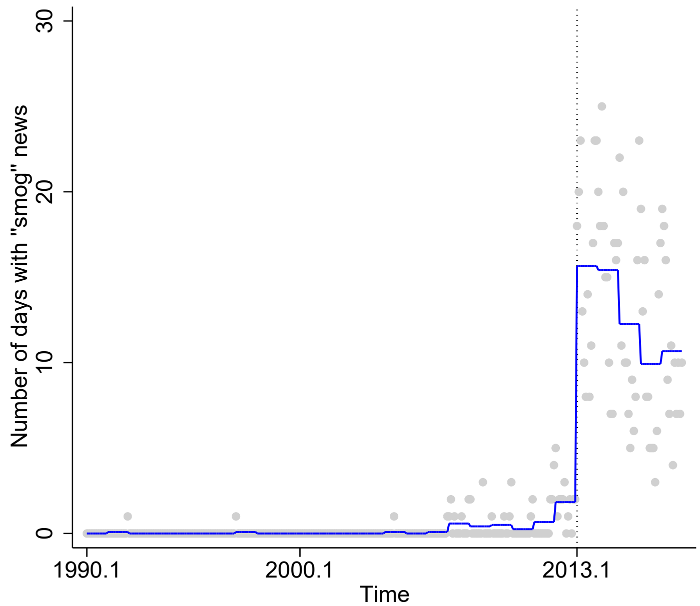
Notes: This figure illustrates a “widespread, dense fog event” on November 27, 2011 which is likely a major pollution event. Panel A, sourced from China Meteorological Administration, shows official news coverage of the event. Panel B, sourced from NASA, shows the satellite view of China on the same day. Panel C, sourced from NASA MODIS algorithm, shows the satellite-based measure of pollution (aerosol optical depth). The black regions have missing data (with cloud cover or water surfaces) and dark red regions have high levels of pollution.

Figure 2: Information Program Roll-Out and Mortality Data Availability

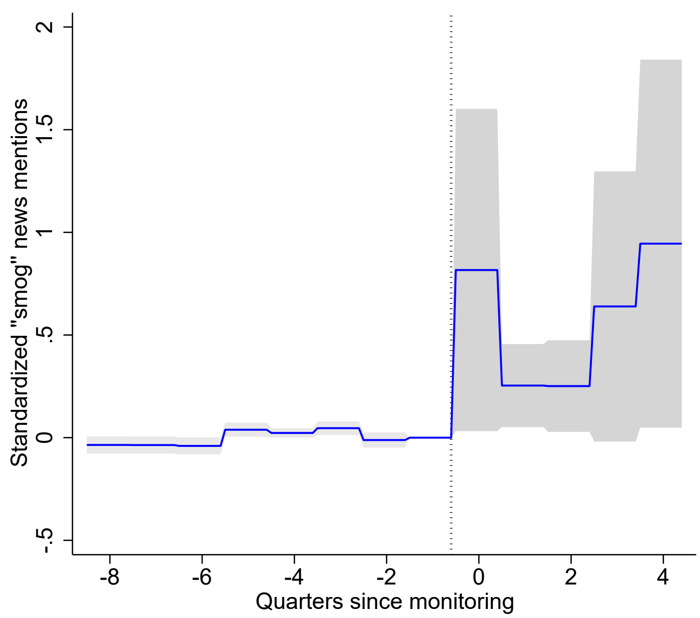



Notes: This map shows prefecture-cities by the completion date of the air pollution monitoring-and-disclosure program. "Not mentioned" are cities where the timing of monitoring is not mentioned in the government's policy notice. "Mortality sample" are centroids of counties included in the DSP mortality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

Figure 3: Changes in Pollution Information Access – News Mentions



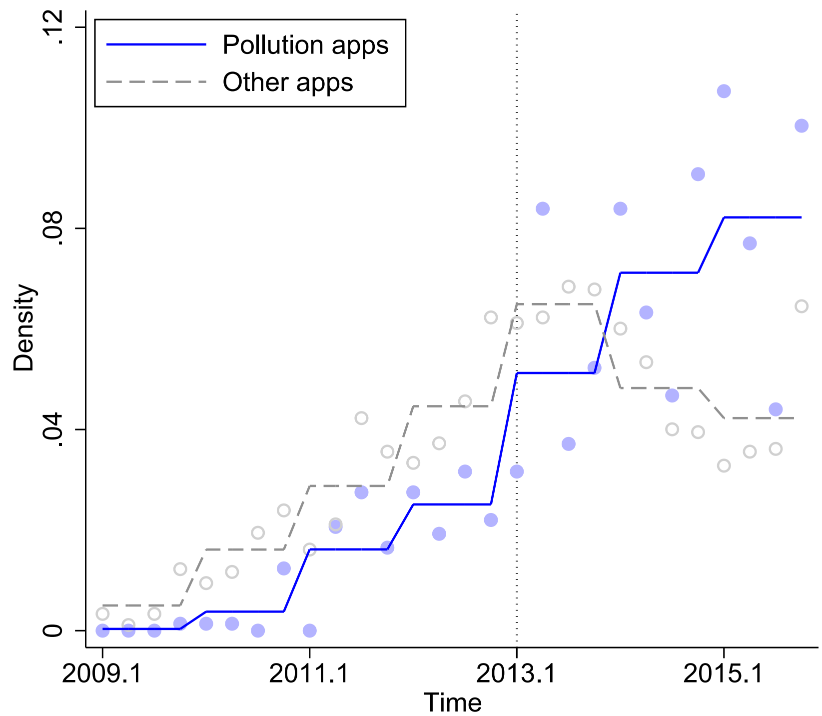

(a) *People's Daily*'s "smog" news




(b) Local "Smog" news before and after monitoring

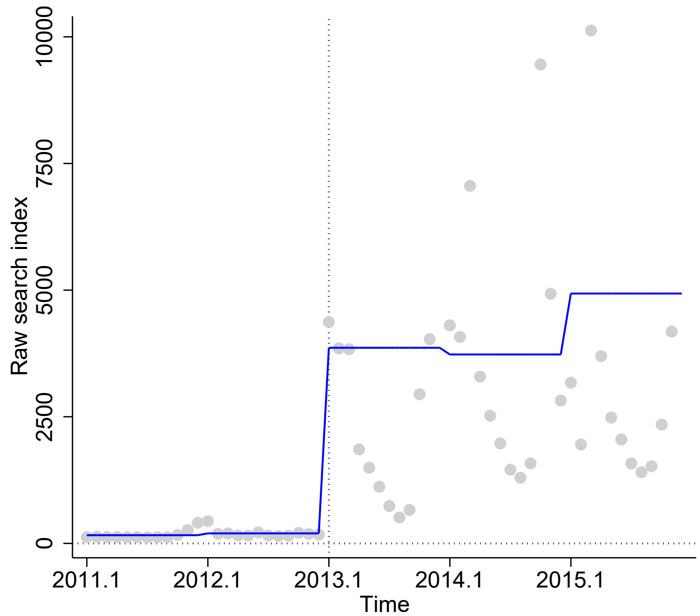
Notes: Panel A plots the number of days in each month when the *People's Daily* (the official newspaper of the Chinese government) published articles containing "smog" in content. Each dot represents a month. Line shows annual averages. Panel B plots standardized city-level "smog" mentions, defined as news that mentions both "smog" and the city name, as a function of quarters since the completion of the information program in a given city. Event quarter -1 is normalized to 0. The underlying regression contains no control variables to show raw data patterns. Shaded region shows the 95% confidence interval constructed from standard errors clustered at the perfecture-city level.

Figure 4: Changes in Pollution Information Access – Mobile Phone Apps

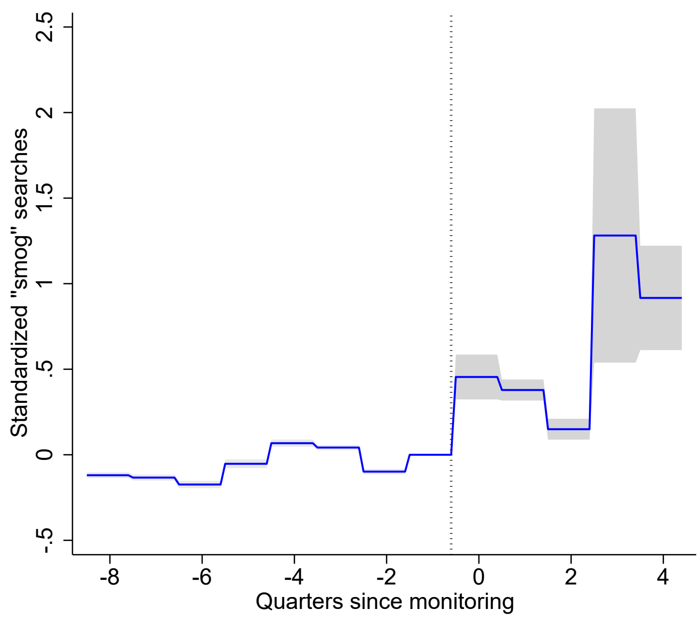



Notes: This chart shows release-date distribution of Apple App Store apps related to pollution (solid dots and line). Release-time distribution for apps in other categories (dashed dots and line) includes game, music, video, reading, finance, sports, education, shopping, and navigation. For each category, sample is restricted to the first 200 apps returned by the Apple API given the search key. Data are accessed on December 27, 2015. Pollution apps released before 2013 typically stream weather information and later incorporate real-time air quality content post 2013. These apps are categorized as pollution apps when we queried the Appstore data in 2015.

