# Instrumental-Variable 

Ruben Zamar<br>Department of Statistics UBC

March 12, 2014

## THE LINEAR REGRESSION MODEL

- Ordinary linear regression model

$$
\mathbf{y}=1 \alpha+X \beta+\varepsilon
$$

## THE LINEAR REGRESSION MODEL

- Ordinary linear regression model

$$
\mathbf{y}=\mathbf{1} \alpha+X \beta+\varepsilon
$$

- Design Matrix

$$
X_{c}=\left(\begin{array}{cccc}
x_{11}-\bar{x}_{1} & x_{12}-\bar{x}_{2} & \cdots & x_{1 p}-\bar{x}_{p} \\
x_{21}-\bar{x}_{1} & x_{22}-\bar{x}_{2} & \cdots & x_{2 p}-\bar{x}_{p} \\
x_{31}-\bar{x}_{1} & x_{32}-\bar{x}_{2} & \cdots & x_{3 p}-\bar{x}_{p} \\
\vdots & \vdots & & \vdots \\
x_{n 1}-\bar{x}_{1} & x_{n 2}-\bar{x}_{2} & \cdots & x_{n p}-\bar{x}_{p}
\end{array}\right)
$$

## THE LS ESTIMATOR

## Ordinary Least Squares Estimate

$$
\widehat{\boldsymbol{\beta}}_{L S}=\left(X_{c}^{\prime} X_{c}\right)^{-1} X_{c}^{\prime} \boldsymbol{y} \quad, \quad \widehat{\alpha}_{L S}=\bar{y}-\overline{\mathbf{x}}^{\prime} \widehat{\boldsymbol{\beta}}_{L S}
$$

## THE LS ESTIMATOR

## Ordinary Least Squares Estimate

$$
\begin{aligned}
& \widehat{\boldsymbol{\beta}}_{L S}=\left(X_{c}^{\prime} X_{c}\right)^{-1} X_{c}^{\prime} \mathbf{y} \quad, \quad \widehat{\alpha}_{L S}=\bar{y}-\overline{\mathbf{x}}^{\prime} \widehat{\boldsymbol{\beta}}_{L S} \\
& \widehat{\Sigma}_{x x}=\frac{1}{n} X_{c}^{\prime} X_{c} \quad \text { (sample covariance matrix) } \\
& \widehat{\Sigma}_{x y}=\frac{1}{n} X_{c}^{\prime} \mathbf{y}
\end{aligned}
$$

## THE LS ESTIMATOR

## Ordinary Least Squares Estimate

$$
\begin{aligned}
& \widehat{\boldsymbol{\beta}}_{L S}=\left(X_{c}^{\prime} X_{c}\right)^{-1} X_{c}^{\prime} \mathbf{y} \quad, \quad \widehat{\alpha}_{L S}=\bar{y}-\overline{\mathbf{x}}^{\prime} \widehat{\boldsymbol{\beta}}_{L S} \\
& \widehat{\Sigma}_{x x}=\frac{1}{n} X_{c}^{\prime} X_{c} \quad \text { (sample covariance matrix) } \\
& \widehat{\Sigma}_{x y}=\frac{1}{n} X_{c}^{\prime} \mathbf{y} \\
& \qquad \widehat{\boldsymbol{\beta}}_{L S}=\widehat{\Sigma}_{x x}^{-1} \widehat{\Sigma}_{x y}
\end{aligned}
$$

## KEY ASSUMPTIONS

- All covariates are exogenous
$X$ and $\varepsilon$ are independent


## KEY ASSUMPTIONS

- All covariates are exogenous


## $X$ and $\varepsilon$ are independent

- Errors have zero mean

$$
E(\varepsilon)=\mathbf{0}
$$

## LS IS UNBIASED

$$
E\left\{\widehat{\boldsymbol{\beta}}_{L S}\right\}=E\left\{E\left\{\widehat{\boldsymbol{\beta}}_{L S} \mid X\right\}\right\}
$$

## LS IS UNBIASED

$$
\begin{aligned}
E\left\{\widehat{\beta}_{L S}\right\} & =E\left\{E\left\{\widehat{\beta}_{L S} \mid X\right\}\right\} \\
& =E\left\{\left(X_{c}^{\prime} x_{c}\right)^{-1} X_{c}^{\prime} E\{\mathbf{y} \mid X\}\right\}
\end{aligned}
$$

