

# Instrumental variables Observational settings

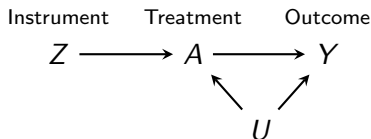
INFO/STSCI/ILRST 3900: Causal Inference

19 Oct 2023

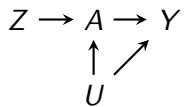
# Learning goals for today

At the end of class, you will be able to:

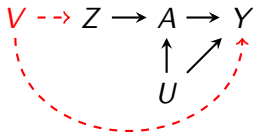
1. Explain requirements for IV in observational settings
  - ▶ instrument exchangeability:  $Z \rightarrow Y$  is identified
  - ▶ no direct effect:  $Z \rightarrow Y$  is entirely  $Z \rightarrow A \rightarrow Y$
  - ▶ relevance:  $Z \rightarrow A$  is sufficiently large
  - ▶ one of the following
    - ▶ homogeneity: effect is the same for everyone
    - ▶ monotonicity: instrument affects treatment in one direction
2. Argue for when these hold or do not hold



## Assumptions that make IV work



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## **Exogeneity:**

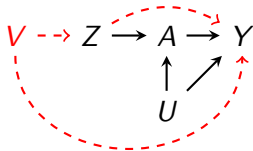
Instrument must be  
unconfounded  
(this path cannot exist)

# Assumptions that make IV work

## Exclusion Restriction:

Instrument must affect  
outcome only through  
treatment

(this edge cannot exist)



## Exogeneity:

Instrument must be  
unconfounded

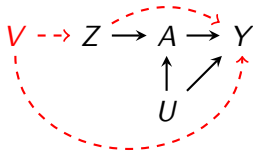
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## Monotonicity:

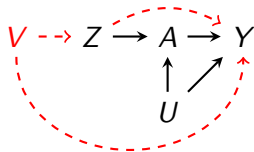
Instrument must affect  
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## Exogeneity:

Instrument must be  
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## Monotonicity:

Instrument must affect  
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Given these three assumptions,  
the average effect among compliers  
is identified by

$$E(Y^{A=1} - Y^{A=0} \mid S = \text{Complier})$$

$$= \frac{E(Y^{Z=1} - Y^{Z=0})}{E(A^{Z=1} - A^{Z=0})}$$

← Effect of Z on Y  
← Effect of Z on A

$$= \frac{E(Y|Z=1) - E(Y|Z=0)}{E(A|Z=1) - E(A|Z=0)}$$

An observational settings that is **clean**



1970 RANDOM SELECTION SEQUENCE, BY MONTH AND DAY

	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
1	305	086	108	032	330	249	093	111	225	359	019	129
2	159	144	029	271	298	228	350	045	161	125	034	328
3	251	297	267	083	040	301	115	261	049	244	348	157
4	215	210	275	081	276	020	279	145	232	202	266	165
5	101	214	293	269	364	028	188	054	082	024	310	056
6	224	347	139	253	155	110	327	114	006	087	076	010
7	306	091	122	147	035	085	050	168	008	234	051	012
8	199	181	213	312	321	366	013	048	184	283	097	105
9	194	338	317	219	197	335	277	106	263	342	080	043
10	325	216	323	218	065	206	284	021	071	220	282	041
11	329	150	116	014	037	134	248	324	158	237	046	039
12	221	068	300	346	133	272	015	142	242	072	066	314
13	318	152	259	124	295	069	042	307	175	138	126	163
14	238	004	354	231	178	356	331	198	001	294	127	026
15	017	089	169	273	130	180	322	102	113	171	131	320
16	121	212	166	148	055	274	120	044	207	254	107	096
17	235	189	033	260	112	073	098	154	255	288	143	304
18	140	292	332	090	278	341	190	141	246	005	146	128
19	058	025	200	336	075	104	227	311	177	241	203	240
20	280	302	239	345	183	360	187	344	063	192	185	135
21	186	363	334	062	250	060	027	291	204	243	156	070
22	337	290	265	316	326	247	153	339	160	117	009	053
23	118	057	256	252	319	109	172	116	119	201	182	162
24	059	236	258	002	031	358	023	036	195	196	230	095
25	052	179	343	351	361	137	067	286	149	176	132	084
26	092	365	170	340	357	022	303	245	018	007	309	173
27	355	205	268	074	296	064	289	352	233	264	047	078
28	077	299	223	262	308	222	088	167	257	094	281	123
29	349	285	362	191	226	353	270	061	151	229	099	016
30	164	---	217	208	103	209	287	333	315	038	174	003
31	211	---	030	---	313	---	193	011	---	079	---	100

<https://www.historynet.com/whats-your-number/>



[https://commons.wikimedia.org/wiki/File:1969\\_draft\\_lottery\\_photo.jpg](https://commons.wikimedia.org/wiki/File:1969_draft_lottery_photo.jpg)

