Advanced Statistical Methods for Observational Studies

LECTURE 09

class management

- Problem Set is due Monday, June 1 by 5pm.
  - PDF it and send to Professor Baiocchi.
- If you're doing the class for three credits:
  - Create a slide deck, roughly 10 minutes worth of material.
  - Do a recording of you presenting it.
  - Send the slide deck and recording to Professor Baiocchi.
  - Due Friday, June 12 by 5pm.

propensity score methods

THE ACHILLES HEEL

assumptions

assumptions

- No unobserved confounders

assumptions

- No unobserved confounders
- Possibly even exacerbates the problem in the tails

assumptions

- No unobserved confounders
- Possibly even exacerbates the problem in the tails

assumptions

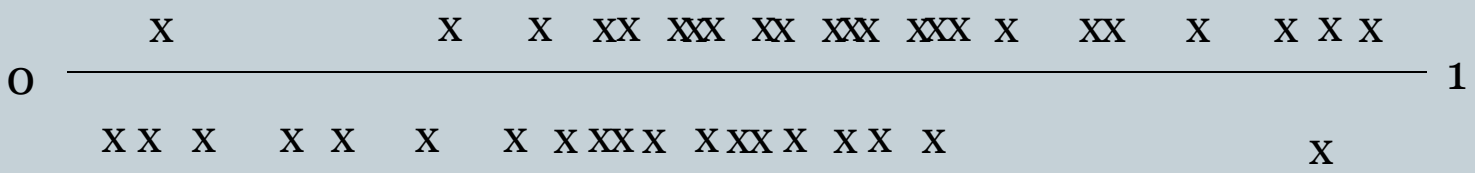
- No unobserved confounders
- Possibly even exacerbates the problem in the tails

assumptions

- No unobserved confounders
- Possibly even exacerbates the problem in the tails

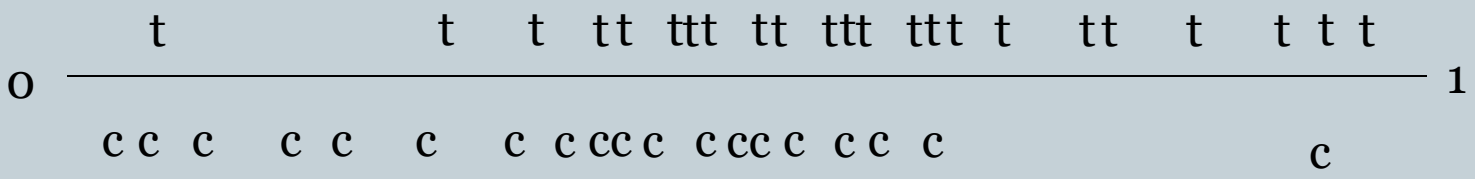
assumptions

- No unobserved confounders
- Possibly even exacerbates the problem in the tails



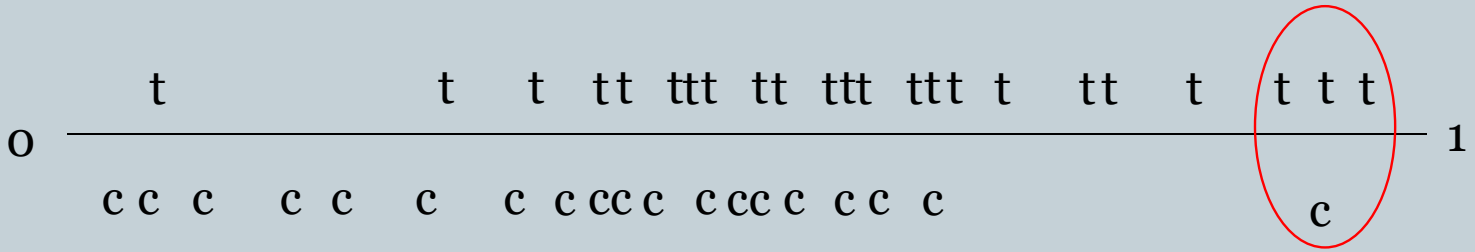
assumptions

- No unobserved confounders
- Possibly even exacerbates the problem in the tails



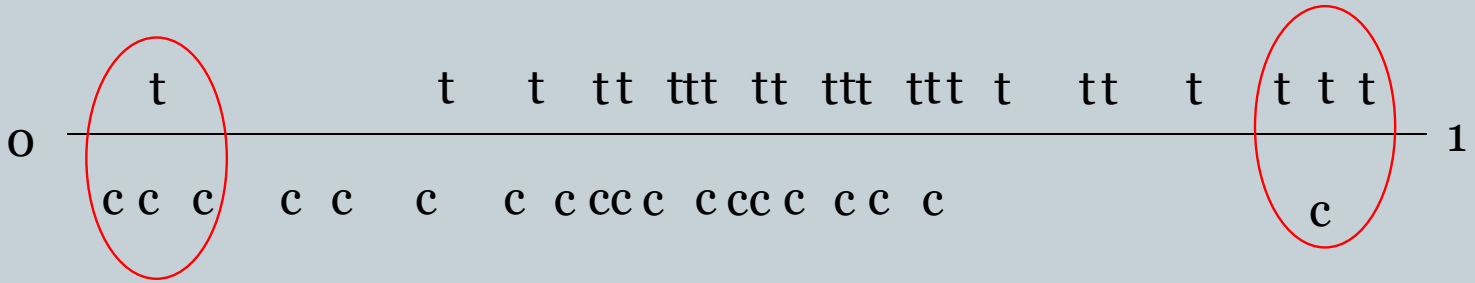
assumptions

- No unobserved confounders
- Possibly even exacerbates the problem in the tails



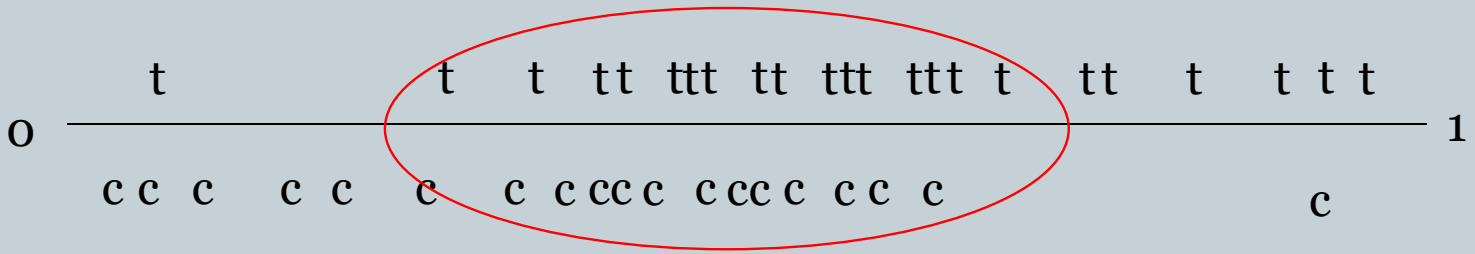
assumptions

- No unobserved confounders
- Possibly even exacerbates the problem in the tails



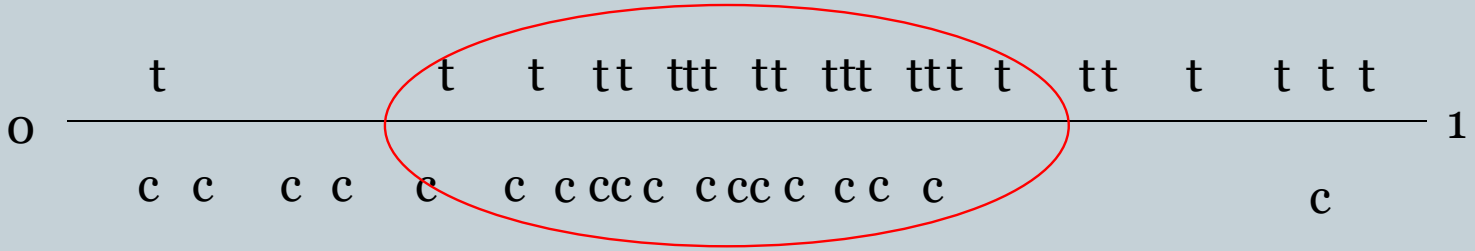
assumptions

- No unobserved confounders
- Possibly even exacerbates the problem in the tails



inverse-probability weighting

- The tails are often up-weighted heavily.
- The standard errors greatly impacted by these weights.
- These tails are the most problematic for strongly ignorable treatment assignment.



naïve model: assumption one

- Strongly Ignorable Treatment Assignment: Those that look alike (in our data set) are alike

$$\pi_i = \Pr(Z_i = 1 | r_{Ti}, r_{Ci}, \boldsymbol{x}_i, u_i) = \Pr(Z_i = 1 | \boldsymbol{x}_i)$$

and

$$0 < \pi_i < 1 \text{ for all } i = 1, 2, \ldots, n$$

- If two subjects have the same propensity score, then their values of $\boldsymbol{x}$ may be different.
- By SITA, if these two subjects have the same $e(\boldsymbol{x})$ then the differences in their $\boldsymbol{x}$ are not predictive of treatment assignment (i.e., $\boldsymbol{x} \perp\!\!\!\perp Z | e(\boldsymbol{x})$).
- Therefore the mismatches in $\boldsymbol{x}$ will be due to chance and will tend to balance. (more details)

assumption

- A version of SITA is used in regression, IPW, pscore matching… basically all methods that don't explicitly have a measurement of randomness.

real world randomness

(MAYBE)

Baiocchi, Cheng and Small (2014) – "Instrumental variable methods for causal inference"


The Children's Hospital of Philadelphia

Outcome

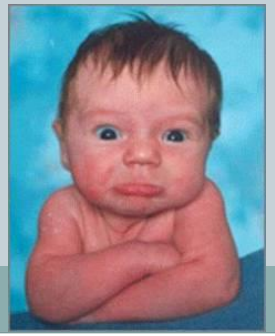
Outcome

2%

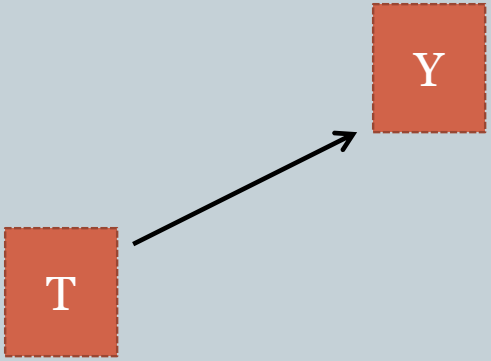
1%

2%

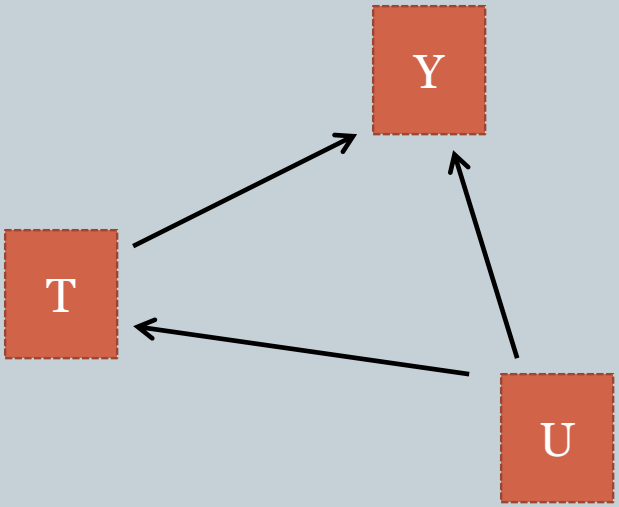
1%



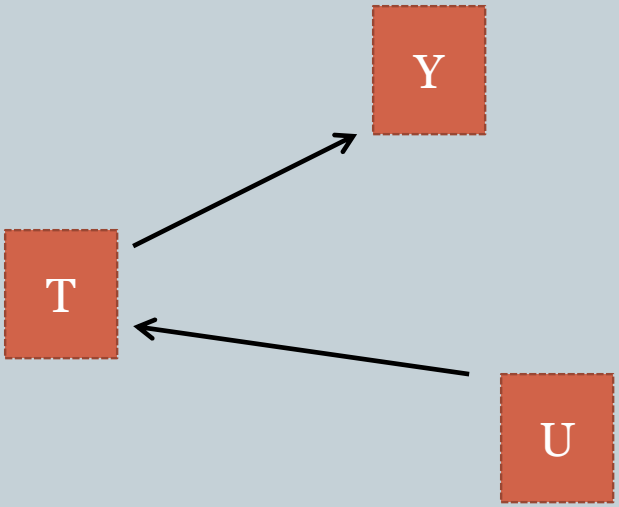
confounding



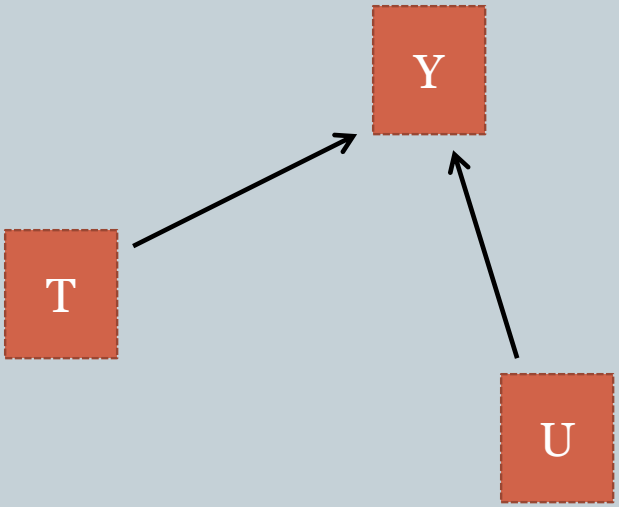
confounding



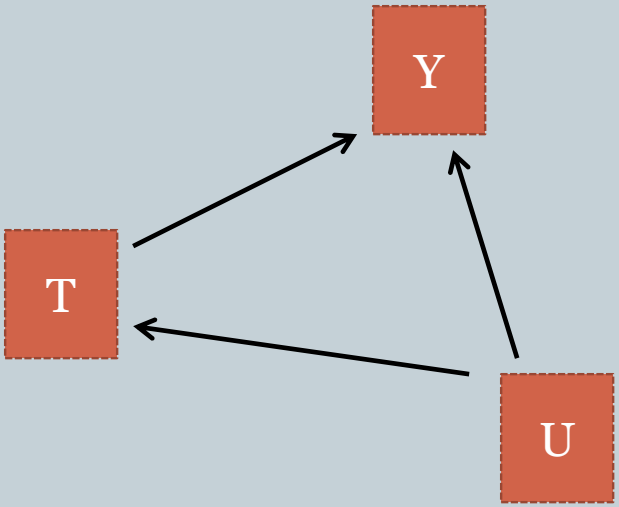
confounding



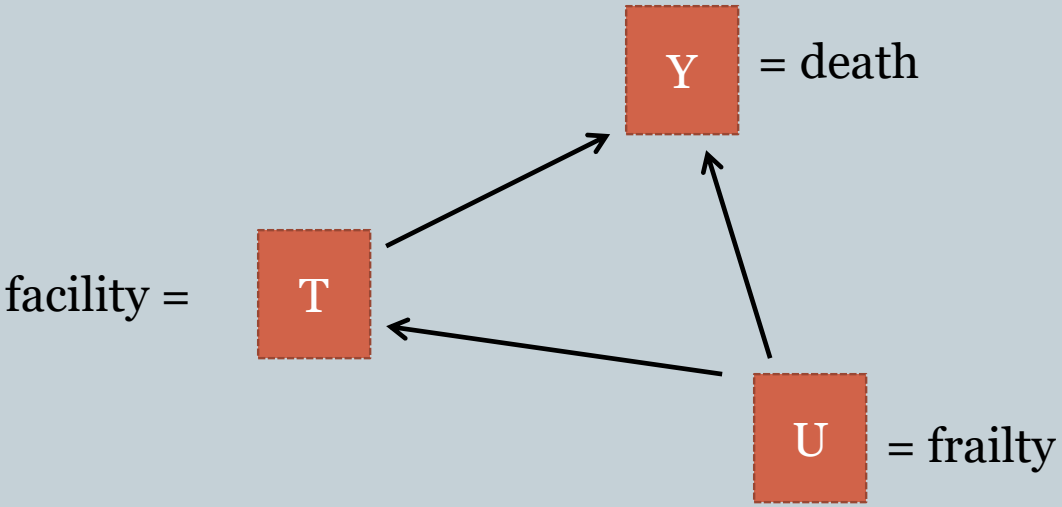
confounding



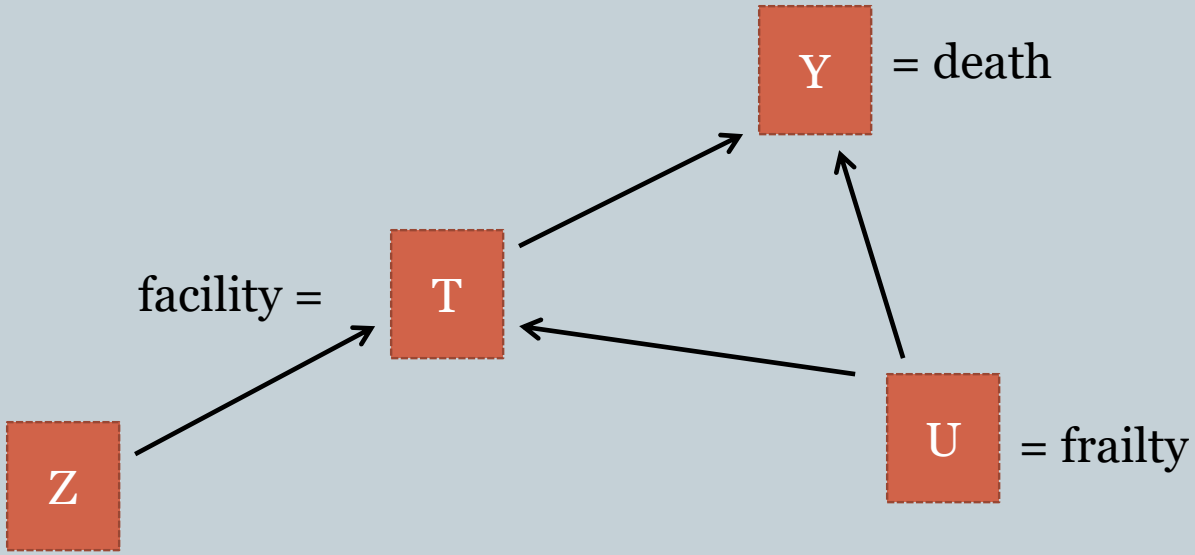
confounding



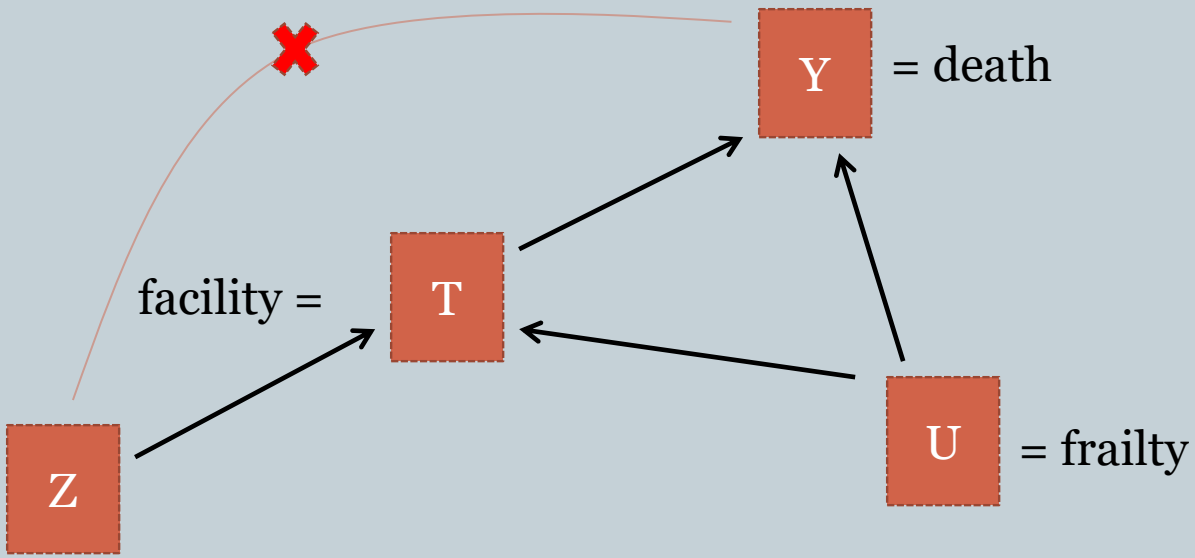
confounding



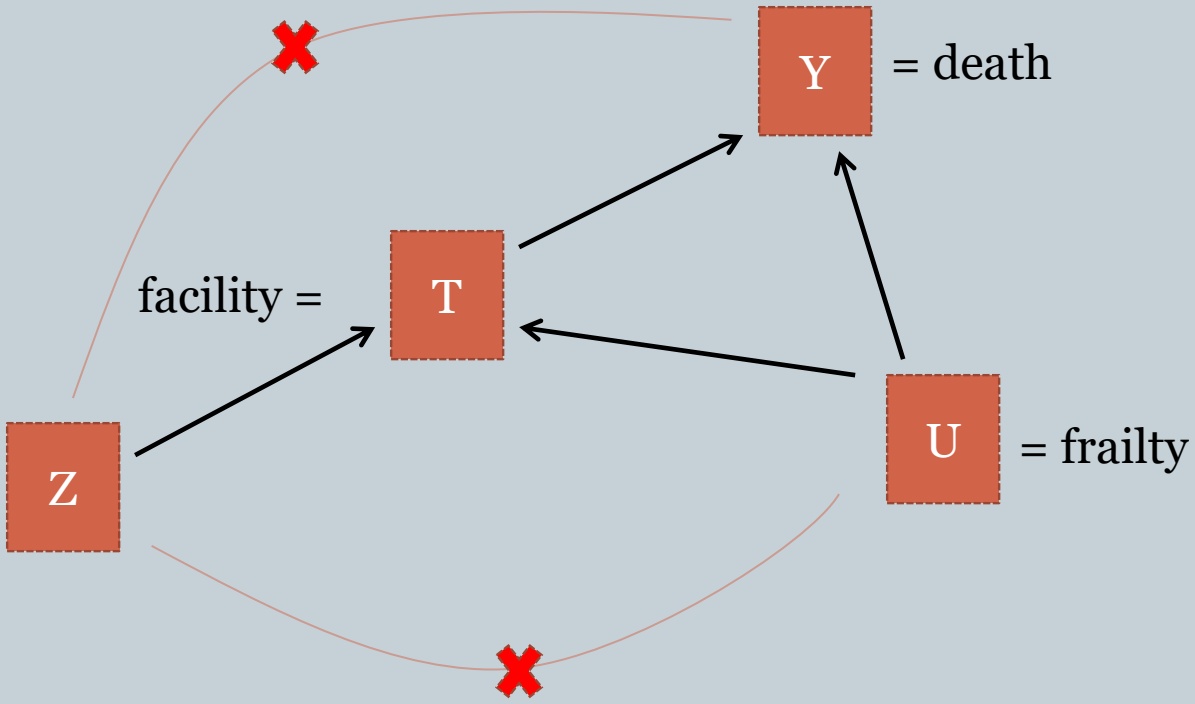
IV techniques – the idea



IV techniques – the idea



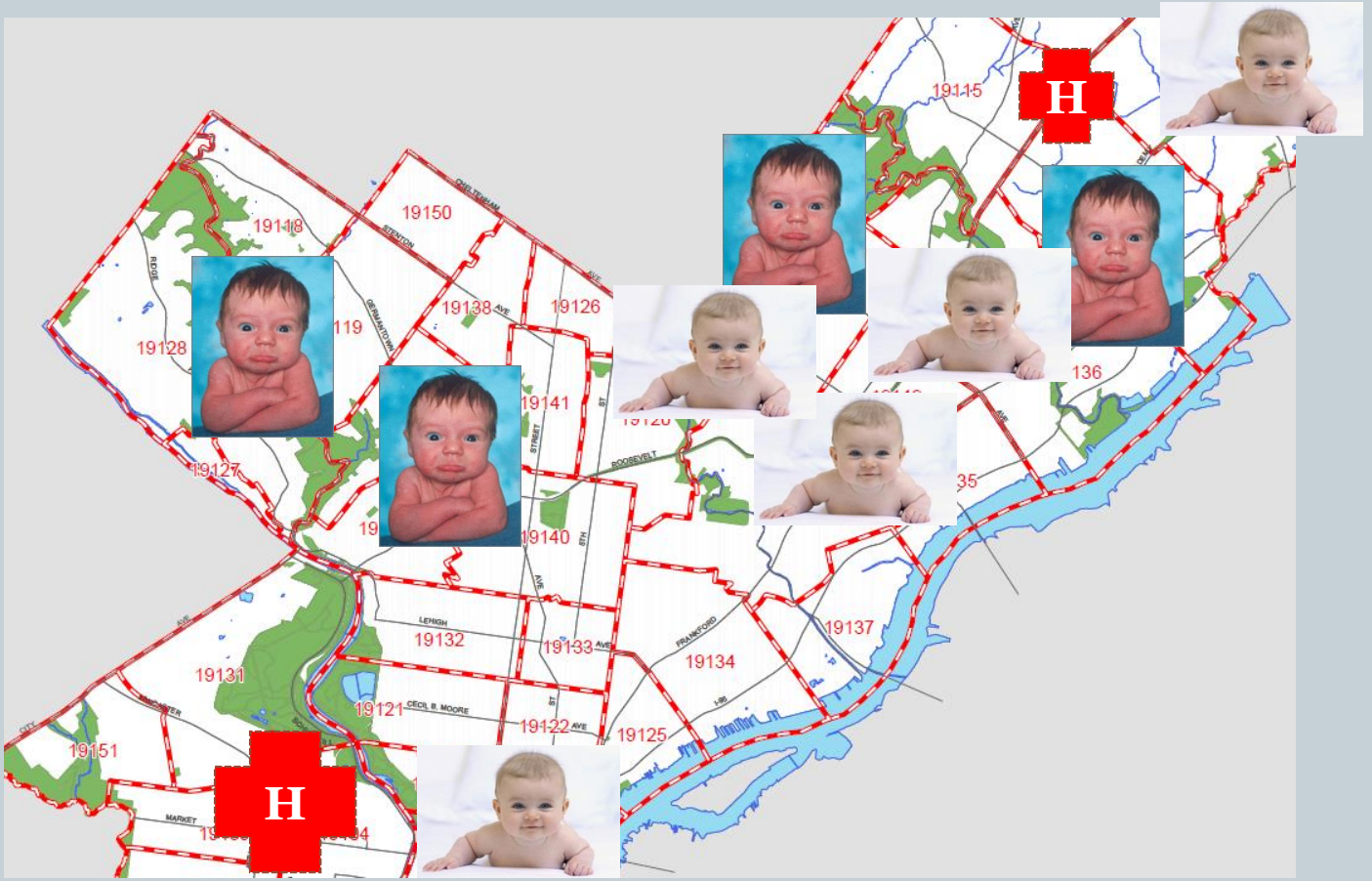
IV techniques – the idea



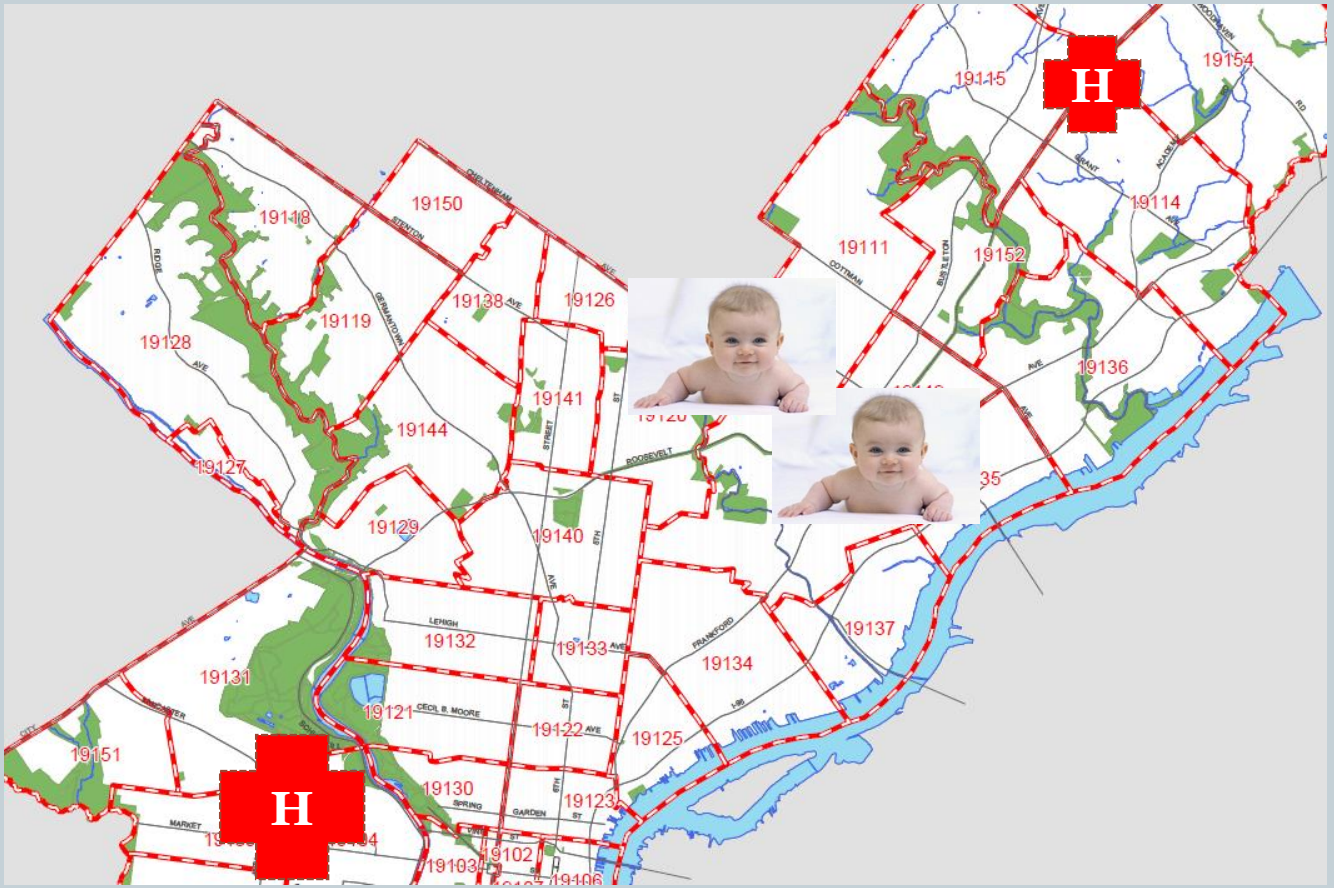
revised design

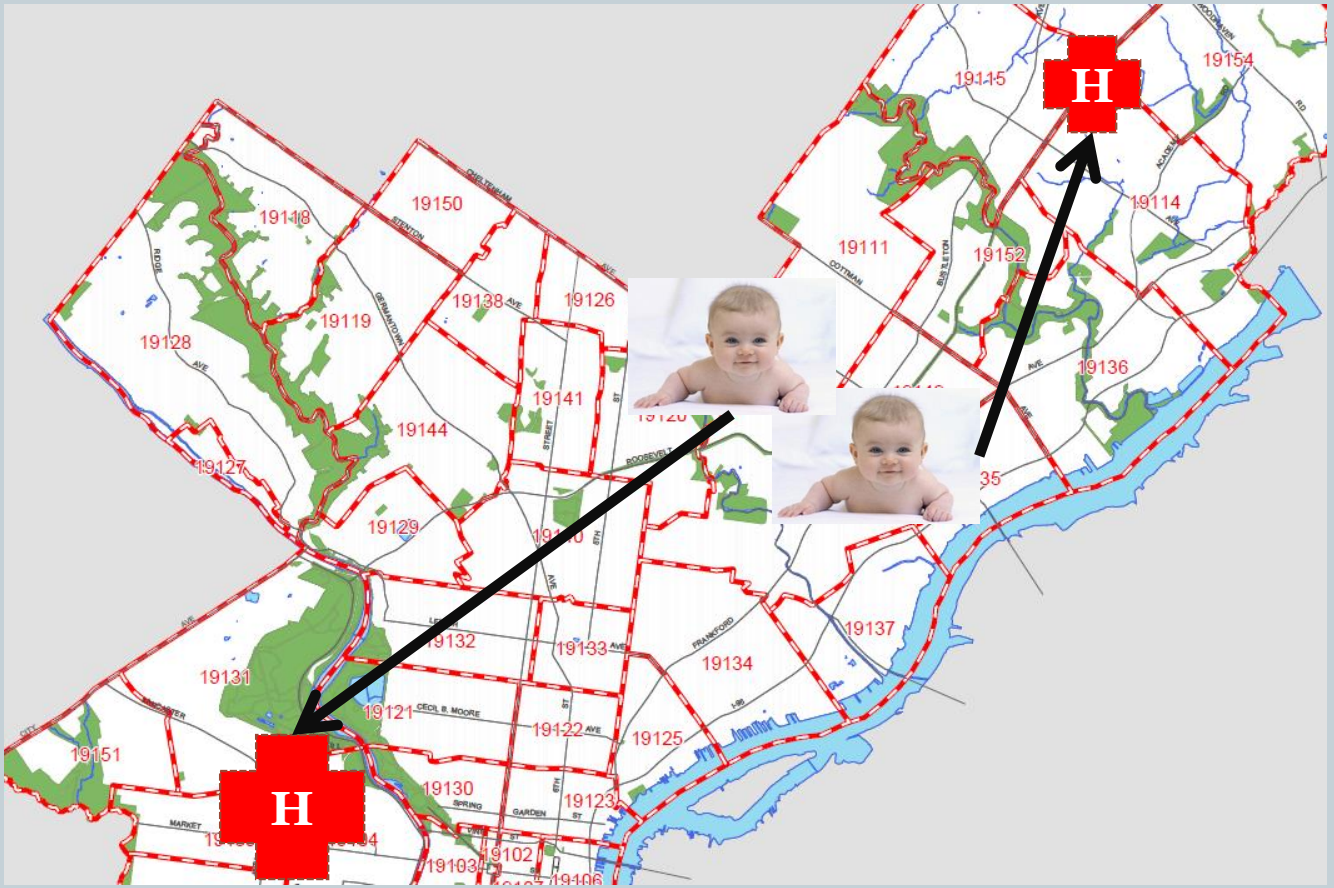
NEAR-FAR MATCHING

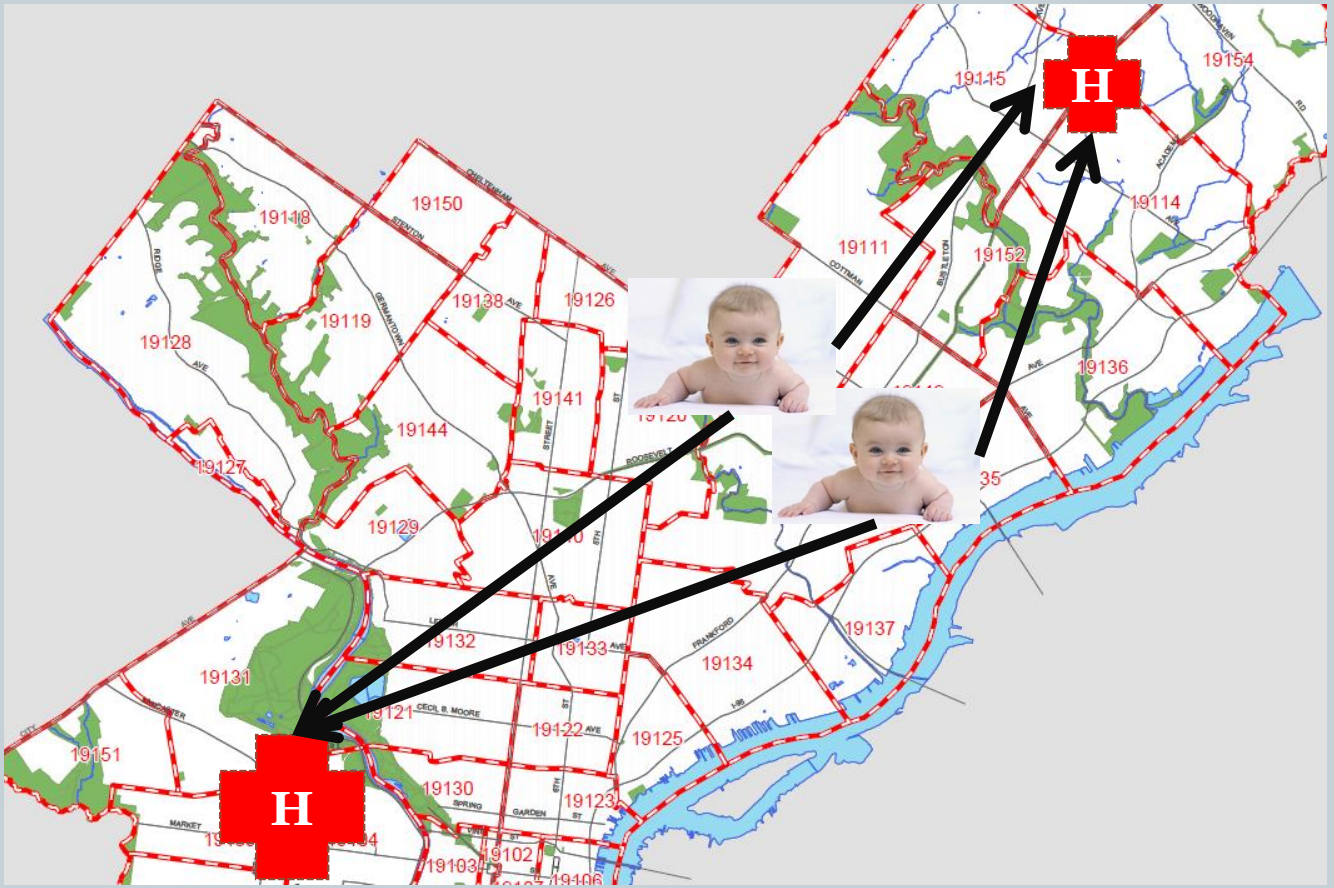
Baiocchi, Small, Lorch and Rosenbaum (2010) – Building a Stronger Instrument in an Observational Study

