(Re)scheduling Pollution Exposure: The Case of Surgery Schedules*

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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 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.

While air pollution is often seen as an *outdoor* problem, indoor exposure may be surprisingly high in many contexts. Modern surgery rooms use high-efficiency filtration technologies to reduce contamination of air to extremely low levels (Mangram et al., 1999; American Institute of Architects, 2001; Chinn and Sehulster, 2003). However, the general hospital indoor environment – unlike a dedicated surgery room – does not have elaborate filtration systems that prevent the penetration of air pollution from outdoor. In fact, hospitals sometimes *prefer* to have wards open to the outside air to help control infection. Our review of available studies on hospital wards air quality suggests a high indoor-outdoor fine particulate matter ($PM_{2.5}$) concentration ratio of up to 0.8 (Section 2.1). Concerns about such exposure may be particularly high for patients who are ill, and those who are recovering from a recent procedure. 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.

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.

[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.

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.

We begin with 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. Our empirical approach 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. Consistent with this view, we find no evidence of any significant differences in patients' observable characteristics across surgeries on high versus low pollution days, which include 17 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.

Next, we present two key features of the surgery-day pollution effect. First, we find that higher post-surgery mortality is particularly associated with high pollution on the day of the surgery – as opposed to pollution exposure that occurs prior to hospital admission, between the admission and the surgery, or after the date of the procedure. That is, the surgery day represents a "critical window" during which the patients are particularly vulnerable to pollution exposure, while similar $PM_{2.5}$ changes on other days have no similar effect on the same patients. Second, 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, high-risk group (6 percent of all patients) composed patients who are over age 60 and are being treated for lung diseases or cancers. These results are the basis of our rescheduling analysis: for a small group of high-risk patients, modifying surgery schedules to lower pollution days may provide significant health gains.

Why is surgery-day pollution particularly bad for patient survival? We provide a survey of the clinical literature that documents $PM_{2.5}$ as an agent that can carry microbes, cause surgical contaminations, and reduce defense function of the body. The patient might be left susceptible to exogenous infections from in-hospital exposure to pollution especially during the first 24-48 hour window when bacteria fighters (such as neutrophils) haven't reached peak population, when the typical surgical wound hasn't yet closed, and when the patient's immune functions might have been suppressed by the surgery itself and anesthesia medications (Salo, 1992; Mangram et al., 1999). Guided by the clinical knowledge, we examine the effect of surgery-day air quality on markers of surgical site infections, finding an increase of infection incidents as pollution level rises. We also find evidence that high surgery-day pollution is linked to in-hospital development of cardiorespiratory complications. Both pieces of evidence corroborate our baseline finding of a particularly pernicious impact of high pollution on the surgery day, and suggest that patients are likely exposed to significant pollution in wards.

On the other hand, we find limited empirical evidence in support of an impact of air pollution on physicians. Because physicians typically follow a rotating work schedule in which a surgeon spends most of her/his prescheduled "operation day" in the operating theater, their pollution exposure during the day is expected to be low. We first show, through balancing tests, that there is no detectable difference in surgical complexity levels across days with high versus low pollution, suggesting a lack of sorting of the type of procedures done as a function of pollution levels. Next, we 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, as we mentioned above, 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. We caution that, 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 directly assess the role of physician treatment style or experience (Gong, 2018; Molitor, 2018). These said, some of our empirical specifications do include granular controls such as hospital by procedure fixed effects that should absorb meaningful variations in overall treatment styles across physicians.

Building on the empirical findings, we present a stylized structural exercise to examine whether hospitals can better internalize the adverse effect of pollution to improve patient survival. We first build and parameterize a 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 such as personnel and administrative costs. 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. 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). This is likely a significant mortality improvement, as the estimated effect size is of same order of magnitude with those from well-known surgical quality improvement programs such as the WHO's Safe Surgery Saves Lives Program and the Veteran Affair's National Surgical Quality Improvement Program. 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.

The disease burden of ambient air pollution has been widely studied (e.g., Dominici, Greenstone, and Sunstein, 2014; Cohen et al., 2017; Landrigan et al., 2018), with a particular focus on the effect of outdoor air pollution on health of the general population.[2] However, few studies have considered the relevance of pollution in the context of healthcare delivery. In this paper, we show that air pollution is a direct determinant of post-surgery survival, one of the most important indicators of the quality of surgical care.[3] Beyond documenting the health effect, we show that the pre-scheduled nature of pollution exposure in the surgical contexts allows for avoidance of unnecessary exposure among the most vulnerable. This is a natural extension of the idea that adaptation can occur through avoidance (Cutter and Neidell, 2009; Neidell, 2009; Graff Zivin and Neidell, 2009), and here we provide a concrete illustration on how better scheduling practices may provide such adaptation in an institutional context. Our study is also related to a nascent literature on the importance of indoor air pollution exposure (Duflo, Hanna, and Greenstone, 2008; Jeuland, Pattanayak, and Bluffstone, 2015; Stafford, 2015; Barron and Torero, 2017; Greenstone, Lee, and Sahai, 2021).

We hope the analysis framework of our paper can be applied to other economic scheduling problems in which outcomes depend on a predictable, future hazard, and modifications of the schedule could provide large health gains, especially among those that are vulnerable. For example, forecasts of both high levels of pollution and temperature extremes are becoming increasingly accurate; these conditions are known to damage the health of at-risk groups, such as infants, the elderly, and those with medical conditions (e.g., Barreca et al., 2016; Knittel, Miller, and Sanders, 2016; Deryugina et al., 2019; Heutel, Miller, and Molitor, 2021); and to reduce human capital, such as cognition and worker productivity (Graff Zivin and Neidell, 2012; Burke, Hsiang, and Miguel, 2015). This suggests that potential gains from strategically scheduling activities on a relatively short horizon when possible (e.g., for outdoor recreational activities, school tests, and agriculture and construction work with leeway on the timing of the most physically demanding activities).

This paper also connects to several strands of literature beyond economics. 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 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.

[2] In particular, this paper is related to the economics literature on the mortality burden of $PM_{2.5}$ exposure (Chay, Dobkin, and Greenstone, 2003; Currie and Neidell, 2005; Moretti and Neidell, 2011; Knittel, Miller, and Sanders, 2016; Ebenstein et al., 2017; Deschenes, Greenstone, and Shapiro, 2017; Deryugina et al., 2019; Anderson, 2020).
[3] 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

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 (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).[4]

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).[5] 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,[6] 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),

[4] 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.

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

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

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.[7] 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 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 evidence is consistent with our conversations with surgeons who reported a lack of pollution filtration in the hospital ward area (Section 5.2). 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

[7] 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.

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.[8] 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.[9] 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.

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. Our data do not contain any cause-of-death information.[10]

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

[8] 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).
[9] WS 445.10-2014 Basic Dataset of Electronic Medical Record—Part 10: Home Page of Inpatient Medical Records.
[10] Death reporting is administered under the Death Certificate Program, which is a separate program that is not directly linked to inpatient records.

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 3.5.

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).[11] 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

[11] 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).

assign each hospital the pollution readings from the nearest monitor. 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 5.

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 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.[12] 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 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.[13]

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 to 3.5 when we present the corresponding results.

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

[13] 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

$$Y_{jkt} = \alpha + \beta \cdot \text{Pollution}_{jkt} + \alpha_{jk} + \alpha_t + \varepsilon_{jkt}$$

in which the regression links the fraction of patients died in hospital k following a procedure j done on date t (Y_{jkt}) to the surgery-day pollution (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.

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 – 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). Our IV estimation yield similar findings with the OLS results. We defer readers to Appendix B.1 for details of the IV analysis.

Overall, our effect estimates are robust to a variety of specification checks; many augmented models we estimate (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 $Pollution_i$ 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 Appendix Table A.2, we also report a distributed leads and lags model which shows similar evidence that pollution on the surgery day, rather than its leads and lags, leads to higher post-surgery mortality.

In a 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.

Measurement Errors, "True" Exposure Effects, and Observed Effects. Before proceeding, we discuss two sources of measurement errors that pertain specifically to our setting, and we offer several thoughts on how they might affect the interpretation of our estimates.

One view is that the "ideal" effect estimate should reflect the true *exposure effect* of pollution on surgery patients' subsequent death – that is, the effect of $PM_{2.5}$ 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* $PM_{2.5}$. Outdoor $PM_{2.5}$ is likely higher than indoor levels, which may bias the effect estimate downward relative to the true exposure effect of $PM_{2.5}$. That said, our review of prior studies on hospital air quality (Section 2.1) suggests that indoor air pollution correlates strongly with outdoor levels, and that the indoor-to-outdoor ratio is near one for some Chinese hospitals, suggesting the magnitude of this measurement error may not be substantial.

Second, our effect estimate only reflects the impact of surgery-day pollution up to the point of hospital discharge. The effect of this measurement error on our estimates is *ex ante* ambiguous: on one hand, we do not observe deaths after patients leave the hospital, which may lead us to understate the total effect of pollution; on the other hand, sicker patients may stay longer in hospital so that the pool of patients that remain in our data have higher average mortality rates compared to those already discharged; this may lead us to overstate the true effect of pollution. One piece of empirical pattern we see, however, is that the curvature of the survival curve flattens out over time, and so does the adverse effect of pollution (Figure 1 and Table 2). This pattern does not support the view that the health composition of longer-staying patients is substantially worse. We provide a more detailed analysis of this issue in Appendix B.2.

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. Empirically, we find the IV estimates are larger but of the same order of magnitude compared to the OLS estimates, suggesting the magnitude of the measurement errors is unlikely to be large. We provide more discussion on these points in Section 3.3 and 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).[14] 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 largest 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 position that changing existing scheduling practices to offer targeted patients surgeries on days with lower levels of pollution may benefit patients' overall survival chances.[15]

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, 14-day, 28-day, and overall in-hospital deaths ("hospital

[14] 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.

[15] In Appendix Table A.8, we further show that these patient characteristics are sufficiently predictive of mortality so that they can rule out a meaningful imbalance in terms of predicted mortality for surgeries done on high versus low pollution days.

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.[16] 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.

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. In Appendix Table A.2, we further report distributed lag models in which we include current, lag, as well as lead terms pollution simultaneously in the regression specification. We show that, once condition on current (surgery-day) pollution, lagged pollution has no additional effects on patient mortality.

[16] 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 $PM_{2.5.}$

We note that the estimates of pollution effects for alternative exposure windows in Figure 2, panel A are quite noisily estimated, and are not statistically distinguishable from the surgery-day pollution effect. 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.

Lagged Effect of Pollution versus the Effect of Lagged Pollution. An alternative, perhaps more concise way to summarize our finding is that (a) the patient mortality effect is driven by the lagged effect of pollution that occurs on the surgery day (Figure 1; Table 2), and (b) there is no evidence of an effect of lagged pollution – that is, the pollution that occurs on days following the surgery – on patient mortality (Figure 2; Appendix Table A.2). Note that (a) is much expected as the vast majority of surgical patient deaths occur *after* the operation (Spence et al., 2019); it is also consistent with the prior literature that suggests transient changes in air pollution can have lagged effect on health which manifests over time (e.g., Schwartz, 2000; Deryugina et al., 2019). (b) is a key finding of our paper: days with high $PM_{2.5}$ are linked to a substantial reduction of survival among patients who undergo surgeries *on that day*, while $PM_{2.5}$ 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.

Our finding that surgery-day pollution is particularly pernicious for patient mortality (compared with pollution on days before or after the surgery day) is important for interpreting the underlying mechanisms. In the next section, we examine institutional knowledge on both physician and patient exposure to pollution during the surgery day, and discuss potential medical underpinnings such as the interaction between pollution, wound healing, immune functions, and infectious responses.

3.4 Mechanisms: Clinical Literature

Why does high pollution on the surgery day reduce subsequent survival? We begin with a survey of the clinical literature on the potential pathways. We present related econometric evidence in Section 3.5.

Patients are Exposed to Indoor $PM_{2.5}$ in Hospital Wards. As we mentioned in Section 2.1, $PM_{2.5}$ features a strong outdoor-to-indoor penetration (e.g., Hanley et al., 1994; Riley et al., 2002; Chen and Zhao, 2011). While operation rooms are equipped with laminar air filtration systems that can reduce contamination of air to extremely low levels, most hospital wards do not have elaborate filtration systems that prevent the penetration of air pollution from outdoors. Field measurement in hospitals is scarce, but our review of available studies on hospital wards air quality suggests a high indoor-outdoor $PM_{2.5}$ concentration ratio of up to 0.8 (Cyrys et al., 2004; Zheng, 2014).

$PM_{2.5}$ can Carry Microbes. $PM_{2.5}$ can stay suspended in air for an extended period of time; it is a mixture of substances, including sulfates, nitrates, organic compounds, and metals, as well as biological components – often known as bioaerosols – including bacteria, viruses, and fungi that make up to 25% of atmospheric aerosol (Jaenicke, 2005). The role of $PM_{2.5}$ as an agent to carry bacteria, microbial allergens and pathogens has been documented in the environmental science literature, including studies that examine heavy pollution in Chinese cities (e.g., Cao et al., 2014; Li et al., 2015; Du et al., 2018). $PM_{2.5}$ particles have also been shown to be able to carry viruses such as SARS-CoV-2 (Nor et al., 2021). Inhalation of virus-laden particulates is therefore another potential pathway for PM exposure to cause diseases.

Airborne Bacteria is an Important Source of Surgical Contamination. Airborne bacteria can be deposited near the surgical site and can cause surgical site infections. Since the 1970s, airborne bacteria in the operating room have been recognized as an important source of surgical site infection (Gryska and O'Dea, 1970; Charnley, 1972; Lidwell et al., 1982). One study finds over 35-fold difference in bacterial counts near surgical wounds for operations randomly allocated to be conducted in a conventionally ventilated room rather than in a laminar-flow room; it also finds that the most important and consistent route of contamination was airborne (Whyte, Hodgson, and Tinkler, 1982). This line of study has prompted the (now standard) use of high-efficiency air-filtration technologies in operating rooms.

