(Re)scheduling Pollution Exposure: The Case of Surgery Schedules and Patient Mortality

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Jialin Huang (Peking University)

Jianwei Xing (Peking University)

Eric Zou (University of Oregon)

Motivation

- Many economic activities can be strategically scheduled around environmental hazards to mute their impacts
  - Ex: We adjust daily schedules to changes in weather
- This paper: the potential of such adaptation with respect to air pollution
  - Existing literature: people use pollution "nowcasts" and forecasts to rearrange daily activities – such as outdoor recreation – and avoid pollution exposure (e.g., Cutter and Neidell, 2009; Neidell, 2009; Graff Zivin and Neidell, 2009)
  - We extend this idea to a high-stakes healthcare delivery context: inpatient surgery
- Key findings
  - Reduced form: High pollution on the day of surgery adversely affects patients' survival
  - Structural: Minor adjustments in surgery schedules could mitigate this effect

This Paper

- What's familiar: Pollution is bad
  - HDFE regressions, downwind IV …
  - Dose response
  - Some subpopulation is more vulnerable
  - …

- What's new:
  - A critical exposure window: surgery-day pollution is the culprit
  - A high-risk patient group: some 6% of patients bear 60% of pollution's adverse effects
  - A structural exercise: minor changes in high-risk patients' surgery dates can improve survival
  - New data: high-quality inpatient databases in China are coming online!

Data

- Inpatient surgery records from Guangzhou (China), 2014-2017
  - "Home Page of Inpatient Medical Records"
  - De-identified inpatient surgery records from 23 "3-A" hospitals of Guangzhou (100% sample, total 2.2 million observations)
  - Patient info: age, gender, date of death
  - Hospitalization info: admission & discharge diagnoses (ICD-10)
  - Surgery info: procedure (ICD-9-CM)
  - Layout of the data resembles HCUP State Inpatient Database

Outline

- Institutional setting
- The baseline: surgery-day pollution is bad for patient survival
- Two key findings:
  - The importance of "surgery day" pollution
  - The high risk group
- Rescheduling exercise
- Other extensions

Study location: The city of Guangzhou

One of the largest cities in China; rich healthcare resources

Economic statistics (as 2017):

Population = 14.5 million

GDP total = 319 billion USD (4th largest city)

GDP per cap = 22,317 USD

Healthcare resources (per 1,000 residents):

2.8 physicians

4.6 nurses

4.6 hospital beds

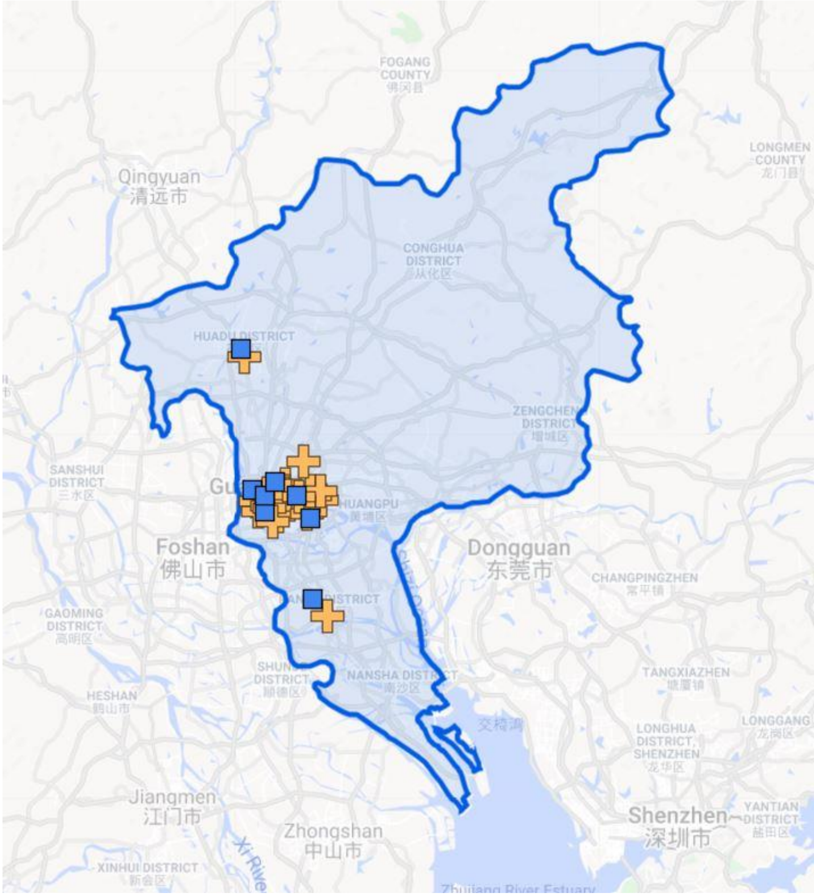
Health spending per cap = 1,541 PPP USD

Notes: This map shows location of Guangdong province (light blue) and the city of Guangzhou (deep blue). Lines are provincial borders.

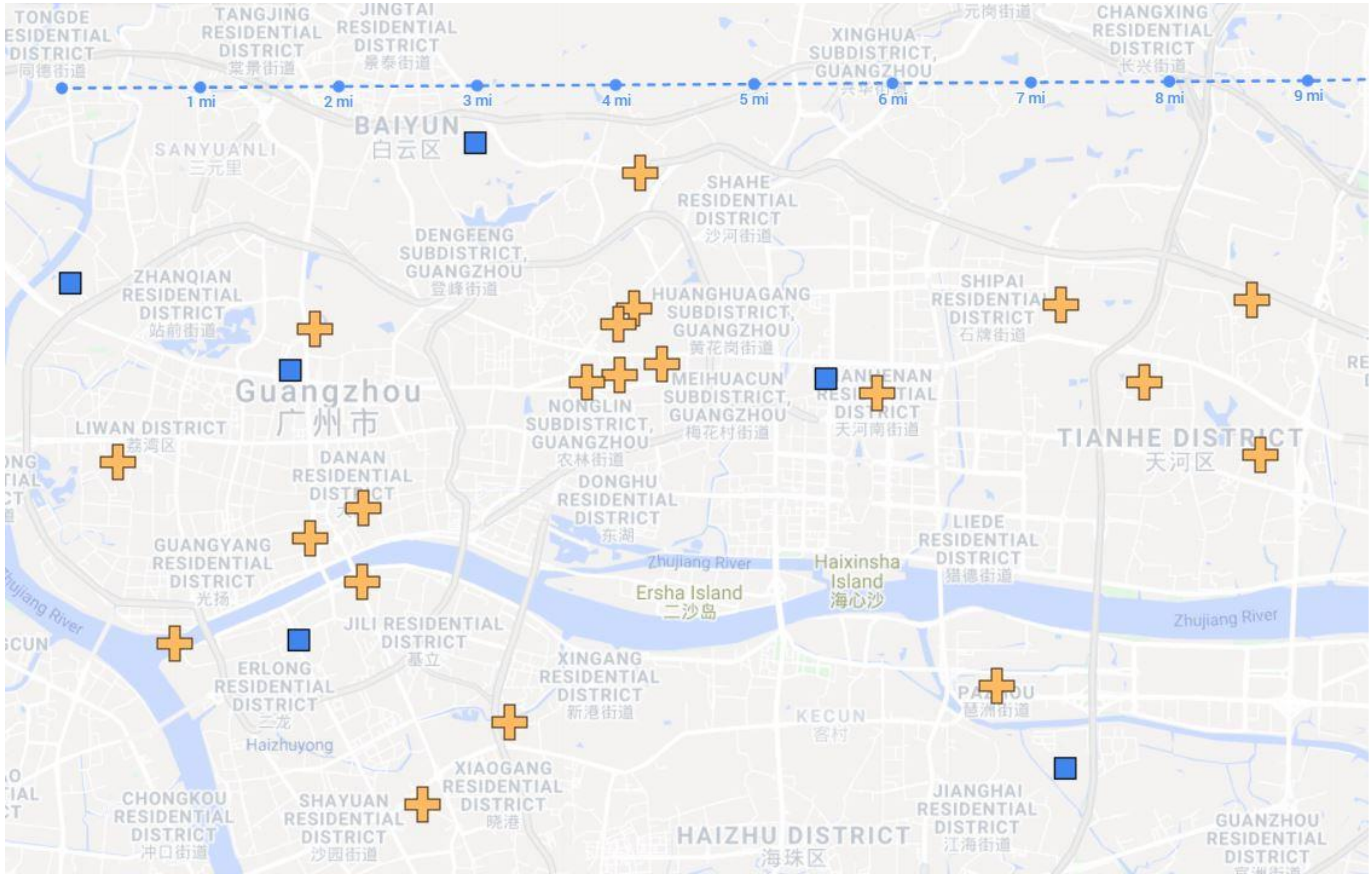
Study location: Hospital (+) and pollution monitor (■) locations