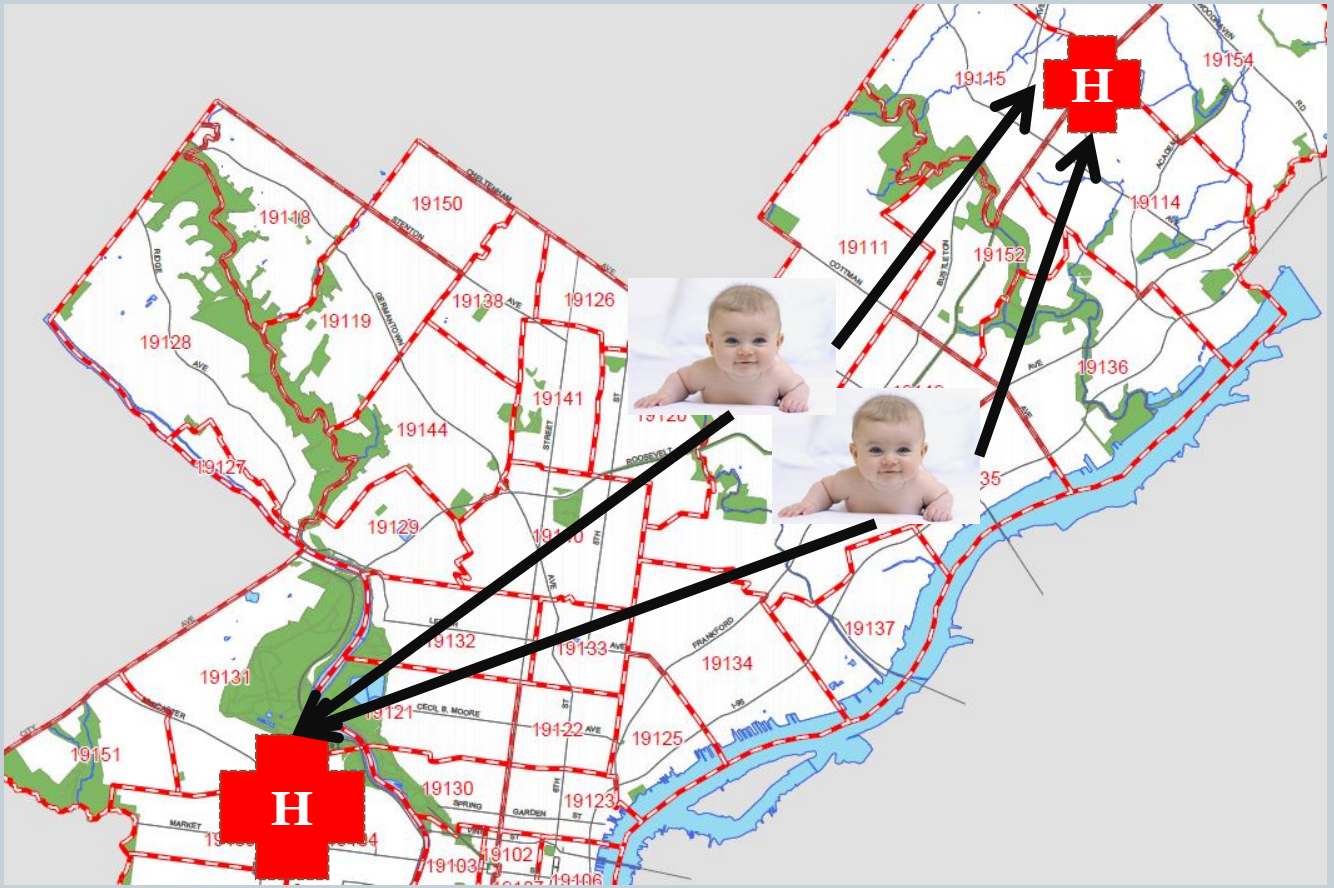

19118
19150
19138 AVE
19126
19128
19141
19127
19140
19132
19133 AVE
19131
19121
CECIL B. MOORE
19122 AVE
19125
19151
19115
19137
19134
136
35
H
H


19118
19150
19138 AVE
19126
19128
19141
19127
19140
19132
19133 AVE
19131
19121
CECIL B. MOORE
19122 AVE
19151
19125
19137
19134
19115
136
35
H
H

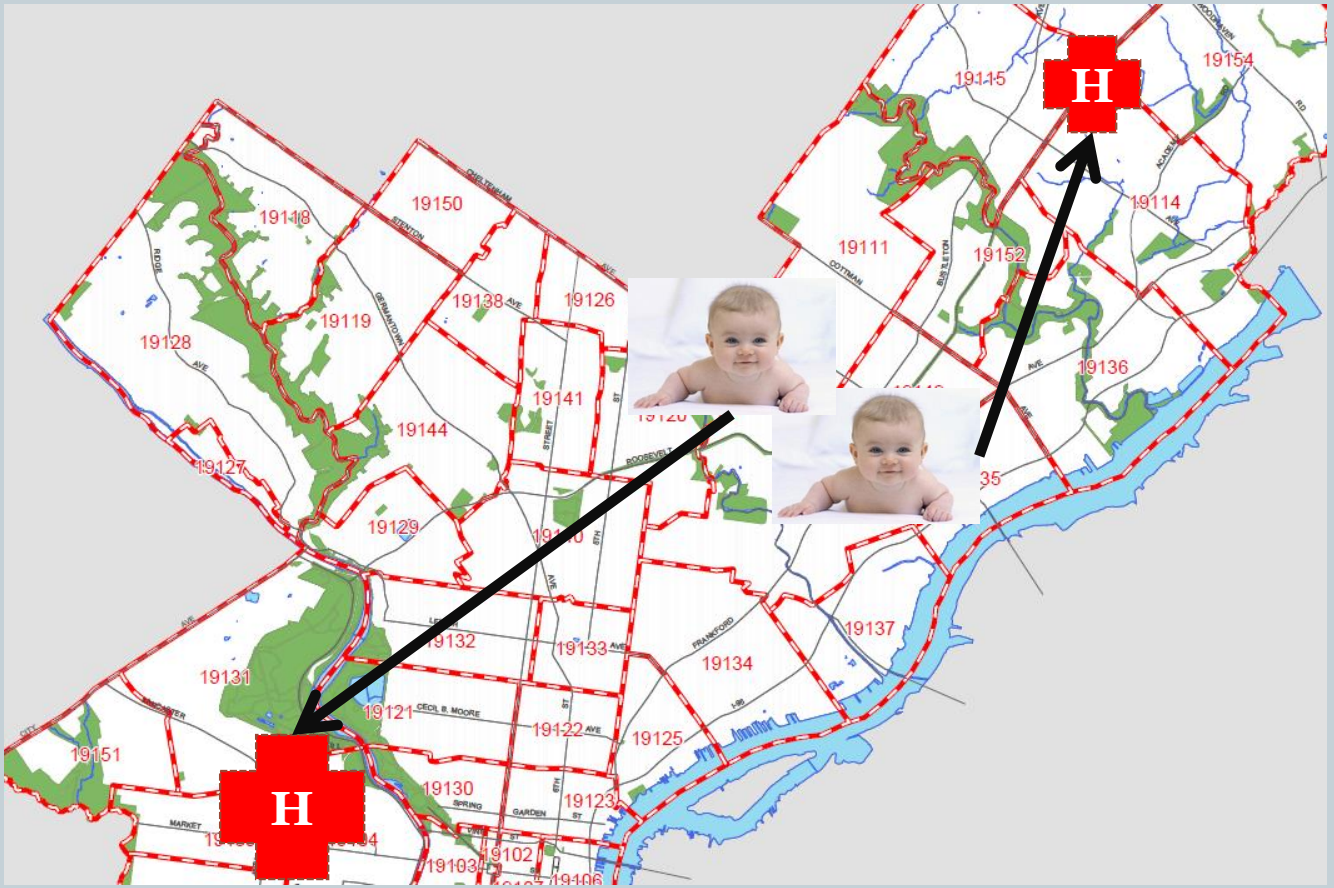

H
H
19154
19145
19114
19111
19152
19136
19150
19118
19119
19138
19126
19128
19141
19144
19127
19129
19140
19135
19137
19132
19133
19134
19131
19121
19122
19125
19151
19130
19123
19102
19103
19106


H
H
19154
19145
19114
19111
19152
19136
19118
19150
19119
19138
19126
19128
19141
19144
19127
19129
19137
19132
19133
19134
19131
19121
19122
19125
19151
19130
19123
19102
19103
19106


H
H
19154
19115
19114
19111
19152
19136
19118
19150
19119
19138
19126
19128
19141
19144
19127
19129
19132
19133
19131
19121
19122
19125
19151
19130
19123
19102
19137
19134
19135

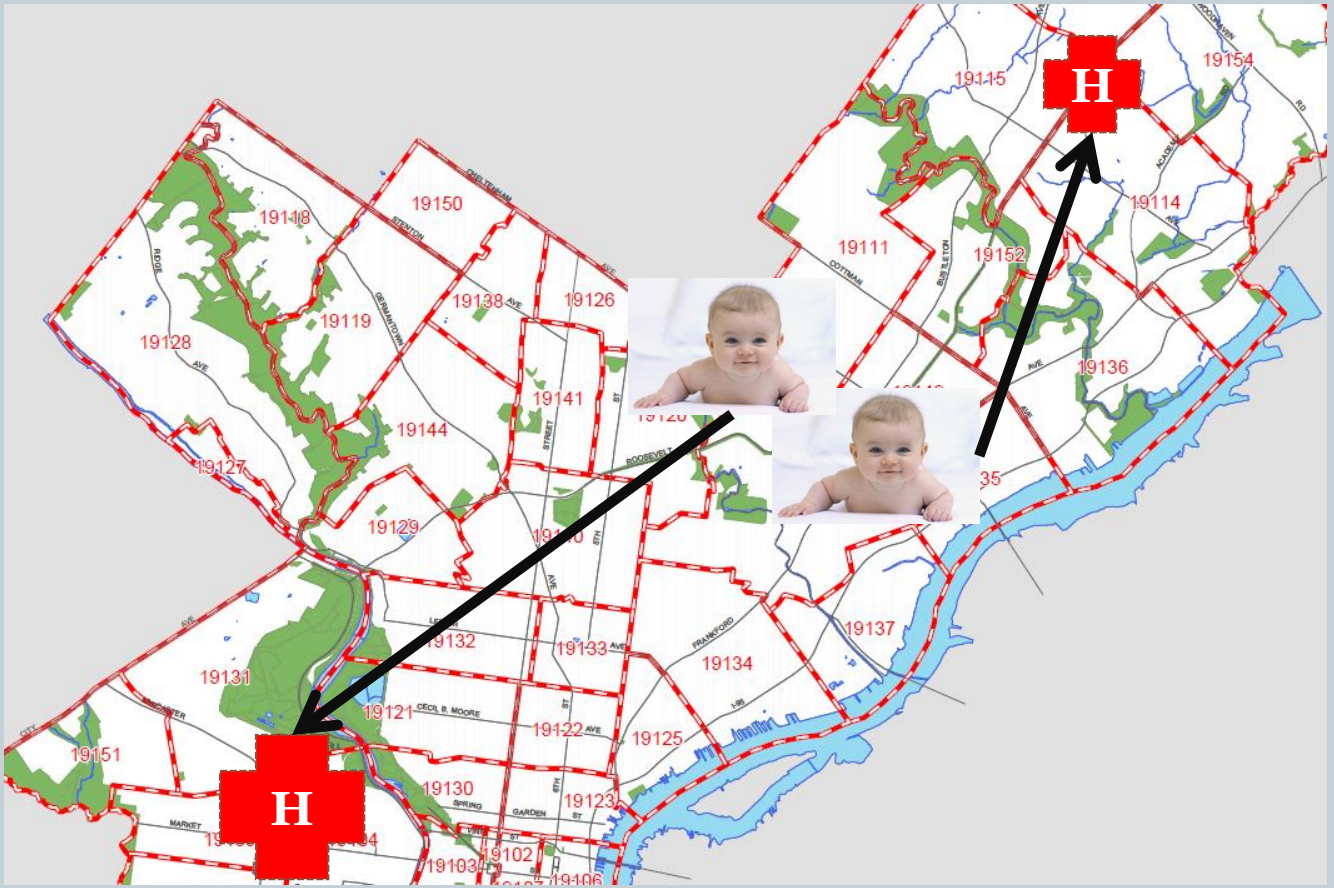


Sorting is potentially biased!

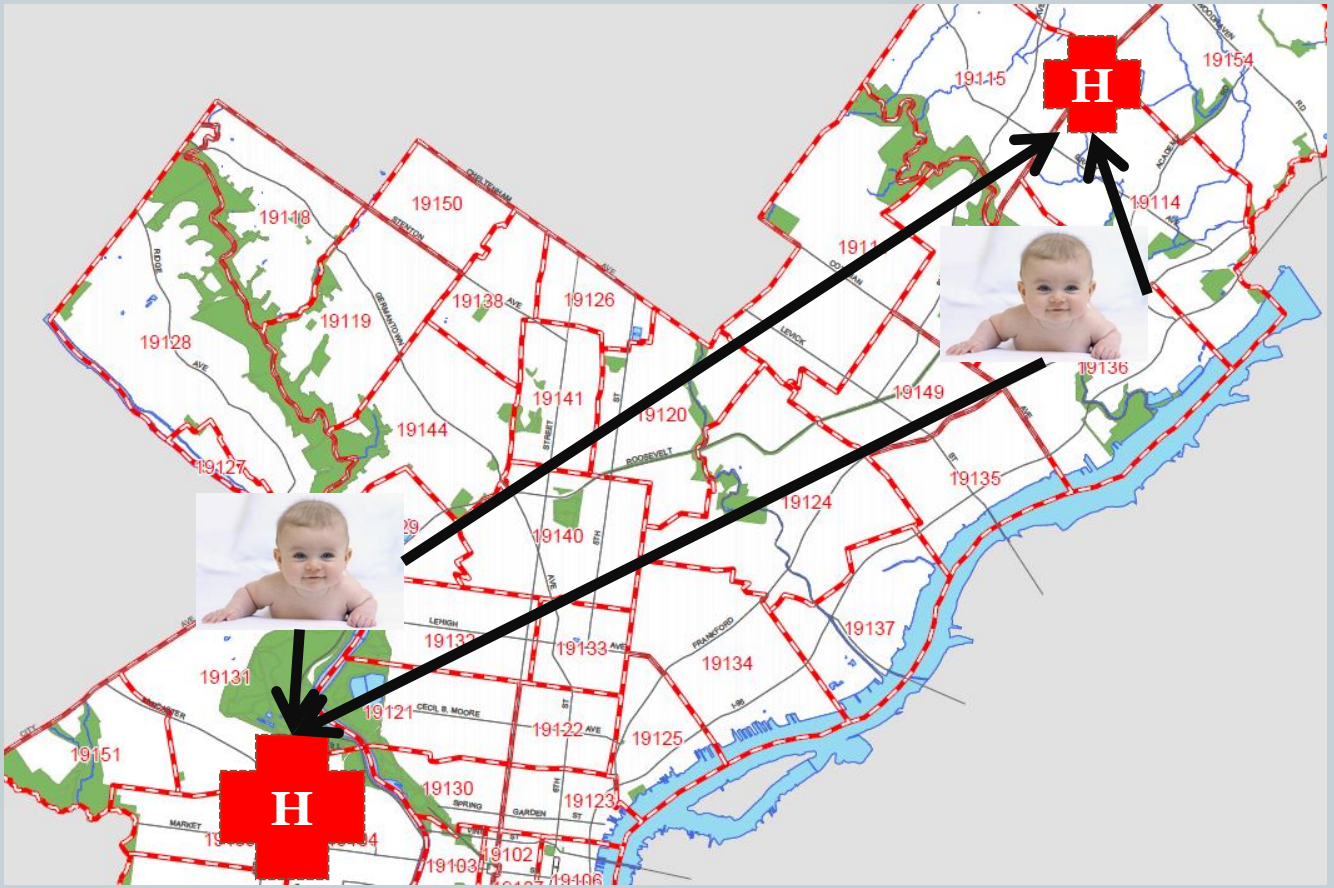


Sorting is potentially biased!

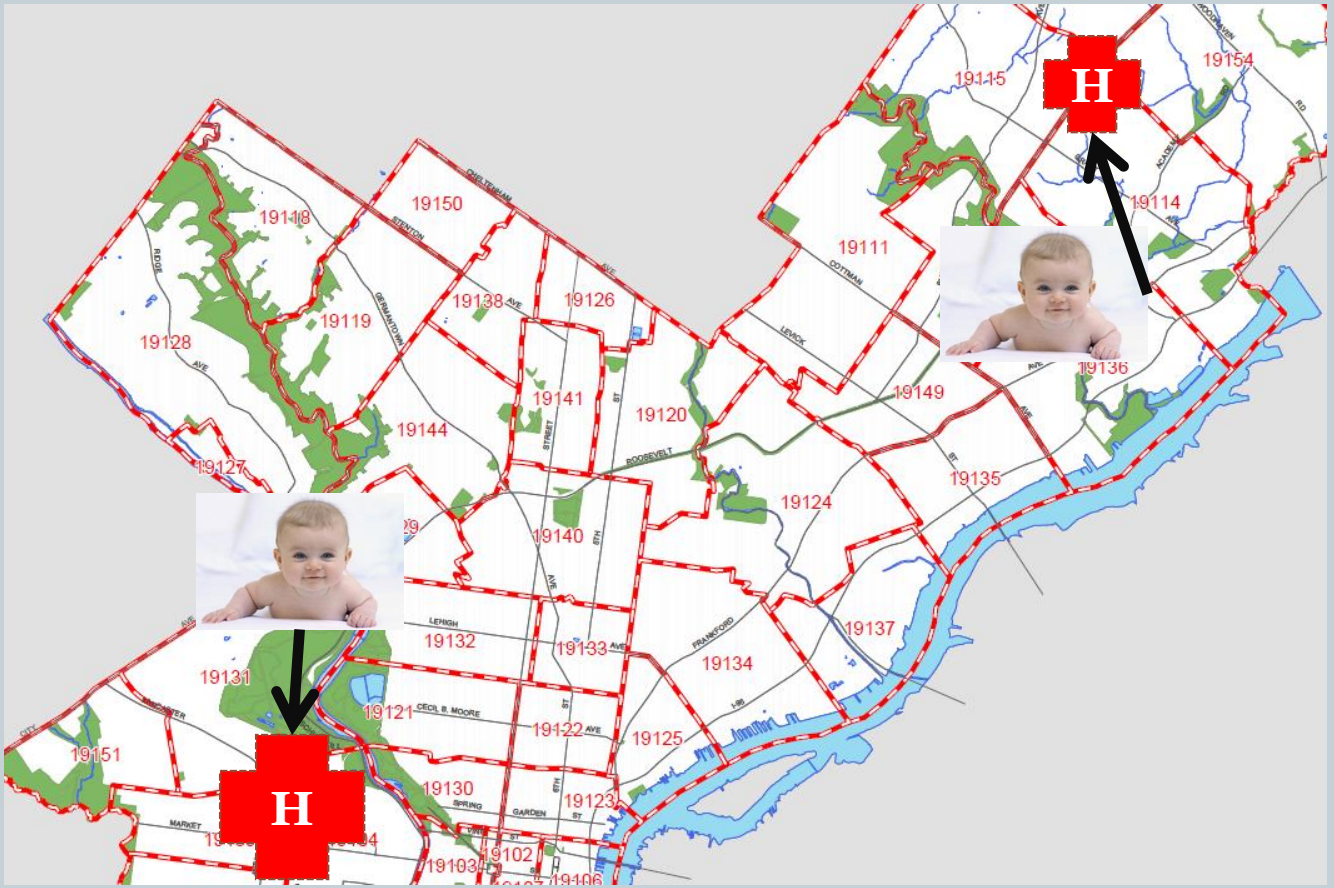
Bhattacharya and Vogt (2007) – [Do Instrumental Variables Belong in Propensity Scores?]



Sorting is potentially biased!

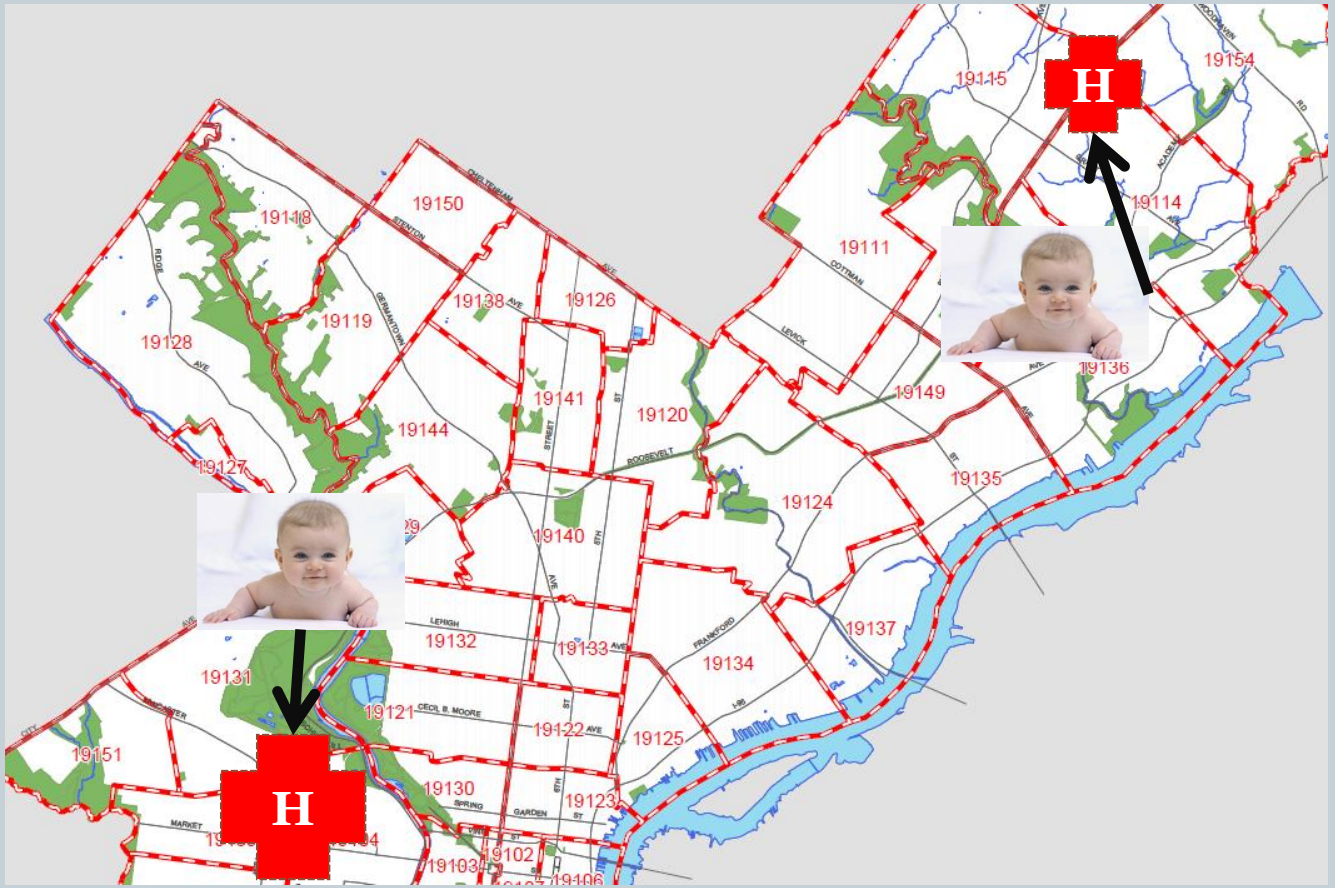


Sorting largely due to the randomness!



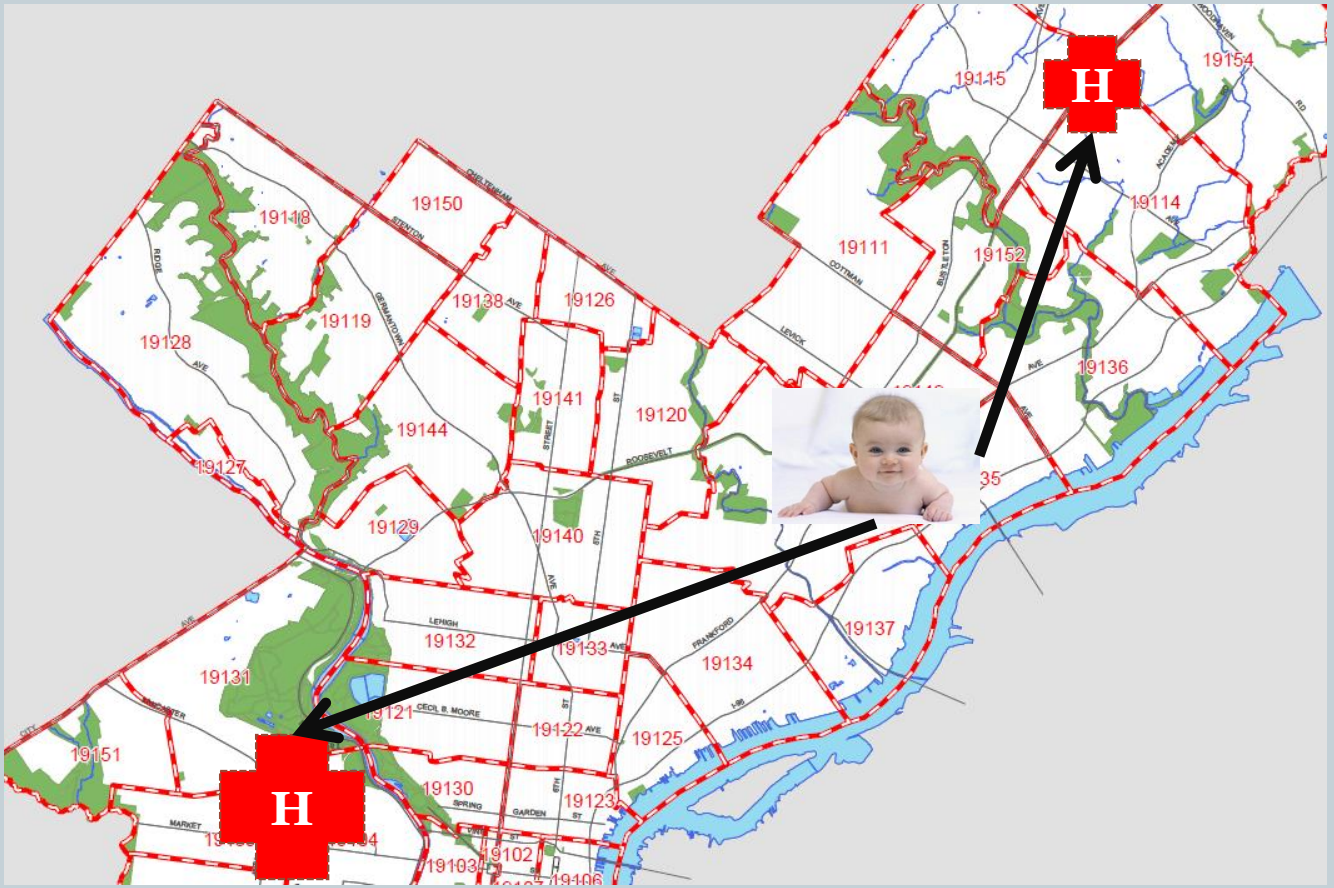
Sorting largely due to the randomness!