Figure 5: Changes in Pollution Awareness – Baidu Smog Search Index



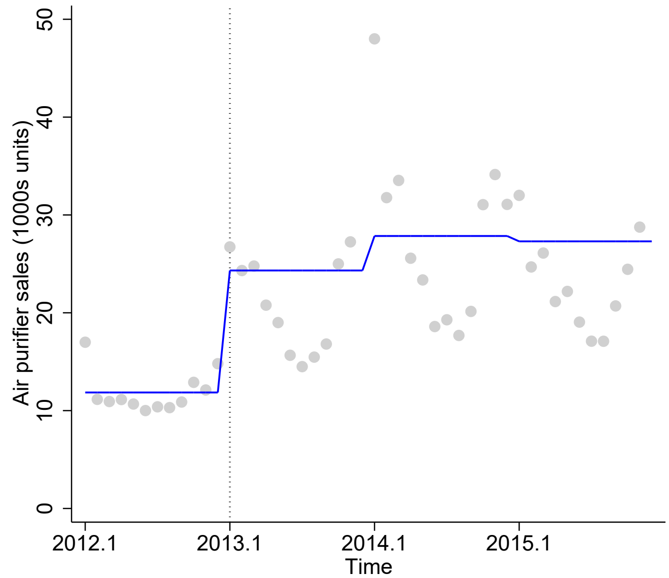

(a) Baidu "smog" search index at the national level



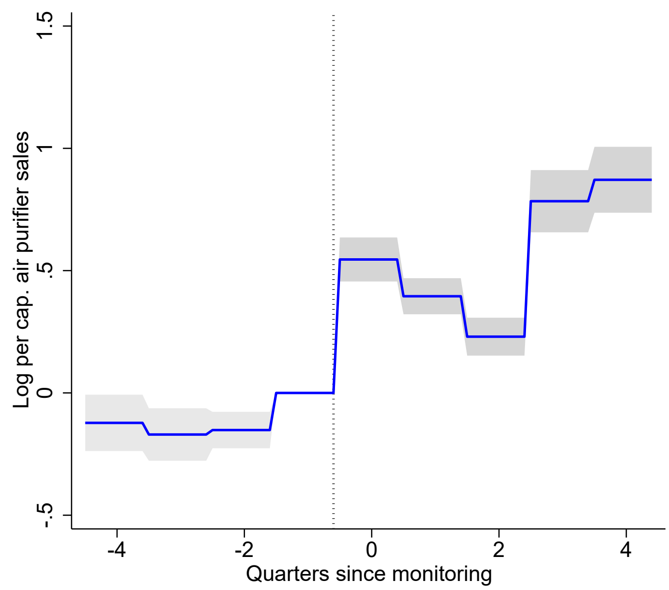

(b) Baidu "Smog" search index before and after a city implements the information program

Notes: Panel A plots raw monthly trends in Baidu Search Index for key word "smog". The graph omits two dots with exceptionally high search index (December 2013 with index = 20,942 and December 2015 with index = 24,679) for readability. Line shows annual averages. Panel B plots standardized "smog" search index as a function of quarters since the completion of the information program in a given city. Event quarter -1 is normalized to 0. The underlying regression contains no control variables to show raw data patterns. Shaded region shows the 95% confidence interval constructed from standard errors clustered at the prefecture-city level.

Figure 6: Changes in Pollution Awareness – Air Purifier Sales in 50 Cities



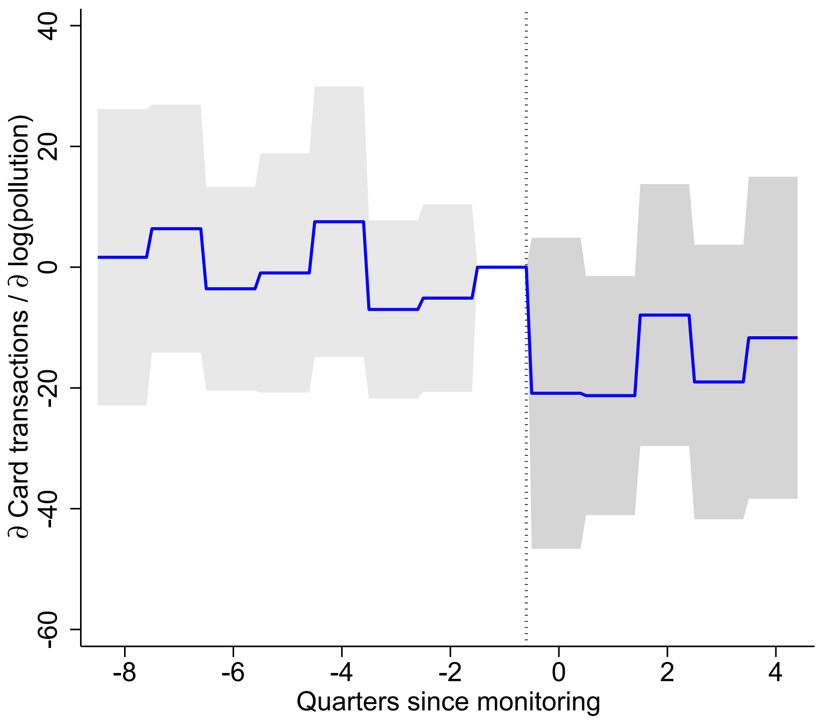

(a) National air purifier sales




(b) City-level event study

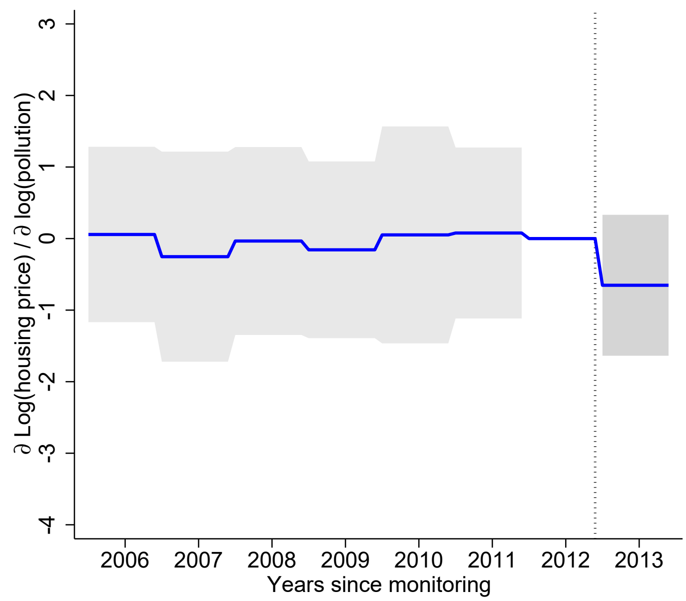
Notes: Panel A plots raw monthly trends in national air purifier sales from offline venues. The graph omits two dots with exceptionally high sales for readability. These dots correspond to December 2013 (sales = 61,605 units) and December 2015 (sales = 74,352 units). Line shows annual averages. Panel B plots log per capita air purifier sales as a function of quarters since the completion of the information program in a given city. Event quarter -1 is normalized to 0. The underlying regression contains no control variables to show raw data patterns. We report four quarters of pre-treatment coefficients because the air purifier data are available since January 2012 which is one year before the first wave of cities received monitoring roll-out. Shaded region shows the 95% confidence interval constructed from standard errors clustered at the prefecture-city level.

