Homework 2

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```
# Load the dataframe
load("401k_w271.RData")
desc
```

```
##   variable                          label
## 1    prate     participation rate, percent
## 2    mrate            401k plan match rate
## 3  totpart         total 401k participants
## 4   totelg    total eligible for 401k plan
## 5      age                age of 401k plan
## 6   totemp  total number of firm employees
## 7     sole = 1 if 401k is firm's sole plan
## 8  ltotemp                   log of totemp
```

Question 1

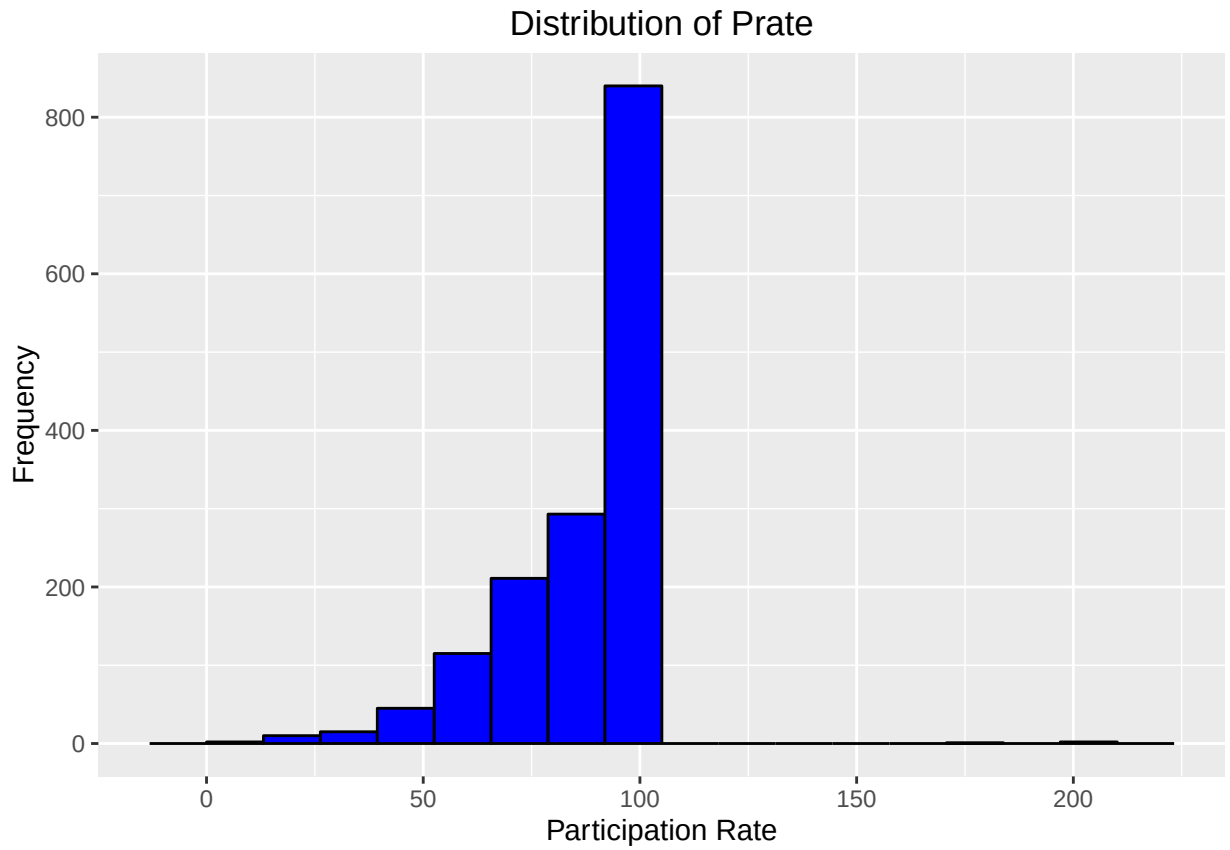
```
summary(data$prate)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    3.00   78.10   95.70   87.56  100.00  200.00
```

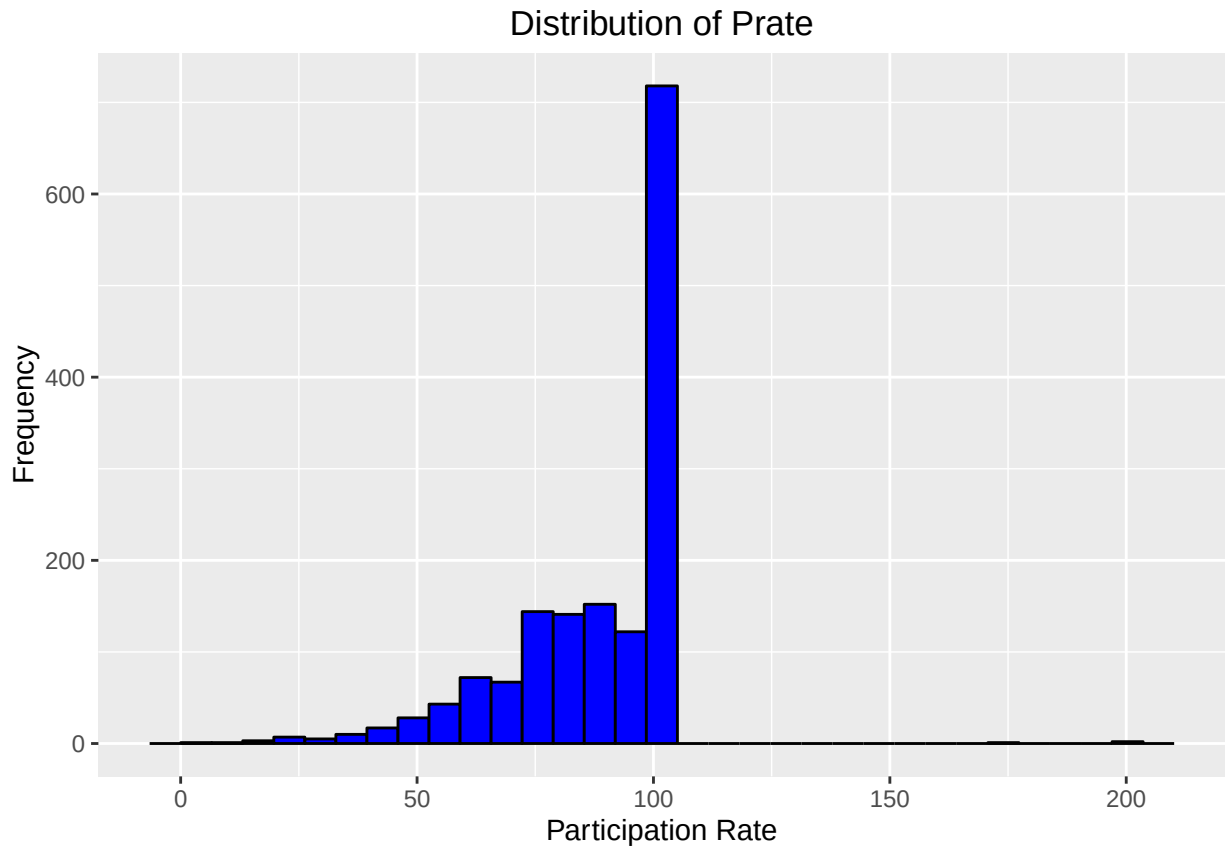
```
print(quantile(data$prate, probs = c(0.01, 0.05, 0.1,
    0.25, 0.5, 0.75, 0.9, 0.95, 0.99, 1)))
```

