Analysis of Ontario wages in relation to economic factors based on Ontario Data Catalogue (1997-2019)

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1 Loading the Data

We will use the following data sets:

```r
wages = read.csv("wages.csv") %>% mutate_if(is.character, str_trim)

wages$Education.level =
  factor(wages$Education.level,
         levels = c("Above bachelor's degree",
                    "Bachelor's degree",
                    "University certificate below bachelors degree",
                    "University degree",
                    "Community college, CEGEP",
                    "Trade certificate or diploma",
                    "Post-secondary certificate or diploma",
                    "Some post-secondary",
                    "High school graduate",
                    "Some high school",
                    "PSE  (5,6,7,8,9))",
                    "No PSE  (0,1,2,3,4)",
                    "0 - 8  years",
                    "Total, all education levels"),
         ordered = TRUE)

wages$Age.group =
  factor(wages$Age.group,
         levels = c("25-64 years",
                    "25-54 years",
                    "25-34 years",
                    "20-34 years",
                    "15-24 years",
                    "55 years and over",
                    "25 years and over",
                    "15 years and over"),
         ordered = TRUE)

# Fuel
fuel = read.csv("fuel.csv") %>% mutate_if(is.character, str_trim)

fuel <- fuel %>% rename(
  Toronto.West = Toronto.West.Ouest,
  Toronto.East = Toronto.East.Est,
  St.Catharine = St..Catharine.s,
  Ontario.Average = Ontario.Average.Moyenne.provinciale,
  Southern.Average.Ontario = Southern.Average.Moyenne.du.sud.de.l.Ontario,
  Northern.Average.Ontario = Northern.Average.Moyenne.du.nord.de.l.Ontario
) %>% select(!(Type.de.carburant))
```

2 Description of the Data set

2.1 Wages by education level

The `wages` data set includes the average weekly wages rates by education level and immigration status for Canada and Ontario in the years from 1997 to 2019. It includes the following columns:

```
names(wages)
```

```
## [1] "YEAR"            "Geography"       "Type.of.work"    "Wages"
## [5] "Education.level" "Age.group"       "Both.Sexes"      "Male"
## [9] "Female"
```

1. `YEAR`: Indicates the year in which the data was collected.
2. `Geography`: Indicates the region from which the data was collected. Its possible values include Canada as well as the Canadian provinces and territories.
3. `Type.of.work`: Indicates whether the data in the row is for full-time employees or part-time employees or both.
4. `Wages`:
    1. `Total employees`: The number of employees in the given age range, education level, and job status.
    2. `Average hourly wage rate`: The average hourly wage of the employees in the given age range, education level, and job status.
    3. And so on for `Average weekly wage rate`, `Median hourly wage rate`, and `Median weekly wage rate`.
5. `Education.level`: Indicates the level of education. It can include the following:

Education.level
Above bachelor's degree
Bachelor's degree
University certificate below bachelors degree
University degree
Community college, CEGEP
Trade certificate or diploma
Post-secondary certificate or diploma
Some post-secondary
High school graduate
Some high school
PSE (5,6,7,8,9))
No PSE (0,1,2,3,4)
0 - 8 years
Total, all education levels

6. `Age.group`: Indicates the age range of the individuals under consideration. It can include the following:

Age.group
25-64 years
25-54 years
25-34 years
20-34 years
15-24 years
55 years and over
25 years and over
15 years and over

7. `Both.sexes`: The data not seperated by gender.
8. `Male`: The data for males.
9. `Female`: The data for females.

2.2 Fuels price survey information

```
names(fuel)
```

```
##  [1] "Date"                      "Ottawa"
##  [3] "Toronto.West"              "Toronto.East"
##  [5] "Windsor"                   "London"
##  [7] "Peterborough"              "St.Catharine"
##  [9] "Sudbury"                   "Sault.Saint.Marie"
## [11] "Thunder.Bay"               "North.Bay"
## [13] "Timmins"                   "Kenora"
## [15] "Parry.Sound"               "Ontario.Average"
## [17] "Southern.Average.Ontario" "Northern.Average.Ontario"
## [19] "Fuel.Type"
```

1. `Date`: Indicates the date on which the data was collected.
2. `Fuel Price`: Represents the price of fuel.
3. `Ottawa`, `Toronto.West`, `Toronto.East`, `Windsor`, `London`, `Peterborough`, `St.Catharine`, `Sudbury`, `Sault.Saint.Marie`, `Thunder.Bay`, `North.Bay`, `Timmins`, `Kenora`, `Parry.Sound`: Represents the fuel price in various locations in Ontario, Canada.
4. `Ontario.Average`: Indicates the average fuel price across different regions of Ontario.
5. `Southern.Average.Ontario`: Indicates the average fuel price across the southern regions of Ontario.
6. `Northern.Average.Ontario`: Indicates the average fuel price across the northern regions of Ontario.
7. `Fuel.Type`: Indicates the type of fuel associated with the data.

3 The Background of the Data

The labor and demographic dataset from the Ministry of Labour, Immigration, Training, and Skills Development provides insights into Ontario's workforce demographics, including age groups, employment types, educational levels, wages, and immigration statuses. It is annually updated and used by policymakers, researchers, and economists to inform decisions regarding education, training, workforce development, and immigration policies in the province.

