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(RE)SCHEDULING POLLUTION EXPOSURE: THE CASE OF SURGERY SCHEDULES AND PATIENT MORTALITY

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ABSTRACT

Many human activities can be strategically timed around forecastable natural hazards to mute their impacts. We study air pollution shock mitigation in a high-stakes healthcare setting: hospital surgery scheduling. Using newly available inpatient surgery records from a major city in China, we track post-surgery survival for over 1 million patients, and document a significant increase of hospital mortality among those who underwent surgeries on days with high particulate matter pollution. This effect has two special features. First, pollution on the surgery day, rather than exposure prior to hospitalization, before or after the surgery, is primarily explanatory of the excess mortality. Second, a small but high-risk group – elderly patients undergoing respiratory or cancer operations – bears a majority of pollution's damages. Based on these empirical findings, we build and analyze a model of hospital surgery scheduling. For over a third of the high-risk surgeries, there exists an alternative, lower-pollution day within three days such that moving the surgery may lead to a Pareto improvement in survival.

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1. Introduction

Scheduling activities around looming natural hazards is an important human adaptation strategy in the face of the changing environment. Today, we adjust daily schedules to changes in weather, thanks to the development of weather forecasting technologies. This paper eyes on the potential of adaptation with respect to air pollution, another environmental hazard that a growing number of technologies can provide "nowcasts" and forecasts about. Recent economic analysis reveals people are already using such information to arrange activities, such as outdoor recreation, to avoid exposure (Cutter and Neidell, 2009; Neidell, 2009; Graff Zivin and Neidell, 2009). In this paper, we further explore the potential value of such adaptation and adjustment of scheduled activities in a high-stakes healthcare context. We examine how high levels of pollution that coincide with the date of surgery affect patients' post-surgery mortality risk, and whether adjustments in hospital surgery schedules could improve survival.

We highlight two broad motivations for this study. First, air pollution imposes a substantial mortality burden (e.g., Currie and Neidell, 2005; Dominici, Greenstone, and Sunstein, 2014; Cohen et al., 2017; Landrigan et al., 2018; Deryugina et al., 2019). Although hospital's indoor environment shields patients from most weather fluctuations, it provides limited protection against air pollutants, such as fine particulate matter, which can easily penetrate the air inside buildings (Section 2.1). Concerns about such exposure may be particularly high for patients who are ill, and whose conditions require surgery. On the other hand, many surgical procedures are arranged days ahead, making patients' exposure to pollution *pre-scheduled* in nature. This raises the possibility of using strategic surgery scheduling to mitigate pollution exposure at such a sensitive time, and for any particularly vulnerable patients.

Second, knowledge about the adverse determinants of post-surgery death (known as *perioperative mortality*) – and ways to mitigate them – is of academic and clinical importance in its own right. Death is the most feared consequence of surgery care. An estimated 30 percent of the global burden of disease requires surgery care (Shrime et al., 2015). U.S. and European data show that 5 to 10 percent of patients die following an inpatient surgery (Ghaferi, Birkmeyer, and Dimick, 2009; Pearse et al., 2012). Current understanding on risk factors of perioperative mortality is limited (Bainbridge et al., 2012) and existing studies only examine basic patient demographics and health conditions such as the presence of chronic diseases (e.g., Alves et al., 2005; Bozic et al., 2012) and healthcare provider characteristics (e.g., Aiken et al., 2002; Sahni et al., 2016). A key message of our work is that environmental conditions vary considerably from day to day, which may provide leeway to adjust scheduling to take advantage of better air quality conditions. As we show in this paper, incorporating air pollution levels as one consideration in setting surgery schedules may lead to better survival among certain vulnerable patients.

Our study examines Guangzhou, a major city in China with a population of 15 million. Several features of the city pose an opportunity for our research questions. First, air quality in Guangzhou exhibits substantial day-to-day fluctuations, with a mean $PM_{2.5}$ concentration of 36.5 ug/m^3 (standard deviation = 19.8 ug/m^3).[1] Patients with observably similar characteristics undergo similar surgeries on days with substantially different air quality. This plausibly exogenous variation in pollution allows us to study its impact on patient outcomes. Second, Guangzhou is a city with abundant, advanced healthcare resources. Indeed, it is recognized as the premier healthcare destination in southern China. This setting helps us better tease out the impact of pollution shocks from impact of healthcare resource constraints that could also have an independent impact on surgical outcomes (Meara et al., 2015; Guidetti, Pereda, and Severnini, 2020). Finally, Guangzhou is one of the first cities in China to implement a healthcare informatics reform. Our analysis is based on newly available, rich microdata about patients and the surgical procedures they were provided in operations conducted in all 23 major ("3-A") hospitals in the city. These microdata incorporate information from more than 1.3 million surgical records spanning 2014 to 2017. The data allow us to both benchmark our findings with those of previous studies on the general pollution-mortality link, and to study special characteristics and mechanisms pertaining to the perioperative context.

Our analysis has two parts. **The first part** is a reduced-form econometric exercise that leads to our headline finding: High ambient air pollution levels on the day of a patient's surgery lead to significantly worse post-surgery survival outcomes. We show this with both a classic Kaplan-Meier survival framework, and a fixed effects regression approach that exploits plausibly exogenous day-to-day fluctuations in air pollution levels by controlling flexibly for patient, hospital, and surgery characteristics, and for atmospheric weather patterns and seasonality. We find that a log unit increase in surgery-day $PM_{2.5}$ results in an increase of mortality rate by 0.428 per 1,000 patients over the month following the surgery. This effect size converts to about 1 percent increase in surgery patient mortality per 10 ug/m^3 increase in $PM_{2.5}$.

A main threat to our research design is whether the pollution effect is a result of patient selection. For example, high pollution events may lead sicker people to seek treatment at a hospital; surgery case mix or the severity of patients' conditions may differ across days with high and low levels of pollution. Our study population, however, consists of patients who had *already* been admitted to the hospital and, on average, had spent four days in hospital between the admission and the surgery. Thus, the extent of patient selection with respect to pollution *on the day of the surgery* is low. To verify this claim, we use our primary regression specification to conduct "balance tests," using patients' *pre-surgery* characteristics as outcome

[1] To put these statistics in perspective, the Los Angeles County of California – one of the U.S. counties with the highest $PM_{2.5}$ concentration – had a mean $PM_{2.5}$ level of 11.1 ug/m^3 (standard deviation = 6.6 ug/m^3) during the same time period.

variables. In contrast to selection, we find no evidence of any significant differences in patients' observable characteristics across surgeries on high versus low pollution days, which include 14 indicators for demographics, health, and surgery characteristics. To further alleviate concerns about endogeneity and measurement errors in pollution, we implement an instrumental variable (IV) approach that exploits variation in local $PM_{2.5}$ attributable to pollution transported from upwind cities that locate over 100 kilometers away from Guangzhou. Our IV estimates are similar in magnitude with the ordinary least square (OLS) estimates.

Another potential concern on the interpretation of our results is whether the estimated effect reflects a "special" effect of surgery-day pollution, or just the fact that air pollution is in general harmful for survival. We find that higher post-surgery mortality is particularly associated with high pollution that coincides with the day of the surgery itself – as opposed to pollution exposure that occurs prior to hospital admission, between the admission and the surgery, or after the date of the procedure. In a more generalized exercise, we compare observed pollution effects with the distribution of "placebo" effect estimates that would be obtained by randomly assigning surgery dates to patients. This randomized inference again provides strong evidence that high pollution levels on the day of surgery are particularly bad for post-surgery survival. This is, in fact, a key result of our paper: days with high outdoor $PM_{2.5}$ concentrations are linked to a substantial reduction of survival among patients who undergo surgeries on that day, while similar $PM_{2.5}$ changes on other days have no similar effect on the same patients. This result is the basis of the second part of this paper, which considers alternative surgery scheduling to reduces surgery-day pollution's adverse impact.

How does surgery-day pollution affect patient survival? We examine channels that fall into two groups of explanations: the effects of air pollution on physicians and on patients. We find limited evidence to support a physician effect. We begin with institutional evidence. Our review of both architectural codes of surgery operating room construction and available air quality inspection studies suggests most operating rooms in Guangzhou are equipped with high-efficiency air-filtering technologies that can remove vast majority of particulate pollution. The immediate cognitive stress on a surgeon or other medical staff due to pollution exposure while performing the operation is likely very low. We also look for changes in other performance indicators that may reveal treatment differences, such as antimicrobial agents use, the incidence of non-healing surgical wounds, or medical error-related post-admission injuries. We find no evidence of systematic differences in these indicators of treatment decisions or performance on days with different levels of pollution. Moreover, we find that the mortality risk of high pollution levels on the day of is concentrated among a key group of elderly patients with respiratory and cancer diagnoses, which plausibly contrasts with a physician channel whereby one would expected to observe risks emerging across a broader patient population. Due to privacy restrictions, we do not have access to identifying information on surgeons and other medical personnel, and therefore unable to estimate models with physician fixed effects, or to assess the role of the surgeon's level of experience. We leave these directions for future work to analyze.

On the other hand, we find evidence to support the view that the impacts stem from the effects of pollution on the patient. The general hospital indoor environment – unlike a dedicated surgery room – does not have elaborate filtration systems that prevent the penetration of fine particulate pollution. In fact, hospitals sometimes *prefer* to have wards open to the outside air to help control infection. In such situations, the exposure to outdoor pollution for a patient is high, even when the patient is inside the hospital building. We document a series of empirical patterns that echo those that have emerged from prior studies about air pollution's effects on health outcomes in the general population. First, patients' vulnerability to pollution on the day of surgery varies substantially across subgroups. In our case, over 60 percent of the observed effects are explained by a small group (6 percent of all patients) composed patients who are over age 60 and are being treated for lung diseases or cancers. Second, the relationship between post-surgery mortality and pollution features a concentration response, with damage rising sharply for initial increases in pollution levels, and then flattening out at very high levels (above 40 ug/m^3). Finally, $PM_{2.5}$ concentrations tend to be the most robust predictor for patient survival, as indicated by a multiple-pollutant model that also considers the simultaneous impacts of other harmful air pollutants including ozone, nitrogen dioxides, sulfur dioxides, and carbon monoxides on the surgery day. These characteristics on subgroup heterogeneity, dosage, and pollutant-specific effects have been reported in previous studies on the mortality effects of $PM_{2.5}$ (Jerrett et al., 2009; Brook et al., 2010; Pope III et al., 2011; Crouse et al., 2012; Pope III, Cropper, Coggins, and Cohen, 2015; Deryugina et al., 2019). Together, these familiar characteristics suggest that the pollution effects we observe in our study likely share common toxicological and physiological underpinnings that have been evidenced in prior studies – although the day-of-surgery effect we document might stem from the particular vulnerability of patients at that time, leaving them exposed to greater risk of pollution's effects than otherwise would have been the case.

The second part of our paper presents a structural econometric analysis that builds on the observed link between pollution and post-surgery survival. We examine whether hospitals can better internalize the adverse effect of pollution to improve patient survival through relatively targeted, small changes in the status quo scheduling practices. We first build and parameterize a simple model of hospital surgery scheduling, and estimate key parameters that represent hospitals' implicit trade-offs between patient mortality hazard and other non-health-related considerations. We then consider counterfactual scenarios in which the hospital would take into account the adverse consequences of surgery-day $PM_{2.5}$ exposure, and observe how hospitals would re-optimize surgery schedules as a result.

Surgery scheduling is a complex undertaking. Large shifts in scheduling practices may induce unintended consequences that are not captured by our stylized structural model. For example, rescheduling many surgeries to days with good air quality may add to capacity stress on those days, strain healthcare resources, and cause adverse outcomes. We exploit two empirical features that allow us to consider relatively modest changes in surgery schedules. First, our model considers rescheduling only for the aforementioned high-risk patients (respiratory and cancer patients aged over 60) – that is, the 6 percent of all patients who account for 60 percent of the negative health effects. We verify that this restriction ensures that the impact of rescheduling on surgical capacity is very small compared to the hospital's overall capacity constraints. Second, we limit our counterfactual scenarios to include only those patients who were originally intended to undergo surgery within three days of their hospital admission (41 percent of all surgical cases), and consider alternative days for surgery that are within this three-day window. In practice, this short-term approach means pollution expectation is more accurate; it also circumvents practical problems such as patient consent and any health consequences that might surface with longer delays. As we show in the paper, there is abundant day-to-day variations in air pollution levels to allow for a meaningful rescheduling exercise even within such a narrow time window.

The structural exercise reveals important opportunities for patient survival improvements. For about 40 percent of the surgery cases among our targeted patient group, there exists a better air quality day within the three-day window such that switching the surgery to that day would likely improve post-surgery survival. The average "switcher" patient experiences a 4.2 percent improvement in mortality risk relative to the mean (a risk reduction of 1.6 deaths per 1,000 patients). We expect little change in health hazards among the rest of the patients whose surgeries are not rescheduled. This is because the counterfactual surgery schedule differs little from the original surgery schedule in terms of *overall* surgery capacity utilization, and is well below capacity constraints of the facility. Besides the main structural exercise, we also provide an example surgery-postponing rule in which the hospital preserves the status quo scheduling practice, but pushes high-risk surgeries back on days when pollution is exceptionally high. This practice does not reschedule surgeries to *earlier* days, a practice that is allowed in the full structural exercise but could be costly to implement in practice, while still able to achieve important survival improvements.

This paper contributes to several strands of literature. Our general study scope relates to a multidisciplinary body of research on the disease burden of ambient air pollution (Cohen et al., 2017; Landrigan et al., 2018). A growing economics literature has contributed to the causal identification of $PM_{2.5}$'s effect on mortality (Chay, Dobkin, and Greenstone, 2003; Currie and Neidell, 2005; Moretti and

Neidell, 2011; Schlenker and Walker, 2016; Knittel, Miller, and Sanders, 2016; Ebenstein et al., 2017; Deschenes, Greenstone, and Shapiro, 2017; Deryugina et al., 2019; Anderson, 2020). We believe that we are the first to study the mortality effect of pollution exposure in a perioperative context, and to document the critical impact of exposure to pollution on the day of surgery and for certain types of vulnerable patients.

A key contribution of our analysis is the operation-level relevance of the findings: the fact that it is feasible to mitigate the adverse effect of pollution exposure through better scheduling of the surgeries. In this respect, we also add to the epidemiology literature on the incidents and risk factors of perioperative mortality (Ghaferi, Birkmeyer, and Dimick, 2009; Bainbridge et al., 2012; Pearse et al., 2012), and to the operation research literature on surgery theater management (Cardoen, Demeulemeester, and Beliën, 2010). To the best of our knowledge, neither field has previously considered the relevance of air quality. In economics, this paper is also related to the literature on air pollution information and individuals' avoidance behavior, such as the reduction of outdoor activities on high-pollution days (Cutter and Neidell, 2009; Neidell, 2009; Graff Zivin and Neidell, 2009). We extend this idea to the high-stakes context of surgical care, and we demonstrate that econometric tools can be used to avoid unnecessary exposure. More broadly, the analysis framework of our paper may be applied to other economic scheduling problems where the outcomes depend on a predictable future hazard.[2]

Section 2 continues with a brief survey of institutional background on Guangzhou's healthcare system and in-hospital air pollution exposure; it also introduces the primary data sources. Section 3 presents the reduced-form analysis of the effect of pollution on patients' post-operative survival. Section 4 describes the structural model of surgery scheduling, and discusses possible counterfactuals. Section 5 concludes.

2. Background and Data

2.1 Background

Guangzhou, the focal city of our study, is a prefecture-level city located near the southern coast of China (Appendix Figure A.1, panel A). Guangzhou is one of the four most-developed, "Tier-1" cities in China (along with Beijing, Shanghai, and Shenzhen). In 2017, the city has a population of 14.5 million, a total GDP of 318.5 billion USD (ranked fourth among all cities), and a per capita GDP of 22,317 USD (ranked seventh). Widely recognized as the healthcare center in southern China, Guangzhou has some of the best healthcare resources in the country. For every 1,000 residents, Guangzhou has 2.8 physicians

[2] It is perhaps also worthwhile to mention that we are among the first to use a large database of Chinese administrative medical records in economic research. This was made possible as a result of ongoing health informatics reform in China. We discuss our data sources in Section 2.2.

