Data Analysis 2 - ECBS5142 - Assignment 1

In this assignement, we will try to discover the gender wage gap with the level of education for occupations in Production (***occ2012*** code from 7700 to 8965).

Table of Contents

In [1]:
```
%%capture
pip install -r requirements.txt;
```

In [2]:
```
# import libs
import os
import sys
import warnings

import numpy as np
import pandas as pd
from mizani.formatters import percent_format
from plotnine import *
from datetime import datetime
import statsmodels.api as sm
import statsmodels.formula.api as smf
from scipy.stats import norm, chisquare
from IPython.core.display import HTML
from stargazer.stargazer import Stargazer
import statsmodels.nonparametric.kernel_regression as loess

from mizani.transforms import log_trans
from mizani.formatters import percent_format
from mizani.formatters import log_format

warnings.filterwarnings("ignore")
```

In [3]:
```
# Import the prewritten helper functions
from py_helper_functions import *
```

In [4]:
```
# read the data from the csv file
all_df = pd.read_csv('morg-2014-emp.csv')
```

In [5]:
```
# Filter the data for occ2012 between 7700 and 8965, work week > 0 and work minimum 20hr
comp_sample = all_df[(all_df['occ2012'] >= 7700)
                     & (all_df['occ2012'] <= 8965)
                     & (all_df['uhours'] >= 20)
                     & (all_df['earnwke'] > 0)][['hhid', 'earnwke', 'uhours', 'grade92',
#drop the all_df
del(all_df)
# Add a column 'hourly_wage' to the DataFrame
comp_sample['hourly_wage'] = comp_sample['earnwke'] / comp_sample['uhours']
# Add the natural log of wage (ln_wage) column
```

```
comp_sample['ln_wage'] = np.log(comp_sample['hourly_wage'])
# add column female to have boolean for male or female
comp_sample['female'] = comp_sample['sex'].apply(lambda x: 1 if x == 2 else 0)
# Add the sex_text column for descriptive values
comp_sample['sex_text'] = comp_sample['female'].apply(lambda x: '[1] female' if x == 1 e
# Describe the comp_sample
comp_sample.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 9083 entries, 2 to 149293
Data columns (total 10 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   hhid         9083 non-null   int64  
 1   earnwke      9083 non-null   float64
 2   uhours       9083 non-null   int64  
 3   grade92      9083 non-null   int64  
 4   sex          9083 non-null   int64  
 5   occ2012      9083 non-null   int64  
 6   hourly_wage  9083 non-null   float64
 7   ln_wage      9083 non-null   float64
 8   female       9083 non-null   int64  
 9   sex_text     9083 non-null   object 
dtypes: float64(3), int64(6), object(1)
memory usage: 780.6+ KB
```

