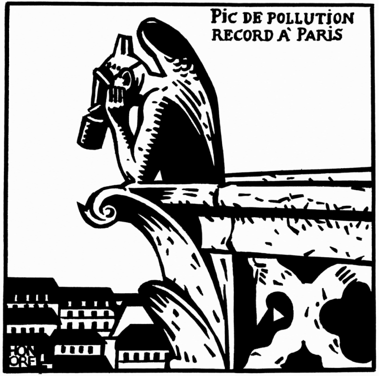
Why Acute Health Effects of Air Pollution Could Be Inflated

Job Market Talk



Léo Zabrocki & Vincent Bagilet

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Paris School of Economics
Columbia University

The *Short-Term* Effects of Air Pollution?

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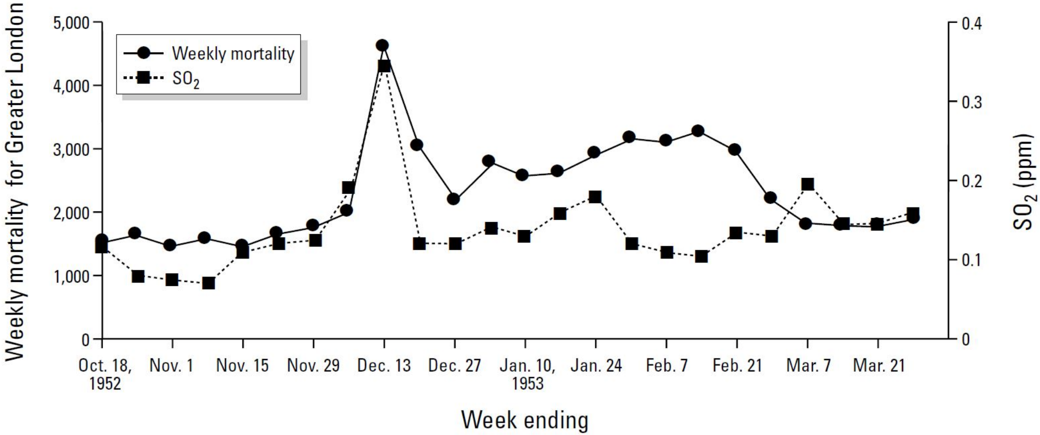

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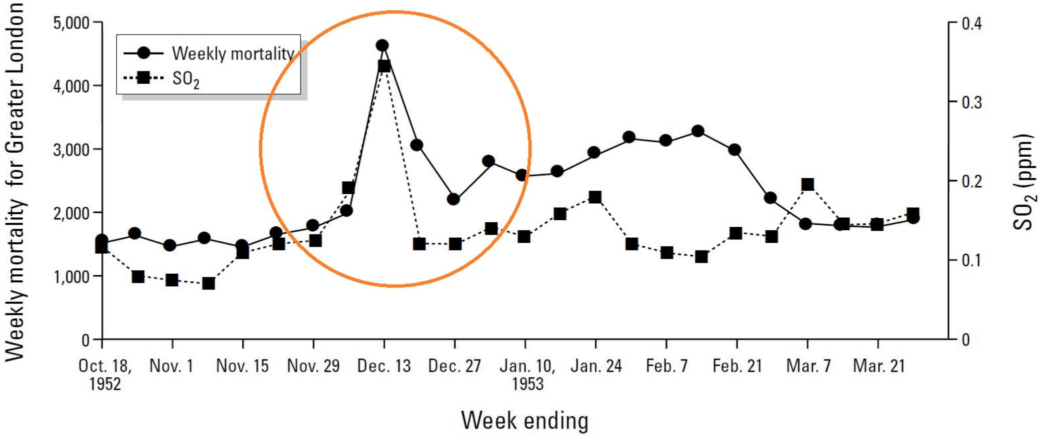

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... estimating its adverse effects
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Liu et al. (NEJM, 2019):

652 cities

A 10 µg/m³ increase in $PM_{2.5}$

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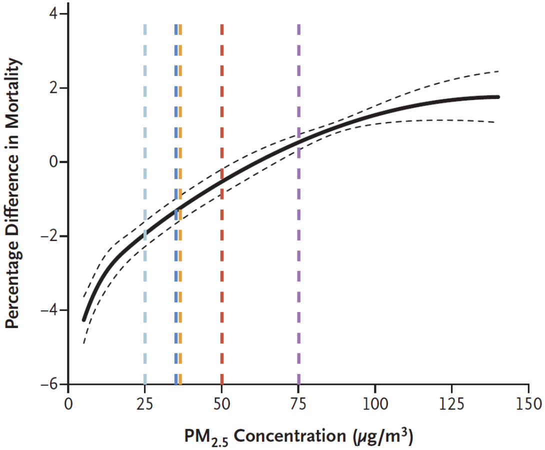

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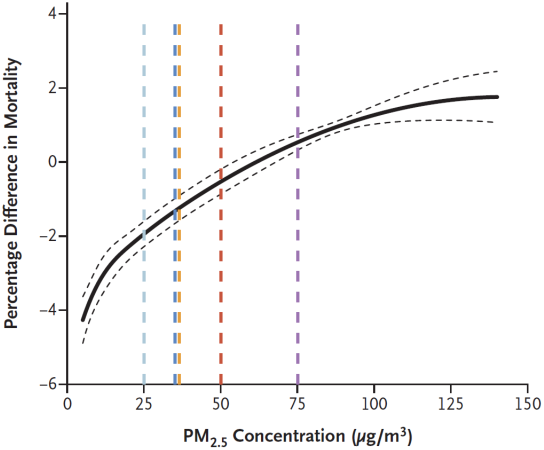

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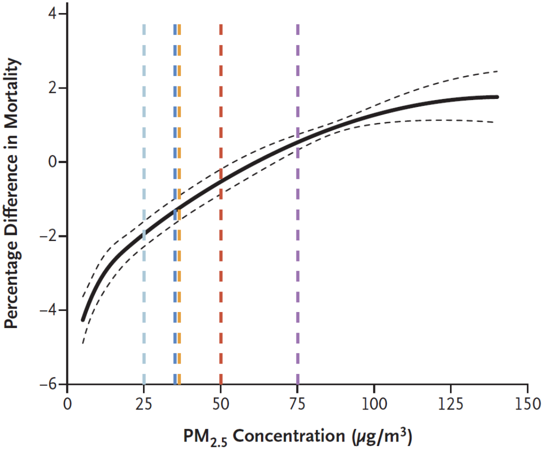

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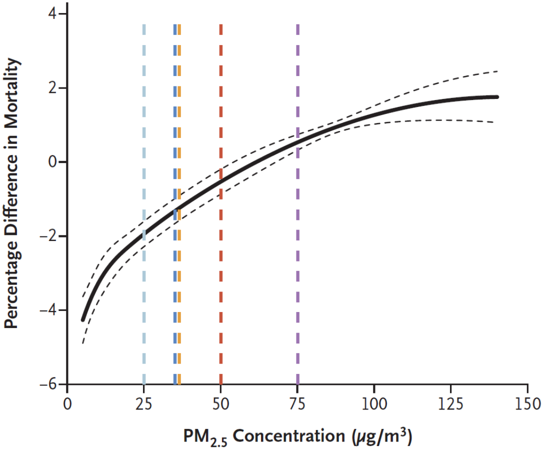
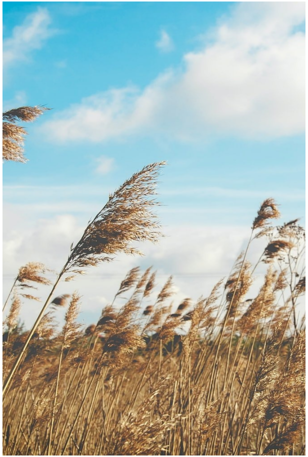


The *Short-Term* Effects of Air Pollution?

Accurate and **precise** estimates are needed as they guide air quality standards

What About Causal Inference?



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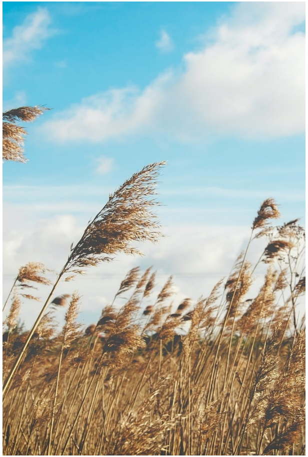

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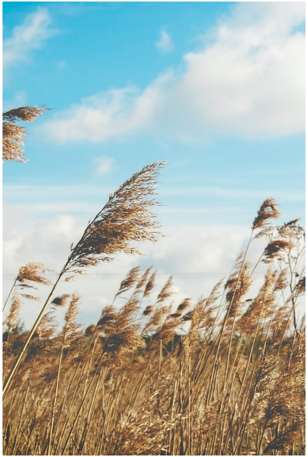

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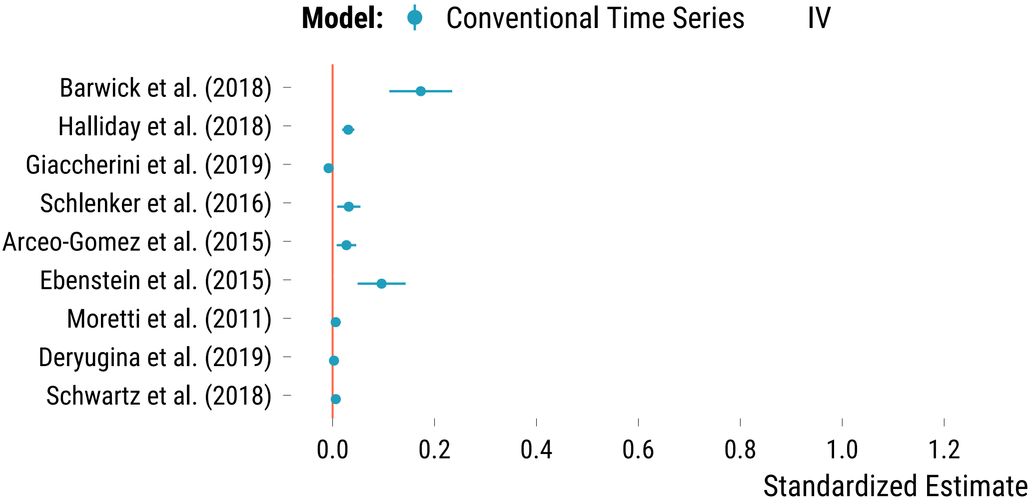
Air Quality Alerts

Causal Estimates are Much Bigger



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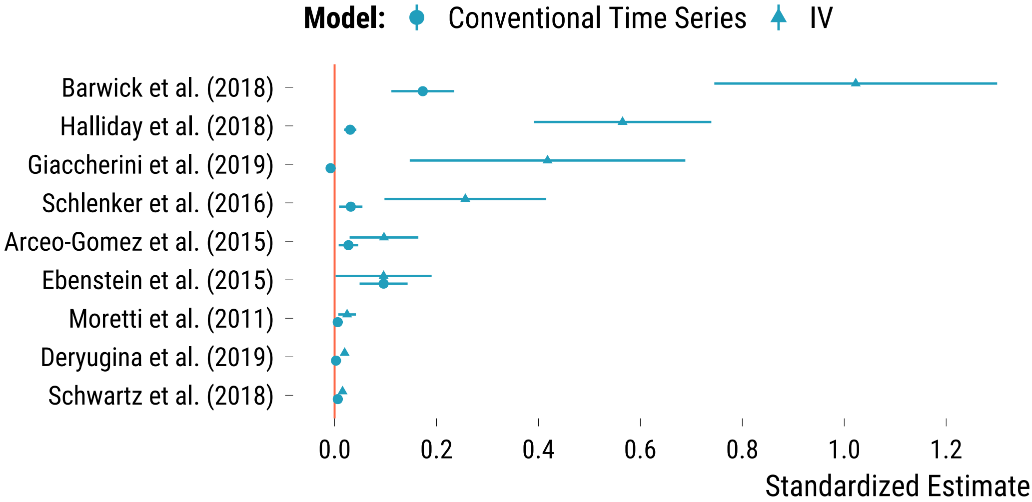

