education_income

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1 Education and Earnings: Unraveling the Impact of Higher Education on Income

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1.1 1. Introduction

One of the motivating factors for an individual to seek higher education is the belief that an advanced degree will lead to higher earning potential. For instance, according to a 2021 survey by the Bipartisan Policy Center and the American Association of Colleges and Universities, 60% of American adults believe that a college degree is "worth the time and money involved." But does a degree actually lead to higher earnings?

A study of 2005 Ontario graduates supports this idea: researchers found statistically significant increases in earnings for each level of university education (Frank and Walters). A study by Kim et al. agreed but found significant variability in earning potential for different genders and fields of study. We will aim to confirm that a higher level of education leads to higher earnings, using a larger and more geographically widespread sample than the Ontario study.

In this report, we will ask whether a person's education level had an effect on their chance of earning more than \$50,000 in 1994. We will investigate whether the proportion of people earning more than $50,000 is significantly higher for those with a bachelor's degree versus those without and whether it is again significantly higher for those with a master's degree.

1.2 2. Preliminary Results

1.2.1 Data Cleaning

[1]:
```
install.packages("gridExtra")
library('tidyverse')
library("stringr")
library("broom")
library("infer")
library("gridExtra")
options(repr.plot.width=8, repr.plot.height=6)
set.seed(812)
```

```
Updating HTML index of packages in '.Library'

Making 'packages.html' …
```

```
 done

  Attaching packages                                   tidyverse
1.3.2
 ggplot2 3.3.6       purrr   0.3.4
 tibble  3.1.8       dplyr   1.0.10
 tidyr   1.2.1       stringr 1.4.1
 readr   2.1.2       forcats 0.5.2
  Conflicts
tidyverse_conflicts()
 dplyr::filter() masks stats::filter()
 dplyr::lag()    masks stats::lag()

Attaching package: ‘gridExtra’


The following object is masked from ‘package:dplyr’:

    combine
```

The dataset we will be using to answer this question is the "Adult" dataset from the UC Irvine Machine Learning Repository. We downloaded the dataset to the `data` folder. Now we will read the data from the dataset and store it in `adult_data`.

[2]:
```
bold <- function(text) {
  paste0("\033[1m", text, "\033[0m")
}
```

[3]:
```
data_url <- "https://raw.githubusercontent.com/Julian-UBC/project-32/main/data/
 ↪adult.data"
adult_data <- read.table(data_url, header=FALSE, sep= ",",
                  col.names = c("age", "workclass", "fnlwgt", "education",␣
 ↪"education_num", "marital_status", "occupation", "relationship",
                                "race", "sex", "capital_gain", "capital_loss",␣
 ↪"hours_per_week", "native_country", "class"))

adult_df <- as.data.frame(apply(adult_data, 2, str_remove_all, " "))

cat("\n\n")
cat(bold("Table 1: Original dataset with column names added"))
head(adult_df)

nrow(adult_df)
cat("\n\n")
cat("\n\n")
```

```
cat(bold("Table 2: A data frame showing the number of missing values in each␣
 ↪column"))
adult_df |> summarize(across(everything(), list(na = ~ sum(is.na(.)))))
```

Table 1: Original dataset with column names added

A data.frame: 6 × 15

	age <chr>	workclass <chr>	fnlwgt <chr>	education <chr>	education_num <chr>	marital_status <chr>
1	39	State-gov	77516	Bachelors	13	Never-married
2	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse
3	38	Private	215646	HS-grad	9	Divorced
4	53	Private	234721	11th	7	Married-civ-spouse
5	28	Private	338409	Bachelors	13	Married-civ-spouse
6	37	Private	284582	Masters	14	Married-civ-spouse

32561

Table 2: A data frame showing the number of missing values in each column

A data.frame: 1 × 15

age_na <int>	workclass_na <int>	fnlwgt_na <int>	education_na <int>	education_num_na <int>	marital_statu <int>
0	0	0	0	0	0

Our dataset contains 32561 observations with information taken from the 1994 US census database, and contains no missing values in any column.

We need to change some variable types before progressing:

[4]:
```
dt <- adult_df %>%
    mutate(above_50_k = (class == ">50K"),
           hours_per_week = as.integer(hours_per_week))
```

Since we are primarily interested in people who received their education at research universities, we will now filter out irrelevant categories in `education`. For our purposes, we will also redefine the variable to group people into three segments: people without a bachelor's degree, people with a bachelor's degree, and those who earned a master's degree or higher.

[5]:
```
data <- dt %>%
    filter(!education %in% c("Some-college", "Prof-school", "Assoc-acdm",␣
 ↪"Assoc-voc")) %>%
    mutate(education = if_else(education == "Doctorate" | education ==␣
 ↪"Masters", "Master's or higher",
```

```
                        if_else(education == "Bachelors", "Bachelor's", "No␣
 ↪Bachelor's"))) %>%
    mutate(education = factor(education, levels = c("No Bachelor's",␣
 ↪"Bachelor's", "Master's or higher")))

cat("\n\n")
cat(bold("Table 3: A cleaned and tidy version of the original dataset"))
head(data)
```

Table 3: A cleaned and tidy version of the original dataset

A data.frame: 6 × 16

	age <chr>	workclass <chr>	fnlwgt <chr>	education <fct>	education_num <chr>	marital_st <chr>
1	39	State-gov	77516	Bachelor's	13	Never-mar
2	50	Self-emp-not-inc	83311	Bachelor's	13	Married-ci
3	38	Private	215646	No Bachelor's	9	Divorced
4	53	Private	234721	No Bachelor's	7	Married-ci
5	28	Private	338409	Bachelor's	13	Married-ci
6	37	Private	284582	Master's or higher	14	Married-ci

1.2.2 Descriptive Statistics

After data wrangling, we would like to have some insight into the demographic composition of different groups who make either more or less than 50k. These will help us make reasonable decisions in adding more filtering layers to ensure the incomes for people with different education levels are comparable. It will also deepen our understanding of the divergence between groups that might be valuable in later reasoning for these differences.