We are unaware of a clinical literature that examines the effect of *in-ward* pollution or airborne bacteria exposure. Our interview with several surgeons in China suggests that the lack of evidence is likely related to the fact that surgical wounds are covered after the surgery, which is believed to protect the wound from exogenous infections. As we discuss further below, however, our empirical analysis finds evidence of an increase of surgical site infection as pollution levels rise on the day of surgery. Given that patients are not exposed to pollution in operating rooms, this evidence points to the possibility that exposure outside of the surgical theater after the procedure itself may be the culprit. We believe this is an area that merits future study.

Pollution Exposure Reduces Defense Functions of the Body. Beyond bacterial contamination, exposure to $PM_{2.5}$ has been shown to weaken the body's defense functions. Most of the existing evidence focuses on the respiratory system, where there is abundant evidence from human, animal, and in-vitro experiments that particulate matter exposure depresses defense mechanisms of the respiratory tracts and the lungs. $PM_{2.5}$ exposure impacts the barrier functions of the airway epithelium, often known as the "first line of host defense" against pathogens, by impairing the bronchial mucociliary system, which is responsible for removing most foreign bodies inhaled into the lungs (Houtmeyers et al., 1999), and by triggering epithelial cells to release inflammatory cytokines that promote inflammation (Quay et al., 1997). Pollution exposure has also been linked to alterations of the respiratory tract microecology by causing a decline of indigenous microflora in the upper respiratory tract, an important component of the respiratory tract's natural immune function (Xiao et al., 2013). In the lung, pollution exposure can impact immune cells, such as alveolar macrophages, reducing their ability to fight against pathogen invasion. Animal models have shown that $PM_{2.5}$ exposure can prime the lungs for increased susceptibility to pathogens by causing a reduction in the ability of macrophages to produce antimicrobial oxidants (Yang et al., 2001; Sigaud et al., 2007; Zhao et al., 2014).

Besides direct respiratory channels, particles of ultra-fine size may also penetrate the air-blood barrier and enter the bloodstream (Cristaldi et al., 2022). A direct consequence of this penetration is the harm to functionalities of the heart (Mills et al., 2009; Shah et al., 2013). Many other observational studies have linked $PM_{2.5}$ exposure to non-cardiorespiratory diseases that potentially tie back to the air-to-blood penetration. For example, fine particles accumulate in brain tissues (Maher et al., 2016), and exposure to $PM_{2.5}$ has been shown to cause damages to and diseases of the brain (Chen et al., 2017; Bishop, Ketcham, and Kuminoff, 2018). Black carbon particles that originate from combustion sources have been detected in human placentae (Bove et al., 2019) and in the urine of healthy children (Saenen et al., 2017). Though evidence on the exact clinical underpinnings in these contexts are less abundant than that in respiratory studies, the proliferation of evidence does strongly suggest the ability of particulates to breach the body's defense mechanisms and ubiquitously reach various organ systems.

Patients' Immune Functions are Weakened after Surgeries. A final factor to consider in our study context is that the patients might be particularly vulnerable to environmental shocks immediately following surgeries. The typical surgical wound takes one to two days to close after the operation (Mangram et al., 1999); the first 24 hours following a surgery is critical, as bacteria fighters such as neutrophils typically reach peak population 24 to 48 hours after the initial injury. Surgery itself and anesthesia medications (which typically stay in the body for up to 24 hours) could suppress immune functions, making the patients more prone to exogenous infections (Salo, 1992).

The remaining uncertainty therefore boils down to whether post-surgery patients are indeed exposed to significant pollution in hospital wards, and whether such exposure really matters for healing of the wound and other aspects of patient's health. We provide more econometric evidence next.

3.5 Mechanisms: Econometric Evidence

Surgery-Day Pollution and Surgical Site Infection. A natural interpretation of our findings is that surgical patients are not shielded from air pollution after all. One way to test this hypothesis is to look at intermediate outcomes that are well known to be directly influenced by pollution exposure. Our survey in Section 3.4 suggests that airborne bacteria in the operating room was recognized as an important source of surgical site infection (Gryska and O'Dea, 1970; Charnley, 1972; Lidwell et al., 1982), which prompted the use of high-efficiency air-filtration technologies in operating room (Mangram et al., 1999; American Institute of Architects, 2001; Chinn and Sehulster, 2003). We show with our data that such pollution-infection link holds in the *post-surgery* context as well: Appendix Table A.3, panel A suggests an increase of incidents of infection as outdoor pollution level rises. Panel B shows the impact of pollution appears to be larger among patients with diabetes and hypertension, consistent with prior findings that these chronic conditions amplify the impact of air pollution on inflammatory responses (Dubowsky et al., 2006). Panel C suggests the same heterogeneity pattern holds for hospital mortality as well. Panel D further estimates heterogeneous mortality effects by the presence of non-healing surgical wounds. While surgery-day pollution does not change the incidents of non-healing wounds per se (Table 3), we find that the mortality effects of pollution exposure are stronger for patients who exhibit wound complications.

In-Hospital Development of Cardiorespiratory Complications. Another way of testing whether surgical patients are indeed exposed to pollution is to look for evidence of in-hospital development of cardiorespiratory complications. Appendix B.3 reports an exercise that examines whether surgery-day $PM_{2.5}$ increases cardiovascular and respiratory complications measured at discharge. The evidence suggests that surgery-day pollution does not lead to an overall increase of cardiorespiratory complications. However, exposure to pollution triggers a significant increase in the development of the most life-threatening complications, defined as those associated with the top-20 (about 20%) highest in-hospital mortality rate (Appendix Table A.4). These results resonate with growing evidence that air pollution has disproportionate effects across the vulnerability spectrum. For example, Deryugina et al. (2019) shows that the causal effect of air pollution on elderly mortality in the United States concentrates among 20 percent of the elderly population that are most vulnerable, indicated by the presence of pre-existing chronic medical conditions. Our findings suggest that pollution's impact is concentrated; for a small group of surgical patients, pollution triggers highly dangerous cardiorespiratory complications.

High-Risk Patient Groups. Our survey of the literature suggests that certain patient groups may be particularly vulnerable to impact of pollution, such as those with weakened respiratory functionality, or those with compromised immune system in general. Table 4 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.[17] Table 4 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.

Other Evidence. Our data also 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. In Appendix Figure A.4, we show that the surgery-day pollution and patient mortality

[17] 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.9 and A.10. 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%, 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 those who have recently undergone endoscopic procedures.

relationship exhibits a concave dose response, where 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). In Appendix Table A.5, we further use a multivariate regression framework to document that $PM_{2.5}$ remains a robust and statistically significant predictor of post-surgery survival when controlling for variation in other air pollutants including ozone (O_3), nitrogen dioxide (NO_2), sulfur dioxide (SO_2), and carbon monoxide (CO). This finding echoes a strand of the epidemiology and economics 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; Deryugina et al., 2019). 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.

3.6 Physician Effects

Finally, we explore the possibility that similar patients are *treated* differently on days with varying pollution levels. **One possibility** is physician sorting that causes physician or surgical quality to differ across days with different levels of pollution – that is, if physicians are assigned to patients based on some factors that correlate outdoor pollution, or if hospital rules allow physicians to manipulate which patients they treat (e.g., complexity of cases) and when the surgeries are performed.

We provide two sets of evidence against physician sorting in practice. First, in many large hospitals, surgeons' work schedules follow predetermined rotation where each surgeon has "operation days" when he or she occupies an operating room for the whole day and conduct multiple surgeries for his or her patients. Such arrangement is intended to increase efficiency and reduce operating room traffic and contamination. Our conversations with several surgeons confirm the prevalence of this practice (Section 5.2). Due to the prescheduled nature of surgeon rotation and the works involved in surgery preparation, it is difficult for surgeons to swap surgery schedules on short notice.

Second, our balancing tests in Table 1 shows that there is no detectable difference in surgical complexity levels across days with high versus low pollution. Table 1 further tests if surgery-day pollution can predict the number of "similar" procedures being done for other patients at the same hospital on the same day, where "similar" procedures are defined by procedures of the same complexity level, the same disease type, or just the exact same procedure. Because there are only a fixed set of surgeons conducting similar surgeries on a given day, we use the number of similar procedures done to (inversely) proxy for the duration of the procedure. Table 1 shows that surgery-day pollution is not explanatory of these measures, suggesting a lack of surgery scheduling sorting based on the time duration of the procedure.

Another possibility is that pollution exposure reduces the same physician's ability to perform cognitively demanding operation tasks.[18] 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.[19]

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 infections especially for larger incisions (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.[20] 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."

Table 3 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.6, 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.

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[18] 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.

[19] This said, because of the practice of surgeon rotation we mentioned earlier, surgeons spend almost the whole day in operating room on the surgery day (Section 5.2), and therefore even cumulative exposure is expected to be low.

[20] The companion dataset of this paper contains a list of ICD-10 codes we use to identify medical errors.

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).

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:

$$u_{id} = -\alpha h_{id} + \lambda_{id} + e_{id} \qquad (2)$$

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 (e.g., the personnel costs of scheduling certain surgeries), 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 $Pollution$ term is omitted because we assume hospitals do not internalize the mortality hazard of pollution in the baseline model.[21] 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:

$$\lambda_{id} = \sum_g \beta_g \cdot 1(d_{id} = g) + \varphi_{workday} \quad (3)$$

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. $\varphi_{workday}$ may also capture differences in physician availability between weekdays and weekends, which matters for hospitals' cost considerations.

Patient Pool. 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 $d \in \{0,1,2,3\}$.[22] 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.

[21] Our conversation with surgeons suggests status quo surgery scheduling does not internalize pollution information. We report more details in Section 5.2

[22] Appendix Figure A.8 and Appendix Table A.2 extends the placebo test in Figure 2 by checking the leads and lags effect of pollution within finer, plus or minus three days exposure windows. We find that, conditional on surgery-day pollution, the pollution on the surrounding windows has no additional impact on patient mortality.

Section 5.1 presents evidence on short-term accuracy of pollution forecast in Guangzhou. 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 and Counterfactual Analysis. Our estimation therefore boils down to a maximum likelihood estimation of parameters $\theta = (\alpha, \beta_0, \beta_1, \beta_2, \varphi_{workday})$. With these parameter estimates, we can 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 $\mathrm{Pollution}$ term "switched on", which generates a counterfactual surgery schedule $\{d'_i\}_{i=1}^{N}$. We include more details about the parameter estimation, diagnostics, and counterfactual analysis in Appendix B.4.

Figure 3 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 3 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 3, 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 3 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 Compare Effect Sizes to Existing Surgical Improvement Programs

From Sections 4.1, the mortality benefit of the rescheduling exercises among the switchers is about **1.6 deaths per 1,000 patients**. How large is such effect size? To put numbers in context, here we briefly review two surgical quality improvement programs that are widely studied in the medical literature.

The Safe Surgery Saves Lives Program. In 2008, the World Health Organization (WHO) published a surgical safety checklist identifying multiple recommended practices to ensure the safety of surgical patients (WHO, 2008). Some example entries of the checklist include "Before induction of anesthesia, members of the team orally confirm that the patient has verified his or her identity, the surgical site and procedure, and consent"; "Before skin incision, the entire team orally confirms that prophylactic antibiotics have been administered ≤ 60 min before incision is made or that antibiotics are not indicated"; "Before the patient leaves the operating room, nurse reviews items aloud with the team that the needle, sponge, and instrument counts are complete (or not applicable)". Haynes et al. (2009) and de Vries et al. (2010) studied a pilot intervention program that instituted such a checklist in eight hospitals of different countries. Results indicate patient rate of death decreased from 1.5 percent (i.e., 15 deaths per 1,000 patients) before the program to 0.8 percent after the program. The absolute mortality gain is thus about **7 deaths per 1,000 patients**.

The National Surgical Quality Improvement Program. The National Surgical Quality Improvement Program (NSQIP) was developed in the 1990s by the Veterans Health Affairs to improve surgical outcomes in the Veterans Affairs (VA) Health System. The program involves annual reports of patient characteristics and outcomes, peer conducted site visits, among other measures, and is shown to have led to substantial improvements in surgical quality (Ingraham et al., 2010). NSQIP is since introduced to non-VA settings. Hall et al. (2009) studied the American College of Surgeons NSQIP program that was implemented in 118 private-sector hospitals since 2004. The results indicate a mean improvement of observed/expected mortality by 0.174 based on an average mortality rate of about 1.8 percent, which works to about an absolute mortality gain of **3 deaths per 1,000 patients**.

In terms of absolute mortality reduction, the pollution rescheduling exercise generates an effect size with same order of magnitude compared to these well-known surgical quality improvement programs. Because we study a high-risk patient group with higher baseline mortality rate (about 38 deaths per 1,000 patients), the relative effect size of pollution rescheduling can be up to an order of magnitude smaller than these programs (e.g., 4.2 percent mortality improvement in Section 4.1, compared to about 47 percent improvement in the Safe Surgery Saves Lives Program).

5. Discussion and Conclusion

5.1 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 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.[23] 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.6 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 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. In Appendix Figure A.7, we repeat the main rescheduling exercise of Figure 3 but infuse the true $PM_{2.5}$ with mean-zero, normally-distributed errors $N(0, \sigma)$. We show that more accurate forecasts (smaller σ) lead to better patient survival through rescheduling.

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

[23] 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.

errors or endogenous physician schedule sorting, 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.

