

PLSC 503 – Spring 2022

Dichotomous Covariates and Transformations

February 9, 2022

“Dummies” ...

- ... “naturally” dichotomous, including
 - Structural breaks
 - Proper nouns
- “Factors”:

$$\text{partyid} = \begin{cases} 0 = \text{Labor} \\ 1 = \text{Liberal} \\ 2 = \text{Conservative} \end{cases}$$

- Ordinal variables...
- Continuous variables...

“Dummy coding”:

$$\text{female} = \begin{cases} 0 & \text{if male} \\ 1 & \text{if female} \end{cases}$$

vs. “Effect coding”:

$$\text{female} = \begin{cases} -1 \text{ (or } -0.5) & \text{if male} \\ 1 \text{ (or } 0.5) & \text{if female} \end{cases}$$

TL;DR: Use the former.

For

$$Y_i = \beta_0 + \beta_1 D_i + u_i$$

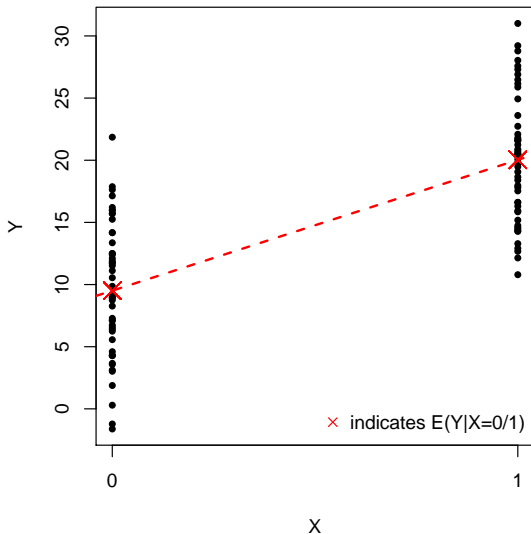
we have

$$E(Y|D = 0) = \beta_0$$

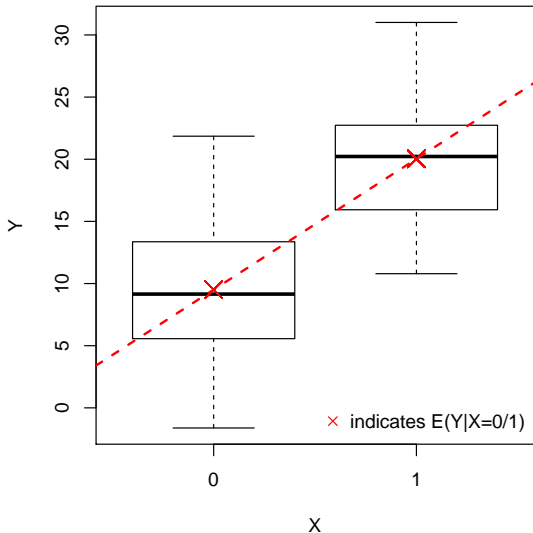
and

$$E(Y|D = 1) = \beta_0 + \beta_1.$$

Dichotomous X , Graphically (No!)



Dichotomous X , Graphically (Yes!)



Many Dummies

For

$$Y_i = \beta_0 + \beta_1 D_{1i} + \beta_2 D_{2i} + \dots + \beta_\ell D_{\ell i} + u_i$$

- $E(Y|D_k = 0) \forall k \in \ell = \beta_0$,
- Otherwise, $E(Y) = \beta_0 + \sum_{k=1}^{\ell} \beta_k \forall k \text{ s.t. } D_k = 1$.

Note: where the D_ℓ are mutually exclusive and exhaustive:

- The expected values are the same as the within-group means.
- Identification requires that we either
 - omit a “reference category,” or
 - omit β_0 .

Dummies and Ordinal X s

Suppose we have:

$$\text{gopscale} = \begin{cases} -2 = \text{Strong Democrat} \\ -1 = \text{Weak Democrat} \\ 0 = \text{Independent} \\ 1 = \text{Weak Republican} \\ 2 = \text{Strong Republican} \end{cases}$$

Might estimate:

$$\text{closeness}_i = 46.0 + 17.5(\text{gopscale}_i) + u_i$$

Dummies and Ordinal Xs

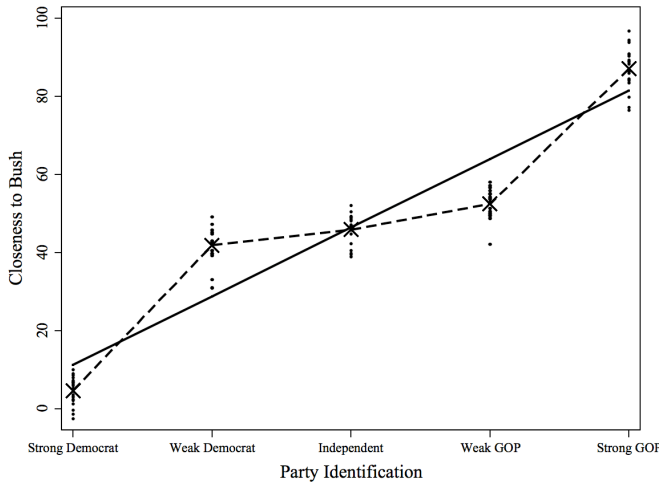
Alternative: “dummy out” gopscale:

$$\text{closeness}_i = \beta_0 + \beta_1(\text{strongdem}_i) + \beta_2(\text{weakdem}_i) + \beta_3(\text{weakgop}_i) + \beta_4(\text{stronggop}_i) + u_i$$

yielding:

$$\text{closeness}_i = 45.5 - 40(\text{strongdem}_i) - 6(\text{weakdem}_i) + 7(\text{weakgop}_i) + 42(\text{stronggop}_i) + u_i$$

Ordinal, Illustrated



Dichotomous + Continuous X

E.g.,

$$Y_i = \beta_0 + \beta_1 D_i + \beta_2 X_i + u_i$$

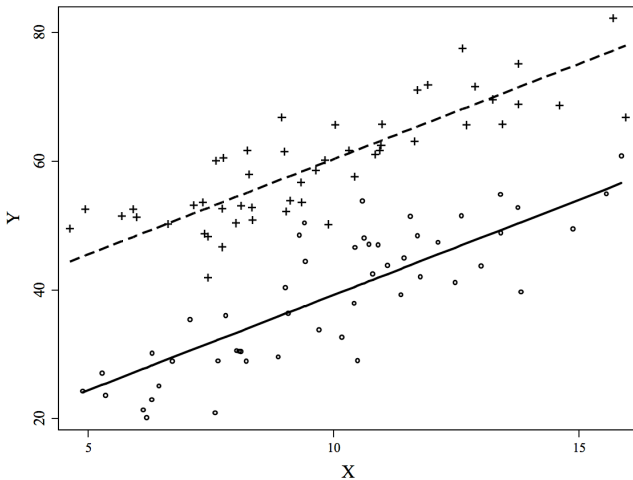
we have

$$E(Y|X, D = 0) = \beta_0 + \beta_2 X_i$$

and

$$E(Y|X, D = 1) = (\beta_0 + \beta_1) + \beta_2 X_i.$$

Dichotomous + Continuous X



Examples: SCOTUS (OT1953-1985)

From the “phase II” database...

```
> summary(SCOTUS)
```

id		term	Namici		lctdiss	multlaw	
Min.	: 1	Min.	:53.00	Min.	: 0.000	Min.	:0.0000
1st Qu.:	1791	1st Qu.:	64.00	1st Qu.:	0.000	1st Qu.:	0.0000
Median	:3581	Median	:72.00	Median	: 0.000	Median	:0.0000
Mean	:3581	Mean	:71.12	Mean	: 0.842	Mean	:0.1490
3rd Qu.:	5371	3rd Qu.:	79.00	3rd Qu.:	1.000	3rd Qu.:	0.0000
Max.	:7161	Max.	:85.00	Max.	:39.000	Max.	:1.0000
		NA's	: 4.00			NA's	:5.0000

civlibs		econs	constit		lctlib		
Min.	:0.0000	Min.	:0.0000	Min.	: 0.0000		
1st Qu.:	0.0000	1st Qu.:	0.0000	1st Qu.:	0.0000		
Median	:1.0000	Median	:0.0000	Median	: 0.0000		
Mean	:0.5009	Mean	:0.1709	Mean	:0.2536	Mean	: 0.3742
3rd Qu.:	1.0000	3rd Qu.:	0.0000	3rd Qu.:	1.0000	3rd Qu.:	1.0000
Max.	:1.0000	Max.	:1.0000	Max.	:1.0000	Max.	: 1.0000
					NA's	:120.0000	

Creating Dummies

All civil rights & economics cases:

```
> SCOTUS$civil.econ<-SCOTUS$civlibs + SCOTUS$econs
```

Factors:

```
> SCOTUS$termdummies<-factor(SCOTUS$term)
```

```
> is.factor(SCOTUS$termdummies)
```

```
[1] TRUE
```

```
> summary(SCOTUS$termdummies)
```

53	54	55	56	57	58	59	60	61	62	63	64	65	66	67
126	109	128	162	196	165	157	160	148	189	223	156	187	201	285
68	69	70	71	72	73	74	75	76	77	78	79	80	81	
207	185	227	262	269	267	223	253	254	244	244	221	255	269	
82	83	84	85	NA's										
277	298	301	309	4										

Regressions (vs. *t*-tests...)

```
> fit1<-with(SCOTUS, lm(Namici~civlibs))
> summary(fit1)
```

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	0.91774	0.03661	25.069	< 2e-16 ***
civlibs	-0.15136	0.05173	-2.926	0.00344 **