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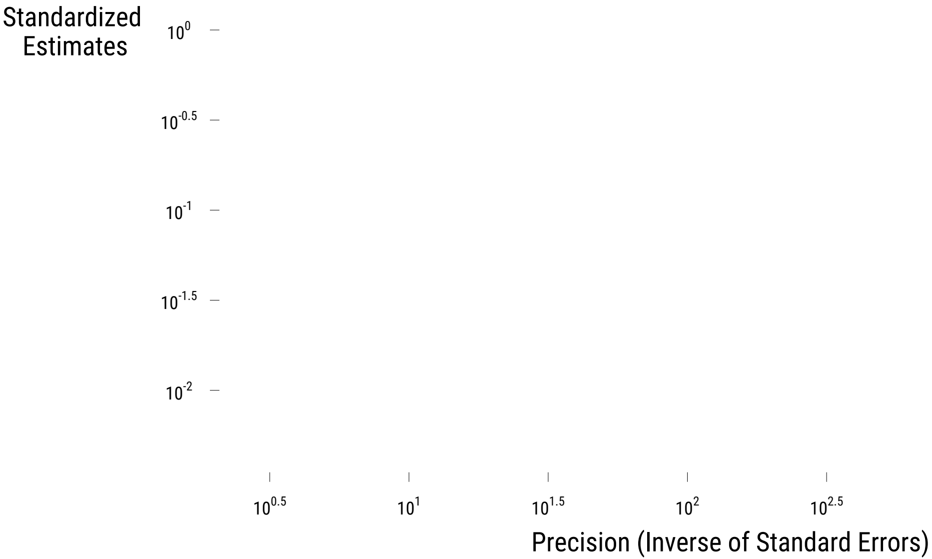

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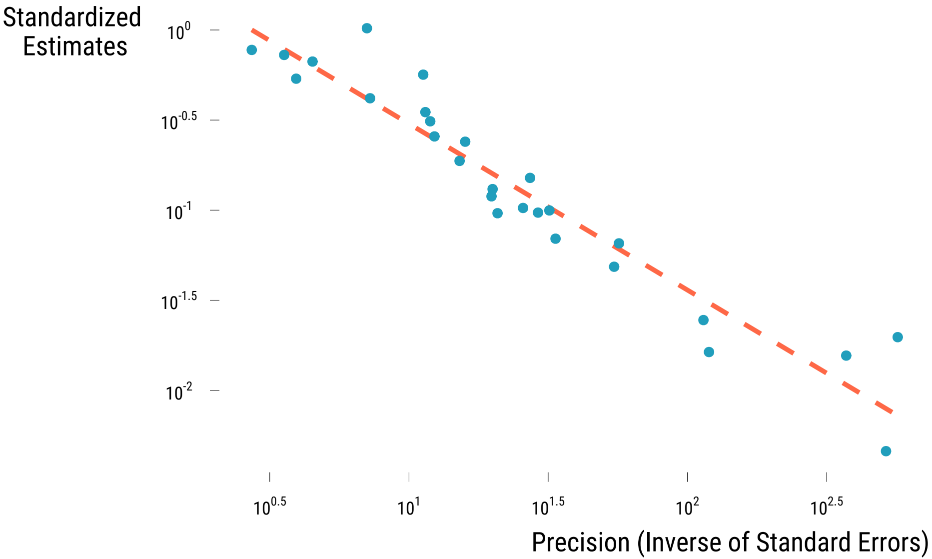

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R.A. Fisher

Studies with low statistical power

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... to reach statistically significance
(Ioannidis 2008, Gelman and Carlin 2014)

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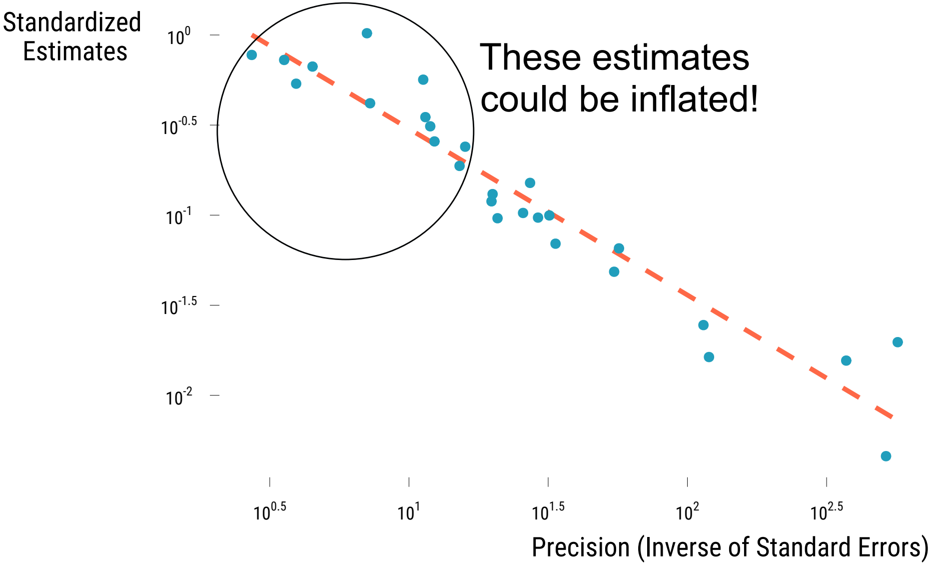

Our Research Questions

Are the short-term health effects of air pollution inflated in some studies?

How can we improve the design of our studies?

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Our corpus:

668 papers from Epidemiology

29 Causal Inference papers

Two questions:

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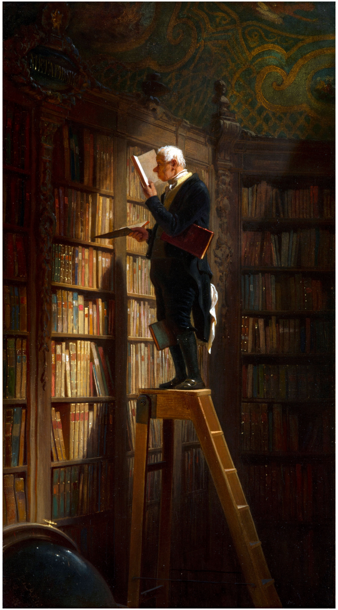

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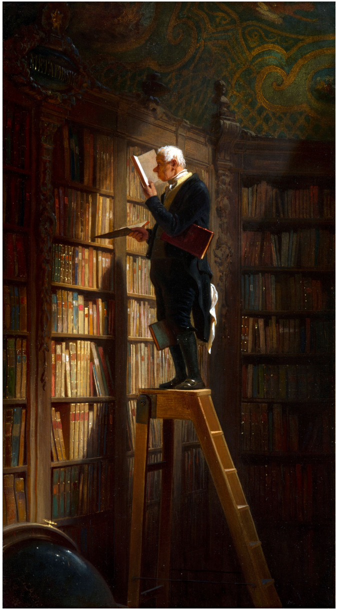

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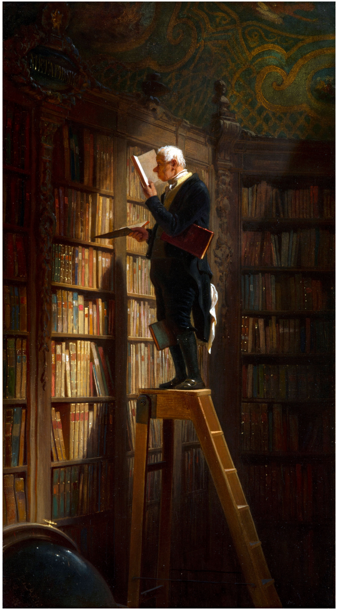

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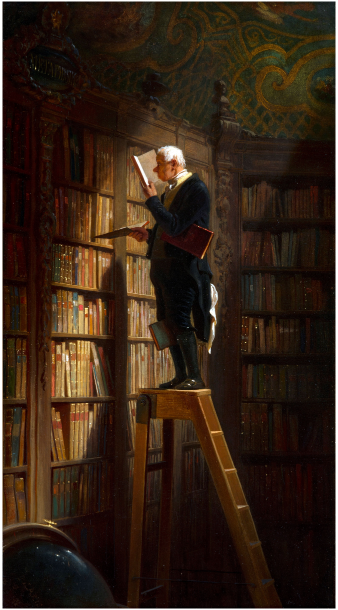

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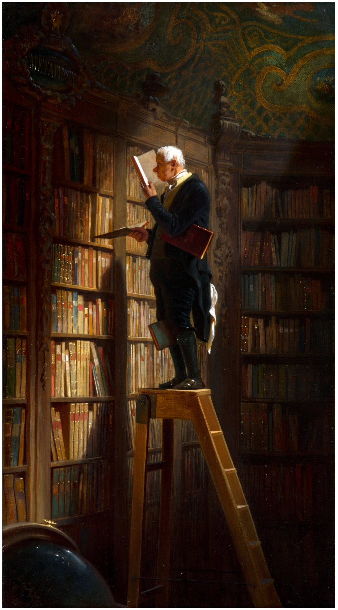

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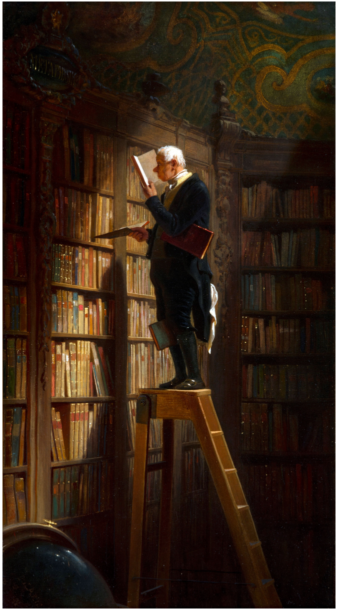

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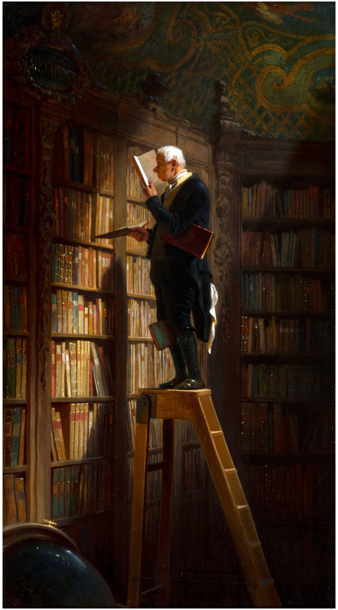


Power Simulation Analysis

Our simulations procedure:

Real data from the NMMAPS

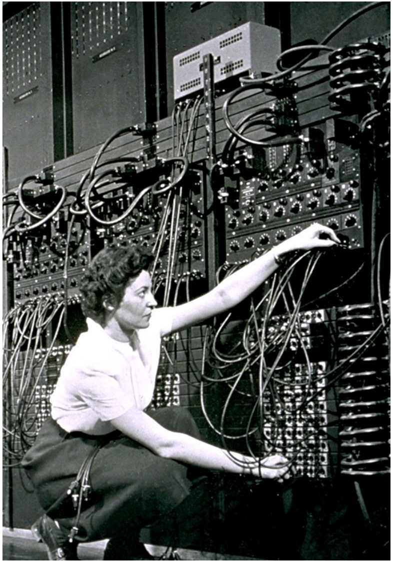
Add fake exogenous shocks

Simulate research designs

Two questions:

Which parameters drive power?