Drafted to serve  
in Vietnam

Served in  
military

Earnings in 1980s

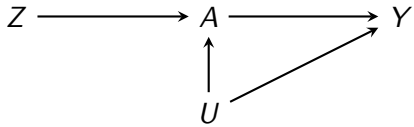
$Z$

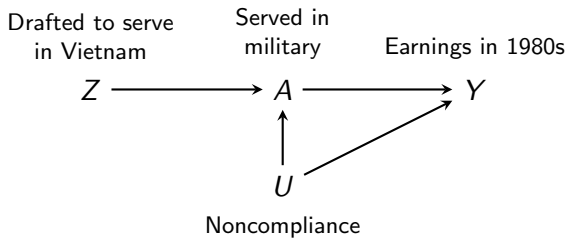
$A$

$Y$

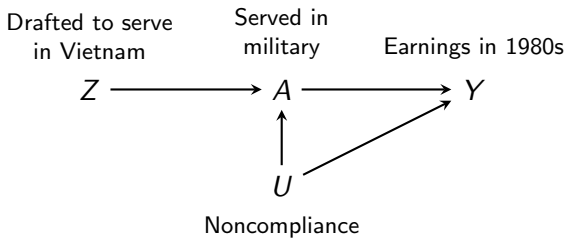
$U$

Noncompliance



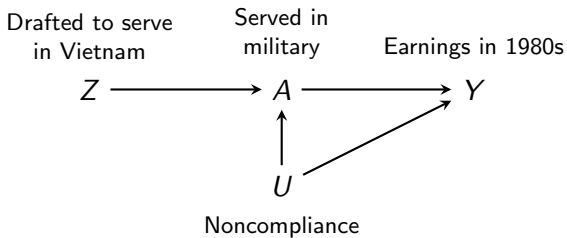


This is credible



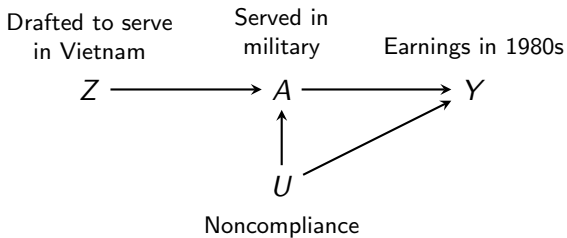
This is credible

- Exogeneity: Randomly selected draft numbers



This is credible

- ▶ Exogeneity: Randomly selected draft numbers
- ▶ Exclusion: Being drafted affects earnings only through service



This is credible

- ▶ Exogeneity: Randomly selected draft numbers
- ▶ Exclusion: Being drafted affects earnings only through service
- ▶ Monotonicity: No one joins the military in defiance of not being drafted

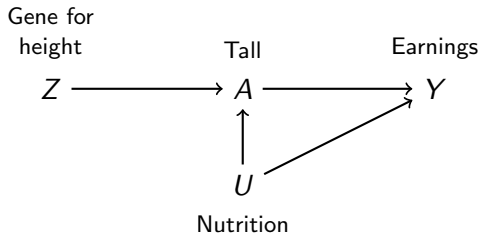
Angrist, J. D. (1990). [Lifetime earnings and the Vietnam era draft lottery: Evidence from Social Security administrative records](#). The American Economic Review, 313-336.

Observational settings that are **less straightforward**

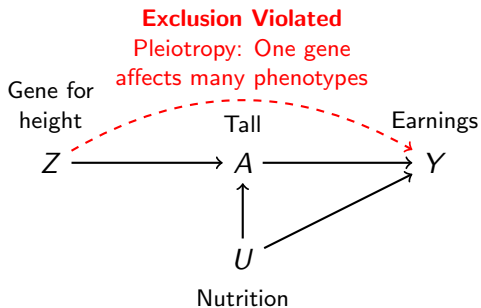


A difficult example: Genes as instruments

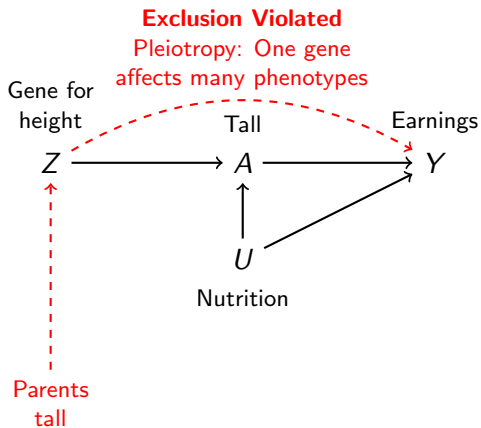
## A difficult example: Genes as instruments