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

Residual standard error: 2.189 on 7159 degrees of freedom
Multiple R-squared: 0.001195, Adjusted R-squared: 0.001055
F-statistic: 8.563 on 1 and 7159 DF, p-value: 0.003442

```
> with(SCOTUS, t.test(Namici~civlibs))
```

Welch Two Sample t-test

data: Namici by civlibs
t = 2.9258, df = 7114.116, p-value = 0.003446
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
0.04995001 0.25277126
sample estimates:
mean in group 0 mean in group 1
0.9177392 0.7663786

Effect Coding

```
> SCOTUS$civlibeffect<-SCOTUS$civlibs  
> SCOTUS$civlibeffect[SCOTUS$civlibs==0]<-(-1)  
> fit2<-with(SCOTUS, lm(Namici~SCOTUS$civlibeffect))  
> summary(fit2)
```

Call:

```
lm(formula = Namici ~ SCOTUS$civlibeffect)
```

Residuals:

Min	1Q	Median	3Q	Max
-0.918	-0.918	-0.766	0.082	38.234

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	0.84206	0.02586	32.559	< 2e-16 ***
SCOTUS\$civlibeffect	-0.07568	0.02586	-2.926	0.00344 **

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

Residual standard error: 2.189 on 7159 degrees of freedom

Multiple R-squared: 0.001195, Adjusted R-squared: 0.001055

F-statistic: 8.563 on 1 and 7159 DF, p-value: 0.003442

Many D_i s

```
> fit3<-with(SCOTUS, lm(Namici~lctdiss+multlaw+civlibs+
+                      econs+constit+lctlb))
> summary(fit3)
```

Call:

```
lm(formula = Namici ~ lctdiss + multlaw + civlibs + econs + constit +
    lctlb)
```

Residuals:

```
    Min      1Q  Median      3Q      Max
-2.582 -0.976 -0.472 -0.260  37.086
```

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	0.47245	0.05273	8.960	< 2e-16 ***
lctdiss	0.36760	0.07173	5.125	3.06e-07 ***
multlaw	0.61306	0.07445	8.235	< 2e-16 ***
civlibs	-0.21255	0.06022	-3.530	0.000419 ***
econs	0.08772	0.07652	1.146	0.251691
constit	0.53793	0.06372	8.442	< 2e-16 ***
lctlb	0.50309	0.05396	9.323	< 2e-16 ***

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

Residual standard error: 2.15 on 7033 degrees of freedom
(121 observations deleted due to missingness)

Multiple R-squared: 0.05013, Adjusted R-squared: 0.04932

F-statistic: 61.86 on 6 and 7033 DF, p-value: < 2.2e-16

Change Over Time: Linear Trend

```
> fit4<-with(SCOTUS, lm(Namici~lctdiss+multlaw+civlibs+
+                      econs+constit+lctlib+term))
> summary(fit4)
```

Call:

```
lm(formula = Namici ~ lctdiss + multlaw + civlibs + econs + constit +
    lctlib + term)
```

Residuals:

Min	1Q	Median	3Q	Max
-2.968	-0.906	-0.428	0.143	36.958

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-2.726962	0.202367	-13.475	< 2e-16 ***
lctdiss	0.359494	0.070415	5.105	3.39e-07 ***
multlaw	0.649932	0.073109	8.890	< 2e-16 ***
civlibs	-0.289314	0.059295	-4.879	1.09e-06 ***
econs	0.199464	0.075419	2.645	0.00819 **
constit	0.515435	0.062559	8.239	< 2e-16 ***
lctlib	0.339891	0.053901	6.306	3.04e-10 ***
term	0.046142	0.002821	16.354	< 2e-16 ***

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

Residual standard error: 2.11 on 7032 degrees of freedom
(121 observations deleted due to missingness)

Multiple R-squared: 0.08493, Adjusted R-squared: 0.08402

F-statistic: 93.24 on 7 and 7032 DF, p-value: < 2.2e-16

Change Over Time: Using factor

```
> fit5<-with(SCOTUS, lm(Namici~lctdiss+multlaw+civlibs+  
+                      econs+constit+lctlib+as.factor(term)))  
> summary(fit5)
```

Call:

```
lm(formula = Namici ~ lctdiss + multlaw + civlibs + econs + constit +  
    lctlib + as.factor(term))
```

Residuals:

Min	1Q	Median	3Q	Max
-3.064	-0.920	-0.384	0.106	36.831

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-0.16153	0.19530	-0.827	0.408200
lctdiss	0.34558	0.07067	4.890	1.03e-06 ***
multlaw	0.64348	0.07334	8.774	< 2e-16 ***
civlibs	-0.27137	0.05967	-4.548	5.51e-06 ***
econs	0.20039	0.07581	2.643	0.008232 **
constit	0.54280	0.06297	8.620	< 2e-16 ***
lctlib	0.33863	0.05458	6.205	5.80e-10 ***
.				
.				
.				

