Racial Differences in Earnings in the United States

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This coding example estimates racial differences in earnings using data from the National Longitudinal Survey of Youth '79. Let's load the packages we need as well as the data.

```
rm(list=ls())
library(tidyverse)
library(fixest)

# load nlsy79.Rdata
load(url("https://github.com/tomvogl/econ121/raw/main/data/nlsy79.rds"))
```

To get started, Let's look at the structure of the dataset.

```
glimpse(nlsy79)
```

```
## Rows: 12,686
## Columns: 19
## $ caseid     <dbl> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, ~
## $ perweight  <dbl> 563563, 763795, 536272, 565820, 764753, 636938, 674417, 148~
## $ age79      <dbl> 20, 20, 17, 16, 19, 18, 14, 20, 15, 18, 19, 19, 20, 15, 15,~
## $ region79   <fct> NORTHEAST, NORTHEAST, NORTHEAST, NORTHEAST, NORTHEAST, NORT~
## $ foreign    <dbl> 1, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0,~
## $ urban14    <dbl> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,~
## $ mag14      <dbl> 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 1, 1, 1, 1,~
## $ news14     <dbl> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1,~
## $ lib14      <dbl> 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,~
## $ educ_mom   <dbl> 8, 5, 10, 11, 12, 12, 12, 9, 12, 12, 12, 15, 12, 12, 12, 12~
## $ educ_dad   <dbl> 8, 8, 12, 12, 12, 12, 12, 6, 10, 12, 12, 12, 16, 12, 12, 12~
## $ numsibs    <dbl> 1, 8, 3, 3, 1, 1, 1, 7, 4, 3, 1, 3, 2, 2, 1, 3, 2, 2, 3, 2,~
## $ afqt81     <dbl> NA, 12, 51, 62, 90, 99, 33, 43, 55, 27, 71, 94, 78, 88, 83,~
## $ laborinc18 <dbl> NA, 25000, 80000, 0, NA, 117000, NA, 51313, NA, NA, NA, NA,~
## $ hours18    <dbl> NA, 1820, 2244, 2765, NA, 2080, NA, 2600, NA, NA, NA, NA, N~
## $ educ       <dbl> 12, 12, 12, 14, 18, 16, 12, 14, 14, 9, 16, 16, 16, 19, 16, ~
## $ black      <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,~
## $ hisp       <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,~
## $ male       <dbl> 0, 0, 0, 0, 1, 1, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 1, 0, 0,~
```

What are the mean and SD of labor income?

```
mean(nlsy79$laborinc18,na.rm=TRUE)
```

```
## [1] 44887.57
```

```
sd(nlsy79$laborinc18,na.rm=TRUE)
```

```
## [1] 65078.64
```