## LS IS UNBIASED

$$
\begin{aligned}
E\left\{\hat{\boldsymbol{\beta}}_{L S}\right\} & =E\left\{E\left\{\hat{\boldsymbol{\beta}}_{L S} \mid X\right\}\right\} \\
& =E\left\{\left(X_{c}^{\prime} X_{c}\right)^{-1} X_{c}^{\prime} E\{\mathbf{y} \mid X\}\right\} \\
& =E\left\{\left(X_{c}^{\prime} X_{c}\right)^{-1} X_{c}^{\prime} E\{\mathbf{1} \alpha+X \beta+\boldsymbol{\varepsilon} \mid X\}\right\}
\end{aligned}
$$

## LS IS UNBIASED

$$
\begin{aligned}
& E\left\{\widehat{\beta}_{L S}\right\}=E\left\{E\left\{\widehat{\beta}_{L S} \mid X\right\}\right\} \\
& =E\left\{\left(X_{c}^{\prime} X_{c}\right)^{-1} X_{c}^{\prime} E\{y \mid X\}\right\} \\
& =E\left\{\left(X_{c}^{\prime} X_{c}\right)^{-1} X_{c}^{\prime} E\{1 \alpha+X \beta+\varepsilon \mid X\}\right\} \\
& =E\{\overbrace{\left(X_{c}^{\prime} x_{c}\right)^{-1} X_{c}^{\prime} 1 \alpha}^{=0}+\overbrace{\left(X_{c}^{\prime} x_{c}\right)^{-1} X_{c}^{\prime} X}^{=1}+\left(X_{c}^{\prime} x_{c}\right)^{-1} X_{c}^{\prime} E\{\varepsilon\}\}
\end{aligned}
$$

## LS IS UNBIASED

$$
\begin{aligned}
& E\left\{\widehat{\beta}_{L S}\right\}=E\left\{E\left\{\widehat{\beta}_{L S} \mid X\right\}\right\} \\
&=E\left\{\left(X_{c}^{\prime} X_{c}\right)^{-1} X_{c}^{\prime} E\{y \mid X\}\right\} \\
&=E\left\{\left(X_{c}^{\prime} X_{c}\right)^{-1} X_{c}^{\prime} E\{1 \alpha+X \beta+\varepsilon \mid X\}\right\} \\
&=E\{\overbrace{\left(X_{c}^{\prime} X_{c}\right)^{-1} X_{c}^{\prime} 1 \alpha}^{=0}+\overbrace{\left(X_{c}^{\prime} X_{c}\right)^{-1} X_{c}^{\prime} X \beta}^{=}+\left(X_{c}^{\prime} X_{c}\right)^{-1} X_{c}^{\prime} e^{\prime}=0 \\
&=\beta
\end{aligned}
$$

## LS IS CONSISTENT

$$
\widehat{\beta}_{L S}=\widehat{\Sigma}_{x x}^{-1} \widehat{\Sigma}_{x y} \longrightarrow \Sigma_{x x}^{-1} \Sigma_{x y}, \quad \text { by LLN }
$$

## LS IS CONSISTENT

$$
\begin{aligned}
& \widehat{\boldsymbol{\beta}}_{L S}=\widehat{\Sigma}_{x x}^{-1} \widehat{\Sigma}_{x y} \longrightarrow \Sigma_{x x}^{-1} \Sigma_{x y}, \quad \text { by LLN } \\
& \Sigma_{x x}^{-1} \Sigma_{x y}=\Sigma_{x x}^{-1} \operatorname{Cov}(\mathbf{x}, y)
\end{aligned}
$$

## LS IS CONSISTENT

$$
\begin{aligned}
& \widehat{\boldsymbol{\beta}}_{L S}=\widehat{\Sigma}_{x x}^{-1} \widehat{\Sigma}_{x y} \longrightarrow \Sigma_{x x}^{-1} \Sigma_{x y}, \quad \text { by LLN } \\
& \begin{aligned}
\Sigma_{x x}^{-1} \Sigma_{x y} & =\Sigma_{x x}^{-1} \operatorname{Cov}(\mathbf{x}, y) \\
& =\Sigma_{x x}^{-1} \operatorname{Cov}\left(\mathbf{x}, \alpha+\mathbf{x}^{\prime} \boldsymbol{\beta}+\varepsilon\right)
\end{aligned}
\end{aligned}
$$