Additionally, fuel price survey information from the Ministry of Energy offers weekly retail prices for gasoline, diesel, auto propane, and compressed natural gas across ten Ontario markets. This data aids in monitoring fuel price fluctuations and analyzing trends in the energy sector, supporting research and analysis efforts in economics, environmental studies, and energy policy.

4 Overall Research Question

4.1 Trend Analysis

- How has the average hourly wage rate changed over the years across different age groups?
- Are there any noticeable trends in the median weekly wage rate for full-time employees over the past decade?
- What is the overall trend in the number of full-time employees versus part-time employees across different age groups?

4.2 Regional Disparities

- How do average hourly wage rates vary between different Canadian provinces and territories?
- Are there significant differences in the employment rates between urban and rural areas within a specific province?

4.3 Educational Attainment

- How does the average hourly wage rate differ across various education levels?
- Are there any trends in the employment rates based on different levels of education attainment?
- Is there a correlation between educational attainment and the likelihood of being employed full-time versus part-time?

4.4 Age Groups Analysis

- How do wage rates vary across different age groups, and is there a trend in wage growth as individuals age?
- Are there noticeable differences in employment rates between younger and older age groups?
- What is the distribution of educational attainment among different age groups, and how does it correlate with employment status and wage rates?

4.5 Gender Analysis

- Is there a significant gender wage gap, and how has it evolved over time?
- Are there differences in the distribution of employment types (full-time vs. part-time) between males and females?
- How does educational attainment affect the gender wage gap within specific age groups or regions?

4.6 Overall Employment Trends

- How has the total number of employees changed over the years?
- Are there seasonal variations in employment rates or wage rates within certain industries?
- What industries or sectors have shown the highest growth in employment rates, and how does this correlate with wage rates?

5 Summary

5.1 How has the average hourly wage rate changed over the years across different age groups?

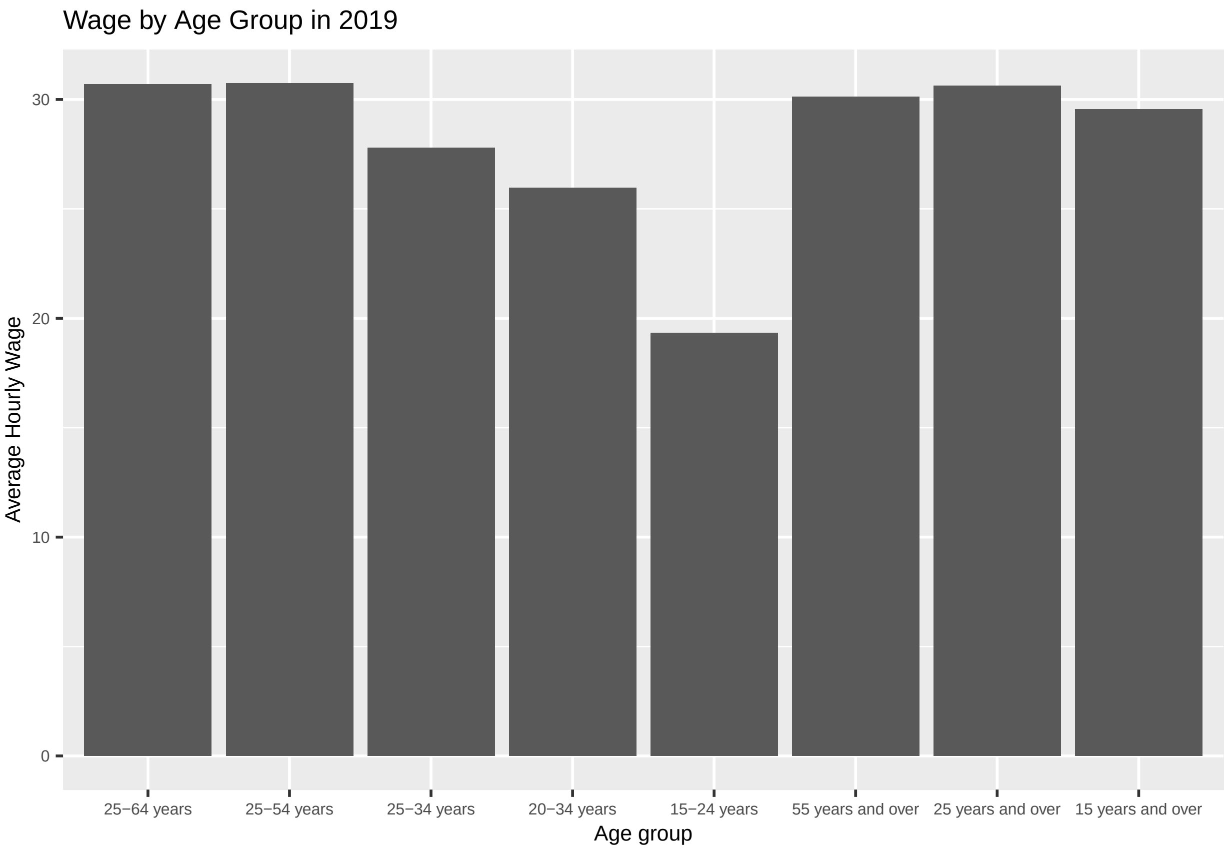
```r
avg_wage_by_age <- wages %>%
  filter(Wages == "Average hourly wage rate",
         Geography == "Canada",
         Type.of.work == "Full-time",
         Education.level == "Total, all education levels") %>%
  select(YEAR, Age.group, Both.Sexes) %>%
  group_by(YEAR, Age.group) %>%
  summarise(Avg_Hourly_Wage = mean(Both.Sexes))
```