```
##      1%      5%     10%     25%     50%     75%     90%     95%     99%
##  31.763  53.995  62.760  78.100  95.700 100.000 100.000 100.000 100.000
##    100%
## 200.000
```

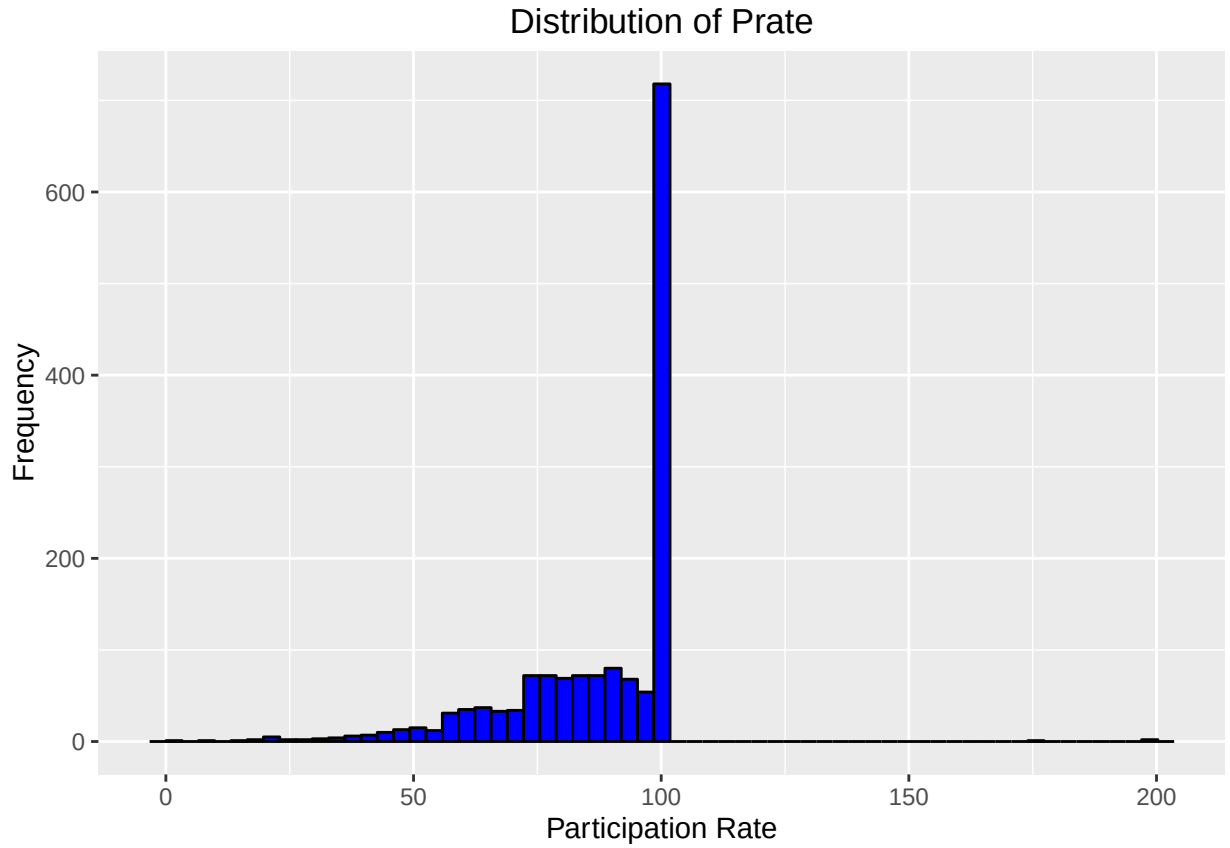
```
# Plot the histogram of at 15 bins
prate.hist <- ggplot(data, aes(prate)) + theme(legend.position = "none") +
    geom_histogram(fill = "Blue", colour = "Black",
        binwidth = (range(data$prate)[2] - range(data$prate)[1])/15) +
    labs(title = "Distribution of Prate", x = "Participation Rate",
        y = "Frequency")

plot(prate.hist)
```




```
# Plot the histogram at 30 bins
prate.hist <- ggplot(data, aes(prate)) + theme(legend.position = "none") +
    geom_histogram(fill = "Blue", colour = "Black",
        binwidth = (range(data$prate)[2] - range(data$prate)[1])/30) +
    labs(title = "Distribution of Prate", x = "Participation Rate",
        y = "Frequency")

plot(prate.hist)
```




```
# Plot the histogram at 60 bins
prate.hist <- ggplot(data, aes(prate)) + theme(legend.position = "none") +
    geom_histogram(fill = "Blue", colour = "Black",
        binwidth = (range(data$prate)[2] - range(data$prate)[1])/60) +
    labs(title = "Distribution of Prate", x = "Participation Rate",
        y = "Frequency")

plot(prate.hist)
```




```
data$prate.clean = data$prate
data$prate.clean[data$prate.clean > 100] = NA
summary(data$prate.clean)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##    3.00   78.05   95.70   87.35  100.00  100.00       3
```

The variable has higher frequency at higher values of participation rates with a particularly large spike at 100% participation, indicating that most companies have all employees participating in the 401k. There also seem to be erroneous values of 200% which we will code as NA.

