Gender Disparity in

2022 Aggie Hacks x Google Cloud Hackathon

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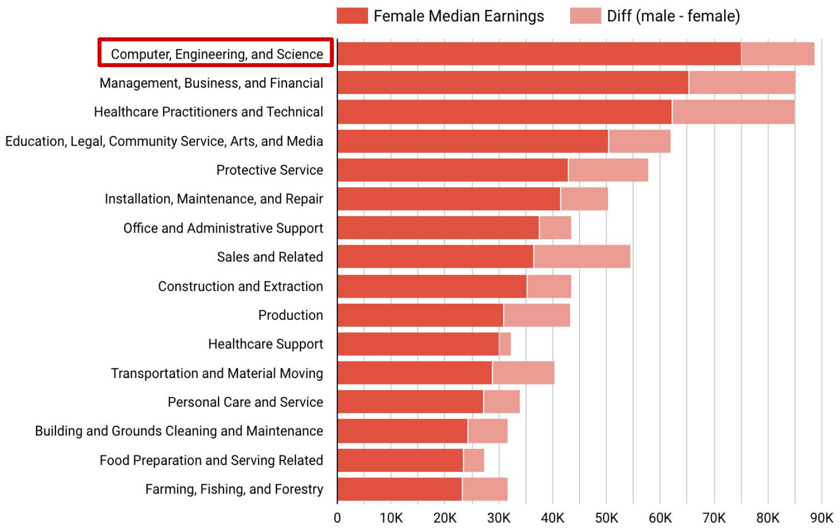
“Employers cannot discriminate against employees based on gender or reproductive choices.”

