Lecture 13: Dummy Variables

ECON 480 - Econometrics - Fall 2018

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November 7, 2018

Dummy Variables

Recoding Dummies

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Overview of the Remainder of the Course

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HOOD COLLEGE

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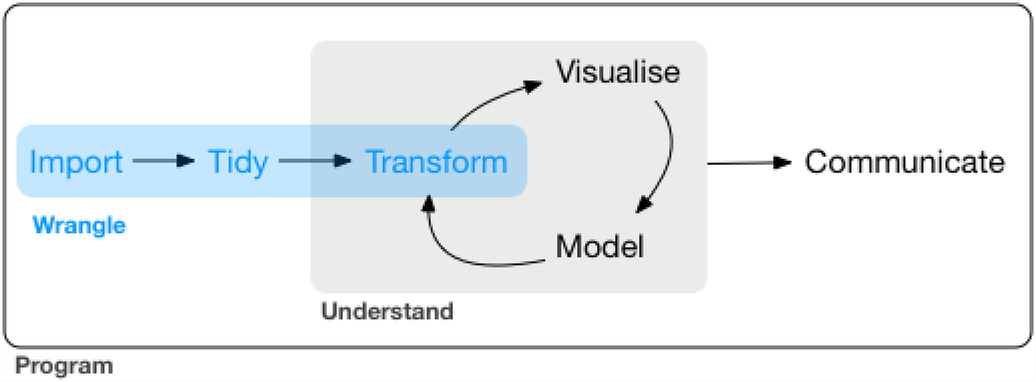
    - Difference-in-difference models
    - Instrumental variables models
    - Linear probability, logit, and probit models

- "Data wrangling" is a term for altering and cleaning data from raw form (often unusable) to a form that is useful for analysis (e.g. plotting and regressions)



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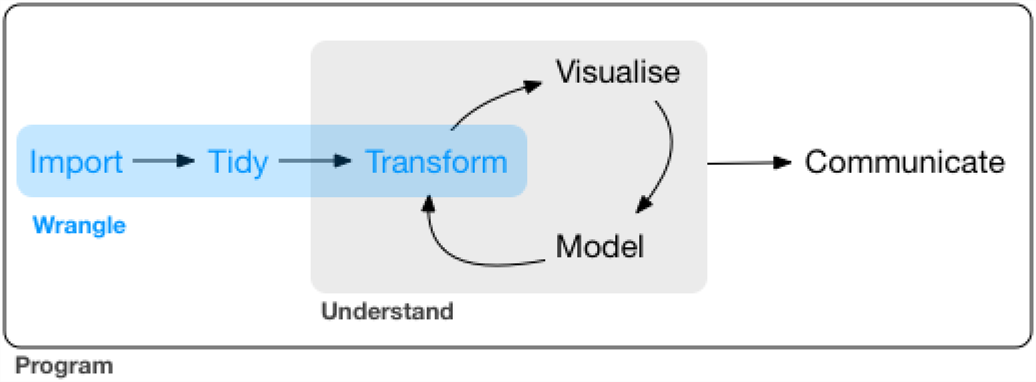
- A **significant portion** of data analysis is initial data wrangling



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- Also recall R calls this type of data a `factor`

Example

Do men earn higher wages on average than women?

- Using basic statistics, we can test for a statistically significant difference in group means with a t-**test**[1]

[1] See the **Handout** on Blackboard for this example.

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Example

$$\widehat{Wage_i} = \hat{\beta}_0 + \hat{\beta}_1 Female_i \quad \text{where } Female_i = \begin{cases} 1 & \text{if } i \text{ is } Female \\ 0 & \text{If } i \text{ is } Male \end{cases}$$

- Again, $\hat{\beta}_1$ makes less sense as the "slope" of a line in this context

