Regression Project – Group 3 (Intermediate Report)

Reema abolahum and Muzammil Mohammed

2025-10-12

Table of contents


```
suppressPackageStartupMessages({
  library(tidyverse)
  library(readxl)
  library(simFrame)
  library(dplyr)        # data manipulation
  library(ggplot2)      # visualization
  library(tidyr)        # data tidying
```

```
  library(forcats)      # factor management
  library(effects)  # effect plots
  library(gt)
  library(corrplot)
  library(forcats)
  library(splines)
  library(car)

})
```

1 1. Introduction

This report analyzes determinants of employment income (`py010n`) in South Austria. We focus on data preparation, descriptive statistics, and regression modeling using polynomial and spline methods. Interactions between predictors are explored, and diagnostic checks are performed to validate model assumptions.

2 2. Data Collection and Preparation

```
data("eusilcP")

dat <- eusilcP %>%
  select(py010n, gender, citizenship, hsize, age, region) %>%
  filter(region %in% c("Carinthia", "Styria")) %>%
  filter(py010n > 0)

dat$hsize <- as.numeric(as.character(dat$hsize))
dat <- na.omit(dat)
```

3 3. Descriptive Analysis

3.1 3.1 Numeric Summaries

```
num_vars <- dat %>% select(py010n, age, hsize)
summary(num_vars)
```

```
     py010n                age             hsize
 Min.   :     1.93   Min.   :16.00   Min.   :1.00
 1st Qu.: 10066.01   1st Qu.:29.00   1st Qu.:2.00
 Median : 16225.84   Median :40.00   Median :3.00
 Mean   : 16952.35   Mean   :39.73   Mean   :3.19
 3rd Qu.: 21939.78   3rd Qu.:49.00   3rd Qu.:4.00
 Max.   :118362.27   Max.   :97.00   Max.   :9.00
```

3.2 3.2 Frequency Tables

```
table(dat$gender)
```

```
  male female
  3004   2263
```

```
table(dat$citizenship)
```

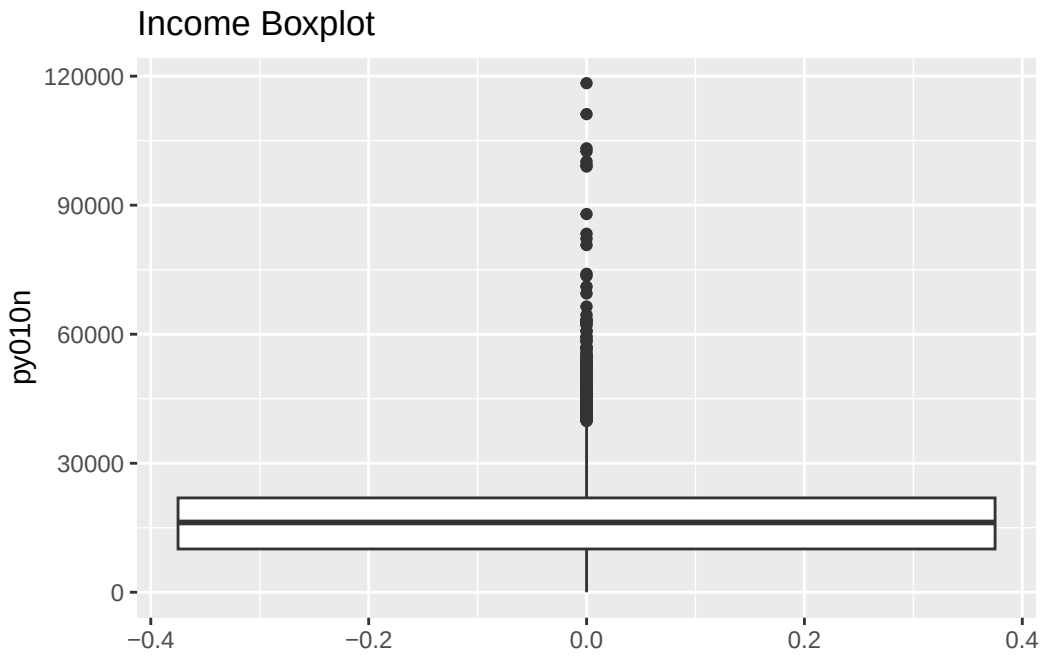
```
   AT    EU Other
 5021    79   167
```

```
table(dat$gender, dat$citizenship)
```