How methods perform?



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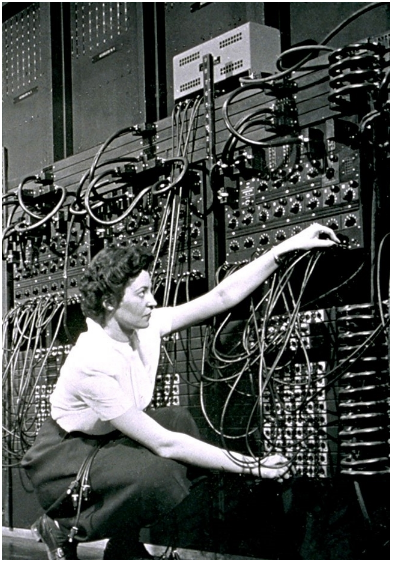

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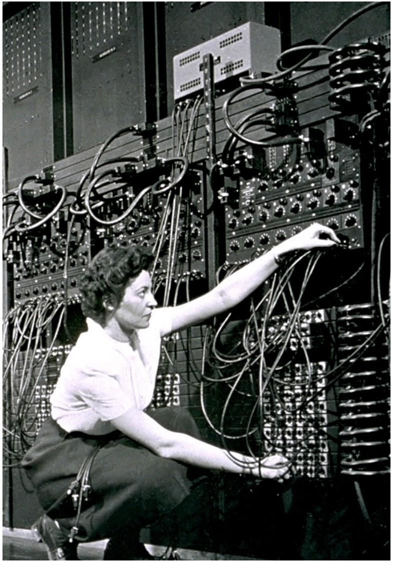

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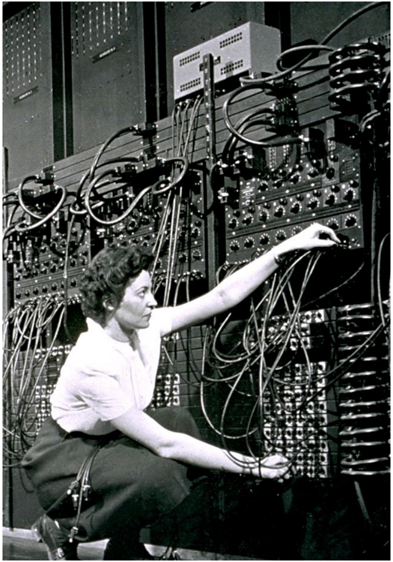

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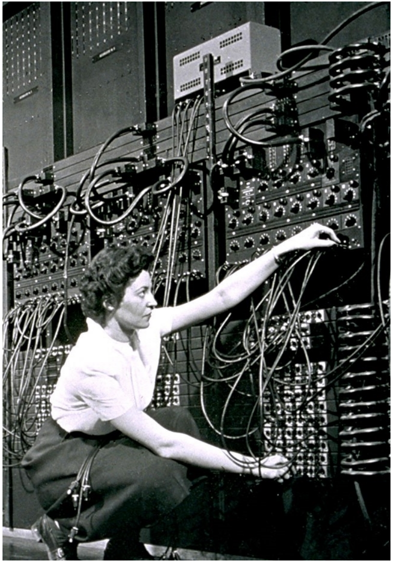

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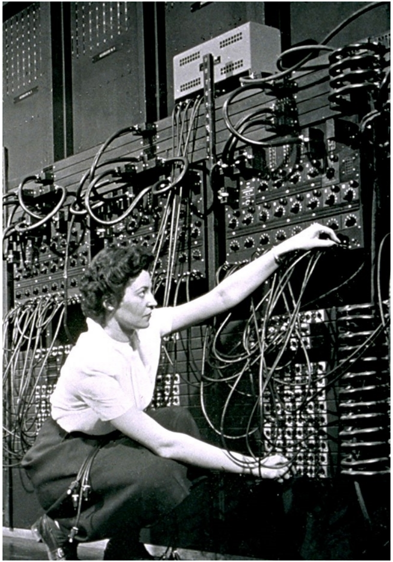

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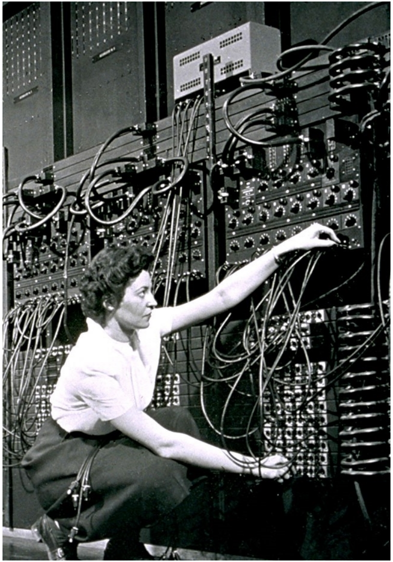

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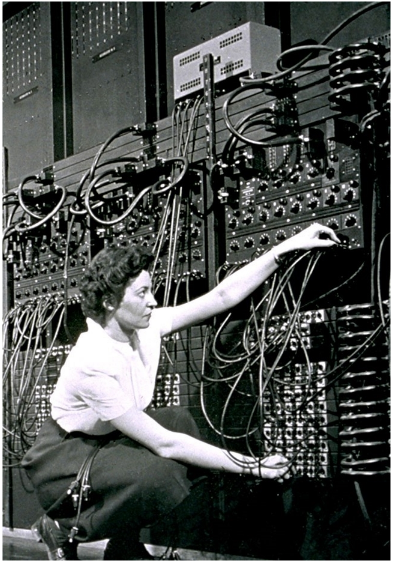

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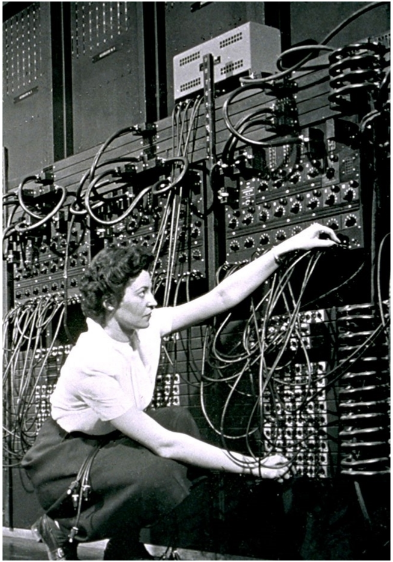

Preview of Results

1. About **half** of the studies could be under-powered and produce estimates **2 times** too large

2. The **number** of exogenous shocks and the **number of cases** of health outcomes matter a lot

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Why We Should Care About Statistical Power?

A Fictional Experiment

1. The study takes place in a major city over 365 days
2. A mad scientist randomly increases $PM_{2.5}$ concentration by 10 µg/m^3 for half of the days
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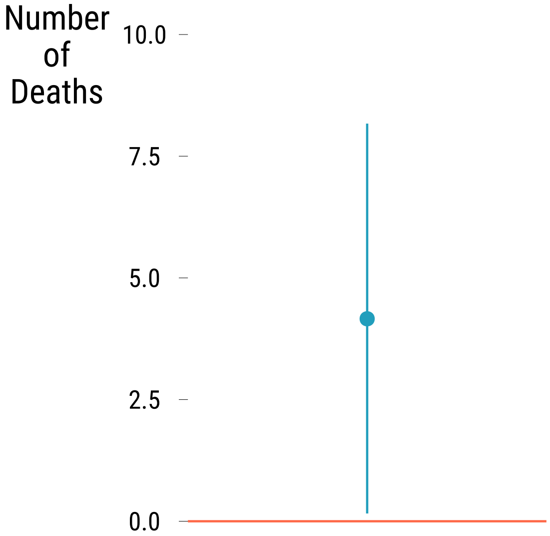

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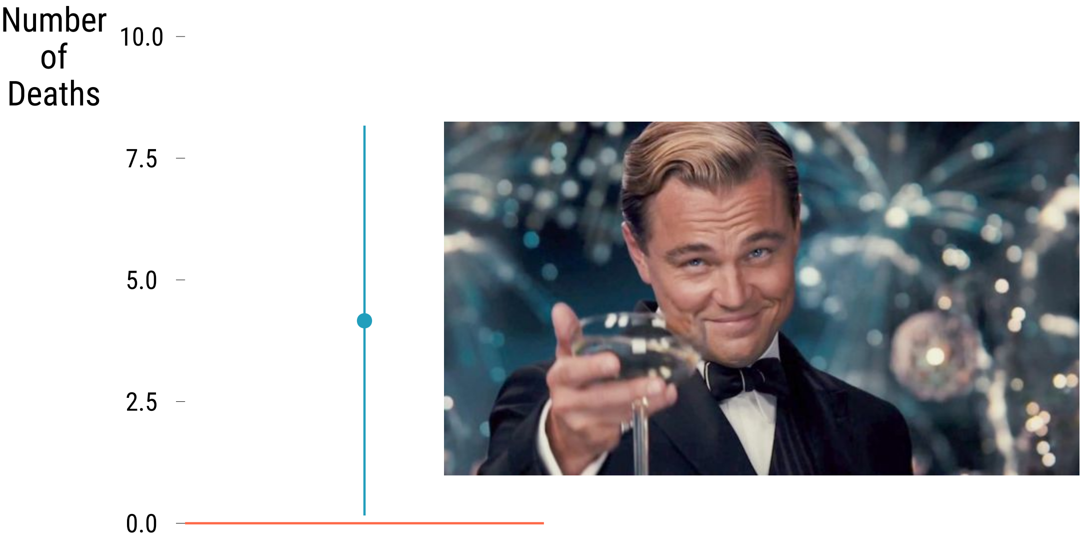

The True Effect is Known

Day Index	$Y_i(0)$	$Y_i(1)$	τ_i	W_i	Y_i^{obs}
1	122	124	+2	0	122
2	94	94	+0	0	94
3	153	154	+1	1	154
⋮	⋮	⋮	⋮	⋮	⋮
364	160	160	+0	1	160
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Averages	103	104	+1		

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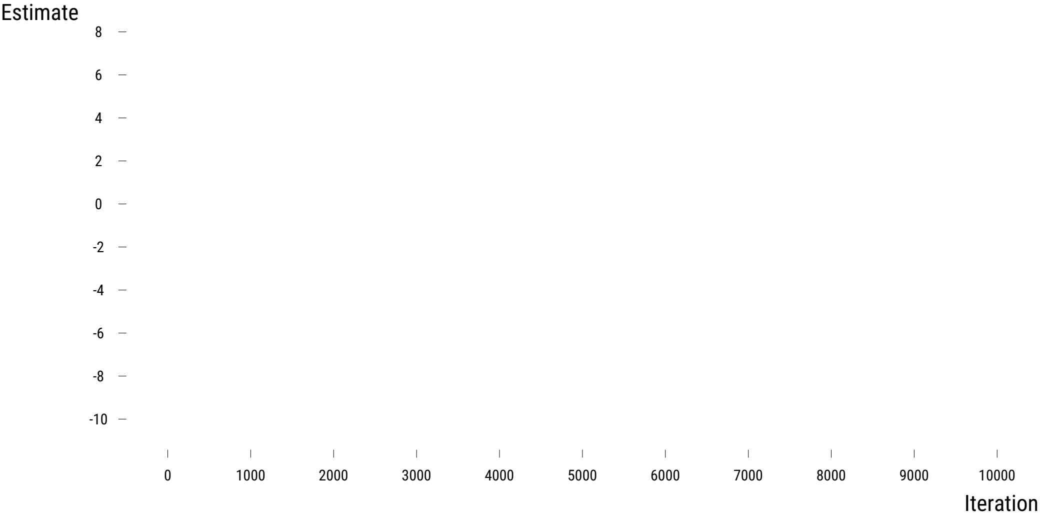
Replicating The Experiment