Using factor (continued)

```
as.factor(term)54 0.26276 0.27934 0.941 0.346918
as.factor(term)55 0.20958 0.26804 0.782 0.434309
as.factor(term)56 0.12536 0.25126 0.499 0.617859
as.factor(term)57 0.06432 0.24227 0.265 0.790654
as.factor(term)58 0.08353 0.25274 0.331 0.741025
.
.
.
as.factor(term)71 0.62313 0.23019 2.707 0.006806 **
as.factor(term)72 0.59503 0.22929 2.595 0.009476 **
as.factor(term)73 0.78179 0.22918 3.411 0.000650 ***
as.factor(term)74 0.53254 0.23636 2.253 0.024287 *
as.factor(term)75 0.80353 0.23118 3.476 0.000513 ***
as.factor(term)76 0.49269 0.23138 2.129 0.033262 *
as.factor(term)77 1.07725 0.23265 4.630 3.72e-06 ***
as.factor(term)78 1.04335 0.23243 4.489 7.27e-06 ***
as.factor(term)79 0.85363 0.23696 3.602 0.000318 ***
as.factor(term)80 1.21205 0.23183 5.228 1.76e-07 ***
as.factor(term)81 1.49347 0.22925 6.515 7.80e-11 ***
as.factor(term)82 1.46004 0.22858 6.388 1.79e-10 ***
as.factor(term)83 1.29417 0.22549 5.739 9.90e-09 ***
as.factor(term)84 1.23434 0.22517 5.482 4.36e-08 ***
as.factor(term)85 1.59037 0.22491 7.071 1.68e-12 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

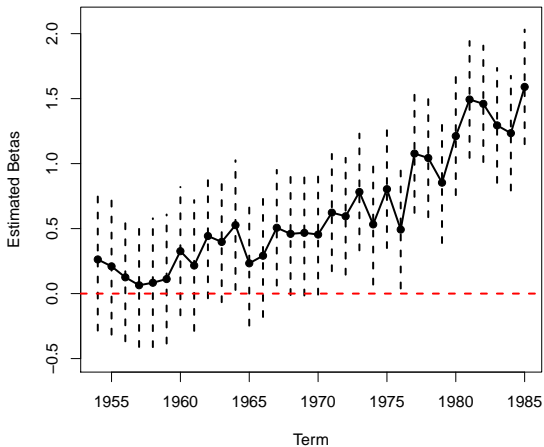
Residual standard error: 2.108 on 7001 degrees of freedom

(121 observations deleted due to missingness)

Multiple R-squared: 0.0914, Adjusted R-squared: 0.08647

F-statistic: 18.53 on 38 and 7001 DF, p-value: < 2.2e-16

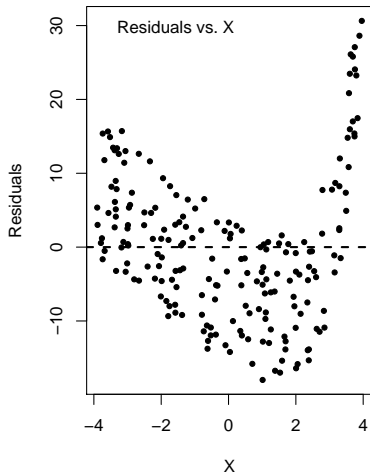
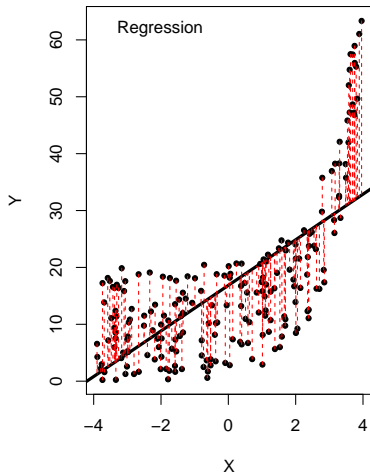
factor results, plotted (1953 = 0)



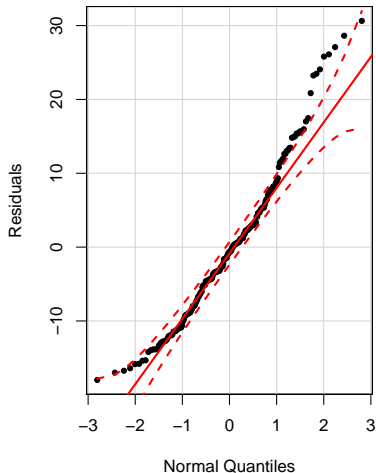
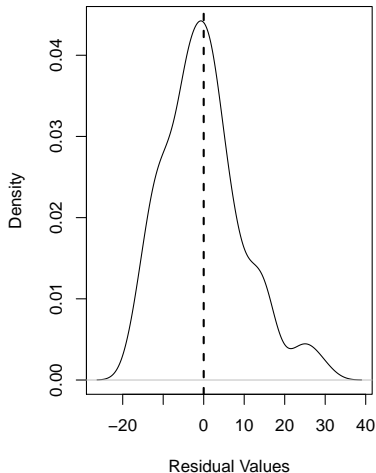
Why Transform?

- Normality (of u_i s)
- Linearity
- Additivity
- Interpretation / Model Specification

What Difference Does It Make? (Part I)



Residuals Are Still (Pretty) Normal...



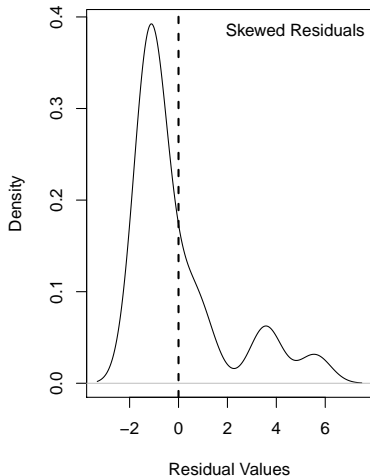
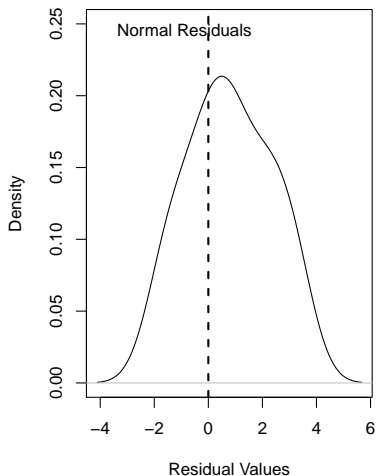
What Difference Does It Make? (Part II)