```
# Creating a clean version of the variable
data$prate.clean = data$prate
data$prate.clean[data$prate.clean > 100] = NA
summary(data$prate.clean)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##    3.00   78.05   95.70   87.35  100.00  100.00       3
```

Question 2

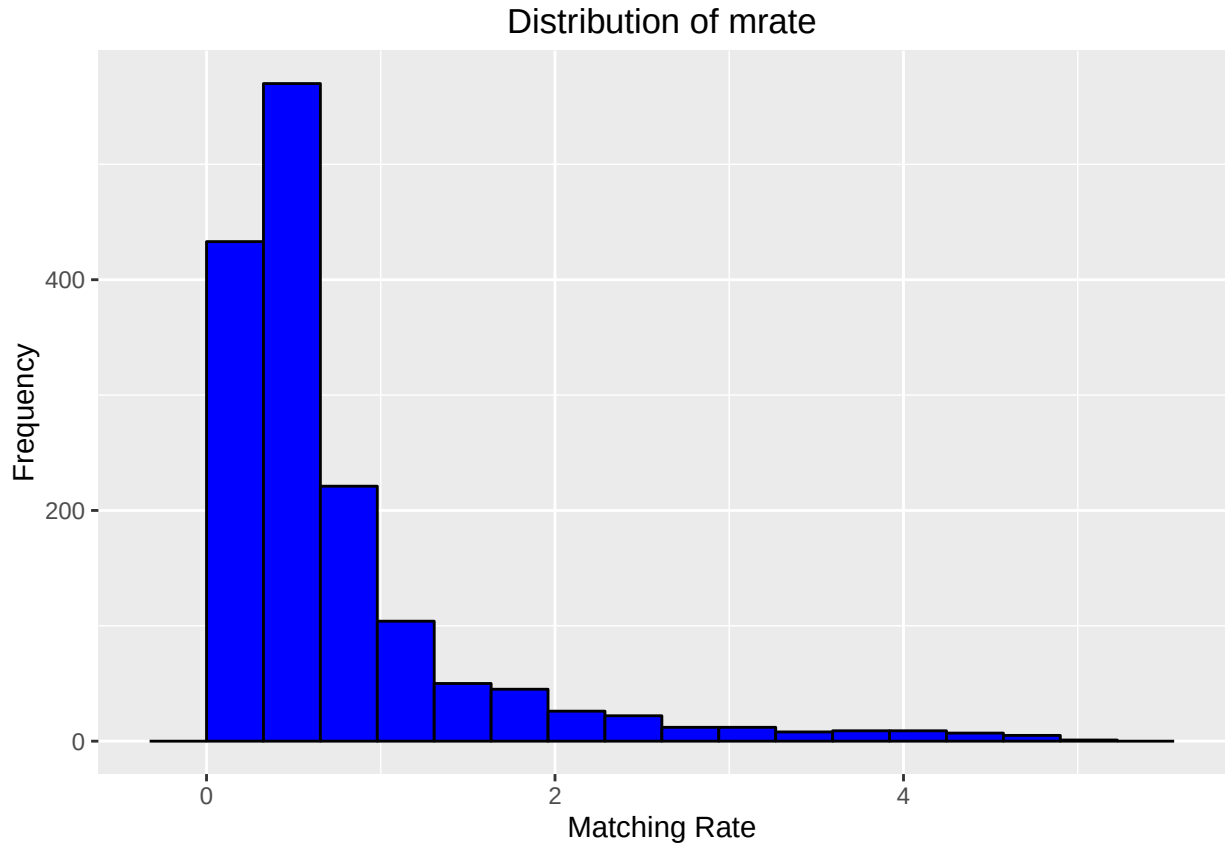
```r
summary(data$mrate)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.0100  0.3000  0.4600  0.7315  0.8300  4.9100
```