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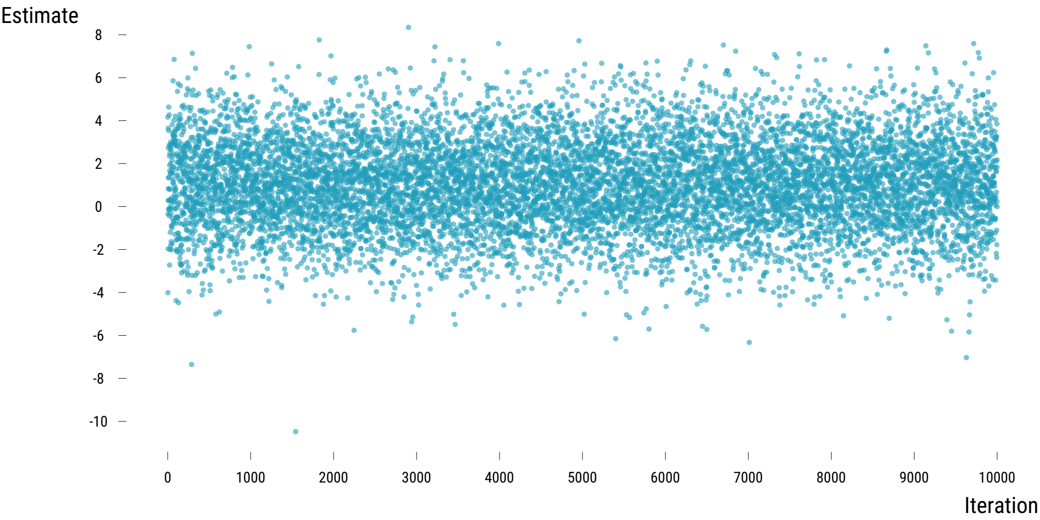

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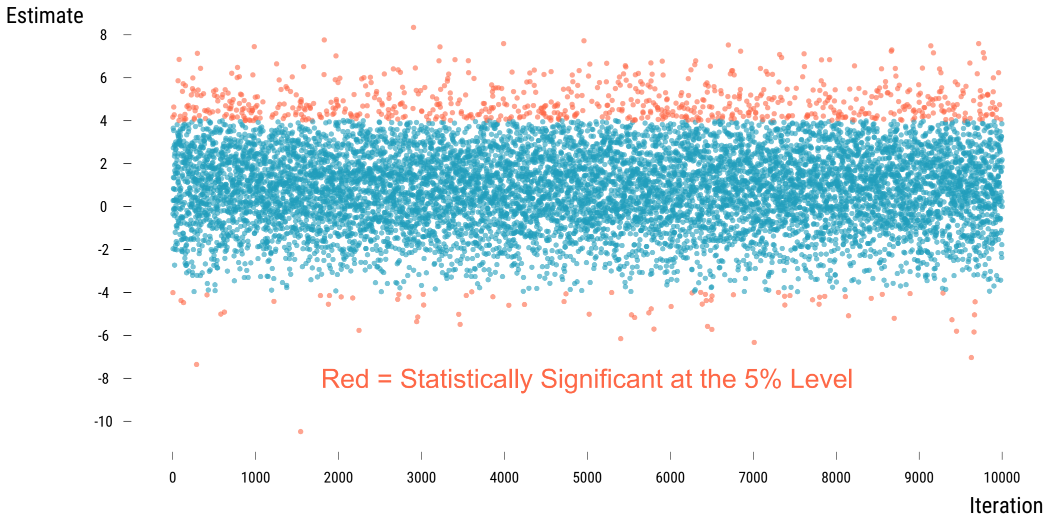

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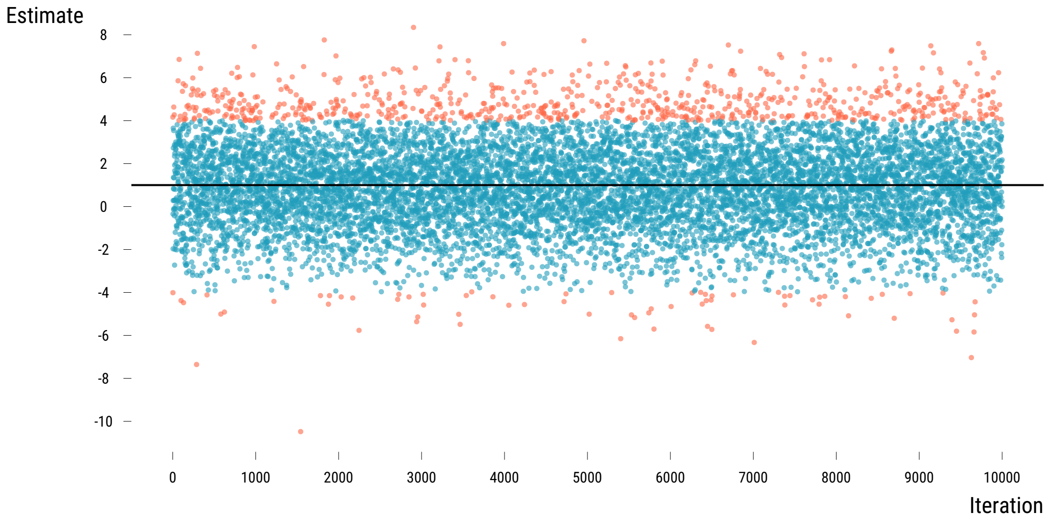

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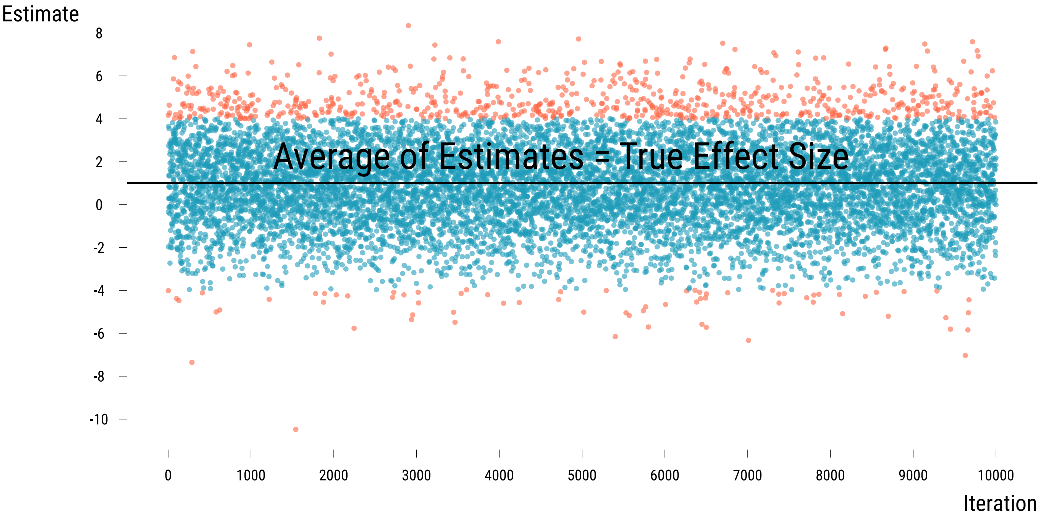

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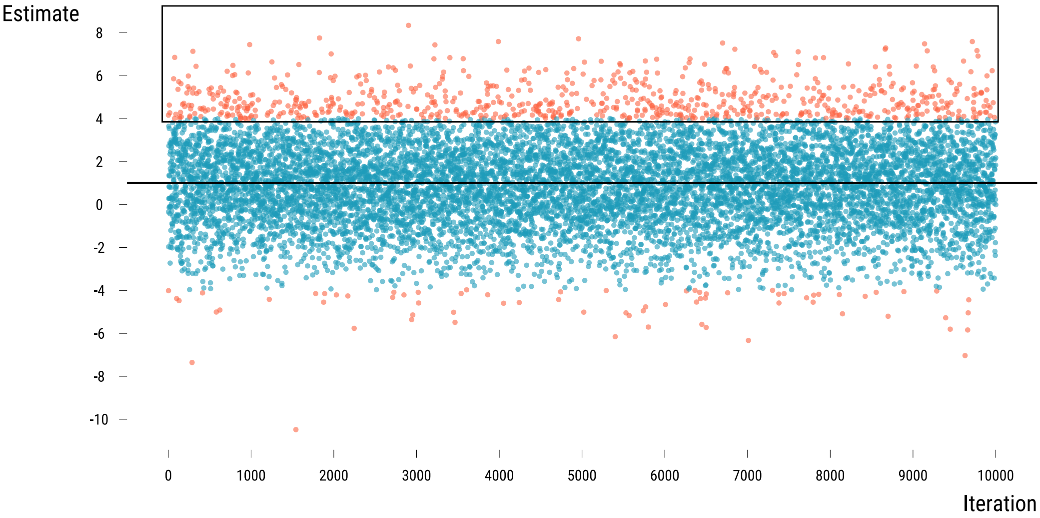

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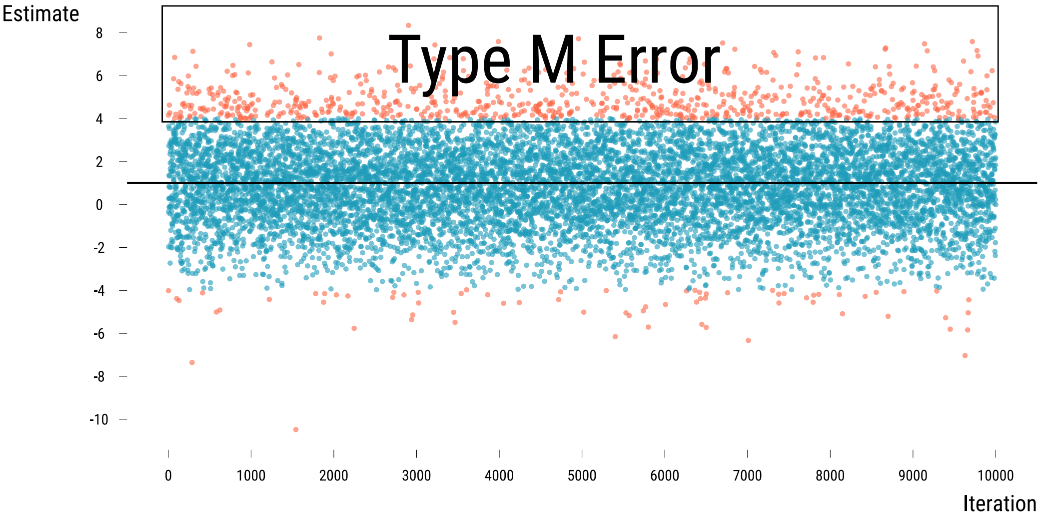

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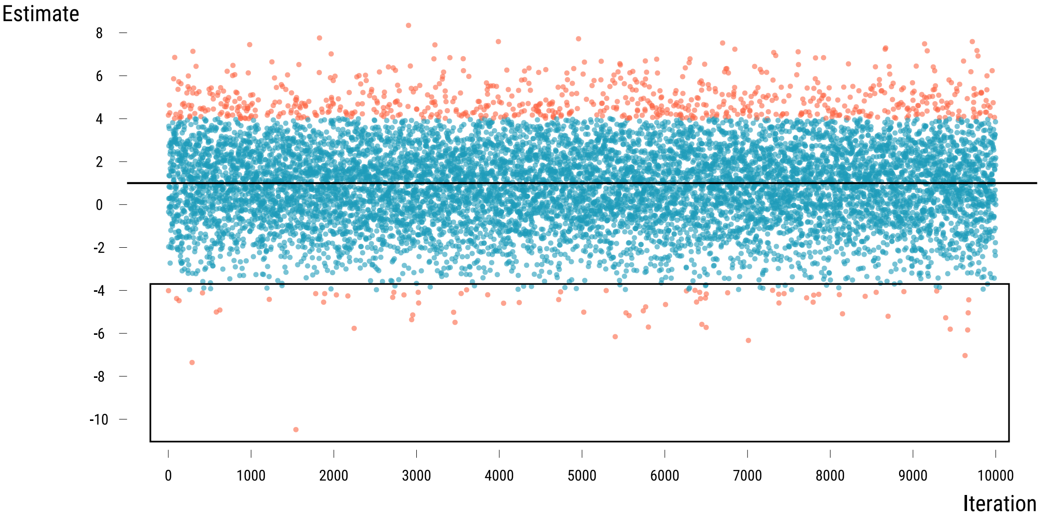

Replicating The Experiment

Three Important Metrics

In our fictional experiment:

Statistical power is **8%**.