How about percentiles?

```r
summary(nlsy79$laborinc18)
```

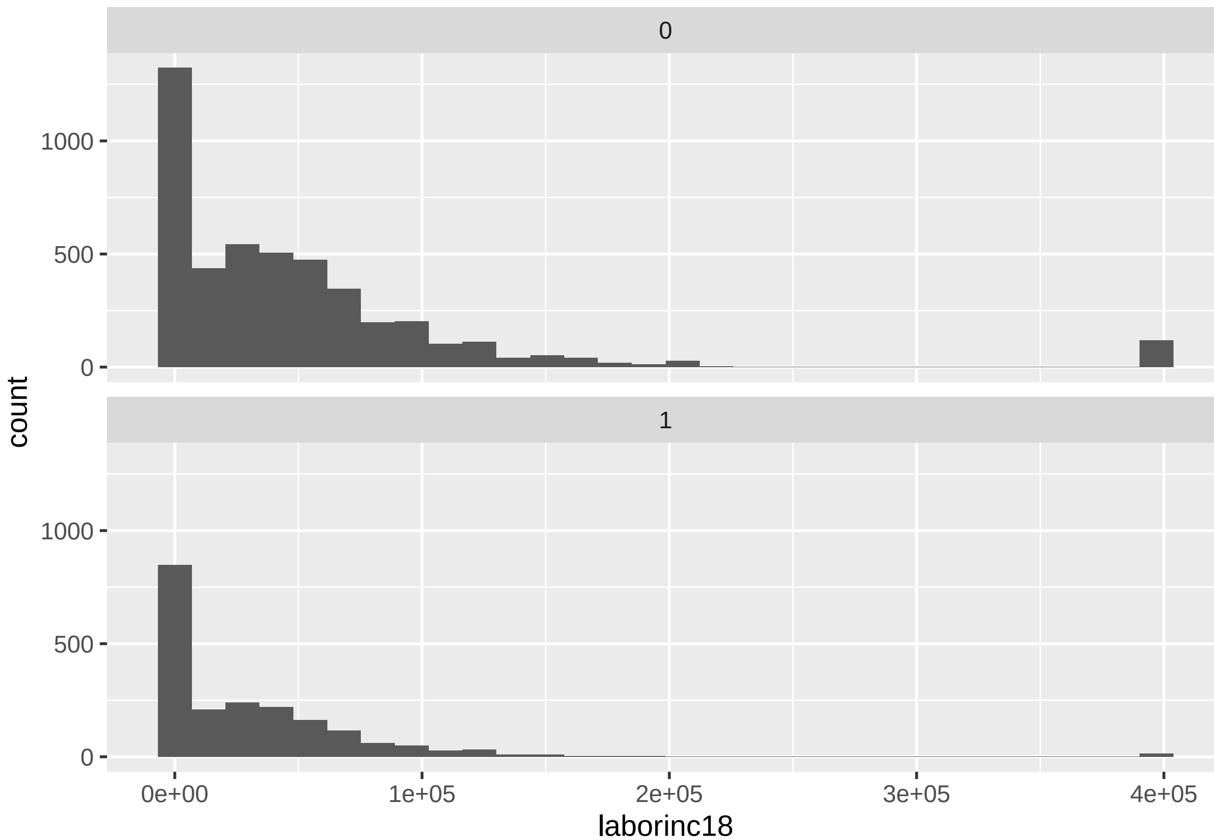
```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##       0       0   30000   44888   60000  396970    6115
```

We can see more detail when we plot histograms by race.

```r
nlsy79 %>%
  ggplot(aes(x = laborinc18)) +
    geom_histogram() +
    facet_wrap(~black, ncol=1) # separate graphs by race, stacked into one column
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.

## Warning: Removed 6115 rows containing non-finite values (`stat_bin()`).
```



We will estimate differences in mean income between blacks and non-blacks. Let's look at means by race.

```r
nlsy79 %>%
  drop_na(laborinc18) %>% # removes NA values so we don't need to use na.rm below
  group_by(black) %>%
  summarize(mean=mean(laborinc18),
            sd=sd(laborinc18),
            n=n())
```

```
## # A tibble: 2 x 4
##   black   mean     sd     n
##   <dbl>  <dbl>  <dbl> <int>
## 1     0 50798. 70856.  4558
## 2     1 31505. 46907.  2013
```

These results give us all the information we need to test for differences by race. The difference is:

```r
50798-31505
```

```
## [1] 19293
```

And the t-statistic is

```r
(50798-31505)/sqrt(70856^2/4558 + 46907^2/2013)
```

```
## [1] 13.02358
```

which is well above 1.96, so statistically significant by the usual standards.

An alternative way to run this test is the t-test with unequal variances:

```r
t.test(laborinc18 ~ black, data = nlsy79)
```

```
##
##  Welch Two Sample t-test
##
## data:  laborinc18 by black
## t = 13.023, df = 5599.6, p-value < 2.2e-16
## alternative hypothesis: true difference in means between group 0 and group 1 is not equal to 0
## 95 percent confidence interval:
##  16388.20 22196.42
## sample estimates:
## mean in group 0 mean in group 1
##        50797.69        31505.38
```

Equivalently, we can run a regression with heteroskedasticity-robust SEs, using feols() from fixest package

```r
feols(laborinc18 ~ black, data = nlsy79, vcov = 'hetero')
```

```
## NOTE: 6,115 observations removed because of NA values (LHS: 6,115).
```

```
## OLS estimation, Dep. Var.: laborinc18
## Observations: 6,571
## Standard-errors: Heteroskedasticity-robust
##             Estimate Std. Error  t value  Pr(>|t|)
## (Intercept)  50797.7    1049.56  48.3989 < 2.2e-16 ***
## black       -19292.3    1481.35 -13.0234 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## RMSE: 64,463.1   Adj. R2: 0.018528
```