(national average: 2.0), 4.6 nurses (national average: 2.7), and 4.6 hospital beds (national average: 4.3) according to data from 2017. Annual per capita healthcare spending in 2018 was 1,541 PPP USD (national average: 838 PPP USD).[3]

Air Quality in the Operating Room. Are patients exposed to particulate pollution while undergoing surgery? An examination of the potential for pollution exposure inside the operating room itself warrants an understanding of China's operating room standards and compliance in the city of Guangzhou. The construction of hospital operation theaters follows a set of protocols in the Architectural Technical Code for Hospital Clean Operating Department (2002).[4] Based on their ability to maintain a nearly particulate-free environment, operating rooms are classified into one of four main categories. For example, Class I (cleanest) operating rooms are those that meet International Organization for Standardization (ISO) Class 5 cleanliness standards,[5] which correspond to a maximum particle concentration of 3,500 particles per cubic meter of air for particles over 0.5 micrometers; Class II (second cleanest) operating rooms are defined by ISO Class 6 cleanliness (concentration $\leq$ 35,000 particles/m^3 for particles over 0.5 micrometers), and so forth. These high levels of cleanliness are often achieved through the use of High Efficiency Particulate Air (HEPA) or Ultra Low Particulate Air (ULPA) filters combined with a laminar (unidirectional) air flow system. In practice, this means that Class I, II, III and IV operating rooms filter out, respectively, over 99.99%, 99%, 95%, and 70% of particles over 0.5 micrometers. Filtration rates for larger particles, such as $PM_{2.5}$ (particles over 2.5 micrometers) are expected to be even higher.

While the filtering capacity of operating rooms must comply with these standards, actual performance also depends on appropriate practices, such as timely cleaning and replacement of air filters. The best data we are aware of come from the Guangzhou Center for Disease Control and Prevention, which inspected 53 operating rooms across 18 hospitals in 2014 (Li et al., 2014). The study found that over 83% of inspected operating rooms satisfy the particulate cleanliness standards.[6] Overall, we believe particulate pollution exposure inside the operating room is likely very low.

Air Quality in Other Hospital Areas. Outside of the operating rooms and other cleanrooms with special purposes (such as the Intensive Care Units), air pollution control within the hospitals is limited. For

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[3] For reference, in the United States in 2017, the corresponding national average figures were 2.6 physicians, 0.6 nurses, and 2.9 beds for every 1,000 residents. Annual per capita healthcare spending in that year was 10,210 USD. The statistics from China are taken from the National Health Yearbook and the Guangdong Province Health Yearbook. The raw statistics are scaled to reflect accounting definitions used by the World Health Organization's Global Health Observatory and the Global Health Expenditure Database.

[4] GB 50333-2002 and GB 50333-2013.

[5] ISO 14644 Part 1: Classification of Air Cleanliness.

[6] A critical finding of Li et al. (2014), however, is that some hospitals tend to achieve high particle-filtration rates by overusing air changes, causing less-than-optimal humidity conditions in the operating room.

small particulate pollution such as $PM_{2.5}$, outdoor-to-indoor penetration is likely a major source of indoor exposure (e.g., Hanley et al., 1994; Riley et al., 2002; Chen and Zhao, 2011). Data on indoor air pollution in hospital settings are scarce. One useful case study monitored indoor and outdoor air pollution in two hospital rooms in Erfurt, Germany, finding an average indoor/outdoor $PM_{2.5}$ ratio of 0.83 (open-window) and 0.63 (closed-window); outdoor $PM_{2.5}$ also strongly predicts indoor $PM_{2.5}$ *variation*, with a linear regression R-squared of 0.84 (Cyrys et al., 2004). In examining seven peer-reviewed studies conducted in Chinese hospitals between 2007 and 2014, Zheng (2014) finds that indoor/outdoor $PM_{2.5}$ ratios are generally near one. The health benefits of ventilation and air quality control in hospital wards and patient rooms remain an important but underexplored area in both research and practice.

2.2 Data and Summary Statistics

Surgery Records. Our surgery data are based on the universe of hospitalization records in Guangzhou from 2014 to 2017. These data are sourced from administrative medical records submitted by individual hospitals to the Guangzhou Health Information Center. Access to the data was granted by the Guangzhou Municipal Health Commission. Because we are among the first researchers to use this type of inpatient database in China, below we discuss some relevant institutional details of the data source.

The availability of the healthcare data is linked with the ongoing health informatics reform in China in the wake of the establishment of the Health Level Seven (HL7) China committee in 2006.[7] As part of this agenda, legislation in 2014 created a national electronic health records system, the Basic Dataset of Electronic Medical Records. The Basic Dataset covers various aspects of healthcare. Our data are extracted from Part 10 of the Basic Dataset, known as the Home Page of Inpatient Medical Records.[8] These data provide an "abstract" of each inpatient record, containing the most critical information associated with the hospital stay including patient demographics, hospital admission, inpatient care (including surgery care), and payment. The Home Page information is primarily filled out by the attending physician(s), and then verified by a clinical coder to ensure consistency in the diagnosis and procedure codes. Participation in this digital reporting system is mandatory. Each hospital's compliance is reviewed and graded annually by the National Health Commission. Digital medical records are also the basis of public and private insurance reimbursements, creating a strong incentive for the hospitals to comply with reporting.

[7] HL7 is one of the American National Standards Institute (ANSI)-accredited international standards for the transfer of clinical and administrative data between healthcare providers (https://www.hl7.org/implement/standards/index.cfm).
[8] WS 445.10-2014 Basic Dataset of Electronic Medical Record—Part 10: Home Page of Inpatient Medical Records.

Our research data file is an extract of the Home Page data. Each observation in the database corresponds to a unique hospital stay, allowing us to observe (scrambled) patient identity, basic demographics, surgery information, and insurance payment information. The layout of the data resembles the typical inpatient records dataset available in the U.S. setting, such as the Healthcare Cost and Utilization Project (HCUP) State Inpatient Database. Below we discuss several points on variable construction that are important for our empirical analysis.

Admissions, discharges, and patient deaths. In the database, admission time is recorded as the date the patient entered the ward and began receiving treatment. Discharge time is recorded as the time when the treatment was terminated, and the patient exited the ward. For patients who died during the hospitalization, discharge time is recorded as the date of death, with the manner of discharge flagged as "death." Our primary hospitalization mortality outcome variable is constructed from the discharge time and manner-of-discharge fields.

Diagnosis and procedure codes. Disease diagnoses are coded in the International Classification of Diseases 10th revision (ICD-10). Operations are coded in the ICD-9-CM Volume 3 codes. These are standard coding practices used, for example, by the U.S. Agency for Healthcare Research and Quality (AHRQ) in maintaining state inpatient databases and the Centers for Medicare & Medicaid Services (CMS) in medical insurance claims data. We use these ICD codes to construct diagnosis and procedure fixed effects control variables in our main regressions.

Multiple surgeries. A patient may undergo multiple surgeries during a hospital stay. In these cases, we focus on the "primary" surgery defined by the Home Page data protocol as the operation most directly related to the primary diagnosis. The primary surgery is often the most technically challenging and risky operation. This focus implies that each observation in our estimation sample corresponds to a unique hospital stay.

Medical personnel information. Our data use agreement precludes us from accessing any hospital personnel information. Thus, we do not observe the attending physicians, nurses, or any medical assistants involved at the admission or with the surgery. This is a shortcoming that limits our ability to test a physician-side response and mechanism. We do attempt to examine a potential pollution-induced medical error channel by inferring potential medical errors from injury-related patient discharge codes that were not present at admission (Van Den Bos et al., 2011; David et al., 2013). These exercises are reported in Section 3.4.

Our dataset consists of all hospitalization records submitted by 23 "3-A" hospitals (N = 2,233,969). These 3-A hospitals are the major healthcare facilities in the city, and they have the best-quality data. To improve statistical power, we restrict to surgery categories with an average death rate of at least 1 per 1,000 patients (remaining N = 1,381,283).[9] Appendix Table A.1 reports that our main mortality effect estimation coefficients are smaller, yet still statistically significant, when including these low-risk procedures. The average post-surgery death rate in our final estimation sample is 12.1 deaths per 1,000 patients; this rate represents 44.4% of all in-hospital deaths and 28.5% of all deaths in the city of Guangzhou during the study period. Table 1 contains more summary statistics of our estimation sample.

Air Pollution Monitoring Data. Guangzhou began real-time broadcast of air quality in 2013, following China's ambient air pollution disclosure reform (Greenstone et al., 2020; Barwick et al., 2020). We obtain daily air pollution concentration data between 2014 and 2017 from all eight monitoring sites in Guangzhou. Appendix Figure A.1 panel B plots monitoring sites and hospital locations. Note that data coverage is sufficient; most hospitals have monitors within several miles of the facility. In practice, we aggregate site-specific data to a pollution time series. Appendix Figure A.2 panel A shows the distribution of daily $PM_{2.5}$ values in Guangzhou (mean = 36.5 ug/m^3, s.d. = 19.8 ug/m^3).

One common concern with government-provided air quality data in China is about political tampering due to city official's promotion motives (Andrews, 2008; Chen, Jin, Kumar, and Shi, 2012; Ghanem and Zhang, 2014; Ghanem, Shen, and Zhang, 2020). Accuracy of air quality data since the 2013 reform has improved substantially as sampling is now automated and reported in real time (Greenstone et al., 2020). In Appendix Figure A.2 panel B, we compare the government $PM_{2.5}$ data with $PM_{2.5}$ data collected independently by the U.S. Consulate in Guangzhou from 2012 to 2017. The figure shows the two time series are consistent with each other.

Section 3 uses air pollution *monitoring* data to study the link between air quality and post-surgery survival. Section 4 studies surgery scheduling based on *forecasted* air pollution. We discuss issues related to the accuracy of air pollution forecasts in Section 4.3.

3. Evidence

3.1 Raw Data Pattern: Surgery-Day Pollution and Patient Survival

We first investigate patient survival patterns in a standard Kaplan-Meier framework, considering high pollution levels on the surgery day as a "treatment." In Figure 1, we compare the 30-day survival functions of patients in two groups: those whose surgeries took place on highly polluted days, which we

[9] The excluded categories are operations on the endocrine system (ICD-9-CM V3 code block: 06-07), the eye (08-16), the ear (18-20), the nose, mouth and pharynx (21-29), the male genital organs (60-64), the female genital organs (6571), and obstetrical procedures (72-75).

define as those days when $PM_{2.5}$ levels were within the highest 20 percentile of measurements recorded in our sample (i.e., days with $PM_{2.5} > 50$ ug/m^3; N=298,292); and those received surgeries on best 20 percent pollution days (i.e., days with $PM_{2.5} < 20$ ug/m^3; N=264,120). The raw data pattern shows that those who underwent surgery on high pollution days exhibit lower survival probability, and the effect appear to manifest gradually throughout the month following the operation. By day 30, the observed gap in survival in the high and low pollution groups is 0.151 percentage points, which is about a 15 percent difference in mortality. The patterns are robust to alternative definitions of "high" and "low" air pollution days, such as above- and below- median $PM_{2.5}$ values. Appendix Figure A.3 reports these robustness checks.

Figure 1 suggests a clear difference in survival trajectories for patients whose surgeries took place on days with high versus low pollution. How much of this difference is due to pollution exposure *alone*, as opposed to other factors that are correlated with pollution? Are patients scheduled to undergo surgeries on highly polluted days fundamentally different (e.g., in terms of baseline health) than patients who were scheduled to undergo surgeries on days with low pollution levels? Do physicians treat patients differently on days with high or low levels of pollution? In the next subsection, we describe a regression approach that allows us to investigate these questions.

3.2 Regression Framework

Our regression model links a patient's post-surgery survival to the ambient air pollution concentration on the day of surgery. The workhorse regression equation is

$$Y_i = \alpha + \beta \cdot \text{Pollution}_i + X_i\gamma + \varepsilon_i \quad (1)$$

Y_i is the outcome of interest for patient i. In our primary mortality analysis, Y_i is an indicator variable for whether the patient died during the hospitalization following the surgery ("hospital mortality"). The regressor of interest is Pollution_i, which is the logged ambient $PM_{2.5}$ concentration recorded at the air monitoring site closest to patient i's hospital on the day of surgery.[10] X_i denotes a series of control variables that may potentially correlate with both pollution and mortality. These controls are of three types: (1) patient-level controls that include age in five-year bins, a gender indicator, a marital status indicator, and an indicator for any history of allergies, (2) weather controls that include daily average temperature in 10-degree Celsius bins, precipitation, and precipitation squared, and (3) fixed effects control for primary diagnosis, hospital, department, procedure, year (of surgery), month of year, and day of week. ε_i is the

[10] Appendix Figure A.1 panel B shows that most hospitals in our study sample have air pollution monitoring sites within two miles.

error term. To account for serial correlation both within hospital and across different hospitals on the same day, we two-way cluster standard errors at the hospital and the date levels.[11]

Though simple, this regression framework allows us to test a variety of hypotheses on whether and how pollution severity affects post-surgery survival. Here we briefly describe four groups of questions we can assess through variants of equation (1). We provide more details throughout sections 3.3 and 3.4 when we present the corresponding results.

Are Patients Scheduled on High-Pollution Days Fundamentally Different? One might worry about two potential types of patient selection. The first is about patient selection at admission: sicker patients are more likely to be admitted to the hospital on high-pollution days, thus driving up the mortality rate in some ways. Notice, however, that our analysis is conditioned on patients who have *already* been admitted to the hospital; these patients have spent, on average, four days in hospital between the admission and the surgery. Because our treatment of interest is pollution on the (pre-scheduled) day of surgery, rather than the day of admission, the scope for endogenous selection is likely low. In Appendix Table A.1, we report that the estimation results are similar, although less precise, when excluding patients who received surgery on the same day they were admitted, or in the two days following the day of admission. In addition, Section 3.3 shows that, for the average patient, pollution levels around hospital admission day does not predict post-surgery survival. Second, higher inpatient volume may add staffing stress and lead to worse outcomes for patients scheduled to undergo surgery on that day (Aiken et al., 2002; Needleman et al., 2011; Ball et al., 2018). In Appendix Table A.1, we show that the findings are robust to controlling for hospital or hospital-department patient volume (or surgery volume) in equation (1).

A second type of concern is whether sicker patients are more likely to be *scheduled* to undergo surgery on high pollution day. If patients scheduled to undergo surgery on highly polluted days are fundamentally different than patients who undergo surgeries on low-pollution days (e.g., due to scheduling practices unbeknownst to the researchers), then β may capture a "compositional difference" in patients, rather than the effect of pollution. We address this concern by using patient's *pre-surgery* characteristics –

[11] Note equation (1) is essentially a cross-sectional regression in which an observation is a surgery, and the primary outcome of interest is post-surgery death. But because surgeries occur on different dates, we can use time fixed effects to exploit different sources of air pollution variation. An equivalent formulation of equation (1) is a panel estimation model

$$\mathrm{Y_{jkt}} = \alpha + \beta \cdot \mathrm{Pollution_{jkt}} + \alpha_{jk} + \alpha_t + \varepsilon_{jkt}$$

in which the regression links the fraction of patients died in hospital k following a procedure j done on date t ($\mathrm{Y_{jkt}}$) to the surgery-day pollution ($\mathrm{Pollution_{jkt}}$), controlling for procedure-by-hospital fixed effects (α_{jk}) and time fixed effects (α_t). Equation (1) is essentially a micro-data version of this panel formulation.

such as basic demographic characteristics, health conditions, socioeconomic status – as outcome variable Y_i in equation (1). In the spirit of a balance test in randomized experiment, this exercise tells us if there is evidence of selection into high and low pollution day surgeries based on patients' observable characteristics. In addition to the balance test on observable characteristics, we have also tackled selection on unobservables using time-invariant fixed effects controls (for hospital, procedure, etc.) and temporal fixed effects controls (month, day of week, etc.). The evidence suggests that the degree of patient selection is low.

Does β Capture the Causal Effect of Pollution? A more general endogeneity concern is that some variation in air pollution may be correlated with factors that independently affect post-surgery survival, leading to the omitted variable bias. We use a fixed effects approach to tease out plausibly exogeneous, day-to-day pollution variation. Our baseline specification includes surgery-year, surgery-month-of-year, and surgery-day-of-week fixed effects to parse out annual, seasonal, and within-week factors that may confound the pollution-survival relationship. Besides the time fixed effects, all regressions control for hospital, department, diagnosis, and procedure (or procedure-by-hospital) fixed effects, as well as for patient-level characteristics to account for time-invariant determinants of post-surgery survival.

