Econ 142 Final Project

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Load packages

```r
library(stargazer)
library(matrixStats)
library(lemon)
knit_print.data.frame <- lemon_print
library(dplyr)
library(AER)
library(ggplot2)
```

Load the data

```
# dd dataset
dd <- read.csv("~/Desktop/Econ142/FinalProj/project2020_dd.csv")
head(dd)
```

y	age	educ	female	exp	yl1	yl2	yl3	yp1	yp2	owage2	owage1
2.570021	48	12	0	30	2.620926	2.616735	2.608906	2.784972	2.791555	1.191211	1.122809
2.298948	46	12	1	28	2.296236	2.284491	2.275459	2.309241	2.320770	2.397997	2.485690
2.401098	46	12	1	28	2.347023	2.354368	2.302642	2.409914	2.419748	2.397585	2.485626
1.230435	42	12	0	24	1.232543	1.256243	1.177653	1.198927	1.174227	1.103486	1.016370
2.298948	48	12	0	30	2.296236	2.284491	2.275459	2.309241	2.320770	2.397997	2.485690
2.298948	47	12	0	29	2.296236	2.284491	2.275459	2.309241	2.320770	2.397997	2.485690

Prepare Data

```
# males in dd dataset, 10575 obs
male_dd <- subset(dd, dd$female == 0)

# females in dd dataset, 6394 obs
female_dd <- subset(dd, dd$female == 1)

# calculate column means of these categories
table1_categories <- c("educ", "age", "y", "owage2")


male.means <- colMeans(male_dd[,table1_categories])
female.means <- colMeans(female_dd[,table1_categories])
all.means <- colMeans(dd[,table1_categories])


# get column SD for t-statistic
male_sds <- colSds(as.matrix(male_dd[,table1_categories]))
female_sds <- colSds(as.matrix(female_dd[,table1_categories]))
tstat <- (male.means-female.means)/(sqrt((male_sds^2/10575) + (female_sds^2/6394)))

# create new dataframe
table1 <- data.frame(all.means, female.means, male.means, tstat)
colnames(table1) <- c("All", "Female", "Male", "T statistic")
rownames(table1) <- c("Education", "Age", "Log Wage", "Mean Log Wage of Other Worker")
```

```
# find quartiles of the data
dd$quartiles <- ntile(dd$y, 4)

quartile1 <- subset(dd, dd$quartiles==1)
quartile2 <- subset(dd, dd$quartiles==2)
quartile3 <- subset(dd, dd$quartiles==3)
quartile4 <- subset(dd, dd$quartiles==4)

quartile1_male <- mean(quartile1$female==0)
quartile1_female <- mean(quartile1$female==1)
quartile2_male <- mean(quartile2$female==0)
quartile2_female <- mean(quartile2$female==1)
```

```
quartile3_male <- mean(quartile3$female==0)
quartile3_female <- mean(quartile3$female==1)
quartile4_male <- mean(quartile4$female==0)
quartile4_female <- mean(quartile4$female==1)


quartile1_frac <- c(quartile1_female, quartile1_male)
quartile2_frac <- c(quartile2_female, quartile2_male)
quartile3_frac <- c(quartile3_female, quartile3_male)
quartile4_frac <- c(quartile4_female, quartile4_male)

ttable <- t(data.frame(quartile1_frac, quartile2_frac, quartile3_frac, quartile4_frac))
```

```
# analysis of experience buckets
exp5 <- subset(dd, dd$exp==5)
exp6_13 <- subset(dd, dd$exp >= 6 & dd$exp <= 13)
exp14_20 <- subset(dd, dd$exp >= 14 & dd$exp <= 20)
exp21_30 <- subset(dd, dd$exp >= 21 & dd$exp <= 30)

exp5_male <- mean(exp5$female == 0)
exp5_female <- mean(exp5$female == 1)
exp6_13_male <- mean(exp6_13$female == 0)
exp6_13_female <- mean(exp6_13$female == 1)
exp14_20_male <- mean(exp14_20$female == 0)
exp14_20_female <- mean(exp14_20$female == 1)
exp21_30_male <- mean(exp21_30$female == 0)
exp21_30_female <- mean(exp21_30$female == 1)
```

Table 1

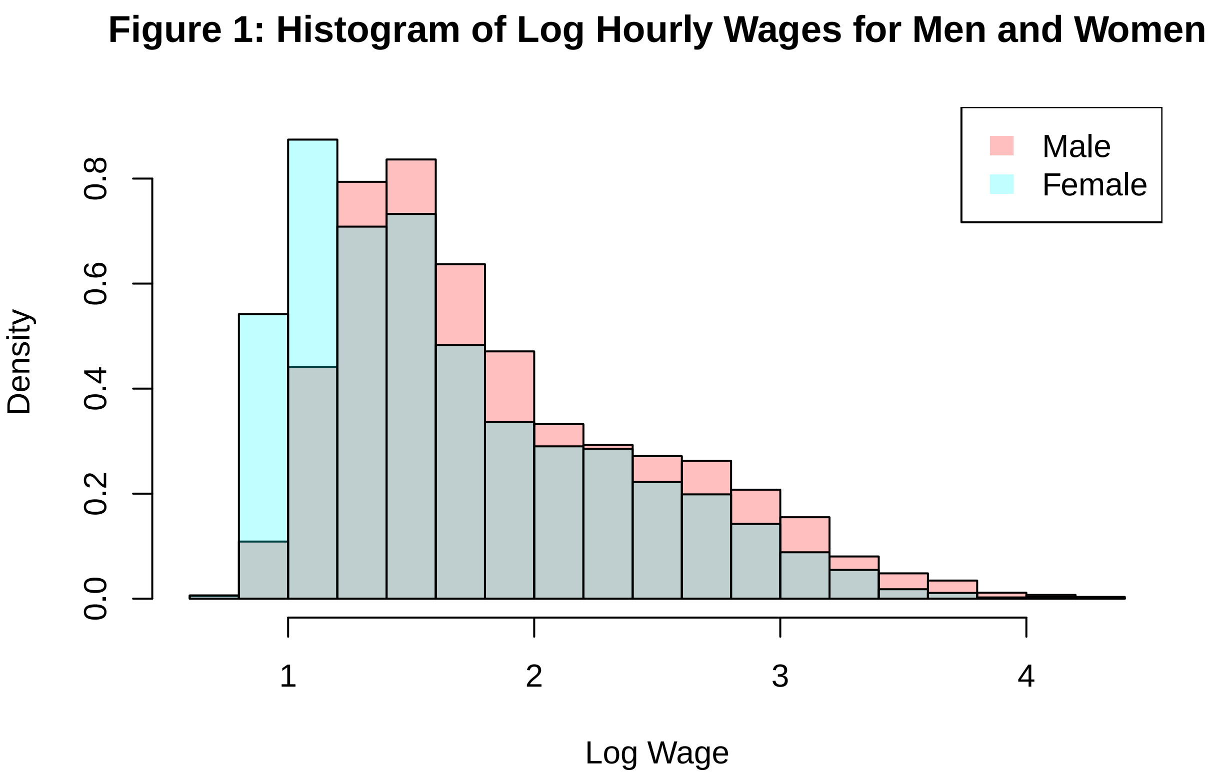
Table 1: Chacteristics of All, Female, and Male Workers with T-Test

	All	Female	Male	T-statistic
Observations (N)	16,969	10,575	6,394	
Education	10.484	10.835	10.272	−9.903
Age	33.559	33.534	33.574	0.436
Log Wage	1.788	1.658	1.866	20.816
Mean Log Wage of Co-Workers	1.692	1.638	1.725	11.676
Wage Quartile 1 Fraction		0.529	0.471	
Wage Quartile 2 Fraction		0.351	0.649	
Wage Quartile 3 Fraction		0.317	0.683	
Wage Quartile 4 Fraction		0.310	0.690	
Fraction with Experience = 5		0.521	0.479	
Fraction with Experience from 6 to 13		0.412	0.588	
Fraction with Experience between 14 and 20		0.348	0.652	
Fraction with Experience between 21 and 30		0.368	0.632	

Figure 1

```
m_hist <- hist(male_dd$y, col=rgb(1,0,0,1/4),
               main = "Figure 1: Histogram of Log Hourly Wages for Men and Women",
               xlab = "Log Wage", freq = F, ylim = c(0,0.9))
f_hist  <- hist(female_dd$y, col=rgb(0,1,1,1/4), freq = F, add = T)

legend('topright',c("Male", "Female"), fill = c(rgb(1,0,0,1/4), rgb(0,1,1,1/4)),
       border = NA)
```



Narrative:

Female workers tend to have a higher level of education (10.835 vs. 10.272) but a lower log wage (1.658 vs 1.866) than male workers, as we can see from Table 1. Furthermore, we can see that female wages are more right skewed and have more mass on the lower end of the wage spectrum, according to figure 1. Although the data contains a lot more observations of male workers than female workers, we can still see that there are progressively high fractions of male workers in higher wage quartiles. The same trend generally holds true for years of experience: the fraction of men increases in general as the years of experience increases. So, in general, men tend to be on average less educated, better paid, and the difference is even bigger for higher wage quartiles and years of experience buckets.