Using Air Purifiers in Hospital Wards. An alternative policy solution is to reduce in-hospital pollution exposure through the use of air purifiers. Appendix B.6 reports a back-of-envelope calculation of the cost of installing and operating high efficiency particulate air (HEPA) filtration technologies in Guangzhou's hospital wards, and the expected health benefits from reduced surgery mortality. Our analysis suggests that the cost of HEPA is relatively small compared to the potential benefits: the mortality benefits measured in value of statistical life (VSL) can justify the cost so long as the HEPA system can achieve a 40% $PM_{2.5}$ removal rate on the surgery day for high-risk patients. Our survey of the relevant literature suggests that, in real-world settings, HEPA's $PM_{2.5}$ removal rate ranges between 20% and 60%; the efficacy rate hinges on proper use, positioning, maintenance, and insulation of the room from outdoor air. Overall, our calculation suggests that using HEPA air filtration in hospital wards may be a promising, cost-effective strategy to improve patient health. Of course, whether the adoption of air filtration technology is indeed a feasible and effective policy solution in practice warrants further research.

5.2 Comments of Practitioners

We communicated our results to surgeons that we reached out to through www.haodf.com, a widely used online platform for virtual healthcare delivery in China. We use these opportunities to both ask surgeons about existing practices – for example, whether hospitals incorporate pollution information in scheduling surgeries – and, without informing them much details about our study, their perspectives on potential mechanisms underlying pollution-related post-operative mortality. We were able to talk to five senior surgeons working in big hospitals. Notably, the answers we obtain from these surgeons are highly correlated, and below we summarize our main takeaways from the conversations. An English translation of full Q&A logs are reported in Appendix C.

First, surgeons' schedules follow predetermined rotation. Typically, an on-call surgeon is in charge of an operating room for the whole day and conduct multiple surgeries; except for emergency cases, other surgeons wishing to use the operating room must wait until the on-call surgeon has finished all scheduled operations of the day. Such arrangement is intended to increase efficiency and reduce operating room traffic and contamination. These comments are supportive of our view that the patient mortality effect we identify in this paper may not be primarily explained by a physician channel: surgeon's exposure to pollution on the surgery day is low as she/he spend most of the day in the operating room; the prescheduled, rotation arrangement also limits the potential for physician sorting as a function of ambient pollution levels (Section 3.6).

Second, all five surgeons reported that (expectation of) air pollution is not considered in surgery scheduling. This is consistent with the evidence from the balancing tests on patient and surgery characteristics (Table 1) and lends further confidence to our modeling assumption that pollution conditions are not incorporated in status quo scheduling practices (Section 4.1).

Third, surgeons are confident that pollution exposure in the operation room is low, but they recognize possible exposure in hospital wards. When asked about whether air pollution damage is internalized in surgical scheduling, all five surgeons mentioned the use of laminar air filter system in operation rooms (Section 2.1) which provides strong protection against pollution exposure. Surgeons recognize that the general ward area does not have pollution filtration. In contrast with in-surgery exposure, the awareness/salience of in-ward pollution exposure might be low: one surgeon said it is just not an issue that she/he thinks explicitly about.

Fourth, surgeons have mixed opinions on the most likely force underlying the mortality response to surgery-day pollution. Regarding infections, several surgeons consider local (wound) infection to be unlikely, citing the practice of wound covering after surgery and the formation of epithelium within 24 to 48 hours; others regard the opportunity of infections to rise generally with higher levels of pollution. A more agreed view, however, is that post-operative deaths are more related to patient characteristics and pre-existing conditions such as the diabetes and coronary artery diseases; one surgeon commented that mortality responses are likely to rise as pollution causes deterioration of health especially when patient's immune system is weak right following the surgical procedure.

5.3 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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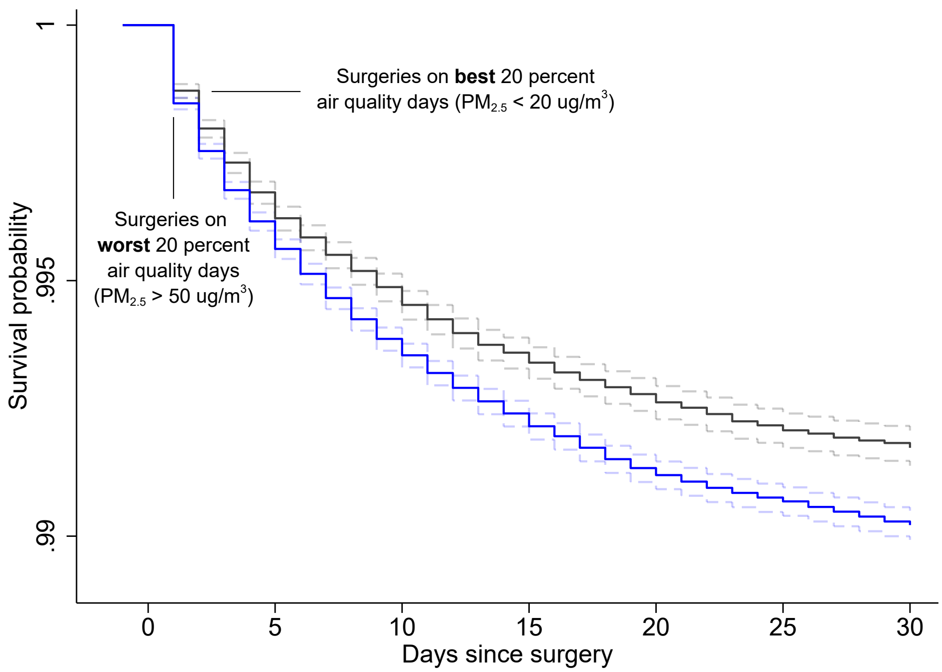
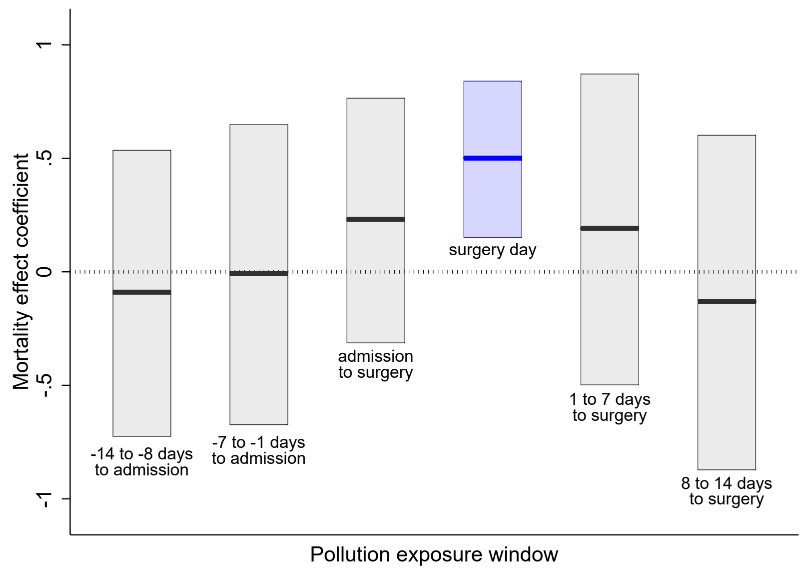
Figure 1. Patient Survival after Surgeries on High versus Low Pollution Days



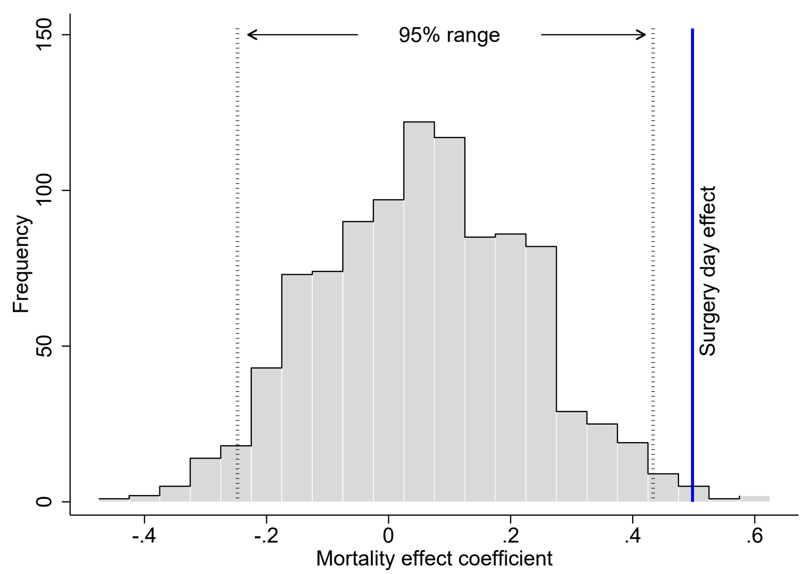
Notes: This graph reports Kaplan-Meier survival estimates and 95% confidence intervals among surgeries conducted on days with the worst quintile $PM_{2.5}$ concentration (>50 ug/m^3) and days with the best quintile $PM_{2.5}$ concentration (<20 ug/m^3).

Figure 2. The Importance of Surgery-Day Pollution Exposure

Panel A. Alternative exposure windows



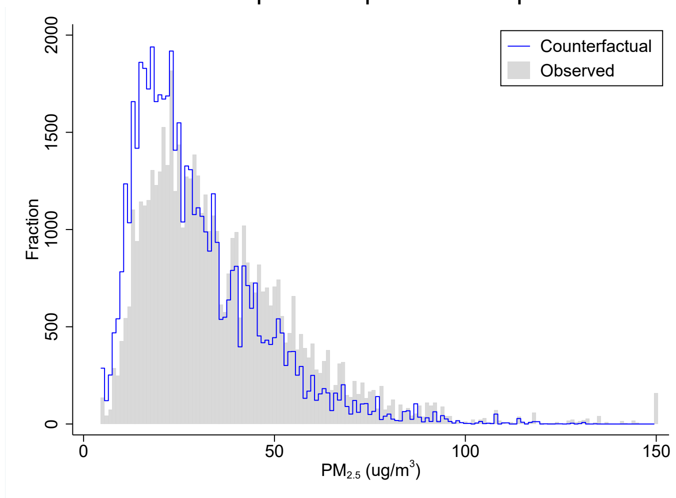
Panel B. "Placebo" exposure windows (1,000 randomized scenarios)



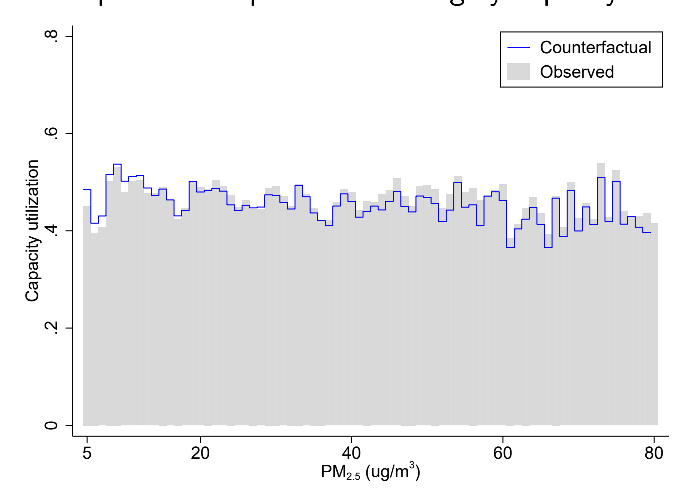
Notes: Panel A reports the alternative estimates of pollution effect when alternative exposure windows are used. Bars represent 95% confidence intervals. Panel B compares the observed, surgery-day pollution effect with the placebo distribution of effect sizes generated from 1,000 placebo estimation using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

Figure 3. Counterfactual Surgery Scheduling that Internalizes Pollution Damages

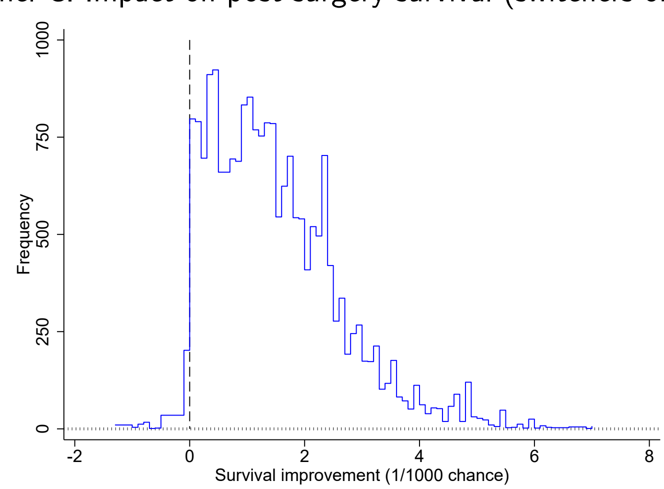
Panel A. Impact on pollution exposure



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 (28.337)	21.331 (29.190)	51.694* (28.049)	38.744 (29.745)
1(male)	mean = 563.3	-0.788 (0.996)	-0.664 (1.027)	-0.349 (0.887)	-0.888 (1.152)
1(married)	mean = 802.8	1.490** (0.621)	1.505** (0.623)	1.970*** (0.651)	1.640*** (0.638)
1(allergy history)	mean = 51.0	0.456 (0.421)	0.565 (0.450)	0.564 (0.541)	0.772 (0.525)
Days of delay	mean = 3,944	-6.435 (14.563)	-6.502 (13.819)	-33.683** (14.002)	-13.556 (13.005)
Number of procedures	mean = 2,050	-0.849 (2.106)	-2.682 (2.458)	-0.577 (1.822)	-0.368 (1.953)
1(general anesthesia)	mean = 491.5	-3.866 (3.953)	-3.722 (4.188)	-3.993* (1.949)	-2.657 (3.165)
1(level-1 operation - easiest)	mean = 283.7	-0.453 (3.038)	-0.477 (2.922)	2.318 (3.250)	0.237 (3.504)
1(level-2 operation)	mean = 321.5	1.325 (2.737)	0.663 (2.812)	-0.632 (2.654)	0.639 (2.689)
1(level-3 operation)	mean = 250.9	0.298 (1.021)	0.375 (0.988)	-0.562 (0.819)	-0.380 (0.916)
1(level-4 operation - hardest)	mean = 144.0	-1.170 (0.776)	-0.561 (0.660)	-1.124** (0.512)	-0.496 (0.633)
N(same procedures being done)	mean=3,204	-3.387 (11.77)	-5.160 (12.91)	13.53 (10.39)	5.934 (11.11)
N(same-type procedures being done)	mean=18,487	-132.45 (99.59)	-123.07 (100.43)	-86.12 (99.76)	-114.82 (95.87)
N(same-complexity procedures being done)	mean=34,163	-100.53 (256.41)	-143.99 (245.74)	44.82 (167.15)	97.72 (193.68)
1(insurance program: City Workers)	mean = 416.1	-0.110 (2.001)	0.263 (1.884)	-0.487 (1.430)	0.206 (1.672)
1(insurance program: New Rural Cooperative)	mean = 61.7	1.289 (0.821)	0.831 (0.751)	0.742 (0.827)	0.600 (0.754)
1(insurance program: none)	mean = 295.0	0.135 (1.155)	0.498 (1.251)	0.377 (0.812)	0.320 (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)
14-day mortality	mean = 8.791	0.241*	0.303**	0.286**	0.257*
		(0.139)	(0.145)	(0.133)	(0.135)
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 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 4. 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					✓

