The Value of Pollution Information: Evidence from China's Air Quality Disclosure[1]

Panle Jia Barwick
Cornell University and NBER

Shanjun Li
Cornell University and NBER

Liguo Lin
Shanghai University of Finance and Economics

Eric Zou
Cornell University

February 2019

Abstract

This study presents the first large-scale empirical examination of the role of pollution monitoring and information disclosure on consumer behavior. In 2013, China launched a nation-wide, real-time air quality monitoring and disclosure program, the first-of-its-kind in history. Exploiting this natural experiment and its staggered introduction across cities and using rich data sets on information roll-out, pollution, economic activities, and health outcomes, we show that information is a key determinant of avoidance behavior. Consumer activities (online searches, day-to-day shopping, and housing demand) are much more responsive to pollution when such information becomes widely available. In addition, free public access to pollution information reduces the mortality rate from pollution exposure by nearly 9%. It generates a health benefit that is equivalent to 10 ug/m^3 reduction in PM_{10}, with an associated social Willingness-to-Pay in the order of RMB 120 billion annually. Among the twenty most polluted countries, only four (including China) have installed comprehensive pollution monitoring system. Our findings therefore highlight the potentially large welfare gains in improving information access in developing countries and provide a benchmark for policy discussions on building information infrastructure in these countries.

[1] Barwick: Department of Economics, Cornell University and NBER (panle.barwick@cornell.edu); Li: Dyson School of Applied Economics and Management, Cornell University and NBER (sl2448@cornell.edu); Lin: School of Economics, Shanghai University of Finance and Economics (lin.liguo@mail.shufe.edu.cn); Zou: Dyson School of Applied Economics and Management, Cornell University (ericzou@cornell.edu).

We thank Trudy Cameron, Todd Gerarden, Grant McDermott, Ed Rubin, Ivan Rudik, Shuang Zhang, seminar participants at Resources for the Future, University of Oregon and Cornell University for helpful comments. We thank Jing Wu and Ziye Zhang for generous help with data. Deyu Rao, Binglin Wang, Tianli Xu, and Nahim bin Zahur provide outstanding research assistance.

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). In some real-world settings, however, choices depend on information that is costly to obtain, difficulty to keep track of, or hardly noticeable. Examples range from food nutritional contents (Bollinger, Leslie, and Sorensen, 2011), occupational safety (Viscusi and Aldy, 2003), taxation (Chetty, Looney, and Kroft, 2009), to the returns to education (Jensen, 2010). In this paper, we focus on the context of air pollution, where most pollutants are odorless, invisible, and vary substantially from day to day even within a small geographic area. Obtaining accurate information on pollution can be particularly challenging in developing countries, where pollution information is not collected or deliberately withheld and public access is often hindered by a lack of infrastructure to disseminate information. Consequently, questions like whether citizens can in fact engage in effective pollution avoidance, what kinds of information provision policies are effective, and what is the value of information remain largely unanswered.

China provides a unique setting for studying the role of pollution information. The daily average concentration of fine particulate matter ($PM_{2.5}$) is over 60 ug/m^3, or about six times of the World Health Organization guideline. Despite the hazardous level of exposure, citizens used to have very limited access to information on pollution. Comprehensive monitoring network is absent. Dissemination of pollution-related information is politically controlled and, in many cases, forbidden. In 2013, in response to the social outcry on the lack of transparency, China launched a nation-wide, real-time air quality monitoring and disclosure program. The social impact of this program is profound. For example, the term "smog" ("wu mai" in Chinese) has become for the first time a buzzword in social media in China in 2013 and has remained a popular search phrase since then.

The emergence of the monitoring and disclosure program provides a unique opportunity to study changes in behavior upon a sharp and permanent increase in the availability of pollution information. We use this natural experiment of improved information provision and exploit its staggered introduction across cities to study how short- and long-term avoidance behavior, as well as the health consequence of pollution exposure, changes with better information. In particular, our study focuses on how the *same* amount of air pollution affects outcomes *differently* before versus after individuals have pollution information. To overcome the challenge that reliable pollution monitoring data are only available after disclosure, we draw air pollution measure from satellite data. Thus, our estimation framework allows us to isolate *changes* in the outcome-pollution relationships due to improved pollution information.

We compile a rich database on information, pollution, economic activities, and health outcomes in China that spans both before and after the disclosure program took place. We begin by presenting evidence that the disclosure program substantially changes the public access to pollution information and raises public awareness about pollution issues. On the access side, we show that the frequency of newspaper articles on air pollution related topics rises significantly from once-per-week to essentially daily. In addition, there is a rapid increase in the availability of mobile phone applications ("apps") that stream air pollution monitoring data to users. On the awareness side, we document a sharp increase in air pollution related searches (such as "smog", "masks", or "air purifiers") after pollution disclosure is implemented in a city.

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

Our long-run avoidance analysis turns to the housing market. We start with a commonly-used, publicly available real estate price index for 100 major cities and relate the index to cross-city variation in air quality. Exploiting the staggered roll-out of the disclosure program, we find an increase in air pollution's explanatory power over the real estate price index after the program is in place. Motivated by such aggregate-level evidence, we then leverage geo-location information from the universe of new home sales in Beijing during 2006-2014 to conduct transaction-level analyses. We examine changes in the relationship between housing values and pollution levels induced by the program using two different research designs.

First, we employ pixel-averaging technique ("oversampling") to enhance the original satellite data's spatial resolution from 10-by-10 km to 1-by-1 km by sacrificing temporal resolution from daily to annual (e.g., Fioletov et al., 2011; Streets et al., 2013). The high-resolution pollution measure allows us to conduct cross-sectional comparison of home values within fine geographic regions, such as zip codes. We estimate a home value-pollution elasticity of -0.6 to -0.8 post disclosure. In contrast, for periods before the disclosure program, the elasticity is small and statistically insignificant (-0.10 to 0.09).

Second, we link China's emission inventory database with business registries to identify locations of a fixed group of major polluters in Beijing: the 10% of facilities that account for 90% of total industrial air emissions. This allows us to estimate separate "distance gradient" curves (e.g., Currie et al., 2015) that express the home value as a function of proximity to the nearest major polluter before and after pollution disclosure. While there is no correlation between housing prices and proximity to polluters prior to the monitoring and disclosure program, housing values are 27% lower within 3 km of a major polluter afterwards, which corresponds to 42% of the interquartile range of the housing price dispersion.[2] Thus, the disclosure program facilitates residential sorting and the capitalization of air quality in the housing market, with a potential to improve social welfare.

Our last set of empirical analyses examine changes in the mortality-pollution relationship as information access improves. Using nationally representative mortality data from the Chinese Center for Disease Control and Prevention (CDC), we find a 5 to 7 percentage points reduction in the mortality-pollution elasticity (especially for cardio-respiratory causes) post monitoring. Assuming a linear dose-response function and combining our findings with existing estimate on the causal effect of pollution on mortality in China (e.g., Ebenstein et al., 2017), access to pollution information has reduced premature deaths attributable to air pollution exposure by nearly 9%.

We make four main contributions to the literature. First, our study presents the first large-scale empirical examination of the role of pollution monitoring and information disclosure on avoidance behavior. A recurrent theme in our finding is that information is a key determinant of avoidance. There is little evidence that consumer activities (online searches, day-to-day shopping, and housing demand) respond to pollution until such information became widely available. Existing literature on pollution avoidance and revealed-preference estimation of the value of clean air (Chay and Greenstone, 2005; Cutter and Neidell, 2009; Graff Zivin and Neidell, 2009, 2013; Currie et al., 2015; Muehlenbachs, Spiller, and Timmins, 2015; Ito and Zhang, 2016; Deschênes, Greenstone, and Shapiro, 2017; Sun, Kahn, and Zhang, 2017; Barwick et al., 2018) implicitly assumes that agents have *perfect* information on their actual pollution exposure and the relationship between exposure and health. Examination of the departure from the perfect information assumption is largely theoretical (Leggett, 2002; Kunminoff, Smith, and Timmins,

[2] The average housing price in Beijing grew by 262% during our sample period.

2013), and we provide the first real-world analysis of a transition from restrained access to free public access to information on pollution exposure. Our findings could provide an explanation for why environmental quality appears to be severely undervalued in developing countries (Greenstone and Jack, 2015), where a comprehensive and well-functioning information infrastructure is often lacking.

Second, our study presents the first quantification exercise of the value of pollution information that arises from a reduction in mortality rates through more effective avoidance. Free public access to pollution information reduces the mortality rate from pollution exposure by nearly 9%. It generates a health benefit that is equivalent to 10 ug/m^3 reduction in PM_{10}, with an associated social Willingness-to-Pay in the order of RMB 120 billion annually using recent WTP estimates in the literature (Ito and Zhang, 2018). Our findings highlight the potentially colossal welfare gains in improving information access in developing countries, many of which are experiencing the worst mortality damage from pollution exposure in the world. Among the 20 countries with the highest $PM_{2.5}$ level (annual median > 46 ug/m^3), only four (Nepal, Saudi Arabia, India, and China) have installed comprehensive pollution monitoring system. [3] China's success provides a benchmark for policy discussions on building information infrastructure in these countries.

Third, our study to our knowledge is the first to demonstrate the success of a national pollution disclosure program in a developing country setting. We show that, first, there are strong demands on the release of pollution monitoring data and pollution-related topics, both from the media and from the general public. Second, pollution disclosure ultimately alters ways in which individuals cope with pollution exposure both in the short and in the long run. One of the most prominent examples in a developed country is the launch of the U.S. Toxic Release Inventory (TRI) that publicizes toxic emissions from major emitters (e.g., Hamilton, 1995; Bui and Mayer, 2003; Oberholzer-Gee and Mitsunari, 2006; Konar and Cohen, 2006; Banzhaf and Walsh, 2008; Sanders, 2012; Mastromonaco, 2015). Most related to our work, Sanders (2012) and Mastromonaco (2015) show that strengthening in TRI's reporting rule has a negative and significant impact on value of homes near toxic pollution emitters.

More broadly, our work contributes to the information economics of consumer choice by focusing on information of environmental quality. Growing evidence suggests that consumers often misperceive

[3] According to WHO's $PM_{2.5}$ statistics 2016, the top 20 most polluted countries (starting with highest annual median $PM_{2.5}$ concentration) include Nepal (94 ug/m^3), Qatar, Egypt, Saudi Arabia, Niger, Bahrain, Cameroon, India, Bangladesh, Iraq, Kuwait, Pakistan, Afghanistan, Chad, Central African Republic, China, Nigeria, Uganda, Sudan, and Equatorial Guinea (46 ug/m^3).

product attributes, such as food nutritional contents (Bollinger, Leslie, and Sorensen, 2011), insurance policy costs (Kling et al., 2012), vehicle fuel economy (Allcott, 2013), and retirement savings (Bernheim et al., 2015). Information programs are sometimes observed to help consumers' perception of product attributes (e.g., Smith and Johnson, 1988), improve consumer choices (e.g., Hastings and Weinstein, 2008), and even drive up average product quality (e.g., Jin and Leslie, 2003; Bai, 2018). We extend this literature to citizens' air pollution exposure. By providing the first evidence on the effect of a national-scale air quality disclosure program, our study shows that the absence of reliable information on air quality can lead to suboptimal choices in terms of avoidance behavior and residential locations and can have important health and welfare consequences.

The rest of this paper is organized as follows. Section 2 reviews institutional details on pollution disclosure and awareness in China. Section 3 describes data sources. Sections 4 to 7 report the effect of disclosure on information access, pollution awareness, short-term avoidance behavior, and long-term avoidance behavior, respectively. Section 8 examines mortality effects. Section 9 concludes.

2. Institutional Background

2.1. Pre-Disclosure Pollution Awareness in China

This section briefly introduces air pollution awareness in China before the implementation of the disclosure program. We first discuss general awareness to air pollution problems and awareness of pollution *exposure* such as short run fluctuations in local air pollution levels.

Awareness of air pollution problems existed even among the ancient Chinese. The Chinese word for "smog" is composed of two characters: the first represents "fog", and the second means "muddy air". Usage of this second character and the meaning date back at least to the Han dynasty (206 BC - 220 AD). Air pollution continues to be a relatively frequent topic in the modern era. For example, *People's Daily*, the official newspaper of the Chinese government, contained articles related to "air pollution" or "atmospheric pollution" in about 15% of the daily issues since 1980 (9.2% in the 1980s, 12.7% in the 1990s, 22.3% in the 2000s). Awareness of pollution problems can also be inferred from individuals' reported willingness to trade off income for better environmental quality. Among the 1,000 Chinese respondents who took the World Value Survey in 1990, more than 75% reported to be willing to "give part of their income" if they were certain that the money would be used to prevent environmental pollution, and more than 80% would agree to “an increase in taxes if the extra money were used to prevent environmental pollution”.

We believe that public access to pollution *exposure*, i.e. daily fluctuations, is almost absent prior to the reform. The official source of pollution information was MEP’s website, which began to publish a daily air pollution index (API) in June 2000 for 86 major cities. Public access to the information had at least two obstacles. First, API was not well incorporated into the mass media publications or broadcasts prior to the disclosure reform. No documentation that we are aware of exists as to whether any TV or radio programs has broadcast API on a regular basis. Second, the reported API prior to the reform only partially reflected true air quality because it did not incorporate $PM_{2.5}$, which turns out to be the major air pollutant in many Chinese cities. Recent academic investigation has also found evidence of manipulation of the API data (Chen, Jin, Kumar and Shi, 2012; Ghanem and Zhang, 2014). Anecdotal evidence of the lack of awareness in air pollution exposure until perhaps very shortly prior to the reform came from a public outcry in early 2012 that the government API corresponded poorly with the Air Quality Index (AQI) published by the U.S. Embassy and consulates in several major cities.[4] Interestingly, the U.S. Embassy has been reporting AQI since as early as 2008. The absence of large-scale, public complaints about information inconsistency until this very recent event likely reflects the long-standing lack of general awareness to pollution exposure. In fact, the debate was triggered to a large extent by the rising use of social media which spread the U.S. Embassy’s data.

2.2. The Pollution Disclosure Program

Regulation of air pollution in China started in 1982 with the establishment of the Atmospheric Environmental Quality Standards (AEQS) which set limits for six air pollutants including Total Suspended Particulate (TSP), coarse particulate matter (PM_{10}), sulfur dioxide (SO_2), nitrogen oxides (NO_x) and ozone (O_3). The AEQS was renamed the Ambient Air Quality Standards (AAQS) in 1996, and it initiated monitoring of four additional pollutants including nitrogen dioxide (NO_2), lead (Pb), fluoride and Benzo[a]pyrene.

The natural experiment of this study is the 2013 revision of the AAQS, which we refer to as the disclosure program. The program is promulgated under the backdrop of China’s 12th and 13th five-year plans that set pollution reduction as one of the bureaucratic hard targets (e.g., Wang, 2018). The

[4] Part of this is confusion. Both API and AQI are piecewise linear functions of pollutant concentration, but the functional forms are different.

disclosure program was described by the Ministry of Environmental Protection of China (MEP) as an effort to improve environmental quality, and to protect human health, with the focus of building a scientific system of air quality monitoring. The program contained two major provisions. First, it initiated continuous monitoring of major air pollutants, including $PM_{2.5}$, PM_{10}, O_3, CO, NO_2, and SO_2. This led to the installation of a comprehensive network of monitors which were built in three waves. In the first wave, monitoring networks were built and active monitoring started by December 31, 2012 in 74 cities that represented the country's key population and economic centers such as the provincial capital cities. By October 31, 2013, the second wave was completed, adding an additional 116 cities. In the final wave, achieved by November 20, 2014, the program reached the remaining 177 cities. Roll-out of the program is plotted in Figure 1. 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, it established a pollution data dissemination system to report a real-time Air Quality Index (AQI) that incorporates multiple pollutants' concentrations and translates them from units of measurement (such as ug/m^3 for $PM_{2.5}$) to a single scale of 0-500. Monitoring results are displayed in real-time on MEP's website. Both hourly and daily AQIs are available at individual station and city levels, with an interactive map showing locations of monitoring stations. We provide a screenshot of the website interface in the Appendix. Importantly, the government allows private parties to access and stream data directly from the web. This functionality spurs a surge in private websites and mobile phone applications that report real-time air quality information. We provide more details in Section 4.

2.3. The Internet Environment

Rising Internet and mobile phone usage among the Chinese provides a unique opportunity to investigate pollution awareness. Data from the China Internet Network Information Center (CINIC) show that, by the end of 2012, China had about 0.56 billion (or about 40% of population) Internet users, more than 80% of whom were active search engine users. A dozen search engines are freely available to the public. Among the various search engines, Baidu is the most popular. CINIC's 2013 survey of more than 2,800 phone respondents shows more than 99% of Internet users have heard of the Baidu search engine (seconded by Google, 87%), and 98% have used it in the past six months (seconded by *360*, 43%). National Bureau of Statistics data show that mobile phone (traditional phone and smartphone) prevalence rose from 73.5 per 100 population in 2011 to 95.6 per 100 population in 2016. Nielsen's data show a smartphone penetration rate of 72% in 2013.

3. Data

3.1. Mass Media Data

We draw on two sources of media data to illustrate the evolution of pollution information access. First, we look at publication trends by *People's Daily*, the government's official newspaper. From *People's Daily*'s digital archive, we apply a keyword search to pull articles whose title or content contain "air pollution", "atmospheric pollution", or "smog". This data allows us to construct trends in the prevalence of pollution-related topics over time.

Second, we measure availability of mobile phone applications ("apps") that contain air pollution information. We apply keyword search (including "air pollution", "atmospheric pollution", or "smog") using Apple's App Store API to obtain apps' initial release information. The API returns the 200 most relevant apps for the input keyword. As will be explained in Section 4, for comparison purpose, we also obtain release information for other major categories such as gaming, reading, and shopping.

3.2. Web Search Data

We use search index data from Baidu, the most widely used search engine in China. The index data began 2011 and summarizes search for a given search query in a city on a given day among both desktop and mobile users. Our measurement of awareness is search index for the word "smog", which is the buzzword for air pollution. The index captures all search queries for "smog" as well as terms that contain the word "smog". While the exact mapping between the index and the underlying raw search traffic is unknown, it is likely based on a similar algorithm for Google Trends which reflects search intensity, e.g., total number of searches of the topic relative to all other topics in a city and day.

