Session 9

Prof Amit Mehra

Example of one sided non-compliance, ITT and LATE

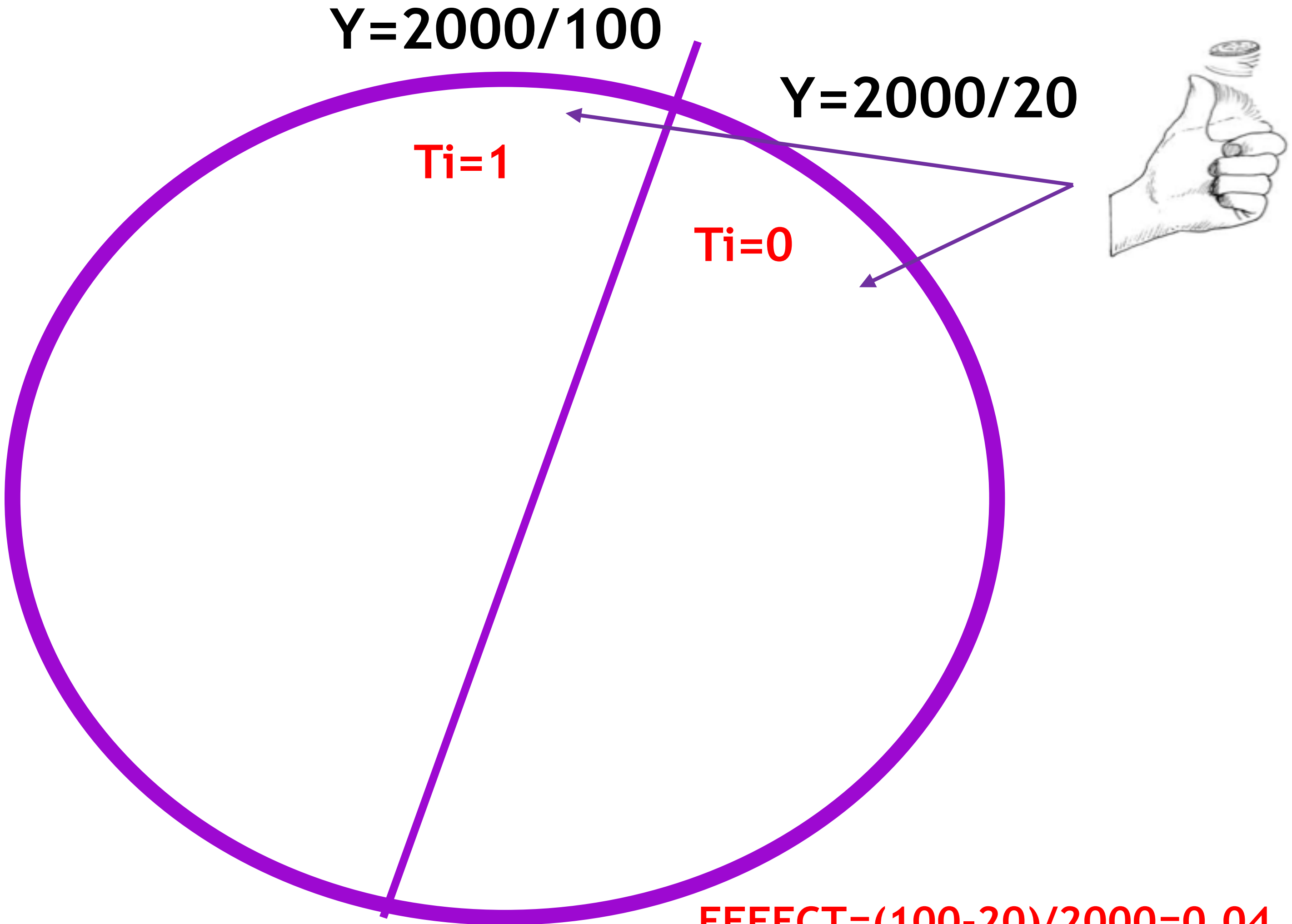
ITT – Intention to treat

LATE – Local Average Treatment Effect

Effect of sending emails

- **Private Firm Case:**
  - Does sending emails to people about new product lead them to try it out?
- **Public Policy Case:**
  - Does sending email to people about a new diet lead them to try it out?
- **Some people read these emails other people do not!**
- **Whether one does it's up to her even if we randomize who gets the emails!**
- **Outcomes of interest**: Y
  - Private Firm: how many people try out the new product?
  - Public Policy Case: how many people try out the diet?

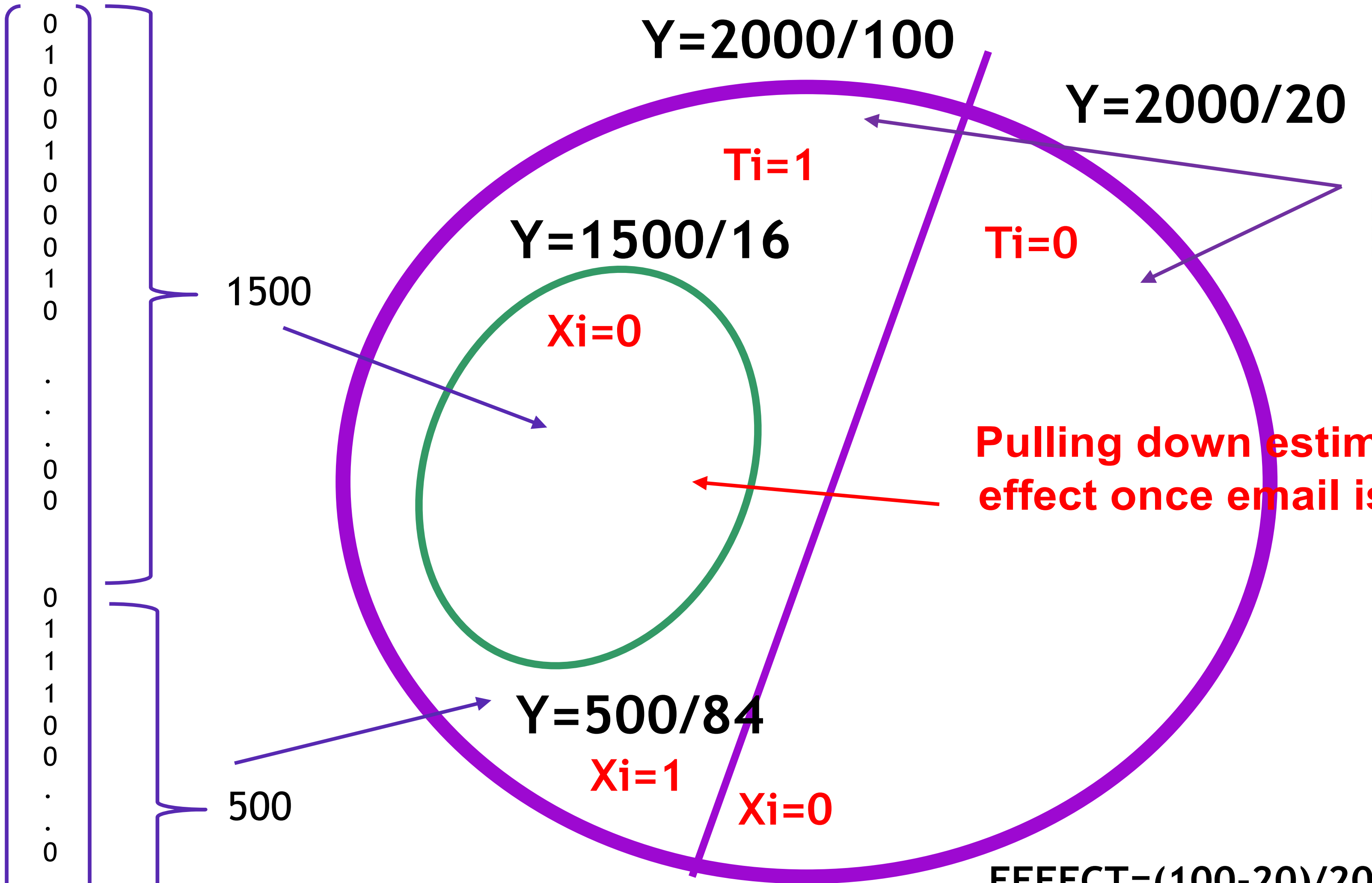
ITT: Causal effect of sending email



ITT answers:
Does sending the email change try out rate?

EFFECT=(100-20)/2000=0.04
CAUSAL EFFECT OF INTENTION TO TREAT

ITT is lower bound for the effect of reading emails



EFFECT=(100-20)/2000=0.04

CAUSAL EFFECT OF INTENTION TO TREAT

LATE - Local ATE

It is the causal effect
of reading emails on the
set of people who do read
the emails

That's why this is
a "local" effect
and not a "global" effect
that applies to entire
Population

Some people who are sent
Emails may not read them.
People not sent emails can
never read them – people
in treatment may not comply
but those in control do
e.g. one-sided non-compliance
In such case: LATE > ITT

Effect of sending emails vs. reading emails

- **Private Firm Case:**
  - Does sending emails to people about new product lead them to try out?
- **Public Policy Case:**
  - Does sending email to people about a new diet lead them to try it out?
- Imagine that we conclude that ITT=0, sending emails does not make a difference
- **Manager 1.0, Policy Maker 1.0:** “Ok, let’s stop sending emails, we just wasting resources on something that does not make a difference”

Effect of sending emails vs. reading emails

- **Private Firm Case:**
  - Does sending emails to people about new product lead them to try out?
- **Public Policy Case:**
  - Does sending email to people about a new diet lead them to try it out?
- Imagine that we conclude that ITT=0, sending emails does not make a difference
- **Manager 1.0, Policy Maker 1.0:** “Ok, let’s stop sending emails, we just wasting resources on something that does not make a difference”
- **Manager 2.0**: “Ok, but some people must have read our emails. Did they try out the product? Did they like it?”
- **Policy Maker 2.0**: “Ok, but some people must have read our emails. Did they tried the new diet? Did it work for them?”