## LS IS CONSISTENT

$$
\begin{aligned}
& \widehat{\widehat{\beta}}_{L S}=\widehat{\Sigma}_{x x}^{-1} \widehat{\Sigma}_{x y} \longrightarrow \Sigma_{x x}^{-1} \Sigma_{x y}, \quad \text { by LLN } \\
& \begin{aligned}
\Sigma_{x x}^{-1} \Sigma_{x y} & =\Sigma_{x x}^{-1} \operatorname{Cov}(\mathbf{x}, y) \\
& =\Sigma_{x x}^{-1} \operatorname{Cov}\left(\mathbf{x}, \alpha+\mathbf{x}^{\prime} \beta+\varepsilon\right) \\
& =\Sigma_{x x}^{-1} \overbrace{\operatorname{Cov}\left(\mathbf{x}, \mathbf{x}^{\prime} \beta\right)}^{\Sigma_{x x} \beta}+\Sigma_{x x}^{-1} \overbrace{\operatorname{Cov}(\mathbf{x}, \varepsilon)}^{0}
\end{aligned}
\end{aligned}
$$

## LS IS CONSISTENT

$$
\begin{aligned}
& \widehat{\boldsymbol{\beta}}_{L S}= \widehat{\Sigma}_{x x}^{-1} \widehat{\Sigma}_{x y} \longrightarrow \Sigma_{x x}^{-1} \Sigma_{x y}, \quad \text { by LLN } \\
& \begin{aligned}
\Sigma_{x x}^{-1} \Sigma_{x y} & =\Sigma_{x x}^{-1} \operatorname{Cov}(\mathbf{x}, y) \\
& =\Sigma_{x x}^{-1} \operatorname{Cov}\left(\mathbf{x}, \alpha+\mathbf{x}^{\prime} \beta+\varepsilon\right) \\
& =\Sigma_{x x}^{-1} \overbrace{\operatorname{Cov}\left(\mathbf{x}, \mathbf{x}^{\prime} \boldsymbol{\beta}\right)}^{\Sigma_{x x} \beta}+\Sigma_{x x}^{-1} \overbrace{\operatorname{Cov}(\mathbf{x}, \varepsilon)}^{0} \\
& =\beta
\end{aligned}
\end{aligned}
$$

## ENDOGENEITY

- Some covariates (called endogenous ) are correlated with the error term


## ENDOGENEITY

- Some covariates (called endogenous ) are correlated with the error term
- This problem arises in several contexts:


## ENDOGENEITY

- Some covariates (called endogenous ) are correlated with the error term
- This problem arises in several contexts:

Errors-in-variables: Some covariates are measured with errors

## ENDOGENEITY

- Some covariates (called endogenous ) are correlated with the error term
- This problem arises in several contexts:

Errors-in-variables: Some covariates are measured with errors

Omitted covariates: Some model covariates are correlated with unoserved predictors

## ENDOGENEITY

- Some covariates (called endogenous ) are correlated with the error term
- This problem arises in several contexts:

Errors-in-variables: Some covariates are measured with errors

Omitted covariates: Some model covariates are correlated with unoserved predictors

Simultaneity: Some covariates simultaneously affect and are affected by the response variable

## ENDOGENEITY

- The (additive) asymptotic bias due to endogeneity is given by

$$
A B=\Sigma_{x x}^{-1} \operatorname{Cov}(\mathbf{x}, \varepsilon)
$$

## ENDOGENEITY

- The (additive) asymptotic bias due to endogeneity is given by

$$
\begin{aligned}
A B & =\Sigma_{x x}^{-1} \operatorname{Cov}(\mathbf{x}, \varepsilon) \\
& =\frac{\operatorname{Cov}(x, \varepsilon)}{\operatorname{Var}(x)} \quad \text { (single linear regression) }
\end{aligned}
$$

## ENDOGENEITY

- The (additive) asymptotic bias due to endogeneity is given by

$$
\begin{aligned}
A B & =\Sigma_{x x}^{-1} \operatorname{Cov}(\mathbf{x}, \varepsilon) \\
& =\frac{\operatorname{Cov}(x, \varepsilon)}{\operatorname{Var}(x)} \quad \text { (single linear regression) } \\
& =\operatorname{Corr}(x, \varepsilon) \frac{\operatorname{sd}(\varepsilon)}{s d(x)} \quad \text { (single linear regression) }
\end{aligned}
$$

## ERRORS IN VARIABLES (EIV)

A simple example:

$$
\begin{aligned}
& y_{i}=1+2 v_{i}+\varepsilon_{i}, \quad i=1,2, \ldots, n \\
& x_{i}=v_{i}+e_{i} \quad(\text { error-in-variable })
\end{aligned}
$$

## ERRORS IN VARIABLES (EIV)

A simple example:

$$
\begin{aligned}
& y_{i}=1+2 v_{i}+\varepsilon_{i}, \quad i=1,2, \ldots, n \\
& x_{i}=v_{i}+e_{i} \quad(\text { error-in-variable })
\end{aligned}
$$