Most hospitals have pollution monitor within several miles

A. City view



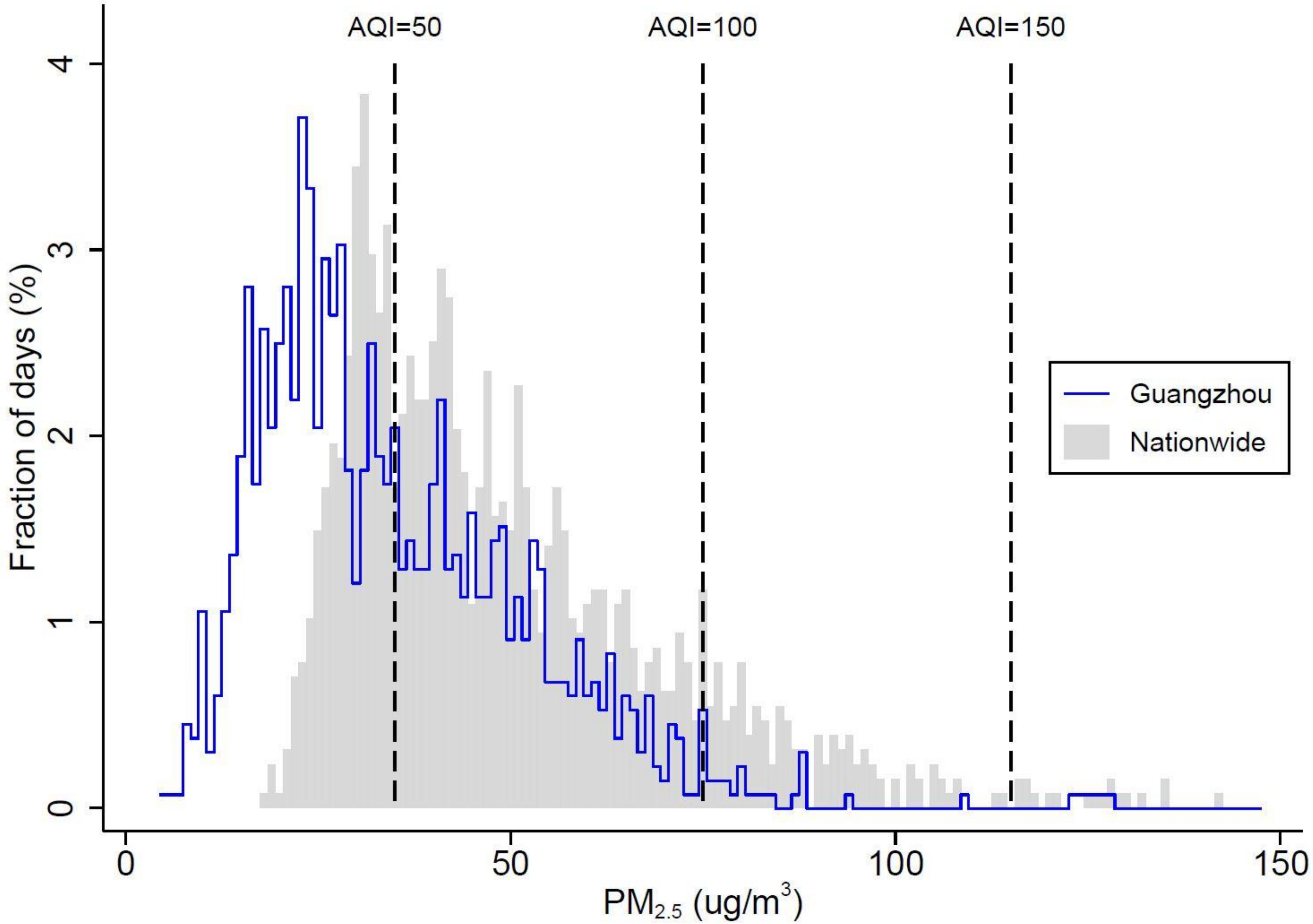
B. City center view



Notes: Location of hospitals (crosses) and air pollution monitors (squares) in study sample.

PM2.5 pollution in Guangzhou: Mean = 36.5 ug/m3 (SD = 19.8 ug/m3)

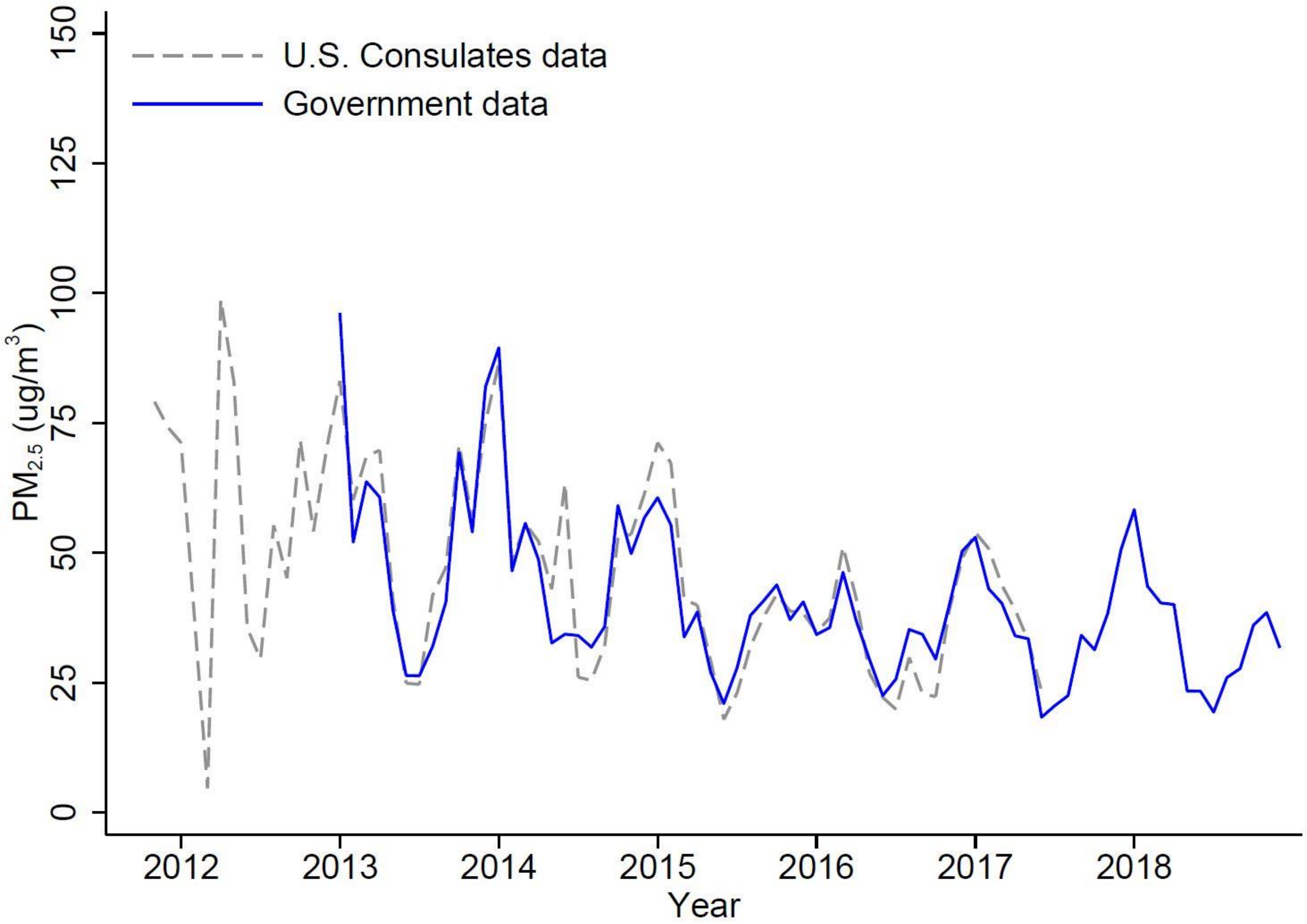
Cleaner than average Chinese city, but substantial pollution/variation



Notes: Distribution of daily PM2.5 in the city of Guangzhou and nationwide. Vertical dashed lines correspond to Air Quality Cutoffs for Good, Moderate, Unhealthy for Sensitive Groups, and Unhealthy.

PM2.5 data in Guangzhou: Government data vs. U.S. Consulate data

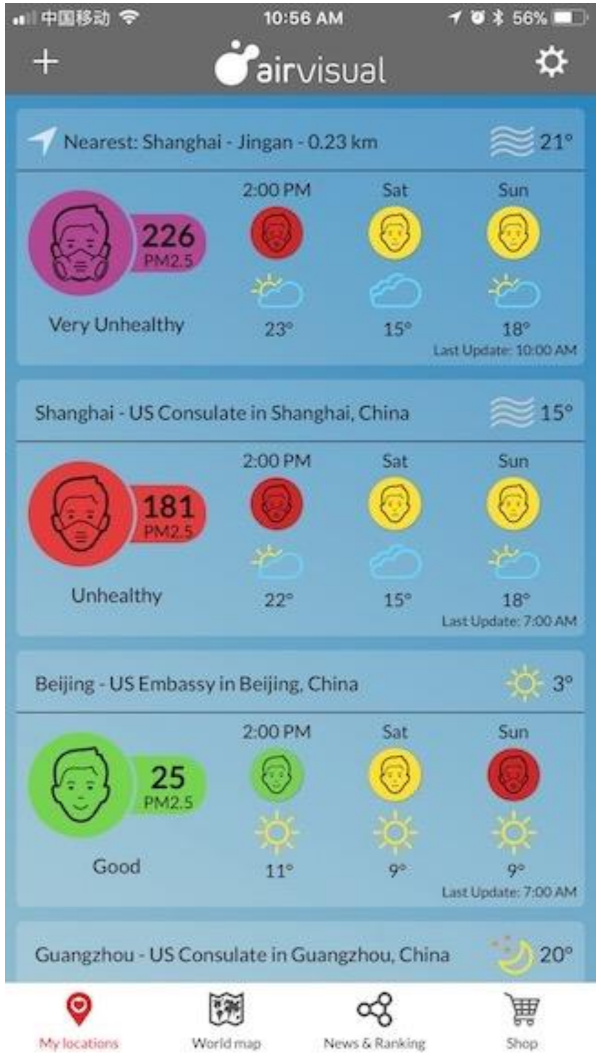
New monitoring system starting 2013 improves accuracy quite a bit



Notes: Greenstone, He, Li, Zou (2021)

Pollution information: Pollution now/forecasts widely available

An example mobile phone app



Source: airvisual.