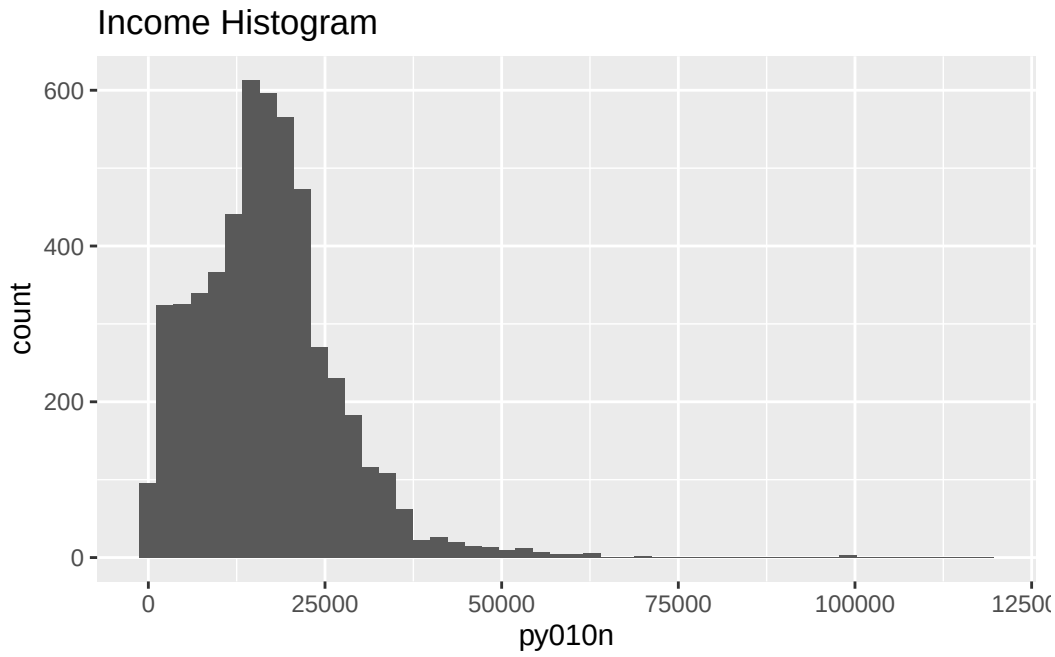
```
           AT   EU Other
  male   2867   40    97
  female 2154   39    70
```

3.3 3.3 Univariate Plots

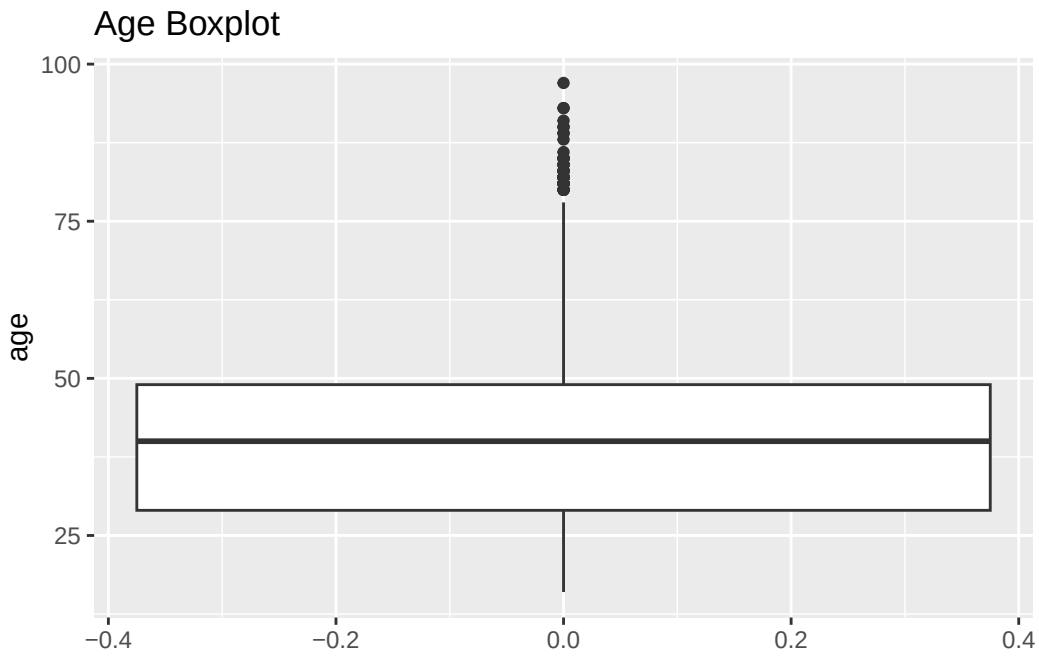
```
# Income
 ggplot(dat, aes(y=py010n)) + geom_boxplot() + labs(title="Income Boxplot")
```