Baiocchi, Small, Lorch and Rosenbaum (2010) – Building a Stronger Instrument in an Observational Study

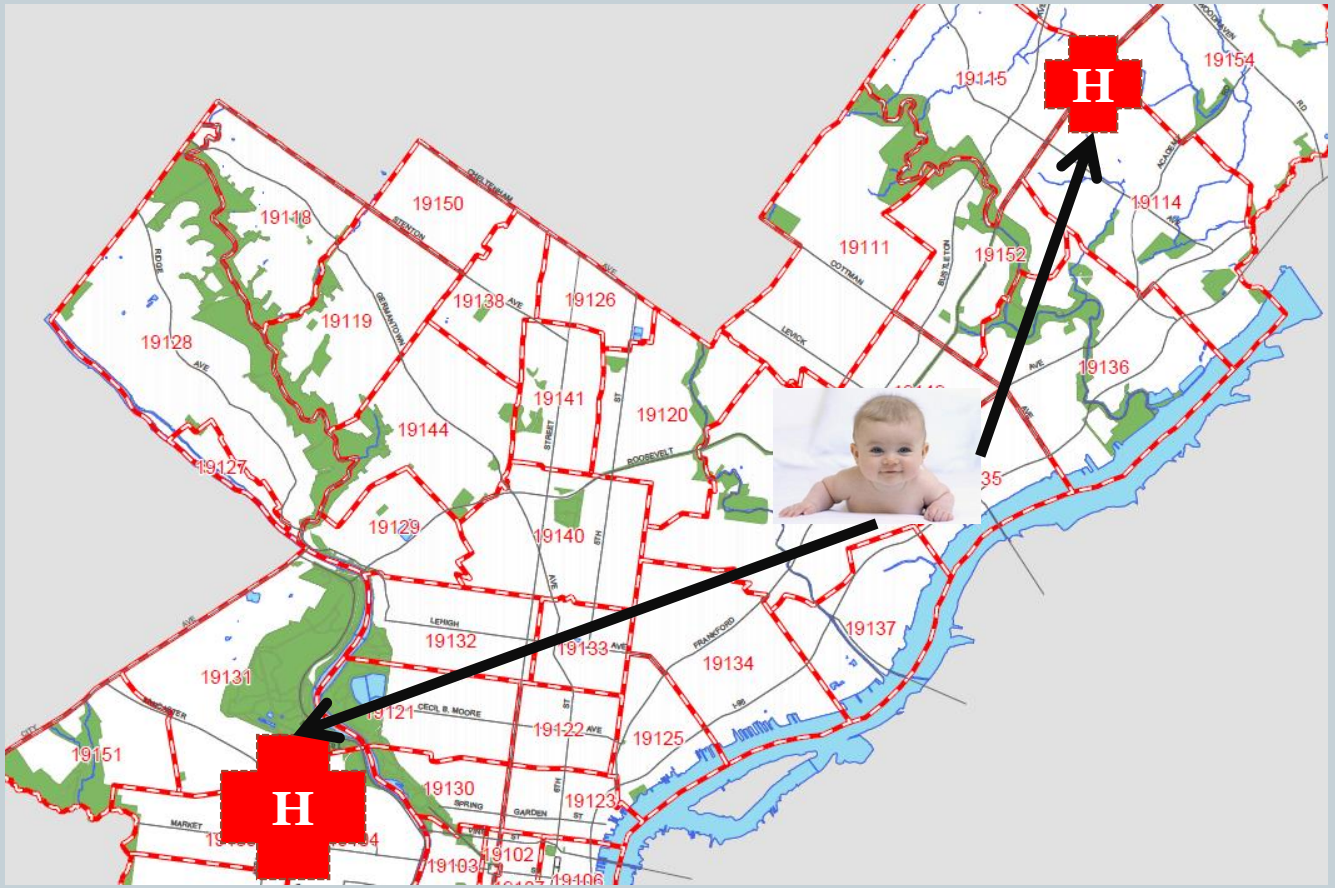


Sorting largely due to the randomness!

instrumental variable: excess travel time

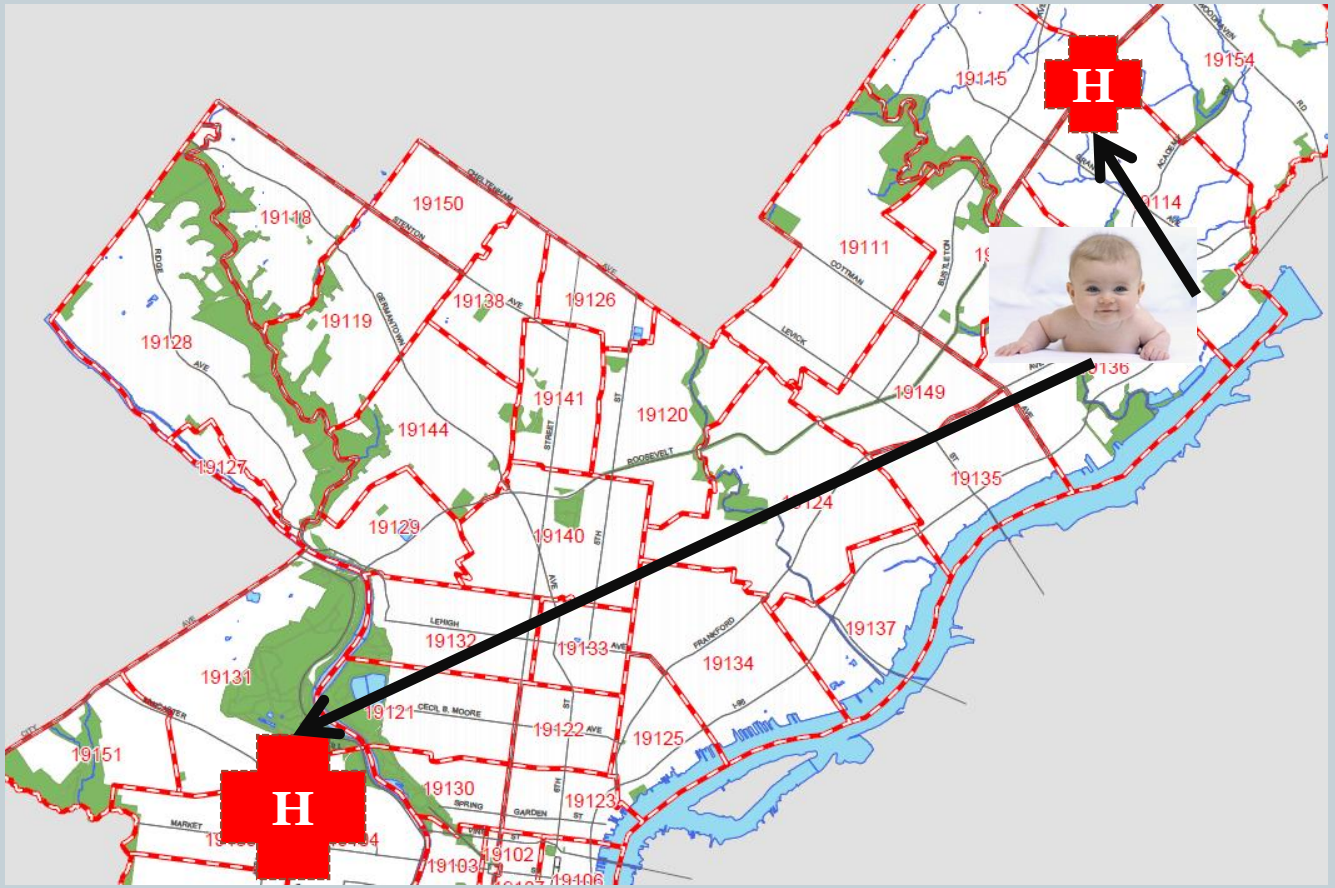


instrumental variable: excess travel time



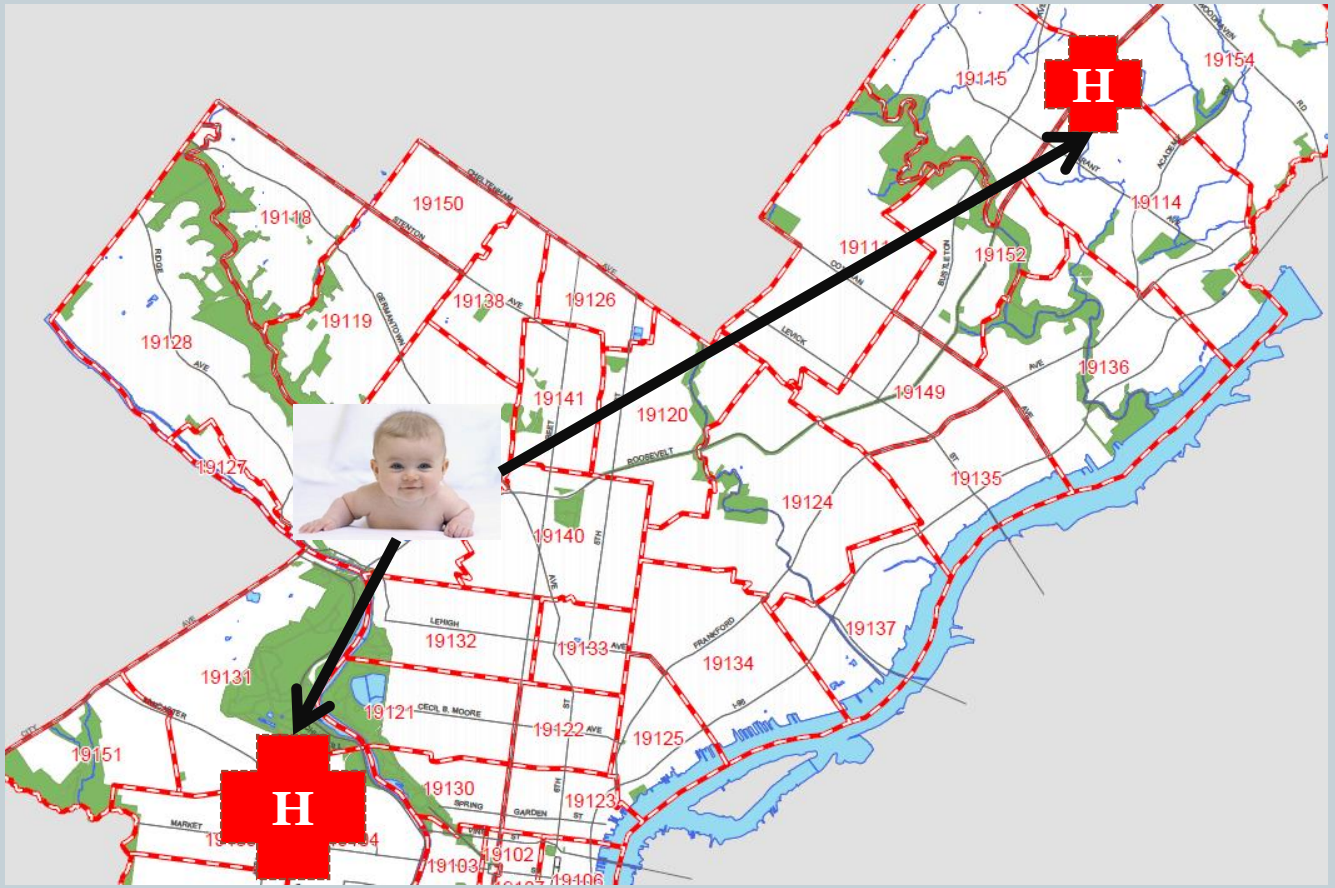
Excess Travel Time

instrumental variable: excess travel time



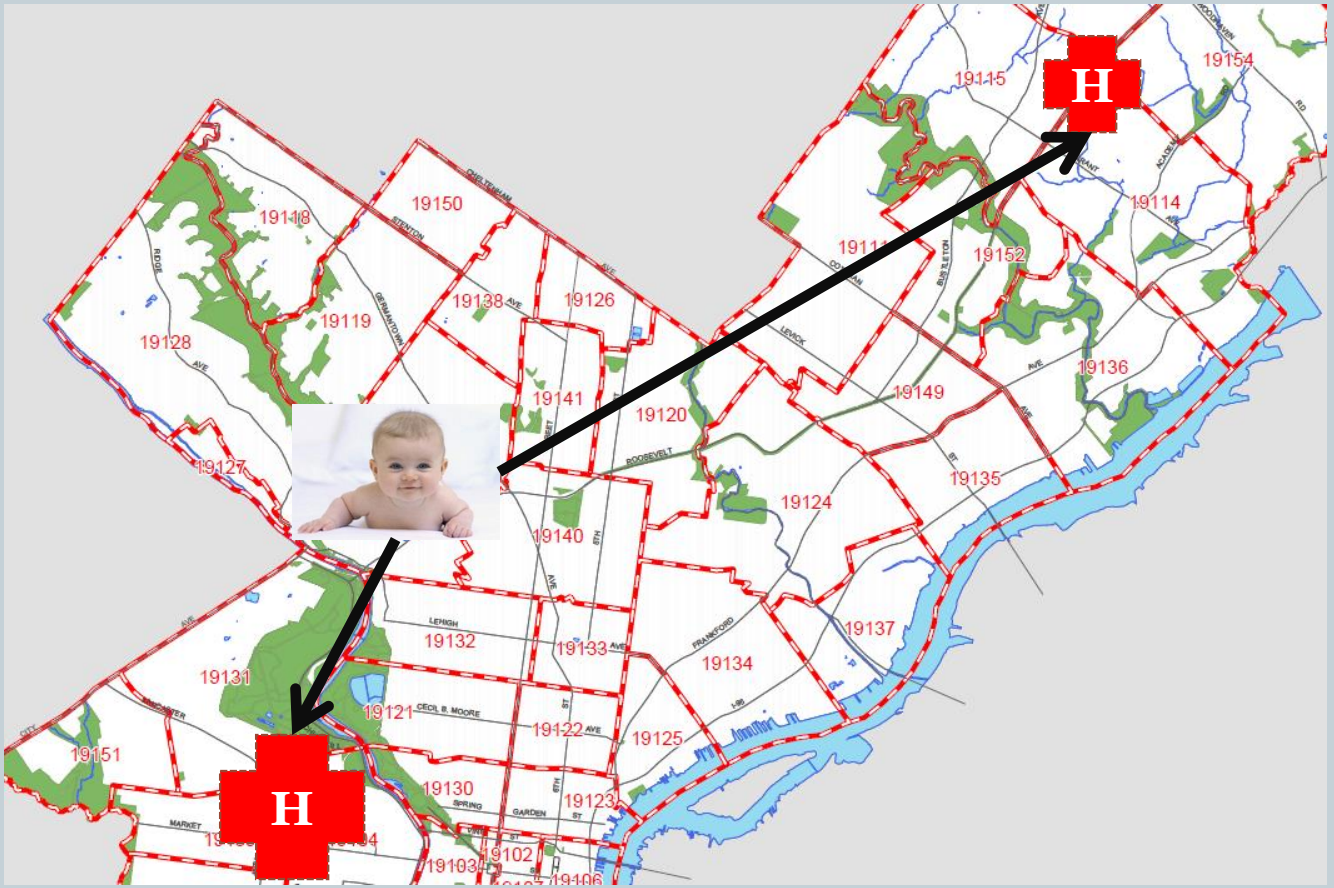
Excess Travel Time

instrumental variable: excess travel time



Excess Travel Time

instrumental variable: excess travel time



McClellan, McNeil & Newhouse; "**Does more intensive treatment of acute myocardial infarction reduce mortality?**" *JAMA*. 272(11): 859-66, September 1994

instrumental variables

NEAR-FAR MATCHING

Baiocchi, Small, Lorch and Rosenbaum (2010) – Building a Stronger Instrument in an Observational Study

design-based IVs: a quick sketch

design-based IVs: a quick sketch

- Use the idea of “block design” / “pair matching” to control **observed** variation.

design-based IVs: a quick sketch

- Use the idea of “block design” / “pair matching” to control **observed** variation.

- Use the idea of instrumental variables/encouragement to control **unobserved** variation.

design-based IVs: 1st step

- Summarize discrepancies in subjects' covariates

- We used Mahalanobis distance

$$D_M(\boldsymbol{x}_1, \boldsymbol{x}_2) = \sqrt{(\boldsymbol{x}_1 - \boldsymbol{x}_2)' S^{-1} (\boldsymbol{x}_1 - \boldsymbol{x}_2)}$$

design-based IVs: 1st step

$$\boldsymbol{D_x} = \begin{pmatrix} d_{11} & d_{12} & d_{13} & \cdots & \cdots & d_{1n} \\ d_{21} & d_{22} & & & & \vdots \\ d_{31} & & \ddots & & & \vdots \\ \vdots & & & \ddots & & \vdots \\ \vdots & & & & \ddots & \vdots \\ d_{n1} & \cdots & \cdots & \cdots & \cdots & d_{nn} \end{pmatrix}$$

d_{ij} = Mahalanobis distance between preemies ***i*** and ***j***

design-based IVs: 2nd step

- Create a penalty for preemies with similar instrument values (e.g., calipers)

design-based IVs: 2nd step

$$\boldsymbol{D_x} = \begin{pmatrix} d_{11} & d_{12} & d_{13} & \cdots & \cdots & d_{1n} \\ d_{21} & d_{22} & & & & \vdots \\ d_{31} & & \ddots & & & \vdots \\ \vdots & & & \ddots & & \vdots \\ \vdots & & & & \ddots & \vdots \\ d_{n1} & \cdots & \cdots & \cdots & \cdots & d_{nn} \end{pmatrix}$$

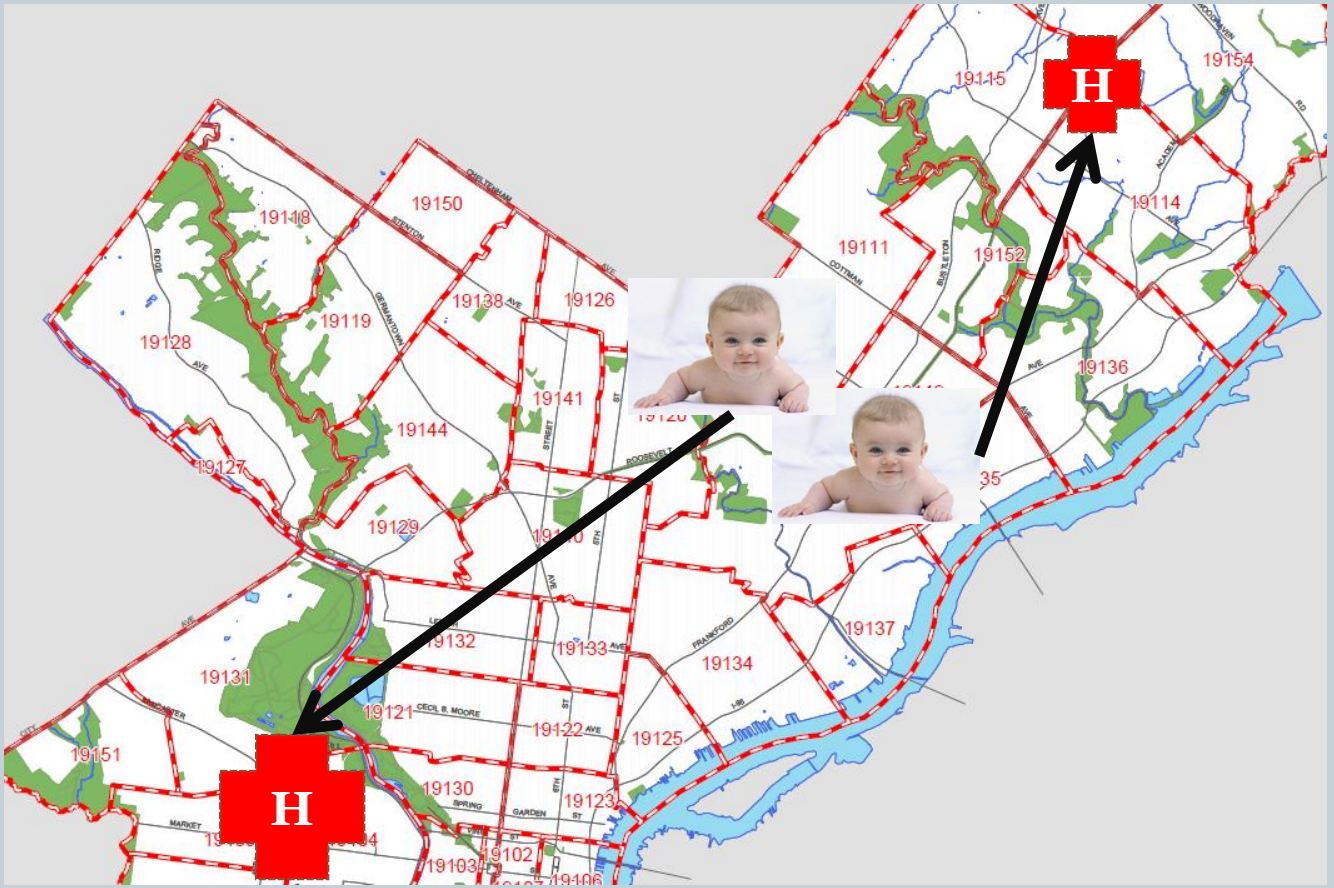
design-based IVs: 2nd step

$$\boldsymbol{D_x} = \begin{pmatrix} d_{11} & d_{12} & d_{13} & \cdots & \cdots & d_{1n} \\ d_{21} & d_{22} & & & & \vdots \\ d_{31} & & \ddots & & & \vdots \\ \vdots & & & \ddots & & \vdots \\ \vdots & & & & \ddots & \vdots \\ d_{n1} & \cdots & \cdots & \cdots & \cdots & d_{nn} \end{pmatrix}$$

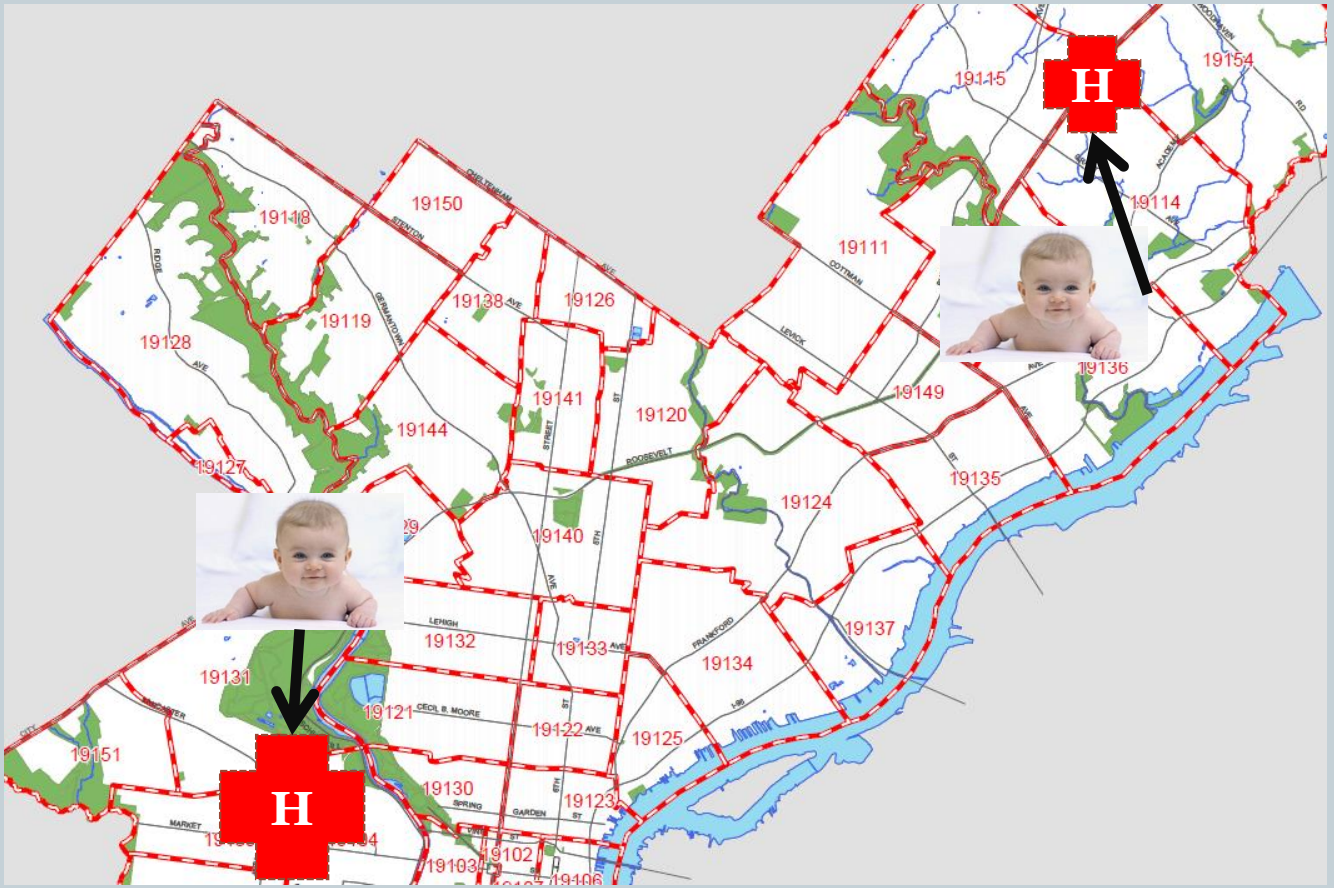
design-based IVs: 2nd step

$$\boldsymbol{D_x} = \begin{pmatrix} d_{11} & d_{12} & d_{13} & \cdots & \cdots & d_{1n} \\ d_{21} & d_{22} & & & & \vdots \\ d_{31} & & \ddots & & & \vdots \\ \vdots & & & \ddots & & \vdots \\ \vdots & & & & \ddots & \vdots \\ d_{n1} & \cdots & \cdots & \cdots & \cdots & d_{nn} \end{pmatrix}$$

$$\boldsymbol{C_z} = \begin{pmatrix} c_{11} & c_{12} & c_{13} & \cdots & \cdots & c_{1n} \\ c_{21} & c_{22} & & & & \vdots \\ c_{31} & & \ddots & & & \vdots \\ \vdots & & & \ddots & & \vdots \\ \vdots & & & & \ddots & \vdots \\ c_{n1} & \cdots & \cdots & \cdots & \cdots & c_{nn} \end{pmatrix}$$



Selection is potentially biased!



Selection largely due to the instrument!

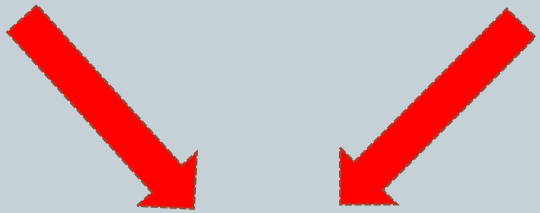
design-based IVs: 2nd step

$$\boldsymbol{D_x} = \begin{pmatrix} d_{11} & d_{12} & d_{13} & \cdots & \cdots & d_{1n} \\ d_{21} & d_{22} & & & & \vdots \\ d_{31} & & \ddots & & & \vdots \\ \vdots & & & \ddots & & \vdots \\ \vdots & & & & \ddots & \vdots \\ d_{n1} & \cdots & \cdots & \cdots & \cdots & d_{nn} \end{pmatrix}$$

$$\boldsymbol{C_z} = \begin{pmatrix} c_{11} & c_{12} & c_{13} & \cdots & \cdots & c_{1n} \\ c_{21} & c_{22} & & & & \vdots \\ c_{31} & & \ddots & & & \vdots \\ \vdots & & & \ddots & & \vdots \\ \vdots & & & & \ddots & \vdots \\ c_{n1} & \cdots & \cdots & \cdots & \cdots & c_{nn} \end{pmatrix}$$

design-based IVs: 2nd step

$$\boldsymbol{D_x} = \begin{pmatrix} d_{11} & d_{12} & d_{13} & \cdots & \cdots & d_{1n} \\ d_{21} & d_{22} & & & & \vdots \\ d_{31} & & \ddots & & & \vdots \\ \vdots & & & \ddots & & \vdots \\ \vdots & & & & \ddots & \vdots \\ d_{n1} & \cdots & \cdots & \cdots & \cdots & d_{nn} \end{pmatrix} \qquad \boldsymbol{C_z} = \begin{pmatrix} c_{11} & c_{12} & c_{13} & \cdots & \cdots & c_{1n} \\ c_{21} & c_{22} & & & & \vdots \\ c_{31} & & \ddots & & & \vdots \\ \vdots & & & \ddots & & \vdots \\ \vdots & & & & \ddots & \vdots \\ c_{n1} & \cdots & \cdots & \cdots & \cdots & c_{nn} \end{pmatrix}$$



Diff Covariates + Diff Encouragement = Discrepancy Matrix

design-based IVs: 2nd step

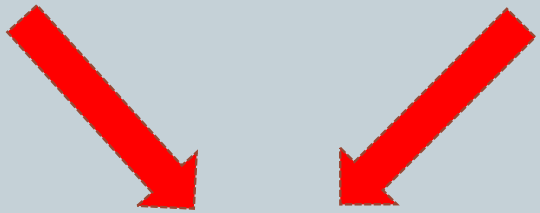
$$\boldsymbol{D_x} = \begin{pmatrix} d_{11} & d_{12} & d_{13} & \cdots & \cdots & d_{1n} \\ d_{21} & d_{22} & & & & \vdots \\ d_{31} & & \ddots & & & \vdots \\ \vdots & & & \ddots & & \vdots \\ \vdots & & & & \ddots & \vdots \\ d_{n1} & \cdots & \cdots & \cdots & \cdots & d_{nn} \end{pmatrix} \qquad \boldsymbol{C_z} = \begin{pmatrix} c_{11} & c_{12} & c_{13} & \cdots & \cdots & c_{1n} \\ c_{21} & c_{22} & & & & \vdots \\ c_{31} & & \ddots & & & \vdots \\ \vdots & & & \ddots & & \vdots \\ \vdots & & & & \ddots & \vdots \\ c_{n1} & \cdots & \cdots & \cdots & \cdots & c_{nn} \end{pmatrix}$$

Diff Covariates + Diff Encouragement = Discrepancy Matrix

(near) (far) (barrier to being paired)

design-based IVs: 2nd step

$$\boldsymbol{D_x} = \begin{pmatrix} d_{11} & d_{12} & d_{13} & \cdots & \cdots & d_{1n} \\ d_{21} & d_{22} & & & & \vdots \\ d_{31} & & \ddots & & & \vdots \\ \vdots & & & \ddots & & \vdots \\ \vdots & & & & \ddots & \vdots \\ d_{n1} & \cdots & \cdots & \cdots & \cdots & d_{nn} \end{pmatrix} \qquad \boldsymbol{C_z} = \begin{pmatrix} c_{11} & c_{12} & c_{13} & \cdots & \cdots & c_{1n} \\ c_{21} & c_{22} & & & & \vdots \\ c_{31} & & \ddots & & & \vdots \\ \vdots & & & \ddots & & \vdots \\ \vdots & & & & \ddots & \vdots \\ c_{n1} & \cdots & \cdots & \cdots & \cdots & c_{nn} \end{pmatrix}$$



$$\boldsymbol{D_x + C_z = D}$$

design-based IVs: 3rd step

- Something has got to give:

design-based IVs: 3rd step

- Something has got to give:
  - As we force separation in the instrument, it will be more difficult to find preemies with similar covariates.

design-based IVs: 3rd step

- Something has got to give:
  - As we force separation in the instrument, it will be more difficult to find preemies with similar covariates.
- Allow some subjects to be removed from the study design by matching to sinks.

design-based IVs: 3rd step

- Let k=number of sinks. Then augment the matrix like so:

$$\begin{pmatrix} \boldsymbol{D} & \mathbf{0} \\ \mathbf{0}' & \infty \end{pmatrix}$$

$\boldsymbol{D} = n \times n$ discepancy matrix, after first two steps

$\mathbf{0} = n \times k$ matrix, with all entries 0

$\infty = k \times k$ matrix, with entries ∞

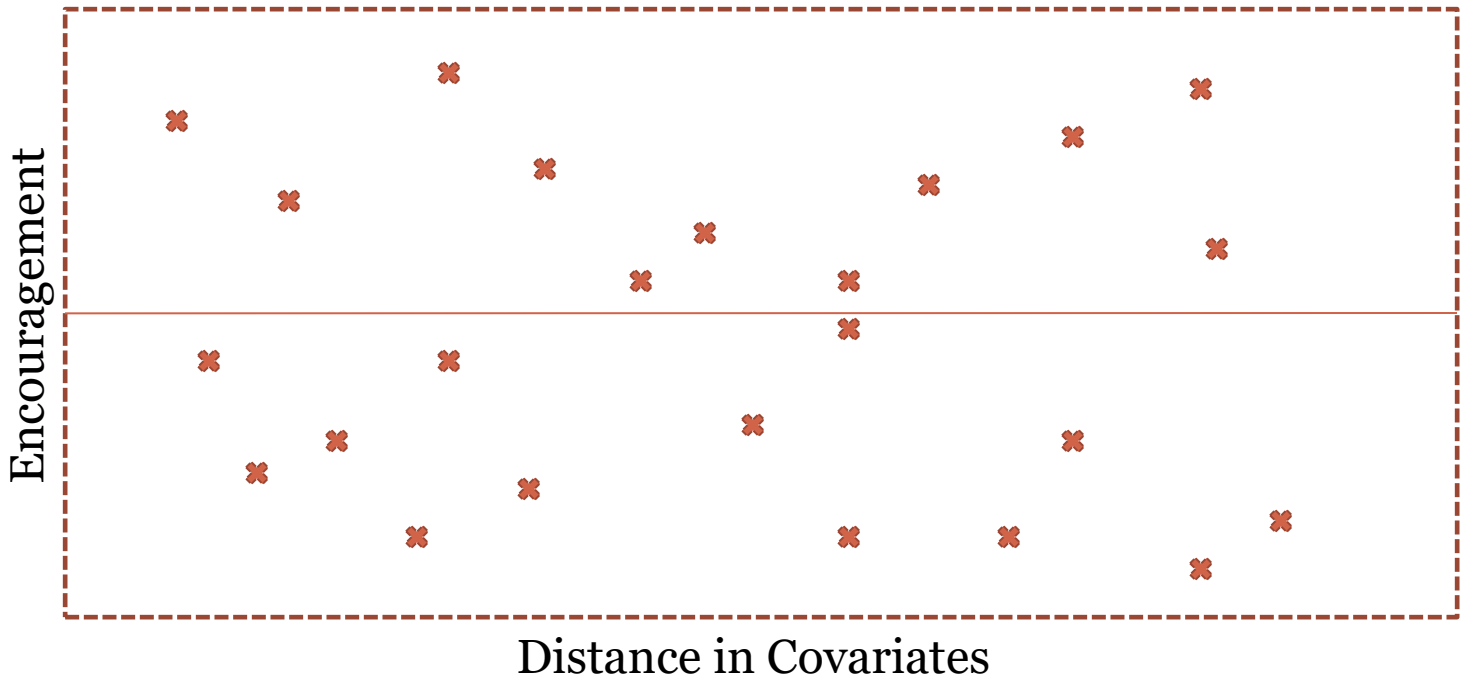
	Variable Type	High NICU	Low NICU	sd	Δ/sd
Mortality	Outcome	2.26%	1.25%	13.33%	0.08
Difference in Travel Time	Instrument	4.57	19.00	17.18	-0.84
% attending high level NICU	Treatment	100.0%	0.0%	49.7%	2.01
Birth weight	Preemie covariates	2,454.07	2,693.24	739.27	-0.32
Gestational age		34.61	35.69	2.80	-0.39
GI	% of preemies with type of congenital disorders	0.9%	0.6%	8.7%	0.04
GU		0.9%	0.8%	9.0%	0.01
CNS		0.9%	0.4%	8.3%	0.05
Pulmonary		0.8%	0.7%	8.8%	0.01
Cardio		1.4%	0.7%	10.5%	0.06
Skeletal		0.7%	0.9%	9.0%	-0.02
Skin		0.0%	0.0%	0.0%	0.00
Chromosomes		0.4%	0.3%	6.3%	0.02
Other_Anomaly		0.8%	0.1%	7.0%	0.09
Gestational_DiabetesM	Mother covariates	4.9%	4.3%	21.0%	0.03
Mother's education		3.76	3.58	1.19	0.16
Insurance - Fee for service		24.0%	24.5%	42.8%	-0.01
Insurance - HMO		32.3%	27.8%	46.0%	0.10
Insurance - Government		23.5%	24.2%	42.6%	-0.02
Insurance - Other		16.8%	21.4%	39.1%	-0.12
Uninsured		2.2%	1.6%	13.7%	0.04
Prenatal care		2.51	2.37	1.30	0.11
Single birth (y/n)		79.0%	86.1%	38.3%	-0.18
Parity		2.08	2.09	1.31	-0.01
Mother's age		28.41	27.71	6.25	0.11
Median income	Census level covariates	41,484.25	40,258.92	14,587.24	0.08
Median home value		97,663.00	95,083.15	48,762.43	0.05
% completed high school		79.9%	80.0%	9.7%	-0.01
% completed college		22.2%	19.4%	13.1%	0.21
% renting		31.4%	27.9%	12.8%	0.28
% below poverty line		13.4%	11.8%	9.9%	0.16

