A Taste of Problems and Fixes in Program Evaluation

Causality Worries for Economists

Nick Mader

Data Science for Social Good Summer Fellowship, 2013

Outline

An economist, why?

- An economist?
- Leading projects on education and motherhood?
- Don't you have something better to do?
- Like ruin an economy with flawed models of the macroeconomy?

An economist, why?

- An economist?
- Leading projects on education and motherhood?
- Don't you have something better to do?
- Like ruin an economy with flawed models of the macroeconomy?

An economist, why?

- An economist?
- Leading projects on education and motherhood?
- Don't you have something better to do?
- Like ruin an economy with flawed models of the macroeconomy?

An economist, why?

- An economist?
- Leading projects on education and motherhood?
- Don't you have something better to do?
- Like ruin an economy with flawed models of the macroeconomy?

An economist, why?

- I'm a microeconomist. We deal with data and empirics.
    - Unlike macroeconomists
- I don't deal with money
    - Turns out that the human beings economists have been studying *are the same ones that sociologists and psychologists have been studying!*
- Economists still differ from sociologists and statisticians are distinguished by our toolkit
    - Many important questions do not come/can't be put in an experimental framework
    - Econometrics as a field developed to deal with inability to experiment

An economist, why?

- I'm a microeconomist. We deal with data and empirics.
  - Unlike macroeconomists
- I don't deal with money
  - Turns out that the human beings economists have been studying *are the same ones that sociologists and psychologists have been studying!*
- Economists still differ from sociologists and statisticians are distinguished by our toolkit
  - Many important questions do not come/can't be put in an experimental framework
  - Econometrics as a field developed to deal with inability to experiment

An economist, why?

- I'm a microeconomist. We deal with data and empirics.
    - Unlike macroeconomists
- I don't deal with money
    - Turns out that the human beings economists have been studying *are the same ones that sociologists and psychologists have been studying!*
- Economists still differ from sociologists and statisticians are distinguished by our toolkit
    - Many important questions do not come/can't be put in an experimental framework
    - Econometrics as a field developed to deal with inability to experiment

An economist, why?

- I'm a microeconomist. We deal with data and empirics.
  - Unlike macroeconomists
- I don't deal with money
  - Turns out that the human beings economists have been studying *are the same ones that sociologists and psychologists have been studying!*
- Economists still differ from sociologists and statisticians are distinguished by our toolkit
  - Many important questions do not come/can't be put in an experimental framework
  - Econometrics as a field developed to deal with inability to experiment

An economist, why?

- I'm a microeconomist. We deal with data and empirics.
  - Unlike macroeconomists
- I don't deal with money
  - Turns out that the human beings economists have been studying *are the same ones that sociologists and psychologists have been studying!*
- Economists still differ from sociologists and statisticians are distinguished by our toolkit
  - Many important questions do not come/can't be put in an experimental framework
  - Econometrics as a field developed to deal with inability to experiment

An economist, why?

- I'm a microeconomist. We deal with data and empirics.
  - Unlike macroeconomists
- I don't deal with money
  - Turns out that the human beings economists have been studying *are the same ones that sociologists and psychologists have been studying!*
- Economists still differ from sociologists and statisticians are distinguished by our toolkit
  - Many important questions do not come/can't be put in an experimental framework
  - Econometrics as a field developed to deal with inability to experiment

An economist, why?

- I'm a microeconomist. We deal with data and empirics.
  - Unlike macroeconomists
- I don't deal with money
  - Turns out that the human beings economists have been studying *are the same ones that sociologists and psychologists have been studying!*
- Economists still differ from sociologists and statisticians are distinguished by our toolkit
  - Many important questions do not come/can't be put in an experimental framework
  - Econometrics as a field developed to deal with inability to experiment

Improving public policy

- There are phenomena that we care about, and want to improve – crime, poverty, poor educational attainment
- Question is: what's effective in changing them?
- Causes are complex, and the data only partially reflects all the things that matter

Improving public policy

- There are phenomena that we care about, and want to improve – crime, poverty, poor educational attainment
- Question is: what's effective in changing them?
- Causes are complex, and the data only partially reflects all the things that matter

Improving public policy

- There are phenomena that we care about, and want to improve – crime, poverty, poor educational attainment
- Question is: what's effective in changing them?
- Causes are complex, and the data only partially reflects all the things that matter

Some things that we do

- Plot variables, run correlations, calculate conditional averages
- Bivariate comparisons are interesting, but correlation $\neq$ causation
- Graduation rates differ by race. If minority kids...
  - ...go to bad schools, reform the schools;
  - ...have unstable families, support them;
  - ...are bad at school, forget about them.
- Can only close the door on incorrect hypotheses when we have data
- Big danger when we're missing important data, and don't sweat over what that is.