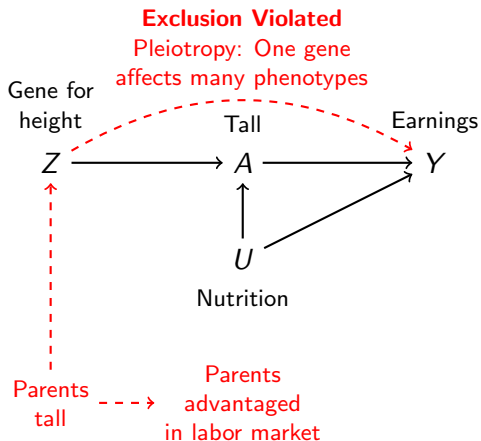
# A difficult example: Genes as instruments



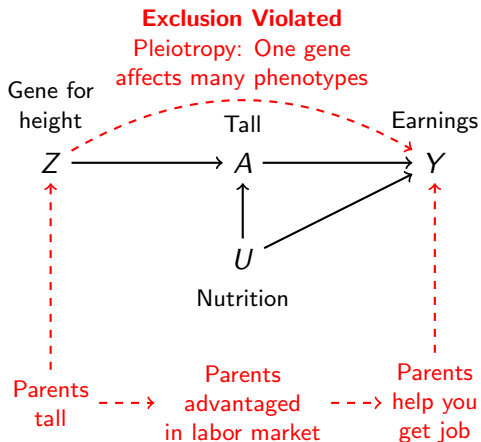
# A difficult example: Genes as instruments



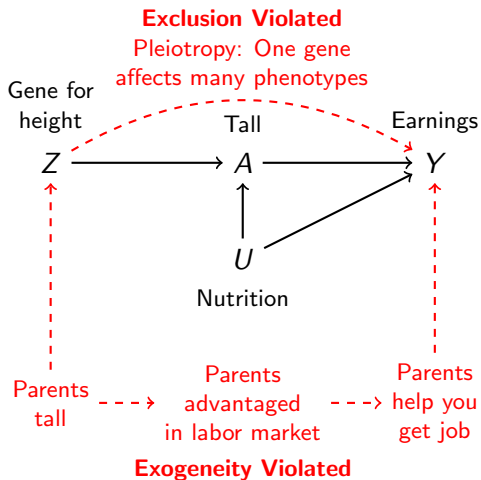
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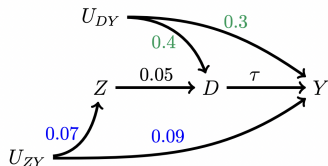


# A difficult example: Genes as instruments



## Warning: IV is very sensitive to assumptions

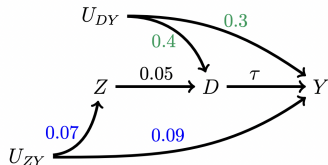
Fig 5 from Felton, C., & Stewart, B. M. (2022). [Handle with Care: A Sociologist's Guide to Causal Inference with Instrumental Variables](#). SocArXiv.





## Warning: IV is very sensitive to assumptions

Fig 5 from Felton, C., & Stewart, B. M. (2022). [Handle with Care: A Sociologist's Guide to Causal Inference with Instrumental Variables](#). SocArXiv.



Asymptotic Bias of OLS

$$= 0.3 \times 0.4 = \mathbf{0.12}$$

Asymptotic Bias of IV

$$= (0.07 \times 0.09) / 0.05 = \mathbf{0.126}$$

Examples where things are very hard

## Examples where things are very hard

From Table 1 in Felton, C., & Stewart, B. M. (2022). Working paper. [Handle with Care: A Sociologist's Guide to Causal Inference with Instrumental Variables.](#)

1. Kirk (2009)<sup>1</sup> studies recidivism among parolees
  - ▶ Z: Parolee released before or after Hurricane Katrina
  - ▶ A: Parolee returns to home neighborhood upon release
  - ▶ Y: Recidivism

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<sup>1</sup>Kirk, D. S. (2009). [A natural experiment on residential change and recidivism: Lessons from Hurricane Katrina](#). American Sociological Review, 74(3), 484-505.

From Table 1 in Felton, C., & Stewart, B. M. (2022). Working paper.

## Handle with Care: A Sociologist's Guide to Causal Inference with Instrumental Variables.

Study	Causal Structure	Identification Assumptions
Kirk (2009)	<p>The diagram illustrates the causal structure for Kirk (2009). It features five nodes: 'Post-Katrina Release' (blue text), 'Unobserved Traits' (black text), 'Residential Change' (green text), 'Employment' (black text), and 'Recidivism' (black text). A solid black arrow points from 'Post-Katrina Release' to 'Residential Change'. A solid black arrow points from 'Unobserved Traits' to 'Residential Change'. A solid black arrow points from 'Residential Change' to 'Recidivism'. A solid black arrow points from 'Unobserved Traits' to 'Recidivism'. A red dotted arrow points from 'Post-Katrina Release' to 'Employment'. A red dotted arrow points from 'Employment' to 'Recidivism'.</p>	(1) Post-Katrina release induces moves away from a parolee's home neighborhood. (2) Post-Katrina release affects recidivism <i>only through</i> residential change and not, e.g., employment or police resources. (3) The timing of release shares no common causes with recidivism. (4) Post-Katrina release <i>never discourages</i> residential change.