```r
print(quantile(data$mrate, probs = c(0.01, 0.05, 0.1,
    0.25, 0.5, 0.75, 0.9, 0.95, 0.99, 1)))
```

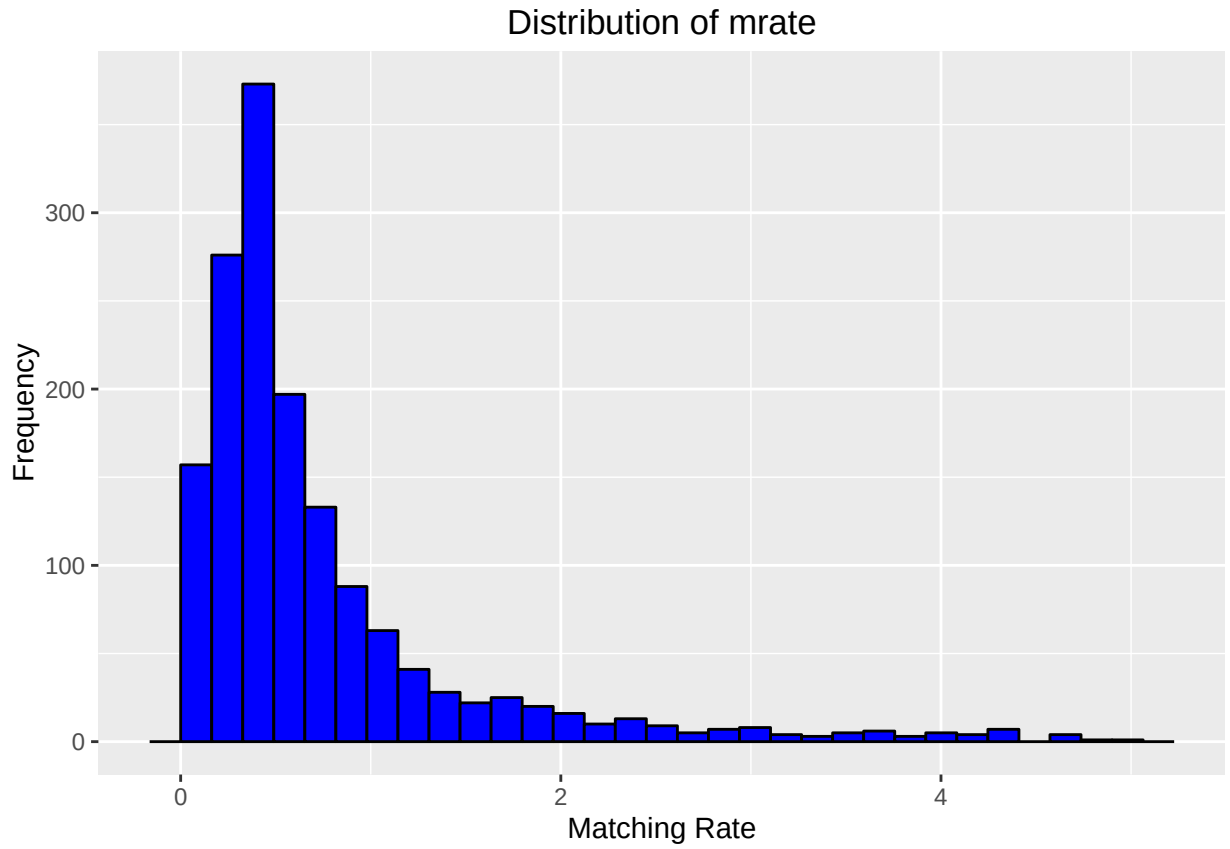
```
##     1%     5%    10%    25%    50%    75%    90%    95%    99%   100%
## 0.0300 0.1100 0.1600 0.3000 0.4600 0.8300 1.6570 2.3635 4.1267 4.9100
```

```r
# Plot the histogram of bwght at 15 bins
mrate.hist <- ggplot(data, aes(mrate)) + theme(legend.position = "none") +
    geom_histogram(fill = "Blue", colour = "Black",
        binwidth = (range(data$mrate)[2] - range(data$mrate)[1])/15) +
    labs(title = "Distribution of mrate", x = "Matching Rate",
        y = "Frequency")

plot(mrate.hist)
```

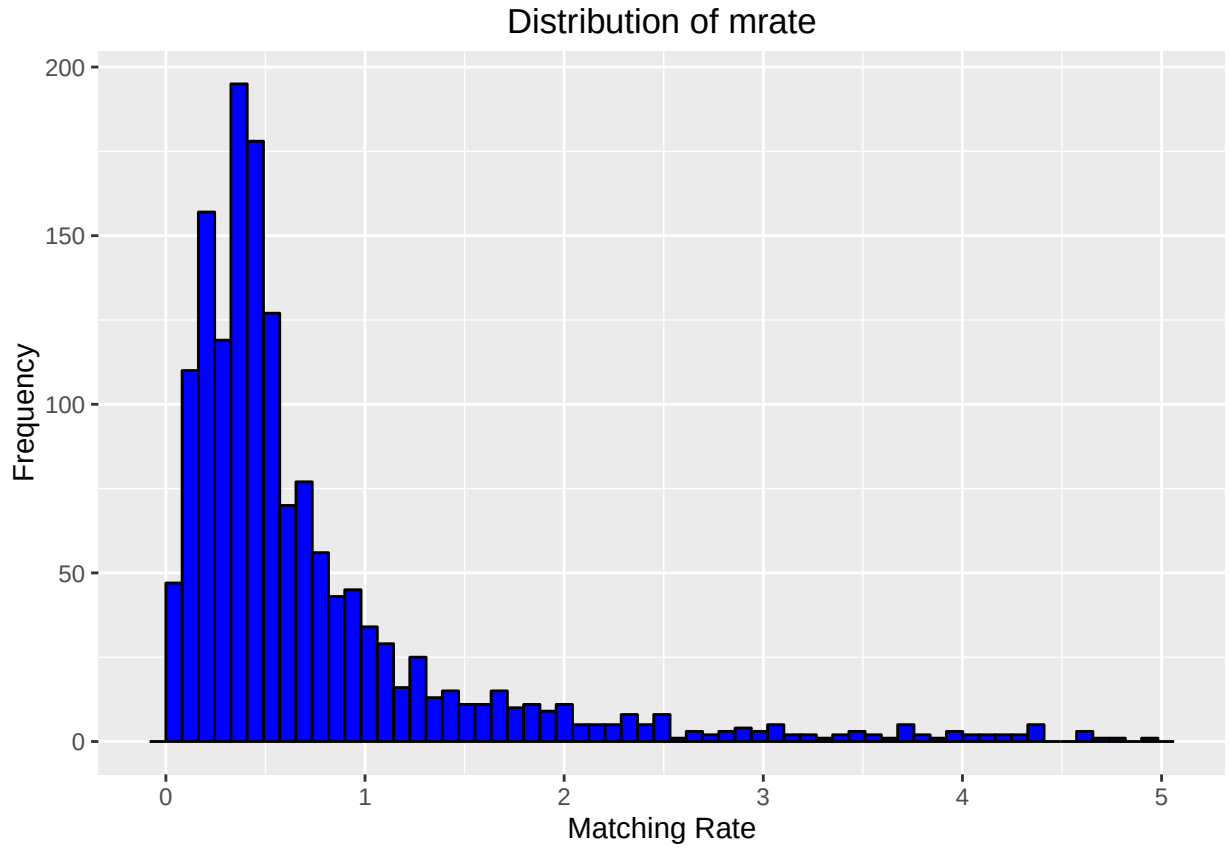



```r
# Plot the histogram of bwght at 30 bins
mrate.hist <- ggplot(data, aes(mrate)) + theme(legend.position = "none") +
    geom_histogram(fill = "Blue", colour = "Black",
```