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

```r
kable(avg_wage_by_age %>%
  pivot_wider(names_from = Age.group, values_from = Avg_Hourly_Wage))
```

YEAR	25-64 years	25-54 years	25-34 years	20-34 years	15-24 years	55 years and over	25 years and over	15 years and over
1997	17.41	17.35	15.29	14.08	9.82	17.92	17.40	16.54
1998	17.64	17.57	15.66	14.41	10.06	18.15	17.62	16.76
1999	18.13	18.06	16.11	14.77	10.33	18.65	18.11	17.19
2000	18.69	18.63	16.72	15.31	10.81	19.04	18.67	17.72
2001	19.28	19.23	17.48	15.97	11.21	19.63	19.27	18.29
2002	19.87	19.80	17.94	16.34	11.37	20.19	19.84	18.83
2003	20.28	20.19	18.15	16.55	11.66	20.85	20.26	19.24
2004	20.80	20.70	18.54	16.88	11.77	21.31	20.77	19.71
2005	21.44	21.32	19.25	17.50	12.23	21.98	21.41	20.32
2006	22.12	22.03	19.94	18.15	12.84	22.56	22.10	20.99
2007	22.91	22.84	20.77	18.94	13.40	23.07	22.87	21.74
2008	23.86	23.77	21.69	19.81	14.06	24.16	23.83	22.67
2009	24.60	24.55	22.32	20.47	14.57	24.63	24.56	23.48
2010	25.09	24.98	22.70	20.86	14.76	25.39	25.04	23.97
2011	25.54	25.45	23.16	21.29	15.13	25.73	25.50	24.42
2012	26.27	26.20	23.92	21.98	15.50	26.31	26.22	25.13
2013	26.85	26.76	24.35	22.36	15.86	27.02	26.81	25.70
2014	27.33	27.29	24.89	22.87	16.20	27.25	27.28	26.17
2015	28.10	28.14	25.64	23.52	16.53	27.57	28.03	26.88
2016	28.69	28.66	26.18	24.05	16.81	28.48	28.62	27.47
2017	29.12	29.16	26.55	24.41	17.01	28.49	29.03	27.88
2018	29.75	29.75	27.10	25.07	17.96	29.38	29.68	28.56
2019	30.69	30.75	27.79	25.97	19.32	30.12	30.62	29.56

```r
ggplot(avg_wage_by_age %>% filter(YEAR == "2019"),
       aes(x = Age.group, Avg_Hourly_Wage)) +
  geom_bar(stat = "identity") +
  labs(x = "Age group",
       y = "Average Hourly Wage",
       title = "Wage by Age Group in 2019") +
  theme(text = element_text(size = 8))
```



From the data, we can observe the following trends:

1. Across all age groups, there is a general trend of increasing average hourly wage rates over the years.
2. The wage rates tend to increase with age, with the highest rates typically observed in the 55 years and over age group.
3. The 15-24 years age group consistently has the lowest average hourly wage rates, which gradually increase as individuals move into older age groups.

These observations provide an overview of how the average hourly wage rates have changed over the years across different age groups.

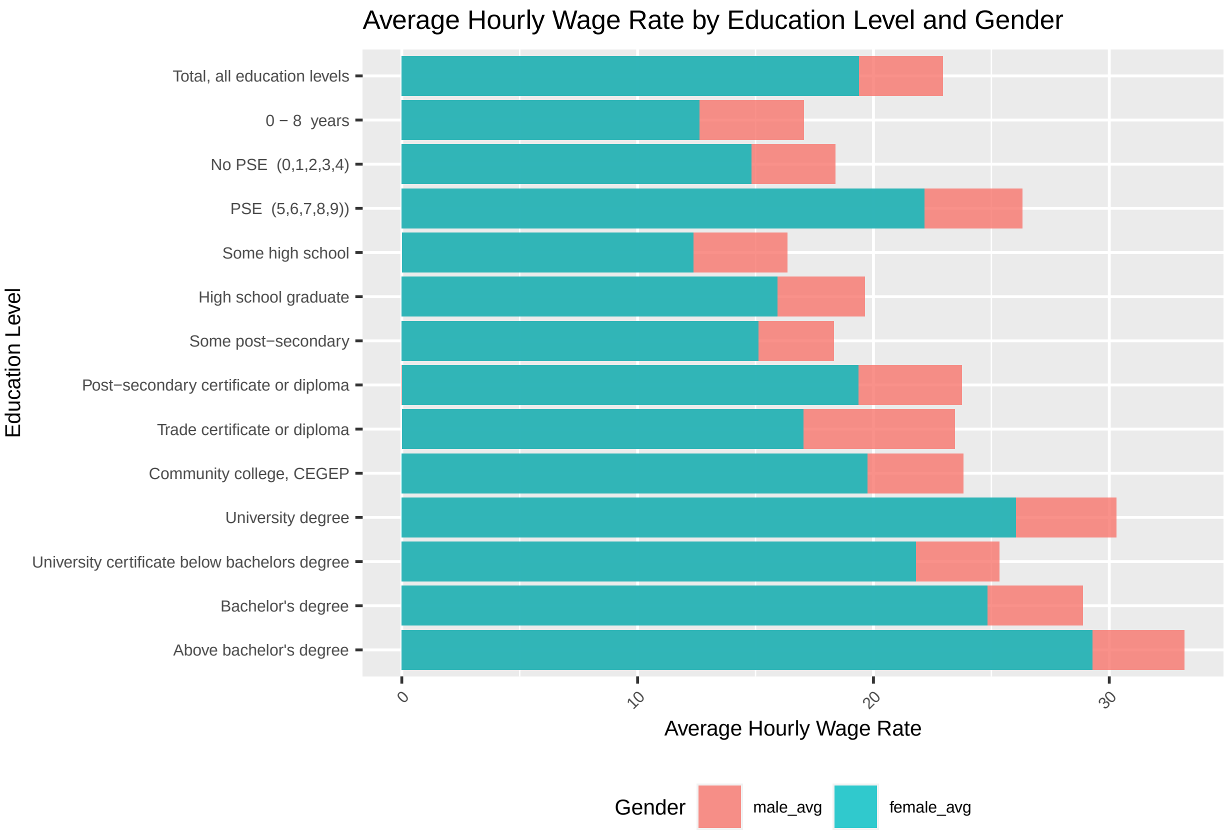
5.2 How does the average hourly wage rate differ across various education levels for different genders?

```
avg_wage_by_education <- wages %>%
  filter(Wages == "Average hourly wage rate",
         Geography == "Canada",
         Age.group == "15 years and over",
         Type.of.work == "Both full- and part-time") %>%
  select(Education.level, Male, Female) %>%
  group_by(Education.level) %>%
  summarise(male_avg = mean(Male),
            female_avg = mean(Female))

kable(avg_wage_by_education)
```

