Project1 - Unobserved Ability, Efficiency Wages, and Interindustry Wage Differentials

Ieva Jankevičiūtė Ilja Jurčenko

2023-12-08

1. Introduction

This project analyses data from Wooldridge Source: M. Blackburn and D. Neumark (1992), "Unobserved Ability, Efficiency Wages, and Interindustry Wage Differentials," Quarterly Journal of Economics 107, 1421-1436. It loads lazily data from **wooldbridge package**.

In this exploration, we aim to unpack the hypothesis suggesting that married people have higher wages. As we navigate the intricacies of a linear regression model, our focus extends beyond scrutinizing the "married" variable alone. We delve into not only the coefficient and significance of marital status but also other pertinent correlations with wage.

For more statistical data information see appendix.

A data.frame with 935 observations on 17 variables: Removing missing values, total 663 observations

wage: monthly earnings.
hours: average weekly hours.
IQ: IQ score.
KWW: knowledge of world work score.
educ: years of education.
exper: years of work experience.
tenure: years with current employer.
age: age in years.
married: =1 if married.
black: =1 if black.
south: =1 if live in south.
urban: =1 if live in SMSA (Standard Metropolitan Statistical Area).
sibs: number of siblings.
brthord: birth order.
meduc: mother's education.
feduc: father's education.
lwage: natural log of wage.

```
library(wooldridge)
library(Hmisc)

data('wage2')
# Removing missing values, total 663 observations
wage2=na.omit(wage2)
#describe(wage2)
head(wage2)
```

```
##   wage hours  IQ KWW educ exper tenure age married black south urban sibs
## 1  769    40  93  35   12    11      2  31       1     0     0     1    1
## 3  825    40 108  46   14    11      9  33       1     0     0     1    1
## 4  650    40  96  32   12    13      7  32       1     0     0     1    4
## 5  562    40  74  27   11    14      5  34       1     0     0     1   10
## 7  600    40  91  24   10    13      0  30       0     0     0     1    1
## 9 1154    45 111  37   15    13      1  36       1     0     0     0    2
##   brthord meduc feduc    lwage
## 1       2     8     8 6.645091
## 3       2    14    14 6.715384
## 4       3    12    12 6.476973
## 5       6     6    11 6.331502
## 7       2     8     8 6.396930
## 9       3    14     5 7.050990
```

2. Data visualisation

Visualizing data to provide some insight on the research. Figure 1, 2, 3 are simple scatter plots between IQ and Wage colored by binary class. It shows some tendency that people with higher IQ tend to have higher wages.

Figure 1 - shows people with higher IQ tend to have higher wages and are married.
Figure 2 - shows people with lower IQ and lower wages tend to be African.
Figure 3 - shows people with higher IQ and higher wages live in cities.
Figure 4 - provides first information on dependencies between variables and its distributions. The lines are regression lines provided via LM parameter. The interesting dependencies are distinguished by the slope of the line. The dots are blured for better readability. Ellipses in the scatterplot matrix represent confidence ellipses for the scatterplots. These ellipses provide a visual representation of the bivariate relationships between pairs of variables and show the spread and orientation of the data.
It is hard to read correlation between the data via big scatterplot that is why Figure 5 provides Pearson correlation information.

Figure 5 - provides information on correlation. Crossed variables are not significant. Color saturation reflects the impact. Blue have positive correlation, while red negative.

From the figures the lwage is most impacted by IQ, KWW, Educ, Age, Married, Meduc, Feduc The interesting thing is that exper has very low correlation and not signifact in Figure 5.