To fix ideas suppose that

$$
\begin{gathered}
v_{i}, \varepsilon_{i} \text { and } e_{i} \text { are independent } \\
v_{i} \sim N(0,1), \quad \varepsilon_{i}, e_{i} \sim N(0,0.5)
\end{gathered}
$$

## EIV (continued)

$$
\begin{aligned}
y_{i} & =1+2 v_{i}+\varepsilon_{i} \\
& =1+2\left(x_{i}-e_{i}\right)+\varepsilon_{i} \\
& =1+2 x_{i}+\left(\varepsilon_{i}-2 e_{i}\right) \\
& =1+2 x_{i}+\Delta_{i}
\end{aligned}
$$

$$
\Delta_{i}=\varepsilon_{i}-2 e_{i}
$$

## EIV (continued)

$$
\begin{aligned}
y_{i} & =1+2 v_{i}+\varepsilon_{i} \\
& =1+2\left(x_{i}-e_{i}\right)+\varepsilon_{i} \\
& =1+2 x_{i}+\left(\varepsilon_{i}-2 e_{i}\right) \\
& =1+2 x_{i}+\Delta_{i} \\
\Delta_{i} & =\varepsilon_{i}-2 e_{i} \\
\operatorname{cov}\left(x_{i}, \Delta_{i}\right) & =-2 \times 0.5=-1 \quad \text { (endogeneity) } \\
\operatorname{Var}\left(x_{i}\right) & =1.5
\end{aligned}
$$

## EIV (continued)

$$
\begin{aligned}
& y_{i}=1+2 v_{i}+\varepsilon_{i} \\
&=1+2\left(x_{i}-e_{i}\right)+\varepsilon_{i} \\
&=1+2 x_{i}+\left(\varepsilon_{i}-2 e_{i}\right) \\
&=1+2 x_{i}+\Delta_{i} \\
& \Delta_{i}=\varepsilon_{i}-2 e_{i} \\
& \operatorname{cov}\left(x_{i}, \Delta_{i}\right)=-2 \times 0.5=-1 \quad \text { (endogeneity) } \\
& \operatorname{Var}\left(x_{i}\right)=1.5 \\
& \mathrm{AB}=\frac{\operatorname{cov}\left(x_{i}, \Delta_{i}\right)}{\operatorname{Var}\left(x_{i}\right)}=-\frac{1}{1.5}=-0.667
\end{aligned}
$$

## OMITTED VARIABLES

Suppose that the "true" model is

$$
y_{i}=\alpha+\beta_{1} \overbrace{x_{1 i}}^{\text {included }}+\beta_{2} \overbrace{x_{2 i}}^{\text {omitted }}+\overbrace{\varepsilon_{i}}^{\text {independent errors }}
$$

## OMITTED VARIABLES

Suppose that the "true" model is

$$
y_{i}=\alpha+\beta_{1} \overbrace{x_{1 i}}^{\text {included }}+\beta_{2} \overbrace{x_{2 i}}^{\text {omitted }}+\overbrace{\varepsilon_{i}}^{\text {independent errors }}
$$

To fix ideas suppose that

$$
\operatorname{Var}\left(x_{1 i}\right)=\operatorname{Var}\left(x_{2 i}\right)=1, \quad \operatorname{var}\left(\varepsilon_{i}\right)=0.1
$$

and

$$
\operatorname{Cov}\left(x_{1 i}, x_{2 i}\right)=0.4
$$

## OMITTED VARIABLES (continued)

Suppose variable $x_{2}$ is omitted and we fit the model

$$
y_{i}=\alpha+\beta x_{1 i}+\Delta_{i}
$$

## OMITTED VARIABLES (continued)

Suppose variable $x_{2}$ is omitted and we fit the model

$$
\begin{aligned}
y_{i} & =\alpha+\beta x_{1 i}+\Delta_{i} \\
\Delta_{i} & =\beta_{2} x_{2 i}+\varepsilon_{i} \\
\operatorname{cov}\left(\Delta_{i}, x_{1 i}\right) & =0.4 \beta_{2} \quad \text { (endogeneity) }
\end{aligned}
$$

## OMITTED VARIABLES (continued)

Suppose variable $x_{2}$ is omitted and we fit the model

$$
\begin{gathered}
y_{i}=\alpha+\beta x_{1 i}+\Delta_{i} \\
\Delta_{i}=\beta_{2} x_{2 i}+\varepsilon_{i} \\
\operatorname{cov}\left(\Delta_{i}, x_{1 i}\right)=0.4 \beta_{2} \quad \text { (endogeneity) } \\
\mathrm{AB}=\frac{\operatorname{cov}\left(x_{1 i}, \Delta_{i}\right)}{\operatorname{Var}\left(x_{1 i}\right)}=0.4 \beta_{2}
\end{gathered}
$$