Some things that we do

- Plot variables, run correlations, calculate conditional averages
- Bivariate comparisons are interesting, but correlation $\neq$ causation
- Graduation rates differ by race. If minority kids...
  - ...go to bad schools, reform the schools;
  - ...have unstable families, support them;
  - ...are bad at school, forget about them.
- Can only close the door on incorrect hypotheses when we have data
- Big danger when we're missing important data, and don't sweat over what that is.

Some things that we do

- Plot variables, run correlations, calculate conditional averages
- Bivariate comparisons are interesting, but correlation $\neq$ causation
- Graduation rates differ by race. If minority kids...
    - ...go to bad schools, reform the schools;
    - ...have unstable families, support them;
    - ...are bad at school, forget about them.
- Can only close the door on incorrect hypotheses when we have data
- Big danger when we're missing important data, and don't sweat over what that is.

Some things that we do

- Plot variables, run correlations, calculate conditional averages
- Bivariate comparisons are interesting, but correlation $\neq$ causation
- Graduation rates differ by race. If minority kids...
    - ...go to bad schools, reform the schools;
    - ...have unstable families, support them;
    - ...are bad at school, forget about them.
- Can only close the door on incorrect hypotheses when we have data
- Big danger when we're missing important data, and don't sweat over what that is.

Some things that we do

- Plot variables, run correlations, calculate conditional averages
- Bivariate comparisons are interesting, but correlation $\neq$ causation
- Graduation rates differ by race. If minority kids...
    - ...go to bad schools, reform the schools;
    - ...have unstable families, support them;
    - ...are bad at school, forget about them.
- Can only close the door on incorrect hypotheses when we have data
- Big danger when we're missing important data, and don't sweat over what that is.

Some things that we do

- Plot variables, run correlations, calculate conditional averages
- Bivariate comparisons are interesting, but correlation $\neq$ causation
- Graduation rates differ by race. If minority kids...
  - ...go to bad schools, reform the schools;
  - ...have unstable families, support them;
  - ...are bad at school, forget about them.
- Can only close the door on incorrect hypotheses when we have data
- Big danger when we're missing important data, and don't sweat over what that is.

Some things that we do

- Plot variables, run correlations, calculate conditional averages
- Bivariate comparisons are interesting, but correlation $\neq$ causation
- Graduation rates differ by race. If minority kids...
  - ...go to bad schools, reform the schools;
  - ...have unstable families, support them;
  - ...are bad at school, forget about them.
- Can only close the door on incorrect hypotheses when we have data
- Big danger when we're missing important data, and don't sweat over what that is.

Some things that we do

- Plot variables, run correlations, calculate conditional averages
- Bivariate comparisons are interesting, but correlation $\neq$ causation
- Graduation rates differ by race. If minority kids...
    - ...go to bad schools, reform the schools;
    - ...have unstable families, support them;
    - ...are bad at school, forget about them.
- Can only close the door on incorrect hypotheses when we have data
- Big danger when we're missing important data, and don't sweat over what that is.

A cautionary tale from the NLSY79

- Let's look at descriptives
- Let's add explanatory variables
- Is everything in the data set? Are we happy with our conclusions?

A cautionary tale from the NLSY79

- Let's look at descriptives
- Let's add explanatory variables
- Is everything in the data set? Are we happy with our conclusions?

A cautionary tale from the NLSY79

- Let's look at descriptives
- Let's add explanatory variables
- Is everything in the data set? Are we happy with our conclusions?

Bias due to unobserved factors

- Suppose that the truth is:

$$y_i = \beta' x_i + \alpha d_i + \varepsilon_i$$

Where:

- y_i is the outcome that we're interested in (for simplicity, a continuous variable), observed for individuals $i = 1, ..., N$
- x_i is a vector of information about individuals - gender, race, neighborhood, prior school attendance patterns
- d_i is a binary variable reflecting whether i received some treatment ($d_i = 1$) or not ($d_i = 0$)
- ε_i is everything else not in our data that influences y_i - e.g. motivation, family stability, socio-emotional stability, high quality relationships, positive outlook
- α and β are parameters that measure the rates at which d_i and x_i transfer into y_i.