Sample Distribution of Weekly Hours Worked

[6]:
```
plot_below_50k <- data %>%
    filter(above_50_k == FALSE) %>%
    ggplot() +
    geom_histogram(aes(hours_per_week, ..density..), binwidth = 5) +
    scale_x_continuous(n.breaks = 10) +
    labs(x = "Hours per week",
         y = "Proportion",
         title = "Sample Distribution of Weekly Hours Worked \nfor People with␣
 ↪Incomes Less Than or Equal To $50k") +
    theme(text = element_text(size = 16)) +
    theme_bw()
plot_below_50k
cat("\n\n")
cat(bold("Figure 1: A histogram of different groups with incomes less than or␣
 ↪equal to $50k USD"))
```

```
plot_above_50k <- data %>%
    filter(above_50_k == TRUE) %>%
    ggplot() +
    geom_histogram(aes(hours_per_week, ..density..), binwidth = 5) +
    scale_x_continuous(n.breaks = 10) +
    theme(text = element_text(size = 16)) +
    labs(x = "Hours per week",
         y = "Proportion",
         title = "Sample Distribution of Weekly Hours Worked \nfor People with␣
 ↪Incomes Greater Than $50k") +
    theme_bw()
plot_above_50k
cat("\n\n")
cat("\n\n")
cat(bold("Figure 2: A histogram of different groups with incomes more than $50k␣
 ↪USD"))
```

Figure 1: A histogram of different groups with incomes less than or equal to $50k USD

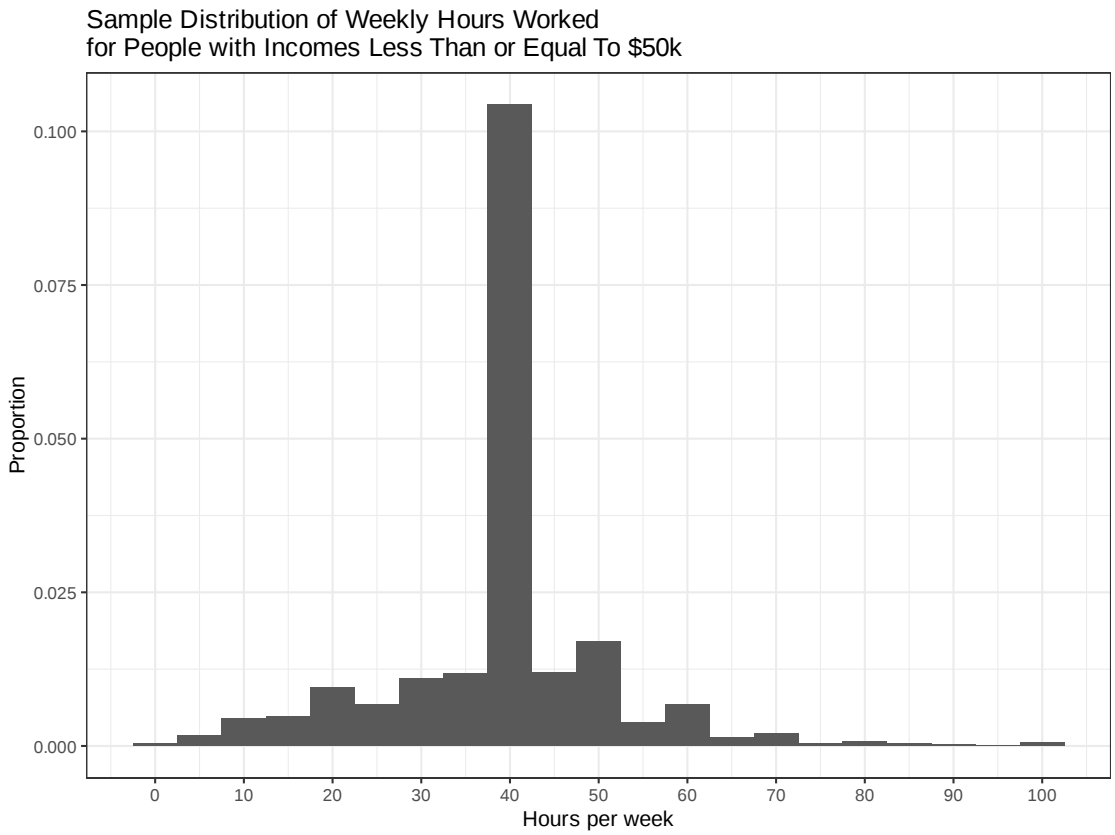
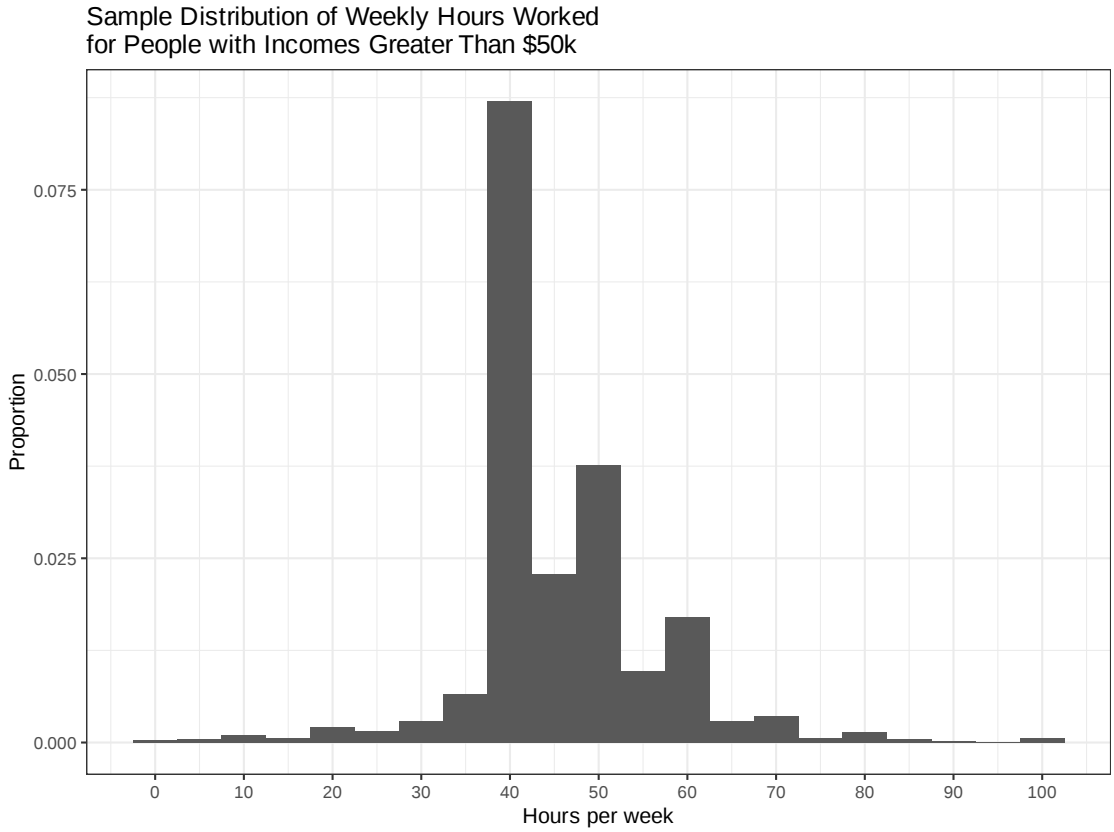