Education.level	male_avg	female_avg
Above bachelor’s degree	33.18565	29.29043
Bachelor’s degree	28.89087	24.83000
University certificate below bachelors degree	25.33957	21.80435
University degree	30.29478	26.04565
Community college, CEGEP	23.81000	19.74957
Trade certificate or diploma	23.44783	17.01913
Post-secondary certificate or diploma	23.75652	19.35348
Some post-secondary	18.32478	15.12348
High school graduate	19.64739	15.93130
Some high school	16.34565	12.35565
PSE (5,6,7,8,9))	26.32174	22.16043
No PSE (0,1,2,3,4)	18.38304	14.83043
0 - 8 years	17.05087	12.62870
Total, all education levels	22.94130	19.38304

```
ggplot(avg_wage_by_education %>% melt(),
       aes(x = Education.level, fill = variable)) +
  geom_bar(aes(y = value),
           stat = "identity",
           alpha = 0.8,
           show.legend = TRUE,
           position = position_identity()) +
  labs(title = "Average Hourly Wage Rate by Education Level and Gender",
       x = "Education Level",
       y = "Average Hourly Wage Rate",
       fill = "Gender") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1),
        text = element_text(size = 8),
        legend.position = "bottom") +
  coord_flip()
```

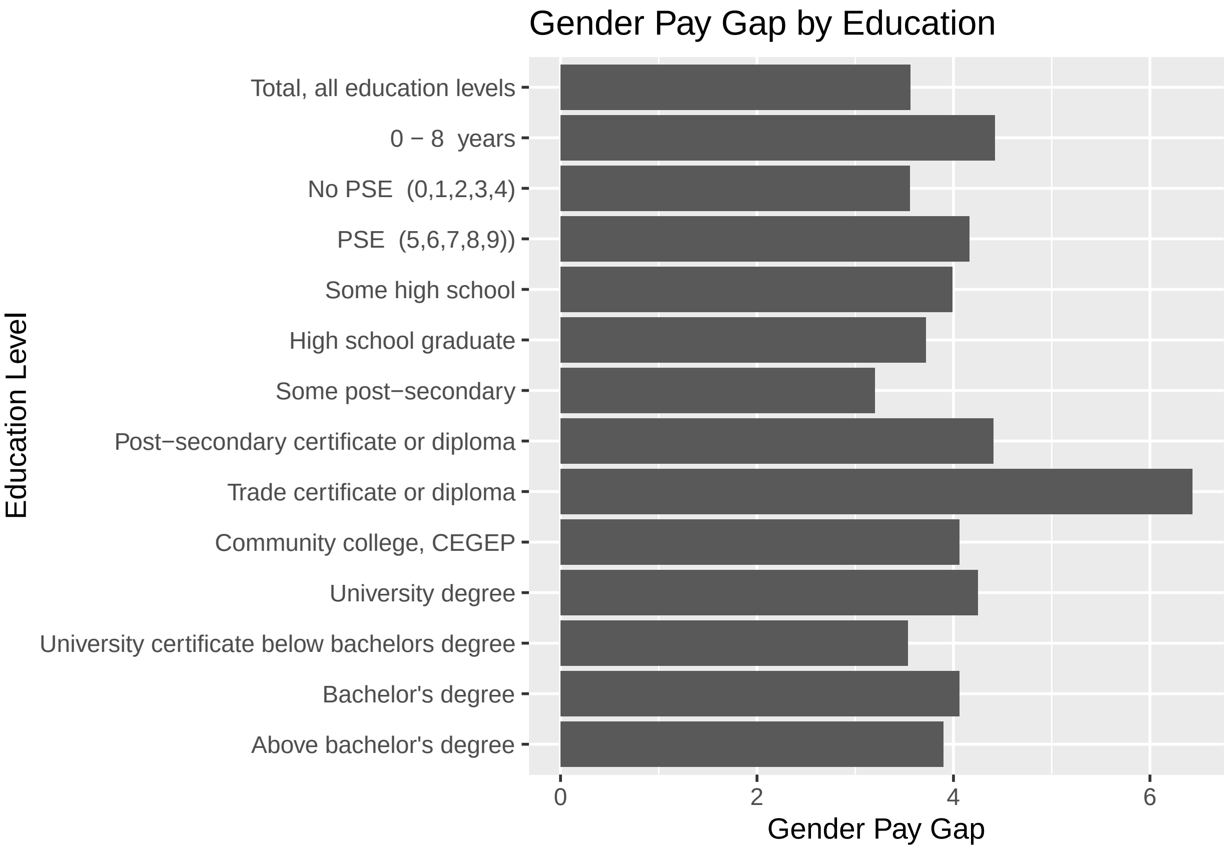
```
## Using Education.level as id variables
```



```
kable(avg_wage_by_education %>%
  mutate(pay.gap = male_avg - female_avg))
```

