ISID
INSTITUTE FOR THE STUDY OF INTERNATIONAL DEVELOPMENT
INSTITUT D'ÉTUDE DU DÉVELOPPEMENT INTERNATIONAL

WED LAB

Using Quantitative Methodologies to Study Women's Empowerment

Women's Empowerment in Development (WED) Lab Seminar Series

McGill UNIVERSITY

IDRC | CRDI
International Development Research Centre
Centre de recherches pour le développement international

Panelists

Franque Grimard, McGill University (Facilitator)

Carl Asuncion, MEDA

Bouba Housseini, IDRC

Seminar/Webinar Format

- Opening presentation by facilitator
- Audience Q&A

Break

- Expert panel discussion
- Audience Q&A

Participants on Zoom can email questions to: kathleen.grantham@mcgill.ca

Dr. Franque Grimard (Facilitator)

Associate Professor, Department of Economics,
McGill University

Using Quantitative Methodologies to Study Women's Empowerment

Franque Grimard
McGill University

Today's Presentation

- Why measure quantitatively, Why and when use IE ?
- Impact Evaluation Principles: Counterfactual
- Examples from Progresa
- Randomization: RCTs
- Discussion
- Appendices
  - Other techniques: RDD, DiD, PSM
  - Examples
  - Web links

Principles for Measuring the impact of Programs

- This material is based on a recent book on Impact Evaluation:
  - Gertler, P. J.; Martinez, S., Premand, P., Rawlings, L. B. and Christel M. J. Vermeersch, 2016, Impact Evaluation in Practice: 2nd Edition, The World Bank, Washington DC (www.worldbank.org/ieinpractice).

Monitoring

A continuous process of collecting and analyzing information,

- to compare how well a project, program or policy is performing against expected results, and
- to inform implementation and program management.

Evaluation

A systematic, objective assessment of an on-going or completed project, program, or policy, its design, implementation and/or results,

- to determine the relevance and fulfillment of objectives, development efficiency, effectiveness, impact and sustainability, and
- to generate lessons learned to inform the decision making process,
- tailored to key questions.

Impact Evaluation

An assessment of the **causal** effect of a project , program or policy on beneficiaries. ***Uses a counterfactual…***

- to estimate what the state of the beneficiaries would have been in the absence of the program *(the control or comparison group),* compared to the observed state of beneficiaries *(the treatment group),* and
- to determine intermediate or final outcomes attributable to the intervention .

When to use Impact Evaluation?

Evaluate impact when project is:

- Innovative
- Replicable/scalable
- Strategically relevant for reducing poverty
- Evaluation will fill knowledge gap
- Substantial policy impact

Use impact evaluation within a program to test alternatives and improve programs

MEASURING IMPACT

Impact Evaluation Principles for Researchers, Decision and Policy Makers

Our Objective

Estimate the causal effect (impact) of intervention (P) on outcome (Y).

(P) = Program or Treatment

(Y) = Indicator, Measure of Success

Our Objective

Estimate the causal effect (impact) of intervention (P) on outcome (Y).

(P) = Program or Treatment

(Y) = Indicator, Measure of Success

Example: What is the effect of a Cash Transfer Program (P) on Household Consumption (Y)?

Causal Inference

What is the impact of (P) on (Y)?

Causal Inference

What is the impact of (P) on (Y)?

$$\alpha = (Y \mid P=1) - (Y \mid P=0)$$

Causal Inference

What is the impact of (P) on (Y)?

$$\alpha = (Y \mid P=1) - (Y \mid P=0)$$

Can we all go home?

Problem of Missing Data

$$\alpha = (Y \mid P=1) - (Y \mid P=0)$$

For a program beneficiary:

we observe
(Y | P=1): Household Consumption (Y) with a cash transfer program (P=1)

but we do not observe
(Y | P=0): Household Consumption (Y) without a cash transfer program (P=0)

Solution ?

- Estimate what ***would*** have happened to *Y* in the absence of *P*.

Solution ?

- Estimate what ***would*** have happened to *Y* in the absence of *P*.

We call this the **Counterfactual.**

Solution ?

- Estimate what ***would*** have happened to *Y* in the absence of *P*.

We call this the **Counterfactual.**

Estimating impact of *P* on *Y*

$$\alpha = (Y \mid P=1) - (Y \mid P=0)$$

OBSERVE $(Y \mid P=1)$

Outcome with treatment

ESTIMATE $(Y \mid P=0)$

The Counterfactual

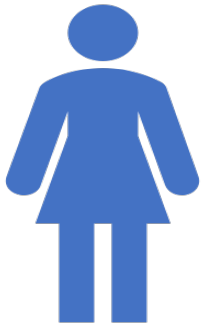
IMPACT = Outcome with treatment - counterfactual

- Intention to Treat (**ITT**) –*Those to whom we wanted to give treatment*
- Treatment on the Treated (**TOT**) – *Those actually receiving treatment*

- Use **comparison** or **control** group

Example: What is the Impact of…

Giving Maria



Example: What is the Impact of…

Giving Maria

additional pocket money

(P)

Example: What is the Impact of…

Giving Maria

additional pocket money

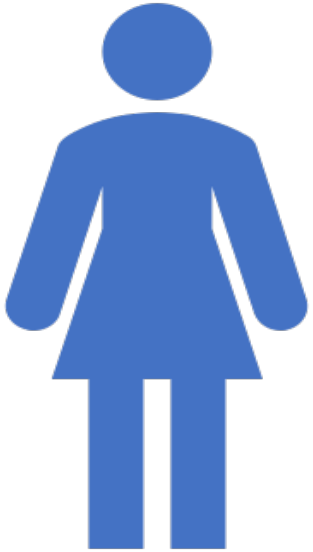
(P)

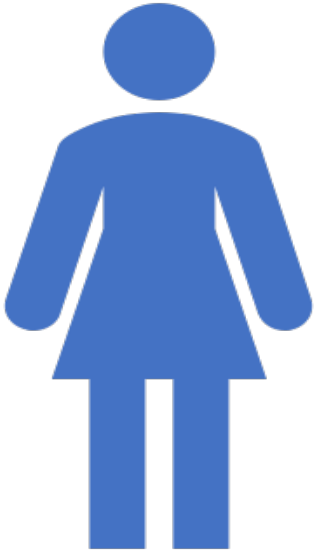
On Maria's consumption of candies

(Y)?

