

PLSC 503 – Spring 2025

Multivariate Regression

January 27, 2025

“Multivariate” linear regression:

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

or:

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

or:

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

Residuals:

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

The inner product of \mathbf{u} :

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

Start with:

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

Now get:

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

Solve:

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

“Do not compute the least squares estimates using $(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{Y}$!”

– Weisberg (2013, p. 61)

Most software uses a **QR decomposition** of \mathbf{X} :

$$\mathbf{X} = \mathbf{QR}$$

where \mathbf{Q} is orthogonal ($\mathbf{Q}'\mathbf{Q} = \mathbf{Q}\mathbf{Q}' = \mathbf{I}$) and \mathbf{R} is upper-triangular.

Why? See e.g. [here](#), [here](#), or [section 3.19 of this](#).

Estimation Issues (continued)

By decomposing \mathbf{X} into \mathbf{QR} , we can have:

$$\begin{aligned}\mathbf{X}'\mathbf{X}\beta &= \mathbf{X}'\mathbf{Y} \\ (\mathbf{QR})'(\mathbf{QR})\beta &= (\mathbf{QR})'\mathbf{Y} \\ \mathbf{R}'\mathbf{Q}'\mathbf{Q}\mathbf{R}\beta &= \mathbf{R}'\mathbf{Q}'\mathbf{Y} \\ \mathbf{R}'\mathbf{R}\beta &= \mathbf{R}'\mathbf{Q}'\mathbf{Y} \\ \mathbf{R}\beta &= \mathbf{Q}'\mathbf{Y}\end{aligned}$$

Here, $\mathbf{Q}'\mathbf{Y}$ is a vector, so we might write:

$$\mathbf{R}\beta = \mathbf{V}$$

...which is an upper-triangular system of equations that can be easily solved by [backward substitution](#). Doing this avoids inverting $(\mathbf{X}'\mathbf{X})$ entirely, which is good for [a few reasons](#).

OLS Assumptions

1. Expectation-Zero Disturbances

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

2. Homoscedasticity / No Error Correlation

$$\begin{aligned}\mathbf{u}\mathbf{u}' &= \begin{bmatrix} u_1 \\ u_2 \\ \vdots \\ u_N \end{bmatrix} \begin{bmatrix} u_1 & u_2 & \cdots & u_N \end{bmatrix} \\ &= \begin{bmatrix} u_1^2 & u_1 u_2 & \cdots & u_1 u_N \\ u_2 u_1 & u_2^2 & \cdots & u_2 u_N \\ \vdots & \vdots & \ddots & \vdots \\ u_N u_1 & u_N u_2 & \cdots & u_N^2 \end{bmatrix}\end{aligned}$$

Assumption: Expectation must be:

$$E(\mathbf{u}\mathbf{u}') = \begin{bmatrix} \sigma^2 & 0 & \cdots & 0 \\ 0 & \sigma^2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \sigma^2 \end{bmatrix} = \sigma^2 \mathbf{I}_{N \times N}$$

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

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

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

Means:

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

[5. Normal Disturbances]

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

OLS: Unbiasedness (again)

Start with:

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{u}$$

Substitute OLS $\hat{\boldsymbol{\beta}}$:

$$\begin{aligned}\hat{\boldsymbol{\beta}} &= (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'(\mathbf{X}\boldsymbol{\beta} + \mathbf{u}) \\ &= (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{X}\boldsymbol{\beta} + (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{u} \\ &= \boldsymbol{\beta} + (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{u}\end{aligned}$$

and so:

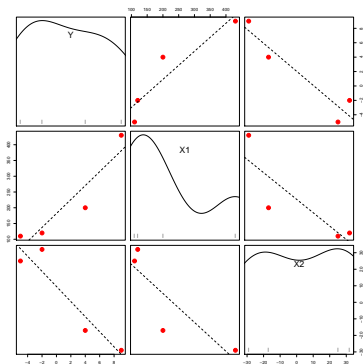
$$\hat{\boldsymbol{\beta}} - \boldsymbol{\beta} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{u}.$$

By $\text{Cov}(\mathbf{X}, \mathbf{u}) = \mathbf{0}$, we have $E(\hat{\boldsymbol{\beta}}) = \boldsymbol{\beta}$.