Pollution exposure inside hospital

- In operating rooms:
  - All operating rooms High Efficiency Particulate Air (HEPA) or Ultra Low Particulate Air (ULPA) filters combined with a laminar (unidirectional) air flow system
  - Over 90% of particles of 0.5 micrometers are filtered out
  - Filtration rate for PM (2.5 micrometers) expected to be even higher

- In other hospital areas:
  - Other than the ICUs, pollution control is limited
  - For PM2.5, outdoor-to-indoor penetration rate is high
    Ex: Cyrys et al. 2004 Germany case study: 0.83 (open window) and 0.63 (closed window)
    Ex: Zheng 2014 China case study: generally near 1.0

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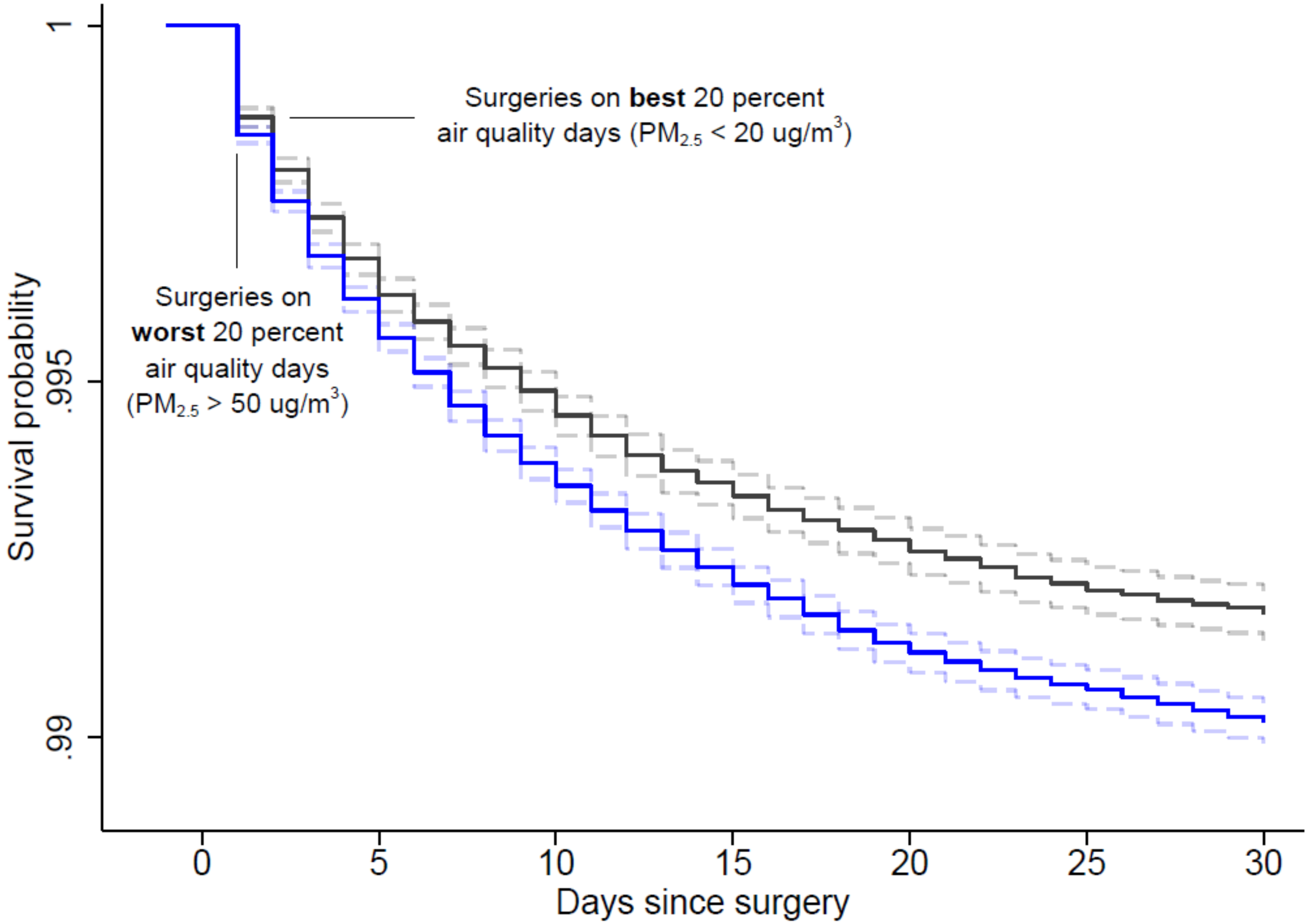
  - The high risk group
- Rescheduling exercise
- Other extensions

Raw survival pattern: Does surgery-day pollution matter for patient survival?

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 PM2.5 concentration (>50 ug/m3) and days with the best quintile PM2.5 concentration (<20 ug/m3).

Regression Analysis

- Workhorse regression equation:

$$1(\text{Die in hospital})_i = \alpha + \beta \cdot \text{Log}(\text{SurgeryDay Pollution})_i + X_i \gamma + \epsilon_i$$

  - Source of variation: cross-patient variation in pollution on the (pre-schedule) surgery day

  - X_i = control variables
    1) Patient demographics: age, gender, marital, allergy
    2) Fixed effects: hospital, department, diagnosis, procedure, surgery year, month, day-of-week
    3) Weather: temperature, precipitation

  - Two-way cluster SEs at the hospital and the day-of-sample level

Main regression: Does surgery-day pollution matter for patient survival?

Higher surgery-day pollution leads to worse survival outcome

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

Notes: Each cell reports a separate regression of a measure of post-surgery mortality on surgery-day pollution. Each mortality variable is an indicator for whether the patient died in hospital following k-day since surgery, multiplied by 1,000 to increase readability.

What about selection?

- Threat to identification: Patients select into high and low pollution days

- Paper contains detailed discussion. Here, outline some main tests:

1. Sicker patients more likely to show up in hospital on high-pollution days?
2. Sicker patients more likely to be scheduled to receive surgery on high-pollution days?
3. Maybe some other kinds of endogeneity and measurement error issues?

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   - Study population is patients <u>already</u> admitted to the hospital
   - The average patients in our analysis has waited for <u>four days</u> before surgery
   - Similar results when we drop patients who received surgeries on the admission day
2. Sicker patients more likely to be scheduled to receive surgery on high-pollution days?
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2. Sicker patients more likely to be scheduled to receive surgery on high-pollution days?
   - We use the regression framework to do a balance test on patient's pre-surgery characteristics
   - Demographics, health conditions, surgery characteristics, payment methods..
3. Maybe some other kinds of endogeneity and measurement error issues?

Balance test: Does pollution predict *pre-surgery* characteristics?

No evidence that high- and low-pollution day surgery patients are observably different

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

Notes: This graph reports Kaplan-Meier survival estimates and 95% confidence intervals among surgeries conducted on days with the worst quintile PM2.5 concentration (>50 ug/m3) and days with the best quintile PM2.5 concentration (<20 ug/m3).

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FEs: hospital		✓			
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FEs: month		✓	✓		
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FEs: procedure×hospital			✓	✓	
FEs: year×month				✓	
FEs: procedure×hospital×month					✓

Two messages from this table:

1. High- and low-pollution surgery patients are not observably different

2. Hospitals' *status quo* scheduling practice does not appear to consider pollution vulnerability

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3. Other endogeneity and measurement error issues?
   - Instrument $\text{Log(SurgeryDay PM}_{2.5})_i$ with downwind pollution from cities > 100 km away from Guangzhou
   - Ex: Barwick et al. (2018); Deryugina et al. (2019); Anderson (2020); Graff Zivin et al. (2020)
   - We find IV > OLS; literature often finds IV >> OLS; see discussions in the paper

Pollution instrumental variable (IV): **Finding exogenous variation in pollution**

Transported pollution from upwind cities

- The basic version

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

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  - $\max\{0,\cos(\phi_{\mathrm{ct}})\}\cdot \mathrm{PM2.5_{ct}}$: The vector component of $\mathrm{PM2.5_{ct}}$ that's expected to move toward Guangzhou, given the wind direction ϕ_{ct} in city c on day t

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  - … take average across all donor cities $c \in \{1, \ldots, 305\}$, inversely weighted by city c's distance to Guangzhou

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  - … take average across all donor cities $c \in \{1,\ldots,305\}$, inversely weighted by city c's distance to Guangzhou

- IV = "variation in Guangzhou's $PM_{2.5}$ attributable to transported pollutants from upwind cities"

Pollution instrumental variable (IV): Finding exogenous variation in pollution

Transported pollution from upwind cities

- The basic version

$$IV_t = \boxed{(1/305)\sum_{c\in\{1,\ldots,305\}}} \max\{0, \cos(\phi_{ct})\} \cdot PM2.5_{ct} \cdot \left(\frac{1/\text{distance}_c}{1/\sum_i (1/\text{distance}_c)}\right)$$

  - To minimize endogeneity concerns, use all cities <u>at least 100 km away</u> from Guangzhou as donors (305 cities)
  - Using all 305 cities can be inefficient
    Ex: Variation of air quality in Qinghai is unlikely to be predictive of PM2.5 in Guangzhou

Pollution instrumental variable (IV): **Finding exogenous variation in pollution**