Figure 7: Changes in Short-Run Avoidance – Card Transaction-Pollution Gradient

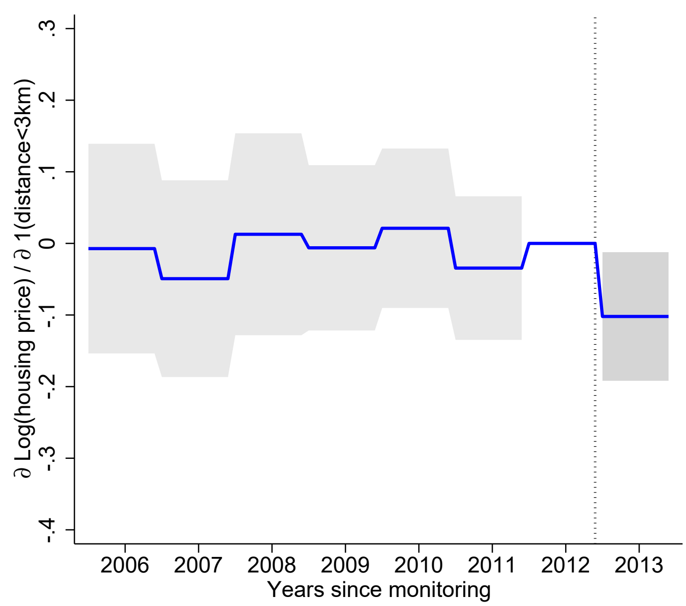



Notes: This graph shows coefficients from a regression of bank card transaction rate on log satellite-based pollution as a function of quarters since the completion of the information program in a given city. Event quarter -1 is normalized to 0. Each line segment represents a coefficient estimate. The underlying regression controls for prefecture-city FEs, week-of-year FEs, and year FEs. Shaded region shows the 95% confidence interval constructed from standard errors clustered at the prefecture-city level.

Figure 8: Changes in Long-run Capitalization – Housing Price-Pollution Gradient, Beijing



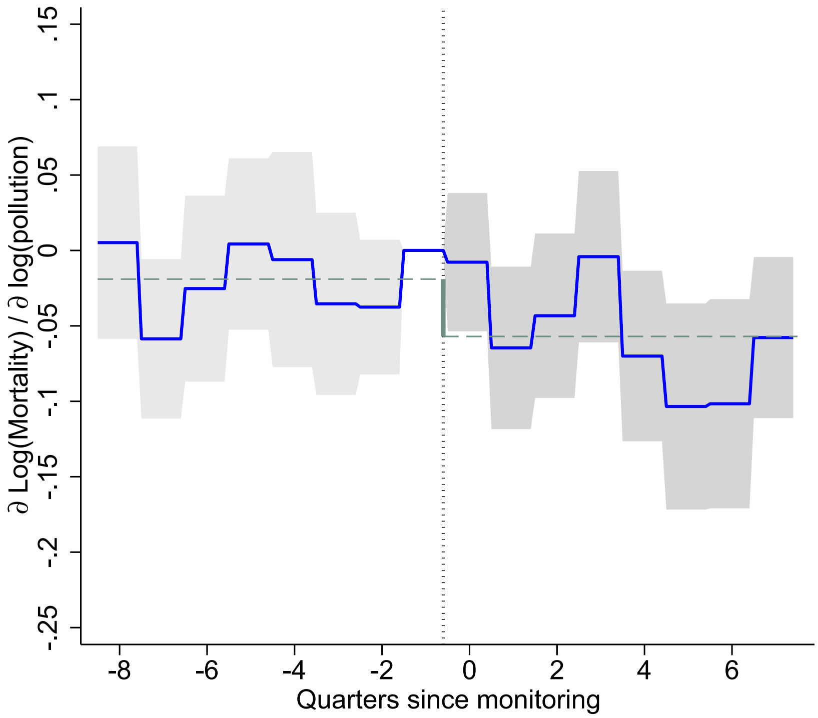

(a) Effect of ambient pollution




(b) Effect of being close to major polluters

Notes: This graph shows coefficients from a regression of Beijing's complex×annual log housing prices on log satellite-based pollution (panel A) and an indicator for being <3 km to a major polluter (panel B) as a function of year. Year 2012 is normalized to 0. Each line segment represents a coefficient estimate. The underlying regression controls for district×year FEs, ZIP Code FEs, and years-on-market FEs. Shaded region shows the 95% confidence interval constructed from standard errors two-way clustered at the ZIP Code level and the district×year level.

Figure 9: Changes in Health Outcome – 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 the completion of the information program in a given city. Event quarter -1 is normalized to 0. Each line segment represents a coefficient estimate. Dashed lines show before and after averages. The underlying regression controls for prefecture-city FEs, week-of-year FEs, and year FEs. Shaded region shows the 95% confidence interval constructed from standard errors clustered at the prefecture-city level.

Table 1: Summary Statistics

| | Cities available | Years available | Frequency | Mean | SD |
|---|---|---|---|---|---|
| *People's Daily* "smog" articles (count per week) | 313 | 2011.1-2016.4 | weekly | 0.031 | 0.310 |
| Baidu web "smog' searches (raw index) | 292 | 2011.1-2016.4 | weekly | 285.3 | 916.5 |
| Air purifier purchases (units per capita) | 50 | 2012.1-2016.4 | monthly | 0.063 | 0.090 |
| Bank card transactions: all (swipes per 1,000 cards) | 334 | 2011.1-2016.4 | weekly | 869.1 | 347.6 |
| Bank card transactions: deferrable (swipes per 1,000 cards) | 334 | 2011.1-2016.4 | weekly | 314.4 | 161.3 |
| Housing price (million RMB) | Beijing | 2006.1-2014.4 | transaction | 2.57 | 4.01 |
| Mortality rate: general (deaths per 100,000) | 131 | 2011.1-2016.12 | weekly | 10.36 | 3.46 |
| Mortality rate: cardiorespiratory (deaths per 100,000) | 131 | 2011.1-2016.12 | weekly | 5.63 | 2.58 |
| Aerosol optical depth (pollution index) | 334 | 2006.1-2016.12 | weekly | 0.550 | 0.419 |

Notes: Except for air purifier purchases and housing transactions, all other data sets are national or nationally representative in scope. The 50 cities with air purifier purchases data cover 28% of the total population. Bank card transactions data cover all cities and account for 59% of national consumption. Beijing, the capital city where we have housing data, has an average of 19.6 million population during the study period. Beijing's housing price is about 15,618 RMB per square meter (SD = 12,764 RMB), or 200 dollars per square foot, based on 660,000 transactions in the sample. The 131 cities with mortality data constitute a 5% representative sample of the total population. Satellite pollution data covers the entire nation.

Table 2: Changes in Short-Run Avoidance – Card Transaction-Pollution Gradient

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Panel A. All transactions | | | | |
| 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) |
| Panel B. Merchant type: Deferrable (supermarket, dining, entertainment) | | | | |
| Log(Pollution) | 6.46 | 5.99 | 9.20*** | 10.3*** |
| | (4.60) | (5.04) | (2.67) | (3.30) |
| Log(Pollution) × 1(after monitoring) | -14.7*** | -15.8*** | -17.1*** | -20.7*** |
| | (4.33) | (5.39) | (3.53) | (4.40) |
| Panel C. Merchant type: Non-deferrable | | | | |
| Log(Pollution) | 1.93 | 0.08 | -1.24 | 0.06 |
| | (5.01) | (5.43) | (4.41) | (5.50) |
| Log(Pollution) × 1(after monitoring) | -5.14 | -7.06 | -2.26 | -4.36 |
| | (6.16) | (7.18) | (6.22) | (7.86) |
| FEs: city | ✓ | ✓ | ✓ | ✓ |
| FEs: week-of-year | ✓ | | | |
| FEs: year | ✓ | | | |
| FEs: week-of-sample | | ✓ | ✓ | |
| FEs: region×year | | | ✓ | |
| FEs: region×week-of-sample | | | | ✓ |

Notes: Number of observations is 83,122. “Log(Pollution)” is logged AOD in a city×week. Dependent variable is city×weekly bank card transactions per 10,000 active cards. Mean of the dependent variable is 869.1 (panel A), 314.4 (panel B), and 554.8 (panel C). Hence, the coefficient for the Log(Pollution) × 1(after monitoring) interaction term in Column 4 is equivalent to a three-percentage point change, a six-percentage point change, and a one-percentage point change in the transaction-pollution elasticity in panel A, B, and C, respectively. “Non-deferrable” includes all transactions that do not fall in the categories of supermarket, dining, or entertainment. “region” is a conventional partition of cities by location: north (36 cities), northeast (38 cities), east (105 cities), central south (81 cities), southwest (54 cities), and northwest (52 cities). Standard errors are clustered at the prefecture-city level. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Table 3: Changes in Long-run Capitalization – Beijing's Housing Price-Pollution Gradient

| | (1) | (2) |
|---|---|---|
| *Panel A. Effect of pollution* | | |
| Log(pollution) | -0.031 | -0.005 |
| | (0.244) | (0.224) |
| Log(pollution)×1(after 2013) | -0.543* | -0.617** |
| | (0.318) | (0.301) |
| *Panel B. Effect of being close to major polluters* | | |
| 1(Near) | -0.004 | -0.004 |
| | (0.063) | (0.062) |
| 1(Near)×1(after 2013) | -0.086* | -0.091* |
| | (0.051) | (0.053) |
| FEs: ZIP Code | ✓ | ✓ |
| FEs: district×year | ✓ | ✓ |
| FEs: years-on-market | | ✓ |