```
        binwidth = (range(data$mrate)[2] - range(data$mrate)[1])/30) +
    labs(title = "Distribution of mrate", x = "Matching Rate",
        y = "Frequency")

plot(mrate.hist)
```




```
# Plot the histogram of bwght at 60 bins
mrate.hist <- ggplot(data, aes(mrate)) + theme(legend.position = "none") +
    geom_histogram(fill = "Blue", colour = "Black",
        binwidth = (range(data$mrate)[2] - range(data$mrate)[1])/60) +
    labs(title = "Distribution of mrate", x = "Matching Rate",
        y = "Frequency")

plot(mrate.hist)
```



mrate is heavily positively skewed, with most companies matching between 30% and 83%. Though the variable has a mean of 73%, the median here is a better measure of central tendency.

We will ignore variables above 100% as they are not practical real matching values for corporations. We will also do an arithmetic transformation and multiply the values by 100 in order to keep it consistent with the prate variable.

```
# Creating clean version of the variable
data$mrate.clean = data$mrate * 100
data$mrate.clean[data$mrate.clean > 100] = NA
summary(data$mrate.clean)
```

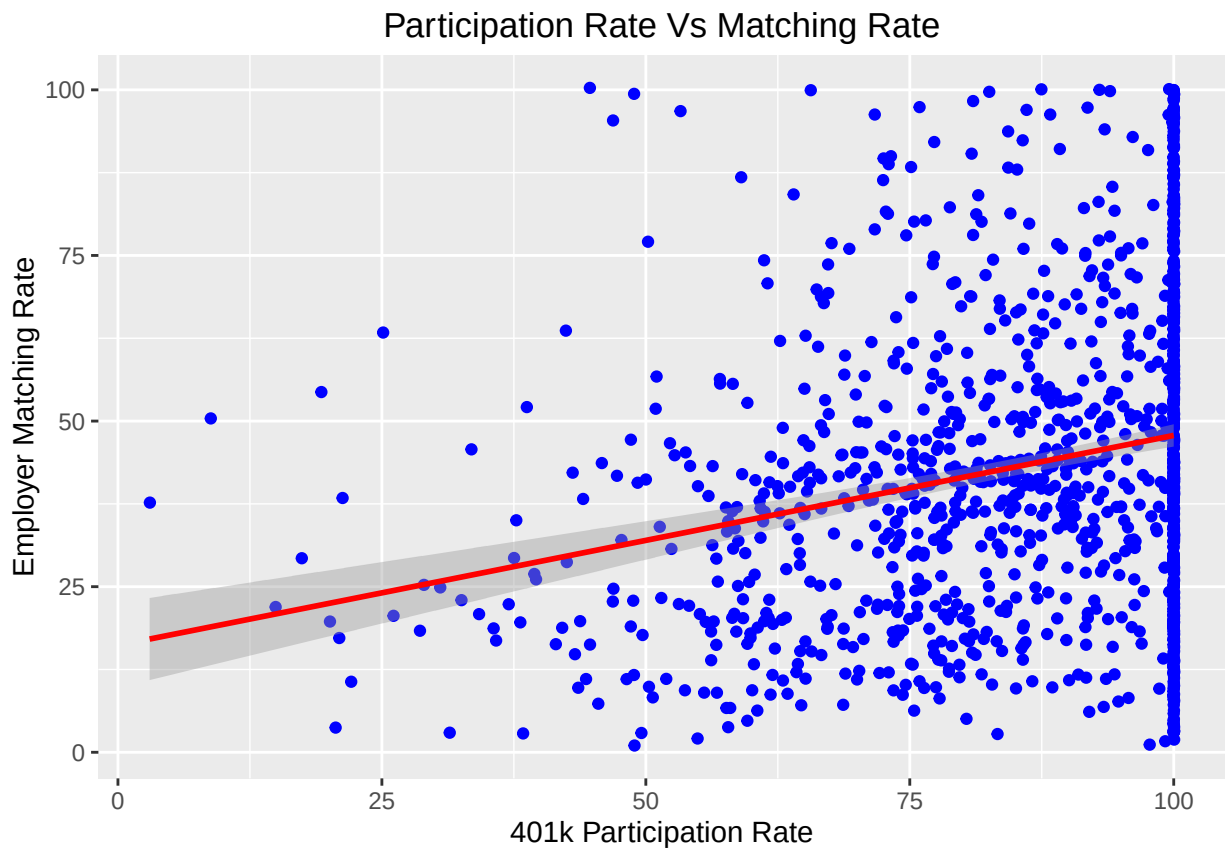
```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##    1.00   24.00   40.00   43.09   57.00  100.00     292
```

Question 3

```
# Create a scatterplot of prate vs mrate
scatter.prate.mrate <- ggplot(data, aes(prate.clean,
    mrate.clean)) + geom_point(colour = "Blue", position = "jitter") +
    geom_smooth(method = "lm", colour = "Red") + labs(x = "401k Participation Rate",
    y = "Employer Matching Rate", title = "Participation Rate Vs Matching Rate")
plot(scatter.prate.mrate)
```

```
## Warning: Removed 294 rows containing non-finite values (stat_smooth).
```

```
## Warning: Removed 294 rows containing missing values (geom_point).
```




```
# Running linear regression
model = lm(prate.clean ~ mrate.clean, data = data)
summary(model)
```

```
##
## Call:
## lm(formula = prate.clean ~ mrate.clean, data = data)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -81.295  -9.336   4.867  13.139  21.863
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 77.79474    0.99887  77.883   <2e-16 ***
## mrate.clean  0.17105    0.02031   8.423   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 16.9 on 1238 degrees of freedom
##   (294 observations deleted due to missingness)
```