Note that lm() is the base-R way to estimate a regression, but it doesn't directly allow for robust standard errors, and you need to use summary() to even see classical standard errors. feols() from fixest is more convenient.

```r
model1 <- lm(laborinc18 ~ black, data = nlsy79)
model1
```

```
##
## Call:
## lm(formula = laborinc18 ~ black, data = nlsy79)
##
## Coefficients:
## (Intercept)        black
##       50798       -19292
```

```r
summary(model1)
```

```
##
## Call:
## lm(formula = laborinc18 ~ black, data = nlsy79)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -50798 -32798 -15798  15495 365465
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)    50798        955   53.19   <2e-16 ***
## black         -19292       1725  -11.18   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 64470 on 6569 degrees of freedom
##   (6115 observations deleted due to missingness)
## Multiple R-squared:  0.01868,    Adjusted R-squared:  0.01853
## F-statistic:   125 on 1 and 6569 DF,  p-value: < 2.2e-16
```

It is actually uncommon to test for average differences in the level (rather than log) of earnings, including zeros from the non-employed. It would be much more typical to restrict to employed individuals. So let's restrict to people restrict to people who worked for pay for at least 1000 hours: equivalent to a part-time job of 20 hours per week for 50 weeks.

```r
summary(nlsy79$hours18)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##       0       0    2040    1513    2172    8736    5866
```

```r
nlsy79_workers <-
  nlsy79 %>%
  filter(hours18>=1000 & laborinc18>0)

summary(nlsy79_workers$hours18)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    1000    2080    2080    2245    2515    8736
```

Means by race in the workers sample:

```r
nlsy79_workers %>%
  drop_na(laborinc18) %>%
  group_by(black) %>%
  summarize(mean=mean(laborinc18),
            sd=sd(laborinc18),
            n=n())
```

```
## # A tibble: 2 x 4
##   black   mean     sd     n
##   <dbl>  <dbl>  <dbl> <int>
## 1     0 73786. 76195.  3015
## 2     1 55632. 52303.  1078
```

Still a $19k difference.

Now let's look at log earnings.

```r
nlsy79_workers <-
  nlsy79_workers %>%
    mutate(loginc18 = log(laborinc18))

nlsy79_workers %>%
  drop_na(loginc18) %>%
  group_by(black) %>%
  summarize(mean=format(mean(loginc18, na.rm = TRUE)),   # the format() function is just to report more
            sd=sd(loginc18, na.rm = TRUE),
            n=n())
```

```
## # A tibble: 2 x 4
##   black mean        sd     n
##   <dbl> <chr>    <dbl> <int>
## 1     0 10.85106 0.867  3015
## 2     1 10.61642 0.849  1078
```

The difference is:

```r
10.851-10.616
```

```
## [1] 0.235
```

This difference in logs can by roughly interpreted as a 23.5% gap in earnings, although this interpretation relies on calculus [dln(y)/dx]. Since we are doing a comparison by a discrete variable, we can think of 23.5% as an approximation .

The t-statistic is now:

```r
(10.851-10.616)/sqrt(.867^2/3015 + .849^2/1078)
```

```
## [1] 7.756312
```

Again well above 1.96, so statistically significant by the usual standards.

As an alterantive way to do the same thing, we can run a t-test with unequal variances:

```r
t.test(loginc18 ~ black, data = nlsy79_workers)
```

```
##
##  Welch Two Sample t-test
##
## data:  loginc18 by black
## t = 7.7464, df = 1935.7, p-value = 1.514e-14
## alternative hypothesis: true difference in means between group 0 and group 1 is not equal to 0
## 95 percent confidence interval:
##  0.1752323 0.2940397
## sample estimates:
## mean in group 0 mean in group 1
##        10.85106        10.61642
```

Or run a regression with heteroskedasticity-robust standard errors:

```r
feols(loginc18 ~ black, data = nlsy79_workers, vcov = 'hetero')
```

```
## OLS estimation, Dep. Var.: loginc18
## Observations: 4,093
## Standard-errors: Heteroskedasticity-robust
##             Estimate Std. Error   t value   Pr(>|t|)
```

```
## (Intercept) 10.851056   0.015799 686.82440  < 2.2e-16 ***
## black       -0.234636   0.030285  -7.74749 1.1741e-14 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## RMSE: 0.862284   Adj. R2: 0.013921
```

Same results. That is to say, a regression on a "dummy variable" for black leads to the same results as a difference of means Note that the t-statistic is very slightly different from what we computed "by hand." That's likely due to rounding errors.