Table 2

(a) Pooled

```r
# constant and female dummy
pooled_simple <- lm(y ~ female, data = dd)
# constant, education, cubic in experience, female dummy
pooled_lm1 <- lm(y ~female + educ + exp + I(exp^2) + I(exp^3), data = dd)
```

(b) Separate for Men and Women

```r
# men
men_lm1 <- lm(y ~ educ + exp + I(exp^2) + I(exp^3), data = male_dd)

# women
women_lm1 <- lm(y ~ educ + exp + I(exp^2) + I(exp^3), data = female_dd)
```

```r
stargazer(pooled_simple, pooled_lm1, men_lm1, women_lm1,
          column.labels = c("Pooled", "Pooled", "Men", "Women") ,
          omit.stat=c("f", "ser"),
          dep.var.labels = c("Log Wage in Period 0"),
          covariate.labels = c("Female", "Education", "Experience", "Experience Squared", "Experience Cu
          header = F,
          title = "Regression Models for Pooled and Male/Female Log Wages")
```

Table 2: Regression Models for Pooled and Male/Female Log Wages

	Dependent variable:			
	Log Wage in Period 0			
	Pooled	Pooled	Men	Women
	(1)	(2)	(3)	(4)
Female	−0.208***	−0.273***		
	(0.010)	(0.007)		
Education		0.149***	0.149***	0.149***
		(0.001)	(0.001)	(0.002)
Experience		0.033***	0.034**	0.043***
		(0.011)	(0.015)	(0.016)
Experience Squared		0.001	0.001	−0.0002
		(0.001)	(0.001)	(0.001)
Experience Cubed		−0.00004***	−0.00005***	−0.00002
		(0.00001)	(0.00002)	(0.00002)
Constant	1.866***	−0.264***	−0.315***	−0.529***
	(0.006)	(0.060)	(0.082)	(0.085)
Observations	16,969	16,969	10,575	6,394
R^2	0.024	0.562	0.532	0.588
Adjusted R^2	0.024	0.562	0.532	0.588
Note:				*p<0.1; **p<0.05; ***p<0.01

Oaxaca Decompositions (2 alternatives): Pooled vs. Separate

$\bar{y}^b - \bar{y}^a$ where b is males and a is females,

$= (\bar{x}^b)'\hat{\beta}^b - (\bar{x}^a)'\hat{\beta}^a$

$= (\bar{x}^b - \bar{x}^a)'\hat{\beta}^a + (\bar{x}^b)(\hat{\beta}^b - \hat{\beta}^a)$

$= (\bar{x}^b - \bar{x}^a)'\hat{\beta}^b + (\bar{x}^a)(\hat{\beta}^b - \hat{\beta}^a)$

First way of Oaxaca Decomposition: Using Pooled Regression

```
copy_male <- male_dd
copy_female <- female_dd

# add new column of cubed exp
copy_male["exp2"] <- copy_male['exp']^2
copy_female["exp2"] <- copy_female['exp']^2
copy_male["exp3"] <- copy_male['exp']^3
copy_female["exp3"] <- copy_female['exp']^3

# pooled betas
betas_pooled <- coef(pooled_lm1)

# x bar and y bar for males and females
xbar_m  <- c(1,0,mean(copy_male$educ, na.rm=TRUE), mean(copy_male$exp, na.rm = TRUE),
             mean(copy_male$exp2, na.rm = TRUE), mean(copy_male$exp3, na.rm = TRUE));
xbar_f  <- c(1,1,mean(copy_female$educ, na.rm=TRUE),  mean(copy_female$exp, na.rm = TRUE),
             mean(copy_female$exp2, na.rm = TRUE), mean(copy_female$exp3, na.rm = TRUE));
ybar_male <- xbar_m %*% betas_pooled
ybar_female <- xbar_f %*% betas_pooled

# log wage gap
oaxaca_pooled <-  ybar_male - ybar_female
```

Second Way of doing Oaxaca Decomposition: Using split male and female regressions

```
# get betas from male and female regression
betas_male <- coef(men_lm1)
betas_female <- coef(women_lm1)
new_cat <- c("educ", "exp", "exp2", "exp3")

# construct right hand side of the second Oaxaca method
rhs1 <- betas_male[1] - betas_female[1];
rhs2 <- (colMeans(copy_male[,new_cat], na.rm=TRUE)
         - colMeans(copy_female[,new_cat], na.rm=TRUE)) %*% betas_male[2:5];
rhs3 <- colMeans(copy_female[,new_cat], na.rm=TRUE) %*% (betas_male[2:5]-betas_female[2:5]);

# log wage gap
oaxaca_separate <- c(rhs3 + rhs2 + rhs1)
```

Oaxaca Decomposition by Method

	Pooled	Separate
Oaxaca Decomposition of Log Wage Gap	0.2084035	0.2084035

Note: The estimates of pooled and separate are roughly the same after rounding.

Narrative:

Both ways of the decomposition give a 0.2084 log point wage gap between men and women. Men and women have roughly the exact same coefficient on the education variable, suggesting that education plays an equal role in raising wages for both male and female workers.

However, women have a much lower constant term than men. The constant for men is statistically signifcant while it isn't for women. This means that there are some unobserved characteristics or phenomenon for men that are not captured by our sample. Examples of those could be connections, ambition, interest, and choice difference between men and women in society. This difference in the constant term may be the factor that understates the gender wage gap.

Table 3

```r
pooled_t3_simple <-  lm(y ~ female + owage2, data = dd)
pooled_t3 <- lm(y ~ female + owage2 + educ + exp + I(exp^2) + I(exp^3), data = dd)

men_t3 <- lm(y ~ owage2 + educ+ exp + I(exp^2) + I(exp^3), data = male_dd)
women_t3 <- lm(y ~ owage2 + educ + exp + I(exp^2) + I(exp^3), data = female_dd)

stargazer(pooled_t3_simple, pooled_t3, men_t3, women_t3,
          column.labels = c("Pooled", "Pooled", "Men", "Women") ,
          omit.stat=c("f", "ser"),
          dep.var.labels = c("Log Wage in Period 0"),
          covariate.labels = c("Female", "Other Worker Wage","Education",
                               "Experience", "Experience Squared", "Experience Cubed"),
          header = F,
          title = "Table 3: Regression Models for Pooled and Male/Female Log Wages")
```

Table 3: Regression Models for Pooled and Male/Female Log Wages

	Dependent variable:			
	Log Wage in Period 0			
	Pooled	Pooled	Men	Women
	(1)	(2)	(3)	(4)
Female	-0.121^{***}	-0.192^{***}		
	(0.007)	(0.006)		
Other Worker Wage	1.006^{***}	0.638^{***}	0.662^{***}	0.604^{***}
	(0.007)	(0.007)	(0.009)	(0.011)
Education		0.098^{***}	0.099^{***}	0.094^{***}
		(0.001)	(0.001)	(0.002)
Experience		0.025^{***}	0.022^{*}	0.039^{***}
		(0.009)	(0.012)	(0.013)
Experience Squared		0.001^{*}	0.001^{*}	-0.0003
		(0.001)	(0.001)	(0.001)
Experience Cubed		-0.00003^{***}	-0.00004^{***}	-0.00001
		(0.00001)	(0.00001)	(0.00001)
Constant	0.131^{***}	-0.716^{***}	-0.809^{***}	-0.816^{***}
	(0.013)	(0.049)	(0.068)	(0.070)
Observations	16,969	16,969	10,575	6,394
R^2	0.549	0.703	0.685	0.720
Adjusted R^2	0.548	0.703	0.684	0.720
Note:				*p<0.1; **p<0.05; ***p<0.01

Oaxaca Decomposition, Pooled Way:

```
# pooled betas
betas_pooled_t3 <- coef(pooled_t3)

# x bar and y bar for males and females
xbar_m_t3  <- c(1,0, mean(copy_male$owage2, na.rm = TRUE), mean(copy_male$educ, na.rm=TRUE),
                mean(copy_male$exp, na.rm = TRUE), mean(copy_male$exp2, na.rm = TRUE),
                mean(copy_male$exp3, na.rm = TRUE));
xbar_f_t3  <- c(1,1, mean(copy_female$owage2, na.rm = TRUE), mean(copy_female$educ, na.rm=TRUE),
                mean(copy_female$exp, na.rm = TRUE), mean(copy_female$exp2, na.rm = TRUE),
                mean(copy_female$exp3, na.rm = TRUE));
ybar_male_t3 <- xbar_m_t3 %*% betas_pooled_t3
ybar_female_t3 <- xbar_f_t3 %*% betas_pooled_t3

# log wage gap
oaxaca_pooled_t3 <-  ybar_male_t3 - ybar_female_t3
```

Separate way:

```
# get betas from male and female regression
betas_male_t3 <- coef(men_t3)
betas_female_t3 <- coef(women_t3)
categ_t3 <- c("owage2", "educ", "exp", "exp2", "exp3")

# construct right hand side of the second Oaxaca method
rhs1_t3 <- betas_male_t3[1] - betas_female_t3[1]
rhs2_t3 <- (colMeans(copy_male[,categ_t3], na.rm=TRUE)
            - colMeans(copy_female[,categ_t3], na.rm=TRUE)) %*% betas_male_t3[2:6];
rhs3_t3 <- colMeans(copy_female[,categ_t3], na.rm=TRUE) %*%
            (betas_male_t3[2:6]-betas_female_t3[2:6])

# log wage gap
oaxaca_separate_t3 <- rhs3_t3 + rhs2_t3 + rhs1_t3
```

Comparison of RHS of Separate Oaxaca before and after adding owage2:

	Before owage2	After owage2
rhs1 (constant)	0.2138200	0.0064446
rhs2 (difference in x's)	-0.0618744	0.0199844
rhs3 (difference in betas)	0.0564579	0.1819744
sum (log wage gap)	0.2084035	0.2084035

Oaxaca Decomposition by Method after owage2

	Pooled	Separate
Oaxaca Decomposition Log Wage Gap	0.2084035	0.2084035

Narrative:

As we can see in the pooled log wage gap, log wage gap is still 0.2084 after accounting for owage2. However, in the second Oaxaca method, the components rhs1, rhs2, rhs3 are very different from before accounting for owage2 despite adding up to the same 0.2084.