Figure 1: Scatter Plot of IQ and Wage Colored By Married Status

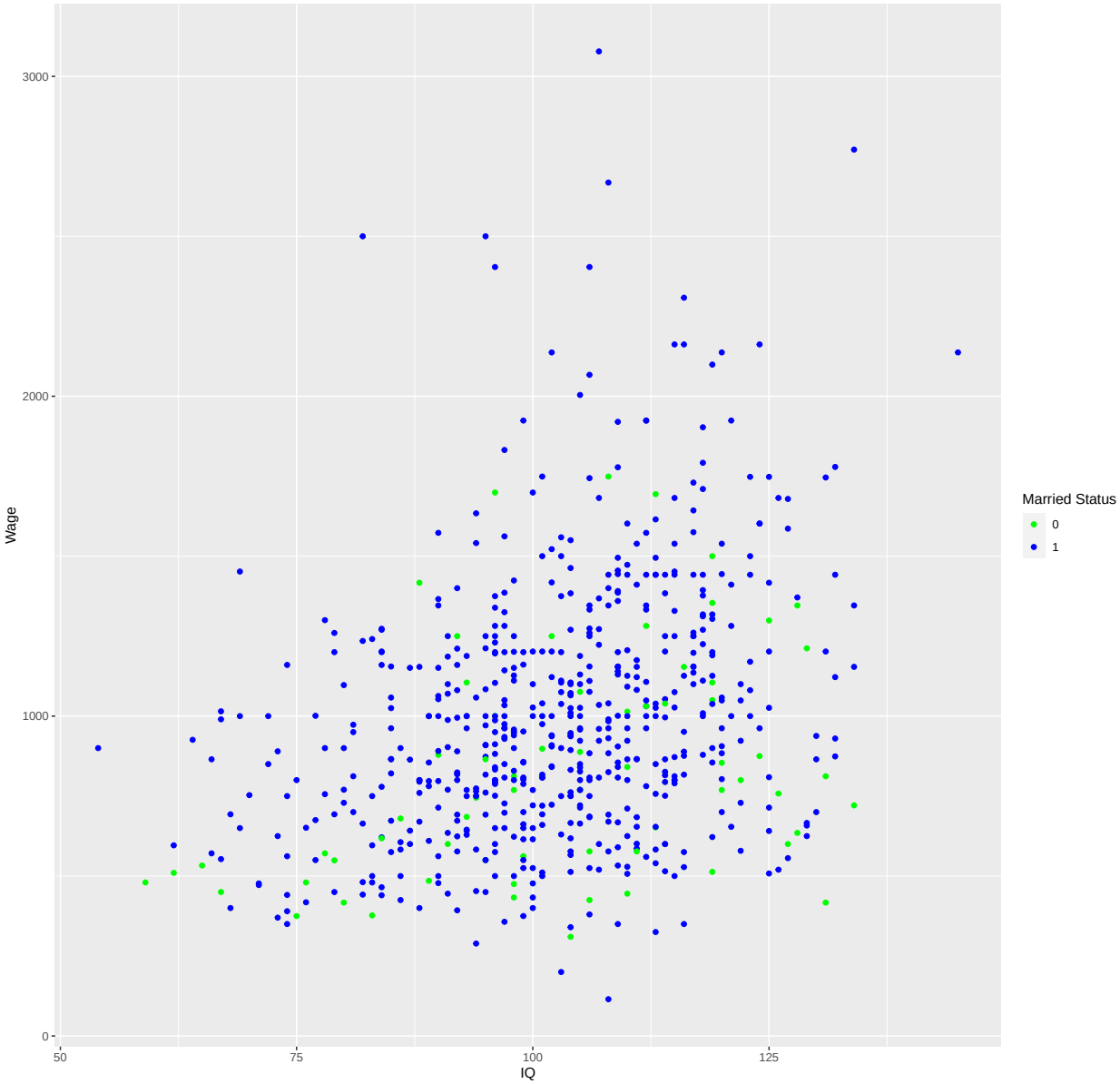


Figure 1: Dependency between IQ and Wage, distinguished by married status

Figure 2: Scatter Plot of IQ and Wage Colored By Race