	Variable Type	High NICU	Low NICU	sd	Δ/sd
Mortality	Outcome	2.26%	1.25%	13.33%	0.08
Difference in Travel Time	Instrument	4.57	19.00	17.18	-0.84
% attending high level NICU	Treatment	100.0%	0.0%	49.7%	2.01
Birth weight	Preemie covariates	2,454.07	2,693.24	739.27	-0.32
Gestational age		34.61	35.69	2.80	-0.39

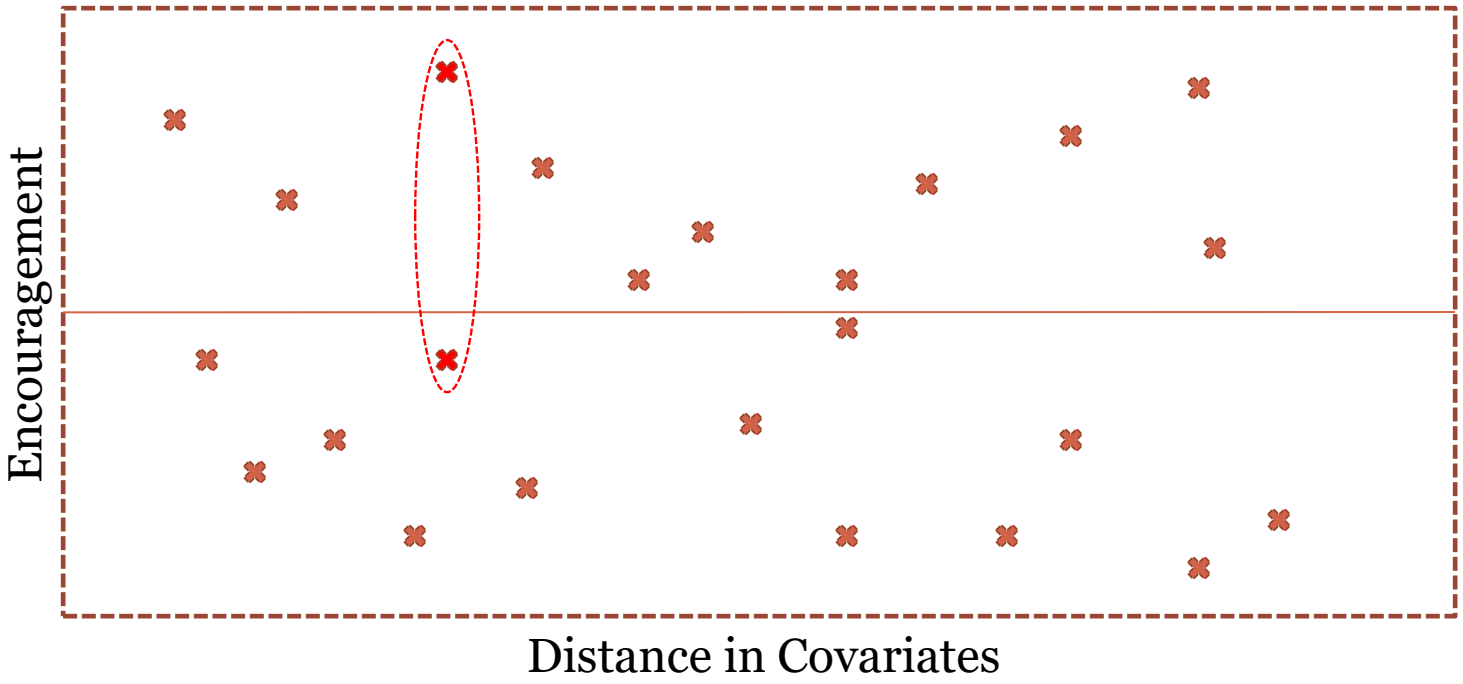
	1st Quartile	2nd Quartile	3rd Quartile	4th Quartile	max(Δ/sd)
Mortality	1.93%	2.08%	1.47%	1.74%	0.05
Difference in Travel Time	(3.19)	1.12	10.15	35.35	2.24
% attending high level NICU	81.1%	69.8%	49.9%	21.6%	1.20
Birth weight	2,556.17	2,494.15	2,579.15	2,620.74	0.17
Gestational age	35.08	34.82	35.14	35.35	0.19

Matched Pairs 49,587	Variable Type	Encouraged Mean	Unencouraged Mean	sd	Δ/sd
Mortality	Outcome	1.54%	1.94%	12.86%	-0.03
Difference in Travel Time	Instrument	0.67	34.78	18.05	-1.89
% attending high level NICU	Treatment	68.6%	25.4%	49.7%	0.87
Birth weight	Preemie covariates	2,586.15	2,581.77	727.45	0.01
Gestational age		35.17	35.16	2.68	0.01