Education.level	male_avg	female_avg	pay.gap
Above bachelor's degree	33.18565	29.29043	3.895217
Bachelor's degree	28.89087	24.83000	4.060870
University certificate below bachelors degree	25.33957	21.80435	3.535217
University degree	30.29478	26.04565	4.249130
Community college, CEGEP	23.81000	19.74957	4.060435
Trade certificate or diploma	23.44783	17.01913	6.428696
Post-secondary certificate or diploma	23.75652	19.35348	4.403043
Some post-secondary	18.32478	15.12348	3.201304
High school graduate	19.64739	15.93130	3.716087
Some high school	16.34565	12.35565	3.990000
PSE (5,6,7,8,9))	26.32174	22.16043	4.161304
No PSE (0,1,2,3,4)	18.38304	14.83043	3.552609
0 - 8 years	17.05087	12.62870	4.422174
Total, all education levels	22.94130	19.38304	3.558261

```
ggplot(avg_wage_by_education %>% mutate(pay.gap = male_avg - female_avg),
       aes(x = Education.level, y = pay.gap)) +
  geom_bar(stat = "identity") +
  labs(y = "Gender Pay Gap",
       x = "Education Level",
       title = "Gender Pay Gap by Education") +
  coord_flip()
```



Observations:

1. In almost all cases, the average hourly wage for males is higher than for females across various education levels.
2. The largest wage gaps are observed at "Trade certificate or diploma" where
3. At higher education levels, such as "Above bachelor's degree" and "Bachelor's degree", the wage gap is relatively smaller compared to lower education levels but still exists.

These observations highlight disparities in wages between genders across different education levels, indicating the presence of gender-based wage inequality.

5.3 What is the overall trend in the number of full-time employees versus part-time employees across different age groups?

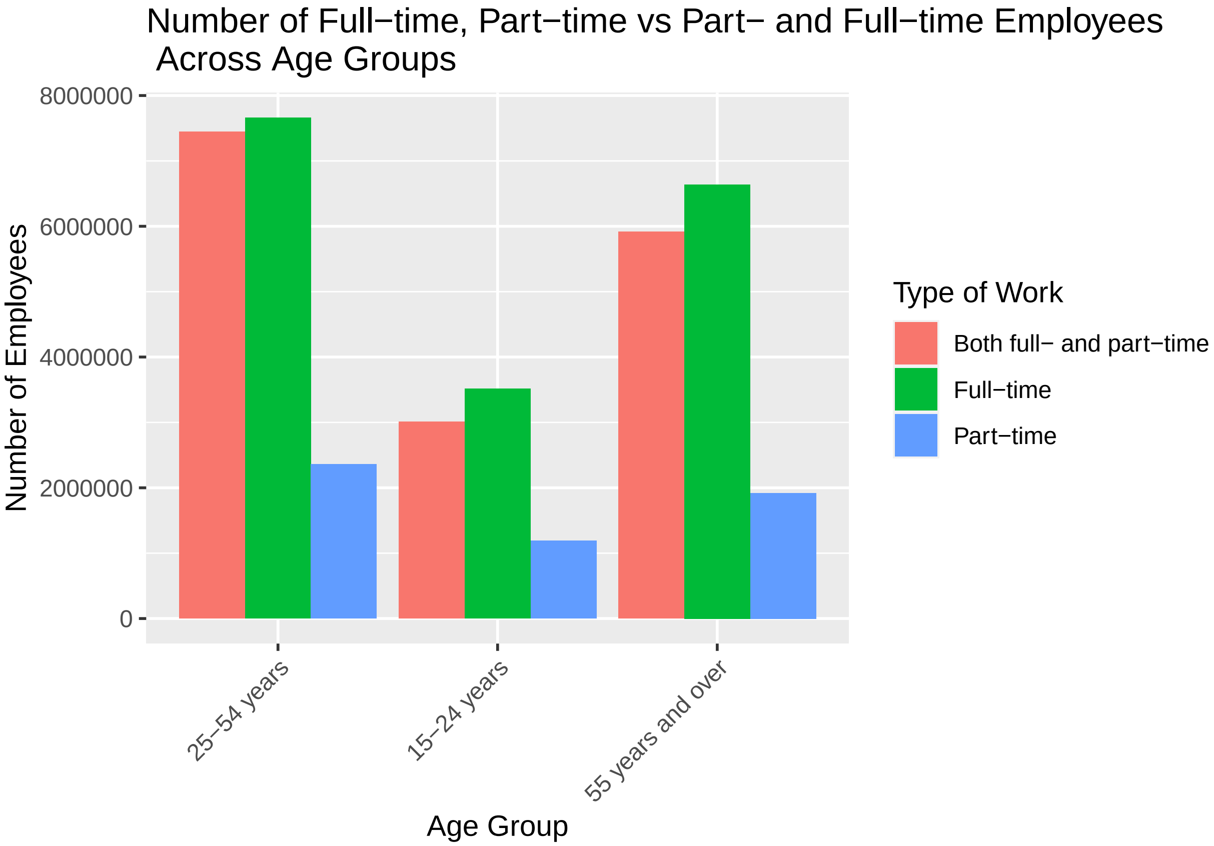
```
unique(wages$Type.of.work)
```

```
## [1] "Both full- and part-time" "Full-time"
## [3] "Part-time"
```

```
full_time_part_time <- wages %>%
  filter(Age.group %in% c("15-24 years",
                          "25-54 years",
                          "55 years and over")) %>%
  group_by(Age.group, Type.of.work) %>%
  summarise(Employees = sum(Both.Sexes))
```