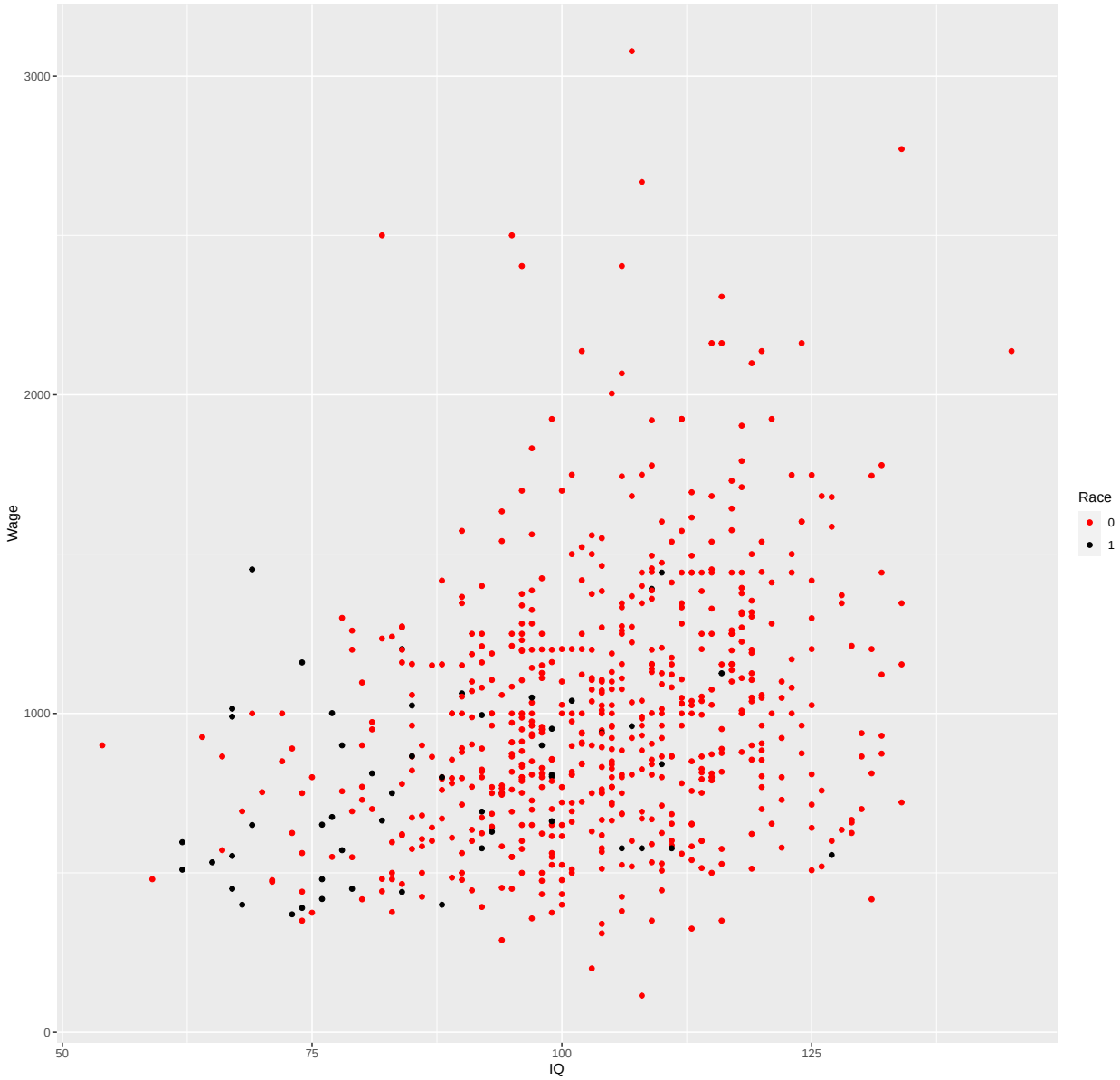


Figure 2: Dependency between IQ and Wage, distinguished by race

Figure 3: Scatter Plot of IQ and Wage Colored By Urban

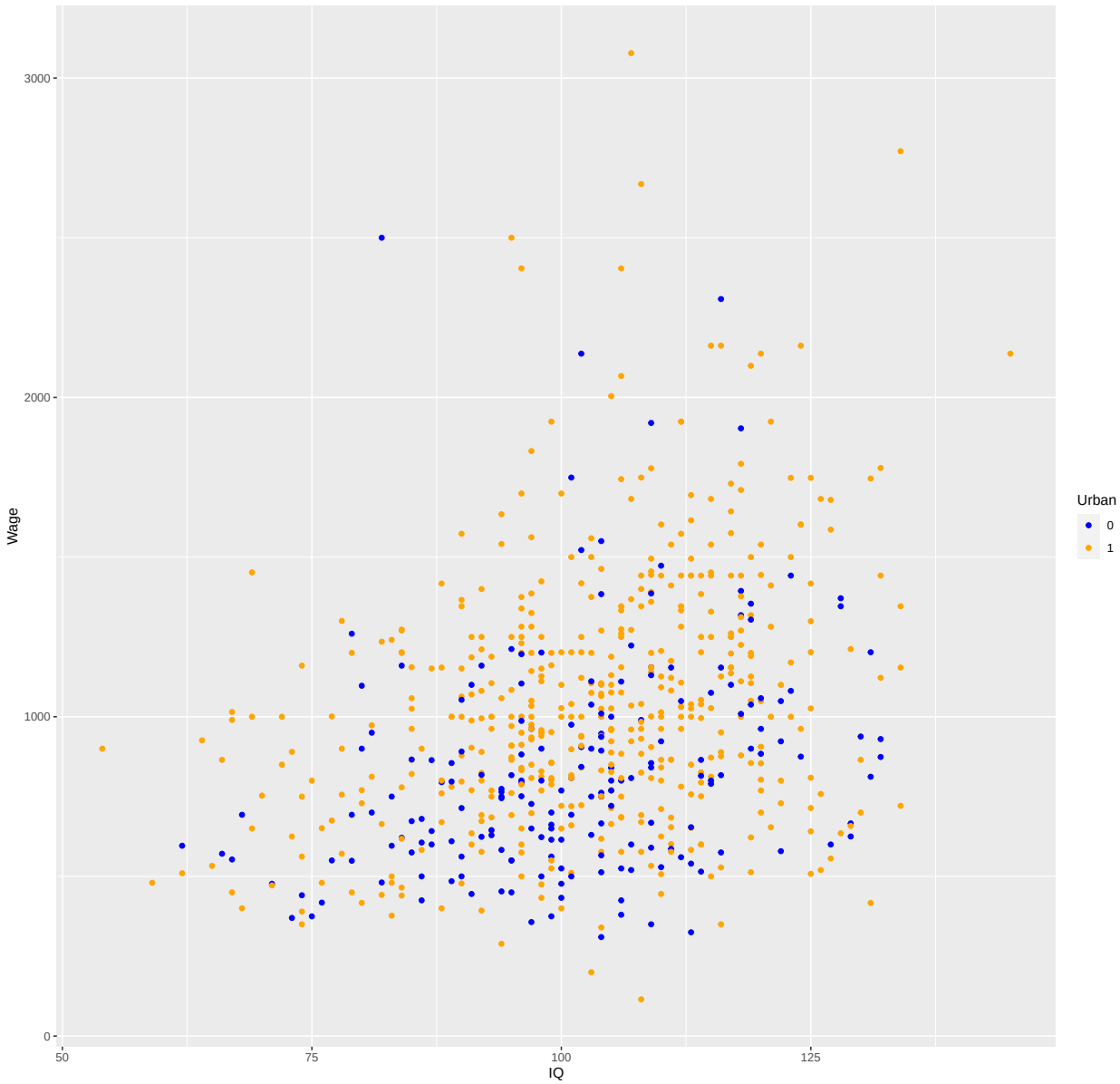
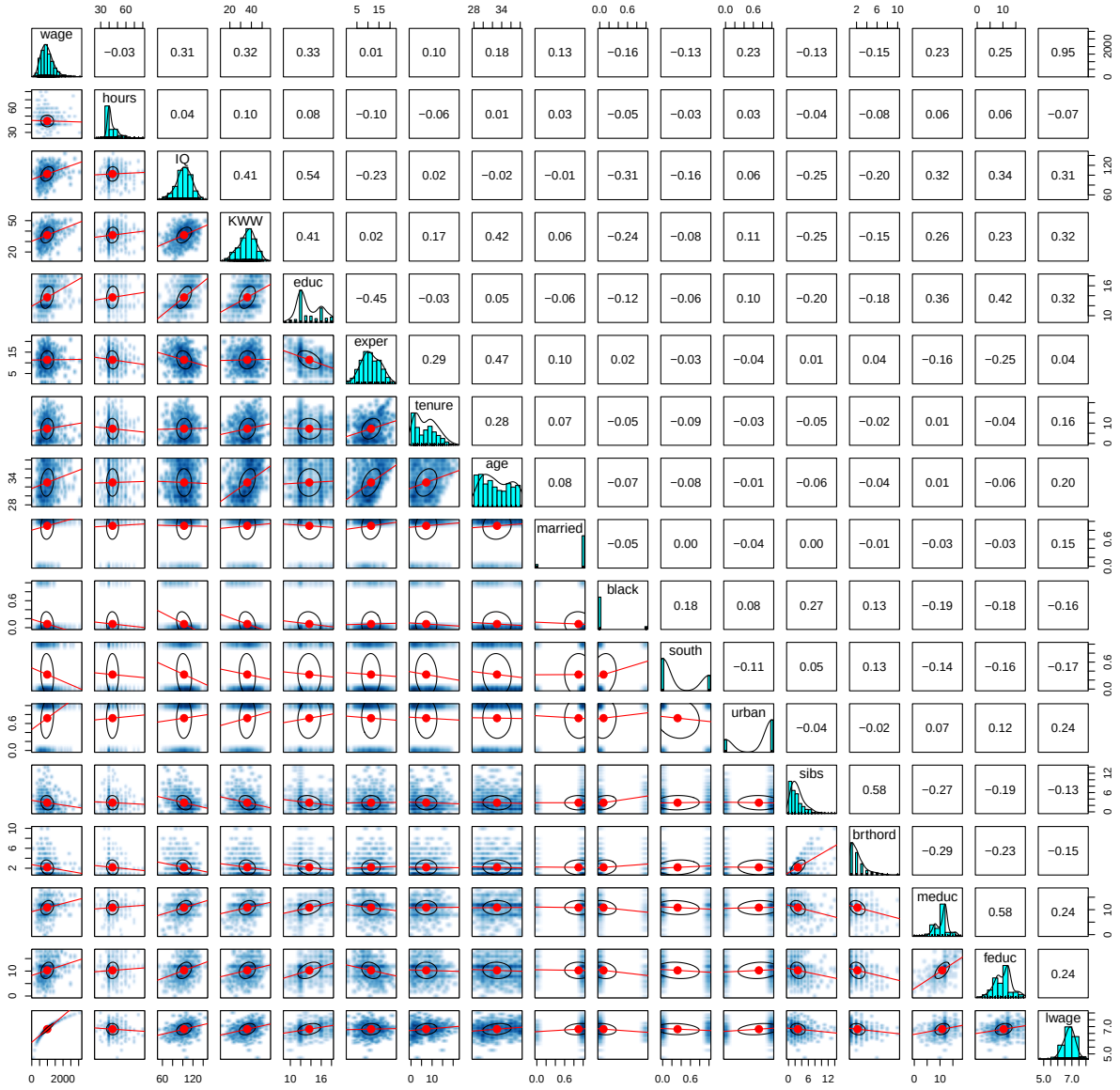