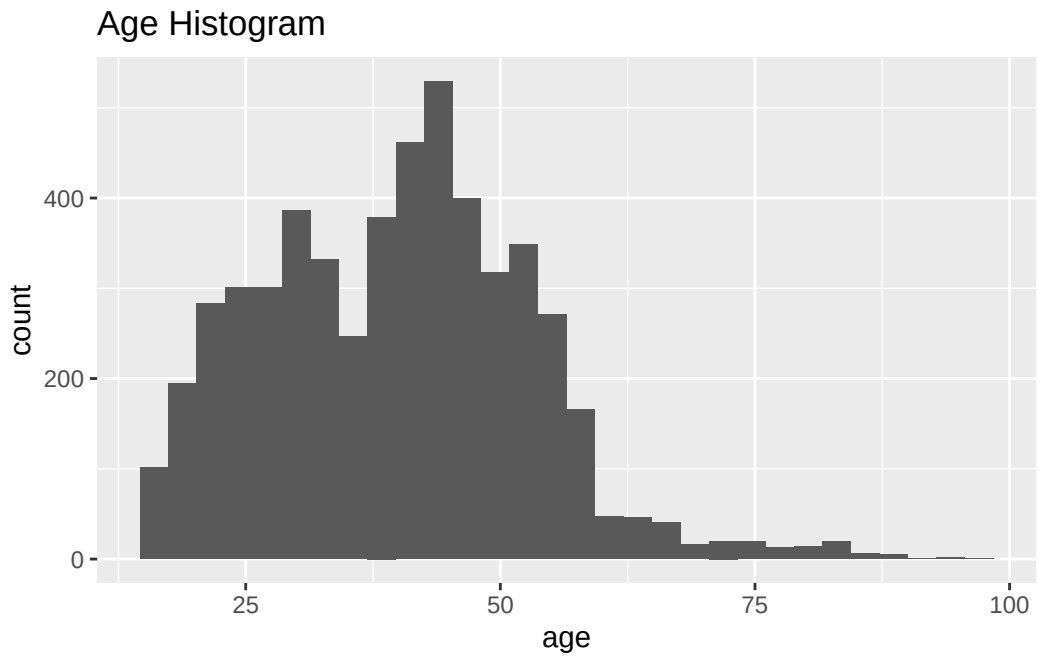

```
ggplot(dat, aes(x=py010n)) + geom_histogram(bins=50) + labs(title="Income Histogram")
```



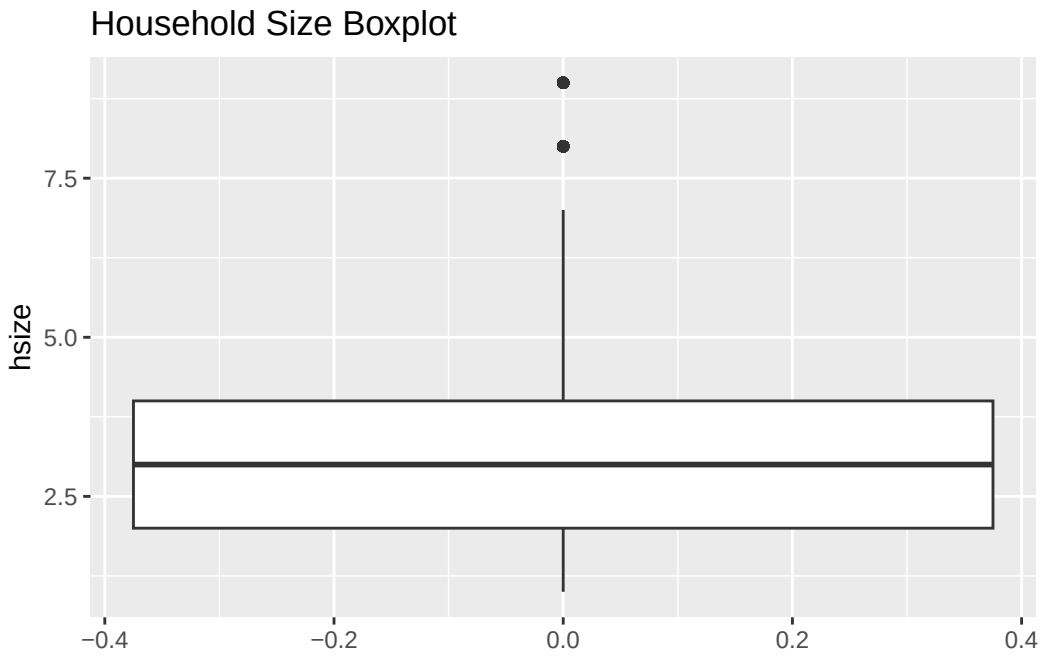
```r
# Age
 ggplot(dat, aes(y=age)) + geom_boxplot() + labs(title="Age Boxplot")
```



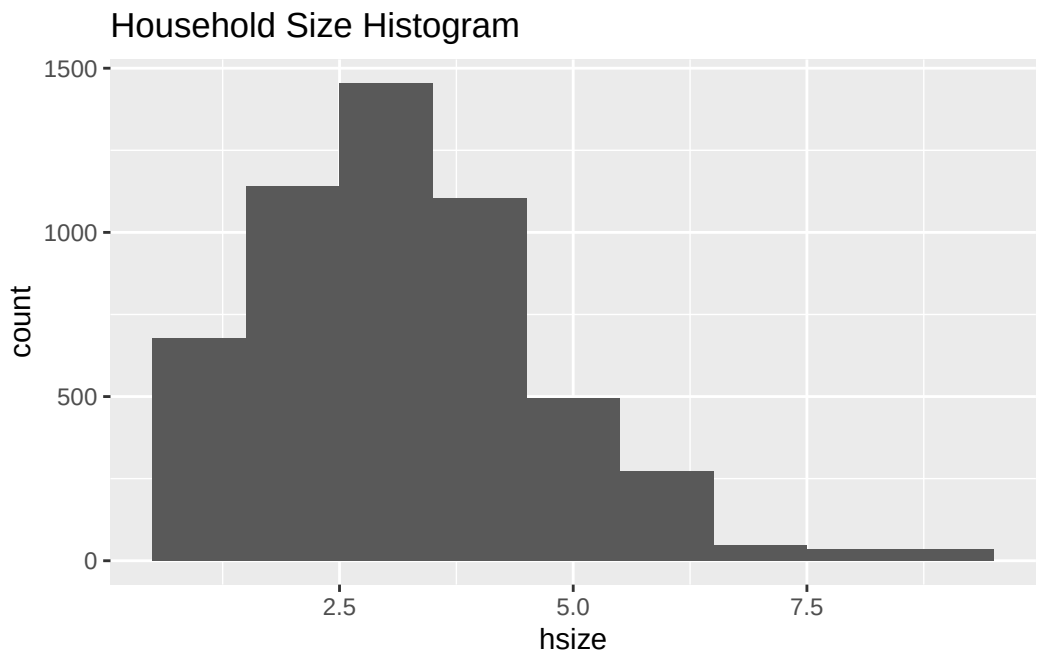

```r
 ggplot(dat, aes(x=age)) + geom_histogram(bins=30) + labs(title="Age Histogram")
```