```
N <- 20 # pretty small sample size
u <- rnorm(N,0,2) # mean zero, s.d = 2

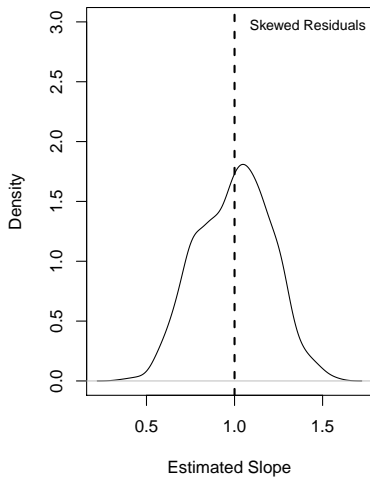
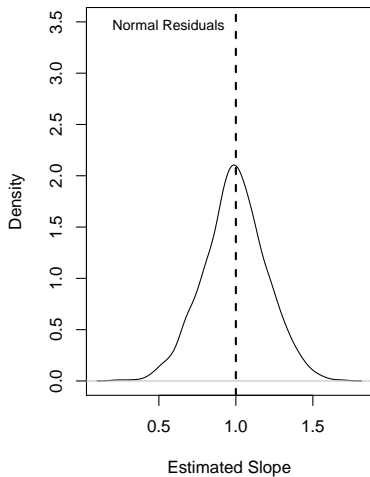
# Exponentiate:
eu <- exp(u)
eu <- eu-mean(eu) # new residuals are mean-zero
eu <- (eu/sd(eu))*2 # and also sd = 2

