

GSERM 2024

Regression for Publishing

June 17, 2024

“Regression for Publishing”

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 - Twitter / Instagram / etc.: [@prisonrodeo](#)
- Class: June 17-21, 2024, 09:15 - 15:15 CET, at the [University of St. Gallen SQUARE](#) building, room 11-0101, “Gallus.”
- The course outline / syllabus is [here](#).
- More important: The syllabus, slides, readings, code, data, etc. are all available on the course [github repo](#) (viewable at <https://github.com/PrisonRodeo/GSERM-RFP-2024>).

Evaluation at GSERM isn't easy... the plan:

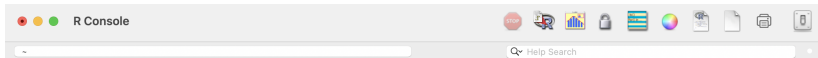
- One “homework exercise”
 - Practical exercise – “real” data analysis and discussion
 - Assigned Tuesday (June 18); due Friday (June 21)
 - Worth 300 possible points
- Final Examination
 - Multiple essay-style questions + “real” data analysis
 - Some choice of questions to answer
 - Assigned Friday (June 21) around 12:00 CET
 - Due either Friday, June 21, 2024 by 20:00 CET (“in-class” alternative) or Friday, June 28, 2024 (“take-home” alternative)
 - Worth 700 possible points
- Total course = 1000 possible points
- Grades assessed on Swiss (1 - 6) scale

R

- All examples, plots, etc. are generated using R
- Current version is 4.4.0
- Desktop: Be sure to get the [RStudio](#) / [Posit](#) IDE...
- Alternatively: Can be run in a browser, using [Posit Cloud](#)
- The course Github repo contains a bit of [introductory code](#) for people who may never have used R, and a list of [R resources](#).

Stata

- Current version is 18
- Main linear regression command is `-regress-` (or `reg`)



R version 4.4.0 (2024-04-24) -- "Puppy Cup"
Copyright (C) 2024 The R Foundation for Statistical Computing
Platform: aarch64-apple-darwin20

R is free software and comes with ABSOLUTELY NO WARRANTY.
You are welcome to redistribute it under certain conditions.
Type 'license()' or 'licence()' for distribution details.

Natural language support but running in an English locale

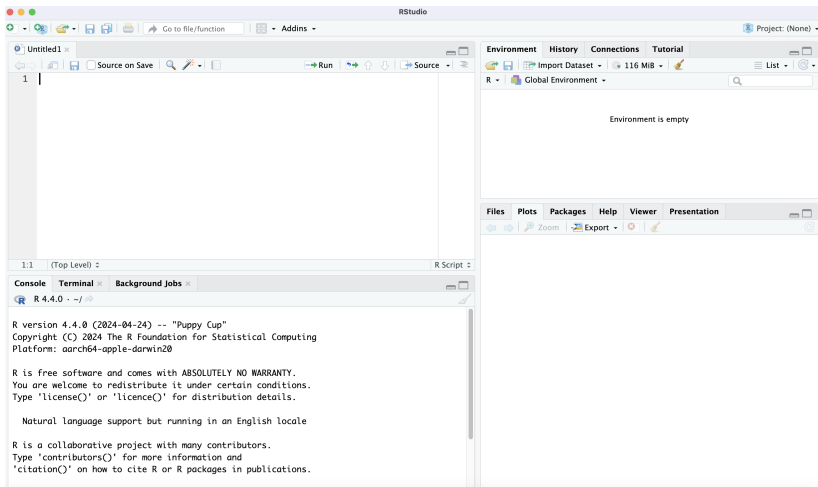
R is a collaborative project with many contributors.
Type 'contributors()' for more information and
'citation()' on how to cite R or R packages in publications.

Type 'demo()' for some demos, 'help()' for on-line help, or
'help.start()' for an HTML browser interface to help.
Type 'q()' to quit R.

[R.app GUI 1.80 (8376) aarch64-apple-darwin20]

[History restored from /Users/cuz10/.Rapp.history]

> |



RStudio (annotated)

This is the "Source" window.

- It's the place where you'll type the code that will then be sent to R.
- It's basically a text editor. You can open text files of any kind here if you want.
- Files that appear here end in (and should be saved with) the extension ".R" (as in "MyCode.R").

You'll spend most of your time working here.

Click here to save your source code. Save often!

Highlight text in the Source window, then click this button to "run" the code.

This is the "Environment" window. It is where you can find all the various "objects" that you create, grouped by object type (data frames, lists, graphs, etc.). Environment is empty

There's also a "History" tab above; switching to that will show what has transpired in the Console window recently.

This is the "working directory." Anything you save will be saved here, unless you tell the program to save it somewhere else.

This is the "Console." When you run the code in the Source window, the results that aren't graphics appear here.

Type 'demo()' for some demos, 'help()' for on-line help, or 'help.start()' for an HTML browser interface to help. Type 'q()' to quit R.

Plots (graphs) that you have created

Packages that are loaded

Help results (obtained by typing "?XXX" in the Console window, e.g. "?table").

Things We Will And Won't Do

Will: "Regression":

$$Y = f(\mathbf{X})$$

Won't: Multivariate regression:

$$\mathbf{Y} = f(\mathbf{X})$$

Won't: Measurement (e.g. PCA, factor analysis, IRT, etc.):

$$\mathbf{Y} = \mathbf{W}^T \mathbf{X}$$

Won't: Classification:

- Cluster Analysis / Network Models / etc.
- Classification and Regression Trees \rightarrow Random Forests.
- Pattern Recognition
- Machine Learning (beyond regression), Support Vector Machines, etc.

Friday = “Participants’ Choice”



PennState

Please rank order these possible choices for topics for the Friday (June 21) class session (1 = most preferred to 8 = least preferred). When you have finished ranking them, please click on the arrow below.

Extended GLMs

Panel / TSCS Models

Causal Inference

Measurement Models

Bayesian Statistics

Sample Selection Models

Survival Analysis

Analysis of Text / LLMs

Why Regression?

	Description	Explanation	Prediction
Task	Summarize data	Correlation/causation	Forecast OOS / future data
Emphasis	Data	Theory / Hypotheses	Outcomes
Focus	Univariate	Multivariate	Multivariate
Typical Application	Summarize / "reduce" data	Discuss marginal associations between predictors and an outcome of interest	Optimize out-of-sample predictive power / minimize prediction error

“Regression,” conceptually:

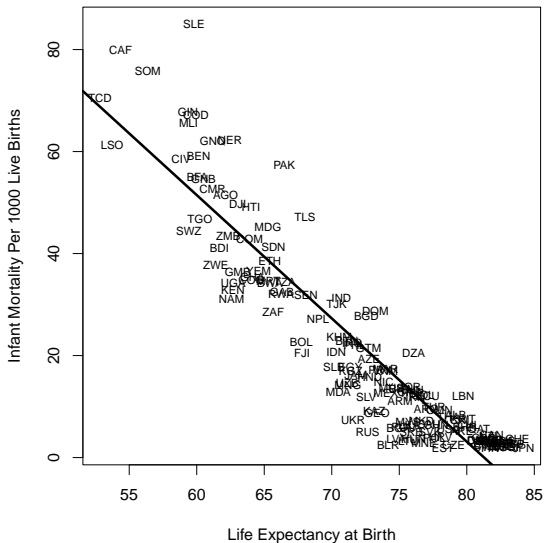
$$\Pr(Y|\mathbf{X}) = f(\mathbf{X})$$

Two important things:

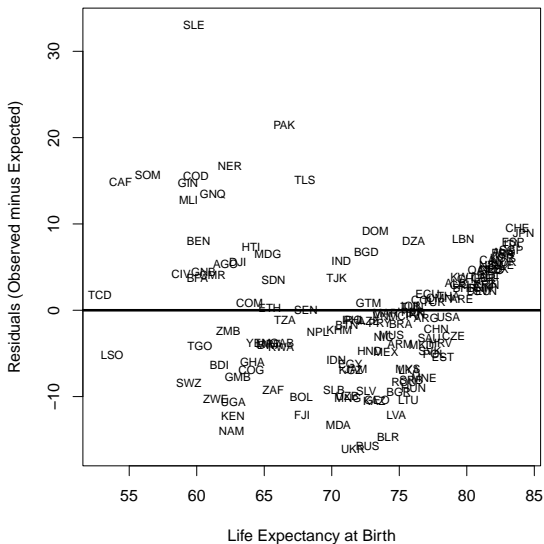
- The distribution of Y is *conditional on all variables in \mathbf{X}* , and
- The conditional distribution of Y is conditional on the *joint distribution* of the elements of \mathbf{X} .

→ Regression is hard...