## SOME EXAMPLES OF ENDOGENEITY

- Risk factors of coronary heart disease

Carrol, Enciclopedy of Biostatistics, 2005: patients's long-term blood pressure may be measured with error (errors-in-variables)

## SOME EXAMPLES OF ENDOGENEITY

- Risk factors of coronary heart disease

Carrol, Enciclopedy of Biostatistics, 2005: patients's long-term blood pressure may be measured with error (errors-in-variables)

- Effect of smoking on birth weight Permutt and Hebel, Biometrics, 1989: smoking by pregnant mothers may be correlated with unobserved socioeconomic factors which affect their infant birth weight (omitted covariates)


## SOME EXAMPLES OF ENDOGENEITY

- Risk factors of coronary heart disease

Carrol, Enciclopedy of Biostatistics, 2005: patients's long-term blood pressure may be measured with error (errors-in-variables)

- Effect of smoking on birth weight Permutt and Hebel, Biometrics, 1989: smoking by pregnant mothers may be correlated with unobserved socioeconomic factors which affect their infant birth weight (omitted covariates)
- Atherosclerotic cardiovascular disease Holmes et al., PloS ONE, 2010: C-reactive protein (CPR) may cause atherogenesis or may be produced by inflammation within atherosclerotic plaque. Thus CPR may be a cause and a result of atherosclerosis (simultaneity)


## THE METHOD OF

## INSTRUMENTAL VARIABLES

## OVERVIEW

- First introduced in Appendix B of a book authored by Philip G. Wright, "TheTariff on Animal and Vegetable Oils", published in 1928.


## OVERVIEW

- First introduced in Appendix B of a book authored by Philip G. Wright, "TheTariff on Animal and Vegetable Oils", published in 1928.
- Some people attribute the authorship of Appendix B to Philip's eldest son, Sewal Wright


## OVERVIEW

- First introduced in Appendix B of a book authored by Philip G. Wright, "TheTariff on Animal and Vegetable Oils", published in 1928.
- Some people attribute the authorship of Appendix B to Philip's eldest son, Sewal Wright
- The method consists of using "instruments" (variables not included in the model) to consistently estimate the regression coefficients of endogenous covariates


## OVERVIEW

- First introduced in Appendix B of a book authored by Philip G. Wright, "TheTariff on Animal and Vegetable Oils", published in 1928.
- Some people attribute the authorship of Appendix B to Philip's eldest son, Sewal Wright
- The method consists of using "instruments" (variables not included in the model) to consistently estimate the regression coefficients of endogenous covariates
- Very useful to investigate possible causal relations in observational studies


## INSTRUMENTAL VARIABLES

- "Instruments" are variables

$$
\mathbf{z}_{i}=\left(\begin{array}{c}
z_{1 i} \\
z_{2 i} \\
\vdots \\
z_{q i}
\end{array}\right) \quad i=1,2, \ldots n, \quad q \geq p
$$

## INSTRUMENTAL VARIABLES

- "Instruments" are variables

$$
\mathbf{z}_{i}=\left(\begin{array}{c}
z_{1 i} \\
z_{2 i} \\
\vdots \\
z_{q i}
\end{array}\right) \quad i=1,2, \ldots n, \quad q \geq p
$$

- $\mathbf{z}_{i}$ is correlated with the endogenous covariates


## INSTRUMENTAL VARIABLES

- "Instruments" are variables

$$
\mathbf{z}_{i}=\left(\begin{array}{c}
z_{1 i} \\
z_{2 i} \\
\vdots \\
z_{q i}
\end{array}\right) \quad i=1,2, \ldots n, \quad q \geq p
$$

- $\mathbf{z}_{i}$ is correlated with the endogenous covariates
- $\mathbf{z}_{i}$ is uncorrelated with the error term


## INSTRUMENTAL VARIABLES

- "Instruments" are variables

$$
\mathbf{z}_{i}=\left(\begin{array}{c}
z_{1 i} \\
z_{2 i} \\
\vdots \\
z_{q i}
\end{array}\right) \quad i=1,2, \ldots n, \quad q \geq p
$$

- $\mathbf{z}_{i}$ is correlated with the endogenous covariates
- $\mathbf{z}_{i}$ is uncorrelated with the error term
- rank of $\operatorname{Cov}\left(\mathbf{z}_{i}\right)=q$


## INSTRUMENTAL VARIABLES

- "Instruments" are variables

$$
\mathbf{z}_{i}=\left(\begin{array}{c}
z_{1 i} \\
z_{2 i} \\
\vdots \\
z_{q i}
\end{array}\right) \quad i=1,2, \ldots n, \quad q \geq p
$$