3.3. Card Transactions Data

We measure purchase trips using UnionPay's administrative records on the universe of debit and credit card transactions from 2011-2015. UnionPay is the only inter-bank payment network and the largest such network in the world in terms of both the number and value of transactions, ahead of Visa and Mastercard. The UnionPay data captures a big swath of the total economy: during our study period, total transaction values in the UnionPay database sums up to RMB 66 trillion, which amounts to about 59% of national consumption and 22% of total GDP. This is to our knowledge the most comprehensive data with fine spatial and temporal resolution on consumption activities for China. The size of the original database is about 20 gigabytes per day worth of transactions. To reduce computational burden, we focus on all transactions of a 1% random sample of cards.[5] For each transaction, we observe the corresponding merchant name, transaction amount and time, and we use these information to assign the transaction to a unique city by week. Our key outcome variable is purchase rate, defined as the ratio between (1) total number of transactions occurred in a city by week, and (2) total number of cards with any transactions in the city by year, i.e. "active cards".[6] In our 1% sample, we observe a total of 350 million transactions and an average of 163,000 active cards at any given point in time.

Two additional features of the data worth mentioning. First, our data contains a small fraction (about 4%) of card transactions that are made online. Penetration of online shopping grows during our study period and varies substantially across cities. For this study, we drop online transactions and focus on transactions made through traditional point-of-sale (POS) venues. Second, we do not observe purchase items associated with each transaction. However, UnionPay does have a taxonomy of merchants by broad categories, such as department stores, supermarkets, etc. We use merchant category information in some of our specifications below.

3.4. Housing Market Data

We draw housing market data from two sources. First, we use new real estate price index for 100 major cities from the China Real Estate Index System (CREIS). These cities account for over 46% of population, and we map out the location of these cities in Figure 1. CREIS index is computed as area-weighted sum of price quotes among all new real estate projects (including both residential and commercial projects) in a city and month. The underlying sample includes all new projects with at least

[5] We take a 1% random sample of cards on Jan 2011, and we pull the universe of their transactions through Dec 2015. We then take a 1% random sample of new cards opened on Feb 2011, and pull the universe of their transactions through Dec 2015, and so forth.

[6] It is intrinsically difficult to identify when does a card "die" as unused cards may be used in the future. Instead, we choose to focus on "active" cards, i.e., those that we see any transactions during the year.

10,000 m^2 in total floor area.[7] CREIS constraints the influence of exceptionally large projects on the index by winsorizing each individual project's weight in a city and month to be at most 3%.

We also obtain transaction-level data for nearly all new homes sold in Beijing from January 2006 to April 2014. The data contains housing transaction date and price, along with other characteristics of the transacted unit, including geo-location of the apartment complex, floor and size of the transacted unit. We observe a total of over 660,000 transactions in about 1,300 apartment-complexes in our data. The vast majority of the complexes are on market for a streak of years before sold out. The market is fluid in general. Among all 660,000 transactions, over 84% occur when the associated complex is on market for less than a year, and less than 4% are on market for over 5 years. Among all the 1,300 complexes, 64% are entirely sold out in 3 years.

In the Appendix, we use the Beijing transaction data to replicate CREIS housing index in Beijing. We find that the overall trends between CREIS and transaction data agree with each other, but the time path of CREIS index appears much smoother. There are several potential explanations. First, CREIS includes non-residential projects, and therefore may have a larger underlying sample. Second, CREIS' winsorization rule, explained above, may reduce fluctuations in the index. We recognize that errors in the CREIS measurement may attenuate our identification of the housing value – pollution relationship. However, we choose to incorporate to include CREIS data in our analysis as (1) it covers a much wider geographic extent than our transaction data, and (2) it is publicly available and is the most widely used indicator of real estate prosperity in China. Below we refer to the CREIS data as simply the housing index.

3.5. Satellite Data

We measure ambient air pollution using aerosol optical depth (AOD) from NASA's MODIS algorithm installed on satellite Terra's platform. The original data has a geographic resolution of 10 km x 10 km and a scanning frequency of 30 min, which we used to compute average AOD levels at the city by day level from 2006-2015. MODIS records, under cloud-clear condition, the degree to which sunlight is scattered or absorbed in the entire atmospheric column corresponding to the overpassed area. As such, AOD captures concentration of particle pollution such as sulfates, nitrates, black carbons, and sea salts, and therefore can serve as a proxy for outdoor particulate matter pollution (e.g., van Donkelaar, 2006). In

[7] For Beijing, Shanghai, Guangdong, Shenzhen the inclusion cutoff is 30,000 m^2.

the appendix, we document the strong correspondence between AOD and the post-disclosure $PM_{2.5}$ monitoring data from China.

We favor the MODIS AOD measurement over alternatives (such as satellite-based ground-level $PM_{2.5}$ predictions) for several reasons. First, MODIS data can be easily aggregated from daily to monthly and annual levels. This allows us to use the same pollution measure throughout our analysis. In contrast, processed satellite-based $PM_{2.5}$ data products are often provided only at certain temporal interval (e.g., annual) and cannot be dis-aggregated in a straightforward manner. Second, MODIS AOD allows us to observe overlapping 10 km x 10 km grid cells it scans, which is essential for the oversampling exercise in Section 7. Processed data products are often mapped onto a fixed set of grid cells. Finally, while MODIS AOD is a common input in most satellite-based data products that predict ground-level $PM_{2.5}$, the precise relationship between AOD and $PM_{2.5}$ is far from being nailed in either the economics literature or the atmospheric science literature. We choose to abstract away from the modeling complexity in this study. Of course, an obvious disadvantage is that our elasticity estimates throughout the paper should be interpreted in terms of changes in AOD.

3.6. Polluter Data

We draw emission sources data from the Chinese Environmental Statistics (CES) database which is MEP's annual survey of all major industrial polluters. CES firms are required to report detailed environmental emissions data every year, and the data are ultimately used to produce environmental Yearbook statistics. While the exact criteria that MEP uses to define major polluter is unknown, CES provides the most comprehensive coverage of polluters' emission information in China (Liu, Shadbegian, and Zhang, 2017; Zhang, Chen, and Guo, 2018). We use the 2007 CES which is the most recent round we have access to. We observe a total of 587 polluters in Beijing, and we obtain information on each polluter's name and total industrial emissions (i.e., summation of volumes across all pollutants).

Because we only observe a cross-section of polluters in 2007, and our study period spans 2006-2014, we need to identify polluters that are present for the most of our study period. We do so by linking firms' names to firm registry data from Qixin, or "firm information" (www.qixin.com). Among the 587 polluters in Beijing, we are able to match 532 on Qixin and obtain their operation status and address in

2018.[8] Among the matched firms, 407 are still operating in 2018. Our study therefore focuses on these 407 polluters.

3.7 Mortality Data

Our mortality data is sourced from the Chinese Center for Disease Control and Prevention's (CDC) Disease Surveillance Points (DSP) system. During our sample period of 2011-2014, DSP covers 161 counties with a total of 73 million, or about a 5% representative sample of China's population. DSPs death information is drawn from hospital records and surveys on the deceased person's household. DSP is one of the highest-quality health databases that has been used in recent medical (e.g., Zhou et al., 2016) and economic research (e.g., Ebenstein et al., 2017). Our analysis is based on an extract of DSP 2011-2014 prepared by the CDC for the purpose of this research project. In this extract, an observation is a county x week x sex x age-group, and for each observation, we observe the number of people in the county covered by the DSP, total death counts, and death counts for the following six cause-of-death groups: chronic obstructive pulmonary disease, heart diseases, cerebrovascular diseases, respiratory infections, digestive diseases, and traffic accidents.[9] The first four causes are intended to measure deaths related to cardiovascular diseases, which have been observed to be closely related to air pollution exposure, while the latter two causes are intended to serve as placebo-style outcomes.[10]

4. Pollution Disclosure and Information Access: News Media

We consider two venues through which the general public are most likely to access pollution information: newspapers and mobile phone apps. In Figure 2, panel A, we count number of days in each month when *People's Daily*, the government's official newspaper, mention "air pollution", "atmospheric pollution", or "smog" in any articles. Prevalence of pollution topic is low in the 1990s, growing gradually overtime to reach a rate of about 5 days of mention per month shortly before 2013. Almost immediately following the disclosure program's initial roll-out, frequency of pollution mention jumped to roughly 20

[8] We use Baidu's Map API to geo-locate firms using Qixin's address information.
[9] We have also requested deaths due to diarrhea (as a subgroup to digestive diseases), but due to very low number of deaths in this cause group, we do not turn out to use it in the analysis below.
[10] The ideal data would of course contain a more comprehensive list of causes, but we are constrained by administrative complications of data extraction.

days per month. It is obvious, by simply browsing pollution-related articles before and after 2013, that the increase in news mention is partly explained by news media's new ability to talk about pollution "in numbers" thanks to the disclosure program, e.g., exceptionally high pollution events, ranking of cities in terms of average air quality, etc.

We then examine availability of pollution-related mobile phone apps. Unlike newspapers, which provide pollution information at a daily frequency, information from apps are more readily accessible in real time. Given the high mobile phone penetration in China, pollution apps may serve as a significant venue through which the public learn about their pollution exposure at the moment. As described in section 3, because for each category we only observe the 200 most relevant apps at a given point in time, the release time distribution likely contains a survivorship component: some oldest apps have lost popularity, while some newest apps might still take time to rise to the top. In other words, the release time distribution using the most relevant apps might contain too little mass in the tails than the distribution of all apps. To difference out the survivorship component, we compare release time distribution of pollution apps with a "control" group of apps from various categories which we believe capture the majority of commonly-used apps. These categories are gaming, music, video, reading, finance, sports, education, shopping, and navigation.

Figure 2, panel B presents the distribution of release time of apps. The graphical pattern shows a clear surge in the density of apps released after disclosure, relative to non-pollution apps. The largest jump in release risk occurs in the quarter following the disclosure program's initial roll-out. In total, about 82% of pollution apps are released post Jan 2013. This fraction is 62% for non-pollution apps. In the Appendix, we provide an example screenshot from one of the pollution apps. These apps typically contain a chart that displays the evolution of hourly pollution levels in the past. Some apps also provide general health behavior guidelines (e.g., avoid outdoor activities) when pollution is high.

5. Pollution Disclosure and Pollution Awareness: Web Searches

In this section, we present evidence that the disclosure program increases the public's awareness of pollution-related issues. One way to measure awareness is by the demand for pollution-related information. We do so by looking at internet searches of terms related to the buzzword "smog" using data from Baidu, the go-to search engine in China.

We first document the national, overall trend of smog searches. Figure 3, panel A plots raw search index time series for the term "smog". Our data suggests a sharp increase in smog searches starting January 2013, i.e. the month of initial roll-out. Post-2013 smog searches also exhibit a strong secular pattern where the index is highest in winter seasons. This pattern coincides with the fact that smog is more severe in winter partly due to coal-fueled heating.

We also leverage the roll-out timing to conduct event study of smog searches shortly before and after a city begins to disclose air pollution. For this examination, we use city x daily search index for "smog", which breaks down the national time series by over 300 prefecture cities. Due to substantial differences in search activities across cities and the frequent presence of days with zero search indexes for small cities, we present the event study on normalized (mean 0, standard deviation 1) scale. Figure 3, panel B plots the mean of standardized search indexes in the year before and the year after monitoring roll-out. We estimate the event study conditioning only on month-of-year dummies (12 indicators) and year dummies (5 indicators), and we normalize search index to 0 in the month prior to the roll-out (i.e., event month "-1"). The graphical pattern suggests a flat and stable pre-trend in smog searches in the city. Searches began to rise rapidly when the disclosure program started. By one year after disclosure, smog searches have increased by about 75% of a standard deviation. In the Appendix, we report estimates of the search event study using a flexible range of econometric specifications. We have also examined other pollution-related search terms such as "mask" and "air purifier", and the event studies show similar results.

6. Pollution Disclosure and Short-Run Avoidance: Purchase Trips

We conceptualize purchase trips as a function of ambient pollution levels, and we examine how such relationship changes as pollution disclosure occurs in the city. Our estimation equation is as follows:

$$\text{PurchaseRate}_{ct} = \sum_{k=-12}^{12} \beta_k \times \ln \text{avg Pollution}_{ct} \times 1(t=k) + \sum_{k=-12}^{12} \alpha_k \times 1(t=k) + X_{ct} \cdot \gamma + \varepsilon_{ct} \quad (1)$$

The outcome variable "PurchaseRate_{ct}" is number of card consumptions in city *c* on week *t* per 100 active cards in the city by year (see Section 3). The pollution measure "$\ln \text{avg Pollution}_{ct}$" is logged AOD in the city x week. The key parameters of interest is β, which represents changes in purchase rate per 1% increase in AOD. To examine changes in the purchase-pollution relationship before vs. after disclosure, we allow β to vary by event month k relative to the disclosure time. Because roll-out time varies, cities do not have equal number of available pre and post periods. In our analysis, we look at an event window of 39 months (24 months before and 15 months after disclosure). This event window is chosen so that there are nearly identical county by day observations underlying each event month. In other words, there is no composition change underlying the event study graph, and so changes in the β_k coefficients are not due to sample selection. We identify β using week-to-week variations in air pollution net of a flexible set of geographic and time controls (X_{ct}) that include city fixed effects, week-of-year fixed effects, and year fixed effects. As detailed below, we also experiment with increasingly stringent fixed effects to test the robustness of our change-in-gradient estimates. So that our β estimates are representative of the average card, we weight the regression using denominator of the dependent variable, i.e., number of active cards. ε_{ct} is an idiosyncratic error term. Standard errors are clustered at the city level. In the Appendix, we show our estimation is robust to ex-ante reasonable but substantially different econometric specifications.

Figure 4 summarizes the β_k coefficients. Here we present binned β_k coefficients that vary at the quarterly (3-month) level to aggregate out noises in time trends. Two patterns emerge. First, before disclosure, the β_k estimates remain flat and statistically indistinguishable from zero. This suggests a stable and weak relationship between purchase and satellite-based pollution measure before individuals have access to information. Second, β_k estimates exhibit a level-shift and become strongly negative following disclosure. There is some suggestive pattern that the post-disclosure purchase-pollution gradient weakens overtime. Potential explanations include (1) fatigue, where citizens may only pay close attention to daily pollution data for a limited period of time, and (2) stocking of defensive investments, where increased ownership of anti-smog equipment, such as air masks, helps citizens to achieve pollution reduction without having to staying indoor on high pollution days.

Table 1 provides point-estimates view of Figure 4. The econometric specifications in this table are modified from equation (1) in two ways. First, we include full interactions between the pollution term and the post-disclosure dummy variable, so that the coefficient on "Log(Pollution)" represents the OLS purchase-pollution gradient before monitoring, and the coefficient on "Log(Pollution) x 1(after monitoring)" represents changes in the gradient after monitoring. Second, we increasingly tighten the fixed effects strategy we use to exploit finer variation in the data. Column 1 uses simple city, week-of-year, and year fixed effects, which corresponds to the specification in Figure 4. Column 2 uses city and week-of-sample fixed effects. This is essentially a cross-sectional specification, exploiting variation in pollution in the same week-in-time, across cities with high vs. low pollution. Column 3 further adds region x year fixed effects to column 2's specification, allowing for potentially common trends in transactions and pollution that are specific to each region.[11] Column 4 is our most stringent specification, controlling for city and region x week-of-sample fixed effects. We obtain similar estimation results across the board.

Although we find that pollution information matters for short-term avoidance, the magnitude of the effect is modest. The average change-in-gradient estimate in Table 1, inversely weighted by the standard errors across columns 1-4, is 21.9 weekly transactions per 100 cards. This represents a 2.5% change relative to the dependent variable mean 870.6. In the appendix, we use POS merchant category information to look at changes in purchase-pollution gradient for several major categories including supermarkets, dining, and entertainment. We focus on these groups because the "deferrable" nature of these purchase trips likely makes them more subject to pollution avoidance. We find strong evidence that over 75% of the change in overall purchase-pollution gradient is explained by these purchases. On the other hand, we conduct placebo-style tests looking at the impact of information roll-out on "scheduled" consumptions including billings (e.g., bills in utilities, insurance, telecommunication, and cable services), government services (e.g., court costs, fines, taxes), large enterprise wholesales, as well as cancer treatment centers. We find no statistical evidence that information availability changes "scheduled" consumptions' responses to air pollution. In the next section, we begin to examine longer term avoidance behavior through the housing market.

7. Pollution Disclosure and Long-Run Avoidance: Housing Market

We now turn to assess housing market responses to pollution disclosure. In Section 7.1, we evaluate how pollution disclosure changes the dynamic relationship between monthly real estate index and pollution exposure in 100 major cities. In Section 7.2, we use transaction-level data in Beijing to study how pollution disclosure changes the cross-sectional relationship between home value and pollution exposure. In Section 7.3, we replicate the analysis in Section 7.2, but using distance to major polluter, rather than ambient air quality, as a proxy for pollution exposure. In Section 7.4, we discuss our findings in the context of the current literature.

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

7.1. Pollution and Real Estate Prices in 100 Cities

Consider estimating a dynamic relationship between housing index and air pollution. We regress housing index in city (*c*) and month (*t*) on current air pollution, air pollution in the recent past, and, as a placebo-style exercise, air pollution in the near future:

$$\ln \text{HousingIndex}_{ct} = \sum_{s=-3}^{3} \beta_s \times \ln \text{avg Pollution}_{c(t+s)} + X_{ct} \cdot \gamma + \varepsilon_{ct} \quad (2)$$

where the β_s' are leads ($\beta_3, \beta_2, \beta_1$), current ($\beta_0$), and lags ($\beta_{-1}, \beta_{-2}, \beta_{-3}$) coefficients on logged AOD.[12] We include city by month-of-year fixed effects and year fixed effects controls in X_{ct} to mirror our control strategy in bank-card daily usage analysis. Standard errors are clustered at the city level. To examine the role of information, we estimate equation (2) separately for periods before and after pollution disclosure, and compare how β_s' coefficients differ.