Bias due to unobserved factors

- Suppose that the truth is:

$$y_i = \beta' x_i + \alpha d_i + \varepsilon_i$$

Where:

- y_i is the outcome that we're interested in (for simplicity, a continuous variable), observed for individuals $i = 1, ..., N$
- x_i is a vector of information about individuals - gender, race, neighborhood, prior school attendance patterns
- d_i is a binary variable reflecting whether i received some treatment ($d_i = 1$) or not ($d_i = 0$)
- ε_i is everything else not in our data that influences y_i - e.g. motivation, family stability, socio-emotional stability, high quality relationships, positive outlook
- α and β are parameters that measure the rates at which d_i and x_i transfer into y_i.

Bias due to unobserved factors

- Suppose that the truth is:

$$y_i = \beta' x_i + \alpha d_i + \varepsilon_i$$

Where:

- y_i is the outcome that we're interested in (for simplicity, a continuous variable), observed for individuals $i = 1, ..., N$
- x_i is a vector of information about individuals - gender, race, neighborhood, prior school attendance patterns
- d_i is a binary variable reflecting whether i received some treatment ($d_i = 1$) or not ($d_i = 0$)
- ε_i is everything else not in our data that influences y_i - e.g. motivation, family stability, socio-emotional stability, high quality relationships, positive outlook
- α and β are parameters that measure the rates at which d_i and x_i transfer into y_i.

Bias due to unobserved factors

- Suppose that the truth is:

$$y_i = \beta' x_i + \alpha d_i + \varepsilon_i$$

Where:

- y_i is the outcome that we're interested in (for simplicity, a continuous variable), observed for individuals $i = 1, ..., N$
- x_i is a vector of information about individuals - gender, race, neighborhood, prior school attendance patterns
- d_i is a binary variable reflecting whether i received some treatment ($d_i = 1$) or not ($d_i = 0$)
- ε_i is everything else not in our data that influences y_i - e.g. motivation, family stability, socio-emotional stability, high quality relationships, positive outlook
- α and β are parameters that measure the rates at which d_i and x_i transfer into y_i.

Bias due to unobserved factors

- Suppose that the truth is:

$$y_i = \beta' x_i + \alpha d_i + \varepsilon_i$$

Where:

- y_i is the outcome that we're interested in (for simplicity, a continuous variable), observed for individuals $i = 1, ..., N$
- x_i is a vector of information about individuals - gender, race, neighborhood, prior school attendance patterns
- d_i is a binary variable reflecting whether i received some treatment $(d_i = 1)$ or not $(d_i = 0)$
- ε_i is everything else not in our data that influences y_i - e.g. motivation, family stability, socio-emotional stability, high quality relationships, positive outlook
- α and β are parameters that measure the rates at which d_i and x_i transfer into y_i.

Bias due to unobserved factors

- Suppose that the truth is:

$$y_i = \beta' x_i + \alpha d_i + \varepsilon_i$$

Where:

- y_i is the outcome that we're interested in (for simplicity, a continuous variable), observed for individuals $i = 1, ..., N$
- x_i is a vector of information about individuals - gender, race, neighborhood, prior school attendance patterns
- d_i is a binary variable reflecting whether i received some treatment $(d_i = 1)$ or not $(d_i = 0)$
- ε_i is everything else not in our data that influences y_i - e.g. motivation, family stability, socio-emotional stability, high quality relationships, positive outlook
- α and β are parameters that measure the rates at which d_i and x_i transfer into y_i.

Bias due to unobserved factors

- Resources: $\{x_i, d_i, y_i\}_{i=1}^N$
- Interests: $\{\alpha, \beta\}$
- We've got a linear setup–how about a linear projection of y_i on the space defined by $(x_{i,} d_i)$ to recover the slope parameters?

$$\mathbf{E}\left[y_i | x_i, d_i\right] = \beta' x_i + \alpha d_i + \mathbf{E}\left[\varepsilon_{\mathbf{i}} | \mathbf{x}_{\mathbf{i}}, \mathbf{d}_{\mathbf{i}}\right]$$

- Oops. ε_i isn't orthogonal to x_i and d_i.
  - That sounds technical. Is a problem?