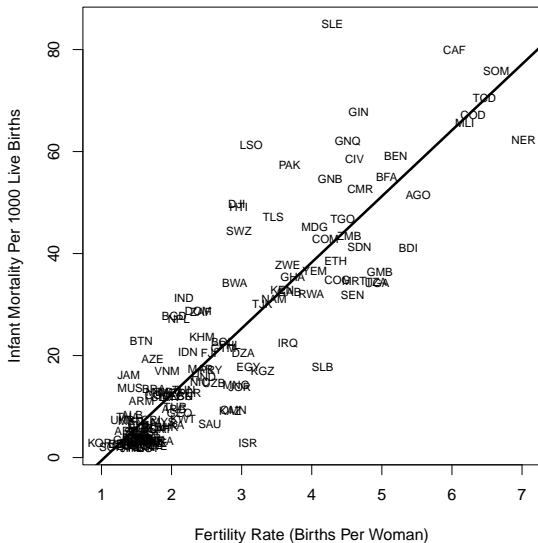
Example: Infant Mortality and Life Expectancy (2018)



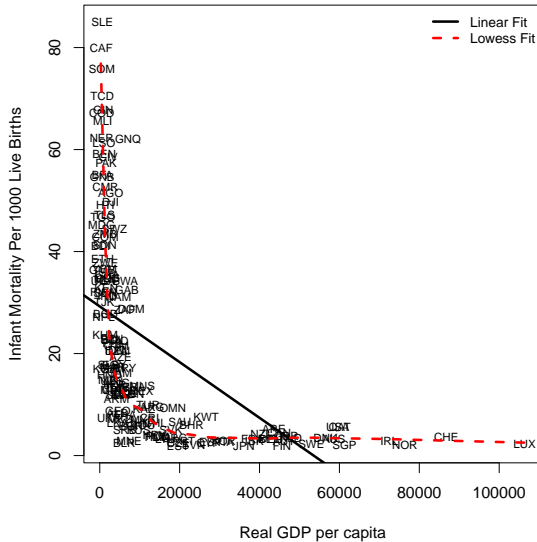
Infant Mortality and Life Expectancy: “Residuals”



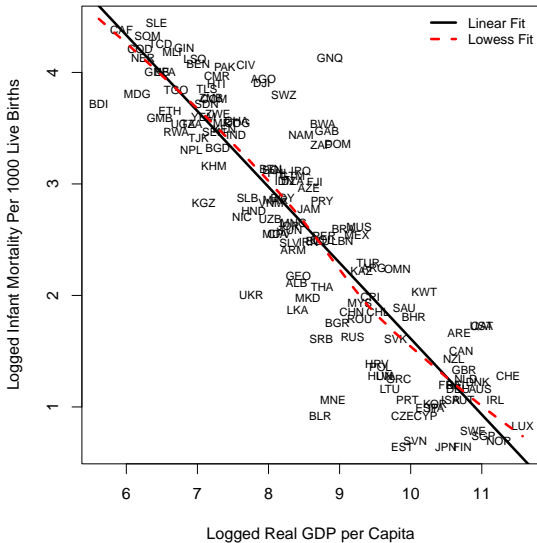
Infant Mortality and Fertility

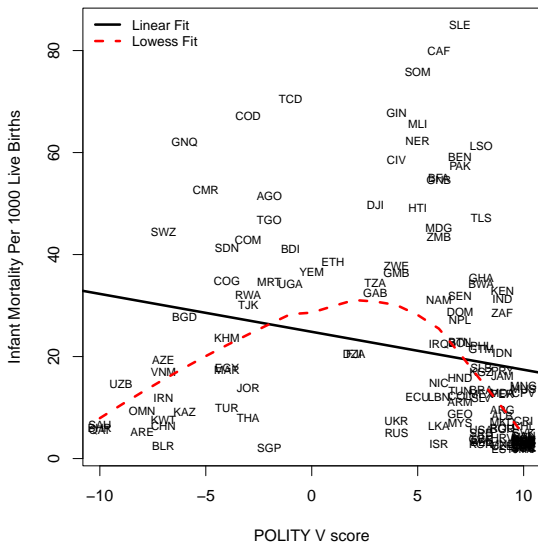


Infant Mortality and Wealth

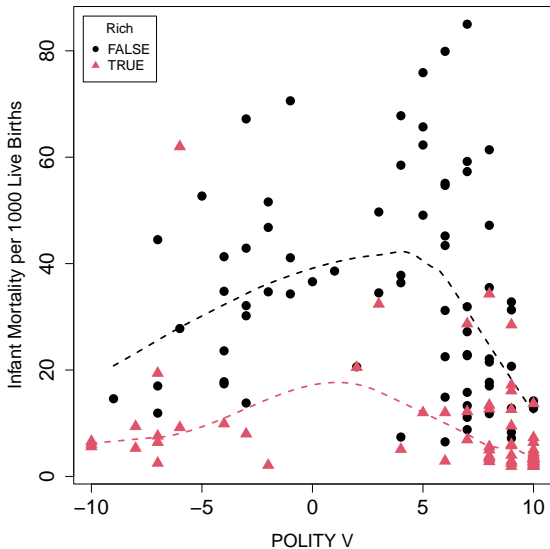


(Logged) Infant Mortality and (Logged) Wealth





Infant Mortality, (Dichotomized) Wealth, and Democracy



Consider random variable Y :

$$Y_i = \mu + u_i \quad (1)$$

$$\mu_i = \beta_0 + \beta_1 X_i$$

so:

$$Y_i = \beta_0 + \beta_1 X_i + u_i \quad (2)$$

Goals:

- Estimate $\hat{\beta}_0$ and $\hat{\beta}_1$
- Estimate the *variability* $\hat{\beta}_0$ and $\hat{\beta}_1$
- Assess *model fit*

Bivariate OLS - Estimation

For a bivariate regression:

$$\begin{aligned}\hat{\beta}_1 &= \frac{\sum_{i=1}^N (X_i - \bar{X})(Y_i - \bar{Y})}{\sum_{i=1}^N (X_i - \bar{X})^2} \\ &= \frac{\text{Covariance of } X \text{ and } Y}{\text{Variance of } X}\end{aligned}\tag{3}$$

and

$$\hat{\beta}_0 = \bar{Y} - \hat{\beta}_1 \bar{X}\tag{4}$$

$$\text{Var}(\hat{\beta}_1)$$

Assume (for now):

$$u_i \sim \text{i.i.d. } N(0, \sigma^2)$$

meaning:

$$\text{Var}(Y|X, \beta) = \sigma^2$$

so:

$$\begin{aligned} \text{Var}(\hat{\beta}_1) &= \text{Var} \left[\frac{\sum_{i=1}^N (X_i - \bar{X}) Y_i}{\sum_{i=1}^N (X_i - \bar{X})^2} \right] \\ &= \left[\frac{1}{\sum (X_i - \bar{X})^2} \right]^2 \sum (X_i - \bar{X})^2 \text{Var}(Y) \\ &= \left[\frac{1}{\sum (X_i - \bar{X})^2} \right]^2 \sum (X_i - \bar{X})^2 \sigma^2 \\ &= \frac{\sigma^2}{\sum (X_i - \bar{X})^2}. \end{aligned}$$

$$\text{Var}(\hat{\beta}_0) \text{ and } \text{Cov}(\hat{\beta}_0, \hat{\beta}_1)$$

Similarly:

$$\text{Var}(\hat{\beta}_0) = \frac{\sum X_i^2}{N \sum (X_i - \bar{X})^2} \sigma^2$$

and :

$$\text{Cov}(\hat{\beta}_0, \hat{\beta}_1) = \frac{-\bar{X}}{\sum (X_i - \bar{X})^2} \sigma^2$$

Note that:

- $\text{Var}(\hat{\beta}_0)$ and $\text{Var}(\hat{\beta}_1) \propto \sigma^2$
- $\text{Var}(\hat{\beta}_0)$ and $\text{Var}(\hat{\beta}_1) \propto -\sum (X_i - \bar{X})$
- $\text{Var}(\hat{\beta}_0)$ and $\text{Var}(\hat{\beta}_1) \propto -N$
- $\text{sign}[\text{Cov}(\hat{\beta}_0, \hat{\beta}_1)] = -\text{sign}(\bar{X})$

If $u_i \sim N(0, \sigma^2)$, then:

$$\hat{\beta}_0 \sim N[\beta_0, \text{Var}(\hat{\beta}_0)]$$

and

$$\hat{\beta}_1 \sim N[\beta_1, \text{Var}(\hat{\beta}_1)]$$

Means:

$$\begin{aligned} z_{\hat{\beta}_1} &= \frac{(\hat{\beta}_1 - \beta_1)}{\sqrt{\text{Var}(\hat{\beta}_1)}} \\ &= \frac{(\hat{\beta}_1 - \beta_1)}{\text{s.e.}(\hat{\beta}_1)} \\ &= \sim N(0, 1) \end{aligned}$$

A Small Problem...

$$\sigma^2 = ???$$

Solution: use

$$\hat{\sigma}^2 = \frac{\sum \hat{u}_i^2}{N - k}$$

Gives:

$$\widehat{\text{Var}(\hat{\beta}_1)} = \frac{\hat{\sigma}^2}{\sum (X_i - \bar{X})^2},$$

and

$$\widehat{\text{Var}(\hat{\beta}_0)} = \frac{\sum X_i^2}{N \sum (X_i - \bar{X})^2} \hat{\sigma}^2$$