Figure 3: Dependency between IQ and Wage, distinguished by location

Figure 4: Scatter Plot Matrix for Wage2 Dataset and correlations



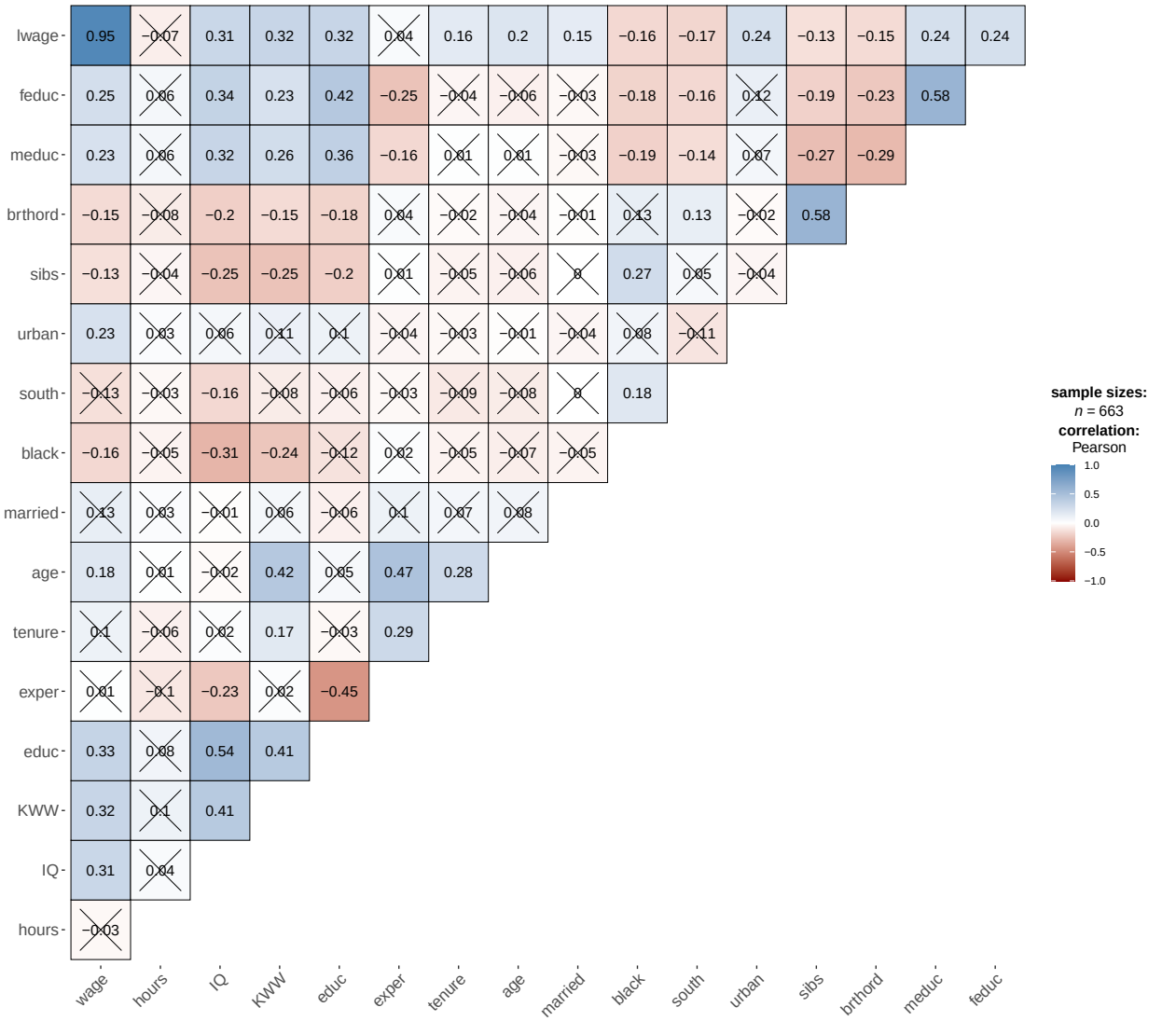


Figure 5: correlation matrix between variables. The most interesting is first row, where lwage correlations are calculated between other variables