Transported pollution from upwind cities

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

- The "fancy" version

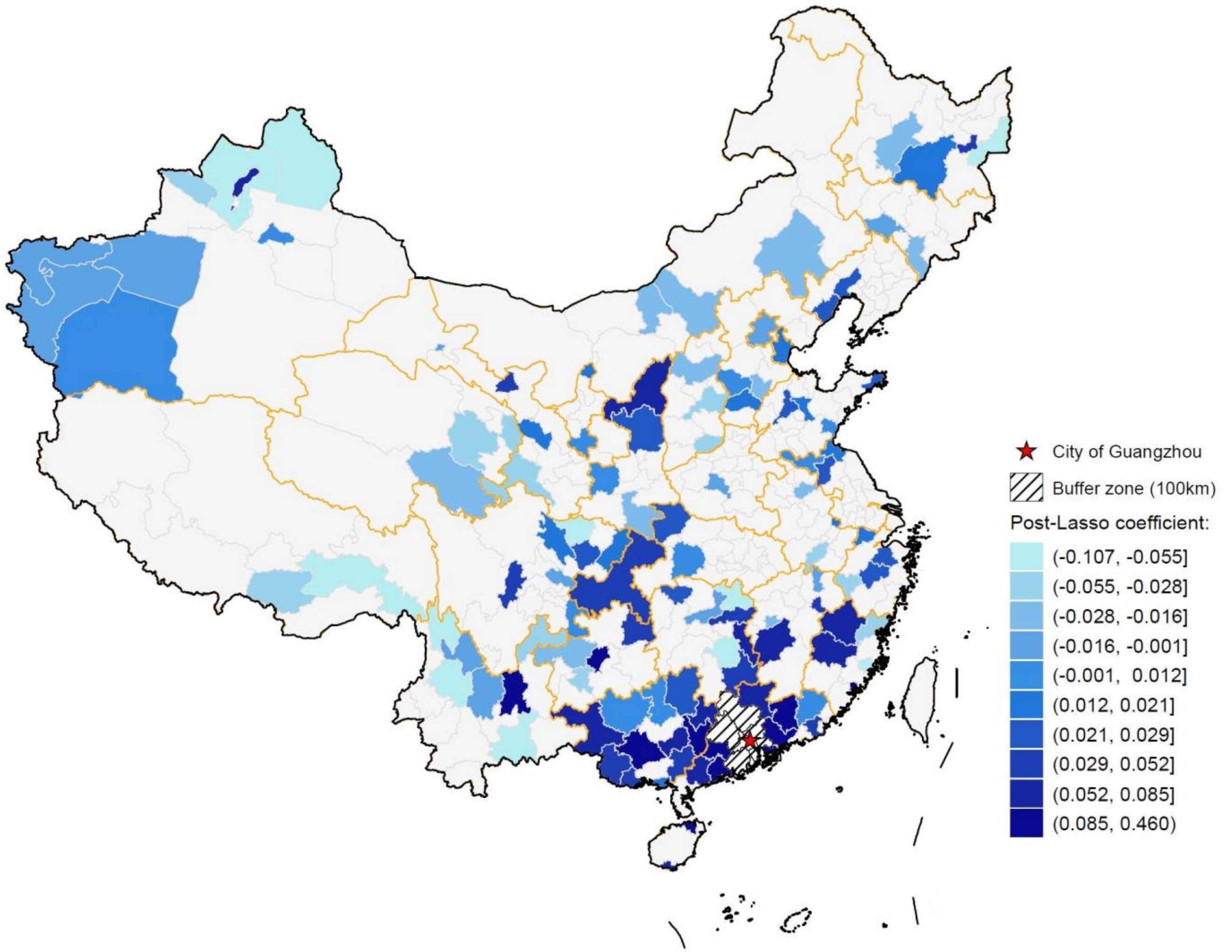
$$IV_t = \boxed{(1/\#\mathbf{S})\sum_{c\in\mathbf{S}}} \max\{0,\cos(\phi_{ct})\}\cdot PM2.5_{ct}\cdot\left(\frac{1/\mathrm{distance}_c}{1/\sum_i(1/\mathrm{distance}_c)}\right)$$

  - where set **S** is the subset of (119) <u>most predictive cities</u> selected by a "zero stage" linear Lasso regression

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

Pollution instrumental variable (IV): Zero-stage Lasso results

Which cities' upwind pollution is most predictive of Guangzhou's $PM_{2.5}$?



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 $PM_{2.5}$.

IV results: The effect of instrumented pollution on surgery outcome

2SLS regressions using upwind pollution from distant cities as the IV

	(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

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- ML doubles the first-stage F-stat

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2SLS regressions using upwind pollution from distant cities as the IV

	(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

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

OLS

	(1)	(2)	(3)	(4)
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

IV

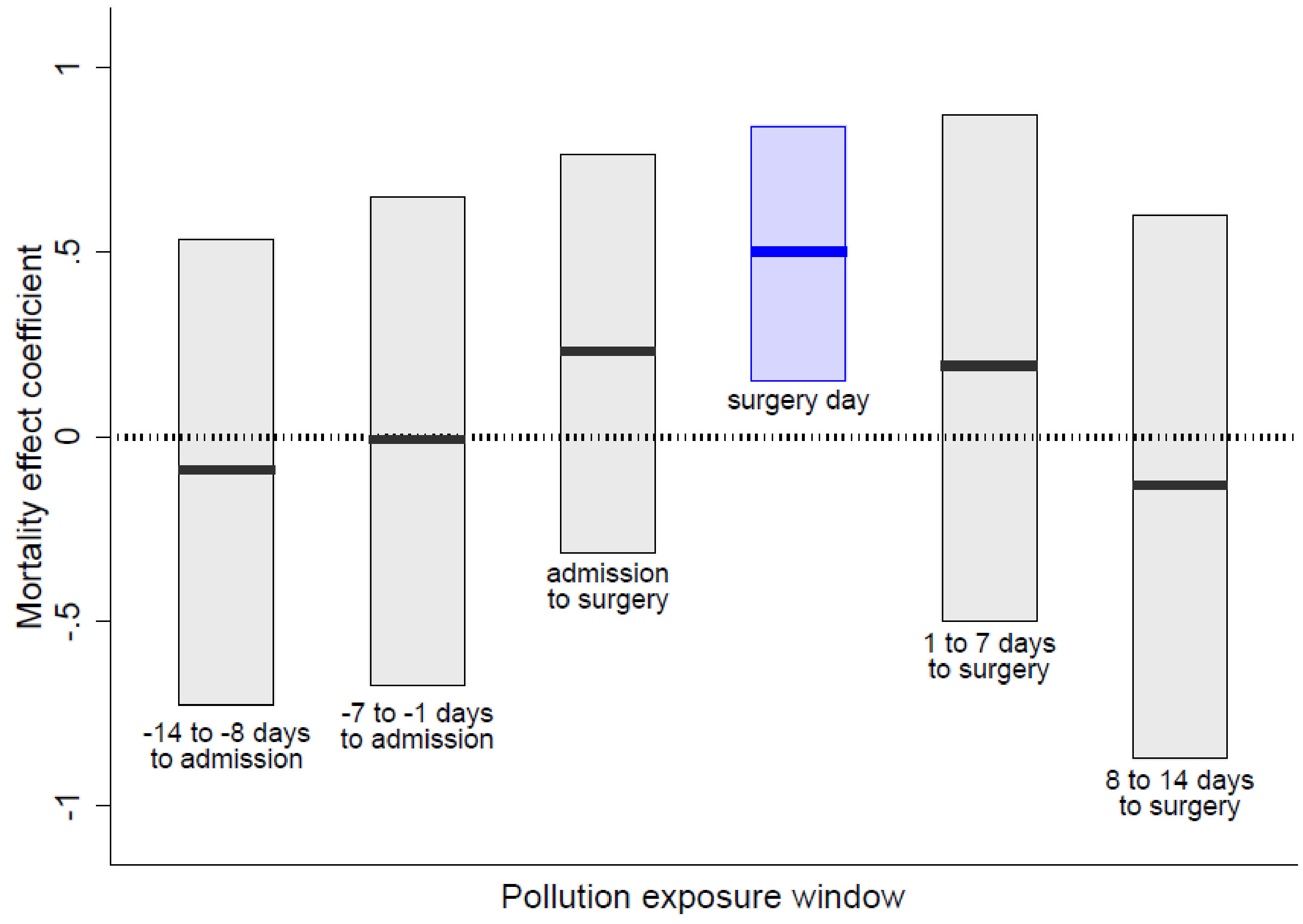
- ML doubles the first-stage F-stat
- IV > OLS, but not >> OLS; suggests pollution exposure in our setting may not be so endogeneous after all
  - Measurement error: all hospitals have pollution monitors within several miles; surgery patients don't much around that much
  - Selection: we explore pollution on a pre-scheduled surgery day
- For the rest of paper, stick with OLS for the sake of efficiency

Outline

- Institutional setting
- The baseline: pollution day is bad for patient survival
- Two key findings:
  - The importance of “surgery day” pollution
  - The high risk group
- Rescheduling exercise
- Other extensions

