Introduction to Empirical Economics

Instrumental Variables

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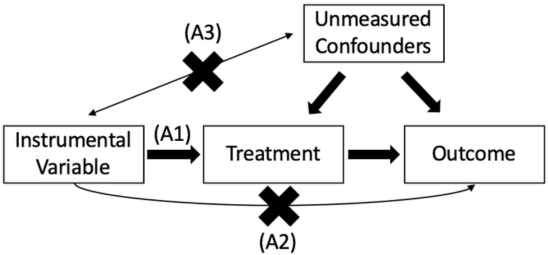
École Normale Supérieure



Program

- Today's course on IV
- Then two courses on RDD and DiD
- One course on the replication crisis
- Courses on specific topics

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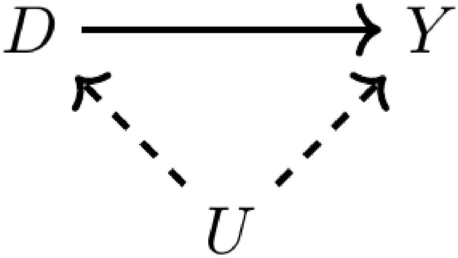
Materials of the course

https://github.com/lzabrocki/empirical_economics

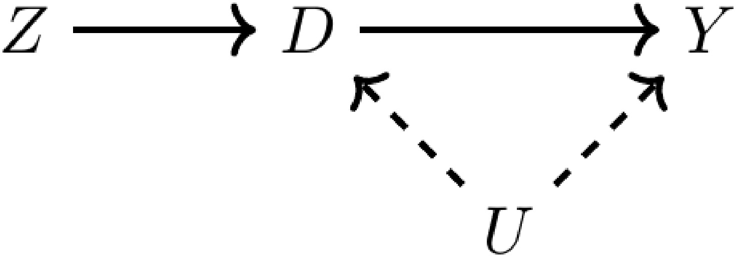
Today's slides are heavily based on *Mastering Metrics*

Who can summarize the previous class?

How to Overcome Unobserved Condounding?



Solution: Finding an Instrumental Variable



Road Map

1. Intuition for instrumental variables
2. Fixing broken experiment with IV
3. Why Isn't the Whole World Developed? (borrows from Christina and David Romer's course)

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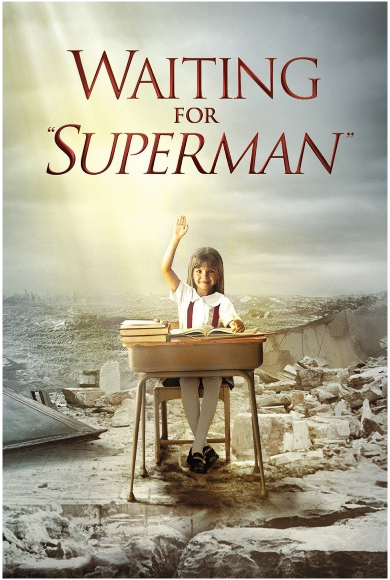
The Charter Conundrum

What are charter schools in the US?

The Charter Conundrum

INTERVIEWER: Have your mom and dad told you about the lottery?

DAISY: The lottery ... isn't that when people play and they win money?



What Are Charter Schools?

- Public schools that are more autonomous
- Free to structure their curricula and school environments
- Teachers rarely belong to labor unions.

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Knowledge Is Power Program

- 140 schools
- *No Excuses* approach to public education
  - Long school day
  - An extended school year
  - Selective teacher hiring
  - Focus on traditional reading and math skills.
- Student body is 95% black and Hispanic
- 80% qualify for subsidized lunch program.

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The American Debate over Education Reform

Focuses on the achievement gap

Black and Hispanic children score below on standardized tests

How should policy-makers react?

First view focuses on the capacity of schools to produce better outcomes

Second view argues that schools alone are unlikely to close achievement gaps

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What About KIPP?

KIPP students, as a group, enter KIPP with substantially higher achievement than the typical achievement of schools from which they came.... [T]eachers told us either that they referred students who were more able than their peers, or that the most motivated and educationally sophisticated parents were those likely to take the initiative ... and enroll in KIPP.

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Lynn KIPP

First KIPP school in New England

"Lynn, Lynn, city of sin, you never come out the way you came in."