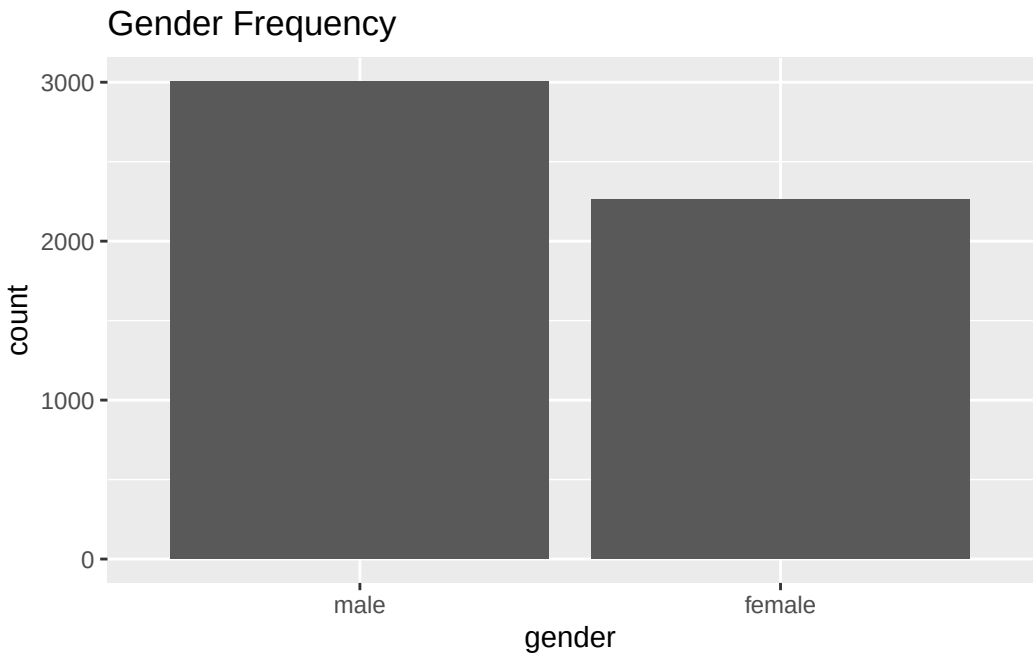

```
# Household Size
 ggplot(dat, aes(y=hsize)) + geom_boxplot() + labs(title="Household Size Boxplot")
```



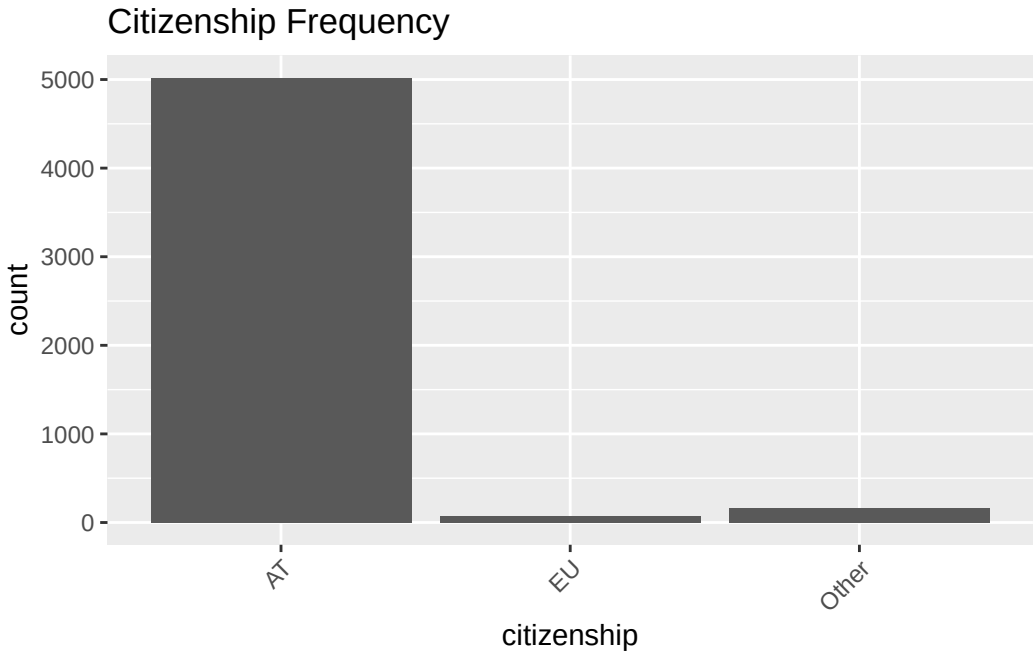
```
ggplot(dat, aes(x=hsize)) + geom_histogram(binwidth=1) + labs(title="Household Size Histogra
```




```
# Gender
 ggplot(dat, aes(x=gender)) + geom_bar() + labs(title="Gender Frequency")
```