The Perfect *Clone*

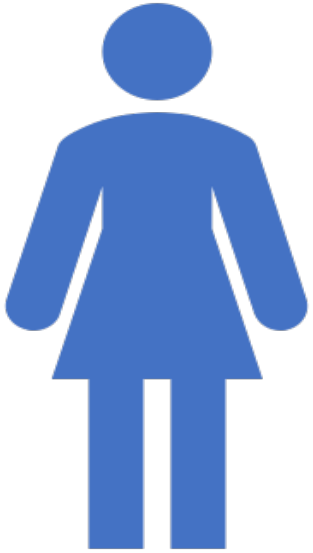
Maria





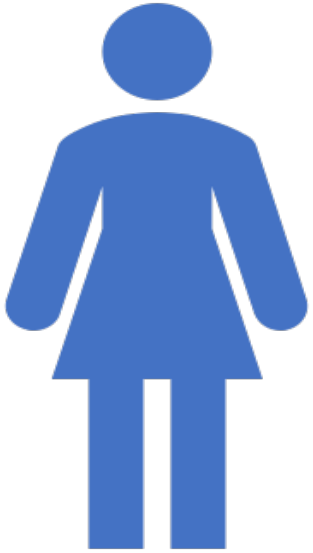
The Perfect *Clone*

Maria



The Perfect *Clone*

Maria

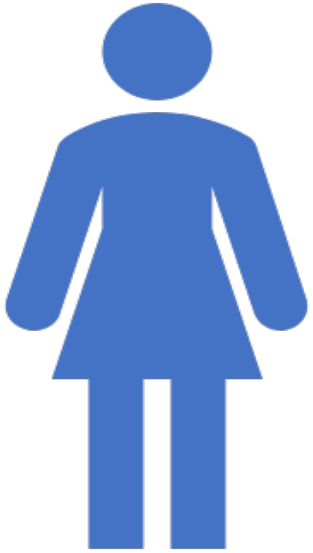


X

Maria's Clone

The Perfect *Clone*

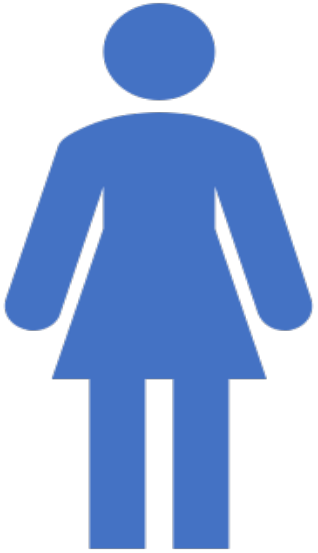
Maria



6 candies

X

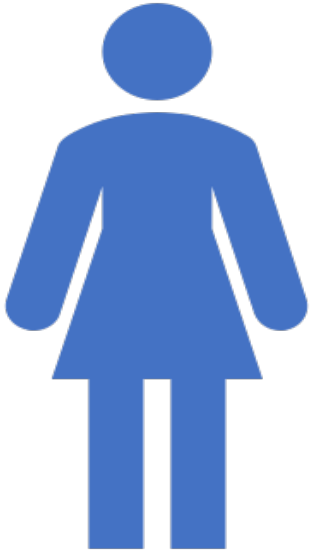
Maria's Clone



4 candies

The Perfect *Clone*

Maria



6 candies

X

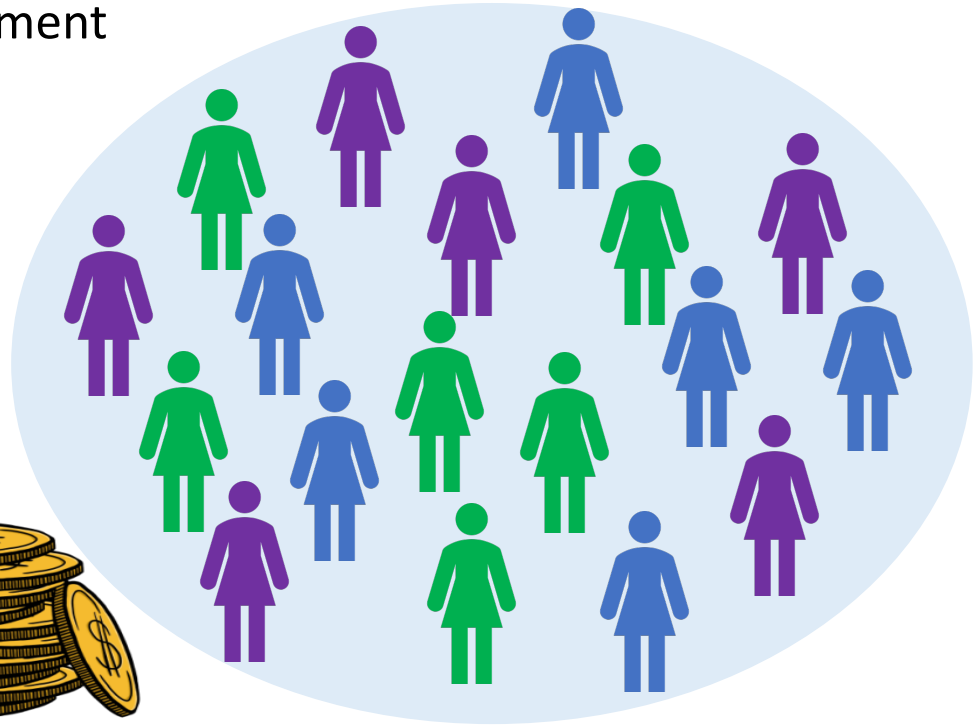
Maria's Clone

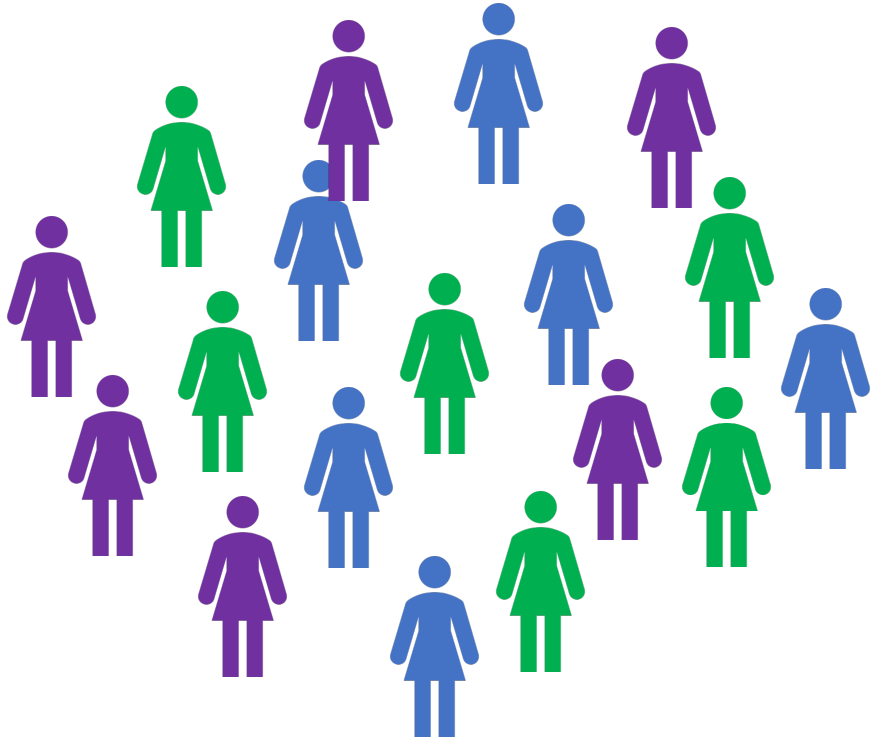
4 candies

IMPACT=6-4=2 Candies

In reality, use statistics

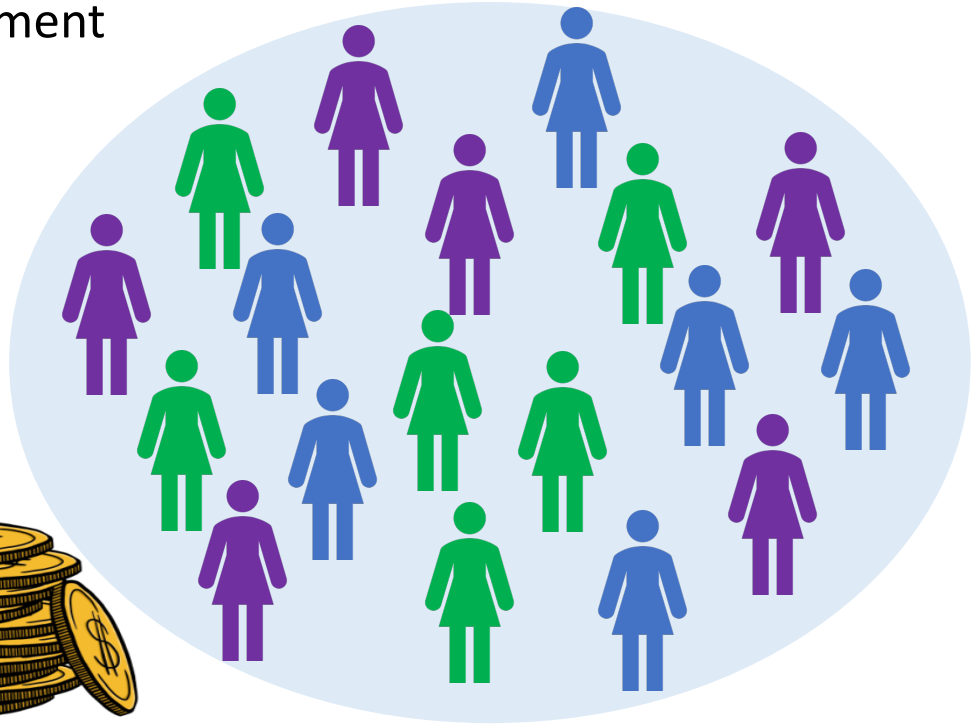
Treatment





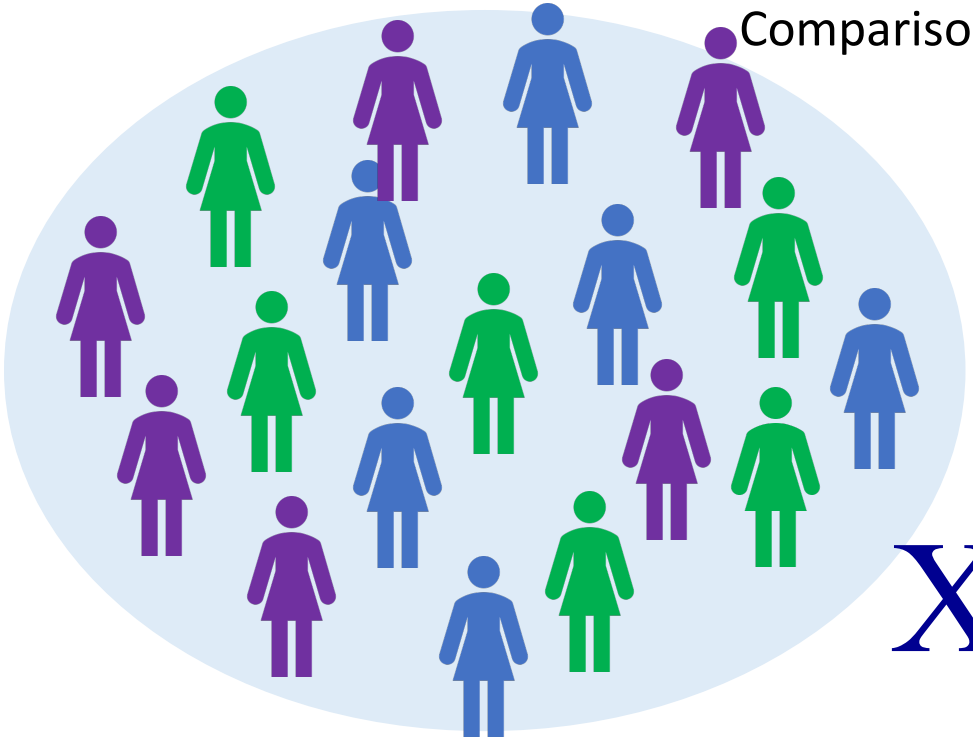
In reality, use statistics

Treatment



Average Y=6 candies

Comparison

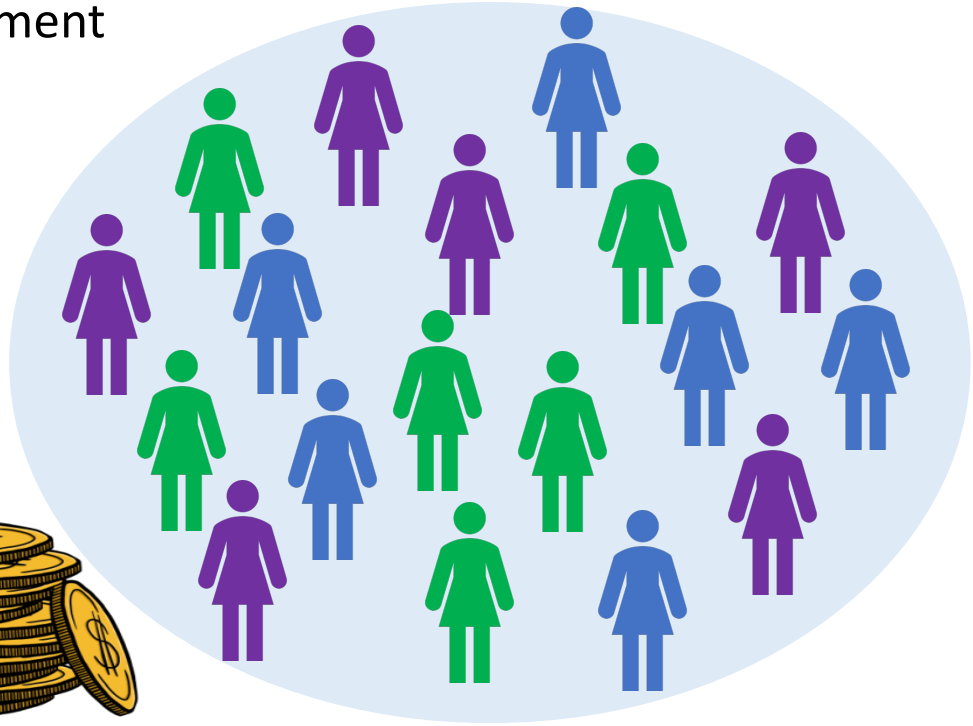


X

Average Y=4 Candies

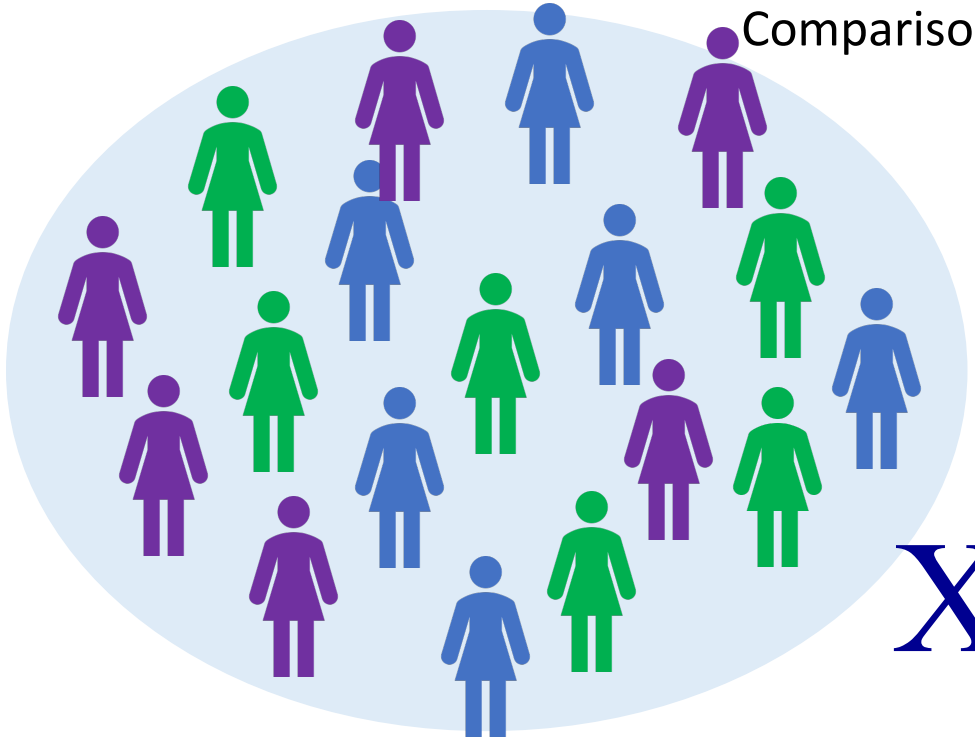
In reality, use statistics

Treatment



Average Y=6 candies

Comparison



X

Average Y=4 Candies

IMPACT=6-4=2 Candies

Finding good comparison groups

We want to find **clones** for the Marias in our programs.

The treatment and comparison groups should

- have identical characteristics
- except for benefiting from the intervention.

In practice, use program eligibility & assignment rules to construct valid counterfactuals

Finding good comparison groups

We want to find **clones** for the Marias in our programs.

The treatment and comparison groups should

- have identical characteristics
- [illegible] the intervention.

[illegible]ity & assignment rules to construct valid
[illegible]nterfactuals

With a good comparison group, the only reason for different outcomes between treatments and comparisons is the intervention (P)

ISID
INSTITUTE FOR THE STUDY OF INTERNATIONAL DEVELOPMENT
INSTITUT D'ÉTUDE DU DÉVELOPPEMENT INTERNATIONAL

WED LAB

Finding good Comparison Groups: Impact Evaluation Methods Toolbox

Randomization: Assignment or Offering/Promotion

Finding good Comparison Groups: Impact Evaluation Methods Toolbox

Randomization: Assignment or Offering/Promotion

Discontinuity Design

Finding good Comparison Groups: Impact Evaluation Methods Toolbox

Randomization: Assignment or Offering/Promotion

Discontinuity Design

Difference-in-Differences

Finding good Comparison Groups: Impact Evaluation Methods Toolbox

Randomization: Assignment or Offering/Promotion

Discontinuity Design

Difference-in-Differences

Matching

Finding good Comparison Groups: Impact Evaluation Methods Toolbox

Case Study: Progresa

National anti-poverty program in Mexico

- Started 1997
- 5 million beneficiaries by 2004

Case Study: Progresa

National anti-poverty program in Mexico

- Started 1997
- 5 million beneficiaries by 2004
- Eligibility – based on poverty index

Cash Transfers

- Conditional on school and health care attendance.

Case Study: Progresa

- Rigorous impact evaluation with rich data
  - 506 communities, 24,000 households
  - Baseline 1997, follow-up 1998

- Many outcomes of interest

  Here: Consumption per capita

- What is the effect of Progresa (P) on Consumption Per Capita (Y)?
  - If impact is an increase of **$20** or more,
  - then scale up nationally

Case Study: Progresa

- How do we find counterfactuals?

1. False counterfactual #1

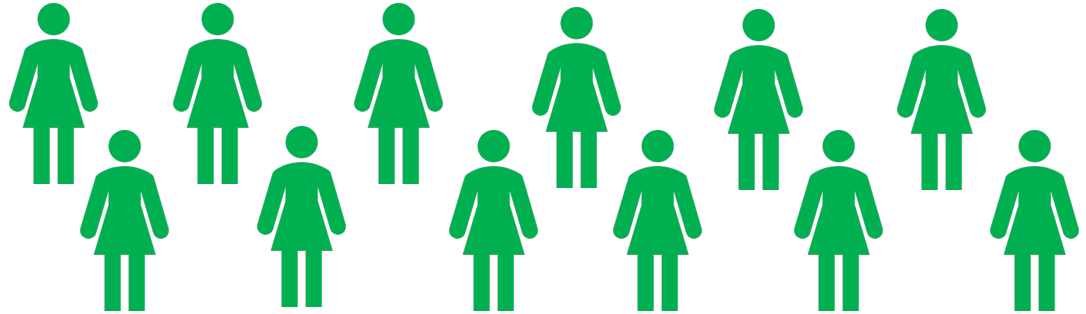
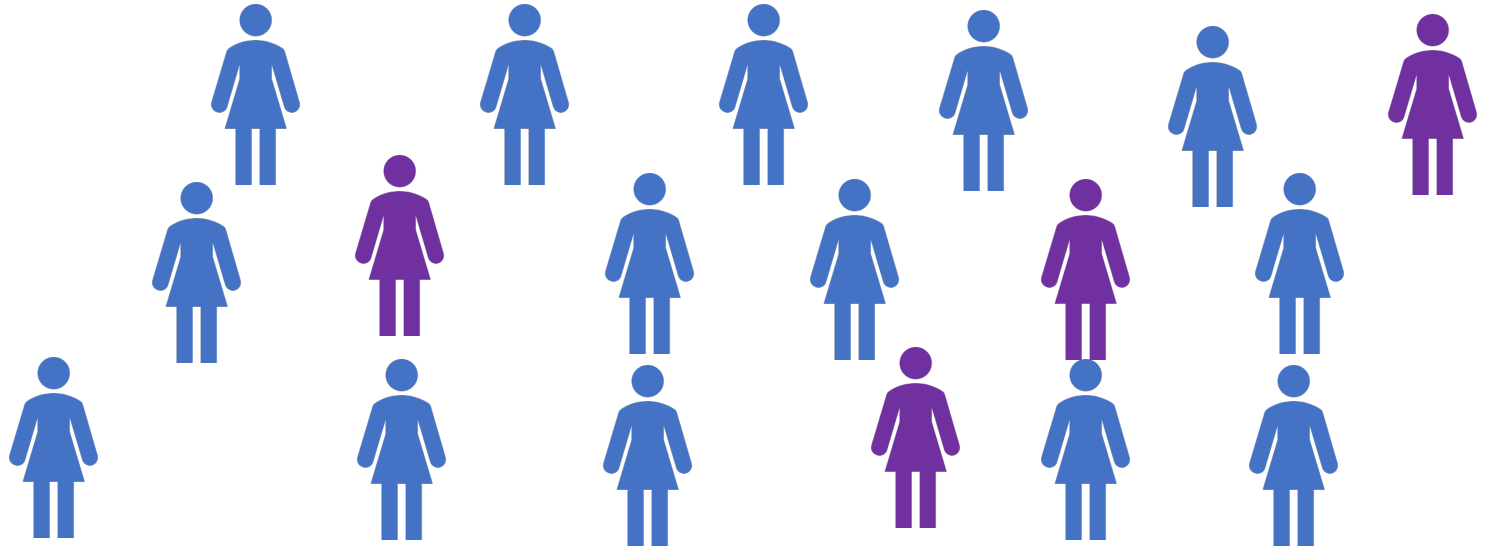
Before and after

2. False counterfactual #2

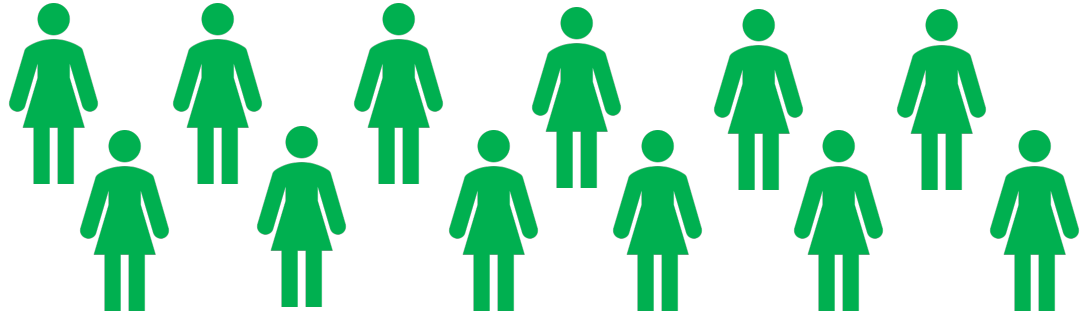
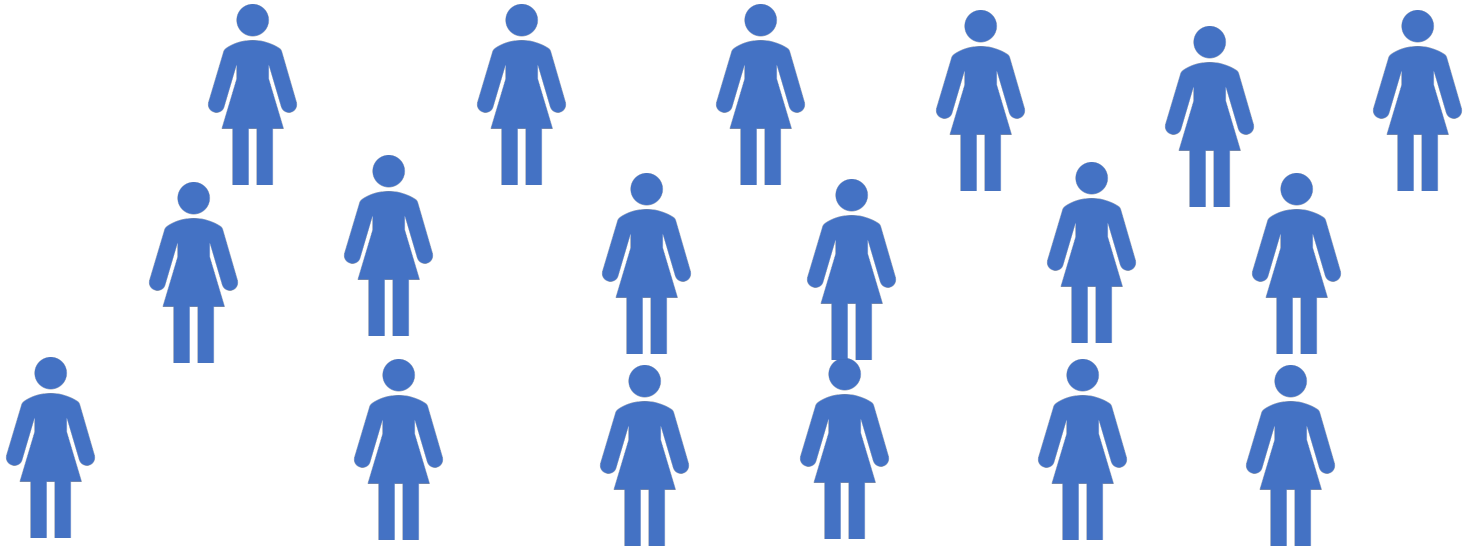
Looking at enrollment/eligibility:

- enrolled vs non-enrolled

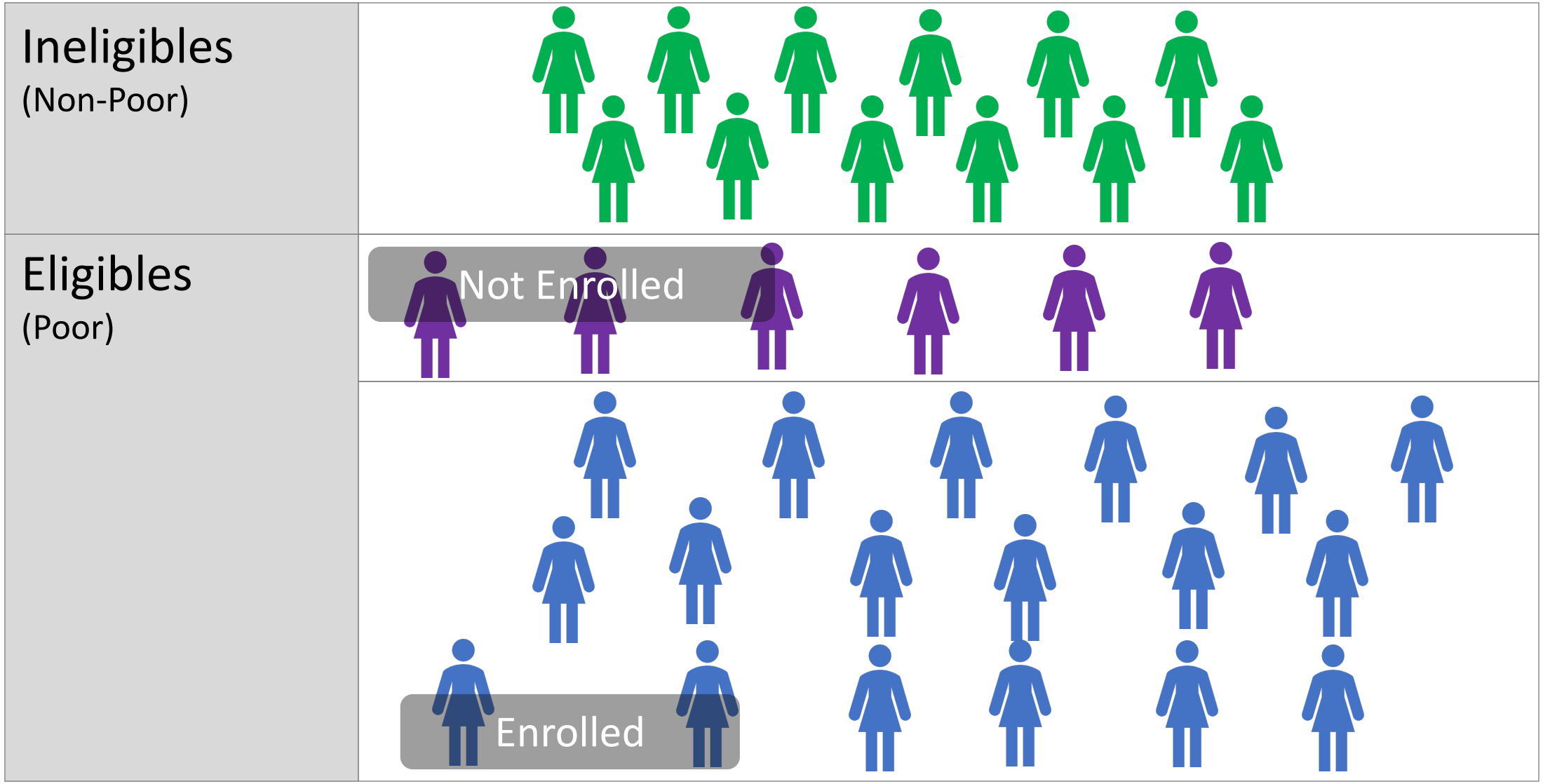
Eligibility and Enrollment

Ineligibles (Non-Poor)	
Eligibles (Poor)	 