We summarize the results in Figure 5. In the spirit of an event study, we present leads pollution coefficients reversely on the left-hand-side of the chart, followed by current pollution coefficient, and lags pollution coefficients on the right-hand-side. Before disclosure, pollution exposure does not seem to matter: lead terms in pollution are insignificant and flat in trend, so are current and lagged pollution terms. For periods after disclosure, the leads pollution coefficients again show a flat and insignificant pattern as before. However, the current pollution term is more negatively related to the real estate index, with lagged pollution coefficients to be even more negative. The graphical pattern in Figure 5 suggests that, post disclosure, (1) air pollution becomes more explanatory of the real estate index among the 100 cities, and (2) air pollution may affect real estate price beyond its impact in the current month.

We now turn to estimate the effect of pollution disclosure on the housing-pollution elasticity. We estimate a counterpart of equation (1), but now at the monthly level. To capture lagged effect of pollution, we define our pollution measure to be "$\ln \text{avg Pollution}$", or the log of mean pollution across months t, t-1, t-2, and t-3. Essentially, we are estimating the effect of pollution in the past quarter on housing price

[12] We focus on 3 leads and 3 lags. We have confirmed that our estimation results persistent if we expand the window of examination, e.g., 6 leads and 6 lags, although each additional lead or lag coefficient we include decreases our study sample mechanically by one more month.

this month. The rest of the estimation framework mirrors the bank-card analysis. We examine how the relationship between "$\ln \text{HousingIndex}$" and "$\ln \text{avg Pollution}$" evolves as a function of event time k relative to the disclosure month. Our estimation equation is:

$$\ln \text{HousingIndex}_{ct} = \sum_{k=-32}^{36} \beta_k \times \ln \text{avg Pollution}_{c(t,t-1,t-2,t-3)} \times 1(t=k) + \sum_{k=-32}^{36} \alpha_k \times 1(t=k) + X_{ct} \cdot \gamma + \varepsilon_{ct} \quad (3)$$

We choose an event window of 32 months before and 36 months after. Given the time span of our data, this window ensures a balanced number of observations for each event month. To obtain more precise time path, we allow β_k to vary at the quarter level, i.e., one elasticity estimate per event quarter. $1(t=k)$ are indicators for event quarter k. X_{ct} include city x month-of-year fixed effects and year fixed effects.[13] We also include leads pollution coefficients in X_{ct} to mirror our specification in equation (1). Standard errors are clustered at the city level.

Figure 6 is the event study plot. The average pre-disclosure housing-pollution elasticity is about 2% and statistically insignificant. The event quarter estimates trended flat for the pre-period, followed by a sharp decrease promptly in the disclosure roll-out quarter (event quarter 0). The post-disclosure elasticity is about 3% and is significant at the conventional statistical level. To interpret the coefficients, first notice the connection between Figure 5 and Figure 6. The pre-disclosure (post-disclosure) elasticity estimate in Figure 6 is mechanically the sum of the coefficients on exposure months 0, 1, 2, and 3 for the pre-disclosure (post-disclosure) period. So together, Figures 5 and 6 suggest that, on average, current and lagged pollution are explanatory of the housing market after disclosure (but not before disclosure), and that such change occurs promptly around the time when pollution disclosure begins in the city.

In Table 2, we experiment with specification changes in the same manner with Table 1. It is perhaps useful to note that our cross-city price-pollution elasticity estimate is close to previous work using similar data (e.g., Zheng et al., 2014). But due to CREIS index's winsorization issues we mentioned in Sectiont 4, we next move to the examination of housing market responses using transaction-level data.

[13] In the Appendix, we show our results are robust to a series of alternative fixed effects controls.

7.2. Pollution and Housing Prices in Beijing

We now examine the impact of pollution disclosure using detailed transaction-level data on the universe of new homes sold in Beijing from Jan 2006 to April 2014. We rely on the following features of the data that we consistently observe for every unit sold: transaction price, transaction date, apartment complex name and address, floor level, and unit size. We again employ a change-in-slope approach and estimate the degree to which the housing price-pollution relationship shifts before and after pollution disclosure. Although we observe each individual transaction, our pollution measure is at a more aggregated level. Below we describe how we collapse the effective amount of information in the transaction data to match the granularity of the satellite-based pollution data.

Outcome variable: quality-adjusted apartment-complex x year price levels. We first take the universe of transactions in our data and construct the outcome variable from the following regression:

$$\ln \text{TransactionPrice}_{ict} = X_{ict} \cdot \gamma + \eta_{cy} + \varepsilon_{ict} \quad (4)$$

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

Pollution variable: AOD at 1-by-1km x year resolution. Our sub-city level analysis requires a pollution measure with a high level of spatial resolution. We employ a frontier method in atmospheric science called "oversampling" that re-processes the original AOD data to increase its spatial resolution from 10-by-10 km to 1-by-1 km, while sacrificing the temporal resolution from daily to annual. Oversampling takes advantage of the fact that MODIS scans a slightly different, but overlapping, set of pixels at a given location on each of the satellite's overpass. When the researcher is not interested in the high temporal dimension (such as in our case, where we only need annual information on pollution), it is possible to average across the overlapping overpasses to enhance the geo-spatial resolution of the AOD measure.[14] Figure 7 presents pre- and post-oversampling average AOD concentration in the city of Beijing.

We then put our housing and pollution variables in a hedonic regression:

$$\hat{\eta}_{cy} = \alpha \cdot \ln \text{avg Pollution}_{cy} + 1(\text{PostDisclosure} = k) \\ + \beta \cdot \ln \text{avg Pollution}_{cy} \times 1(\text{PostDisclosure} = k) + Z_{cy} \cdot \gamma + \varepsilon_{cy} \quad (5)$$

where $\ln \text{avg Pollution}_{cy}$ is logged oversampled AOD level in year *y* in the 1-by-1km region that contains the apartment-complex *c*. Because we only have 14 months of post-disclosure housing market, we allow β, the housing-pollution elasticity estimate, to simply vary by pre- vs. post-disclosure periods.

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

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

The two specifications therefore exploit rather different sources of pollution variation, with the former focusing more on year-to-year variation within the same location, the latter focusing more on cross-sectional variation at a given point in time. To account flexibly for potential autocorrelation in both

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

housing price and pollution across time and over space, we two-way cluster standard errors at the zip code level and the district x year level.

We report equation (5) results in Table 3. Begin with column 1. We find that doubling of annual pollution corresponds to an insignificant 9% increase in housing prices, or about a 0.09 elasticity. The change elasticity for the post-disclosure period is -59 percentage points and significant at the 10% confidence level. In column 2, we examine the effect of lagged pollution in addition to current year's pollution exposure. We obtain similar results – a marginally significant -73 percentage points change in elasticity – on current pollution, but a noisy effect with lagged pollution. Columns 3 and 4 correspond to our cross-sectional specification estimates. These specification yields a similar reduction-in-elasticity estimates of -85 percentage points. Estimates from columns 3 and 4 seem larger in magnitude relative to estimates from columns 1 and 2. One potential explanation is that the oversampled AOD data does a better job capturing idiosyncratic pollution variation in the cross-section, rather than year-to-year pollution variation. Looking across all columns, however, the 95% confidence intervals from the two types of specifications overlap, and so the elasticity estimates do not differ significantly from each other.

Our cross-sectional estimates of housing price-pollution elasticity for the post-disclosure period therefore ranges from -0.6 to -0.8. This is somewhat larger than those obtained in U.S. setting. For example, Chay and Greenstone (2005) exploits permanent reduction in Total Suspended Particle pollution (TSP) due to the 1970s U.S. Clean Air Act. They estimate a price-pollution elasticity of -0.25. Taking into account moving costs and variation in air quality across U.S. metro areas, Bayer, Keohane, and Timmins (2009) show a price-pollution elasticity of roughly -0.34 to -0.42. Our estimates are similar to those obtained in China settings. In a hedonic regression exercise using Beijing's housing transactions and land parcel data, Zheng and Kahn (2008) find a price-PM_{10} elasticity of -0.41. In a recent residential-sorting exercise, Freeman et al. (2017) use moving costs and housing value information from China Population Census micro-level data to estimate a price-$PM_{2.5}$ elasticity of -0.71 to -1.10.

7.3. Proximity to Major Polluters and Housing Prices in Beijing

We further take advantage of the geographic richness of our data to estimate a housing price with respect to the unit's distance to the nearest major pollution sources (e.g., Davis, 2011; Currie et al., 2015; Muehlenbachs, Spiller, and Timmins, 2015). We then examine how does the distance gradient shifts before versus after pollution disclosure. Although residents may not know the variation in pollution across fine geographic areas with a city or a district, the large polluters tend to be visible and well known landmarks in the city. The pollution disclosure could raise the salience of the potential health impacts of these large polluters in residents' housing choice decisions.

As described in Section 3, our distance-gradient analysis begins with a set of major polluters we identify as always-there in Beijing from 2007 – 2018. By using census emission measure from 2007, we find 41 top-decile polluters that account for nearly 90% of total emissions. Using geo-locations of these major polluters, we construct a time-invariant "distance to major polluter" variable at the apartment-complex level, and we use this variable to replace the $\ln \text{Pollution}_{cy}$ term in equation (5). We use the cross-sectional-style specification (district by year fixed effects, zip code fixed effects, and year-on-market fixed effects). We cannot perform the time-series specification as the distance measure is time-invariant which perfectly colinears with apartment-complex fixed effects. We control additionally for distance to non-top-decile polluters in the regression.

Figure 8 presents the results. In panel A, we present distance gradients separately for periods before and after disclosure. We detect no statistically significant distance gradient curve before disclosure. The shape of the curve shifted substantially after disclosure, where a near-monotonic price-distance relationship emerges. In panel B, we estimate the difference version of panel A to test the statistical precision of the change in distance gradient. Results show a relative reduction of housing value of about 27% for transactions within 3 km to the nearest major polluter. The effect fades with distance, and no effect is detected for regions over 6 km.

8. Pollution Disclosure and Mortality Outcome

8.1. Pollution and Mortality

Our endpoint analysis is to examine if the same amount of pollution exposure is associated with fewer deaths after information becomes widely available. Our estimation equation is again similar to equation (1), where we regress logged mortality rate in county *c* x quarter *t* on the corresponding logged pollution level, while allowing the coefficient to vary by event quarter *k*, i.e., the *k*-th quarter since pollution disclosure:

$$\ln \text{Mortality}_{ct} = \sum_{k=-10}^{6} \beta_k \times \ln \text{avg Pollution}_{ct} \times 1(t = k) + \sum_{k=-10}^{6} \alpha_k \times 1(t = k) + X_{ct} \cdot \gamma + \varepsilon_{ct} \quad (6)$$

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

Figure 9 plots the β_k coefficient estimates. We find that mortality-pollution elasticity exhibits a roughly flat trend before disclosure, followed by a decline post disclosure. In the graphical analysis, we condition the regression on city, quarter-of-year, and year fixed effects. We examine robustness of the results in Table 4 where, similar to Tables 1 and 2, we experiment with stringency of our fixed effects controls, e.g., by including quarter-of-sample, or region x quarter-of-sample fixed effects dummies. Notice in this version, we include pollution main effect in the regression, so that the pre-disclosure mortality-pollution elasticity is identified by the coefficient on the term "Log(Pollution)". We find a statistically significant 5-7 percentage point reduction in mortality-pollution elasticity post disclosure. The results are similar across specifications and consistent with the graphical evidence from Figure 9.

In the Appendix, we conduct two additional tests to examine the plausibility of the reduction in the mortality-pollution elasticity estimates. First, looking at age-specific mortality rates we construct from our DSP extract, we find that the effect is most precisely estimated among people aged over 40 who are presumably more vulnerable to pollution exposure than younger age groups. There is no change in the mortality-pollution relationship for infant (less than one-year old), which may seem counterintuitive. Pollution exposure among infants is low to begin with because they stay mostly indoors. Next, we find that changes in the mortality-pollution relationship concentrate in cardio-respiratory causes, such as COPD, heart diseases, and cerebrovascular diseases, which are widely considered as most relevant consequences of pollution exposure. The impact on mortality-pollution relationship from respiratory infection and digestive diseases is both small and insignificant. For traffic fatalities, the relationship post disclosure appears to become flatter though the change is not statistically significant.[15]

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

8.2. The Value of Pollution Information

The value of information (VOI) arises from the power of information in changing decisions. Our analysis shows that information on pollution disclosure affected a range of behavioral and market outcomes that reflect consumers' effort to mitigate the negative health consequences of air pollution. We can measure the VOI as the fraction of pollution-caused deaths that can be avoided by providing information access, holding pollution exposure constant.[16] In our study context, a proxy for VOI is the ratio between the *change* in mortality-pollution elasticity due to pollution disclosure (i.e., the interaction coefficient in Table 4) and the *level* of mortality-pollution elasticity prior to pollution disclosure. While the coefficient estimate on the "Log(Pollution)" main effect term has a level-of-elasticity interpretation, it is likely to be endogenous. In fact, the magnitude of the main effect estimate is similar to existing estimates on the correlation between PM exposure and mortality in China (e.g., Yin et al., 2017; Ebenstein et al., 2017). However, studies based on quasi-experimental methods have yielded much larger effect sizes, suggesting that correlational estimates might suffer from endogeneity or measurement problems (e.g., Chen et al., 2013; He, Fan, and Zhou, 2016; Ebenstein et al., 2017).

To alleviate the endogeneity concern, we borrow causal estimates on the mortality-pollution relationship from previous studies. We refer to a recent paper by Ebenstein et al. (2017) that examines the long-term mortality effects of PM exposure. We favor this study because it is based on well-established quasi-experimental design, also uses DSP as their mortality measurement, and it is based on years 2004-2012, which is before pollution disclosure took place. Similar to our estimate, the paper also reports a simple OLS regression between logged cardio-respiratory mortality and logged PM_{10} exposure and yields an elasticity estimate of 0.02. Using a regression discontinuity (RD) design that leverages a free coal-based heating policy available only to cities to the north of the Huai River, the authors find that PM_{10} just to the north of the river is roughly 41.7 ug/m^3 (about 35%) higher, while the corresponding difference in all-cause mortality rate is 26%, suggesting a mortality-PM_{10} elasticity of 0.70. Assuming a linear dosage-

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

response function, our estimate of a 5-7 percentage point reduction in the mortality-pollution elasticity therefore indicates a roughly 9% reduction in deaths attributable to the same pollution exposure.[17]

To conceptualize the effect size, we note that under the assumption of linear mortality-pollution dose response function, the benefit of a 9% reduction in mortality-pollution elasticity is roughly the same with the benefit of a 9% reduction in pollution concentration. This corresponds to roughly 10 ug/m^3 reduction in PM_{10} or 5 ug/m^3 reduction in $PM_{2.5}$ in China. We perceive the effect size as moderate for several reasons. First, the effect size is moderate compared to the average cross-city variation in $PM_{2.5}$ post-disclosure (SD = 20.4 ug/m^3, IQR = 25.2 ug/m^3). Second, the effect size is moderate compared several government programs that have been shown to shift pollution levels. For example, the winter heating policy implemented to the north of the Huai River is shown to increase PM_{10} by about 41.7 ug/m^3 (Ebenstein et al., 2017). Large-scale inspection and cleanup efforts across China since 2013 are associated with over 50 ug/m^3 reduction in $PM_{2.5}$ for some northern cities (Greenstone and Schwarz, 2008).

On the other hand, we believe the disclosure program brings meaningful economic and health benefits to the society. For example, using Ito and Zhang (2018)'s WTP estimate based on air purifier purchases in China, a 10 ug/m^3 reduction in PM_{10} is about RMB 90 ($13.4) per year, which aggregates to RMB 122 billion per year nationwide. In Barwick et al. (2017), an individual saves RMB 38 ($5.7) in out-of-pocket health spending from a 5 ug/m^3 reduction in $PM_{2.5}$ exposure, aggregating to RMB 52 billion per year nationwide.

9. Conclusion

In this study, we examine the role of pollution information in shaping how pollution exposure affects economic and health outcomes. We study a large-scale policy rollout in China whereby air pollution monitoring stations are installed and real-time information is made public by the Ministry of the Environment. We document the effect of information by examining a chain of outcomes from information

[17] We have also tried to estimate the causal effect of pollution on mortality using our own DSP sample. We exploited two different quasi-experimental designs. First, we replicate the Ebenstein et al. (2017) results for periods before disclosure, finding a similar mortality gap at the Huai River; we find suggestive evidence that the mortality gap attenuates for periods after disclosure. However, with a much shorter study sample (2011-2014) we are not powered to precisely estimate the pre- vs. post-disclosure difference in the mortality gap. Second, we follow Barwick et al. (2017) to exploit day-to-day variations in wind pattern to trace out changes in a city's pollution level due to long-range transport from upwind cities. Again, we find qualitatively similar effect of pollution on mortality. These results are reported in the Appendix.

access, pollution awareness, daily purchase trips, housing choices, to health outcome. Examination of these outcomes yields consistent evidence of increased pollution access, awareness, avoidance, as well as decreased pollution-related health damage when people have access to better pollution information.

Policies to raise public awareness of pollution exposure could range from “low-frequency” community right-to-know programs, such as emission inventory, to “high-frequency” advisory programs, such as air quality alerts. China’s experience suggests that providing “background-frequency” real-time pollution monitoring data, combined with effective dissemination infrastructures, could effectively improve public awareness of pollution issues. In particular, access to real-time pollution data has allowed people to respond to exposure both in the short and the long run. Furthermore, the compound effect of information access likely led to reduced health damages at the same levels of pollution exposure.

Our findings could have important implications for other emerging and developing countries that are experience severe pollution challenges. The infrastructure for monitoring environmental quality and for information disclosure is often inadequate in those countries. Results from this study suggest that benefit for this type of infrastructure investment could be large. Beyond the literature on the value of air quality, our results also contribute to the growing literature on the information economics. Previous studies have focused on small-scale settings in which misperceived product attributes caused distorted product choices. Our analysis suggests that misperception even exists in one’s day-to-day exposure to environmental pollutants. We hope such evidence may call for further investigations on mismatches between perceived vs. actual attributes, and therefore the role of better information, in other large-scale environmental settings.

References

Allcott, Hunt. "The welfare effects of misperceived product costs: Data and calibrations from the automobile market." *American Economic Journal: Economic Policy* 5, no. 3 (2013): 30-66.