Effect of sending emails vs. reading emails

- Imagine that we conclude that ITT=0, sending emails does not make a difference
- **Manager 1.0, Policy Maker 1.0:** “Ok, let’s stop sending emails, we just wasting resources on something that does not make a difference”
- **Manager 2.0**: “Ok, but some people must have read our emails. Did they try out the product? Did they like it?”
- **Policy Maker 2.0**: “Ok, but some people must have read our emails. Did they tried the new diet? Did it work for them?”
- **The effect of sending emails is different from the effect of reading emails. Both of them may be important**
- Imagine that we conclude that LATE>0, reading emails does make a difference!
- Then **Manager 2.0, Policy Maker 2.0**: “We shouldn’t stop sending emails, what we need is to make sure more people read them. Send more, or target better!”

Response to treatment may be of different type

- Let Ti 0/1 indicate if unit of analysis i was treated e.g. received email
- Let Xi 0/1 indicate if unit of analysis i took the treatment e.g. read email

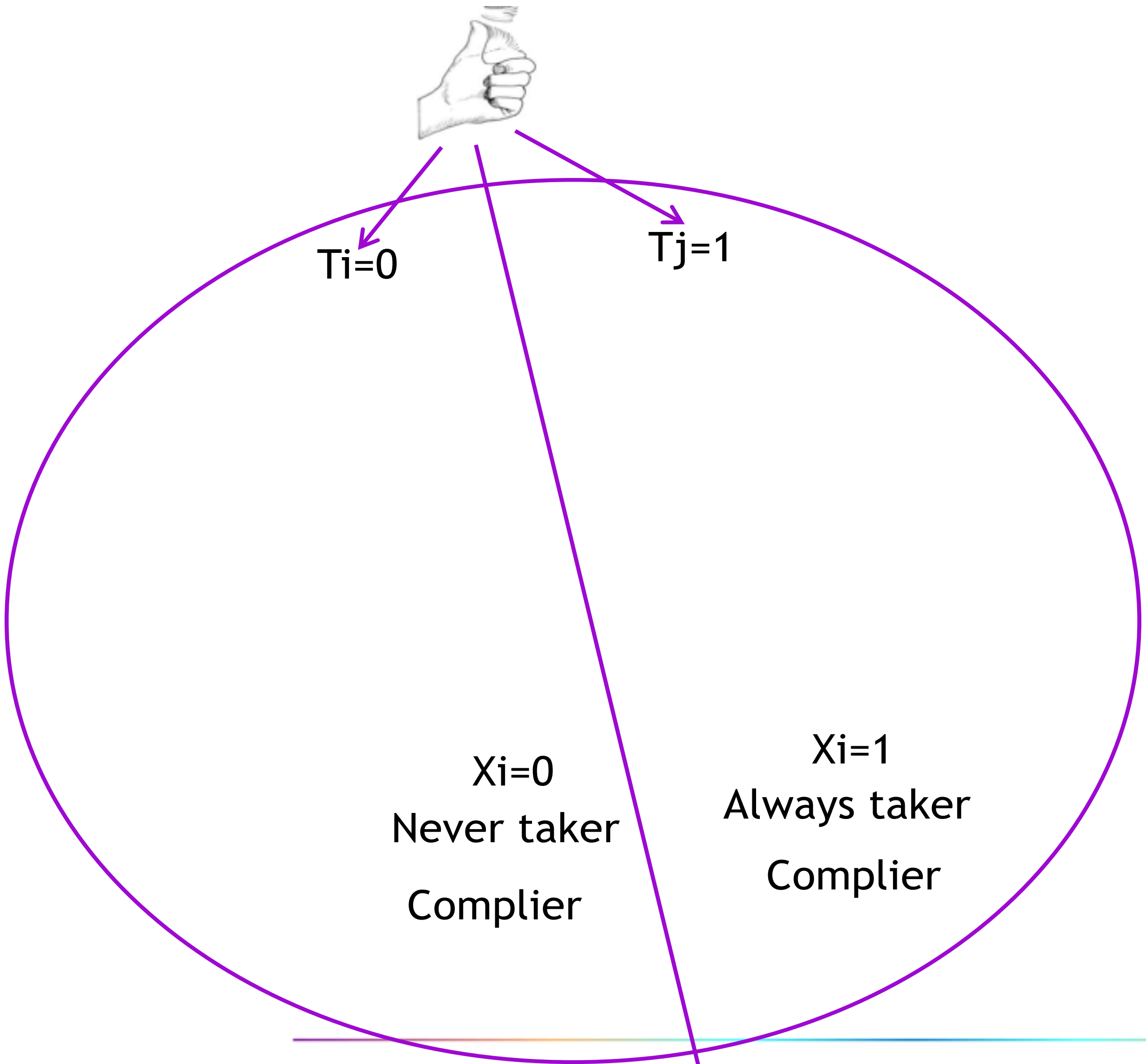
- There are four types of units of analysis in A/B tests:

  - **Compliers**: Xi=Ti
  - **Defiers**: Xi=1-Ti (do exactly the opposite)
  - **Always Takers**: Xi=1 irrespective of Ti (always take the treatment)
  - **Never Takers**: Xi=0 irrespective of Ti (never take the treatment)

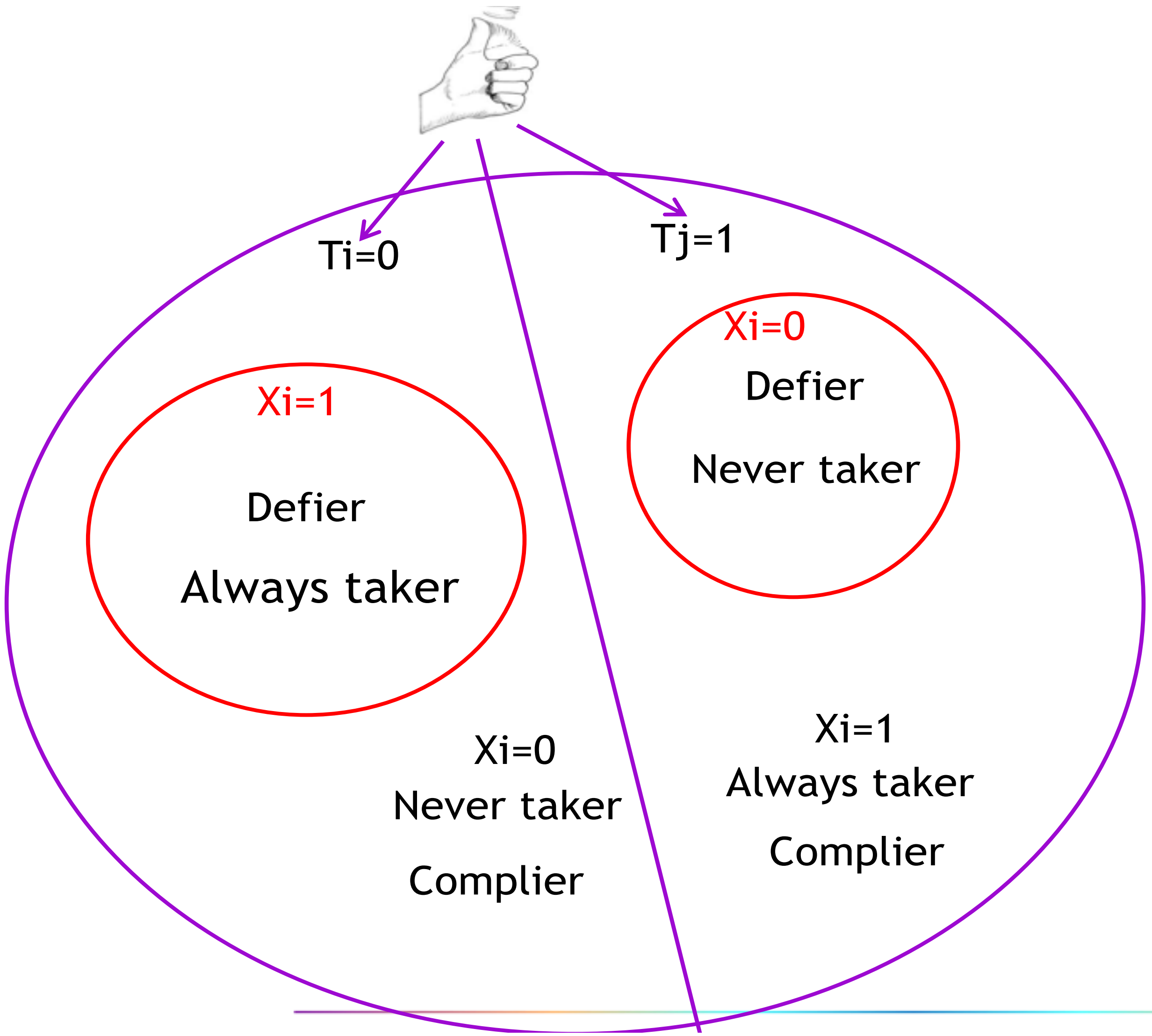
- The tricky part is to know **who is who**!