Bias due to unobserved factors

- Resources: $\{x_i, d_i, y_i\}_{i=1}^{N}$
- Interests: $\{\alpha, \beta\}$
- We've got a linear setup–how about a linear projection of y_i on the space defined by $(x_{i,} d_i)$ to recover the slope parameters?

$$\mathbf{E}[y_i | x_i, d_i] = \beta' x_i + \alpha d_i + \mathbf{E}[\boldsymbol{\varepsilon}_\mathbf{i} | \mathbf{x}_\mathbf{i}, \mathbf{d}_\mathbf{i}]$$

- Oops. ε_i isn't orthogonal to x_i and d_i.
  - That sounds technical. Is a problem?

Bias due to unobserved factors

- Resources: $\{x_i, d_i, y_i\}_{i=1}^{N}$
- Interests: $\{\alpha, \beta\}$
- We've got a linear setup–how about a linear projection of y_i on the space defined by $(x_{i,}d_i)$ to recover the slope parameters?

$$\mathbf{E}[y_i | x_i, d_i] = \beta' x_i + \alpha d_i + \mathbf{E}[\varepsilon_\mathbf{i} | \mathbf{x_i}, \mathbf{d_i}]$$

- Oops. ε_i isn't orthogonal to x_i and d_i.
  - That sounds technical. Is a problem?

Bias due to unobserved factors

- Resources: $\{x_i, d_i, y_i\}_{i=1}^{N}$
- Interests: $\{\alpha, \beta\}$
- We've got a linear setup–how about a linear projection of y_i on the space defined by $(x_{i,} d_i)$ to recover the slope parameters?

$$\mathbf{E}\left[y_i | x_i, d_i\right] = \beta' x_i + \alpha d_i + \mathbf{E}\left[\varepsilon_\mathbf{i} | \mathbf{x_i}, \mathbf{d_i}\right]$$

- Oops. ε_i isn't orthogonal to x_i and d_i.
  - That sounds technical. Is a problem?

Bias due to unobserved factors

- Resources: $\{x_i, d_i, y_i\}_{i=1}^N$
- Interests: $\{\alpha, \beta\}$
- We've got a linear setup–how about a linear projection of y_i on the space defined by $(x_{i,}d_i)$ to recover the slope parameters?

$$\mathbf{E}[y_i | x_i, d_i] = \beta' x_i + \alpha d_i + \mathbf{E}[\boldsymbol{\varepsilon_i} | \mathbf{x_i}, \mathbf{d_i}]$$

- Oops. ε_i isn't orthogonal to x_i and d_i.
  - That sounds technical. Is a problem?

Bias due to unobserved factors

- There's a theoretical relationship between what we don't observe and what we do:

$$\varepsilon_{\mathbf{i}} = \pi_x' x_i + \pi_d d_i + \eta_i$$

  where π are projection parameters, and η_i represents unobserved factors that truly are orthogonal to (x_i, d_i).
- $\pi \neq 0$ means that there's some relationship between what we don't observe and what we do observe
  - Unobserved neighborhood processes will hang with indicators of neighborhood of residence
  - Delinquency and disengagement will hang with (low) attendance
  - $\pi_d < 0$ means that program participation is associated with negative unobservables

Bias due to unobserved factors

- There's a theoretical relationship between what we don't observe and what we do:

$$\varepsilon_{\mathbf{i}} = \pi_x' x_i + \pi_d d_i + \eta_i$$

  where π are projection parameters, and η_i represents unobserved factors that truly are orthogonal to (x_i, d_i).
- $\pi \neq 0$ means that there's some relationship between what we don't observe and what we do observe
  - Unobserved neighborhood processes will hang with indicators of neighborhood of residence
  - Delinquency and disengagement will hang with (low) attendance
  - $\pi_d < 0$ means that program participation is associated with negative unobservables
    - Very likely when treatment targets at-risk populations

Bias due to unobserved factors

- There's a theoretical relationship between what we don't observe and what we do:

$$\varepsilon_{\mathbf{i}} = \pi_x' x_i + \pi_d d_i + \eta_i$$

where π are projection parameters, and η_i represents unobserved factors that truly are orthogonal to (x_i, d_i).

- $\pi \neq 0$ means that there's some relationship between what we don't observe and what we do observe
    - Unobserved neighborhood processes will hang with indicators of neighborhood of residence
    - Delinquency and disengagement will hang with (low) attendance
    - $\pi_d < 0$ means that program participation is associated with negative unobservables
        - Very likely when treatment targets at-risk populations

Bias due to unobserved factors

- There's a theoretical relationship between what we don't observe and what we do:

$$\varepsilon_{\mathbf{i}} = \pi_x' x_i + \pi_d d_i + \eta_i$$

where π are projection parameters, and η_i represents unobserved factors that truly are orthogonal to (x_i, d_i).