I agree more with model 2, the idea that getting a job with highly paid co-workers is likely a function of a person possessing high levels of cognitive skills or ambition, and likely varies by gender. This seems plausible because among people who possess high level skills and tremendous ambition, regardless of their gender, are likely to pursue jobs with high pay and enjoy being with other people who are also ambitious and are highly-skilled. The regression model shows that the effect of owage2 is higher for men than women, suggesting that men are more likely to be ambitious or possess traits that make them pursue prestigious jobs with high co-worker pay.

Table of Tercile Cutoffs for owage1 and owage2

	owage1	owage2
0%	0.7183212	0.7164346
33.33333%	1.3938337	1.4419053
66.66667%	1.7197770	1.7807178
100%	3.8084919	3.8042665

```
#create copy of dd
dd_copy <- dd

# find terciles for owage1 and owage2 and divide workers
dd_copy$owage1_tercile <- ntile(dd_copy$owage1, 3)
dd_copy$owage2_tercile <- ntile(dd_copy$owage2, 3)

# separate workers into nine groups based on terciles of owage1 and owage2
dd_copy$nine_groups <- ifelse((dd_copy$owage1_tercile==1 & dd_copy$owage2_tercile==1), 1,
                       ifelse(dd_copy$owage1_tercile==1 & dd_copy$owage2_tercile==2, 2,
                       ifelse(dd_copy$owage1_tercile==1 & dd_copy$owage2_tercile==3, 3,
                       ifelse(dd_copy$owage1_tercile==2 & dd_copy$owage2_tercile==1, 4,
                       ifelse(dd_copy$owage1_tercile==2 & dd_copy$owage2_tercile==2, 5,
                       ifelse(dd_copy$owage1_tercile==2 & dd_copy$owage2_tercile==3, 6,
                       ifelse(dd_copy$owage1_tercile==3 & dd_copy$owage2_tercile==1, 7,
                       ifelse(dd_copy$owage1_tercile==3 & dd_copy$owage2_tercile==2, 8,
                       ifelse(dd_copy$owage1_tercile==3 & dd_copy$owage2_tercile==3, 9, 0)))))))))
```

Table of Classification of 9 Groups of Workers

owage1 tercile	owage2 tercile	final 9 groups
1	1	1
1	2	2
1	3	3
2	1	4
2	2	5
2	3	6
3	1	7
3	2	8
3	3	9

```
timeframe <- c("yl3", "yl2", "yl1", "y", "yp1", "yp2")

for (i in (1:9)){
  groupi <- subset(dd_copy, dd_copy$nine_groups == i)
  plot(seq(-3,2,1), colMeans(groupi[,timeframe]),
       main=paste("Figure 2: Plot of Mean Wages over Time of Group", seq(1,9,1)[i]),
       xlab = "Event Time", ylab = "Mean Log Wage in Period",  pch = 22, bg = "blue")
}
```