High rates of unemployment, crime, and poverty

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After 2005, more than 200 students applying for about 90 seats!

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The decision to attend a charter school is never entirely random

Even among applicants, some of those offered a seat nevertheless choose to go elsewhere

While a few lottery losers find their way in by other means.

However, comparisons of applicants who are and are not offered a seat as a result of random admissions lotteries should be satisfyingly apples to apples in nature.

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Assuming the only difference created by winning the lottery is in the likelihood of charter enrollment

IV turns randomized *offer* effects into causal estimates of the effect of charter *attendance*

IV estimates capture causal effects on the sort of child who enrolls in KIPP when offered a seat in a lottery but wouldn't manage to get in otherwise.

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Back to Lynn KIPP

Joshua D. Angrist et al. (2008) collected data on applicants to KIPP Lynn from fall 2005 through fall 2008

Some applicants bypass the lottery

Those with previously enrolled siblings are guaranteed admission.

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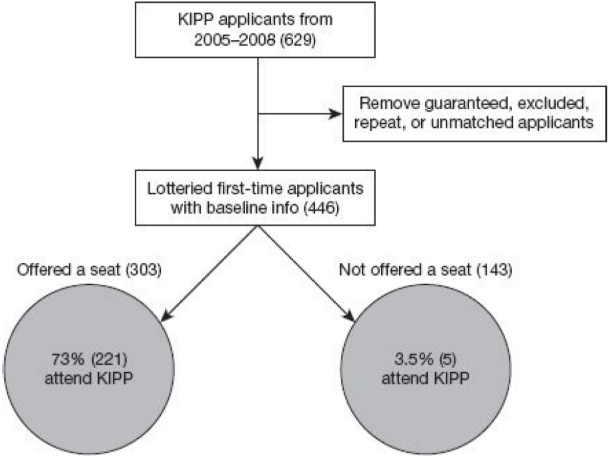
Lottery Results



Balance?

KIPP lotteries randomize the offer of a charter seat.

Random assignment of offers should balance the demographic characteristics of applicants who were and were not offered seats.

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Balance?

	Means for 2005–2008			Balance regression
	Lynn 5th graders	KIPP Lynn 5th graders	KIPP Lynn applicants	Winners vs. Losers
	(1)	(2)	(3)	(4)
Hispanic	0.418	0.565	0.538	−0.052
				(0.053)
Black	0.173	0.235	0.254	0.027
				(0.044)
Asian	0.108	0.021	0.022	0.026*
				(0.015)
Female	0.480	0.474	0.484	−0.010
				(0.054)
Free/reduced price lunch	0.770	0.842	0.825	−0.030
				(0.041)
Special education	0.185	0.189	0.197	−0.013
				(0.042)
Limited English proficient	0.221	0.172	0.206	−0.075
				(0.047)
Baseline (4th grade) math score	−0.307	−0.336	−0.390	0.097
				(0.114)
Baseline (4th grade) ELA score	−0.356	−0.399	−0.438	0.054
				(0.118)
Fourth grade applicant			0.768	0.056
				(0.046)
p-value from joint *F*-test				0.671

Results of Offers

The offer of a seat at KIPP Lynn:

- Boosts Math scores by $0.36\sigma \pm 0.12$
- Increases Verbal skills by $0.11\sigma \pm 0.12$

What does an offer effect of 0.36σ tell us about the effects of KIPP Lynn attendance?

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IV Estimator

The IV estimator converts KIPP *offer* effects into KIPP *attendance* effects

The instrumental variable here is a dummy variable indicating KIPP applicants who receive offers

In general, an IV must meet *three* requirements

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Three Requirements

1. The instrument has a causal effect on the variable whose effects we're trying to capture, in this case KIPP enrollment.
2. The instrument is randomly assigned or "as good as randomly assigned"
3. IV logic requires an exclusion restriction. The exclusion restriction describes a single channel through which the instrument affects outcomes.