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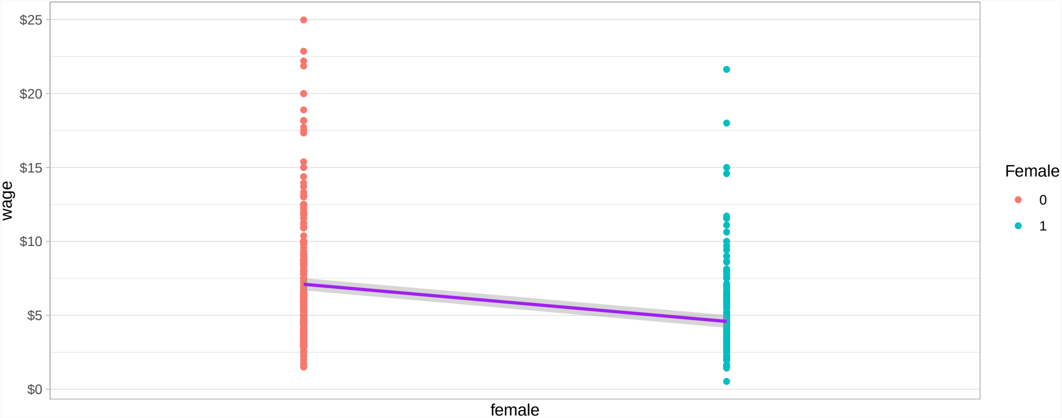
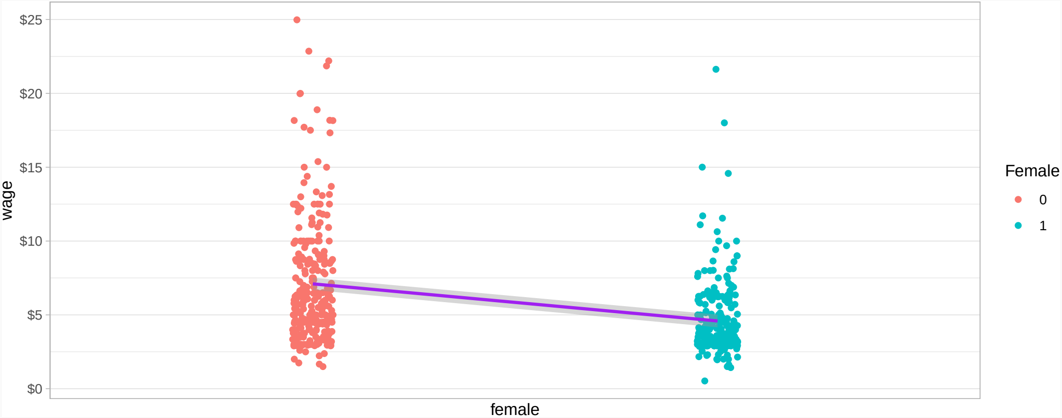
Comparing Groups in Regression: Scatterplot

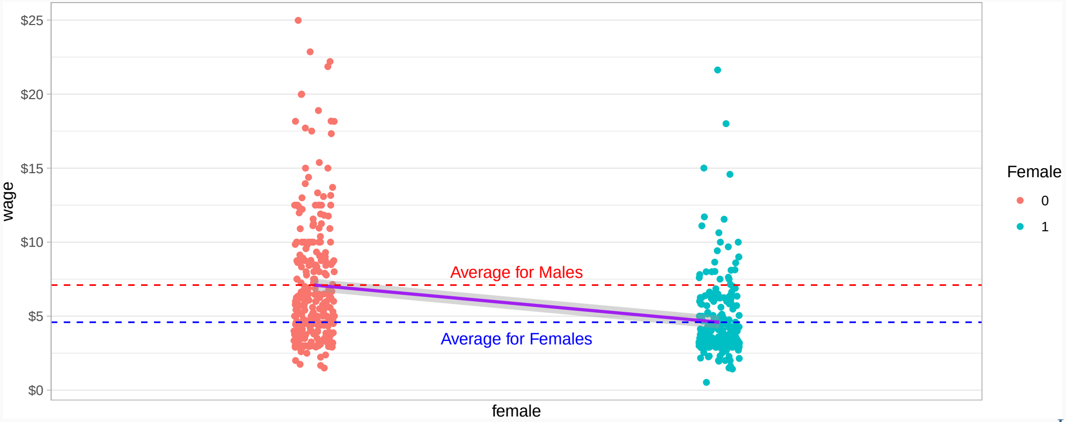


Comparing Groups in Regression: Scatterplot with Jittering



- use `geom_jitter()` instead of `geom_point()` to "jitter" the data to avoid overplotting