A Toy Example

$$\mathbf{Y} = \begin{bmatrix} 4 \\ -2 \\ 9 \\ -5 \end{bmatrix}$$

$$\mathbf{X} = \begin{bmatrix} 1 & 200 & -17 \\ 1 & 120 & 32 \\ 1 & 430 & -29 \\ 1 & 110 & 25 \end{bmatrix}$$



So:

$$\mathbf{X}'\mathbf{X} = \begin{bmatrix} 4 & 860 & 11 \\ 860 & 251400 & -9280 \\ 11 & -9280 & 2779 \end{bmatrix}$$

$$(\mathbf{X}'\mathbf{X})^{-1} = \begin{bmatrix} 3.2453 & -0.0132 & -0.05694 \\ -0.0132 & 0.000058 & 0.0002468 \\ -0.0569 & 0.000247 & 0.001409 \end{bmatrix}$$

$$\mathbf{X}'\mathbf{Y} = \begin{bmatrix} 6 \\ 3880 \\ 518 \end{bmatrix}$$

...which means that:

$$\begin{aligned} \hat{\beta} &= \begin{bmatrix} 3.2453 & -0.0132 & -0.05694 \\ -0.0132 & 0.000058 & 0.0002468 \\ -0.0569 & 0.000247 & 0.001409 \end{bmatrix} \begin{bmatrix} 6 \\ 3880 \\ 518 \end{bmatrix} \\ &= \begin{bmatrix} -2.264 \\ 0.0190 \\ -0.1141 \end{bmatrix} \end{aligned}$$

Minimal Example: Correlation

```
Y<-c(4,-2,9,-5)
X1<-c(200,120,430,110)
X2<-c(-17,32,-29,25)
data<-cbind(Y,X1,X2)
```

```
cor(data)
```

	Y	X1	X2
Y	1.0000	0.9285	-0.9425
X1	0.9285	1.0000	-0.8613
X2	-0.9425	-0.8613	1.0000

OLS via lm:

```
> fit<-lm(Y~X1+X2)
```

```
> summary(fit)
```

Call:

```
lm(formula = Y ~ X1 + X2)
```

Residuals:

1	2	3	4
0.531	1.639	-0.201	-1.970

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-2.2643	4.7284	-0.48	0.72
X1	0.0190	0.0200	0.95	0.52
X2	-0.1141	0.0985	-1.16	0.45

Residual standard error: 2.62 on 1 degrees of freedom

Multiple R-Squared: 0.941, Adjusted R-squared: 0.823

F-statistic: 7.99 on 2 and 1 DF, p-value: 0.243

One approach is “testing”:

- Pick some $\mathbf{H}_A : \boldsymbol{\beta} = \boldsymbol{\beta}_A$
- Estimate $\hat{\boldsymbol{\beta}}$
- Determine distribution of $\hat{\boldsymbol{\beta}}$ under \mathbf{H}_A
- Form a *test statistic* $\hat{\mathbf{S}} = h(\boldsymbol{\beta}, \hat{\boldsymbol{\beta}})$
- Assess $\Pr(\hat{\mathbf{S}}|\mathbf{H}_A)$

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

Start with:

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

Rewrite:

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

Taking expectations:

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

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

Empirical estimate:

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

Yields:

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

Single Coefficient Hypothesis Tests

We know that:

$$\hat{\beta} \sim \mathcal{N}[\beta, \sigma^2(\mathbf{X}'\mathbf{X})^{-1}].$$

In practice, using $\hat{\sigma}^2$ means

$$\hat{\beta} - \beta \sim t_{N-K}$$

Procedure:

- Choose a value of β_k that you want to test (say, $\beta_k = 0$),
- Calculate the t -statistic for the coefficient associated with X_k , which is:

$$\hat{t}_k = \frac{\hat{\beta}_k - \beta_k}{\sqrt{\widehat{\mathbf{V}}(\hat{\beta}_k)}}$$

- Compare \hat{t}_k to a t distribution with $N - K$ degrees of freedom.