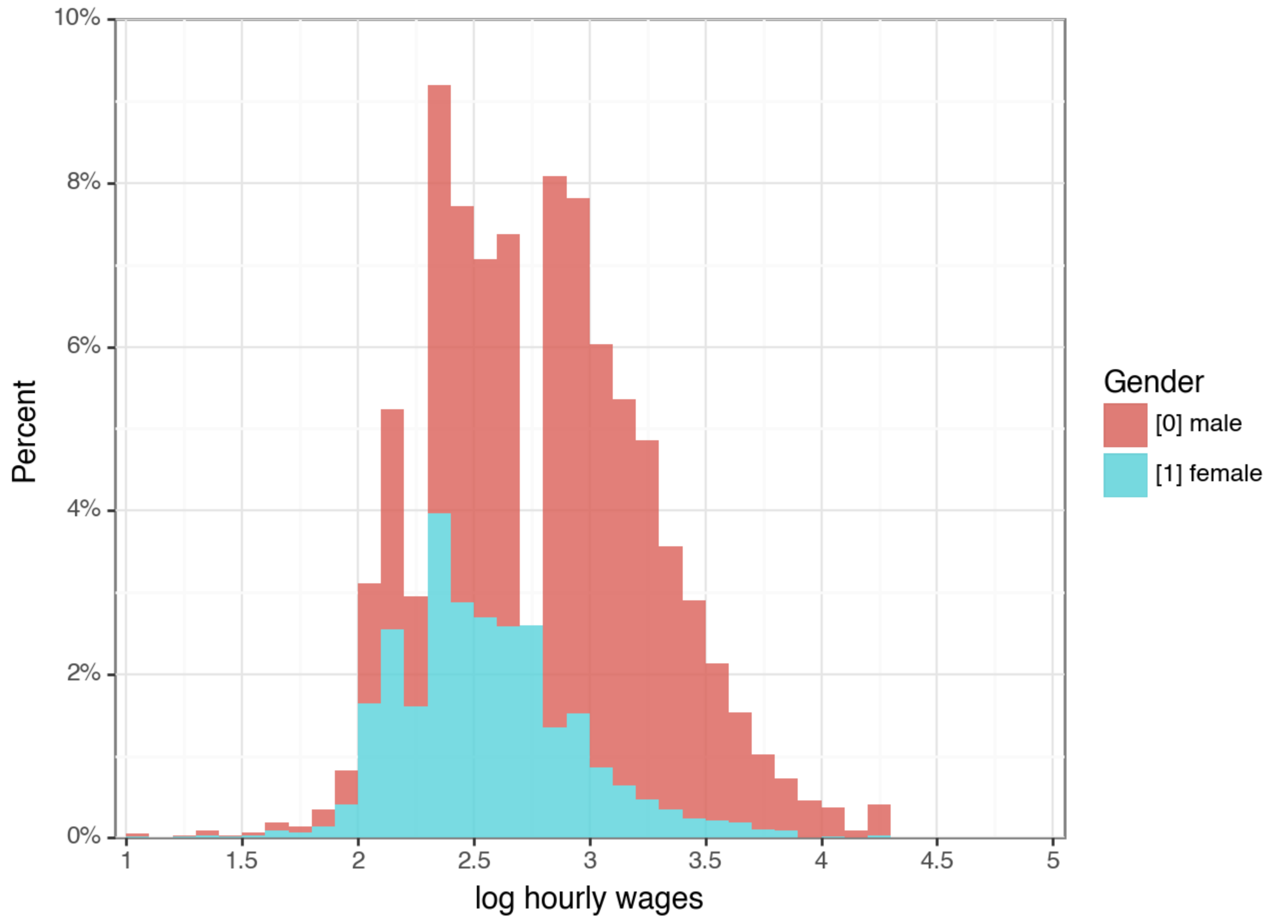
Comment

In the Production Occupations sample, we have a total of 9083 observations, none of which has missing values. Let's examine the distribution of the sample.

Distribution of wage by gender

In [6]:

```
(
    ggplot(comp_sample, aes(x="ln_wage", y="stat(count)/sum(stat(count))", fill='factor(
    + geom_histogram(
        binwidth=0.1,
        boundary=0,
        size=0.25,
        alpha=0.8,
        show_legend=True,
        na_rm=True,
    )
    + labs(x="log hourly wages", y="Percent", fill="Gender")
    + expand_limits(x=0.01, y=0.01)
    + scale_x_continuous(expand=(0.01, 0.01), limits=(1, 5), breaks=seq(1, 5, 0.5))
    + scale_y_continuous(
        expand=(0.0, 0.0),
        limits=(0, 0.1),
        breaks=seq(0, 0.1, 0.02),
        labels=percent_format(), #mizani
    )
    + theme_bw()
)
```



Out[6]: <Figure Size: (640 x 480)>

Comment

From the above histogram, it seems like in our sample, there are a lot more observations for male's wage than female's wage (almost 3 to 1!). We see that the Production Occupations mighty male-dominant.

The unconditional gender gap

Here we will examine the hourly wage gap between male and female in our sample.

Reg1 - Regression of ln(wage) on gender

In [7]:
```
reg1 = smf.ols(formula="ln_wage~female", data=comp_sample).fit(cov_type="HC1")
reg1.summary()
```

Out[7]:

OLS Regression Results

Dep. Variable:	ln_wage	**R-squared:**	0.074
Model:	OLS	**Adj. R-squared:**	0.073
Method:	Least Squares	**F-statistic:**	829.1
Date:	Tue, 21 Nov 2023	**Prob (F-statistic):**	1.51e-174
Time:	18:09:55	**Log-Likelihood:**	-6324.2
No. Observations:	9083	**AIC:**	1.265e+04
Df Residuals:	9081	**BIC:**	1.267e+04

Df Model:	1
Covariance Type:	HC1

	coef	std err	z	P>|z|	[0.025	0.975]
Intercept	2.8505	0.006	458.776	0.000	2.838	2.863
female	-0.3065	0.011	-28.794	0.000	-0.327	-0.286

Omnibus:	3672.023	**Durbin-Watson:**	1.931
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	93657.937
Skew:	-1.372	**Prob(JB):**	0.00
Kurtosis:	18.490	**Cond. No.**	2.45

Notes:
[1] Standard Errors are heteroscedasticity robust (HC1)

Analysis Explanation

From the regression, we see that the P value is 0.000, which indicates that we have strong evidences to reject the hypothesis that there is no difference in wage between male and female.