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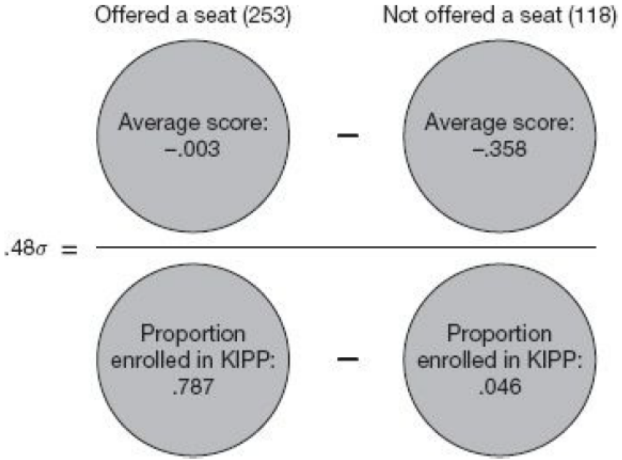
Results of Attendance



How Results Are Presented in the Article

Controls	First stage (1)	Reduced form (2)	2SLS (3)
Panel A. Math (N=856 w/baseline scores)			
Basic	1.222***	0.431***	0.353***
	(0.063)	(0.116)	(0.095)
Demographics & baseline scores	1.228***	0.425***	0.346***
	(0.066)	(0.066)	(0.052)
Panel B. ELA (N=856 w/baseline scores)			
Basic	1.223***	0.183	0.150
	(0.063)	(0.117)	(0.094)
Demographics & baseline scores	1.234***	0.149**	0.120**
	(0.066)	(0.073)	(0.058)

Theory

The instrument Z_i is a dummy variable that equals 1 for applicants randomly offered a seat at KIPP

The treatment variable D_i is a dummy variable that equals 1 for those who attended KIPP

The outcome variable Y_i is the fifth-grade math scores.

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First Stage

$$E[D_i|Z_i = 1] - E[D_i|Z_i = 0]$$

It is the difference in KIPP attendance rates between those who were and were not offered a seat in the lottery

It is equal to 75 percentage points.

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Reduced Form

$$E[Y_i|Z_i = 1] - E[Y_i|Z_i = 0]$$

It is the difference in average test scores between applicants who were and were not offered a seat in the lottery

It is equal to 0.36 standard deviation.

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The Local Average Treatment Effect

$$\text{LATE} = \frac{E[Y_i|Z_i = 1] - E[Y_i|Z_i = 0]}{E[D_i|Z_i = 1] - E[D_i|Z_i = 0]}$$

LATE is the difference in scores between winners and losers divided by the difference in KIPP attendance rates between winners and losers

It is equal to 0.48 standard deviation.

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The Local Average Treatment Effect

Who is LATE for charter school?

LATE is the average causal effect for children whose KIPP enrollment status is determined solely by the KIPP lottery.

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Intuition

Applicants like Alvaro are dying to go to KIPP; if they lose the lottery, their mothers get them into KIPP anyway *(always-takers)*

Applicants like Camila are happy to go to KIPP if they win, but stoically accept the verdict if they lose *(compliers)*

Applicants like Normando worry about long days and lots of homework. Normando doesn't really want to go to KIPP and refuses to do so when hearing that he has won a seat *(never-takers)*

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Principal Stratification

The four types of children

		Lottery losers $Z_i = 0$	
		Doesn't attend KIPP $D_i = 0$	Attends KIPP $D_i = 1$
Lottery winners $Z_i = 1$	Doesn't attend KIPP $D_i = 0$	Never-takers (*Normando*)	Defiers
	Attends KIPP $D_i = 1$	Compliers (*Camila*)	Always-takers (*Alvaro*)

LATE = Compliers Average Causal Effect

$$\text{LATE} = \frac{E[Y_i|Z_i = 1] - E[Y_i|Z_i = 0]}{E[D_i|Z_i = 1] - E[D_i|Z_i = 0]}$$

$$= E[Y_i(1) - Y_i(0)|\text{Compliers}]$$

Policy Relevance?

Compliers are children likely to attend KIPP were the network to expand and offer additional seats in a lottery

In Massachusetts, where the number of charter seats is capped by law, the consequences of charter expansion is the education policy question of the day.

Abuse Busters

The case of O. J. Simpson

The police were called at least nine times over the course of his marriage to Nicole Brown Simpson.

O. J. Simpson was arrested only once, in 1989, when he pleaded no contest to a charge of spousal abuse in an episode that put Nicole in the hospital.

Simpson paid a small fine, did token community service, and was ordered to seek counseling from the psychiatrist of his choice.

The prosecutor in the 1989 case, Robert Pingle, noted that Nicole had not been very cooperative with authorities in the aftermath of her severe beating.