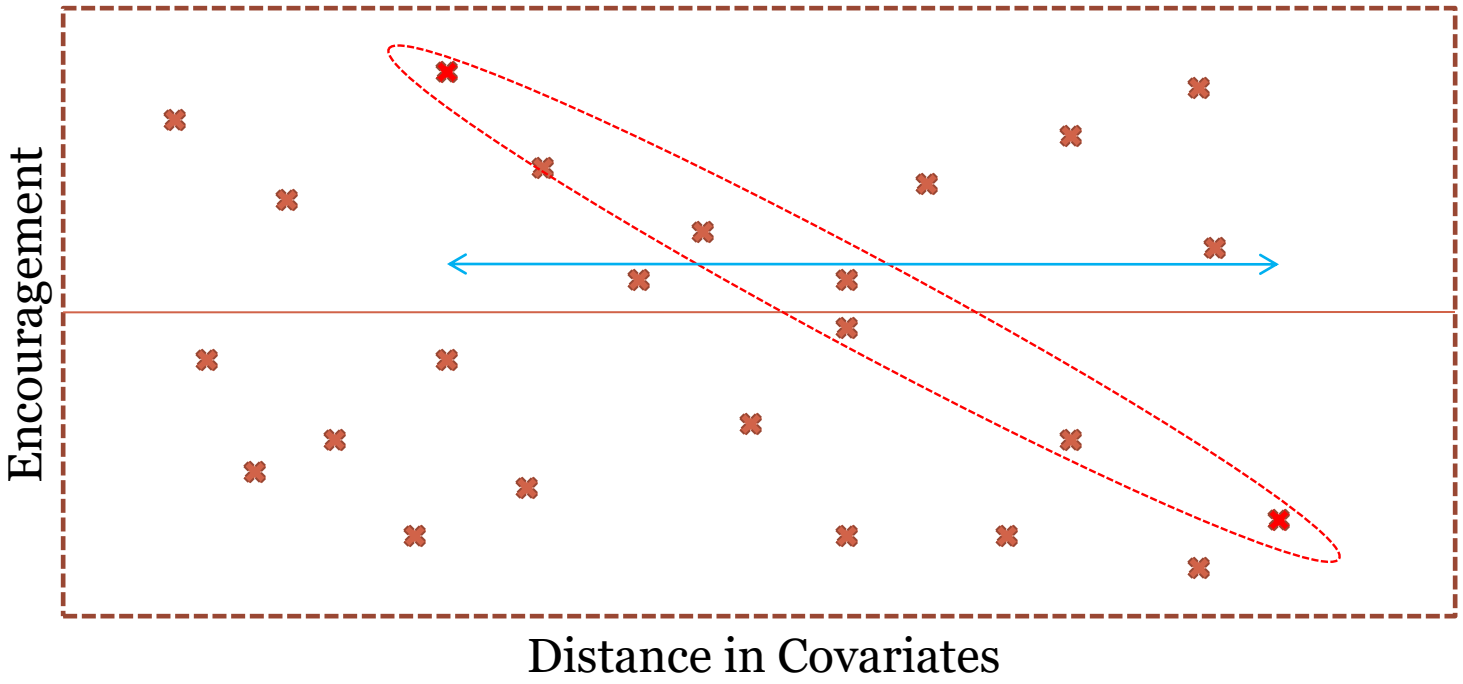
Our method – two criteria for matching



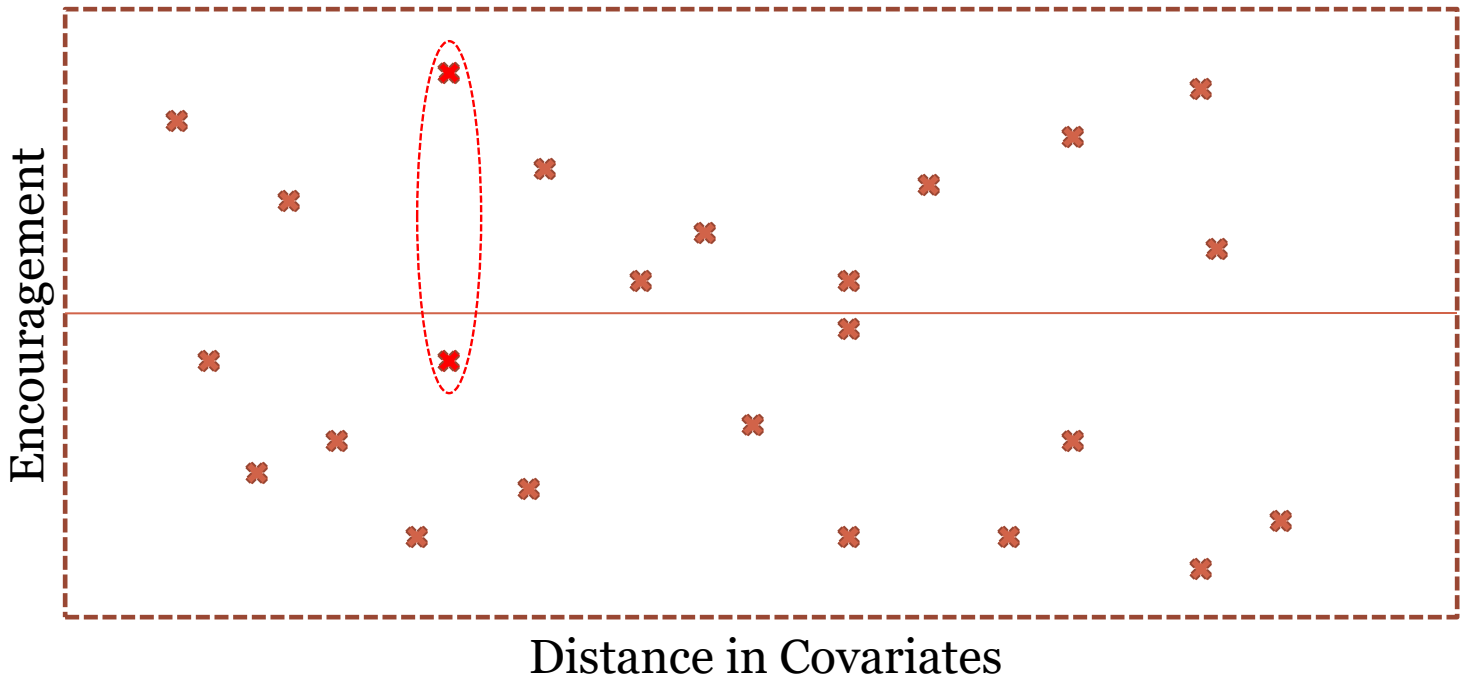
Our method – “near” in covariates



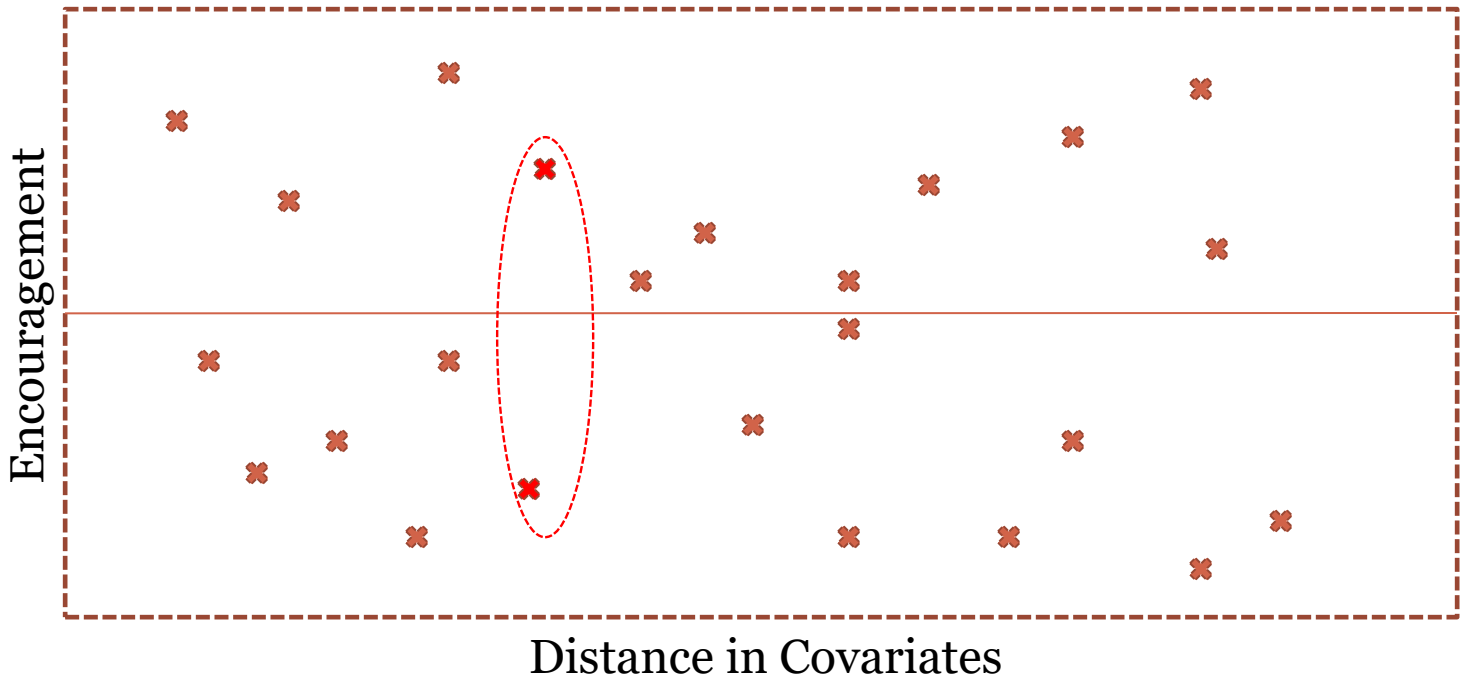
Our method – “far” in covariates



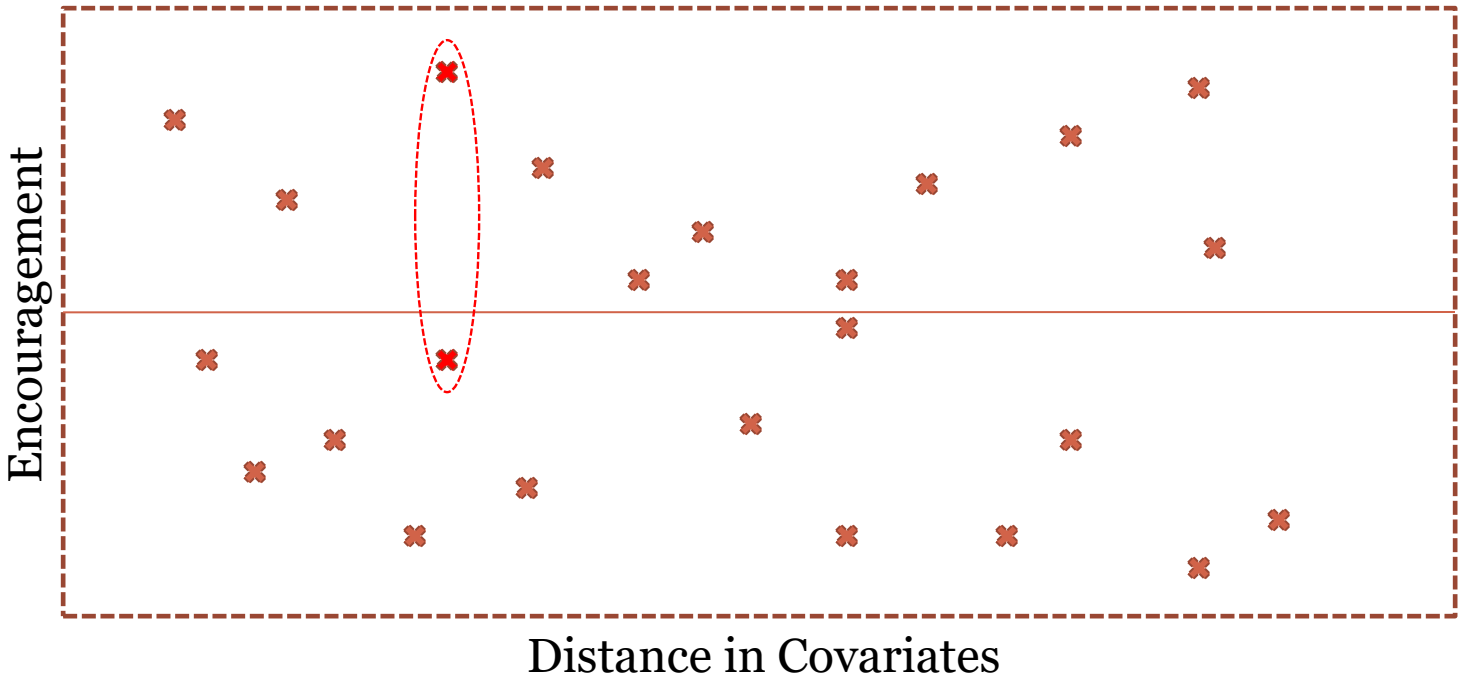
Our method – good pair



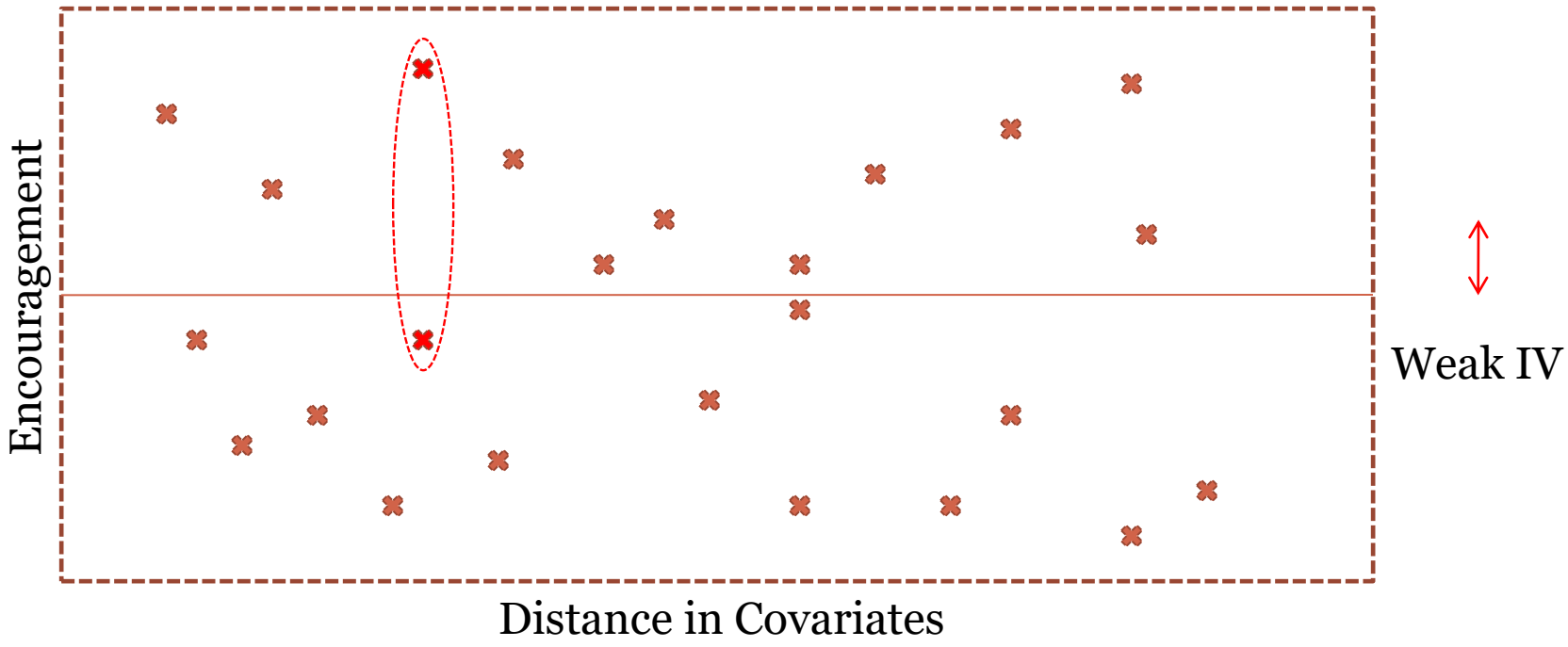
Our method – ok pair



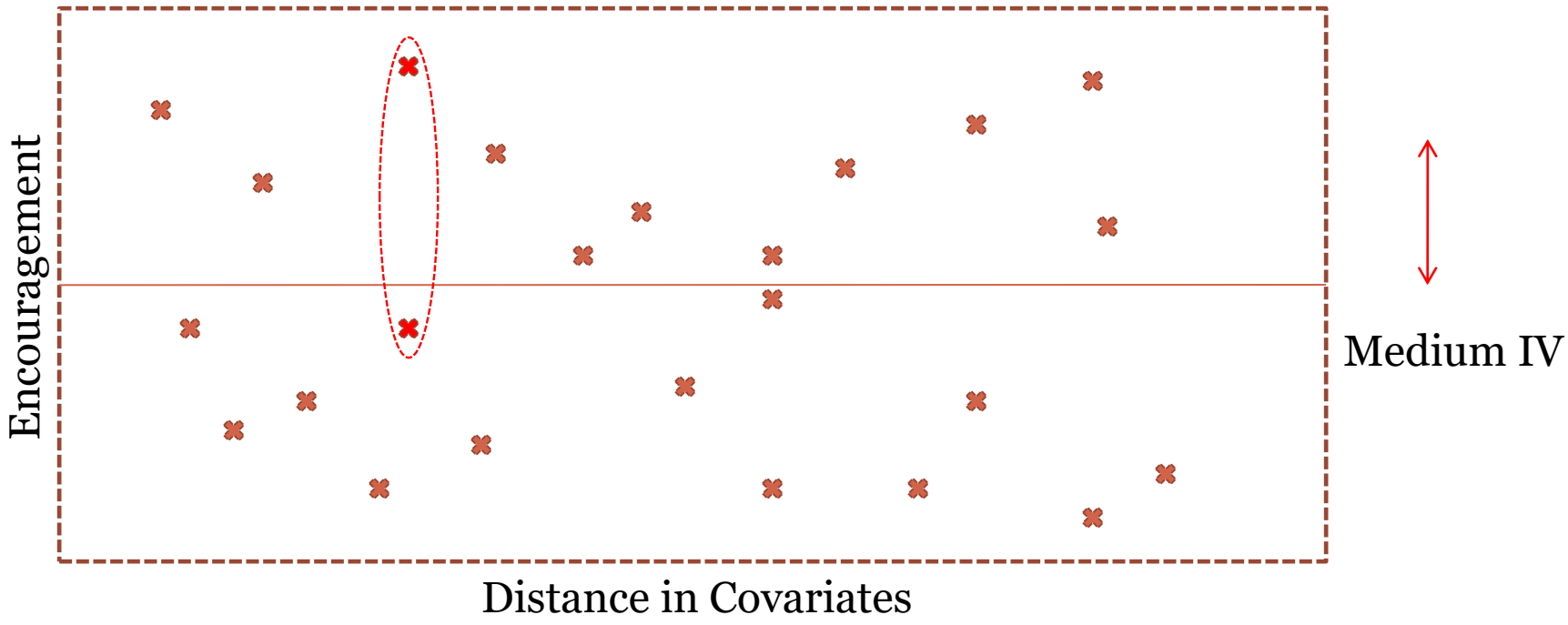
Our method – strength of instrument



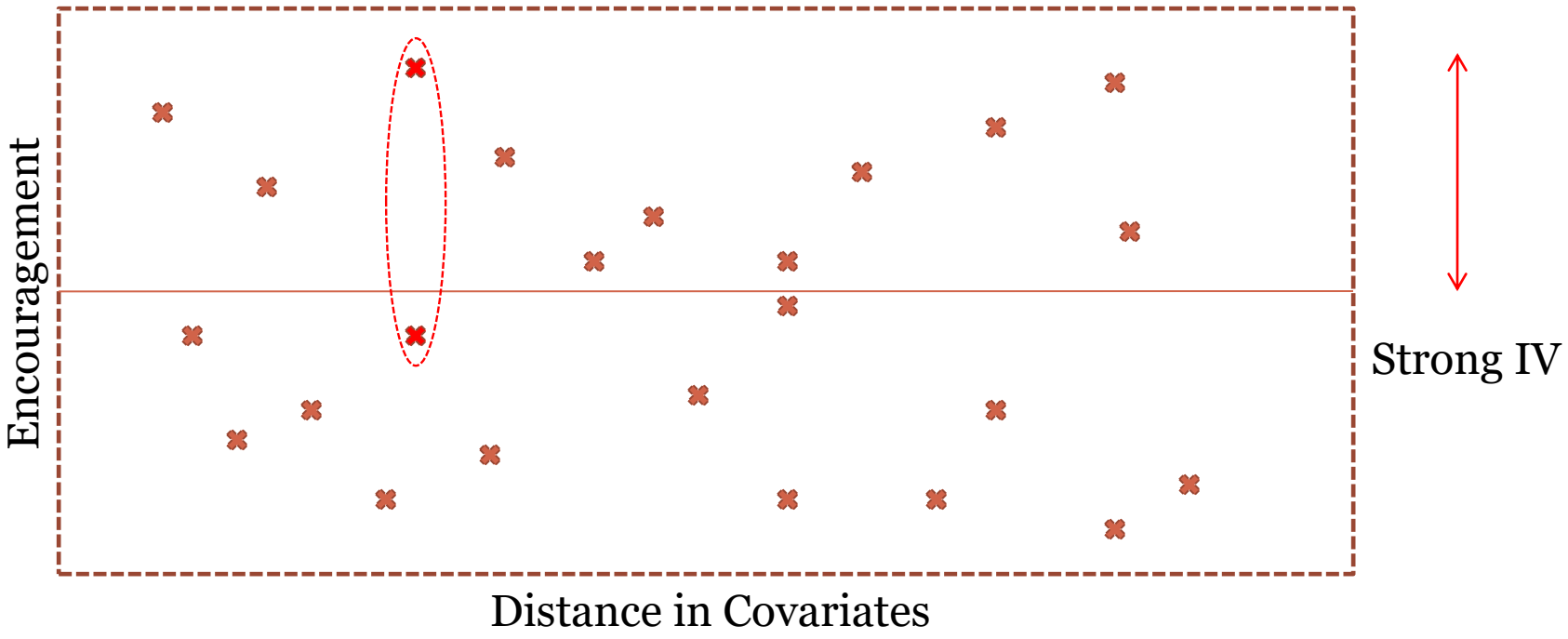
Our method – strength of instrument



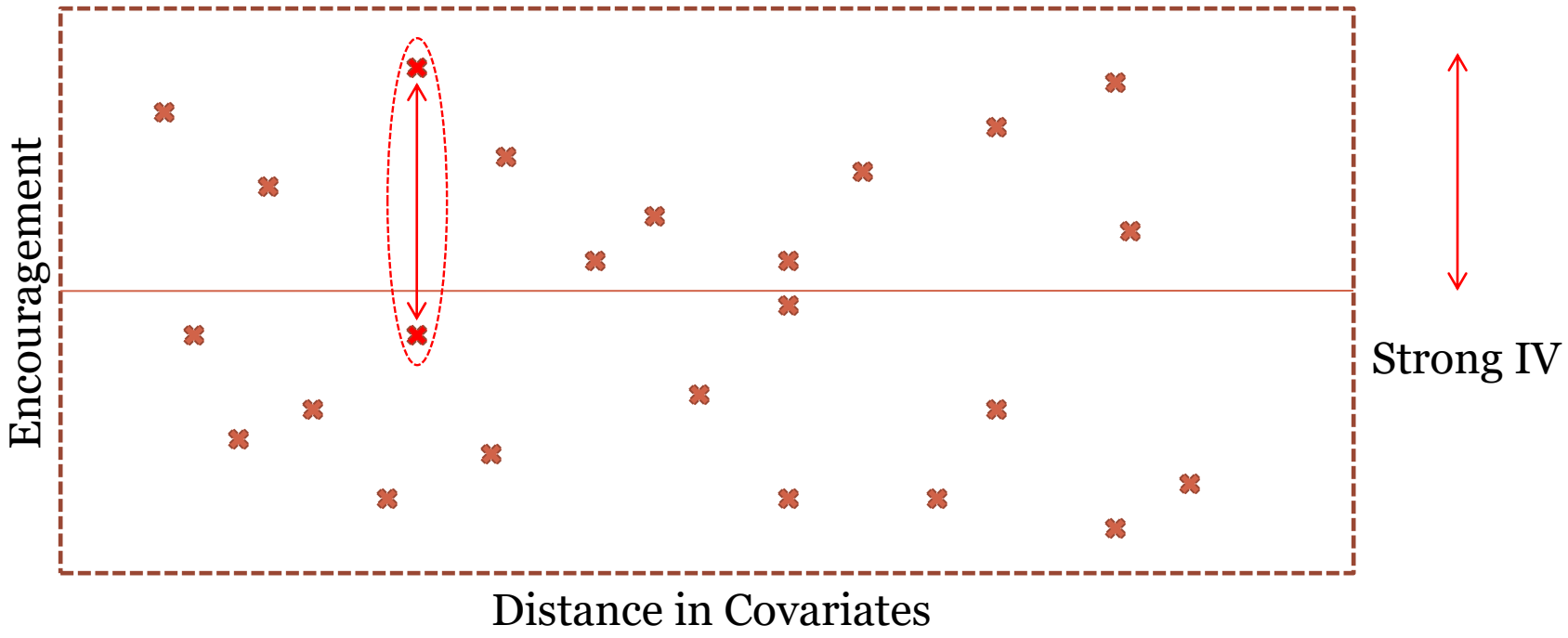
Our method – strength of instrument



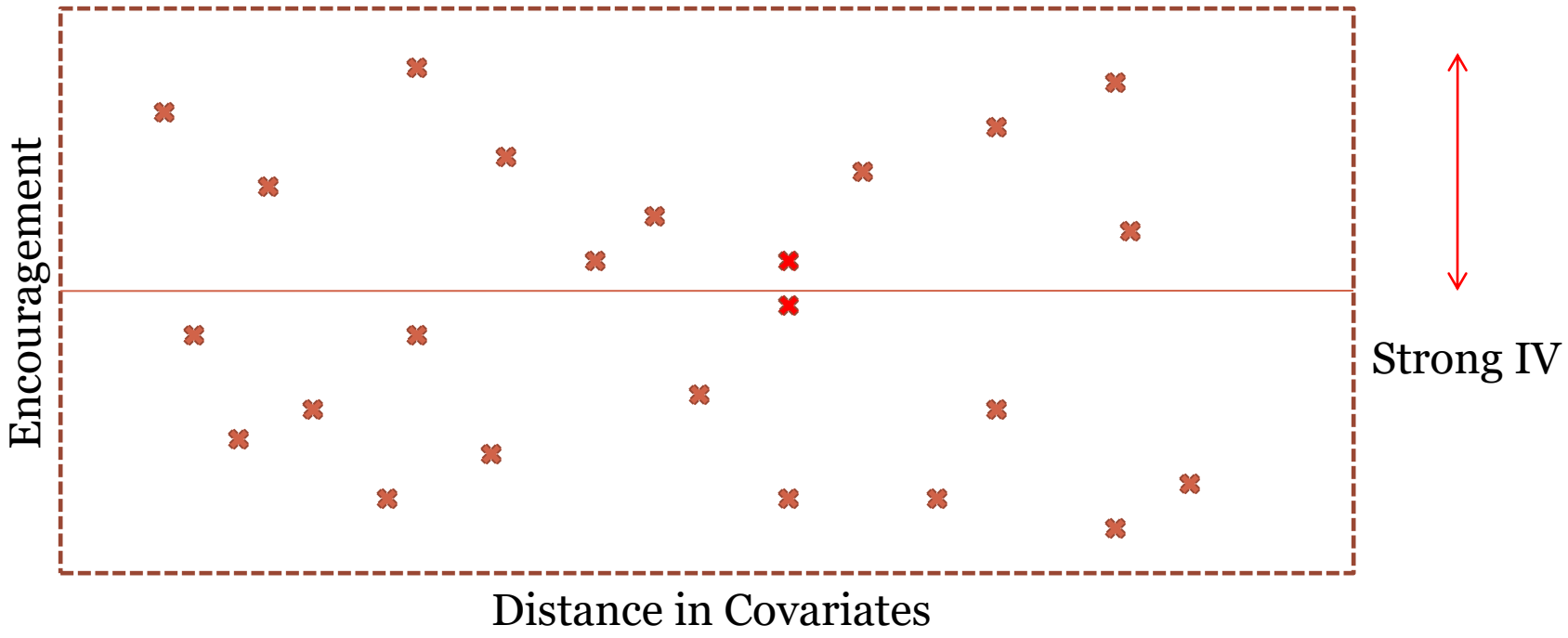
Our method – strength of instrument



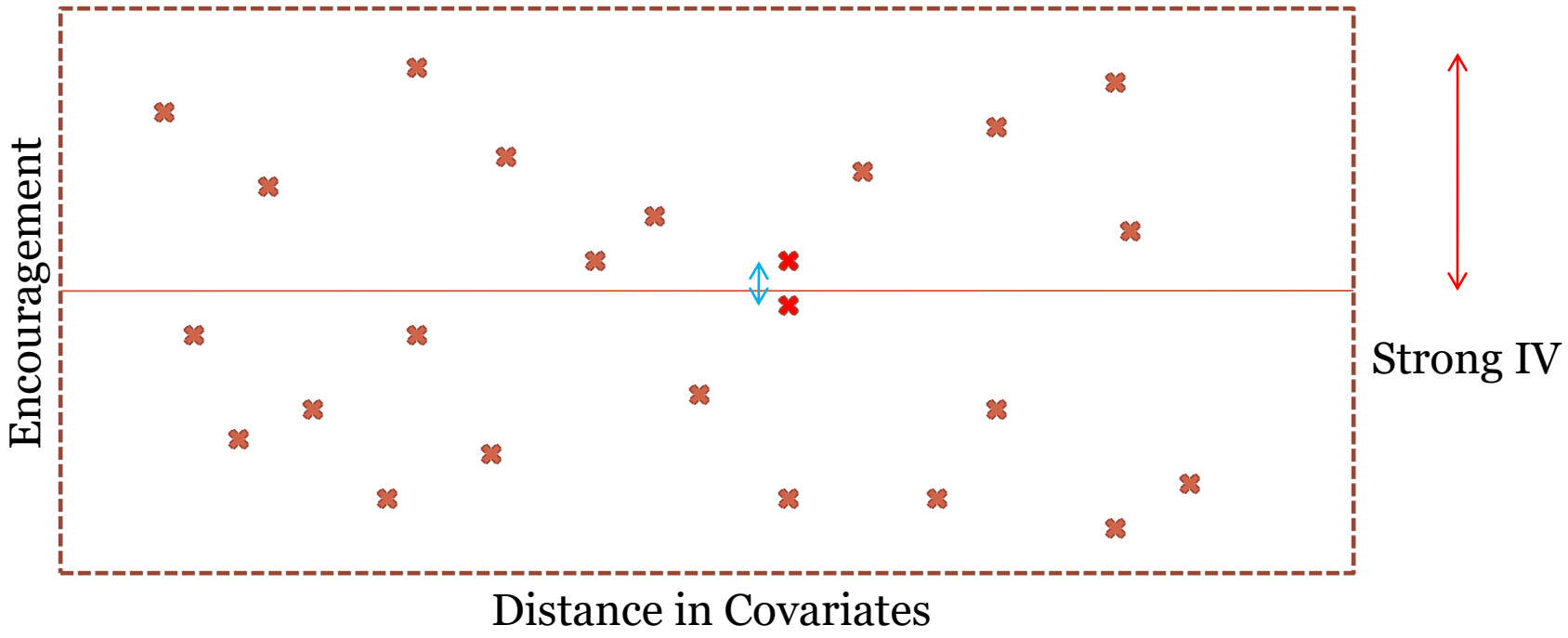
Our method – good pair



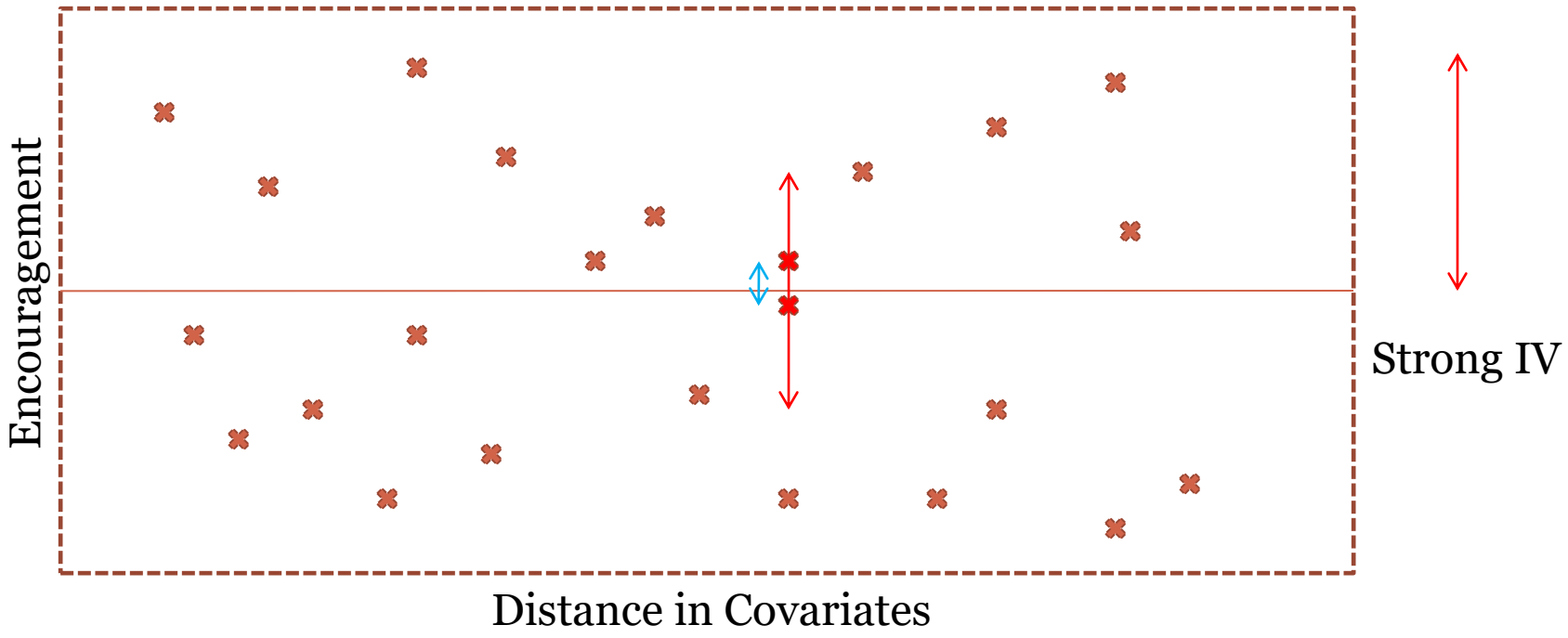
Our method – "near" in instrument



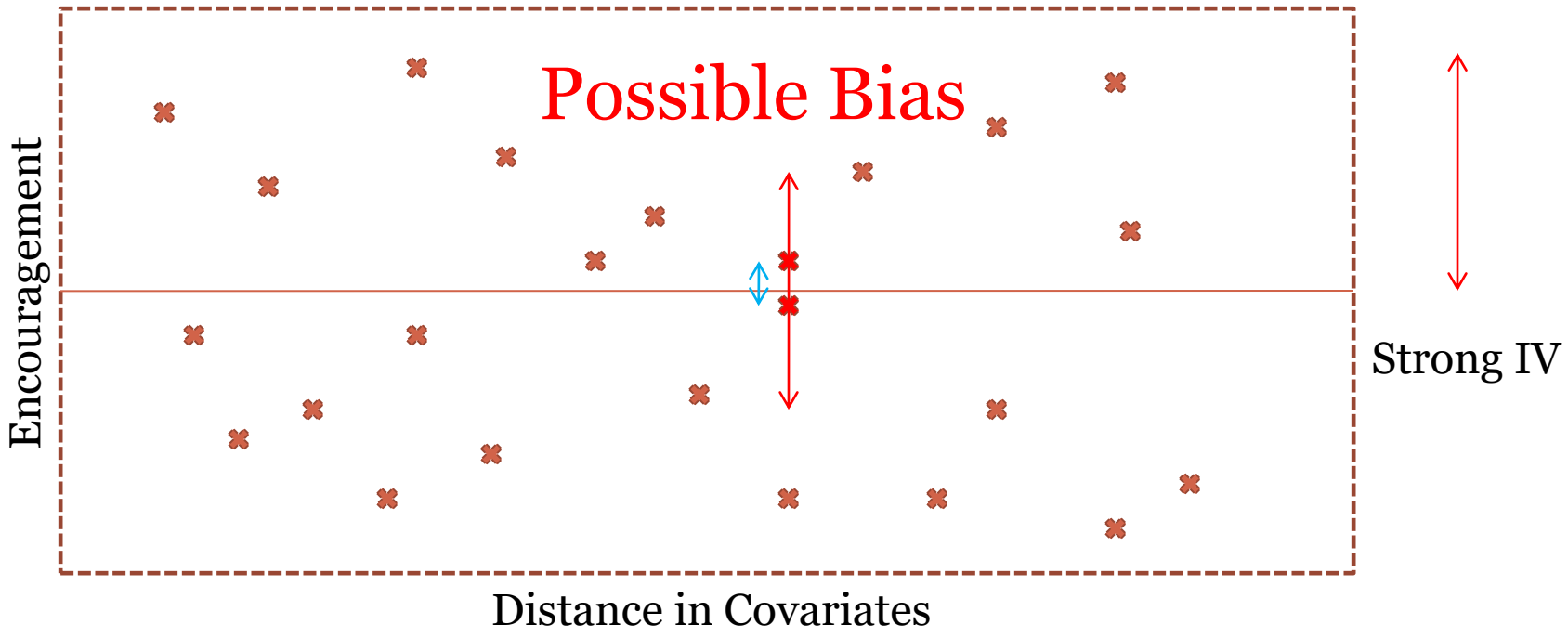
Our method – "near" in instrument



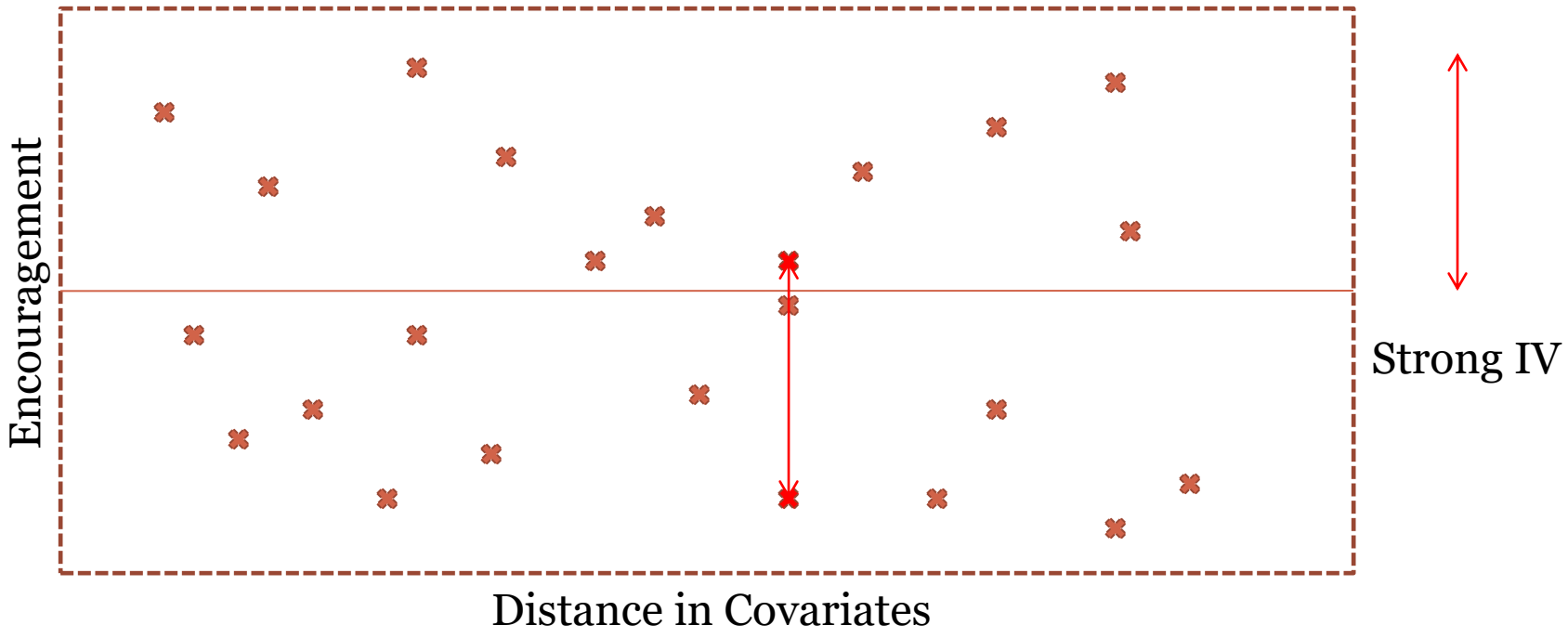
Our method – “near” in instrument



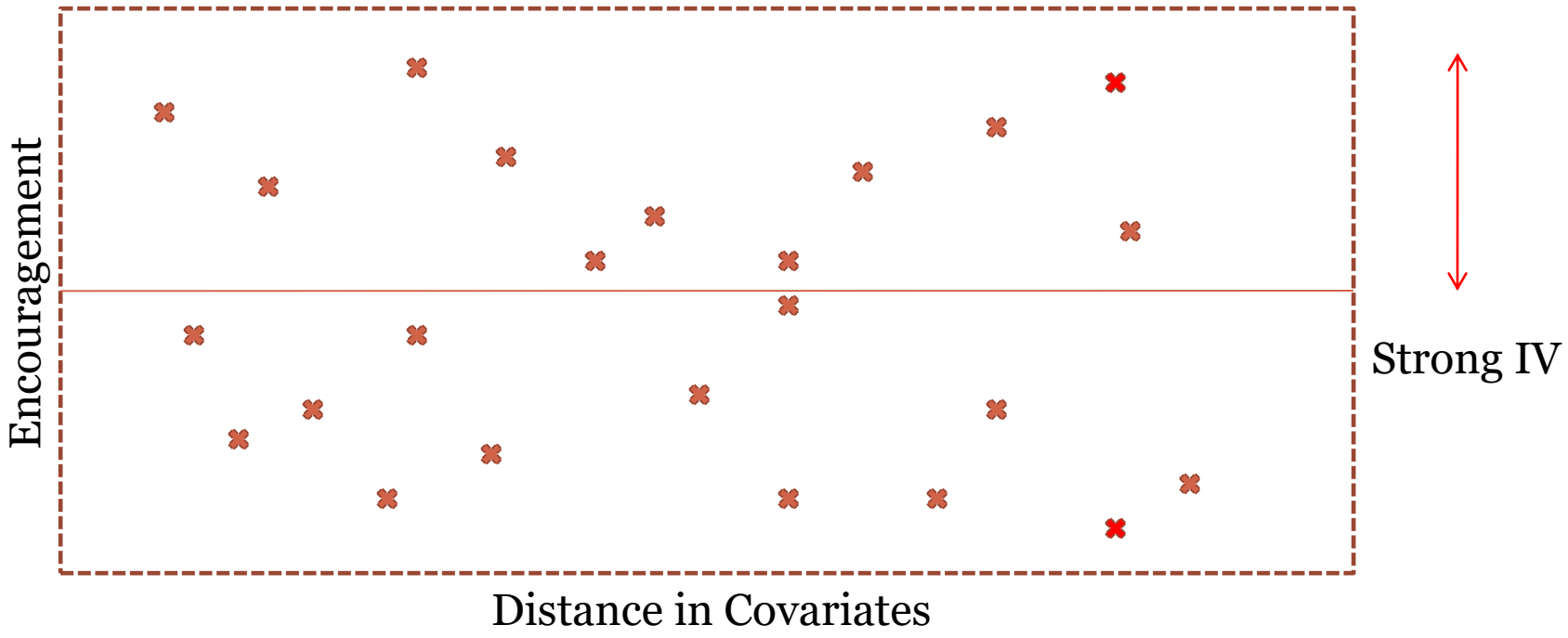
Our method – "near" in instrument



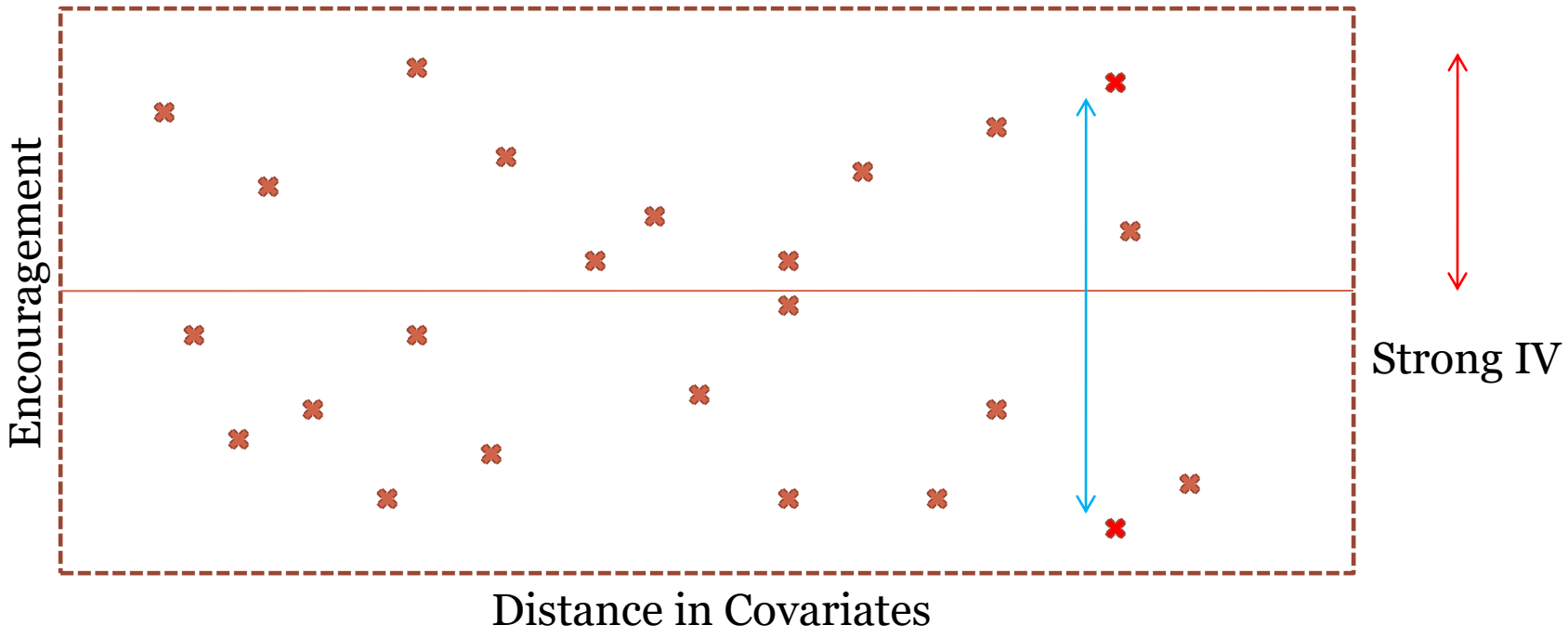
Our method – "near" in instrument



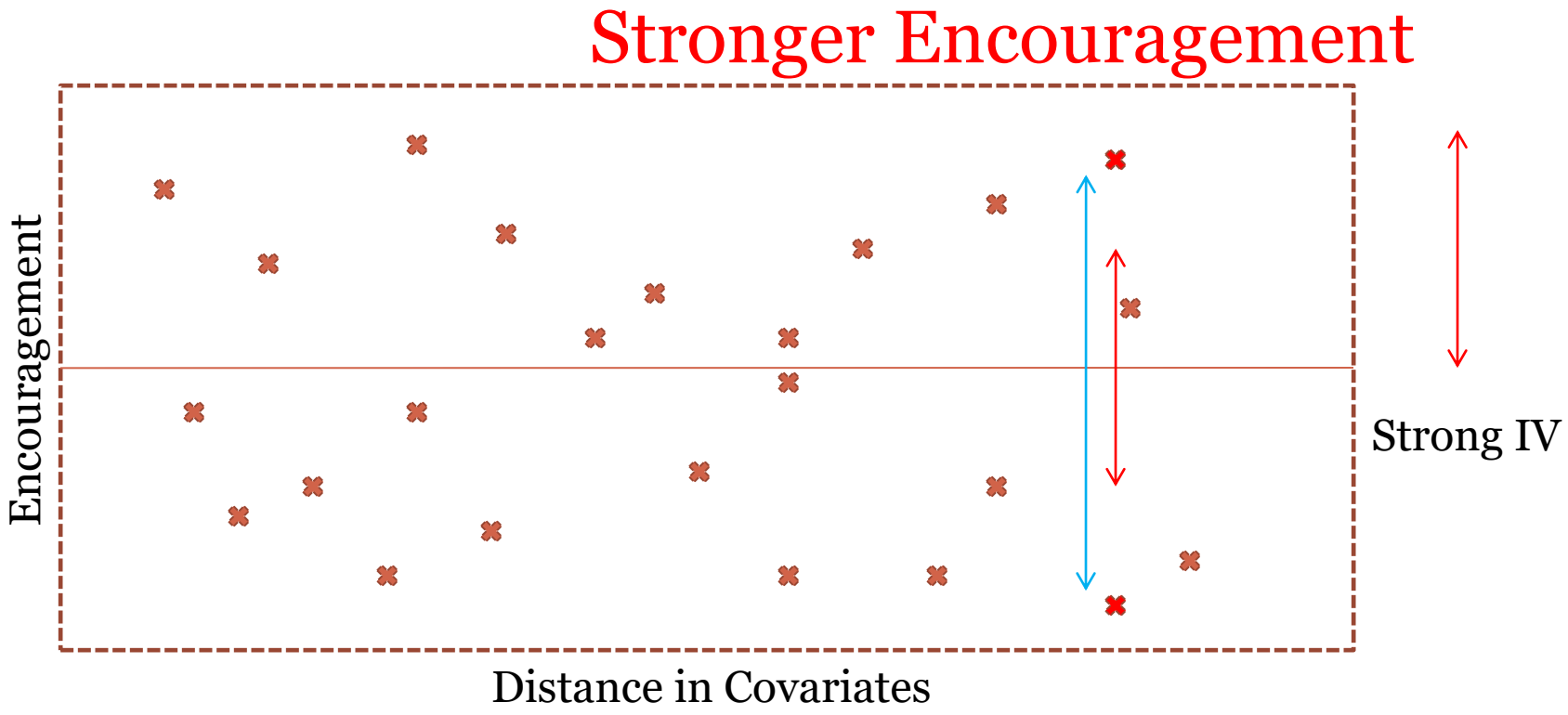
Our method – "far" in instrument



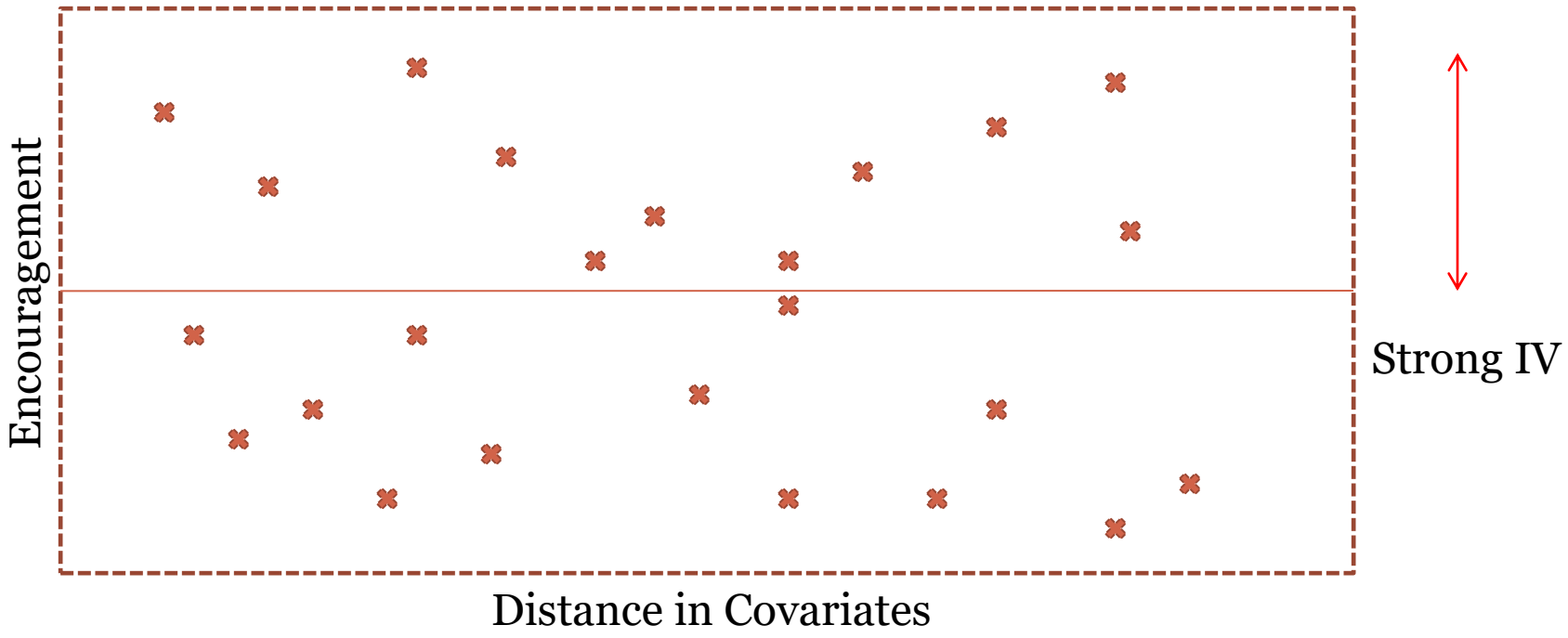
Our method – "far" in instrument



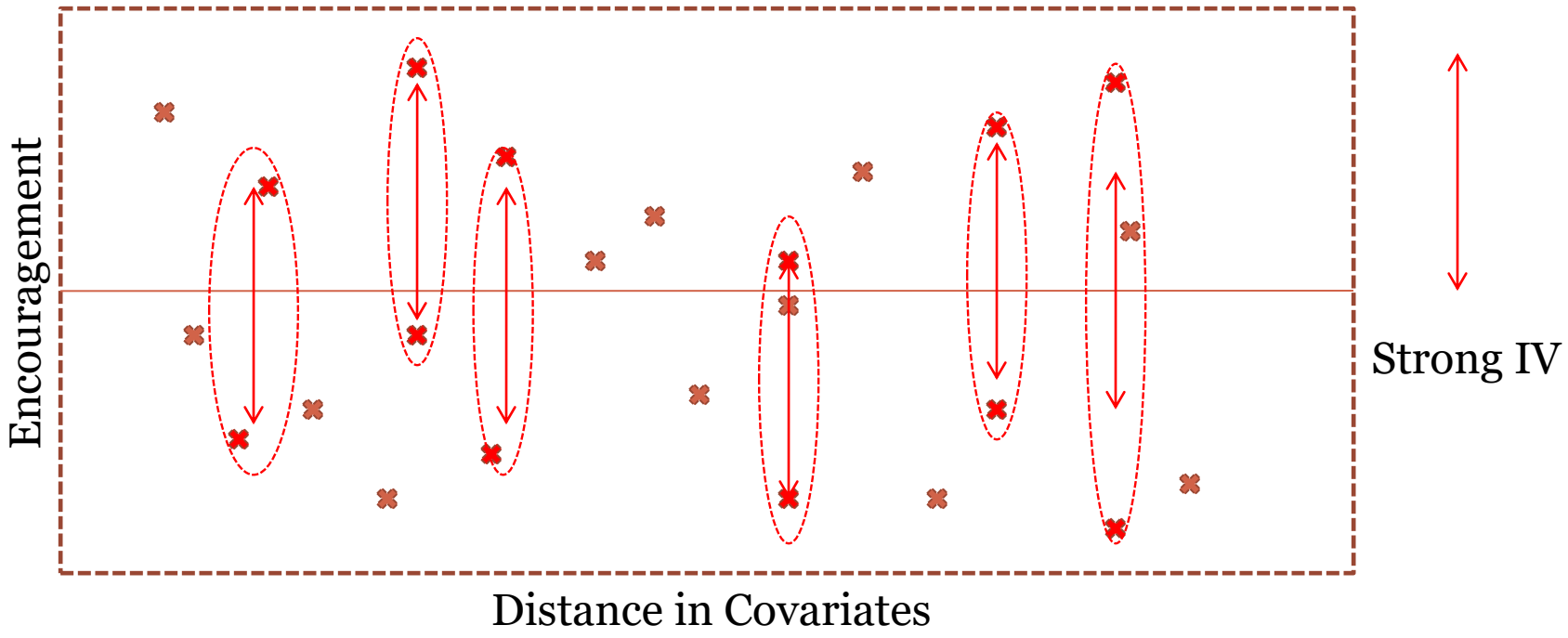
Our method – "far" in instrument



Find the experiment



Find the experiment



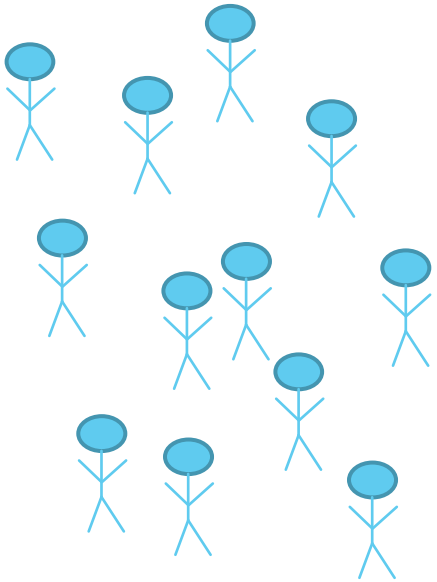
near-far matching

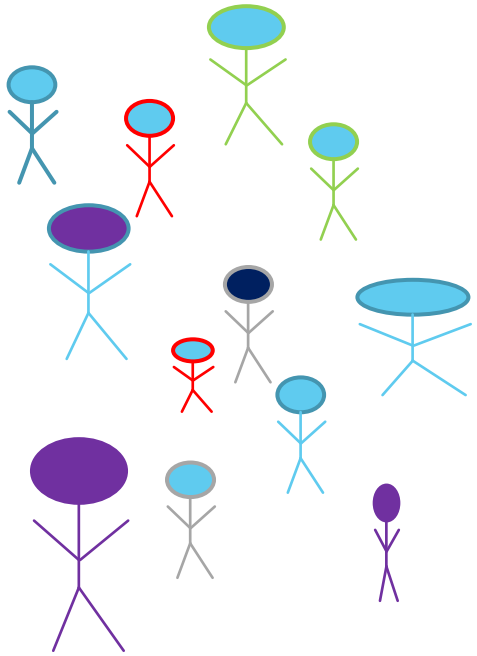
- Tutorial: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6207198/
- CRAN: https://cran.r-project.org/web/packages/nearfar/nearfar.pdf

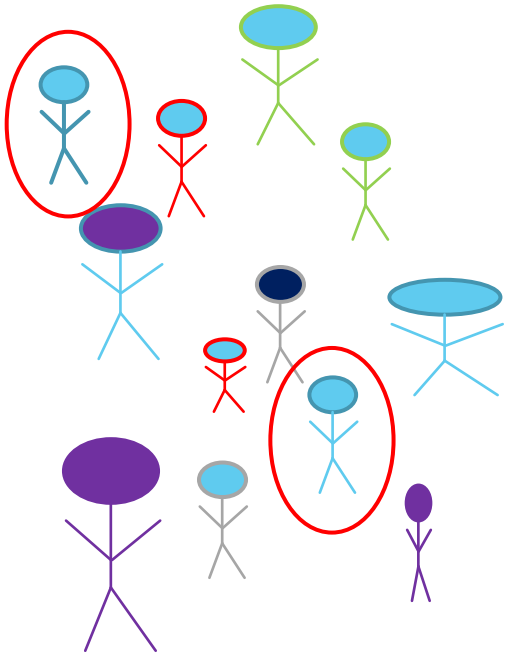
second IV example

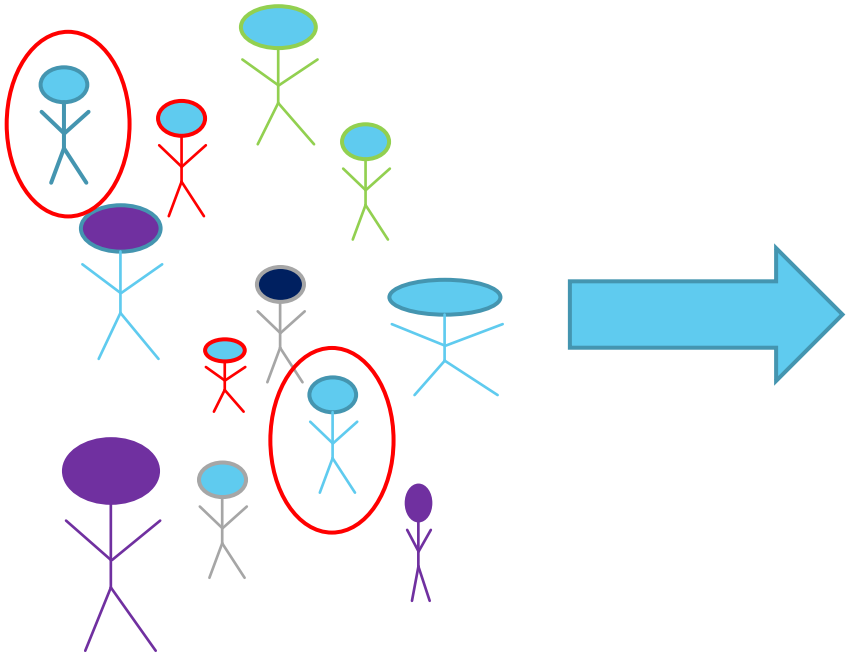
what is the impact of money-bail?