Comparing Groups in Regression: Scatterplot with Jittering II



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- So the *difference* in group means:

$$\begin{aligned} &= E[Y_i|D_i = 1] - E[Y_i|D_i = 0] \\ &= (\hat{\beta}_0 + \hat{\beta}_1) - (\hat{\beta}_0) \\ &= \hat{\beta}_1 \end{aligned}$$

Example

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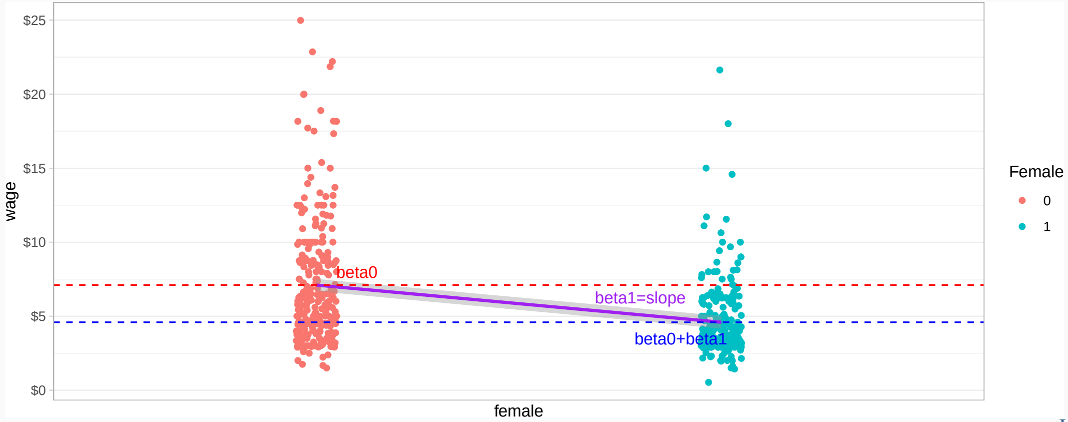
$25
$20
$15
$10
$5
$0
wage
female
beta0
beta1=slope
beta0+beta1
Female
0
1

- OLS Regression: $\widehat{Wage_i} = \underset{(0.21)}{7.10} - \underset{(0.30)}{2.51}\, Female_i$

Dummy Regression vs. Group Means

- OLS Regression: $$\widehat{\text{Wage}_i} = 7.10 - 2.51\,Female_i$$ $$\quad\quad(0.21)\quad(0.30)$$
- Simple tabulation of group means:

Sex	Avg. Wage ($\bar{Y}$)	SE(avg) (s_Y)	n
Female	4.59	0.16	252
Male	7.10	0.21	274
Difference	-2.51	(0.30)	-

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- Differences in means: $\overline{Y_F} - \overline{Y_M} = 4.59 - 7.10 = -2.51$
- $SE(\overline{Y_F} - \overline{Y_M}) = \sqrt{\frac{s_M^2}{n_M} + \frac{s_F^2}{n_F}} = \sqrt{\frac{0.21^2}{274} + \frac{0.16^2}{252}} \approx 0.30$

```r
# Our data comes from WAGE1.dta which you can find in Blackboard under data

# Load WAGE1 as wages
library("foreign") # to load .dta Stata files
wages<-read.dta("../Data/WAGE1.dta")

# there's a lot of variables in wages, let's only look at wage and female for no
wages<-subset(wages, select=c("wage","female"))
```

Looking at the Data *Conditionally* II

```r
# just get a sense of the data

head(wages)
```

```
##   wage female
## 1 3.10      1
## 2 3.24      1
## 3 3.00      0
## 4 6.00      0
## 5 5.30      0
## 6 8.75      0
```

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Looking at the Data *Conditionally* III

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- Syntax: `data[df$variable condition]` where `condition` is likely:

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LOOKING AT THE DATA *CONDITIONALLY* III