Multivariate Hypothesis Testing

E.g.: $H_0 : \beta_1 = \beta_2 = \dots = \beta_K = 0$

or: $H_0 : \beta_3 = \beta_6 = 0$

Generally: *Linear restrictions*:

$$\underset{q \times k}{\mathbf{R}} \underset{k \times 1}{\boldsymbol{\beta}} = \underset{q \times 1}{\mathbf{r}}$$

E.g.:

$$\beta_2 = -2 \iff (0 \ 1 \ 0) \begin{pmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \end{pmatrix} = -2$$

Recall:

$$\mathbf{TSS} = \mathbf{MSS} + \mathbf{RSS}$$

Consider:

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \beta_4 X_{4i} + u_{Ui}$$

and the restriction:

$$H_a : \beta_2 = \beta_4 = 0.$$

Restricted model:

$$\begin{aligned} Y_i &= \beta_0 + \beta_1 X_{1i} + 0X_{2i} + \beta_3 X_{3i} + 0X_{4i} + u_i \\ &= \beta_0 + \beta_1 X_{1i} + \beta_3 X_{3i} + u_{Ri} \end{aligned}$$

F-tests: Sums of Squared Residuals

“Unrestricted”:

$$RSS_U \equiv \hat{\mathbf{u}}_U' \hat{\mathbf{u}}_U = \sum_{i=1}^N \hat{u}_{Ui}^2$$

“Restricted”:

$$RSS_R \equiv \hat{\mathbf{u}}_R' \hat{\mathbf{u}}_R = \sum_{i=1}^N \hat{u}_{Ri}^2$$

F-statistic:

$$\begin{aligned}\mathbf{F} &= \frac{(\text{RSS}_R - \text{RSS}_U)/q}{\text{RSS}_U/(N-K)} \\ &= \frac{(R_U^2 - R_R^2)/q}{(1 - R_U^2)/(N-K)}\end{aligned}$$

Testing:

$$\mathbf{F} \sim F_{q, N-K}$$

Consider:

$$\begin{aligned}H_b : \quad & \beta_1 + \beta_4 = 1 \\ & \beta_1 = 1 - \beta_4\end{aligned}$$

Implies:

$$\begin{aligned}Y_i &= \beta_0 + (1 - \beta_4)X_{1i} + \beta_2X_{2i} + \beta_3X_{3i} + \beta_4X_{4i} + u_{R'i} \\ &= \beta_0 + X_{1i} - \beta_4X_{1i} + \beta_2X_{2i} + \beta_3X_{3i} + \beta_4X_{4i} + u_{R'i} \\ &= \beta_0 + X_{1i} + \beta_2X_{2i} + \beta_3X_{3i} + \beta_4(X_{4i} - X_{1i}) + u_{R'i}\end{aligned}$$

...which further implies the restricted model:

$$Y_i - X_{1i} = \beta_0 + \beta_2X_{2i} + \beta_3X_{3i} + \beta_4(X_{4i} - X_{1i}) + u_{R'i}$$

Note that:

$$F = \frac{(\hat{\beta}_q - \beta_q^H)' \hat{\mathbf{V}}_q^{-1} (\hat{\beta}_q - \beta_q^H)}{q \hat{\sigma}^2}$$

...which implies that, for some confidence level α :

$$\Pr \left[\frac{(\hat{\beta}_q - \beta_q^H)' \hat{\mathbf{V}}_q^{-1} (\hat{\beta}_q - \beta_q^H)}{q \hat{\sigma}^2} \leq F_{q, N-K} \right] = 1 - \alpha.$$