We also assess the robustness of results using alternative sources of pollution variation. For example, we present results with month-of-sample (i.e., year-by-month-of-year) fixed effects; these exploit variation in pollution across different days of the same month. In yet another specification, we include hospital-by-procedure-by-month-of-year fixed effects; these exploit variation among patients who receive the same procedure in the same hospital during the same time of year, but across different years when pollution levels are different. In Appendix Table A.1, we further report that our effect estimates are similar with or without the weather covariates (daily temperature and precipitation), which suggests a limited role played by atmospheric conditions.

To further alleviate concerns about potential endogeneity and measurement errors in pollution, we implement a wind-transport instrumental variable (IV) approach in the spirit of Barwick et al. (2018), Deryugina et al. (2019), and Anderson (2020). The goal is to tease out variation in Guangzhou's air pollution attributable to transported pollutants from upwind cities. We begin with a daily panel dataset of $PM_{2.5}$ in all 305 prefecture-level cities that are at least 100 kilometers away from Guangzhou. For each city c and day t, we calculate the (radian) angle ϕ_{ct} between city c's local wind direction and the vector pointing from city c to Guangzhou (e.g., $\phi_{ct} = 0$ if city c is exactly upwind from Guangzhou on day t). The IV is a time-series variable constructed using the following formula:

$$\mathrm{IV}_t = (1/305)\sum_{c\in\{1,\cdots,305\}} \max\{0, \cos(\phi_{ct})\} \cdot \mathrm{PM2.5}_{ct} \cdot \left(\frac{1/\mathrm{distance}_c}{1/\sum_i(1/\mathrm{distance}_c)}\right) \qquad (2)$$

where the $\max\{0, \cos(\phi_{ct})\} \cdot \mathrm{PM2.5}_{ct}$ term – which we call "upwind pollution" – is the vector component of air pollution in city c on day t that is expected to move toward Guangzhou. We assume upwind pollution is zero if ϕ_{ct} is an obtuse angle, i.e., winds in city c on day t are blowing *away* from the direction toward Guangzhou. On any date t, the IV is the average of individual cities upwind pollution terms, inversely weighted by city c's distance to Guangzhou ($\mathrm{distance}_c$). We then estimate a two-stage least squares (2SLS) version of equation (1) where we instrument for patient i's surgery-day pollution ($\mathrm{Pollution}_i$) using the corresponding IV_t value.

The identifying assumptions of the IV strategy are (a) *first stage:* upwind pollution is a strong predictor of air pollution variation in Guangzhou, and (b) *exclusion restriction:* except for its influence on local air quality, transported pollution from distant cities does not otherwise affect patients' post-surgery survival in Guangzhou. In a set of robustness checks, we explore alternative IV constructions that vary the balance between (a) and (b): exploiting pollution variation in very far-away cities helps the exclusion restriction, but it necessarily weakens the predictive power of the first stage. We have experimented with excluding cities over 1,000 km away, using inverse-distance-squared weighting, or employing a data-driven method that selects the most predictive upwind cities in a "zero-stage" Lasso regression.[12] Our IV estimation yield similar findings with the OLS results. This further supports the view that endogeneity and measurement error concerns are limited in our study context. For the rest of the analysis, we use OLS outlined in equation (1) as our preferred estimation strategy for the sake of efficiency.

Overall, our effect estimates are robust to a variety of specification checks; many augmented models we estimate (many discussed in this subsection) appear to be well behaved in relation to prior studies. We therefore interpret β as capturing the effect of exogeneous pollution changes.

Does β Capture the General Effect of Pollution or the Special Effect of Surgery-Day Pollution? A deeper concern is to what degree β captures the *special* effect of high pollution on the day of surgery, as opposed to the adverse effects that high pollution may *generally* have on survival. We approach this concern by altering the time window during which $\mathrm{Pollution}_i$ is defined. In one exercise, we replace surgery-day pollution with pollution levels prior to hospital admission, between admission and surgery, or after the surgery. We then estimate the effects of pollution that occur in these alternative time frames. In a

[12] Specifically, before constructing the IV variable, we estimate the following estimation equation with linear Lasso

$$\mathrm{PM2.5}_{\mathrm{Guangzhou,t}} = \lambda_0 + \sum_{c\in\{1,\cdots,305\}} \lambda_c \cdot \max\{0, \cos(\phi_{ct})\} \cdot \mathrm{PM2.5}_{ct} + \epsilon_t$$

which selects a subset of 119 upwind cities. In Appendix Figure A.4, we map out the location of the selected cities and report the $\hat{\lambda}_c$ coefficients from the post-Lasso regression. We then conduct the IV construction outlined in equation (2) using these 119 selected cities (rather than all 305 cities) as upwind cities.

second, more generalized exercise, we *randomly* assign surgery dates to patients, and estimate the effect of pollution under the "placebo" scenario. Repeating this process many times yields a distribution of placebo effect sizes under the null hypothesis that "surgery-day pollution is just as bad as pollution on any other day." Comparing the true effect size with these alternative scenarios, we conclude that high levels of pollution on the day of surgery is particularly bad for post-surgery survival.

***Why* Does Surgery-Day Pollution Affect Patient Survival?** In the absence of patient selection on days with different levels of pollution, what are some of the other channels through which surgery-day pollution influences post-surgery survival? We first test a hypothesis that pollution may affect how physicians treat patients. Such an effect may have numerous causes, such as the possibility that doctors face increased cognitive stress on heavily polluted days. Without physician-level information, we cannot pin down a physician effect per se, but we can examine related procedures and outcomes that can serve as proxies to measure behavioral changes that could be linked to pollution levels. With this in mind, we examine changes in procedures and outcomes that have been used elsewhere in the literature: the use of antimicrobial agents (which are commonly used to prevent and combat wound infection), incidences of non-healing surgical wounds, and a measurement of medical error based on post-hospitalization injuries (Van Den Bos et al., 2011; David et al., 2013). In each case, we find limited evidence that pollution affects these treatment and performance indicators.

Turning to the patient side, we next estimate a series of augmented models that are commonly presented in prior research of pollution in epidemiology and economics. We estimate a concentration-response function model, a multiple pollutants model, and a heterogeneous treatment effect model with respect to subgroup vulnerability. Overall, we find results that are qualitatively similar to prior studies, suggesting that the pollution effects we observe likely share common toxicological and physiological mechanisms that have been evidenced in prior studies, while the surgeries might have left the patients exposed to greater risk of pollution's effects.

Observed Effects versus "True" Exposure Effects. Yet another interpretation issue bears mentioning. One view is that the "ideal" effect estimate should reflect the true *exposure effect* of pollution on surgery patients' subsequent death (i.e., the effect of real $PM_{2.5}$ exposure inside the hospital on patient deaths that occur either during or after hospitalization). Our estimation departs from this ideal in two ways. First, the pollution measure we use is *outdoor* $PM_{2.5}$. As discussed in Section 2.1, outdoor $PM_{2.5}$ is likely higher than indoor levels, which may bias the effect estimate downward relative to the true exposure effect of $PM_{2.5}$. Second, our effect estimate only reflects the impact of surgery-day pollution up to the point of hospital discharge because we do not observe deaths after patients leave the hospital. Both of these caveats suggest β is likely a lower bound on the true effect of pollution exposure.

While our estimate departs from the "ideal", it puts forward a relevant estimate. Most hospitals have information available (through $PM_{2.5}$ readings and forecasts) about outdoor, rather than indoor, air quality levels. At the same time, hospitals likely focus on patient's outcome to the greatest extent during the period in which patients are in their care. Thus, our estimated β is a more relevant piece of knowledge than the "ideal" estimate. We provide more discussion on this point in Section 4.

3.3 Main Results

Balance Test of Patient Characteristics. In the spirit of a balance test in randomized experiment, we first use equation (1) to test whether surgery-day pollution (Pollution_i) can predict patients' *pre-surgery* characteristics. Table 1 reports the results. We test a wide variety of characteristics ranging from basic demographic and health condition (age, gender, marital status, history of allergies), surgical information (delay, number of procedures, anesthesia methods, levels of operations) and payment (whether the stay is reimbursed through the City Workers Health Insurance Program, the New Rural Cooperative Insurance Scheme, or out of pocket).[13] While this is not an exhaustive list, we believe they are broad enough to encompass a patient's overall characteristics.

Results in Table 1 show that patients are well-balanced in observable characteristics with respect to surgery-day pollution. The estimated coefficients are generally small and statistically insignificant. One exception is that patients who underwent surgery on high-pollution days appear to be statistically more likely to be married. However, the magnitude of the correlation is small: we can reject a 0.5% effect using the strongest estimate from column 3, i.e., (1.970+2*0.651)/802.8 = 0.41% out of the mean level of the indicator of married patient.

These results suggest that patients who undergo surgeries on high pollution days are on average no different from those undergo surgeries on low pollution days, conditional on the control variables in equation (1). Another implication of these results is that hospitals are not systematically scheduling patients according to pollution levels: older patients or patients undergoing more intensive procedures are, on average, equally likely to be assigned to high-pollution or low-pollution days, etc. This determination serves as one basis of the rescheduling structural analysis we conduct in Section 4, and it informs our

[13] The City Workers Health Insurance Program and the New Rural Cooperative Insurance Scheme are also proxies for the patient's urban and rural status, respectively.

position that changing existing scheduling practices to offer targeted patients surgeries on days with lower levels of pollution may benefit patients' overall survival chances.

The Effect of Pollution on Post-Surgery Mortality. Table 2 presents our main mortality estimation. Like Table 1, the columns are organized by the fixed effects choices; the rows are organized by mortality at different post-surgery time horizons. We first examine "1-day mortality", defined as whether the patient died on the day of surgery. The mean of that variable is 1.322, meaning the average rate at which patients die on the day of surgery is 1.322 per 1,000 patients. While the point estimates are positive across specifications, we find no statistical evidence that pollution is associated with any significant increase in 1-day mortality, i.e., pollution does not increase the odds of deaths during or immediately following the surgery. The rest of the rows show that the effect of pollution manifests as we expand the post-surgery window to 7-day, 28-day, and overall in-hospital deaths ("hospital mortality"). This evidence is consistent with the raw trends we presented in Section 3.1: high- and low-pollution surgery survival gap does not surface on the day of operation itself, but rather emerges over time.

The average of the hospital mortality regression coefficients (shown across the four columns in Table 2) is 0.428, which means that one log increase in surgery-day $PM_{2.5}$ concentration increases the post-surgery hospital mortality rate by 0.428 per 1,000 patients; this is an increase of about 3.5 percent in the average hospital mortality rate.[14] As discussed in section 3.2, we interpret this effect size as a lower bound on the true *exposure effect* of $PM_{2.5}$. That said, from a practical perspective, the β coefficient contains the most immediately relevant knowledge for the hospital because (a) the outdoor (rather than indoor) $PM_{2.5}$ forecast is what is available for use in planning and scheduling, and (b) minimizing mortality that occurs during hospitalization is an important goal for the hospital. This logic also underlies our structural modeling of surgery schedule in Section 4.

Instrumental Variable Estimation. Table 3 summarizes the IV estimation results. Upwind pollution is a strong predictor of air pollution in Guangzhou. Our first-stage Kleibergen-Paap F-statistics range from a smallest 169.7 in panel A that uses the baseline IV construction outlined in equation (2), to a largest 559.8 in panel D that uses a "zero-stage" Lasso to select the most important upwind cities. The IV results are slightly larger in magnitude and noisier than the OLS estimates of Table 2, but the qualitative findings are consistent across the two estimation approaches. This is in contrast to a common finding in the general pollution-health literature that IV estimates tend to be order-of-magnitude larger than their OLS counterparts (e.g., Ebenstein et al., 2017; Deryugina et al., 2019). We believe this difference is due to two

[14] Given the average $PM_{2.5}$ level of 36.5 ug/m^3, our effect size translates to about 0.95% increase in hospital mortality per 10 ug/m^3 increase in $PM_{2.5.}$

important departures of our settings. First, we consider patients already admitted to the hospital for a few days, and we exploit variation in air pollution on the (pre-scheduled) day of surgery. This means the usual endogeneity concerns, such as confoundedness by road traffic, are muted in our setting. Second, most hospital locations in our study sample have air pollution monitors within several miles, and thus the measurement error in pollution may be smaller than national-scale studies that often need to rely on imputed pollution values from monitors tens of miles away, especially among rural locations where monitoring network coverage is sparse. For the sake of estimation efficiency, in the rest of the analysis we will use the OLS approach in equation (1) as our preferred estimation strategy.

The Importance of *Surgery-Day* Pollution. While our analysis focuses on the effect of pollution on the day a surgical procedure takes place, literatures in both epidemiology and economics have documented the *general* effect of pollution on health outcomes such as hospital visits and mortality (e.g., Schlenker and Walker, 2016; Deryugina et al., 2019; Xia, Xing, Xu, and Pan, 2020). The question then arises concerning the extent to which β picks up a "special" effect of pollution exposure on the surgery day.

We approach this concern by altering the time window during which pollution is defined. Figure 2 panel A presents the results. We first replace Pollution_i in equation (1) with average $PM_{2.5}$ concentrations in the second week prior to the hospital admission. The estimate is close to zero (0.095) and statistically insignificant. We find similar conclusion for pollution during the week prior to admission ("-7 to -1 days to admission"). Together, these estimates suggest that the post-surgery survival effect is not a consequence of any lagged effects of exposure prior to hospitalization. We then examine other post-hospitalization exposure windows, such as average $PM_{2.5}$ concentrations between the admission to the hospital and the date of the surgery, and the weeks following the surgery. We find generally positive but statistically insignificant effects. The lone exception is the positive and statistically significant "surgery day" coefficient, suggesting that surgery-day exposure is particularly detrimental to survival.

Another way to test whether surgery-day pollution plays a unique role in patient mortality is to implement a permutation-style inference. For each surgery patient, we pick a random date during the patient's hospitalization as the "placebo" surgery day, and then re-estimate equation (1). We repeat this exercise 1,000 times and obtain a set of β estimates under each of the 1,000 "placebo" scenario. By construction, the placebo β estimates reflect the distribution of the mortality effect of $PM_{2.5}$ under the null hypothesis that surgery-day exposure is just as bad as exposure on any other day during one's hospitalization period. We can thus calculate a *p*-value for the observed effect (with true surgery dates) by comparing it with the placebo effect distribution. Figure 2, panel B shows that the observed effect falls outside the 95% range of the placebo estimates. This again points to a special effect of exposure to pollution on the day of the surgery itself on patient survival.

3.4 Mechanisms

Why does high pollution on the surgery day reduce subsequent survival? We present additional evidence to shed light on the underlying mechanisms

Physician Effects. Evidence in sections 3.2 and 3.3 suggest that surgery patients on high pollution days are unlikely to be significantly different from those who undergo operations on low pollution days. We next explore the possibility that similar patients are treated differently on days with varying pollution levels. One such possibility is that pollution exposure reduces physicians' ability to perform cognitively demanding operation tasks.[15] The physicians in our study samples (3-A hospitals) are among China's most distinguished and experienced surgeons. Recall, too, that the operating rooms in which the surgeries are performed are designed to be nearly particulate free (Section 2.1). Of course, these factors cannot not exclude the possibility that physicians' *cumulative* pollution exposure during the day outside the operating room may have adversely impacted surgical performance.

As we mentioned in Section 2.2, we cannot observe physician identifiers and characteristics from our dataset. Instead, we exploit three pieces of information available from the surgery records to indirectly test for any effects on physicians. First, we examine the utilization of antimicrobial agents, a common practice to prevent and combat wound infection. We observe the monetary value of antimicrobial agents used related to the surgery, and we use equation (1) to test if higher surgery-day $PM_{2.5}$ predicts more usage. Second, we test if higher $PM_{2.5}$ levels on the date of the surgery increases the odds that patients suffer from non-healing surgical wounds, which can be related to surgical site infection (Mathieu, Linke, and Wattel, 2006). About 1.7 per 1,000 patients in our study sample experienced such non-healing surgical wounds. Finally, we examine a proxy for medical error. We follow Van Den Bos et al. (2011) and David et al. (2013) to construct an umbrella proxy for medical error based on injury and infection-related patient discharge diagnosis codes that were not present at admission.[16] These diagnoses do not necessarily imply medical errors, but they are more likely to occur in the presence of one. We examine whether higher levels of surgery-day pollution influence this measure of "medical error."