Note: Always takers have the intent to take the treatment, but the design may preclude them from doing so. E.g. they cannot read the emails if they don't have the emails.
But, suppose, the treatment is to join a job counselling service in a university, and even though control people are asked not to join, always takers will still join

Always Takers, Never Takers, Defiers and Compliers



Always Takers, Never Takers, Defiers and Compliers

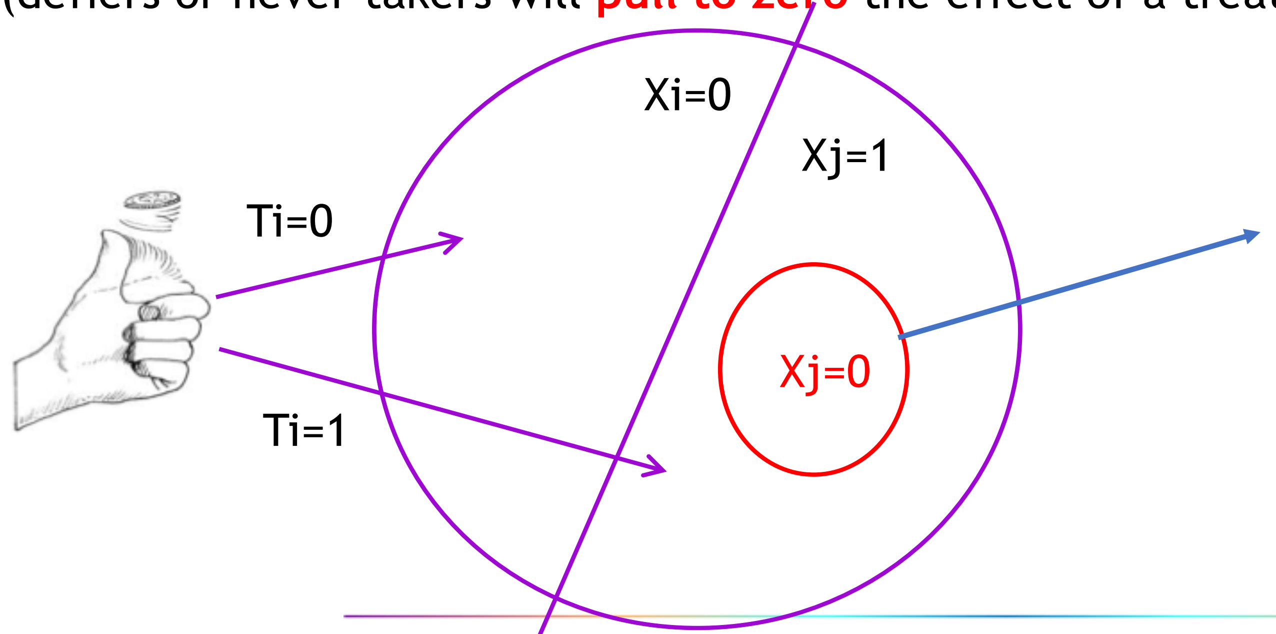


One sided non-compliance, ITT and LATE

- In many cases one can ensure that the individuals randomly assigned to the control condition do not obtain access to the treatment – email example

- Another example: give people at random “prescriptions” to take a drug (Ti). Then people can decide whether to actually take a drug (Xi). People that do not have the prescription will never take the drug (Ti=0 implies Xi=0) (drug not available OTC)

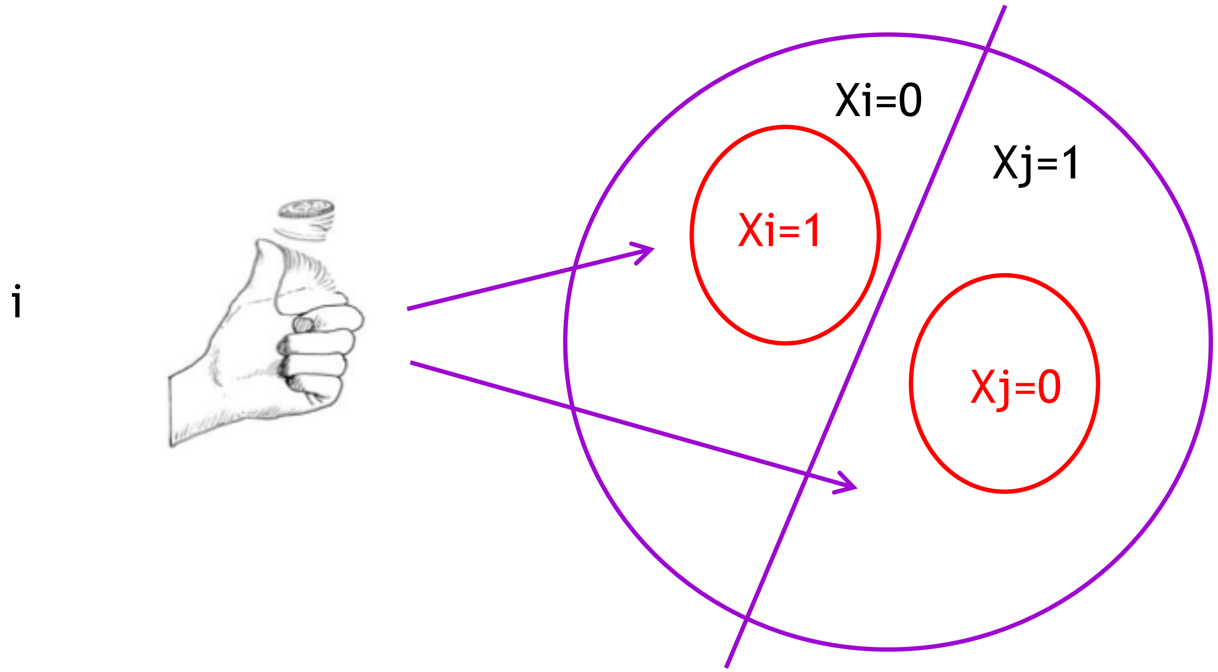
- In this case, the effect of the **Intention to Treat is a lower bound for the effect of the drug** (defiers or never takers will **pull to zero** the effect of a treatment (Xi=1))



Effect of defiers and never takers is ZERO.
If they were treated,
The effect of drug would go up

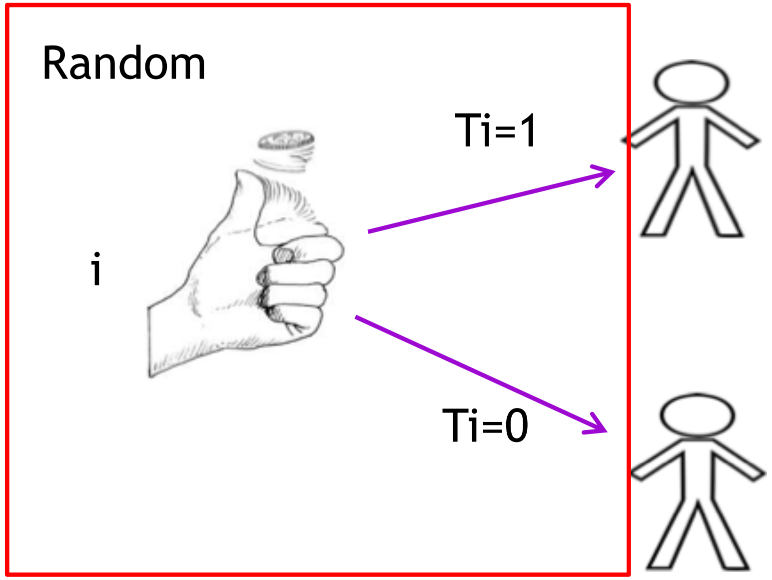
Two sided non-compliance

- But what if individuals **do not comply with the assigned condition**?
- Some individuals assigned to not go to the hospital **decide to go!**
- Some individuals assigned to go to the hospital **do not go!**