→ “confidence region” of all points satisfying:

$$(\hat{\beta}_q - \beta_q^H)' \hat{\mathbf{V}}_q^{-1} (\hat{\beta}_q - \beta_q^H) \leq q \hat{\sigma}^2 F_{q, N-K}.$$

The linear prediction:

$$\hat{Y}_j = \mathbf{x}_j \hat{\boldsymbol{\beta}}$$

...has variance:

$$\widehat{\mathbf{V}(\hat{Y}_j)} = \hat{\sigma}^2 [1 + \mathbf{x}_j (\mathbf{X}'\mathbf{X})^{-1} \mathbf{x}_j']$$

...→ standard error:

$$\widehat{\text{s.e.}(\hat{Y}_j)} = \sqrt{\hat{\sigma}^2 [1 + \mathbf{x}_j (\mathbf{X}'\mathbf{X})^{-1} \mathbf{x}_j']}$$

Example: Africa Data

```
> Data<-read_csv("https://raw.githubusercontent.com/PrisonRodeo/PLSC503-2025-git/master/Data/africa2001.csv")
> Data<-with(Data, data.frame(adrate,polity,
+   subsaharan=as.numeric(as.factor(subsaharan))-1,
+   muslperc,literacy))
```

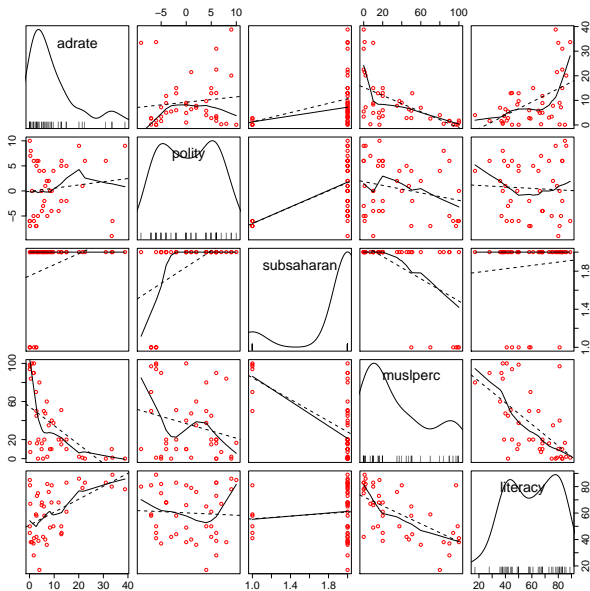
```
> describe(Data)
```

	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
adrate	1	43	9.37	9.96	6	7.58	6.38	0.1	38.8	38.7	1.44	1.23	1.52
polity	2	43	0.51	5.41	0	0.46	7.41	-9.0	10.0	19.0	0.01	-1.38	0.82
subsaharan	3	43	0.86	0.35	1	0.94	0.00	0.0	1.0	1.0	-2.01	2.08	0.05
muslperc	4	43	35.96	34.58	20	32.87	29.65	0.0	100.0	100.0	0.68	-1.04	5.27
literacy	5	43	60.07	18.94	61	60.63	26.69	17.0	89.0	72.0	-0.20	-1.18	2.89

```
> cor(Data)
```

	adrate	polity	subsaharan	muslperc	literacy
adrate	1.0000	0.11794	0.33129	-0.5709	0.51489
polity	0.1179	1.00000	0.52820	-0.2392	-0.05079
subsaharan	0.3313	0.52820	1.00000	-0.5773	0.09473
muslperc	-0.5709	-0.23917	-0.57725	1.0000	-0.61960
literacy	0.5149	-0.05079	0.09473	-0.6196	1.00000

Africa Data



A Regression

```
> model<-lm(adrate~polity+subsaharan+muslperc+literacy,data=Data)
> summary(model)
```