The probability to make a type S error is **9%**.

The average Type M error is **5**.

Three Important Metrics

In our fictional experiment:

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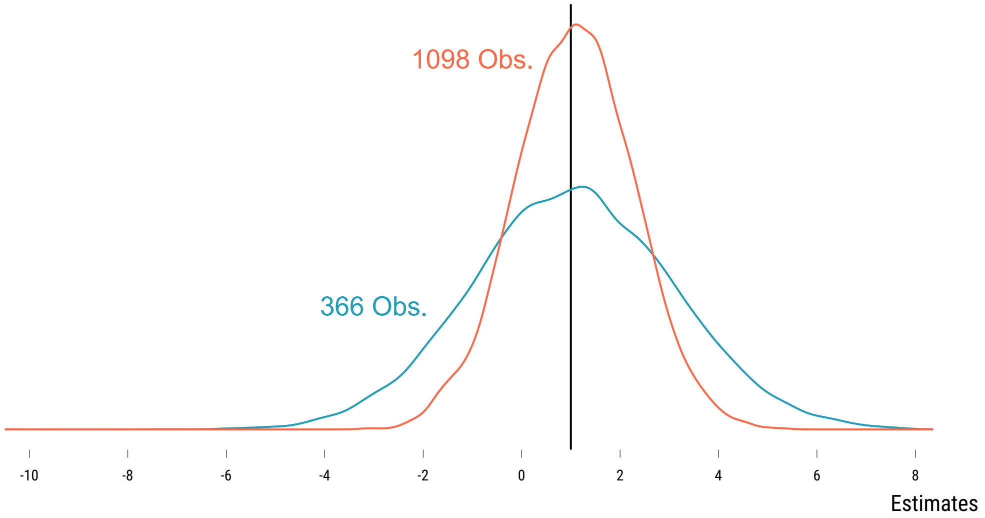
Sample Size is Critical



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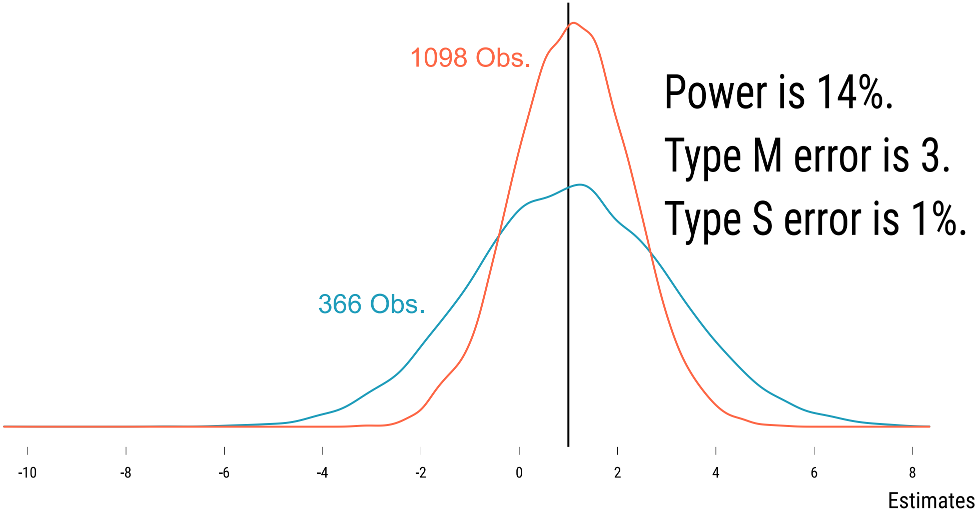

Power is 14%.

Type M error is 3.

Type S error is 1%.

Does The Literature Run Into Statistical Power Issues?

How to Run Retro Power Calculations?

Three ingredients (Gelman and Carlin, 2014):

1. The point estimate,
2. Its standard error,
3. And a guess about the *true* effect size.

But the true effect size is never observed

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An Example

Deryugina et al. (AER, 2019):

- Study the effect of $PM_{2.5}$ on elderly mortality
- County $\times$ daily level (1999-2013)
- 2 million observations
- Instrument $PM_{2.5}$ concentration with variation in wind direction

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A 1 µg/m³ increase in $PM_{2.5}$ exposure leads to 0.69±0.061 additional deaths per million elderly individuals.

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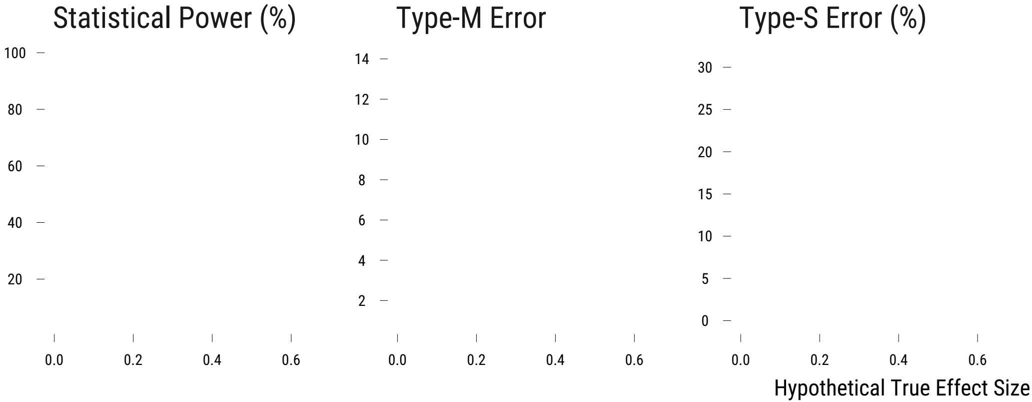
An Example


Statistical Power (%)
100
80
60
40
20
0.0
0.2
0.4
0.6
Type-M Error
14
12
10
8
6
4
2
0.0
0.2
0.4
0.6
Type-S Error (%)
30
25
20
15
10
5
0
0.0
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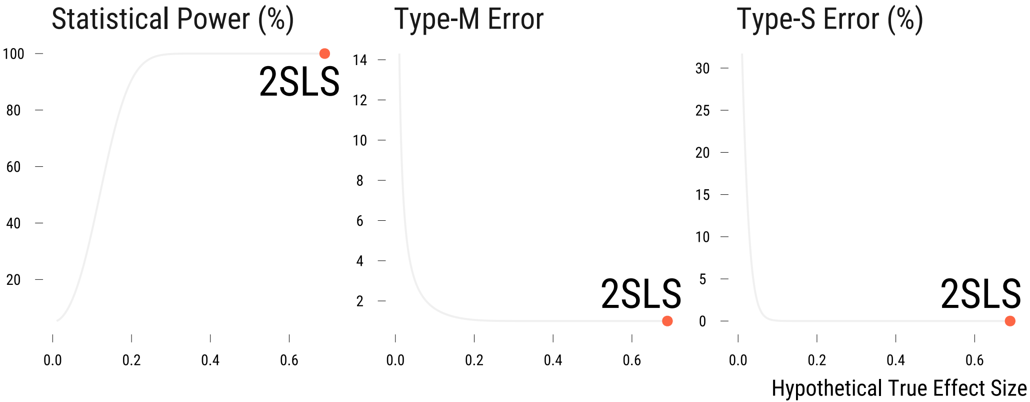
Hypothetical True Effect Size

An Example



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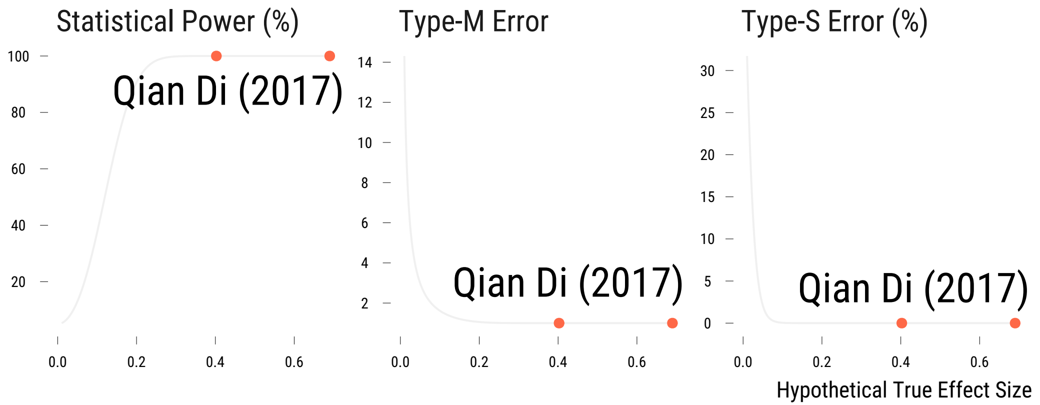

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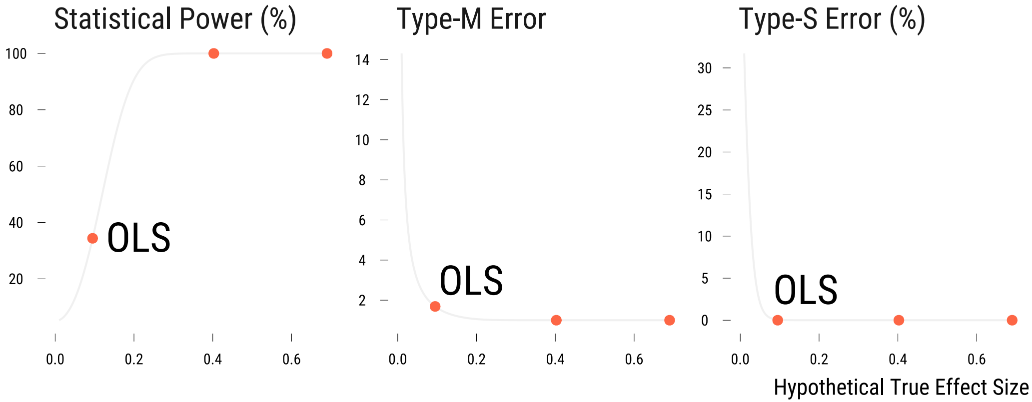

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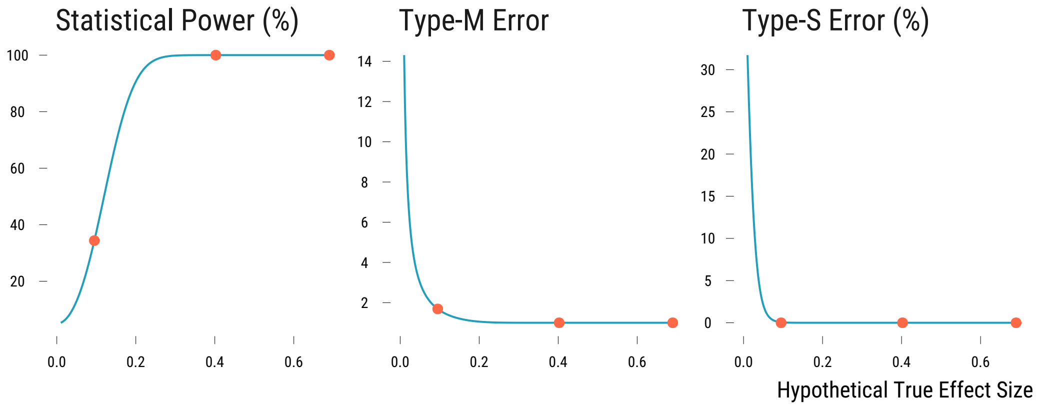
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Our Data

We search for papers from:

- The epidemiology literature based on generalized additive models.
- The causal inference literature.