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

```
options(scipen = 999)
ggplot(full_time_part_time,
       aes(x = Age.group, y = Employees, fill = Type.of.work)) +
  geom_bar(stat = "identity", position = "dodge") +
  labs(title = "Number of Full-time, Part-time vs Part- and Full-time Employees\n Across Age Groups",
       x = "Age Group",
       y = "Number of Employees",
       fill = "Type of Work") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```



Conclusions:

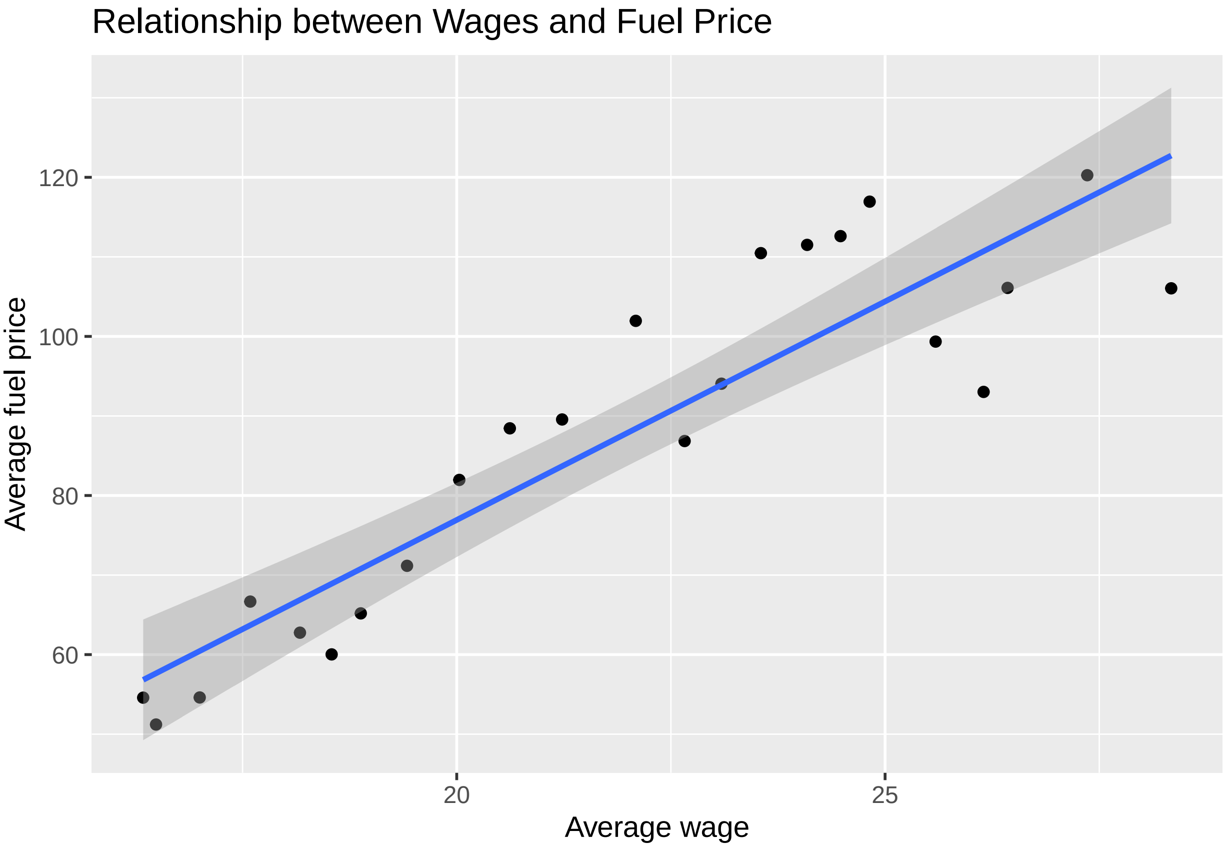
1. Across all age groups, the number of full-time employees is consistently higher than the number of part-time employees.
2. The age group of 25-54 years has the highest total number of employees, followed by the age group of 55 years and over, and then the age group of 15-24 years.
3. The data suggests a trend where as individuals grow older, they tend to transition towards full-time employment.
4. Further analysis, such as examining trends over time or considering demographic factors, may provide additional insights into the employment dynamics across different age groups.

5.4 What is the relationship between Wages and Fuel Price?