Call:

```
lm(formula = adrate ~ polity + subsaharan + muslperc + literacy,
    data = Data)
```

Residuals:

Min	1Q	Median	3Q	Max
-15.4681	-4.3947	-0.5251	3.4246	22.9358

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-4.39843	14.94744	-0.294	0.7702
polity	-0.01390	0.27969	-0.050	0.9606
subsaharan	3.72969	5.43093	0.687	0.4964
muslperc	-0.08689	0.06282	-1.383	0.1747
literacy	0.16575	0.09433	1.757	0.0869 .

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

Residual standard error: 8.264 on 38 degrees of freedom

Multiple R-squared: 0.3771, Adjusted R-squared: 0.3115

F-statistic: 5.751 on 4 and 38 DF, p-value: 0.001013

A Regression, Annotated

```
> model<-lm(adrate~polity+subsaharan+muslperc+literacy,data=Data)
```

```
> summary(model) ← Summarizing the model object...
```

Showing you what
model you fit...

Call:

```
lm(formula = adrate ~ polity + subsaharan + muslperc + literacy,  
    data = Data)
```

Residuals:

	Min	1Q	Median	3Q	Max
	-15.4681	-4.3947	-0.5251	3.4246	22.9358

Median, minimum, maximum, and 25th/75th
percentiles of the model residuals (u-hats);
ideally the median is close to zero, and the
other numbers symmetrical around it

t-statistics associated with the
test of the null hypothesis that
that particular beta equals zero

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-4.39843	14.94744	-0.294	0.7702
polity	-0.01390	0.27969	-0.050	0.9606
subsaharan	3.72969	5.43093	0.687	0.4964
muslperc	-0.08689	0.06282	-1.383	0.1747
literacy	0.16575	0.09433	1.757	0.0869

Beta-hats

Standard errors [square roots
of the diagonal of Var(Beta)]

Two-tailed P-values associated
with the t-statistics

Indicators of what
the little "stars"
(asterisks) next to
the P-values mean

The R-squared and
adjusted R-squared
values of the model

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

RSE: the size of a "typical" residual
in the model (in units of Y)

Residual standard error: 8.264 on 38 degrees of freedom

Multiple R-squared: 0.3771, Adjusted R-squared: 0.3115

F-statistic: 5.751 on 4 and 38 DF, p-value: 0.001013

The F-statistic and
associated P-value
for the joint null
hypothesis that all
the betas except the
intercept are zero

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

Matrix:

```
> options(digits=4)
> vcov(model)
```

	(Intercept)	polity	subsaharan	muslperc	literacy
(Intercept)	223.4259	1.088030	-72.2628	-0.771309	-1.002421
polity	1.0880	0.078229	-0.6642	-0.000293	0.001968
subsaharan	-72.2628	-0.664212	29.4950	0.206067	0.171765
muslperc	-0.7713	-0.000293	0.2061	0.003946	0.004098
literacy	-1.0024	0.001968	0.1718	0.004098	0.008898

→ standard error estimates:

```
> sqrt(diag(vcov(model)))
```

(Intercept)	polity	subsaharan	muslperc	literacy
10.41131167	0.27969425	5.43093195	0.06281584	0.09432686

```
> summary(model)[[4]][,2]
```

(Intercept)	polity	subsaharan	muslperc	literacy
10.41131167	0.27969425	5.43093195	0.06281584	0.09432686

Diversion: “Added Variable Plots”

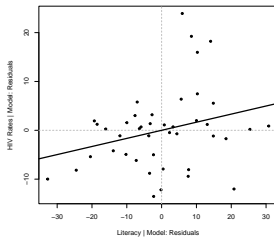
“Added variable plot”: If X_J is the (potential) added variable:

- Regress Y on X_1, X_2, \dots and save the residuals \hat{u}_i ,
- Regress X_J on X_1, X_2, \dots and save the residuals (call these \hat{e}_i),
- Plot \hat{u}_i (conventionally on the y -axis) vs. \hat{e}_i (conventionally on the x -axis).