X = non−significant at $p < 0.05$ (Adjustment: Holm)

3. Normality

Checking the normality of the data. This block of code checks for normality of the data. Wage is skewed to left as expected, but the log of wage is more towards normal distribution

```
library('ggpubr')
par(mfrow=c(2,2))
shapiro.test(wage2$wage)
```

```
##
##  Shapiro-Wilk normality test
##
```

```
## data:  wage2$wage
## W = 0.93802, p-value = 5.575e-16
```

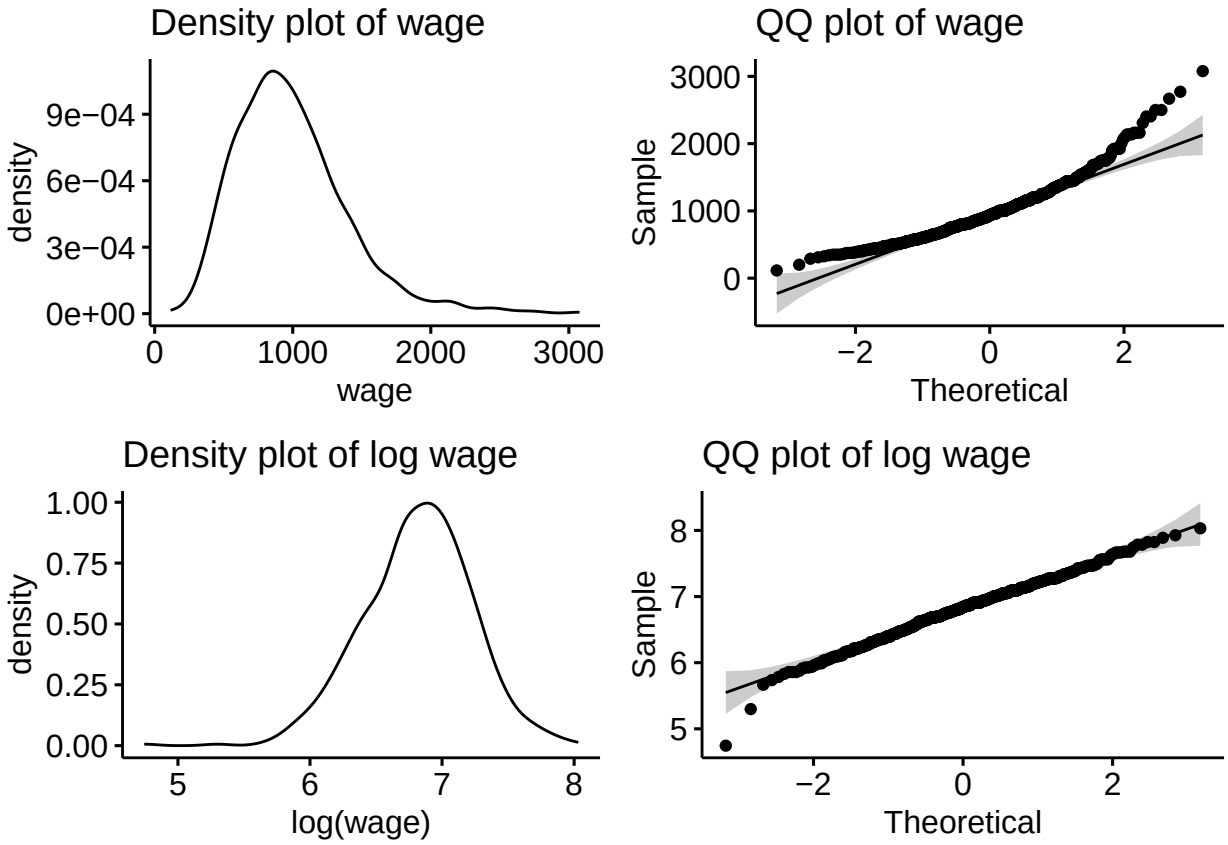
```
shapiro.test(wage2$lwage)
```

```
##
##  Shapiro-Wilk normality test
##
## data:  wage2$lwage
## W = 0.99131, p-value = 0.0006163
```

```
plot0 <- ggdensity(wage2$wage, main="Density plot of wage", xlab="wage")
plot1 <- ggqqplot(wage2$wage, title="QQ plot of wage")

plot2 <- ggdensity(wage2$lwage, main="Density plot of log wage", xlab="log(wage)")
plot3 <- ggqqplot(wage2$lwage, title="QQ plot of log wage")

ggarrange(plot0, plot1, plot2, plot3, ncol=2, nrow=2)
```



4. Linear regression

Creating a model with lwage as a dependent variable. Removing actual wage from the model and creating a linear regression model.

Additionally, adding a stepwise selection process to get a simpler model with only necessary variables. Stepwise model selection is a method used in statistical modeling to automatically select a subset of variables or features from a larger set of candidates. It's a process where variables are added or removed from the model one at a time based on a predefined criterion, such as the improvement in the model's fit or the significance of the variables. In this way we get simplier model with only important variables. But this method is not silver bullet.