Eligibility and Enrollment

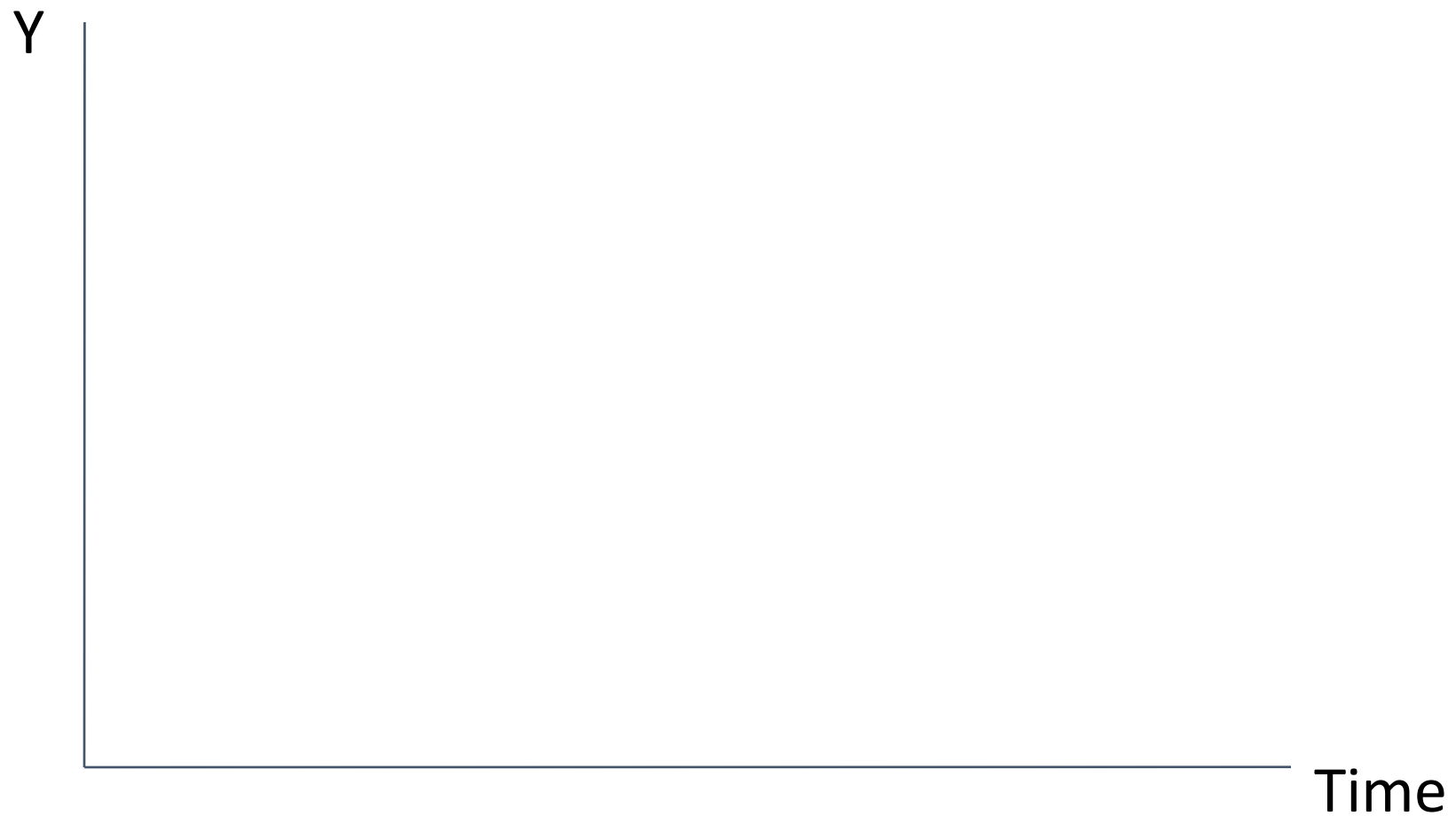
Ineligibles (Non-Poor)	
Eligibles (Poor)	
	