Critical exposure window: The importance of Surgery-Day Pollution

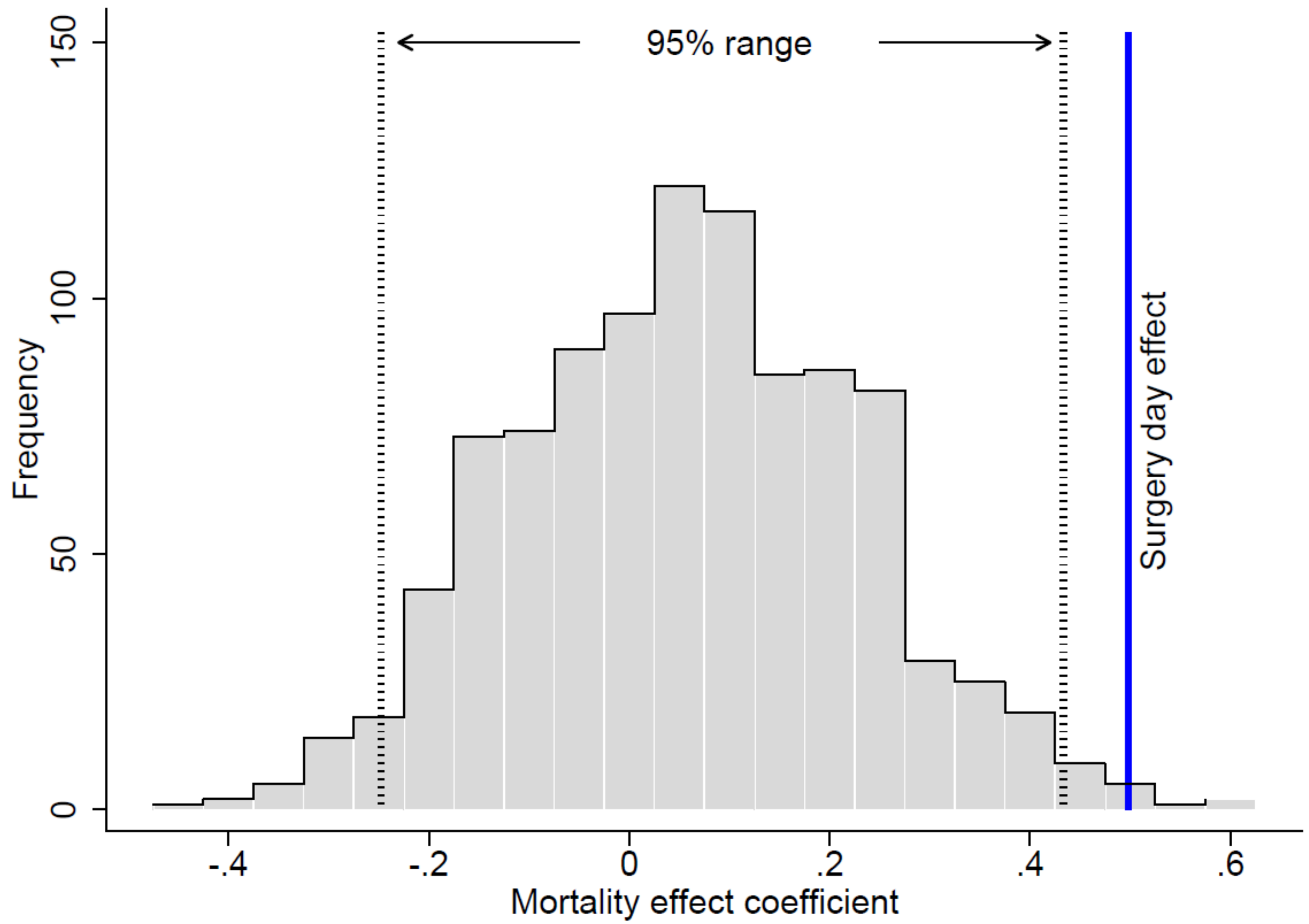
Regression results with alternative exposure windows



Notes: Alternative estimates of pollution effect when alternative exposure windows are used. Bars show 95% CIs.

Critical exposure window: The importance of Surgery-Day Pollution

Regression results with 1,000 “placebo” exposure windows



Notes: Here we compare 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.

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High risk patients: Respiratory and cancer patients aged over 60

6% of patients explain 60% of the observed effect

		(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 PM2.5 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.

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  - Comments on mechanisms
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Comments on mechanisms

- How does surgery-day pollution affect patient survival?

1. Effect of pollution on the physician?
2. Effect of pollution on the patient?

Comments on mechanisms

- How does surgery-day pollution affect patient survival?

1. Effect of pollution on the physician?
   - Institutional evidence that exposure to pollution in the operating room is extremely low
   - No evidence of changes in surgery performance indicators
2. Effect of pollution on the patient?

Physician effect? **Surgery performance indicators**

No evidence that surgery-day pollution leads to worse performance

		(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 performance indicator on surgery-day pollution. Measurement of "medical error" is based on post-hospitalization injuries defined in Van Den Bos et al. (2011) and David et al. (2013).

Comments on mechanisms

- How does surgery-day pollution affect patient survival?

1. Effect of pollution on the physician?
   - Institutional evidence that exposure to pollution in the operating room is extremely low
   - No evidence of changes in surgery performance indicators
   - But, cannot *rule out* a physician channel: we don't have access to physician identifiers, and so cannot implement a within-physician design (Gong, 2018; Molitor, 2018)
2. Effect of pollution on the patient?

Comments on mechanisms

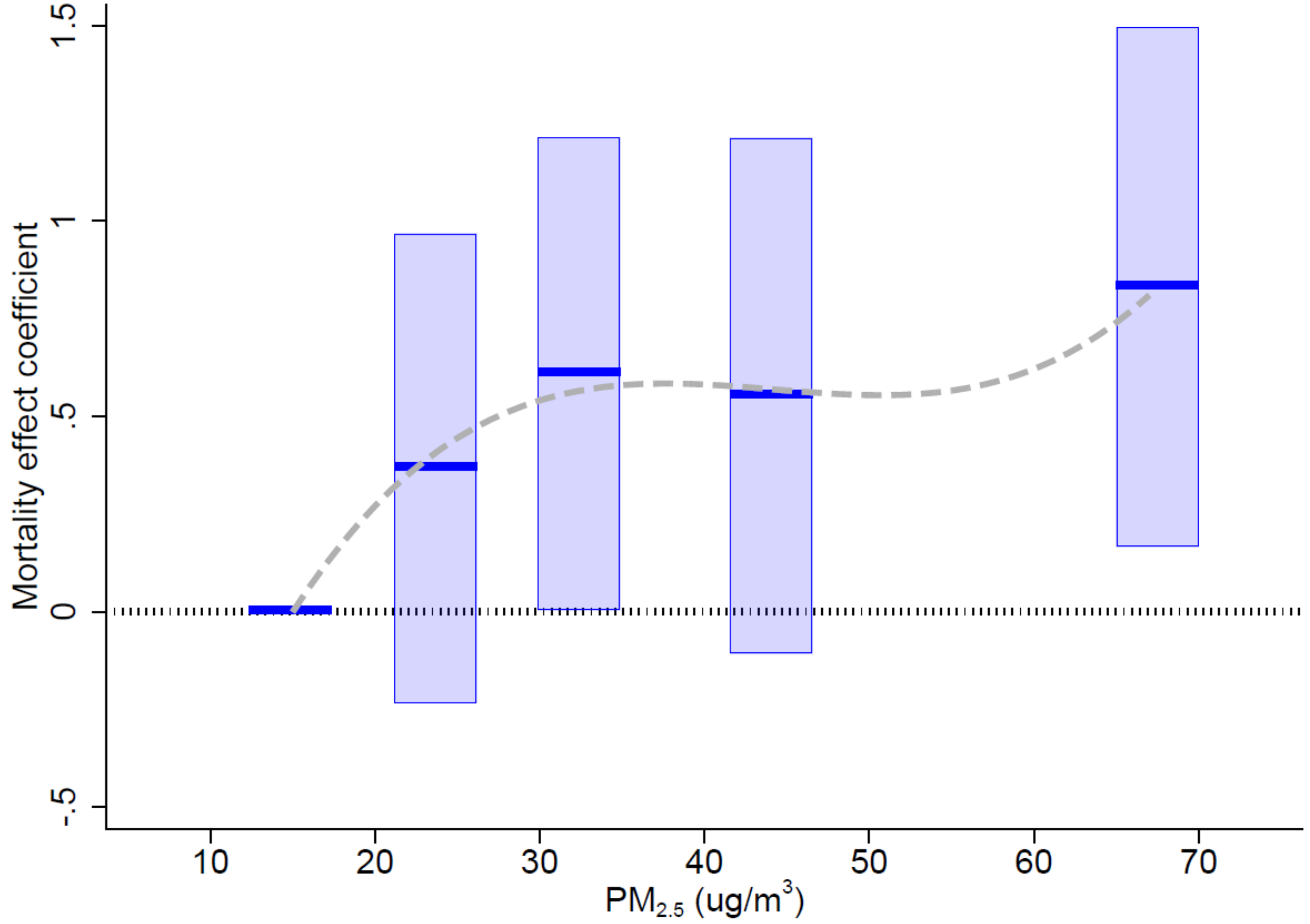
- How does surgery-day pollution affect patient survival?

1. Effect of pollution on the physician?
2. Effect of pollution on the patient?
   - Our evidence points more toward an effect on the patient
   - Paper shows surgical site infection (SSI) increases as surgery-day pollution rises, especially for hypertensive and diabetic patients; echoes an old medical literature (Gryska and O'Dea, 1970; Charnley, 1972; Lidwell et al., 1982)

     ... this result may arise as the typical surgical wound takes 24 to 48 hours to close after the operation (Mangram et al., 1999), leaving the patient susceptible to exogenous infections from in-hospital exposure to pollution.
   - We also recover a series of empirical patterns that have commonly emerged in prior studies on air pollution's effects on general population health (see paper for details)

Ex: Concentration-response function

Supra-linear dosage effect of surgery-day PM2.5 exposure



Notes: This graph reports the effect of surgery-day PM2.5 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.