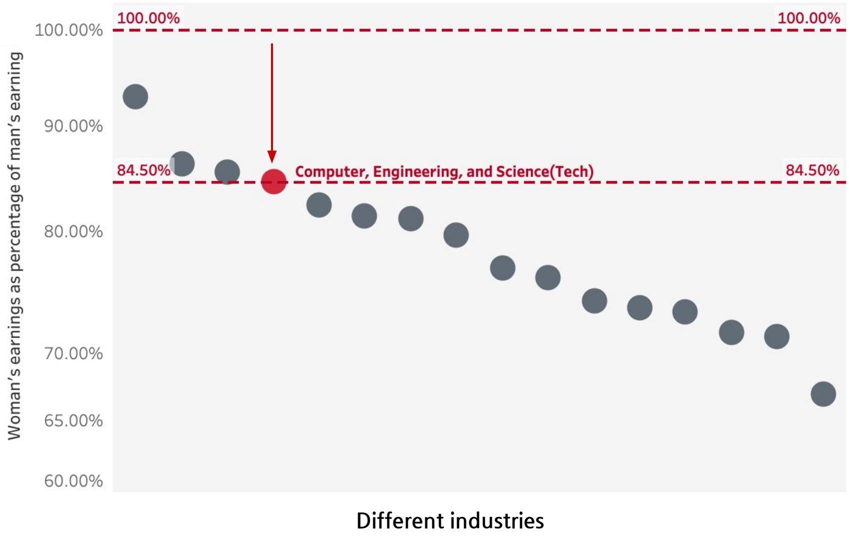
——Ruth Bader Ginsburg

Problem: Women earn less than men in tech industry

Salary across industry



Woman Salary as percentage of Man salary



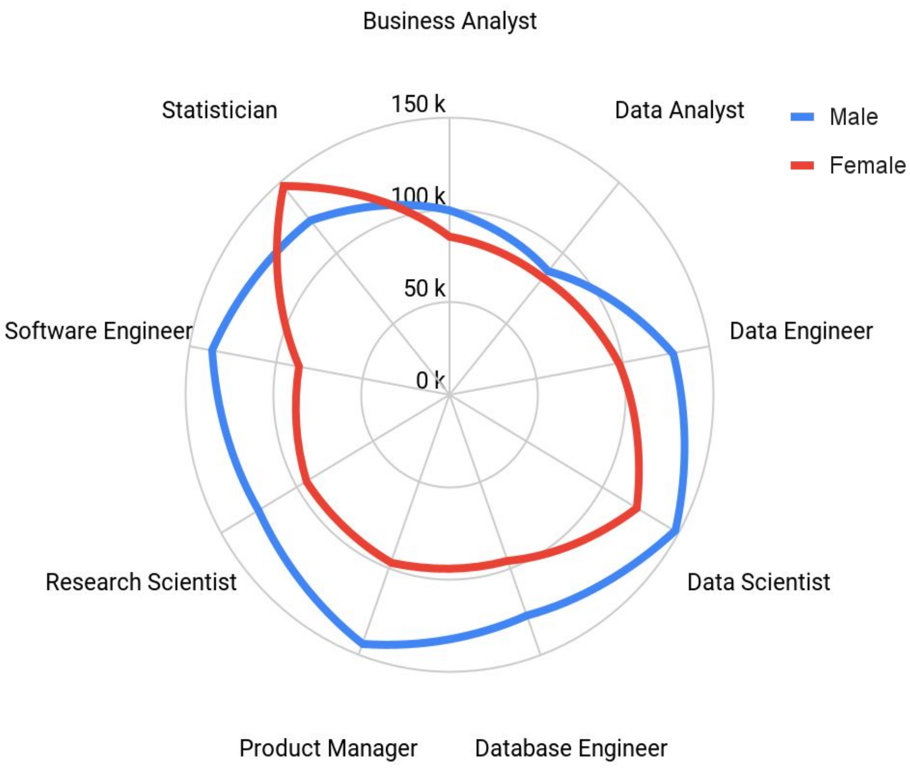
- Although women in tech industry have the ***highest*** median salary vs. other industries, there is still a ***~$13k*** gap between gender
- Woman in tech industry have earnings ***84.5%*** of man's earnings, showing salary disparity

Bar chart built in Google Data Studio

Source: 2019 United States Census Bureau

Women earn less in the same position

Average Compensation Comparison

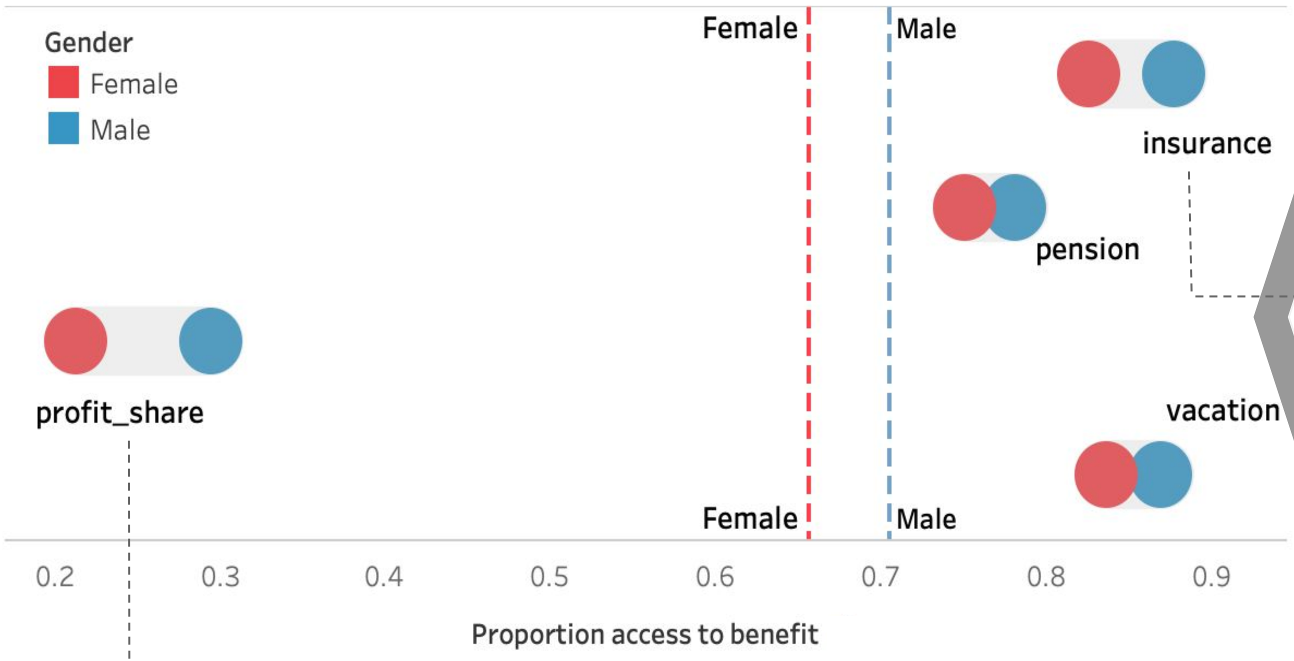


In the same tech position, women's average compensation is **lower** than male.