- $\mathbf{z}_{i}$ is correlated with the endogenous covariates
- $\mathbf{z}_{i}$ is uncorrelated with the error term
- rank of $\operatorname{Cov}\left(\mathbf{z}_{\mathbf{i}}\right)=q$
- rank of $\operatorname{Cov}\left(\mathbf{z}_{i}, \mathbf{x}_{i}\right)=p$


## THE CENTERED INSTRUMENT MATRIX

$$
Z_{c}=\left(\begin{array}{cccc}
z_{11}-\mathbf{z}_{1} & z_{12}-z_{2} & \cdots & z_{1 p^{-}} \bar{z}_{p} \\
z_{21}-\bar{z}_{1} & z_{22}-\bar{z}_{2} & \cdots & z_{2 p^{-}} \bar{z}_{p} \\
z_{31}-\bar{z}_{1} & z_{32}-\bar{z}_{2} & \cdots & z_{3 p^{-}} \bar{z}_{p} \\
\vdots & \vdots & & \vdots \\
z_{n 1}-\bar{z}_{1} & z_{n 2}-\bar{z}_{2} & \cdots & z_{n p^{-}} \bar{z}_{p}
\end{array}\right)
$$

## THE METHOD

- First, project the model covariates on the space generated by the instruments

$$
\widehat{X}_{c}=\overbrace{\left[Z_{c}\left(Z_{c}^{\prime} Z_{c}\right)^{-1} Z_{c}^{\prime}\right]}^{\text {projection matrix }} X_{c}=P_{z} X_{c}
$$

## THE METHOD

- First, project the model covariates on the space generated by the instruments

$$
\widehat{X}_{c}=\overbrace{\left[Z_{c}\left(Z_{c}^{\prime} Z_{c}\right)^{-1} Z_{c}^{\prime}\right]}^{\text {projection matrix }} X_{c}=P_{z} X_{c}
$$

- $\widehat{X}_{c}$ represents the part of $X_{c}$ uncorrelated with $\varepsilon$


## THE METHOD (CONTINUED)

- Second, apply ordinary LS but using the design matrix $\widehat{X}_{c}$ instead of $X_{c}$ :


## THE METHOD (CONTINUED)

- Second, apply ordinary LS but using the design matrix $\widehat{X}_{c}$ instead of $X_{c}$ :

$$
\begin{aligned}
\widehat{\boldsymbol{\beta}}_{I V} & =\left(\widehat{X}_{c}^{\prime} \widehat{X}_{c}\right)^{-1} \widehat{X}_{c} \mathbf{y} \\
& =\left(X_{c}^{\prime} P_{z} X_{c}\right)^{-1} X_{c}^{\prime} P_{z} \mathbf{y} \\
& =\left(X_{c}^{\prime} Z_{c}\left(Z_{c}^{\prime} Z_{c}\right)^{-1} Z_{c}^{\prime} X_{c}\right)^{-1} X_{c}^{\prime} Z_{c}\left(Z_{c}^{\prime} Z_{c}\right)^{-1} Z_{c}^{\prime} \mathbf{y}
\end{aligned}
$$

## THE METHOD (CONTINUED)

- Second, apply ordinary LS but using the design matrix $\widehat{X}_{c}$ instead of $X_{c}$ :

$$
\begin{aligned}
\widehat{\boldsymbol{\beta}}_{I V} & =\left(\widehat{X}_{c}^{\prime} \widehat{X}_{c}\right)^{-1} \widehat{X}_{c} \mathbf{y} \\
& =\left(X_{c}^{\prime} P_{z} X_{c}\right)^{-1} X_{c}^{\prime} P_{z} \mathbf{y} \\
& =\left(X_{c}^{\prime} Z_{c}\left(Z_{c}^{\prime} Z_{c}\right)^{-1} Z_{c}^{\prime} X_{c}\right)^{-1} X_{c}^{\prime} Z_{c}\left(Z_{c}^{\prime} Z_{c}\right)^{-1} Z_{c}^{\prime} \mathbf{y} \\
& =\left(\widehat{\Sigma}_{x z} \widehat{\Sigma}_{z z}^{-1} \widehat{\Sigma}_{z x}\right)^{-1} \widehat{\Sigma}_{x z} \widehat{\Sigma}_{z z}^{-1} \widehat{\Sigma}_{z y}
\end{aligned}
$$