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- Can do this in base R by **subsetting** data using square brackets `[ ]`[3]
- Syntax: `data[df$variable condition]` where `condition` is likely:
  - A logical test, i.e. `>`, `<`, `!=`, `<=`, `>=`, `==` some value

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Looking at the Data *Conditionally* IV

```r
# look at average wage for men
summary(wages$wage[wages$female==0])
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   1.500   4.143   6.000   7.099   8.765  24.980
```

```r
sd(wages$wage[wages$female==0]) # get sd
```

```
## [1] 4.160858
```

```r
# look at average wage for women
summary(wages$wage[wages$female==1])
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   0.530   3.000   3.750   4.588   5.510  21.630
```

```r
sd(wages$wage[wages$female==1]) # get sd
```

```
## [1] 2.529363
```

```r
dummyreg<-lm(wage~female, data=wages)
summary(dummyreg)
```

```
##
## Call:
## lm(formula = wage ~ female, data = wages)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -5.5995 -1.8495 -0.9877  1.4260 17.8805
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   7.0995     0.2100  33.806  < 2e-16 ***
## female       -2.5118     0.3034  -8.279 1.04e-15 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.476 on 524 degrees of freedom
```

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The Dummy Regression: Just Checking!

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$$(0.21) \quad (0.30)$$

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- Are there variables for which the following is true?

$$corr(wage, Z) \neq 0$$
$$corr(female, Z) \neq 0$$

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- Does this mean we've accurately measured the gender-wage gap as \$2.51/hr?
- Are there variables for which the following is true?

$$corr(wage, Z) \neq 0$$
$$corr(female, Z) \neq 0$$

- `female` is probably endogenous, must include other control variables

Recoding Dummies

- What if instead of *female* we had used:

Example

$$\widehat{Wage_i} = \hat{\beta}_0 + \hat{\beta}_1 Male_i$$

$$Male_i = \begin{cases} 1 & \text{if } i \text{ is } Male \\ 0 & \text{If } i \text{ is } Female \end{cases}$$

- What if instead of *female* we had used:

Example

$$\widehat{Wage_i} = \hat{\beta}_0 + \hat{\beta}_1 Male_i$$

$$Male_i = \begin{cases} 1 & \text{if } i \text{ is } Male \\ 0 & \text{If } i \text{ is } Female \end{cases}$$

- *female* is a variable already in the data, we need to generate the *male* variable

- Again, a very useful R function is

```
ifelse(conditions, do.this.if.true, do.this.if.false)
```

Recoding Dummies

- Again, a very useful R function is

```r
ifelse(conditions, do.this.if.true, do.this.if.false)
```

- So let's create a `male` variable in our `wages` dataframe that we define as `1` if `female==0` and `0` otherwise (i.e. if `female==1`)