```
fuel.year = fuel %>%
  mutate(Year = year(as.Date(Date))) %>%
  group_by(Year) %>%
  summarise(Avg.Price = mean(Ontario.Average))
```

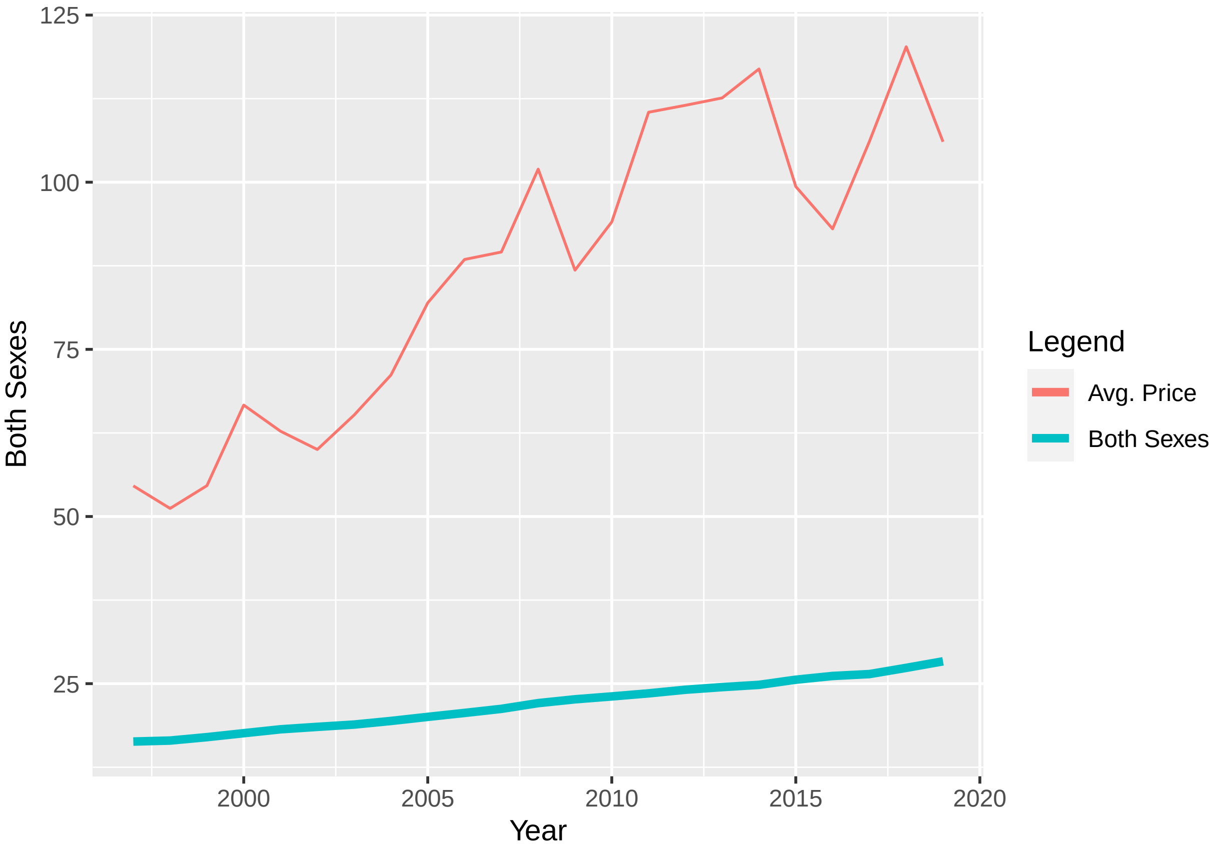
```
wages.year = wages %>%
  filter(Geography == 'Ontario',
         Wages == 'Average hourly wage rate',
         Type.of.work == 'Both full- and part-time',
         Education.level == 'Total, all education levels',
         Age.group == '15 years and over') %>%
  select(YEAR, Both.Sexes)

merged_data <- merge(wages.year, fuel.year, by.x = "YEAR", by.y = "Year")

ggplot(merged_data, aes(x = Both.Sexes, y = Avg.Price)) +
  geom_point() +
  geom_smooth(method = "lm") +
  labs(x = "Average wage",
       y = "Average fuel price",
       title = "Relationship between Wages and Fuel Price")
```

```
## `geom_smooth()` using formula = 'y ~ x'
```



```
# fuel and wage vs year
ggplot(merged_data, aes(x = YEAR)) +
  geom_line(aes(y = Both.Sexes, color = "Both Sexes"), size = 1.5) +
  geom_line(aes(y = Avg.Price, color = "Avg. Price")) +
  # scale_y_continuous(sec.axis = sec_axis(~./0.1, name = "Avg. Price")) +
  labs(x = "Year", y = "Both Sexes", color = "Legend")
```