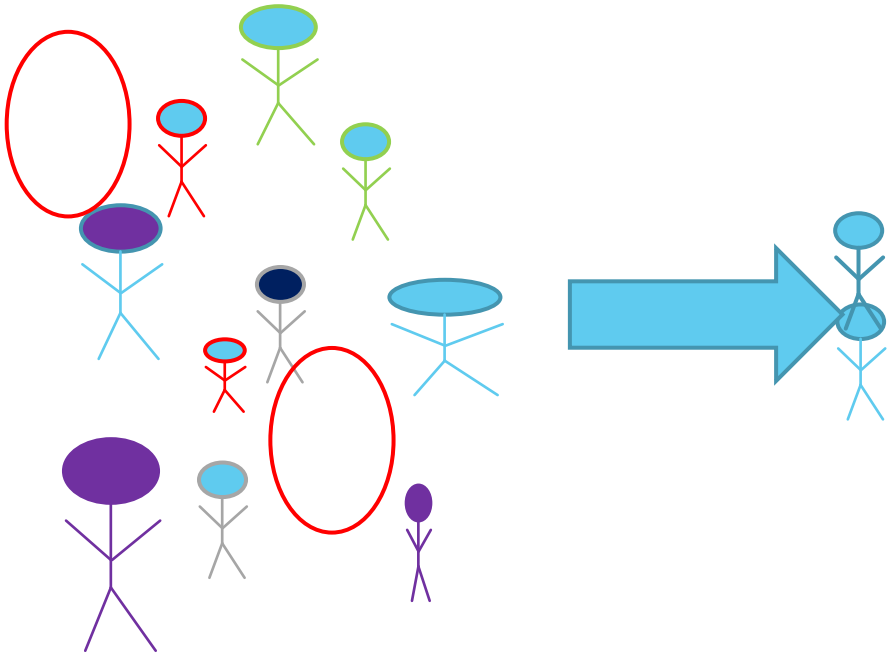
- This is a tough question because pre-trial detention is determined by variables that are also linked to probability of guilt (e.g., “looks guilty”)
- One way to do this is by finding a “natural experiment”
  - Almost all decisions have some sort of haphazardness in them
- Location – just over the border
- Judges – before/after lunch
- We used judges’ disposition:
  - Some judges are “strict” and some are “lenient”
  - Looked at historical records for a given judge, for a given charge, in a given location
- This is known as an “instrumental variable” study design

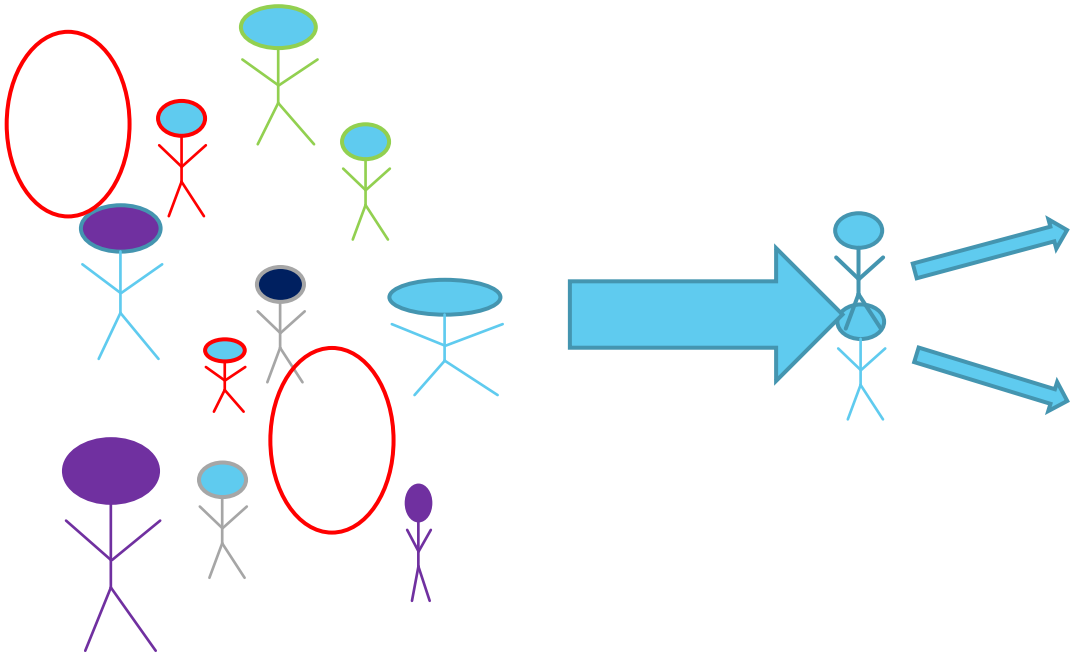


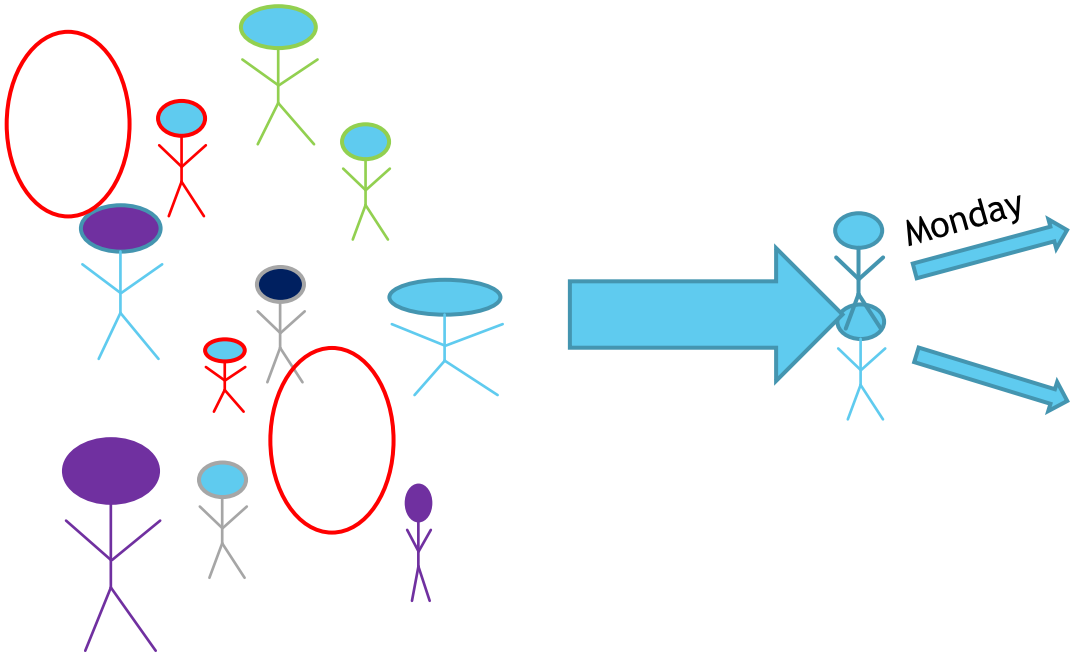


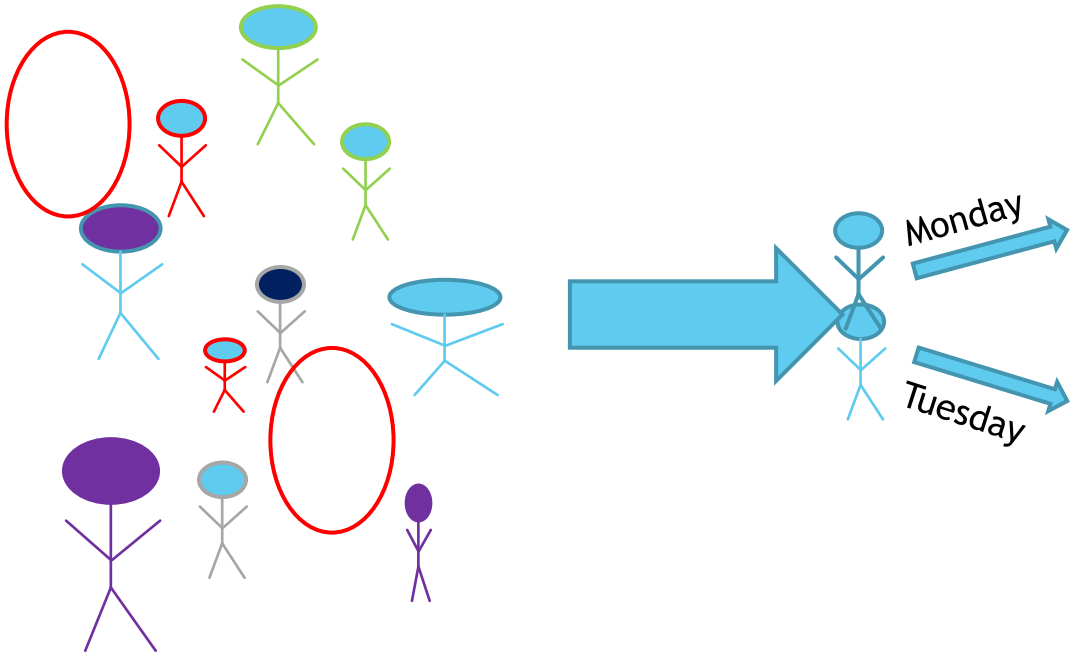


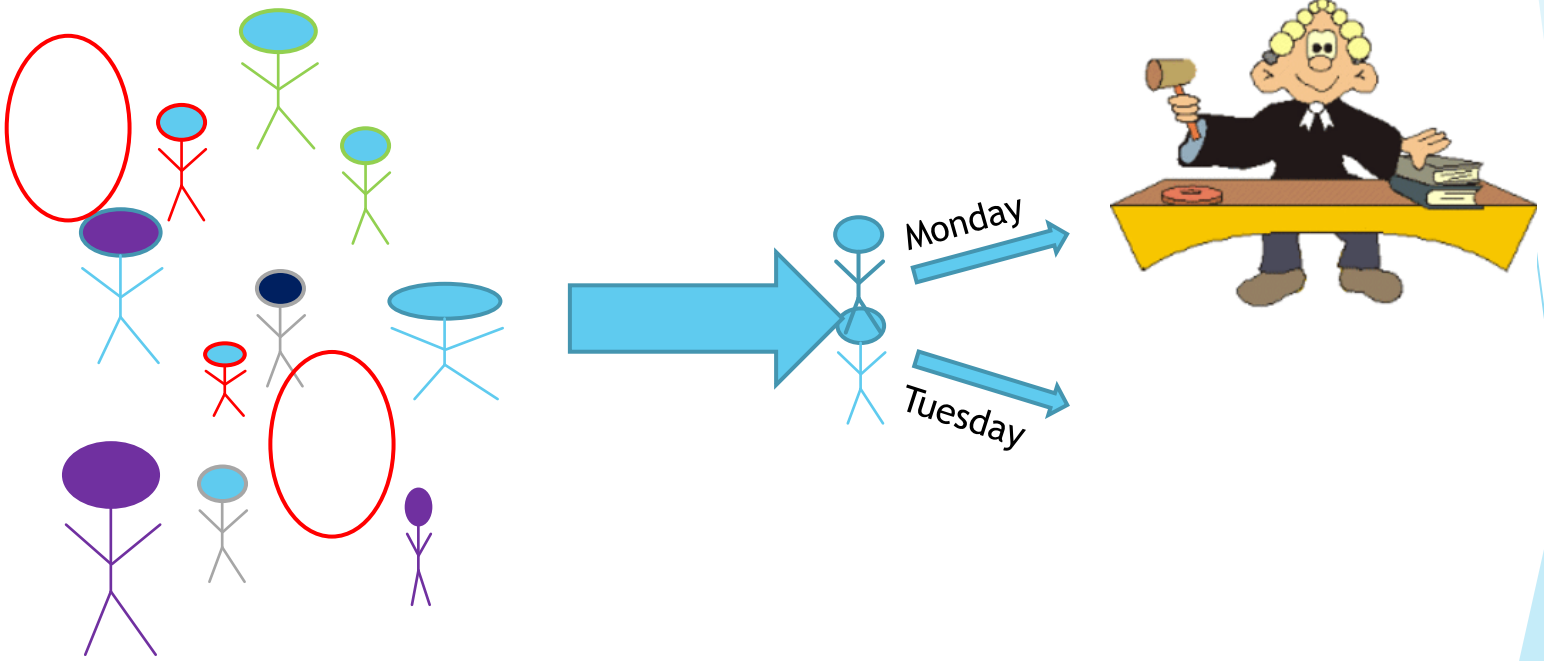


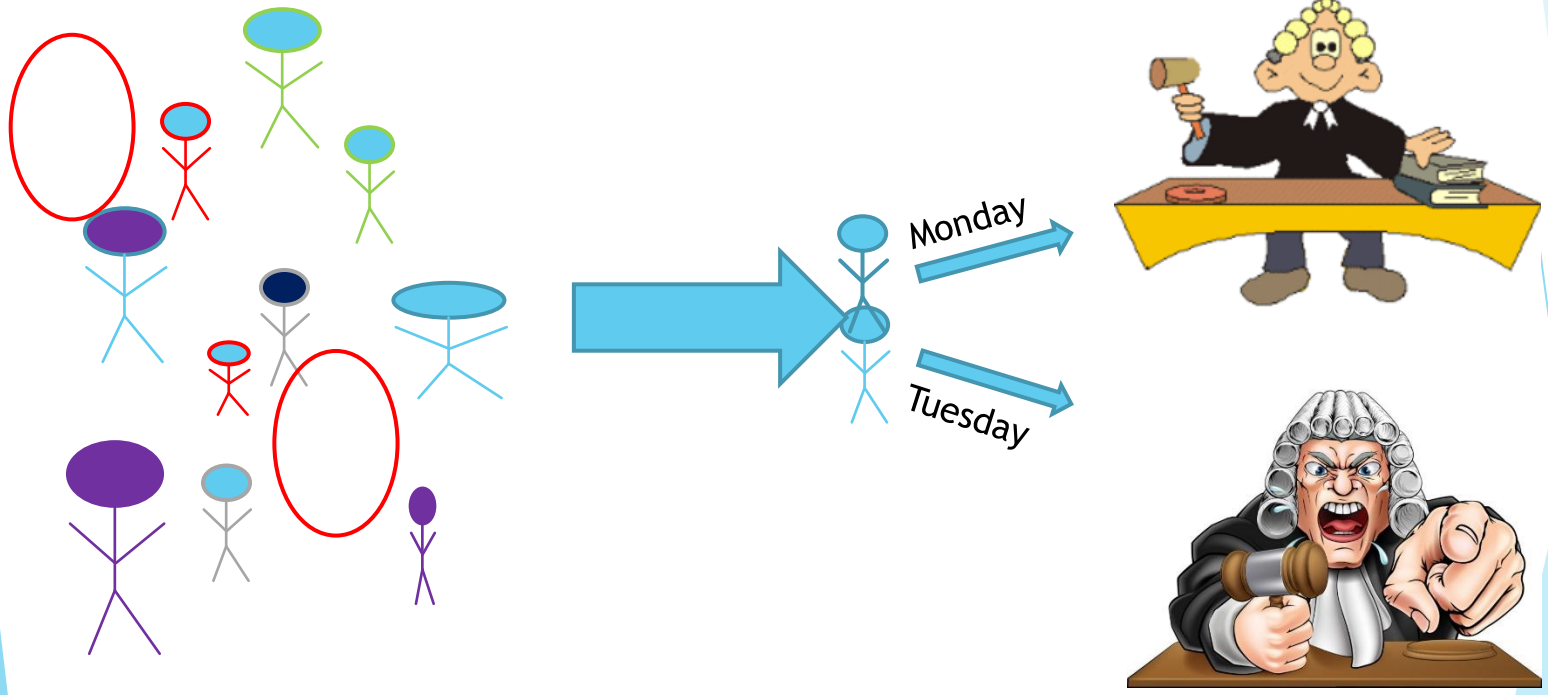


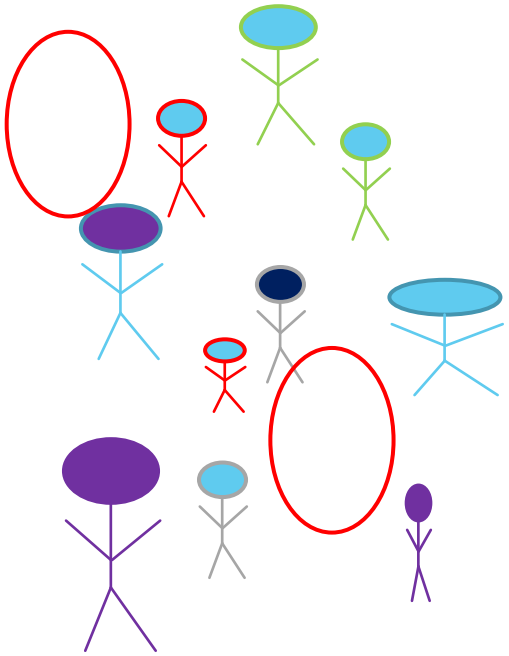


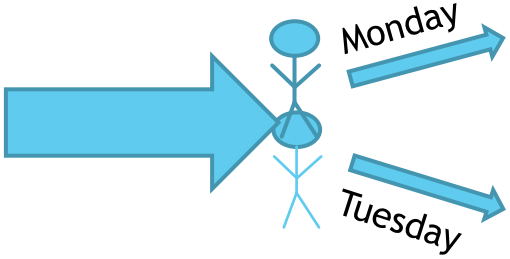

Monday


Monday
Tuesday

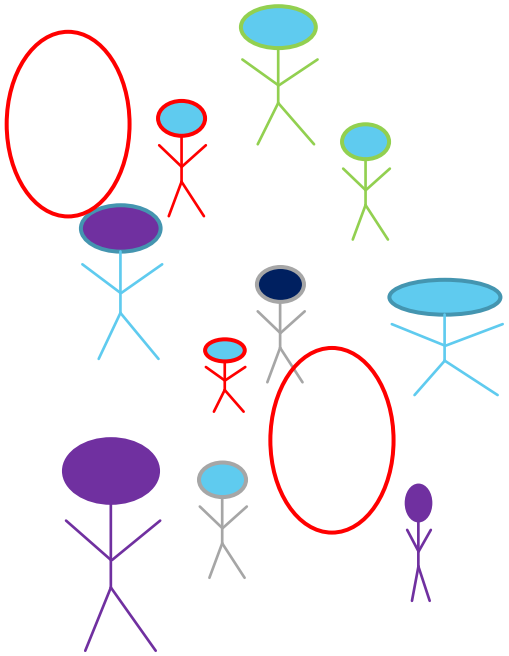

Monday
Tuesday


Monday
Tuesday

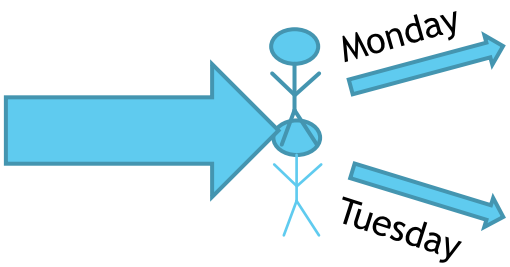




"near" in all the observed covariates.



"near" in all the observed covariates.



"far" in the assignment.

the IV

the IV

- The judge plays an important role in the assignment to bail.

the IV

- The judge plays an important role in the assignment to bail.
- The judge's decision only PARTLY reflects the issues with the accused.

the IV

- The judge plays an important role in the assignment to bail.
- The judge's decision only PARTLY reflects the issues with the accused.
- Constructed the IV as: the judge's record, for the crime-type, at that location, not including the given case.

the IV

- The judge plays an important role in the assignment to bail.
- The judge's decision only PARTLY reflects the issues with the accused.
- Constructed the IV as: the judge's record, for the crime-type, at that location, not including the given case.

- Have to make sure there aren't any other patterns:

the IV

- The judge plays an important role in the assignment to bail.
- The judge's decision only PARTLY reflects the issues with the accused.
- Constructed the IV as: the judge's record, for the crime-type, at that location, not including the given case.

- Have to make sure there aren't any other patterns:
  - Judge A works on Mondays where most weekend-shenanigans.

the IV

- The judge plays an important role in the assignment to bail.
- The judge's decision only PARTLY reflects the issues with the accused.
- Constructed the IV as: the judge's record, for the crime-type, at that location, not including the given case.

- Have to make sure there aren't any other patterns:
  - Judge A works on Mondays where most weekend-shenanigans.
  - Judge B works on "Murder Tuesdays."

the IV

- The judge plays an important role in the assignment to bail.
- The judge's decision only PARTLY reflects the issues with the accused.
- Constructed the IV as: the judge's record, for the crime-type, at that location, not including the given case.

- Have to make sure there aren't any other patterns:
  - Judge A works on Mondays where most weekend-shenanigans.
  - Judge B works on "Murder Tuesdays."
  - Stacks come in in some order?

the IV

- The judge plays an important role in the assignment to bail.
- The judge's decision only PARTLY reflects the issues with the accused.
- Constructed the IV as: the judge's record, for the crime-type, at that location, not including the given case.

- Have to make sure there aren't any other patterns:
  - Judge A works on Mondays where most weekend-shenanigans.
  - Judge B works on "Murder Tuesdays."
  - Stacks come in in some order?

- To be challenges, these patterns need to contain information about the accused that isn't in your data set. (That is, conditionally random on the observed covariates.)

pre-matching differences

	No Bail n=62826	Bail n=14057	Abs St Dif
Guilty	0.33	0.73	1.04
Bail Set	0.00	1.00	2.04
IV	0.01	-0.02	0.22
Age	31.93	35.94	0.32
White	0.29	0.28	0.02
Black	0.48	0.61	0.26
Non-Hispanic	0.63	0.66	0.08
Male	0.79	0.90	0.30
Prior Records 2014	0.38	1.36	0.70
Weekly Income	67.41	63.94	0.02
Any Income	0.15	0.14	0.02
Reported Employer	0.21	0.21	0.00
Reported Phone Number	0.18	0.19	0.04
Reported Address	0.89	0.93	0.12

Table 3: Table of pre-match standardized differences.

pre-matching differences

	No Bail n=62826	Bail n=14057	Abs St Dif
Guilty	0.33	0.73	1.04
Bail Set	0.00	1.00	2.04
IV	0.01	-0.02	0.22
Age	31.93	35.94	0.32
White	0.29	0.28	0.02
Black	0.48	0.61	0.26
Non-Hispanic	0.63	0.66	0.08
Male	0.79	0.90	0.30
Prior Records 2014	0.38	1.36	0.70
Weekly Income	67.41	63.94	0.02
Any Income	0.15	0.14	0.02
Reported Employer	0.21	0.21	0.00
Reported Phone Number	0.18	0.19	0.04
Reported Address	0.89	0.93	0.12

Table 3: Table of pre-match standardized differences.

pre-matching differences

	No Bail n=62826	Bail n=14057	Abs St Dif
Guilty	0.33	0.73	1.04
Bail Set	0.00	1.00	2.04
IV	0.01	-0.02	0.22
Age	31.93	35.94	0.32
White	0.29	0.28	0.02
Black	0.48	0.61	0.26
Non-Hispanic	0.63	0.66	0.08
Male	0.79	0.90	0.30
Prior Records 2014	0.38	1.36	0.70
Weekly Income	67.41	63.94	0.02
Any Income	0.15	0.14	0.02
Reported Employer	0.21	0.21	0.00
Reported Phone Number	0.18	0.19	0.04
Reported Address	0.89	0.93	0.12

Table 3: Table of pre-match standardized differences.

pre-matching differences

	No Bail n=62826	Bail n=14057	Abs St Dif
Guilty	0.33	0.73	1.04
Bail Set	0.00	1.00	2.04
IV	0.01	-0.02	0.22
Age	31.93	35.94	0.32
White	0.29	0.28	0.02
Black	0.48	0.61	0.26
Non-Hispanic	0.63	0.66	0.08
Male	0.79	0.90	0.30
Prior Records 2014	0.38	1.36	0.70
Weekly Income	67.41	63.94	0.02
Any Income	0.15	0.14	0.02
Reported Employer	0.21	0.21	0.00
Reported Phone Number	0.18	0.19	0.04
Reported Address	0.89	0.93	0.12

Table 3: Table of pre-match standardized differences.

post-matching

post-matching

	Strict n=28367	Lenient n=28367	Abs St Dif
Guilty	0.41	0.40	0.03
Bail Set	0.21	0.16	0.12
IV	-0.07	0.07	1.18
Age	32.69	32.71	0.00
White	0.28	0.28	0.00
Black	0.52	0.52	0.00
Non-Hispanic	0.65	0.65	0.00
Male	0.81	0.81	0.00
Prior Records 2014	0.54	0.53	0.00
Weekly Income	53.00	52.75	0.00
Any Income	0.12	0.12	0.00
Reported Employer	0.17	0.17	0.00
Reported Phone Number	0.15	0.15	0.00
Reported Address	0.91	0.91	0.00

Table 5: Table of post-match standardized differences. Summary of data analyzed.

assessing the IV

	mean (sd)	Q.1	Q.2	Q.3	Q.4
Age	32.61 (12.53)	33.74	31.32	31.75	33.59
Black	0.5	0.53	0.51	0.49	0.49
White	0.29	0.29	0.27	0.28	0.3
Non-Hispanic	0.63	0.65	0.63	0.62	0.63
Male	0.81	0.81	0.83	0.8	0.78
Reported Employer	0.21	0.24	0.22	0.2	0.2
Reported Phone Number	0.18	0.2	0.17	0.17	0.19
Reported Address	0.9	0.9	0.9	0.89	0.89
Weekly Income	66.32 (222.63)	78.27	64.04	61.27	61.55
Any Income	0.15	0.16	0.15	0.14	0.14
Prior Records 2014	0.56 (1.39)	0.68	0.48	0.47	0.59

Table 4: Summary of Covariates by IV Quartile

pre-matching differences

	No Bail n=62826	Bail n=14057	Abs St Dif
Guilty	0.33	0.73	1.04
Bail Set	0.00	1.00	2.04
IV	0.01	-0.02	0.22
Age	31.93	35.94	0.32
White	0.29	0.28	0.02
Black	0.48	0.61	0.26
Non-Hispanic	0.63	0.66	0.08
Male	0.79	0.90	0.30
Prior Records 2014	0.38	1.36	0.70
Weekly Income	67.41	63.94	0.02
Any Income	0.15	0.14	0.02
Reported Employer	0.21	0.21	0.00
Reported Phone Number	0.18	0.19	0.04
Reported Address	0.89	0.93	0.12

Table 3: Table of pre-match standardized differences.

third IV example

acute aortic dissection

acute aortic dissection

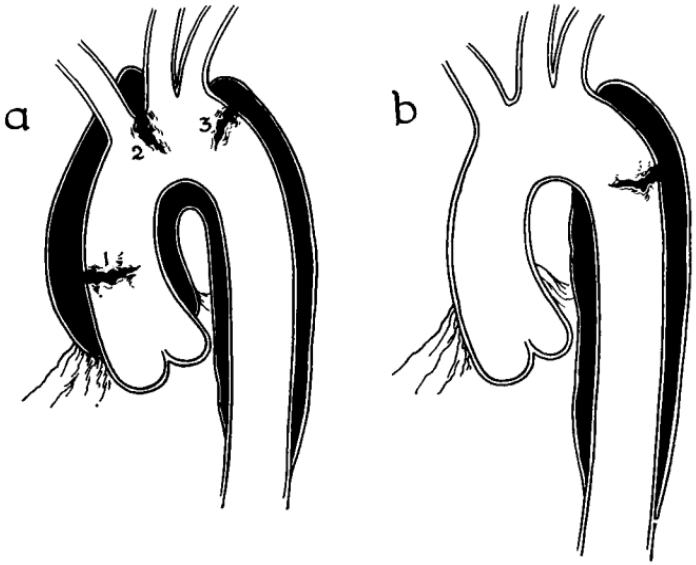


FIG. 3. Classification of aortic dissections. In type A the ascending aorta is dissected (a). *The intimal tear has always been at position* 1, *but it can occur at positions* 2 *or* 3 *(see text). In type B dissection the dissection is limited to the descending aorta* (b), *and the intimal tear is usually within 2 to 5 cm. of the left subclavian artery.*

Daily et al., *Ann Thorac Surg,* 1970

aortic dissection

It's a particularly scary situation:

- Incidence is 4-7 per 100,000
- Mortality for untreated acute type A
  - First 24hrs = 25%
  - First 48hrs = 40%
- Upon diagnosis patients are rushed to operating room.
- Operative mortality in the range of 19-28%

what are we really trying to do here?

what are we really trying to do here?

what are we really trying to do here?

what are we really trying to do here?

what are we really trying to do here?

what are we really trying to do here?

what are we really trying to do here?

35%

what are we really trying to do here?

35%

10%

what are we really trying to do here?

35%

40%

what are we really trying to do here?

35%

40%

high-quality causal inference

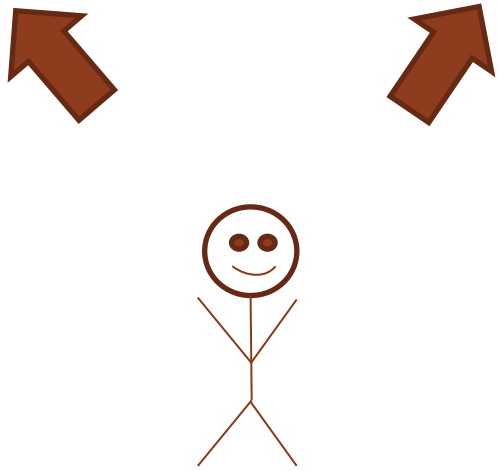
high-quality causal inference

Randomized controlled trials are (currently) the best way to generate data for causal inference.

high-quality causal inference

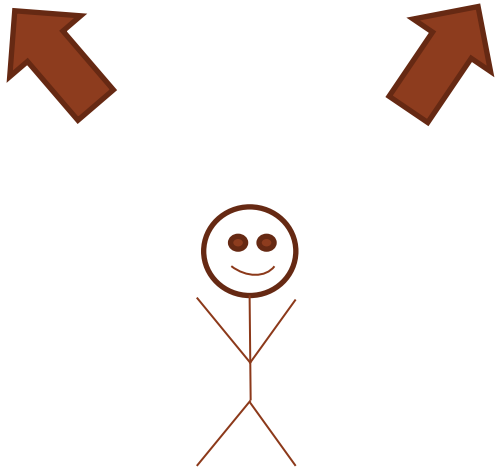
Randomized controlled trials are (currently) the best way to generate data for causal inference.

What's special about RCTs?



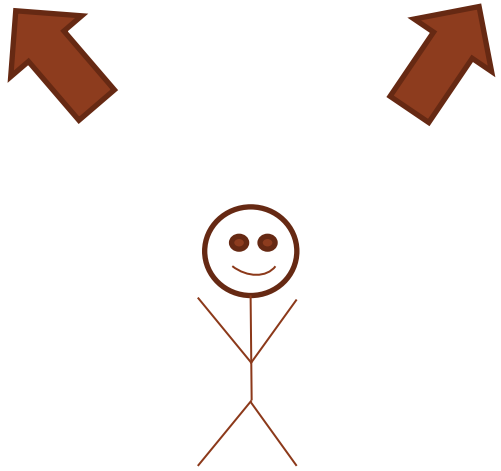
Coin flip?

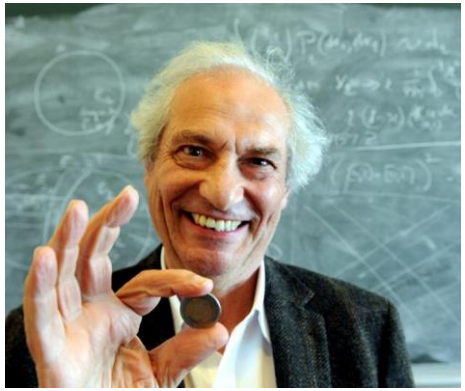
Coin flip?



