

# Causa Nostra: The Potentially Legitimate Business of Drawing Causal Inferences from Observational Data

Dr. James A. Rogers PhD  
October 9, 2018

# Overview

# A Triage System for Causal Inference with Observational Data

# A Triage System for Causal Inference with Observational Data

- There is something called G-computation.

# A Triage System for Causal Inference with Observational Data

- There is something called G-computation.
  - You already use it.

# A Triage System for Causal Inference with Observational Data

- There is something called G-computation.
  - You already use it.
  - All the time.

# A Triage System for Causal Inference with Observational Data

- There is something called G-computation.
  - You already use it.
  - All the time.
  - That's good.

# A Triage System for Causal Inference with Observational Data

- There is something called G-computation.
  - You already use it.
  - All the time.
  - That's good.
- It's not always clear how to do G-computation correctly. Causal diagrams can help.



# A Triage System for Causal Inference with Observational Data

- There is something called G-computation.
  - You already use it.
  - All the time.
  - That's good.
- It's not always clear how to do G-computation correctly. Causal diagrams can help.
- Sometimes G-computation is not enough. Then you need something like propensity adjustments or case-matching (not covered here).

# A Simple Example

TABLE II—*Success rate of treatment\** (figures are numbers (%) of patients)

|                                       | Group 1         | Group 2         | Overall         |
|---------------------------------------|-----------------|-----------------|-----------------|
| Nephrolithotomy/pyelolithotomy        | 12 (92)         | 154 (71)        | 166 (72)        |
| Pyelolithotomy                        | 26 (84)         | 38 (84)         | 64 (84)         |
| Ureterolithotomy                      | 43 (100)        |                 | 43 (100)        |
| <b>All open procedures</b>            | <b>81 (93)</b>  | <b>192 (73)</b> | <b>273 (78)</b> |
| <b>Percutaneous nephrolithotomy†</b>  | <b>234 (87)</b> | <b>55 (69)</b>  | <b>289 (83)</b> |
| ESWL                                  | 200 (98)        | 101 (82)        | 301 (92)        |
| Percutaneous nephrolithotomy and ESWL |                 | 15 (62)         | 15 (62)         |

\*Success defined as no stones at three months or stone reduced to particles <2 mm in size.

†52 with electrohydraulic lithotripsy, 69 with ultrasound.

## Taken From

Taken from: Charig et al., Comparison of treatment of renal calculi by open surgery, percutaneous nephrolithotomy, and extracorporeal shockwave lithotripsy. *BMJ* 1986;**292**:879–882.

# Simpson's "Paradox"

As you can see from that table, based on point estimates:

# Simpson's "Paradox"

As you can see from that table, based on point estimates:

- Open surgery has better efficacy for subjects with small stones,

# Simpson's "Paradox"

As you can see from that table, based on point estimates:

- Open surgery has better efficacy for subjects with small stones,
- Open surgery has better efficacy for subjects with large stones,

# Simpson's "Paradox"

As you can see from that table, based on point estimates:

- Open surgery has better efficacy for subjects with small stones,
- Open surgery has better efficacy for subjects with large stones,
- Each subject falls into one of those two categories ... and yet:

# Simpson's "Paradox"

As you can see from that table, based on point estimates:

- Open surgery has better efficacy for subjects with small stones,
- Open surgery has better efficacy for subjects with large stones,
- Each subject falls into one of those two categories ... and yet:
- Point estimates from the naive analysis imply that percutaneous surgery is better "overall".



# The World's Simplest Example of G-Computation

Overall, 51% percent of patients have small stones and 49% percent of patients have large stones,

So “standardized” response rates are:

$$\text{open: } 0.51 * 0.93 + 0.49 * 0.73 = 0.83$$

$$\text{percutaneous: } 0.51 * 0.87 + 0.49 * 0.69 = 0.78$$

# PMX Simulation-based Inference = G-computation

# PMX Simulation-based Inference = G-computation

1. In simulation world, fix treatment at one level, e.g. “open surgery”.

# PMX Simulation-based Inference = G-computation

1. In simulation world, fix treatment at one level, e.g. “open surgery”.
2. Independently of treatment simulate the distribution of stone size. We would typically do this by re-sampling from the empirical distribution of the covariates.