Eligibility and Enrollment



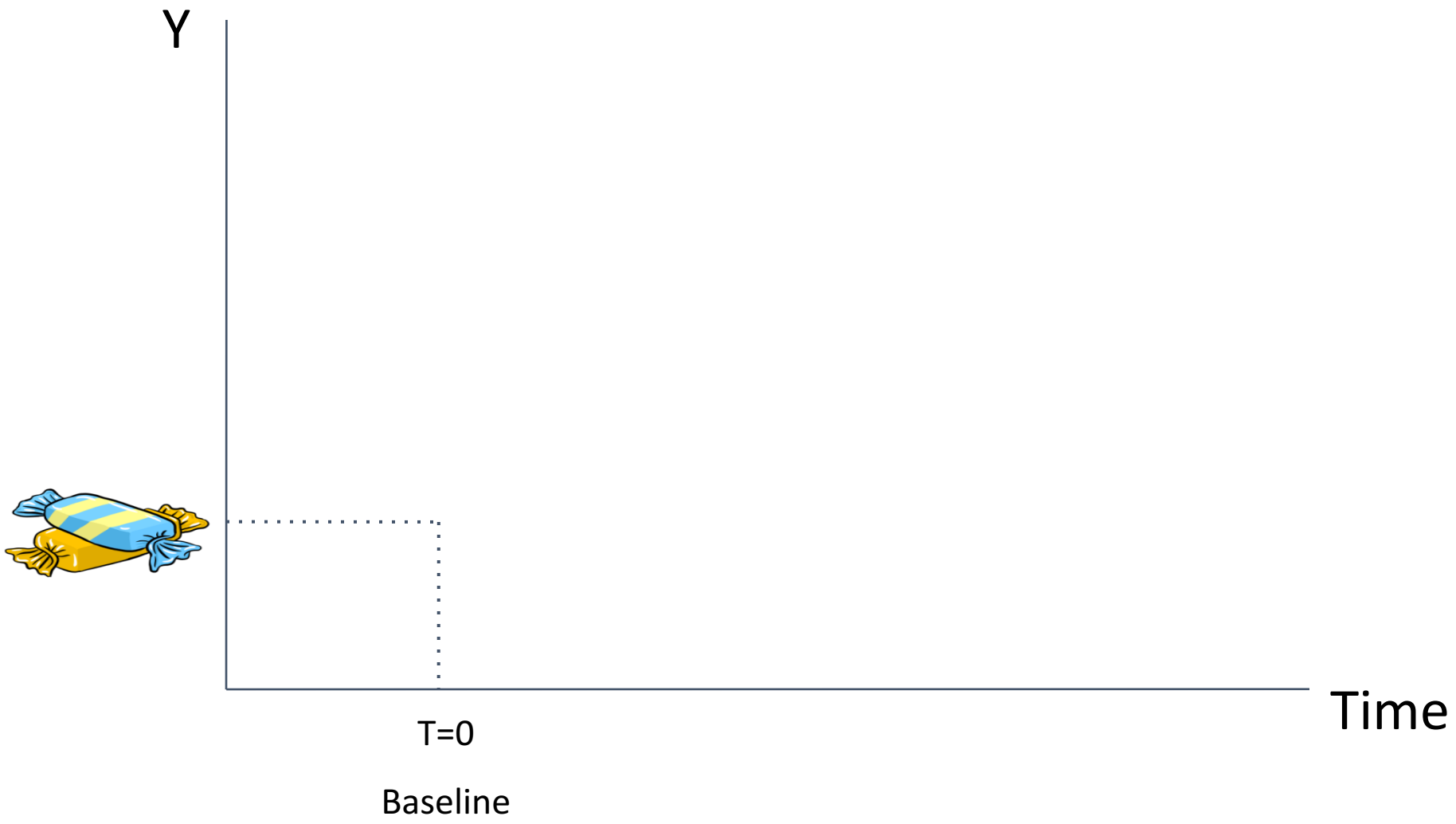
False Counterfactual #1

Before & After



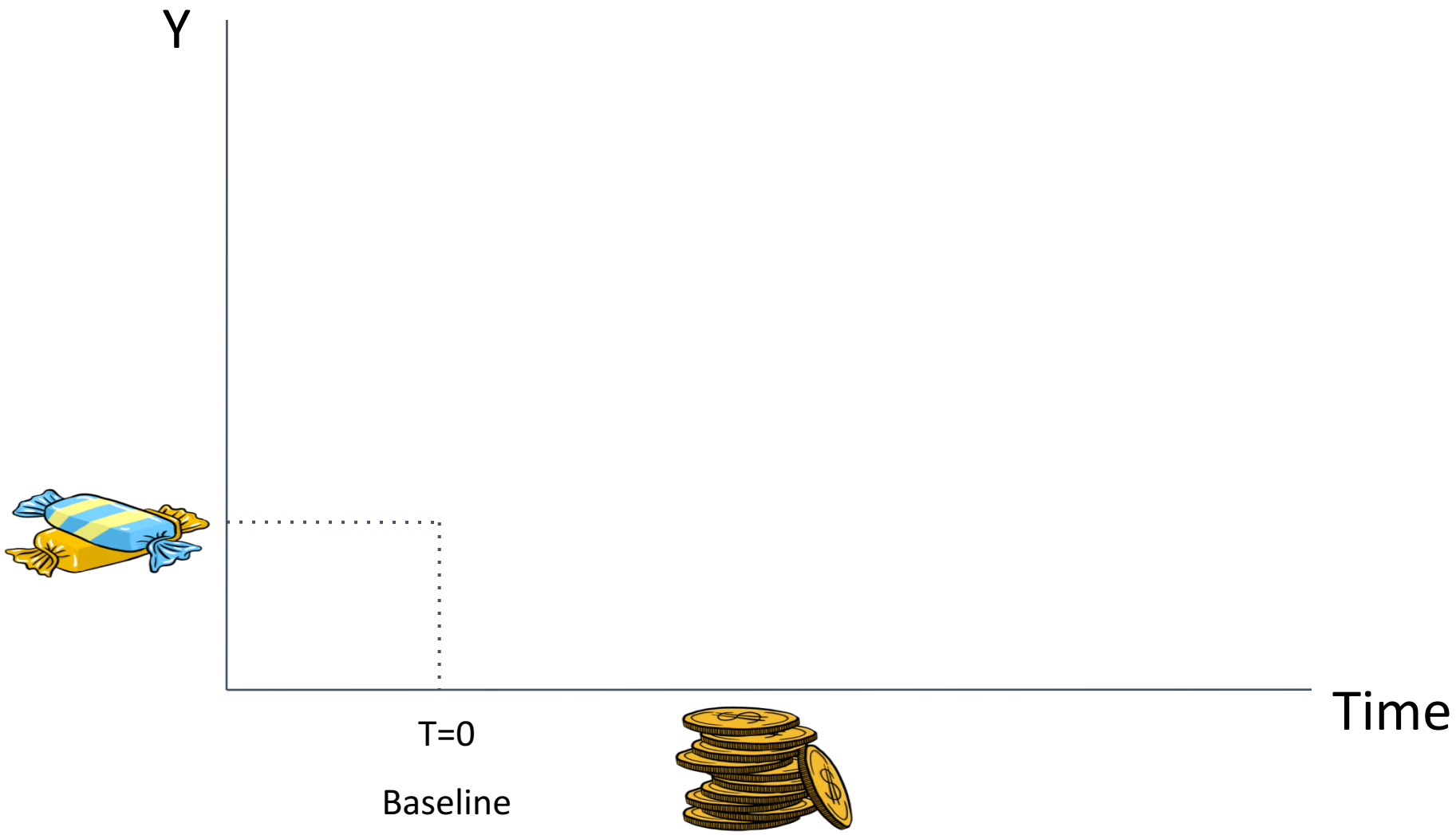
False Counterfactual #1

Before & After



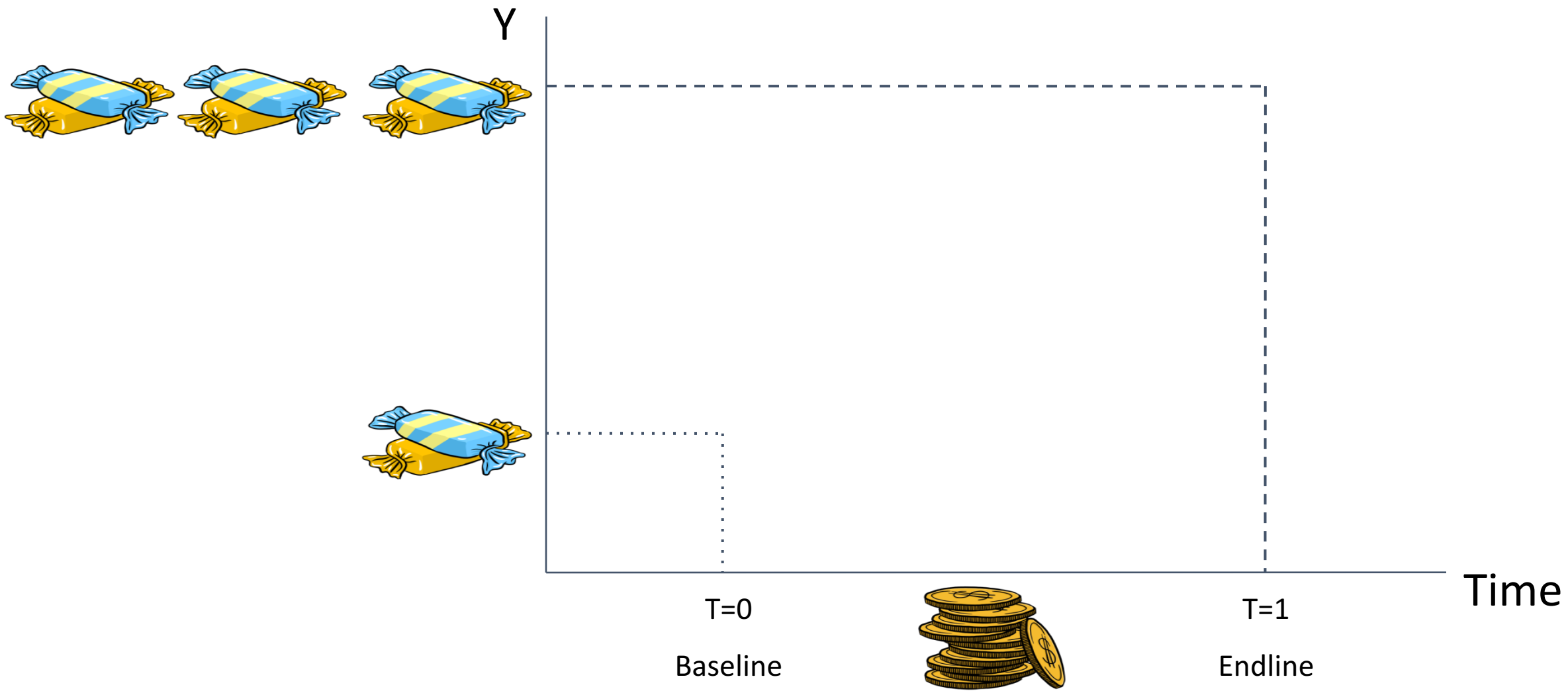
False Counterfactual #1

Before & After



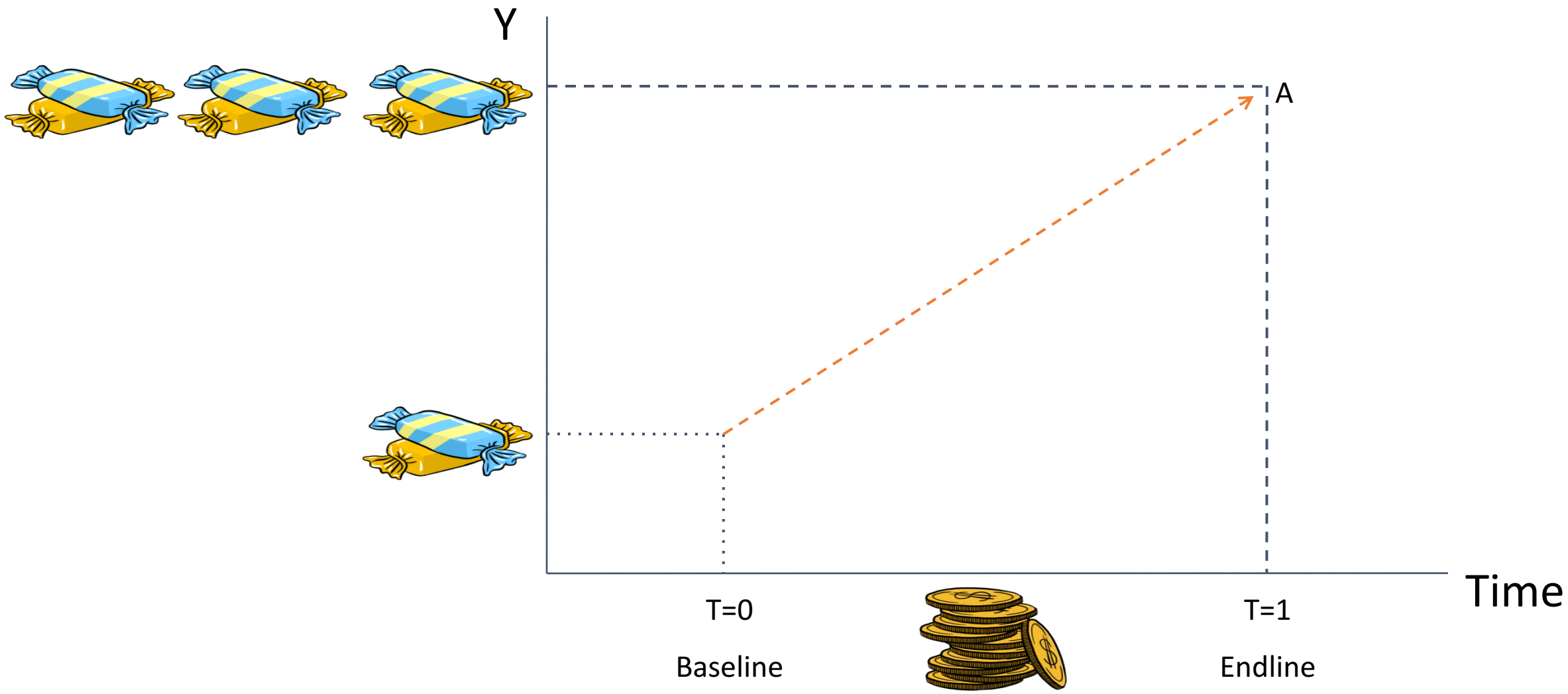
False Counterfactual #1

Before & After



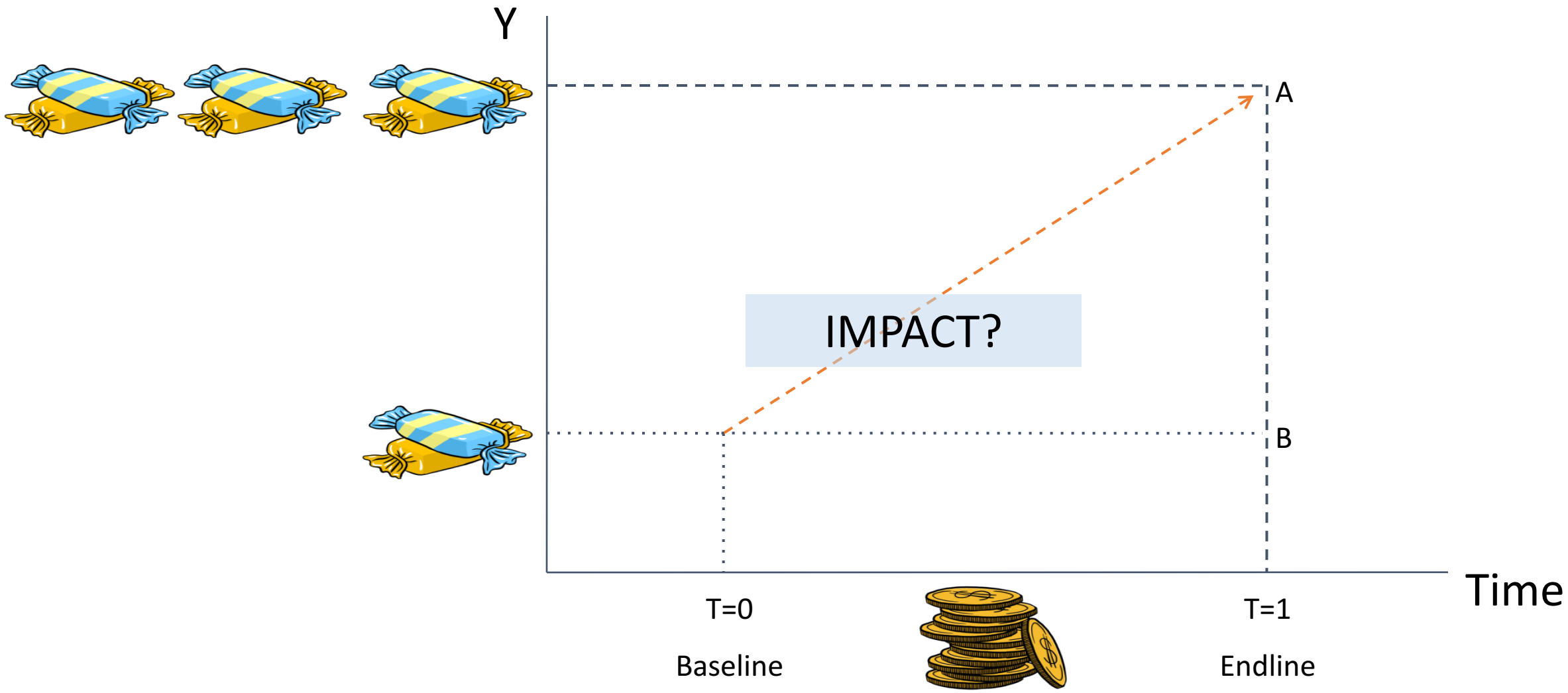
False Counterfactual #1

Before & After



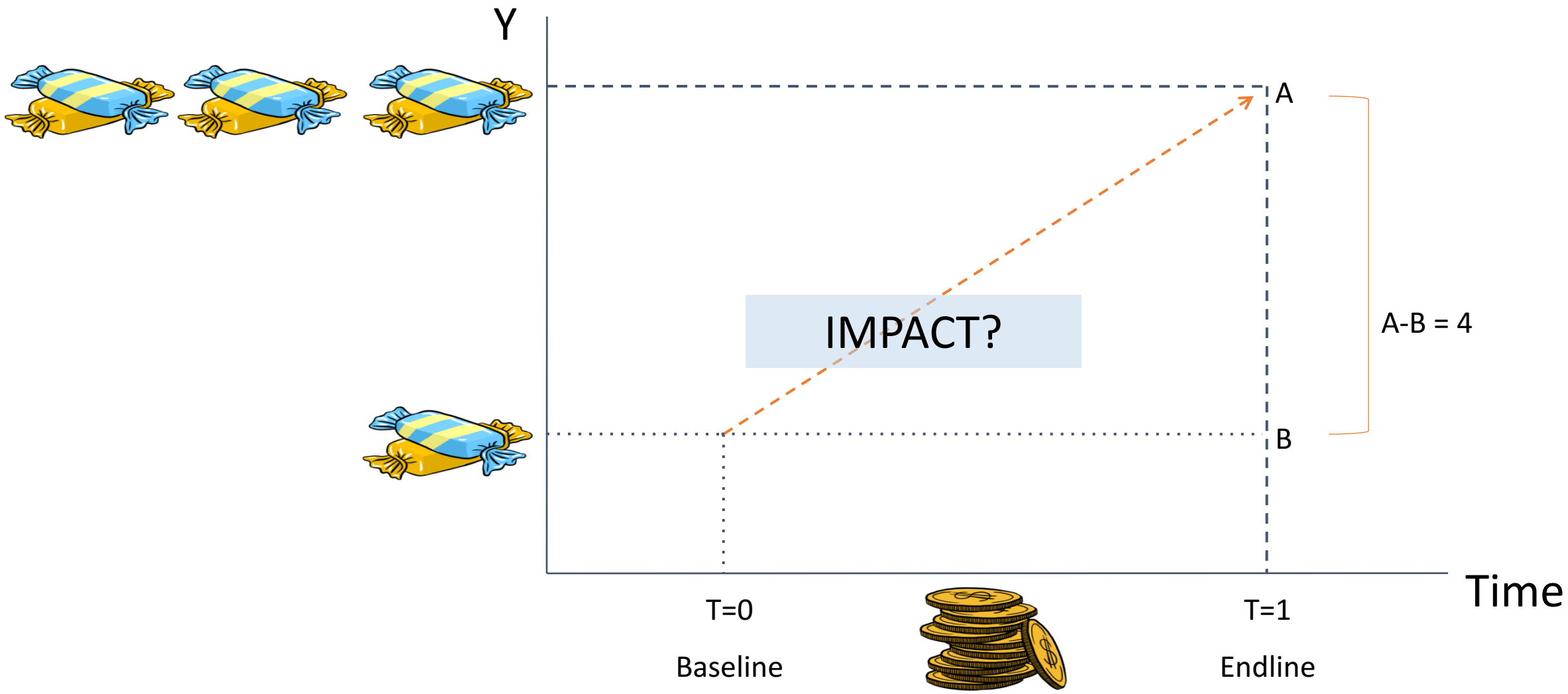
False Counterfactual #1

Before & After



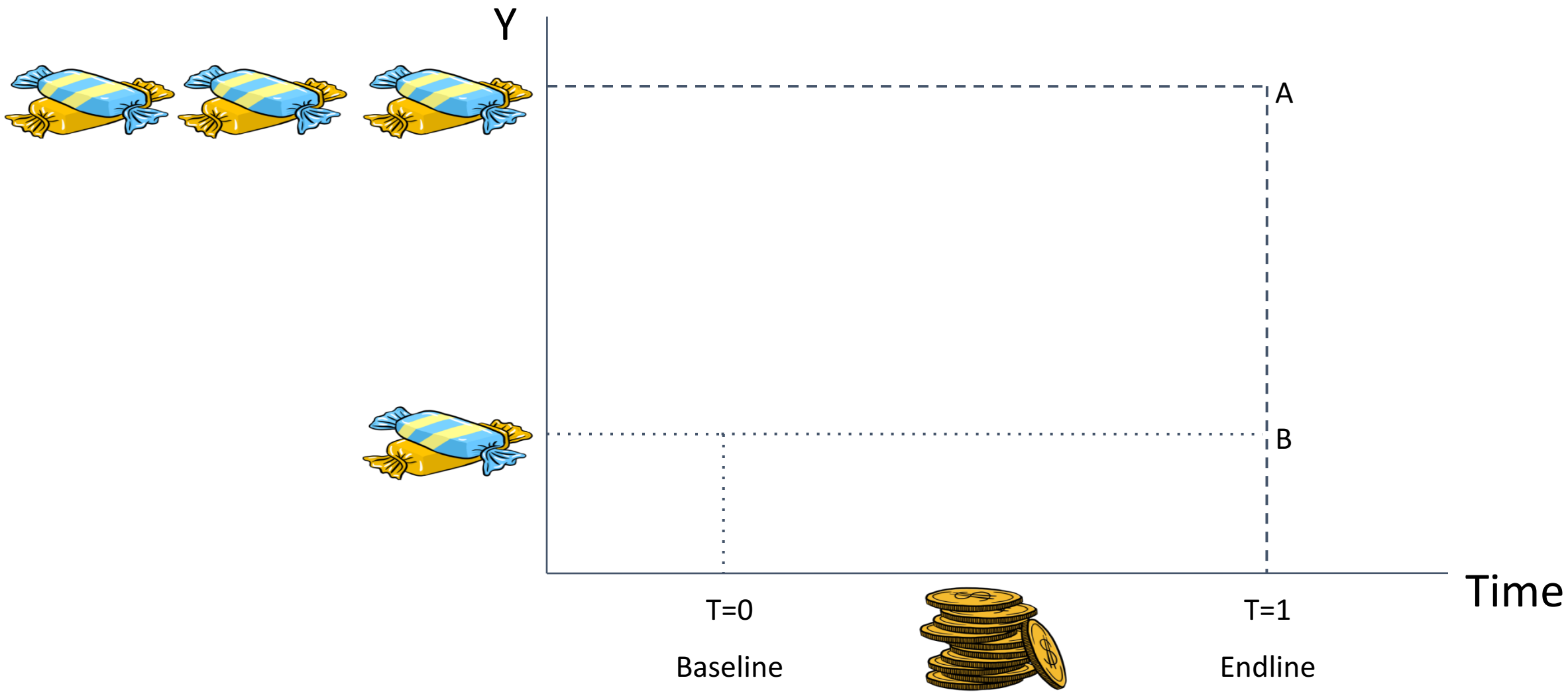
False Counterfactual #1

Before & After



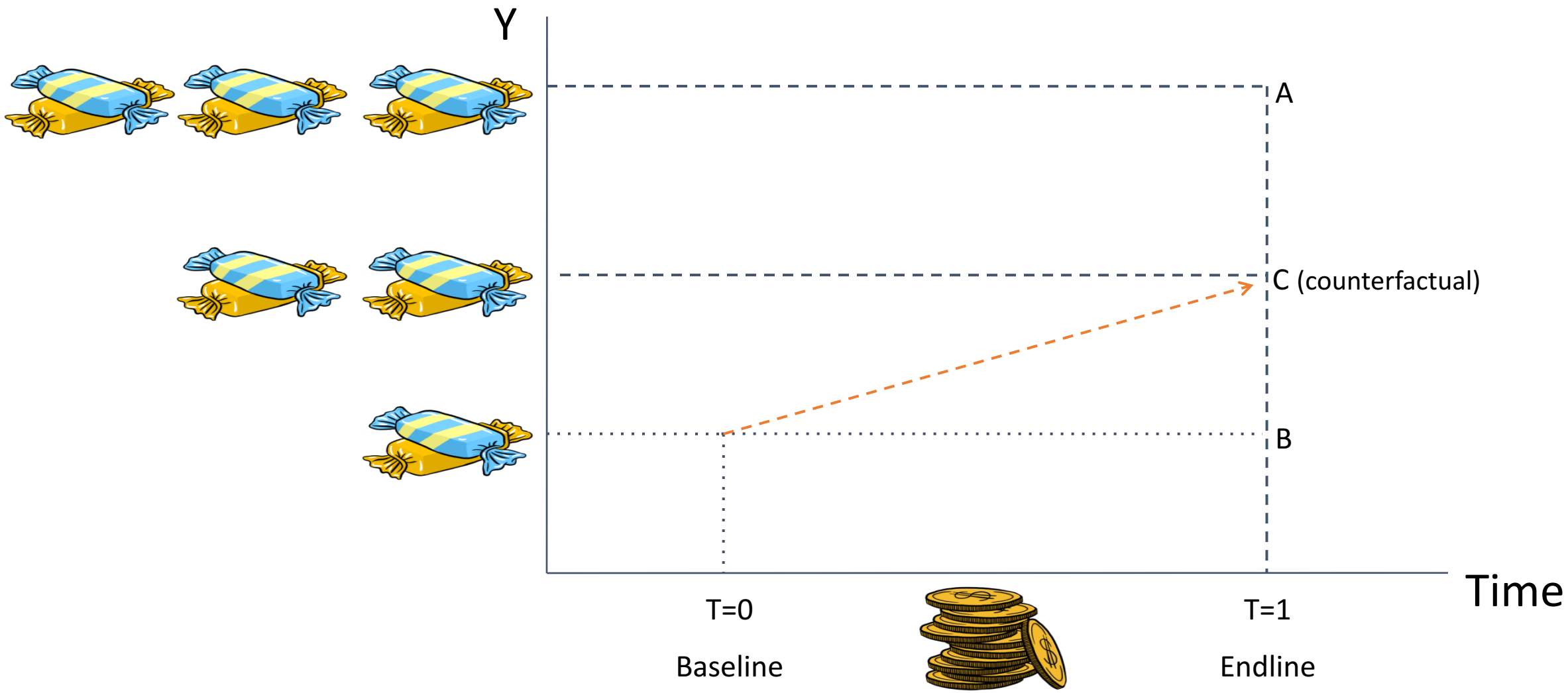
False Counterfactual #1

Before & After



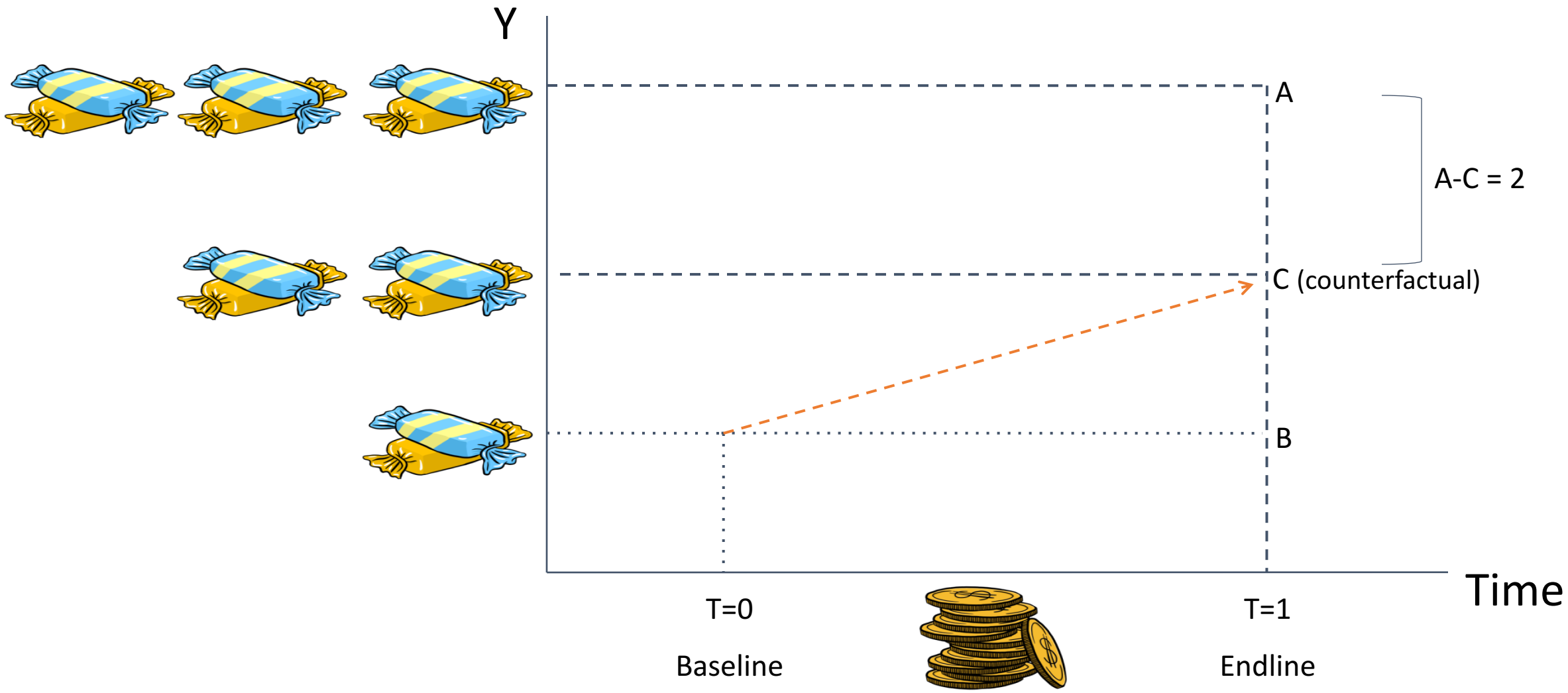
False Counterfactual #1

Before & After



False Counterfactual #1

Before & After



Case 1: Before & After

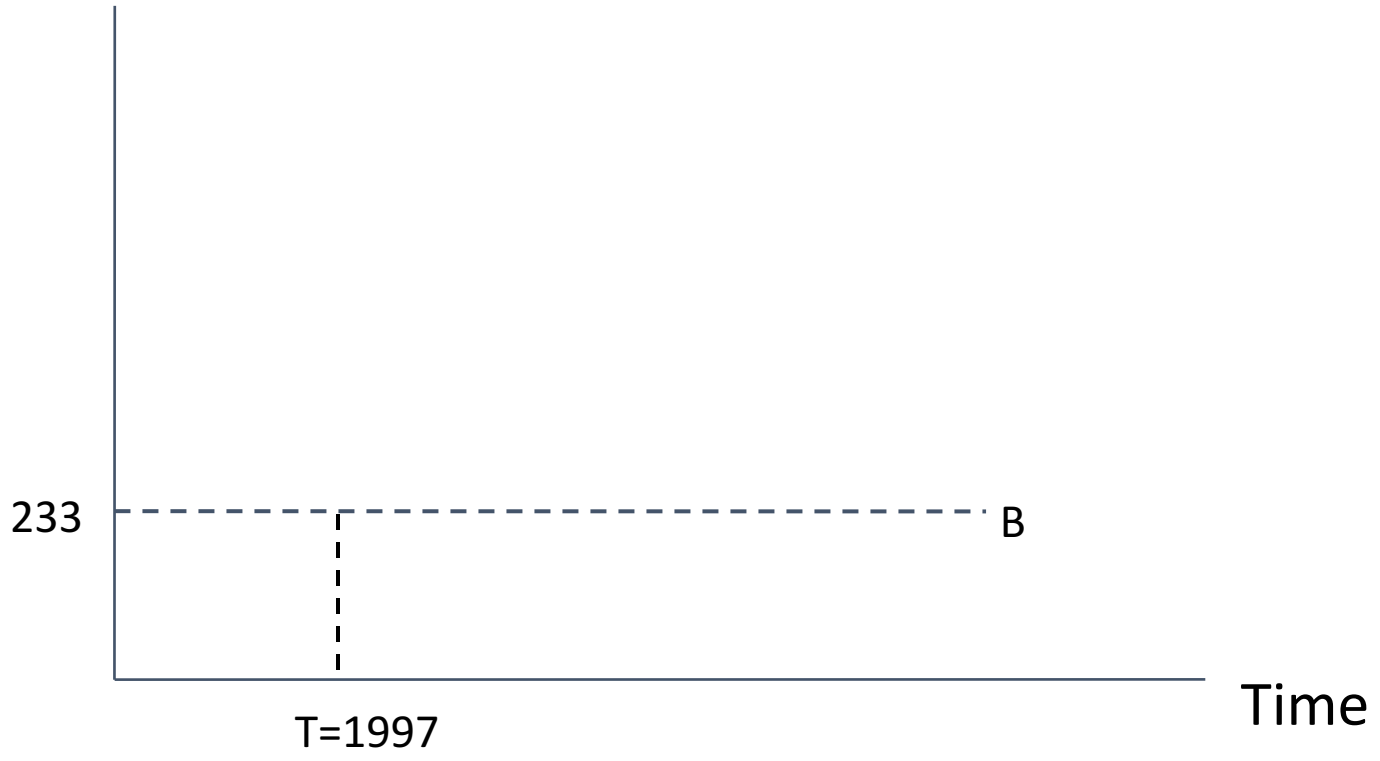
What is the effect of Progresa (P) on consumption (Y)?

Case 1: Before & After

What is the effect of Progresa (P) on consumption (Y)?