The direction of stepwise is both forward and backward.

Model0:

Variables Included: Intercept, hours, IQ, KWW, educ, exper, tenure, age, married, black, south, urban, sibs, brthord, meduc, feduc.
Significant Variables (at 5% level): Intercept, hours, IQ, educ, exper, tenure, married, urban.
Adjusted R-squared: 0.2761, indicating that approximately 27.61% of the variability in the response variable is explained by the model.
Residual Standard Error: 0.3507, representing the typical difference between the observed and predicted values.

Model1: with stepwise

Variables Included: Intercept, hours, IQ, KWW, educ, exper, tenure, age, married, black, south, urban, meduc.
Variables Removed: sibs, brthord, feduc, sibs.
Significant Variables (at 5% level): Intercept, hours, IQ, educ, exper, tenure, married, urban, meduc.
Adjusted R-squared: 0.275, indicating that approximately 27.5% of the variability in the response variable is explained by the model.
Residual Standard Error: 0.351, similar to Model0.

For predictive model 27% R^2 is low, but for descriptive is is sufficient.
Model1 removes sibs, brthord, feduc, sibs.

```
# Remove the wage from the model
wage2 <- subset(wage2, select = -wage)

# Standard model
model0 <- lm(wage2$lwage~., data = wage2)

library(MASS)
# step select smaller model
fit <-  lm(wage2$lwage~.,data = wage2)
model1 <- stepAIC(fit, direction='both', trace=0)

summary(model0)
```

```
##
## Call:
## lm(formula = wage2$lwage ~ ., data = wage2)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.96887 -0.19460  0.00923  0.22401  1.34185
##
```

```
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  5.156439   0.225286  22.888  < 2e-16 ***
## hours       -0.006548   0.001934  -3.385 0.000754 ***
## IQ           0.003186   0.001223   2.604 0.009425 **
## KWW          0.003735   0.002390   1.562 0.118662
## educ         0.041267   0.008942   4.615 4.74e-06 ***
## exper        0.010749   0.004435   2.424 0.015629 *
## tenure       0.007102   0.002894   2.454 0.014401 *
## age          0.009107   0.005977   1.524 0.128058
## married      0.200760   0.045998   4.365 1.48e-05 ***
## black       -0.105141   0.055667  -1.889 0.059373 .
## south       -0.049076   0.030753  -1.596 0.111019
## urban        0.195658   0.031240   6.263 6.88e-10 ***
## sibs         0.009619   0.007876   1.221 0.222423
## brthord     -0.018465   0.011569  -1.596 0.110975
## meduc        0.009633   0.006167   1.562 0.118753
## feduc        0.005590   0.005398   1.036 0.300804
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.3507 on 647 degrees of freedom
## Multiple R-squared:  0.2925, Adjusted R-squared:  0.2761
## F-statistic: 17.84 on 15 and 647 DF,  p-value: < 2.2e-16
```

```
summary(model1)
```

```
##
## Call:
## lm(formula = wage2$lwage ~ hours + IQ + KWW + educ + exper +
##     tenure + age + married + black + south + urban + meduc, data = wage2)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2.01294 -0.20059  0.01195  0.22524  1.32195
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  5.134460   0.217379  23.620  < 2e-16 ***
## hours       -0.006371   0.001932  -3.298  0.00103 **
## IQ           0.003273   0.001221   2.681  0.00753 **
## KWW          0.003546   0.002377   1.492  0.13612
## educ         0.042825   0.008799   4.867 1.42e-06 ***
## exper        0.010333   0.004424   2.336  0.01981 *
## tenure       0.006943   0.002895   2.398  0.01676 *
## age          0.009068   0.005958   1.522  0.12849
## married      0.203743   0.046006   4.429 1.11e-05 ***
## black       -0.096556   0.054384  -1.775  0.07629 .
## south       -0.057885   0.030457  -1.901  0.05781 .
## urban        0.196127   0.031141   6.298 5.55e-10 ***
## meduc        0.013480   0.005348   2.521  0.01195 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

```
## Residual standard error: 0.351 on 650 degrees of freedom
## Multiple R-squared:  0.2882, Adjusted R-squared:  0.275
## F-statistic: 21.93 on 12 and 650 DF,  p-value: < 2.2e-16
```

5. Collinearity

If higher than 5 indicates collinearity. Here we do not have this issue, but if we did, we would remove one of the variables with high VIF from the model.

```
library(car)
vif(model0)
```

```
##    hours       IQ      KWW     educ    exper   tenure      age  married
## 1.032256 1.737404 1.743251 2.142799 1.919560 1.152359 1.803937 1.022335
##    black    south    urban     sibs  brthord    meduc    feduc
## 1.249702 1.114358 1.061829 1.676644 1.594288 1.631398 1.695625
```

```
vif(model1)
```

```
##    hours       IQ      KWW     educ    exper   tenure      age  married
## 1.027821 1.727252 1.720755 2.071801 1.907037 1.151330 1.789792 1.021123
##    black    south    urban    meduc
## 1.190886 1.091371 1.053447 1.224933
```

6. Heteroscedasticity

Model 1 and 2 have a heteroscedasticity, the null hypothesis about Homoscedasticity is rejected. That is why recalculating robust standard errors with coeftest and heteroscedasticity-robust covariance matrix estimator (HC3).

Model0:

Breusch-Pagan Test:

Test Statistic (BP): 38.914 Degrees of Freedom (df): 15 p-value: 0.00066 (indicating rejection of the null hypothesis of homoscedasticity) T-Test of Coefficients:

The table displays the estimated coefficients for each predictor variable along with their standard errors, t-values, and p-values. Variables like Intercept, hours, IQ, educ, exper, tenure, married, black, and urban have significant coefficients.

Model1:

Breusch-Pagan Test:

Test Statistic (BP): 37.256 Degrees of Freedom (df): 12 p-value: 0.000203 (indicating rejection of the null hypothesis of homoscedasticity) T-Test of Coefficients:

Similar to Model0, this table provides coefficients with standard errors, t-values, and p-values. Variables like Intercept, hours, IQ, educ, exper, tenure, married, black, south, and urban have significant coefficients.