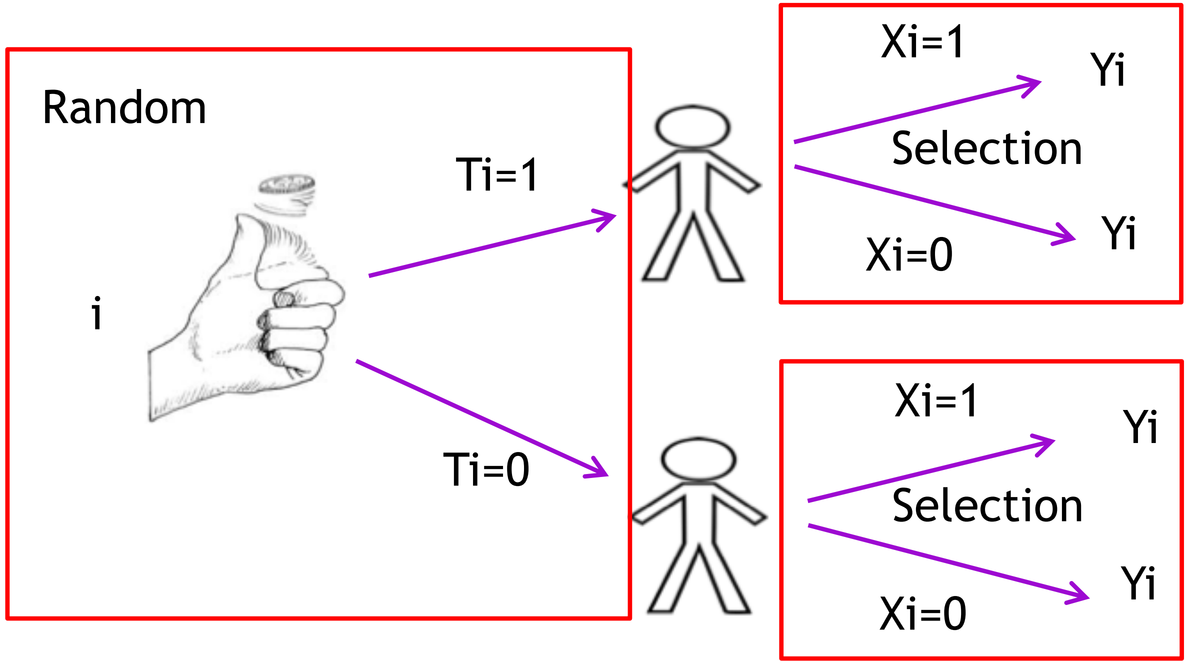
ITT in two sided non-compliance

- Ti=0/1 = individual i **was told** not to go / to go to the hospital



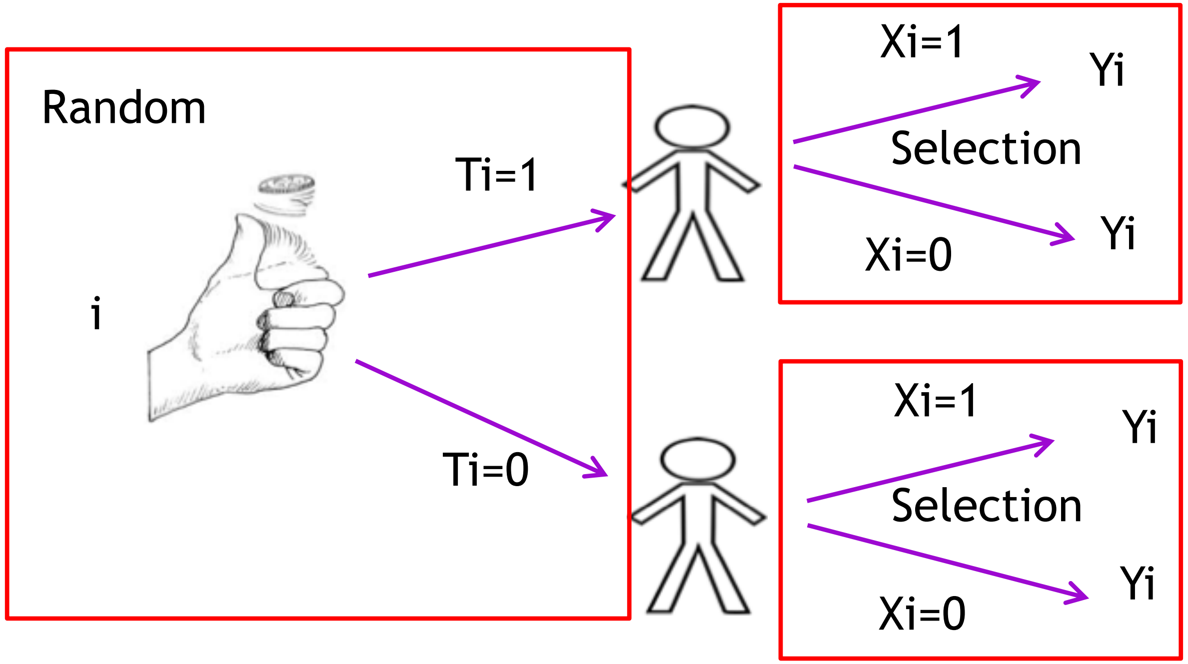
ITT in two sided non-compliance

- Ti=0/1 = individual i **was told** not to go / to go to the hospital
- Then **people decide (select!)** whether they want to go to the hospital (decide Xi)



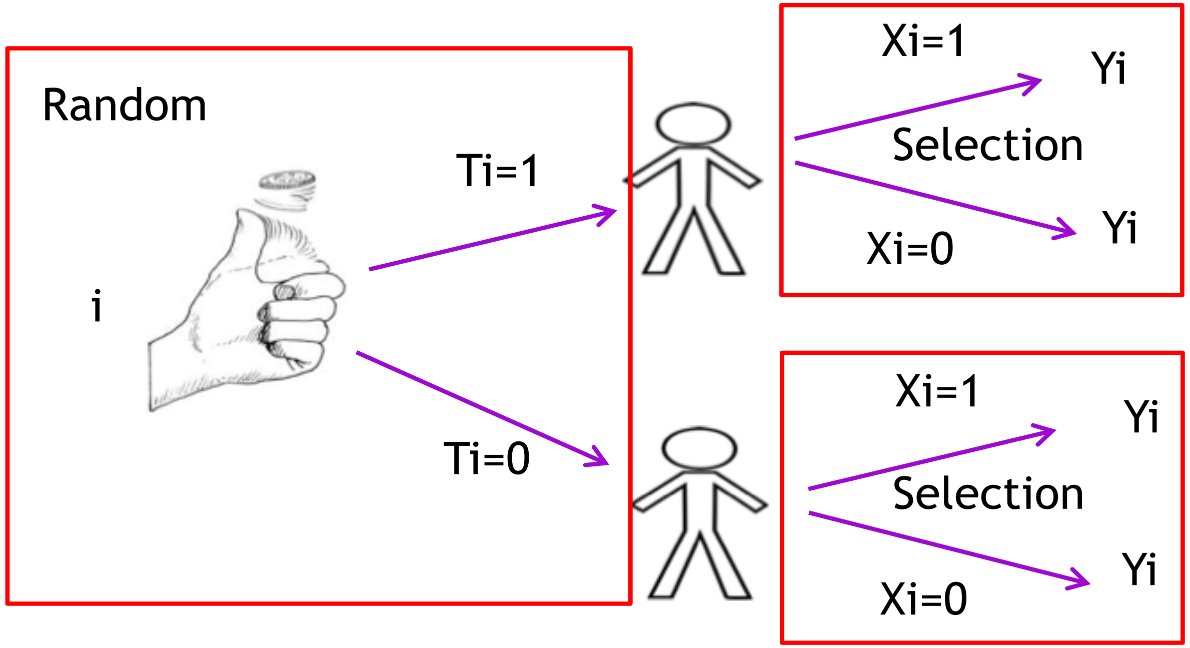
ITT in two sided non-compliance

- Ti=0/1 = individual i **was told** not to go / to go to the hospital
- Then **people decide (select!)** whether they want to go to the hospital (decide Xi)
- **Xi!=Ti** and causal effect of **Ti on Yi is different** from the causal effect of **Xi on Yi**
- The causal effect of Ti on Yi is called the effect of the **Intention To Treat (ITT)**



ITT, LATE and two sided non-compliance

- The Intention to Treat is the effect of **telling people to go to the hospital**
- We can **compute** the **Intention to Treat (ITT): Y=a+b*T+e**, T randomly chosen
- But often we would like to know the **"true effect" of treatment: Y=c+d*X+u**
- This would be the effect of people **(effectively) going to the hospital**



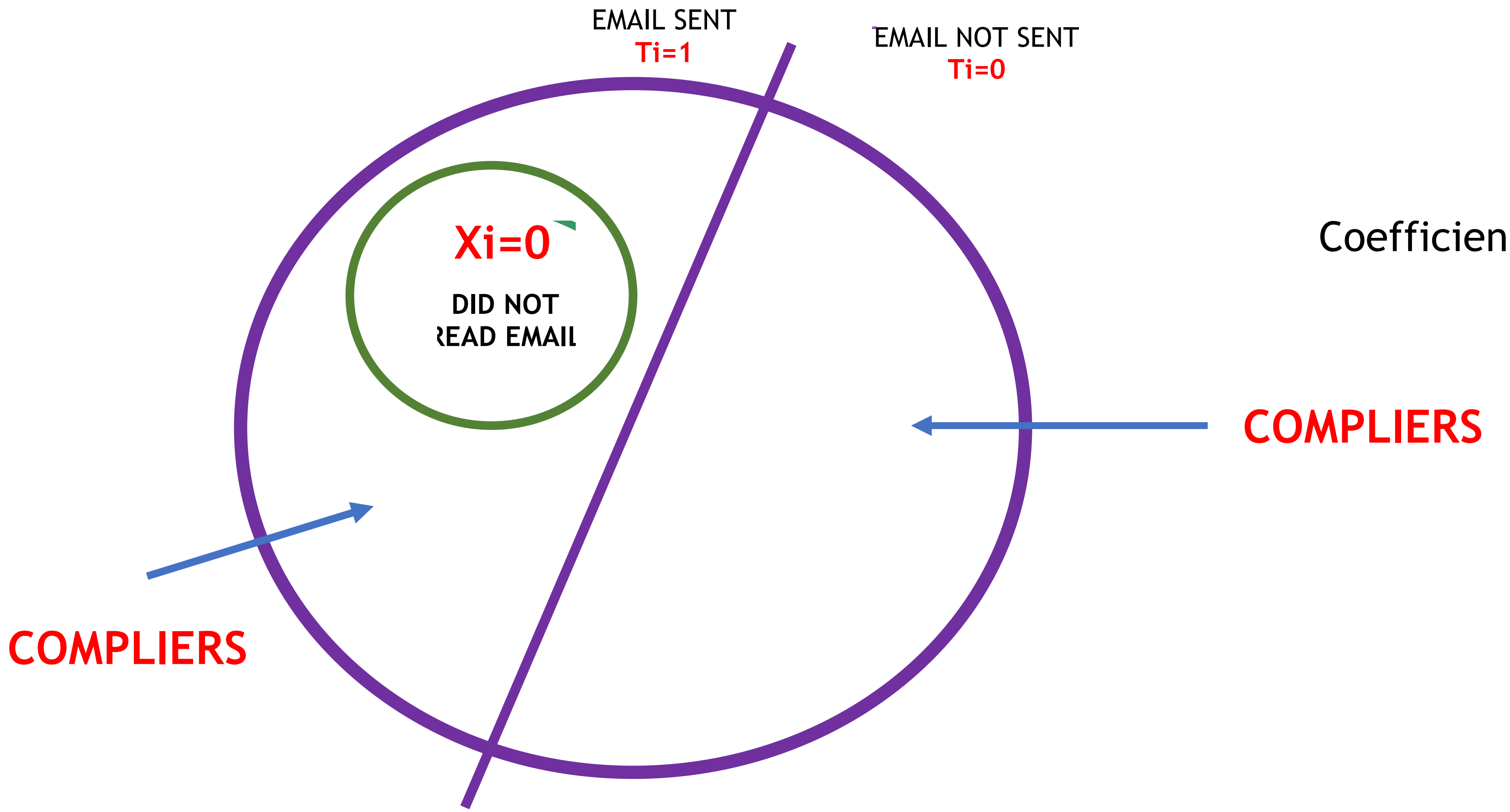
LATE in one sided and two sided compliance