X <- runif(N,-4,4)
Y1 <- 0 + 1*X + 1*u
Y2 <- 0 + 1*X + 1*eu # same Xs in both
```

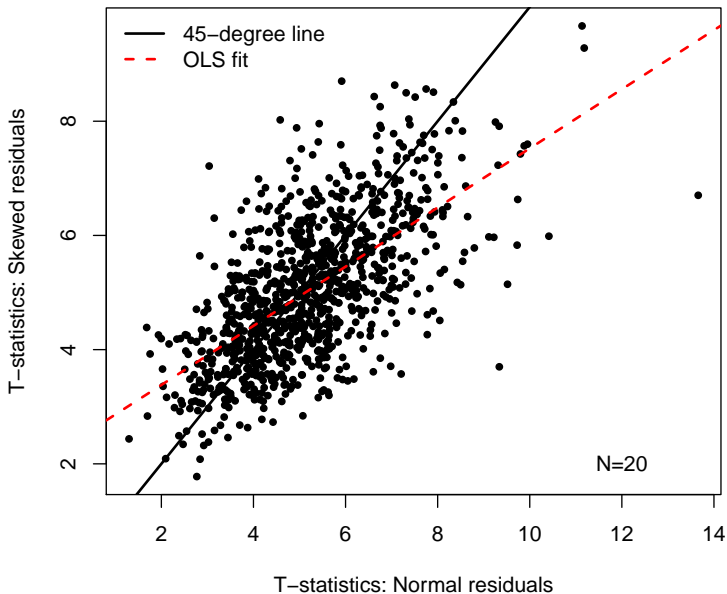
What Difference Does It Make? (Part II)



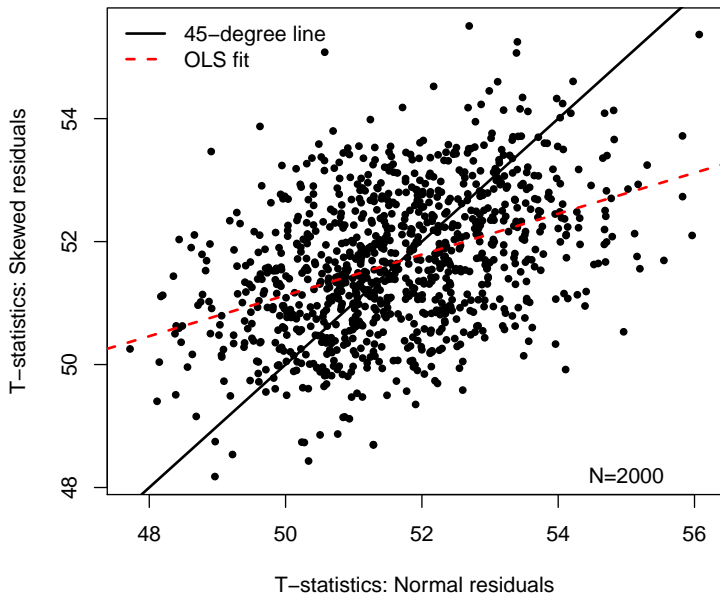
Little Effect On $\hat{\beta}$



Important Differences in Inference



With $N = 2000$? Not So Much...



This:

$$Y_i = \beta_0 X_i^{\beta_1} u_i$$

becomes this:

$$\ln(Y_i) = \ln(\beta_0) + \beta_1 X_i + \ln(u_i)$$

And this:

$$\exp(Y_i) = \beta_0 + \beta_1 X_i + u_i$$

becomes this:

$$Y_i = \ln(\beta_0) + \beta_1 \ln(X_i) + \ln(u_i)$$

Monotonic Transformations

The “Ladder of Powers”:

Transformation	p	$f(X)$	Fox's $f(X)$
Cube	3	X^3	$\frac{X^3-1}{3}$
Square	2	X^2	$\frac{X^2-1}{2}$
(None/Identity)	(1)	(X)	(X)
Square Root	$\frac{1}{2}$	\sqrt{X}	$2(\sqrt{X} - 1)$
Cube Root	$\frac{1}{3}$	$\sqrt[3]{X}$	$3(\sqrt[3]{X} - 1)$
Log	0 (sort of)	$\ln(X)$	$\ln(X)$
Inverse Cube Root	$-\frac{1}{3}$	$\frac{1}{\sqrt[3]{X}}$	$\frac{(\frac{1}{\sqrt[3]{X}}-1)}{-\frac{1}{3}}$
Inverse Square Root	$-\frac{1}{2}$	$\frac{1}{\sqrt{X}}$	$\frac{(\frac{1}{\sqrt{X}}-1)}{-\frac{1}{2}}$
Inverse	-1	$\frac{1}{X}$	$\frac{(\frac{1}{X}-1)}{-1}$
Inverse Square	-2	$\frac{1}{X^2}$	$\frac{(\frac{1}{X^2}-1)}{-2}$
Inverse Cube	-3	$\frac{1}{X^3}$	$\frac{(\frac{1}{X^3}-1)}{-3}$

A General Rule

Using higher-order power transformations (e.g. squares, cubes, etc.) “inflates” large values and “compresses” small ones; conversely, using lower-order power transformations (logs, etc.) “compresses” large values and “inflates” (or “expands”) smaller ones.

Power Transformations: Two Issues

1. X must be *positive*; so:

$$X^* = X + (|X_I| + \epsilon)$$

with (CZ's Rule of Thumb):

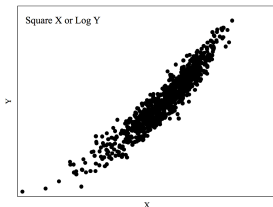
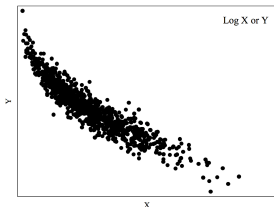
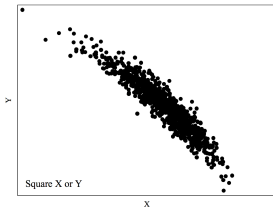
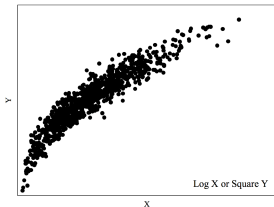
$$\epsilon = \frac{X_{I+1} - X_I}{2}$$

2. Power transformations generally require that:

$$\frac{X_h}{X_l} > 5 \text{ (or so)}$$

Which Transformation?