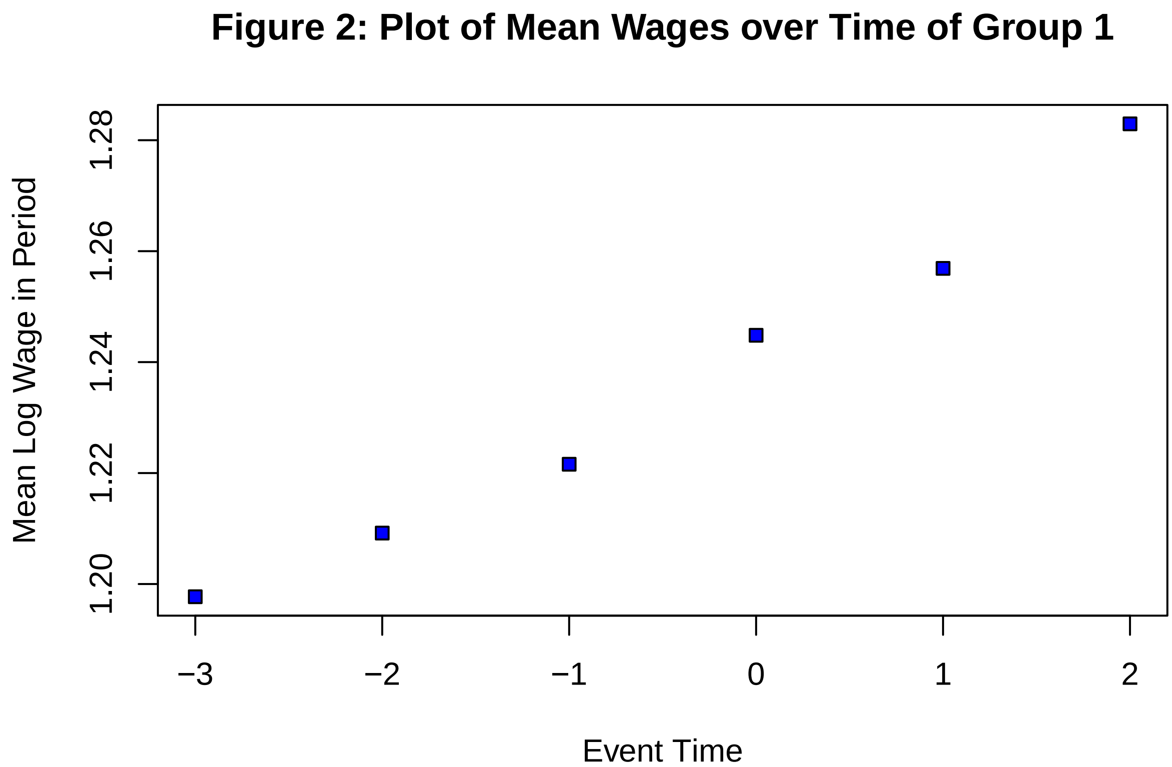


Figure 2: Plot of Mean Wages over Time of Group 2

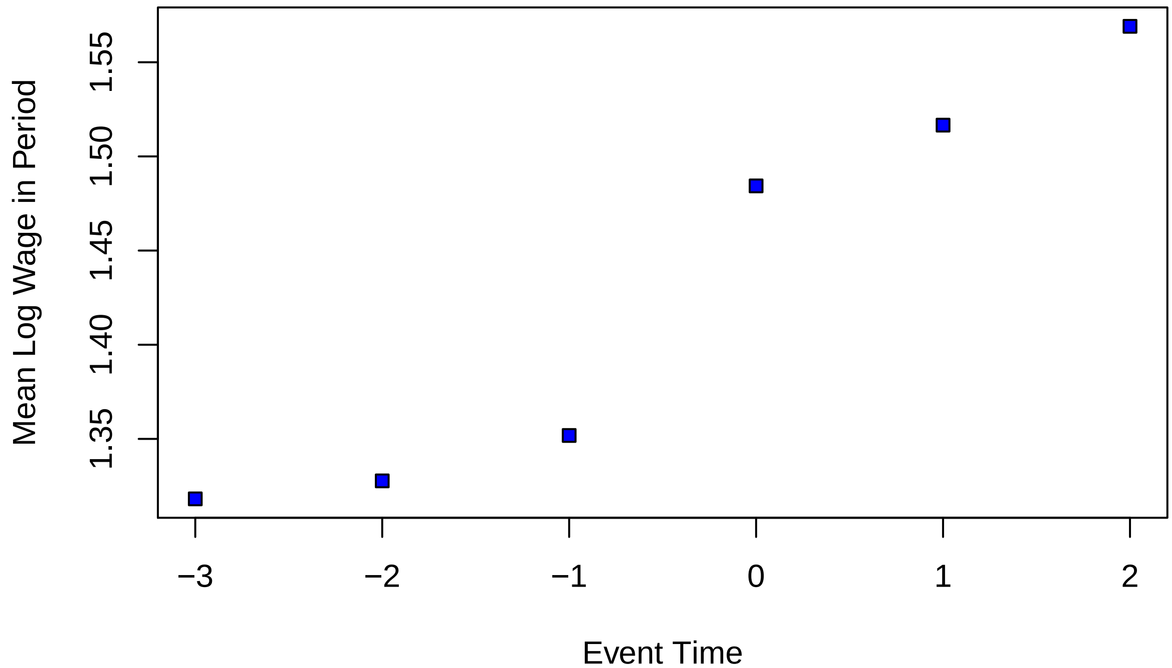


Figure 2: Plot of Mean Wages over Time of Group 3

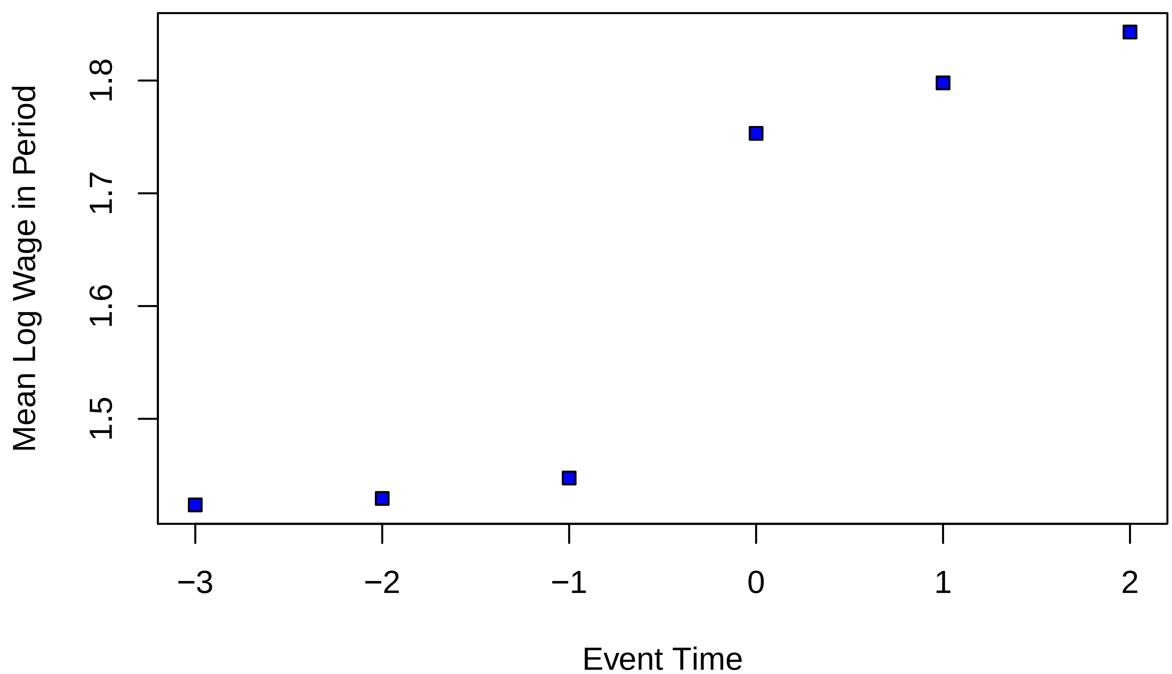


Figure 2: Plot of Mean Wages over Time of Group 4

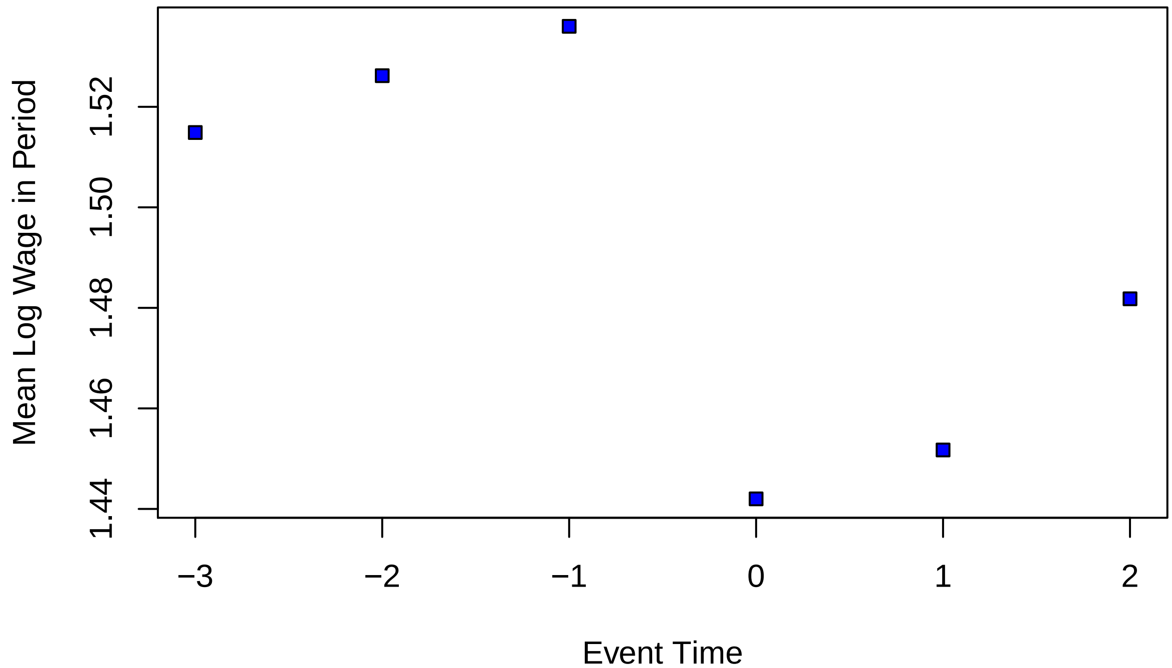


Figure 2: Plot of Mean Wages over Time of Group 5

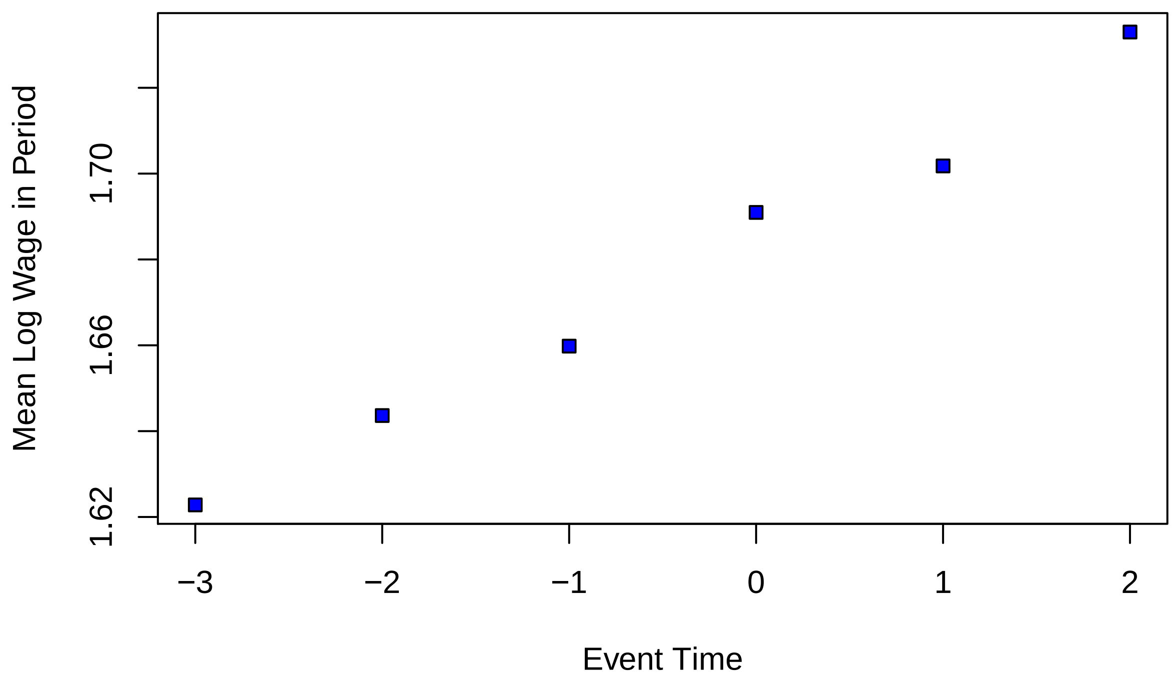


Figure 2: Plot of Mean Wages over Time of Group 6

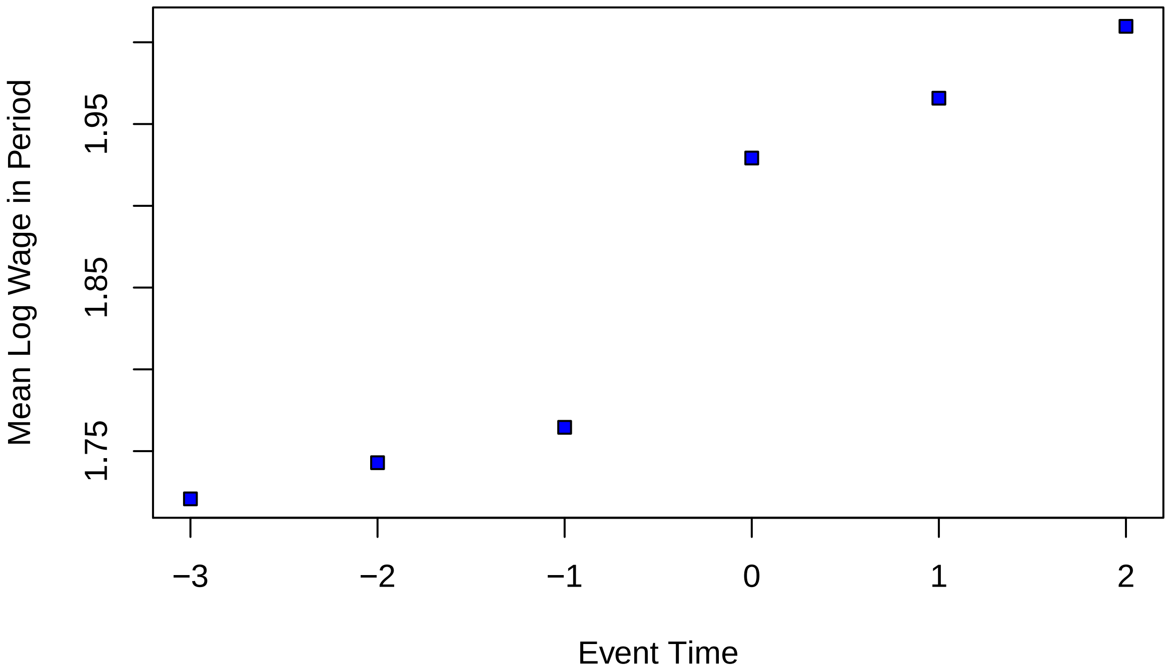


Figure 2: Plot of Mean Wages over Time of Group 7

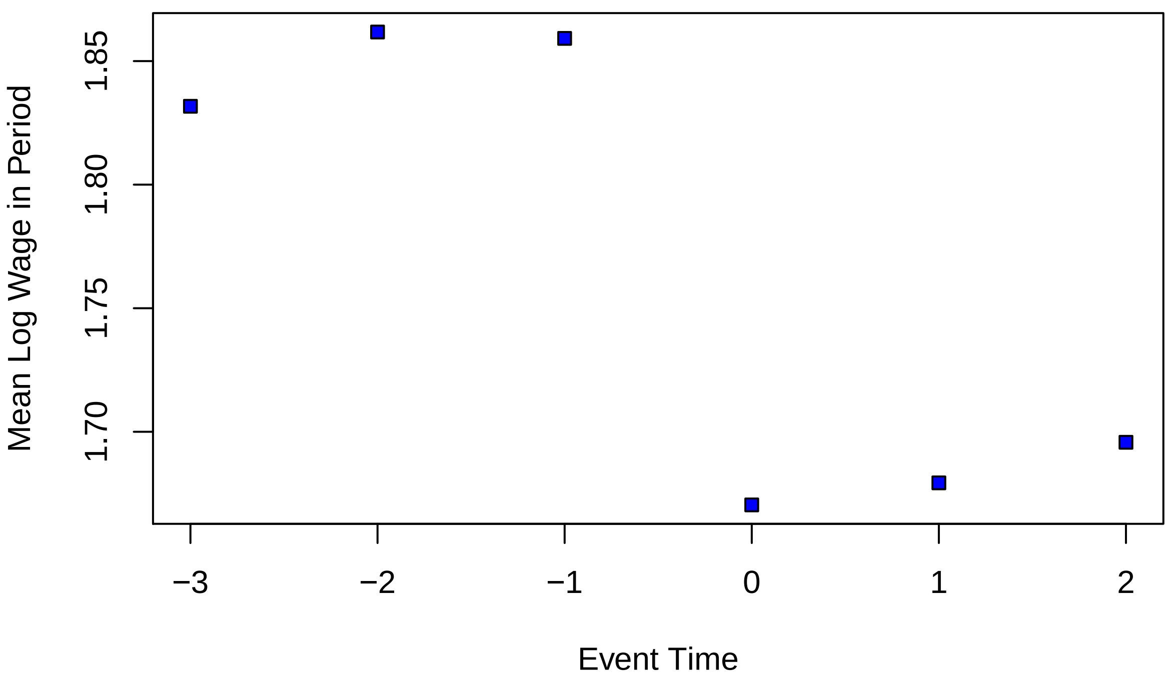


Figure 2: Plot of Mean Wages over Time of Group 8

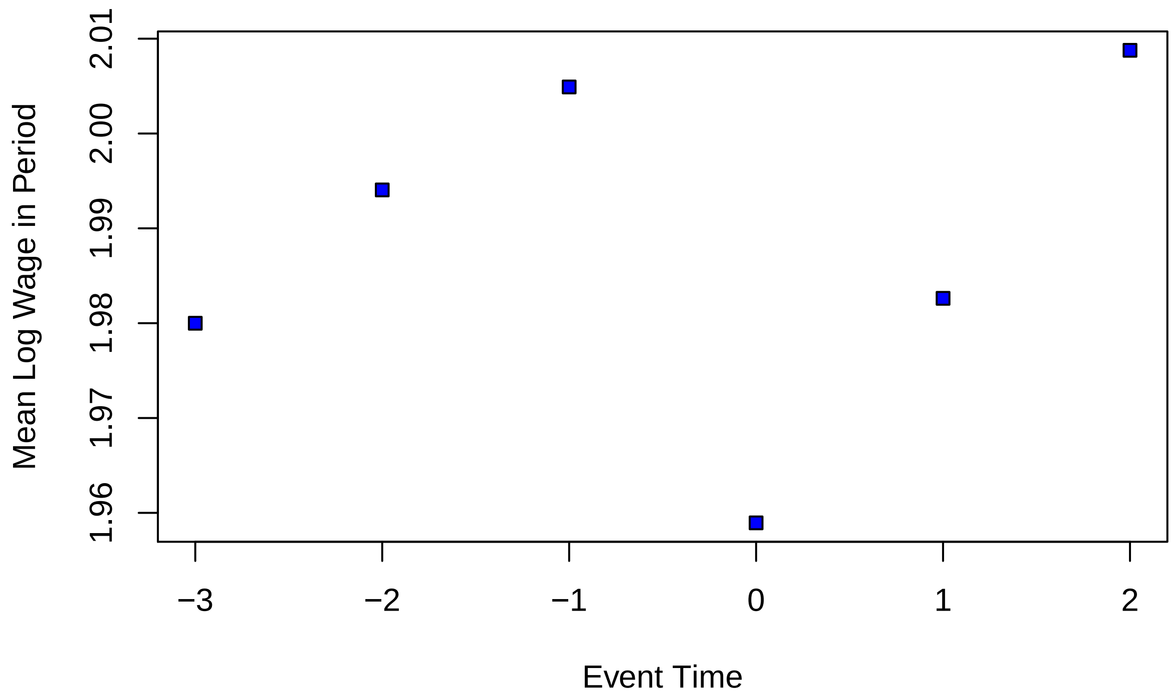
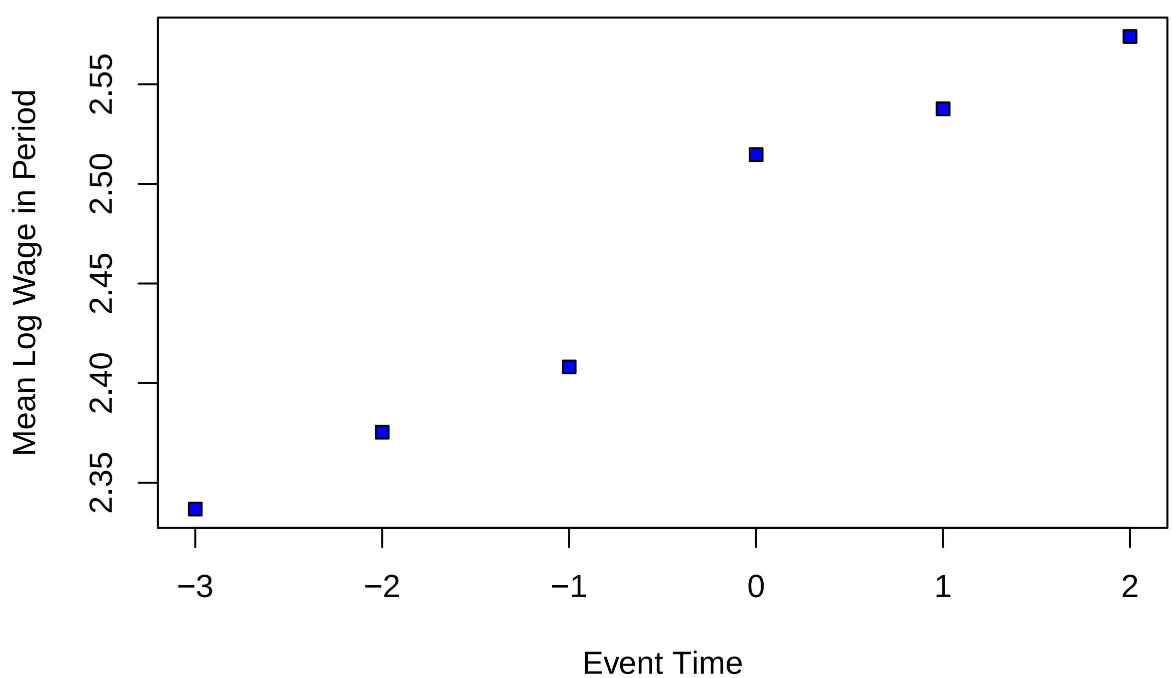


Figure 2: Plot of Mean Wages over Time of Group 9



Narrative:

These graphs provide more support for model 2. In the plots, we see that workers who move from a higher owage2 tercile to a lower owage2 tercile when they switch jobs see their own mean wages diminish along with their new co-workers. Clearly, this is not a consequence of “bad luck” and losing connections even if we assume model 1 to be true. This is likely a result of external factors, some of which could be diminishing ambition (perhaps due to age) or other external factors