Bai, Jie. “Melons as Lemons: Asymmetric Information, Consumer Learning and Quality Provision”. Working paper.

Banzhaf, H. Spencer, and Randall P. Walsh. "Do people vote with their feet? An empirical test of Tiebout." *American Economic Review* 98, no. 3 (2008): 843-63.

Barwick, Panle Jia, Shanjun Li, Deyu Rao, and Nahim Bin Zahur. The Morbidity Cost of Air Pollution: Evidence from Consumer Spending in China. No. w24688. National Bureau of Economic Research, 2018.

Bayer, Patrick, Nathaniel Keohane, and Christopher Timmins. "Migration and hedonic valuation: The case of air quality." *Journal of Environmental Economics and Management* 58, no. 1 (2009): 1-14.

Bernheim, B. Douglas, Andrey Fradkin, and Igor Popov. "The welfare economics of default options in 401 (k) plans." *American Economic Review* 105, no. 9 (2015): 2798-2837.

Bollinger, Bryan, Phillip Leslie, and Alan Sorensen. "Calorie posting in chain restaurants." *American Economic Journal: Economic Policy* 3, no. 1 (2011): 91-128.

Bui, Linda TM, and Christopher J. Mayer. "Regulation and capitalization of environmental amenities: evidence from the toxic release inventory in Massachusetts." *Review of Economics and statistics* 85, no. 3 (2003): 693-708.

Chay, Kenneth Y., and Michael Greenstone. "Does air quality matter? Evidence from the housing market." *Journal of Political Economy* 113, no. 2 (2005): 376-424.

Chen, Yuyu, Avraham Ebenstein, Michael Greenstone, and Hongbin Li. "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, no. 32 (2013): 12936-12941.

Chetty, Raj, Adam Looney, and Kory Kroft. "Salience and taxation: Theory and evidence." *American Economic Review* 99, no. 4 (2009): 1145-77.

Cohen, Aaron J., Michael Brauer, Richard Burnett, H. Ross Anderson, Joseph Frostad, Kara Estep, Kalpana Balakrishnan et al. "Estimates and 25-year trends of the global burden of disease attributable to ambient air pollution: an analysis of data from the Global Burden of Diseases Study 2015." *The Lancet* 389, no. 10082 (2017): 1907-1918.

Currie, Janet, Joshua Graff Zivin, Jamie Mullins, and Matthew Neidell. "What do we know about short-and long-term effects of early-life exposure to pollution?." *Annual Review of Resource Economics* 6, no. 1 (2014): 217-247.

Currie, Janet, Lucas Davis, Michael Greenstone, and Reed Walker. "Environmental health risks and housing values: evidence from 1,600 toxic plant openings and closings." *American Economic Review* 105, no. 2 (2015): 678-709.

Cutter, W. Bowman, and Matthew Neidell. "Voluntary information programs and environmental regulation: Evidence from 'Spare the Air'." *Journal of Environmental Economics and Management* 58, no. 3 (2009): 253-265.

Davis, Lucas W. "The effect of power plants on local housing values and rents." *Review of Economics and Statistics* 93, no. 4 (2011): 1391-1402.

Deschênes, Olivier, Michael Greenstone, and Joseph S. Shapiro. "Defensive investments and the demand for air quality: Evidence from the NOx budget program." *American Economic Review* 107, no. 10 (2017): 2958-89.

Ebenstein, Avraham, Maoyong Fan, Michael Greenstone, Guojun He, and Maigeng Zhou. "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* (2017): 201616784.

Fioletov, V. E., C. A. McLinden, N. Krotkov, M. D. Moran, and K. Yang. "Estimation of SO2 emissions using OMI retrievals." *Geophysical Research Letters* 38, no. 21 (2011).

Freeman, Richard, Wenquan Liang, Ran Song, and Christopher Timmins. "Willingness to Pay for Clean Air in China. " No. w24157. National Bureau of Economic Research, 2017.

Graff Zivin, Joshua, and Matthew Neidell. "Days of haze: Environmental information disclosure and intertemporal avoidance behavior." *Journal of Environmental Economics and Management* 58, no. 2 (2009): 119-128.

Graff Zivin, Joshua, and Matthew Neidell. "Environment, health, and human capital." *Journal of Economic Literature* 51, no. 3 (2013): 689-730.

Greenstone, Michael, and B. Kelsey Jack. "Envirodevonomics: A research agenda for an emerging field." *Journal of Economic Literature* 53, no. 1 (2015): 5-42.

Greenstone, Michael, and Patrick Schwarz. "Is China winning its war on pollution?" Air Quality Life Index™ update. March 2018.

Hamilton, James T. "Pollution as news: Media and stock market reactions to the toxics release inventory data." *Journal of Environmental Economics and Management* 28, no. 1 (1995): 98-113.

Hastings, Justine S., and Jeffrey M. Weinstein. "Information, school choice, and academic achievement: Evidence from two experiments." *The Quarterly Journal of Economics* 123, no. 4 (2008): 1373-1414.

He, Guojun, Maoyong Fan, and Maigeng Zhou. "The effect of air pollution on mortality in China: evidence from the 2008 Beijing Olympic Games." *Journal of Environmental Economics and Management* 79 (2016): 18-39.

Ito, Koichiro, and Shuang Zhang. Willingness to pay for clean air: Evidence from air purifier markets in China. No. w22367. National Bureau of Economic Research, 2016.

Jensen, Robert. "The (perceived) returns to education and the demand for schooling." *The Quarterly Journal of Economics*125, no. 2 (2010): 515-548.

Jin, Ginger Zhe, and Phillip Leslie. "The effect of information on product quality: Evidence from restaurant hygiene grade cards." *The Quarterly Journal of Economics* 118, no. 2 (2003): 409-451.

Kling, Jeffrey R., Sendhil Mullainathan, Eldar Shafir, Lee C. Vermeulen, and Marian V. Wrobel. "Comparison friction: Experimental evidence from Medicare drug plans." *The Quarterly Journal of Economics* 127, no. 1 (2012): 199-235.

Konar, Shameek, and Mark A. Cohen. "Does the market value environmental performance?" *Review of Economics and Statistics* 83, no. 2 (2001): 281-289.

Landrigan, Philip J., Richard Fuller, Nereus JR Acosta, Olusoji Adeyi, Robert Arnold, Abdoulaye Bibi Baldé, Roberto Bertollini et al. "The Lancet Commission on pollution and health." *The Lancet* (2017).

Leggett, Christopher G. "Environmental valuation with imperfect information the case of the random utility model." *Environmental and Resource Economics* 23, no. 3 (2002): 343-355.

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

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

Muehlenbachs, Lucija, Elisheba Spiller, and Christopher Timmins. "The housing market impacts of shale gas development." *American Economic Review* 105, no. 12 (2015): 3633-59.

Oberholzer-Gee, Felix, and Miki Mitsunari. "Information regulation: Do the victims of externalities pay attention?." *Journal of Regulatory Economics* 30, no. 2 (2006): 141-158.

Sanders, Nicholas J. Toxic assets: How the housing market responds to environmental information shocks. Working paper (2012).

Smith, V. Kerry, and F. Reed Johnson. "How do risk perceptions respond to information? The case of radon." *The Review of Economics and Statistics* (1988): 1-8.

Stigler, George J. "The economics of information." *Journal of Political Economy* 69, no. 3 (1961): 213-225.

Streets, David G., Timothy Canty, Gregory R. Carmichael, Benjamin de Foy, Russell R. Dickerson, Bryan N. Duncan, David P. Edwards et al. "Emissions estimation from satellite retrievals: A review of current capability." *Atmospheric Environment* 77 (2013): 1011-1042.

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

van Donkelaar, Aaron, Randall V. Martin, and Rokjin J. Park. "Estimating ground-level PM2. 5 using aerosol optical depth determined from satellite remote sensing." *Journal of Geophysical Research: Atmospheres* 111, no. D21 (2006).

Viscusi, W. Kip, and Joseph E. Aldy. "The value of a statistical life: a critical review of market estimates throughout the world." *Journal of Risk and Uncertainty* 27, no. 1 (2003): 5-76.

Wang, Alex L. "Explaining Environmental Information Disclosure in China." *Ecology Law Quarterly* 44 (2017): 865-924.

Weil, David, Archon Fung, Mary Graham, and Elena Fagotto. "The effectiveness of regulatory disclosure policies." *Journal of Policy Analysis and Management* 25, no. 1 (2006): 155-181.

Viscusi, W. Kip, and Clayton J. Masterman. "Income elasticities and global values of a statistical life." *Journal of Benefit-Cost Analysis* 8, no. 2 (2017): 226-250.

Yin, Peng, Guojun He, Maoyong Fan, Kowk Yan Chiu, Maorong Fan, Chang Liu, An Xue et al. "Particulate air pollution and mortality in 38 of China’s largest cities: time series analysis." *BMJ* 356 (2017): j667.

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

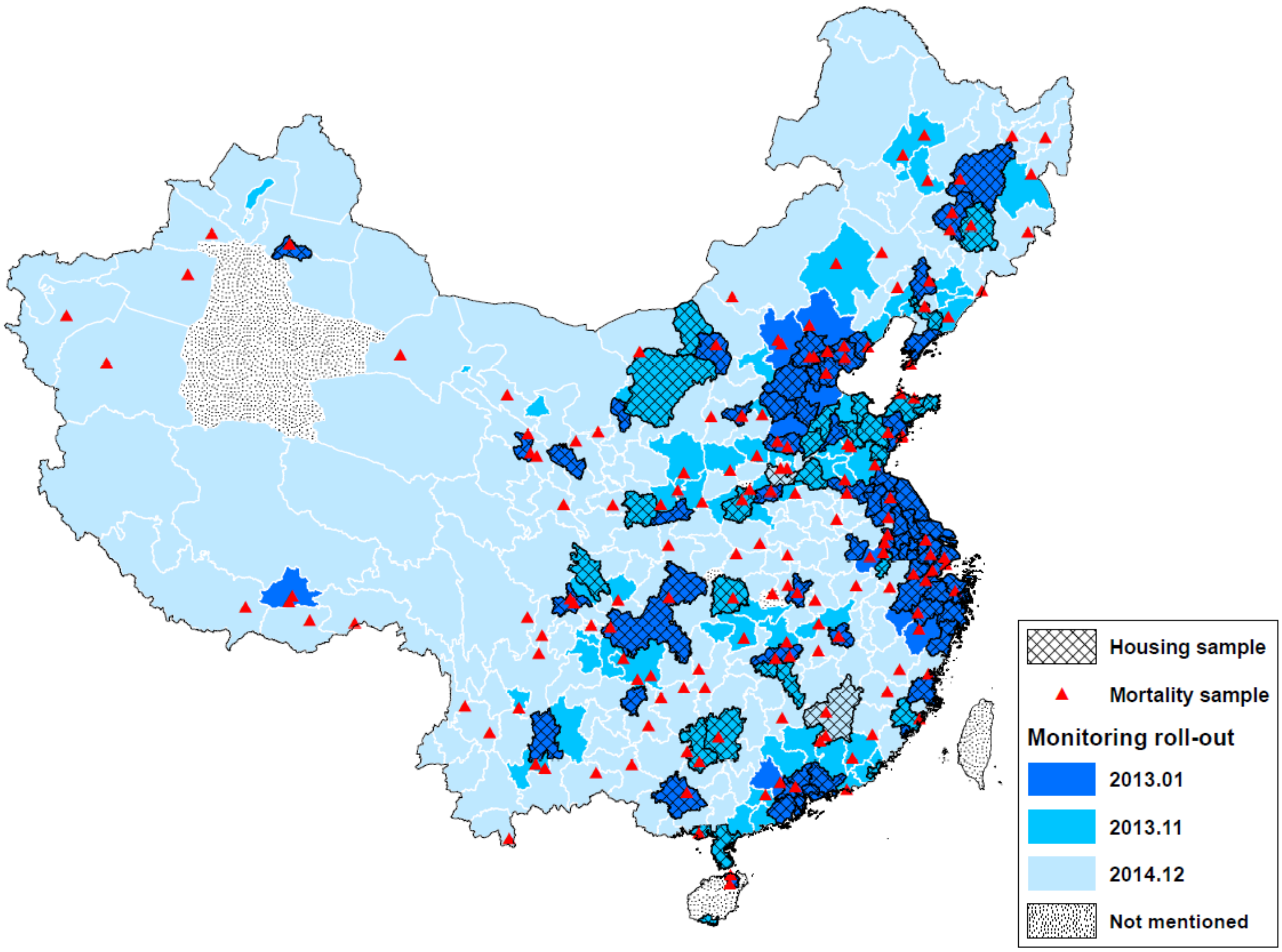
Zhang, Xin, Xi Chen, and Xiaobo Zhang. “The Impact of Exposure to Air Pollution on Cognitive Performance.” *the Proceedings of National Academy of Sciences* 115(2018): 9193-9197.

Zheng, Siqi, Jing Cao, Matthew E. Kahn, and Cong Sun. "Real estate valuation and cross-boundary air pollution externalities: evidence from Chinese cities." *The Journal of Real Estate Finance and Economics* 48, no. 3 (2014): 398-414.

Zheng, Siqi, and Matthew E. Kahn. "Land and residential property markets in a booming economy: New evidence from Beijing." *Journal of Urban Economics* 63, no. 2 (2008): 743-757.

Zhou, Maigeng, Haidong Wang, Jun Zhu, Wanqing Chen, Linhong Wang, Shiwei Liu, Yichong Li et al. "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, no. 10015 (2016): 251-272.

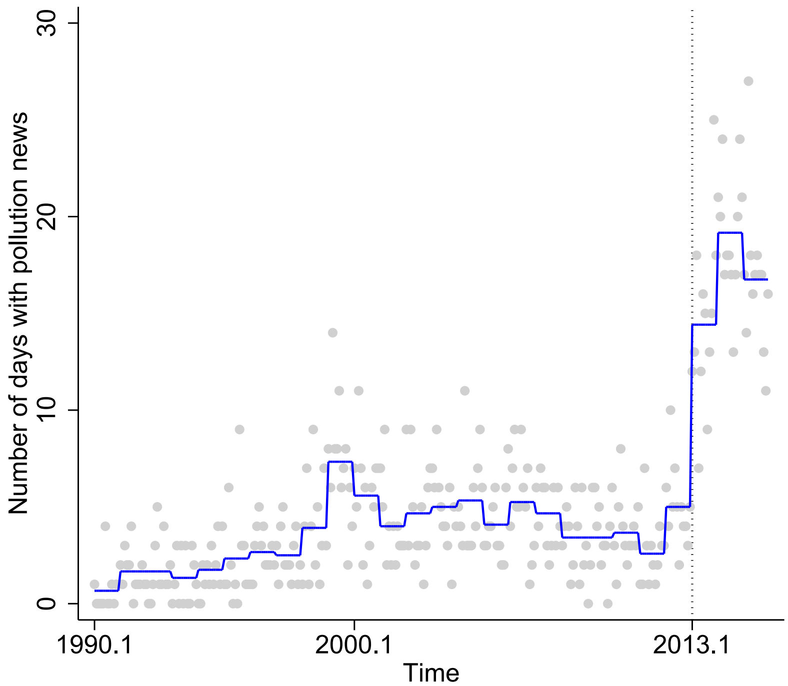
Figure 1. Air Pollution Monitoring Rollout Timing



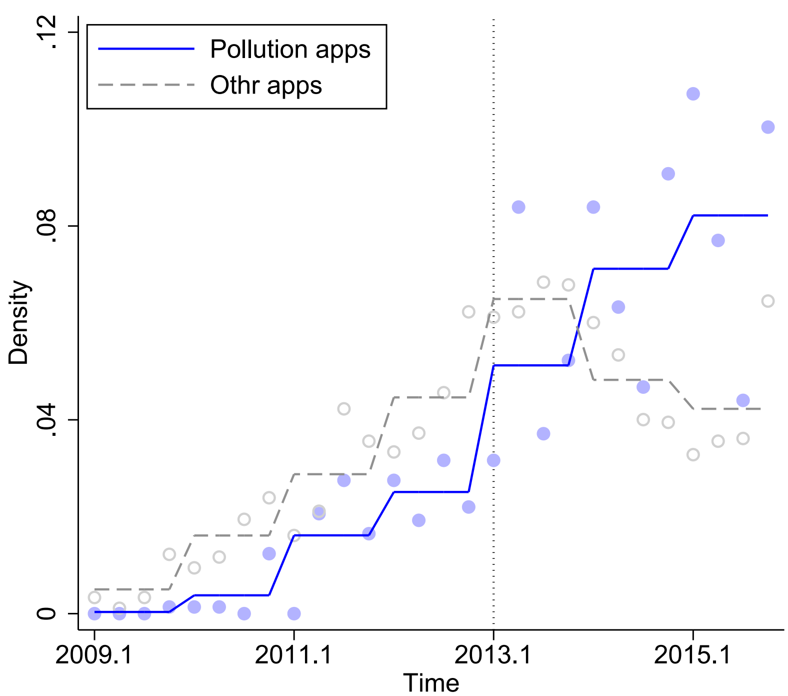
Notes: This map shows prefecture-city by the initiation date of real-time air pollution monitoring. "Not mentioned" are cities where the timing of monitoring is not mentioned in the MEP's policy notice. "Housing sample" highlights cities included in the housing price analysis. "Mortality sample" are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

Figure 2. Changes in Pollution Information Exposure

Panel A. *People's Daily* pollution-related news (days per month)