Mosteller and Tukey's "Bulging Rule":



Simple solution: Polynomials...

- Second-order / quadratic:

$$Y_i = \beta_0 + \beta_1 X_i + \beta_2 X_i^2 + u_i$$

- Third-order / cubic:

$$Y_i = \beta_0 + \beta_1 X_i + \beta_2 X_i^2 + \beta_3 X_i^3 + u_i$$

- p th-order:

$$Y_i = \beta_0 + \beta_1 X_i + \beta_2 X_i^2 + \beta_3 X_i^3 + \dots + \beta_p X_i^p + u_i$$

Transformed X s: Interpretation

For:

$$\ln(Y_i) = \beta_0 + \beta_1 X_i + u_i,$$

then:

$$E(Y) = \exp(\beta_0 + \beta_1 X_i)$$

and so:

$$\frac{\partial E(Y)}{\partial X} = \exp(\beta_1).$$

Transformed X s: Interpretation

Similarly, for:

$$Y_i = \beta_0 + \beta_1 \ln(X_i) + u_i$$

we have:

$$\frac{\partial E(Y)}{\partial \ln(X)} = \beta_1.$$

So doubling X (say, from X_ℓ to $2X_\ell$):

$$\begin{aligned}\Delta E(Y) &= E(Y|X = 2X_\ell) - E(Y|X = X_\ell) \\ &= [\beta_0 + \beta_1 \ln(2X_\ell)] - [\beta_0 + \beta_1 \ln(X_\ell)] \\ &= \beta_1 [\ln(2X_\ell) - \ln(X_\ell)] \\ &= \beta_1 \ln(2)\end{aligned}$$

Log-Log Regressions

Specifying:

$$\ln(Y_i) = \beta_0 + \beta_1 \ln(X_i) + \dots + u_i$$

means:

$$\text{Elasticity}_{YX} \equiv \frac{\% \Delta Y}{\% \Delta X} = \beta_1.$$

IOW, a one-percent change in X leads to a $\hat{\beta}_1$ -percent change in Y .

An Example: Military Spending and GDP

Data are from Fordham and Walker...

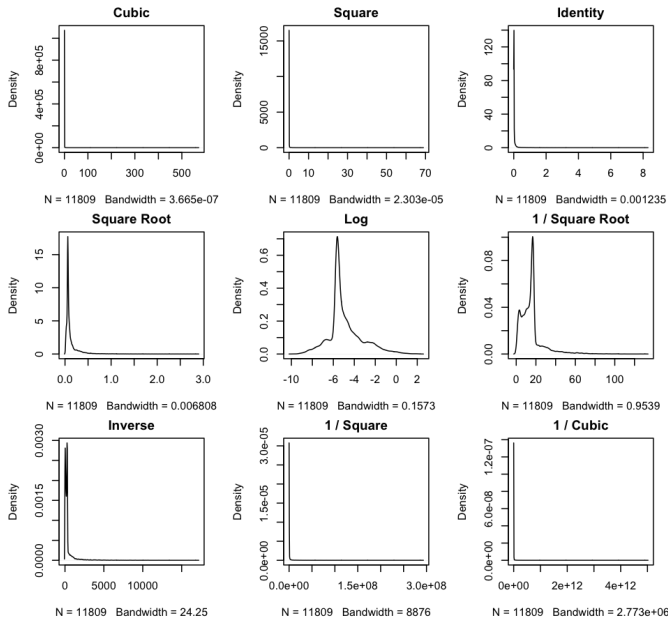
```
> with(Data, summary(milgdp))
```

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	NA's
0.000	0.238	0.749	2.115	2.104	136.900	4327

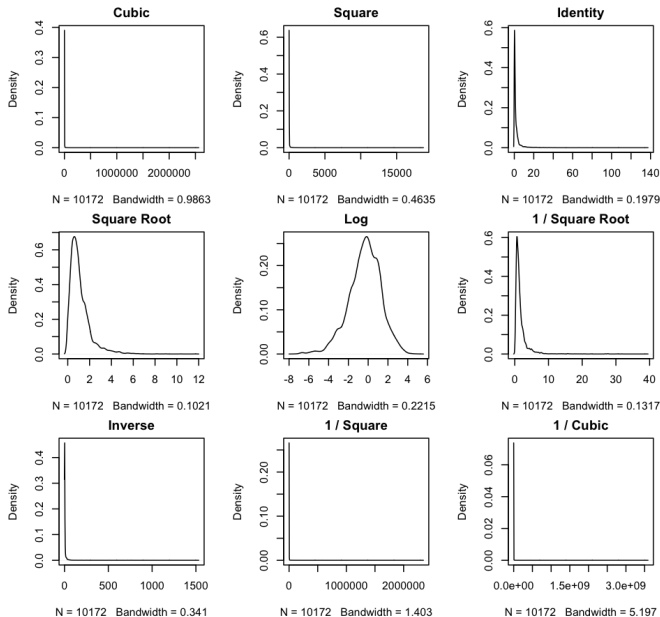
```
> with(Data, summary(gdp))
```

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	NA's
0.0001	0.0033	0.0047	0.0534	0.0153	8.3010	2690

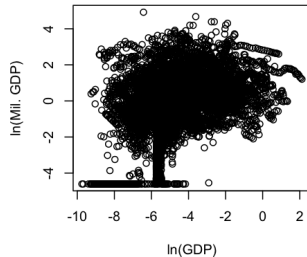
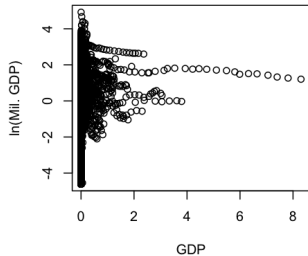
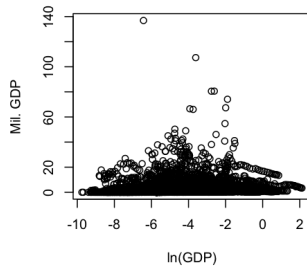
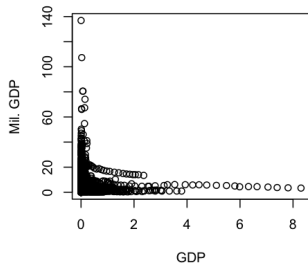
“Ladder of Powers”: GDP



“Ladder of Powers”: Military Spending



Scatterplots



Some Regressions

Untransformed:

```
> with(Data, summary(lm(milgdp~gdp)))
```

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	2.0538	0.0481	42.696	< 2e-16 ***
gdp	1.0038	0.1540	6.518	7.45e-11 ***

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

Residual standard error: 4.757 on 10170 degrees of freedom
(4327 observations deleted due to missingness)

Multiple R-squared: 0.00416, Adjusted R-squared: 0.004062

F-statistic: 42.49 on 1 and 10170 DF, p-value: 7.454e-11

Some Regressions

Logging X :

```
> with(Data, summary(lm(milgdp~log(gdp))))
```

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	4.60137	0.13969	32.94	<2e-16 ***
log(gdp)	0.52196	0.02766	18.87	<2e-16 ***

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

Residual standard error: 4.686 on 10170 degrees of freedom
(4327 observations deleted due to missingness)

Multiple R-squared: 0.03384, Adjusted R-squared: 0.03374

F-statistic: 356.2 on 1 and 10170 DF, p-value: < 2.2e-16

Some Regressions

Logging Y:

```
> with(Data, summary(lm(log(milgdp+0.01)~gdp)))
```

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-0.45918	0.01669	-27.51	<2e-16 ***
gdp	0.75794	0.05343	14.18	<2e-16 ***

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

Residual standard error: 1.651 on 10170 degrees of freedom
(4327 observations deleted due to missingness)

Multiple R-squared: 0.0194, Adjusted R-squared: 0.0193

F-statistic: 201.2 on 1 and 10170 DF, p-value: < 2.2e-16

Some Regressions

Logging X and Y :

```
> with(Data, summary(lm(log(milgdp+0.01)~log(gdp))))
```

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	1.644270	0.044736	36.76	<2e-16 ***
log(gdp)	0.431875	0.008858	48.76	<2e-16 ***

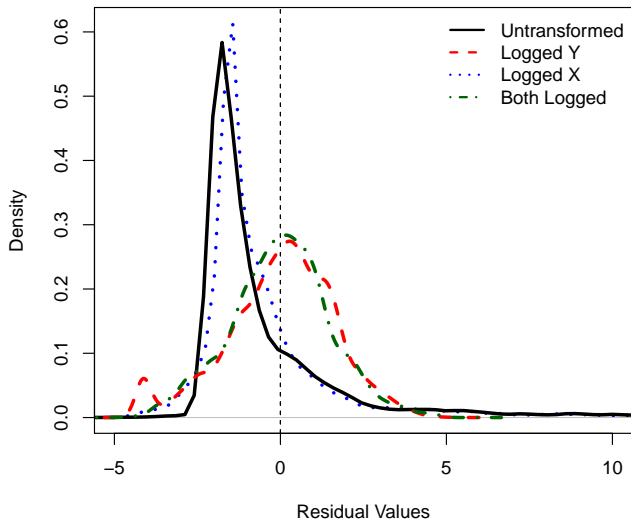
Signif. codes: 0 *** 0.001 ** 0.01 * 0.05 . 0.1 1

Residual standard error: 1.501 on 10170 degrees of freedom
(4327 observations deleted due to missingness)

Multiple R-squared: 0.1895, Adjusted R-squared: 0.1894

F-statistic: 2377 on 1 and 10170 DF, p-value: < 2.2e-16

Density Plots of \hat{u}_i s



- **Theory is valuable.**
- **Try different things.**
- **Look at plots.**
- **It takes practice.**