```
## Multiple R-squared:  0.05421,    Adjusted R-squared:  0.05344
## F-statistic: 70.95 on 1 and 1238 DF,  p-value: < 2.2e-16
```

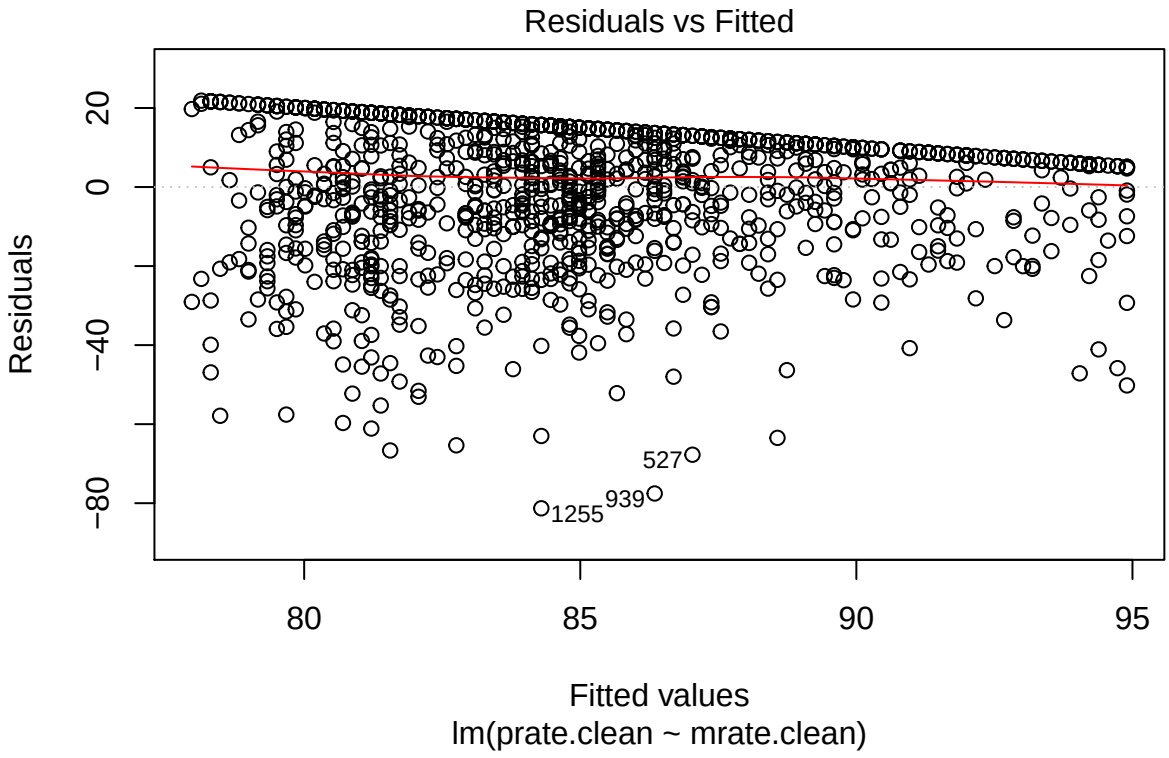
```
# Print the coefficient
print(model$coefficients[2])
```

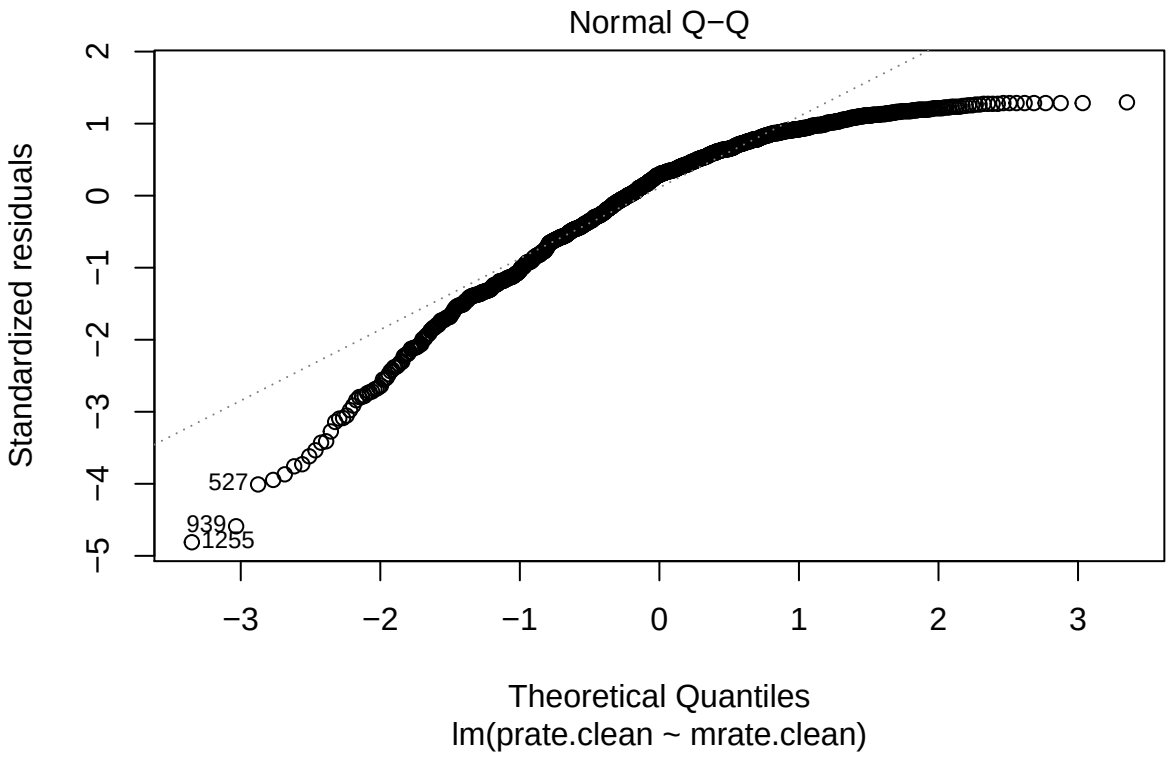
```
## mrate.clean
##    0.171055
```

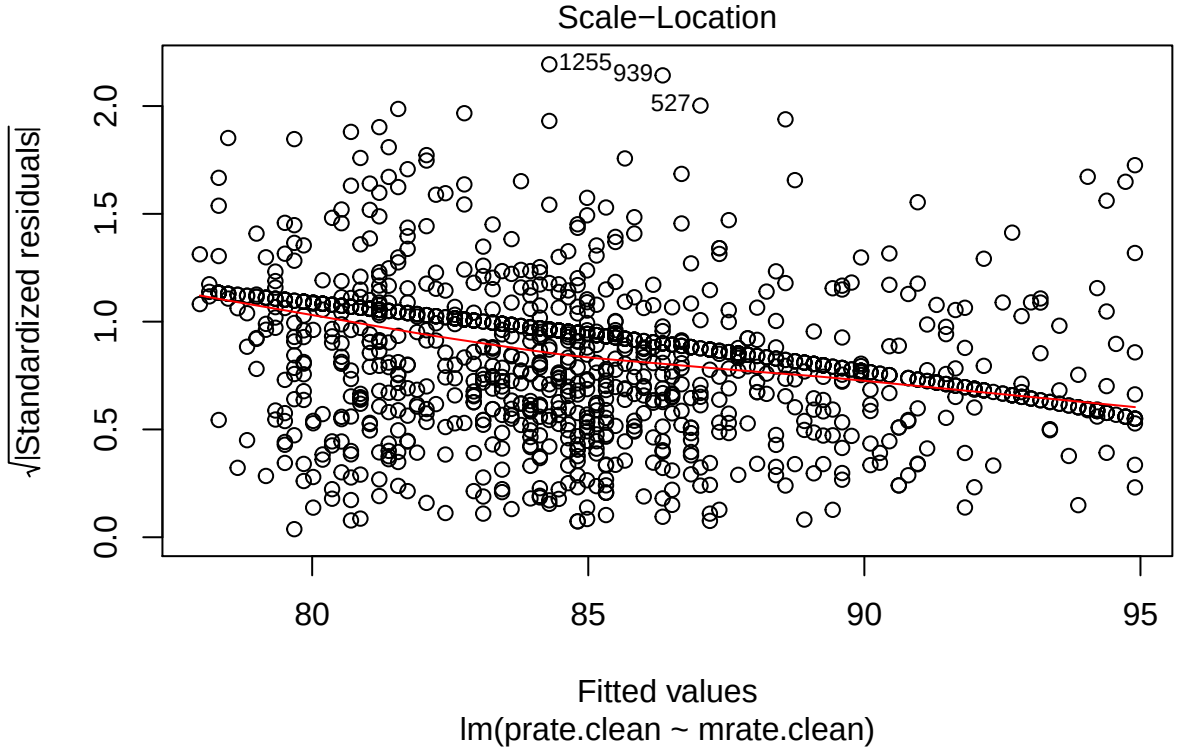
We get a slope coefficient of 0.17

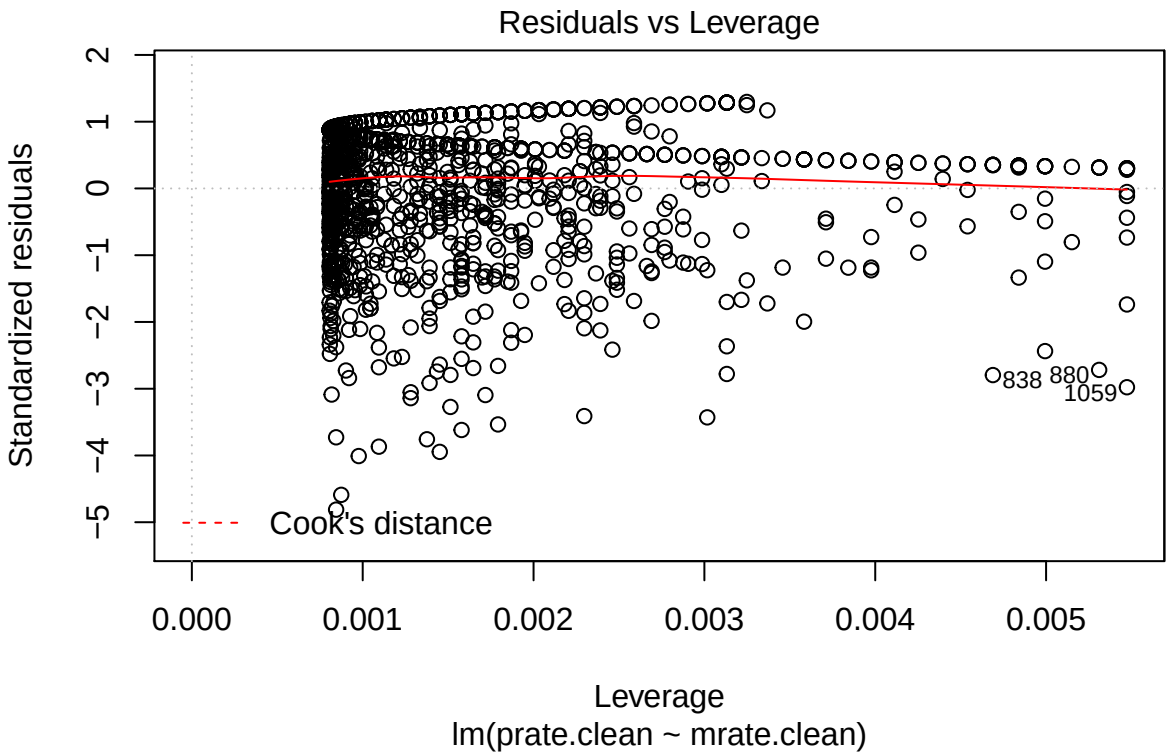
Question 4