[15] For example, exposure to air pollution has been causally linked to reduced work productivity in sectors that require various levels of cognitive abilities (Graff Zivin and Neidell, 2012; Archsmith, Heyes, and Saberian, 2018; Adhvaryu, Kala, and Nyshadham, 2019; Chang, Graff Zivin, Gross, and Neidell, 2019; He, Liu, and Salvo, 2019). We are unaware of any existing evidence that pertains specifically to physicians.
[16] The companion dataset of this paper contains a list of ICD-10 codes we use to identify medical errors.

Table 4 reports the results. We find no evidence that these indicators for treatment style and medical errors change as a consequence of $PM_{2.5}$ variation on the day of surgery; the estimates can rule out small effect size. In Appendix Table A.2, we further test heterogeneous effect by surgery complexity levels (level I being the easiest, and level IV being the hardest), finding no evidence that the impact of pollution is systematically larger for harder procedures.

To be clear, while physician effects do not appear to be the main channel, we cannot completely *rule out* the possibility due to the limited information we have on physician characteristics. Future research may better exploit this channel using other physician-level mediating factors, such as experience (Sosa et al., 1998).

Patient Effects. Our data allow us to benchmark our findings with those from several other commonly performed tests in prior studies on the effect of ambient air pollution on health of the general population. First, we estimate a concentration-response relationship by replacing the $Pollution_i$ term in equation (1) with quintile bins of $PM_{2.5}$ concentrations. This model thus allows for a flexibly nonlinear relationship between post-surgery mortality and $PM_{2.5}$ levels. Figure 3 presents the results. The first quintile bin (average $PM_{2.5}$ = 14.8 ug/m^3) is the omitted category, and the other estimates show the differences in mortality rate on higher-pollution days relative to days when pollution falls in the first quintile bin. Note that the relationship between this figure and the point estimate β in Table 2: β is essentially the slope of a linear fit across the five point estimates in the concentration-response figure, while the figure allows the relationship to be nonlinear. Figure 3 suggests that the mortality damage of pollution rises quickly at first, and then flattens out when it passes the third quintile (average $PM_{2.5}$ = 32.4 ug/m^3). A similar "concave" pattern between general and cardiovascular mortality and both short- and long-term $PM_{2.5}$ exposure has been reported in other epidemiological studies (e.g., Pope III et al., 2011; Crouse et al., 2012; Pope III, Cropper, Coggins, and Cohen, 2015). The dosage relationship suggests that pollution is the culprit underlying the mortality damage, and that even exposure at the low end of the distribution deserves attention.

Next, we augment equation (1) with additional air pollutant covariates, including ozone (O_3), nitrogen dioxide (NO_2), sulfur dioxide (SO_2), and carbon monoxide (CO).[17] Table 5 columns 1 through 4 sequentially add these pollutants as an additional covariate in equation (1), whereas column 5 includes all five pollutants simultaneously. The coefficient estimates from these regressions should be interpreted with caution because these pollutant terms are interdependent. For example, both nitrates and sulfates act as precursors to particulate matter and ozone formation; high particulate concentration scavenges

[17] The same monitoring site that samples $PM_{2.5}$ is also equipped with samplers for these other air pollutants.

hydroperoxyl radicals, which suppress ozone production. However, Table 5 does suggest that $PM_{2.5}$ is a robust and statistically significant predictor of post-surgery survival. This finding echoes a strand of the epidemiology literature that suggests that ozone does not have a first-order impact on cardiovascular morbidity and mortality once $PM_{2.5}$ is controlled for (Jerrett et al., 2009; Brook et al., 2010). In the related causal inference literature, Deryugina et al. (2019) examine a two-pollutant model in which $PM_{2.5}$ and O_3 are simultaneously instrumented for using variations in local wind directions. They find that the estimated effect of $PM_{2.5}$ on elderly mortality is five times as large as the O_3 effect, with the O_3 effect showing the "wrong" sign (mortality reduction). Table 5 column 1 shows that a similar conclusion holds in the context of patients' post-surgery survival.

Finally, we try to identify high-risk patients**.** The impact of pollution likely varies across different groups of patients. Table 6 reports estimates from an augmented version of regression equation (1) in which we fully interact $PM_{2.5}$ with an indicator for a proposed high-risk group of patients – respiratory and neoplasm surgeries for patients aged over 60. This regression specification allows us to estimate the impact of surgery-day $PM_{2.5}$ separately for the high-risk group patients and all other patients.[18] Table 6 suggests the impact of pollution concentrates in the high-risk group, where a log unit increase in $PM_{2.5}$ leads to a 2.91 per 1,000 patients increase in post-surgery mortality (the average coefficient estimate across four columns). The corresponding increase for other patients is 0.17 per 1,000 patients. Part of this difference is because the high-risk group has a higher *average* post-surgery mortality rate: 38.35 per 1,000 patients, compared to 8.74 per 1,000 patients for those who are not in this high-risk group. Note, however, that the effect of $PM_{2.5}$ is also larger even in *percentage* terms for the high-risk group: a 7.59 percent increase in mortality surfaces per one log unit increase in pollution, compared with a 1.96 percent increase among other patients.

This is an important finding we will leverage in our structural exploration in Section 4. High-risk patients constitute a small fraction (6 percent) of surgery cases but account a majority (60 percent) of the mortality effect. This provides us with opportunity to achieve survival improvement by targeting better surgery scheduling to address this particular group of patients. We discuss this point in greater detail in Section 4.

To further examine plausibility, we assess the exact surgical procedures performed with the high-risk group. For respiratory patients, the five most common procedures are *fiber-optic bronchoscopy* (14.9% of all respiratory procedures, ICD-9-CM Volume 3 code: 33.22), *other bronchoscopy* (6.5%, code 33.23), *insertion of intercostal catheter for drainage* (6.3%, code 34.04), *insertion of endotracheal tube* (4.9%,

[18] We came up with this high-risk group by first estimating similar heterogeneous effect specifications by diagnosis categories and by age groups separately. These first-step results are reported in Appendix Tables A.3 and A.4.

code 96.04), and *venous catheterization* (4.8%, code 38.93). For neoplasm patients, the most common procedures are *other gastroscopy* (2.1%, code 44.13), *endoscopic destruction of other lesion or tissue of large intestine* (2.0%, code 45.43), *endoscopic polypectomy of large intestine* (2.0%, code 45.42), *other transurethral excision or destruction of lesion or tissue of bladder* (1.9%, code 57.49), and *closed percutaneous needle biopsy of lung* (1.9%, code 33.26). Our findings suggest that it is possible that pollution is the most detrimental for one patient group: those who have recently undergone endoscopic procedures.

Summary. We briefly summarize our findings about underlying mechanisms. First, statistical selection of surgery patients is unlikely to be the explanation. This is supported by various analyses of patient characteristics, which do not differ in the surgeries performed on days with high or low levels of pollution. An instrumental-variable design exploiting transported pollution from upwind cities also supports the claim. Second, while we do not fully know whether the effect works through pollution's effect of physician treatment decision and/or surgery performance, we are able to reject some specific channels that can serve as proxies for greater errors or issues that might occur on highly polluted days. A lack of information on attending surgeons and other medical personnel precludes us from exploring further possibilities. Third, the same toxicological and biological mechanisms that underpin general mortality effects of pollution may also be at play in the perioperative context. This is reflected by some similar effect characteristics reported in previous studies such as those that examine concentration response, pollutant-specific effects, and subpopulation heterogeneity.

4. (Re)scheduling Pollution Exposure

The empirical evidence in Section 3 invites a question: is it possible to improve a patient's post-surgery survival by avoiding operating on days when pollution is high? In this section, we use structural methods to characterize the hospitals' status quo decision-making processes that govern patient surgery scheduling. We then analyze how hospitals could incorporate knowledge about the potential adverse impact of pollution on patients' mortality risks.

We keep a "Pareto" principle in mind throughout the structural exercise. That is, while some patients are made better off when surgery is rescheduled to a day with better air quality, no patient should be made worse off under the counterfactual schedule. With this in mind, we seek to switch surgery dates for only a small group of patients who would benefit the most from having surgeries on days with lower levels of pollution, and we only consider small deviations from originally scheduled dates. This conservative approach leads to a small impact on the hospital's overall surgery capacity utilization, while still able to discover substantial opportunity for survival improvement.

4.1 A Model of Surgery Scheduling

Setup and Parameterization. We model the decision of a hospital to schedule surgeries for newly admitted patients. The hospital chooses the operation date for each patient as d days after the admission date. For simplicity, we consider a static version of the problem, where we take the pool of all N patients ever admitted to the hospital during our study period, and model how the hospital optimally chooses the admission-to-surgery delay profile $\{d_i\}_{i=1}^{N}$. Below, we use subscript i to denote a patient. The hospital maximizes its utility function for scheduling an operation for patient i on the d days following admission:

$$u_{id} = -\alpha h_{id} + \lambda_{id} + e_{id} \qquad (3)$$

where h_{id} is the *perceived* patient mortality hazard from performing a procedure, α represents the scaling weight of the mortality hazard when the hospital makes scheduling decisions, λ_{id} captures non-health-related payoffs, and e_{id} captures idiosyncratic considerations of the hospital in scheduling surgeries, which we assume follow an i.i.d. type-I extreme value distribution.

The perceived mortality hazard h_{id} follows the exact same specification as in our reduced form regression equation (1), except that the $\mathrm{Pollution}$ term is omitted because we assume hospitals do not internalize the mortality hazard of pollution in the baseline model. We parameterize non-health-related payoffs λ_{id} as a stepwise function of admission-to-surgery delays d (days), and a dummy variable indicating whether the surgery day is on a workday:

$$\lambda_{id} = \sum_g \beta_g \cdot 1(d_{id} = g) + \varphi_{workday} \qquad (4)$$

The workday indicator variable $\varphi_{workday}$ is important because both air pollution and surgery mortality exhibit strong weekday-weekend cycles. Our data suggest that the odds of post-surgery death are higher for procedures done on the weekend. On the other hand, air pollution tends to be higher during the weekdays.

Next, we impose several constraints to our modeling exercise to maximize the practical relevance of our counterfactual analysis. First, we focus on patients receiving respiratory and neoplasm surgeries who were over 60 years old at the time of admission. As we report in Section 3, the pollution effect concentrates among this vulnerable group, which constitutes of 6% of the overall surgery sample but explains 60% of the total effect size. From a practical perspective, restricting to a relatively small group of procedures helps avoid causing periods of extremes in surgical capacity. Only 1.3% of counterfactual case assignments exceed capacity, which can be handled by reassigning to the second-best day (more below).

Second, we set the maximum value of delay d to be three days, meaning that we only model scheduling for patients whose observed surgery dates are up to three days after the date of hospital admission. That is, we assume that the hospital chooses delay $d \in \{0,1,2,3\}$. About 41% of age 60+ respiratory/neoplasm patients fall in this situation (N = 130,440). This restriction also implies that all counterfactual surgery schedules occur within this window. This specification choice is motivated by several considerations. First and foremost, air quality forecasting is the most accurate in the near term. Our modeling assumption that delays *per se* have no effect on mortality hazards (h_{id}) is also more likely to hold if we consider short-term rescheduling. Other practical issues may arise as well, such as patient agreement and the deterioration of patient's condition, when long delays are involved.

Estimation. Our estimation therefore boils down to a maximum likelihood estimation of parameters $\theta = (\alpha, \beta_0, \beta_1, \beta_2, \varphi_{workday})$. Assuming e_{id} follows a type-I extreme value distribution, the probability that the patient i is assigned a delay of d is

$$P_{id}(\theta) = \frac{\exp(\alpha h_{id} + \lambda_{id})}{\sum_{g=0}^{3} \exp(\alpha h_{ig} + \lambda_{ig})} \quad (5)$$

where h_{id} is the predicted mortality risk for the patient i from our reduced form estimation of equation (1). λ_{id} follows the exact definition from equation (4), with an additional d index to make explicit that the term depends on the delay. The patient's individual likelihood is given by

$$R_i(\theta) = P_{id}(\theta) \prod_{g \neq d} (1 - P_{ig}(\theta)) \quad (6)$$

Because optimal scheduling decisions are independent across patients, the model likelihood function is

$$L(\theta) = \prod_{i=1}^{N} R_i(\theta) \quad (7)$$

We report estimation results $\hat{\theta}$ in Appendix Table A.5. Note we estimate the model separately for respiratory and neoplasm patients because the health and non-health trade-offs are expected to be different across different diagnoses. In Appendix Figure A.5 we report that the predicted surgery schedule from these parameterizations matches well with the observed schedule for both respiratory and neoplasm patient groups.

Counterfactual Analysis. We now consider counterfactual surgery scheduling that reflects what could be devised if a hospital were to internalize the impact of air pollution on post-surgery survival (Table

2). We compute predicted mortality hazard h'_{id} using equation (1), now with the Pollution term “switched on.” We then substitute h'_{id} into equation (5) holding fixed $\hat{\theta}$, which gives us a list of probabilities $P_{id}(\hat{\theta})$ that patient i is assigned surgery with a delay $d_i \in \{0,1,2,3\}$. Patient i’s counterfactual surgery delay is therefore corresponding to the day with the maximum (counterfactual) surgery probability, namely $\text{argmax}_{d\in\{0,1,2,3\}} P_{id}(\hat{\theta})$. We repeat this exercise for every patient, and generate a counterfactual surgery schedule $\{d'_i\}_{i=1}^{N}$.

Figure 4 summarizes the results. Panel A displays the observed and counterfactual surgery-day $PM_{2.5}$ distributions among patients in the high-risk group (respiratory/neoplasm patients aged 60+). The counterfactual distribution is much more skewed to the right, compared to the observed distribution, suggesting that a significant share of high-pollution surgeries are shifted towards days with better air quality.

With many cases shifting, one might worry that the counterfactual schedule may exceed the hospital department’s surgery capacity, especially during days with particularly low levels of air pollution. To gauge the likelihood of such situation, we estimate each hospital’s respiratory and neoplasm surgery capacity as the maximum single-day surgery patient volume during the study period (mean = 10.0, s.d. = 5.0 for respiratory surgeries; mean = 33.4, s.d. = 26.8 for neoplasm surgeries). We calculate that in about 1.3% cases, the counterfactual scheduling causes an assignment of the patient to a date when the hospital department’s surgery capacity is already full. Panel B of Figure 4 shows average hospital respiratory and neoplasm surgery capacity utilization rate by 1-ug/m^3 pollution bins. The pattern suggests that while the counterfactual scheduling makes the surgery departments a little busier on low-pollution days, such scheduling does not come close to jeopardizing overall capacity. This result stems largely from the focus tailoring the rescheduling to target the vulnerable groups, which constitute a small share of patients, but a large share of health damage.

In panel C of Figure 4, we plot the distribution of improvement in survival probability for “switcher” patients whose observed surgery dates are different from the counterfactual. Overall, our method switched the date of surgery for 20,853 patients out of a total of 52,406 patients in the vulnerable group. A vast-majority of switchers (98.6%) improved survival probability. This is a desirable result: although hospitals could in principle switch patients to better air quality days with higher revenue potential but *worse* mortality potential, such behavior does not often arise according to the revealed health and revenue trade-offs for most hospitals in our data. The mortality reduction for the average switcher is 1.6 deaths per 1,000 patients, or about a 4.2 percent improvement upon the baseline mortality rate of 38.4 per 1,000 patients in the high-risk group.

The big picture takeaway from Figure 4 is that for nearly half of the scheduled surgeries, there exists an alternative, lower-pollution day within three days of the originally scheduled day such that moving the surgery would (a) not surpass the overall surgery capacity of the alternative day, (b) yield an average 4 percent better post-surgery survival, and (c) meet the basic cost-and-benefit trade-offs according to revealed hospital preference from historical surgery records.

4.2 A Practical Example

The structural exercise suggests there are potential gains from *taking pollution into account* when scheduling surgeries. This could mean many things in practice: more salient reminders of pollution levels, better education on the adverse effect of pollution on patients, or an established protocol on avoiding surgeries on vulnerable patients on high-pollution days, for example. Exactly which approach to adopt depends on the individual hospital's constraints and preferences. Here we consider the feasibility of a simple rescheduling (postponing) process that responds to a high level of pollution on a given day by delaying scheduled surgery to the near future. The intention of this exercise is to set a concrete example of how hospitals *might* consider pollution in scheduling decisions.