# PMX Simulation-based Inference = G-computation

1. In simulation world, fix treatment at one level, e.g. “open surgery”.
2. Independently of treatment simulate the distribution of stone size. We would typically do this by re-sampling from the empirical distribution of the covariates.
3. Based on that fixed value of treatment and the simulated values of covariates, use the conditional distribution of the response, conditional on covariates and random effects (if there were any), to simulate new responses. Compute the proportion of successes in those simulated responses.

# PMX Simulation-based Inference = G-computation

1. In simulation world, fix treatment at one level, e.g. “open surgery”.
2. Independently of treatment simulate the distribution of stone size. We would typically do this by re-sampling from the empirical distribution of the covariates.
3. Based on that fixed value of treatment and the simulated values of covariates, use the conditional distribution of the response, conditional on covariates and random effects (if there were any), to simulate new responses. Compute the proportion of successes in those simulated responses.
4. Repeat the above steps with treatment now fixed at the other level, “percutaneous surgery”.

# PMX Simulation-based Inference = G-computation

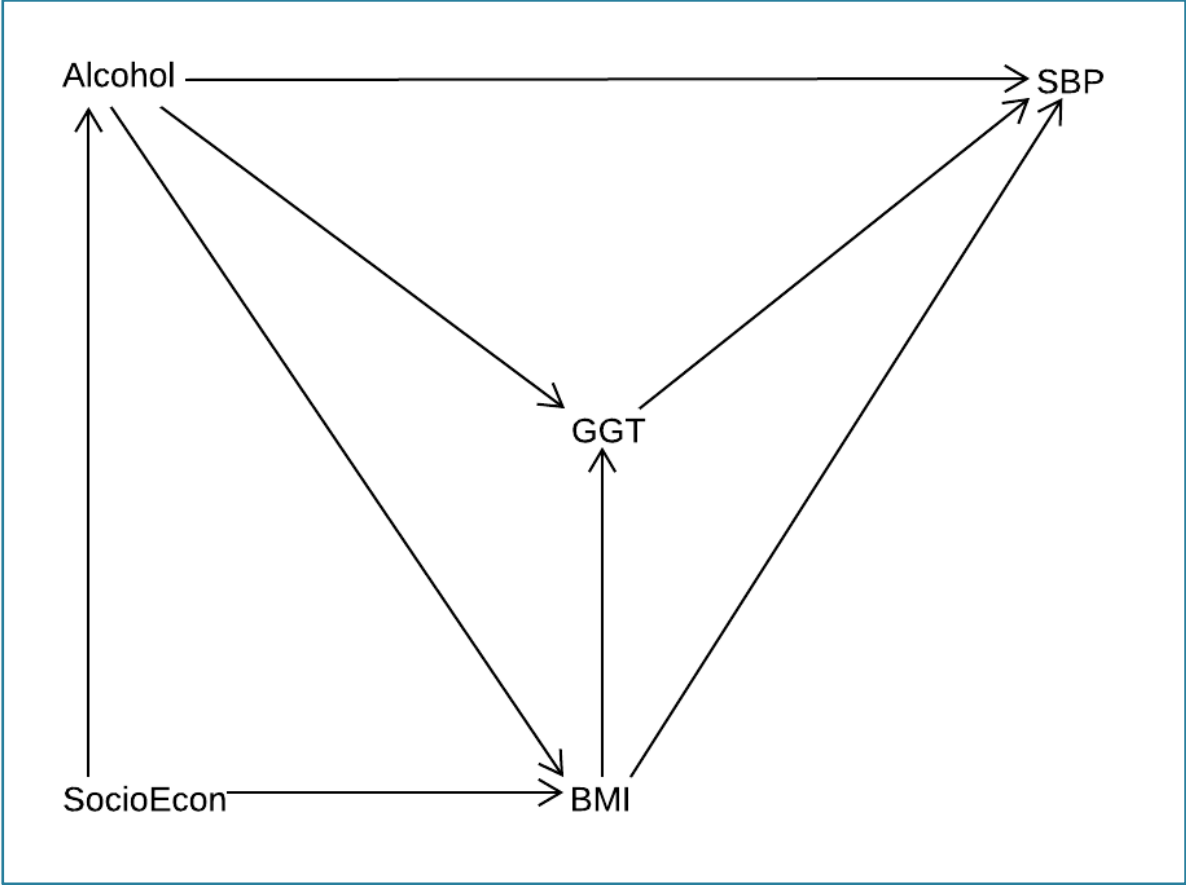
1. In simulation world, fix treatment at one level, e.g. “open surgery”.
2. Independently of treatment simulate the distribution of stone size. We would typically do this by re-sampling from the empirical distribution of the covariates.
3. Based on that fixed value of treatment and the simulated values of covariates, use the conditional distribution of the response, conditional on covariates and random effects (if there were any), to simulate new responses. Compute the proportion of successes in those simulated responses.
4. Repeat the above steps with treatment now fixed at the other level, “percutaneous surgery”.
5. Compare the two proportions you obtained.