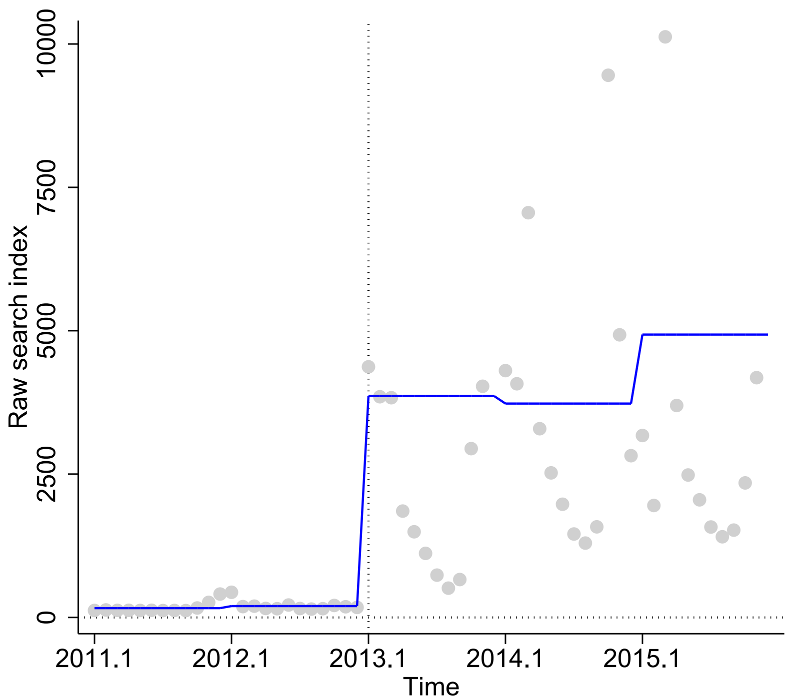
Panel B. Apple App Store pollution-related apps release



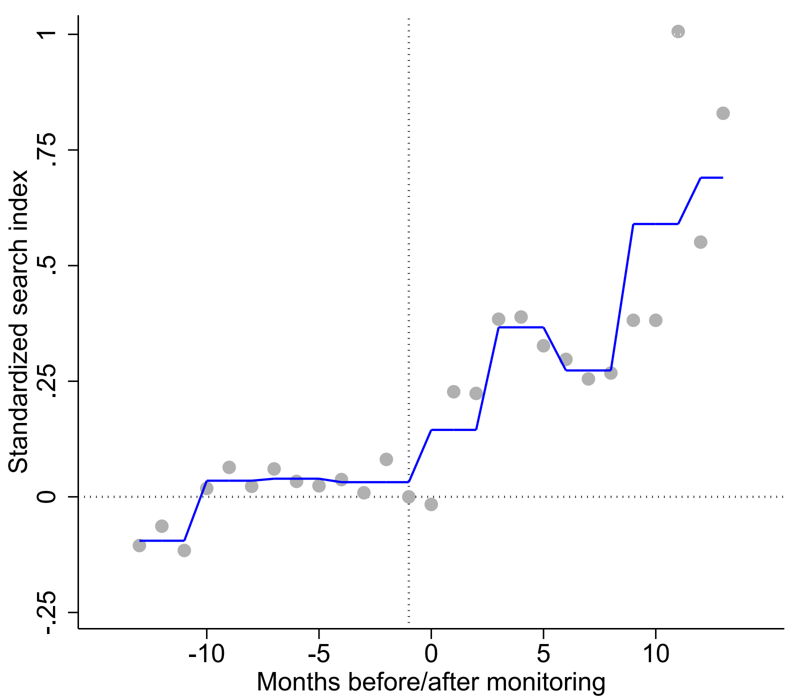
Notes: Panel A plots the number of days in each month when the *People's Daily* (official newspaper of the Chinese government) published articles containing "air/atmospheric pollution" in titles. Dots show monthly day counts. Line shows annual averages. Panel B shows release-date distribution of Apple App Store apps related to pollution (solid dots and line). Averaged release-time distribution for apps in other categories (dashed dots and line) includes game, music, video, reading, finance, sports, education, shopping, and navigation. For each category, sample is restricted to the first 200 apps returned by the Apple API given the search key. Data are accessed on Decembet 27, 2015.

Figure 3. Changes in Pollution Awareness

Panel A. Baidu search index for "smog"

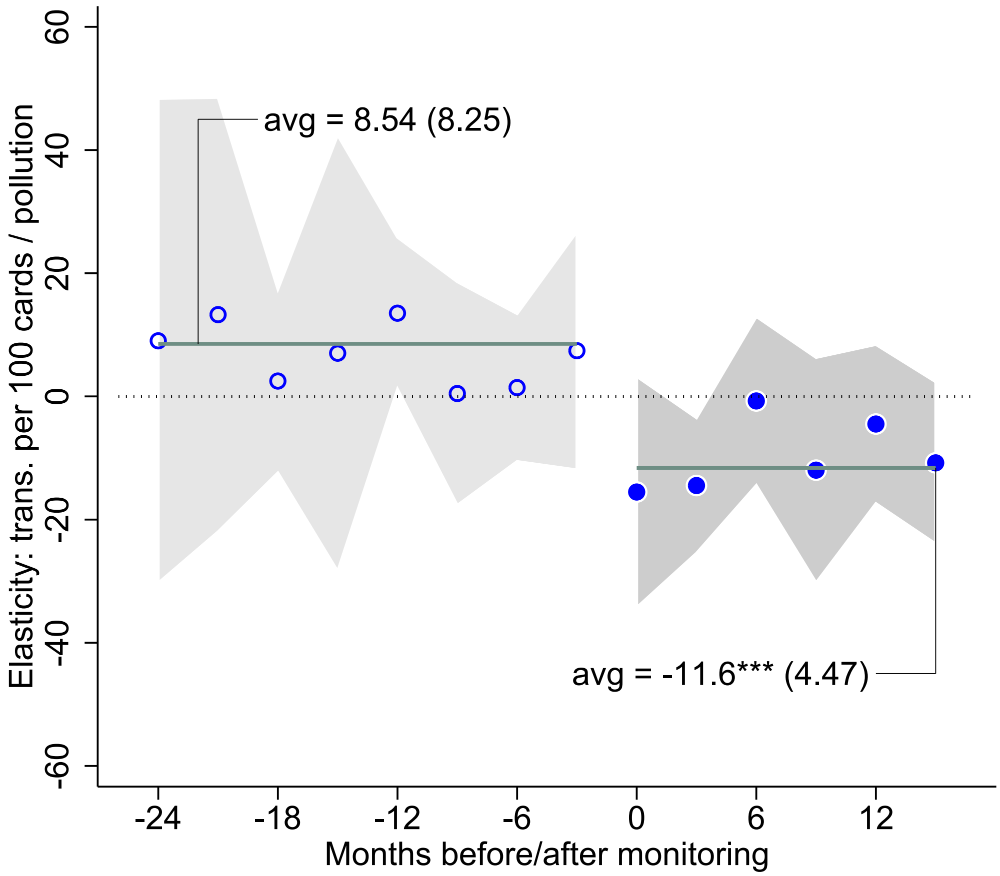


Panel B. Responses of "smog" search to pollution information



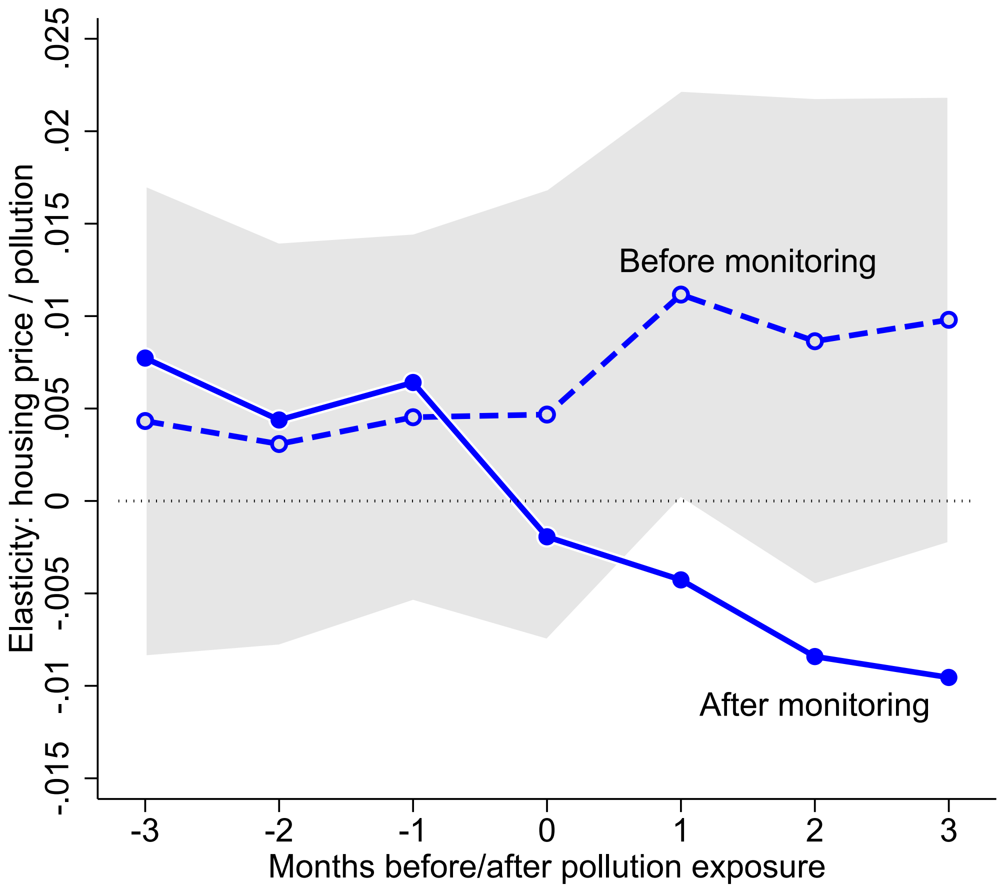
Notes: Panel A plots raw monthly trends in Baidu Search Index for the word "smog". The graph omits two dots with exceptionally high search index for readability purpose. These dots correspond to December 2013 (index = 20,942) and Decembet 2015 (index = 24,679). Line shows annual average. Panel B plots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

Figure 4. Changes in Weekly Bank Card Transaction-Pollution Gradient



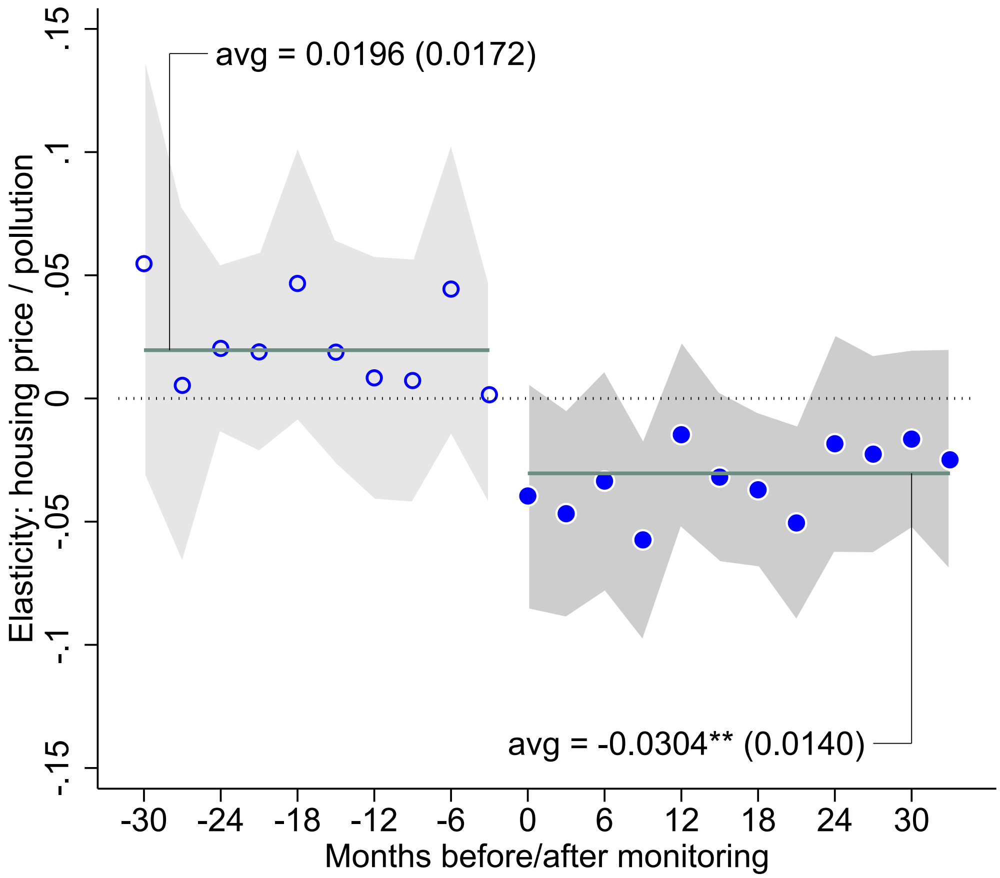
Notes: This graph shows the relationship between weekly bank card transcation rate and log satellite-based pollution as a function of time since monitoring initiation. The regression controls for prefectiry-city FEs, week-of-year FEs, and year FEs. "Avg" shows mean effect before and after monitoring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

Figure 5. Changes in Monthly Housing Prices-Pollution Dynamics



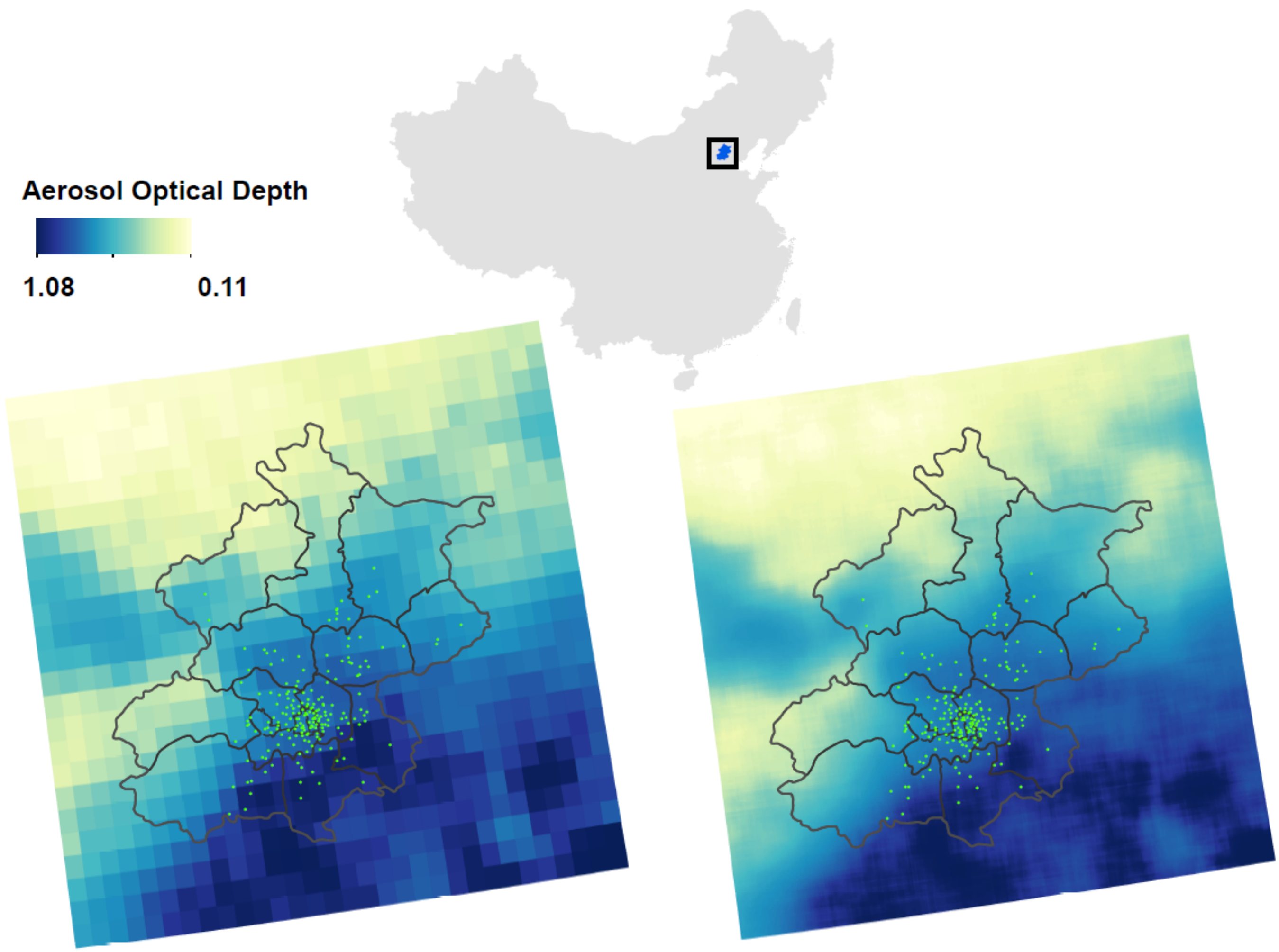
Notes: This graph shows coefficients from a regression of log housing prices on log satellite-based pollution in the months after, the month of (t=0), and the months prior to exposure (i.e., lead, contemporaneous and lagged effects). Estimations are done separately for time before (dashed line) and after (solid line) monitoring began. All regressions control for prefecture-city$\times$month-of-year FEs and year FEs. Shaded region shows 95% confidence interval constructed from standard errors clustered at the prefecture-city level.

Figure 6. Changes in Monthly Housing Prices-Pollution Gradient



Notes: This graph shows coefficients from a regression of log housing prices on log satellite-based pollution in the prior 4-month window (i.e., sum of contemporaneous and lagged effects), as a function of time since monitoring initiation. The (-30 to 33) month event window is chosen so that the underlying sample is a balanced panel of all 100 cities. Coefficients are obtained from a single regression, controlling for 3-month leads in pollution, prefectiry-city×month-of-year FEs and year FEs. "Avg" shows mean effect before and after monitoring began. Shaded region shows 95% confidence interval constructed from standard errors clustered at the prefecture-city level.