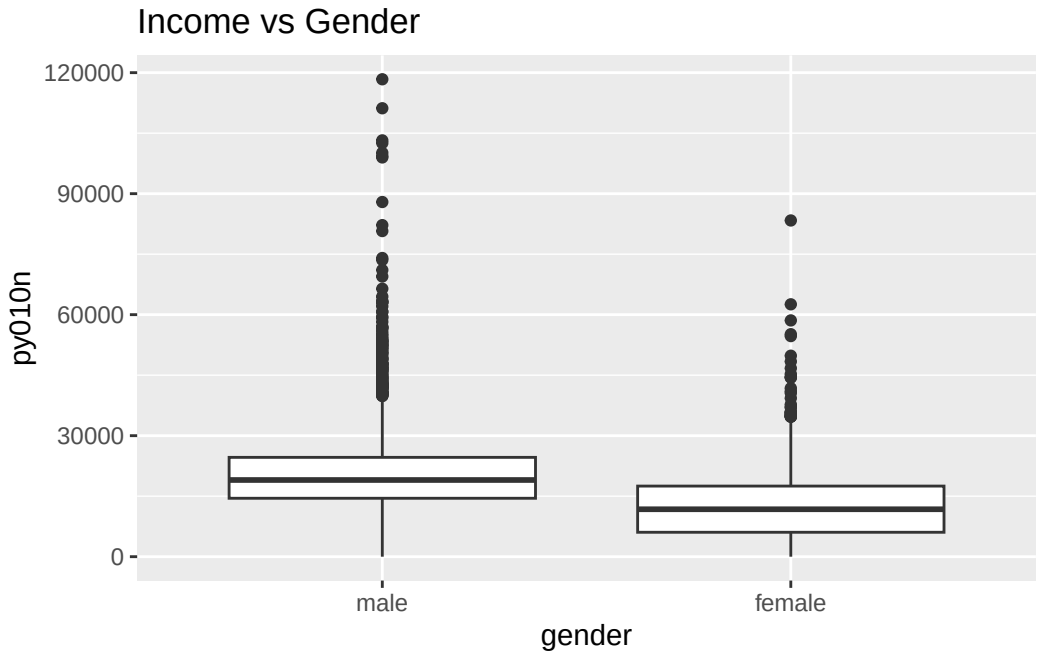



```
# Citizenship
 ggplot(dat, aes(x=citizenship)) + geom_bar() +
  theme(axis.text.x=element_text(angle=45,hjust=1)) + labs(title="Citizenship Frequency")
```