Figure 2: A histogram of different groups with incomes more than $50k USD



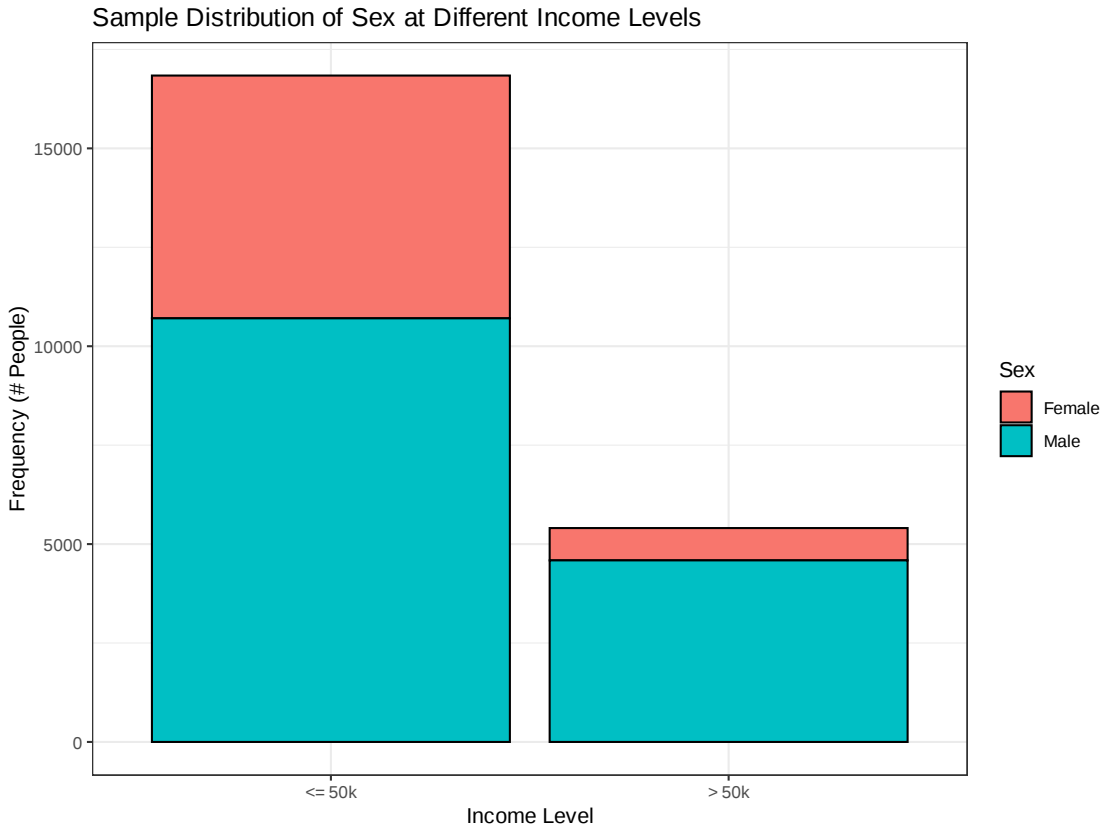
From the plots, we see people who make more than $50k tend to spend more hours working than their lower-income counterparts. Specifically, more data are clustered greater than 40 hours for the higher-income group, while there is a higher density of data below 40 hours for the lower-income group. To disinvolve this potential confounding variable, we will focus on individuals who worked for exactly 40 hours per week.

Sample Distribution of Sex

[7]:
```
sex_plot <- data %>%
    ggplot(aes(x = above_50_k)) +
    geom_bar(aes(fill = sex), position="stack", color='black') +
    scale_x_discrete(labels=c("FALSE" = "<= 50k", "TRUE" = "> 50k")) +
```

```
    labs(x = "Income Level",
         y = "Frequency (# People)",
         fill = "Sex",
         title = "Sample Distribution of Sex at Different Income Levels") +
    theme(text = element_text(size = 16)) +
    theme_bw()
sex_plot
cat("\n\n")
cat(bold("Figure 3: A bar plot for the distribution of sex at each income␣
 ↪level"))
```

Figure 3: A bar plot for the distribution of sex at each income level

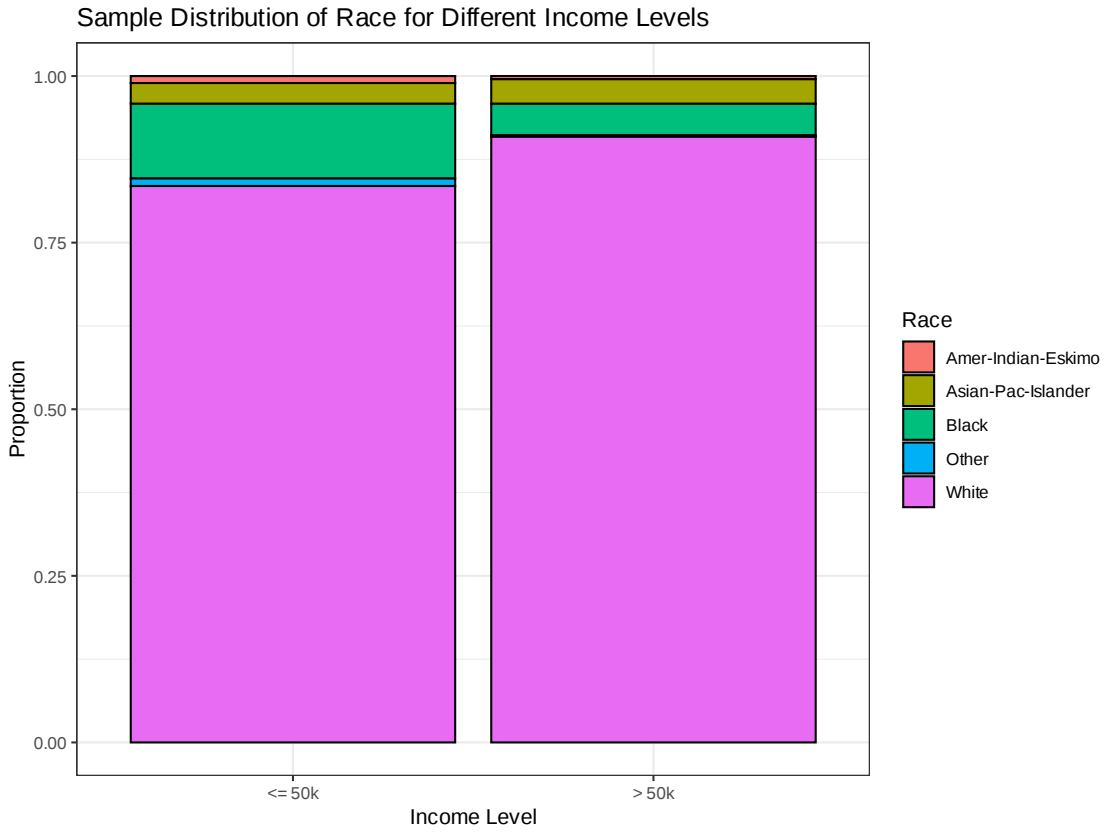


The stacked barplot above shows that the proportion of female people in the low-income group is much higher than that in the high-income group.