Coin flips are a completely deterministic process.

Coin flip?





Persi Diaconis

Coin flips are a completely deterministic process.

high-quality causal inference

Randomized controlled trials are (currently) the best way to generate data for causal inference.

high-quality causal inference

Randomized controlled trials are (currently) the best way to generate data for causal inference.

What's special about RCTs?

high-quality causal inference

Randomized controlled trials are (currently) the best way to generate data for causal inference.

What's special about RCTs?

1.

2.

high-quality causal inference

Randomized controlled trials are (currently) the best way to generate data for causal inference.

What's special about RCTs?

1. RCTs make use of assignment mechanisms which are determined by a noninformative process
2.

high-quality causal inference

Randomized controlled trials are (currently) the best way to generate data for causal inference.

What's special about RCTs?

1. RCTs make use of assignment mechanisms which are determined by a noninformative process (technically: conditionally orthogonal).
2.

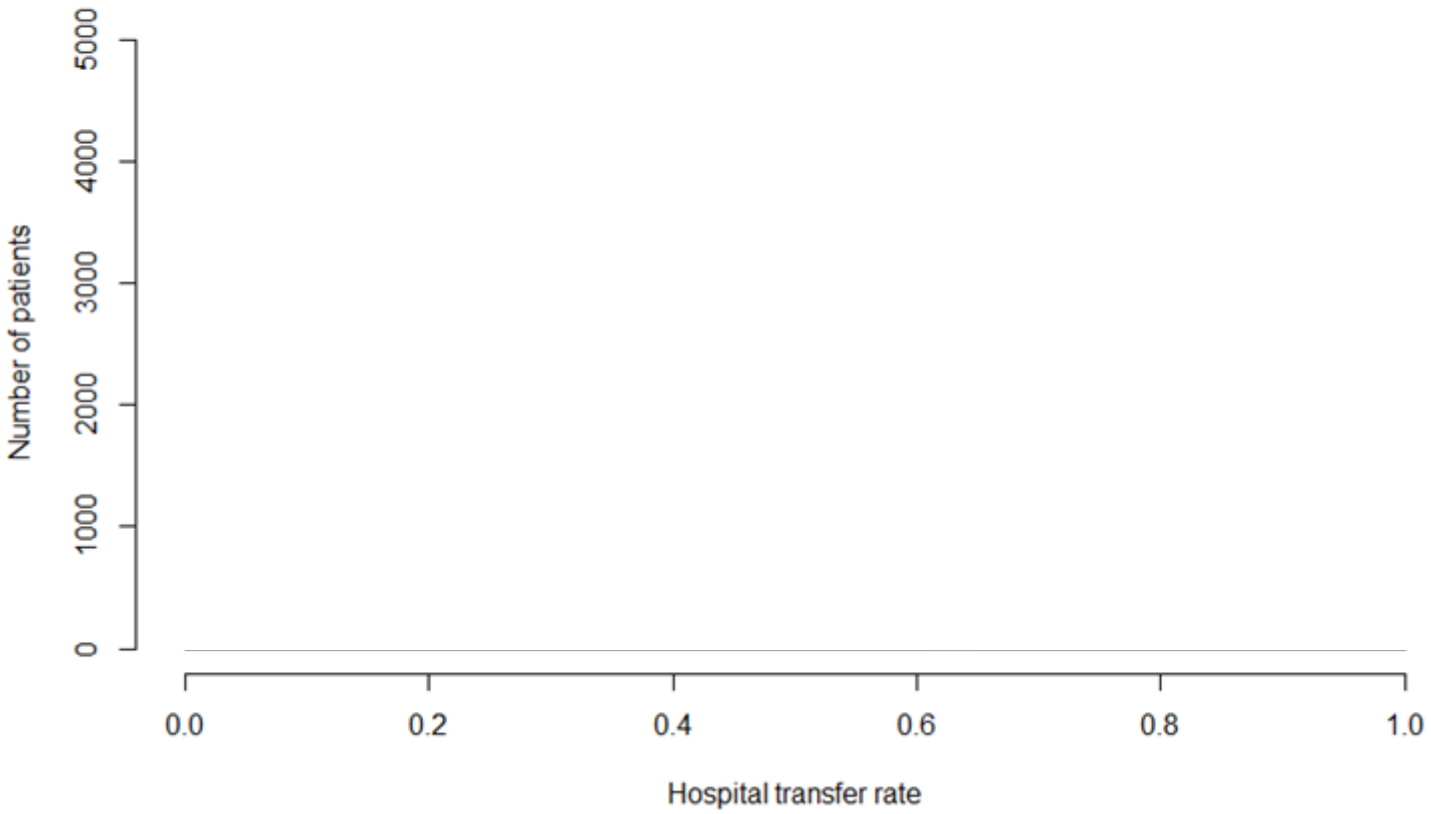
high-quality causal inference

Randomized controlled trials are (currently) the best way to generate data for causal inference.

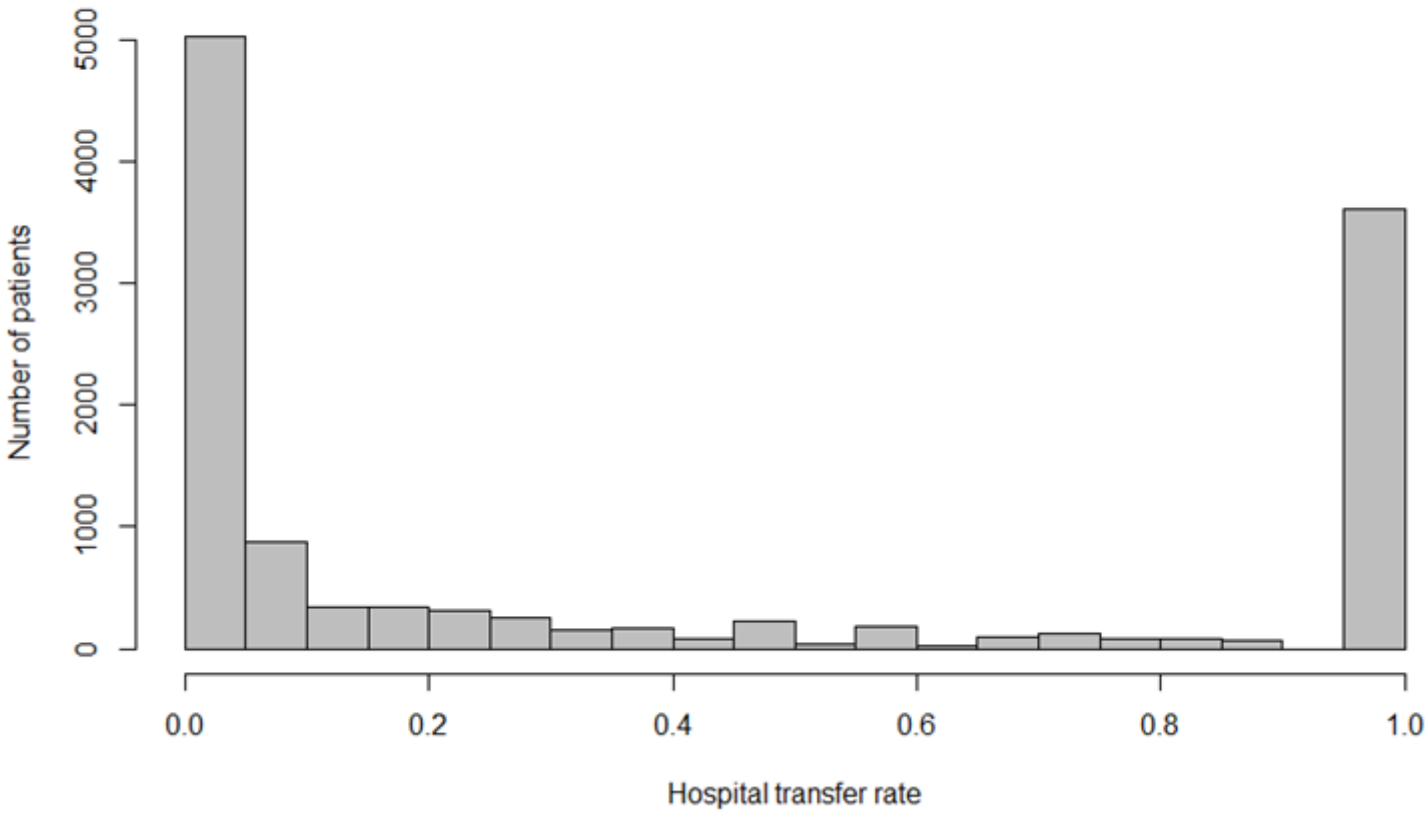
What's special about RCTs?

1. RCTs make use of assignment mechanisms which are determined by a noninformative process (technically: conditionally orthogonal).
2. Imposing control over "nuisance" variation.

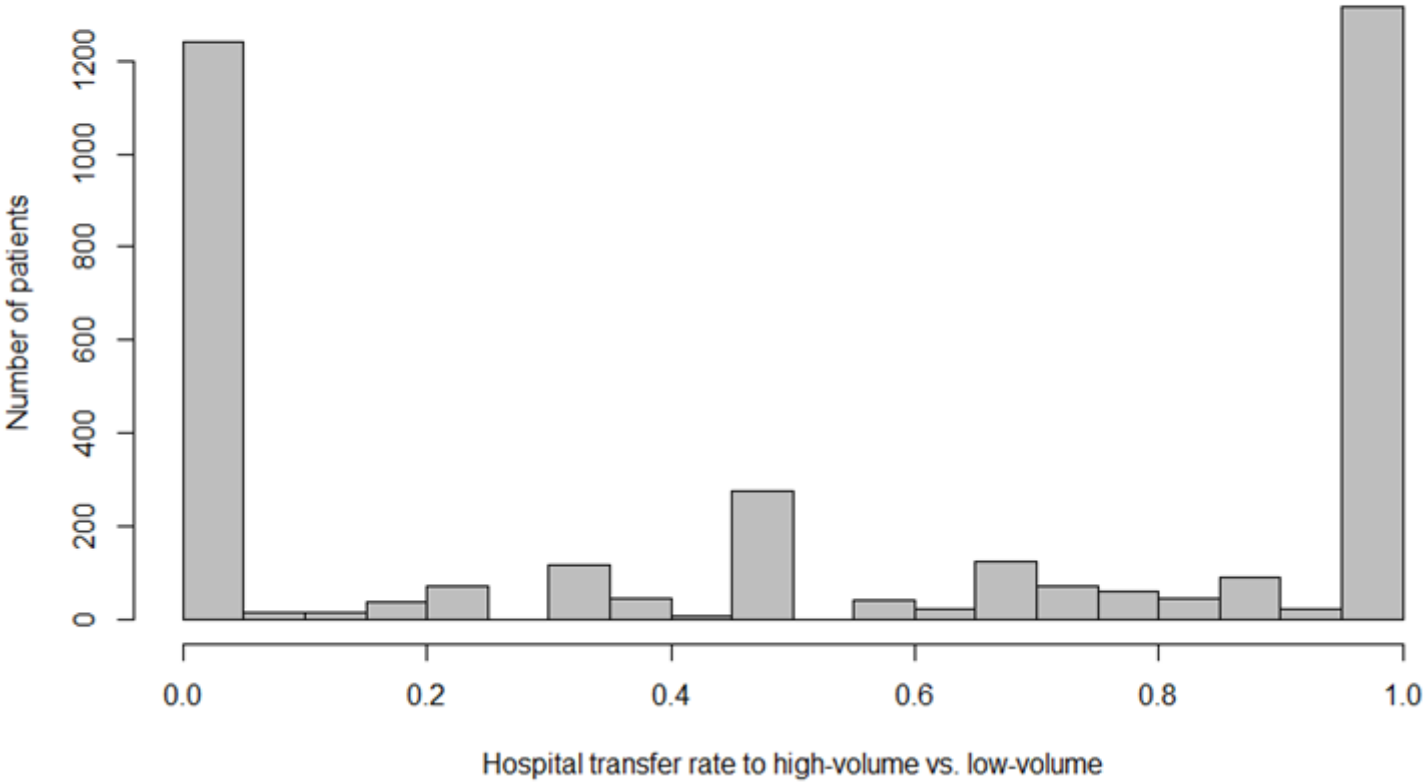
B Distribution of patients presenting to hospitals with varying transfer rates for acute type A aortic dissection



B Distribution of patients presenting to hospitals with varying transfer rates for acute type A aortic dissection

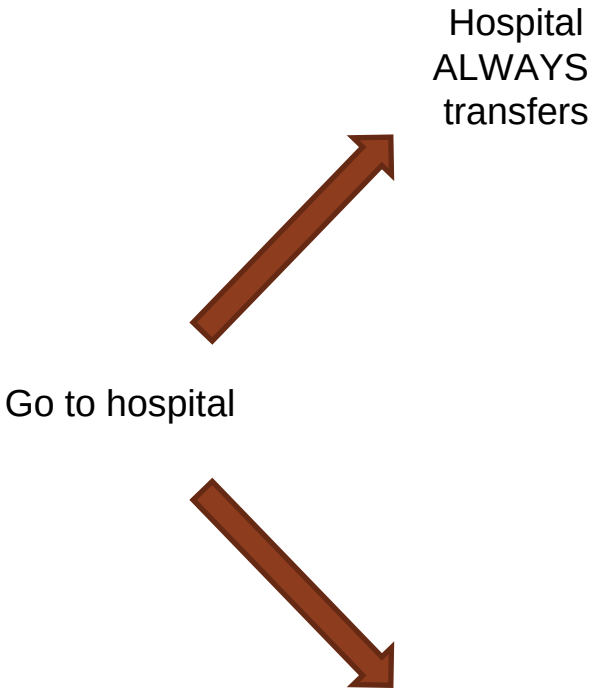


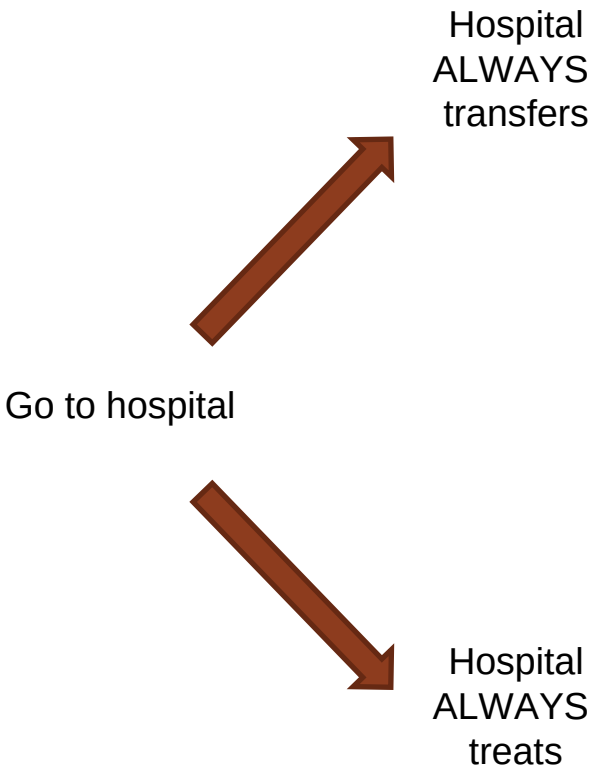
D Distribution of patients presenting to hospitals with varying transfer rates to high-volume centers among hospitals that always transferred patients with acute type A aortic dissection



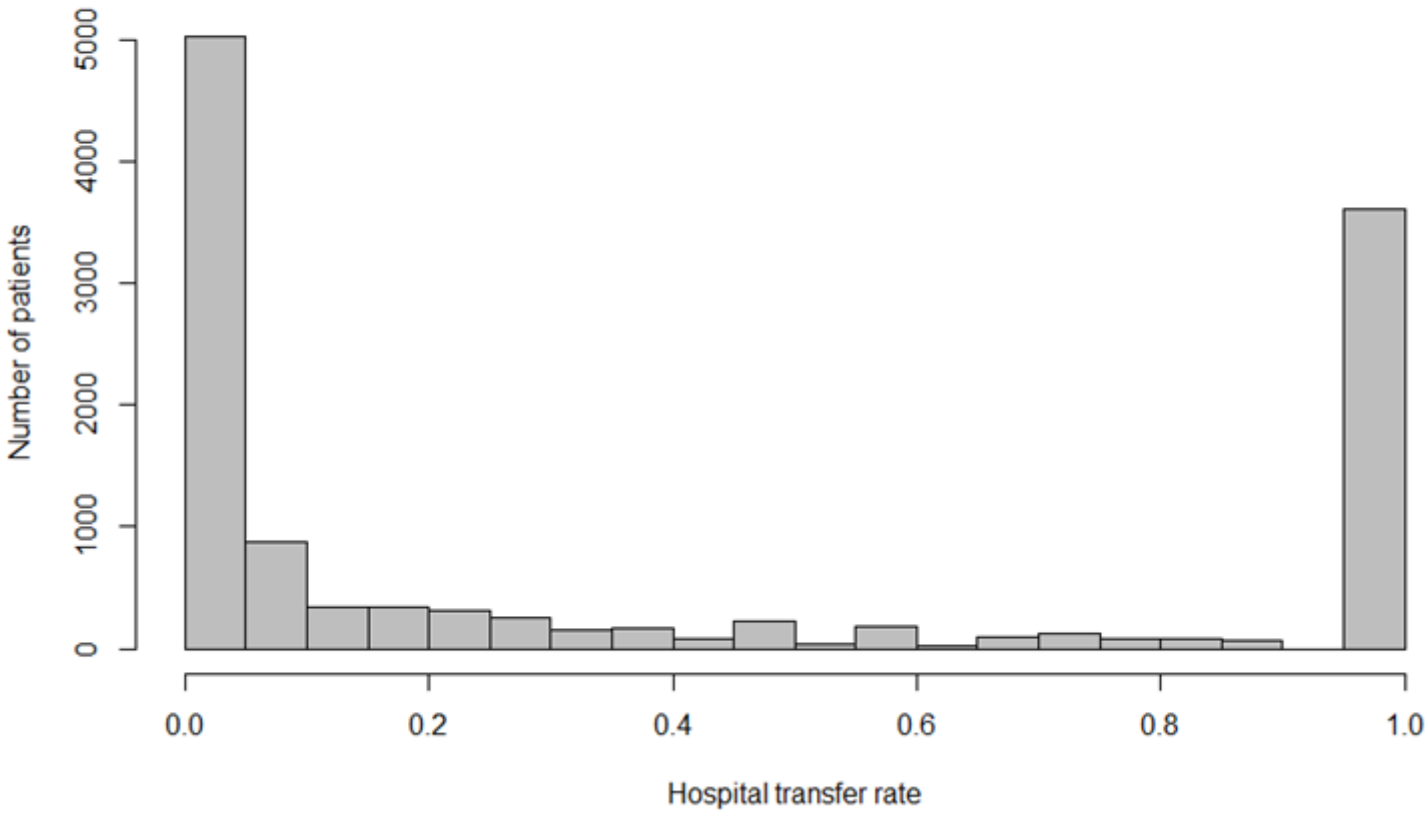
Go to hospital

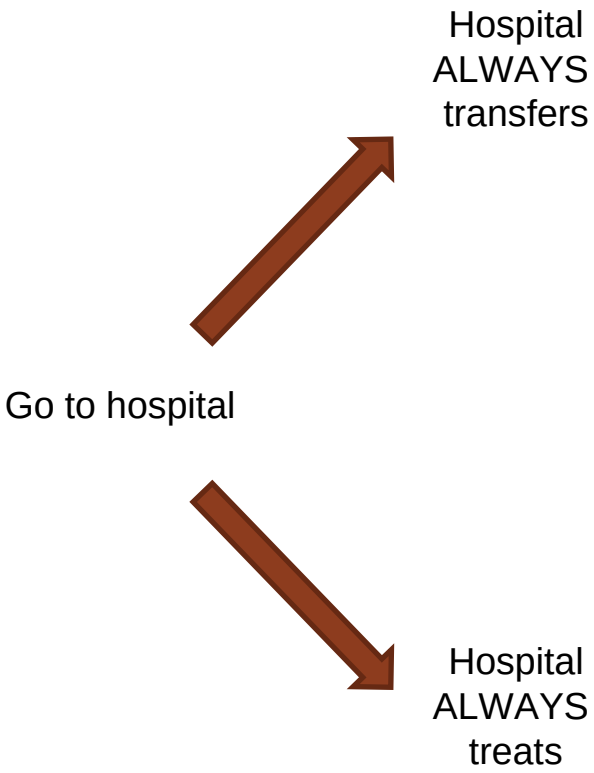
Go to hospital

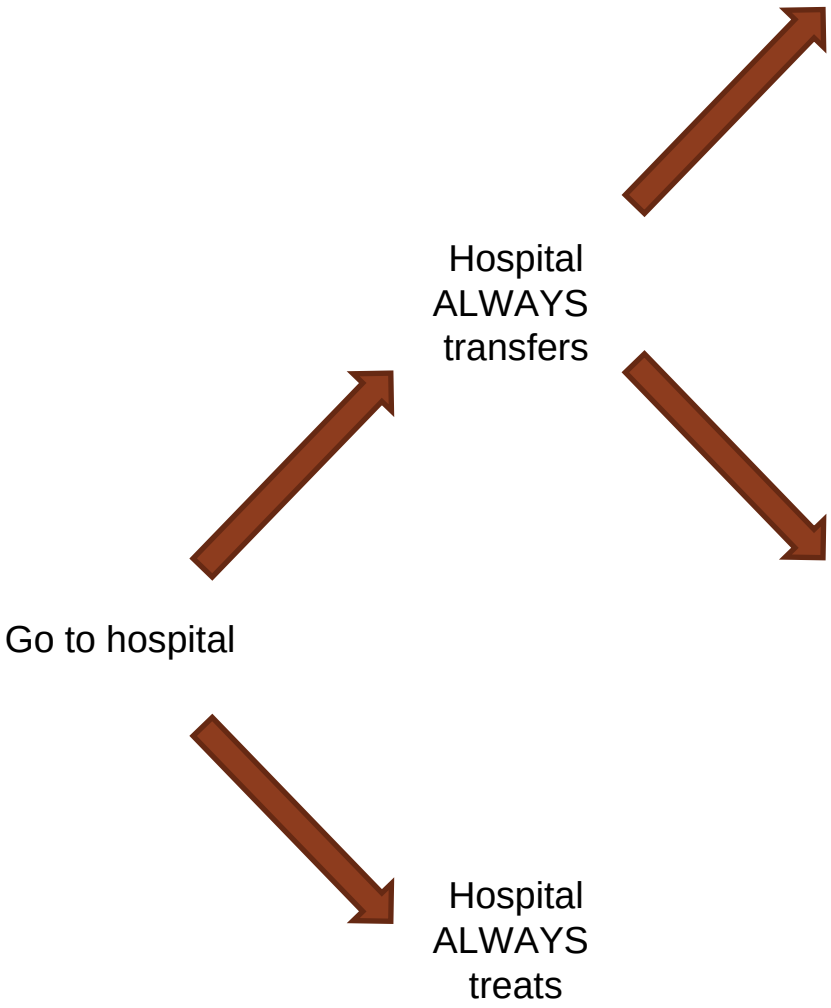

Hospital
ALWAYS
transfers
Go to hospital

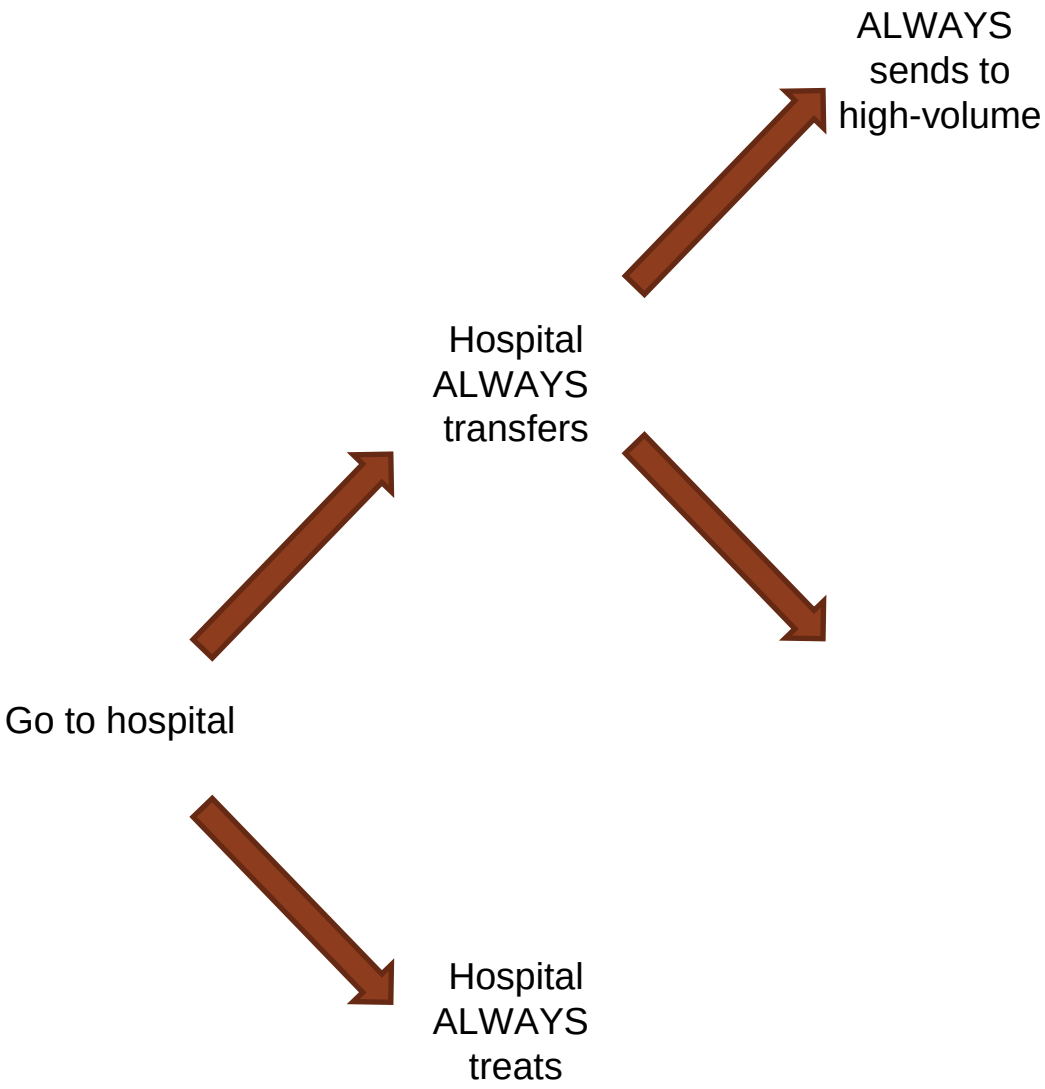

Hospital
ALWAYS
transfers
Go to hospital
Hospital
ALWAYS
treats

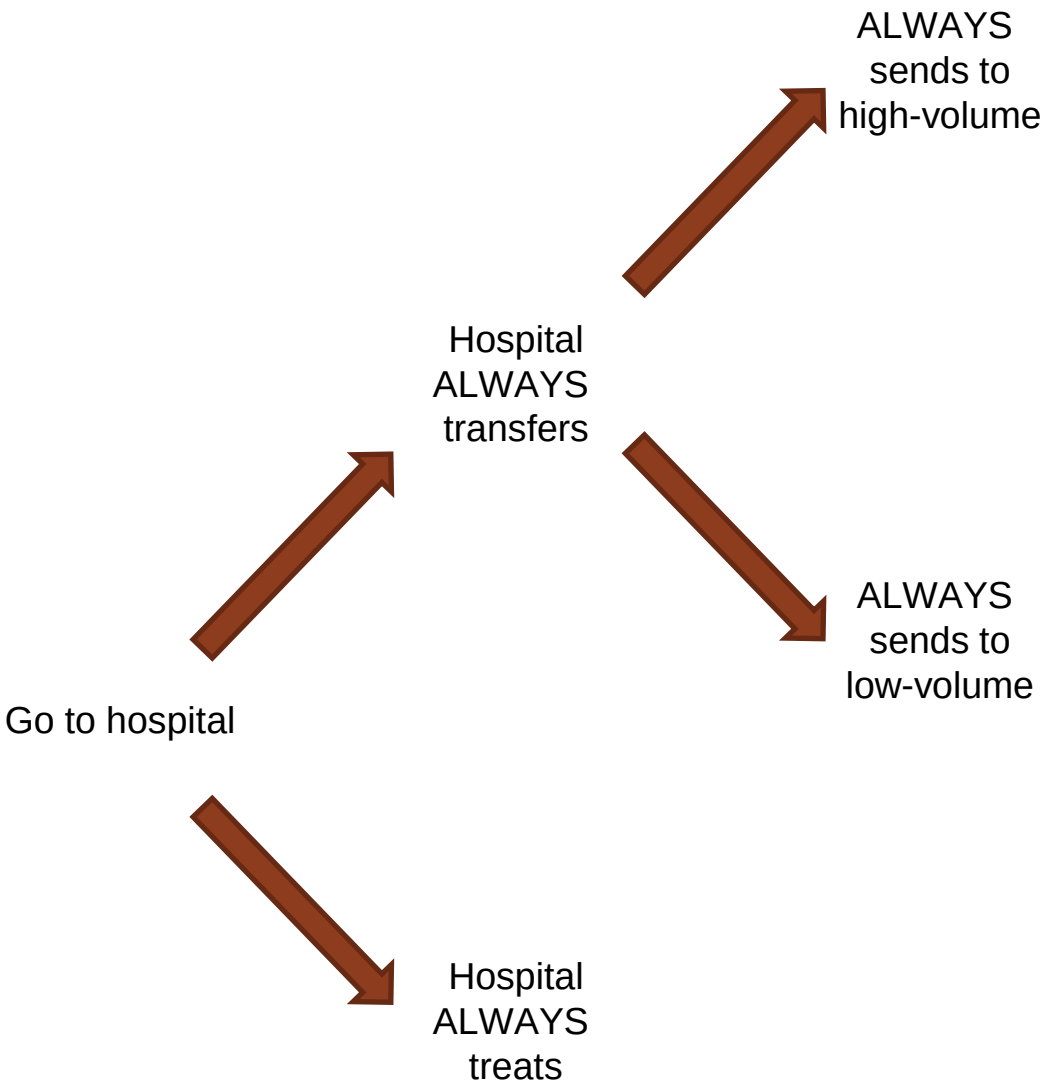
B Distribution of patients presenting to hospitals with varying transfer rates for acute type A aortic dissection

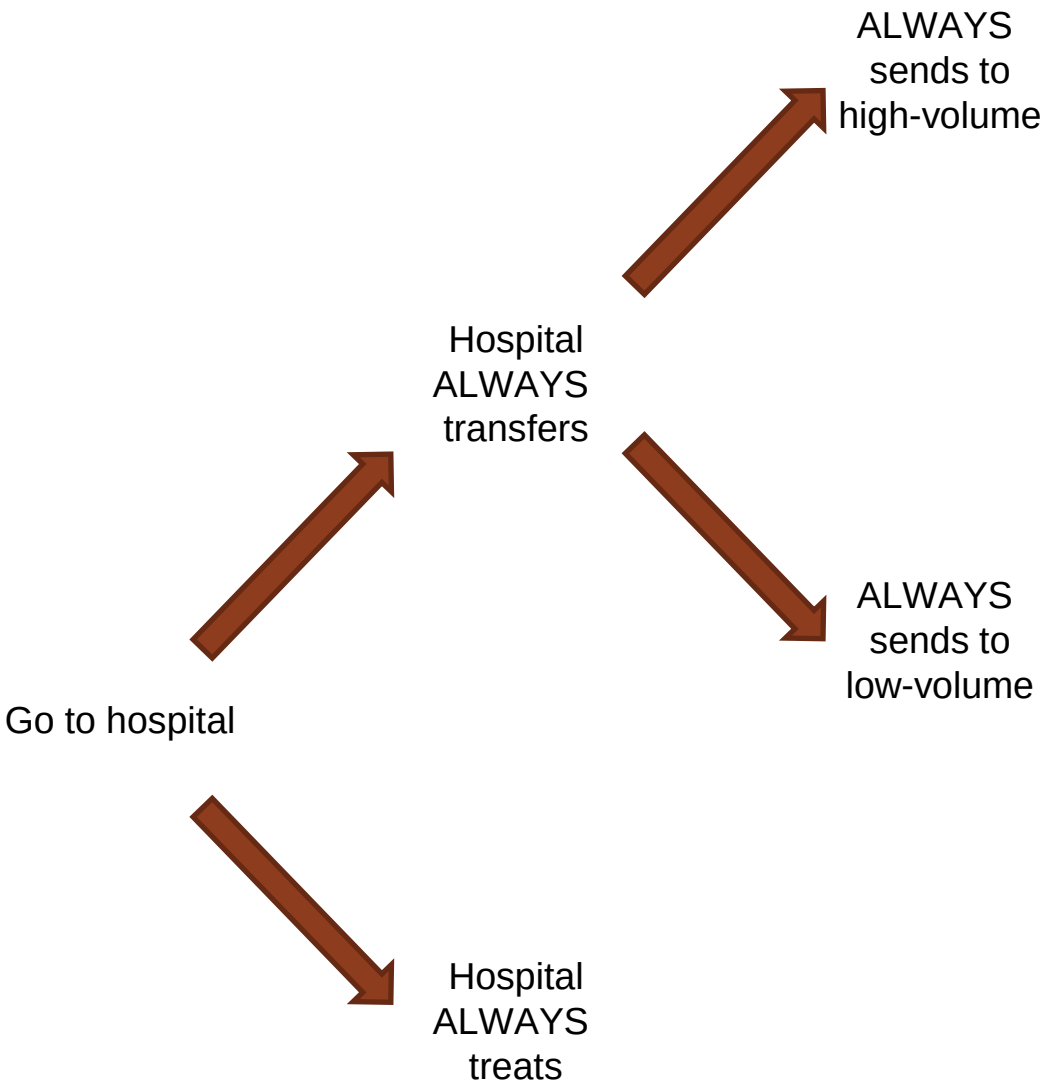



Hospital
ALWAYS
transfers
Go to hospital
Hospital
ALWAYS
treats


Hospital
ALWAYS
transfers
Go to hospital
Hospital
ALWAYS
treats

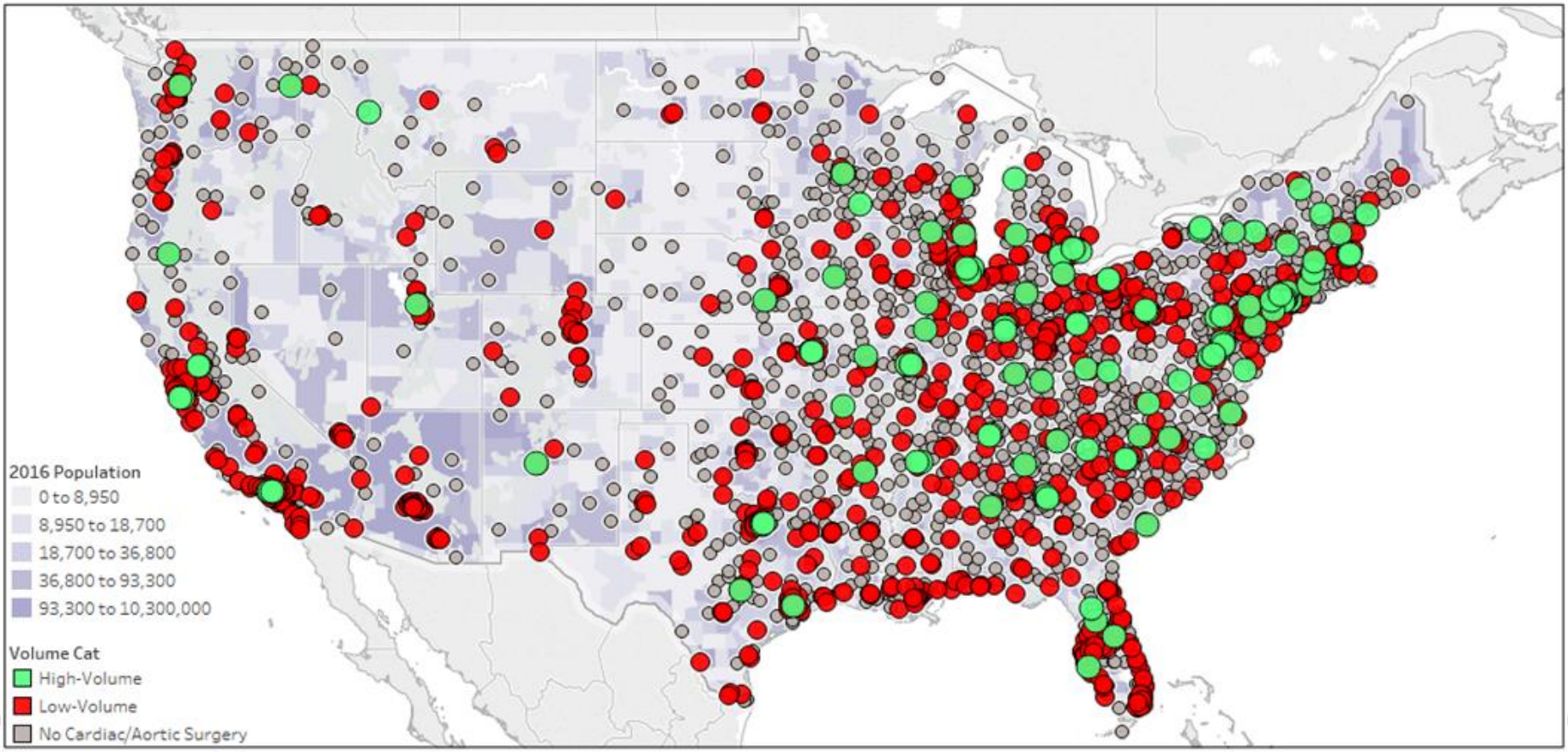

ALWAYS
sends to
high-volume
Hospital
ALWAYS
transfers
Go to hospital
Hospital
ALWAYS
treats


ALWAYS
sends to
high-volume
Hospital
ALWAYS
transfers
ALWAYS
sends to
low-volume
Go to hospital
Hospital
ALWAYS
treats



	high	low
transfer		
stay		

A Distribution of United States Hospitals Categorized by Proximal Aortic Surgery Volume, 1999-2010



is our sorting process “orthogonal”?

is our sorting process “orthogonal”?