2. Laidley & Conley (2018)<sup>2</sup> study variation in sunlight exposure across days for children observed repeatedly

- ▶ Z: Sunlight
- ▶ A: Exercise
- ▶ Y: Test scores

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<sup>2</sup>Laidley, T., & Conley, D. (2018). [The effects of active and passive leisure on cognition in children: Evidence from exogenous variation in weather](#). *Social Forces*, 97(1), 129-156.

From Table 1 in Felton, C., & Stewart, B. M. (2022). Working paper.

## Handle with Care: A Sociologist's Guide to Causal Inference with Instrumental Variables.

Laidley  
and  
Conley  
(2018)



(1) More sunlight causes kids to exercise more. (2) Sunlight affects test scores *only through* exercise and not, e.g., mood. (3) When person fixed effects are included, within-person sunlight variation shares no common causes with test scores. (4) Sunnier weather *never discourages* exercise.

### 3. Sampson & Winter (2018)<sup>3</sup> study child development

- ▶ Z: Proximity to a smelting plant
- ▶ A: Lead exposure
- ▶ Y: Delinquent behavior

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<sup>3</sup>Sampson, R. & Winter, A. (2018). [Poisoned development: Assessing childhood lead exposure as a cause of crime in a birth cohort followed through adolescence](#). *Criminology*, 56(2), 269-301.



From Table 1 in Felton, C., & Stewart, B. M. (2022). Working paper.

## Handle with Care: A Sociologist's Guide to Causal Inference with Instrumental Variables.

Sampson  
and  
Winter  
(2018)



- (1) Proximity to a smelting plant increases lead exposure. (2) Proximity affects delinquency *only through* lead exposure. (3) Proximity shares no common causes—such as neighborhood disadvantage—with delinquency. (4) Moving closer to a smelting plant *never* causes someone to experience less lead exposure.

4. Harding et al. (2018)<sup>4</sup> study defendants in criminal court.

- ▶ Z: Which judge is assigned for the trial
- ▶ A: Sentence of incarceration
- ▶ Y: Employment after release

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<sup>4</sup>Harding, D. J., Morenoff, J. D., Nguyen, A. P., & Bushway, S. D. (2018). [Imprisonment and labor market outcomes: Evidence from a natural experiment.](#) American Journal of Sociology, 124(1), 49-110.

From Table 1 in Felton, C., & Stewart, B. M. (2022). Working paper.

## Handle with Care: A Sociologist's Guide to Causal Inference with Instrumental Variables.

Harding  
et al.  
(2018)



(1) Judge assignment affects the probability of being incarcerated. (2) Judge assignment affects employment *only through* incarceration. (3) Judge assignment shares no common causes with future employment. (4) If assigned to a more lenient judge, a defendant will *never* receive a harsher sentence.

# Summary

Instrumental variable estimation requires strong assumptions

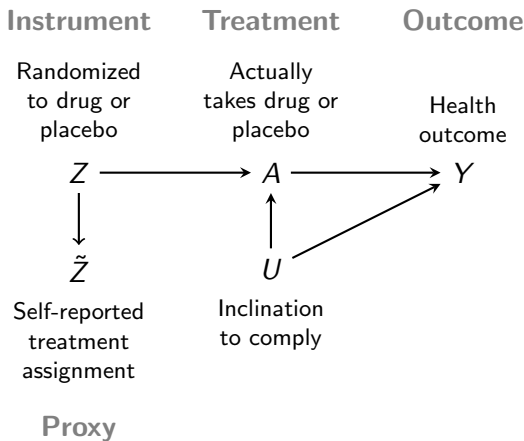
- ▶ **Exogeneity:** Instrument is unconfounded
- ▶ **Exclusion:** Instrument effect on outcome is mediated fully through the treatment
- ▶ **Monotonicity:** Instrument affects treatment in the same direction for everyone
  - ▶ Example: No defiers

Works well in randomized studies with noncompliance.

In observational settings, keep the experimental ideal in mind!  
Usefulness depends on how close it is to that ideal.

# Complications we have not addressed today

- ▶ Non-binary instruments
- ▶ Non-binary treatments
- ▶ Proxy instruments



# Learning goals for today

At the end of class, you will be able to:

1. Explain requirements for IV in observational settings
  - ▶ instrument exchangeability:  $Z \rightarrow Y$  is identified
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