So:

$$\begin{aligned}
 \widehat{\text{s.e.}}(\hat{\beta}_1) &= \sqrt{\widehat{\text{Var}}(\hat{\beta}_1)} \\
 &= \sqrt{\frac{\hat{\sigma}^2}{\sum (X_i - \bar{X})^2}} \\
 &= \frac{\hat{\sigma}}{\sqrt{\sum (X_i - \bar{X})^2}}
 \end{aligned}$$

which implies:

$$\begin{aligned}
 t_{\hat{\beta}_1} \equiv \frac{(\hat{\beta}_1 - \beta_1)}{\widehat{\text{s.e.}}(\hat{\beta}_1)} &= \frac{(\hat{\beta}_1 - \beta_1)}{\frac{\hat{\sigma}}{\sqrt{\sum (X_i - \bar{X})^2}}} \\
 &= \frac{(\hat{\beta}_1 - \beta_1) \sqrt{\sum (X_i - \bar{X})^2}}{\hat{\sigma}} \\
 &\sim t_{N-k}
 \end{aligned}$$

Predictions and Variance

Point prediction:

$$\hat{Y}_k = \hat{\beta}_0 + \hat{\beta}_1 X_k$$

\hat{Y}_k is unbiased:

$$\begin{aligned} E(\hat{Y}_k) &= E(\hat{\beta}_0 + \hat{\beta}_1 X_k) \\ &= E(\hat{\beta}_0) + X_k E(\hat{\beta}_1) \\ &= \beta_0 + \beta_1 X_k \\ &= E(Y_k) \end{aligned}$$

Variability:

$$\begin{aligned} \text{Var}(\hat{Y}_k) &= \text{Var}(\hat{\beta}_0 + \hat{\beta}_1 X_k) \\ &= \frac{\sum X_i^2}{N \sum (X_i - \bar{X})^2} \sigma^2 + \left[\frac{\sigma^2}{\sum (X_i - \bar{X})^2} \right] X_k^2 + 2 \left[\frac{-\bar{X}}{\sum (X_i - \bar{X})^2} \sigma^2 \right] X_k \\ &= \sigma^2 \left[\frac{1}{N} + \frac{(X_k - \bar{X})^2}{\sum (X_i - \bar{X})^2} \right] \end{aligned}$$

Variability of Predictions

Prediction variation:

$$\text{Var}(\hat{Y}_k) = \sigma^2 \left[\frac{1}{N} + \frac{(X_k - \bar{X})^2}{\sum (X_i - \bar{X})^2} \right]$$

means that $\text{Var}(\hat{Y}_k)$:

- Decreases in N
- Decreases in $\text{Var}(X)$
- Increases in $|X - \bar{X}|$

Standard error of the prediction:

$$\widehat{\text{s.e.}}(\hat{Y}_k) = \sqrt{\sigma^2 \left[\frac{1}{N} + \frac{(X_k - \bar{X})^2}{\sum (X_i - \bar{X})^2} \right]}$$

→ (e.g.) confidence intervals:

$$95\% \text{ c.i.}(\hat{Y}_k) = \hat{Y}_k \pm [1.96 \times \widehat{\text{s.e.}}(\hat{Y}_k)]$$

We can decompose variation in Y :

$$\begin{aligned}\text{Var}(Y) &= \text{Var}(\hat{Y} + \hat{u}) \\ &= \text{Var}(\hat{Y}) + \text{Var}(\hat{u}) + 2 \text{Cov}(\hat{Y}, \hat{u}) \\ &= \text{Var}(\hat{Y}) + \text{Var}(\hat{u})\end{aligned}$$

$$\begin{array}{ccccc}\mathbf{TSS} & = & \mathbf{MSS} & + & \mathbf{RSS} \\ \text{("Total")} & & \text{("Estimated," or "Model")} & & \text{("Residual")}\end{array}$$

“R-squared” :

$$\begin{aligned} R^2 &= \frac{\text{MSS}}{\text{TSS}} \\ &= \frac{\sum(\hat{Y}_i - \bar{Y})^2}{\sum(Y_i - \bar{Y})^2} \\ &= 1 - \frac{\text{RSS}}{\text{TSS}} \\ &= 1 - \frac{\sum \hat{u}_i^2}{\sum(Y_i - \bar{Y})^2} \end{aligned}$$

R-squared:

- is “the proportion of variance explained”
- $\in [0, 1]$
 - $R^2 = 1.0 \equiv$ a “perfect (linear) fit”
 - $R^2 = 0 \equiv$ no (linear) $X - Y$ association

For a single X ,

$$\begin{aligned} R^2 &= \hat{\beta}_1^2 \frac{\sum (X_i - \bar{X})^2}{\sum (Y_i - \bar{Y})^2} \\ &= r_{XY}^2 \end{aligned}$$

“Adjusted” R^2 :

$$R_{adj.}^2 = 1 - \frac{(1 - R^2)(N - c)}{(N - k)}$$

where $c = 1$ if there is a constant in the model and $c = 0$ otherwise.

$R_{adj.}^2$:

- $R_{adj.}^2 \rightarrow R^2$ as $N \rightarrow \infty$
- $R_{adj.}^2$ can be > 1 , or < 0 ...
- $R_{adj.}^2$ increases with model “fit,” but
- The extent of that increase is discounted by a factor proportional to the number of covariates.

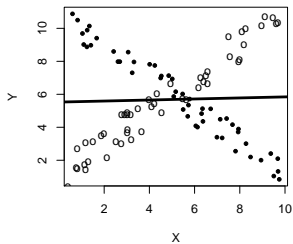
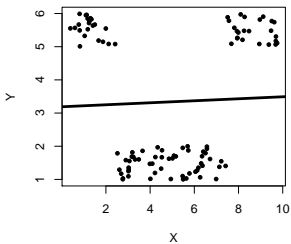
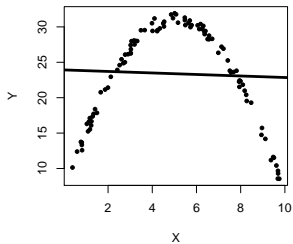
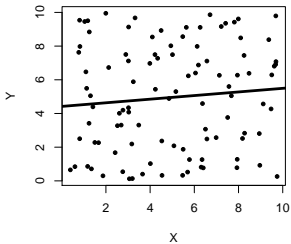
Alternative single measures of model fit include:

- The Standard Error of the Estimate:

$$SEE = \sqrt{\frac{RSS}{N - k}}$$

- F -tests
- ROC / AUC
- Graphical methods

Caution: Different Ways to get $R^2 = 0$



Linear Regression: K Predictors

Now consider:

$$\underset{N \times 1}{\mathbf{Y}} = \underset{N \times K}{\mathbf{X}} \underset{K \times 1}{\boldsymbol{\beta}} + \underset{N \times 1}{\mathbf{u}}$$

equivalently:

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \dots + \beta_K X_{Ki} + u_i$$

$$\begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_N \end{bmatrix} = \begin{bmatrix} 1 & X_{11} & X_{21} & \cdots & X_{K1} \\ 1 & X_{12} & X_{22} & \cdots & X_{K2} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & X_{1N} & X_{2N} & \cdots & X_{KN} \end{bmatrix} \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_K \end{bmatrix} + \begin{bmatrix} u_1 \\ u_2 \\ \vdots \\ u_N \end{bmatrix}.$$

Residuals:

$$\mathbf{u} = \mathbf{Y} - \mathbf{X}\beta$$

The inner product of \mathbf{u} :

$$\begin{aligned} \mathbf{u}'\mathbf{u} &= \begin{bmatrix} u_1 & u_2 & \cdots & u_N \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \\ \vdots \\ u_N \end{bmatrix} \\ &= u_1^2 + u_2^2 + \dots + u_N^2 \\ &= \sum_{i=1}^N u_i^2 \end{aligned}$$

Sum of squared residuals:

$$\begin{aligned}\mathbf{u}'\mathbf{u} &= (\mathbf{Y} - \mathbf{X}\beta)'(\mathbf{Y} - \mathbf{X}\beta) \\ &= \mathbf{Y}'\mathbf{Y} - 2\beta'\mathbf{X}'\mathbf{Y}' + \beta'\mathbf{X}'\mathbf{X}\beta\end{aligned}$$

Now get:

$$\frac{\partial \mathbf{u}'\mathbf{u}}{\partial \beta} = -2\mathbf{X}'\mathbf{Y} + 2\mathbf{X}'\mathbf{X}\beta$$

Solve:

$$\begin{aligned}-2\mathbf{X}'\mathbf{Y} + 2\mathbf{X}'\mathbf{X}\beta &= 0 \\ -\mathbf{X}'\mathbf{Y} + \mathbf{X}'\mathbf{X}\beta &= 0 \\ \mathbf{X}'\mathbf{X}\beta &= \mathbf{X}'\mathbf{Y} \\ (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{X}\beta &= (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{Y} \\ \beta &= (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{Y}\end{aligned}$$

The Importance of $\mathbf{V}(\hat{\beta})$

Variance-covariance matrix:

$$\begin{aligned}\mathbf{V}(\hat{\beta}) &= E[\hat{\beta} - E(\hat{\beta})]^2 \\ &= E\{[\hat{\beta} - E(\hat{\beta})][\hat{\beta} - E(\hat{\beta})]'\}\end{aligned}$$