Sample Distribution of Race

[8]:
```
race_plot <- data %>%
    ggplot(aes(x = above_50_k)) +
    geom_bar(aes(fill = race), position="fill", color='black') +
    scale_x_discrete(labels=c("FALSE" = "<= 50k", "TRUE" = "> 50k")) +
    labs(x = "Income Level",
         y = "Proportion",
         fill = "Race",
         title = "Sample Distribution of Race for Different Income Levels") +
    theme(text = element_text(size = 16)) +
    theme_bw()
race_plot
cat("\n\n")
cat(bold("Figure 4: A bar plot for the distribution of race at each income␣
 ↪level"))
```

Figure 4: A bar plot for the distribution of race at each income level



In particular, this plot shows that the proportion of Black people in the higher-income group is much lower than that in the lower-income group.

Paramater of Interest: Education and Income Level Our parameters of interest are the proportions of people who make more than 50k per year at each level of education. We present them in a summary table here.

[9]:
```
# 40 hours of work per week only
data_40 <- data %>%
    filter(hours_per_week == 40)

p_tbl <- data_40 %>%
    group_by(education, above_50_k) %>%
    summarize(prop = n()/nrow(data)) %>%
    group_by(education) %>%
    summarize(above_50_k = above_50_k,
              p = round(prop/sum(prop), 4))

cat("\n\n")
cat(bold("Table 4: Proportion of people who make more than 50k with different␣
 ↪eduation backgrounds"))
p_tbl %>% filter(above_50_k == TRUE) %>% select(-above_50_k)
```

```
`summarise()` has grouped output by 'education'. You can override using
the
`.groups` argument.
`summarise()` has grouped output by 'education'. You can override using
the
`.groups` argument.
```

Table 4: Proportion of people who make more than 50k with different eduation backgrounds

A grouped_df: 3 × 2

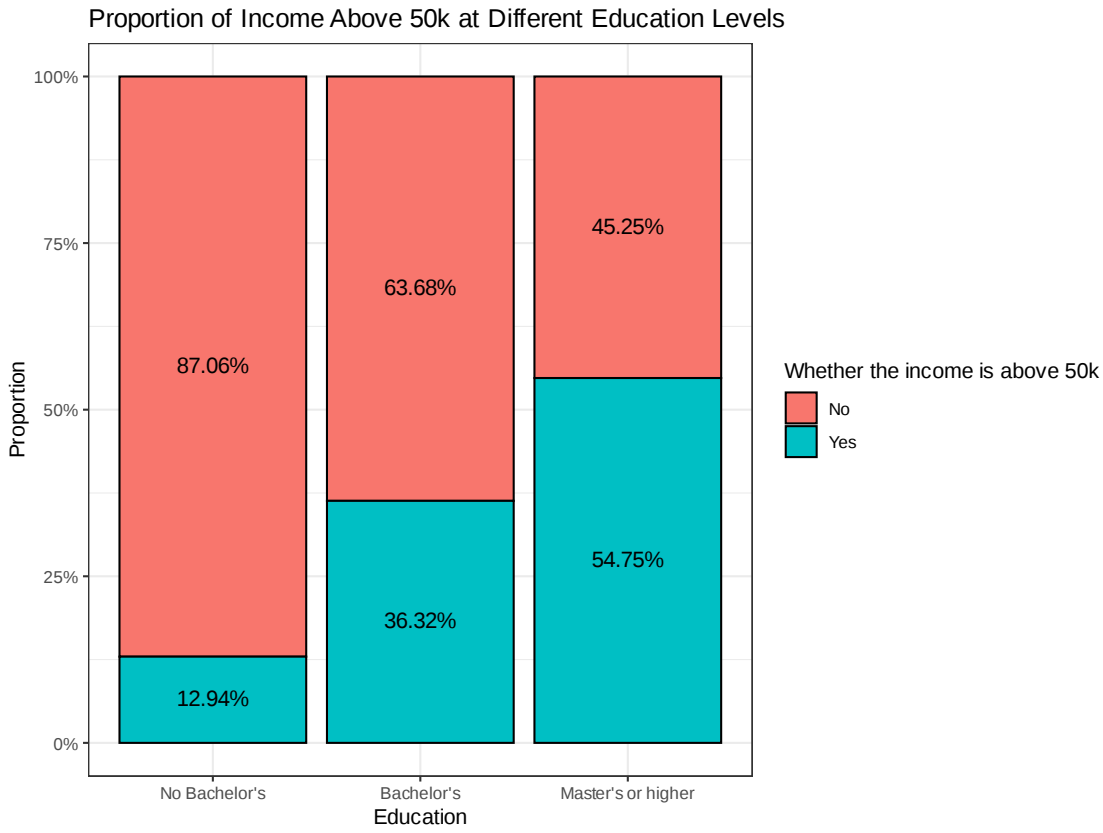
education	p
<fct>	<dbl>
No Bachelor's	0.1294
Bachelor's	0.3632
Master's or higher	0.5475

The following plot allows us to visualize these parameters:

[10]:
```
education_proportion_plot <- p_tbl %>%
  ggplot(aes(x = education, y = p, fill = above_50_k)) +
  geom_bar(position = "fill", stat = "identity", color='black', width=0.9) +
  scale_y_continuous(labels = scales::percent) +
  geom_text(aes(label = paste0(p*100,"%")),
            position = position_stack(vjust = 0.5), size = 4) +
  labs(x = "Education",
       y = "Proportion",
       fill = "Whether the income is above 50k",
```

```
      title = "Proportion of Income Above 50k at Different Education Levels") +
  theme(text = element_text(size = 16)) +
  scale_fill_discrete(labels=c('No', 'Yes')) +
  theme_bw()
education_proportion_plot
cat("\n\n")
cat(bold("Figure 5: A bar plot showing proportion of income above 50k at␣
 ↪different education levels"))
```

Figure 5: A bar plot showing proportion of income above 50k at different education levels



Both from the table and the plot, we see a sharp increase in the proportion of people who make more than 50k as people gain higher educational degree. We will use the statistical inferential method to further demonstrate it.