Example: Estimate the regression:

$$\text{HIV Rate} = \beta_0 + \beta_1 \text{POLITY} + \beta_2 \text{Subsaharan} + \beta_3 \text{Muslim Pct.} + u$$

and consider the added variable literacy:



Test $H_0 : \beta_{\text{polity}} = \beta_{\text{subsaharan}} = 0$:

```
> library(lmtest)
> modelsmall<-lm(adrate~muslperc+literacy,data=Data)
> waldtest(model,modelsmall)
```

Wald test

Model 1: adrate ~ polity + subsaharan + muslperc + literacy

Model 2: adrate ~ muslperc + literacy

	Res.Df	Df	F	Pr(>F)
1	38			
2	40	-2	0.27	0.76

Test $H_0 : \beta_{\text{muslperc}} = 0.1$:

```
> library(car)
> linearHypothesis(model,"muslperc=0.1")
```

Linear hypothesis test

Hypothesis:
muslperc = 0.1

Model 1: restricted model

Model 2: adrate ~ polity + subsaharan + muslperc + literacy

	Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
1	39	3200				
2	38	2595	1	605	8.85	0.0051 **

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

Test $H_0 : \beta_{\text{literacy}} = \beta_{\text{muslperc}}$:

```
> linearHypothesis(model,"literacy=muslperc")
```

Linear hypothesis test

Hypothesis:

- muslperc + literacy = 0

Model 1: restricted model

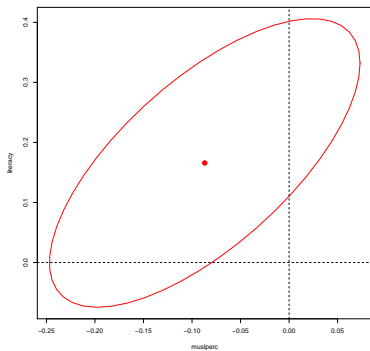
Model 2: adrate ~ polity + subsaharan + muslperc + literacy

	Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
1	39	3534				
2	38	2595	1	938	13.7	0.00067 ***

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

Confidence Regions / Ellipses

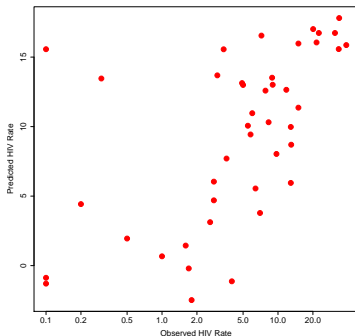
```
> confidenceEllipse(model=model,which.coef=c(4,5),  
                    xlab="Muslim Percentage",ylab="Literacy")  
> abline(h=0,v=0,lty=2)
```



Predicted Values

```
> hats<-fitted(model)
> # Or, alternatively:
> fitted<-predict(model,se.fit=TRUE, interval=c("confidence"))
> scatterplot(model$fitted~adrate,log="x",smooth=FALSE,boxplots=FALSE,
  reg.line=FALSE,xlab="Observed HIV Rate",ylab="Predicted HIV Rate",
  pch=16,cex=2)
```

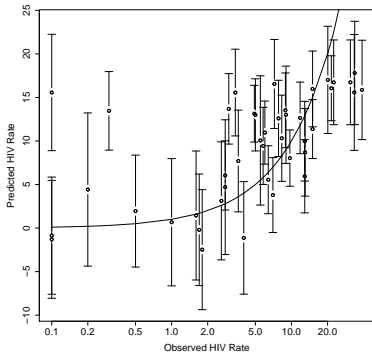
Predicted and Actual HIV/AIDS Rates (X-Axis Logged)