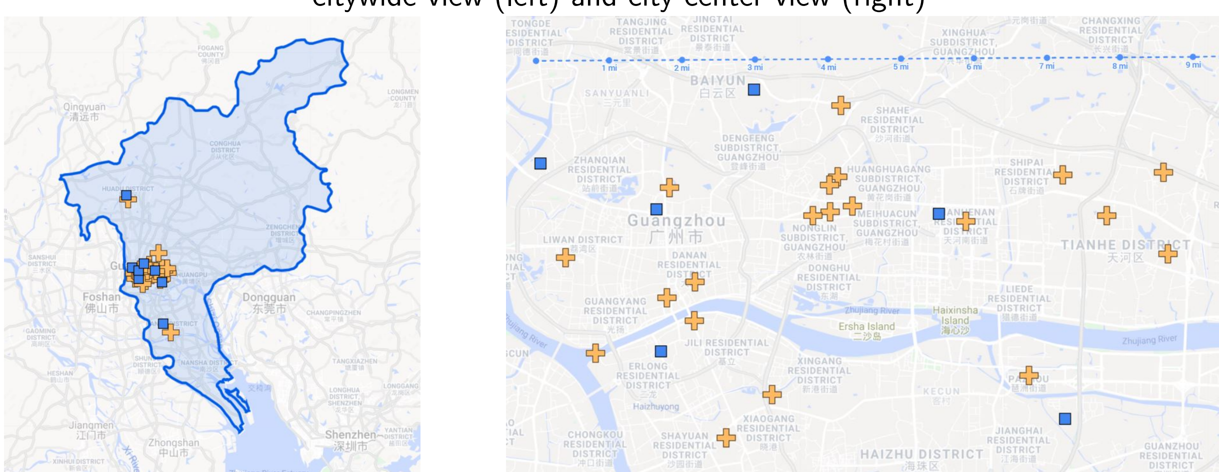
Notes: Each column reports a separate regression that allows the effect of $PM_{2.5}$ on hospital mortality to vary by patient groups. The outcome variable is an indicator for whether the patient died in hospital following the surgery, multiplied by 1,000 to increase readability. "High-risk" group consists 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). *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Appendix A. Additional Figures and Tables

Figure A.1. Study Location

Panel A. City location

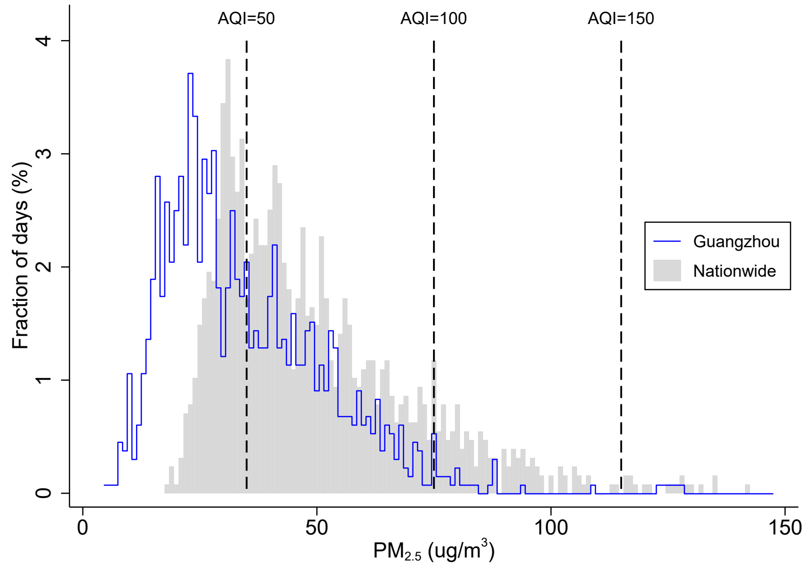
Panel B. Hospital and pollution monitor locations
citywide view (left) and city center view (right)



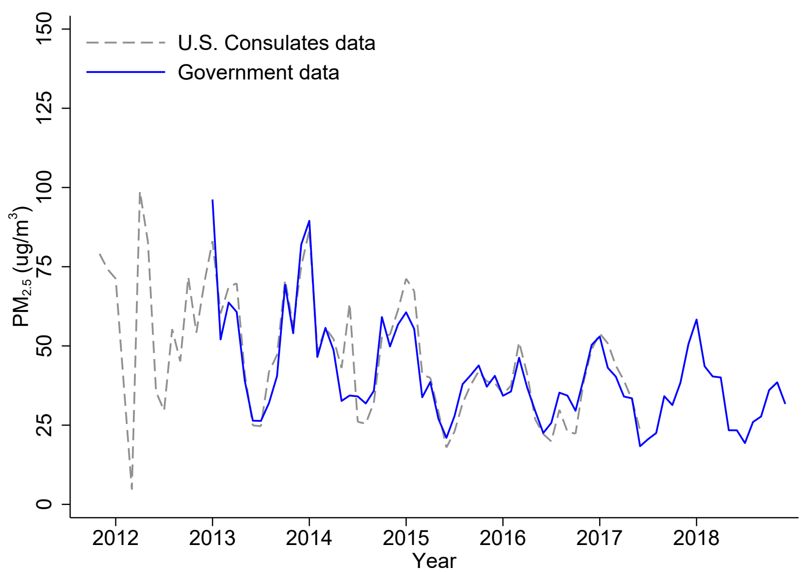
Notes: Panel A highlights the province of Guangdong (light blue) and the city of Guangzhou (dark blue). Panel B shows the location of hospitals (crosses) and air pollution monitors (squares) in our study sample.

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

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



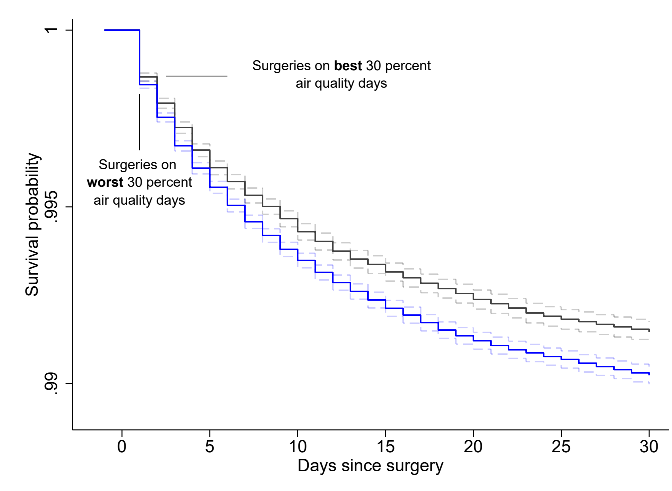
Panel B. Time series of monthly $PM_{2.5}$, government versus U.S. consulate data



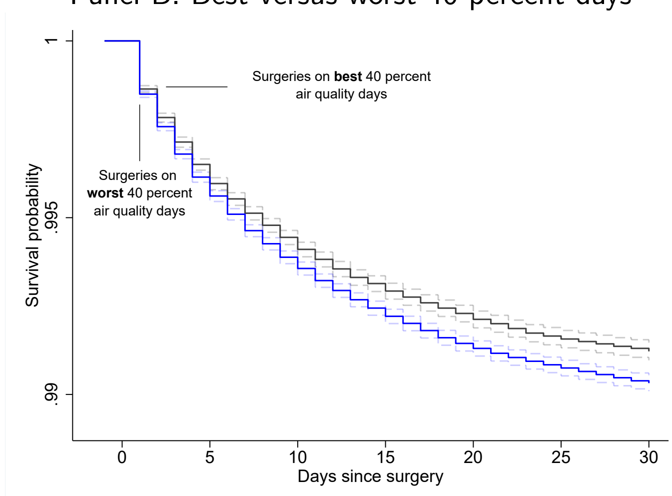
Notes: Panel A compares distribution of daily $PM_{2.5}$ in the city of Guangzhou and nationwide. Vertical dashed lines correspond to Air Quality Cutoffs for Good, Moderate, Unhealthy for Sensitive Groups, and Unhealthy. Panel B compares monthly $PM_{2.5}$ using data from the Chinese government and independent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

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

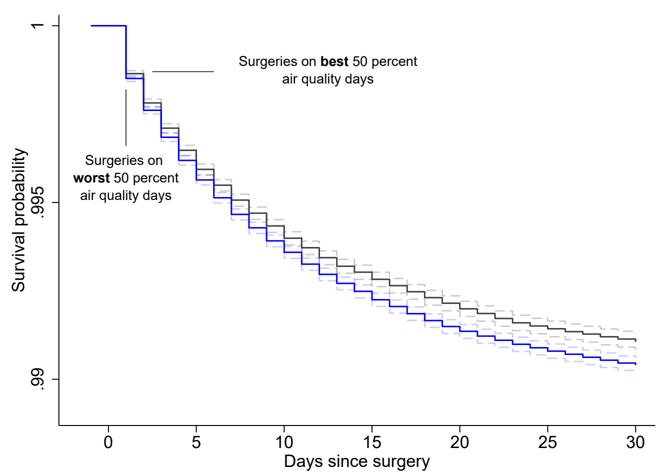
Panel A. Best versus worst 30 percent days



Panel B. Best versus worst 40 percent days

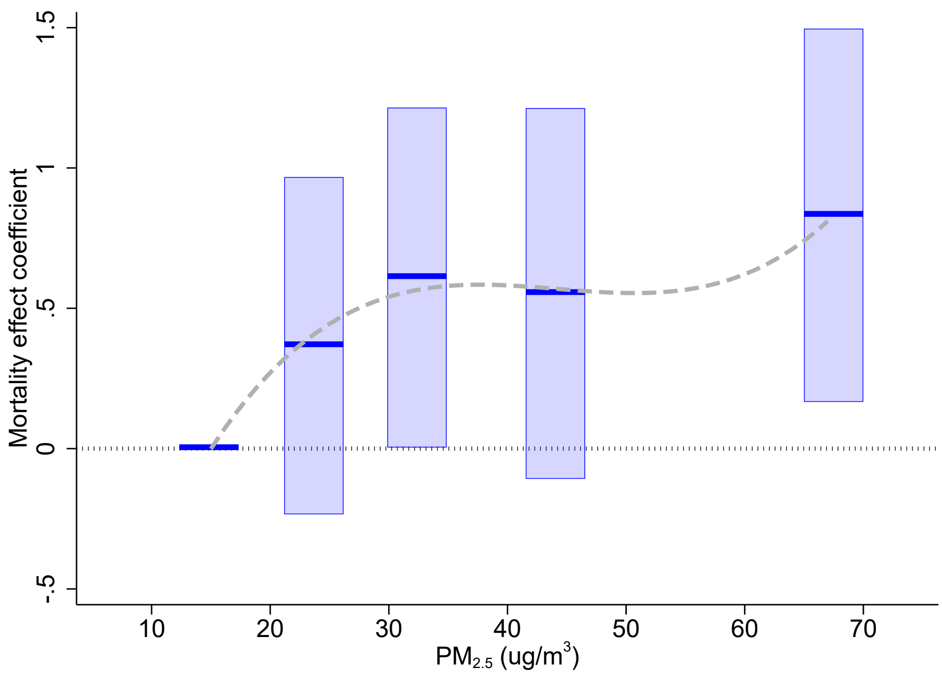


Panel C. Best versus worst 50 percent days (i.e., above versus below median)



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

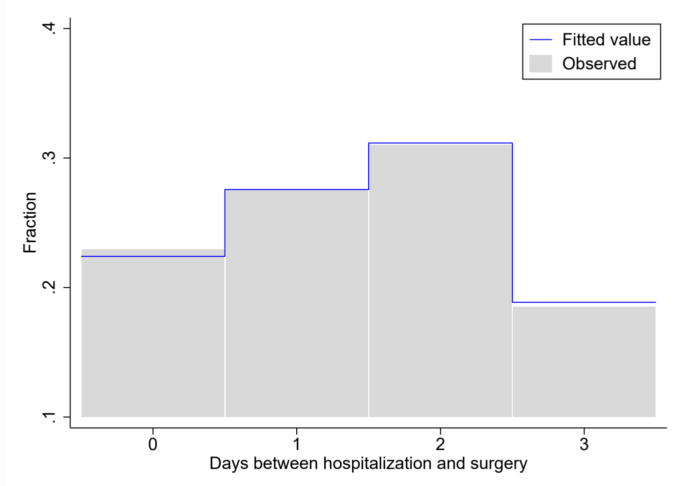
Figure A.4. Concentration Response of Surgery-Day Pollution



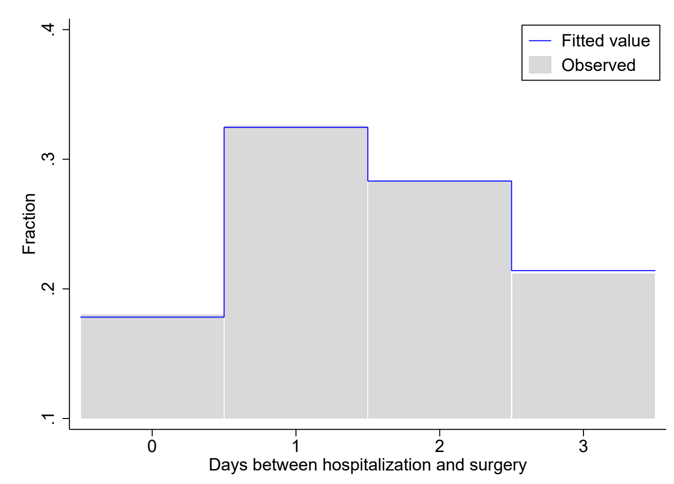
Notes: This graph reports the effect of surgery-day $PM_{2.5}$ on post-surgery mortality by quintile bins. Bars represent 95% confidence intervals. The first pollution quintile bin is the reference category. Dashed line shows a cubic fit.