1.3 3. Methods & Results

The report starts with a clear data cleaning process and clearly defines the parameter of interest and includes descriptive statistics to provide insights. The data is taken from a reliable source through UCI Machine Learning Repository where we have a large sample of an equal representation. However, visualizations and point estimates alone are not sufficient for making informed decisions. To draw robust conclusions, we will conduct hypothesis tests to assess whether the observed differences in the proportions of individuals earning more than $50k across education levels are statistically significant or if they could have occurred due to random chance.

1.3.1 ANOVA test

Since we are dealing with more than two groups, we will first conduct an ANOVA test to see if the differences in proportions of individuals earning more than $50k are significant. The hypothesis tests we are using:

H_0: the proportions of people with an annual salary > 50k are equal among the three educati

H_a: at least one proportion of people with an annual salary > 50k is different to the other

[11]:
```
sample_statistics <- data_40 |>
    group_by(education) |>
    summarize(prop = mean(above_50_k), n = n())

cat("\n\n")
cat(bold("Table 5: A table showing the proportion of incomes above $50k and the␣
 ↪sample size for each education level"))
sample_statistics
```

Table 5: A table showing the proportion of incomes above $50k and the sample size for each education level

	education	prop	n
	<fct>	<dbl>	<int>
A tibble: 3 × 3	No Bachelor's	0.1293915	7543
	Bachelor's	0.3632014	2299
	Master's or higher	0.5475285	789

[12]:
```
cat("\n\n")
cat(bold("Table 6: Summary of the analysis of variance model"))
aov(above_50_k ~ education, data_40) |> tidy()
```

Table 6: Summary of the analysis of variance model

A tibble: 2 × 6

term	df	sumsq	meansq	statistic	p.value
<chr>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
education	2	192.8483	96.424162	649.8767	5.380854e-267
Residuals	10628	1576.9084	0.148373	NA	NA

From this analysis of variance, at a 0.1% significance level we reject the null and conclude that at least one of the proportions is different to the others. We will now run paired z-tests/paired comparisons to find out which ones are different by using asymptotics and computer simulation to the sampling distribution.

1.3.2 Paired z-tests: Asymptotic Approach

Let p_1 and p_2 denote the proportions of people with an annual salary $>$ 50k in the two groups under comparison, where p_2 is always the proportion for the group of the higher educational level. Then the hypothesis tests that we use are:

$H_0 : p_2 - p_1 = 0$

$H_a : p_2 - p_1 > 0$ (or equivalently $H_a : p_1 - p_2 < 0$)

Since the population distribution of whether earning a salary above 50k only takes 0 or 1, we have to rely on the Central Limit Theorem (CLT) to approximate the normality of the sampling distribution. We check if the assumptions for CLT are met:

[13]:
```
pooled_p <- function(p1, p2, n1, n2) {
    return((n1*p1 + n2*p2) / (n1 + n2))}

data1 <- data_40 |> filter(education == "Bachelor's" | education == "No␣
 ↪Bachelor's")
data2 <- data_40 |> filter(education == "Bachelor's" | education == "Master's␣
 ↪or higher")
data3 <- data_40 |> filter(education == "No Bachelor's" | education ==␣
 ↪"Master's or higher")

assumptions <- tibble(sample = c("Bachelor's vs. None", "Master's vs.␣
 ↪Bachelor's", "Master's vs. None"),
                      p_hat = c(pooled_p(sample_statistics$prop[2],␣
 ↪sample_statistics$prop[1], sample_statistics$n[2], sample_statistics$n[1]),
                                pooled_p(sample_statistics$prop[3],␣
 ↪sample_statistics$prop[2], sample_statistics$n[3], sample_statistics$n[2]),
                                pooled_p(sample_statistics$prop[3],␣
 ↪sample_statistics$prop[1], sample_statistics$n[3], sample_statistics$n[1])),
                       n = c(nrow(data1), nrow(data2), nrow(data3))) |>
                  mutate(np = p_hat*n, n1_p = (1-p_hat)*n)

cat("\n\n")
cat(bold("Table 7: A table for comparison assumptions for education-level␣
 ↪proportions"))
assumptions
```

Table 7: A table for comparison assumptions for education-level proportions

	sample	p_hat	n	np	n1_p
	<chr>	<dbl>	<int>	<dbl>	<dbl>
A tibble: 3 × 5	Bachelor's vs. None	0.1840073	9842	1811	8031
	Master's vs. Bachelor's	0.4102979	3088	1267	1821
	Master's vs. None	0.1689870	8332	1408	6924

From the `np` and `n1_p` columns, we see our sample size is large enough that $n\hat{p}$ and $n(1-\hat{p})$ for all three subgroups that contain two education levels are much larger than 10. Thus, we confirm that the approximation of the sampling distribution under H_0 of the test statistic Z by $N(0,1)$ is good.

Now we compute the test statistics Z and its corresponding p-values.

[14]:
```
test_z <- function(p1, p2, n1, n2) {
    pooled = (n1*p1 + n2*p2) / (n1 + n2)
    return((p1 - p2) / sqrt(pooled*(1 - pooled) * (1/n1 + 1/n2)))
}
test_statistics <- tibble(test = c("Bachelor's vs. None", "Master's vs.␣
 ↪Bachelor's", "Master's vs. None"),
                          z = c(test_z(sample_statistics$prop[2],␣
 ↪sample_statistics$prop[1], sample_statistics$n[2], sample_statistics$n[1]),
                                test_z(sample_statistics$prop[3],␣
 ↪sample_statistics$prop[2], sample_statistics$n[3], sample_statistics$n[2]),
                                test_z(sample_statistics$prop[3],␣
 ↪sample_statistics$prop[1], sample_statistics$n[3], sample_statistics$n[1])))␣
 ↪|>
    mutate(p_value = pnorm(-z))

cat("\n\n")
cat(bold("Table 8: A table for Z-test statistics and P-values for␣
 ↪education-level proportion comparisons"))
test_statistics
```

Table 8: A table for Z-test statistics and P-values for education-level proportion comparisons

	test	z	p_value
	<chr>	<dbl>	<dbl>
A tibble: 3 × 3	Bachelor's vs. None	25.328069	7.839183e-142
	Master's vs. Bachelor's	9.082232	5.318526e-20
	Master's vs. None	29.821120	1.039981e-195

Since we implement three z-tests at a time, we do p-value correction by using the Bonferroni

adjustment.