Rewrite:

$$\begin{aligned}\mathbf{V}(\hat{\beta}) &= E(\hat{\beta} - \beta)(\hat{\beta} - \beta)' \\ &= E\{[(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{u}][(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{u}]'\} \\ &= E[(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{u}\mathbf{u}'\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}]\end{aligned}$$

The Importance of $\mathbf{V}(\hat{\beta})$

Taking expectations:

$$\begin{aligned}\mathbf{V}(\hat{\beta}) &= (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{E}(\mathbf{u}\mathbf{u}')\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1} \\ &= (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\sigma^2\mathbf{I}\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1} \\ &= \sigma^2(\mathbf{X}'\mathbf{X})^{-1}\end{aligned}$$

Estimating $\mathbf{V}(\hat{\beta})$

Empirical estimate:

$$\hat{\sigma}^2 = \frac{\hat{\mathbf{u}}'\hat{\mathbf{u}}}{N - K}$$

Yields:

$$\widehat{\mathbf{V}(\hat{\beta})} = \hat{\sigma}^2(\mathbf{X}'\mathbf{X})^{-1}$$

1. Zero Expectation Disturbances

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

2. Homoscedasticity / No Error Correlation

$$E(\mathbf{u}\mathbf{u}') = \begin{bmatrix} \sigma^2 & 0 & \dots & 0 \\ 0 & \sigma^2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \sigma^2 \end{bmatrix}$$

OLS Assumptions (continued)

3. "Fixed" \mathbf{X} ...

- No *measurement error* in the \mathbf{X} s, and
- $\text{Cov}(\mathbf{X}, \mathbf{u}) = \mathbf{0}$.

4. \mathbf{X} is of full column rank.

Means:

- no exact linear relationship among \mathbf{X} , and
- $K < N$.

5. Normal Disturbances

$$\mathbf{u} \sim \mathbf{N}(\mathbf{0}, \sigma^2 \mathbf{I})$$

Under these assumptions, the OLS estimate of $\hat{\beta}$ is:

- **Unbiased**
- **Fully Efficient**

(i.e., **“BLUE”**)

Multivariate Regression, Conceptually

Begin with:

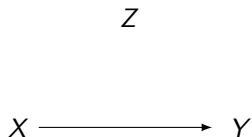
- An *outcome* Y
- A *predictor* X
- Another variable Z

We are mainly interested in $\text{Cov}(Y, X|Z)$...

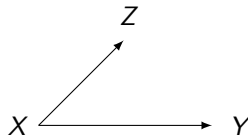
- Possibly *but not necessarily* the causal relationship (cf. Berk 2010)
- Key question is *model specification*...

The Easiest Case

Things are easiest if:



or



Implies that:

- Z is unimportant to understanding $\text{Cov}(X, Y)$
- $\rightarrow Z$ is *ignorable*

Simulations For Everyone!

```
> N<-50
> set.seed(7222009)
> X<-rnorm(N)          # Predictor
> Z<-(X+rnorm(N))/1.5  # Z "caused by" X
> Y<-X+rnorm(N)        # Outcome Y (unrelated to Z)

> print(summary(lm(Y~X)))

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)    0.028      0.144    0.19   0.85
X              0.978      0.162    6.05 0.00000021 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

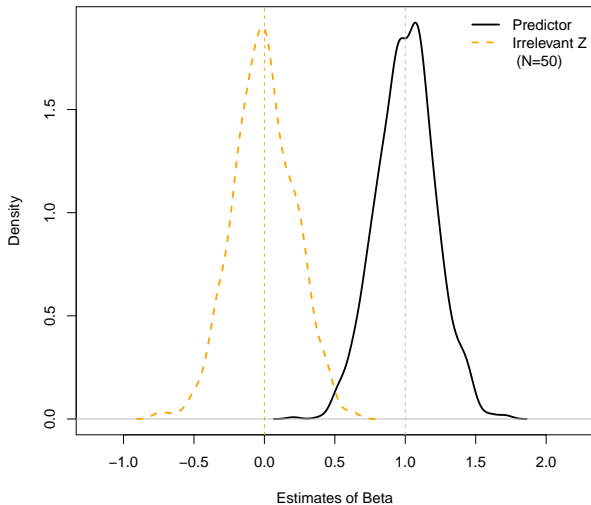
Residual standard error: 1 on 48 degrees of freedom
Multiple R-squared:  0.432, Adjusted R-squared:  0.421
F-statistic: 36.6 on 1 and 48 DF, p-value: 0.000000212

> print(summary(lm(Y~X+Z)))

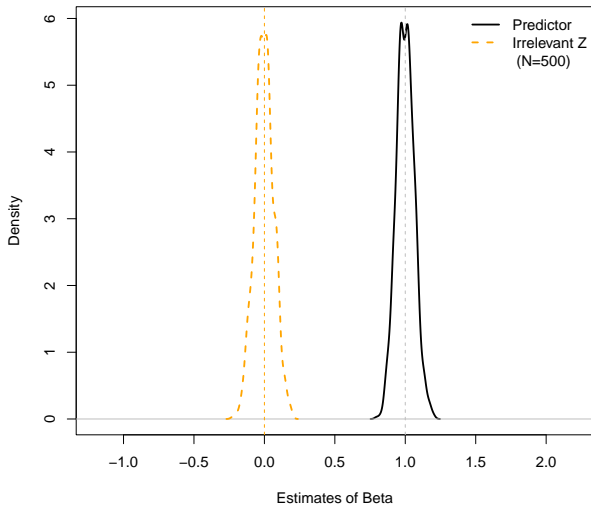
Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)    0.0335    0.1460    0.23   0.82
X              0.9322    0.2161    4.31 0.000082 ***
Z              0.0659    0.2019    0.33   0.75
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1 on 47 degrees of freedom
Multiple R-squared:  0.434, Adjusted R-squared:  0.41
F-statistic: 18 on 2 and 47 DF, p-value: 0.00000157
```

Do That 999 More Times

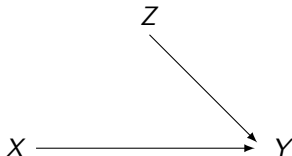


Same, But With $N = 500$



Slightly More Challenging

Suppose instead that:



This means that:

- Z is important to / influential on understanding Y, *but*
- Z is unrelated to X...

One Regression

```
> N<-50
> set.seed(7222009)
> X<-rnorm(N)          # Predictor
> Z<-rnorm(N)          # Z orthogonal to X
> Y<-X+Z+rnorm(N)      # Outcome Y

> print(summary(lm(Y~X)))

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.0956     0.2167   -0.44  0.66119
X             1.0301     0.2439    4.22  0.00011 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

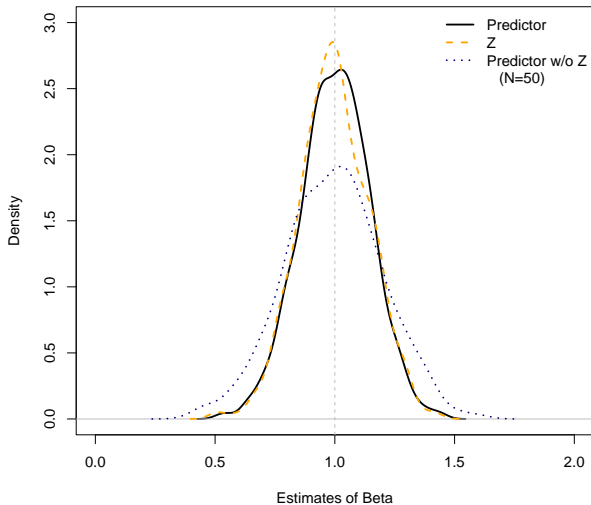
Residual standard error: 1.5 on 48 degrees of freedom
Multiple R-squared:  0.271, Adjusted R-squared:  0.256
F-statistic: 17.8 on 1 and 48 DF,  p-value: 0.000107

> print(summary(lm(Y~X+Z)))

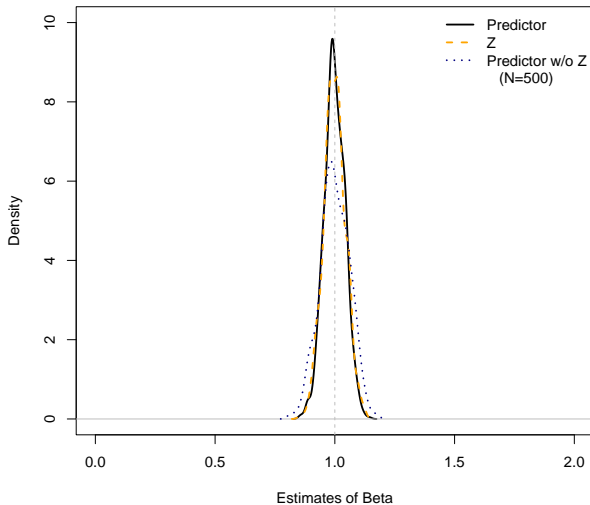
Coefficients:
            Estimate Std. Error t value      Pr(>|t|)
(Intercept)  0.0335     0.1460    0.23         0.82
X             0.9761     0.1634    5.97 0.00000029670 ***
Z             1.0439     0.1346    7.75 0.00000000059 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1 on 47 degrees of freedom
Multiple R-squared:  0.68, Adjusted R-squared:  0.666
F-statistic:  50 on 2 and 47 DF,  p-value: 0.00000000000233
```