that cause them to move to a lower paying job (perhaps frictional and structural unemployment related causes). The thing that is concerning in the trends is what prompted these workers to choose a less “prestigious” job with lower owage2, which translates to probably a lower paying job properly. What is concerning to me is why a worker with at least three years of experience in a higher paying job would choose a lower paying job?

Table 4

```r
pooled_fig2_simple <- lm(I(y-yl1) ~ female + I(owage2-owage1), data = dd)
pooled_fig2 <- lm(I(y-yl1) ~ female + I(owage2-owage1) + I(exp-1) + I((exp-1)^2), data = dd)

men_fig2 <- lm(I(y-yl1) ~  I(owage2-owage1) + I(exp-1) + I((exp-1)^2), data = male_dd)
women_fig2 <- lm(I(y-yl1) ~  I(owage2-owage1) + I(exp-1) + I((exp-1)^2), data = female_dd)

stargazer(pooled_fig2_simple, pooled_fig2, men_fig2, women_fig2,
          column.labels = c("Pooled", "Pooled", "Men", "Women") ,
          omit.stat=c("f", "ser"),
          dep.var.labels = c("Change in Log Wage from Period -1 to Period 0"),
          header = F,
          covariate.labels = c("Female", "Dwage",
                        "Experience in Period -1", "Experience Squared in Period -1"),
          title = "Regression Models for Pooled and Male/Female Change in Log Wages")
```