Notes: The estimation sample is a repeated cross-section of apartment complexes in years when any apartment units within the complex are sold. Number of observations is 3,860 in Panel A and 3,334 in Panel B. The dependent variable is complex-year level logged average nominal housing price adjusted for quadratic floor size, floor indicators, and sale month-of-year indicators. An apartment complex is similar to a census block group in size. Beijing is divided into 16 districts, and 180 ZIP Codes. "Log(pollution)" is logged AOD at the oversampled 1km resolution corresponding to the complex's geographic coordinates. "1(Near)" is an indicator variable for apartment complexes within 3 km to the nearest major polluter. Standard errors are two-way clustered by ZIP Code and district×year. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Table 4: Changes in the Health Outcome – Mortality-Pollution Gradient

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Panel A. General Mortality | | | | |
| Log(Pollution) | 0.008 | 0.006 | 0.005 | 0.003 |
| | (0.005) | (0.006) | (0.006) | (0.006) |
| Log(Pollution) × 1(after monitoring) | -0.032*** | -0.026*** | -0.022** | -0.021** |
| | (0.009) | (0.009) | (0.009) | (0.010) |
| Panel B. Causes of death: Cadiorespiratory | | | | |
| Log(Pollution) | 0.008 | 0.006 | 0.005 | 0.002 |
| | (0.007) | (0.008) | (0.007) | (0.008) |
| Log(Pollution) × 1(after monitoring) | -0.036*** | -0.026** | -0.021* | -0.019 |
| | (0.011) | (0.011) | (0.011) | (0.013) |
| Panel C. Causes of death: Non-cadiorespiratory | | | | |
| Log(Pollution) | 0.011 | 0.010 | 0.010 | 0.008 |
| | (0.009) | (0.010) | (0.010) | (0.012) |
| Log(Pollution) × 1(after monitoring) | -0.032** | -0.029** | -0.027** | -0.023 |
| | (0.013) | (0.014) | (0.013) | (0.015) |
| Panel D. Causes of death: Injury | | | | |
| Log(Pollution) | -0.014* | -0.020** | -0.018** | -0.020* |
| | (0.008) | (0.009) | (0.009) | (0.011) |
| Log(Pollution) × 1(after monitoring) | -0.006 | 0.007 | 0.007 | 0.013 |
| | (0.013) | (0.015) | (0.014) | (0.016) |
| FEs: city | ✓ | ✓ | ✓ | ✓ |
| FEs: week-of-year | ✓ | | | |
| FEs: year | ✓ | | | |
| FEs: week-of-sample | | ✓ | ✓ | |
| FEs: region×year | | | ✓ | |
| FEs: region×week-of-sample | | | | ✓ |

Notes: Numbers of observations are: 30,882 (panel A), 30,760 (panel B), 30,795 (panel C), and 27,649 (panel D). "Log(Pollution)" is logged AOD in a city×week. Dependent variable is city×weekly logged mortality rate. "region" is a conventional partition of cities by location: north (36 cities), northeast (38 cities), east (105 cities), central south (81 cities), southwest (54 cities), and northwest (52 cities). Standard errors are clustered at the prefecture-city level. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Table 5: Changes in the Health Outcome – Age-Specific Mortality-Pollution Gradient

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Panel A. Age groups: Infants | | | | |
| Log(Pollution) | 0.005 | 0.003 | 0.003 | 0.002 |
| | (0.008) | (0.008) | (0.008) | (0.010) |
| Log(Pollution) × 1(after monitoring) | 0.001 | -0.002 | -0.003 | -0.006 |
| | (0.014) | (0.015) | (0.015) | (0.018) |
| Panel B. Age groups: 1-59 | | | | |
| Log(Pollution) | 0.001 | -0.004 | -0.006 | -0.008 |
| | (0.006) | (0.007) | (0.007) | (0.008) |
| Log(Pollution) × 1(after monitoring) | -0.021** | -0.012 | -0.006 | -0.001 |
| | (0.008) | (0.010) | (0.010) | (0.011) |
| Panel C. Age groups: 60 and above | | | | |
| Log(Pollution) | 0.011** | 0.010** | 0.010** | 0.008 |
| | (0.005) | (0.005) | (0.005) | (0.006) |
| Log(Pollution) × 1(after monitoring) | -0.041*** | -0.032*** | -0.031*** | -0.030*** |
| | (0.008) | (0.008) | (0.008) | (0.009) |
| FEs: city | ✓ | ✓ | ✓ | ✓ |
| FEs: week-of-year | ✓ | | | |
| FEs: year | ✓ | | | |
| FEs: week-of-sample | | ✓ | ✓ | |
| FEs: region×year | | | ✓ | |
| FEs: region×week-of-sample | | | | ✓ |

Notes: Numbers of observations are: 12,041 (panel A), 30,026 (panel B), and 30,801 (panel C). "Log(Pollution)" is logged AOD in a city×week. Dependent variable is city×weekly logged mortality rate. "region" is a conventional partition of cities by location: north (36 cities), northeast (38 cities), east (105 cities), central south (81 cities), southwest (54 cities), and northwest (52 cities). Standard errors are clustered at the prefecture-city level. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Table 6: Heterogeneity by City Characteristics

| City characteristics: | (1) Per cap. income | (2) Frac. urban | (3) Per cap. hospitals | (4) Per cap. residential electricity | (5) Per cap. mobile phones |
|---|---|---|---|---|---|
| **Panel A. Mortality** | | | | | |
| Log(Pollution) × 1(after monitoring) × 1(below average) | -0.015 | -0.025** | -0.018* | -0.017 | -0.019* |
| | (0.013) | (0.010) | (0.010) | (0.011) | (0.011) |
| Log(Pollution) × 1(after monitoring) × 1(above average) | -0.030** | -0.028** | -0.044*** | -0.037** | -0.041*** |
| | (0.012) | (0.011) | (0.014) | (0.018) | (0.013) |
| Equality $p-$value | 0.429 | 0.842 | 0.140 | 0.363 | 0.204 |
| $N$ | 30,100 | 26,359 | 26,359 | 25,300 | 26,359 |
| **Panel B. Card transactions** | | | | | |
| Log(Pollution) × 1(after monitoring) × 1(below average) | -13.0* | -14.2 | -15.1* | -20.2** | -0.191 |
| | (7.48) | (9.10) | (9.11) | (8.20) | (7.05) |
| Log(Pollution) × 1(after monitoring) × 1(above average) | -25.5** | -25.8** | -33.1*** | -22.6** | -35.1*** |
| | (12.0) | (10.3) | (10.6) | (10.6) | (11.6) |
| Equality $p-$value | 0.354 | 0.340 | 0.175 | 0.859 | 0.006 |
| $N$ | 66,854 | 66,854 | 67,046 | 64,540 | 67,046 |

Notes: This table reports heterogeneous changes in the mortality-pollution gradient (panel A) and purchase-pollution gradient (panel B) by above and 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 usage; column 5 = share of mobile phone users. City characteristics are computed as the 2011-2015 average. Cities with missing attributes are omitted from the analysis. "Equality $p-$value" tests for equality between the above/below average coefficients. All regressions control for city, week-of-sample, and region-by-year fixed effects, as well as 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:

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

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

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

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):

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

Applying the implicit function theorem to $f$, we obtain:

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

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, $C + D \leq 0$.[47] Similarly, $A + B \geq 0$. Hence, avoidance increases weakly in (perceived) pollution. The key assumption for this result is $\partial h^2/\partial a > 0$. When pollution deteriorates, avoidance restores health more effectively (that is, the marginal benefit of

[47] At the optimal $a$ and $X$, $U_h + \lambda \cdot w \cdot g(h) > 0$ 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 avoidance.

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 fully respond to day-to-day changes in actual pollution. The total derivative of health w.r.t. pollution is:

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

where $0 < dc_0/dc < 1$. 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:

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

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 (and accurate) 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:

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

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

# Appendix B: Proof of Proposition 2

To examine the impact of the information program on the pollution-outcome relationship, our analysis uses the framework as outlined in Equation (3), in matrix form:

$$Y = \alpha \times P + \beta \times P \cdot \mathrm{d} + X\gamma + \varepsilon, \tag{B.2}$$

where '$\cdot$' is an element-by-element product. $Y, P, d$, and $\varepsilon$ are $N$ by 1 vectors, $X$ is a $N$ by $k$ matrix. $\alpha, \beta$ are scalors while $\gamma$ is a $k$ by 1 vector. $P$ measures ambient air quality and could be correlated with $\varepsilon$ due to unobservables or measurement error as discussed in the main text. $d$ represents the treatment dummy and is equal to one based on the staggered roll-out schedule. The key parameter of interest is $\beta$, the change in the slope of pollution-outcome relationship.