(a) We begin with 6,093 surgeries among the high-risk group that are scheduled on days when the Air Quality Index is over 100 ($PM_{2.5}$ > 75 ug/m^3) with Air Quality Index below 100 during at least one of the following three days.[19] Our goal is to reschedule these surgeries scheduled on days with high pollution levels to one of the subsequent days with lower pollution to improve post-surgery survival (according to the health function estimated in Section 3).

(b) Consider rescheduling all 6,093 patients to the day with the *lowest* level of pollution in the upcoming three-day period. Although exposure is reduced in every case, survival does not necessarily improve because pollution is not the only determinant of mortality hazards (h_{id}). For example, a patient could be reassigned from a weekday that has high pollution to a weekend day with low pollution – even though, as we have previously discussed, the mortality hazard is on average higher during the weekend. Our analysis shows that under this scenario, 1,935 of the 6,093 patients would actually see a decline in survival.

(c) Thus, to make sure that no patient is harmed by rescheduling, we reassign the cases that experience negative effects to the day with the *second-lowest* level of pollution day that occurs in the following three-day period, or, if that scenario still results in negative effects, we reschedule again to the day with the *third-lowest* pollution day. With such adjustments, we are able to obtain positive survival

[19] $PM_{2.5}$ concentration exceeds 75 ug/m^3 in about 5 percent of days in Guangzhou.

benefits for 902 out of the 1,935 patients who would have potentially experienced negative effects from a blanket approach to rescheduling. For the rest of 1,033 patients, the second / third lowest pollution day over the next three days, in fact, have mortality risks that are higher than those on the originally scheduled day of surgery Therefore, for these patients, the surgery schedule would remain the same.

(d) Over the course of the rescheduling exercise, there are 238 incidents in which the hospital would have found its daily surgery capacity would be exceeded. We treat these cases in the same way we did with negative survival improvement cases, assigning them to the next-best air quality day. As in Section 4.1, surgery capacity overall is not a binding constraint because we focus on a relatively small group of patients.

Appendix Figure A.6 presents the effect of rescheduling process on patients' pollution exposure, hospital capacity utilization, and survival improvements. Panel A shows the observed surgery-day $PM_{2.5}$ value for the 6,093 patients; by design, these values all lie above AQI 100 (75 ug/m^3). Panel A also contrasts this with the counterfactual exposure that would have occurred if steps (a) through (d) were followed. Panel B shows that rescheduling increases surgery capacity utilization of the associated hospital departments on low pollution days, but not to such an extent that the rescheduling would approach capacity constraints. Panel C illustrates the distribution of survival improvements after step (a) shown by the hollow bar, and after steps (a) through (d) shown by the filled bar. Overall, the process switched surgery days for 5,060 patients out of a total of 6,093 patients. The mortality reduction rate for the average switcher is 2.8 deaths per 1,000 patients, which is about a 7.3 percent improvement upon the baseline mortality rate of 38.4 per 1,000 patients in the high-risk group.[20]

4.3 Limitations and Future Research

Before concluding the paper, we discuss several issues that we are not able to fully pin down with this study, and potential directions for future work.

Static versus Dynamic Scheduling Problem. For simplicity, we employ a retrospective, static approach in the structural scheduling exercise. In reality, hospitals schedule patients sequentially based on dynamically changing surgery capacity. Another state variable in a dynamic scheduling is the patient's health condition, which changes stochastically over time. The scheduling decision is thus based on the

[20] The *per-patient* (rather than per-switcher) improvement is 0.11 per 1,000 patients. This is much smaller than the structural results in Section 4.1. This is both because the rescheduling process only focuses on a subset of days with very high pollution levels, and because the process does not seek to strike the optimal cost-benefit trade-offs as does the structural method.

patient's health condition upon arrival *and* the expectation of future health changes. Certain patients may even need multiple operations and frequent adjustments of treatment plans as a function of surgical outcomes.

Although we abstract away from these dynamic details, static models may still be a reasonable approximation because we only consider a local change in observed surgery scheduling. In particular, we have shown that surgery capacity is far from binding on a vast majority of days both with the observed and the counterfactual scheduling. Our focus on the short-term (i.e., next three-day) scheduling horizon also limits the scope for stochastic changes in patient health changes.

Accuracy of Pollution Forecasts. Throughout the counterfactual scheduling exercise we assume that hospitals can perfectly anticipate air pollution levels in the next three days. Here we survey the current forecasting technology used by Guangzhou and its performance.

Air pollution forecast in Guangzhou is primarily based on outputs from four Eulerian Chemical Transport Models: NAQPMS, CMAQ, CAMx, and WRF-Chem.[21] These models combine weather predictions with data from ambient pollution monitoring, emission monitoring, and emission inventory to provide simulations of atmospheric chemistry, and to generate numerical forecasts of air quality in the next 72 hours. The automated model outputs are then post-processed by scientists at the Guangzhou Environmental Monitoring Center and the Weather Bureau. The scientists use statistical methods and ad hoc knowledge on pollution events to improve upon the numerical forecasts.

We do not have access to historical pollution forecasts in Guangzhou. Instead, we rely on several reports from the city, province, and national environmental agencies that compare forecasts and observed pollution. Appendix Figure A.7 shows daily time-series plots of the 24-hour forecasted and observed Air Quality Index (AQI) in Guangzhou throughout the year of 2016 (taken from Zhang et al., 2017 and Zhang et al., 2018). These plots suggest that forecasted AQIs match well overall with observed values. The correlation coefficient between the two time series is 0.72. A simple linear regression of observed AQI on forecasted AQI yields a slope coefficient of 0.95. A separate, province-wide analysis by Shen et al. (2017) shows 24-hour forecasted AQI categories (below 50, the "Green-Good" category; between 50 and 100, the "Yellow-Moderate" category, etc., as shown in Appendix Figure A.2) are correct over 70 percent of the time in Guangzhou, with almost perfect accuracy when $PM_{2.5}$ is the predominant pollutant of the day. The only report of longer-term, 72-hour forecast accuracy we can find is in the data appendix of the central

[21] These are the Nested Air Quality Prediction Modeling System developed by the Chinese Academy of Sciences, the Community Multiscale Air Quality Model developed by the U.S. Environmental Protection Agency, the Comprehensive Air Quality Model with Extensions by the Ramdoll U.S. Corporation, and the Weather Research and Forecasting Model Coupled to Chemistry by the U.S. National Oceanic and Atmospheric Administration.

government's Technical Guideline for Numerical Forecasting of Ambient Air Quality of 2020 (HJ 1130-2020). Using forecasting data from 17 cities, the Technical Guideline reports that forecasted AQI categories coincide with observed categories 75 percent of the time, with the hit rates similar across 24-hour, 48-hour, and 72-hour time horizons.

Both in China and internationally, air pollution forecasting is a growing and high-interest research field. As we argue in this paper, endowing the general public with better abilities to anticipate air pollution events may have important health values.

Physician Mechanisms. One question we did not fully address in Section 3 is whether a physician effect may explain the main mortality finding. We excluded some channels, such as injury-related medical errors, but a lack of information on attending surgeons and other medical personnel precludes us from exploring further possibilities.

The rescheduling exercise per se does not fully hinge on knowledge of the mechanism: so long as surgery-day pollution is a cause for higher mortality, rescheduling to alternative surgery days may provide benefit – no matter what the exact underlying mechanisms at work. That said, a fuller understanding on the physician effect may help create even better surgery scheduling practices. For example, if the pollution effect only changes performance of a certain group of physicians, it might be more efficient to re-optimize surgeon schedules rather than patient schedules.

5. Conclusion

We use data from more than 1 million surgical records from a major city in China to study the link between day-to-day variation in fine particulate matter pollution (mean = 36.5 ug/m^3, s.d. = 19.8 ug/m^3) and post-surgery mortality. We find that undergoing an operation on a high pollution day is associated with a significant reduction in post-surgery survival – especially elderly patients undergoing respiratory and neoplasm operations. The excess mortality is linked to pollution on the day of the surgery, rather than pollution exposure prior to hospital admission, during the waiting period, or following the date of the operation. Building upon these empirical patterns, we build and analyze a structural model of hospital surgery scheduling, and consider counterfactual scheduling that could improve patient survival. We demonstrate that relatively small changes in surgical dates for a small group of patients can improve survival rates. Such changes in scheduling can accommodate the patients who are likely to benefit most from undergoing such procedures on a day with better air quality. We conclude that there may be important potential for hospitals to consider air pollution forecasts in day-to-day surgery scheduling.

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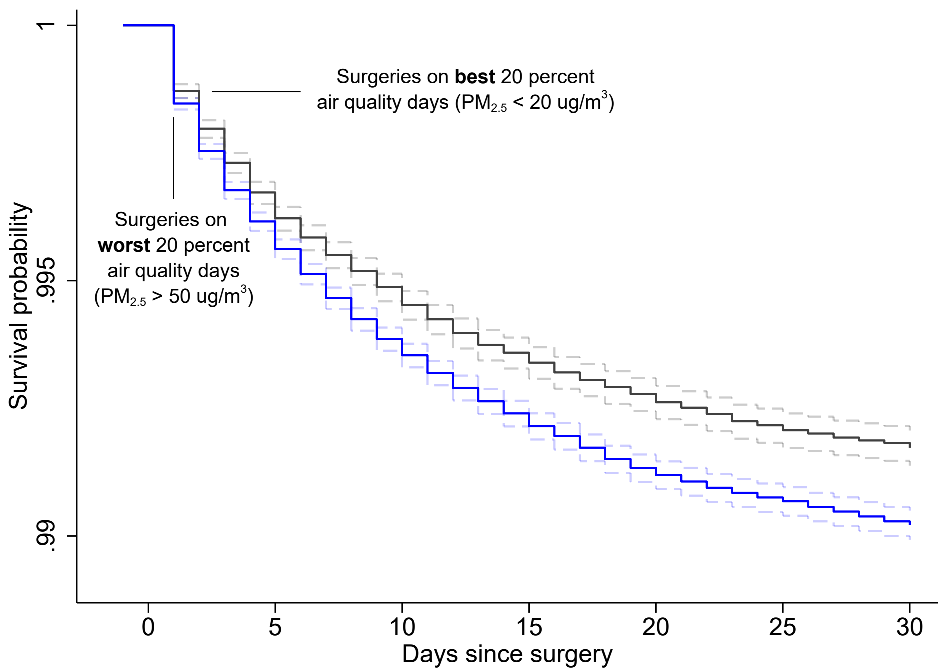
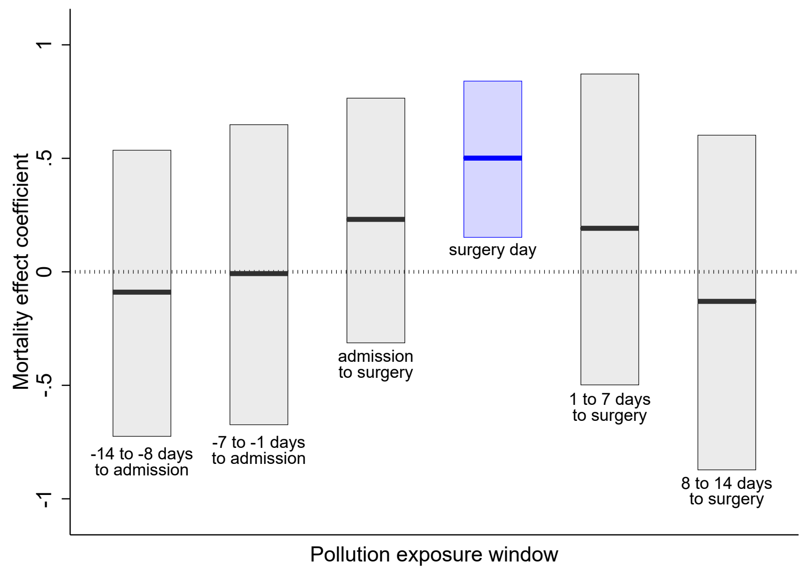
Figure 1. Patient Survival after Surgeries on High versus Low Pollution Days



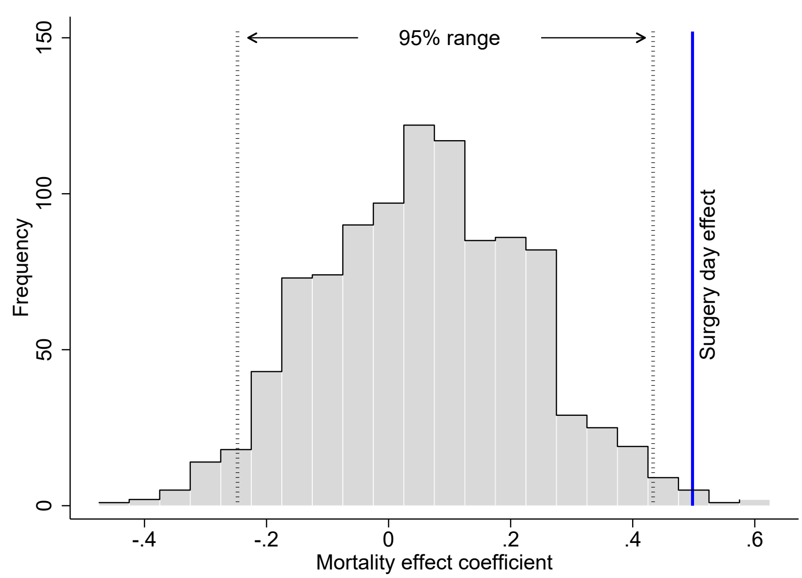
Notes: This graph reports Kaplan-Meier survival estimates and 95% confidence intervals among surgeries conducted on days with the worst quintile $PM_{2.5}$ concentration (>50 ug/m^3) and days with the best quintile $PM_{2.5}$ concentration (<20 ug/m^3).

Figure 2. The Importance of Surgery-Day Pollution Exposure

Panel A. Alternative exposure windows

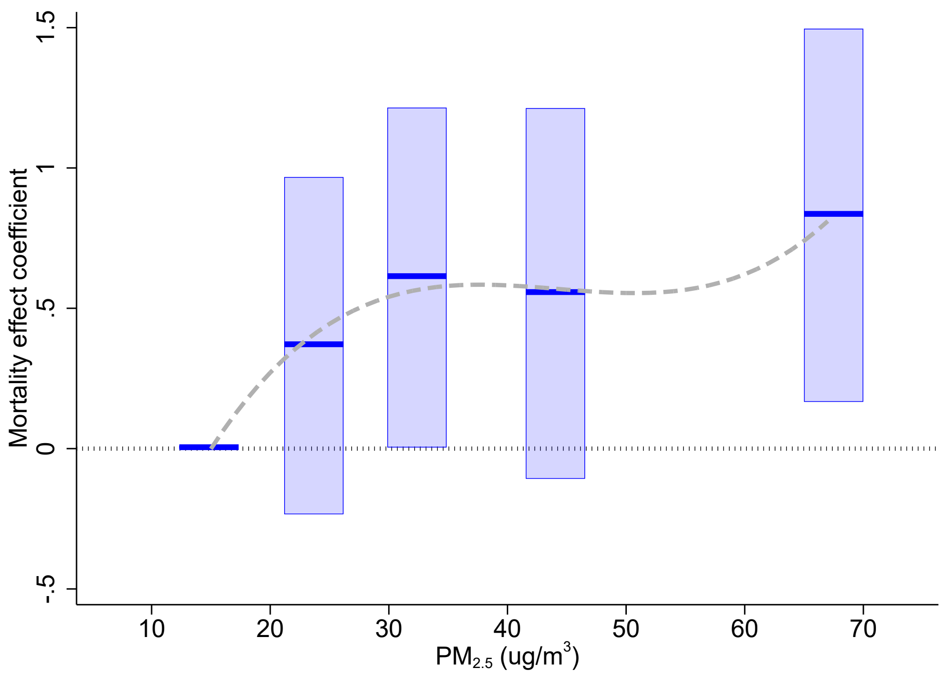


Panel B. "Placebo" exposure windows (1,000 randomized scenarios)



Notes: Panel A reports the alternative estimates of pollution effect when alternative exposure windows are used. Bars represent 95% confidence intervals. Panel B compares the observed, surgery-day pollution effect with the placebo distribution of effect sizes generated from 1,000 placebo estimation using the same data and the same regression specification but with randomly-dated surgeries.