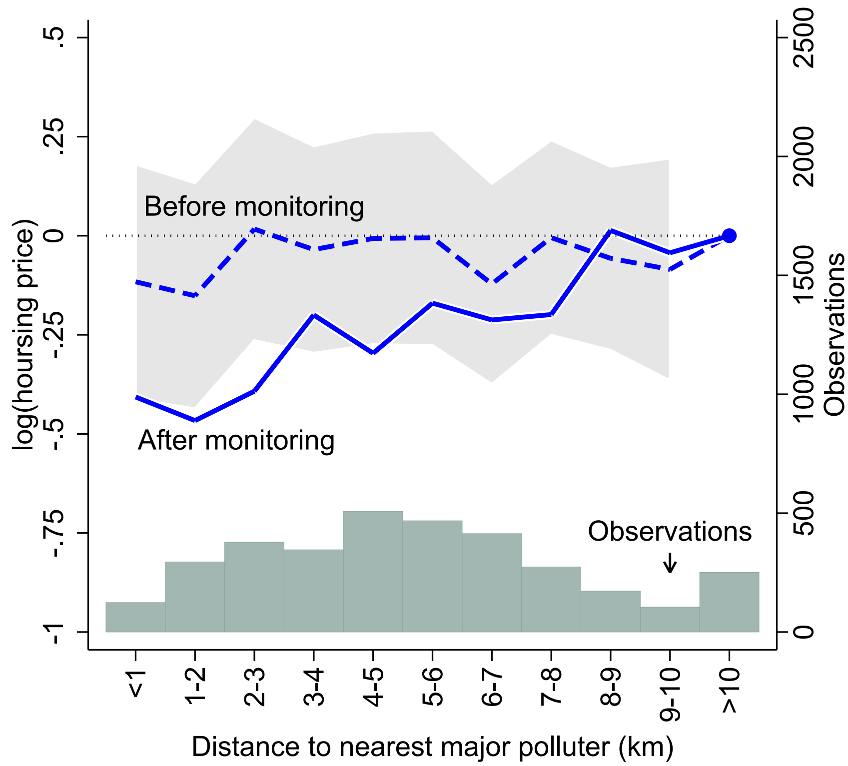
Figure 7. Original (10km) vs. "Oversampled" (1km) Aerosol Optical Depth, Beijing 2006-2014



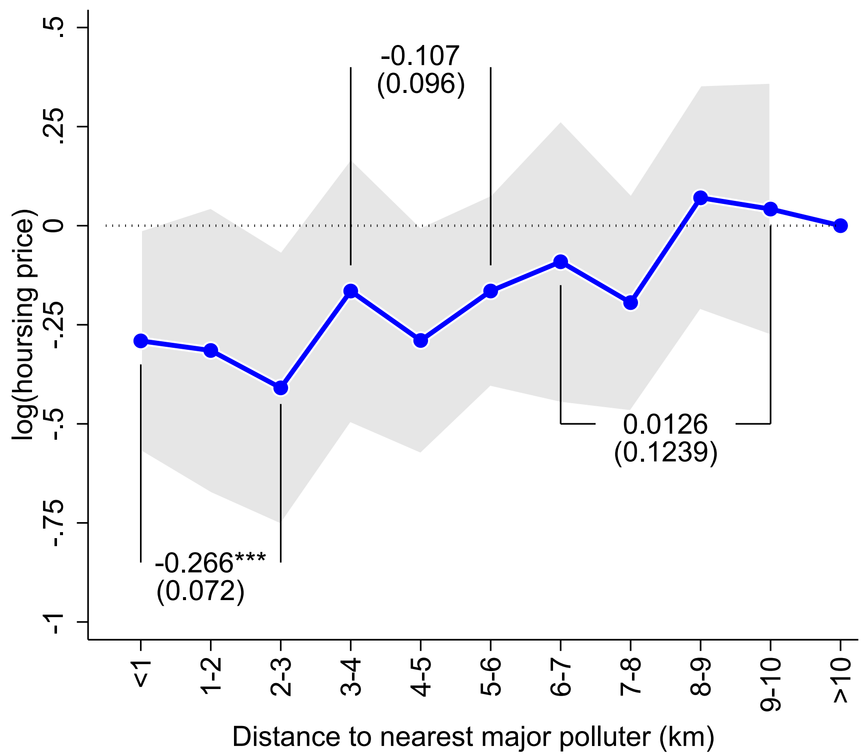
Notes: This map shows 2006-2014 average aerosol optical depth (AOD) level for the prefecture of Beijing. Left panel shows MODIS AOD at the original 10×10km resolution. Right panel shows AOD oversampled to 1×1km resolution. Dots show centroid locations of communities (i.e., "jiedao") in the housing transaction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

Figure 8. Changes in Annual Housing Prices-Distance to Polluter Gradient, Beijing

Panel A. Before vs. after monitoring

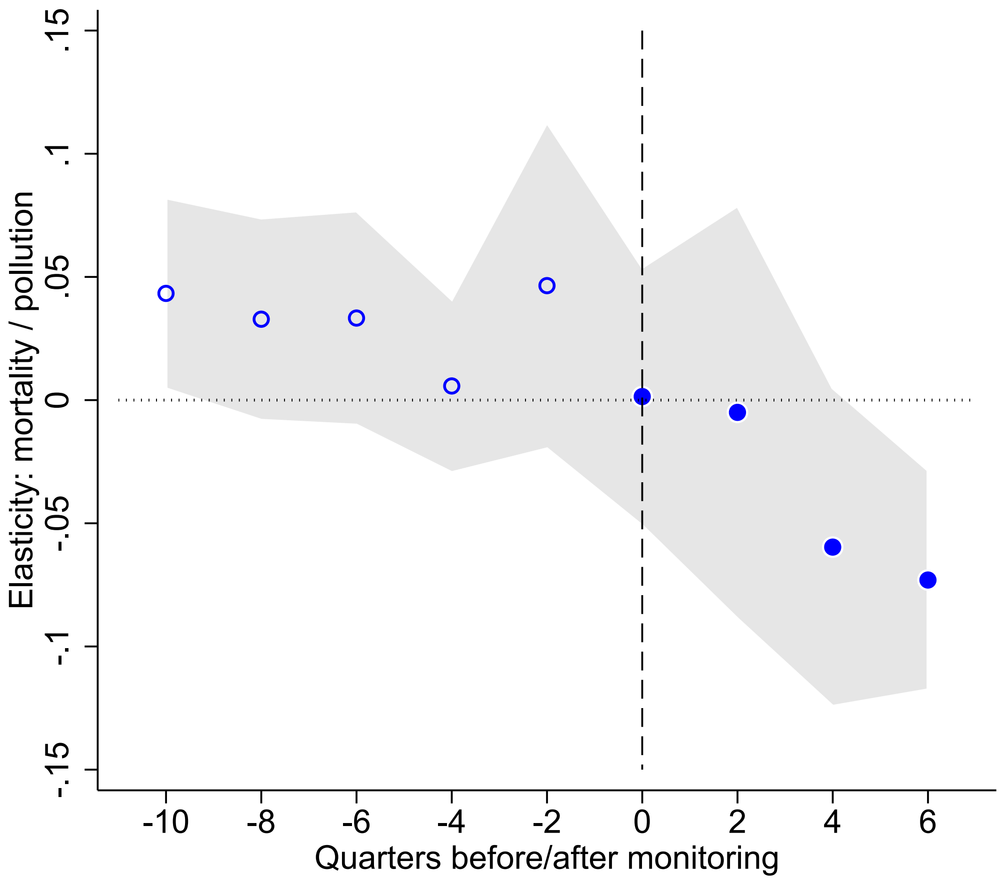


Panel B. Difference estimates



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

Figure 9. Changes in Quarterly Mortality-Pollution Gradient



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

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

Dep. var.: Number of transactions per 100 active cards in a city×week				
	(1)	(2)	(3)	(4)
Log(Pollution)	8.54	6.25	8.17	10.5
	(8.25)	(8.86)	(5.80)	(7.28)
Log(Pollution) × 1(after monitoring)	-20.1**	-23.2**	-19.8**	-25.6**
	(8.71)	(10.9)	(7.83)	(10.2)
FEs: city	✓	✓	✓	✓
FEs: week-of-year	✓			
FEs: year	✓			
FEs: week-of-sample		✓	✓	
FEs: region×year			✓	
FEs: region×week-of-sample				✓
N	81,544	81,544	81,544	81,544

Notes: "Log(Pollution)" is logged AOD in the city×week. Mean of dependent variable is 870.6 transactions per week per 100 cards. "region" is a conventional partition of cities by location: North (36 cities), Northeast (38 cities), East (105 cities), Centralsouth (81 cities), Southwest (54 cities), Northwest (52 cities). Standard errors are clustered at the prefecture-city level. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Table 2. Changes in Monthly Housing Index-Pollution Gradient

Dep. var.: Log housing price index in a city×month				
	(1)	(2)	(3)	(4)
Log(Pollution)	0.013	0.011	0.011	0.016
	(0.010)	(0.010)	(0.010)	(0.013)
Log(Pollution) × 1(after monitoring)	-0.036***	-0.036**	-0.026*	-0.038**
	(0.013)	(0.014)	(0.014)	(0.018)
FEs: city	✓	✓	✓	✓
FEs: month-of-year	✓			
FEs: year	✓			
FEs: month-of-sample		✓	✓	
FEs: region×year			✓	
FEs: region×month-of-sample				✓
N	6,629	6,629	6,629	6,582

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

Table 3. Changes in Beijing's Housing Price-Pollution Gradient

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

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

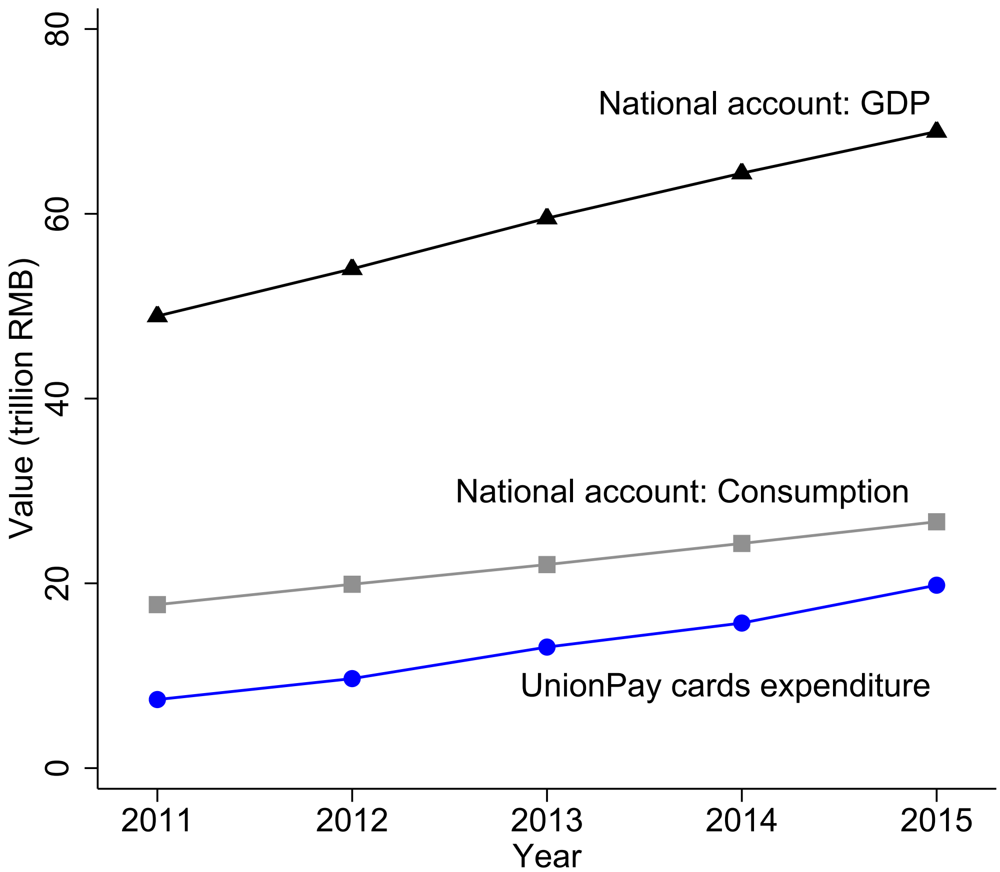
Table 4. Changes in Quarterly Mortality-Pollution Gradient

Dep. var.: Log mortality rate in a city×quarter				
	(1)	(2)	(3)	(4)
Log(Pollution)	0.036*	0.039*	0.043**	0.039**
	(0.019)	(0.020)	(0.020)	(0.019)
Log(Pollution) $\times$ 1(after monitoring)	-0.069***	-0.066***	-0.059**	-0.051**
	(0.017)	(0.019)	(0.024)	(0.021)
FEs: city	✓	✓	✓	✓
FEs: quarter-of-year	✓			
FEs: year	✓			
FEs: quarter-of-sample		✓	✓	
FEs: region×year			✓	
FEs: region×quarter-of-sample				✓
N	2,096	2,096	2,096	2,096

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

Additional Figures and Tables

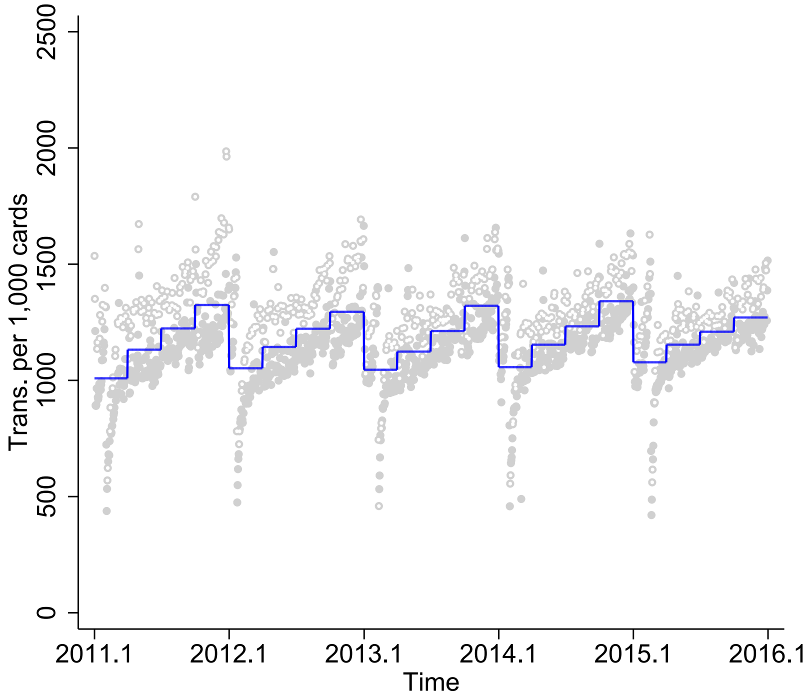
Figure A.1. Consumption Trends: UnionPay vs. National Accounts



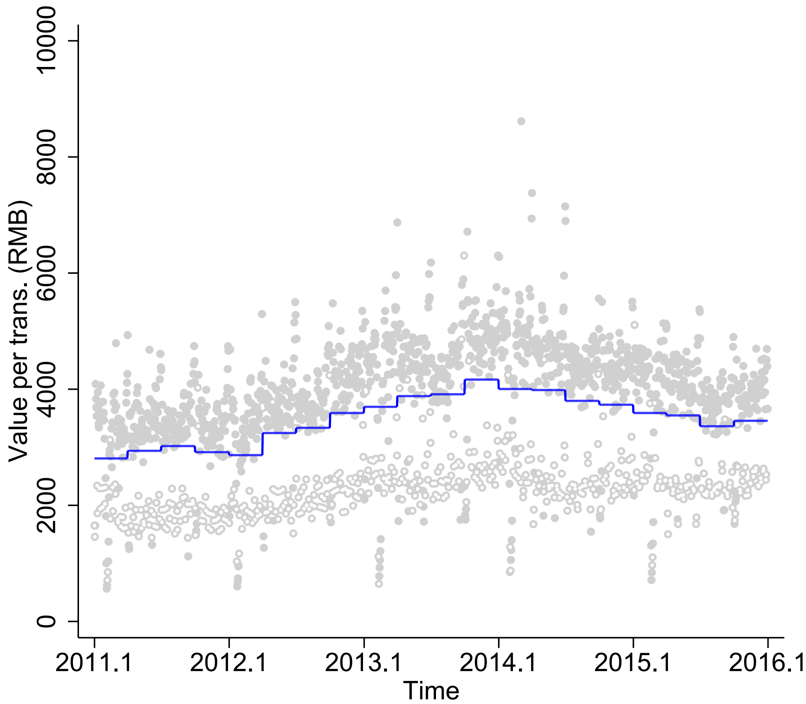
Notes: This figure plots annual GDP (triangles), consumption (squares) reported by the National Bureau of Statistics of China (NBS), and total bank card spendings ×100 (circles) aggregated from the UnionPay 1% bank card data. UnionPay data excludes transactions in the business wholesale categories.