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

Panel A. Respiratory patients



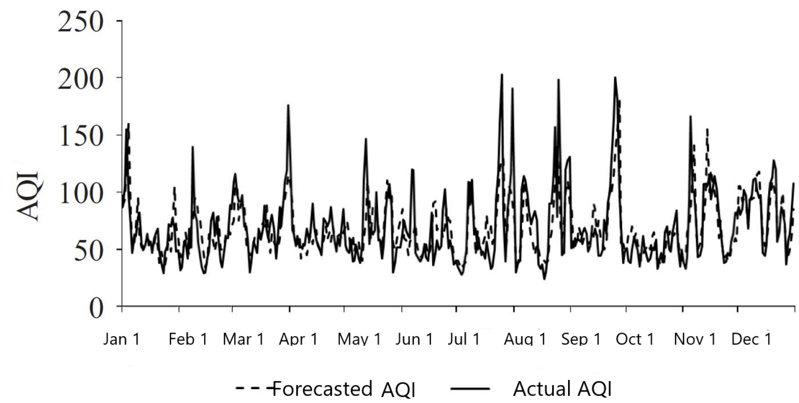
Panel B. Neoplasm patients



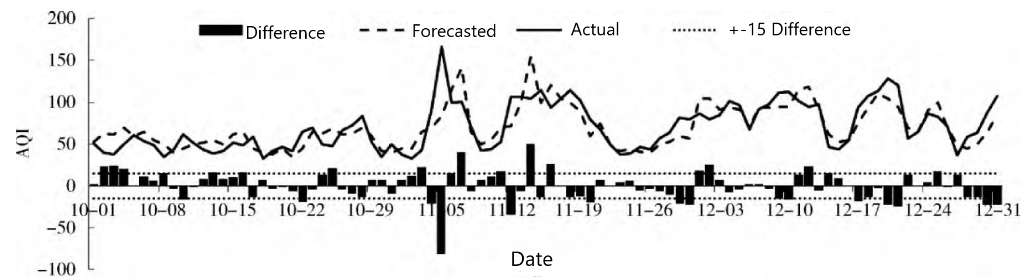
Notes: Samples restrict to patients aged over 60 and those scheduled to receive surgeries within three days of hospital admission.

Figure A.6. Forecasted versus Observed Air Quality Index in Guangzhou (Zhang et al., 2017, 2018)

Panel A. Year 2016

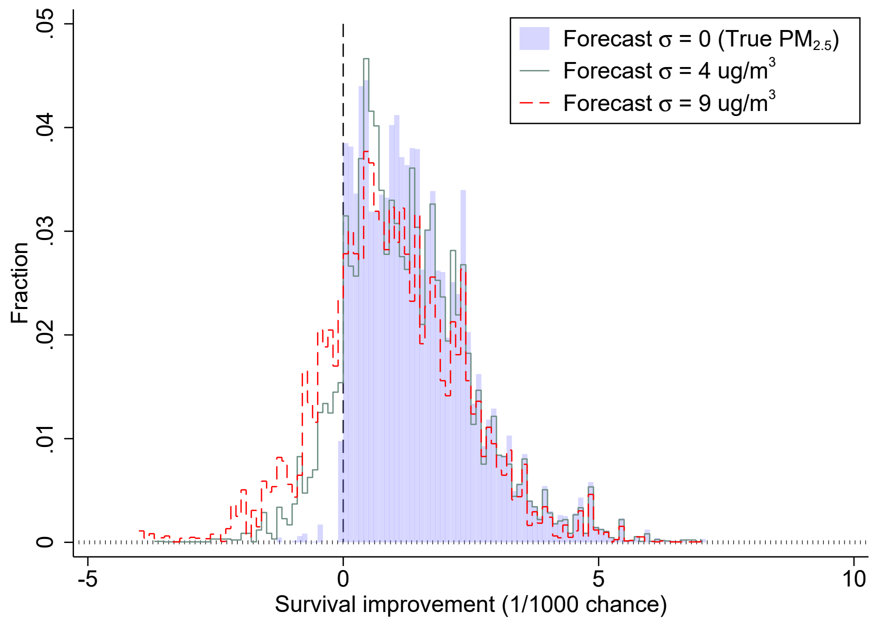


Panel B. October to December, 2016



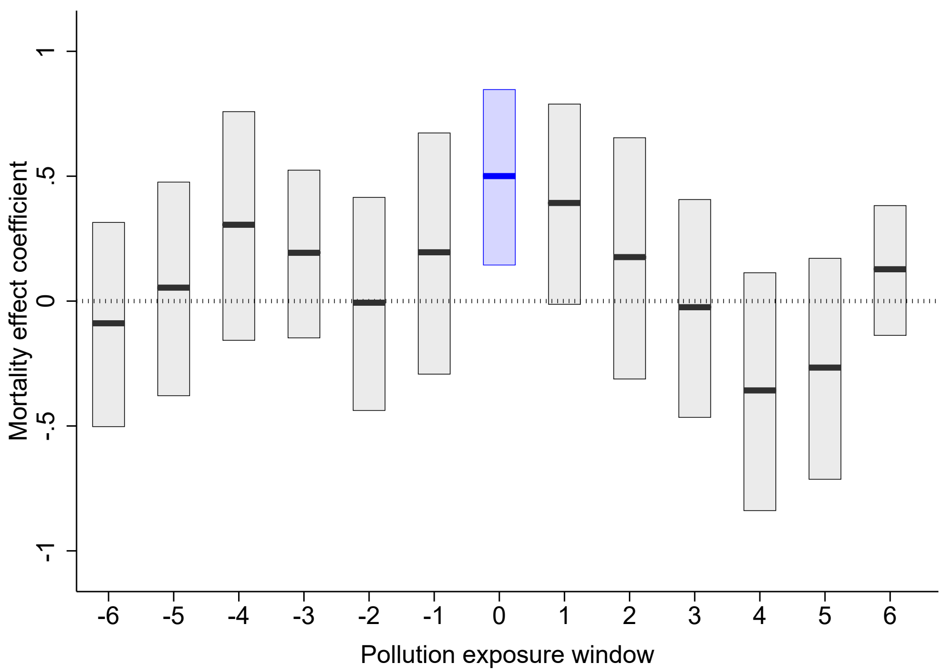
Notes: These figures are taken from Zhang et al.(2017) and Zhang et al. (2018) respectively, with superimposed English translation. Panel A reports 24-hour-ahead forecasted (dashed line) and observed (solid line) Air Quality Index throughout the year of 2016. Panel B zooms in to October to December of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

Figure A.7. Pollution Forecasting Accuracy and Patient Survival Improvement



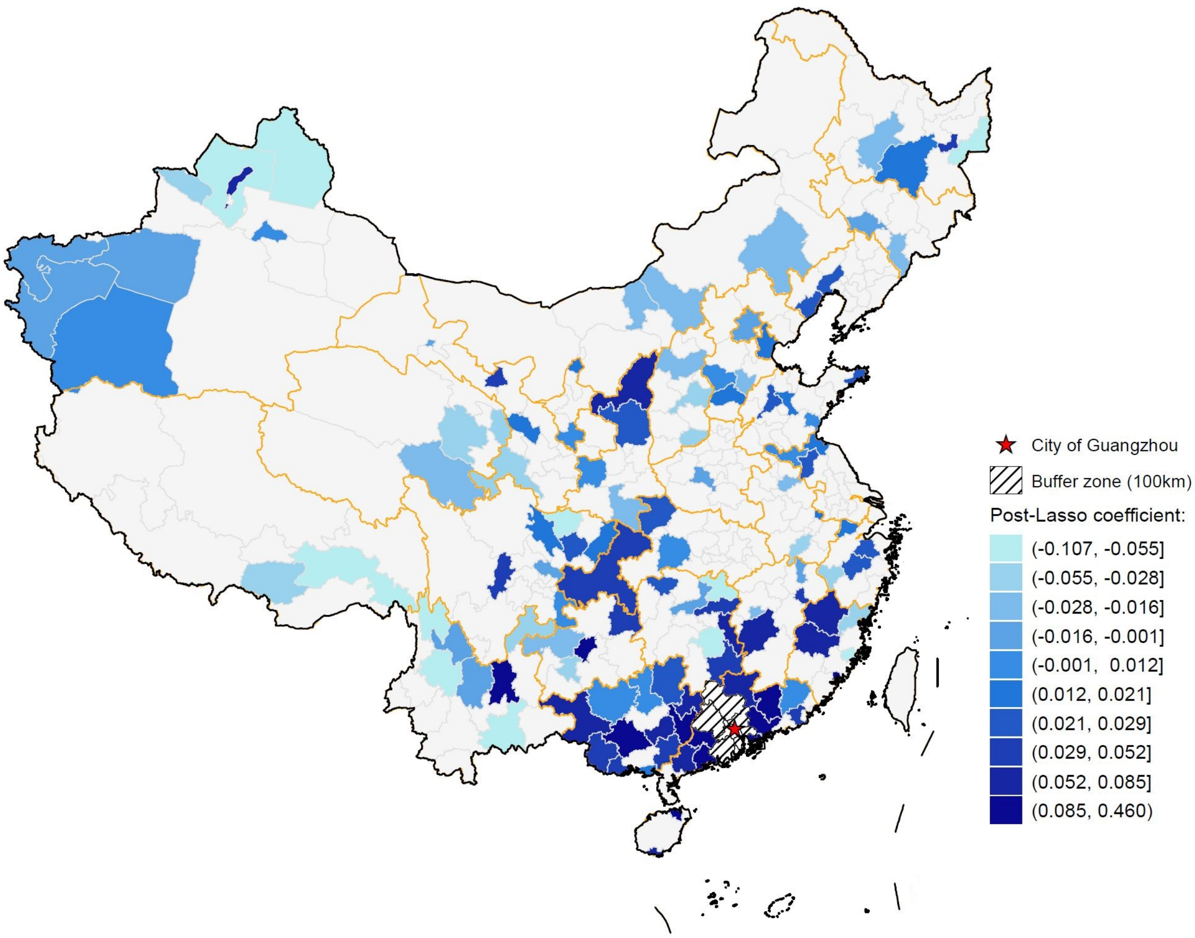
Notes: This graph plots the distribution of survival improvements among "switcher" patients whose counterfactual surgery day is different from the observed day. Blue histogram repeats Panel C of Figure 3. Green and red histograms show survival improvement when true $PM_{2.5}$ values are infused with N(0, $\sigma = 4$ ug/m^3) and N(0, $\sigma = 9$ ug/m^3) noise.

Figure A.8. Surgery-Day Pollution and Patient Mortality: Distributed Leads & Lags Model



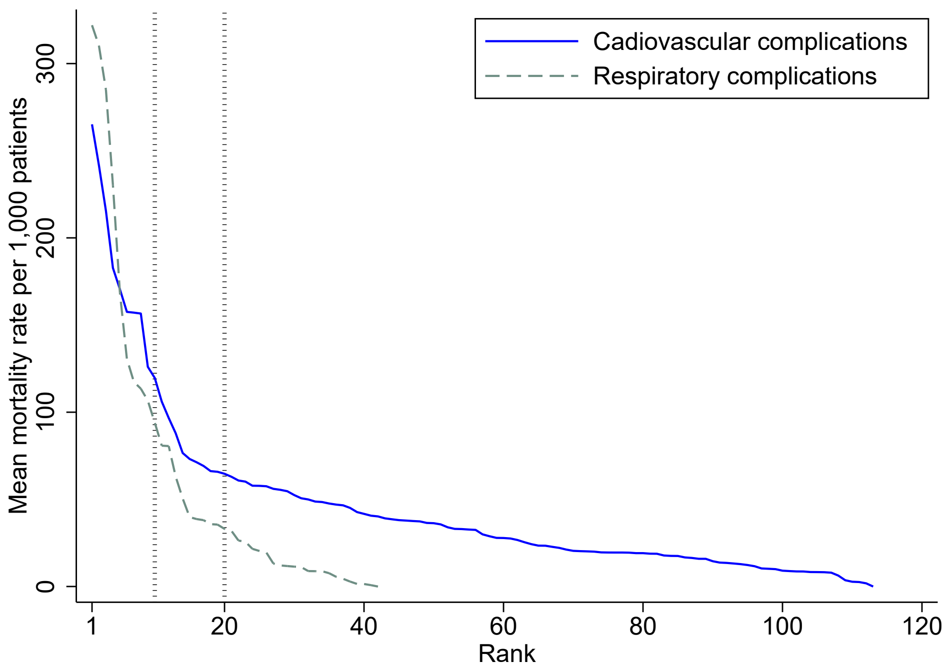
Notes: This figure plots coefficients from a regression of hospital mortality on leads (negative), current, and lags (positive) of daily log $PM_{2.5}$. Bars represent 95% confidence intervals using standard errors two-way clustered at the hospital and day level.