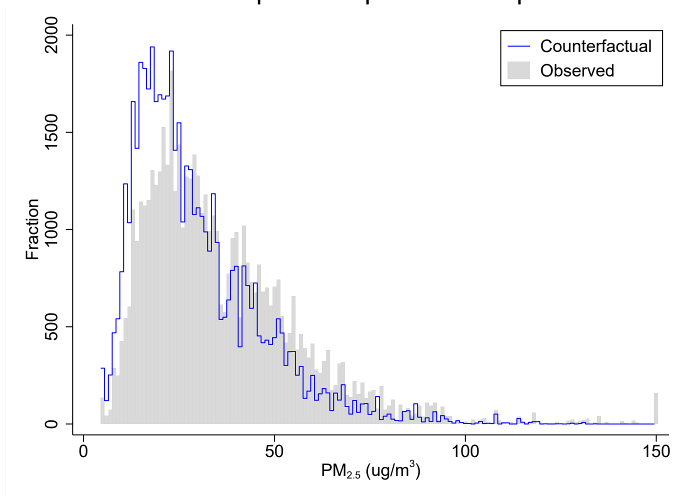
Figure 3. Concentration Response of Surgery-Day Pollution



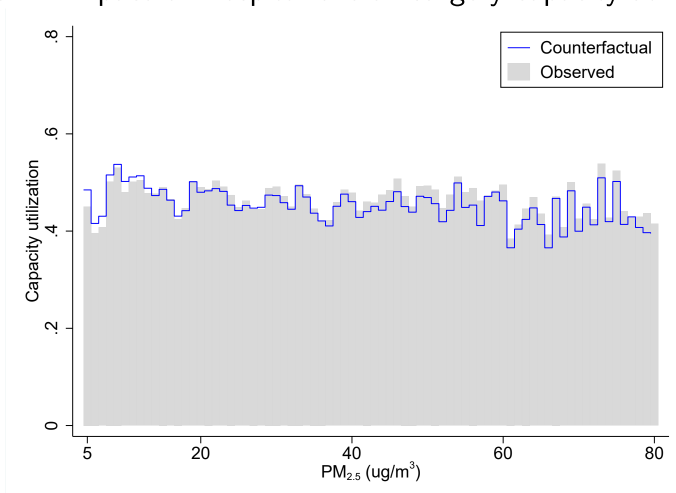
Notes: This graph reports the effect of surgery-day $PM_{2.5}$ on post-surgery mortality by quintile bins. Bars represent 95% confidence intervals. The first pollution quintile bin is the reference category. Dashed line shows a cubic fit.

Figure 4. Counterfactual Surgery Scheduling that Internalizes Pollution Damages

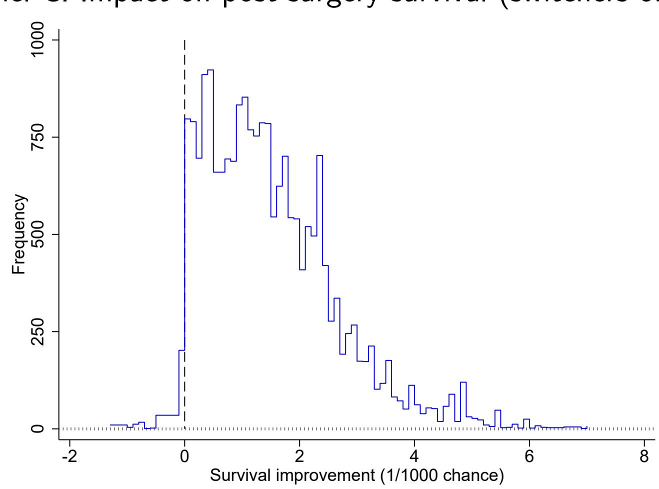
Panel A. Impact on pollution exposure



Panel B. Impact on hospital overall surgery capacity utilization



Panel C. Impact on post-surgery survival (switchers only)



Notes: Panel A compares observed and counterfactual surgery profile's $PM_{2.5}$ distribution among the high-risk patient group. Panel B compares hospitals' daily overall surgery capacity utilization rates averaged by 1-ug/m^3 bins. We omit few observations for days above 80 mg/m3. Panel C plots the distribution of survival improvements among "switcher" patients whose counterfactual surgery day is different from the observed day.

Table 1. Surgery-Day Pollution and Pre-surgery Patient/Surgery Characteristics

		(1)	(2)	(3)	(4)
		Indep. var.: Log $PM_{2.5}$ concentration			
Age	mean = 47,964	30.264	21.331	51.694*	38.744
		(28.337)	(29.190)	(28.049)	(29.745)
1(male)	mean = 563.3	-0.788	-0.664	-0.349	-0.888
		(0.996)	(1.027)	(0.887)	(1.152)
1(married)	mean = 802.8	1.490**	1.505**	1.970***	1.640***
		(0.621)	(0.623)	(0.651)	(0.638)
1(allergy history)	mean = 51.0	0.456	0.565	0.564	0.772
		(0.421)	(0.450)	(0.541)	(0.525)
Days of delay	mean = 3,944	-6.435	-6.502	-33.683**	-13.556
		(14.563)	(13.819)	(14.002)	(13.005)
Number of procedures	mean = 2,050	-0.849	-2.682	-0.577	-0.368
		(2.106)	(2.458)	(1.822)	(1.953)
1(general anesthesia)	mean = 491.5	-3.866	-3.722	-3.993*	-2.657
		(3.953)	(4.188)	(1.949)	(3.165)
1(level-1 operation - easiest)	mean = 283.7	-0.453	-0.477	2.318	0.237
		(3.038)	(2.922)	(3.250)	(3.504)
1(level-2 operation)	mean = 321.5	1.325	0.663	-0.632	0.639
		(2.737)	(2.812)	(2.654)	(2.689)
1(level-3 operation)	mean = 250.9	0.298	0.375	-0.562	-0.380
		(1.021)	(0.988)	(0.819)	(0.916)
1(level-4 operation - hardest)	mean = 144.0	-1.170	-0.561	-1.124**	-0.496
		(0.776)	(0.660)	(0.512)	(0.633)
1(insurance program: City Workers)	mean = 416.1	-0.110	0.263	-0.487	0.206
		(2.001)	(1.884)	(1.430)	(1.672)
1(insurance program: New Rural Cooperative)	mean = 61.7	1.289	0.831	0.742	0.600
		(0.821)	(0.751)	(0.827)	(0.754)
1(insurance program: none)	mean = 295.0	0.135	0.498	0.377	0.320
		(1.155)	(1.251)	(0.812)	(1.028)
FEs: diagnosis		✓	✓	✓	✓
FEs: department		✓	✓	✓	✓
FEs: procedure		✓			
FEs: hospital		✓			
FEs: year		✓	✓		✓
FEs: month		✓	✓		
FEs: day-of-week		✓	✓	✓	✓
FEs: procedure×hospital			✓	✓	
FEs: year×month				✓	
FEs: procedure×hospital×month					✓

Notes: Each cell reports a separate regression of a characteristics on surgery-day pollution. All characteristics variables are multiplied by 1,000 to increase readability. "Days of delay" is number of days between hospitalization and surgery. Numbers of observations are 1,317,099 (column 1), 1,307,307 (columns 2 and 3), and 1,236,997 (column 4). *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Table 2. Surgery-Day Pollution and Patient Mortality

		(1)	(2)	(3)	(4)
		Indep. var.: Log $PM_{2.5}$ concentration			
1-day mortality	mean = 1.322	0.060	0.083	0.087	0.137
		(0.074)	(0.073)	(0.074)	(0.080)
7-day mortality	mean = 5.987	0.200	0.248*	0.230	0.231*
		(0.127)	(0.128)	(0.136)	(0.118)
28-day mortality	mean = 10.28	0.339**	0.405**	0.456***	0.381**
		(0.136)	(0.149)	(0.147)	(0.176)
Overall hospital mortality	mean = 12.11	0.378**	0.434**	0.498***	0.400*
		(0.176)	(0.182)	(0.172)	(0.218)
FEs: diagnosis		✓	✓	✓	✓
FEs: department		✓	✓	✓	✓
FEs: procedure		✓			
FEs: hospital		✓			
FEs: year		✓	✓		✓
FEs: month		✓	✓		
FEs: day-of-week		✓	✓	✓	✓
FEs: procedure×hospital			✓	✓	
FEs: year×month				✓	
FEs: procedure×hospital×month					✓

Notes: Each cell reports a separate regression of a measure of post-surgery mortality on surgery-day pollution. Each mortality variable is an indicator for whether the patient died in hospital following k-day since surgery, multiplied by 1,000 to increase readability. All regressions control additionally for individual characteristics including age in 5-year bins, gender indicator, marital status indicator, and an indicator for any history of allergy, and weather controls including daily average temperature in 10-degree Celsius bins, precipitation, and precipitation squared. Numbers of observations are 1,317,099 (column 1), 1,307,307 (columns 2 and 3), and 1,236,997 (column 4). *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Table 3. Surgery-Day Pollution and Patient Mortality: Instrumental Variable Estimation

	(1)	(2)	(3)	(4)
	Dep. var.: Hospital mortality			
Panel A. IV = upwind pollution from all cities (distance^{-1} weighted)				
Log $PM_{2.5}$	0.471	0.462	0.705*	0.562
	(0.429)	(0.435)	(0.410)	(0.392)
Kleibergen-Paap F-stat.	211.8	226.8	169.7	236.8
Panel B. IV = upwind pollution from cities≤1,000 km (distance^{-1} weighted)				
Log $PM_{2.5}$	0.655*	0.740**	0.908***	0.841***
	(0.333)	(0.319)	(0.281)	(0.281)
Kleibergen-Paap F-stat.	337.4	345.4	290.2	368.5
Panel C. IV = upwind pollution from all cities (distance^{-2} weighted)				
Log $PM_{2.5}$	0.532*	0.595**	0.806***	0.619***
	(0.263)	(0.254)	(0.191)	(0.218)
Kleibergen-Paap F-stat.	454.5	464.9	391.3	497.0
Panel D. IV = upwind pollution from 119 cities ("0-stage" Lasso, distance^{-1} weighted)				
Log $PM_{2.5}$	0.448*	0.493*	0.656***	0.490**
	(0.255)	(0.262)	(0.222)	(0.235)
Kleibergen-Paap F-stat.	503.9	515.1	420.5	559.8
FEs: diagnosis	✓	✓	✓	✓
FEs: department	✓	✓	✓	✓
FEs: procedure	✓			
FEs: hospital	✓			
FEs: year	✓	✓		✓
FEs: month	✓	✓		
FEs: day-of-week	✓	✓	✓	✓
FEs: procedure×hospital		✓	✓	
FEs: year×month			✓	
FEs: procedure×hospital×month				✓

Notes: Each cell reports a separate two-stage least squares (2SLS) regression of post-surgery mortality on surgery-day pollution, using upwind pollution from cities at least 100km away from Guangzhou as the instrumental variable (IV). All IV regressions are exactly identified with one endogenous variable (log $PM_{2.5}$) and one excluded instrument (upwind pollution). In panel A, the IV is logged inverse-distance-weighted average upwind $PM_{2.5}$ vector from all cities over 100km away. In panel B, the IV is logged inverse-distance-weighted average upwind $PM_{2.5}$ vector from all cities between 100-1,000km away. In panel C, the IV is logged inverse-distance-squared-weighted average upwind $PM_{2.5}$ vector from all cities over 100km away. In panel D, a "zero-stage" linear Lasso of Guangzhou's $PM_{2.5}$ on upwind $PM_{2.5}$ vectors are run to first select 119 contributing cities (also restricted to those over 100km away from Guangzhou). The IV is then constructed as logged inverse-distance-squared-weighted average upwind $PM_{2.5}$ vector from the selected cities. All regressions control additionally for individual characteristics including age in 5-year bins, gender indicator, marital status indicator, and an indicator for any history of allergy, and weather controls including daily average temperature in 10-degree Celsius bins, precipitation, and precipitation squared. Numbers of observations are some 1.3 million. *: p < 0.10; **: p < 0.05; ***: p < 0.01.

Table 4. Surgery-Day Pollution and Treatment Differences

		(1)	(2)	(3)	(4)
		Indep. var.: Log $PM_{2.5}$ concentration			
Log(antimicrobial agents use)	mean = 3.381	-0.009	-0.006	0.001	-0.004
		(0.007)	(0.007)	(0.005)	(0.006)
1(non-healing surgical wounds)×1,000	mean = 1.664	-0.021	0.005	0.051	0.076
		(0.088)	(0.084)	(0.084)	(0.067)
1("medical error")×1,000	mean =6.138	0.189	0.198	0.256	0.198
		(0.226)	(0.230)	(0.238)	(0.257)
FEs: diagnosis		✓	✓	✓	✓
FEs: department		✓	✓	✓	✓
FEs: procedure		✓			
FEs: hospital		✓			
FEs: year		✓	✓		✓
FEs: month		✓	✓		
FEs: day-of-week		✓	✓	✓	✓
FEs: procedure×hospital			✓	✓	
FEs: year×month				✓	
FEs: procedure×hospital×month					✓

Notes: Each cell reports a separate regression of a measure of treatment/performance on surgery-day pollution. The indicator variables are multiplied by 1,000 to increase readability. "Medical errors" is a proxy built from patient injury at discharge following Van Den Bos et al. (2011) and David et al. (2013). All regressions control additionally for individual characteristics including age in 5-year bins, gender indicator, marital status indicator, and an indicator for any history of allergy, and weather controls including daily average temperature in 10-degree Celsius bins, precipitation, and precipitation squared. Numbers of observations are 1,317,099 (column 1), 1,307,307 (columns 2 and 3), and 1,236,997 (column 4). *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Table 5. Surgery-Day Pollution and Patient Mortality: Multiple Pollutants Model

	(1)	(2)	(3)	(4)	(5)
	Dep. var.: Hospital mortality				
Log $PM_{2.5}$	0.545***	0.887***	0.470**	0.405**	0.906***
	(0.163)	(0.264)	(0.194)	(0.167)	(0.300)
Log O_3	-0.166				-0.213
	(0.125)				(0.137)
Log NO_2		-0.843*			-1.017**
		(0.448)			(0.476)
Log SO_2			0.010		0.135
			(0.198)		(0.191)
Log CO				0.311	0.393
				(0.263)	(0.243)
FEs: diagnosis	✓	✓	✓	✓	✓
FEs: department	✓	✓	✓	✓	✓
FEs: day-of-week	✓	✓	✓	✓	✓
FEs: procedure×hospital	✓	✓	✓	✓	✓
FEs: year×month	✓	✓	✓	✓	✓

Notes: Each column is a separate regression. Mortality variable is an indicator for whether the patient died in hospital, multiplied by 1,000 to increase readability. All regressions control additionally for individual characteristics including age in 5-year bins, gender indicator, marital status indicator, and an indicator for any history of allergy, and weather controls including daily average temperature in 10-degree Celsius bins, precipitation, and precipitation squared. Number of observations are is 1,307,307.*: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Table 6. Surgery-Day Pollution and Patient Mortality: High-Risk Patients

		(1)	(2)	(3)	(4)
		Dep. var.: Hospital mortality			
Log $PM_{2.5}$ × 1(high-risk patients)	mean mortality = 38.35	2.769**	2.993**	3.044**	2.837**
		(1.263)	(1.173)	(1.156)	(1.233)
Log $PM_{2.5}$ × 1(other patients)	mean mortality = 8.74	0.134	0.176	0.224	0.151
		(0.191)	(0.205)	(0.207)	(0.217)
FEs: diagnosis		✓	✓	✓	✓
FEs: department		✓	✓	✓	✓
FEs: procedure		✓			
FEs: hospital		✓			
FEs: year		✓	✓		✓
FEs: month		✓	✓		
FEs: day-of-week		✓	✓	✓	✓
FEs: procedure×hospital			✓	✓	
FEs: year×month				✓	
FEs: procedure×hospital×month					✓