The coefficient of -0.3097 and the standard error of 0.011 suggest that female employees earn between 29.8%-32.0% less than male employees. If our sample is a representative sample, this behavior is very likely to happen in the population since our p-value is < 0.01.

> However, the R-squared for this model is only 0.073, which means the model only explains about 7.3% of the variance in the wage. There might be other factors that contribute to the wage aside from gender.

The gender wage gap and education level

Let's create some dummy variables for the education level:

1. Bachelor
2. Post-Graduate Degree

In [8]:
```
# create dummy variables
comp_sample['ed_BA'] = (comp_sample["grade92"] == 43).astype(int)
comp_sample['ed_PostGrad'] = (comp_sample["grade92"] >= 44).astype(int)
```

Gender wage gap with type of degree earned

In [9]:
```
reg2 = smf.ols(formula="ln_wage~female+ed_BA+ed_PostGrad", data=comp_sample).fit(cov_typ
```

In [10]:
```
stargazer = Stargazer([reg1, reg2])
stargazer.show_model_numbers(True)
stargazer.cov_spacing = 1.5
stargazer.covariate_order(
    [
        "female",
```

```
        "ed_BA",
        "ed_PostGrad",
        "Intercept"
    ]
)
stargazer.rename_covariates(
    {
        "Intercept": "Constant"
    }
)
stargazer
```

Out[10]:

	Dependent variable: ln_wage	
	(1)	(2)
female	-0.307***	-0.306***
	(0.011)	(0.010)
ed_BA		0.258***
		(0.020)
ed_PostGrad		0.449***
		(0.050)
Constant	2.850***	2.827***
	(0.006)	(0.006)
Observations	9083	9083
R^2	0.074	0.099
Adjusted R^2	0.073	0.099
Residual Std. Error	0.486 (df=9081)	0.479 (df=9079)
F Statistic	829.072*** (df=1; 9081)	383.000*** (df=3; 9079)
Note:		*p<0.1; **p<0.05; ***p<0.01

Analysis Explanation

- (1) $\ln(w) = \alpha + \beta female + \varepsilon$
- (2) $\ln(w) = \beta_0 + \beta_1 female + \beta_2 ed\_BA + \beta_3 ed\_PostGrad + e$

> [The comparison group is employees without a Bachelor or Post Graduate Degree]

When comparing the employees with the same gender, we we discover some insights as follow:

- Those with a Bachelor degree are expected to earn on average 26% more than those that do not have a degree.
- With a Post Graduate degree, employees are expected to earn on average 45% more than those that do not have a degree.

Both of the insights above are significant at 1%. We can also see that by including the education, the model (2) fit (R-squared) is better than the unconditional model (1).

From the model, estimated coefficient on *female* is smaller (-0.306) when education is included. It seems women appear to be more likely to be in lower-earner without a degree than in higher-earner with a degree - but only small part.

There is a positive correlation between the level of education (academic degree earners) and the wage. How about the wage gap behavior among the top degree earners?

Gender wage gap among Post Graduate degree earners

Now let's consider only among the Post Graduate degree earners:

In [11]:
```
# employees with post graduate degree
degree_sample = comp_sample[(comp_sample['grade92'] >= 44)]
degree_sample["ed_MA"] = (degree_sample["grade92"] == 44).astype(int)
degree_sample["ed_Prof"] = (degree_sample["grade92"] == 45).astype(int)
degree_sample["ed_PhD"] = (degree_sample["grade92"] == 46).astype(int)
```

In [12]:
```
reg3 = smf.ols(formula="ln_wage~female", data=degree_sample).fit(cov_type="HC1")
reg4 = smf.ols(formula="ln_wage~female+ed_Prof+ed_PhD", data=degree_sample).fit(cov_type
reg5 = smf.ols(formula="ln_wage~female+ed_Prof+ed_MA", data=degree_sample).fit(cov_type=
```

In [13]:
```
stargazer = Stargazer([reg3, reg4, reg5])
stargazer.show_model_numbers(True)
stargazer.cov_spacing = 1.5
stargazer.covariate_order(
    [
        "female",
        "ed_Prof",
        "ed_MA",
        "ed_PhD",
        "Intercept"
    ]
)
stargazer.rename_covariates(
    {
        "Intercept": "Constant"
    }
)
stargazer
```