(1) Observe only beneficiaries (P=1)

(2) Two observations in time: Consumption at T=0

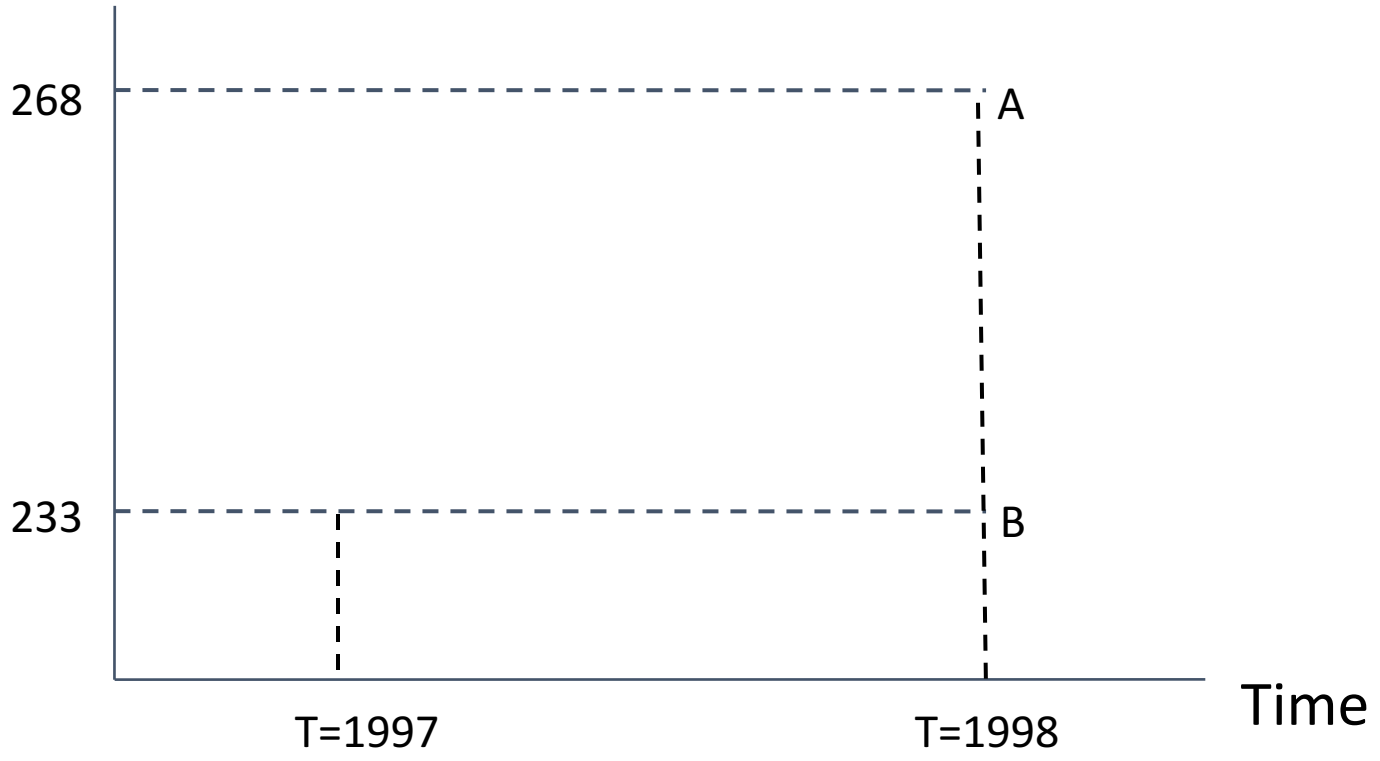


Case 1: Before & After

What is the effect of Progresa (P) on consumption (Y)?

(1) Observe only beneficiaries (P=1)

(2) Two observations in time:
Consumption at T=0
and consumption at T=1.

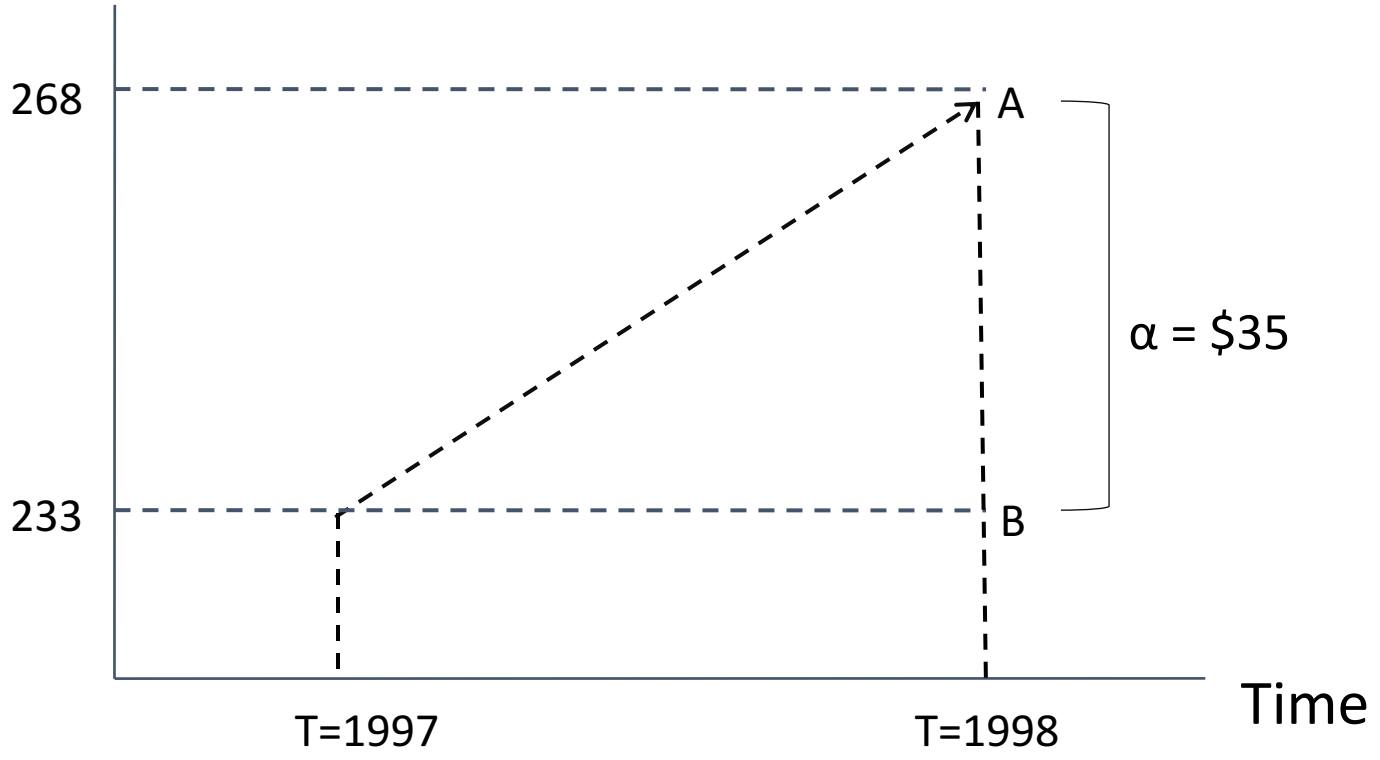


Case 1: Before & After

What is the effect of Progresa (P) on consumption (Y)?

(1) Observe only beneficiaries (P=1)

(2) Two observations in time: Consumption at T=0 and consumption at T=1.



IMPACT=A-B= $35

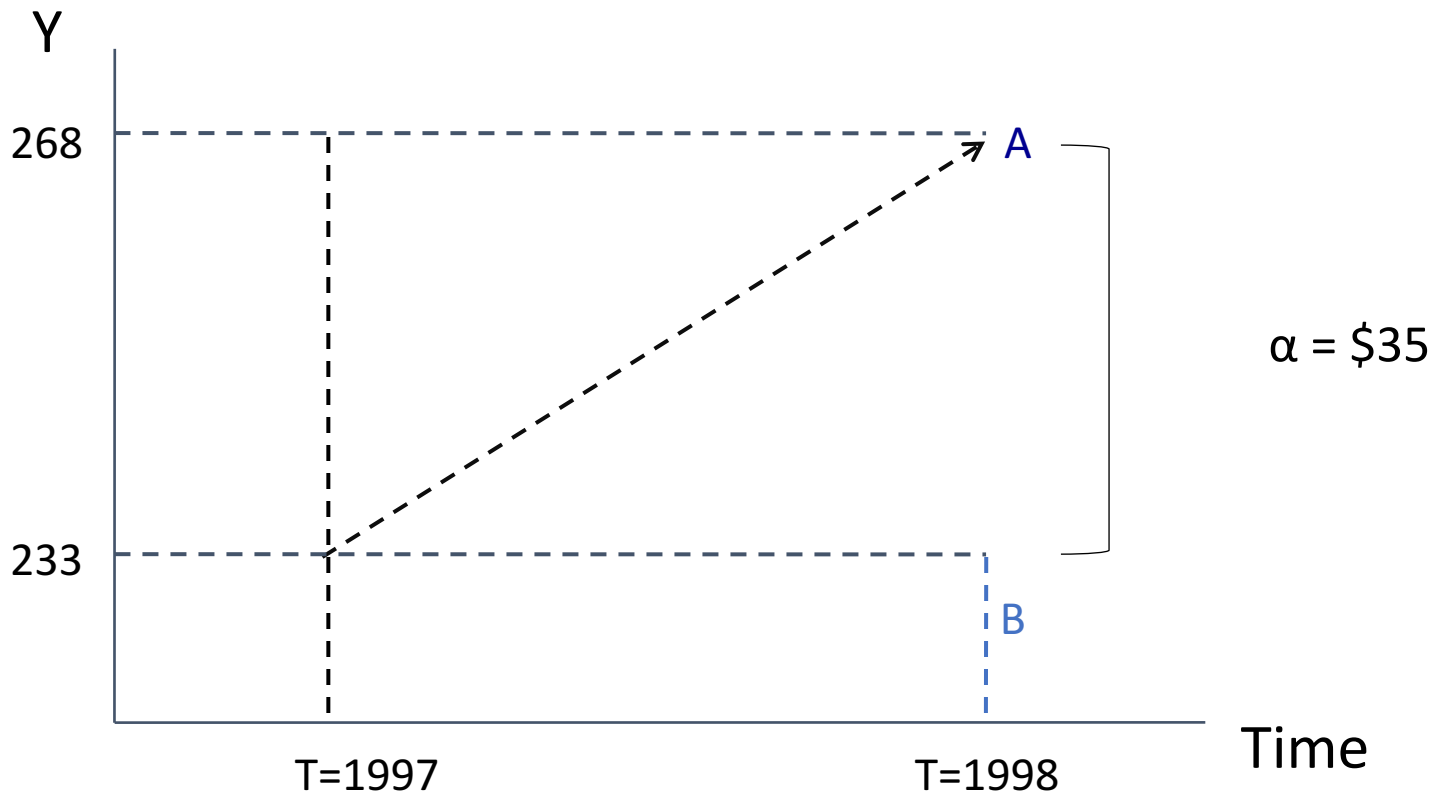
Case 1: Before & After

Consumption (Y)	
Outcome with Treatment *(After)*	268.7
Counterfactual *(Before)*	233.4
Impact *(Y | P=1) - (Y | P=0)*	35.3***

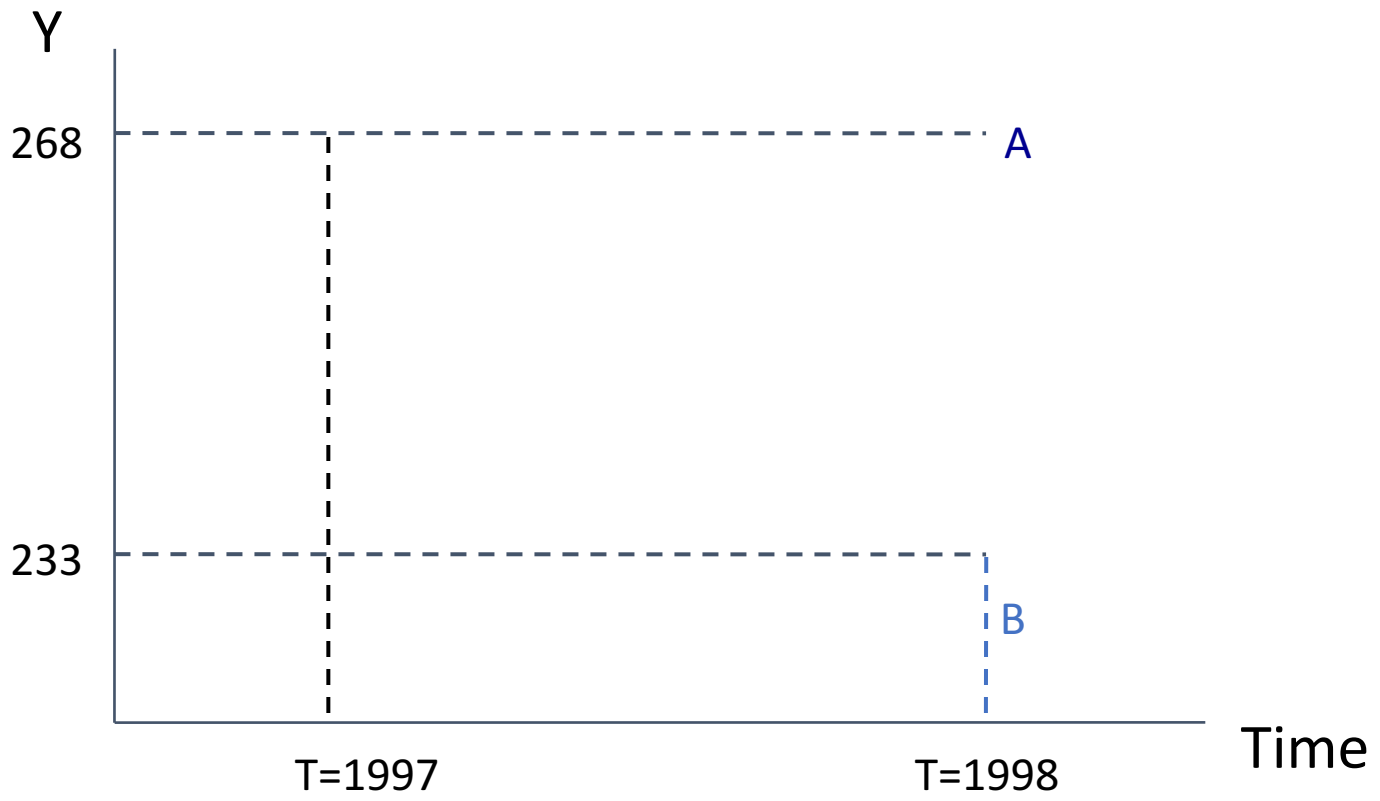
Estimated Impact on Consumption (Y)	
Linear Regression	35.27**
Multivariate Linear Regression	34.28**

:If the effect is statistically significant at the 1% significance level, we label the estimated impact with 2 stars (**).

Case 1: What's the problem?



Case 1: What's the problem?

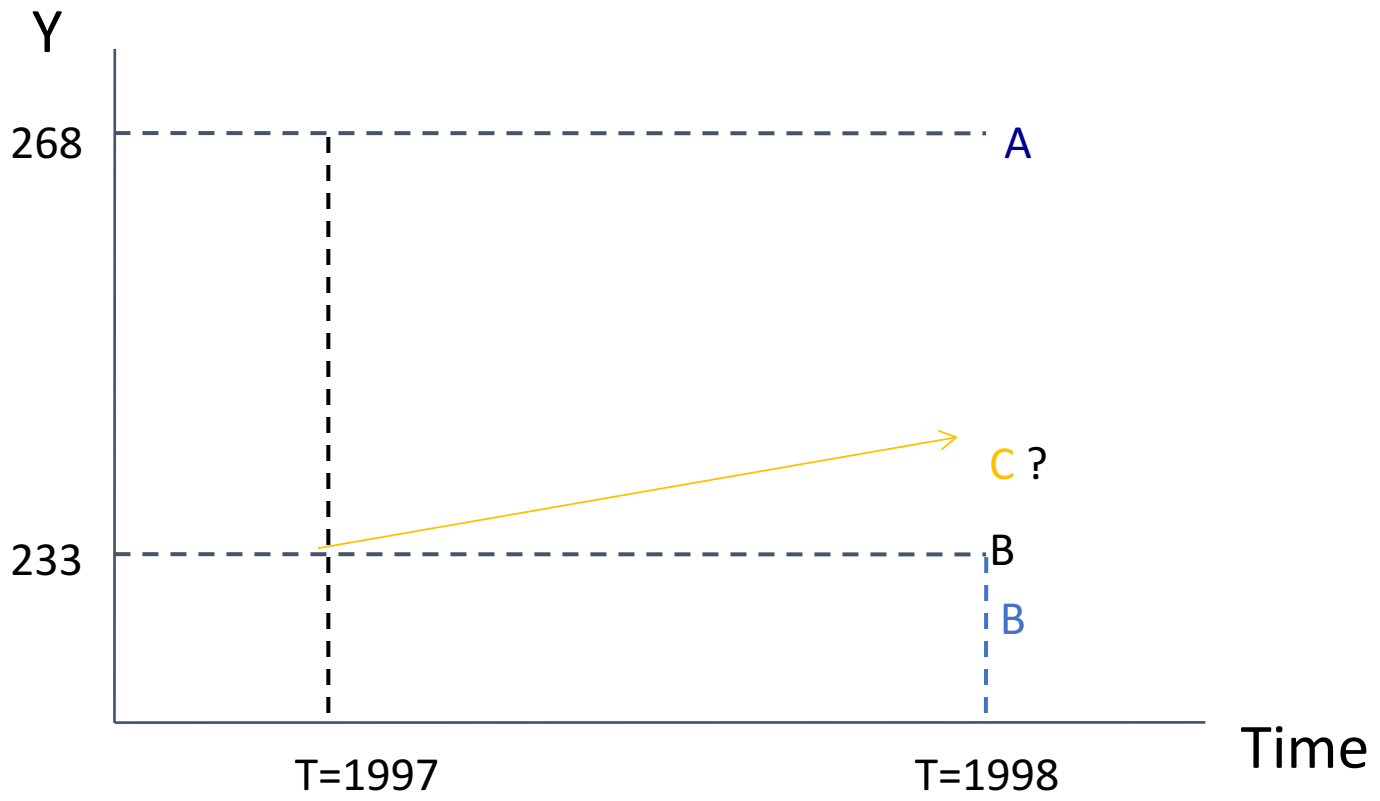


Case 1: What's the problem?

DÉVELOPPEMENT INTERNATIONAL

WED LAB

Economic Boom:



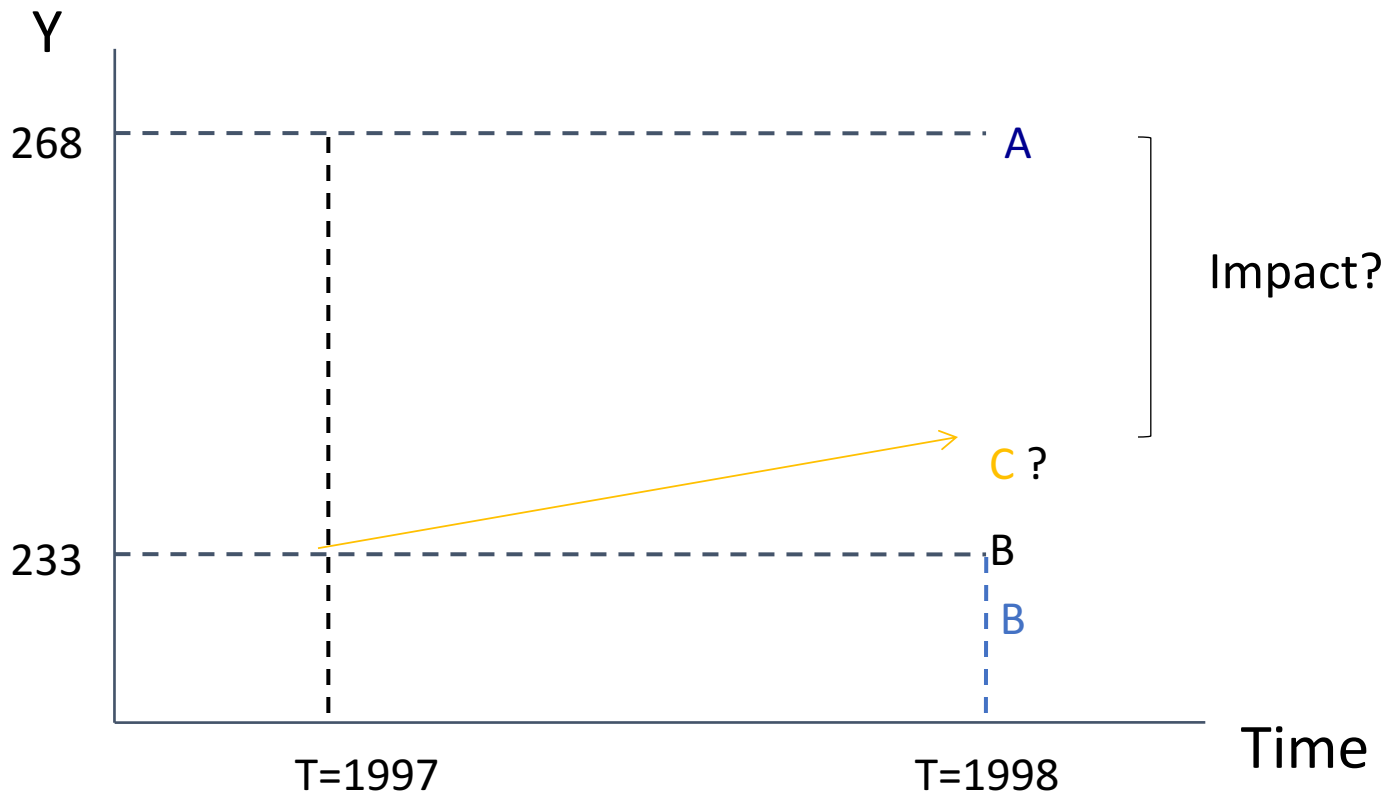
Case 1: What's the problem?