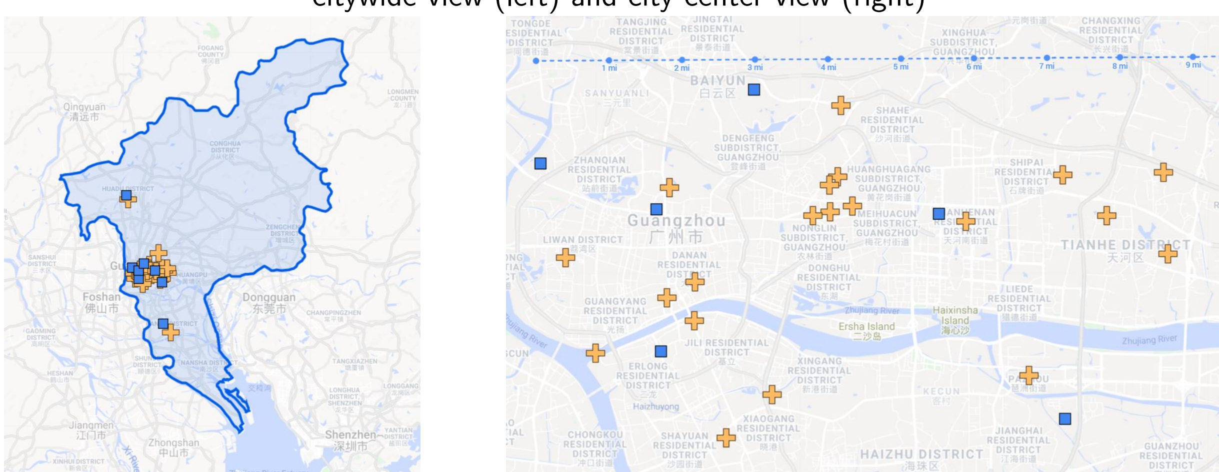
Notes: Each column reports a separate regression that allows the effect of $PM_{2.5}$ on hospital mortality to vary by patient groups. The outcome variable is an indicator for whether the patient died in hospital following the surgery, multiplied by 1,000 to increase readability. "High-risk" group consists of respiratory and neoplasm patients aged over 60. "Mean mortality" shows average hospital mortality rate among the two groups of patients. All regressions control additionally for individual characteristics including age in 5-year bins, gender indicator, marital status indicator, and an indicator for any history of allergy, and weather controls including daily average temperature in 10-degree Celsius bins, precipitation, and precipitation squared. Numbers of observations are 1,317,099 (column 1), 1,307,307 (columns 2 and 3), and 1,236,997 (column 4). *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Additional Figures and Tables

Figure A.1. Study Location

Panel A. City location

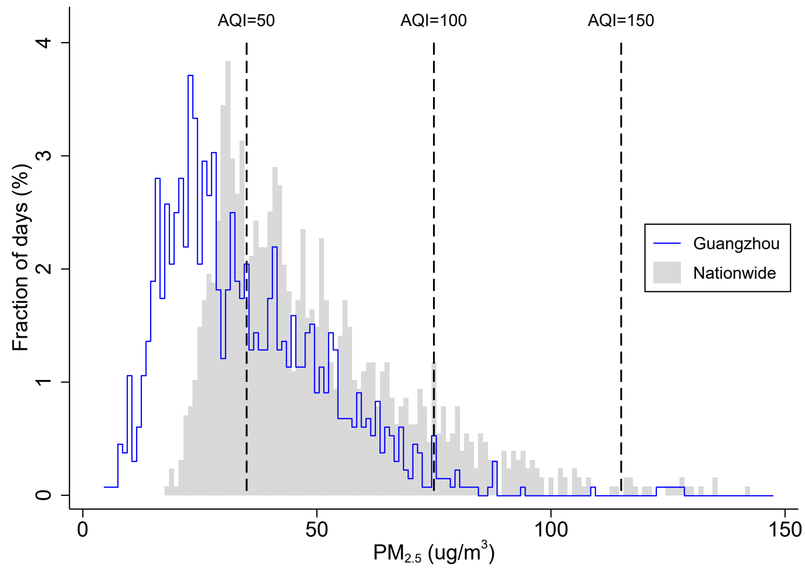
Panel B. Hospital and pollution monitor locations
citywide view (left) and city center view (right)



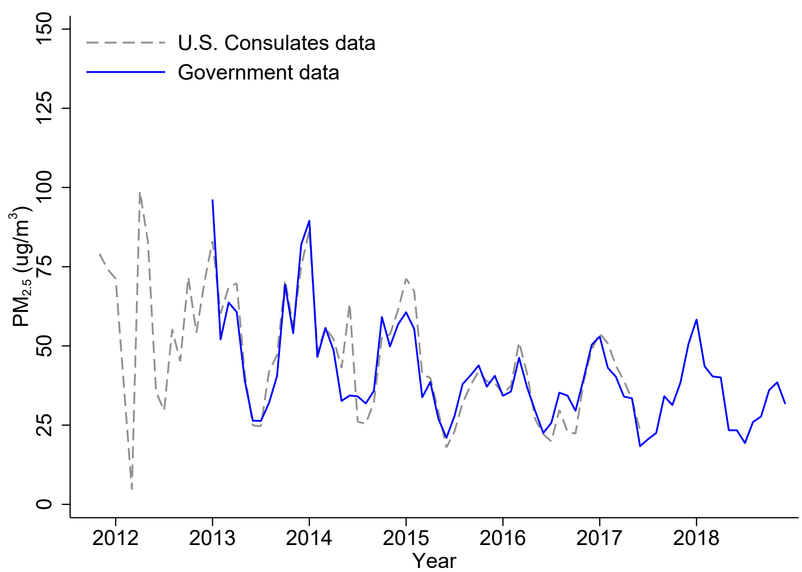
Notes: Panel A highlights the province of Guangdong (light blue) and the city of Guangzhou (dark blue). Panel B shows the location of hospitals (crosses) and air pollution monitors (squares) in our study sample.

Figure A.2. $PM_{2.5}$ Pollution Monitoring Data

Panel A. Distribution of daily $PM_{2.5}$, Guangzhou versus nationwide



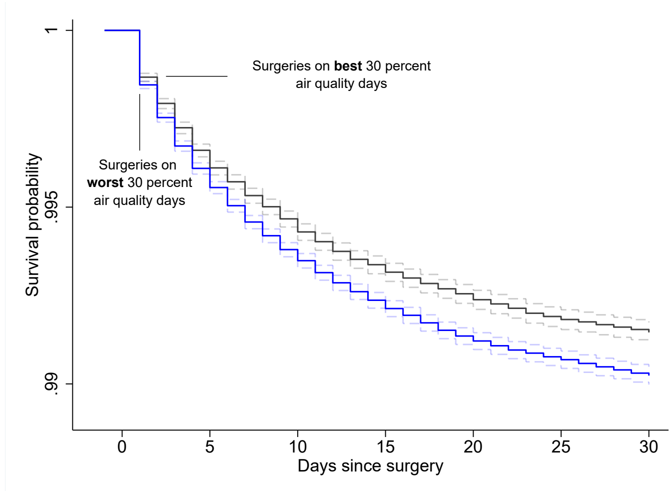
Panel B. Time series of monthly $PM_{2.5}$, government versus U.S. consulate data



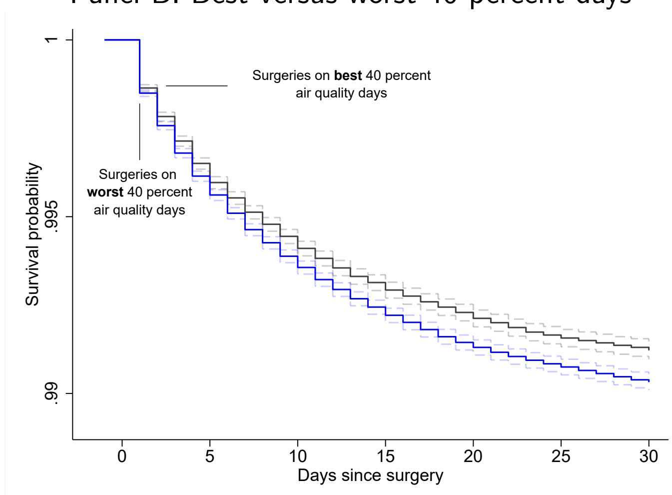
Notes: Panel A compares distribution of daily $PM_{2.5}$ in the city of Guangzhou and nationwide. Vertical dashed lines correspond to Air Quality Cutoffs for Good, Moderate, Unhealthy for Sensitive Groups, and Unhealthy. Panel B compares monthly $PM_{2.5}$ using data from the Chinese government and independent monitoring data from the U.S. consulate at Guangzhou.

Figure A.3. Patient Survival after Surgeries on High versus Low Pollution Days: Alternative Cutoffs

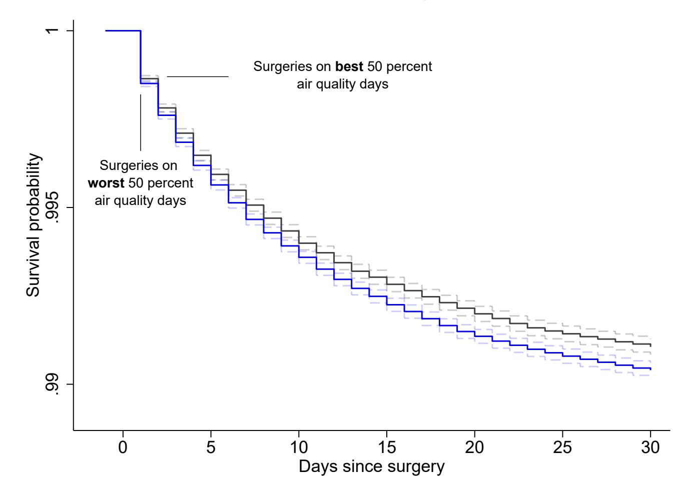
Panel A. Best versus worst 30 percent days



Panel B. Best versus worst 40 percent days

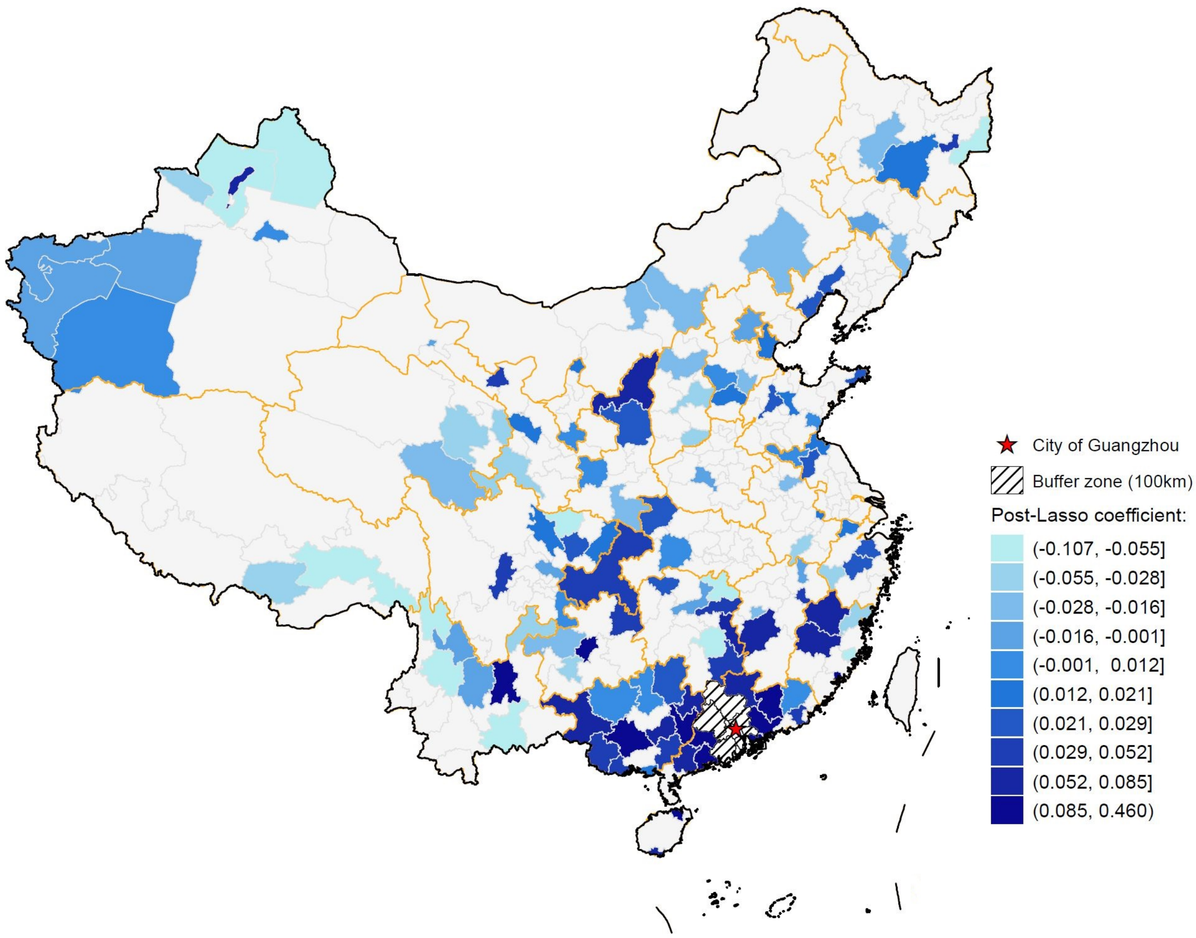


Panel C. Best versus worst 50 percent days (i.e., above versus below median)



Notes: This graph reports robustness of the Kaplan-Meier survival estimates with respect to alternative high versus low pollution day cutoffs.

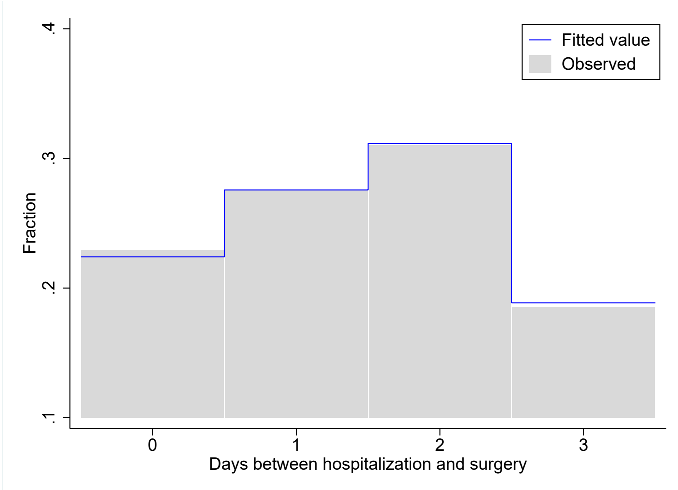
Figure A.4. Upwind Cities Selected by the "Zero-Stage" Lasso Regression



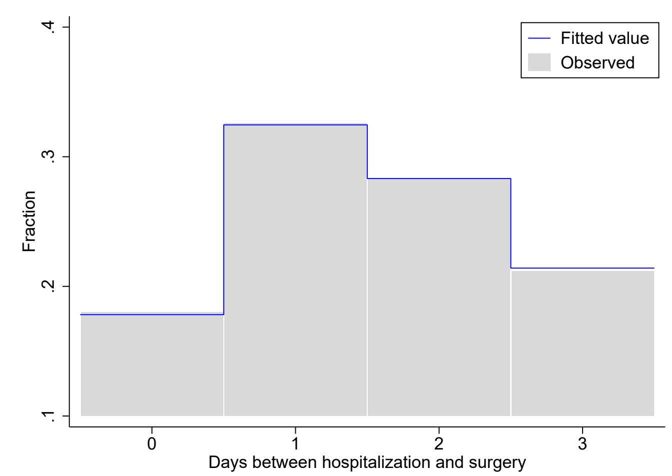
Notes: This map highlights 119 cities selected by a "zero-stage" Lasso regression of Guangzhou's daily $PM_{2.5}$ on all other 305 cities' upwind component vector $PM_{2.5}$. See text for details.