Figure A.9. Upwind Cities Selected by the "Zero-Stage" Lasso Regression



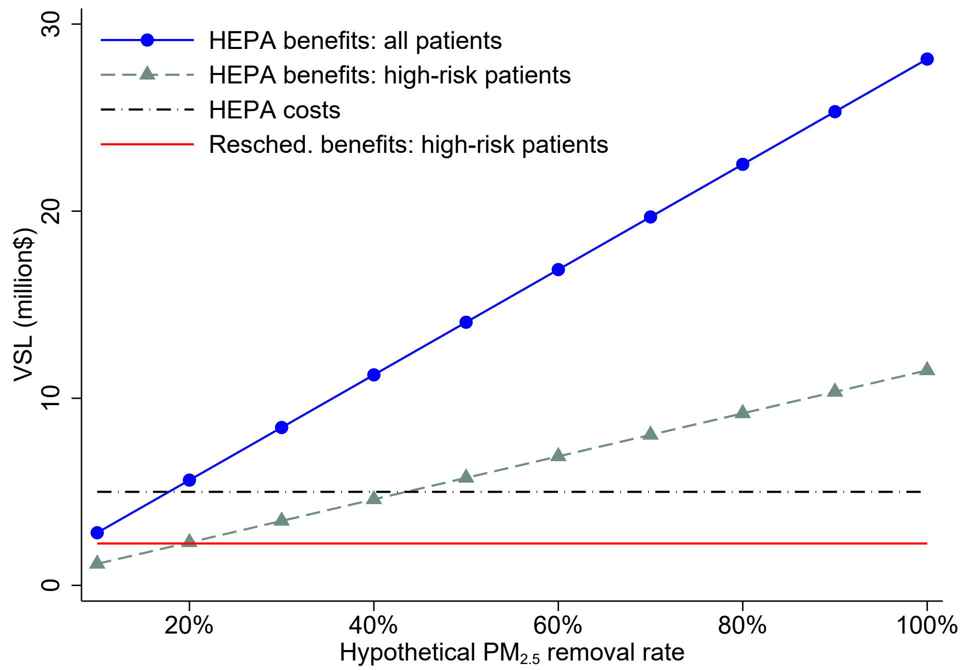
Notes: This map highlights 119 cities selected by a "zero-stage" Lasso regression of Guangzhou's daily $PM_{2.5}$ on all other 305 cities' upwind component vector $PM_{2.5}$. See text for details.

Figure A.10. In-Hospital Mortality of Cardiovascular and Respiratory Complications



Notes: Rankings of 113 cardiovascular complications (blue solid line) and 42 respiratory complications (green dashed line) by the average in-hospital mortality rate among patients that developed them during hospitalization. Vertical dotted lines highlight the top-10 and top-20 complications with the highest average mortality rates.

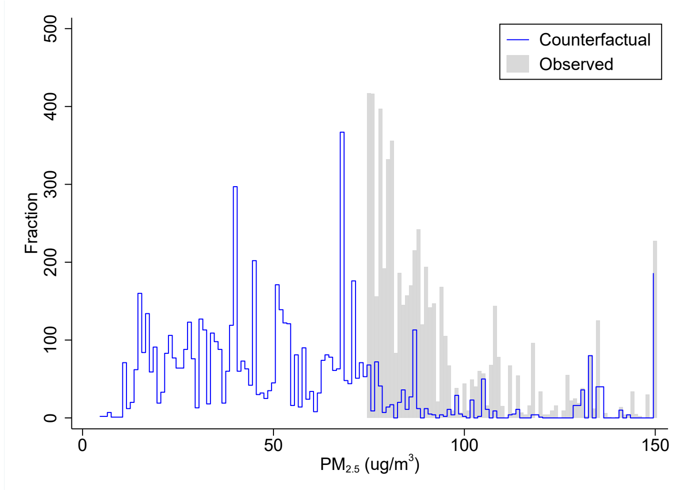
Figure A.11. Predicted Annual Surgery VSL Gains from Installing HEPA in Hospital Wards



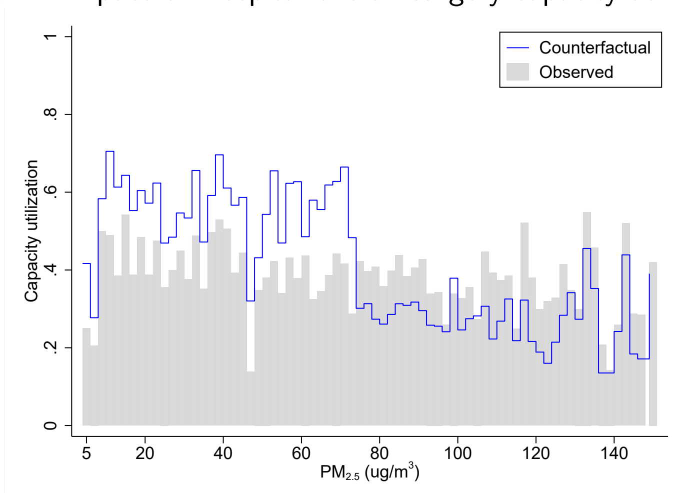
Notes: : This figure plots back-of-envelope estimates of annual surgery VSL gains from installing HEPA in all of our study hospitals. The two upward sloping lines show HEPA benefits as a function of hypothetical $PM_{2.5}$ removal rate on the surgery day for all patients (circles) and for high-risk patients (triangles). The flat dotted line shows annualized cost of installing and operating HEPA. The flat solid line shows annual VSL benefits from the rescheduling exercise.

Figure A.12. Counterfactual Surgery Scheduling that Internalizes Pollution Damages: Practical Example

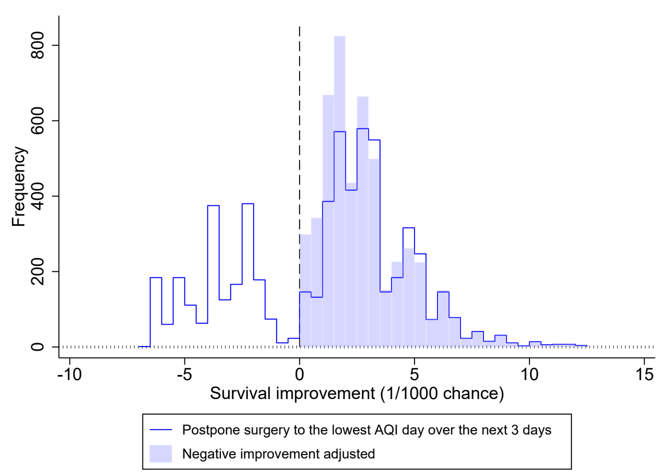
Panel A. Impact on pollution exposure



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.

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: Distributed Leads & Lags Models

	(1)	(2)	(3)	(4)
	Dep. var.: Hospital mortality			
Surgery-day $PM_{2.5}$ (t)	0.499***	0.499***	0.514***	0.469**
	(0.170)	(0.173)	(0.178)	(0.182)
Lag $PM_{2.5}$ (t+1 to t+3)	-0.066	-0.074	-0.087	-0.115
	(0.242)	(0.274)	(0.238)	(0.283)
Lag $PM_{2.5}$ (t+4 to t+6)		0.112		0.098
		(0.291)		(0.283)
Lead $PM_{2.5}$ (t-1 to t-3)			-0.032	0.053
			(0.284)	(0.275)
Lead $PM_{2.5}$ (t-4 to t-6)				-0.234
				(0.242)
FEs: diagnosis	✓	✓	✓	✓
FEs: department	✓	✓	✓	✓
FEs: day-of-week	✓	✓	✓	✓
FEs: procedure×hospital	✓	✓	✓	✓
FEs: year×month	✓	✓	✓	✓

Notes: "Lag $PM_{2.5}$" is pollution observed in days after the surgery. "Lead $PM_{2.5}$" is pollution observed in days before the surgery. 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 some 1.3 million depending on leads/lags included.*: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Table A.3. Surgery-Day Pollution and Surgical Site Infection

	(1)	(2)	(3)	(4)
Panel A. Average SSI effect				
Log $PM_{2.5}$	0.076	0.076*	0.102**	0.100*
	(0.046)	(0.042)	(0.047)	(0.050)
Panel B. SSI effects by pre-existing conditions				
Log $PM_{2.5}$ × 1(hypertensive or diabetic patients)	0.096	0.111	0.137*	0.138
	(0.072)	(0.067)	(0.067)	(0.091)
Log $PM_{2.5}$ × 1(others)	0.070	0.065	0.091*	0.088*
	(0.053)	(0.046)	(0.052)	(0.049)
Panel C. Mortality effects by pre-existing conditions				
Log $PM_{2.5}$ × 1(hypertensive or diabetic patients)	1.270***	1.268***	1.332***	1.400***
	(0.448)	(0.380)	(0.387)	(0.458)
Log $PM_{2.5}$ × 1(others)	0.103	0.174	0.238	0.081
	(0.145)	(0.169)	(0.152)	(0.183)
Panel D. Mortality effects of patients with non-healing surgical wounds				
Log $PM_{2.5}$ × 1(presence of non-healing wounds)	1.142***	1.209***	1.199***	0.951***
	(0.318)	(0.304)	(0.298)	(0.277)
Log $PM_{2.5}$ × 1(normal cases)	-0.066	-0.056	-0.070	-0.186
	(0.161)	(0.188)	(0.195)	(0.181)
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. In panel A, the outcome variable is an indicator for whether the patient had surgical site infection (SSI), multiplied by 1,000 to increase readability. The mean of the dependent variable is 0.563 incidents per 1,000 patients. Panel B allows the effect of $PM_{2.5}$ on SSI to vary by patient's pre-existing hypertension or diabetes conditions. Panel C repeats the same regressions in panel B, but use hospital mortality as the outcome variable. Panel D repeats panel C but looking at interaction effect with a presence of non-healing surgical wounds. 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 1,317,407 (column 1), 1,307,616 (columns 2 and 3), and 1,237,297 (column 4). *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Table A.4. Surgery-Day Pollution and In-Hospital Cardiorespiratory Complications

	(1)	(2)	(3)
	cardio. complication	resp. complication	cardio. or resp. complication
A. All relevant complications			
Log $PM_{2.5}$	-0.501	-0.060	-0.121
	(0.919)	(0.477)	(0.837)
Outcome mean	319.7	130.6	383.3
B. Top-20 most deadly complications			
Log $PM_{2.5}$	0.676***	0.177	0.614
	(0.224)	(0.391)	(0.403)
Outcome mean	39.88	85.06	110.2
C. Top-10 most deadly complications			
Log $PM_{2.5}$	0.646***	0.206	0.664***
	(0.209)	(0.264)	(0.219)
Outcome mean	17.77	16.46	30.65
FEs: diagnosis	✓	✓	✓
FEs: department	✓	✓	✓
FEs: day-of-week	✓	✓	✓
FEs: procedure×hospital	✓	✓	✓
FEs: year×month	✓	✓	✓

Notes: Each panel-column is a separate regression. Mortality variable is an indicator for whether the patient developed cardiovascular or respiratory complications 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. Standard errors are two-way clustered at the hospital and day level. Number of observations is 1,307,616. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Table A.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 A.6. 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.7. 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.

Table A.8. Correlates of Hospital Mortality

		(1)	(2)	(3)	(4)
Panel A. Dep. var. = Hospital mortality					
Age	mean = 48.0	0.306***	0.284***	0.284***	0.283***
		(0.032)	(0.029)	(0.029)	(0.028)
1(male)	mean = 0.563	0.060	0.025	0.028	-0.036
		(0.341)	(0.326)	(0.325)	(0.315)
1(married)	mean = 0.803	-6.244***	-5.806***	-5.797***	-5.641***
		(1.045)	(0.999)	(1.001)	(0.986)
1(allergy history)	mean = 0.051	1.357*	1.343*	1.341*	1.453*
		(0.678)	(0.745)	(0.743)	(0.827)
Days of delay	mean = 3.94	0.081	0.082	0.082	0.108
		(0.063)	(0.066)	(0.066)	(0.083)
Number of procedures	mean = 2.05	4.188***	4.463***	4.468***	4.614***
		(0.578)	(0.642)	(0.641)	(0.672)
1(general anesthesia)	mean = 0.492	0.099	-0.189	-0.176	-0.297
		(0.468)	(0.493)	(0.516)	(0.577)
1(level-1 operation - easiest)	mean = 0.284	4.493**	2.565**	2.535**	2.710*
		(1.718)	(1.202)	(1.221)	(1.353)
1(level-2 operation)	mean = 0.322	1.994	1.349	1.324	1.325
		(1.301)	(0.963)	(0.965)	(1.109)
1(level-3 operation)	mean = 0.251	1.423*	0.710	0.683	0.742
		(0.811)	(0.675)	(0.669)	(0.766)
N(same procedures being done)	mean=3.20	0.039	0.028	0.027	0.045
		(0.078)	(0.035)	(0.035)	(0.036)
N(same-type procedures being done)	mean=18.49	-0.037	-0.014	-0.012	-0.022
		(0.028)	(0.016)	(0.017)	(0.018)
N(same-complexity procedures being done)	mean=34.16	-0.031***	-0.028***	-0.027***	-0.029***
		(0.009)	(0.008)	(0.008)	(0.010)
1(insurance program: City Workers)	mean = 0.416	2.759**	2.410**	2.405**	2.412**
		(1.005)	(0.968)	(0.971)	(0.982)
1(insurance program: New Rural Cooperative)	mean = 0.062	-3.118***	-3.291***	-3.286***	-3.219***
		(0.814)	(0.768)	(0.768)	(0.811)
1(insurance program: none)	mean = 0.295	0.256	0.015	0.010	0.132
		(0.614)	(0.597)	(0.595)	(0.583)
Panel B. Dep. var. = Predicted mortality using characteristics in Panel A					
Log $PM_{2.5}$	mean = 10.69	0.014	0.002	-0.000	0.011
		(0.024)	(0.021)	(0.009)	(0.017)
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 panel-column represents a separate regression. In panel A, dependent variable is an indicator for whether the surgery patient died in hospital, multiplied by 1,000 to increase readability of the results. Mean of each regressor is reported. In panel B, dependent variable is predicted mortality from the regressions in panel A. 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. Standard errors are two-way clustered at the hospital and day level. Number of observations is 1,307,616. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Table A.9. 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.10. 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.11. 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 A.12. Surgery-Day Pollution and Patient Length of Stay