## THE METHOD (CONTINUED)

- Second, apply ordinary LS but using the design matrix $\widehat{X}_{c}$ instead of $X_{c}$ :

$$
\begin{aligned}
\widehat{\boldsymbol{\beta}}_{I V} & =\left(\widehat{X}_{c}^{\prime} \widehat{X}_{c}\right)^{-1} \widehat{X}_{c} \mathbf{y} \\
& =\left(X_{c}^{\prime} P_{z} X_{c}\right)^{-1} X_{c}^{\prime} P_{z} \mathbf{y} \\
& =\left(X_{c}^{\prime} Z_{c}\left(Z_{c}^{\prime} Z_{c}\right)^{-1} Z_{c}^{\prime} X_{c}\right)^{-1} X_{c}^{\prime} Z_{c}\left(Z_{c}^{\prime} Z_{c}\right)^{-1} Z_{c}^{\prime} \mathbf{y} \\
& =\left(\widehat{\Sigma}_{x z} \widehat{\Sigma}_{z z}^{-1} \widehat{\Sigma}_{z x}\right)^{-1} \widehat{\Sigma}_{x z} \widehat{\Sigma}_{z z}^{-1} \widehat{\Sigma}_{z y} \quad \Longleftarrow \text { KEY OBSERVATION }
\end{aligned}
$$

## STATISTICAL PROPERTIES

- $\widehat{\boldsymbol{\beta}}_{I V}$ is consistent and asymptotically normal under mild regularity assumptions


## STATISTICAL PROPERTIES

- $\widehat{\boldsymbol{\beta}}_{I V}$ is consistent and asymptotically normal under mild regularity assumptions
- But data may contain outliers in the
- response variable $y_{i}$
- covariates $\mathrm{x}_{i}$
- instruments $\mathbf{z}_{i}$


## STATISTICAL PROPERTIES

- $\widehat{\boldsymbol{\beta}}_{I V}$ is not robust (sensitive to outliers in the response, covariates and/or instruments)


## STATISTICAL PROPERTIES

- $\widehat{\boldsymbol{\beta}}_{I V}$ is not robust (sensitive to outliers in the response, covariates and/or instruments)
- $\widehat{\beta}_{I V}$ has unbounded influence function


## STATISTICAL PROPERTIES

- $\widehat{\boldsymbol{\beta}}_{I V}$ is not robust (sensitive to outliers in the response, covariates and/or instruments)
- $\widehat{\beta}_{I V}$ has unbounded influence function
- $\widehat{\boldsymbol{\beta}}_{I V}$ has zero breakdown point


## STATISTICAL PROPERTIES

- $\widehat{\boldsymbol{\beta}}_{I V}$ is not robust (sensitive to outliers in the response, covariates and/or instruments)
- $\widehat{\beta}_{I V}$ has unbounded influence function
- $\widehat{\boldsymbol{\beta}}_{I V}$ has zero breakdown point
- $\widehat{\beta}_{I V}$ fails robustness-tests in simulations


## STATISTICAL PROPERTIES

- $\widehat{\beta}_{I V}$ is not robust (sensitive to outliers in the response, covariates and/or instruments)
- $\widehat{\beta}_{I V}$ has unbounded influence function
- $\widehat{\beta}_{I V}$ has zero breakdown point
- $\widehat{\beta}_{I V}$ fails robustness-tests in simulations
- $\widehat{\beta}_{I V}$ has poor performance in some real data examples due to outliers.


## APPLICATION OF INSTRUMENTAL VARIABLES IN MEDICAL RESEARCH

## OVERVIEW

## THE FRAMINGHAM HEART STUDY

- Prior work suggests that high blood pressure can increase the size of the left atrial dimension
(Vaziri et al., 1995; Milan et al., 2009; Benjamin et al., 1995).


## OVERVIEW

## THE FRAMINGHAM HEART STUDY

- Prior work suggests that high blood pressure can increase the size of the left atrial dimension
(Vaziri et al., 1995; Milan et al., 2009; Benjamin et al., 1995).
- We use IV to measure the effect of long-term systolic blood pressure (SBP) on left atrial size (LAD).


## DATA

- Our sample includes $\mathbf{1 6 4}$ male subjects from the original cohort who underwent their 16th biennial examination and satisfy the inclusion criteria employed by Vaziri et al. (1995):
- patient doesn't have a history of heart disease,
- patient is not taking cardiovascular medication
- patient has complete clinical data


## STATISTICAL MODEL

Following Vaziri et al. (1995), we consider the following model:

| Variable | Description | Variable Status |
| :--- | :--- | :--- |
| LAD | Left atrial dimension | Response |
| SBP $_{16}$ | long-term systolic <br> blood pressure <br> (Examination \# 16) | Main covariate <br> Endogenous <br> (measured with error) |
| BMI | Body mass index | Control covariate <br> Exogenous |
| AGE | Subject's age | Control covariate <br> Exogenous |
| SBP $_{15}$ | long-term systolic <br> blood pressure <br> (Examination \# 15) | Instrument |

## RESULTS

|  | SBP | BMI | AGE |
| :--- | :--- | :--- | :--- |
| COEFF. | 0.011 | $\mathbf{3 . 1 9 5}$ | 0.023 |
| P-VALUE | 0.684 | $<0.001$ | 0.685 |

## APPLICATION OF INSTRUMENTAL VARIABLES IN LABOR ECONOMICS

## APPLICATION OF RIV TO LABOR UNIONS DATA

- Our dataset contains 181 industries in the United States for the year 2003.