```
# Printing the diagnostic plots
plot(model)
```




Normal Q−Q
Standardized residuals
Theoretical Quantiles
lm(prate.clean ~ mrate.clean)
527
939
1255


Scale−Location
1255
939
527
√|Standardized residuals|
0.0
0.5
1.0
1.5
2.0
80
85
90
95
Fitted values
lm(prate.clean ~ mrate.clean)



From residuals vs fitted values graph, it seems like there is a very small violation of zero-cond mean, as we see the smoothing curve slope downwards slightly. Nonetheless, since we have a large sample size, we do not need this assumption since we can use the assumption of exogeneity. Therefore, this has very little impact on our regression model.

Question 5

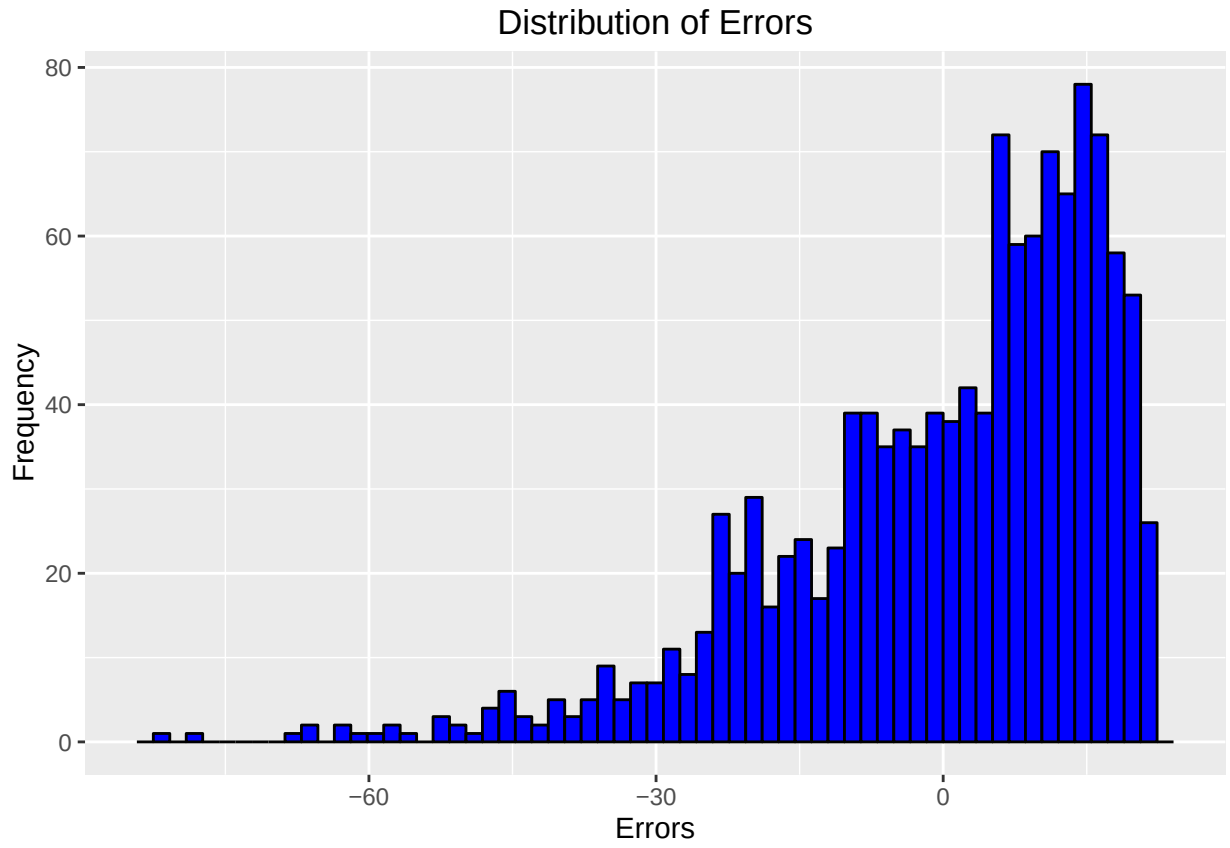
There seems to be a violation of homoskedasticity, albeit not too large 1 - We can see from the residuals vs fitted plot that the variance seems to narrow as we move to higher fitted values. 2 - The same story is told by the scale-location plot where we see that there is a downward trend in the standardized residuals band, where there should be a horizontal band if homoskedasticity was met.

We do not look at the Breusch Pagan test since we have a large number of observations. The implication of heteroskedasticity in the data is that it might cause our standard error to become biased. This may lead to our estimate not being BLUE, or a false negative in the hypothesis test. To correct for this, we will have to use robust standard errors.

Question 6