Ex: Multiple pollutants model

PM2.5 being a robust predictor for surgery survival

	(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: Ozone (O3), nitrogen dioxide (NO2), sulfur dioxide (SO2), carbon monoxide (CO)

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Model: Key Components

- For each patient i, hospital picks admission-to-surgery delay d_i to maximizes utility:

$$u_{id} = -\alpha h_{id} + \lambda_{id} + e_{id}$$

  - h_{id} : *perceived* patient mortality hazard; same with reduced-form regression, but without the Pollution term
  - $\lambda_{id} = \sum_g \beta_g \cdot 1(d_{id} = g) + \phi_{workday}$: non-health payoffs determined by delay and workday

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- Intuition: estimate hospital's implicit tradeoffs when scheduling surgeries
  - Parameterize hospital's utility (Pollution term switched off)
  - Then, generate counterfactual schedules (Pollution term switched on)
  - All boils down to a standard discrete choice ML estimation of parameters $\theta = \{\alpha,\ \beta_g' s, \phi\}$.

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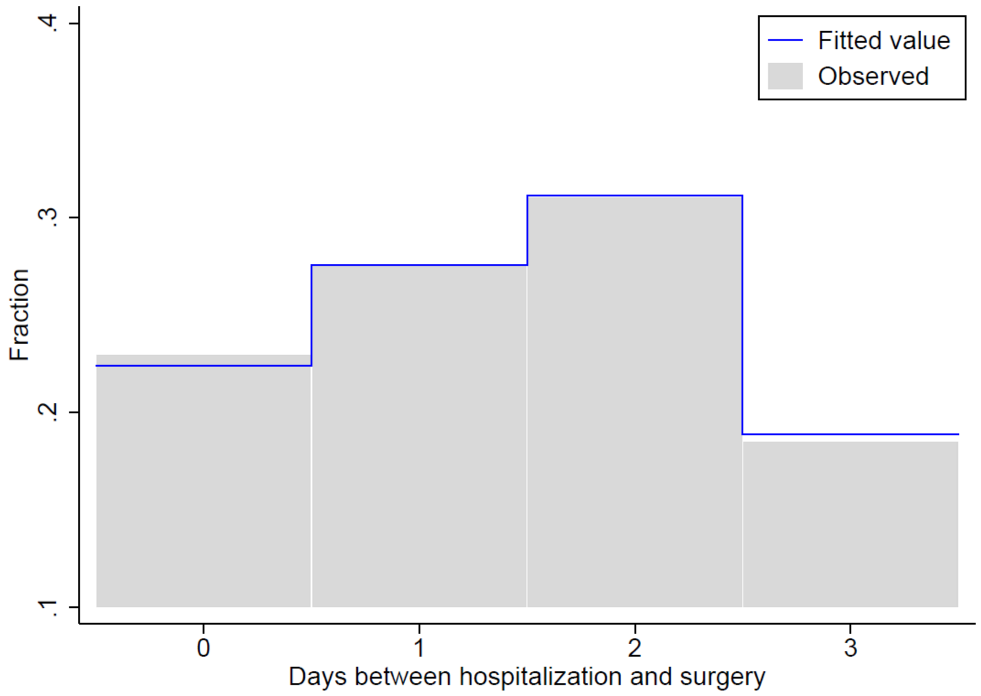
  - All boils down to a standard discrete choice ML estimation of parameters $\theta = \{\alpha,\ \beta_g's, \phi\}$.

- Practicality: only consider "local" rescheduling vis-à-vis the observed schedule
  - Focus on patients in the high-risk group: respiratory & neoplasm patients aged 60+
  - Consider only short-term swaps: $g \in \{0,1,2,3\}$, i.e., look for a better pollution day within 3-day window

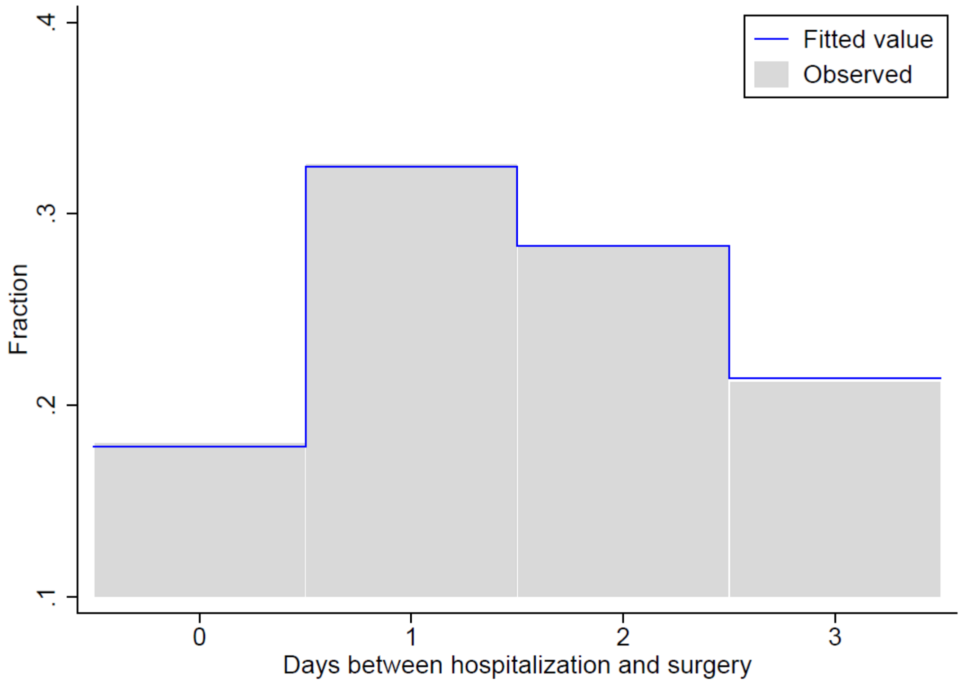
Structural model performance: **Observed vs. Predicted Scheduling**