DÉVELOPPEMENT INTERNATIONAL

WED LAB

Economic Boom:

- Real Impact=A-C



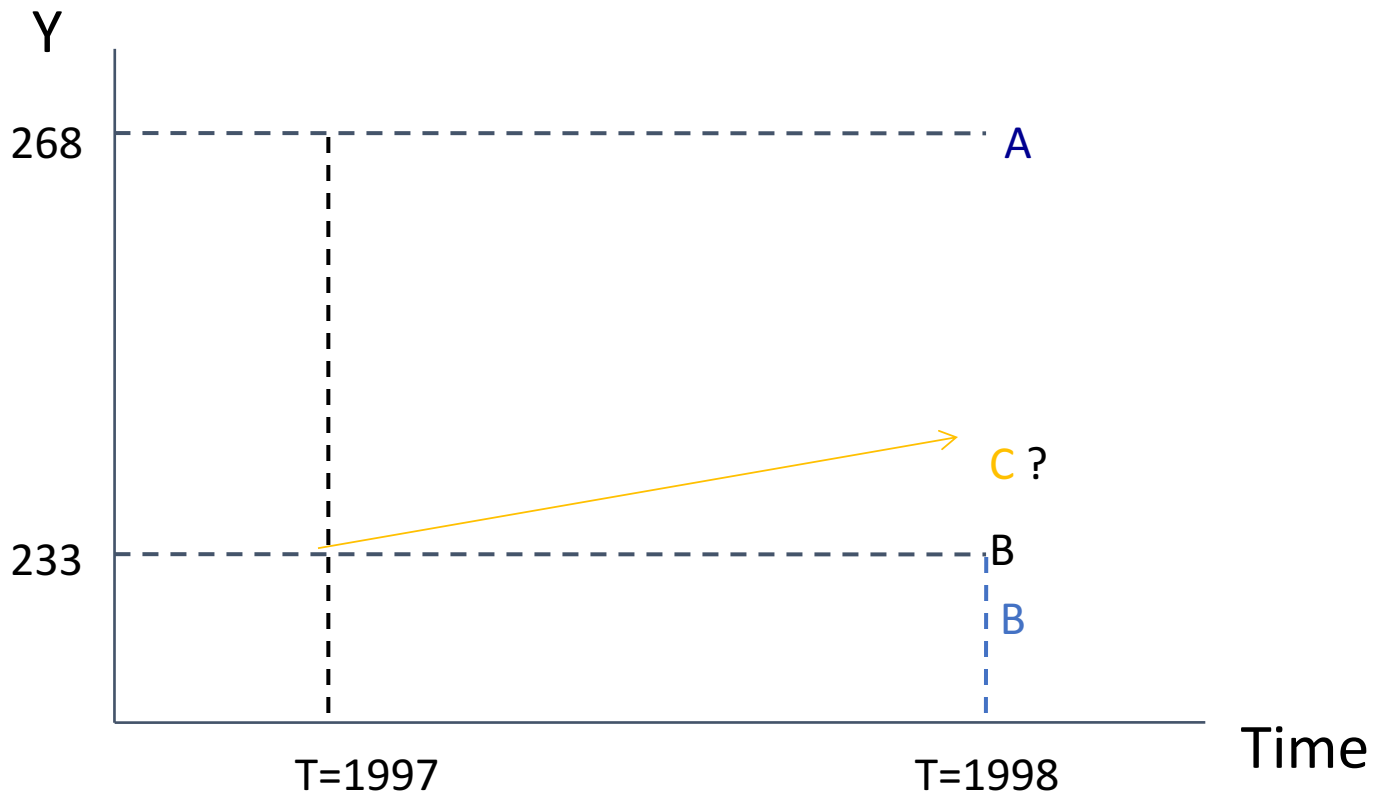
Case 1: What's the problem?

DÉVELOPPEMENT INTERNATIONAL

WED LAB

Economic Boom:

- Real Impact=A-C
- A-B is an *overestimate*



Case 1: What's the problem?

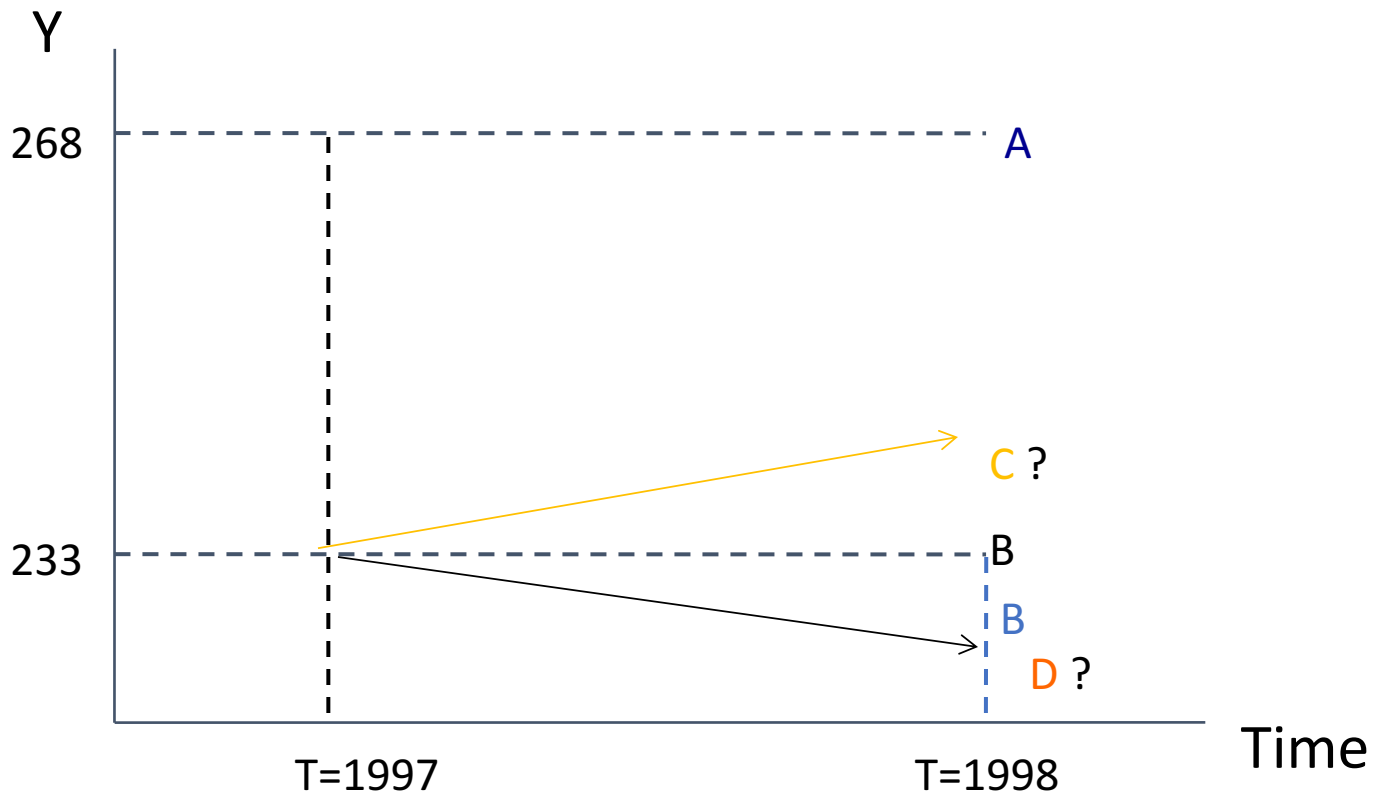
DÉVELOPPEMENT INTERNATIONAL

WED LAB

Economic Boom:

- Real Impact=A-C
- A-B is an *overestimate*

Economic Recession:



Case 1: What's the problem?

DÉVELOPPEMENT INTERNATIONAL

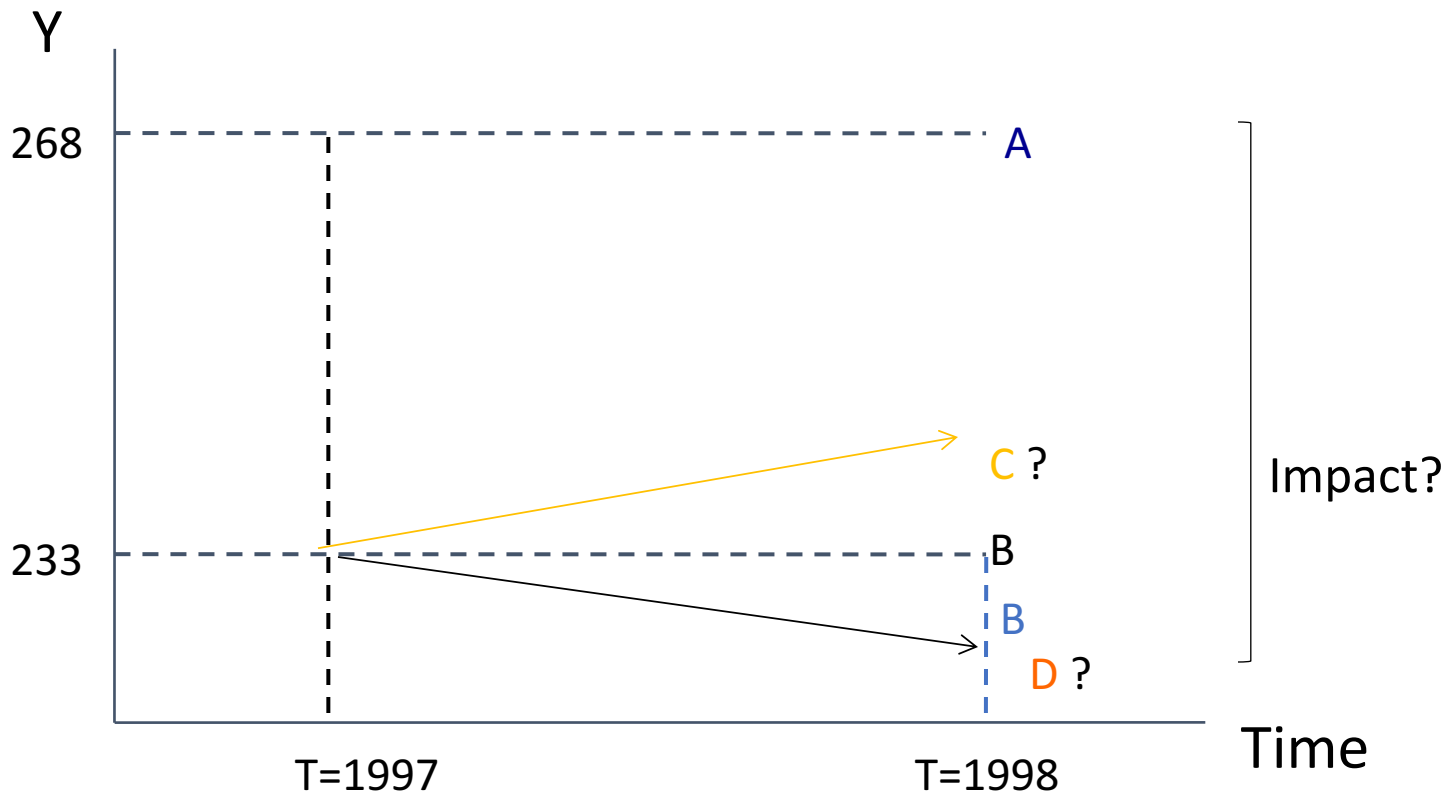
WED LAB

Economic Boom:

- Real Impact=A-C
- A-B is an *overestimate*

Economic Recession:

- Real Impact=A-D



Case 1: What's the problem?

DÉVELOPPEMENT INTERNATIONAL

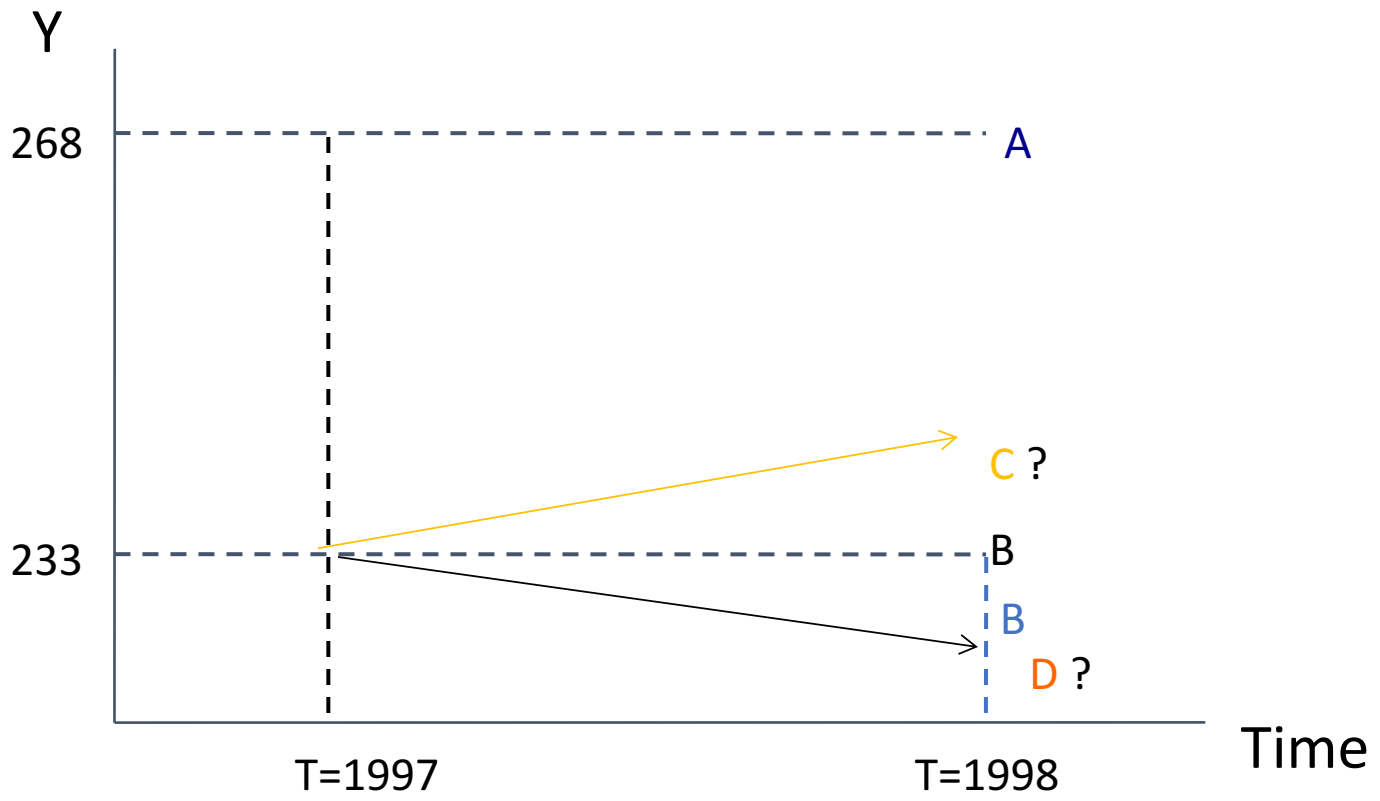
WED LAB

Economic Boom:

- Real Impact=A-C
- A-B is an *overestimate*

Economic Recession:

- Real Impact=A-D
- A-B is an *underestimate*



Case 1: What's the problem?

DÉVELOPPEMENT INTERNATIONAL

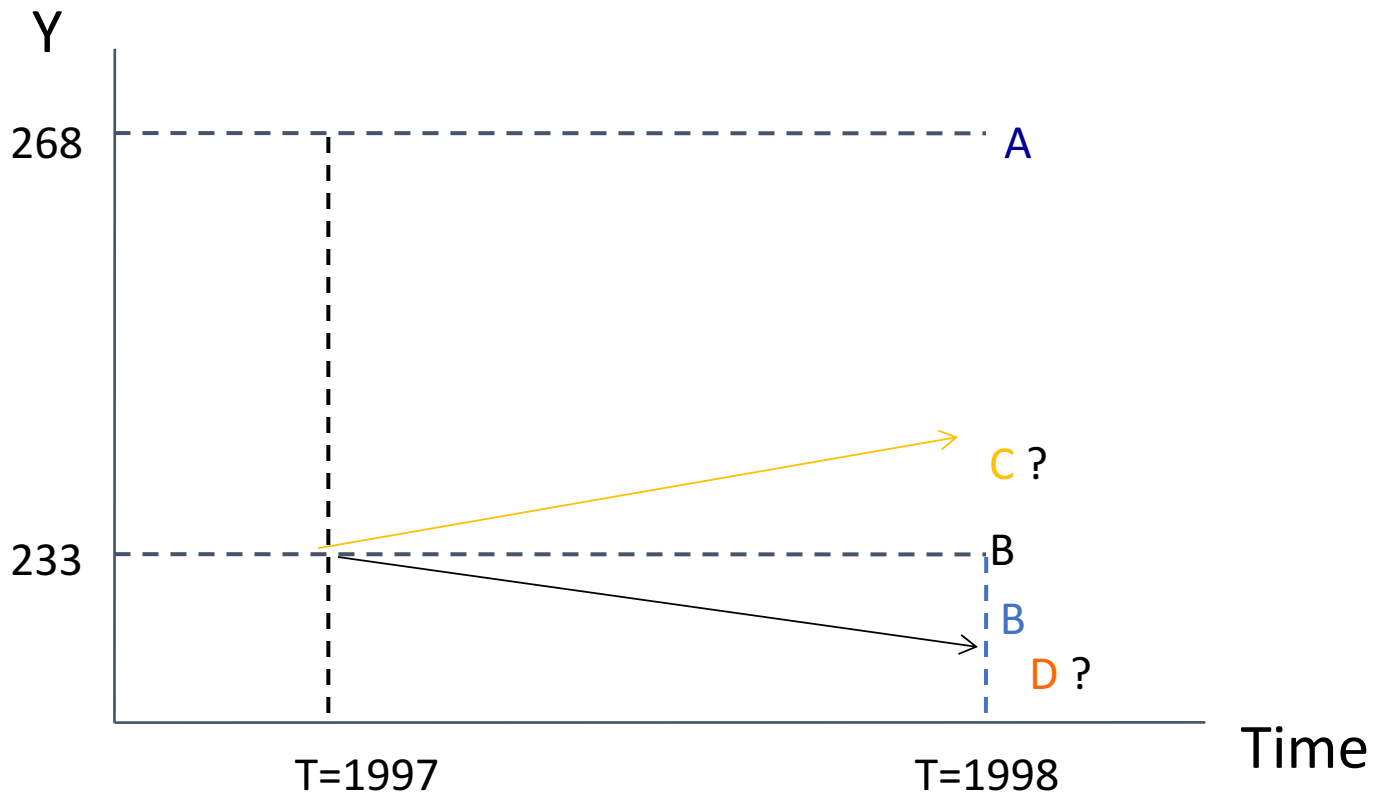
WED LAB

Economic Boom:

- Real Impact=A-C
- A-B is an *overestimate*

Economic Recession:

- Real Impact=A-D
- A-B is an *underestimate*



Before & After doesn't control for other time-varying factors!