Five years later, Nicole Brown Simpson and her companion Ronald Goldman were murdered

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Simpson paid a small fine, did token community service, and was ordered to seek counseling from the psychiatrist of his choice.

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How should police respond to domestic violence?

A Policy Debate

Abuse victims are often reluctant to press charges

Arresting batterers without victim cooperation may be pointless and could serve to aggravate an already bad situation

Social service agencies seem best equipped to respond to domestic violence.

Failure to arrest batterers signals social tolerance for violent acts

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Was designed to assess the value of arresting batterers

Three treatments:

1. Arrest
2. Ordering the suspected offender off the premises for 8 hours (separation)
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In some cases, suspects were arrested even though random assignment called for separation or advice.

A few deviations arose when officers forgot their report forms.

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Assigned treatment	Delivered treatment: Arrest	Coddled: Advise	Coddled: Separate	Total
Arrest	98.9 (91)	0.0 (0)	1.1 (1)	29.3 (92)
Advise	17.6 (19)	77.8 (84)	4.6 (5)	34.4 (108)
Separate	22.8 (26)	4.4 (5)	72.8 (83)	36.3 (114)
Total	43.4 (136)	28.3 (89)	28.3 (89)	100.0 (314)

Treatment delivered was not random

The contrast between arrest, which usually resulted in a night in jail, and gentler alternatives generates the most interesting and controversial findings in the MDVE

Previous table therefore combines the two nonarrest treatments under the heading “coddled.”

A case assigned to be coddled was coddled with probability 0.979

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IV to the Rescue

Analysis of the MDVE based on treatment delivered is misleading because the cases in which police officers were supposed to coddle suspected batterers and actually did so are a nonrandom subset of all cases assigned to coddling.

Comparisons of those who were and were not coddled are therefore contaminated by *selection bias*.

Batterers who were arrested when assigned to coddling were often especially aggressive or agitated.

Use of randomly assigned intention to treat as an instrumental variable for treatment delivered eliminates this source of selection bias.

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First stage is the difference between the probability of being coddled when assigned to be coddled and the probability of being coddled when assigned to be arrested.

Let Z_i indicate assignment to coddling, and let D_i indicate incidents where coddling was delivered.

$E[D_i|Z_i = 1] - E[D_i|Z_i = 0] = 0.797 - 0.011 = 0.786$

A large gap, but still far from the difference of 1 we'd get if compliance had been perfect.

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Reduced Form or Intention-to-Treat

Y_i indicates at least one post-treatment episode of suspected abuse

$ITT = E[Y_i|Z_i = 1] - E[Y_i|Z_i = 0] = 0.211 - 0.097 = 0.114$

Given that the overall recidivism rate is 18%, this estimated difference of 11 percentage points is substantial.

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Local Average Treatment Effect

The LATE estimate that emerges from the MDVE data is impressive

$0.114/0.786 = 0.145$

A fifteen percentage points difference!

Why Isn't the Whole World Developed?

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Industrialization spread rapidly to some areas

Technology is portable

So are institutions

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Three Broad Possibilities

Direct effects of geography

Institutions

Culture

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AJR's Idea

Goal: estimate the impact of institutions on economic performance

Difficult because many variables influence institution and economic performance

Settler mortality affected colonialization strategy, which affected institutions (IV)

These institutional differences have persisted.

Which in turn affect the development of countries

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AJR's Thesis (I)

At one extreme, European powers set up "extractives states" (e.g., the Belgian colonization of the Congo)

These institutions did not introduce much protection for private property, nor did they provide checks and balances against government expropriation

In fact, the main purpose of the extractive state was to transfer as much of the resources of the colony to the colonizer

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At the other extreme, many Europeans migrated and settled in a number of colonies, creating what the historian Alfred Crosby (1986) calls "Neo-Europes"

The settlers tried to replicate European institutions, with strong emphasis on private property and checks against government power.

Primary examples of this include Australia, New Zealand, Canada, and the United States.

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AJR's Thesis (II)

The colonization strategy was influenced by the feasibility of settlements

In places where the disease environment was not favorable to European settlement, the cards were stacked against the creation of Neo-Europes

... and the formation of the extractive state was more likely.

AJR's Thesis (III)

The colonial state and institutions persisted even after independence.