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Standard Epidemiology Literature

Too many papers to read them all

But 668 abstracts often report main point estimates & CIs

Regular expressions to extract relevant statistics

`On average, an increase of 10 µg/m³ in the 2-day moving average of PM₁₀ concentration, which represents the average over the current and previous day, was associated with increases of 0.44% (95% confidence interval [CI], 0.39 to 0.50) in daily all-cause mortality, 0.36% (95% CI, 0.30 to 0.43) in daily cardiovascular mortality, and 0.47% (95% CI, 0.35 to 0.58) in daily respiratory mortality.`

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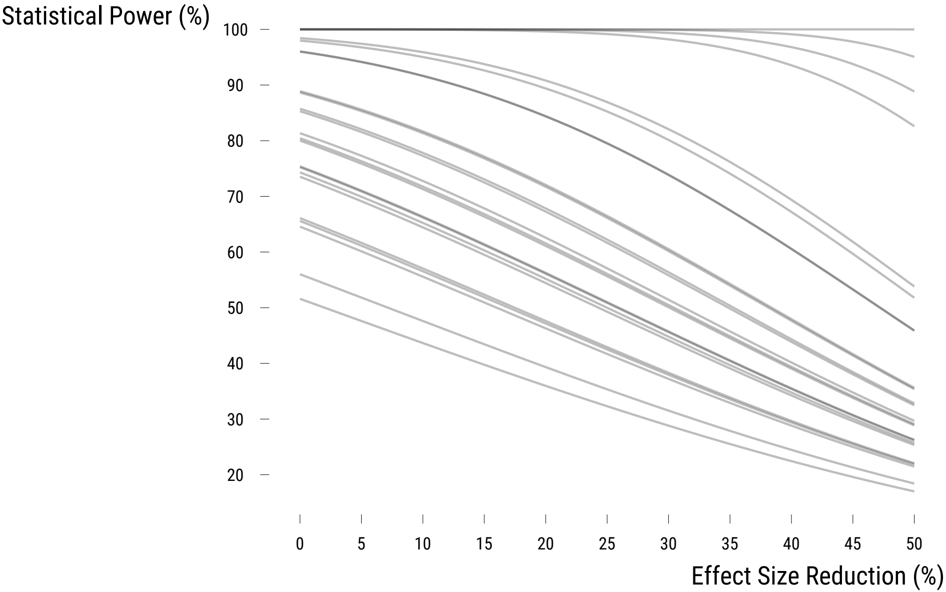
Causal Inference Literature

Article	Location	Health Outcome	Independent Variables	Study Design
Arceo-Gomez 2016	Mexico City, Mexico	Infant Mortality	PM10, Thermal Inversion (IV)	Instrumental Variable
Austin 2020	Counties, USA	Rates of Confirmed COVID-19 Deaths	PM2.5 (air pollutant), Wind Direction (IV)	Instrumental Variable
Baccini 2017	Milan, Italy	Non-Accidental Mortality	Dummy for PM10 Concentration >To 40 $\mu g/m^3$	Propensity Score Matching
Barwick 2018	All Cities, China	Number of Health Spending Transactions	PM2.5, Spatial Spillovers of PM2.5 (IV)	Instrumental Variable
Bauernschuster 2017	5 Largest Cities, Germany	Admissions for Abnormalities of Breathing (age below 5)	PM10, Public Transport Strikes Dummy	Difference in Differences
Beard 2012	Salt Lake County, USA	Emergency Visits For Asthma	Thermal Inversions	Time-stratified case-crossover design
Chen 2018	Toronto, Canada	Asthma-Related Emergency Department Visits	Air Quality Eligibility, Air Quality Altert	Fuzzy Regression Discontinuity
Deryugina 2019	Counties, USA	All Causes of Mortality (Age 65+)	PM2.5, Wind Direction (IV)	Instrumental Variable
Ebenstein 2015	2 Cities, Israel	Hospital Admissions Due To Lung Illnesses	PM10 (air pollutant), Sandstorms (IV)	Instrumental Variable
Forastiere 2020	Milan, Italy	Non-Accidental Mortality	Setting PM10 Daily Exposure Levels >To 40 $\mu g/m^3$ To 40	Generalized Propensity Score
Giaccherini 2019	Municipalities, Italy	Respiratory Hospital Admission	PM10, Public Transport Strikes	Difference in Differences
Godzinski 2019	10 Cities, France	Emergency Admissions for Upper Respiratory System (Age 0-4)	CO, Public Transport Strikes	Difference in Differences
Halliday 2018	Hawaii, USA	ER Admission for Pulmonary Outcomes	PM2.5, SO2 Emissions From Kilauea Volcano and Wind Direction (IV)	Instrumental Variable
He 2016	34 Urban Districts, China	Monthly Standardized Mortality Rate	PM10, Regulation and Traffic Control Status (IV)	Instrumental Variable
He 2020	China	Monthly Number of Deaths for All-Causes	PM2.5, Straw Burning (IV)	Instrumental Variable
Isphording 2021	Counties, Germany	Mortality of Covid-19 Positive Male Patients (Age 80+)	PM10, Wind direction (IV)	Instrumental Variable
Jans 2018	Sweden	Children Health Care Visits for Respiratory Illness	PM10, Thermal Inversion (IV)	Instrumental Variable
Jia 2019	South Korea	Mortality Rates for Respiratory and Cardiovascular Diseases	Dusty Days Times China's AQI	Reduced-Form
Kim 2021	South Korea	Hospital Admissions for Respiratory Illnesses	PM10 (air pollutant), Average PM10 Level By Date (IV)	Instrumental Variable
Knittel 2016	California, USA	Infant Mortality	PM10, Road Traffic Flow and Weather variables (IV)	Instrumental Variable
Moretti 2011	South California, USA	Hospital Admissions for Respiratory Illnesses	O3, Vessel Traffic (IV)	Instrumental Variable
Mullins 2014	Santiago Metropole, Chile	Cumulative Deaths (age >64)	PM10, Air quality Alerts	Matching + Difference in Differences
Schlenker 2016	California, USA	Acute Respiratory Hospitalization	CO, Planes Taxi Time (IV)	Instrumental Variable
Schwartz 2015	Boston, USA	Non-Accidental Mortality	PM2.5, Back Trajectories of PM2.5 (IV)	Instrumental Variable
Schwartz 2017	Boston, USA	Non-Accidental Mortality	PM2.5, Height Of Planetary Boundary Layer and Wind Speed (IV)	Instrumental Variable
Schwartz 2018	135 Cities, USA	Non-Accidental Mortality	PM2.5, Planetary Boundary Layer, Wind Speed, and Air Pressure (IV)	Instrumental Variable
Scheldon 2017	Singapore	Acute Upper Respiratory Tract Infections	Pollutant Index, Indonesian Fire Radiative Power (IV)	Instrumental Variable
Williams 2018	USA	Asthma Rescue Event	PM2.5	Poisson fixed-effects models
Zhong 2017	Beijing, China	Ambulance Call Rate for Coronary Heart Problem	NO2, Number 4 Day (IV)	Instrumental Variable

Power Calculation Results



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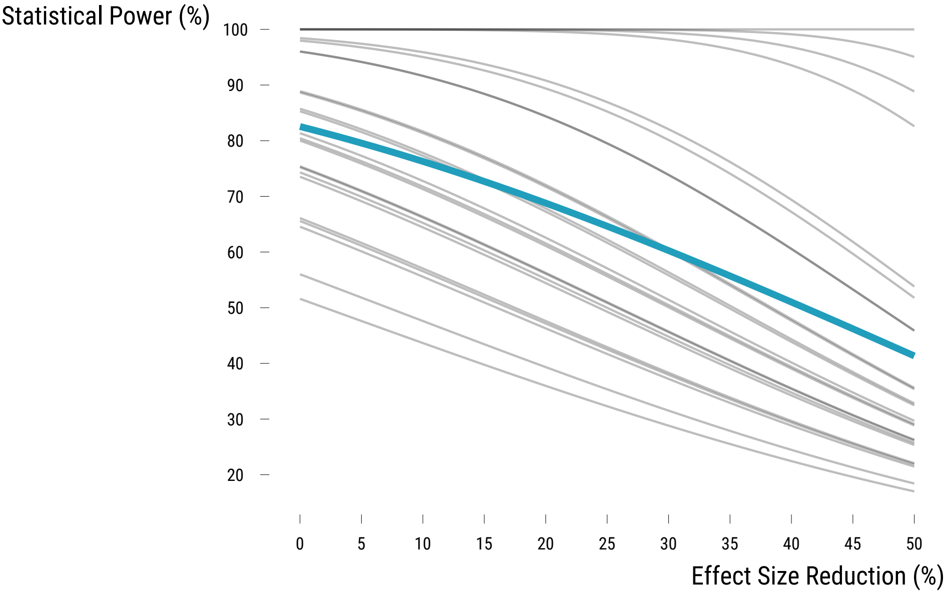

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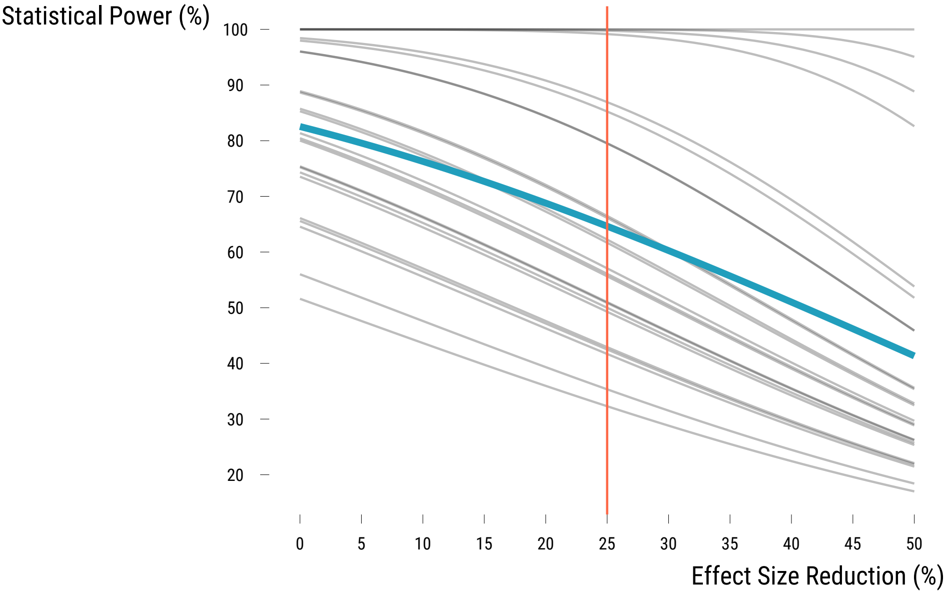