- **In one sided non-compliance**, there is no difference in behavior between the compliers and always takers (if in control group, both do not get treatment and if in treatment group, both get treatment). Hence, they are **together referred to as compliers**
- We ignore defiers (perverse situation). Thus, we are left with compliers and never takers in this case.
- LATE is effect of compliance (e.g. reading emails) on outcome – in one sided non-compliance, it is the effect on compliers and always takers
  - Local: average effect only over a sub-population of individuals – the compliers and always takers (but not the never takers)
- **In two-sided non-compliance**, LATE is the average effect on only the compliers
- This is helpful as this tells us average effect on those whose behavior can be modified by the treatment

How to find LATE?

Doing the analysis

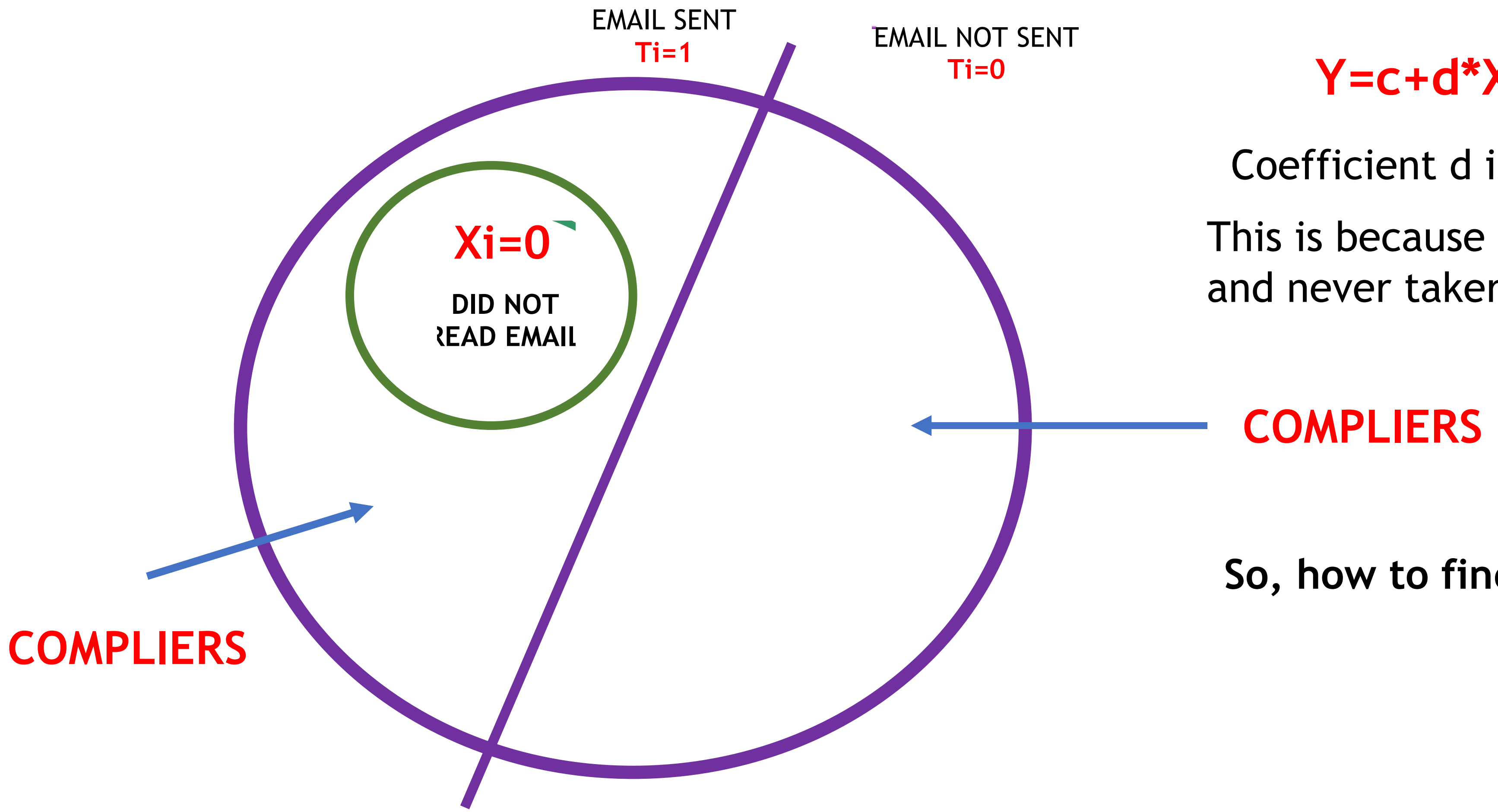
Intention to Treat (ITT)



$Y=a+b*T+e$

Coefficient b is unbiased as $Cov(T,e)=0$

LATE: Effect on Compliers



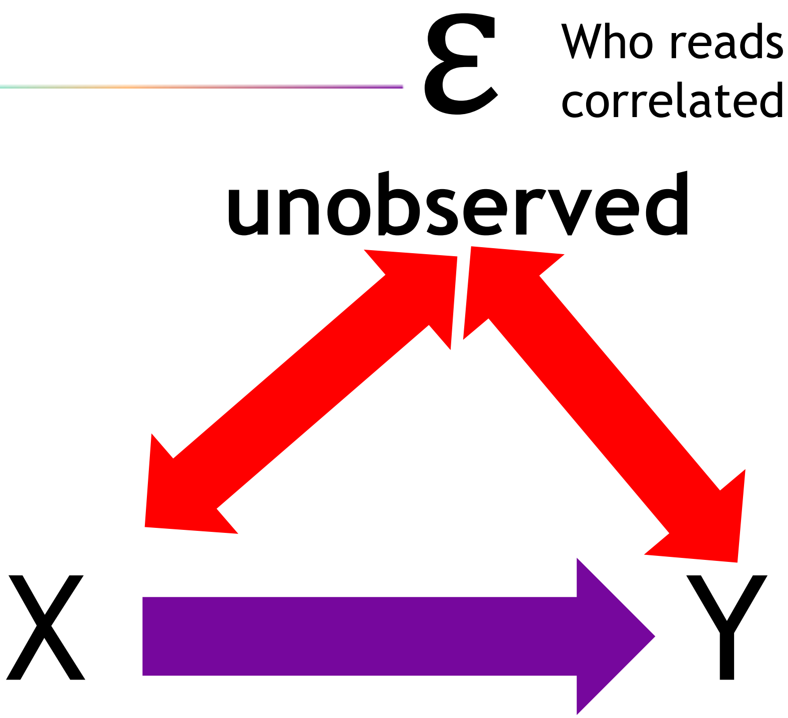
$Y=c+d*X+u$

Coefficient d is biased as $Cov(X,u)!=0$

This is because compliers select to read emails and never takers select not to read emails

So, how to find effect on compliers?

Recall reason for bias in regression



Who reads email may be correlated with age, income and that may also be correlated with outcome (did people try out the product, diet-plan etc.)