Regression results with 1,000 "placebo" exposure windows

A. Respiratory patients



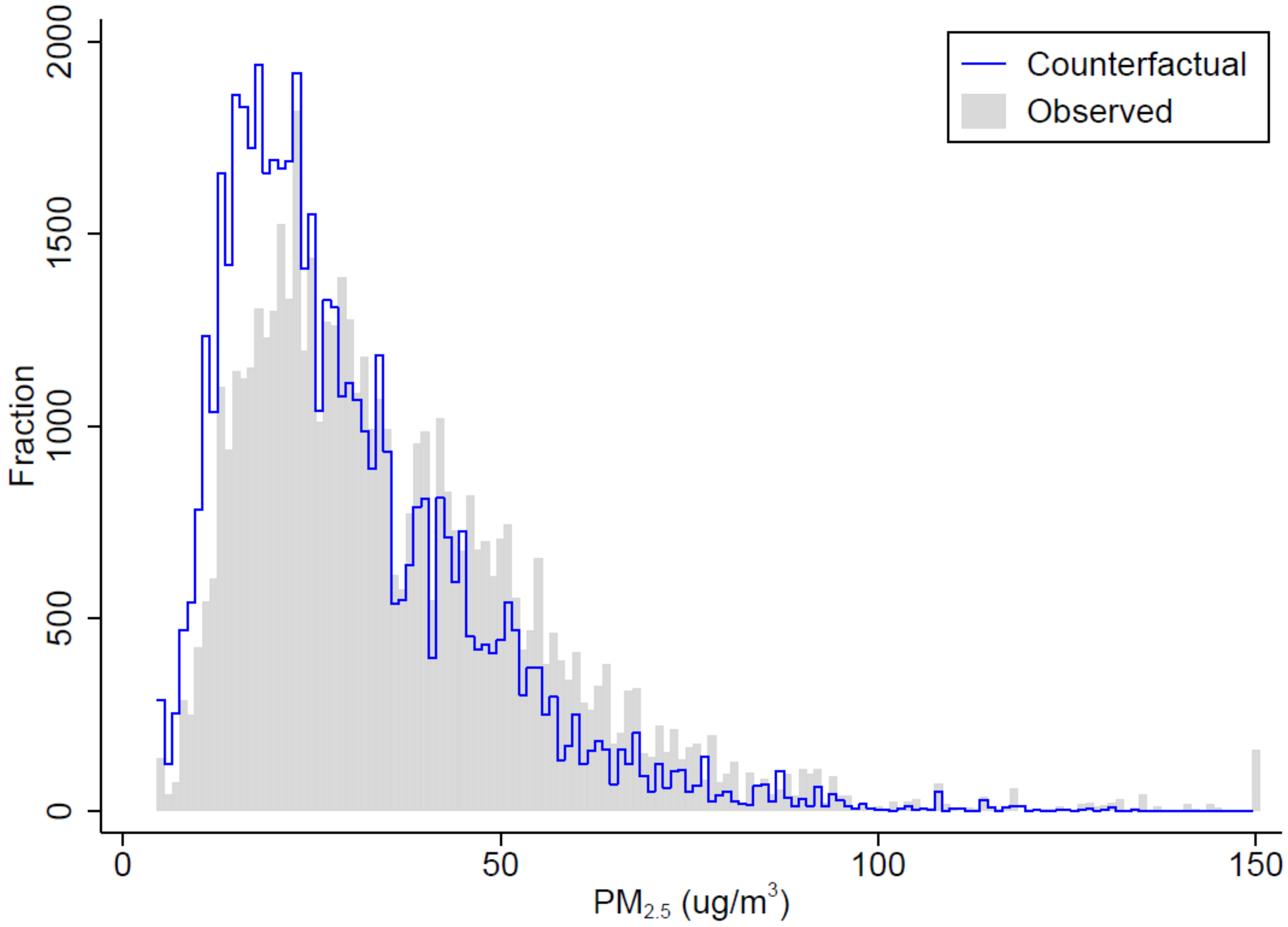
B. Neoplasm patients



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

Counterfactual exposure: **Change in Surgery-Day Pollution**

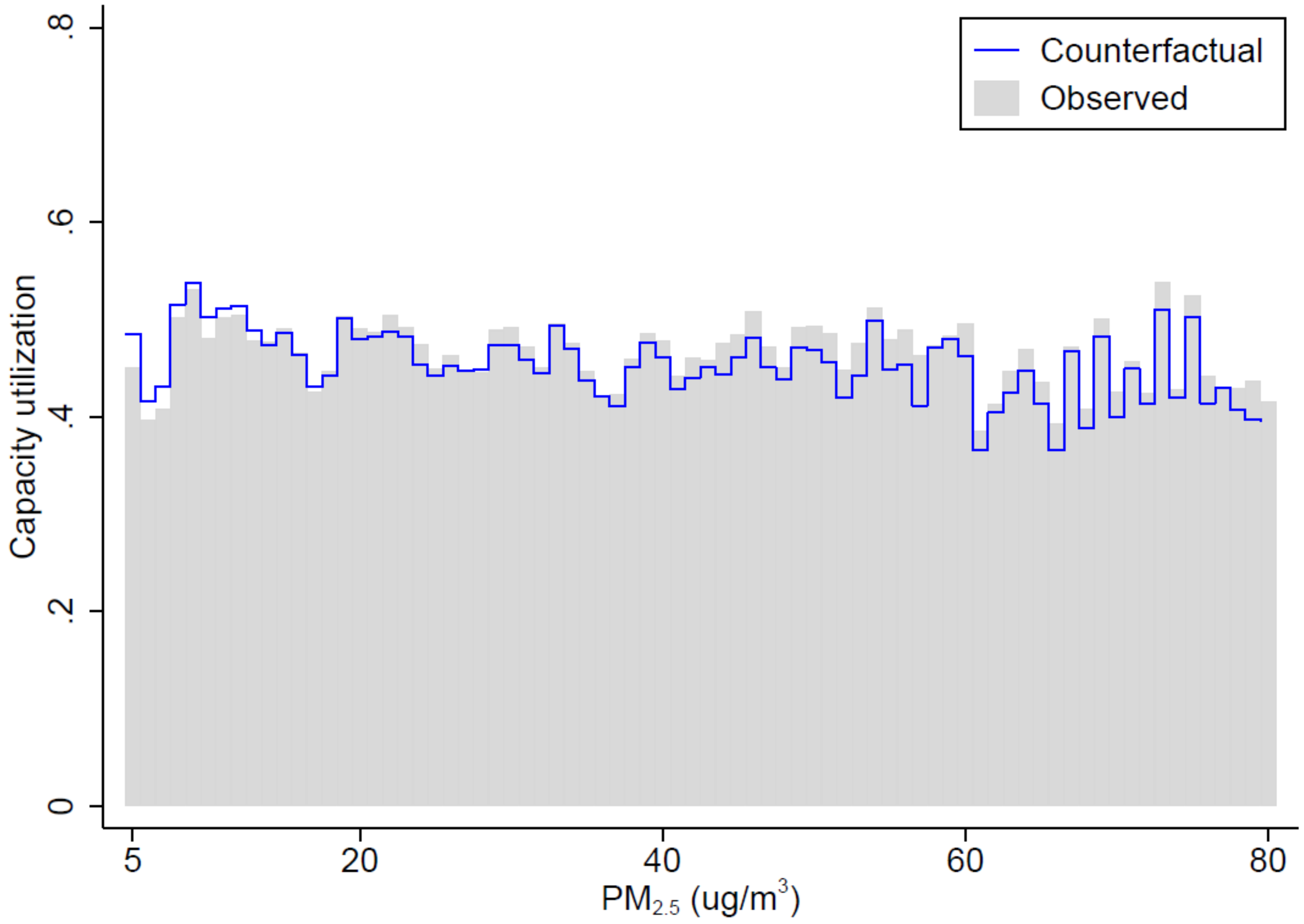
Over 40% of high-risk patients would have been rescheduled to a lower-pollution day



Notes: Observed and counterfactual surgery profile's PM2.5 distribution among the high-risk patient group.

Counterfactual capacity: Does rescheduling influence capacity?

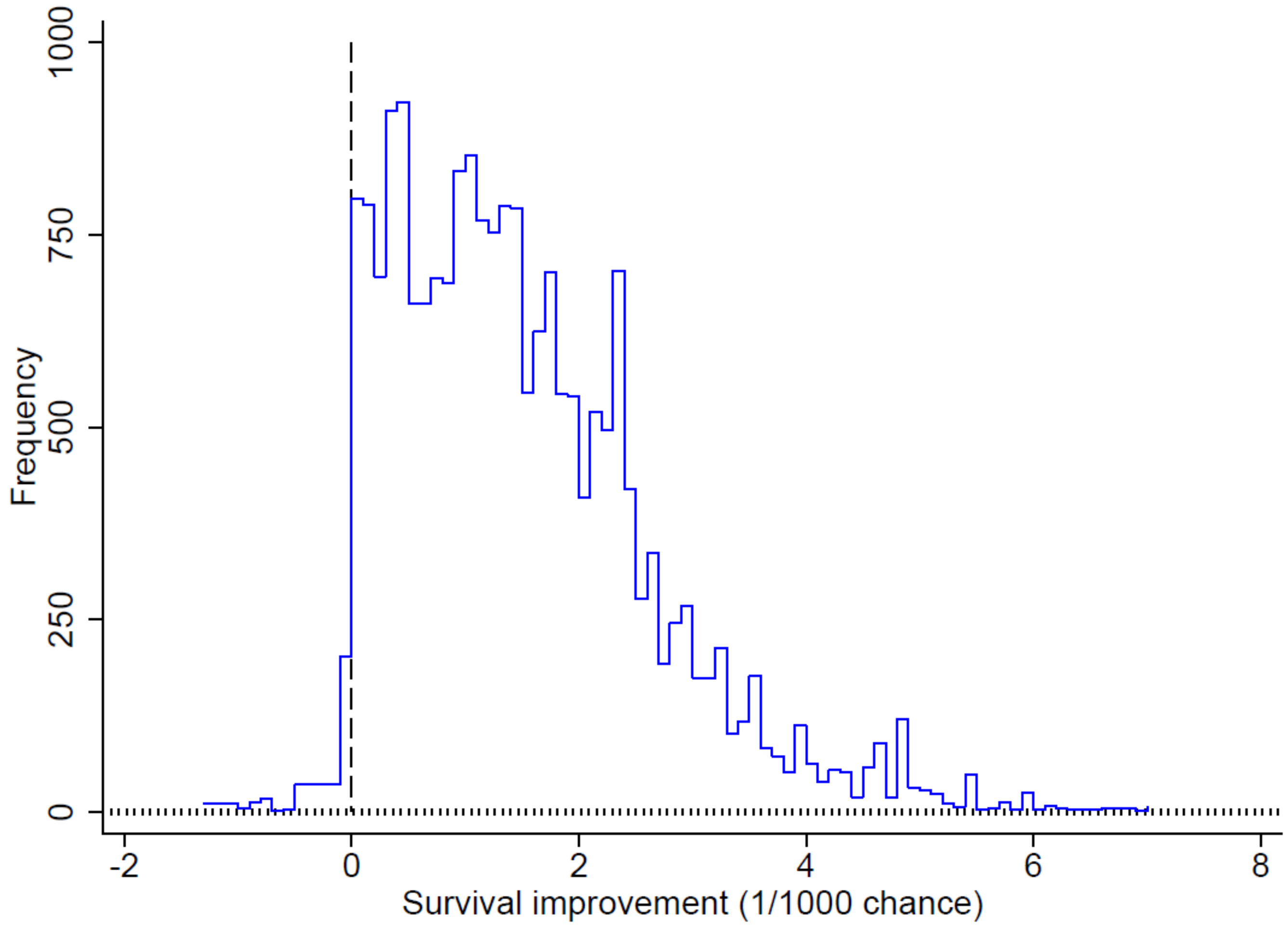
Little impact on overall surgery capacity, as we only consider "local" rescheduling



Notes: Hospitals' daily overall surgery capacity utilization rates averaged by 1-ug/m3 bins.

Survival improvement: Predicted change in patient survival

Vast majority of switchers would improve upon their post-operative survival



Notes: Distribution of survival improvements among “switcher” patients whose counterfactual surgery day is different from the observed day.