```
bptest(model0)
```

```
##
##  studentized Breusch-Pagan test
##
## data:  model0
## BP = 38.914, df = 15, p-value = 0.00066
```

```
model0.fixed <- coeftest(model0, vcov. = vcovHC(model0, type = 'HC3'))
model0.fixed
```

```
##
## t test of coefficients:
##
##               Estimate Std. Error t value  Pr(>|t|)
## (Intercept)  5.1564394  0.2211557 23.3159 < 2.2e-16 ***
## hours       -0.0065480  0.0023551 -2.7803  0.005589 **
## IQ           0.0031857  0.0011042  2.8851  0.004044 **
## KWW          0.0037348  0.0027302  1.3679  0.171809
## educ         0.0412666  0.0094044  4.3880 1.336e-05 ***
## exper        0.0107493  0.0047579  2.2592  0.024201 *
## tenure       0.0071016  0.0030538  2.3255  0.020353 *
## age          0.0091075  0.0062267  1.4626  0.144050
## married      0.2007601  0.0479763  4.1846 3.252e-05 ***
## black       -0.1051412  0.0520714 -2.0192  0.043881 *
## south       -0.0490755  0.0337257 -1.4551  0.146116
## urban        0.1956579  0.0311713  6.2769 6.331e-10 ***
## sibs         0.0096190  0.0074648  1.2886  0.198005
## brthord     -0.0184648  0.0122953 -1.5018  0.133642
## meduc        0.0096331  0.0059212  1.6269  0.104250
## feduc        0.0055897  0.0055074  1.0150  0.310504
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
bptest(model1)
```

```
##
##  studentized Breusch-Pagan test
##
## data:  model1
## BP = 37.256, df = 12, p-value = 0.000203
```

```
model1.fixed <- model1.fixed <- coeftest(model1, vcov. = vcovHC(model1, type = 'HC3'))
model1.fixed
```

```
##
## t test of coefficients:
##
##               Estimate Std. Error t value  Pr(>|t|)
## (Intercept)  5.1344598  0.2194234 23.3998 < 2.2e-16 ***
## hours       -0.0063708  0.0023217 -2.7440  0.006237 **
```

```
## IQ           0.0032725  0.0011007  2.9730  0.003058 **
## KWW          0.0035465  0.0027280  1.3001  0.194043
## educ         0.0428251  0.0094180  4.5472 6.487e-06 ***
## exper        0.0103329  0.0047388  2.1805  0.029578 *
## tenure       0.0069429  0.0030515  2.2752  0.023217 *
## age          0.0090684  0.0062250  1.4568  0.145663
## married      0.2037429  0.0480420  4.2409 2.549e-05 ***
## black       -0.0965560  0.0504821 -1.9127  0.056229 .
## south       -0.0578847  0.0329506 -1.7567  0.079438 .
## urban        0.1961270  0.0311978  6.2866 5.953e-10 ***
## meduc        0.0134802  0.0049654  2.7148  0.006807 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

8. Normality of residuals

For the first set of results:

All four tests (Shapiro-Wilk, Kolmogorov-Smirnov, Cramer-von Mises, Anderson-Darling) indicate a rejection of the null hypothesis of normality. The p-values are very close to zero.

For the second set of results:
Again, all tests suggest a rejection of the null hypothesis of normality. The p-values are low, particularly for Shapiro-Wilk and Anderson-Darling.

As it is not crucial for descriptive analysis, only indicating that normality fails.

```
library(olsrr)

ols_test_normality(model0)
```

```
## -----------------------------------------------
##        Test             Statistic       pvalue
## -----------------------------------------------
## Shapiro-Wilk              0.9804         0.0000
## Kolmogorov-Smirnov        0.0383         0.2838
## Cramer-von Mises          110.23         0.0000
## Anderson-Darling          1.5062          7e-04
## -----------------------------------------------
```

```
ols_test_normality(model1)
```

```
## -----------------------------------------------
##        Test             Statistic       pvalue
## -----------------------------------------------
## Shapiro-Wilk              0.9804         0.0000
## Kolmogorov-Smirnov        0.0358         0.3624
## Cramer-von Mises         109.7335        0.0000
## Anderson-Darling          1.3792         0.0014
## -----------------------------------------------
```

9. Conclusion

The coefficient for "married" appeared statistically significant in both models suggesting a positive association between marital status and wages. Additionally with visual analysis and correlation calculations it has also appeared among descriptive variables.

This implies that, according to the model, being married is not merely incidental but significantly associated with higher earnings. Beyond the exploration of marital status, the top variables are education, hours, urban in the models.

Additionally, from the analysis the top variables which describe higher wages are IQ, KWW (knowledge of work), Education. The negative correlation with wages are race, south and number of siblings. From the logical point of explanation families with more siblings tend to have lower education levels, living in the south provides less opportunities and race due to economic disparities.

In conclusion, the analysis lends support to the hypothesis that married do, indeed, earn higher wages. The statistics show a strong connection, but it doesn't prove that one thing causes the other. Other factors we didn't look at could also play a role.