- $\pi \neq 0$ means that there's some relationship between what we don't observe and what we do observe
  - Unobserved neighborhood processes will hang with indicators of neighborhood of residence
  - Delinquency and disengagement will hang with (low) attendance
  - $\pi_d < 0$ means that program participation is associated with negative unobservables
    - Very likely when treatment targets at-risk populations

Bias due to unobserved factors

- There's a theoretical relationship between what we don't observe and what we do:

$$\varepsilon_{\mathbf{i}} = \pi_x' x_i + \pi_d d_i + \eta_i$$

  where π are projection parameters, and η_i represents unobserved factors that truly are orthogonal to (x_i, d_i).
- $\pi \neq 0$ means that there's some relationship between what we don't observe and what we do observe
  - Unobserved neighborhood processes will hang with indicators of neighborhood of residence
  - Delinquency and disengagement will hang with (low) attendance
  - $\pi_d < 0$ means that program participation is associated with negative unobservables
    - Very likely when treatment targets at-risk populations

Bias due to unobserved factors

- There's a theoretical relationship between what we don't observe and what we do:

$$\varepsilon_{\mathbf{i}} = \pi_x' x_i + \pi_d d_i + \eta_i$$

  where π are projection parameters, and η_i represents unobserved factors that truly are orthogonal to (x_i, d_i).
- $\pi \neq 0$ means that there's some relationship between what we don't observe and what we do observe
  - Unobserved neighborhood processes will hang with indicators of neighborhood of residence
  - Delinquency and disengagement will hang with (low) attendance
  - $\pi_d < 0$ means that program participation is associated with negative unobservables
    - Very likely when treatment targets at-risk populations

Bias due to unobserved factors

- Linear regression gets us clumps of parameters:

$$y_i = (\beta + \pi_x)' x_i + (\alpha + \pi_d) d_i + \eta_i$$

- We're no longer in the world of *ceteris paribus*
- When we vary d_i, we switch on other stuff
  - An effective program ($\alpha > 0$) ...
  - ...that targets kids who are at-risk in ways we can't account for ($\pi_d < 0$) ...
  - may look ineffective (if $\alpha + \pi_d \leq 0$)
- We have data, ran stats that other people can't do. We're very smart. Shouldn't we close programs that look ineffective?
  - Good lord.
  - Loaded question.

Bias due to unobserved factors

- Linear regression gets us clumps of parameters:

$$y_i = (\beta + \pi_x)' x_i + (\alpha + \pi_d) d_i + \eta_i$$

- We're no longer in the world of *ceteris paribus*
- When we vary d_i, we switch on other stuff
  - An effective program ($\alpha > 0$) ...
  - ...that targets kids who are at-risk in ways we can't account for ($\pi_d < 0$) ...
  - may look ineffective (if $\alpha + \pi_d \leq 0$)
- We have data, ran stats that other people can't do. We're very smart. Shouldn't we close programs that look ineffective?
  - Good lord.
  - Loaded question.

Bias due to unobserved factors

- Linear regression gets us clumps of parameters:

$$y_i = (\beta + \pi_x)' x_i + (\alpha + \pi_d) d_i + \eta_i$$

- We're no longer in the world of *ceteris paribus*
- When we vary d_i, we switch on other stuff
  - An effective program ($\alpha > 0$) ...
  - ...that targets kids who are at-risk in ways we can't account for ($\pi_d < 0$) ...
  - may look ineffective (if $\alpha + \pi_d \leq 0$)
- We have data, ran stats that other people can't do. We're very smart. Shouldn't we close programs that look ineffective?
  - Good lord.
  - Loaded question.

Bias due to unobserved factors

- Linear regression gets us clumps of parameters:

$$y_i = (\beta + \pi_x)' x_i + (\alpha + \pi_d) d_i + \eta_i$$

- We're no longer in the world of *ceteris paribus*
- When we vary d_i, we switch on other stuff
  - An effective program $(\alpha > 0)$ ...
  - ...that targets kids who are at-risk in ways we can't account for $(\pi_d < 0)$ ...
  - may look ineffective (if $\alpha + \pi_d \leq 0$)
- We have data, ran stats that other people can't do. We're very smart. Shouldn't we close programs that look ineffective?
  - Good lord.
  - Loaded question.