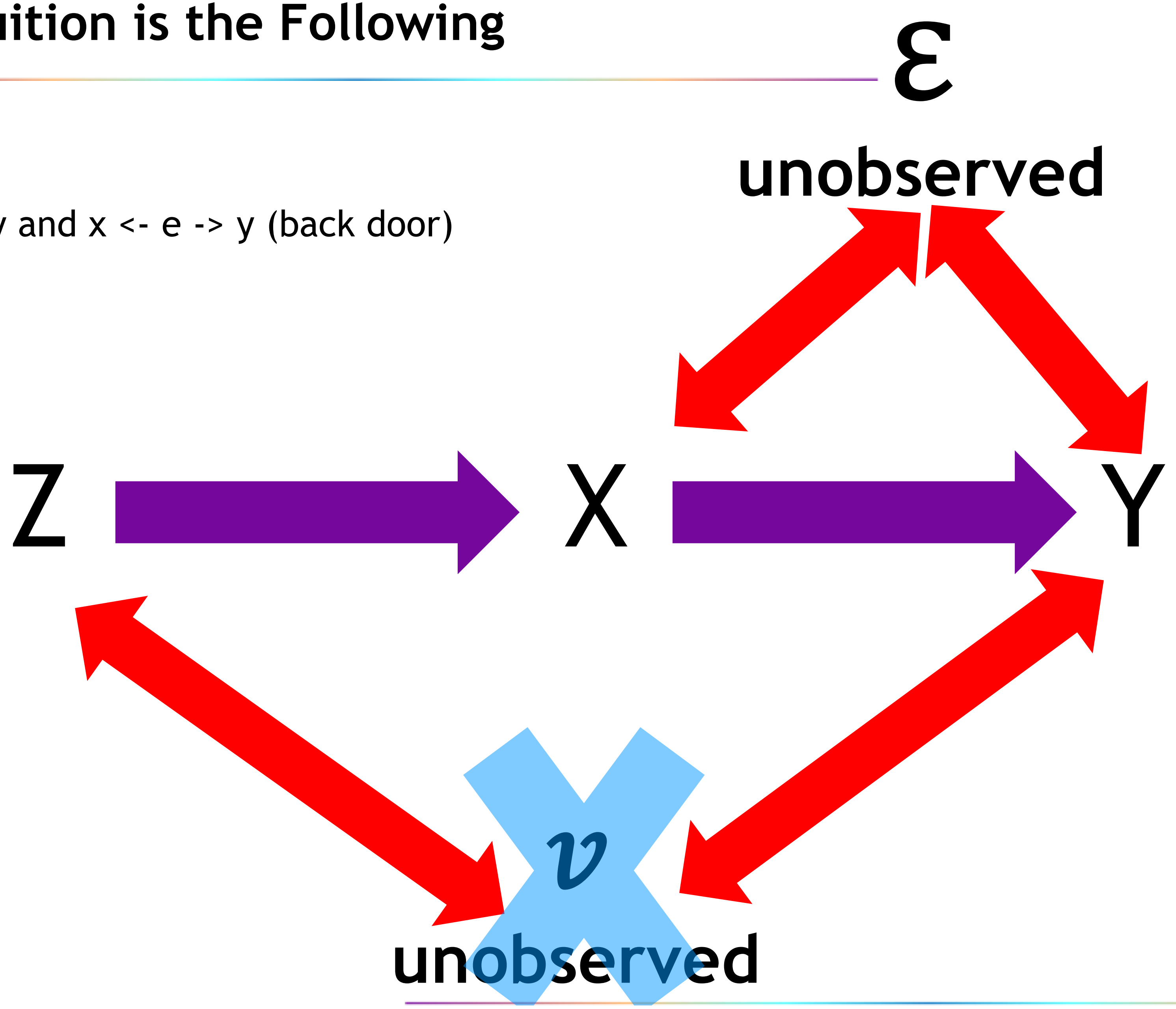
Cor (X, e) ! =0

This biases the coefficient of X

Find a solution by using a new variable Z with some special properties

Intuition is the Following

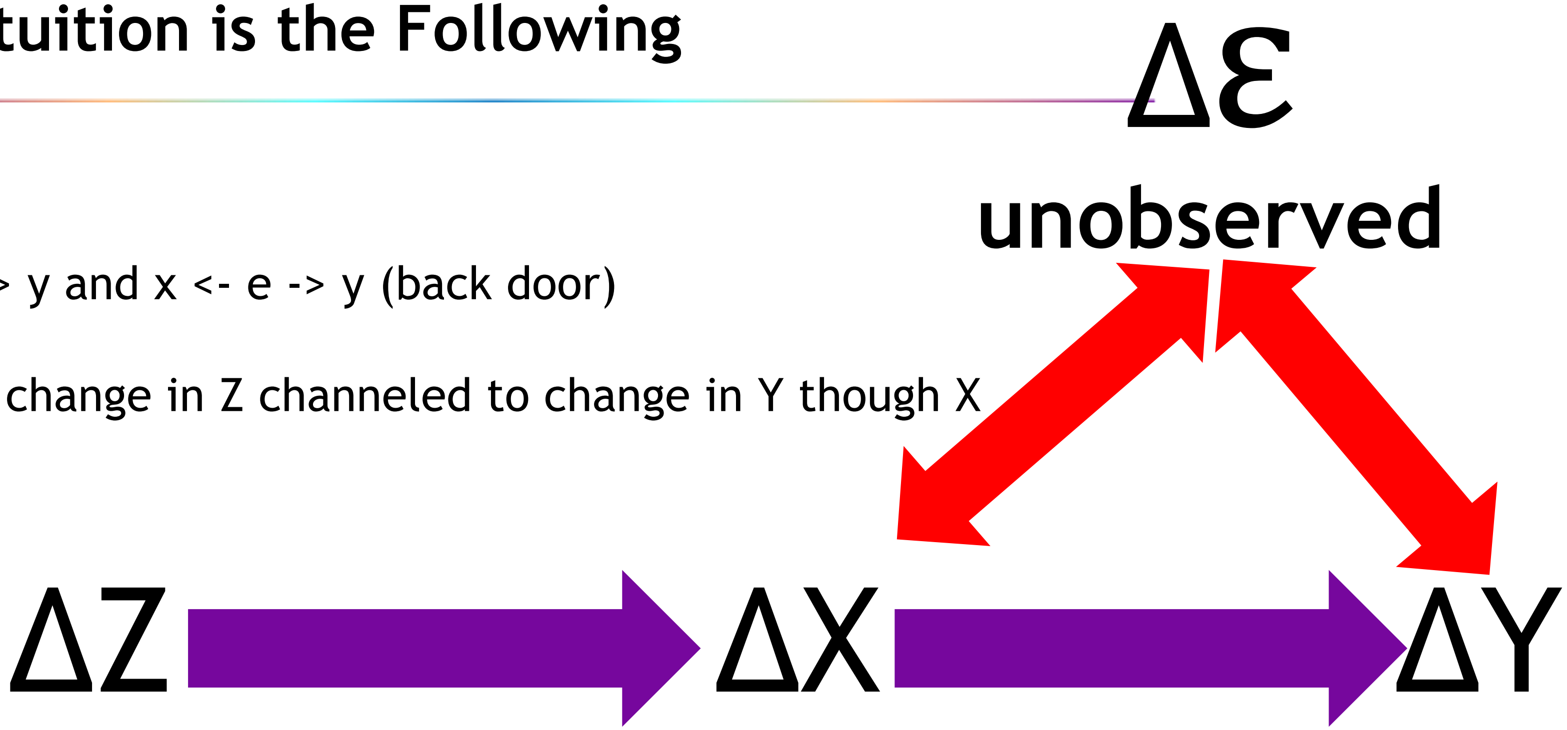
x -> y and x <- e -> y (back door)



Intuition is the Following

x -> y and x <- e -> y (back door)

All change in Z channeled to change in Y though X



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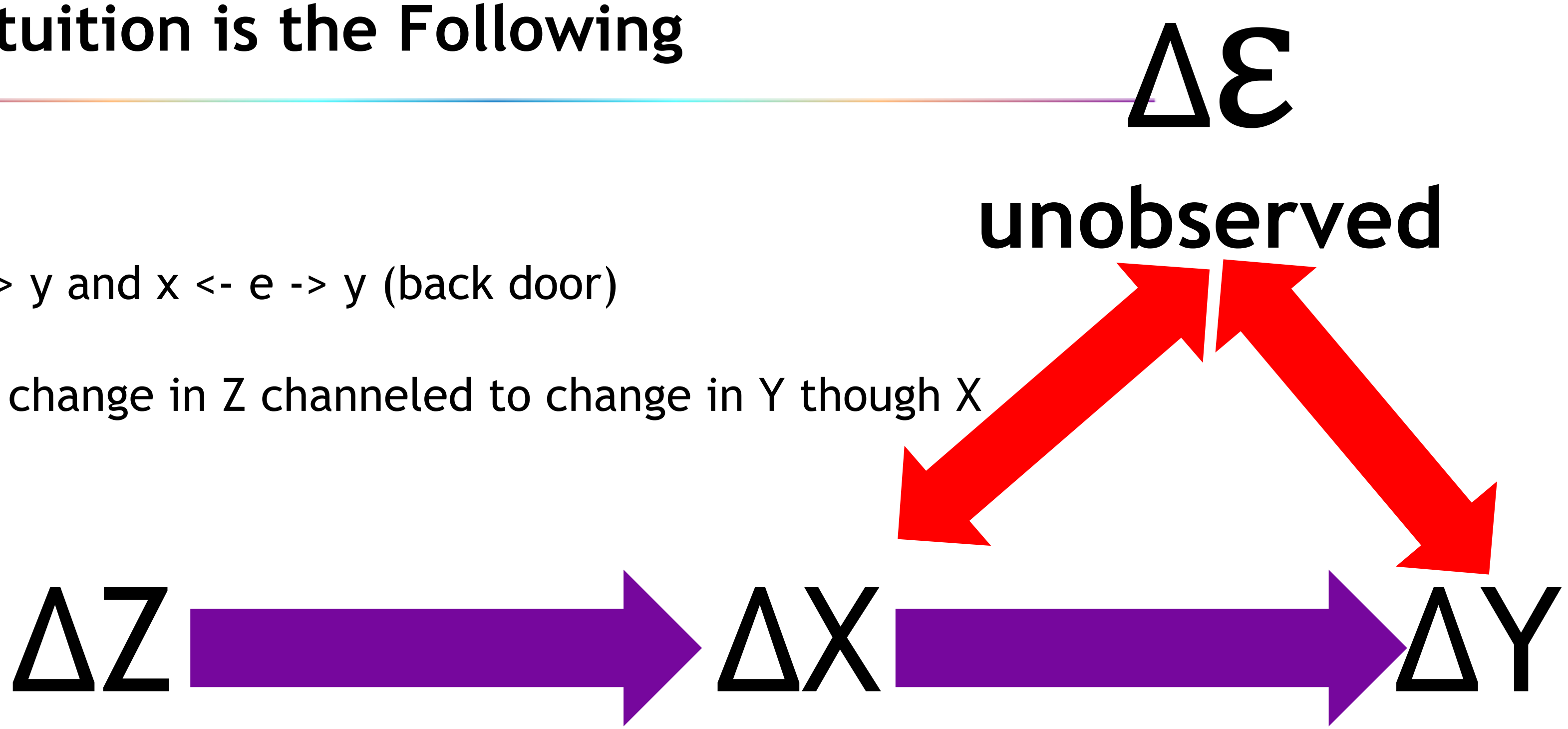