Radar chart built in Google Product

Source: 2019 Kaggle Machine Learning & Data Science Survey

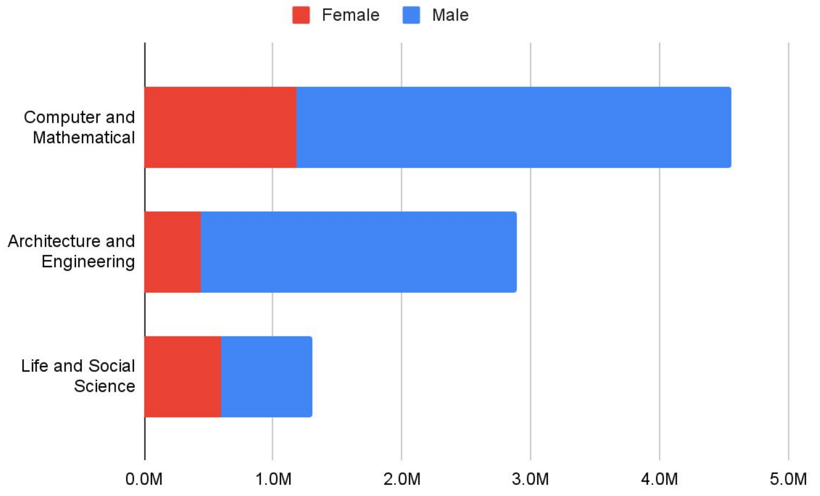
Women has less access to career benefit

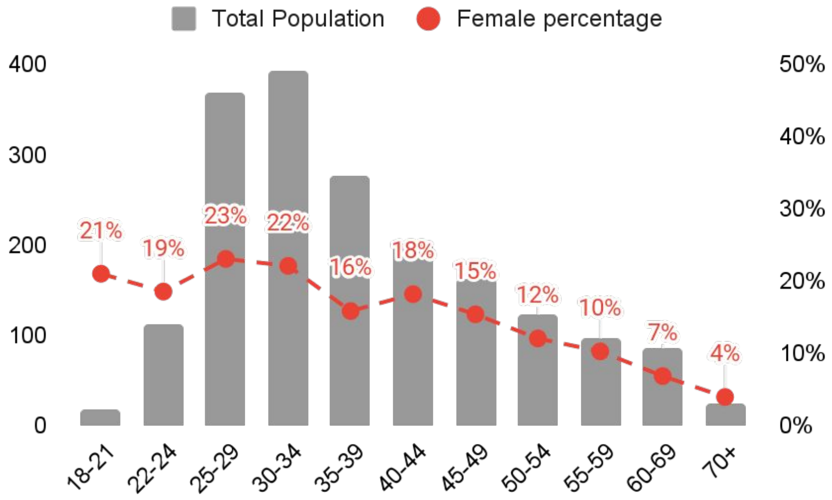


- Woman have ***<u>less access to all four benefits</u>*** versus. Man, on average
- Profit share and insurance benefit has ***<u>significant gender gap</u>*** with both prop-test p-value < 5%

Source: 2019 National Center for Science and Engineering Statistics (NCSES)