AJR's Thesis in One Picture

(potential) settler mortality $\Rightarrow$ settlements

$\Rightarrow$ early institutions $\Rightarrow$ current institutions

$\Rightarrow$ current performance.

Data

For a sample of 75 countries, mortality rates of:

- Soldiers
- Bishops
- Sailors

What were the two principal causes of death?

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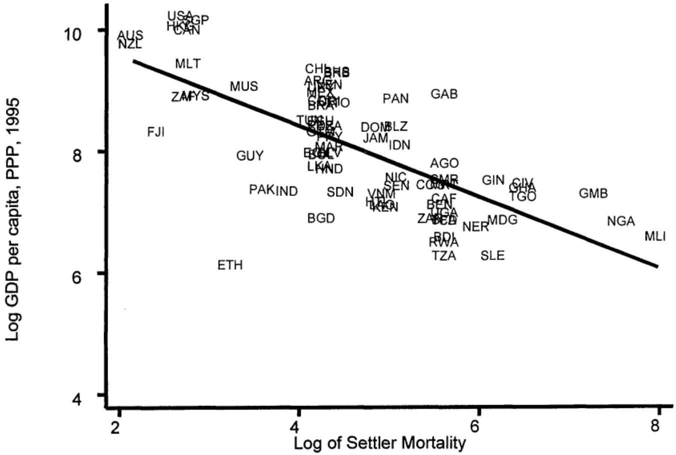
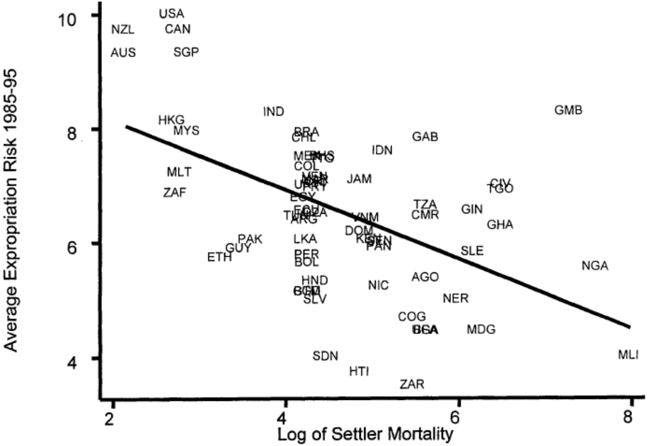


First Stage


Average Expropriation Risk 1985-95
Log of Settler Mortality
10
8
6
4
2
4
6
8
NZL
USA
CAN
AUS
SGP
HKG
MYS
IND
GMB
GAB
IDN
MLT
ZAF
COL
JAM
TZA
CMR
GIN
GHA
PAK
GUY
ETH
LKA
BOL
SLE
NGA
HND
SLV
NIC
AGO
NER
COG
MDG
SDN
HTI
ZAR
MLI

IV Results

Our two-stage least-squares estimate of the effect of institutions on performance is relatively precisely estimated and large. For example, it implies that improving Nigeria's institutions to the level of Chile could, in the long run, lead to as much as a 7-fold increase in Nigeria's income (in practice Chile is over 11 times as rich as Nigeria).

A Scientific Clash

David Y. Albouy (2012):

Acemoglu, Johnson, and Robinson's (2001) seminal article argues property-rights institutions powerfully affect national income, using estimated mortality rates of early European settlers to instrument capital expropriation risk. However, 36 of the 64 countries in the sample are assigned mortality rates from other countries, often based on mistaken or conflicting evidence. Also, incomparable mortality rates from populations of laborers, bishops, and soldiers—often on campaign—are combined in a manner that favors the hypothesis. When these data issues are controlled for, the relationship between mortality and expropriation risk lacks robustness, and instrumental-variable estimates become unreliable, often with infinite confidence intervals.