Bias due to unobserved factors

- Linear regression gets us clumps of parameters:

$$y_i = (\beta + \pi_x)' x_i + (\alpha + \pi_d) d_i + \eta_i$$

- We're no longer in the world of *ceteris paribus*
- When we vary d_i, we switch on other stuff
  - An effective program ($\alpha > 0$) ...
  - ...that targets kids who are at-risk in ways we can't account for ($\pi_d < 0$) ...
  - may look ineffective (if $\alpha + \pi_d \leq 0$)
- We have data, ran stats that other people can't do. We're very smart. Shouldn't we close programs that look ineffective?
  - Good lord.
  - Loaded question.

Bias due to unobserved factors

- Linear regression gets us clumps of parameters:

$$y_i = (\beta + \pi_x)' x_i + (\alpha + \pi_d) d_i + \eta_i$$

- We're no longer in the world of *ceteris paribus*
- When we vary d_i, we switch on other stuff
  - An effective program ($\alpha > 0$) ...
  - ...that targets kids who are at-risk in ways we can't account for ($\pi_d < 0$) ...
  - may look ineffective (if $\alpha + \pi_d \leq 0$)
- We have data, ran stats that other people can't do. We're very smart. Shouldn't we close programs that look ineffective?
  - Good lord.
  - Loaded question.

Bias due to unobserved factors

- Linear regression gets us clumps of parameters:

$$y_i = (\beta + \pi_x)' x_i + (\alpha + \pi_d) d_i + \eta_i$$

- We're no longer in the world of *ceteris paribus*
- When we vary d_i, we switch on other stuff
  - An effective program ($\alpha > 0$) ...
  - ...that targets kids who are at-risk in ways we can't account for ($\pi_d < 0$) ...
  - may look ineffective (if $\alpha + \pi_d \leq 0$)
- We have data, ran stats that other people can't do. We're very smart. Shouldn't we close programs that look ineffective?
  - Good lord.
  - Loaded question.

Bias due to unobserved factors

- Linear regression gets us clumps of parameters:

$$y_i = (\beta + \pi_x)' x_i + (\alpha + \pi_d) d_i + \eta_i$$

- We're no longer in the world of *ceteris paribus*
- When we vary d_i, we switch on other stuff
  - An effective program ($\alpha > 0$) ...
  - ...that targets kids who are at-risk in ways we can't account for ($\pi_d < 0$) ...
  - may look ineffective (if $\alpha + \pi_d \leq 0$)
- We have data, ran stats that other people can't do. We're very smart. Shouldn't we close programs that look ineffective?
  - Good lord.
  - Loaded question.

Bias due to unobserved factors

- Linear regression gets us clumps of parameters:

$$y_i = (\beta + \pi_x)' x_i + (\alpha + \pi_d) d_i + \eta_i$$

- We're no longer in the world of *ceteris paribus*
- When we vary d_i, we switch on other stuff
  - An effective program ($\alpha > 0$) ...
  - ...that targets kids who are at-risk in ways we can't account for ($\pi_d < 0$) ...
  - may look ineffective (if $\alpha + \pi_d \leq 0$)
- We have data, ran stats that other people can't do. We're very smart. Shouldn't we close programs that look ineffective?
  - Good lord.
  - Loaded question.

Strategies for Fixes

- We need to return to a *ceteris paribus* world
- **Instrumental Variables** methods remove the portion of d_i that is associated with unobserved factors
  - Instead, rely only on what known (i.e., *are* in the data), unproblematic factors explain program participation
  - Regress y_i on x_i and $\mathbf{E}[d_i | x_i, z_i]$ where z_i are "unproblematic" variables that explain participation in treatment (the "instrumental variables")
- **Control Function** methods directly account for unobserved factors whose presence we can infer
  - Regress $y_i$on x_i, d_i and $\mathbf{E}[\varepsilon_i | x_i, d_i, z_i]$
- A variety of implementations will yield more and less flexible (and complex) results.

Strategies for Fixes

- We need to return to a *ceteris paribus* world
- **Instrumental Variables** methods remove the portion of d_i that is associated with unobserved factors
  - Instead, rely only on what known (i.e., *are* in the data), unproblematic factors explain program participation
  - Regress y_i on x_i and $\mathbf{E}[d_i | x_i, z_i]$ where z_i are "unproblematic" variables that explain participation in treatment (the "instrumental variables")
- **Control Function** methods directly account for unobserved factors whose presence we can infer
  - Regress y_i on x_i, d_i and $\mathbf{E}[\varepsilon_i | x_i, d_i, z_i]$
- A variety of implementations will yield more and less flexible (and complex) results.