To simplify the proof, we first partial out regressors $X$. Let $M_{\mathrm{x}}$ denote the projection matrix: $M_{\mathrm{x}} = I - X(X'X)^{-1}X'$. Multiplying both sides of equation B.2 with $M_{\mathrm{x}}$, we have:

$$M_{\mathrm{x}}Y = \alpha M_{\mathrm{x}}P + \beta M_{\mathrm{x}}P \cdot d + M_{\mathrm{x}}\varepsilon$$

where $M_{\mathrm{x}}P$ is an $N$ by 1 vector, the projection residual of $P$ on $X$. Collect the two key regressors in $Z = [M_{\mathrm{x}}P, M_{\mathrm{x}}P \cdot d]$. Here we prove Proposition 2 under Assumption B1: $\varepsilon \perp d|X$ and Assumption B2: $\mathrm{d} \perp P|X$.

**Proof:** Let the OLS estimates of $\alpha$ and $\beta$ be denoted as $\hat{\alpha}$ and $\hat{\beta}$.

$$\begin{pmatrix} \hat{\alpha} - \alpha \\ \hat{\beta} - \beta \end{pmatrix} = \begin{pmatrix} (M_{\mathrm{x}}P \cdot d)'(M_{\mathrm{x}}P \cdot d) & -(M_{\mathrm{x}}P)'(M_{\mathrm{x}}P \cdot d) \\ -(M_{\mathrm{x}}P \cdot d)'(M_{\mathrm{x}}P) & (M_{\mathrm{x}}P)'(M_{\mathrm{x}}P) \end{pmatrix} * \begin{pmatrix} (M_{\mathrm{x}}P)'(M_{\mathrm{x}}\epsilon) \\ (M_{\mathrm{x}}P \cdot d)'(M_{\mathrm{x}}\epsilon) \end{pmatrix} * \frac{1}{det[(Z'Z)]}$$

The probability limit of $(\hat{\beta} - \beta)$ converges to the following term multiplied by a constant:

$$-E[(M_{\mathrm{x}}P \cdot d)'(M_{\mathrm{x}}P)]E[(M_{\mathrm{x}}P)'(M_{\mathrm{x}}\epsilon)] + E[(M_{\mathrm{x}}P)'(M_{\mathrm{x}}P)]E[(M_{\mathrm{x}}P \cdot d)'(M_{\mathrm{x}}\epsilon)]$$

Assumption B2 implies that $E\left(d|M_{\mathrm{x}}P\right) = c$. Hence:

$$E[(M_{\mathrm{x}}P \cdot d)'(M_{\mathrm{x}}P)] = E[(M_{\mathrm{x}}P)'(M_{\mathrm{x}}P)E(d|M_xP)] = cE[(M_{\mathrm{x}}P)'(M_{\mathrm{x}}P)].$$

Assumptions B1 and B2 imply that:

$$E[(M_{\mathrm{x}}P \cdot d)'(M_{\mathrm{x}}\epsilon)] = cE[(M_{\mathrm{x}}P)'(M_{\mathrm{x}}\epsilon)].$$

Therefore, $p\lim(\hat{\beta} - \beta) = 0$ and the OLS estimate $\hat{\beta}$ is consistent.

# Appendix C: Figures and Tables

Figure C.1: List of Cities by Roll-out Waves

**Wave 1 cities**

| | | |
|---|---|---|
| Beijing | Xining | Taizhou |
| Tianjin | Hefei | Lanzhou |
| Shijiazhuang | Fuzhou | Hangzhou |
| Tangshan | Yinchuan | Ningbo |
| Qinhuangdao | Wulumuqi | Xi'an |
| Handan | Jinan | Jiaxing |
| Xingtai | Nantong | Huzhou |
| Baoding | Zhengzhou | Shaoxing |
| Zhangjiakou | Wuhan | Jinhua |
| Chengde | Changsha | Lasa |
| Cangzhou | Guangzhou | Zhoushan |
| Langfang | Shenzhen | Taizhou |
| Hengshui | Zhuhai | Kunming |
| Taiyuan | Foshan | Xiamen |
| Huhehaote | Jiangmen | Nanchang |
| Shenyang | Zhaoqing | Wenzhou |
| Yangzhou | Huizhou | Qingdao |
| Changchun | Dongwan | Dalian |
| Haerbin | Zhongshan | Lianyungang |
| Shanghai | Nanning | Huaian |
| Nanjing | Haikou | Xuzhou |
| Wuxi | Chongqing | Quzhou |
| Yancheng | Chengdu | Suqian |
| Changzhou | Guiyang | Lishui |
| Suzhou | Zhenjiang | |

**Wave 2 cities**

| | | | | |
|---|---|---|---|---|
| Wuhu | Jinzhou | Jimo | Wujiang | Yingkou |
| Maanshan | Zhuzhou | Pingdu | Changshu | Panjin |
| Datong | Xiangtan | Laixi | Zhangjiagang | Huludao |
| Yangquan | Yueyang | Zibo | Kunshan | Zigong |
| Changzhi | Changde | Zaozhuang | Taicang | Zhuji |
| Linfen | Zhangjiajie | Dongying | Haimen | Jiayuguan |
| Baotou | Shaoguan | Yantai | Jurong | Deyang |
| Chifeng | Shantou | Laizhou | Fuyang | Laiwu |
| Anshan | Zhanjiang | Penglai | Lin'an | Dezhou |
| Fushun | Pingdingshan | Zhaoyuan | Jiaozhou | Binzhou |
| Benxi | Anyang | Weifang | Yiwu | Heze |
| Yan'an | Jiaozuo | Shouguang | Jiujiang | Sanmenxia |
| Jinzhou | Jinchang | Jining | Quanzhou | Weinan |
| Yichang | Shizuishan | Taian | Eerduosi | Zhangqiu |
| Baoji | Kelamayi | Weihai | Wafangdian | Nanchong |
| Xianyang | Kuerle | Wendeng | Maoming | Yuxi |
| Jilin | Kaifeng | Rongcheng | Meizhou | |
| Qiqihaer | Luoyang | Rushan | Shanwei | |
| Daqinf | Liuzhou | Rizhao | Heyuan | |
| Mudanjiang | Guilin | Zunyi | Yangjiang | |
| Jiaonan | Beihai | Linyi | Qingyuan | |
| Jiangyin | Sanya | Qujing | Chaozhou | |
| Yixing | Tongchuan | Liaocheng | Jieyang | |
| Liyang | Panzhihua | Mianyang | Yunfu | |
| Jintan | Luzhou | Yibin | Dandong | |

**Wave 3 cities**

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Tongling | Jixi | Nanping | Ezhou | Guangyuan | Chuxiong | Dingxi | Shihezi |
| Anqing | Hegang | Longyan | Jinmen | Suining | Honghe | Longnan | Wujiaqu |
| Chuzhou | Shuangyashan | Ningde | Xiaogan | Neijiang | Wenshan | Linxia | |
| Chizhou | Yichun | Jingdezhe | Huanggan | Leshan | Xishuangbanna | Gannan | |
| Xuancheng | jiamusi | Pingxiang | Xianing | Meishan | Dali | Haidong | |
| Lüliang | Qitaihe | Xinyu | Suizhou | Guangan | Dehong | Haibei | |
| Wuhai | Heihe | Yingtan | Enshi | Dazhou | Nujiang | Huangnan | |
| Tongliao | Suihua | Ganzhou | Hengyang | Yaan | Dixing | Hainan | |
| Hulunbeier | Daxinganling | Ji'an | Shaoyang | Bazhong | Changdou | Guoluo | |
| Bayannaoer | Bengbu | Yichun | Yiyang | Ziyang | Shannan | Yushu | |
| Wulanchabu | Huainan | Fuzhou | Chenzhou | Aba | Rikaze | Haixi | |
| Xingan | Huaibei | Shangrao | Yongzhou | Ganzi | Neiqu | Wuzhong | |
| Xilinguole | Jincheng | Hebi | Huaihua | Liangshan | Ali | Guyuan | |
| Alashan | Shuozhou | Xinxiang | Loudi | Liupanshui | Linzhi | Zhongwei | |
| Fuxin | Huangshan | Puyang | Xiangxi | Anshun | Hanzhong | Tulufan | |
| Liaoyang | Jinzhong | Xuchang | Wuzhou | Bijie | Yulin | Hami | |
| Tieling | Fuyang | Luohe | Fangcheng | Tongren | Ankang | Changji | |
| Chaoyang | Suzhou | Nanyang | Qinzhou | Qianxinan | Shangluo | Boertala | |
| Siping | Liuan | Shangqiu | Guigang | Qiandongna | Baiyin | Akesu | |
| Liaoyuan | Haozhou | Xinyang | Yulin | Qiannan | Tianshui | Kezilesu | |
| Tonghua | Yuncheng | Zhoukou | Baise | Baoshan | Wuwei | Kashi | |
| Baishan | Xinzhou | Zhumadia | Hezhou | Shaotong | Zhangye | Hetian | |
| Songyuan | Putian | Huangshi | Hechi | Lijiang | Pingliang | Yili | |
| Baicheng | Sanming | Shiyan | Laibing | Puer | Jiuquan | Tacheng | |
| Yanbian | Zhangzhou | Xiangyang | Chongzuo | Lincang | Qingyang | Aletai | |

**Legend:**

- Jing-Jin-Ji Metropolitan Region, Yangtze River Delta Economic Zone, Pearl River Delta Metropolitan Region, Direct-administered municipalities, Provincial Capitals
- Environmental Improvement Priority Cities (designated 2007), National Environmental Protection Exemplary Cities (awarded between 1997-2012)
- Other prefecture-level cities

Notes: The three panels show cities included in each roll-out wave of the information program. Color coding indicates how cities are logistically divided into roll-out waves, according to the 2012 government notice (GB3095-2012).