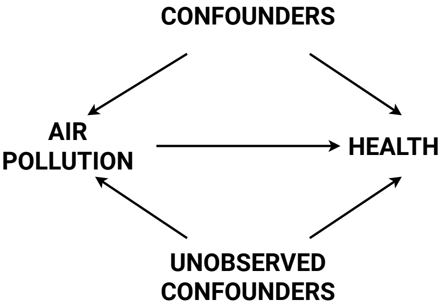
A Scientific Clash

Authors' reply (2012):

> *Acemoglu, Johnson, and Robinson (2001) established that economic institutions today are correlated with expected mortality of European colonialists. David Albouy argues this relationship is not robust. He drops all data from Latin America and much of the data from Africa, making up almost 60 percent of our sample, despite much information on the mortality of Europeans in those places during the colonial period. He also includes a "campaign" dummy that is coded inconsistently; even modest corrections undermine his claims. We also show that limiting the effect of outliers strengthens our results, making them robust to even extreme versions of Albouy's critiques.*

IV in Air Pollution Studies

The Topic of My Thesis



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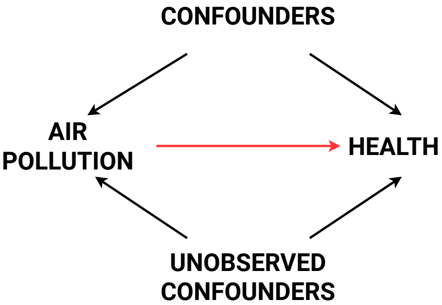

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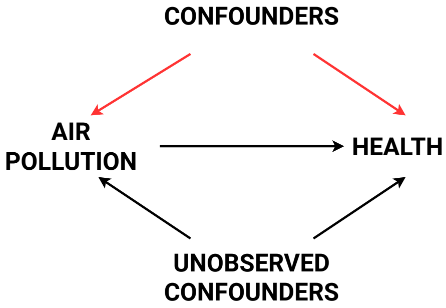

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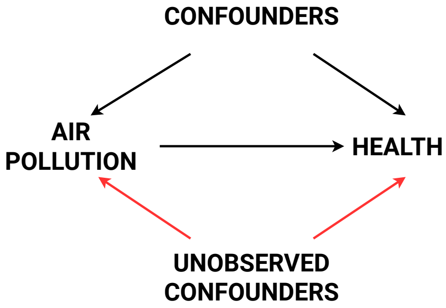

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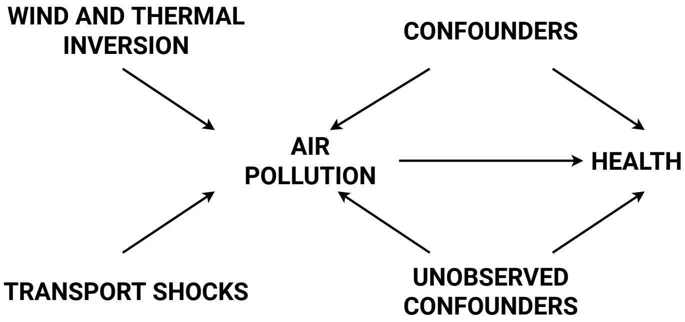

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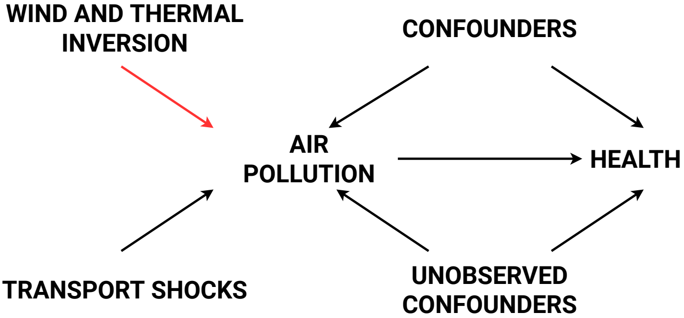
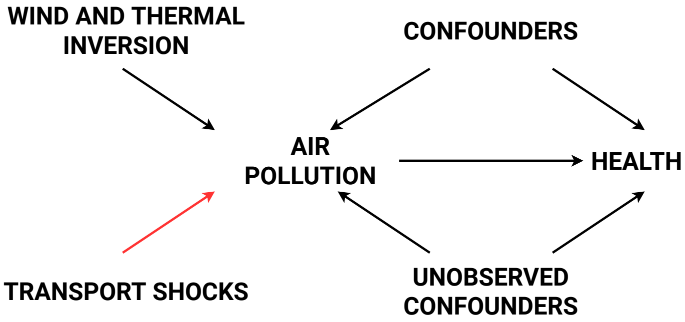


The Topic of My Thesis



Thermal Inversions

A Thermal Inversion in Seattle

Thermal Inversions