		(1)	(2)	(3)	(4)
		Indep. var.: Log $PM_{2.5}$ concentration			
LOS $\geq$ 1 day	mean = 979.6	-0.591	-0.514	-0.443	-0.266
		(0.521)	(0.526)	(0.319)	(0.467)
LOS $\geq$ 7 day	mean = 631.3	-2.689	-2.530	-2.124	-2.442
		(1.931)	(1.879)	(1.679)	(1.720)
LOS $\geq$ 14 day	mean = 284.0	-1.750	-1.655	-1.116	-1.780
		(1.364)	(1.327)	(1.250)	(1.246)
LOS $\geq$ 28 day	mean = 66.0	-0.355	-0.266	0.122	0.127
		(0.499)	(0.494)	(0.359)	(0.478)
Overall LOS (days)	mean = 12,547	33.035	32.270	-34.741	32.870
		(60.442)	(57.188)	(45.012)	(48.097)
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 length of stay (LOS) on surgery-day pollution. Each LOS variable is an indicator for whether the patient's hospitalization lasts over k days, 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. Standard errors are two-way clustered at the hospital and day level. Number of observations is 1,307,616. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Table A.13. Top 10 Cardiovascular and Respiratory Complications Associated with the Highest In-Hospital Mortality Rates

	Cardiovascular		Respiratory	
Rank	ICD-10 code	Description	ICD-10 code	Description
1	I46.000	Cardiac arrest with successful resuscitation	J80.x00	Adult respiratory distress syndrome
2	I50.907	Acute heart failure	J96.900	Respiratory failure
3	I50.905	Cardiogenic shock	J96.000	Acute respiratory failure
4	I24.901	Acute ischemic heart disease	J69.001	Pneumonitis
5	I50.101	Acute left heart failure	J96.100	Chronic obstructive pulmonary disease with acute lower respiratory infection
6	I60.900	Subarachnoid haemorrhage	J44.000	Other chronic obstructive pulmonary disease
7	I50.900	Heart failure	J18.800	Other pneumonia
8	I61.900	Intracerebral haemorrhage	J93.900	Pneumothorax
9	I26.900	Pulmonary embolism	J44.100	Chronic obstructive pulmonary disease with acute exacerbation
10	I27.900	Pulmonary heart disease	J15.900	Bacterial pneumonia

Notes: ICD-10 codes and descriptions for the ten deadliest cardiovascular complications (left panel) and respiratory complications (right panel).

Appendix B. Additional Analysis

B.1. Instrumental Variable Analysis

To 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:

$$\mathrm{IV}_t = (1/305)\sum_{c\in\{1,\cdots,305\}} \max\{0, \cos(\phi_{ct})\} \cdot \mathrm{PM2.5}_{ct} \cdot \left(\frac{1/\mathrm{distance}_c}{1/\sum_i (1/\mathrm{distance}_c)}\right) \qquad \text{(B1)}$$

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) of the paper 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.[1] 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.

[1] 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.9, 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.

Appendix Table A.11 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 (B1), to a largest 559.8 in panel D that uses a "zero-stage" Lasso to select the most important upwind cities. The most conservative IV results (panel D) are over 20 percent larger in magnitude and noisier than the OLS estimates of Table 2, and the qualitative findings are consistent across the two estimation approaches.

Readers familiar with the quasi-experimental economics literature on the air pollution – mortality link may find it surprising that our IV estimates are only moderately larger than their OLS counterparts. For example, some recently published studies including Deschenes, Greenstone, and Shapiro (2017), Ebenstein et al. (2017), and Deryugina et al. (2019) all find that the IV estimates on the effect of ambient pollution on adult mortality is an order of magnitude larger than their OLS estimates. We believe this difference has several explanations that pertain to the special setting of our study context. First, the nature of potential endogeneity concern in our setting is different from prior studies. 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, may be muted in our setting.

Second, most hospital locations in our study sample have air pollution monitors within several miles (Appendix Figure A.1). This might have helped reduce measurement errors in pollution compared to prior studies that, due to larger geographic scope and the need to cover non-urban areas where monitoring network coverage is sparse, often have to rely on imputed pollution values from monitors tens of miles away. That we have pollution measurement from much more nearby monitors may help better capture intra-city variation in air pollution exposure (Hoek et al., 2008; Anderson 2020).

Finally, we study the inpatient surgery population who likely spend the vast majority of time in hospital wards. This feature has two implications on measurement errors: (a) our pollution measurement is less likely to suffer from conventional sources of errors where people's activity locations (and thus pollution exposure) are remarkably different across daytime and nighttime (Ratti et al., 2006; Bhaduri et al., 2007); (b) as we discussed in Section 3.2, that patients staying mostly *indoor* may increase measurement errors compared to prior studies because we only observe *outdoor* pollution. However, some institutional knowledge suggests this source of error might not be enormous considering a high outdoor-to-indoor penetration of fine particulate matter pollutants (Section 2.1).

B.2. In-Hospital vs. Overall Mortality

We discuss two scenarios that can potentially lead to inflated estimates of pollution due to the fact that we only observe mortality events that occur during hospitalization. The first possibility is that if there is selection of who receive surgery on high pollution day that matters for length of stay. For example, sicker patients – who tend to stay longer in the hospital for us to capture mortality events – are more likely to be scheduled to receive surgery on a high pollution day. Several pieces of the evidence suggests this is not the case:

1) Our balancing tests (Table 1 of the paper) shows no evidence that patients' baseline, pre-surgery

characteristics – such as age of the patient and the complexity of the surgical procedure – differ by surgery-day pollution;

2) Table 1 also tests if surgery-day pollution can predict the number of "similar" procedures being done for other patients at the same hospital on the same day, where "similar" procedures are defined by procedures of the same complexity level, the same disease type, or just the exact same procedure. Because there are only a fixed set of surgeons conducting similar surgeries on a given day, we use the number of similar procedures done to (inversely) proxy for the duration of the procedure. Table 1 shows that surgery-day pollution is not explanatory of these measures, suggesting a lack of surgery scheduling sorting based on the time duration of the procedure.

3) These empirical findings are corroborated in our interviews with several surgeons in China, who reported that status quo surgical scheduling does not take expected pollution levels into account.

The second possibility is if high pollution on the surgery-day causes an increase in the patient's length of stay – and therefore the likelihood for us to observe mortality events – relative to other patients. Note that we can directly test for such possibility by regressing length of stay on surgery-day pollution using the main estimation equation (1). To rule out the impact of mortality events on length of stay, we restrict to patients who are still alive by the time of discharge. The results are virtually the same if we include patients who will eventually die in hospital. Analogous to the mortality analysis (Table 2 of the paper), we examine the impact of surgery-day $PM_{2.5}$ on the probability of the patients staying in the hospital for over 1, 7, 14, and 28 days, as well as a continuous variable for the total length of stay (LOS, measured in days). Appendix Table A.12 summarizes the results. We find no evidence that surgery-day pollution predicts the patient's length of stay.

B.3. Surgery-Day Pollution and In-Hospital Cardiorespiratory Complications

We examine new respiratory or cardiovascular complications from the discharge record. We document two facts of cardio-respiratory complications. First, they are common. About 32 percent of the surgery patients developed some form of cardiovascular complications during their stay, and about 13 percent developed respiratory complications. Second, there is substantial heterogeneity in terms of the "seriousness" of these complications. In Appendix Figure A.10, we rank cardiovascular and respiratory complications by the average in-hospital mortality rate of patients that developed them. To filter out noise, we restrict to diagnoses that we have at least 1,000 patient observations. The top-10 most deadly complications are associated with an average death rate of more than 20 percent, and that rate decreases dramatically as we move down the rank.

Appendix Table A.13 tabulates the top-10 deadliest complications. It is important to point out that few patients develop the most dangerous complications. While cardiorespiratory complications are common, about 3 percent of patients developed these deadliest complications listed here.

We then analyze the impact of surgery-day pollution on cardio-respiratory complications measured at the time of discharge. We repeat the main regression specification in equation (1) of the paper, but replace the outcome variable to an indicator of any new complications due to cardiovascular causes, respiratory causes, or due to either groups of causes. To increase readability, we scale up the outcome variable by multiplying it by 1,000. Appendix Table A.4 summarizes the results. Panel A shows that we do not detect an effect of pollution on cardiorespiratory complications generally. The null effect is quite precisely estimated. For example, the 95% confidence interval of the estimate in panel A, column 3 is [-1.76, 1.52], which allows us to exclude a small, 0.5 percent effect relative to a mean complication rate of 383 per 1,000 patients.

Next, we focus on more serious complications using an outcome variable that indicates the presence of new complications with the top-20 and top-10 highest mortality rate (panels B and C). We find evidence that pollution significantly increases the probability of patients developing these dangerous complications. For example, the estimate in panel C, column 3 suggests that a log increase in surgery-day pollution significantly increases the odds of developing top-10 deadliest cardiorespiratory complications at discharge by about 0.66 per 1,000 patients, or a 2.1 percent increase from the average complication rate of 31 per 1,000 patients.

The empirical evidence thus suggests that surgery-day pollution does not lead to the increase of the average cardiorespiratory complications. Rather, exposure to pollution leads to a significant increase in the development of complications associated with the highest mortality rate. These results support our primary mortality findings of the paper, and provide evidence that part of the mortality effects may come from the development of cardiorespiratory complications. These results also resonate with an accumulating amount of evidence that air pollution has disproportionate effects across the vulnerability spectrum. For example, Deryugina et al. (2019) shows that the causal effect of air pollution on elderly mortality in the United States concentrates among 20 percent of the elderly population that are most vulnerable, indicated by the presence of pre-existing chronic medical conditions. Our findings suggest that pollution's impact concentrate on a small group of surgical patients by triggering highly dangerous cardiorespiratory complications.

B.4. Structural Estimation Details

Our estimation 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

$$P_{id}(\theta) = \frac{\exp(\alpha h_{id} + \lambda_{id})}{\sum_{g=0}^{3} \exp(\alpha h_{ig} + \lambda_{ig})} \qquad \text{(B2)}$$

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 (3) of the paper, with an additional d index to make explicit that the term depends on the delay. The patient's individual likelihood is given by

$$R_i(\theta) = P_{id}(\theta) \prod_{g \neq d} (1 - P_{ig}(\theta)) \qquad \text{(B3)}$$

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

$$L(\theta) = \prod_{i=1}^{N} R_i(\theta) \qquad \text{(B4)}$$

We report estimation results $\hat{\theta}$ in Appendix Table A.7. 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.

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 (B2) 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 $\{d'_i\}_{i=1}^{N}$.

B.5. An Example of Rescheduling by Postponing

The structural exercise in Section 4.1 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.

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.[2] 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).

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.

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*

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

pollution day. With such adjustments, we are able to obtain positive survival 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.

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.12 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.[3]

B.6. The Cost and Benefit of Air Filtration Technology

We consider reduce in-hospital pollution exposure through the use of high-efficiency particulate air (HEPA) filtration technology.[4] Here we consider a hypothetical scenario where each hospital bed in our study hospital is assigned one home-use HEPA purifier. We use statistics from Ito and Zhang (2020) and assume that an average purifier costs 510 USD and the average replacement filter costs 56 USD in China. Assuming that a purifier has a life expectancy of 10 years and that the filter replacement cycle is once every 10 months, we calculate that the annualized cost of operating one air purifier is about 120 USD. Multiple this number by the total number of available beds in our study hospital, we find the annualized cost is 3.6 million USD. Assuming each purifier consumes 50 watts of electricity per hour and runs 24/7, at an industrial-use electricity price of 0.092 USD per kWh in Guangzhou, the annual energy cost is 1.2 million USD. The total, capital and operation costs of air purifying hospital wards in our study hospitals are thus about 5 million USD per year.

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[3] 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.

[4] Any air filters meeting the HEPA standard can remove at least 99.95% of particles with diameter equal to 0.3 μm from the air that passes through.

Turning to the benefit calculation, we first calculate how many hospital deaths can be avoided by reducing surgery-day pollution exposure. To do this, we multiple the in-hospital mortality coefficient in Table 2 (0.43 extra deaths per 1,000 patients per log increase in $PM_{2.5}$) by the average number of surgeries per year in our study sample (0.33 million surgeries) to obtain the expected number of avoided deaths for a log unit (i.e., 100 percent) reduction in $PM_{2.5}$. We also calculate a version for the high-risk patient group using the estimated subgroup effect size in Table 4 (2.91 extra deaths per 1,000 patients per log increase in $PM_{2.5}$) and annual case numbers (20,000 surgeries). This latter version will help us compare with the benefits of rescheduling, which is done only among the high-risk group.