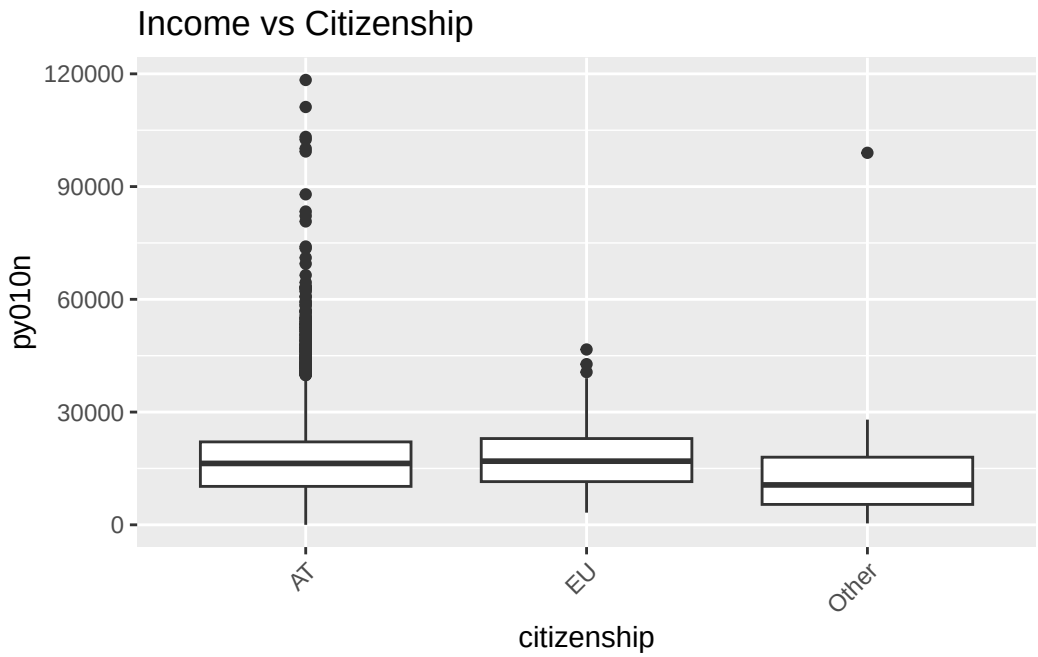


3.4 3.4 Bivariate Plots

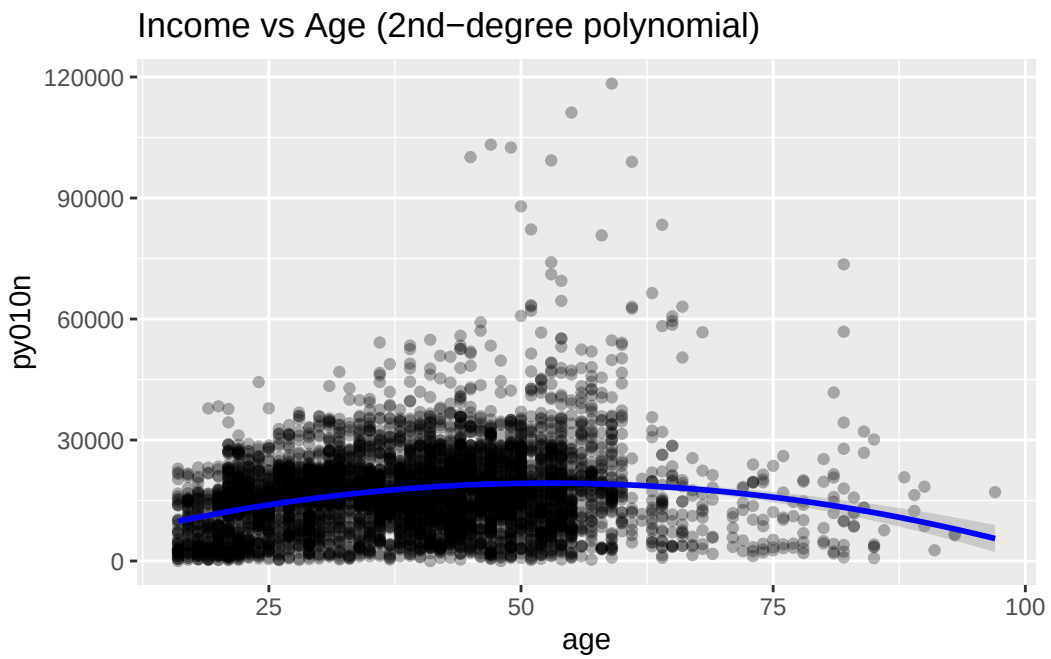
```
# Gender vs Income
ggplot(dat, aes(x=gender, y=py010n)) + geom_boxplot() + labs(title="Income vs Gender")
```



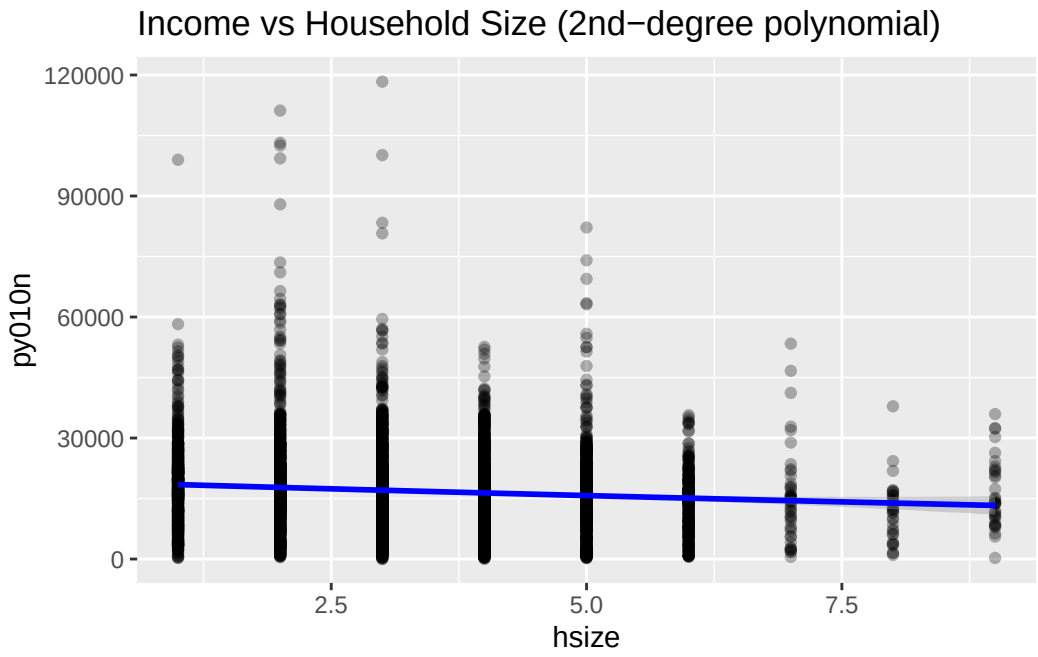

```
# Citizenship vs Income
ggplot(dat, aes(x=citizenship, y=py010n)) +
  geom_boxplot() + theme(axis.text.x=element_text(angle=45,hjust=1)) + labs(title="Income vs
```




```
# Age vs Income (Polynomial)
ggplot(dat, aes(x=age, y=py010n)) +
  geom_point(alpha=0.3) + geom_smooth(method="lm", formula=y~poly(x,2), color="blue") +
  labs(title="Income vs Age (2nd-degree polynomial)")
```