Figure A.2. UnionPay Bank Card Transaction Trends

Panel A. Number of transactions per 1,000 cards



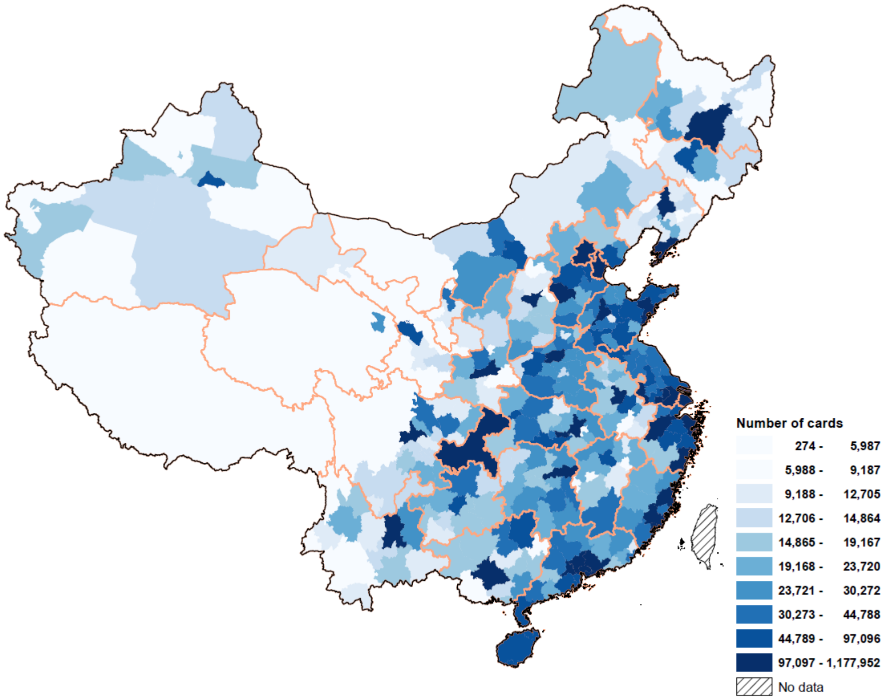
Panel B. Spending per transaction



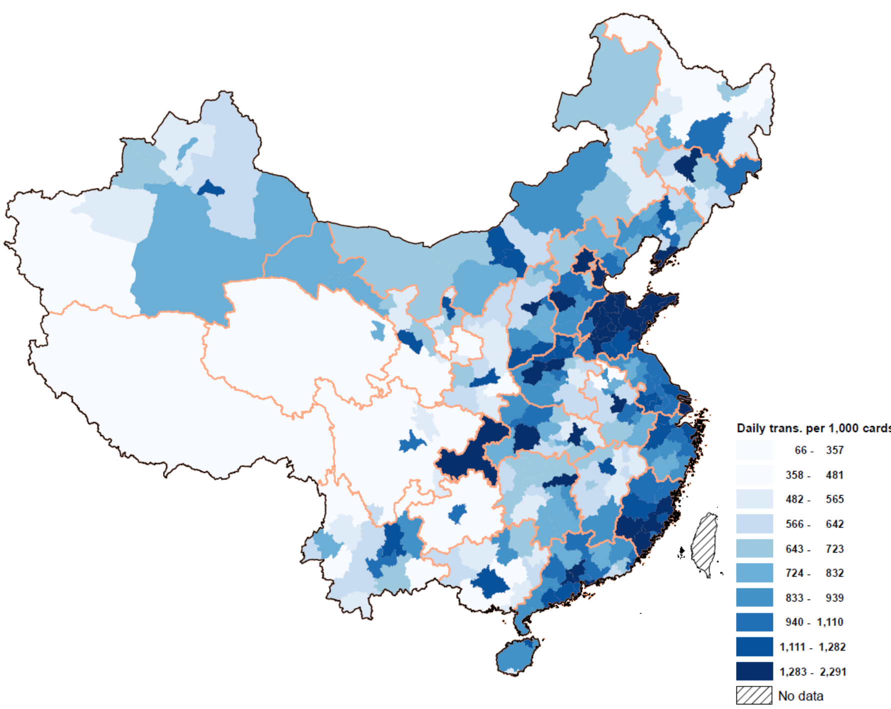
Notes: Each dot represents transaction rate (panel A) and spending per transaction (panel B) on a day. Solid dots show weekdays and hollow dots show weekends. Lines show quarterly averages.

Figure A.3. UnionPay Bank Card Transaction by Prefecture-City, 2011-2015 Average

Panel A. Number of active cards

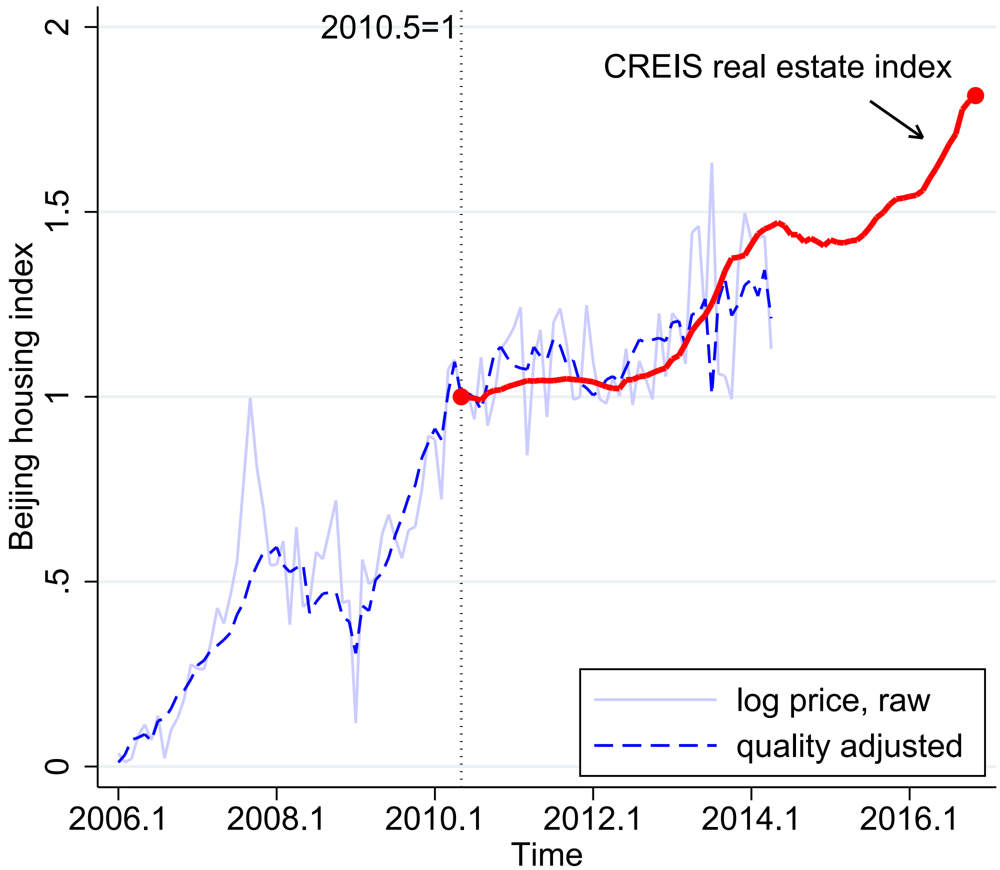


Panel A. Number of transactions per 1,000 cards



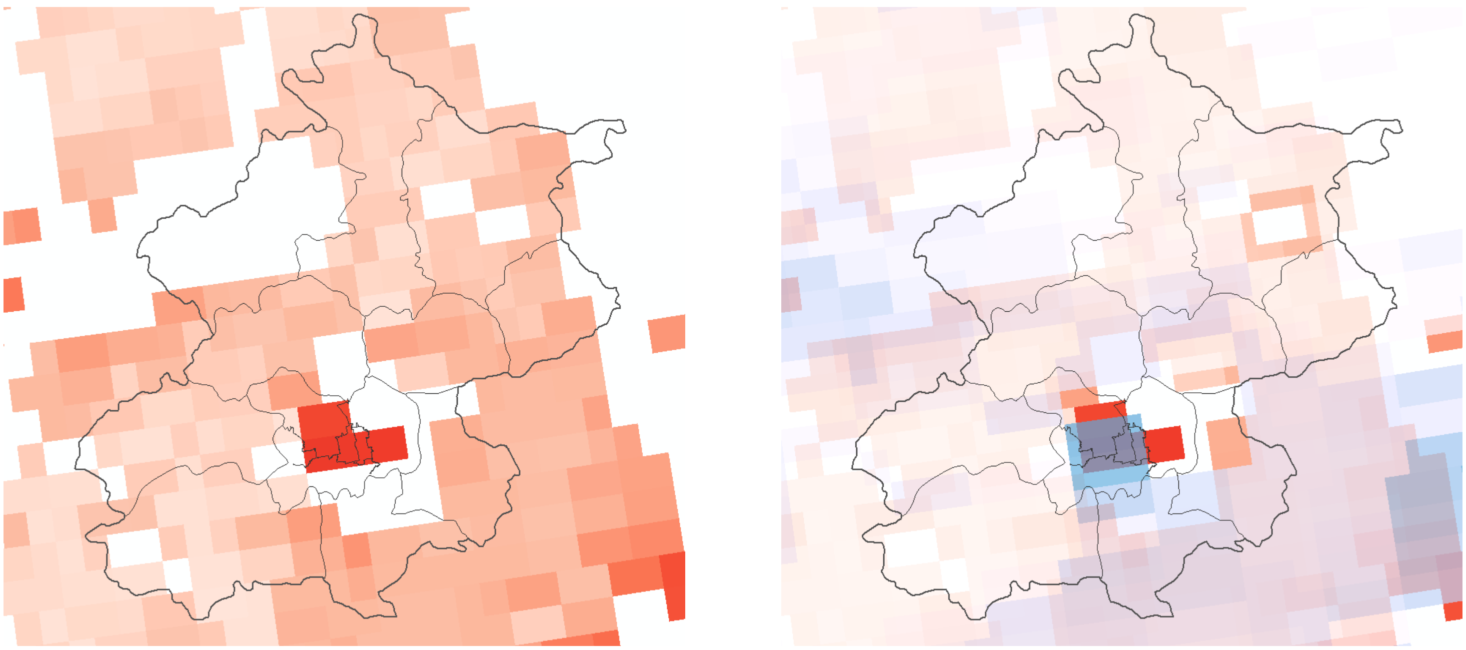
Notes: The maps show 2011-2015 average number of active UnionPay bank cards (panel A) and transactions per 1,000 cards (panel B) at the prefecture-city level. Orange lines show inter-provincial borders.

Figure A.4. Beijing Housing Price Indexes: Transaction Data vs. CREIS Index



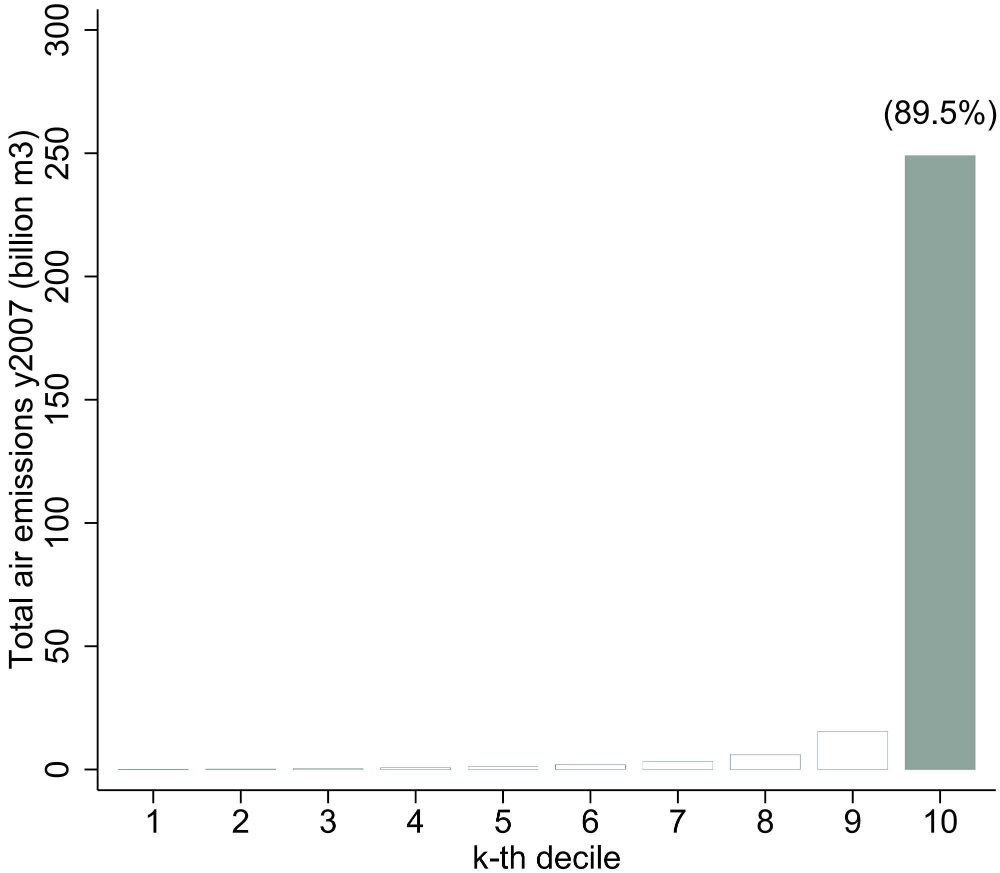
Notes: Red solid line plots Beijing monthly housing price index from the China Real Estate Index System. Blue solid line shows raw log average monthly housing price from Beijing's housing transaction data. Blue dashed line shows the transaction data-based index adjusted for quadratic floor size, floor indicators, and complex indicators. Price indexes are normalized to 1 for May 2010 when CREIS Index was first available.

Figure A.5. An Illustrative Example of Satellite AOD Oversampling



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

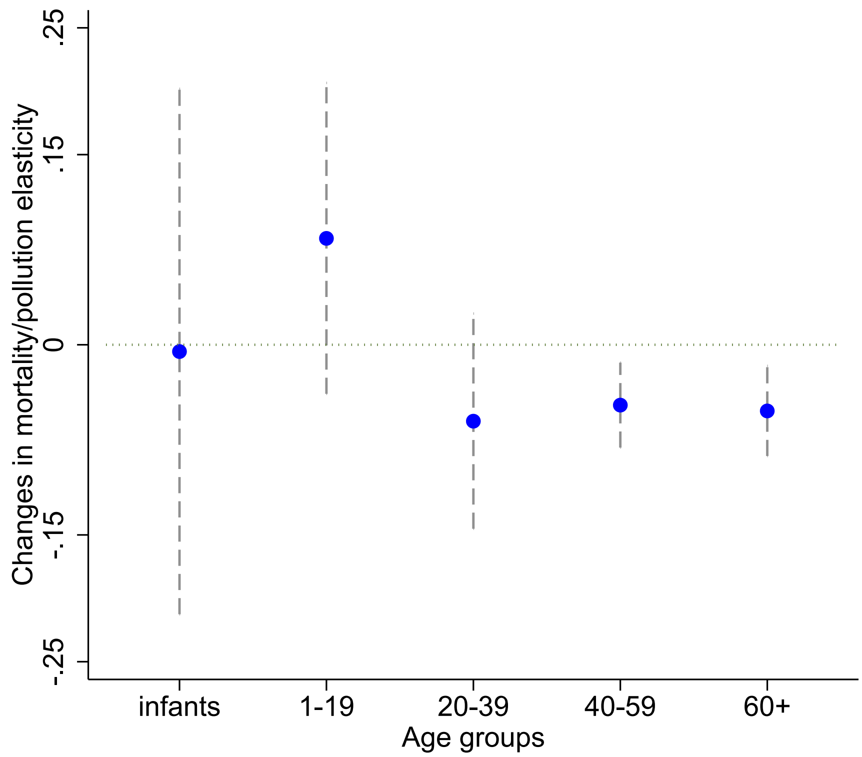
Figure A.6. Total Air Emissions by Emission Deciles, Beijing Polluter Census 2007



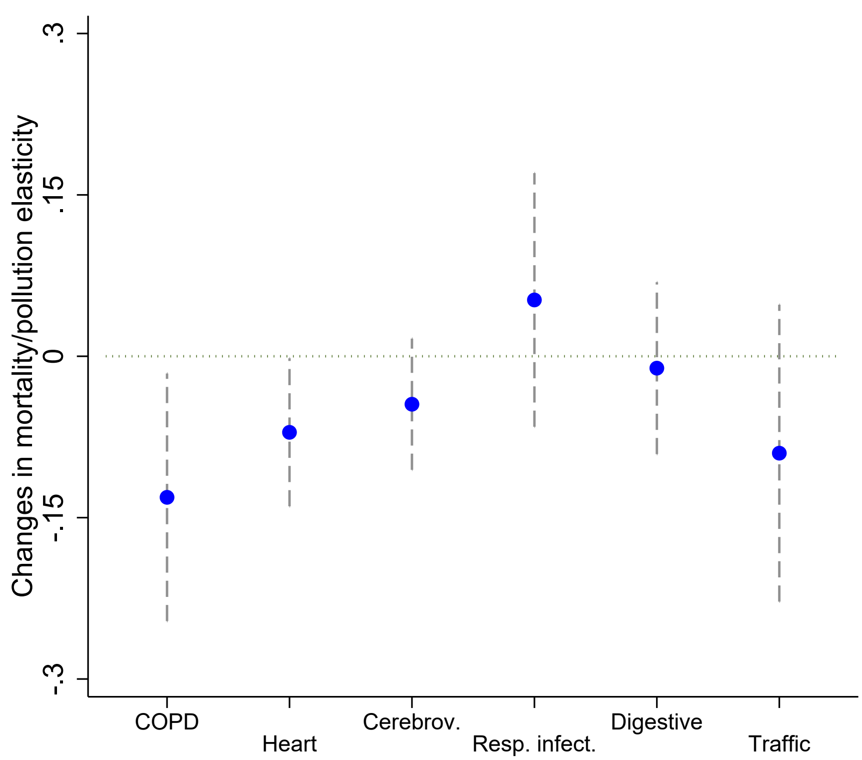
Notes: This graph shows total air emissions (in billion m^3) by Beijing polluters in the k-th decile of annual emission distribution according to the Polluter Census 2007. The sample includes about 440 polluters.