False Counterfactual #2

Enrolled & Not Enrolled

- If we have post-treatment data on
  - Enrolled: treatment group
  - Not-enrolled: “comparison” group (counterfactual)

    Those ineligible to participate.

    Those that choose NOT to participate.

False Counterfactual #2

Enrolled & Not Enrolled

- If we have post-treatment data on
  - Enrolled: treatment group
  - Not-enrolled: "comparison" group (counterfactual)

    Those ineligible to participate.

    Those that choose NOT to participate.
- Selection Bias
  - Reason for not enrolling may be correlated with outcome (Y)

    Control for observables.

    But not un-observables!
  - Estimated impact is confounded with other things.

Case 2: Enrolled & Not Enrolled

Consumption (Y)	
Outcome with Treatment *(Enrolled)*	268
Counterfactual *(Not Enrolled)*	290
Impact *(Y | P=1) - (Y | P=0)*	-22**

Estimated Impact on Consumption (Y)	
Linear Regression	-22**
Multivariate Linear Regression	-4.15

Note: If the effect is statistically significant at the 1% significance level, we label the estimated impact with 2 stars (**).

Progresa Policy Recommendation?

Impact on Consumption (Y)		
Case 1: Before & After	Linear Regression	35.27**
	Multivariate Linear Regression	34.28**
Case 2: Enrolled & Not Enrolled	Linear Regression	-22**
	Multivariate Linear Regression	-4.15

- Will you recommend scaling up Progresa?
- B&A: Are there other time-varying factors that also influence consumption?
- E&NE:
  - Are reasons for enrolling correlated with consumption?
  - Selection Bias.

If the effect is statistically significant at the 1% significance level, we label the estimated impact with 2 stars (**).

Keep in Mind !

B&A

Compare: Same individuals Before and After they receive P.

Keep in Mind !

B&A

Compare: Same individuals Before and After they receive P.

Problem: Other things may have happened over time.

E&NE

Compare: Group of individuals Enrolled in a program with group that chooses not to enroll.

Keep in Mind !

B&A

Compare: Same individuals Before and After they receive P.

Problem: Other things may have happened over time.

E&NE

Compare: Group of individuals Enrolled in a program with group that chooses not to enroll.

Problem: Selection Bias. We don't know why they are not enrolled.

Keep in Mind !

B&A

Compare: Same individuals Before and After they receive P.

Problem: Other things may have happened over time.

E&NE

Compare: Group of individuals Enrolled in a program with group that chooses not to enroll.

Problem: Selection Bias. We don't know why they are not enrolled.

Both counterfactuals may lead to **biased estimates** of the impact.

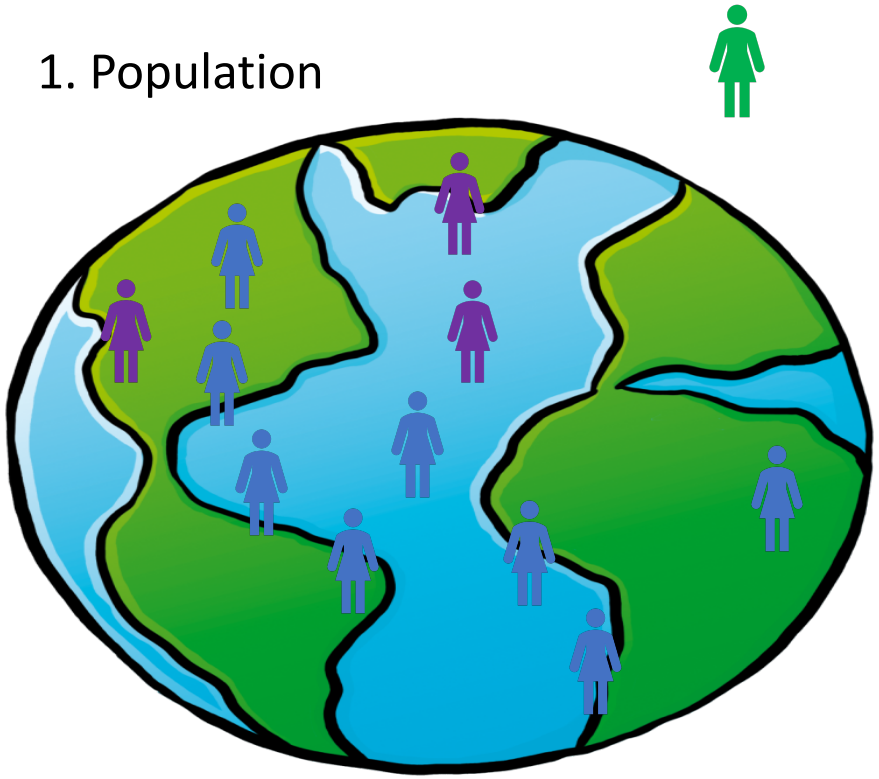
Randomized treatments and comparisons: another way to find a counterfactual

1. Population

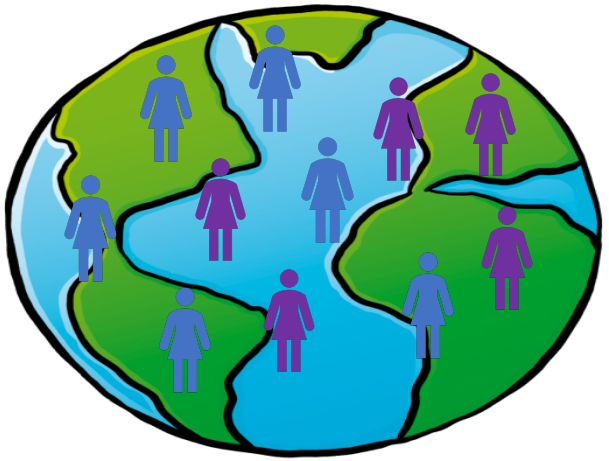
= Ineligible

Randomized treatments and comparisons: another way to find a counterfactual

1. Population



2. Evaluation sample

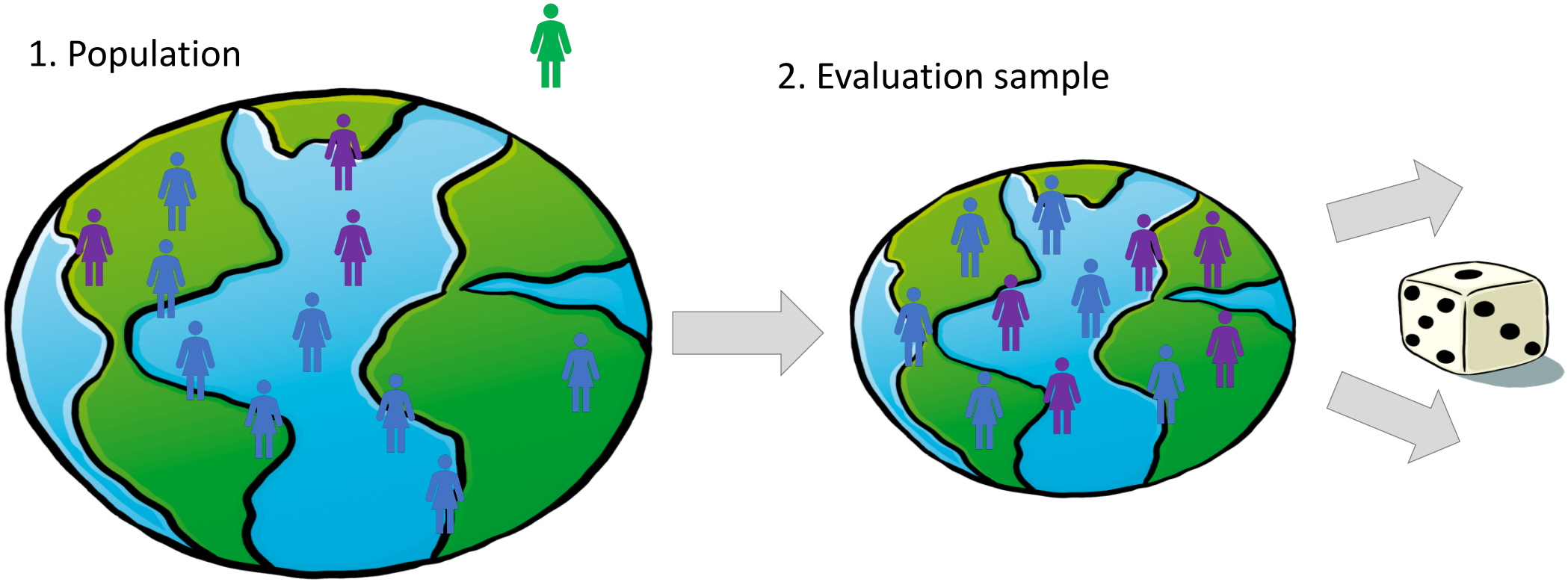


= Ineligible

= Eligible

Randomized treatments and comparisons: another way to find a counterfactual

1. Population



2. Evaluation sample

= Ineligible

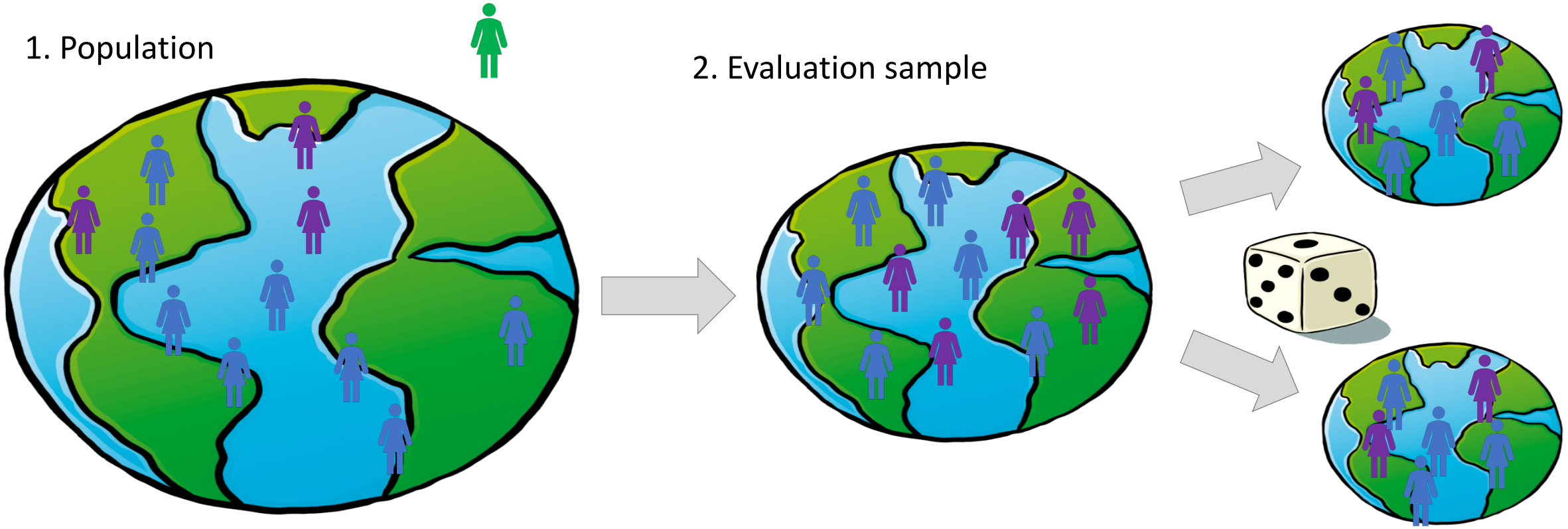
= Eligible

Randomized treatments and comparisons: another way to find a counterfactual

1. Population

2. Evaluation sample

3. Randomize treatment



= Ineligible

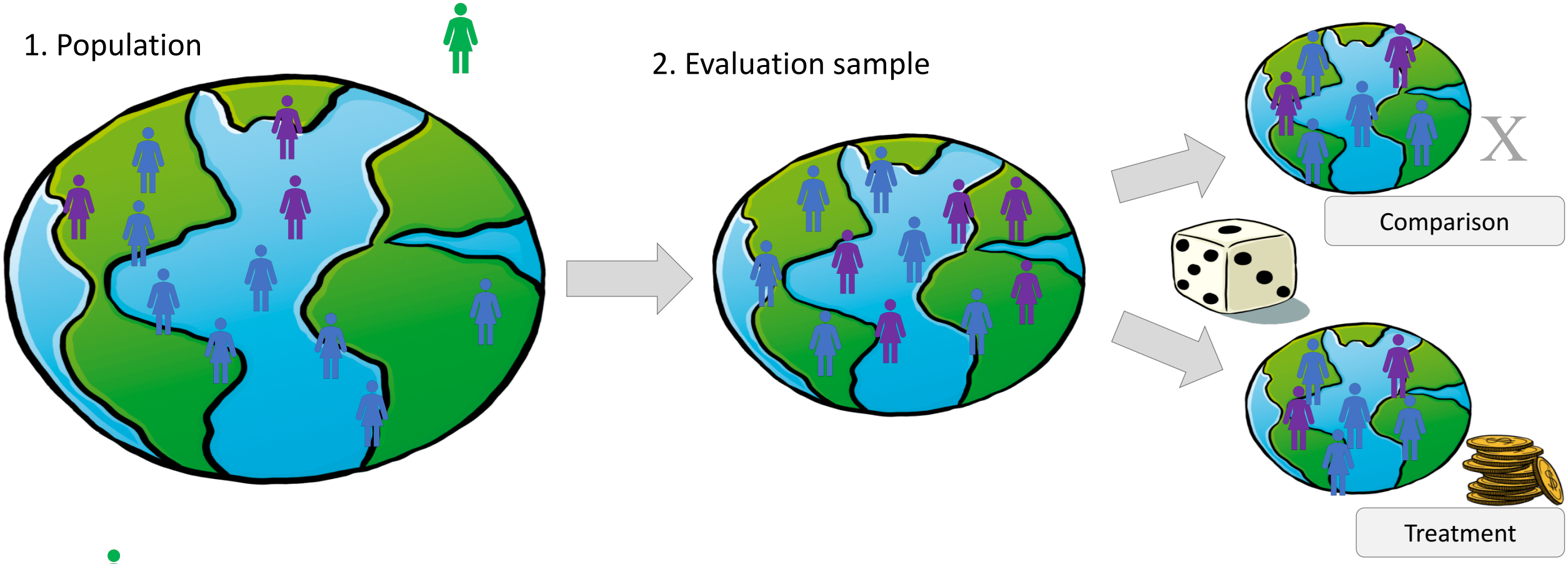
= Eligible

Randomized treatments and comparisons: another way to find a counterfactual

1. Population

2. Evaluation sample

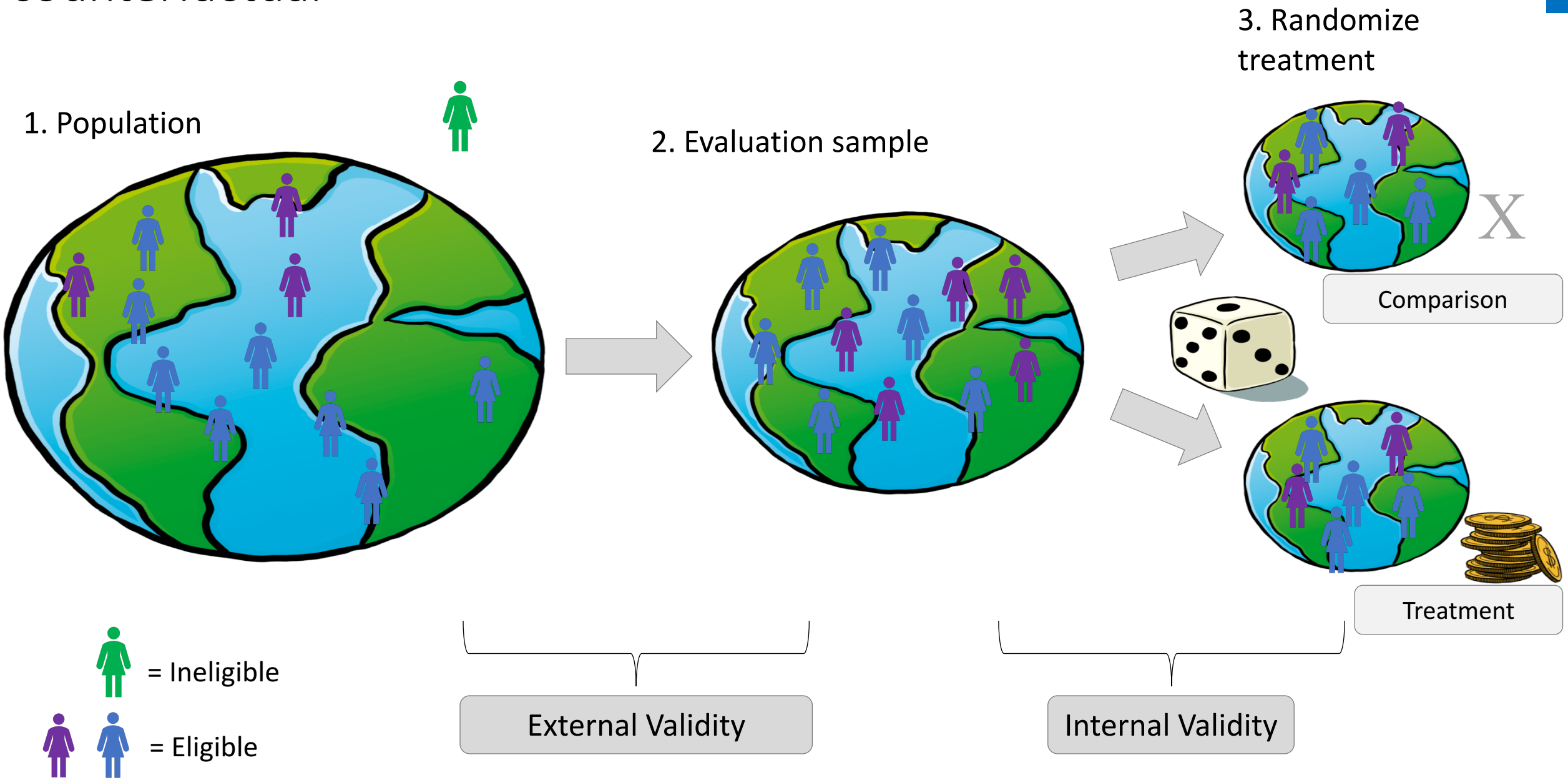
3. Randomize treatment



= Ineligible

= Eligible

Randomized treatments and comparisons: another way to find a counterfactual



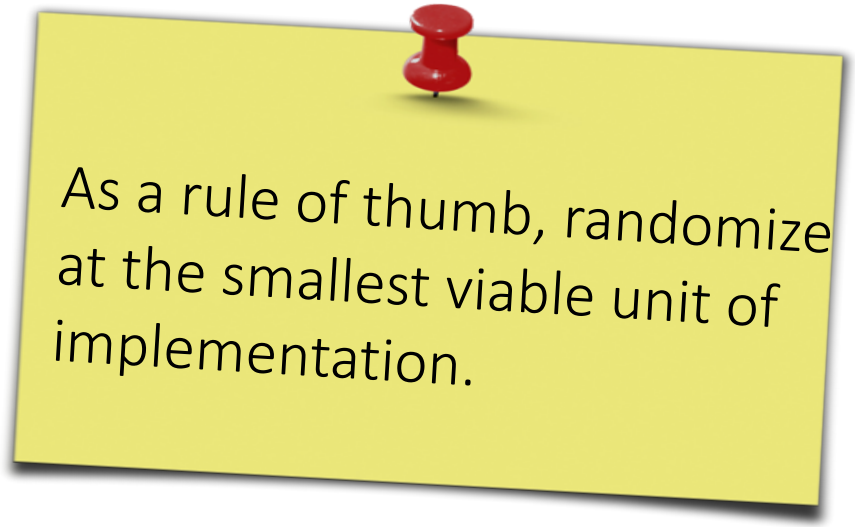
Unit of Randomization

- Choose according to type of program
  - Individual/Household
  - School/Health Clinic/catchment area
  - Block/Village/Community
  - Ward/District/Region