We have to think about the decision making process that goes into these decisions.

is our sorting process “orthogonal”?

We have to think about the decision making process that goes into these decisions.

Why are hospitals always sending? Always keeping?

is our sorting process “orthogonal”?

We have to think about the decision making process that goes into these decisions.

Why are hospitals always sending? Always keeping?

Why are hospitals always sending to one type?

is our sorting process “orthogonal”?

We have to think about the decision making process that goes into these decisions.

Why are hospitals always sending? Always keeping?

Why are hospitals always sending to one type?

We can punt (a little bit) on the above two questions because we can merely observe that this is, in fact, the case.

is our sorting process “orthogonal”?

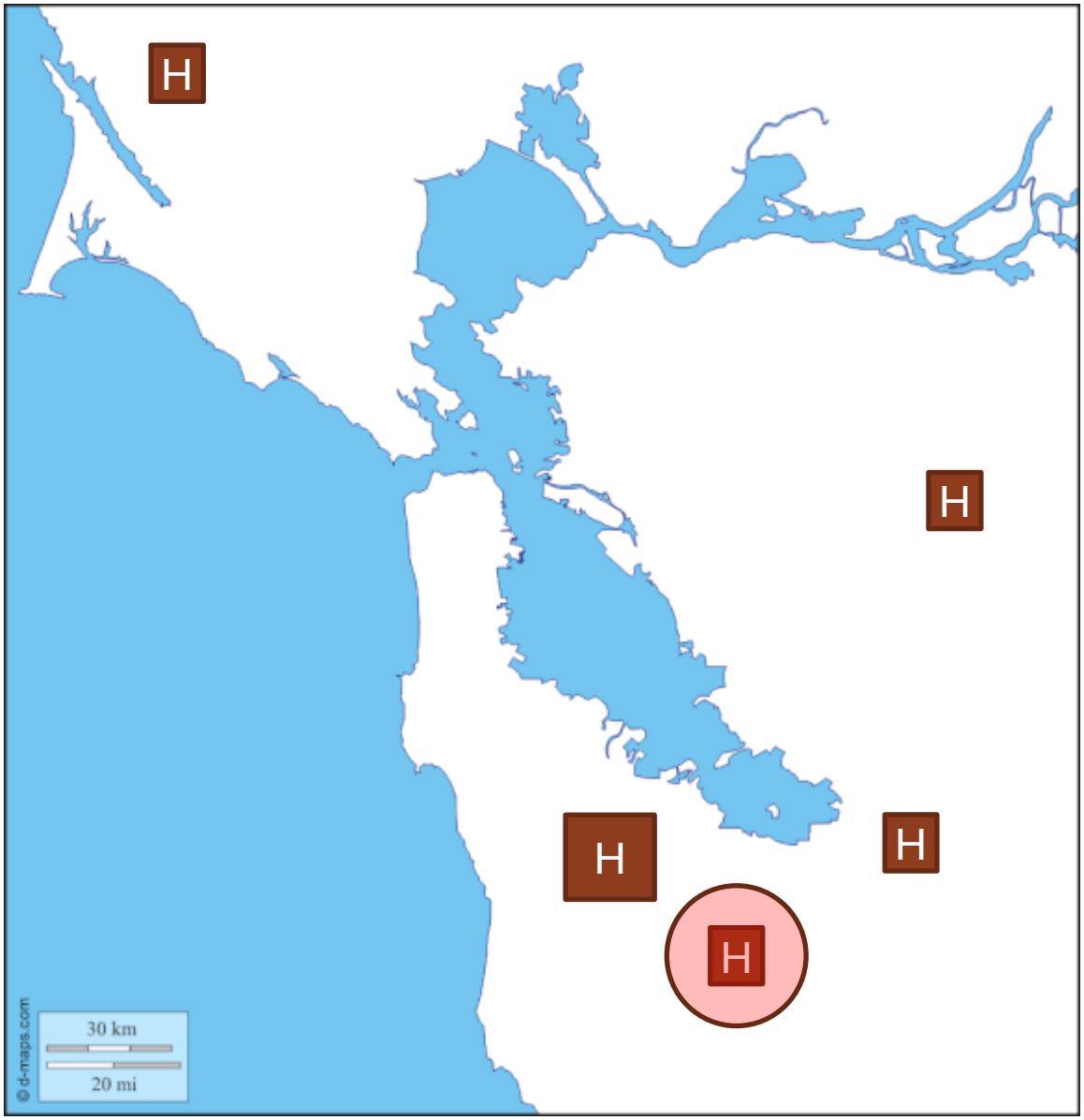
We have to think about the decision making process that goes into these decisions.

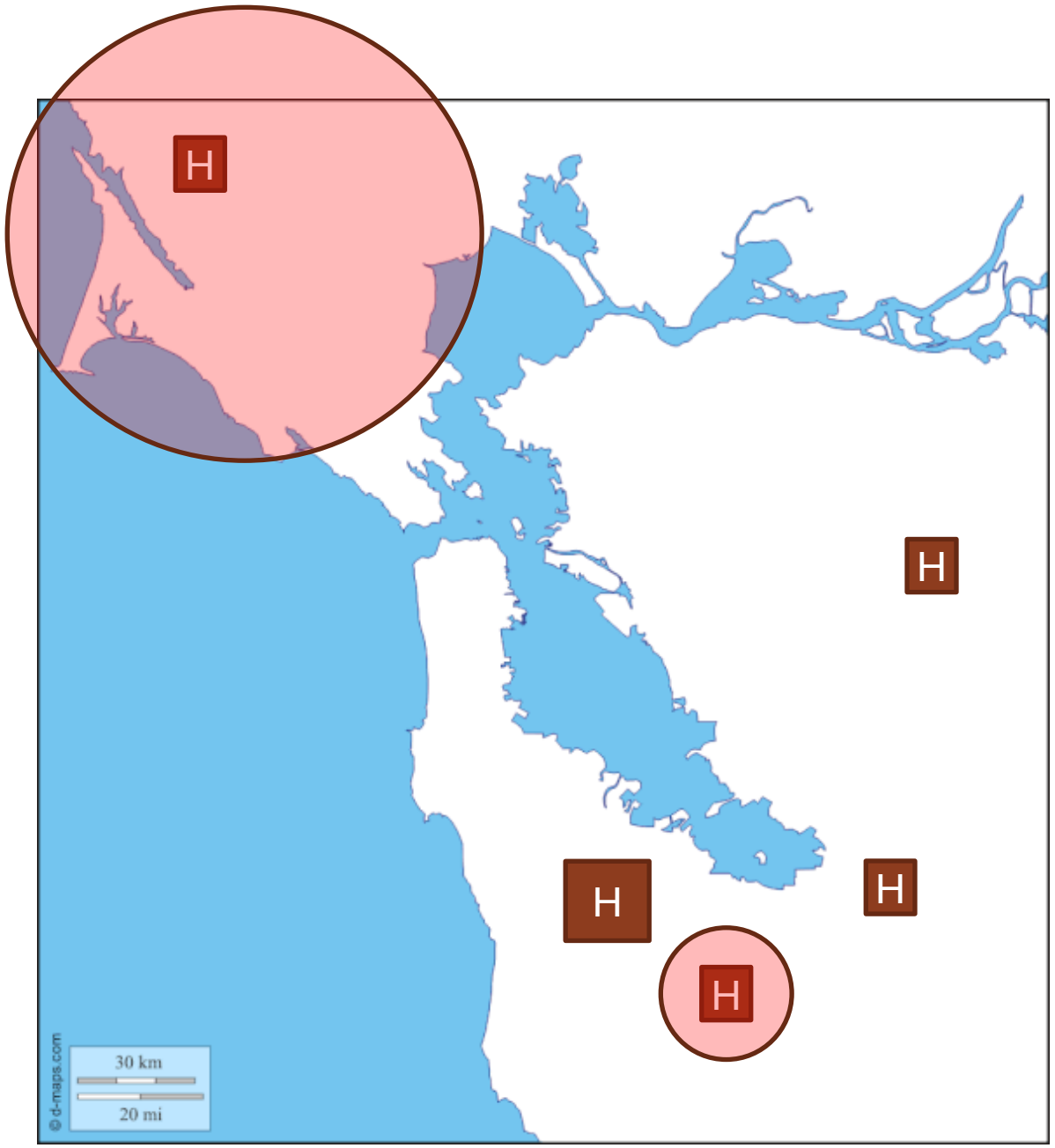
Why are hospitals always sending? Always keeping?

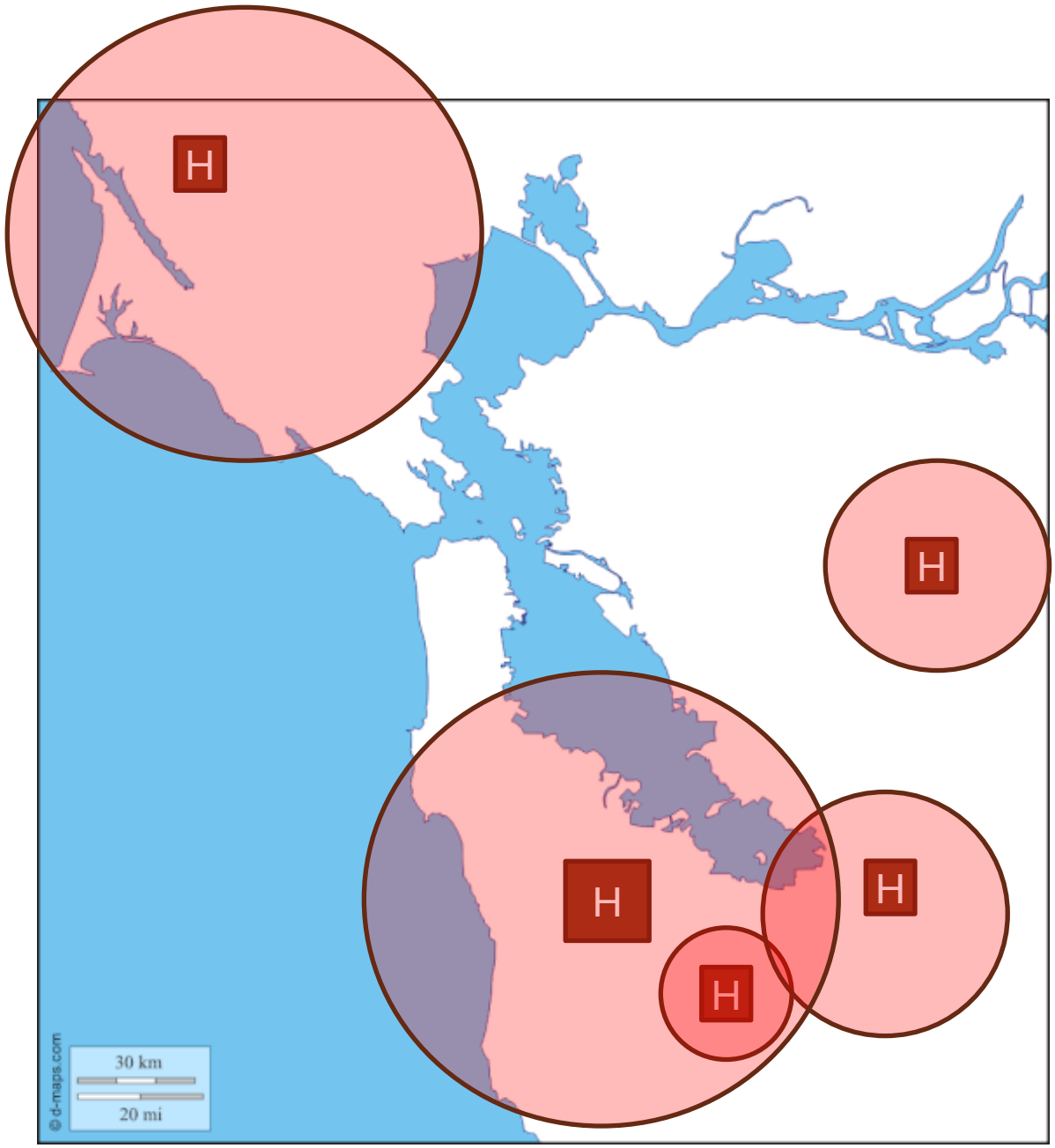
Why are hospitals always sending to one type?

We can punt (a little bit) on the above two questions because we can merely observe that this is, in fact, the case.

How did patients end up at the original hospital?


H
H
H
H
H
30 km
20 mi
© d-maps.com


H
H
H
H
H
30 km
20 mi
© d-maps.com


H
H
H
H
H
30 km
20 mi
© d-maps.com

let’s go find out.

let's go find out.

An undergrad in STATS 60 approached me after class and expressed interest in statistics

let's go find out.

An undergrad in STATS 60 approached me after class and expressed interest in statistics (?!?)

let's go find out.

An undergrad in STATS 60 approached me after class and expressed interest in statistics (?!?)

It turns out Christian Ostberg has been an EMT for a number of years.

let’s go find out.

An undergrad in STATS 60 approached me after class and expressed interest in statistics (?!?)

It turns out Christian Ostberg has been an EMT for a number of years.

out into the real world and

let's go find out.

An undergrad in STATS 60 approached me after class and expressed interest in statistics (?!?)

It turns out Christian Ostberg has been an EMT for a number of years.

out into the real world and

let's go find out.

An undergrad in STATS 60 approached me after class and expressed interest in statistics (?!?)

It turns out Christian Ostberg has been an EMT for a number of years.

We formulated a mixed methods survey for EMTs and identified several EMS providers from different types of communities (e.g., rich/poor, rural/urban).

out into the real world and

let's go find out.

An undergrad in STATS 60 approached me after class and expressed interest in statistics (?!?)

It turns out Christian Ostberg has been an EMT for a number of years.

We formulated a mixed methods survey for EMTs and identified several EMS providers from different types of communities (e.g., rich/poor, rural/urban).

Pulled county-level transport protocols for all of California and summarized their guidelines.

out into the real world and

let's go find out.

An undergrad in STATS 60 approached me after class and expressed interest in statistics (?!?)

It turns out Christian Ostberg has been an EMT for a number of years.

We formulated a mixed methods survey for EMTs and identified several EMS providers from different types of communities (e.g., rich/poor, rural/urban).

Pulled county-level transport protocols for all of California and summarized their guidelines.

NEMSIS data base:

out into the real world and

let's go find out.

An undergrad in STATS 60 approached me after class and expressed interest in statistics (?!?)

It turns out Christian Ostberg has been an EMT for a number of years.

We formulated a mixed methods survey for EMTs and identified several EMS providers from different types of communities (e.g., rich/poor, rural/urban).

Pulled county-level transport protocols for all of California and summarized their guidelines.

NEMSIS data base: (nearly) all EMS transport records in the USA.

out into the real world and

let's go find out.

An undergrad in STATS 60 approached me after class and expressed interest in statistics (?!?)

It turns out Christian Ostberg has been an EMT for a number of years.

We formulated a mixed methods survey for EMTs and identified several EMS providers from different types of communities (e.g., rich/poor, rural/urban).

Pulled county-level transport protocols for all of California and summarized their guidelines.

NEMSIS data base: (nearly) all EMS transport records in the USA.
50% patient/family decision

out into the real world and

let's go find out.

An undergrad in STATS 60 approached me after class and expressed interest in statistics (?!?)

It turns out Christian Ostberg has been an EMT for a number of years.

We formulated a mixed methods survey for EMTs and identified several EMS providers from different types of communities (e.g., rich/poor, rural/urban).

Pulled county-level transport protocols for all of California and summarized their guidelines.

NEMSIS data base: (nearly) all EMS transport records in the USA.
50% patient/family decision, 40% proximity

would regionalizing improve survival?

Table 2. Between-Group Differences in Operative Mortality and Overall Survival for Comparison of Transfer and Regionalization

Operative Mortality	**Transferred vs. Stayed (reference)**			**Rerouted vs. Not Rerouted (reference)***		
Group Contrast Measure	Estimate	95% CI	P Value	Estimate	95% CI	P Value
Absolute Risk Difference (%)	-0.62	-2.6 - 1.34	0.57	-7.5	-10.6 - -4.4	<0.001
Odds Ratio	0.97	0.87 - 1.08	0.55	0.68	0.57 - 0.80	<0.001
Number Needed to Treat (no.)	-	-	-	14	9 - 23	-
Overall Survival	**Transferred vs. Stayed (reference)**			**Rerouted vs. Not Rerouted (reference)**		
Group Contrast Measure	Estimate	95% CI	P Value	Estimate	95% CI	P Value
Hazard Ratio (PH model)	1.02	0.94 - 1.11	0.64	0.8	0.74 - 0.86	<0.001
Restricted Mean Survival Time		15 years			15 years	
Difference (days)	-44.9	-141.2 - 51.5	0.36	232.2	105.2 - 359.1	<0.001
Ratio	0.98	0.94 - 1.02	0.36	1.12	1.05 - 1.18	<0.001
Ratio of Restricted Mean Time Lost	1.02	0.98 - 1.05	0.36	0.93	0.89 - 0.97	<0.001

*Gamma = 1.32 for this comparison. The gamma parameter estimates the amount of unmeasured bias necessary to render the finding null. For interpretation, sickest patients requiring rerouting (to regionalize care) would need to have a 33% increased odds of needing to be rerouted (despite matching) in order for the presented findings to be null.

CI, confidence interval; PH, proportional hazards

would regionalizing improve survival?

Table S7. Propensity Score Analsyis - Between-Group Differences in Operative Mortality and Overall Survival for Comparison of Transfer and Regionalization

Operative Mortality	**Transferred vs. Stayed (reference)**			**High-Volume vs. Low-Volume (reference)***			**Rerouted vs. Not Rerouted (reference)****		
Group Contrast Measure	Estimate	95% CI	P Value	Estimate	95% CI	P Value	Estimate	95% CI	P Value
Absolute Risk Difference (%)	-1.7	-3.2 - -0.001	0.03	-6.1	-7.7 - -4.5	<0.001	-9.6	-11.4 - -7.8	<0.001
Odds Ratio	0.9	0.82 - 0.99	0.03	0.73	0.67 - 0.79	<0.001	0.6	0.54 - 0.67	<0.001
Number Needed to Treat (no.)	-	-	-	17	13 - 23	-	11	9 - 13	-
Overall Survival	**Transferred vs. Stayed (reference)**			**High-Volume vs. Low-Volume (reference)***			**Rerouted vs. Not Rerouted (reference)****		
Group Contrast Measure	Estimate	95% CI	P Value	Estimate	95% CI	P Value	Estimate	95% CI	P Value
Hazard Ratio (PH model)	1.02	0.94 - 1.11	0.64	0.76	0.71 - 0.80	<0.001	0.8	0.74 - 0.86	<0.001
Restricted Mean Survival Time		15 years			15 years			15 years	
Difference (days)	-44.9	-141.2 - 51.5	0.36	300.6	206.4 - 394.7	<0.001	232.2	105.2 - 359.1	<0.001
Ratio	0.98	0.94 - 1.02	0.36	1.15	1.10 - 1.20	<0.001	1.12	1.05 - 1.18	<0.001
Ratio of Restricted Mean Time Lost	1.02	0.98 - 1.05	0.36	0.9	0.88 - 0.93	<0.001	0.93	0.89 - 0.97	<0.001

* Gamma = 1.31

** Gamma = 1.44

Using “all of the data.”

inference

inference

inference

- Historically: two-stage least squares

inference

- Historically: two-stage least squares
- State of the art: residual inclusion models

inference

- Historically: two-stage least squares
- State of the art: residual inclusion models
- Trusty: permutation-based inference

inference: two-stage least squares

- Historically: two-stage least squares

inference: two-stage least squares

- Historically: two-stage least squares
- Model two parts of the process:

inference: two-stage least squares

- Historically: two-stage least squares

- Model two parts of the process:
  1) Selection into the treatment.

inference: two-stage least squares

- Historically: two-stage least squares

- Model two parts of the process:
  1) Selection into the treatment.
  2) The outcome model.

inference: two-stage least squares

- Selection into the treatment:

inference: two-stage least squares

- Selection into the treatment:

$$d = f^d(\boldsymbol{x}, z)$$

inference: two-stage least squares

- Selection into the treatment:

$$d = f^d(\boldsymbol{x}, z)$$

Usually looks like

$$d = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p + \beta_z z + \varepsilon_d$$

inference: two-stage least squares

- Selection into the treatment:

$$d = f^d(\boldsymbol{x}, z)$$

  Usually looks like

$$d = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p + \beta_z z + \varepsilon_d$$

- The outcome model:

$$y = f^y(\boldsymbol{x}, d)$$

inference: two-stage least squares

- Selection into the treatment:

$$d = f^d(\boldsymbol{x}, z)$$

Usually looks like

$$d = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p + \beta_z z + \varepsilon_d$$

- The outcome model:

$$y = f^y(\boldsymbol{x}, d)$$

Usually looks like

$$y = \alpha_0 + \alpha_1 x_1 + \alpha_2 x_2 + \cdots + \alpha_p x_p + \alpha_d d + \varepsilon_y$$

inference: two-stage least squares

- Selection into the treatment:

$$d = f^d(\boldsymbol{x}, z)$$

Usually looks like

$$\hat{d} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2 + \cdots + \hat{\beta}_p x_p + \hat{\beta}_z z$$

- The outcome model:

$$y = f^y(\boldsymbol{x}, d)$$

Usually looks like

$$y = \alpha_0 + \alpha_1 x_1 + \alpha_2 x_2 + \cdots + \alpha_p x_p + \alpha_d d + \varepsilon_y$$

inference: two-stage least squares

- Selection into the treatment:

$$d = f^d(\boldsymbol{x}, z)$$

Usually looks like

$$\hat{d} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2 + \cdots + \hat{\beta}_p x_p + \hat{\beta}_z z$$

- The outcome model:

$$y = f^y(\boldsymbol{x}, d)$$

Usually looks like

$$\hat{y} = \hat{\alpha}_0 + \hat{\alpha}_1 x_1 + \hat{\alpha}_2 x_2 + \cdots + \hat{\alpha}_p x_p + \hat{\alpha}_d d$$

inference: two-stage least squares

- Selection into the treatment:

$$d = f^d(\boldsymbol{x}, z)$$

Usually looks like

$$\hat{d} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2 + \cdots + \hat{\beta}_p x_p + \hat{\beta}_z z$$

- The outcome model:

$$y = f^y(\boldsymbol{x}, d)$$

Usually looks like

$$\hat{y} = \hat{\alpha}_0 + \hat{\alpha}_1 x_1 + \hat{\alpha}_2 x_2 + \cdots + \hat{\alpha}_p x_p + \hat{\alpha}_{\hat{d}} \hat{\boldsymbol{d}}$$

inference: two-stage least squares

- Selection into the treatment:

$$d = f^d(\boldsymbol{x}, z)$$

Usually looks like

$$\hat{d} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2 + \cdots + \hat{\beta}_p x_p + \hat{\beta}_z z$$

- The outcome model:

$$y = f^y(\boldsymbol{x}, d)$$

Usually looks like

$$\hat{y} = \hat{\alpha}_0 + \hat{\alpha}_1 x_1 + \hat{\alpha}_2 x_2 + \cdots + \hat{\alpha}_p x_p + \hat{\alpha}_{\hat{d}} \hat{d}$$

- Generally speaking, 2sls is a "predictor substitution" method.

inference: two-stage least squares

- Selection into the treatment:

$$d = f^d(\boldsymbol{x}, z)$$

Usually looks like

$$\hat{d} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2 + \cdots + \hat{\beta}_p x_p + \hat{\beta}_z z$$

- The outcome model:

$$y = f^y(\boldsymbol{x}, d)$$

Usually looks like

$$\hat{y} = \hat{\alpha}_0 + \hat{\alpha}_1 x_1 + \hat{\alpha}_2 x_2 + \cdots + \hat{\alpha}_p x_p + \hat{\alpha}_{\hat{d}} \hat{d}$$

- Generally speaking, 2sls is a "predictor substitution" method…. which have problems.

inference: two-stage least squares

- Generally speaking, 2sls is a “predictor substitution” method…. which have problems.

inference: two-stage least squares

- Generally speaking, 2sls is a “predictor substitution” method…. which have problems.
- Historically, the big problems came up when the outcomes (y) was not linear.

inference: two-stage least squares

- Generally speaking, 2sls is a “predictor substitution” method…. which have problems.
- Historically, the big problems came up when the outcomes (y) was not linear.
- Take-away: If the outcome is linear…

inference: two-stage least squares

- Generally speaking, 2sls is a “predictor substitution” method…. which have problems.
- Historically, the big problems came up when the outcomes (y) was not linear.
- Take-away: If the outcome is linear AND the treatment is EITHER linear or binary…

inference: two-stage least squares

- Generally speaking, 2sls is a “predictor substitution” method…. which have problems.
- Historically, the big problems came up when the outcomes (y) was not linear.
- Take-away: If the outcome is linear AND the treatment is EITHER linear or binary then two-stage least squares is the path of least resistance.

inference: residual-inclusion models

- State of the art: residual inclusion models

inference: residual-inclusion models

- State of the art: residual inclusion models

- Model two parts of the process:
  1) Selection into the treatment.
  2) The outcome model.

inference: residual inclusion models

- Selection into the treatment:

$$d = f^d(\boldsymbol{x}, z)$$

Usually looks like

$$d = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p + \beta_z z + \varepsilon_d$$

- The outcome model:

$$y = f^y(\boldsymbol{x}, d)$$

Usually looks like

$$y = \alpha_0 + \alpha_1 x_1 + \alpha_2 x_2 + \cdots + \alpha_p x_p + \alpha_d d + \varepsilon_y$$

inference: *two-stage least squares*

- Selection into the treatment:

$$d = f^d(\boldsymbol{x}, z)$$

Usually looks like

$$\hat{d} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2 + \cdots + \hat{\beta}_p x_p + \hat{\beta}_z z$$

- The outcome model:

$$y = f^y(\boldsymbol{x}, d)$$

Usually looks like

$$\hat{y} = \hat{\alpha}_0 + \hat{\alpha}_1 x_1 + \hat{\alpha}_2 x_2 + \cdots + \hat{\alpha}_p x_p + \hat{\alpha}_{\hat{d}} \hat{d}$$

inference: *two-stage least squares*

- Selection into the treatment:

$$d = f^d(\boldsymbol{x}, z)$$

Usually looks like

$$\hat{d} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2 + \cdots + \hat{\beta}_p x_p + \hat{\beta}_z z$$

- The outcome model:

$$y = f^y(\boldsymbol{x}, d)$$

Usually looks like

$$\hat{y} = \hat{\alpha}_0 + \hat{\alpha}_1 x_1 + \hat{\alpha}_2 x_2 + \cdots + \hat{\alpha}_p x_p + \hat{\alpha}_{\hat{d}} \hat{d}$$

$$d_i - \hat{d}_i = \hat{e}_i$$

inference: residual inclusion models

- Selection into the treatment:

$$d = f^d(\boldsymbol{x}, z)$$

Usually looks like

$$\hat{d} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2 + \cdots + \hat{\beta}_p x_p + \hat{\beta}_z z$$

- The outcome model:

$$y = f^y(\boldsymbol{x}, d)$$

Usually looks like

$$\hat{y} = \hat{\alpha}_0 + \hat{\alpha}_1 x_1 + \hat{\alpha}_2 x_2 + \cdots + \hat{\alpha}_p x_p + \hat{\alpha}_d d + \boldsymbol{\hat{\alpha}_{\hat{e}} \hat{e}}$$

$$d_i - \hat{d}_i = \hat{e}_i$$

inference: residual inclusion models

- Residual inclusion models were developed to deal with nonlinear outcomes.

inference: residual inclusion models

- Residual inclusion models were developed to deal with nonlinear outcomes.
- They perform quite well in many of the GLM setting – e.g., logistic.

inference: residual inclusion models

- Residual inclusion models were developed to deal with nonlinear outcomes.
- They perform quite well in many of the GLM setting – e.g., logistic.
- In the linear outcome/linear treatment case 2sls and RIMs are the same.

inference: residual inclusion models

- Residual inclusion models were developed to deal with nonlinear outcomes.
- They perform quite well in many of the GLM setting – e.g., logistic.
- In the linear outcome/linear treatment case 2sls and RIMs are the same.
- Take-away: Probably best to opt for RIMs.

inference: permutation-based

- Trusty: permutation based

inference: permutation-based

- Trusty: permutation based
- Use the Z as the randomizer.

inference: permutation-based

- Trusty: permutation based
- Use the Z as the randomizer.
- Technical reference:
  - Imbens and Rosenbaum (2005) "Robust, accurate confidence intervals with a weak instrument: Quarter of birth and education."

inference: permutation-based

- Trusty: permutation based
- Use the Z as the randomizer.
- Technical reference:
  - Imbens and Rosenbaum (2005) "Robust, accurate confidence intervals with a weak instrument: Quarter of birth and education."
- Applied reference:
  - Greevy, Silber, Cnaan, and Rosenbaum (2004) "Randomization inference with imperfect compliance in the ACE-inhibitor after anthracycline randomized trial."

fin.