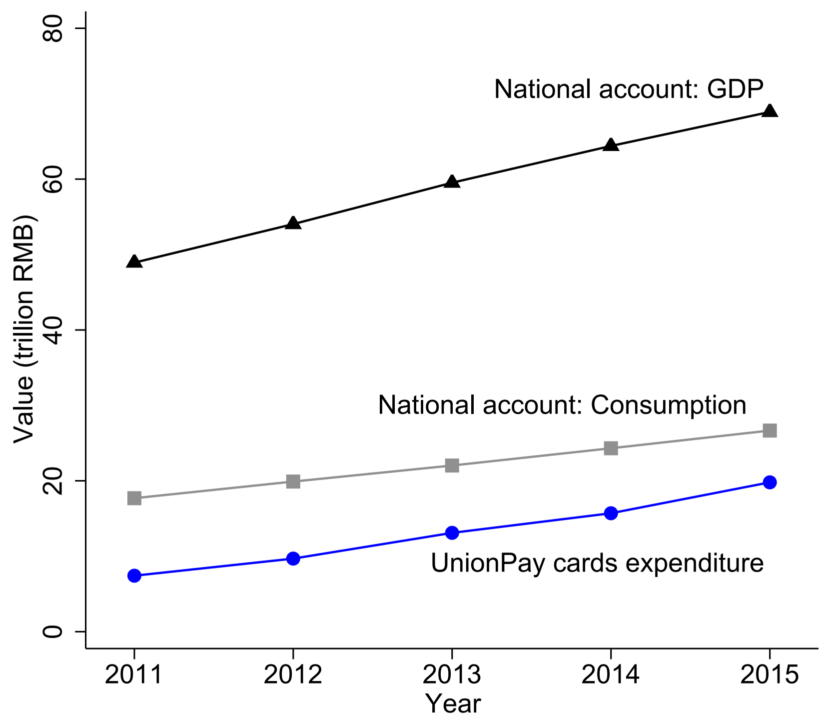
Figure C.2: Screenshot of the Government's Air Quality Disclosure Platform Web Interface


Notes: This figure shows a screenshot of the Ministry of Environmental Protection's real time air quality disclosure platform web interface as of September 25, 2016. The left panel is an interactive map that displays locations of all monitoring stations. The right panel reports real-time measures of six major pollutants for all monitoring stations in the city that is specified (Beijing).

Figure C.3: Screenshot of an Air Quality App

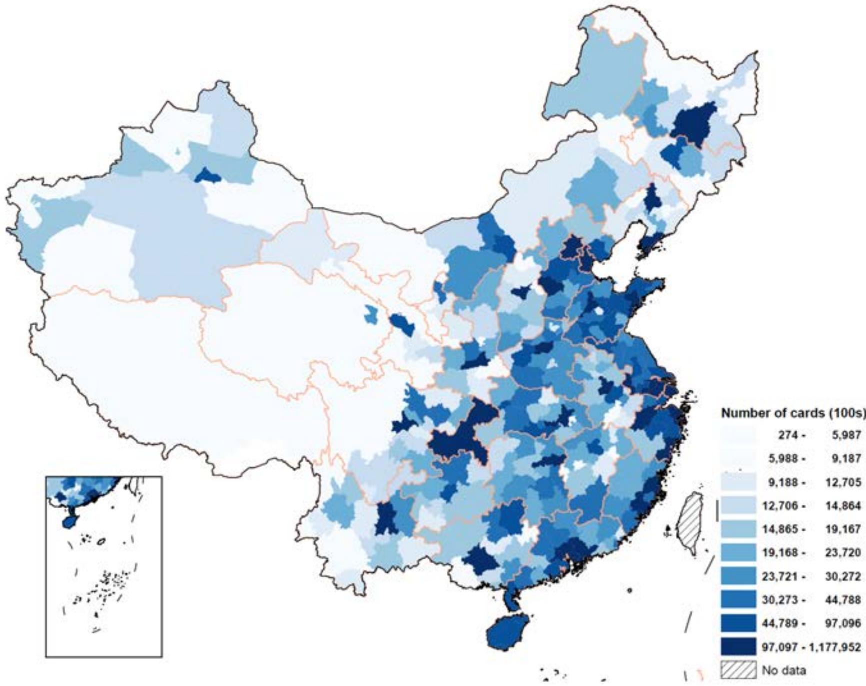

Notes: This figure shows a screenshot of a typical air quality app. The left panel shows the air quality index (AQI) in the city of Shanghai for that hour is 101 and $PM_{2.5}$ is 75 ug/m3. The right panel shows $PM_{2.5}$ and AQI readings at different locations within Shanghai.

Figure C.4: Consumption Trends – UnionPay vs. National Accounts

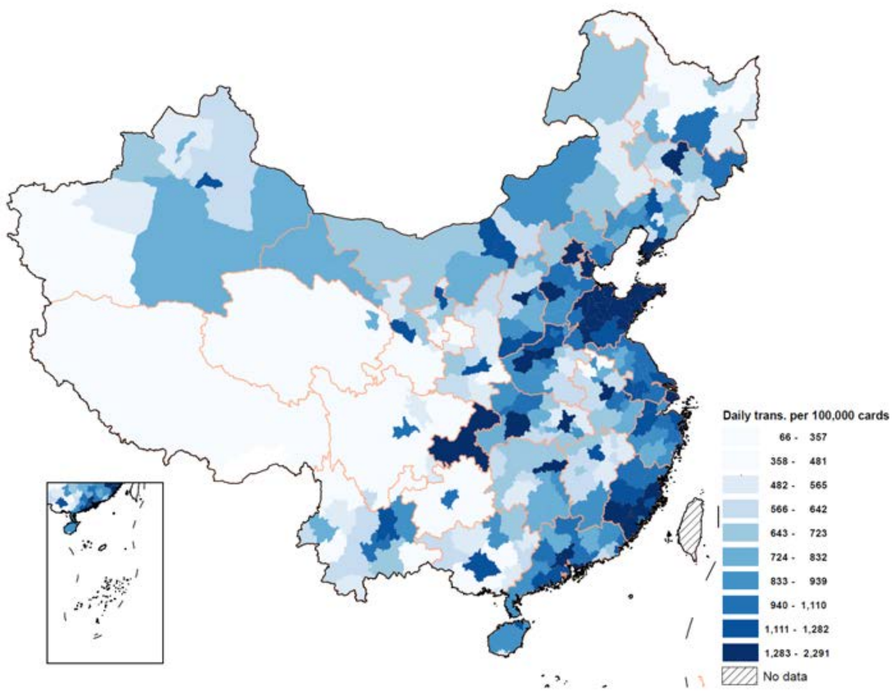



Notes: This figure plots annual GDP (triangles), consumption (squares) reported by the National Bureau of Statistics of China (NBS), and total bank card spendings $\times 100$ (circles) aggregated from the UnionPay 1% bank card data, excluding business to business transactions (the wholesale category).