[15]:
```
test_statistics <- test_statistics |>
    mutate(p_value = p.adjust(p_value, method = "bonferroni"))

cat("\n\n")
cat(bold("Table 9: Adjusted P-values using Bonferroni correction for␣
 ↪education-level proportion comparisons"))
test_statistics
```

Table 9: Adjusted P-values using Bonferroni correction for education-level proportion comparisons

A tibble: 3 × 3

test	z	p_value
<chr>	<dbl>	<dbl>
Bachelor's vs. None	25.328069	2.351755e-141
Master's vs. Bachelor's	9.082232	1.595558e-19
Master's vs. None	29.821120	3.119944e-195

At a 0.1% significance level, we reject all three null hypotheses and conclude that people with bachelor's degrees indeed had a higher chance of earning more than $50,000 annually than people without, and people with master's degrees had a still higher chance of earning higher than this level.

1.3.3 Paired Comparison: Computer-based Approach

Then we want to confirm the results by repeating the hypothesis tests using the bootstrapping method, seeing if it would be consistent to the asymptotics approach.

[16]:
```
n_resamples <- 3000
n_comparisons <- choose(3, 2)
null_model <- function(data, edu1, edu2) {
    data %>%
    specify(formula = above_50_k ~ education, success = "TRUE") %>%
    hypothesize(null = "independence") %>%
    generate(reps = n_resamples, type = "permute") %>%
    calculate(stat = "diff in props", order = c(edu1, edu2))
}
```

[17]:
```
# observed statistics
non_bachelor_bachelor_diff <- sample_statistics$prop[1] -␣
 ↪sample_statistics$prop[2]
bachelor_master_diff <- sample_statistics$prop[2] - sample_statistics$prop[3]
non_bachelor_master_diff <- sample_statistics$prop[1] -␣
 ↪sample_statistics$prop[3]
```

[18]:
```
# simulation-based distribution
null_model_non_bachelor_bachelor <- null_model(data1, "No Bachelor's",␣
 ↪"Bachelor's")
null_model_bachelor_master <- null_model(data2, "Bachelor's", "Master's or␣
 ↪higher")
null_model_non_bachelor_master <- null_model(data3, "No Bachelor's", "Master's␣
 ↪or higher")
```

```
Dropping unused factor levels Master's or higher from the supplied explanatory
variable 'education'.

Dropping unused factor levels No Bachelor's from the supplied explanatory
variable 'education'.

Dropping unused factor levels Bachelor's from the supplied explanatory variable
'education'.
```

We want to visualize the null model and the observed statistics.

[19]:
```
non_bachelor_bachelor_plot <-
    null_model_non_bachelor_bachelor %>%
    visualize() +
    shade_p_value(obs_stat = non_bachelor_bachelor_diff, direction = "left") +
    xlab("Difference in proportions") +
    theme(text = element_text(size = 16)) +
    ggtitle("Simulated null distribution", subtitle = "Non Bachelor's vs.␣
 ↪Bachelor's")

bachelor_master_plot <-
    null_model_bachelor_master %>%
    visualize() +
    shade_p_value(obs_stat = bachelor_master_diff, direction = "left") +
    xlab("Difference in proportions") +
    theme(text = element_text(size = 16)) +
    ggtitle("Simulated null distribution", subtitle = "Bachelor's vs. Master's␣
 ↪or higher")

non_bachelor_master_plot <-
    null_model_non_bachelor_master %>%
    visualize() +
    shade_p_value(obs_stat = non_bachelor_master_diff, direction = "left") +
    xlab("Difference in proportions") +
    theme(text = element_text(size = 16)) +
    ggtitle("Simulated null distribution", subtitle = "Non Bachelor's vs.␣
 ↪Master's or higher")

non_bachelor_bachelor_plot
```

```
cat("\n\n")
cat(bold("Figure 6: Non Bachelor's Vs Bachelor's"))
bachelor_master_plot
cat("\n\n")
cat(bold("Figure 7: Bachelor's Vs Master's"))
non_bachelor_master_plot
cat("\n\n")
cat(bold("Figure 8: Non Bachelor's Vs Masters's"))
```