The female population is extremely lower than male population



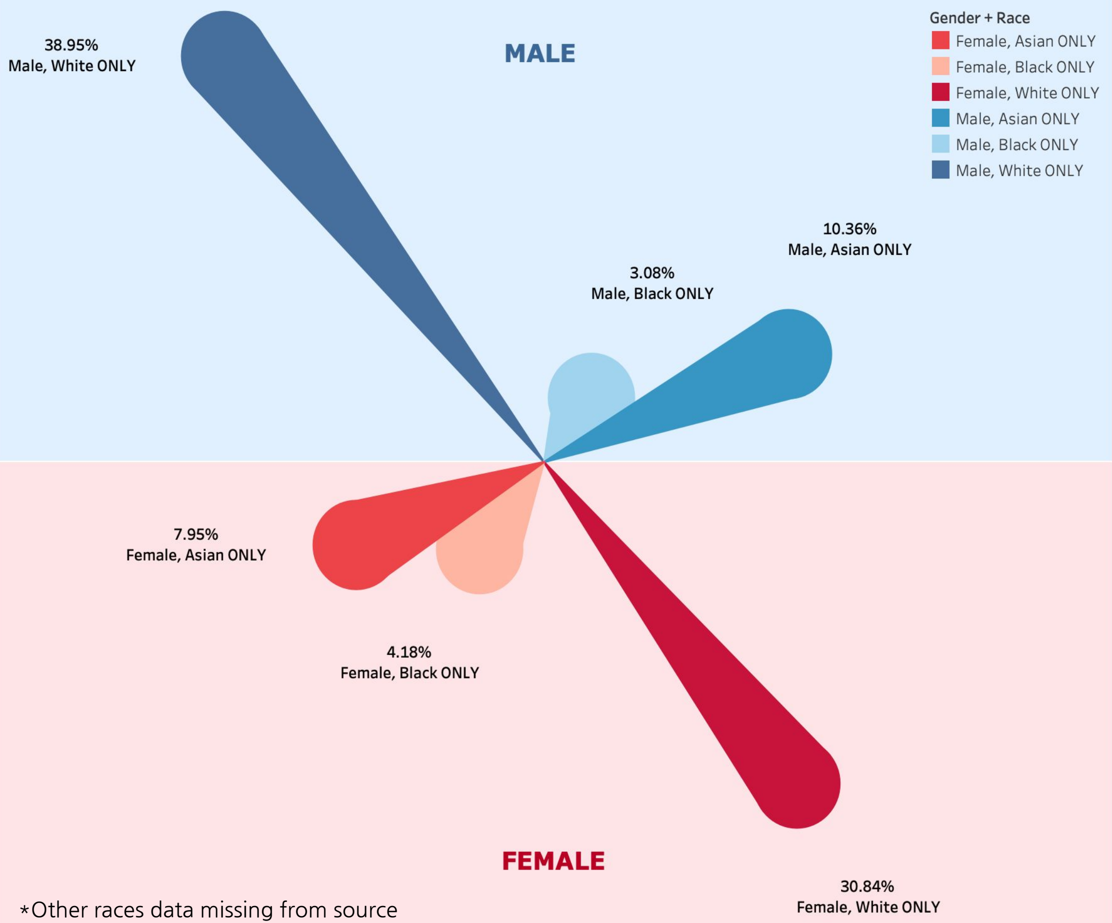


Overall, in the tech industry, the female population is significant less than male group. As the age increased, the gender gap become bigger.

Radar chart built in Google Product

Source: 2019 Kaggle Machine Learning & Data Science Survey / United States Census Bureau

Gender disparity is obvious in the White and Asian group



*Other races data missing from source

In tech industry, female population in **White** and **Asian** group is **less** than male population

Source: 2013-2019 National Center for Science and Engineering Statistics

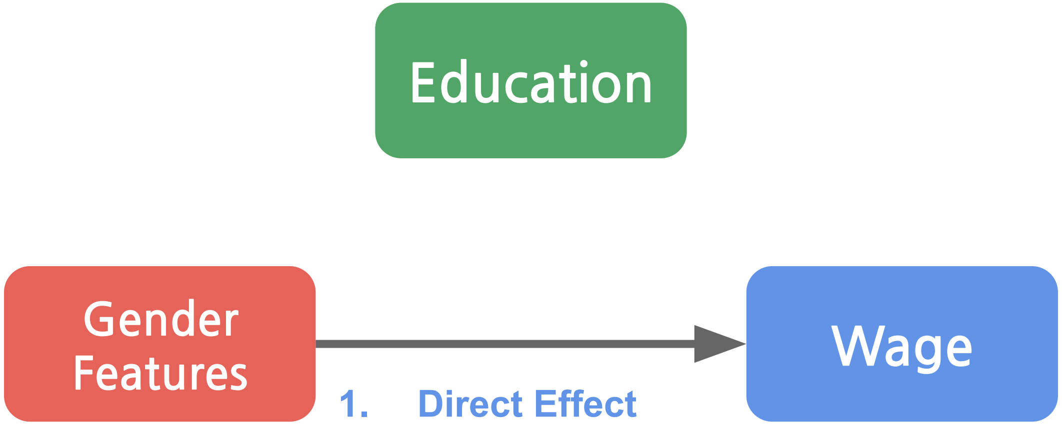
Gender Disparity Exists!