Next, we multiply the avoided death counts by a value of statistical life (VSL) estimate. We are not aware of a consensus estimate of a VSL for the China. Instead, we use a benefit transfer approach (Viscusi and Masterman, 2017) that is based on a U.S. VSL estimate of USD 2.3 million (Ashenfelter and Greenstone, 2004), an income elasticity of VSL of 1.2 (Narain and Sall, 2016), and a per capita income ratio of 1-to-9 between China and U.S. to calculate a VSL of USD 0.2 million for the average Chinese resident.

Appendix Figure A.11 plots the benefits and costs of HEPA air purification in VSL terms. In practice, the degree to which air purifiers can reduce pollution exposure depends on various factors such as proper and consistent use, maintenance, and the need to keep windows always closed to avoid outdoor pollution intrusion. The figure therefore shows VSL gains as a function of the hypothetical percentage reduction in pollution due to air purification.

Two messages emerge from the chart. First, the cost of HEPA is relatively small compared to the potential benefits. Our calculation shows the VSL benefits can justify the cost so long as the HEPA system can achieve a 20% $PM_{2.5}$ removal rate on the surgery day (i.e., the intersection between the blue circled line and the dotted black line), or 40% $PM_{2.5}$ removal rate if we assume HEPA only benefits the high-risk patient groups. Note that these numbers potentially understate the benefits of HEPA as any $PM_{2.5}$ reduction on non-surgery days may also provide some health benefits. Second, the VSL benefits of rescheduling high-risk patients are small relative to installing HEPA, but not trivial. The chart suggests that the benefit of rescheduling high-risk surgeries is similar to the benefit of HEPA under a 20% surgery-day $PM_{2.5}$ removal rate. Note that this number is in line with our finding that the average switcher in the rescheduling exercises experiences a 50% reduction in air pollution on the surgery day, and switchers constitute 40% of all high-risk patients. The pollution reduction for the average high-risk patient is thus expected to be 50% × 40% = 20%.

The remaining question is what $PM_{2.5}$ removal rate can HEPA purifiers achieve when operated in real-world settings.[5] Our survey of the relevant literature suggests that the number ranges between 20-60% in household-use settings, with the efficacy rate hinges on proper use, positioning, maintenance, and insulation of the room from outdoor air (e.g., Batterman et al., 2012; Barn et al., 2018; Lindsley et al., 2021).

Overall, our calculation suggests that using HEPA filtration in hospital wards may be a promising, cost-effective strategy to improve patient health. Of course, whether the adoption of air filtration technology is

[5] While HEPA air filters can theoretically remove virtually all fine particles *from the air that passes through*, their ability to reduce overall pollution levels in a room is subject to many factors.

indeed a feasible and effective policy solution in practice warrants further research.

Appendix C. Surgeons' Comments (Q&A Logs)

Doctor 1: Associate Chief Physician, Department of General Surgery, 3A Hospital in Beijing

Q: First of all, what factors do doctors take into account when scheduling surgeries? Will you consider the impact of air pollution?
A: We normally don't consider it when we schedule surgeries, or we basically ignore it, because the operating rooms are laminar environments, you can think of that as being similar to the protective suits that people wear during the COVID-19 pandemic. The surgery room is equivalent to an environment of negative pressure laminar flows, and its cleanliness has to meet strict requirements. For example, nano or micron particles per cubic meter in the room must not exceed a certain value. As a result, we certainly don't take outdoor air pollution into account when we schedule surgeries. Moreover, the air in the operating room is not connected to the outside, so it could be considered as space with air that flows in a certain direction. This prevents external air pollution from affecting the operating room's environment.
When we arrange surgeries, we usually consider more about the patients' conditions such as the preoperative preparations, general complications, cardiopulmonary functions, whether he or she could tolerate surgeries and anesthesia, and whether the patient could recover smoothly after the surgery. The patient's physical conditions are the main factors we consider when we schedule the surgery. Therefore, according to my communication with other colleagues, we seldom take ambient air pollution into consideration, and of course, I do not rule out the possibility that we will take it into consideration in the future.

Q: Is there any air purifier in the ward?
A: No.

Q: During the actual operation, or before the operation, do you pay attention to the air pollution on that day?
A: We don't pay much attention to the air index or air pollution. Because after we enter the operating room, all the people in the operating room are wearing hats and special operating gowns, and the air environment is – as I mentioned – a laminar environment. Therefore, we are not going to think about the air quality outside, because the high air quality in the operating room is guaranteed.
Therefore, we often make jokes that we are fortunate to stay in the operating room when it was a polluting day outside as the operating room is very safe with very low air pollution concentration. So again, we basically don't consider the impact of PM2.5. Moreover, medical treatment needs to satisfy the requirements of environmental asepsis and it is impossible to perform a surgery in a highly polluted air environment, otherwise the incidence of postoperative complications and infections will certainly be particularly high.

Q: Is surgery usually done by the same doctor all day long, or is it possible that this morning one doctor *does one surgery and then moves on to another doctor?*

A: The general practice is that, one doctor has several patients, and every doctor will have their own surgery day, which is booked in advance. On someone's "surgery day," he or she has the entire day to use the operating room and can perform surgeries for only his or her own patients. As long as the doctor has enough time and there is anesthesiologist availability, he or she could perform 3 or 4 operations a day. For the thyroid treatment, they could perform five or six thyroid operations a day, which means the same doctor could conduct five or six thyroid operations a day in this operating room. For gastrointestinal patients, because of the longer operation time, basically one doctor is only able to perform about three operations a day. If it's not someone's predetermined "surgery day," it's still possible for the doctor to arrange surgeries on that day, but he or she simply has to wait until others finish their surgeries.

Q: Is the risk of infection greatest in the first few hours after the surgery?

A: The probability of postoperative infection does not follow a particularly strong temporal pattern. Postoperative infection usually correlates with the individual's physical conditions, complications, age, and nutritional status. For example, for an emergency case with digestive tract perforation, or the abdominal injury, or knife injury, if the patient is young, has no complication, and has good physical conditions, he or she is definitely less likely to get infected after the surgery. Infection is more correlated with the patient's general condition and the operator's aseptic awareness during the operation.

Q: When the surgery is over, are there still some factors that might cause the post-operative infection?

A: If the surgery is over and the patient has some infection after the surgery, there may be a couple of reasons. One situation is that a trauma patient, for example, may have some external infection sources in the abdomen that has not been cleaned. The lesions are still there, and the doctors did not give him an adequate drainage.

Second, in every part of the body, such as the digestive tract, there is a normal flora (such as lactic acid bacteria in the digestive tract), which is normally in a harmonious symbiotic relationship with the human body. But if under some exogenous conditions, such as when human immunity is extremely low after the surgery, these bacteria may become pathogenic bacteria, that is, conditional pathogenic bacteria.

In addition, foreign objects can also cause inflammation. The body has a defense mechanism to protect itself against foreign objects, including bacteria, and all kinds of wounds. But if this defense mechanism is weakened for any reason, then these foreign or internal pathogens can grow and infect the body.

Q: As you mentioned earlier, this can happen when the immune system is weak. In the first few hours after surgery, whether the body is weakest and most vulnerable to potential risks?

A: The first few hours are risky. The initial period of surgery is the riskiest. Because some vascular ligation is not so exact, such as thyroid surgery, the risk of sudden massive blood vessel bleeding is very high. For example, massive bleeding in the neck may compresses the trachea, which could result in sudden dyspnea and suffocation. For abdominal surgeries, there is a risk of bleeding within several hours after the surgery, which can lead to shocks. However, in terms of the risk of infection, it may not be particularly correlated with the time after surgery, but may be more correlated to the patient's general conditions, nutritional status, whether he or she has diabetes, or coronary heart diseases.

Q: And do you agree with that: if the air pollution on the day of surgery affects the patient's postoperative recovery, the channel may be related to the increased postoperative infection. Or you think there could be other channels?

A: I don't think there is such a direct correlation. However, if this kind of polluted air persists for a long time, the condition of a patient's lung will be worse, and the postoperative recovery will be worse, and the poorer lung function will increase the risk of death. However, if you say that the high air pollution on the day of surgery directly results in the poor postoperative recovery of the patient, I wouldn't think the relationship can be that strong.

Doctor 2: Deputy Chief Physician, Department of Orthopedics, 3A Hospital in Fujian Province

Q: First of all, what factors do doctors take into account when they schedule their surgeries? Do they take air pollution into account?

A: Basically, we don't think much about it because I'm in Fujian, and the air quality in Fujian is generally good. Occasionally there will be polluted days with high PM 2.5, during which a patient could be prone to some respiratory diseases. For example, a patient may suddenly feel uncomfortable in the respiratory tract, and we may consider postponing the operation. If there is no such situation, and the patient's own condition is good, we would not consider to suspend or delay the surgery simply because of the poor ambient air pollution.

Q: Is there any air purifier in the ward?

A: No, there is no air purification system in the ward.

Q: Do you pay attention to air pollution before or during the actual operation on the surgery day?

A: No, because when we perform surgeries, the operating room has a laminar flow system, and thus we don't pay attention to air pollution. Working inside the operating room is intensive, and thus you don't notice the outside environment.

Q: If the patient is exposed to an infectious environment after surgery, like bacteria or something, is the risk of infection greater in the first few hours after surgery?

A: Yes, I think so.

Q: Is the second day less important? The first few hours after surgery are the riskiest?

A: Yes, because at that time when the incision was not entirely closed, and the skin surface had not grown well. After 24 hours, some epidermal cells have formed on the surface of the incision and are able to cover the wound, the exposure is thus less harmful.

Q: If air pollution on the day of surgery affects patients' postoperative recovery, do you think it is through increased postoperative infection, or there is some other channel?

A: I don't think so. I think it's possible that air pollution increases the rate of lung complications.

Doctor 3: Attending Physician, Cardiothoracic Surgery Department, 3A Hospital in Guangzhou

Q: Is air pollution considered when scheduling surgeries?

A: Air pollution surgery has nothing to do with surgery scheduling.

Q: Are air purifiers in the wards?
A: We don't have air purifiers in the wards.

Q: Do you notice any air pollution before or during the actual operation?
A: I'm in Guangzhou and I think the air quality is ok, and I've not noticed that.

Q: If a patient is exposed to an infectious agent, like bacteria or something like that, is the risk of infection greater in the first few hours after surgery and less important in the second day?
A: If you really put the patient next to the source of infection, since the patient's immunity after the surgery is low, it is easy to get infected. I would think the probability of infection is higher in the first three days after surgery. A bacterial infection needs to reach a certain level before it can cause damage to a patient's body. If the patient is placed next to the source of the infection, it is rare that symptoms develop immediately within two or three hours, because a bacterial infection takes some time to manifest.

Q: If it is found that air pollution on the day of surgery affect patients' postoperative recovery, do you think it could be through the increased postoperative infection, or do you think there could be other explanations?
A: I don't think air pollution will affect postoperative recovery. I could not think of any specific channel.

Doctor 4: Attending Physician, Department of Thoracic Surgery, 3A Hospital in Guangzhou

Q: The first question is, do doctors take air pollution into account when scheduling surgeries?

A: No, we don't.

Q: For example, if air pollution is severe today, will the operation be postponed?
A: No.

Q: Will there be air purifiers in the ward after the patient awake from anesthesia?
A: No.

Q: Do you notice air pollution on that day before or during the operation?
A: No.

Q: If being exposed to a contaminant, like bacteria, is it more harmful if it's during the first few hours after surgery, with a higher chance of infection, and less important in the next day as the wound may have already be covered with epidermal cells?
A: I feel there is no big difference because the incision is already covered with dressings

Q: We are doing a study now, and we found through data analysis that the level of pollution on the day of surgery may affect patients' recovery after surgery. Do you think it could be through the increased postoperative infection, or do you think it could be through other channels?
A: First of all, air pollution is mainly some dust, while wound infection is mainly caused by bacterium. It is difficult to say whether these two things are correlated. In addition, the main possible channel of pollution is incision exposure, but incision infection is generally rare and it is not a very serious complication.

Doctor 5: Attending Physician, Spinal Surgery Department, 3A Hospital in Shandong Province

Q: What factors do doctors take into account when scheduling surgeries? Will air pollution be taken into account?

A: Air pollution has not been considered.

Q: Will there be air purifiers in the ward?
A: No.

Q: Do you notice any air pollution before or during the actual operation?
A: No.

Q: Also, does your hospital schedule the surgeries based on predetermined rotation so that each doctor has his or her own "surgery day," or is it possible that the doctor need to perform surgeries, say, every morning?
A: We usually set an operation day for each doctor, which means the doctor on a surgery day performs surgeries from morning to night.

Q: Is exposure to an infectious agent, such as bacteria or other small particles, more harmful in the first few hours after surgery? For example, the contamination may enter the patient's incision more easily in the first few hours after surgery?
A: I haven't studied it, but it should not be the case in general. Because it takes time for bacteria to grow, and patients typically don't develop a high fever until 24 to 48 hours after surgery.

Q: Is it possible that after the surgery, since the epidermal cells on the incision have not healed, external infection sources may be easier to enter the body at that time?
A: Probably not, because the local incision after surgery is covered with aseptic dressing, it should be very difficult for external sources of infection to enter the body. And local skin disinfection generally has a wide coverage, so these skin areas are free of bacteria.

Q: What is aseptic dressing?
A: Now we routinely use a formic acid compound, I forget the exact ingredients.

Q: Next question, if we have a piece of data analysis that suggests air pollution on the day of surgery affects patients' recovery after surgery, could it be through increased infection after surgery? Or do you think there are some other channels that affect postoperative recovery?
A: I haven't really noticed that, but I think it would be possible if it was based on data. I think the most likely channel is that the air pollution leads to the deterioration of patients' physical condition. If there is air pollution, certainly the air in the ward is not good. Especially our hospital is full of elderly patients, and air pollution could cause respiratory problems, leading to poor postoperative recovery. However, I think the channel of local postoperative infection is less likely.