Figure 6: Non Bachelor's Vs Bachelor's

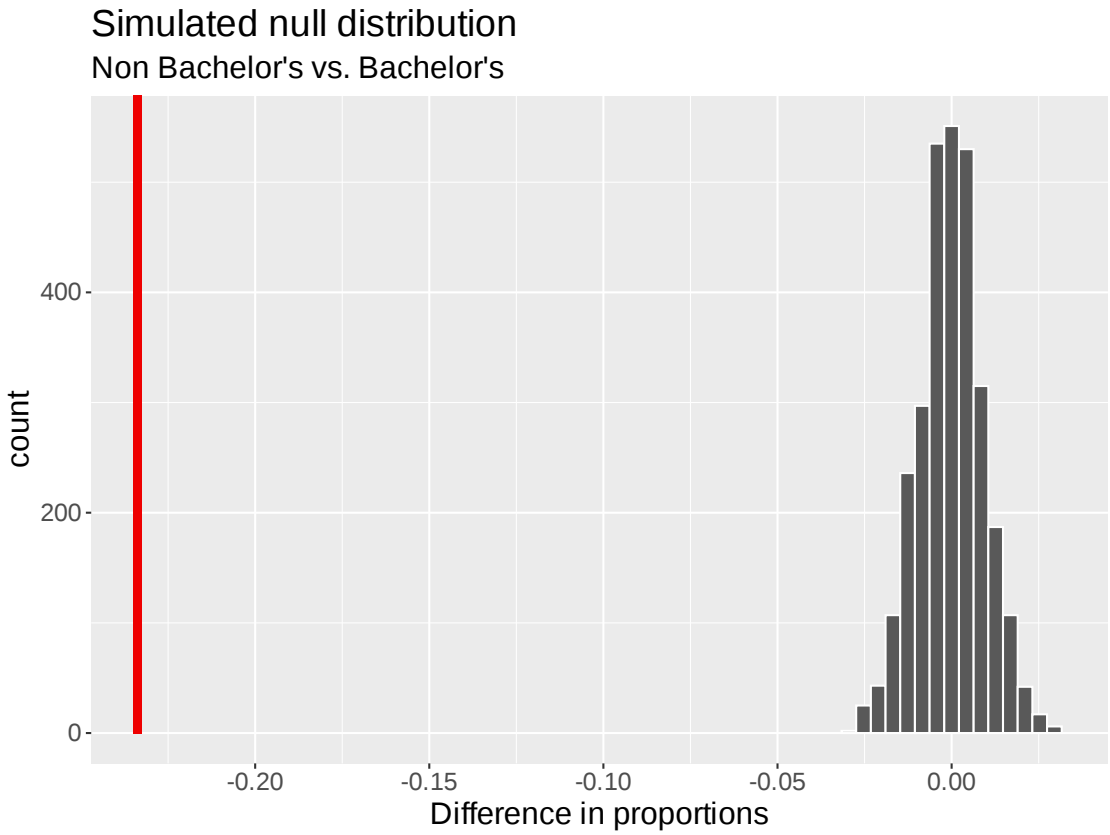


Figure 7: Bachelor's Vs Master's

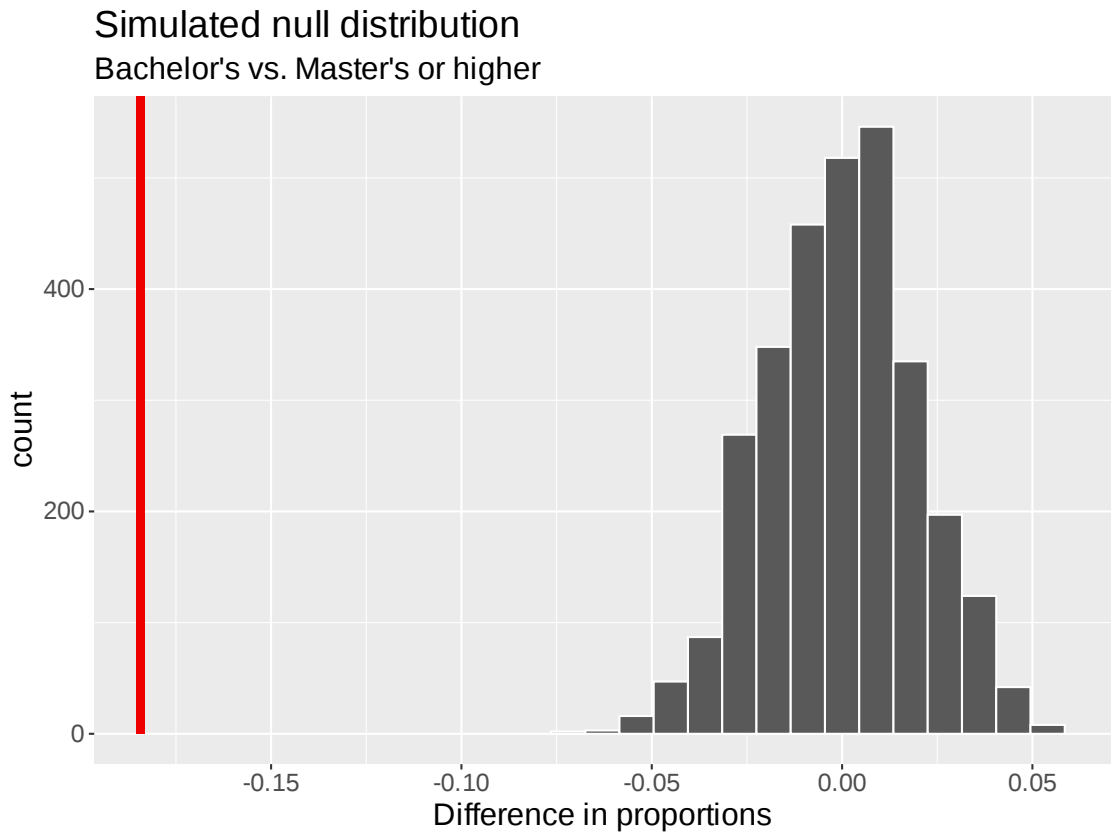
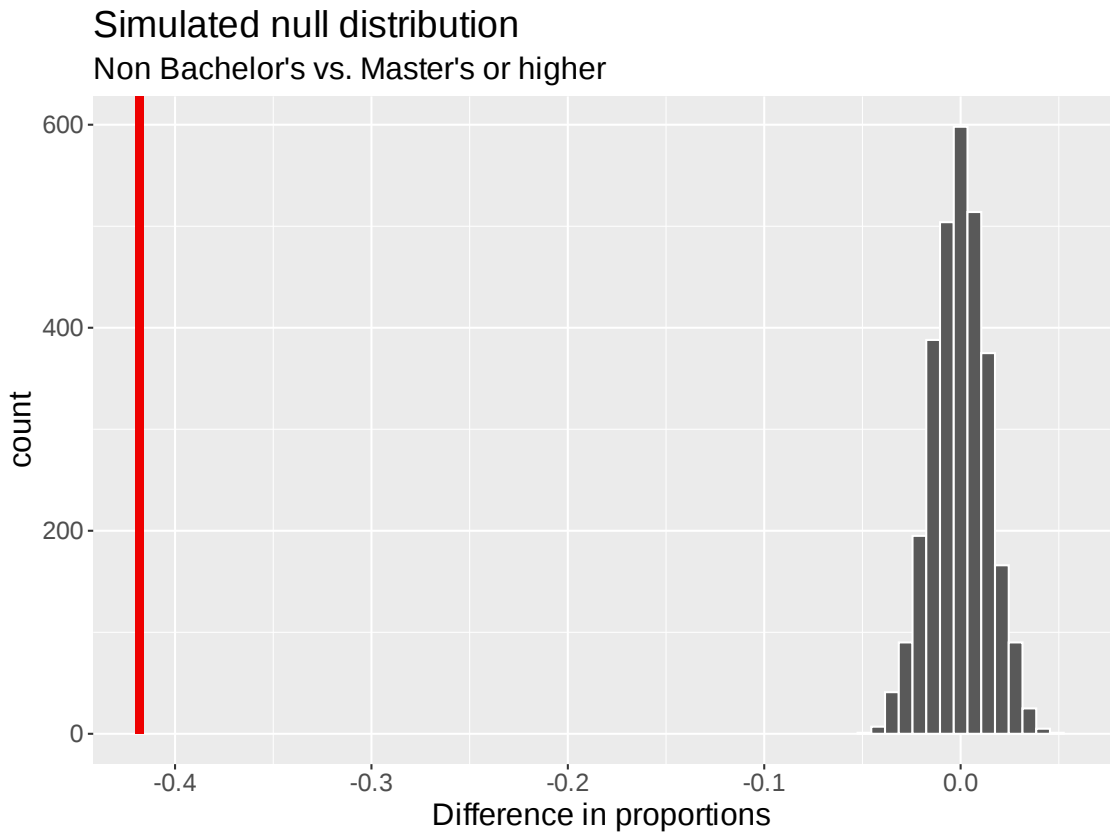


Figure 8: Non Bachelor's Vs Masters's



The plots show that it is very unlikely to obtain the observed differences in proportions if the null hypotheses are true. To confirm it, we compute the p-value:

[20]:
```
non_bachelor_bachelor_p_value <-
    null_model_non_bachelor_bachelor %>%
    get_p_value(obs_stat = non_bachelor_bachelor_diff, direction = "left")

bachelor_master_p_value <-
    null_model_bachelor_master %>%
    get_p_value(obs_stat = bachelor_master_diff, direction = "left")

non_bachelor_master_p_value <-
    null_model_non_bachelor_master %>%
    get_p_value(obs_stat = non_bachelor_master_diff, direction = "left")

bootstrapping_test_results <-
    tibble(test = c("Bachelor's vs. None", "Master's vs. Bachelor's", "Master's␣
 ↪vs. None"),
           p_value = c(non_bachelor_bachelor_p_value, bachelor_master_p_value,␣
 ↪non_bachelor_master_p_value))
```

```
bootstrapping_test_results
cat("\n\n")
cat(bold("Table 10: Computer-based Paired Test Results"))
```

```
Warning message:
"Please be cautious in reporting a p-value of 0. This result is an approximation
based on the number of `reps` chosen in the `generate()` step. See
`?get_p_value()` for more information."
Warning message:
"Please be cautious in reporting a p-value of 0. This result is an approximation
based on the number of `reps` chosen in the `generate()` step. See
`?get_p_value()` for more information."
Warning message:
"Please be cautious in reporting a p-value of 0. This result is an approximation
based on the number of `reps` chosen in the `generate()` step. See
`?get_p_value()` for more information."
```

A tibble: 3 × 2

test	p_value
<chr>	<named list>
Bachelor's vs. None	0
Master's vs. Bachelor's	0
Master's vs. None	0

Table 10: Computer-based Paired Test Results

Again we need to do a p-value correction since we are conducting multiple tests on the same dataset simultaneously. We also replace any zero p-values obtained in this step with an appropriate constraint on the p-value based on the number of resamples.

[21]:
```
bootstrapping_test_results <- bootstrapping_test_results |>
    mutate(p_value = p.adjust(p_value, method = "bonferroni")) |>
    mutate(p_value = ifelse(p_value == 0,
                            paste("<", p.adjust(1/n_resamples, method =␣
 ↪"bonferroni", n = n_comparisons)),
                            p_value))

cat("\n\n")
cat(bold("Table 11: Computer-based Paired Test Results After Correction"))
bootstrapping_test_results
```

Table 11: Computer-based Paired Test Results After Correction

	test	p_value
	<chr>	<chr>
A tibble: 3 × 2	Bachelor's vs. None	< 0.001
	Master's vs. Bachelor's	< 0.001
	Master's vs. None	< 0.001

Again at a 0.1% significance level, we reject all three null hypotheses and conclude that people with bachelor's degrees indeed had a higher chance of earning more than $50,000 annually than people without, and people with master's degrees had a still higher chance.

1.3.4 Comparison between Asymptotics and Computer-based Simulation

The asymptotic and computer-based methods give the similar result that higher educational level is associated with an higher average salary. This is explainable since we can infer from the observed differences in proportions that the effect size of our tests are fairly large, so that both methods would give significant results.

However, since the computer-simulation method does not rely on any assumptions to the data (for example, we are unclear about the data sampling procedure and thus conclude the data are independent), its result would be more accurate and reliable.

1.4 Discussions

Summarize what you found, and the implications/impact of your findings

The research concluded that individuals with bachelor's degrees indeed have a higher chance of making over $50,000 USD compared to those who do not have such an education.

An ANOVA test determined whether there was a major difference in the proportions of individuals earning more than \$50,000 USD at a 0.1% significance level, where we rejected the hypothesis of people with an annual salary of \$50,000 USD or more was equal among the three education levels, concluding at least one of the proportions were different compared to the others.

To follow up, two different test approaches were conducted: a paired Z-test asymptotic approach relying on the Central Limit Theorem and a paired comparison computer-based approach. In both methodologies, at a 0.1% significance level, we reject all three null hypotheses and conclude that people with a bachelor's degree indeed had a higher chance of earning more than non bachelors', and those with masters had even higher of a chance.

The findings could have several implications that would impact educational policies, career choices, and income inequality.

Educational Policies: Since the study found a significant association between higher education levels and increased chances of earning at least $50,000 USD, it may emphasize the importance of educational policies that encourages higher education and skill development. Perhaps this may be in the form of government funding to incentives more individuals to pursue further education.

Career Choices: The findings may impact individuals' career choices and motivations to pursue further education. This might be through investing their years in some sort of post-secondary education to improve their potential earnings as well as selecting degree-required positions. However, this may consequently result in industries that do not necessarily require post-secondary education having a shortage of workers.

Income Inequality: The results can seek out underscore the importance of addressing educational disparities to reduce income inequality, as those who may lack access or are limited to higher education may miss this opportunity to move upwards in their individual economic mobility. As children born in perhaps "better" and richer neighbourhoods have greater exposure to educational assistance such as tutors and academic programs.

If relevant, discuss whether your results were what you expected to find

From the investigation, it seems like the result supports the claim that a higher level of education leads to higher earnings, as individuals with higher education levels (e.g., college or advanced degrees) have a higher likelihood of earning at least $50,000 compared to those with lower education levels (e.g., high school or lower). Previous studies compared community college graduates with individuals with a four-year bachelor's degree and it was "consistently revealed that 2-year entrants" would have a "lower salary growth than their 4-year sector counterparts" (González Canché, 2016). By following analogous patterns, we would anticipate observing similar outcomes.

Discuss future questions/research this study could lead to

Upon analyzing the final results, a natural progression would be to further establish the causation by asking some follow-up questions; Does higher education directly cause higher income or are there other intricating factors involved? It is imperative to distinguish between correlation—merely a connection between variables—and causation, where one directly instigates changes in the other.

Additional research could focus on exploring other factors that may mediate the relationship between education and income, such as job experience. Studies can be conducted on the long-term and short-term effects, such as the trajectories of salary growth with post-education required careers. Perhaps one may want to research the type of education or degrees one pursues and if they can vary the income. Besides, from the preliminary results, gender and racial equality may be issues related to job opportunities which could mediate the relationship between education and income. Future research should take them into account and avoid the potential confounding effects.

The study itself may raise questions about the determinants of income, such as job market conditions, job availability, and other industry factors. For instance, the economic consequences of the coronavirus led to the over-saturation of technological job positions, which caused a subsequent decline in career opportunities post-pandemic. In essence, studying the relationship between education levels and income status can yield valuable insights into the significant role that education potentially plays in economic outcomes.

1.5 References

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