Model: Implications

- For over 1/3 of scheduled surgeries, there exists an alternative, lower-pollution day within three days of the originally scheduled day such that moving the surgery would …
  a) … yield an average 4 percent better post-surgery survival among the switchers
  b) … has little impact on hospital's overall surgery capacity (hence unlikely to impact other patients)
  c) … meet the basic cost-benefit trade-offs according to hospitals' revealed hospital preferences

Model: Implications

- Again, the structural results hinge on several empirical features:

1. Pollution on the surgery day matters (reduced form results)
2. We only need to switch a relatively small pool of patients (reduced form results)
3. Near-term air pollution is forecastable

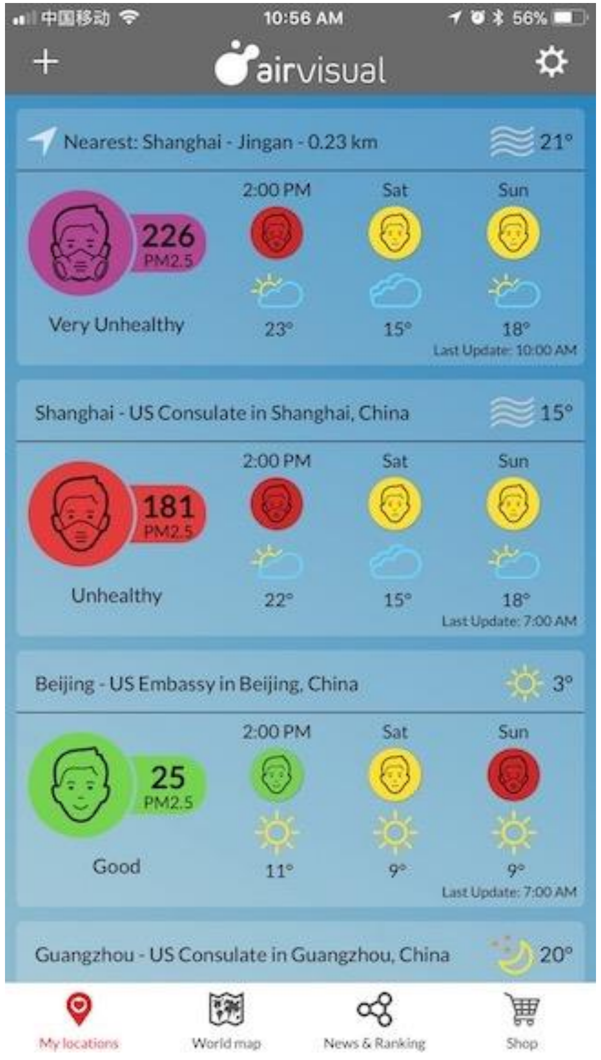
Model: Implications

- Again, the structural results hinge on several empirical features:

1. Pollution on the surgery day matters (reduced form results)
2. We only need to switch a relatively small pool of patients (reduced form results)
3. Near-term air pollution is forecastable

Pollution information: Pollution now/forecasts widely available

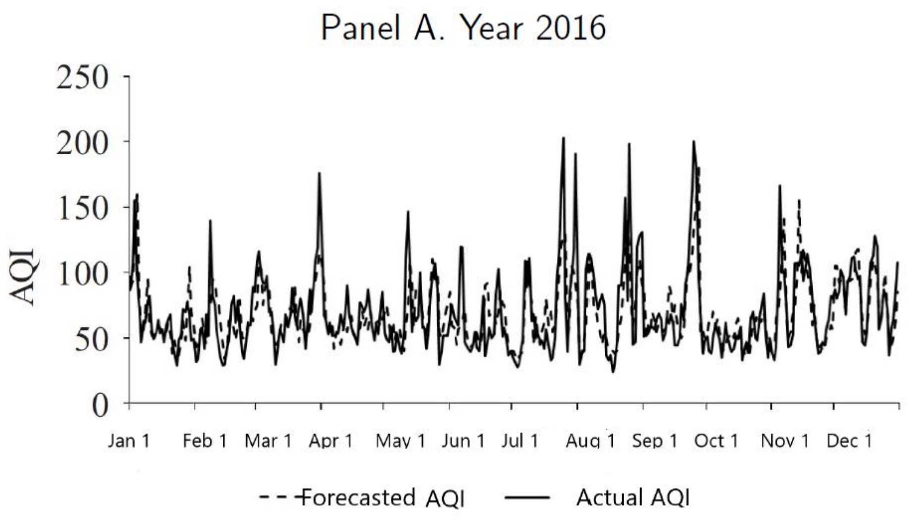
An example mobile phone app

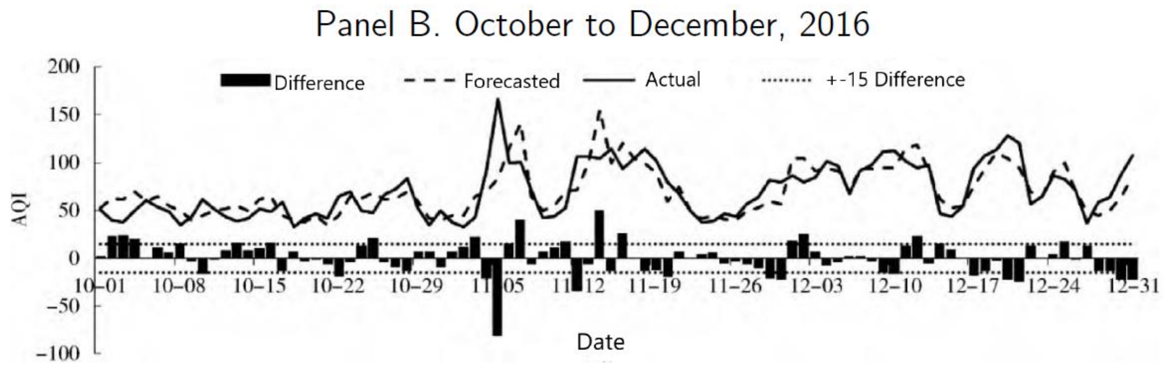


Source: airvisual.

PM2.5 forecasting: Predicted vs. actual PM2.5 in Guangzhou, 2016

Source: Zhang et al. (2017, 2018)

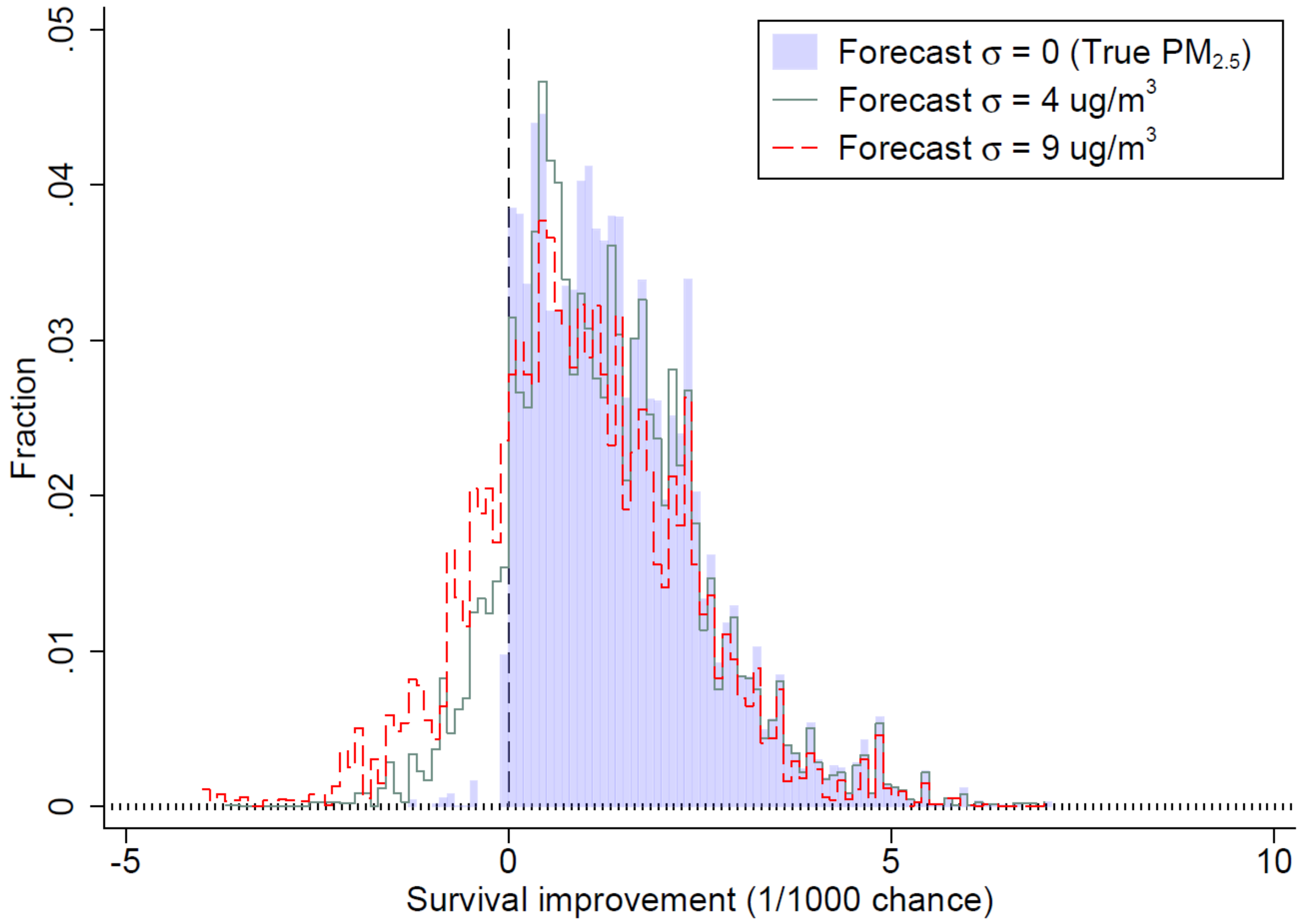




Notes: Panel A reports 24-hour-ahead forecasted (dashed line) and observed (solid line) Air Quality Index throughout the year of 2016. Panel B zooms in to October to December of 2016. Bars on panel B represent differences between observed and forecasted Air Quality Index values.

Value of forecasting accuracy: **Less noise, better patient survival improvements**

Survival improvements among “switcher” patients, with forecasting noise



Notes: Blue histogram repeats the baseline. Green and red histograms show survival improvement when true PM2.5 values are infused with N(0, σ = 4 ug/m3) and N(0, σ = 9 ug/m3) noise..

Thank you!

Jialin Huang (post-doc @ Peking U)

Jianwei Xing (jianweixing.com)

Eric Zou (eric-zou.com)

.. scan QR code to browse the paper!