So, the change in Z can be used to measure how changes in X lead to changes in Y

Intuition: When Z changes, X also changes, but confounding variables like age, income etc. do not change. So, the change we observe in Y due to the change in X that occurred due to change in Y is purely the effect of X

Such a Z variable is called an **Instrumental Variable**, or IV

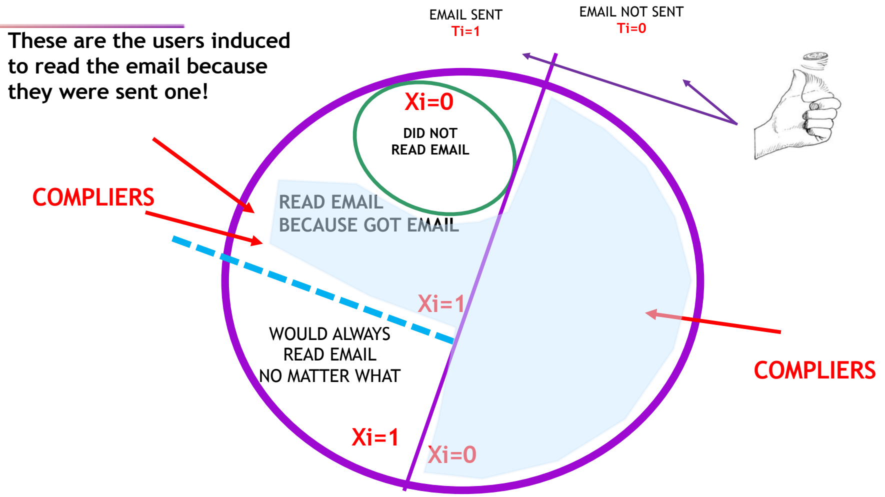
Using the Z variable

- **First stage**: X ~ c+ d Z + u. Find c and d
- Find predicted value of X using Xhat = c + d Z. This component of X depends only on Z and so is not correlated to e
- **Second stage**: Use the regression Y ~ a+ b Xhat + e instead of Y ~ a+ b X + e
- Since Xhat is uncorrelated with e, b is unbiased. We are now able to get a causal estimate of X on Y.

Checking that Z fullfills the criteria

- Our question dY/dX in Y=a+X*b+e
- Our problem: Cov(X,e)!=0
- Proposed solution: use a Z that
  - X=c+f*Z+v with f!=0 -- **significant first stage**
  - Cov(Z,e)=0
- **Ok… so we just "transferred" the problem in X to the same problem in Z**
- Note that we cannot know whether Cov(Z,e)=0 for the same reasons why we also do not know whether Cov(X,e)=0, namely, we cannot compute this because e is unknown
- **Is this any better?** Maybe… if you believe that Cov(Z,e)=0 **"more"** than you believe that Cov(X,e). However, "more" is not usually mathematically defined! **It's intuition!**

We have a great Z variable available



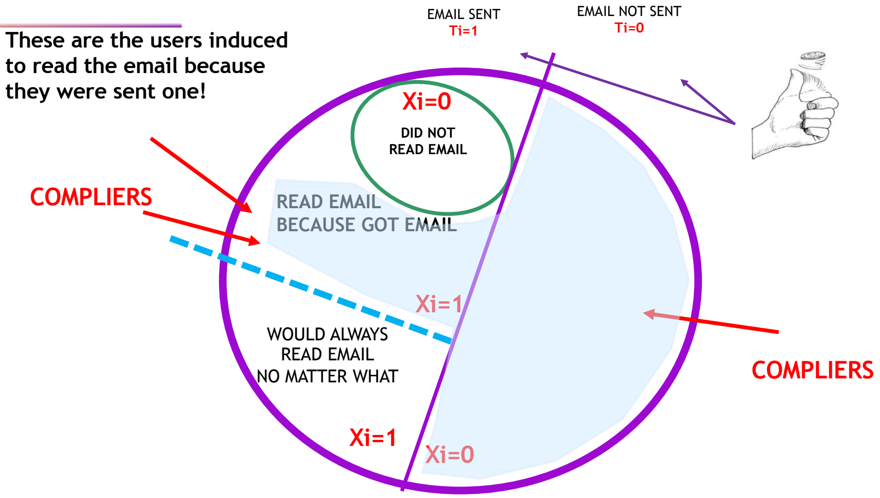
T → Y (ITT)

X → Y (LATE)

T → $\boxed{X \rightarrow Y}$

T is special by construction. Random assignment to T ensures that T is uncorrelated to e
Further, some people who get T=1 read the email. People who have T=0 can never read email.
So, T is correlated to X

How to find LATE?



T → Y (ITT)

X → Y (LATE)

T → $\boxed{X \rightarrow Y}$

Instrumental variable

Effect of Interest:

IVREG(Y ~ X | T)

Working out LATE: Example in Time Shift TV

- A random set of households (~24k); a set of channels that are good to watch with TSTV
- **TREATED**: Offered TSTV on these channels to a random subset of households (~12k)
- **CONTROL**: The remainder of the households obtained channels without TSTV (~12k)

- Find **AVERAGE EFFECT OF OFFERING TSTV ON THESE CHANNELS ON TV VIEWERSHIP**
- These will be **ITT EFFECTS**

- Descriptive statistics:

- min(MyData$week) > 1
- max(MyData$week) > 9
- unique(MyData$week) > 1 2 4 5 6 7 8 9
- length(unique(MyData$id)) > 23476
- length(unique(MyData$id[MyData$treated_tstv==TRUE])) > 11724
- length(unique(MyData$id[MyData$treated_tstv==FALSE])) > 11752
- min(unique(MyData$week[MyData$after==TRUE])) > 4
- max(unique(MyData$week[MyData$after==FALSE])) > 2

A/B Test – Balance should be obtained by design

- A – treated with channels without TSTV
- B – treated with channels with TSTV

- **Balance should be obtained by design**

A/B test balance

```
> t.test(MyData$view_time_total_hr[MyData$treated_tstv==0 & MyData$after==0], MyData$view_time_total_hr[MyData$treated_tstv==1 & MyData$after==0], alternative = c("two.sided"

	Welch Two Sample t-test

data:  MyData$view_time_total_hr[MyData$treated_tstv == 0 & MyData$after ==  and MyData$view_time_total_hr[MyData$treated_tstv == 1 & MyData$after ==     0] and     0]
t = -0.92973, df = 45645, p-value = 0.3525
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -0.08552405  0.03049200
sample estimates:
mean of x mean of y 
 4.640825  4.668341 

> t.test(MyData$view_time_live_hr[MyData$treated_tstv==0 & MyData$after==0], MyData$view_time_live_hr[MyData$treated_tstv==1 & MyData$after==0], alternative = c("two.sided"))

	Welch Two Sample t-test

data:  MyData$view_time_live_hr[MyData$treated_tstv == 0 & MyData$after ==  and MyData$view_time_live_hr[MyData$treated_tstv == 1 & MyData$after ==     0] and     0]
t = -0.54757, df = 45645, p-value = 0.584
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -0.06948615  0.03913923
sample estimates:
mean of x mean of y 
 4.237672  4.252846 

> t.test(MyData$view_time_tstv_hr[MyData$treated_tstv==0 & MyData$after==0], MyData$view_time_tstv_hr[MyData$treated_tstv==1 & MyData$after==0], alternative = c("two.sided"))

	Welch Two Sample t-test

data:  MyData$view_time_tstv_hr[MyData$treated_tstv == 0 & MyData$after ==  and MyData$view_time_tstv_hr[MyData$treated_tstv == 1 & MyData$after ==     0] and     0]
t = -1.2507, df = 45645, p-value = 0.2111
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -0.020005294  0.004419721
sample estimates:
mean of x mean of y 
0.3519868 0.3597795 
```

Intention to treat (ITT) estimates

	Dependent variable:		
	Total TV	Live TV	Time-Shift TV
	(1)	(2)	(3)
treated_tstv	0.102***	0.029*	0.061***
	(0.017)	(0.015)	(0.004)
Constant	4.430***	4.000***	0.380***
	(0.022)	(0.020)	(0.005)
Observations	136,858	136,858	136,858
Adjusted R2	0.003	0.002	0.002

Note: *p<0.1; **p<0.05; ***p<0.01

LATE: The effective effect of treatment

- **What is the effect on those that responded to treatment?**
- **That is, the effect on those that actually used TSTV to watch these channels?**