- Again, a very useful R function is

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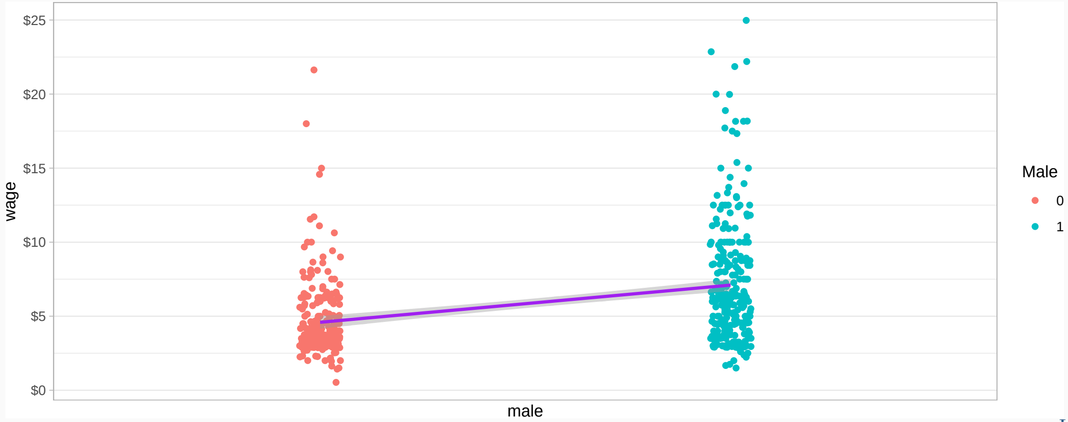
ifelse(conditions, do.this.if.true, do.this.if.false)
```

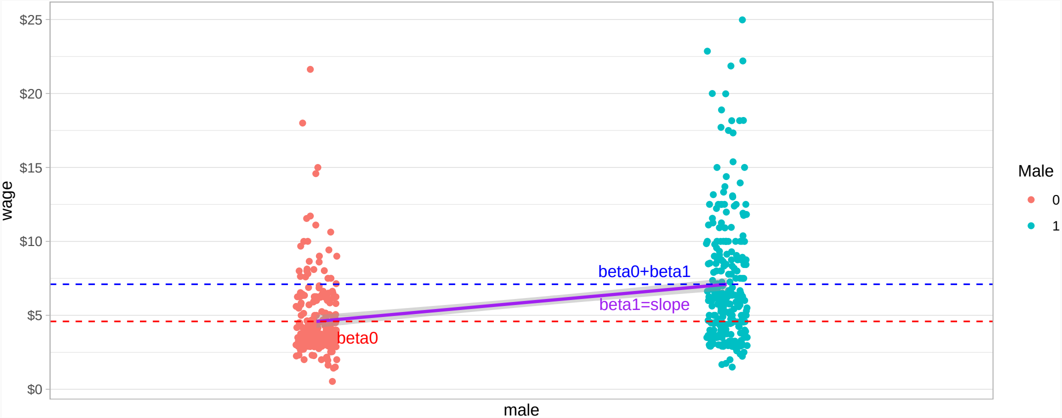
- So let's create a `male` variable in our `wages` dataframe that we define as `1` if `female==0` and `0` otherwise (i.e. if `female==1`)

```
wages$male<-ifelse(wages$female==0,1,0)
head(wages) # verify that it worked
```

```
##   wage female male
## 1 3.10      1    0
## 2 3.24      1    0
## 3 3.00      0    1
## 4 6.00      0    1
## 5 5.30      0    1
## 6 8.75      0    1
```

Scatterplot with Male




$25
$20
$15
$10
$5
$0
wage
male
beta0+beta1
beta1=slope
beta0
Male
0
1

The Dummy Regression with Male

```r
mreg<-lm(wage~male, data=wages)
summary(mreg)
```

```
##
## Call:
## lm(formula = wage ~ male, data = wages)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -5.5995 -1.8495 -0.9877  1.4260 17.8805
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   4.5877     0.2190  20.950  < 2e-16 ***
## male          2.5118     0.3034   8.279 1.04e-15 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.476 on 524 degrees of freedom
```

$$\widehat{Wage_i} = \underset{(0.21)}{4.59} + \underset{(0.30)}{2.51}\, Male_i$$

The Dummy Regression: Male or Female

```r
library("stargazer")
stargazer(dummyreg, mreg, type="latex",
          header=FALSE, float=FALSE)
```

	Dependent variable:	
	wage	
	(1)	(2)
female	-2.512^{***}	
	(0.303)	
male		2.512^{***}
		(0.303)
Constant	7.099^{***}	4.588^{***}
	(0.210)	(0.219)
Observations	526	526
R^2	0.116	0.116
Adjusted R^2	0.114	0.114
Residual Std. Error (df = 524)	3.476	3.476
F Statistic (df = 1; 524)	68.537^{***}	68.537^{***}
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$	

- Note it doesn't matter if we use `male` or `female`, males always earn \$2.51 more than females

The Dummy Regression: Male or Female

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stargazer(dummyreg, mreg, type="latex",
          header=FALSE, float=FALSE)
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F Statistic (df = 1; 524)	68.537^{***}	68.537^{***}
Note:	*p$<$0.1; **p$<$0.05; ***p$<$0.01	

- Note it doesn't matter if we use `male` or `female`, males always earn $2.51 more than females
- Compare the constant (mean for the `D=0` group)