*Population, Benefits, **Wages**,...*

How can we solve it?
Education?

Mediation Regression: Can education improve women wage?

Model Structure



Does our research goal make sense?

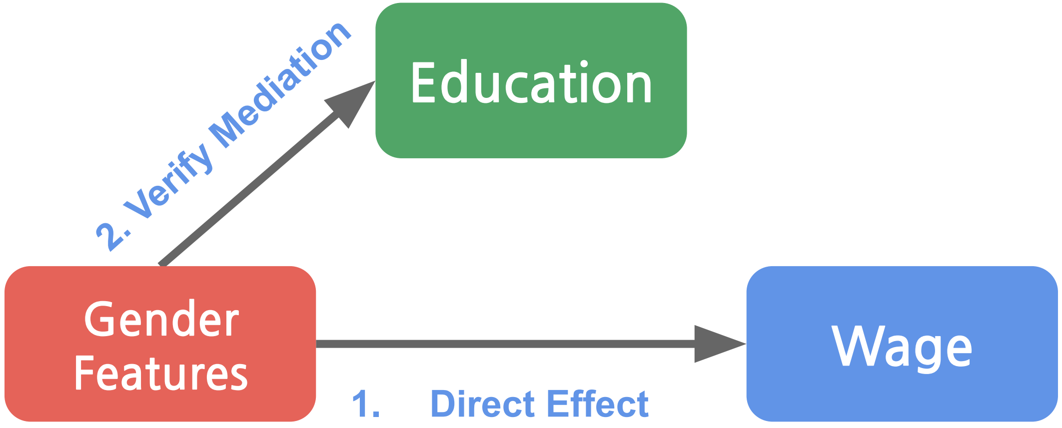
1

Regress Wage ~ Gender Fea
1980 - 2010, 2017 - 2019
x
Female, Male
Gender Fea explains Wage

Source: 1980-2010, 2017-2019 The Panel Study of Income Dynamics (PSID) Family-level

Mediation Regression: Can education improve women wage?

Model Structure



Does our research goal make sense?

1

Regress Wage ~ Gender Fea
1980 - 2010, 2017 - 2019
x
Female, Male
Gender Fea explains Wage

Is Education effective?

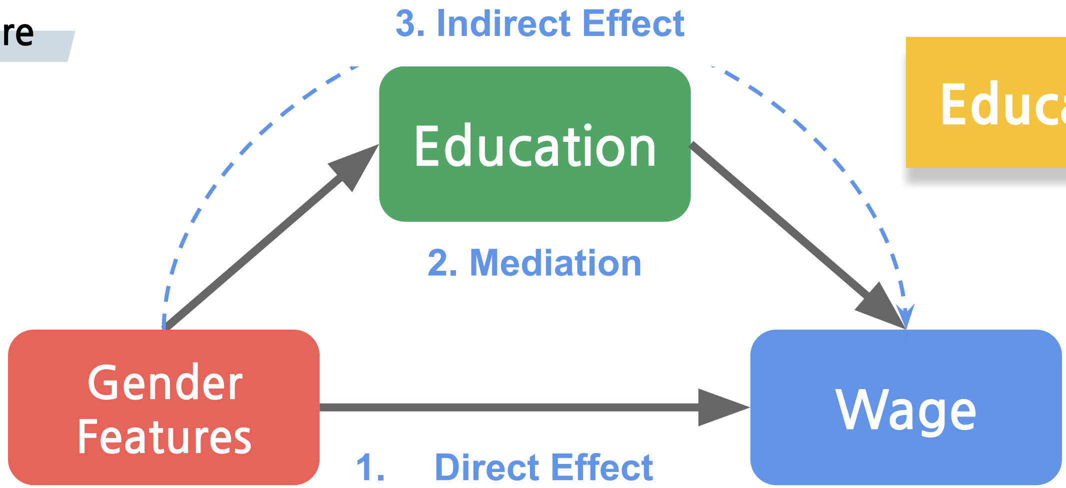
2

Regress Edu ~ Gender Fea
1980 - 2010, 2017 - 2019
x
Female, Male
Gender Fea affects Edu

Source: 1980-2010, 2017-2019 The Panel Study of Income Dynamics (PSID) Family-level

Mediation Regression: Can education improve women wage?