Power Calculation Results

Overall:

- If the true effect sizes of each study was equal to **75%** of observed estimates
- About **half** of papers in the standard and causal inference literatures would be under-powered
- The average Type M error would be respectively equal to **2** and **1.4**

If we make more informed guesses about true effect sizes, results are more worrisome

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For the epidemiology literature:

As true effect sizes, we choose the estimates of two recent meta-analyses by Shah et al. (2015) & Orellano et al. (2020)

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Power Calculation Results

Naive Estimates as True Effect Sizes for IV Designs

Paper	Power (%)	Type S Error (%)	Type M Error
Giaccherini *et al.* (2021)	5	43.3	40.7
Halliday *et al.* (2019)	6	16.6	6.9
Shlenker *et al.* (2016)	7	13.8	6.1
Moretti *et al.* (2011)	11	3.7	3.5
Arceo-Gomez *et al.* (2016)	12	2.4	3.1
Barwick *et al.* (2018)	23	0.3	2.1
Deryugina *et al.* (2019)	34	0.1	1.7
Ebenstein *et al.* (2015)	52	0	1.4
Schwartz *et al.* (2018)	64	0	1.3

Limits of a Retro Power Analysis

A **retrospective** analysis is helpful to think about statistical power once the study is completed

Yet, **hard** to understand why a study is under-powered

Power simulations could help identify these parameters

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Which Parameters of a Study Influence Power?

How to Run Power Simulations

Our simulations procedure:

Based on real-data from the NMMAPS

We simulate several research designs

And vary different parameters

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RESEARCH REPORT
HEALTH EFFECTS INSTITUTE
Number 94, Part II
June 2000
Final Version
The National Morbidity, Mortality, and Air Pollution Study
Part II: Morbidity and Mortality from Air Pollution in the United States
Jonathan M Samet, Scott L Zeger, Francesca Dominici, Frank Curriero, Ivan Coursac, Douglas W Dockery, Joel Schwartz, and Antonella Zanobetti
Includes a Commentary by the Institute's Health Review Committee

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Two Simulations Frameworks

For Reduced-Form & RDD:

We follow the Neyman-Rubin Causal Model

Our Y(0) are the observed deaths

We create a Y(1) according to the treatment effect size

For OLS & IV:

We fit OLS & IV models to the observed data

We modify the coefficients of interest

And simulate new health outcomes with a bit of noise

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2. The sample size
3. The effect sizes
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Simulation Procedure

1. Draw a study period and a sample of cities
2. For IV, RF, and RDD, randomly allocate days to exogenous shocks
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7. Finally compute power, type M and S errors

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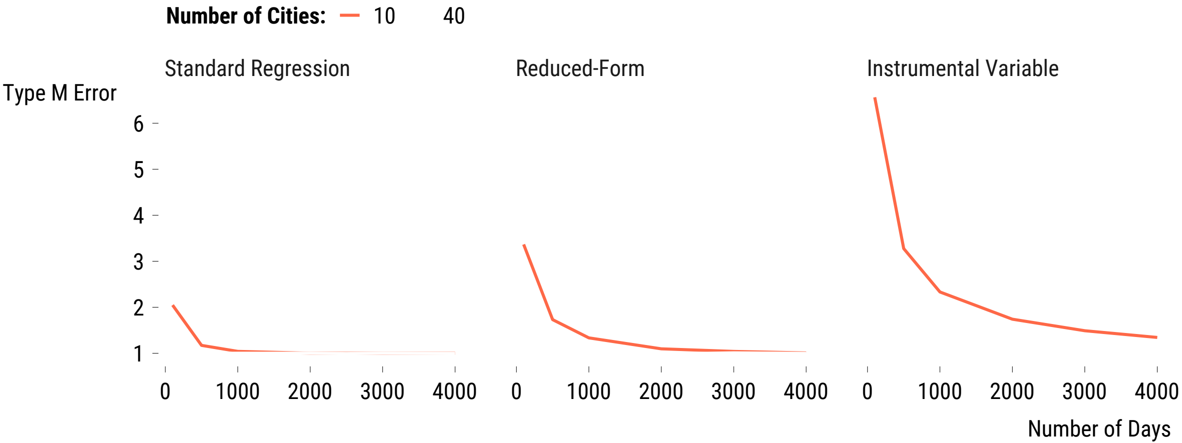

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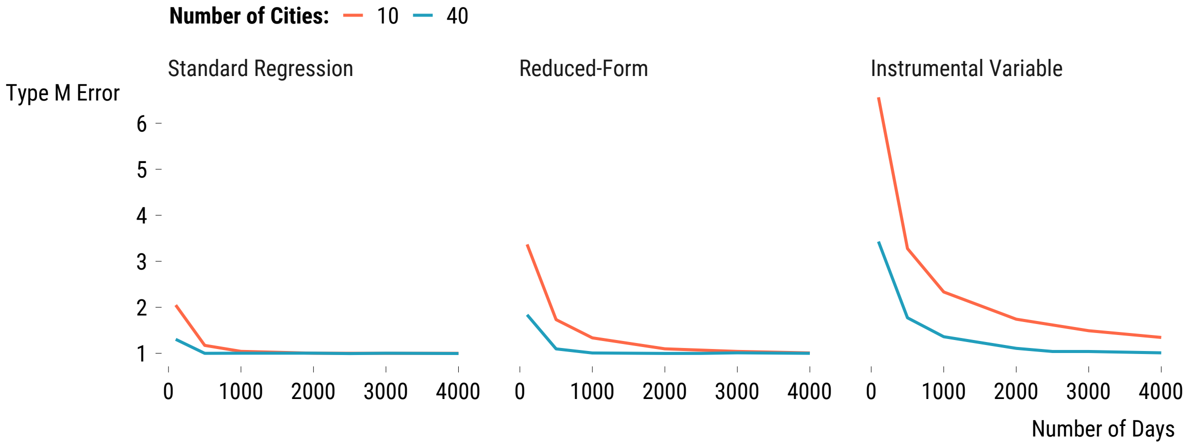

Proportion of Exogenous Shocks

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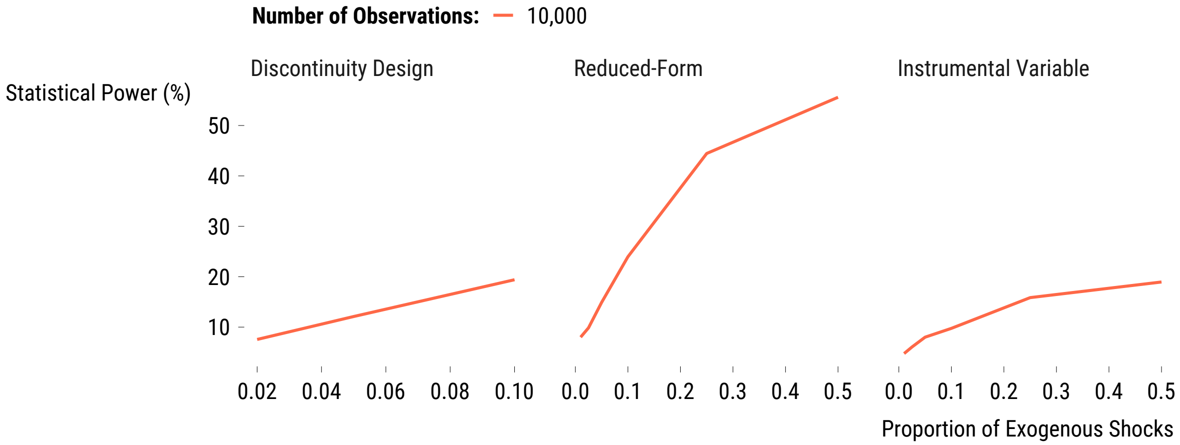

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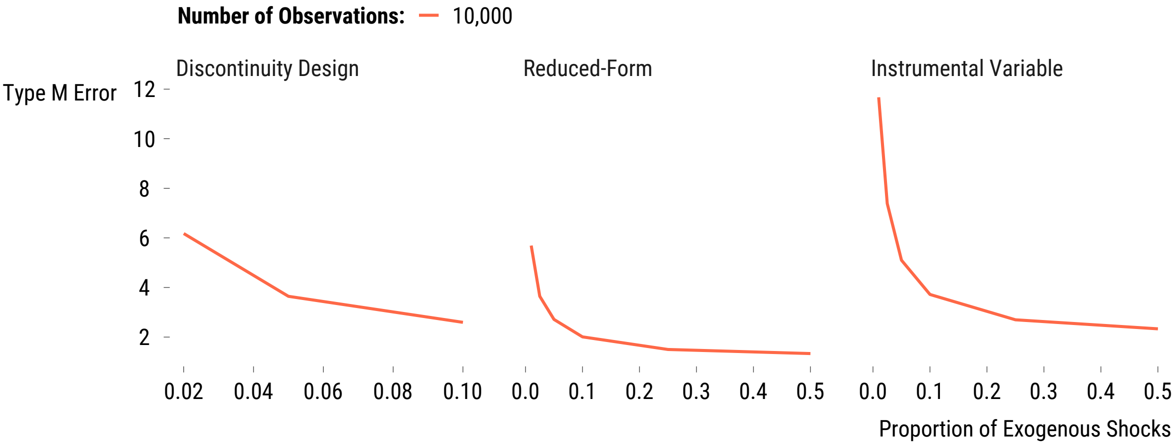
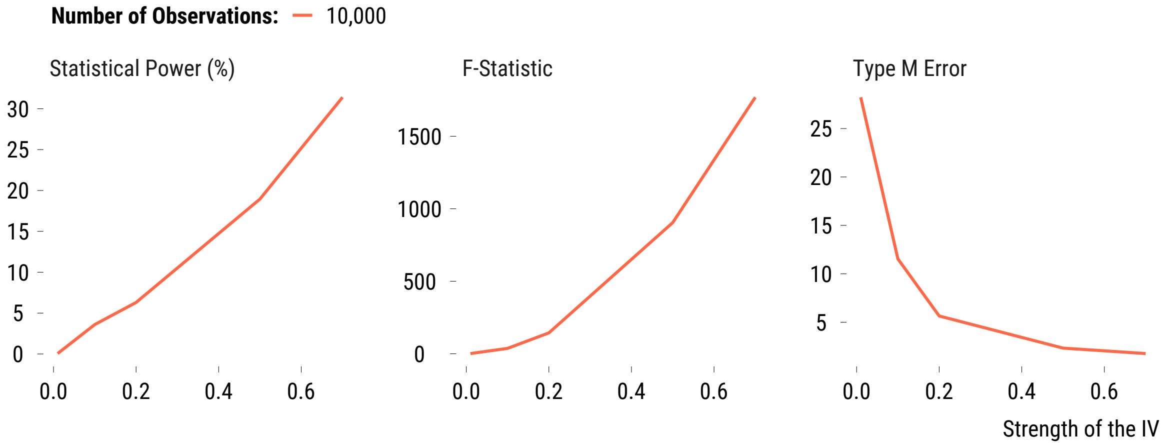


Strength of the IV

Effect size = +1%; Treated units = 50%



Health Outcome Distribution

The average number of cases matters a lot:

IV design with **100,000** observations and an effect size of **+1%**.