Figure A.5. Structural Models of Surgery Scheduling: Fitted versus Observed Schedules

Panel A. Respiratory patients



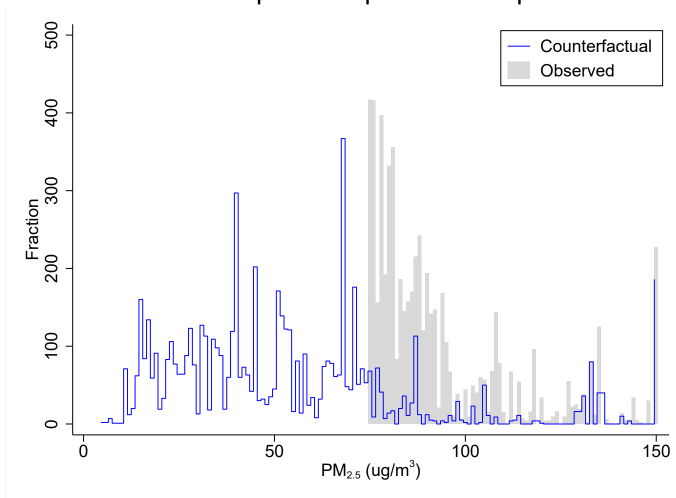
Panel B. Neoplasm patients



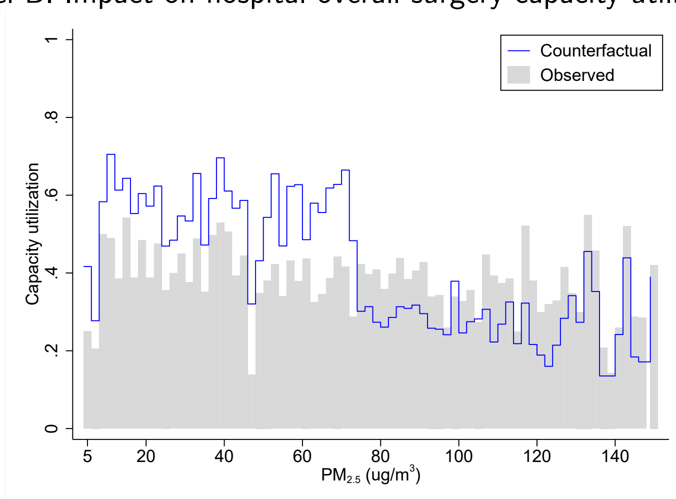
Notes: Samples restrict to patients aged over 60 and those scheduled to receive surgeries within three days of hospital admission.

Figure A.6. Counterfactual Surgery Scheduling that Internalizes Pollution Damages: Practical Example

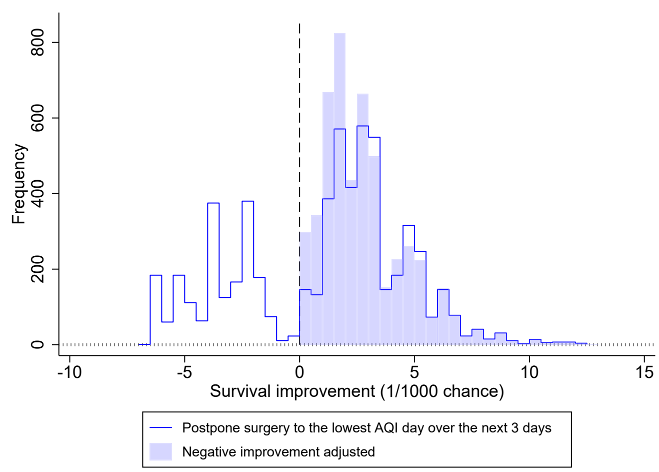
Panel A. Impact on pollution exposure



Panel B. Impact on hospital overall surgery capacity utilization



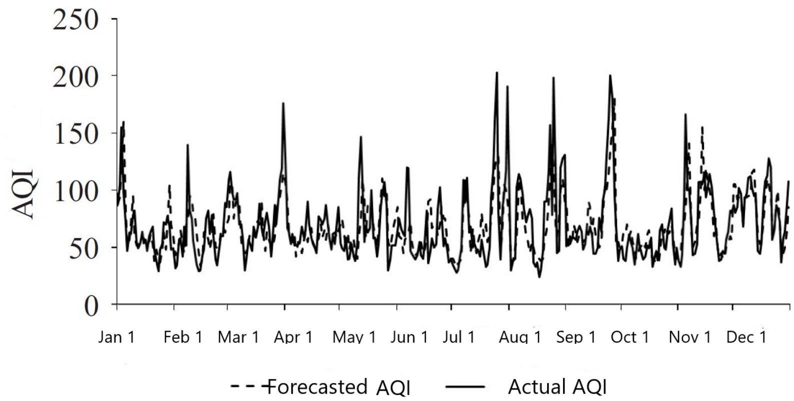
Panel C. Impact on post-surgery survival (switchers only)



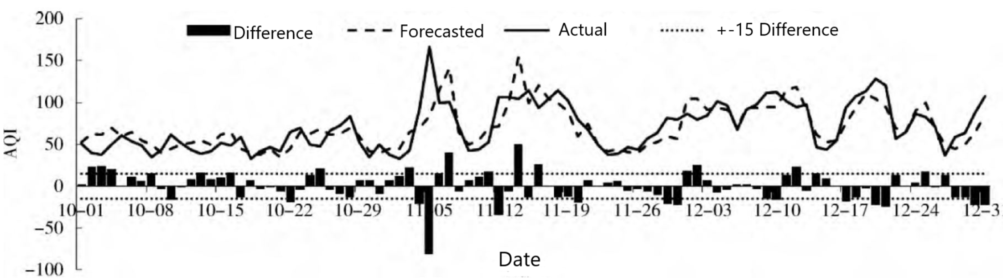
Notes: Panel A compares observed and counterfactual surgery profile's $PM_{2.5}$ distribution among the high-risk patient group. Panel B compares hospitals' daily overall surgery capacity utilization rates averaged by 1-ug/m^3 bins. We omit few observations for days above 80 mg/m3. Panel C plots the distribution of survival improvements among "switcher" patients whose counterfactual surgery day is different from the observed day.

Figure A.7. Forecasted versus Observed Air Quality Index in Guangzhou (Zhang et al., 2017, 2018)

Panel A. Year 2016



Panel B. October to December, 2016



Notes: These figures are taken from Zhang et al.(2017) and Zhang et al. (2018) respectively, with superimposed English translation. Panel A reports 24-hour-ahead forecasted (dashed line) and observed (solid line) Air Quality Index throughout the year of 2016. Panel B zooms in to October to December of 2016. Bars on panel B represent differences between observed and forecasted Air Quality Index values.

Table A.1. Surgery-Day Pollution and Patient Mortality: Robustness

	(1)	(2)	(3)	(4)
	Indep. var.: Log $PM_{2.5}$ concentration			
No patient/weather controls	0.311*	0.354**	0.443**	0.368**
	(0.155)	(0.159)	(0.162)	(0.176)
Add low-risk surgeries	0.226*	0.291**	0.328**	0.228*
	(0.110)	(0.115)	(0.119)	(0.126)
Drop admission-day surgeries	0.284	0.325*	0.361**	0.283
	(0.168)	(0.164)	(0.141)	(0.195)
Drop admission-day & next-two-day surgeries	0.341	0.430	0.447*	0.368
	(0.251)	(0.269)	(0.229)	(0.339)
Control for daily hospital admission volume	0.352**	0.357**	0.362**	0.366**
	(0.168)	(0.168)	(0.166)	(0.168)
Control for daily inpatient surgery volume	0.464**	0.465**	0.465**	0.470**
	(0.167)	(0.167)	(0.167)	(0.166)
FEs: diagnosis	✓	✓	✓	✓
FEs: department	✓	✓	✓	✓
FEs: procedure	✓			
FEs: hospital	✓			
FEs: year	✓	✓		✓
FEs: month	✓	✓		
FEs: day-of-week	✓	✓	✓	✓
FEs: procedure×hospital		✓	✓	
FEs: year×month			✓	
FEs: procedure×hospital×month				✓

Notes: Each cell reports a separate regression of a measure of post-surgery mortality on surgery-day pollution. Each mortality variable is an indicator for whether the patient died in hospital following k-day since surgery, multiplied by 1,000 to increase readability. Unless noted otherwise, all regressions control additionally for individual characteristics including age in 5-year bins, gender indicator, marital status indicator, and an indicator for any history of allergy, and weather controls including daily average temperature in 10-degree Celsius bins, precipitation, and precipitation squared. Numbers of observations are (from top to bottom rows) some 1.3 million, 2.1 million, 1.1 million, 0.6 million, 1.3 million, and 1.3 million. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Table A.2. Surgery-Day Pollution and Patient Mortality: Surgery Complexity Level

	(1)	(2)	(3)	(4)
	Dep. var.: Hospital mortality			
Log $PM_{2.5}$ × 1(level-1 operation - easiest)	0.814**	0.536*	0.601**	0.486
	(0.387)	(0.274)	(0.279)	(0.288)
Log $PM_{2.5}$ × 1(level-2 operation)	0.168	0.297	0.356	0.236
	(0.219)	(0.216)	(0.217)	(0.251)
Log $PM_{2.5}$ × 1(level-3 operation)	0.235	0.372*	0.434**	0.324
	(0.152)	(0.191)	(0.180)	(0.238)
Log $PM_{2.5}$ × 1(level-4 operation - hardest)	0.246	0.639***	0.704***	0.731**
	(0.195)	(0.220)	(0.187)	(0.324)
FEs: diagnosis	✓	✓	✓	✓
FEs: department	✓	✓	✓	✓
FEs: procedure	✓			
FEs: hospital	✓			
FEs: year	✓	✓		✓
FEs: month	✓	✓		
FEs: day-of-week	✓	✓	✓	✓
FEs: procedure×hospital		✓	✓	
FEs: year×month			✓	
FEs: procedure×hospital×month				✓

Notes: Each column reports a separate regression that allows the effect of $PM_{2.5}$ on hospital mortality to vary by the surgery's reported complexity level. The outcome variable is an indicator for whether the patient died in hospital following the surgery, multiplied by 1,000 to increase readability. All regressions control additionally for individual characteristics including age in 5-year bins, gender indicator, marital status indicator, and an indicator for any history of allergy, and weather controls including daily average temperature in 10-degree Celsius bins, precipitation, and precipitation squared. Numbers of observations are 1,317,105 (column 1), 1,307,313 (columns 2 and 3), and 1,237,003 (column 4). *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Table A.3. Surgery-Day Pollution and Patient Mortality: Diagnosis Categories

	(1)	(2)	(3)	(4)
	Dep. var.: Hospital mortality			
Log $PM_{2.5}$ × 1(infectious)	3.389*	3.547*	3.593*	2.985
	(1.963)	(1.945)	(1.942)	(2.228)
Log $PM_{2.5}$ × 1(neoplasms)	0.814	0.908*	0.962**	0.913
	(0.491)	(0.477)	(0.452)	(0.554)
Log $PM_{2.5}$ × 1(blood)	-2.107	-2.335*	-2.310*	-2.046
	(1.265)	(1.236)	(1.233)	(1.464)
Log $PM_{2.5}$ × 1(metabolic)	-0.773	-0.570	-0.523	-0.565
	(1.641)	(1.639)	(1.624)	(2.012)
Log $PM_{2.5}$ × 1(mental)	-0.756	-0.758	-0.676	-0.681
	(0.800)	(0.775)	(0.768)	(0.813)
Log $PM_{2.5}$ × 1(nervous)	1.014	0.488	0.537	1.177
	(1.112)	(1.079)	(1.091)	(1.256)
Log $PM_{2.5}$ × 1(eye)	1.204	1.071	1.109	1.878
	(2.581)	(2.457)	(2.467)	(2.306)
Log $PM_{2.5}$ × 1(ear)	-0.440	0.352	0.480	0.415
	(0.620)	(0.536)	(0.556)	(0.913)
Log $PM_{2.5}$ × 1(circulatory)	0.320	0.443	0.496	0.430
	(0.591)	(0.584)	(0.573)	(0.686)
Log $PM_{2.5}$ × 1(respiratory)	3.883*	4.059**	4.098**	3.889*
	(2.014)	(1.812)	(1.812)	(1.964)
Log $PM_{2.5}$ × 1(digestive)	0.137	0.231	0.271	0.306
	(0.299)	(0.274)	(0.277)	(0.399)
Log $PM_{2.5}$ × 1(skin)	0.435	0.703	0.755	0.774
	(0.812)	(0.866)	(0.891)	(1.018)
Log $PM_{2.5}$ × 1(musculoskeletal)	-0.466	-0.324	-0.283	-0.465
	(0.390)	(0.345)	(0.346)	(0.457)
Log $PM_{2.5}$ × 1(genitourinary)	-0.646*	-0.578	-0.522	-0.548
	(0.337)	(0.344)	(0.349)	(0.391)
Log $PM_{2.5}$ × 1(childbirth)	-0.520	-0.680	-0.606	-3.888
	(1.578)	(2.043)	(2.046)	(3.007)
Log $PM_{2.5}$ × 1(perinatal)	1.630	3.090	3.136	0.043
	(3.371)	(3.382)	(3.411)	(5.037)
Log $PM_{2.5}$ × 1(congenital)	-0.139	-0.051	0.009	0.279
	(0.373)	(0.346)	(0.384)	(0.529)
Log $PM_{2.5}$ × 1(laboratory)	-0.086	0.074	0.097	1.377
	(2.609)	(2.692)	(2.716)	(3.030)
Log $PM_{2.5}$ × 1(injury)	0.211	0.368	0.419	-0.381
	(0.719)	(0.781)	(0.770)	(1.199)
Log $PM_{2.5}$ × 1(health services)	-0.028	-0.335	-0.288	-0.388
	(0.298)	(0.385)	(0.386)	(0.411)
FEs: diagnosis	✓	✓	✓	✓
FEs: department	✓	✓	✓	✓
FEs: procedure	✓			
FEs: hospital	✓			
FEs: year	✓	✓		✓
FEs: month	✓	✓		
FEs: day-of-week	✓	✓	✓	✓
FEs: procedure×hospital		✓	✓	
FEs: year×month			✓	
FEs: procedure×hospital×month				✓

Notes: Each column reports a separate regression that allows the effect of $PM_{2.5}$ on hospital mortality to vary by patient groups. The outcome variable is an indicator for whether the patient died in hospital following the surgery, multiplied by 1,000 to increase readability. All regressions control additionally for individual characteristics including age in 5-year bins, gender indicator, marital status indicator, and an indicator for any history of allergy, and weather controls including daily average temperature in 10-degree Celsius bins, precipitation, and precipitation squared. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Table A.4. Surgery-Day Pollution and Patient Mortality: Elderly Patients

	(1)	(2)	(3)	(4)
	Dep. var.: Hospital mortality			
Log $PM_{2.5}$ × 1(< 60 years old)	0.048	0.159	0.223	0.149
	(0.164)	(0.184)	(0.181)	(0.194)
Log $PM_{2.5}$ × 1(≥ 60 years old)	1.024**	0.971***	1.032***	0.881**
	(0.381)	(0.313)	(0.303)	(0.379)
FEs: diagnosis	✓	✓	✓	✓
FEs: department	✓	✓	✓	✓
FEs: procedure	✓			
FEs: hospital	✓			
FEs: year	✓	✓		✓
FEs: month	✓	✓		
FEs: day-of-week	✓	✓	✓	✓
FEs: procedure×hospital		✓	✓	
FEs: year×month			✓	
FEs: procedure×hospital×month				✓

Notes: Each column reports a separate regression that allows the effect of $PM_{2.5}$ on hospital mortality to vary by patient groups. The outcome variable is an indicator for whether the patient died in hospital following the surgery, multiplied by 1,000 to increase readability. All regressions control additionally for individual characteristics including age in 5-year bins, gender indicator, marital status indicator, and an indicator for any history of allergy, and weather controls including daily average temperature in 10-degree Celsius bins, precipitation, and precipitation squared. Numbers of observations are 1,317,099 (column 1), 1,307,307 (columns 2 and 3), and 1,236,997 (column 4). *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Table A.5. Structural Parameter Estimates

	(1)	(2)	(3)	(4)	(5)
	α	d_0	d_1	d_2	$\varphi_{workday}$
Respiratory patients	0.2301	0.0927	0.3315	0.4991	-0.0600
	(0.0141)	(0.0164)	(0.0155)	(0.0147)	(0.0778)
Neoplasm patients	0.3013	-0.3735	0.2826	0.2694	0.2556
	(0.0079)	(0.0075)	(0.0065)	(0.0065)	(0.0433)

Notes: This table reports parameter estimates in our structural analysis. Sample restricts to patients aged over 60. Patients are separated by main diagnosis categories. Standard errors are in parentheses.