Model Structure



Education matters!

Does our research goal make sense?

1

Regress Wage ~ Gender Fea
1980 - 2010, 2017 - 2019
x
Female, Male
Gender Fea explains Wage

Is Education effective?

2

Regress Edu ~ Gender Fea
1980 - 2010, 2017 - 2019
x
Female, Male
Gender Fea affects Edu

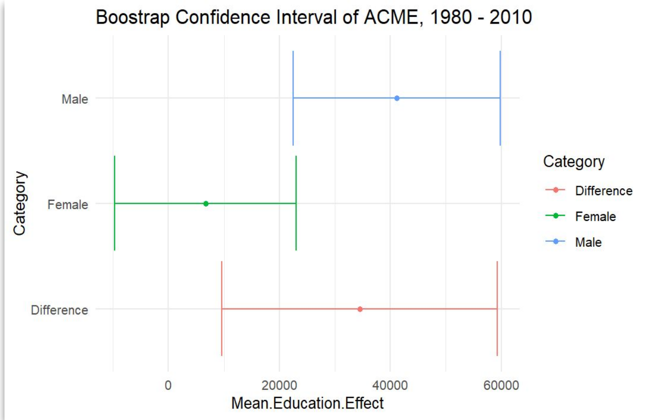
How is the indirect effect of edu?

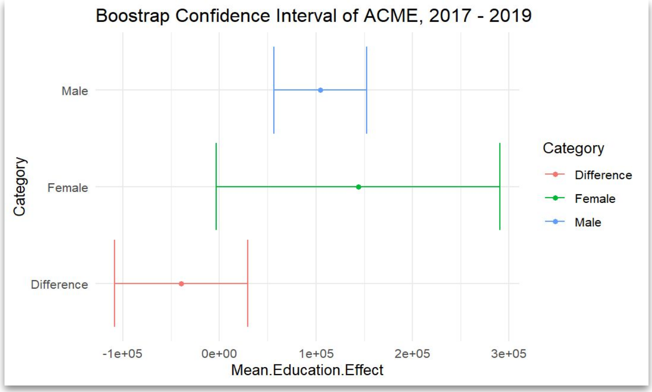
3

Regress Wage ~ Gender Fea + Edu
1980 - 2010, 2017 - 2019
x
Female, Male
Mediation Exists

Source: 1980-2010, 2017-2019 The Panel Study of Income Dynamics (PSID) Family-level

Education for women becomes effective in recent years





Bootstrap

1980 - 2010

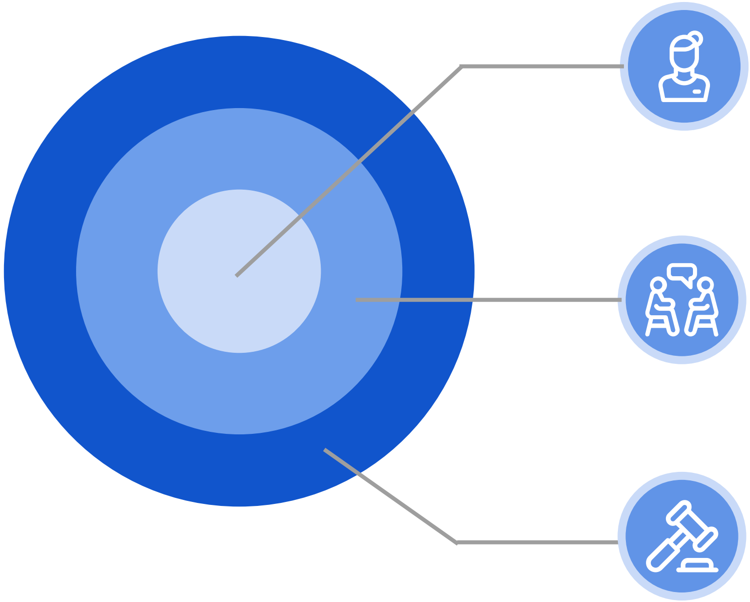
- ➔ More years in education **cannot** benefit **female** wages significantly
- ➔ More years in education can benefit male wages significantly