- Keep in mind
  - Need “sufficiently large” number of units to detect minimum desired impact: Power.
  - Spillovers/contamination
  - Operational and survey costs

Unit of Randomization

- Choose according to type of program
  - Individual/Household
  - School/Health Clinic/catchment area
  - Block/Village/Community
  - Ward/District/Region



- Keep in mind
  - Need “sufficiently large” number of units to detect minimum desired impact: Power.
  - Spillovers/contamination
  - Operational and survey costs

Progresa: Case 3 :Randomized Assignment

- Progresa CCT program
- Unit of randomization: Community
- 506 communities in the evaluation sample
- Randomized phase-in
  - 320 treatment communities (14446 households):

    First transfers in April 1998.
  - 186 comparison communities (9630 households):

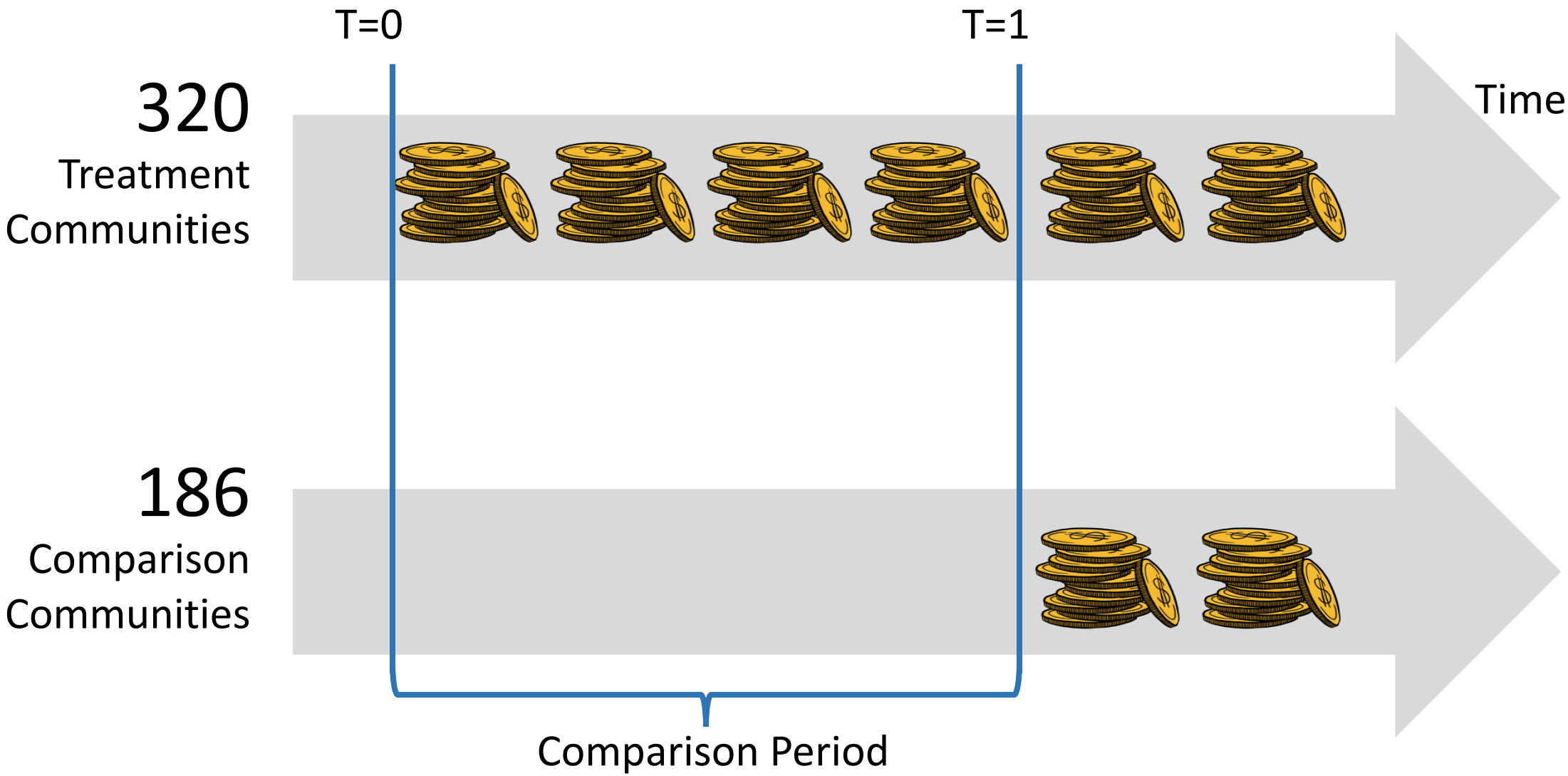
    First transfers November 1999

Case 3: Randomized Assignment

320
Treatment
Communities

186
Comparison
Communities

Case 3: Randomized Assignment



Case 3: Randomized Assignment

	Treatment Group *(Randomized to treatment)*	**Counterfactual** *(Randomized to Comparison)*	**Impact** *(Y | P=1) - (Y | P=0)*
Baseline ***(T=0)*** Consumption (Y)	233.47	233.40	0.07
Follow-up ***(T=1)*** Consumption (Y)	268.75	239.5	29.25**

Estimated Impact on Consumption (Y)	
Linear Regression	29.25**
Multivariate Linear Regression	29.75**

: If the effect is statistically significant at the 1% significance level, we label the estimated impact with 2 stars (**).

Progresa Policy Recommendation?

Impact of Progresa on Consumption (Y)		
Case 1: Before & After	Multivariate Linear Regression	34.28**
Case 2: Enrolled & Not Enrolled	Linear Regression	-22**
	Multivariate Linear Regression	-4.15
Case 3: Randomized Assignment	Multivariate Linear Regression	29.75**

Note: If the effect is statistically significant at the 1% significance level, we label the estimated impact with 2 stars (**).

Keep in Mind

Randomized Assignment

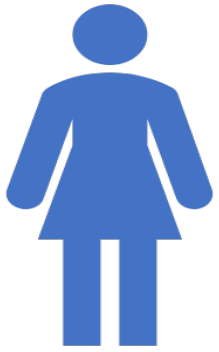
In Randomized Assignment, large enough samples, produces 2 statistically equivalent groups.

We have identified the perfect clone.

Feasible for prospective evaluations with over-subscription/excess demand.

Most pilots and new programs fall into this category.

Randomized beneficiary



Randomized comparison

RCTs and Women Empowerment: Some Research funded by IDRC's GrOW program

- Kenya : Access to Daycare and women's empowerment:
- Tanzania: Cash Transfer and Women's empowerment

But Life is not always a RCT…

- Impact evaluation estimates whether there is an effect. Does not explain **why** there is (or not) an effect. (Glennerster et al. paper)
- Ethical issues
- Costs
- There may be important policy changes that do not lend themselves to randomization
  - For instance, minimum wage policies, foreign aid, trade, etc
- Other methods exist (see appendix 1 for more), but not without problems either.

Quasi-Experimental methods

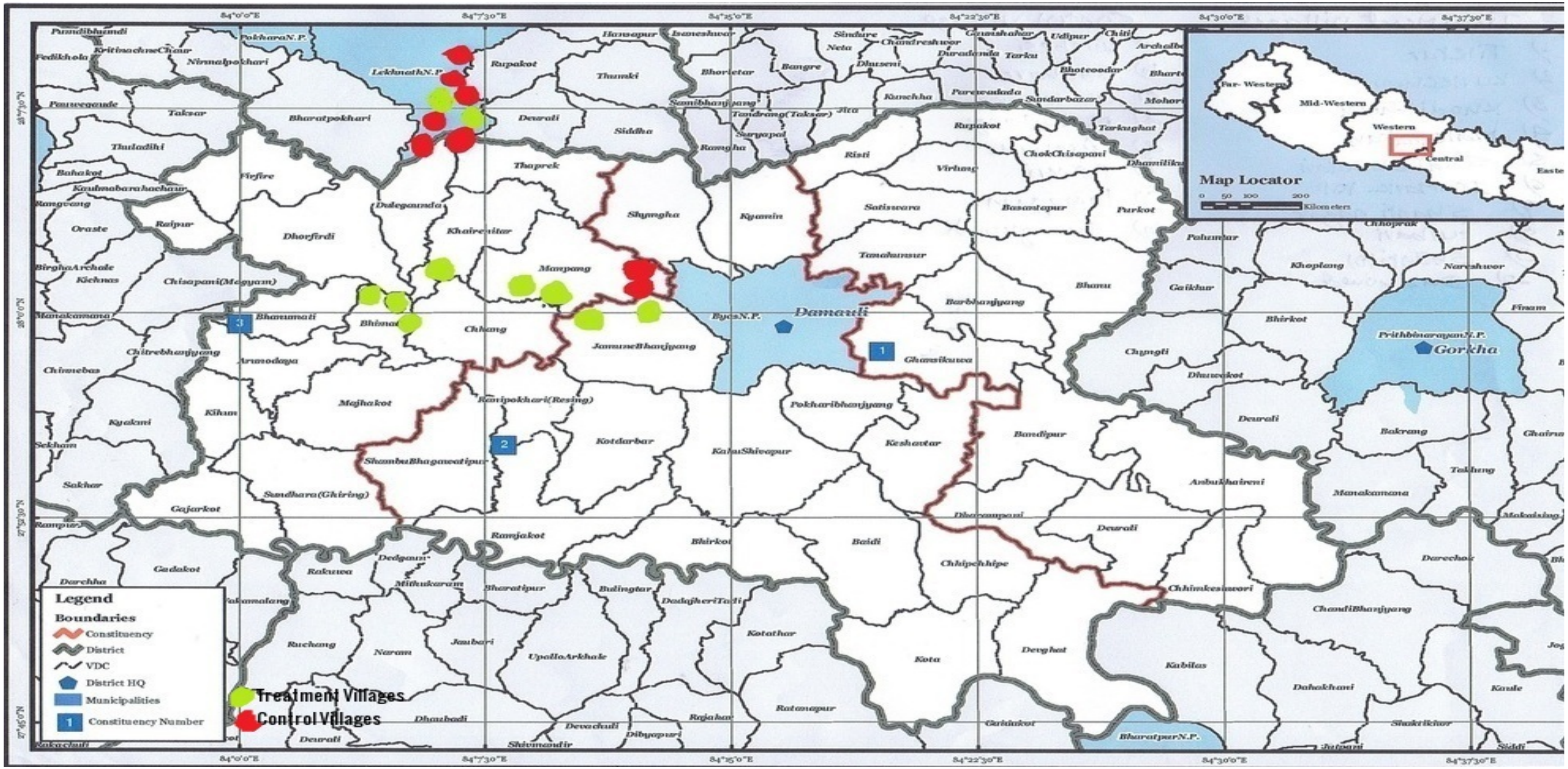
- Wijesiri, M. and F. Grimard 2019 **Microfinance programs and women's empowerment: new evidence from rural middle hills of Nepal**, Forthcoming in Business and Development Studies: Issues and Perspectives
  - data collected from rural women in hill villages in Tanahun district located in the mid-hill region of Nepal from a survey done in collaboration with Nirdhan Utthan Bank Limited (NUBL).
  - We used the quasi-experimental pipeline design approach proposed by Coleman (1999) to select treatment and control groups

Wijesiri and Grimard (2019), **Microfinance programs and women's empowerment: new evidence from rural middle hills of Nepal,**

Women attending a group meeting in Bhimad village, Dulegauda, Tanahun Dstrict, Nepal

Assessing the Impact of the Microfinance…

- Our sample strategy consisted of two main steps.
- **First,** we spoke with the NUBL. We obtained a list of treatment and control villages in Tanahun district from the bank.:
  - The control group consisted of randomly selected villages, pre-identified by the microfinance bank, which would soon receive microfinance support. Women in these villages had been allowed to self-select into the microfinance programs. These women had been organized into groups but no loans had yet been disbursed to them.
  - The treatment group, on the other hand, consisted of randomly selected villages where the bank has been in operation for at least a five-year period.


Legend
Boundaries
Constituency
District
VDC
District HQ
Municipalities
Constituency Number
Treatment Villages
Control Villages
Map Locator
Damauli
Gorkha

Assessing the Impact of the Microfinance…

- In **the second step**, we randomly drew 10 treatment and 8 control villages from the list of villages provided by the bank.
- Care was also taken that the control villages in our sample reflected comparable physical and socio-economic characteristics (availability of infrastructure facilities, level of economic developments, and social and cultural similarities) as the treatment villages. All study villages were approximately 1-2 hours' walking distance from the closest paved road.

- We then surveyed women in both treatment and control villages and we compared their outcomes regarding empowerment

Assessing the Impact of the Microfinance…

- Our results show that women's participation in Nirdhan Bank's microfinance program has had had a significant positive effect on their financial empowerment with respect to financial indicators such as control of income, independent savings, asset purchases and applying for loans.
- On the other hand, our results reveal that access to microfinance did not result in significant impact on in most women's social empowerment outcomes (for instance women's household decision-making regarding groceries, their children's marriage, and women's role as the household head).

Assessing the Impact of the Microfinance…

- How valid are these results?
  - Internally valid?
  - Externally valid?
  - Reproducible?
  - Scalable?

- Not expensive, limited study, but there are trade-offs

Quantitative Approaches used by Practitioners

- Oxfam: Rapid Care Analysis, Household Care Survey
  - https://policy-practice.oxfam.org.uk/publications/rapid-care-analysis-training-modules-620449
- Even Oxfam does some impact evaluation:
  - https://policy-practice.oxfam.org.uk/publications/livelihoods-in-south-sudan-impact-evaluation-of-the-south-sudan-peace-and-prosp-620864
- CARE (Power Africa) https://www.carepowerafrica.com
- 60 million girls NGO

Choosing your IE method(s)

Key information you will need for identifying the right method for your program:

Prospective/Retrospective Evaluation?

Choosing your IE method(s)

Key information you will need for identifying the right method for your program:

Prospective/Retrospective Evaluation?

Eligibility rules and criteria?

- Poverty targeting?
- Geographic targeting?

Choosing your IE method(s)

Key information you will need for identifying the right method for your program:

- Prospective/Retrospective Evaluation?
- Eligibility rules and criteria?
  - Poverty targeting?
  - Geographic targeting?
- Roll-out plan (pipeline)?

Choosing your IE method(s)

Key information you will need for identifying the right method for your program:

Prospective/Retrospective Evaluation?

Eligibility rules and criteria?

- Poverty targeting?
- Geographic targeting?

Roll-out plan (pipeline)?

Is the number of eligible units larger than available resources at a given point in time?

- Budget and capacity constraints?
- Excess demand for program?
- Etc.

Choose the **best possible design** given the operational context:

Best Design

- Best comparison group you can find **+** least operational risk

Choose the **best possible design** given the operational context:

Best Design →
- Best comparison group you can find **+** least operational risk

Have we controlled for everything? →
- Internal validity
- Good comparison group

Choose the **best possible design** given the operational context:

Best Design	○ Best comparison group you can find **+** least operational risk
Have we controlled for everything?	○ Internal validity ○ Good comparison group
Is the result valid for *everyone*?	○ External validity ○ Local versus global treatment effect ○ Evaluation results apply to population we're interested in

Warning: technique is not a panacea, and is not a substitute for thinking carefully about what it is that you want to estimate

- In the case of progresa, here are the various estimates of the returns of the program, according to the estimation methods

Remember

The objective of impact evaluation is to estimate the causal effect or impact of a program on outcomes of interest.

Remember

To estimate impact, we need to estimate the counterfactual.

- what would have happened in the absence of the program and
- use comparison or control groups.

Remember

Choose the best evaluation method that is feasible in the program's operational context.

Remember

- Be cautious with
  - internal validity issues
  - as well as external validity issues

Audience Q&A

Participants on Zoom can email questions to: kathleen.grantham@mcgill.ca

5 minute break

Panelists

Franque Grimard, McGill University (Facilitator)

Carl Asuncion, MEDA

Bouba Housseini, IDRC

1. What type of empirical analysis and results do you use to support your programming and/or funding of research projects? Among the various sources and methods you use, do you also consider impact evaluation? I.e. do you measure results by taking into account a counterfactual? Do you use impact evaluation results from the literature (for instance, 3ieimpact.org) in your programming of projects (MEDA) or in your research financing (IDRC)? Why, why not?

Franque Grimard,
McGill University
(Facilitator)

Carl Asuncion,
MEDA

Bouba Housseini,
IDRC

2. What would you need in your operations to integrate some approaches that would look at results compared to a counterfactual? For instance, more budget? More expertise? A requirement by the funder? Do you think this would change what you do and how you do it?

Franque Grimard, McGill University (Facilitator)

Carl Asuncion, MEDA

Bouba Housseini, IDRC

3. In which directions would you like to see researchers, people in the field, policy analysts and funders (either IDRC and/or GAC) to address how one can learn together to assess what works better, both in terms of replicating activities to empower women as well as scaling them up?

Franque Grimard,
McGill University
(Facilitator)

Carl Asuncion,
MEDA

Bouba Housseini,
IDRC

Audience Q&A

Participants on Zoom can email questions to: kathleen.grantham@mcgill.ca

Franque Grimard, McGill University (Facilitator)

Carl Asuncion, MEDA

Bouba Housseini, IDRC

Visit the WED Lab website for more information on upcoming seminars and to register:

http://womensempowerment.lab.mcgill.ca

WED LAB

WED Lab Seminar Series

Generously supported by:

IDRC | CRDI
International Development Research Centre
Centre de recherches pour le développement international

Social Sciences and Humanities Research Council of Canada
Conseil de recherches en sciences humaines du Canada

Canada