Figure C.5: UnionPay Bank Card Penetration by Prefecture-City, 2011-2015 Average



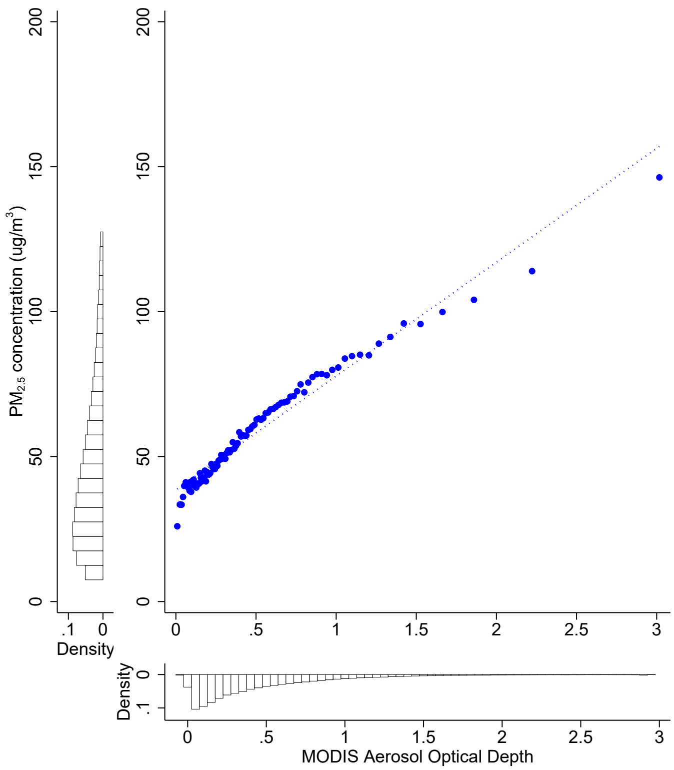

(a) Number of active cards




(b) Number of transactions per 100,000 cards

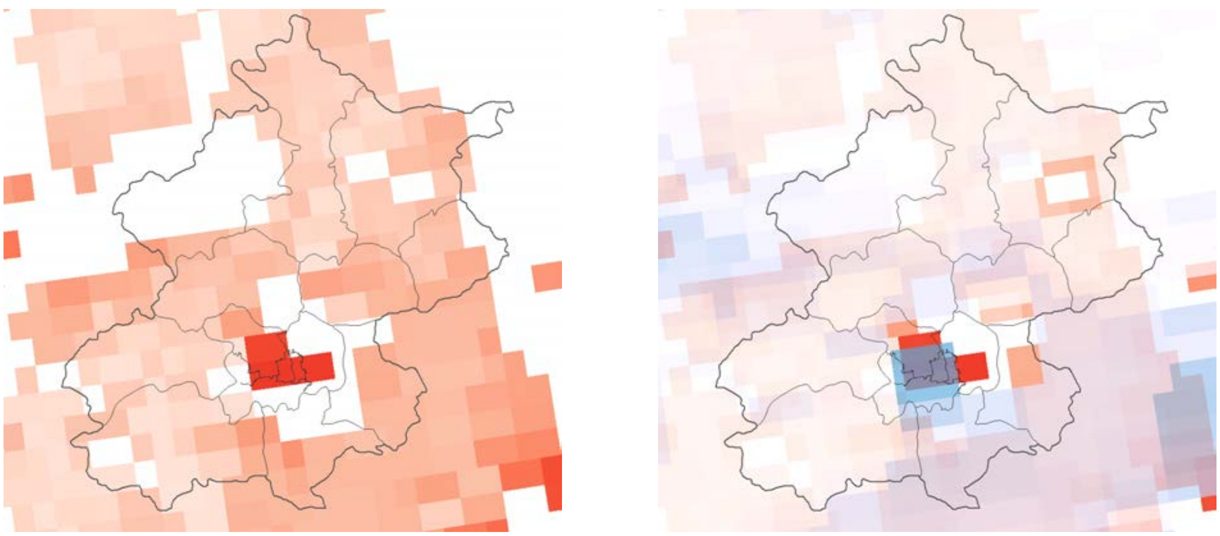
Notes: The maps show the 2011-2015 average number of active UnionPay bank cards (panel A) and transactions per 100,000 cards (panel B) at the prefecture-city level. Orange lines show inter-provincial borders.

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



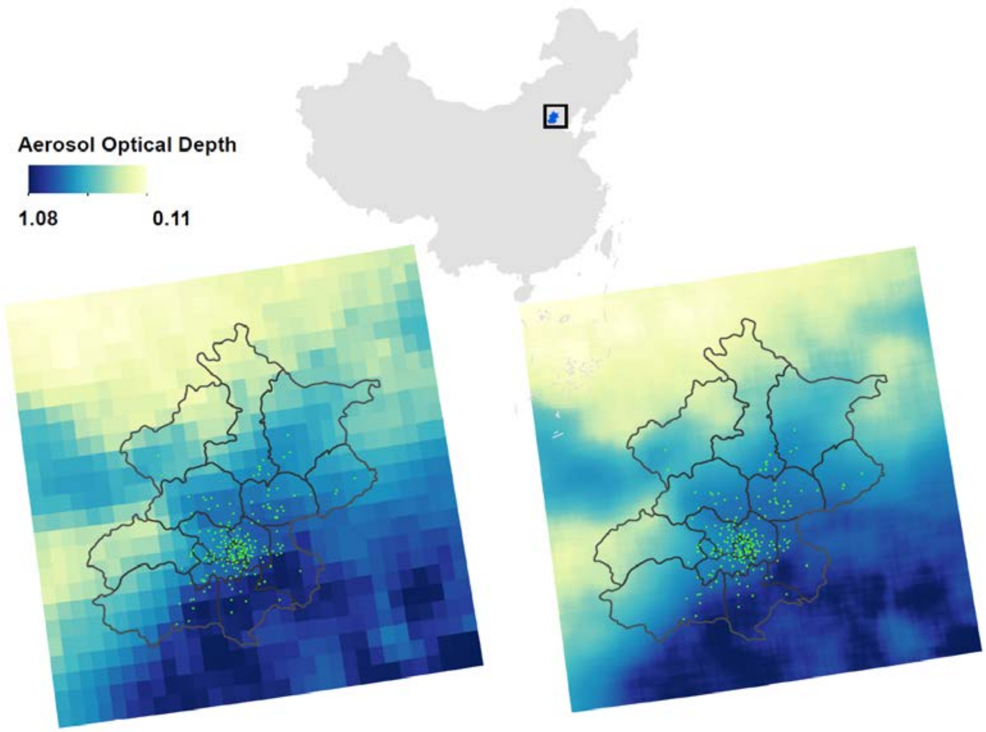

Notes: This graph shows city×day level average $PM_{2.5}$ concentratoin (y-axis) by 100 equal bins of AOD (x-axis), for periods after the information program. There is no reliable information on $PM_{2.5}$ before the program. Histograms show the distribution of the two variables.

Figure C.7: Illustration of Satellite AOD Oversampling



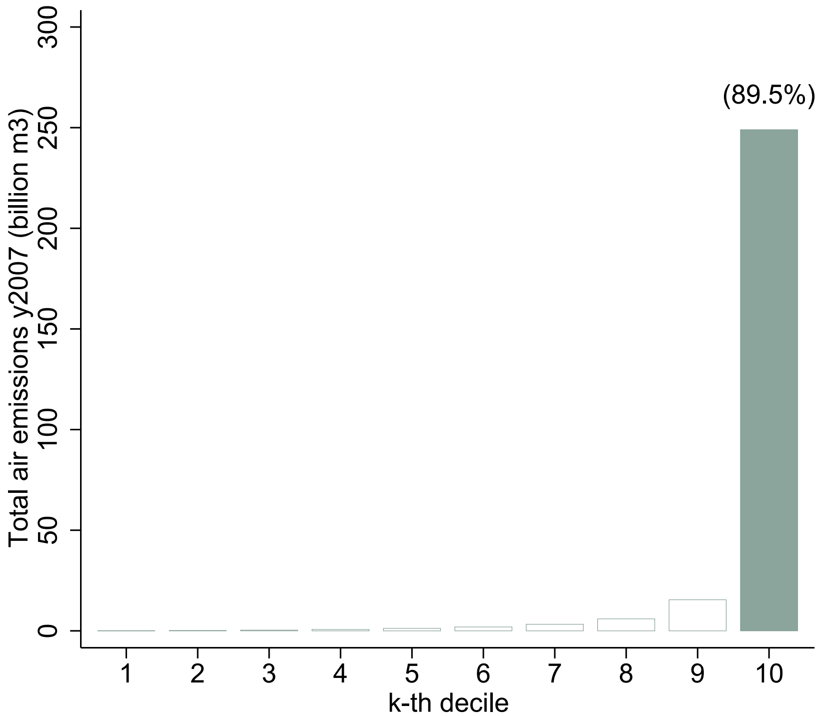
Notes: Left panel shows original MODIS AOD (10×10km) around Beijing on August 30, 2008. Right panel shows an overlay with data on August 31, 2008. In both panels, darker colors indicate higher pollution levels.