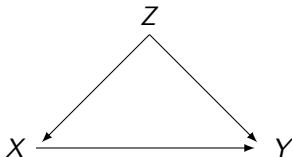
Many Regressions



Same, But With $N = 500$



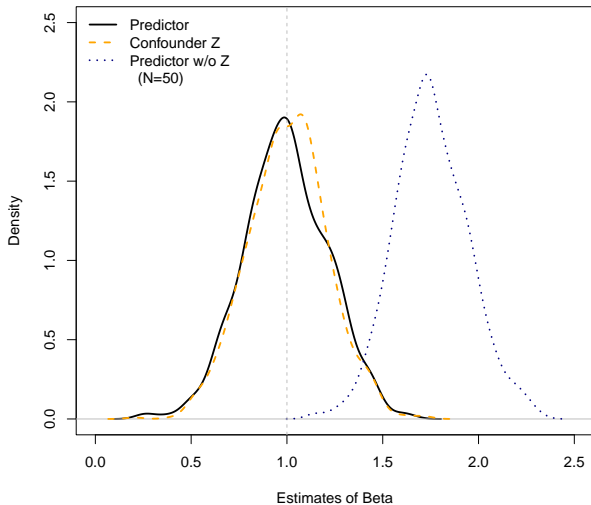
The classic example is:



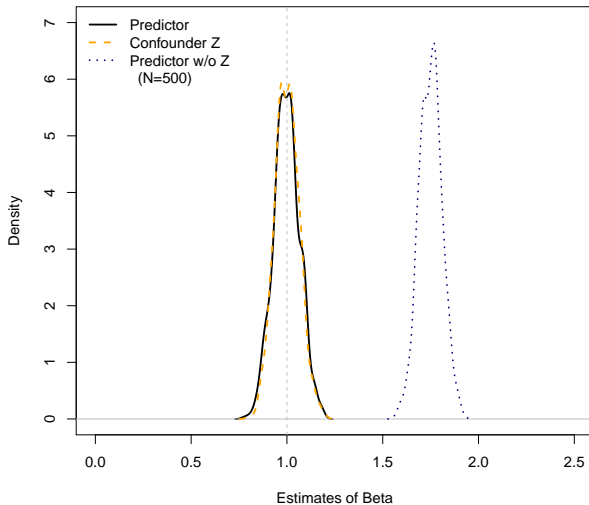
This means that:

- Z is important to / influential on both X and Y
- The marginal association $\text{Cov}(X, Y|Z)$ (obviously) depends on Z ...
- More specifically, $\text{Cov}(X, Y|Z) \neq \text{Cov}(X, Y)$

So Much Confounding

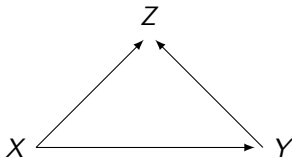


Same, But With $N = 500$



“Collider Bias”

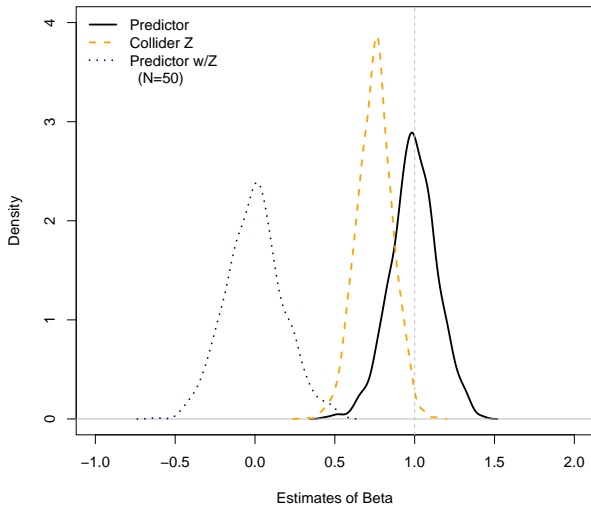
Z is a “collider”:



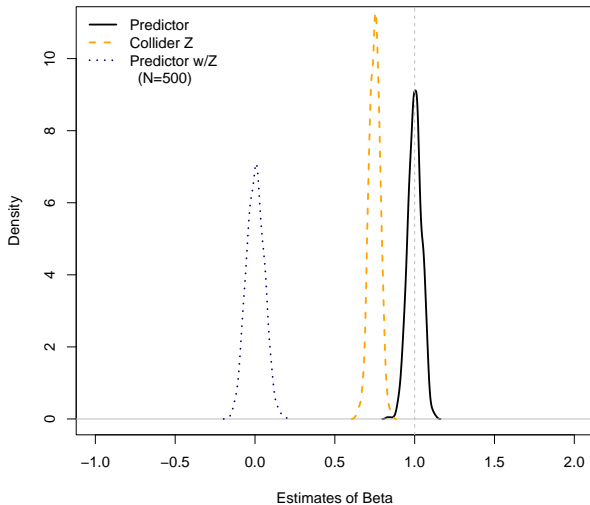
This means that:

- Z is influenced *by* both X and Y
- Once again, $\text{Cov}(X, Y|Z) \neq \text{Cov}(X, Y)$
- Sometimes referred to as **Berkson's paradox**

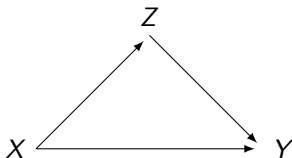
So Much Colliding



Same, But With $N = 500$



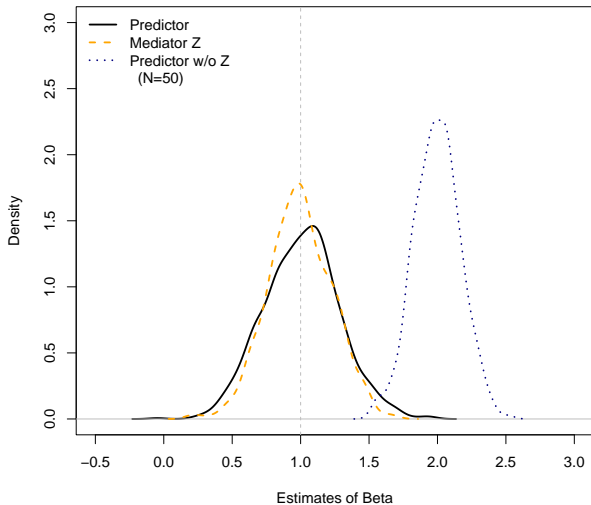
Z is a “mediator”:



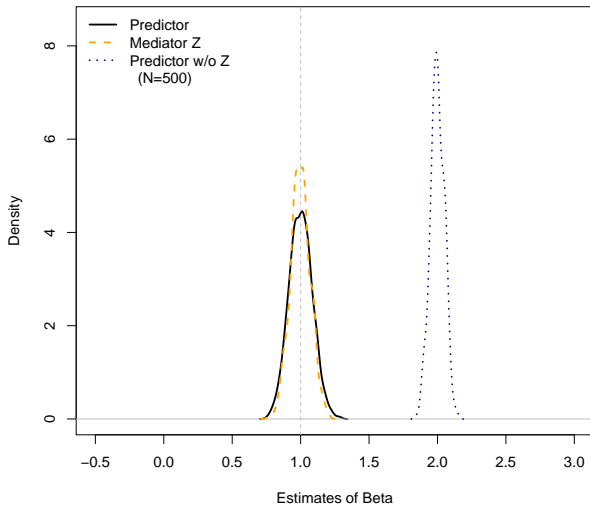
This means that:

- Z is influenced by X ; Y by X and Z
- Once again, $\text{Cov}(X, Y|Z) \neq \text{Cov}(X, Y)$
- Think of $\text{Cov}(X, Y) =$ “total effect” and $\text{Cov}(X, Y|Z) =$ “direct effect”

Mediation Illustrated



Same, But With $N = 500$



Some takeaways... *In a linear model:*

- Variables that are irrelevant (to Y), are irrelevant...
- Variables that are relevant to Y but unrelated to X need not be modeled
- Confounders require that we condition on them, or else there's bias
- Colliders require that we *do not* condition on them, or else there's bias
- Mediators may or may not be good to condition on...

Mostly: **Model specification is hard.**

Example Data: The WDI

Data are drawn from the [World Development Indicators](#):

- Cross-national country-level time series data
- $N = 143$ countries (due to missing data); here we'll focus on one recent year (2018)
- Available as file `WDI-2018-Day-One-24.csv` in the [Data](#) folder at the course Github repo.