Figure A.7. Heterogeneous Changes in Quarterly Mortality-Pollution Gradient

Panel A. Heterogeneity by age groups

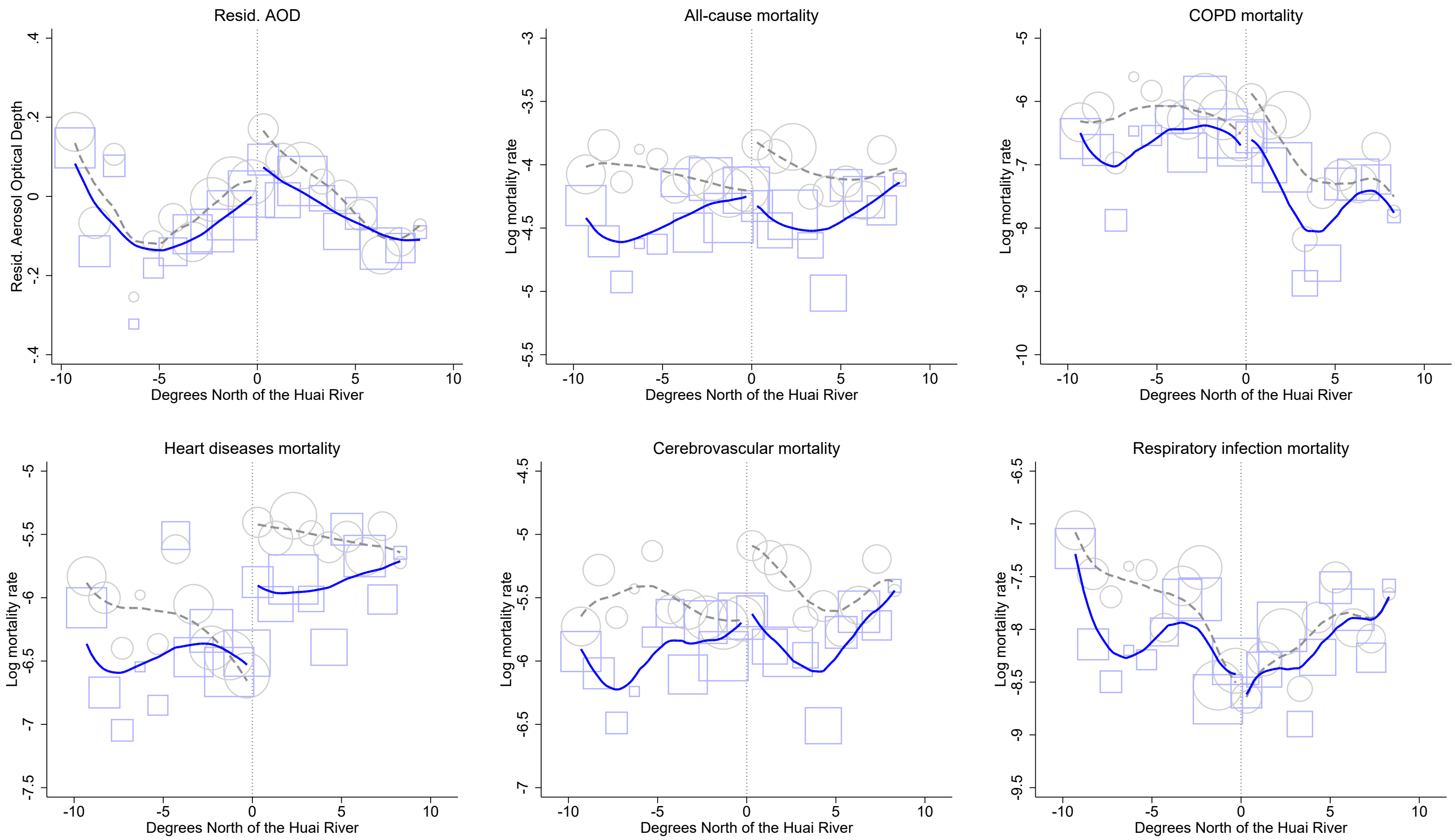


Panel B. Heterogeneity by causes-of-death



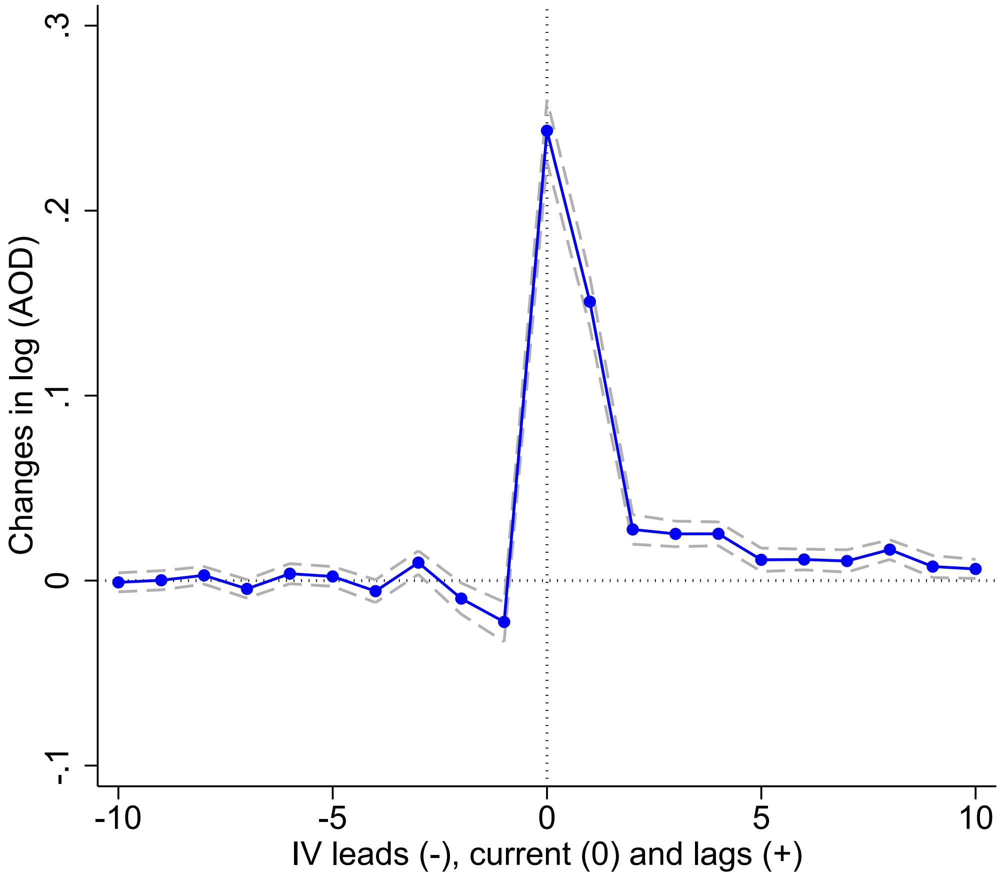
Notes: Each range plot item shows the mortality-pollution elasticity change coefficient (i.e., log(Pollution)$\times$1(after monitoring)) from a separate regression using sub-group log mortality rate as the outcome variable. All regressions control for prefectiry-city FEs and quarter-of-sample FEs. Range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

Figure A.8. Regression Discontinuity at the Huai River Before (Circles, Dashed) and After (Squares, Solid) Monitoring



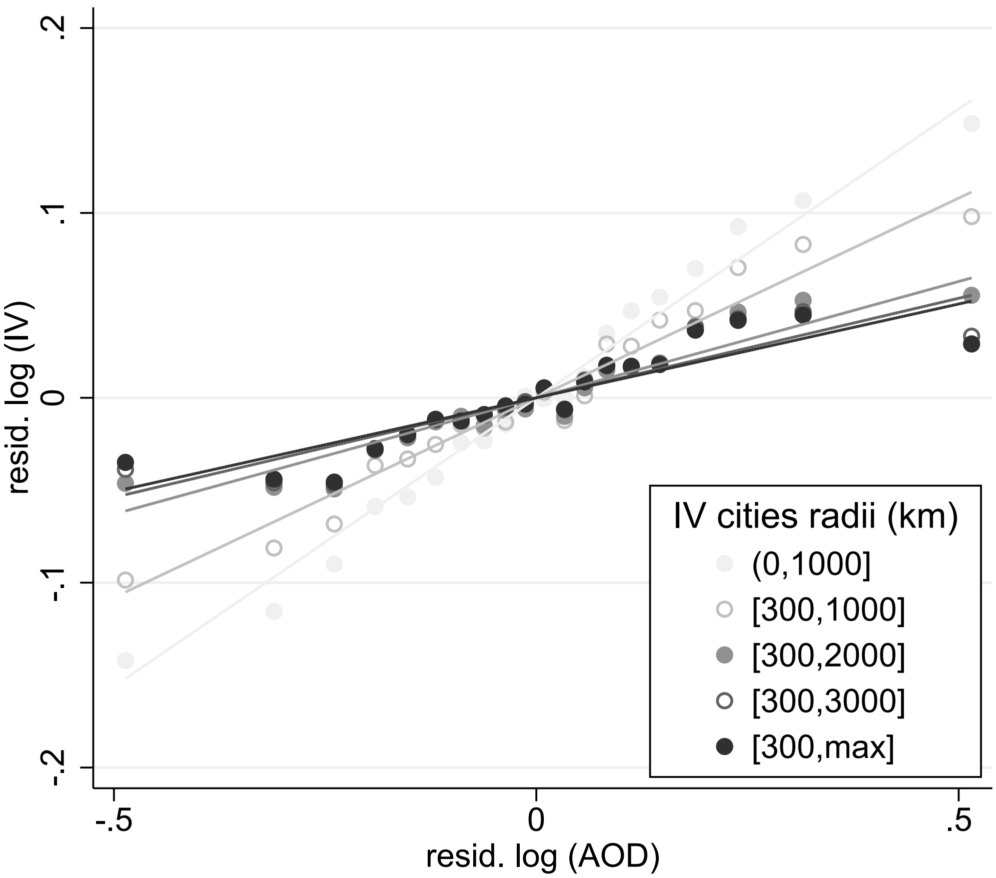
Notes: Scatter plot in each panel shows the local means of the corresponding outcome variable for the period before (circles) and after (squares) monitoring with a bin size of 1 degree (Observations = 99). Residualized AOD is constructed from a regression of DSP's y2011-y2014 avg AOD on a linear function of y2013-y2015 avg $PM_{2.5}$ allowed to vary by the two sides of the Huai River. The horizontal axis is the distance (in degree) to the north of the Huai River, following Ebenstein et al. (2017). Solid (dashed) lines are from local linear regressions estimated separately on each side of the river for the period before (after) monitoring.

Figure A.9. Daily AOD by Leads, Current, and Lags of IV (Distant Cities' AOD $\times$ cosine(wind))



Notes: This plot shows coefficients from a regression of city's daily logged AOD on lead, current, and lag terms of the IV. IV is (logged) inverse-distance weighted average AOD across distant cities. In this case, we use cities locate between 300 to 2000 km to own city. Each distant city's pollution is vectorized by local wind direction of the day, and only the component pointing from the distant city to own city is used in constructing IV. The regression includes prefecture-city FEs and day-of-sample FEs. Standard errors are clustered at the city level.

Figure A.10. Binscatter of First Stage (Quarterly AOD vs. IV)



Notes: This plot shows residualized binscatter of (logged) AOD and IV at the quarterly level. IV is inverse-distance weighted average AOD across distant cities. Each distant city's pollution is vectorized by local wind direction of the day, and only the component pointing from the distant city to own city is used in constructing IV. Both AOD and IV are aggregated to the quarterly level to make the binscatter. Each set of binscatter corresponds to IV constructed using different samples of distant cities, as shown by the legend. All plots are residualized by prefecture-city FEs and quater-of-sample FEs.

Table A.1. Changes in Weekly Bank Card Transaction-Pollution Gradient: "Deferrable" Consumptions

Dep. var.: Number of transactions per 100 active cards in a city×week	(1)	(2)	(3)	(4)
Panel A. Merchant type = supermarkets (mean = 258.5)				
Log(Pollution)	4.70	3.70	7.57***	8.29***
	(3.78)	(4.12)	(2.27)	(2.80)
Log(Pollution) × 1(after monitoring)	-11.3***	-11.4**	-14.5***	-17.7***
	(3.86)	(4.77)	(3.10)	(3.84)
Panel B. Merchant type = dining (mean = 46.8)				
Log(Pollution)	1.35*	1.63*	1.32**	1.61**
	(0.792)	(0.894)	(0.514)	(0.635)
Log(Pollution) × 1(after monitoring)	-2.84***	-3.36***	-2.24***	-2.55***
	(0.533)	(0.625)	(0.639)	(0.762)
Panel C. Merchant type = entertainment (mean = 9.70)				
Log(Pollution)	0.501	0.759**	0.468*	0.533*
	(0.328)	(0.376)	(0.265)	(0.305)
Log(Pollution) × 1(after monitoring)	-0.720	-1.15**	-0.601*	-0.736*
	(0.440)	(0.508)	(0.353)	(0.415)
FEs: city	✓	✓	✓	✓
FEs: week-of-year	✓			
FEs: year	✓			
FEs: week-of-sample		✓	✓	
FEs: region×year			✓	
FEs: region×week-of-sample				✓
N	81,544	81,544	81,544	81,544

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

Table A.2. Changes in Weekly Bank Card Transaction-Pollution Gradient: "Scheduled" Consumptions (Placebo Tests)

Dep. var.: Number of transactions per 100 active cards in a city×week				
	(1)	(2)	(3)	(4)
Panel A. Merchant type = billings (mean = 59.5)				
Log(Pollution)	0.293	0.772	2.68	3.58
	(2.35)	(2.73)	(1.82)	(2.19)
Log(Pollution) × 1(after monitoring)	0.959	-0.473	-3.83	-3.97
	(3.94)	(4.63)	(3.01)	(3.22)
Panel B. Merchant type = government services (mean = 12.4)				
Log(Pollution)	0.372	0.335	0.218	0.568
	(0.680)	(0.731)	(0.736)	(0.859)
Log(Pollution) × 1(after monitoring)	-0.572	-0.702	-0.557	-0.601
	(1.00)	(1.07)	(1.04)	(1.26)
Panel C. Merchant type = business-to-business wholesales (mean = 4.80)				
Log(Pollution)	-0.045	0.063	-0.050	-0.009
	(0.389)	(0.413)	(0.341)	(0.406)
Log(Pollution) × 1(after monitoring)	0.187	-0.115	0.071	0.065
	(0.576)	(0.604)	(0.479)	(0.565)
Panel D. Merchant type = cancer treatment centers (mean = 0.321)				
Log(Pollution)	0.010	0.011	0.016	0.014
	(0.012)	(0.013)	(0.011)	(0.013)
Log(Pollution) × 1(after monitoring)	-0.012	-0.018	-0.022	-0.023
	0.016	(0.019)	(0.016)	(0.019)
FEs: city	✓	✓	✓	✓
FEs: week-of-year	✓			
FEs: year	✓			
FEs: week-of-sample		✓	✓	
FEs: region×year			✓	
FEs: region×week-of-sample				✓
N	81,544	81,544	81,544	81,544

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

Table A.3. Regression Discontinuity at the Huai River Before and After Monitoring

Run. var.: Degrees north of the Huai River	(1) Linear	(2) Quadratic	(3) Cubic	(4) LLR
Panel A. Dep. var. = AOD				
Before monitoring	0.075	0.111	0.070	-0.279
	(0.070)	(0.096)	(0.130)	(0.278)
After monitoring	0.060	0.078	0.006	-0.080
	(0.067)	(0.095)	(0.143)	(0.259)
Panel B. Dep. var. = $PM_{2.5}$-resid. AOD				
Before monitoring	0.185***	0.187**	0.136	0.115
	(0.061)	(0.083)	(0.115)	(0.297)
After monitoring	0.174***	0.165*	0.073	0.151
	(0.064)	(0.086)	(0.130)	(0.165)
Panel C. Dep. var. = All-cause mortality (log)				
Before monitoring	0.242	0.781***	0.728*	0.526*
	(0.166)	(0.263)	(0.421)	(0.305)
After monitoring	-0.296	-0.099	0.655	0.052
	(0.219)	(0.229)	(0.698)	(0.259)
Panel D. Dep. var. = COPD mortality (log)				
Before monitoring	-0.337	0.928*	2.010**	0.779
	(0.389)	(0.531)	(0.866)	(0.850)
After monitoring	-0.844**	-0.013	1.926**	1.132
	(0.352)	(0.457)	(0.861)	(1.416)
Panel E. Dep. var. = Heart diseases mortality (log)				
Before monitoring	1.075***	1.754***	1.620***	1.310**
	(0.227)	(0.343)	(0.590)	(0.529)
After monitoring	0.474*	0.891***	1.638**	1.098***
	(0.265)	(0.310)	(0.775)	(0.381)
Panel F. Dep. var. = Cerebrovascular mortality (log)				
Before monitoring	0.339	1.075***	1.285**	1.268*
	(0.228)	(0.352)	(0.563)	(0.750)
After monitoring	-0.299	0.060	1.128	1.151**
	(0.268)	(0.296)	(0.825)	(0.546)
Panel G. Dep. var. = Respiratory infection mortality (log)				
Before monitoring	-0.244	-0.090	0.212	-1.042
	(0.336)	(0.443)	(0.762)	(1.155)
After monitoring	-0.448	-0.732	0.226	-0.578
	(0.484)	(0.762)	(1.066)	(1.640)

Notes: Each cell reports coefficient for a dummy indicating DSPs north of the Huai River in a separate regression (Observations = 99). Columns 1-3 show parametric RD with linear, quadratic, and cubic control function for the running variable. Column 4 shows local linear regression with triangular kernel and Imbens and Kalyanaraman (2012) bandwidth selection. In column B, residualized AOD is constructed from a regression of DSP's y2011-y2014 avg AOD on a linear function of y2013-y2015 avg $PM_{2.5}$ allowed to vary by the two sides of the Huai River. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Table A.4. 2SLS Estimates of Mortality-Pollution Relationship, Before Monitoring

Dep. var.: Log mortality rate in a city×quarter						
	(1)	(2)	(3)	(4)	(5)	(6)
"IV cities" radii (km)	(0, 1000]	[300, 1000]	[300, 1500]	[300, 2000]	[300, 3000]	[300, max]
Panel A. IV = Distant cities' pollution × cosine(wind), inverse-distance weighted						
Log(Pollution)	0.211**	0.257**	0.285**	0.282*	0.228	0.201
	(0.103)	(0.112)	(0.128)	(0.149)	(0.211)	(0.222)
First stage F-stat	60.7	15.9	19.7	16.5	13.9	11.1
Panel B. IV = Distant cities' pollution, inverse-distance weighted						
Log(Pollution)	0.165***	0.265***	0.395***	0.432***	0.459	0.189
	(0.061)	(0.074)	(0.128)	(0.158)	(0.287)	(0.131)
First stage F-stat	85.2	41.2	13.5	13.6	16.8	14.3
N	1,602	1,602	1,602	1,602	1,602	1,602

Notes: Sample includes 2011q1 - 1 quarter before monitoring began at the city. "Log(Pollution)" is logged AOD in the city×quarter. IV is a function of distant cities' AOD. Column names indicate cities included in constructing the IV. In panel A, distant city's pollution is vectorized by local wind direction, and only the component pointing from the distant city to own city is used in constructing IV. In panel B, no vectorization is applied. All regressions include prefecture-city FEs, quarter-of-sample FEs, and region×year FEs. "region" is a conventional partition of cities by location: North (36 cities), Northeast (38 cities), East (105 cities), Centralsouth (81 cities), Southwest (54 cities), Northwest (52 cities). Standard errors are clustered at the prefecture-city level. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.