Out[13]:

			Dependent variable: ln_wage
	(1)	(2)	(3)
female	-0.137	-0.136	-0.136
	(0.109)	(0.109)	(0.109)
ed_Prof		0.130	0.088
		(0.205)	(0.323)
ed_MA			-0.042
			(0.260)

ed_PhD		0.042	
		(0.260)	
Constant	3.218***	3.204***	3.245***
	(0.059)	(0.064)	(0.255)
Observations	107	107	107
R^2	0.016	0.021	0.021
Adjusted R^2	0.006	-0.007	-0.007
Residual Std. Error	0.516 (df=105)	0.520 (df=103)	0.520 (df=103)
F Statistic	1.593 (df=1; 105)	0.764 (df=3; 103)	0.764 (df=3; 103)
Note:			*p<0.1; **p<0.05; ***p<0.01

Analysis Explanation

- (1) $\ln(w) = \alpha + \beta female + \varepsilon$
- (2) $\ln(w) = \beta_0 + \beta_1 female + \beta_2 ed\_Prof + \beta_3 ed\_PhD + e$

> [The comparison group is employees with the MA degree]

- (3) $\ln(w) = \beta_0 + \beta_1 female + \beta_2 ed\_Prof + \beta_3 ed\_MA + e$

> [The comparison group is employees with the PhD degree]

Intertingly, when considering only the groups of Post Graduate degree earners, it seems like there is no statistical significant difference in wage regarding the type of degree earned (No `*` next to the coefficients). Even the gender wage gap in this group is not statistically significant.

This suggests that there is likely no significant difference in wage regarding gender or type of Post Graduate degree among the top degree earners in the population.

Interaction between gender and level of education

Are wage patterns with education level similar or different for male vs female employees?

- Regress the ln(wage) on level of education separately for male vs female
- Include interaction $gender * degree\_earner$

Let's construct some regression model to exammine how the interaction between gender and degree earned contributes to wage.

In [14]:
```
# add the ed_degree to signify wether the employee has earned an academic degree
comp_sample['ed_degree'] = ((comp_sample['ed_BA'] == 1) | (comp_sample['ed_PostGrad'] ==
reg6 = smf.ols(formula="ln_wage~ed_degree", data=comp_sample.query("female==1")).fit(cov
reg7 = smf.ols(formula="ln_wage~ed_degree", data=comp_sample.query("female==0")).fit(cov
reg8 = smf.ols(formula="ln_wage~female+ed_degree+female*ed_degree", data=comp_sample).fi
```

In [15]:
```
stargazer = Stargazer([reg6, reg7, reg8])
stargazer.custom_columns(['female', 'male', 'all'], [1, 1, 1])
```

```
stargazer.show_model_numbers(True)
stargazer.cov_spacing = 1.5
stargazer.covariate_order(
    [
        "female",
        "ed_degree",
        "female:ed_degree",
        "Intercept"
    ]
)
stargazer.rename_covariates(
    {
        "Intercept": "Constant",
        "female:ed_degree": "female x degree earner"
    }
)
stargazer
```

Out[15]:

			Dependent variable: ln_wage
	female	male	all
	(1)	(2)	(3)
female			-0.314***
			(0.011)
ed_degree	0.361***	0.257***	0.257***
	(0.037)	(0.022)	(0.022)
female x degree earner			0.105**
			(0.043)
Constant	2.515***	2.829***	2.829***
	(0.009)	(0.006)	(0.006)
Observations	2493	6590	9083
R^2	0.052	0.020	0.099
Adjusted R^2	0.052	0.020	0.098
Residual Std. Error	0.420 (df=2491)	0.499 (df=6588)	0.479 (df=9079)
F Statistic	95.158*** (df=1; 2491)	132.647*** (df=1; 6588)	385.567*** (df=3; 9079)
Note:			*p<0.1; **p<0.05; ***p<0.01

Analysis Explanation

- (1): female employees with a degree are expected to earn 36% more, on average
- (2): male employees with a degree are expected to earn 26% more, on average
- (3): the slope of log earnings - level of education pattern is 0.105 more positive for female, on average

Interestingly, the level of education has a higher positive correlation to wage between female to female than that of male to male.

However, there is still a gender wage gap between female and male employees where female earn on average 31% less than male employee with the same academic degree/qualification.