2017 - 2019

- ➔ More years in education **significant benefit female wages**
- ➔ Education effect works **indifferently** for man and women

Source: 1980-2010, 2017-2019 The Panel Study of Income Dynamics (PSID) Family-level

Recommendations



Self Effort

- Females should be more self-motivated to get tech domain knowledge by **obtaining a higher education degree**, **getting certificates**, and **attending industry conferences**

Industry Effort

- build up a women friendly culture

Society Effort

- The government should invest more on improving gender equality in **all race and age groups**.

Q&A

Thank You

Limitations & Next step

1 | LIMITATIONS

- For EDA part, adding more demographic dimensions may give us new findings
- In our regression modeling dataset, we assume individuals graduating from stem-major work in the tech industry, which may bring bias into our model

2 | NEXT STEP

- Explore more EDA insights
- Given more time and data, we can also study how alternative social factors (race, age, location,etc.) would affect gender disparity in tech industries, by applying regression and machine learning models

Appendix & Reference

Datasets

1. 2019 Kaggle Machine Learning & Data Science Survey
   https://www.kaggle.com/c/kaggle-survey-2019/data?select=multiple_choice_responses.csv

2. 2013-2019 National Center for Science and Engineering Statistics
   https://ncsesdata.nsf.gov/builder/nscg

3. 2019 United States Census Bureau
   https://www.census.gov/data/tables/time-series/demo/industry-occupation/median-earnings.html

4. Salary for public sector staffs in SF, 2011- 2018
   https://www.kaggle.com/fedesoriano/gender-pay-gap-dataset

5. 2017-2019 The Panel Study of Income Dynamics (PSID) Family-level
   https://simba.isr.umich.edu/data/data.aspx

Appendix & Reference

```
Call:
lm(formula = WAGES ~ ., data = df_1)

Residuals:
     Min       1Q   Median       3Q      Max 
-11.6605  -0.2348   0.1588   0.5808   3.7381 

Coefficients:
                  Estimate Std. Error t value Pr(>|t|)    
(Intercept)       7.160498   0.734320   9.751  < 2e-16 ***
AGE              -0.008812   0.005036  -1.750   0.0805 .  
YRS.PRES.EMP      0.033051   0.006751   4.896 1.17e-06 ***
WTR.GRADUATED    -0.152699   0.176247  -0.866   0.3865    
WORK.WEEKS        0.085145   0.006594  12.912  < 2e-16 ***
COMPLETED.ED      0.022544   0.034319   0.657   0.5114    
SEX_2            -0.324637   0.173571  -1.870   0.0618 .  
RACE_2           -0.439217   0.213781  -2.055   0.0402 *  
RACE_3           -0.468961   0.786772  -0.596   0.5513    
RACE_4            0.056037   0.205164   0.273   0.7848    
RACE_5            0.819268   1.113097   0.736   0.4619    
RACE_7           -0.861712   0.427955  -2.014   0.0444 *  
CURRENT.REGION_2 -0.291249   0.177581  -1.640   0.1013    
CURRENT.REGION_3 -0.097483   0.166994  -0.584   0.5595    
CURRENT.REGION_4 -0.214227   0.177315  -1.208   0.2273    
CURRENT.REGION_5 -0.058822   1.122990  -0.052   0.9582    
CURRENT.REGION_6 -2.338277   0.556582  -4.201 2.93e-05 ***
YEAR_2019        -0.002080   0.114036  -0.018   0.9855    
year_female       0.181155   0.294027   0.616   0.5380    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.564 on 873 degrees of freedom
Multiple R-squared:  0.231,	Adjusted R-squared:  0.2151 
F-statistic: 14.57 on 18 and 873 DF,  p-value: < 2.2e-16
```

```
Call:
lm(formula = WAGES ~ ., data = df_3)

Residuals:
     Min       1Q   Median       3Q      Max 
-16.2253  -0.7692  -0.0275   0.7824   9.9846 

Coefficients:
                  Estimate Std. Error t value Pr(>|t|)    
(Intercept)       2.328242   0.145085  16.047  < 2e-16 ***
AGE              -0.036052   0.001175 -30.690  < 2e-16 ***
YRS.PRES.EMP      0.060099   0.002060  29.182  < 2e-16 ***
WTR.GRADUATED    -0.103498   0.027208  -3.804 0.000143 ***
WORK.WEEKS        0.164487   0.000988 166.485  < 2e-16 ***
COMPLETED.ED      0.090740   0.006924  13.105  < 2e-16 ***
SEX_2            -0.068868   0.036233  -1.901 0.057356 .  
RACE_2           -0.092317   0.051505  -1.792 0.073089 .  
RACE_3           -0.033317   0.201443  -0.165 0.868639    
RACE_4           -0.100846   0.134831  -0.748 0.454504    
RACE_5            0.265567   0.462624   0.574 0.565944    
RACE_7            0.185191   0.089404   2.071 0.038338 *  
CURRENT.REGION_2 -0.195130   0.057514  -3.393 0.000694 ***
CURRENT.REGION_3 -0.128762   0.054106  -2.380 0.017333 *  
CURRENT.REGION_4 -0.066592   0.060824  -1.095 0.273608    
CURRENT.REGION_5 -0.652585   0.355919  -1.834 0.066743 .  
CURRENT.REGION_6 -0.935387   0.227049  -4.120 3.81e-05 ***
YEAR_2019         0.018504   0.040960   0.452 0.651453    
isstem            0.806376   0.081924   9.843  < 2e-16 ***
stem_female      -0.308907   0.201109  -1.536 0.124553    
year_female       0.080308   0.067124   1.196 0.231555    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 2.116 on 16991 degrees of freedom
Multiple R-squared:  0.7861,	Adjusted R-squared:  0.7859 
F-statistic:  3123 on 20 and 16991 DF,  p-value: < 2.2e-16
```