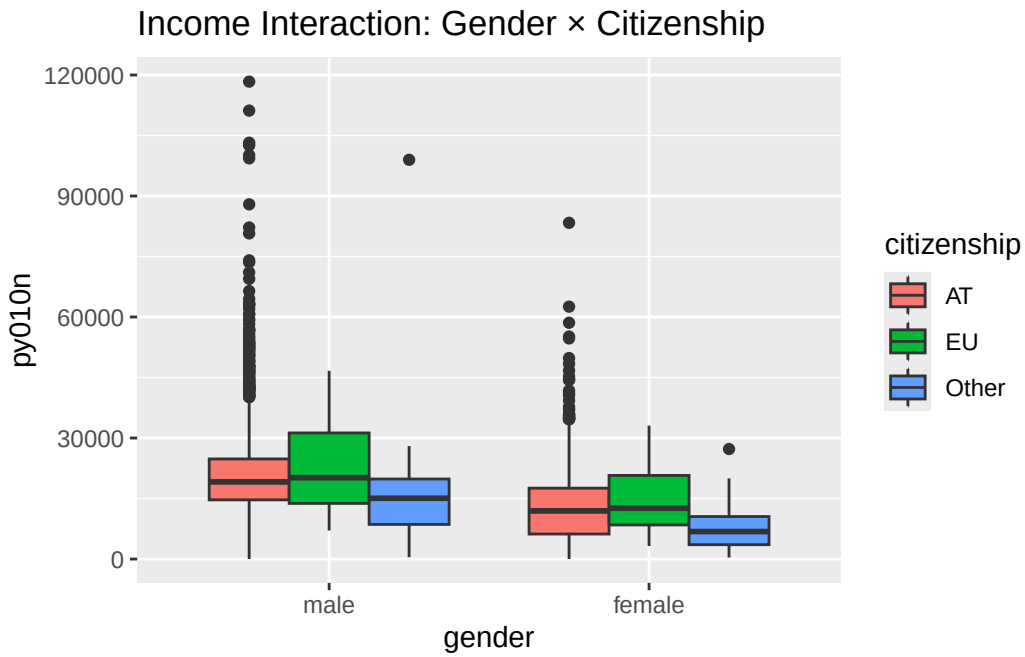



```
# Household size vs Income (Polynomial)
ggplot(dat, aes(x=hsize, y=py010n)) +
  geom_point(alpha=0.3) + geom_smooth(method="lm", formula=y~poly(x,2), color="blue") +
  labs(title="Income vs Household Size (2nd-degree polynomial)")
```



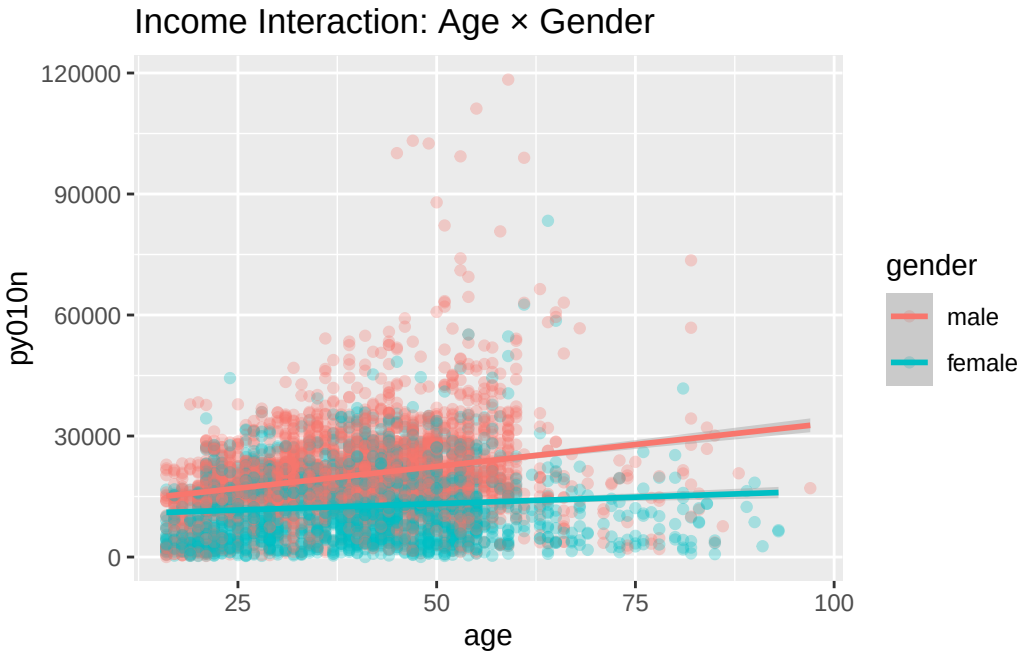
3.5 3.5 Interaction Plots

```
# Gender × Citizenship
ggplot(dat, aes(x=gender, y=py010n, fill=citizenship)) +
  geom_boxplot(position="dodge") + labs(title="Income Interaction: Gender × Citizenship")
```