IV is **highly** correlated to the air pollutant.

For total number deaths (mean ≈ **23 deaths**), power is **100%**.

For respiratory deaths (mean ≈ **2 deaths**), power is **50%** and type M error is **2.4**!

For chronic obstructive pulmonary disease for individuals aged 65-75 (mean ≈ **0.3 death**), type M error is **6**!

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For respiratory deaths (mean $\approx$ **2 deaths**), power is **50%** and type M error is **2.4**!

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Putting the Literature to the Test

Exploring Flagship Publications

Previous simulations help understand how statistical power and type M error evolve with research design parameters

They were however run for **ideal** scenarios

Here, our simulations target **what is done in the literature**

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Few Shocks, Few Health Cases

Bauernschuster et al. (2018):

- 11,000 observations (5 cities)
- 45 strike days
- 0.7 children come to the ED for respiratory disease
- 11% increase in hospital admissions for young children

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Same effect size of 11% and same sample size

The average daily number of cases is 2.1

Results:

Power is equal to 15% and the Type M error is 2.7

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Schwartz et al. (2018):

IV design based on wind

200,000 observations

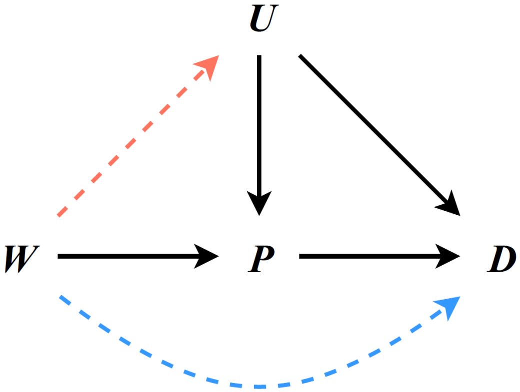
Effect size of 1.8%

IV strength is weak

Power = 16%

Type M error = 2.6

The F-statistic = 320



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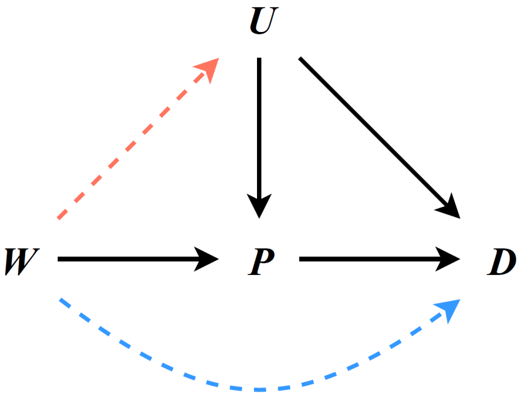

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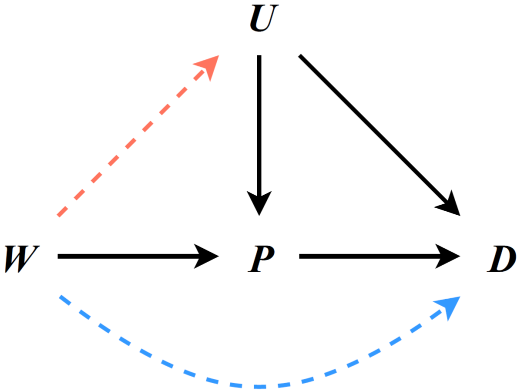

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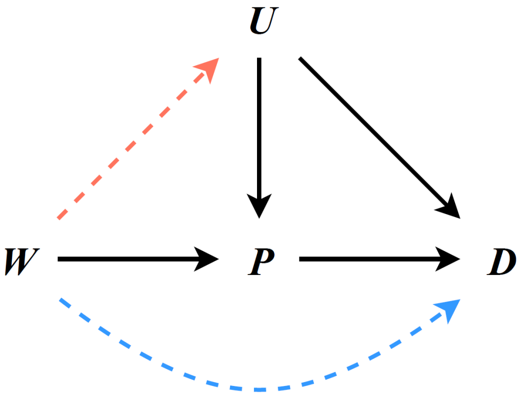

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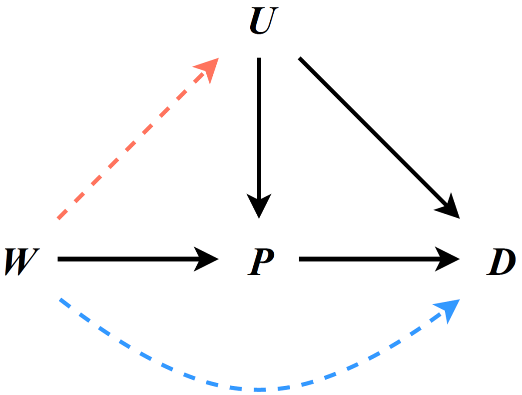

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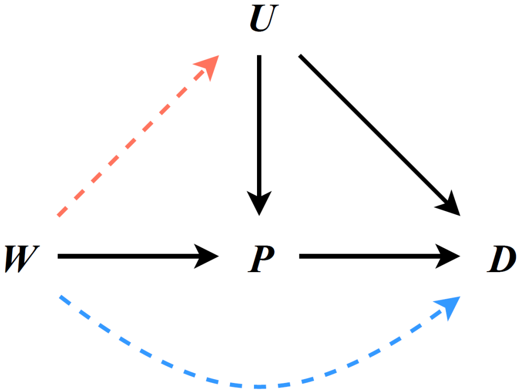

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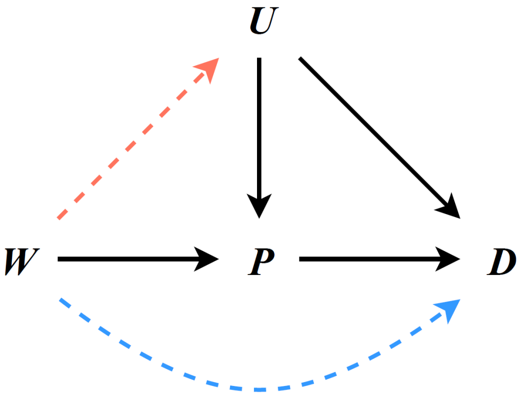

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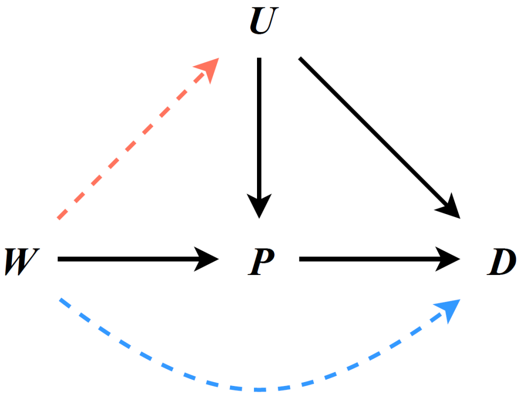

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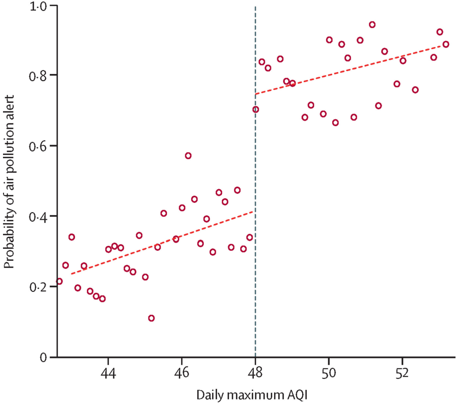

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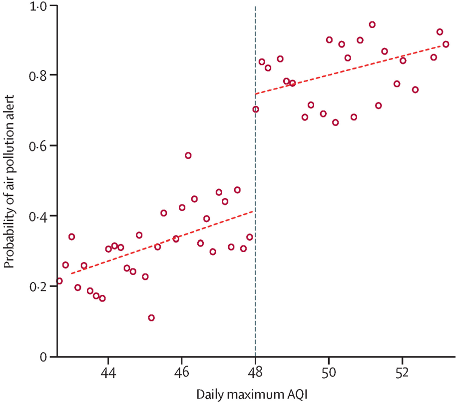

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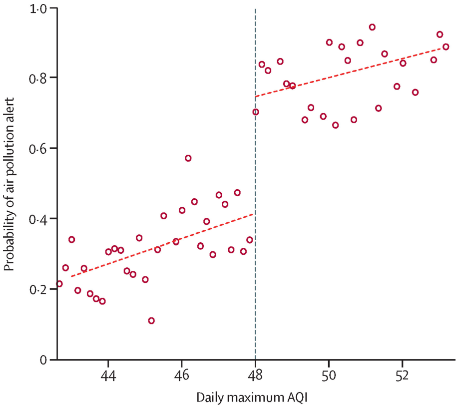

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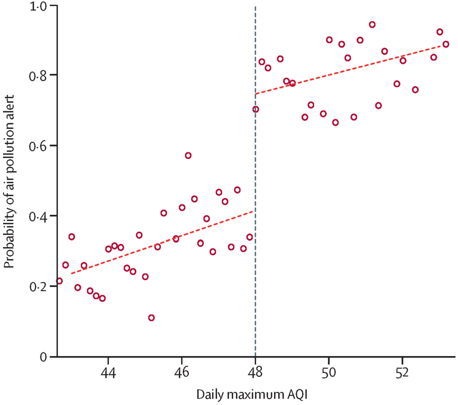

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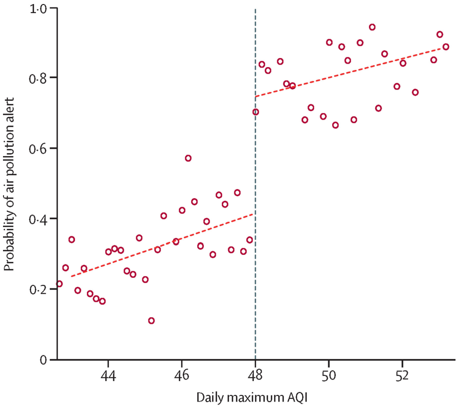

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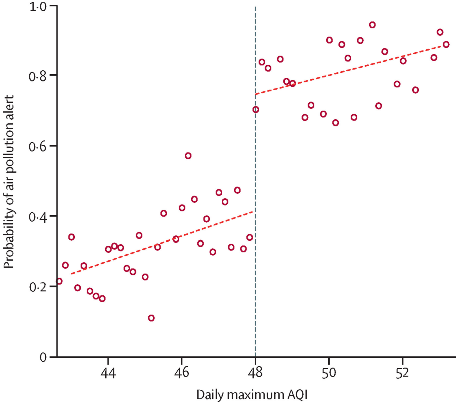

How to Move Forward

Bias in Observational Studies

Gary King and Langche Zeng (2007):

$$\begin{aligned} \text{Bias} = \ & \text{Omitted Variable Bias} + \\ & \text{Post-Treatment Bias} + \\ & \text{Interpolation Bias} + \\ & \text{Extrapolation Bias} \end{aligned}$$

Even if you overcome these 4 types of biases, you need to take into account the power of your study

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At least **half** of studies are under-powered

Some studies can produce **very inflated** estimates

Statistical power has remained **constant** over time

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IVestimates are more prone to Type M error than **OLS** estimates

The fewer the **exogenous shocks**, the lower the power

The fewer the **cases** of an health outcome, the lower the power.

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Or with a similar dataset already published

After running the study:

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Interpret results with regards to parameters which drive power

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Thank You For Your Time!