```
# Plotting Histogram of errors
errors.hist <- ggplot(model, aes(model$residuals)) +
    theme(legend.position = "none") + geom_histogram(fill = "Blue",
    colour = "Black", binwidth = (range(model$residuals)[2] -
```

```
        range(model$residuals)[1])/60) + labs(title = "Distribution of Errors",
    x = "Errors", y = "Frequency")
plot(errors.hist)
```



From inspection of plots, we can see a violation of normality 1 - When we plot the histogram of errors, we see the negative skew. 2 - The negative skew is also apparent in the Q-Q plot of the standardized residuals. We do not conduct the Shapiro Wilk test because knowing that we have a very large sample size, we know almost certainly that we will obtain significance.

In terms of implications, despite non-normality from the plots, we can use OLS asymptotics. Since there is a version of the central limit theorem that tells us that the sampling distribution of coefficient estimates approaches normality with large sample sizes, we do not need the normality assumption of our error. Therefore, the finding that our errors do not follow a normal distribution does not have much of an impact on our regression.

Question 7

```
# Based on the violation of homoskedasticity, we
# must run robust standard errors.
coeftest(model, vcov = vcovHC)
```

```
##
## t test of coefficients:
```

```
##
##              Estimate Std. Error t value  Pr(>|t|)
## (Intercept) 77.794744   1.126004 69.0893 < 2.2e-16 ***
## mrate.clean  0.171055   0.020355  8.4035 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

After running robust standard errors, we get 0.02 as the standard error.

Question 8

```
waldtest(model, vcov = vcovHC)
```

```
## Wald test
##
## Model 1: prate.clean ~ mrate.clean
## Model 2: prate.clean ~ 1
##   Res.Df Df      F    Pr(>F)
## 1   1238
## 2   1239 -1 70.619 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The model is highly statistically significant. It is also practically significant, implying that a change of 1% in the matching rate by an employer corresponds to a change of 0.17% in participation in 401k plans by employees.