Table 4: Regression Models for Pooled and Male/Female Change in Log Wages

	Dependent variable:			
	Change in Log Wage from Period -1 to Period 0			
	Pooled	Pooled	Men	Women
	(1)	(2)	(3)	(4)
Female	-0.019^{***}	-0.022^{***}		
	(0.004)	(0.004)		
Dwage	0.294^{***}	0.290^{***}	0.332^{***}	0.218^{***}
	(0.006)	(0.006)	(0.008)	(0.010)
Experience in Period -1		-0.009^{***}	-0.011^{***}	-0.008^{***}
		(0.002)	(0.002)	(0.002)
Experience Squared in Period -1		0.0002^{***}	0.0002^{***}	0.0001
		(0.00005)	(0.0001)	(0.0001)
Constant	0.045^{***}	0.153^{***}	0.163^{***}	0.123^{***}
	(0.003)	(0.013)	(0.018)	(0.018)
Observations	16,969	16,969	10,575	6,394
R^2	0.110	0.120	0.139	0.088
Adjusted R^2	0.109	0.120	0.139	0.087
Note:	*p<0.1; **p<0.05; ***p<0.01			

Alternative Decomposition

```
# alternative decomposition regressions
adjusted_model_male <- lm(I(y-0.332*(owage2)) ~ educ  + owage2 +  exp + I(exp2) + I(exp3), data = copy_m
adjusted_model_female <- lm(I(y-0.218*(owage2))~ educ+ owage2 + exp + I(exp2) + I(exp3), data = copy_fem

stargazer(adjusted_model_male, adjusted_model_female, summary = F, header = F,
          title = "Alternative Decomposition of Causal Effect of Coworker Wages",
          covariate.labels = c("Education", "owage2", "Experience", "Experience Squared", "Experience Cu
          column.labels = c("Male", "Female"),
          dep.var.labels = c("y-0.332*dwage", "y- 0.218*dwage"))
```

```
stargazer(adjusted_model_male, adjusted_model_female, header = F, summary = F)
```

Table 8

	Dependent variable:	
	I(y - 0.332 $*$(owage2))	I(y - 0.218 $*$(owage2))
	(1)	(2)
educ	0.099***	0.094***
	(0.001)	(0.002)
owage2	0.330***	0.386***
	(0.009)	(0.011)
exp	0.022*	0.039***
	(0.012)	(0.013)
I(exp2)	0.001*	−0.0003
	(0.001)	(0.001)
I(exp3)	−0.00004***	−0.00001
	(0.00001)	(0.00001)
Constant	−0.809***	−0.816***
	(0.068)	(0.070)
Observations	10,575	6,394
R^2	0.562	0.638
Adjusted R^2	0.561	0.638
Residual Std. Error	0.363 (df = 10569)	0.330 (df = 6388)
F Statistic	2,708.813*** (df = 5; 10569)	2,250.413*** (df = 5; 6388)
Note:		*p<0.1; **p<0.05; ***p<0.01

Narrative:

Looking at the coefficients on owage2 and owage2 - owage 1 in table 3 and 4, respectively,

Table 3's owage2

- Pooled: 0.638, men = 0.662, women = 0.604

Table 4's owage-owage1

- Pooled 0.290, men = 0.332, women = 0.218

Observations

- For the pooled model, the OLS model represents 0.290/0.638 = 45% of the causal effect and the 55% represents unobserved factors.
- For men, the OLS model represents 0.332/0.662 = 50% of the causal effect, and the other half represents unobserved factors.
- For women, the OLS model represents 0.218/0.614 = 35% of the causal effect, and the other 65% represents unobserved factors.

The difference between men and women in the causal effect of the OLS estimate indicates that owage2 (effect of moving to a new job) has a stronger effect on increasing log wage for men than for women. Likw mentioned in model 2 earlier, this could be due to multiple factors like ambition, interests, connections, and also sometimes luck.

To get a better estimate of the true causal effect of coworker wages for men and women, we can develop a decomposition where we used the coefficient on dwage (owage2-owage1) from table 4 and regard it as the true value of beta 1 (using the hint in model 1). We use perform a decomposition as follows: regress the exogenous variable $\beta_{dwage} \times (y - owage2)$ on the regressors from table 3 (education, experience, experience squared, experience cubed).

The model will look like this:

$\beta_{dwage}(y - owage2) = \beta_0 + \beta_2 educ + \beta_3 exp + \beta_4 exp^2 + \beta_5 exp^3 + e_i$

Differencing out using the coefficient dwage will remove the differences in the unobserved skills of people who tend to work at high-coworker wage jobs and only keep the causal effect of owage2.And the difference between the coefficients of owage2 between men and women lessened, meaning the impact of co-worker pay and its impact on wages is reduced between men and women. This, in short, means that men and women are more similar in terms of owage2 than we had predicted earlier in table3's OLS.

And since we know $\bar{y} = \beta_0 + \beta_{dwage} ow\bar{a}ge2 + \beta_2 ed\bar{u}c + \beta_3 e\bar{x}p + \beta_4 e\bar{x}p^2 + \beta_5 e\bar{x}p^3$, we can get the correct estimates for the other variables and perform a decomposition for men and women.

Part II (Chile PSU Data)

2.1 Compliers in an RD Model

(i)

$$E[w_i|AT(0)] = E[w_i|D_i = 1, x_i \to 0, z_i = 1] \tag{2}$$

$$E[w_i|AT(0) \text{ } or \text{ } C(0)] = E[w_i|D_i = 1, x_i \to 0, z_i = 1] \tag{3}$$

We know that $E[w_i|AT(0) \text{ } or \text{ } C(0)]$ is a weighted average of always-takers and compliers given in this expression:

$$E[w_i|AT(0) \text{ } or \text{ } C(0)] = \frac{E[w_i|AT(0)] \times Pr(AT(0)) + E[x_i|C(0)] \times Pr(C(0))}{Pr(AT(0) \text{ } or \text{ } C(0))}$$

Rearranging,

$$E[w_i|C(0)] = \frac{E[w_i|AT(0) \text{ } or \text{ } C(0)] \times Pr(AT(0)) - E[w_i|C(0)] \times Pr(AT(0))}{Pr(C(0))}$$

(ii)

Law of Iterated Expections: $E[Y] = E[E[Y|X]]$

$E[w_i D_i|x_i \to 0, z_i = 1]$

Since $w_i D_i$ has two outcomes:

$$w_i D_i = \begin{cases} w_i & \text{if } D_i = 1 \\ 0 & \text{if } D_i = 0 \end{cases}$$

Therefore, $E[w_i D_i|x_i \to 0, z_i = 1] = E[E[w_i D_i|x_i \to 0, z_i = 1] \mid D_i]$

$= E[w_i|D_i = 1, z_i = 1] \times Pr(D_i = 1|z_i = 1)$

$= E[w_i|AT(0) \text{ } or \text{ } C(0)] \times Pr(AT(0) \text{ } or \text{ } C(0))$

(iii)

$E[w_i D_i|x_i \to 0, z_i = 0] =$

By similar reasoning as (ii):

$= E[E[w_i D_i|x_i \to 0, z_i = 0] \mid D_i]$

$= E[w_i \mid D_i = 1, z_i = 0] \times Pr(D_i = 1|z_i = 0)$

$= E[w_i|AT(0)] \times Pr(AT(0))$

(iv)

We know that $\hat{\beta}_1 = \dfrac{\hat{\delta}_1}{\hat{\pi}_1} = \dfrac{E[w_i D_i | x_i \to 0\ ,\ z_i = 1] - E[w_i D_i | x_i \to 0\ ,\ z_i = 0]}{E[D_i | x_i \to 0\ ,\ z_i = 1] - E[D_i | x_i \to 0\ ,\ z_i = 0]}$

The numerator is the difference between what we proved in (iii) and (ii):

Numerator $\hat{\delta}_1$ is: $E[w_i | AT(0)\ or\ C(0)] \times Pr(AT(0)\ or\ C(0)) - E[w_i | AT(0)] \times Pr(AT(0))$

which is equal to the numerator of our proof in part (i) for $E[w_i | C(0)]$

Denominator $\hat{\pi}_1$ is: $E[D_i | x_i \to 0\ ,\ z_i = 1] - E[D_i | x_i \to 0\ ,\ z_i = 0]$

$= Pr(AT(0)\ or\ C(0)) - Pr(AT(0)) = Pr(C(0))$ (from lecture 15)

Putting the numerator and denominator together, we have proved that the $\hat{\beta}_1$ in the "goofy regression" is equivalent to $E[w_i | C(0)]$, the mean characteristic of the compliers.

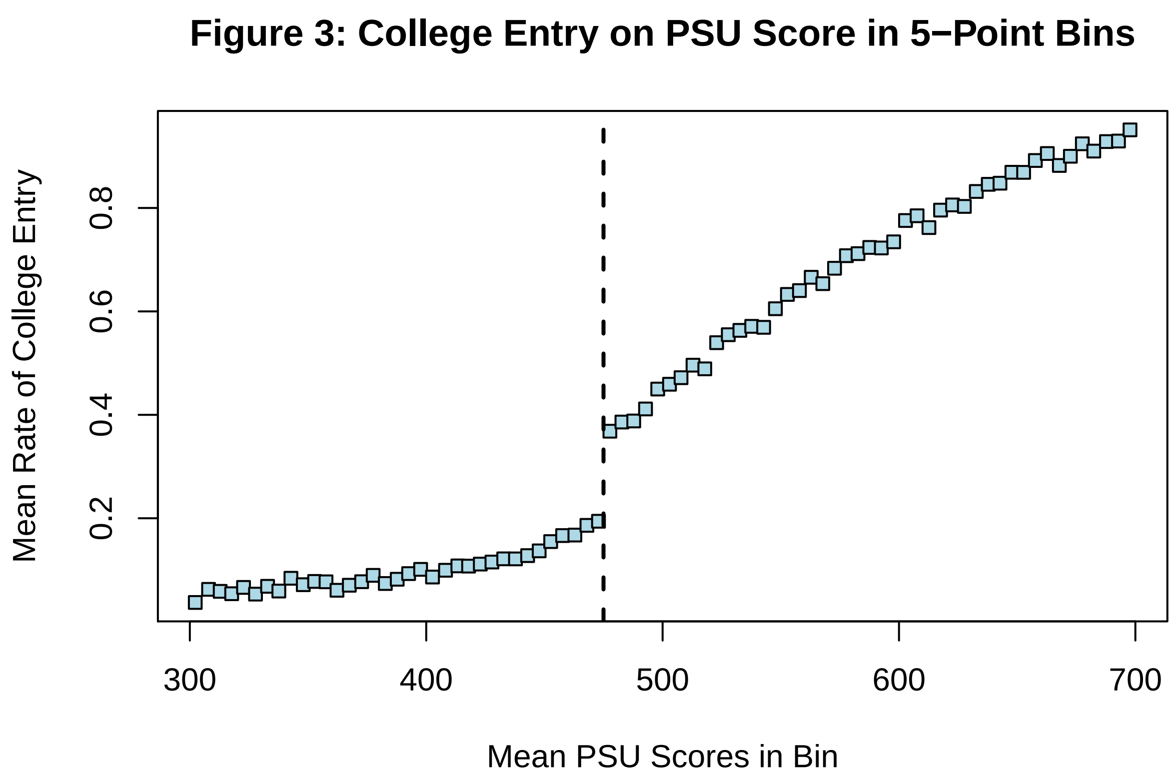
```r
# rd dataset
rd <- read.csv("~/Desktop/Econ142/FinalProj/project2020_rd.csv")
head(rd)
```