# Good News: G-computation Estimates Causal Estimands Correctly



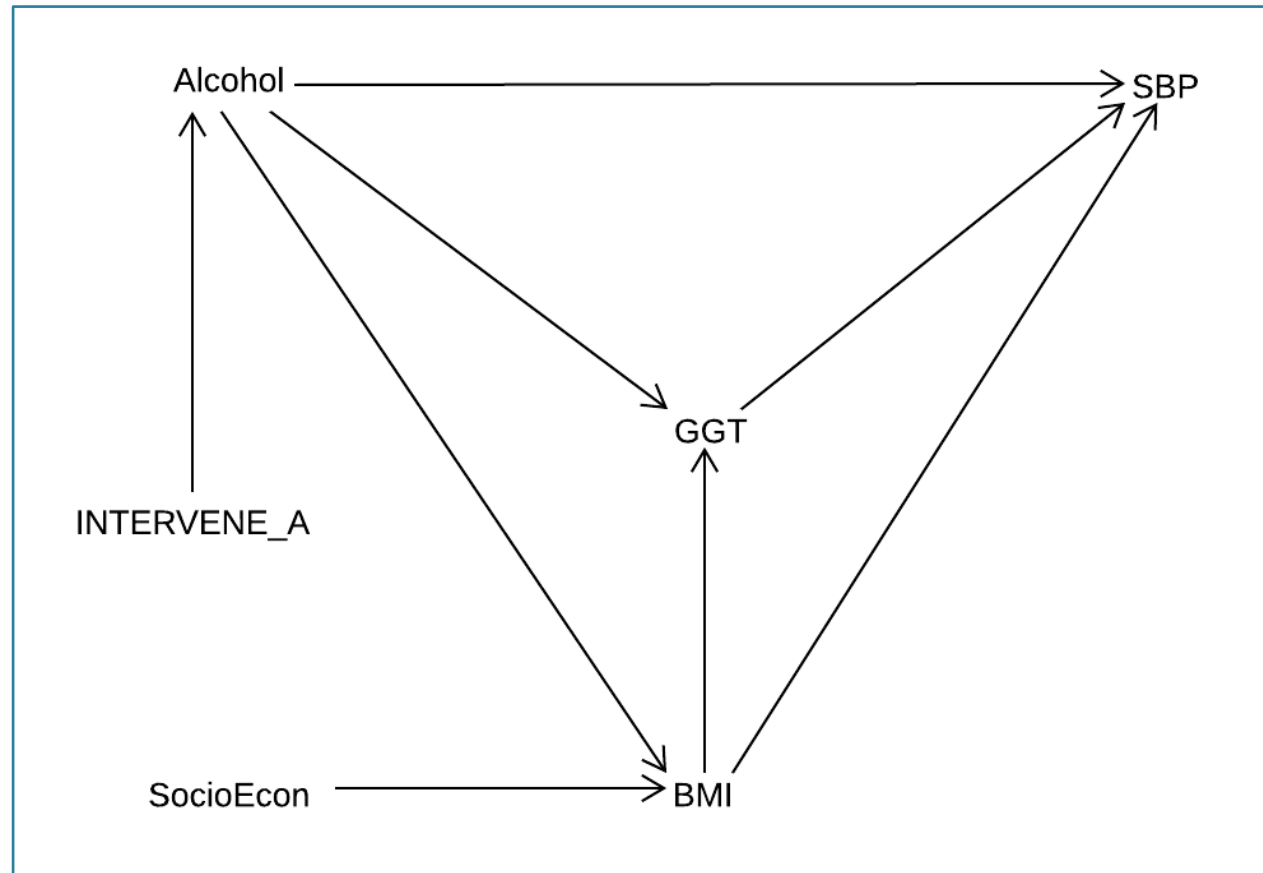
# A More Complex Example

# Observational Data for Effect of Alcohol Consumption on Systolic BP

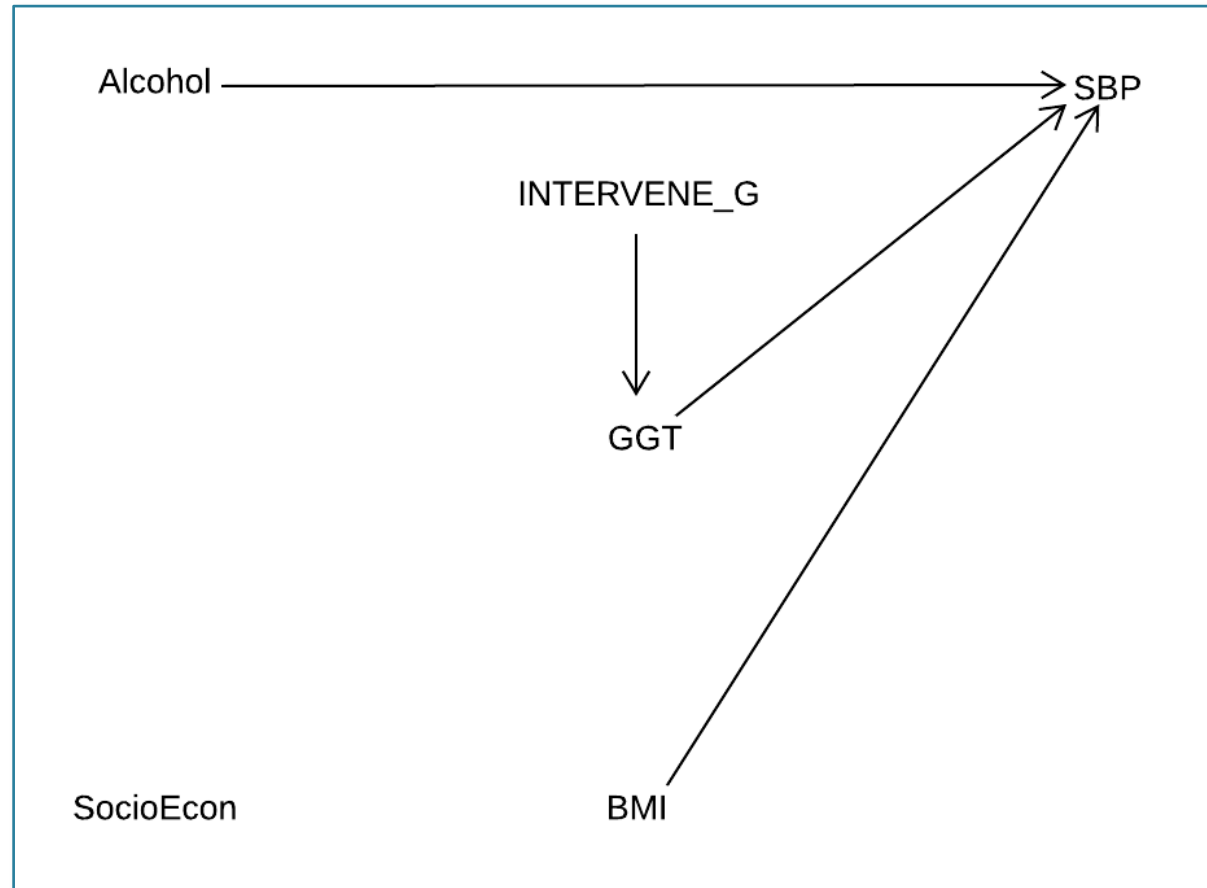


**Adapted from:** Daniel, et al. gformula: Estimating causal effects in the presence of time-varying confounding or mediation using the g-computation formula. The Stata Journal 2011;11:479-517.

# Question About Total Causal Effect of Alcohol Consumption on SBP



# Causal Effect of GGT When Alcohol Consumption is as Observed



# Take-home messages

# Take-home messages

- **If you are in this room, it is highly likely that you base causal inferences on observational data all the time.**

# Take-home messages

- If you are in this room, it is highly likely that you base causal inferences on observational data all the time.
- You probably use G-computation. That's good. It works when you do it right.

# Take-home messages

- If you are in this room, it is highly likely that you base causal inferences on observational data all the time.
- You probably use G-computation. That's good. It works when you do it right.
- Formal causal diagrams and related concepts like backdoor criteria can help you ensure that you are doing G-computation the right way.



the end