## APPLICATION OF RIV TO LABOR UNIONS DATA

- Our dataset contains 181 industries in the United States for the year 2003.
- Unionization rates are obtained from the Union Membership and Coverage Database


## APPLICATION OF RIV TO LABOR UNIONS DATA

- Our dataset contains 181 industries in the United States for the year 2003.
- Unionization rates are obtained from the Union Membership and Coverage Database
- The fraction of male workers comes from the Census Population Survey


## APPLICATION OF RIV TO LABOR UNIONS DATA

- Our dataset contains 181 industries in the United States for the year 2003.
- Unionization rates are obtained from the Union Membership and Coverage Database
- The fraction of male workers comes from the Census Population Survey
- The remaining variables are constructed using data from Compustat


## APPLICATION OF RIV TO LABOR UNIONS DATA

- Our dataset contains 181 industries in the United States for the year 2003.
- Unionization rates are obtained from the Union Membership and Coverage Database
- The fraction of male workers comes from the Census Population Survey
- The remaining variables are constructed using data from Compustat


## EFFECT OF LABOR UNIONS ON FIRMS' PROFITS

| Variable Name | Variable Description | Variable Status |
| :--- | :--- | :--- |
| ROA | Accounting profits <br> scaled by assets | Response variable |
| UNION | Fraction of workers <br> that are unionized | Endogenous, main covariate |
| GROWTH | Sales growth rate | Exogenous, control covariate |
| CAPEX | Capital expenditures <br> scaled by assets | Exogenous, control covariate |

## EFFECT OF LABOR UNIONS ON FIRMS' PROFITS

| Variable Name | Variable Description | Variable Status |
| :--- | :--- | :--- |
| SIZE | Fixed assets (log scale) | Exogenous, control covariate |
| LEV | Total debt scaled <br> by assets | Exogenous, control covariate |
| KL | Capital-labor ratio | Exogenous, control covariate |
| MALE | Fraction of male workers | Instrument |

## UNION

- Why is UNION endogenous?


## UNION

- Why is UNION endogenous?
- There are two possible reasons


## UNION

- Why is UNION endogenous?
- There are two possible reasons

1. UNION and ROA are likely to be simultaneously determined

## UNION

- Why is UNION endogenous?
- There are two possible reasons

1. UNION and ROA are likely to be simultaneously determined

- Industry higher performance may stimulate unionization to get a better profits share


## UNION

- Why is UNION endogenous?
- There are two possible reasons

1. UNION and ROA are likely to be simultaneously determined

- Industry higher performance may stimulate unionization to get a better profits share
- It is conjectured that higher unionization cause industry performance to decline


## UNION

- Why is UNION endogenous?
- There are two possible reasons

1. UNION and ROA are likely to be simultaneously determined

- Industry higher performance may stimulate unionization to get a better profits share
- It is conjectured that higher unionization cause industry performance to decline

2. There may be unobserved industry features that determine performance and are correlated with unionization

## MALE

- Why is MALE a reasonable instrument for UNION?


## MALE

- Why is MALE a reasonable instrument for UNION?
- males have more permanent attachment to the labor market and to internal job ladders


## MALE

- Why is MALE a reasonable instrument for UNION?
- males have more permanent attachment to the labor market and to internal job ladders
$\Rightarrow$ males derive higher wage/non-wage benefits from unionizing


## MALE

- Why is MALE a reasonable instrument for UNION?
- males have more permanent attachment to the labor market and to internal job ladders
$\Rightarrow$ males derive higher wage/non-wage benefits from unionizing
$\Rightarrow$ males are more likely to become unionized.


## RESULTS

UNION GROWTH CAPEX SIZE LEV KL

| coeff. | -0.271 | $\mathbf{0 . 1 2 6}$ | $\mathbf{0 . 1 9 7}$ | 0.003 | $\mathbf{0 . 0 9 4}$ | 0.004 |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| p-value | 0.128 | 0.013 | 0.000 | 0.312 | 0.005 | 0.313 |