An Even More Useful Plot

```
> library(plotrix)
> plotCI(Data$adrate,model$fitted,uiw=(1.96*(fitted$se.fit)),
         log="x",xlab="Observed HIV Rate",ylab="Predicted HIV Rate")
> lines(lowess(Data$adrate>Data$adrate),lwd=2)
```

Predicted and Actual HIV/AIDS Rates, with 95% C.I.s



Presentation: A (De)Fault-y Table

```
> M1<-lm(adrater~polity+subsaharan+muslperc+literacy,data=Data)
> M2<-lm(adrater~polity+subsaharan+muslperc,data=Data)
> M3<-lm(adrater~polity+subsaharan+literacy,data=Data)
>
> stargazer(M1,M2,M3)
```

	<i>Dependent variable:</i>		
	adrater		
	(1)	(2)	(3)
polity	-0.014 (0.280)	-0.051 (0.286)	-0.020 (0.283)
subsaharan	3.730 (5.431)	0.530 (5.252)	8.268* (4.379)
muslperc	-0.087 (0.063)	-0.163*** (0.047)	
literacy	0.166* (0.094)		0.256*** (0.069)
Constant	-0.669 (10.410)	14.800** (5.701)	-13.120** (5.298)
Observations	43	43	43
R ²	0.377	0.326	0.346
Adjusted R ²	0.312	0.275	0.295
Residual Std. Error	8.264 (df = 38)	8.483 (df = 39)	8.361 (df = 39)
F Statistic	5.751*** (df = 4; 38)	6.302*** (df = 3; 39)	6.870*** (df = 3; 39)

Note:

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

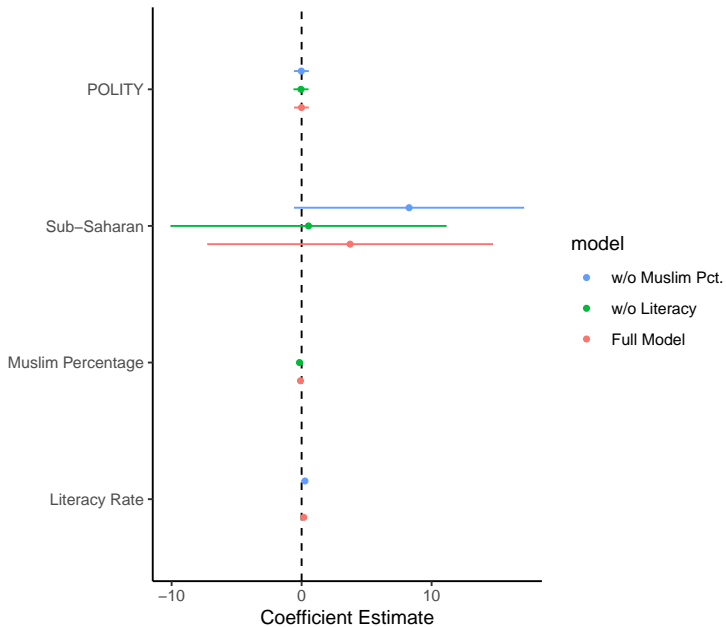
Never hand-type a table!

Some tools (in no particular order):

- `tinytable`
- `texreg`
- `stargazer`
- `xtable`
- `modelsummary`
- `gt`

See also, generally, [this](#).

A Dot-Whisker Plot



Gelman (2008 *Statistics in Medicine*)

Suggestion: Rescale *all* non-binary predictors by **dividing them by two times their standard deviation**.

- Creates a “common scale” for every predictor.
- More specifically: Scales continuous predictors to be comparable to binary (0/1) ones.
- $\hat{\beta}_X$ now represents the change in $E(Y)$ associated with a change in X of two standard deviations (for example, from one s.d. below the mean to one s.d. above the mean).

Note that:

- People don't *routinely* (or even generally) do this. But...
- ...it can be very useful when you have predictor variables that are measured on very different “natural” scales.

A (Better?) Dot-Whisker Plot