Figure C.8: Original (10km) and Oversampled (1km) AOD, Beijing



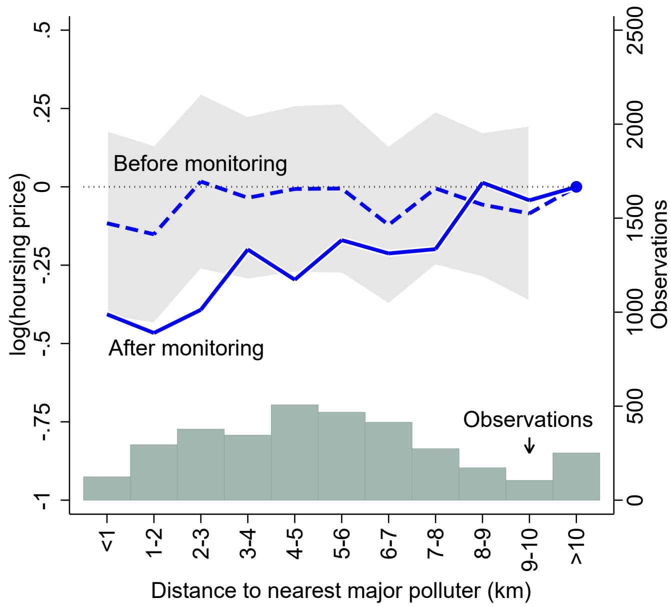

Notes: This map shows the 2006-2014 average aerosol optical depth (AOD) level for the municipality of Beijing. Left panel shows MODIS AOD at the original 10×10km resolution. Right panel shows AOD oversampled to 1×1km resolution. Dots show centroid locations of communities in the housing transaction data.

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

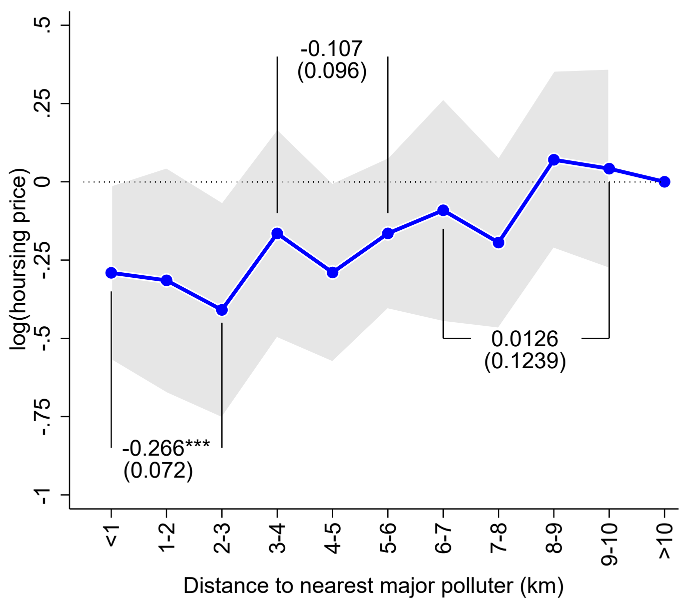



Notes: This graph shows Beijing polluters' total air emissions in billion $m^3$ for each decile of the annual emission distribution according to the Polluter Census 2007. The sample includes about 440 polluters. Firms in the top decile account for 89.5% of total emissions.

Figure C.10: Changes in Long-run Capitalization – Housing Price against Polluter Distance, Beijing



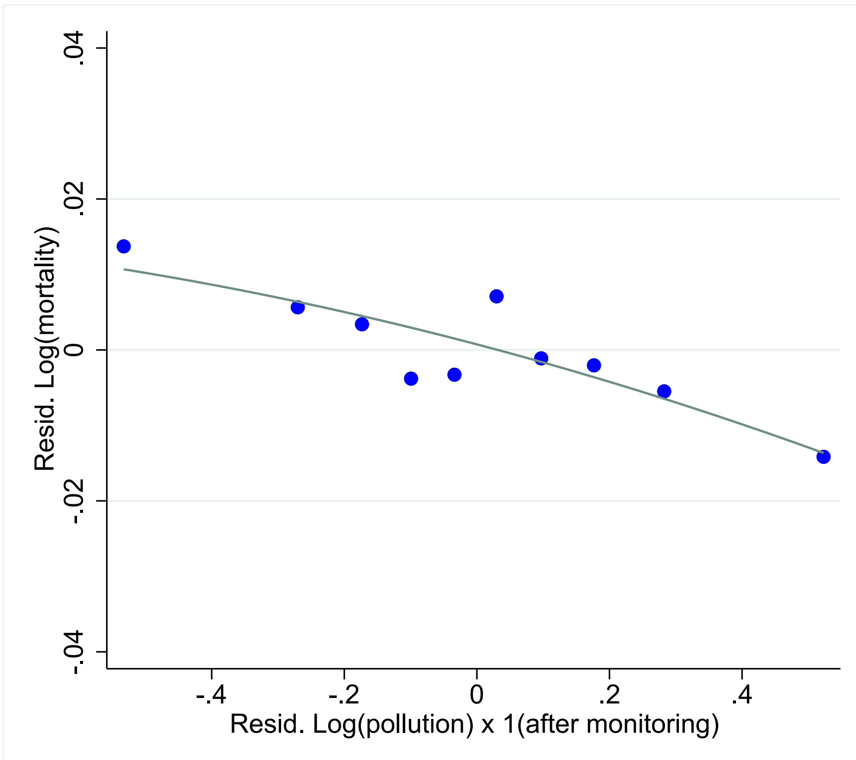

(a) Before vs. after monitoring




(b) Change in price-distance to polluter gradient, by distance bins

Notes: This graph shows coefficients from regressions of attribute-adjusted complex×annual log housing prices on distance in 1-km bins to the nearest major polluter before and after January 2013 when Beijing initiated ambient pollution monitoring. In Panel A, estimations are done separately for periods before (dashed line) and after (solid line) the information program, with the effect on prices normalized to zero for the >10-km bin. The histogram (right axis) plots the total number of observations by distance bins. Panel B pools the sample and estimates the difference. All regressions control for district×year FEs, ZIP Code FEs, and years-on-market FEs. Shaded region shows the 95% confidence interval constructed from standard errors two-way clustered at the ZIP Code level and the district×year level. Number of observations = 3,827.

Figure C.11: Changes in Mortality-Pollution Gradient: Nonlinear Specification




Notes: This graph shows residualized plot between logged mortality rate by 10 equal bins of residualized Log(Pollution) $\times$ $\mathbb{1}$(after monitoring). There is moderate evidence of nonlinearity. All regressions control for city, week-of-sample, and region-by-year fixed effects

Table C.1: Characteristics of Cities by Monitoring Roll-out 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: all characteristics are measured by the 2011-2015 average, except for $PM_{2.5}$ (average over the post-monitoring periods) and industrial $SO_2$ emissions (year 2006). The table report average characteristics for cities in different waves. Standard deviations are in parentheses.

Table C.2: Changes in the Economic and Regulatory Environment Before and 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) |
| 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 | |

Notes: Row names show the dependent variable. "Log(Pollution)" is logged AOD in a city×week. "Anti-corruption cases" are the number of local officials ousted during the anti-corruption campaign, "doc. mayor" indicates whether the current city mayor has a doctoral degree, "pollution regulation news" is 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), central south (81 cities), southwest (54 cities), and northwest (52 cities). Estimation data are at the city × weekly level, except for Panel C which uses city × annual hospital counts. Standard errors are clustered at the prefecture-city level. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Table C.3: Changes in Bank Card Transaction-Pollution Gradient – Robustness

| 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 cities with top 10% anti-corruption cases | -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 variables | -22.3** | -25.8** | -24.3*** | -30.6*** |
| | (9.17) | (11.4) | (8.23) | (10.9) |
| 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 examines the robustness of the changes in the transaction - pollution gradient. 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. Standard errors are clustered at the prefecture-city level. Numbers of observations are (from top to bottom rows): 82,157, 74,903, 82,703, 71,857, 83,122. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Table C.4: Changes in Bank Card Transaction-Pollution Gradient – Triple Difference

| Dep. var.: Number of transactions per 10,000 active cards in a city×week | | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Log(Pollution) × 1(after monitoring) | 3.27 | 1.02 | 2.35 | 4.31 |
| | (7.78) | (8.56) | (7.35) | (8.36) |
| Log(Pollution) × 1(after monitoring) × 1(Treated) | -27.5** | -27.2** | -24.6** | -14.5 |
| | (12.2) | (12.8) | (12.2 ) | (15.9) |
| FEs: city-pair | ✓ | ✓ | ✓ | ✓ |
| FEs: week-of-year | ✓ | | | |
| FEs: year | ✓ | | | |
| FEs: week-of-sample | | ✓ | ✓ | |
| FEs: region×year | | | ✓ | |
| FEs: region×week-of-sample | | | | ✓ |
| $N$ | 193,563 | 193,563 | 193,563 | 193,563 |

Notes: "Log(Pollution)" is logged AOD in a city×week. "1(Treated)" equals 1 for cities in the roll-out wave, 0 for neighboring cities not yet experiencing the roll-out. "region" is a conventional partition of cities by location: north (36 cities), northeast (38 cities), east (105 cities), central south (81 cities), southwest (54 cities), and northwest (52 cities). Standard errors are clustered at the prefecture-city level. The drop in effect size and precision in column 4 is driven by the lack of independent variations among treated and neighboring areas within a region and week, especially for western China where cities are large in geographic area. Grouping the northwest and southwest regions into one region restores both the effect size and precision. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.