Variables (among others):

- `ISO3` - The country's International Standards Organization (ISO) three-letter identification code (e.g., `CHE` for Switzerland).
- `Country` - The name of the country
- `Fertility` - Fertility rate (mean births per woman).
- `Child Mortality` - Average deaths of children under 5 per 1000 live births.
- `Infant Mortality` - Average deaths of infants per 1000 live births.
- `LifeExpectancy` - Life Expectancy at birth (years).
- `DPTPercent` - Percent of children aged 12-24 months w/DPT immunization.
- `GDPPerCapita` - GDP per capita (constant 2010 \$US).
- `FDIIn` - Inward Foreign Direct Investment (FDI) (percent of GDP).
- `NaturalResourceRents` - Total natural resource rents (percent of GDP).
- `UrbanPopulation` - Urban Population (percent of total).
- `GovtExpenditures` - Government Expenditures (percent of GDP).
- `PaidParentalLeave` - Paid Parental Leave (0 = No, 1 = Yes).
- `DemocScore` - POLITY V democracy score (0-10).
- `AutocScore` - POLITY V autocracy score (0-10).
- `POLITY` - POLITY V total score (`DemocScore` - `AutocScore`).

Summary Statistics

```
> describe(IR2018)
```

	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
ISO3*	1	143	72.00	41.42	72.00	72.00	53.37	1.00	143.00	142.00	0.00	-1.23	3.46
Country*	2	143	72.00	41.42	72.00	72.00	53.37	1.00	143.00	142.00	0.00	-1.23	3.46
Fertility	3	143	2.71	1.39	2.15	2.52	1.02	0.98	7.02	6.05	1.09	0.31	0.12
ChildMortality	4	143	28.96	30.52	15.40	23.57	17.20	2.40	123.20	120.80	1.35	0.99	2.55
InfantMortality	5	143	21.55	20.47	13.40	18.45	14.97	1.90	85.00	83.10	1.10	0.27	1.71
LifeExpectancy	6	143	72.37	7.82	73.85	72.82	8.91	52.83	84.21	31.39	-0.45	-0.82	0.65
DPTPercent	7	143	88.90	11.73	93.00	91.19	5.93	42.00	99.00	57.00	-2.06	4.53	0.98
GDPPerCapita	8	143	14093.79	19826.50	5233.28	9823.82	6185.18	274.13	106376.78	106102.65	2.08	4.29	1657.97
FDIIn	9	143	1.37	12.07	2.38	2.45	2.11	-117.37	29.21	146.58	-7.05	64.58	1.01
NaturalResourceRents	10	143	6.73	10.55	2.26	4.34	2.98	0.00	62.77	62.77	2.55	7.40	0.88
UrbanPopulation	11	143	60.40	21.62	61.58	61.13	26.32	13.03	100.00	86.97	-0.24	-0.88	1.81
GovtExpenditures	12	143	15.72	6.45	15.48	15.29	5.72	3.60	56.31	52.71	2.00	10.03	0.54
PaidParentalLeave	13	143	0.29	0.46	0.00	0.24	0.00	0.00	1.00	1.00	0.90	-1.20	0.04
DemocScore	14	143	6.01	3.75	7.00	6.26	4.45	0.00	10.00	10.00	-0.58	-1.23	0.31
AutocScore	15	143	1.55	2.55	0.00	0.97	0.00	0.00	10.00	10.00	1.74	2.05	0.21
POLITY	16	143	4.45	6.01	7.00	5.27	4.45	-10.00	10.00	20.00	-0.97	-0.46	0.50
Rich*	17	143	1.50	0.50	1.00	1.50	0.00	1.00	2.00	1.00	0.01	-2.01	0.04
IMDPTres	18	143	0.00	14.75	-3.75	-1.39	10.15	-38.23	68.41	106.64	1.16	2.43	1.23
IMDPThat	19	143	21.55	14.19	16.59	18.78	7.17	9.33	78.29	68.96	2.06	4.53	1.19

Bivariate OLS Regression

```
> IMDPT<-lm(InfantMortality~DPTPercent,data=IR2018)
> summary.lm(IMDPT)

Call:
lm(formula = InfantMortality ~ DPTPercent, data = IR2018)
```

Residuals:

Min	1Q	Median	3Q	Max
-38.23	-9.64	-3.75	5.18	68.41

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	129.104	9.491	13.6	<2e-16 ***
DPTPercent	-1.210	0.106	-11.4	<2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 14.8 on 141 degrees of freedom

Multiple R-squared: 0.481, Adjusted R-squared: 0.477

F-statistic: 131 on 1 and 141 DF, p-value: <2e-16

Analysis of Variance

```
> anova(IMDPT)
```

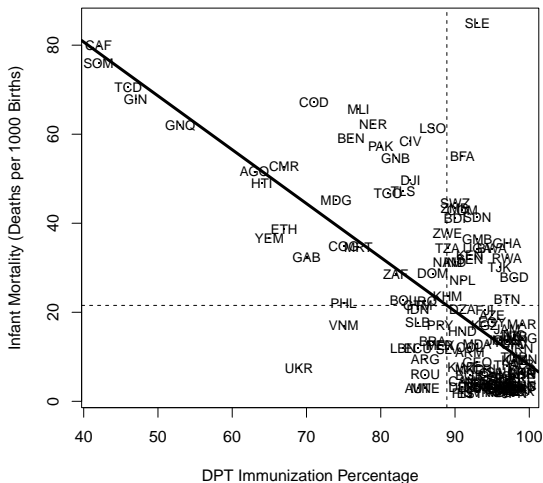
Analysis of Variance Table

Response: InfantMortality

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
DPTPercent	1	28607	28607	131	<2e-16 ***
Residuals	141	30874	219		

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

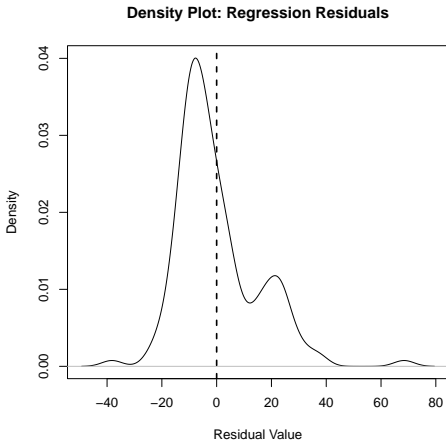
Regression of Infant Mortality on DPT Immunization Rates



Fitted Values, Residuals, etc.

```
> # Residuals (u):  
> IR2018$IMDPTres <- with(IR2018, residuals(IMDPT))  
> describe(IR2018$IMDPTres)
```

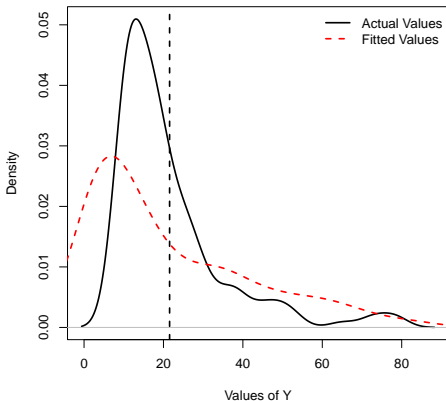
	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
X1	1	143	0	14.8	-3.75	-1.39	10.2	-38.2	68.4	107	1.16	2.43	1.23



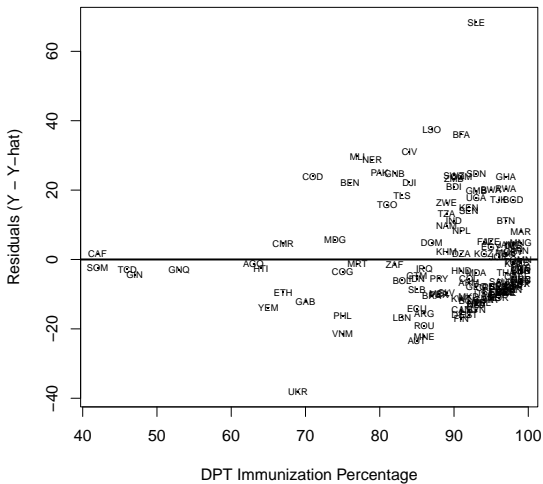
```
> # Fitted Values:  
> IR2018$IMDPThat<-fitted.values(IMDPT)  
> describe(IR2018$IMDPThat)
```

	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
X1	1	143	21.6	14.2	16.6	18.8	7.17	9.33	78.3	69	2.06	4.53	1.19

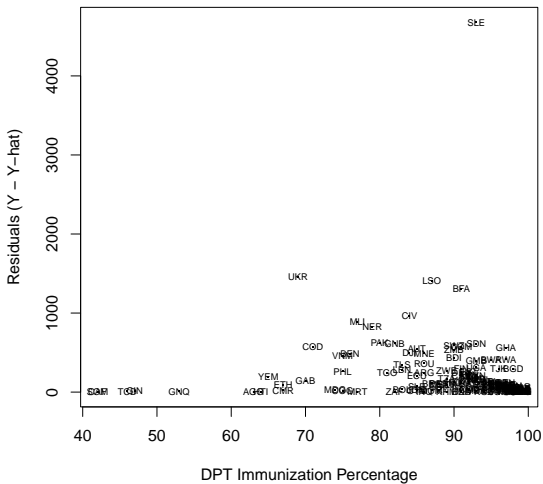
Density Plot: Actual and Fitted Values



Regression Residuals (\hat{u}) vs. DPT Percentage



Squared Residuals vs. DPT Percentage



$\text{Var}(\hat{\beta})$:

```
> vcov(IMDPT)
```

	(Intercept)	DPTPercent
(Intercept)	90.078	-0.9960
DPTPercent	-0.996	0.0112

95 percent c.i.s:

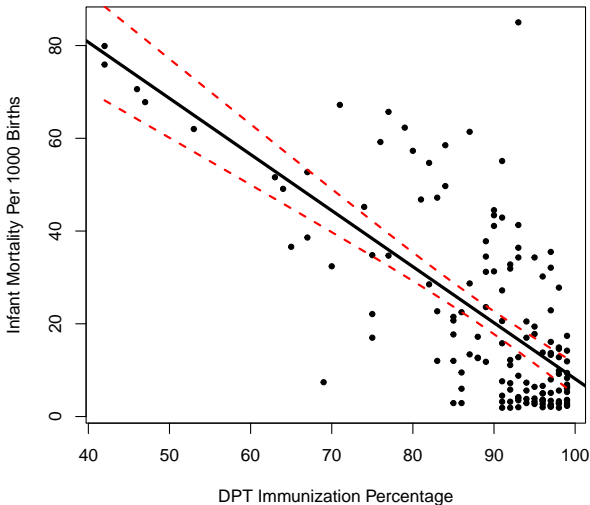
```
> confint(IMDPT)
```

	2.5 %	97.5 %
(Intercept)	110.34	148
DPTPercent	-1.42	-1

```
> SEs<-predict(IMDPT,interval="confidence")
> SEs
      fit   lwr   upr
3  52.88 46.94 58.8
4   9.33  6.10 12.6
6   9.33  6.10 12.6
.
.
<rows omitted>
.
.
212 50.46 44.90 56.0
213 29.90 27.06 32.7
214 20.22 17.76 22.7
215 21.43 18.98 23.9
```

A Plot, With CIs

Scatterplot of Infant Mortality and DPT Immunizations, along with Least-Squares Line and 95% Prediction Confidence Intervals



Multivariate Model: Child Mortality

```
> model<-lm(InfantMortality~DPTPercent+GDPPerCapita+FDIIn+
+           NaturalResourceRents+UrbanPopulation+GovtExpenditures+
+           POLITY+PaidParentalLeave,data=IR2018)
> summary(model)
```

Call:

```
lm(formula = InfantMortality ~ DPTPercent + GDPPerCapita + FDIIn +
    NaturalResourceRents + UrbanPopulation + GovtExpenditures +
    POLITY + PaidParentalLeave, data = IR2018)
```

Residuals:

Min	1Q	Median	3Q	Max
-30.77	-5.97	-1.01	5.25	57.79

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	120.1847454	8.2458035	14.58	< 2e-16 ***
DPTPercent	-0.8508569	0.0936331	-9.09	1.2e-15 ***
GDPPerCapita	-0.0000915	0.0000717	-1.28	0.2044
FDIIn	-0.1000156	0.0897276	-1.11	0.2670
NaturalResourceRents	0.1521474	0.1142324	1.33	0.1852
UrbanPopulation	-0.3295500	0.0571374	-5.77	5.3e-08 ***
GovtExpenditures	0.0036648	0.1727382	0.02	0.9831
POLITY	-0.0928692	0.1947269	-0.48	0.6342
PaidParentalLeave	-7.9426051	2.4968797	-3.18	0.0018 **

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 11.5 on 134 degrees of freedom

Multiple R-squared: 0.703, Adjusted R-squared: 0.685

F-statistic: 39.6 on 8 and 134 DF, p-value: <2e-16

Variance-Covariance Matrix of $\hat{\beta}$

```
> vcov(model)
```

	(Intercept)	DPTPercent	GDPPerCapita	FDIIn	NaturalResourceRents
(Intercept)	67.993276	-0.693611256	0.00012395662	0.00773960	-0.234304691
DPTPercent	-0.693611	0.008767158	-0.00000058798	-0.00019383	0.002875263
GDPPerCapita	0.000124	-0.000000588	0.00000000515	0.00000264	0.000000642
FDIIn	0.007740	-0.000193834	0.00000264192	0.00805104	-0.000201076
NaturalResourceRents	-0.234305	0.002875263	0.00000064215	-0.00020108	0.013049034
UrbanPopulation	-0.084284	-0.000733489	-0.00000204452	-0.00069983	-0.000774746
GovtExpenditures	-0.014527	-0.003418874	-0.00000080316	0.00036455	-0.007817267
POLITY	-0.276336	0.002795967	-0.00000030251	0.00079257	0.010641537
PaidParentalLeave	3.270567	-0.037486336	-0.00004999336	-0.01489057	0.014976307

	UrbanPopulation	GovtExpenditures	POLITY	PaidParentalLeave
(Intercept)	-0.08428441	-0.014527322	-0.276336134	3.27057
DPTPercent	-0.00073349	-0.003418874	0.002795967	-0.03749
GDPPerCapita	-0.00000204	-0.000000803	-0.000000303	-0.00005
FDIIn	-0.00069983	0.000364547	0.000792569	-0.01489
NaturalResourceRents	-0.00077475	-0.007817267	0.010641537	0.01498
UrbanPopulation	0.00326469	-0.000559546	-0.000337250	-0.00822
GovtExpenditures	-0.00055955	0.029838489	-0.010635268	-0.02024
POLITY	-0.00033725	-0.010635268	0.037918563	-0.07426
PaidParentalLeave	-0.00822062	-0.020241192	-0.074256519	6.23441

Test $H_0 : \beta_{\text{FDIIn}} = \beta_{\text{POLITY}} = 0$:

```
> library(lmtest)
> modelsmall<-lm(InfantMortality~DPTPercent+GDPPerCapita+NaturalResourceRents+
+               UrbanPopulation+GovtExpenditures+PaidParentalLeave,
+               data=IR2018)

> waldtest(model,modelsmall) # from -lmtest- package
```

Wald test

```
Model 1: InfantMortality ~ DPTPercent + GDPPerCapita + FDIIn + NaturalResourceRents +
      UrbanPopulation + GovtExpenditures + POLITY + PaidParentalLeave
Model 2: InfantMortality ~ DPTPercent + GDPPerCapita + NaturalResourceRents +
      UrbanPopulation + GovtExpenditures + PaidParentalLeave
  Res.Df Df    F Pr(>F)
1      134
2      136 -2 0.71  0.49
```

Test $H_0 : \beta_{\text{NaturalResourceRents}} = 1.0$:

```
> library(car)
> linearHypothesis(model,"NaturalResourceRents=1") # from -car-
Linear hypothesis test
```

Hypothesis:

NaturalResourceRents = 1

Model 1: restricted model

Model 2: InfantMortality ~ DTPPercent + GDPPerCapita + FDIIn + NaturalResourceRents +
UrbanPopulation + GovtExpenditures + POLITY + PaidParentalLeave

	Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
1	135	24946				
2	134	17678	1	7268	55.1	1.2e-11 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Test $H_0 : \beta_{\text{NaturalResourceRents}} = -\beta_{\text{UrbanPopulation}}$:

```
> linearHypothesis(model, "NaturalResourceRents = -UrbanPopulation")
```

Linear hypothesis test

Hypothesis:

NaturalResourceRents + UrbanPopulation = 0

Model 1: restricted model

Model 2: InfantMortality ~ DPTPercent + GDPPerCapita + FDIIn + NaturalResourceRents +
UrbanPopulation + GovtExpenditures + POLITY + PaidParentalLeave

	Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
1	135	17960				
2	134	17678	1	281	2.13	0.15

Reporting: Making Tables

R

- LaTeX: texreg, xtable, stargazer, and modelsummary packages
- MS Word: generally cut-and-paste (see, e.g., here: <https://sejdemyr.github.io/r-tutorials/basics/tables-in-r/>); also KableExtra
- A pretty good summary of many others is here: <https://rfortherestofus.com/2019/11/how-to-make-beautiful-tables-in-r/>.