LATE: The effective effect of treatment

- **What is the effect on those that responded to treatment?**
- **That is, the effect on those that actually used TSTV to watch these channels?**
- The same as the ITT if there are no compliance issues
- **No compliance** issues means that households given TSTV **used it**
- **Define compliance:** a household complies with the treatment assignment if it uses TSTV for more than 90 in a single day at least once during the experiment

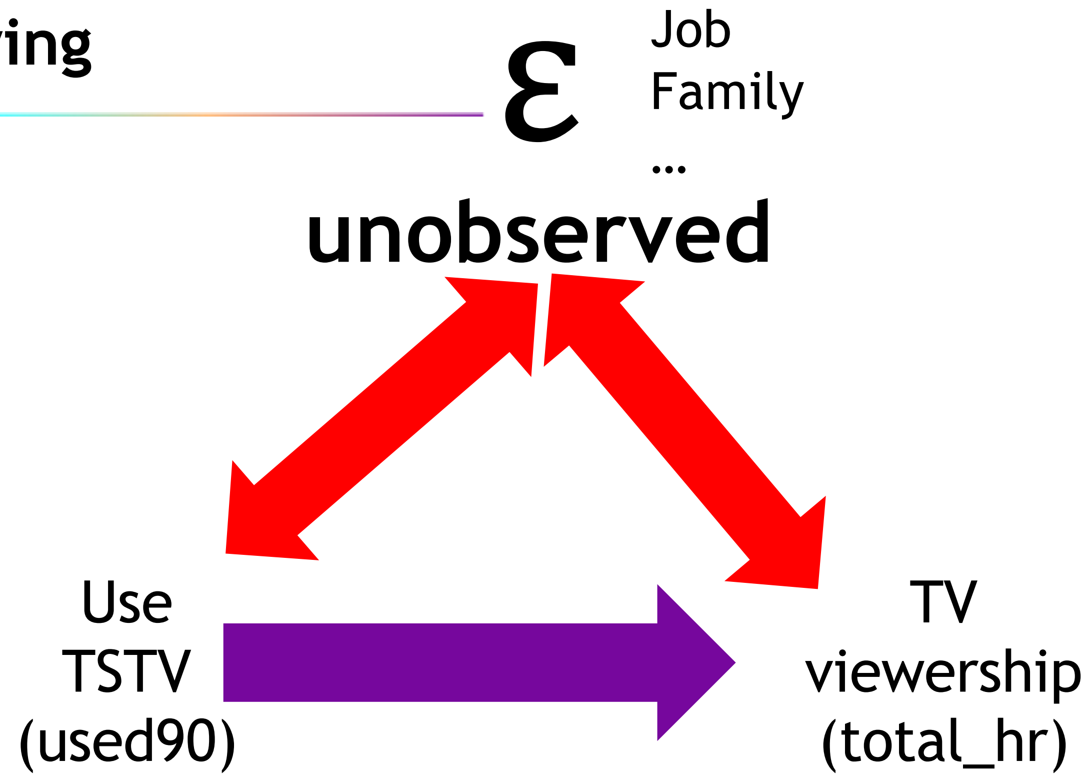
- However, we have compliance problems:

	treated_tstv	used90	n
1	0	0	11722
2	0	1	27
3	1	0	9246
4	1	1	2475

TSTV available, but did not use

Our Setting is the Following

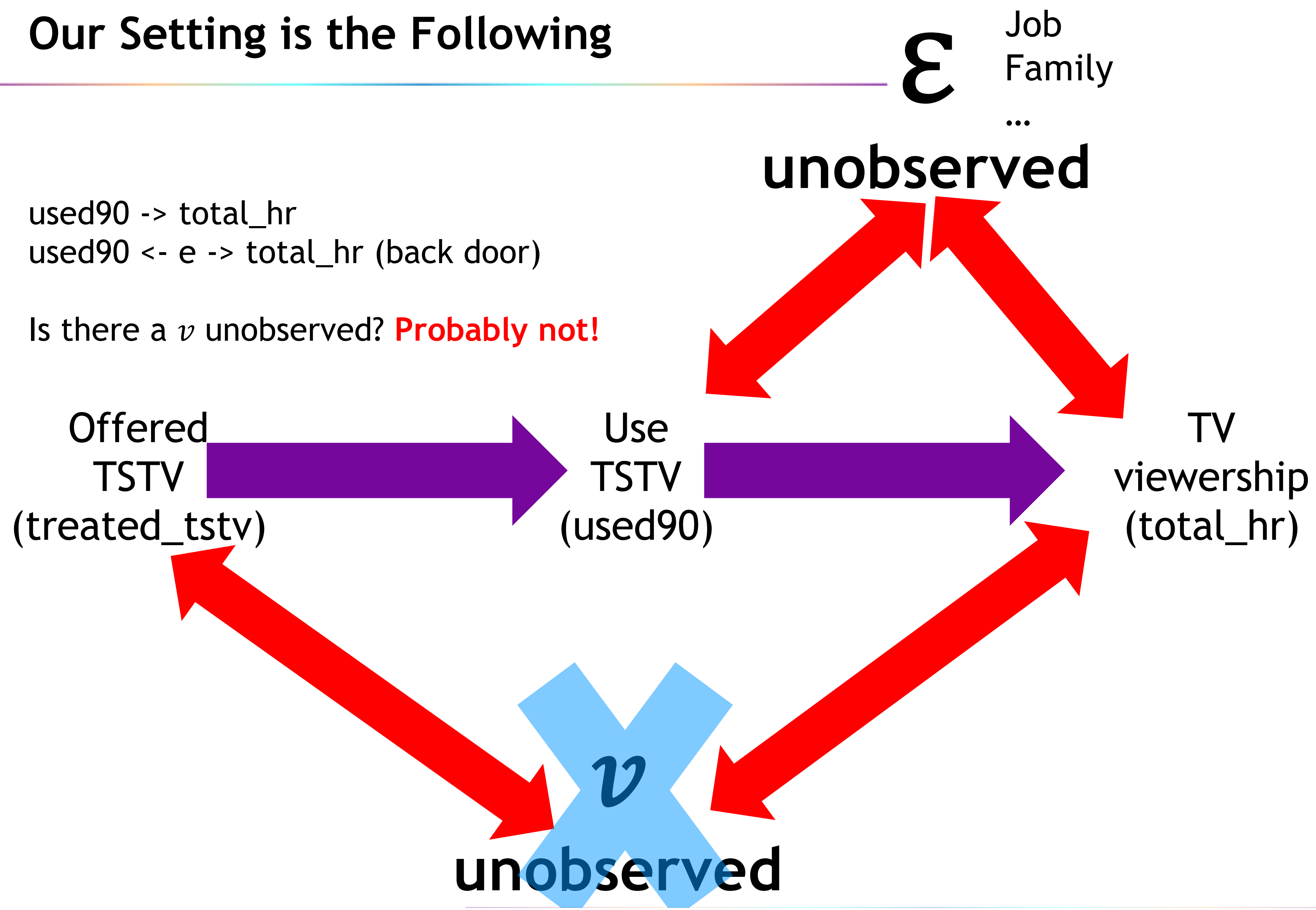
used90 -> total_hr
used90 <- e -> total_hr (back door)



Our Setting is the Following

used90 -> total_hr
used90 <- e -> total_hr (back door)

Is there a v unobserved? **Probably not!**



First Stage Regression

```
                 Dependent variable:
             ----------------------------
                       used90
----------------------------------------
treated_tstv          0.213***
                      (0.002)

Constant               0.002
                      (0.002)

----------------------------------------
Observations          136,858
Adjusted R2            0.117
========================================
Note:        *p<0.1; **p<0.05; ***p<0.01
```

The used90 variable is correlated with treated_tstv as seen above – so, we can use it as an IV

LATE

```
ivreg(view_time_total_hr ~ used90 + factor(week) | treated_tstv + factor(week)
data = MyData[after==TRUE]) (similarly for view_time_live_hr and view_time_tstv_hr)
```

	Dependent variable:					
	view_time_total_hr	view_time_live_hr	view_time_tstv_hr	view_time_total_hr	view_time_live_hr	view_time_tstv_hr
	OLS	OLS	OLS	instrumental variable	instrumental variable	instrumental variable
	(1)	(2)	(3)	(4)	(5)	(6)
treated_tstv	0.102***	0.029*	0.061***			
	(0.017)	(0.015)	(0.004)			
used90				0.479***	0.135*	0.287***
				(0.077)	(0.072)	(0.018)
Constant	4.430***	4.000***	0.380***	4.429***	4.000***	0.379***
	(0.022)	(0.020)	(0.005)	(0.022)	(0.020)	(0.005)
Observations	136,858	136,858	136,858	136,858	136,858	136,858
Adjusted R2	0.003	0.002	0.002	0.014	0.004	0.056

Summary of Compliance in A/B Test

- We looked at some examples of how to design randomized field experiments
- Need to **define the question** leading to **definition of treatment and control**
- Need to be **able to (intent to) treat units of analysis** with the treatment
- Need to **measure the outcome variable for treated and control units of analysis**

- A simple comparison between treated and control yields the **Intention to Treat (ITT)**
- The Intention to Treat **does not generalize to other strategies to induce treatment**

- The true effect of treatment is (most likely) larger in magnitude than the ITT
- The effect can **only be obtained for units that respond to treatment assignment**

- The true effect of treatment is obtained using **instrumental variables regression**
- We stack two regressions: treated on treatment assignment and outcome on former