psu	female	quintile	entercollege	privatehs	hidad	himom	gpa	over475
396.0	1	1	0	0	0	0	60	0
402.5	1	1	0	0	0	0	65	0
485.0	1	3	0	0	0	0	55	1
461.5	0	2	0	0	0	0	0	0
394.0	1	1	0	0	0	0	62	0
409.0	1	1	0	0	0	0	57	0

Figure 3

```r
# bin data using aggregate function
binned_data <- aggregate(rd, list(cut(rd$psu, breaks= (max(rd$psu)-min(rd$psu))/5)), mean)

plot(binned_data$psu, binned_data$entercollege,
      xlab = "Mean PSU Scores in Bin",
      ylab = "Mean Rate of College Entry",
      main = "Figure 3: College Entry on PSU Score in 5-Point Bins",
      pch = 22, bg = "lightblue")
abline(v=475, lty = 2, lwd = 2)
```



```r
bandwidths <- c(25,50,75,100)

bandwidth25 <- rd[(rd$psu >= 475-bandwidths[1]) & (rd$psu <= 475+bandwidths[1]),]
entercollege_25 <- lm(entercollege ~ I(psu-475) + over475 + I((psu-475)*over475), data = bandwidth25)

bandwidth50 <- rd[(rd$psu >= 475-bandwidths[2]) & (rd$psu <= 475+bandwidths[2]),]
entercollege_50 <- lm(entercollege ~ I(psu-475) + over475 + I((psu-475)*over475), data = bandwidth50)

bandwidth75 <- rd[(rd$psu >= 475-bandwidths[3]) & (rd$psu <= 475+bandwidths[3]),]
entercollege_75 <- lm(entercollege ~ I(psu-475) + over475 + I((psu-475)*over475), data = bandwidth75)

bandwidth100 <- rd[(rd$psu >= 475-bandwidths[4]) & (rd$psu <= 475+bandwidths[4]),]
entercollege_100 <- lm(entercollege ~ I(psu-475) + over475 + I((psu-475)*over475), data = bandwidth100)

stargazer(entercollege_25, entercollege_50, entercollege_75, entercollege_100,
          header = F,
          column.labels = c('B = 25', 'B = 50', 'B = 75', 'B = 100') ,
          omit.stat=c("f", "ser"),
          dep.var.labels = c("Entercollege"),
          covariate.labels = c("PSU-475", "over475", "(PSU-475)*over475"),
          title = "Table 5: Regression Models for Probability of Attending College ")
```

Table 5

Table 5: Regression Models for Probability of Attending College

	Dependent variable:			
	Entercollege			
	B = 25	B = 50	B = 75	B = 100
	(1)	(2)	(3)	(4)
PSU-475	0.001	0.002***	0.001***	0.001***
	(0.001)	(0.0002)	(0.0001)	(0.0001)
over475	0.170***	0.165***	0.177***	0.184***
	(0.012)	(0.008)	(0.007)	(0.006)
(PSU-475)*over475	0.003***	0.002***	0.002***	0.002***
	(0.001)	(0.0003)	(0.0002)	(0.0001)
Constant	0.181***	0.188***	0.182***	0.176***
	(0.009)	(0.006)	(0.005)	(0.004)
Observations	22,846	43,852	63,070	79,523
R^2	0.066	0.110	0.152	0.194
Adjusted R^2	0.066	0.110	0.152	0.194
Note:				*p<0.1; **p<0.05; ***p<0.01

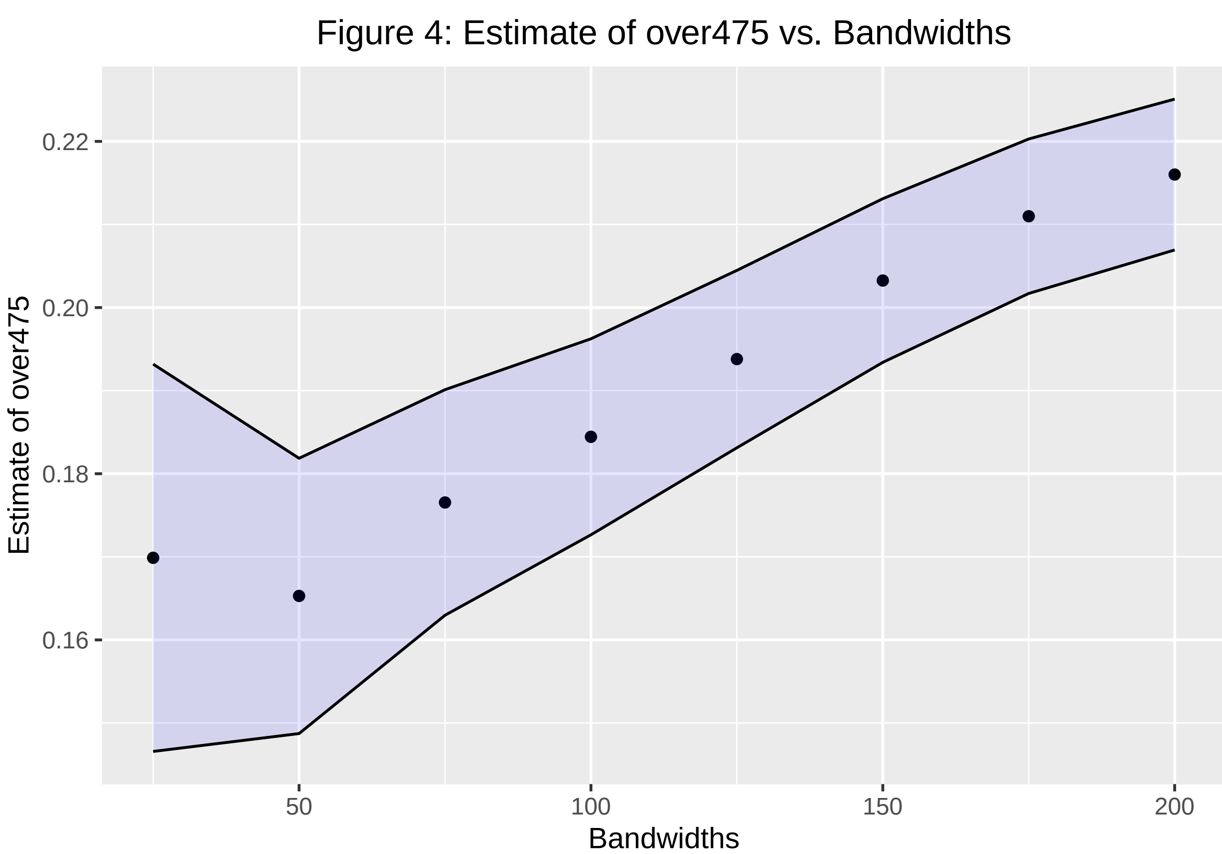
```r
# for figure 4: plot range of bandwidths from 25 to 200
bandwidth_fig4 <- seq(25,200,25)
estimates <- c()
h.ci <-  c()
l.ci <-  c()

for (b_size in bandwidth_fig4) {
  bandwidth_sample <- rd[(rd$psu >= 475 - b_size) & (rd$psu <= 475 + b_size),]
  model <- lm(entercollege ~ I(psu-475) + over475 + I((psu-475)*over475), data = bandwidth_sample)
  pi1 <-  model$coefficients[3]
  estimates <-  append(estimates, pi1)
  sd = summary(model)$coefficients[3,2]
  l.ci = c(l.ci, pi1 - 2*sd)
  h.ci = c(h.ci, pi1 + 2*sd)
}
```

Figure 4:

```r
band_and_est_jumps = data.frame(bandwidth_fig4, estimates)

ggplot(data = band_and_est_jumps, aes(x = bandwidth_fig4, y = estimates)) +
geom_point() + geom_ribbon(aes(ymax = h.ci, ymin = l.ci), fill = 'blue', alpha = 0.1) +
  labs(title = "Figure 4: Estimate of over475 vs. Bandwidths") +
  geom_line(aes(x = bandwidth_fig4, y = l.ci)) + geom_line(aes(x = bandwidth_fig4, y = h.ci)) +
    xlab("Bandwidths") + ylab("Estimate of over475")+
    theme(plot.title = element_text(hjust = 0.5))
```



Narrative:

I think a good choice of bandwidth is one that balances the competing priorities of accuracy (the existence of bias) and precision. A higher bandwidth is more precise because a larger sample size would tend the sample error to go down. We know that the standard error is inversely related to the square root of the sample size.