Strategies for Fixes

- We need to return to a *ceteris paribus* world
- **Instrumental Variables** methods remove the portion of d_i that is associated with unobserved factors
  - Instead, rely only on what known (i.e., *are* in the data), unproblematic factors explain program participation
  - Regress y_i on x_i and $\mathbf{E}[d_i|x_i, z_i]$ where z_i are "unproblematic" variables that explain participation in treatment (the "instrumental variables")
- **Control Function** methods directly account for unobserved factors whose presence we can infer
  - Regress y_i on x_i, d_i and $\mathbf{E}[\varepsilon_i|x_i, d_i, z_i]$
- A variety of implementations will yield more and less flexible (and complex) results.

Strategies for Fixes

- We need to return to a *ceteris paribus* world
- **Instrumental Variables** methods remove the portion of d_i that is associated with unobserved factors
  - Instead, rely only on what known (i.e., *are* in the data), unproblematic factors explain program participation
  - Regress y_i on x_i and $\mathbf{E}[d_i | x_i, z_i]$ where z_i are "unproblematic" variables that explain participation in treatment (the "instrumental variables")
- **Control Function** methods directly account for unobserved factors whose presence we can infer
  - Regress y_i on x_i, d_i and $\mathbf{E}[\varepsilon_i | x_i, d_i, z_i]$
- A variety of implementations will yield more and less flexible (and complex) results.

Strategies for Fixes

- We need to return to a *ceteris paribus* world
- **Instrumental Variables** methods remove the portion of d_i that is associated with unobserved factors
  - Instead, rely only on what known (i.e., *are* in the data), unproblematic factors explain program participation
  - Regress y_i on x_i and $\mathbf{E}[d_i | x_i, z_i]$ where z_i are "unproblematic" variables that explain participation in treatment (the "instrumental variables")
- **Control Function** methods directly account for unobserved factors whose presence we can infer
  - Regress y_i on x_i, d_i and $\mathbf{E}[\varepsilon_i | x_i, d_i, z_i]$
- A variety of implementations will yield more and less flexible (and complex) results.

Strategies for Fixes

- We need to return to a *ceteris paribus* world
- **Instrumental Variables** methods remove the portion of d_i that is associated with unobserved factors
  - Instead, rely only on what known (i.e., *are* in the data), unproblematic factors explain program participation
  - Regress y_i on x_i and $\mathbf{E}[d_i | x_i, z_i]$ where z_i are "unproblematic" variables that explain participation in treatment (the "instrumental variables")
- **Control Function** methods directly account for unobserved factors whose presence we can infer
  - Regress y_i on x_i, d_i and $\mathbf{E}[\varepsilon_i | x_i, d_i, z_i]$
- A variety of implementations will yield more and less flexible (and complex) results.

Strategies for Fixes

- We need to return to a *ceteris paribus* world
- **Instrumental Variables** methods remove the portion of d_i that is associated with unobserved factors
  - Instead, rely only on what known (i.e., *are* in the data), unproblematic factors explain program participation
  - Regress y_i on x_i and $\mathbf{E}[d_i|x_i, z_i]$ where z_i are "unproblematic" variables that explain participation in treatment (the "instrumental variables")
- **Control Function** methods directly account for unobserved factors whose presence we can infer
  - Regress $y_i$on x_i, d_i and $\mathbf{E}[\varepsilon_i|x_i, d_i, z_i]$
- A variety of implementations will yield more and less flexible (and complex) results.

Complications that we can add

- Vector-valued treatment – there are a lot of programs out there
- Non-continuous outcomes

Complications that we can add

- Vector-valued treatment – there are a lot of programs out there
- Non-continuous outcomes

Summary

- **Planning**: Think about what you have–versus what you *need to have*–measured
  - Use partners to get perspective on what you need
  - Worry a lot about what you don't have
- **Implementing**: Respect and manage high stakes
  - In academia, high stakes are getting lit up in seminar
  - In program evaluation, high stakes are killing a good program
  - Communicate caveats
  - But: being smart using data is constructive. Carefully add to the mix.
- **Iterating Solutions**: Your computer is not your only tool
  - Missing data? Go and get it.