```
## Warning: Using `size` aesthetic for lines was deprecated in ggplot2 3.4.0.
## i Please use `linewidth` instead.
## This warning is displayed once every 8 hours.
## Call `lifecycle::last_lifecycle_warnings()` to see where this warning was
## generated.
```



```
kable(avg_wage_by_education %>%
  mutate(pay.gap = male_avg - female_avg))
```

Education.level	male_avg	female_avg	pay.gap
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University degree	30.29478	26.04565	4.249130
Community college, CEGEP	23.81000	19.74957	4.060435
Trade certificate or diploma	23.44783	17.01913	6.428696
Post-secondary certificate or diploma	23.75652	19.35348	4.403043
Some post-secondary	18.32478	15.12348	3.201304
High school graduate	19.64739	15.93130	3.716087
Some high school	16.34565	12.35565	3.990000
PSE (5,6,7,8,9))	26.32174	22.16043	4.161304
No PSE (0,1,2,3,4)	18.38304	14.83043	3.552609
0 - 8 years	17.05087	12.62870	4.422174
Total, all education levels	22.94130	19.38304	3.558261

6 Hypothesis Testing

Null Hypothesis (H0): There is no statistically significant distinction in the average wages between male and female workers (_male = _female).

Alternative Hypothesis (H1): There exists a statistically significant disparity in average wages between male and female workers (_male   _female). To examine this hypothesis, we can employ a two-sample t-test to compare the wage distributions of male and female workers. This entails segregating the dataset into two distinct groups based on gender: male and female.

The resultant p-value derived from the selected statistical test indicates the probability of observing a wage difference as extreme as, or more extreme than, the observed difference, assuming the null hypothesis holds. If the obtained p-value falls below the predetermined significance level (typically 0.05), we reject the null hypothesis, indicating a significant discrepancy in wages between male and female workers.

Moreover, by computing a confidence interval for the disparity in mean wages, we can gauge the plausible range of values for the actual difference between male and female wages.

```
male_wages <- wages %>% filter(Wages == "Average weekly wage rate") %>% select(Male)
female_wages <- wages %>% filter(Wages == "Average weekly wage rate") %>% select(Female)

t.test(male_wages, female_wages)
```

```
##
##  Welch Two Sample t-test
##
## data:  male_wages and female_wages
## t = 69.11, df = 155915, p-value < 0.00000000000000022
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  116.8124 123.6314
## sample estimates:
## mean of x mean of y
##  627.8701  507.6481
```

Conclusions The outcomes derived from the Welch Two Sample t-test underscore a significant contrast in average earnings between male and female workers. With an extraordinarily minute p-value (< 0.00000000000000022), there's compelling evidence to dismiss the null hypothesis, indicating that the mean wages for men and women diverge significantly. The 95% confidence interval for the mean wage discrepancy extends from 116.8124 to 123.6314, suggesting that the actual difference in wages between male and female workers likely lies within this interval.

In summary, the findings overwhelmingly advocate for rejecting the null hypothesis, underscoring a noteworthy disparity in wages between male and female employees. Specifically, the average wage for male workers (627.8701) markedly exceeds that of female workers (507.6481).

7 Bootstrapping

We utilize bootstrapping to estimate the sampling distribution of the mean fuel price for Toronto West and to compute a confidence interval.

```
library(boot)

mean_fuel_price <- function(data) {
  mean(data[["Toronto.West"]])
}
```

```r
set.seed(123)
n_boot <- 1000
bootstrap_means <- replicate(n_boot, {
  sample_data <- fuel[sample(1:nrow(fuel), replace = TRUE), ]
  mean_fuel_price(sample_data)
})

ci <- quantile(bootstrap_means, c(0.025, 0.975))

# Print the results
cat("Mean fuel price for Ontario:", mean(fuel$Toronto.West), "\n")
```

```
## Mean fuel price for Ontario: 80.06227
```

```r
cat("95% confidence interval:", "( ", ci[1], "-", ci[2], " )", "\n")
```

```
## 95% confidence interval: (  79.26425 - 80.78438  )
```

According to our findings, the mean fuel price for Ontario stands at 80.0622744. Our computed 95% confidence interval spans from 79.2642523 to 80.7843823‘. This suggests with 95% confidence that the genuine mean fuel price for Ontario lies within this interval.

8 Random Forest

```r
d = wages %>%
  select(!Both.Sexes) %>%
  filter(Wages == 'Average hourly wage rate',
         Type.of.work == 'Both full- and part-time',
         Geography == 'Canada',
         Education.level != 'Total, all education levels',
         Age.group != '15 years and over') %>%
  pivot_longer(c(Male, Female),
               names_to = "gender",
               values_to = "wage")

d = d %>%
  mutate(group = sample(c('train', 'test'),
                        size = nrow(d),
                        prob = c(0.9, 0.1),
                        replace=TRUE))

train_data = d %>% filter(group == 'train')
test_data = d %>% filter(group == 'test')

model = randomForest(wage ~ Education.level + gender + Age.group,
                     data = train_data,
                     ntree = 10,
                     importance = TRUE)
```

9 Cross Validation

```r
test_data$predicted = predict(model, newdata = test_data)
```

```
mean((test_data$wage - test_data$predicted)^2)
```

```
## [1] 16.248
```

The MSE of around 16.2480022 shows the average difference between actual and predicted wages. Such a value is considered significant, suggesting that the model may not generalize well to new data. This also means, that

10 Summary of Research

11 Appendix