Stata

- estout and esttab commands are standard
- Others: outreg2, tabout, orth_out, etc. (a summary is here: <https://lukestein.github.io/stata-latex-workflows/>)
- MS Word: putdocx

The output:

```
> summary(model)
```

```
Call:
```

```
lm(formula = InfantMortality ~ DPTPercent + GDPPerCapita + FDIIn +  
    NaturalResourceRents + UrbanPopulation + GovtExpenditures +  
    POLITY + PaidParentalLeave, data = IR2018)
```

```
Residuals:
```

```
      Min       1Q   Median       3Q      Max  
-30.77  -5.97  -1.01    5.25   57.79
```

```
Coefficients:
```

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	120.1847454	8.2458035	14.58	< 2e-16 ***
DPTPercent	-0.8508569	0.0936331	-9.09	1.2e-15 ***
GDPPerCapita	-0.0000915	0.0000717	-1.28	0.2044
FDIIn	-0.1000156	0.0897276	-1.11	0.2670
NaturalResourceRents	0.1521474	0.1142324	1.33	0.1852
UrbanPopulation	-0.3295500	0.0571374	-5.77	5.3e-08 ***
GovtExpenditures	0.0036648	0.1727382	0.02	0.9831
POLITY	-0.0928692	0.1947269	-0.48	0.6342
PaidParentalLeave	-7.9426051	2.4968797	-3.18	0.0018 **

```
---
```

```
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Residual standard error: 11.5 on 134 degrees of freedom
```

```
Multiple R-squared:  0.703, Adjusted R-squared:  0.685
```

```
F-statistic: 39.6 on 8 and 134 DF,  p-value: <2e-16
```

The table:

Table 1: OLS Regression Model of Child Mortality Rates, 2018

	Model I
(Constant)	120.00*** (8.25)
DPT Immunization Rate	-0.85*** (0.09)
GDP Per Capita	-0.0001 (0.0001)
Inward FDI	-0.10 (0.09)
Natural Resource Rents (Pct. GDP)	0.15 (0.11)
Urban Population (Pct.)	-0.33*** (0.06)
Government Expenditures (Pct. GDP)	0.004 (0.17)
POLITY V (Democracy) Score	-0.09 (0.19)
Paid Parental Leave	-7.94*** (2.50)
Observations	143
R ²	0.70
Adjusted R ²	0.69
Residual Std. Error	11.50 (df = 134)
F Statistic	39.60*** (df = 8; 134)

Note: Cell entries are coefficient estimates; numbers in parentheses are estimated standard errors.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. See text for details.

Multiple Models (stargazer defaults)

OLS Regression Models of Infant Mortality Rates, 2018

	Univariate	Full	Reduced
(Constant)	129.00*** (9.49)	120.00*** (8.25)	120.00*** (8.10)
DPT Immunization Rate	-1.21*** (0.11)	-0.85*** (0.09)	-0.85*** (0.09)
GDP Per Capita		-0.0001 (0.0001)	-0.0001 (0.0001)
Inward FDI		-0.10 (0.09)	
Natural Resource Rents (Pct. GDP)		0.15 (0.11)	0.17* (0.10)
Urban Population (Pct.)		-0.33*** (0.06)	-0.34*** (0.06)
Government Expenditures (Pct. GDP)		0.004 (0.17)	-0.02 (0.16)
POLITY V (Democracy) Score		-0.09 (0.19)	
Paid Parental Leave		-7.94*** (2.50)	-8.29*** (2.46)
Observations	143	143	143
R ²	0.48	0.70	0.70
Adjusted R ²	0.48	0.69	0.69
Residual Std. Error	14.80 (df = 141)	11.50 (df = 134)	11.50 (df = 136)
F Statistic	131.00*** (df = 1; 141)	39.60*** (df = 8; 134)	52.80*** (df = 6; 136)

Note:

* p<0.1; ** p<0.05; *** p<0.01

Some Guidelines (“Rules”?)

Tables:

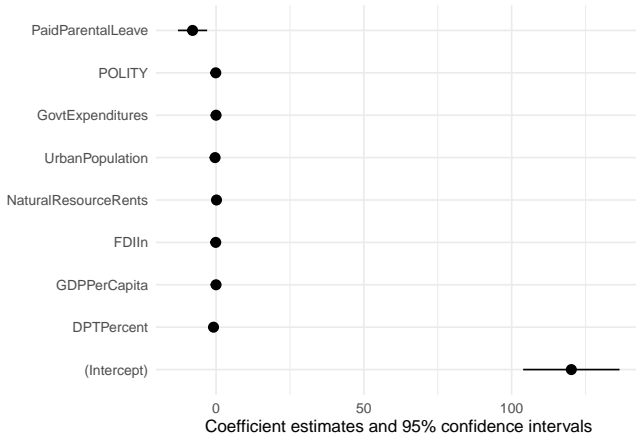
- *Use column headings descriptively.*
- *Use multiple rows / columns rather than multiple tables.*
- *Learn about significant digits, and don't report more than 4-5 of them (at the most).*
- *Use a figure to replace a table when you can.*
- *Be aware of norms about *s.*

Figures:

- *Report the scale of axes, and label them.*
- *Use as much “space” as you need, but no more.*
- *Use color sparingly.*

Plotting Regression Estimates

Ladderplot of OLS Results (using modelplot defaults)



Rescaling Covariates

A la Gelman (2008):

- Continuous = divide by two standard deviations
- Binary = mean 0, difference of 1 between the two categories

```
> modelS<-standardize(model)
> summary(modelS)
```

Call:

```
lm(formula = InfantMortality ~ z.DPTPercent + z.GDPPerCapita +
    z.FDIIn + z.NaturalResourceRents + z.UrbanPopulation + z.GovtExpenditures +
    z.POLITY + c.PaidParentalLeave, data = IR2018)
```

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	21.5469	0.9605	22.43	< 2e-16 ***
z.DPTPercent	-19.9644	2.1970	-9.09	1.2e-15 ***
z.GDPPerCapita	-3.6274	2.8445	-1.28	0.2044
z.FDIIn	-2.4140	2.1657	-1.11	0.2670
z.NaturalResourceRents	3.2110	2.4108	1.33	0.1852
z.UrbanPopulation	-14.2529	2.4712	-5.77	5.3e-08 ***
z.GovtExpenditures	0.0472	2.2269	0.02	0.9831
z.POLITY	-1.1163	2.3407	-0.48	0.6342
c.PaidParentalLeave	-7.9426	2.4969	-3.18	0.0018 **

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

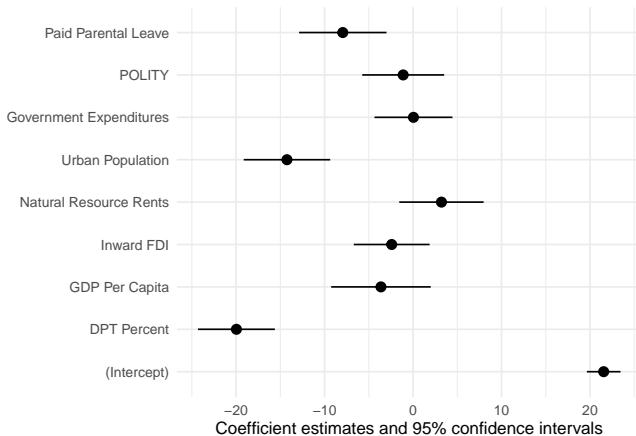
Residual standard error: 11.5 on 134 degrees of freedom

Multiple R-squared: 0.703, Adjusted R-squared: 0.685

F-statistic: 39.6 on 8 and 134 DF, p-value: <2e-16

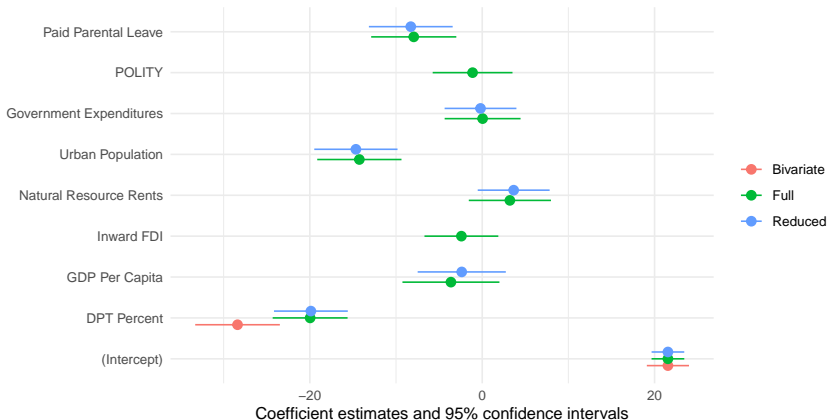
A Better Regression Plot

Ladderplot of Standardized OLS Results



An Even Better Regression Plot

Ladderplot of Standardized OLS Results



- *Be aware of the norms in your discipline / field, and follow them.*
- *If it has uncertainty, you should show it.*
- *Ask for advice.*
- *When in doubt, more information is (probably) better.*

Supplement: R Things

This:

```
> table(df$X)
```

... means “Type the phrase ‘table(df\$X)’ on the command line,” or – equivalently – “Type the phrase ‘table(df\$X)’ into your Source code, and then run it.”

More often, you'll see:

```
with(df, plot(Y~X,pch=19,col="red")) # draw a scatterplot
abline(h=0,lty=2) # add a horizontal line at zero
abline(v=0,lty=2) # add a vertical line at zero
text(df$X,df$Y,labels=df$names,pos=1) # add labels
```

... which means “Put this block of text into your Source code, and then run it.”

Note:

- R / RStudio ignores line breaks
- Anything to the right of a “#” is a comment

Very basic R examples...

(see `GSERM-June-2024-R-Intro.R` in the github repo)

Help For Learning R(Studio)

In rough order of preference:

- Quick-R (<http://www.statmethods.net/>)
- The “Level-Zero” R Tutorial (doesn't integrate RStudio, but is otherwise very good)
- Statistics with R
- The Do It Yourself Introduction to R
- Also be sure to consult the Regression for Publishing “Useful R Resources” guide (on GitHub).