Summary

- **Planning**: Think about what you have–versus what you *need to have*–measured
  - Use partners to get perspective on what you need
  - Worry a lot about what you don't have
- **Implementing**: Respect and manage high stakes
  - In academia, high stakes are getting lit up in seminar
  - In program evaluation, high stakes are killing a good program
  - Communicate caveats
  - But: being smart using data is constructive. Carefully add to the mix.
- **Iterating Solutions**: Your computer is not your only tool
  - Missing data? Go and get it.

Summary

- **Planning**: Think about what you have–versus what you *need to have*–measured
  - Use partners to get perspective on what you need
  - Worry a lot about what you don't have
- **Implementing**: Respect and manage high stakes
  - In academia, high stakes are getting lit up in seminar
  - In program evaluation, high stakes are killing a good program
  - Communicate caveats
  - But: being smart using data is constructive. Carefully add to the mix.
- **Iterating Solutions**: Your computer is not your only tool
  - Missing data? Go and get it.

Summary

- **Planning**: Think about what you have–versus what you *need to have*–measured
  - Use partners to get perspective on what you need
  - Worry a lot about what you don't have
- **Implementing**: Respect and manage high stakes
  - In academia, high stakes are getting lit up in seminar
  - In program evaluation, high stakes are killing a good program
  - Communicate caveats
  - But: being smart using data is constructive. Carefully add to the mix.
- **Iterating Solutions**: Your computer is not your only tool
  - Missing data? Go and get it.

Summary

- **Planning**: Think about what you have–versus what you *need to have*–measured
  - Use partners to get perspective on what you need
  - Worry a lot about what you don't have
- **Implementing**: Respect and manage high stakes
  - In academia, high stakes are getting lit up in seminar
  - In program evaluation, high stakes are killing a good program
  - Communicate caveats
  - But: being smart using data is constructive. Carefully add to the mix.
- **Iterating Solutions**: Your computer is not your only tool
  - Missing data? Go and get it.

Summary

- **Planning**: Think about what you have–versus what you *need to have*–measured
  - Use partners to get perspective on what you need
  - Worry a lot about what you don't have
- **Implementing**: Respect and manage high stakes
  - In academia, high stakes are getting lit up in seminar
  - In program evaluation, high stakes are killing a good program
  - Communicate caveats
  - But: being smart using data is constructive. Carefully add to the mix.
- **Iterating Solutions**: Your computer is not your only tool
  - Missing data? Go and get it.

Summary

- **Planning**: Think about what you have–versus what you *need to have*–measured
  - Use partners to get perspective on what you need
  - Worry a lot about what you don't have
- **Implementing**: Respect and manage high stakes
  - In academia, high stakes are getting lit up in seminar
  - In program evaluation, high stakes are killing a good program
  - Communicate caveats
  - But: being smart using data is constructive. Carefully add to the mix.
- **Iterating Solutions**: Your computer is not your only tool
  - Missing data? Go and get it.

Summary

- **Planning**: Think about what you have–versus what you *need to have*–measured
  - Use partners to get perspective on what you need
  - Worry a lot about what you don't have
- **Implementing**: Respect and manage high stakes
  - In academia, high stakes are getting lit up in seminar
  - In program evaluation, high stakes are killing a good program
  - Communicate caveats
  - But: being smart using data is constructive. Carefully add to the mix.
- **Iterating Solutions**: Your computer is not your only tool
  - Missing data? Go and get it.

Summary

- **Planning**: Think about what you have–versus what you *need to have*–measured
  - Use partners to get perspective on what you need
  - Worry a lot about what you don't have
- **Implementing**: Respect and manage high stakes
  - In academia, high stakes are getting lit up in seminar
  - In program evaluation, high stakes are killing a good program
  - Communicate caveats
  - But: being smart using data is constructive. Carefully add to the mix.
- **Iterating Solutions**: Your computer is not your only tool
  - Missing data? Go and get it.

Summary

- **Planning**: Think about what you have–versus what you *need to have*–measured
  - Use partners to get perspective on what you need
  - Worry a lot about what you don't have
- **Implementing**: Respect and manage high stakes
  - In academia, high stakes are getting lit up in seminar
  - In program evaluation, high stakes are killing a good program
  - Communicate caveats
  - But: being smart using data is constructive. Carefully add to the mix.
- **Iterating Solutions**: Your computer is not your only tool
  - Missing data? Go and get it.