10. Appendix

```
# check the data
head(wage2)
```

```
##   hours  IQ KWW educ exper tenure age married black south urban sibs brthord
## 1    40  93  35   12    11      2  31       1     0     0     1    1       2
## 3    40 108  46   14    11      9  33       1     0     0     1    1       2
## 4    40  96  32   12    13      7  32       1     0     0     1    4       3
## 5    40  74  27   11    14      5  34       1     0     0     1   10       6
## 7    40  91  24   10    13      0  30       0     0     0     1    1       2
## 9    45 111  37   15    13      1  36       1     0     0     0    2       3
##   meduc feduc    lwage
## 1     8     8 6.645091
## 3    14    14 6.715384
## 4    12    12 6.476973
## 5     6    11 6.331502
## 7     8     8 6.396930
## 9    14     5 7.050990
```

```
# summary of data
summary(wage2)
```

```
##      hours             IQ             KWW             educ           exper
##  Min.   :25.00   Min.   : 54.0   Min.   :13.00   Min.   : 9.00   Min.   : 1.0
##  1st Qu.:40.00   1st Qu.: 94.0   1st Qu.:32.00   1st Qu.:12.00   1st Qu.: 8.0
##  Median :40.00   Median :104.0   Median :37.00   Median :13.00   Median :11.0
##  Mean   :44.06   Mean   :102.5   Mean   :36.19   Mean   :13.68   Mean   :11.4
##  3rd Qu.:48.00   3rd Qu.:113.0   3rd Qu.:41.00   3rd Qu.:16.00   3rd Qu.:15.0
##  Max.   :80.00   Max.   :145.0   Max.   :56.00   Max.   :18.00   Max.   :22.0
##      tenure            age           married           black
##  Min.   : 0.000   Min.   :28.00   Min.   :0.0000   Min.   :0.00000
##  1st Qu.: 3.000   1st Qu.:30.00   1st Qu.:1.0000   1st Qu.:0.00000
##  Median : 7.000   Median :33.00   Median :1.0000   Median :0.00000
##  Mean   : 7.217   Mean   :32.98   Mean   :0.9005   Mean   :0.08145
##  3rd Qu.:11.000   3rd Qu.:36.00   3rd Qu.:1.0000   3rd Qu.:0.00000
##  Max.   :22.000   Max.   :38.00   Max.   :1.0000   Max.   :1.00000
##      south            urban             sibs           brthord
##  Min.   :0.0000   Min.   :0.0000   Min.   : 0.000   Min.   : 1.000
##  1st Qu.:0.0000   1st Qu.:0.0000   1st Qu.: 1.000   1st Qu.: 1.000
##  Median :0.0000   Median :1.0000   Median : 2.000   Median : 2.000
##  Mean   :0.3228   Mean   :0.7195   Mean   : 2.846   Mean   : 2.178
##  3rd Qu.:1.0000   3rd Qu.:1.0000   3rd Qu.: 4.000   3rd Qu.: 3.000
##  Max.   :1.0000   Max.   :1.0000   Max.   :14.000   Max.   :10.000
##      meduc            feduc           lwage
##  Min.   : 0.00   Min.   : 0.00   Min.   :4.745
##  1st Qu.: 9.00   1st Qu.: 8.00   1st Qu.:6.550
##  Median :12.00   Median :11.00   Median :6.843
##  Mean   :10.83   Mean   :10.27   Mean   :6.814
##  3rd Qu.:12.00   3rd Qu.:12.00   3rd Qu.:7.090
##  Max.   :18.00   Max.   :18.00   Max.   :8.032
```

```r
# description of data
library(psych)
describe(wage2)
```

```
##         vars   n   mean    sd median trimmed   mad   min    max range  skew
## hours      1 663  44.06  7.16  40.00   42.89  0.00 25.00  80.00 55.00  1.60
## IQ         2 663 102.48 14.69 104.00  103.00 13.34 54.00 145.00 91.00 -0.32
## KWW        3 663  36.19  7.53  37.00   36.46  7.41 13.00  56.00 43.00 -0.32
## educ       4 663  13.68  2.23  13.00   13.54  1.48  9.00  18.00  9.00  0.45
## exper      5 663  11.40  4.26  11.00   11.38  4.45  1.00  22.00 21.00  0.03
## tenure     6 663   7.22  5.06   7.00    6.87  5.93  0.00  22.00 22.00  0.43
## age        7 663  32.98  3.06  33.00   32.92  4.45 28.00  38.00 10.00  0.16
## married    8 663   0.90  0.30   1.00    1.00  0.00  0.00   1.00  1.00 -2.67
## black      9 663   0.08  0.27   0.00    0.00  0.00  0.00   1.00  1.00  3.05
## south     10 663   0.32  0.47   0.00    0.28  0.00  0.00   1.00  1.00  0.76
## urban     11 663   0.72  0.45   1.00    0.77  0.00  0.00   1.00  1.00 -0.97
## sibs      12 663   2.85  2.24   2.00    2.55  1.48  0.00  14.00 14.00  1.57
## brthord   13 663   2.18  1.49   2.00    1.89  1.48  1.00  10.00  9.00  1.79
## meduc     14 663  10.83  2.82  12.00   10.91  1.48  0.00  18.00 18.00 -0.59
## feduc     15 663  10.27  3.29  11.00   10.24  2.97  0.00  18.00 18.00 -0.01
## lwage     16 663   6.81  0.41   6.84    6.82  0.38  4.74   8.03  3.29 -0.32
##         kurtosis   se
## hours       3.69 0.28
## IQ          0.02 0.57
## KWW        -0.29 0.29
## educ       -0.99 0.09
## exper      -0.47 0.17
## tenure     -0.75 0.20
## age        -1.24 0.12
## married     5.13 0.01
## black       7.34 0.01
## south      -1.43 0.02
## urban      -1.05 0.02
## sibs        3.55 0.09
## brthord     3.85 0.06
## meduc       1.25 0.11
## feduc      -0.03 0.13
## lwage       0.83 0.02
```