However, in our Regression discontinuity context (although not always), the bias will increase as a tradeoff of a large bandwidth and higher precision. Choosing a bandwidth is the choice of selecting how far to go to the left and the right when we are right near the boundary where the jump occurs. Observations immediately to the left and right of the boundary are assumed to be very similar to each other. However, the further you go in either direction – as the bandwidth gets larger – we encounter further observations where that have genuine differences from the closest ones to the jump. As a result, our assumption about the similarity of the bandwidth sample on either side no longer holds. As a result, the bias increases as we increase the bandwidth.

By figure 4, the choice of bandwidth I would choose is 100 because this bandwidth choice seems to be the point of inflection of the function before the function switches from convex to concave. In economics, this can be seen as diminishing marginal returns to the estimate of over475 (π_1) as we go over bandwidth of 100. To me, it is the most ideal choice because it strikes a good balance between precision and bias.

```r
# find characteristic means for entire sample
quintile1 <- subset(rd, rd$quintile == 1)
quintile2 <- subset(rd, rd$quintile == 2)
quintile3 <- subset(rd, rd$quintile == 3)
quintile4 <- subset(rd, rd$quintile == 4)

share_q1_all <- nrow(quintile1) / nrow(rd)
share_q2_all <- nrow(quintile2) / nrow(rd)
share_q3_all <- nrow(quintile3) / nrow(rd)
share_q4_all <- nrow(quintile4) / nrow(rd)

share_female_all <- nrow(subset(rd, rd$female == 1)) / nrow(rd)
share_gpa_60_70_all <- nrow(subset(rd, rd$gpa >= 60 & rd$gpa <= 70)) / nrow(rd)
share_gpa_50_60_all <- nrow(subset(rd, rd$gpa >= 50 & rd$gpa < 60)) / nrow(rd)
share_gpa_less50_all <- nrow(subset(rd, rd$gpa < 50)) / nrow(rd)

share_mother_overhs_all <- nrow(subset(rd, rd$himom == 1)) / nrow(rd)
share_father_overhs_all <- nrow(subset(rd, rd$hidad == 1)) / nrow(rd)

entire_sample <- c(share_q1_all, share_q2_all, share_q3_all, share_q4_all,
                   share_female_all, share_gpa_60_70_all, share_gpa_50_60_all, share_gpa_less50_all,
                   share_mother_overhs_all, share_father_overhs_all)



# find characteristic means for my chosen bandwidth
b <- 100

bdata <- rd[(rd$psu >= 475-b) & (rd$psu <= 475+b),]

share_q1_b <- nrow(subset(bdata, bdata$quintile == 1)) / nrow(bdata)
share_q2_b <- nrow(subset(bdata, bdata$quintile == 2)) / nrow(bdata)
share_q3_b <- nrow(subset(bdata, bdata$quintile == 3)) / nrow(bdata)
share_q4_b <- nrow(subset(bdata, bdata$quintile == 4)) / nrow(bdata)


share_female_b <- nrow(subset(bdata, bdata$female == 1)) / nrow(bdata)
share_gpa_60_70_b <- nrow(subset(bdata, bdata$gpa >= 60 & bdata$gpa <= 70)) / nrow(bdata)
share_gpa_50_60_b <- nrow(subset(bdata, bdata$gpa >= 50 & bdata$gpa < 60)) / nrow(bdata)
share_gpa_less50_b <- nrow(subset(bdata, bdata$gpa < 50)) / nrow(bdata)

share_mother_overhs_b <- nrow(subset(bdata, bdata$himom == 1)) / nrow(bdata)
share_father_overhs_b <- nrow(subset(bdata, bdata$hidad == 1)) / nrow(bdata)

b_sample <- c(share_q1_b, share_q2_b, share_q3_b, share_q4_b, share_female_b,
              share_gpa_60_70_b, share_gpa_50_60_b, share_gpa_less50_b,
              share_mother_overhs_b, share_father_overhs_b)
```

```r
# find characteristic means for compliers

rd_copy <- rd
rd_copy$quintile1 <- ifelse(rd_copy$quintile==1, 1, 0)
rd_copy$quintile2 <- ifelse(rd_copy$quintile==2, 1, 0)
rd_copy$quintile3 <- ifelse(rd_copy$quintile==3, 1, 0)
rd_copy$quintile4 <- ifelse(rd_copy$quintile==4, 1, 0)

rd_copy$gpa_60_70 <- ifelse((rd_copy$gpa >= 60 & rd_copy$gpa <= 70), 1, 0)
rd_copy$gpa_50_60 <- ifelse((rd_copy$gpa >= 50 & rd_copy$gpa < 60), 1, 0)
rd_copy$gpa_less50 <- ifelse(rd_copy$gpa < 50, 1, 0)

share_q1_complier <- ivreg(I(quintile1*entercollege) ~ entercollege |
                             over475 + I(psu-475) + I(over475*(psu-475)), data = rd_copy)

share_q2_complier <- ivreg(I(quintile2*entercollege) ~ entercollege |
                             over475 + I(psu-475) + I(over475*(psu-475)), data = rd_copy)

share_q3_complier <- ivreg(I(quintile3*entercollege) ~ entercollege |
                             over475 + I(psu-475) + I(over475*(psu-475)), data = rd_copy)

share_q4_complier <- ivreg(I(quintile4*entercollege) ~ entercollege |
                             over475 + I(psu-475) + I(over475*(psu-475)), data = rd_copy)


share_female_complier <-  ivreg(I(female*entercollege) ~ entercollege |
                                over475 + I(psu-475) + I(over475*(psu-475)),data = rd_copy)

share_gpa_60_70_complier <- ivreg(I(gpa_60_70*entercollege) ~ entercollege |
                                over475 + I(psu-475) + I(over475*(psu-475)),data = rd_copy)

share_gpa_50_60_complier <- ivreg(I(gpa_50_60*entercollege) ~ entercollege |
                                over475 + I(psu-475) + I(over475*(psu-475)),data = rd_copy)

share_gpa_less50_complier <- ivreg(I(gpa_less50*entercollege) ~ entercollege |
                                over475 + I(psu-475) + I(over475*(psu-475)),data = rd_copy)

share_himom_complier <-  ivreg(I(himom*entercollege) ~ entercollege |
                                over475 + I(psu-475) + I(over475*(psu-475)),data = rd_copy)


share_hidad_complier <- ivreg(I(hidad*entercollege) ~ entercollege |
                                over475 + I(psu-475) + I(over475*(psu-475)),data = rd_copy)


complier_sample <- c(share_q1_complier$coefficients[2], share_q2_complier$coefficients[2],
                     share_q3_complier$coefficients[2], share_q4_complier$coefficients[2],
                     share_female_complier$coefficients[2], share_gpa_60_70_complier$coefficients[2],
                     share_gpa_50_60_complier$coefficients[2], share_gpa_less50_complier$coefficients[2
                     share_himom_complier$coefficients[2], share_hidad_complier$coefficients[2])
```

```r
table6 <- data.frame(entire_sample, b_sample, complier_sample, complier_sample/entire_sample)
rownames(table6) <- c("Share with Family Income in Quintile 1",
                      "Share with Family Income in Quintile 2",
                      "Share with Family Income in Quintile 3",
                      "Share with Family Income in Quintile 4",
                      "Share Female", "Share with 60 <= GPA <= 70",
                      "Share with 50 <= GPA <  60", "Share GPA <  50",
                      "Share with Mother Education > HS", "Share with Father Education > HS")
colnames(table6) <- c("Entire Sample", "Bandwidth = 100", "Compliers", "Complier to Sample Ratio")

stargazer(table6, header = F, summary = F,
 title = "Table 6: Characteristics of Entire, Bandwidth = 100, Complier Samples")
```

Table 6

Table 6: Characteristics of Entire, Bandwidth = 100, and Complier Samples

	Entire Sample	Bandwidth = 100	Compliers	Complier to Sample Ratio
Share with Family Income in Quintile 1	0.473	0.503	0.302	0.639
Share with Family Income in Quintile 2	0.216	0.217	0.228	1.052
Share with Family Income in Quintile 3	0.159	0.150	0.212	1.334
Share with Family Income in Quintile 4	0.152	0.130	0.258	1.699
Share Female	0.569	0.586	0.473	0.831
Share with 60 $\geq$ GPA $\leq$ 70	0.319	0.251	0.708	2.219
Share with 50 $\geq$ GPA $<$ 60	0.627	0.692	0.303	0.484
Share GPA $<$ 50	0.055	0.057	-0.011	-0.197
Share with Mother Education $>$ HS	0.148	0.123	0.277	1.868
Share with Father Education $>$ HS	0.156	0.128	0.293	1.886

Narrative:

The claim that many advocates of the PSU loan program talk about is the idea that the loan program would provide opportunities to economically disadvantaged students that do well who otherwise would find it much harder to enroll in college. The jump at PSU score of 475 is the complier group who change from $D_i = 0$ *to* $D_i = 1$ at the boundary. The characteristics of the compliers seem to be drastically different from that of the entire sample.

Compliers in generally seem to be wealthier and more middle-class than the entire sample. The compliers seem to be more heavily male than the entire sample. The GPA of the compliers seem to be in general better than that of the entire sample with the majority scoring between 60 and 70 on GPA. Lastly, compliers seem to have highly educated parents which makes sense because well-educated parents tend to focus a lot more on the quality of education for their children and try harder to actively for the loan program.