Appendix & Reference

```
> pension <- prop.test(x=c(25841, 34115), n=c(34429, 43688))
> pension

	2-sample test for equality of proportions with continuity correction

data:  c(25841, 34115) out of c(34429, 43688)
X-squared = 99.025, df = 1, p-value < 2.2e-16
alternative hypothesis: two.sided
95 percent confidence interval:
 -0.03633945 -0.02429840
sample estimates:
   prop 1    prop 2
0.7505591 0.7808780

> insurance <- prop.test(x=c(28445, 38314), n=c(34429, 43688))
> insurance

	2-sample test for equality of proportions with continuity correction

data:  c(28445, 38314) out of c(34429, 43688)
X-squared = 399.46, df = 1, p-value < 2.2e-16
alternative hypothesis: two.sided
95 percent confidence interval:
 -0.05587484 -0.04572187
sample estimates:
   prop 1    prop 2
0.8261930 0.8769914
```

Appendix & Reference

Mediation Regression, 1980-2010

Code

Data Processing

Hide

```
old <- read.csv("psid_old_stem.csv")
psid_old <- subset(old, select = c(sex, famwgt, age, sch, white, south, LEHS, black, hisp, othrace, west, northeast, northce
ntral, annhrs, realhrwage))
psid_old <- psid_old %>% mutate(annincome = realhrwage * annhrs) # calculate annual salary/wage
psid_old <- subset(psid_old, select = -c(realhrwage, annhrs, othrace))
psid_old$sex <- 1 - psid_old$sex
```

Are X variables influencing wage?

Yes, sex(1 = Male), lower level of education(LEHS) reduces salary, while as age grows, the salary increases. These are highly significant, whereas Black people receiving less salary.

Hide

```
model.0.old.m <- lm(annincome~ . - sch, data = psid_old_male)
summary(model.0.old.m)
```

```
Call:
lm(formula = annincome ~ . - sch, data = psid_old_male)

Residuals:
```

Linear Regression: wage discrimination in tech industry

Race, Working experience
Current region, Age,
Annual working hours,
Year, Gender x Year

Control Variables + Gender → Wage

For Tech Occupations:

$$\ln(\mathit{Wages}) = 7.16 - \boxed{0.32} * \mathit{Is\_Female} + \beta * X$$

Wage Discrimination ***exists***!

Source: 2017-2019 The Panel Study of Income Dynamics (PSID) Family-level