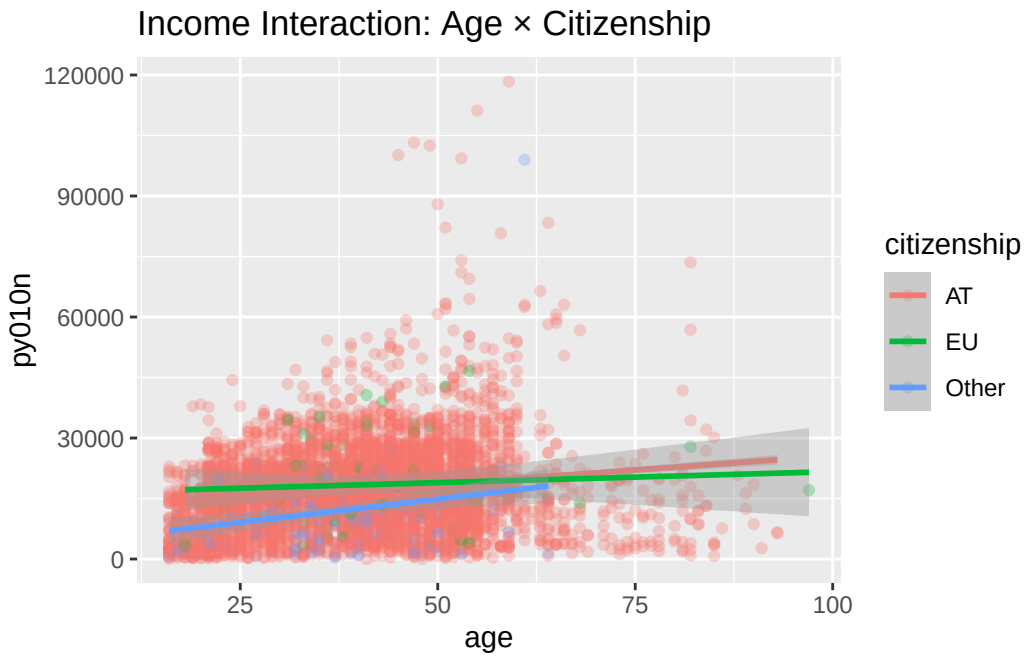

```
# Age × Gender
ggplot(dat, aes(x=age, y=py010n, color=gender)) + geom_point(alpha=0.3) + geom_smooth(method=
  labs(title="Income Interaction: Age × Gender")
```

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



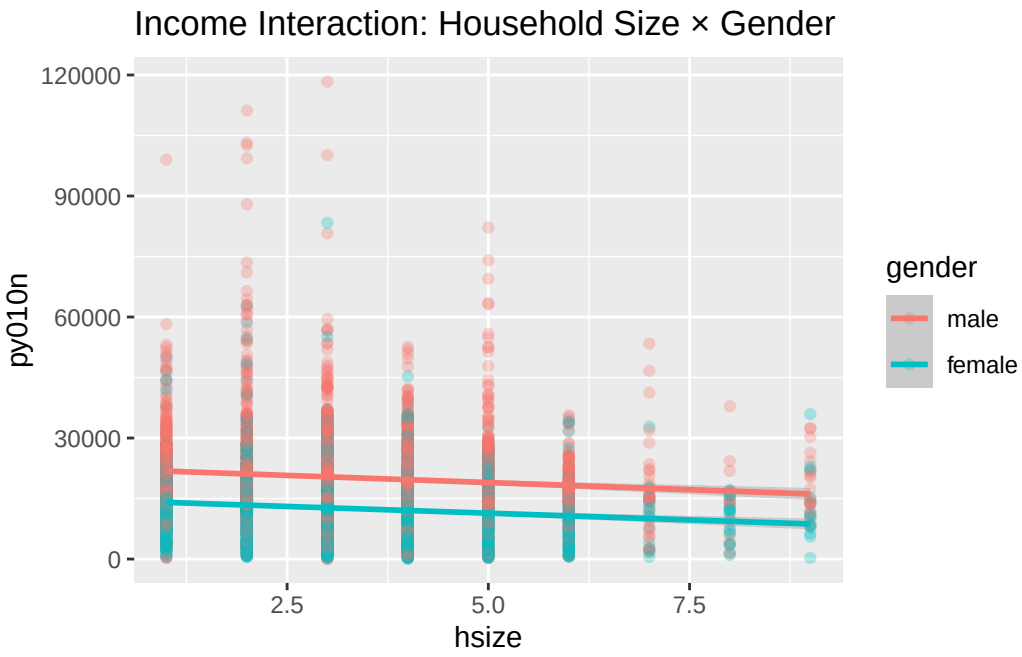

```
# Age × Citizenship
ggplot(dat, aes(x=age, y=py010n, color=citizenship)) + geom_point(alpha=0.3) + geom_smooth(me
  labs(title="Income Interaction: Age × Citizenship")
```

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



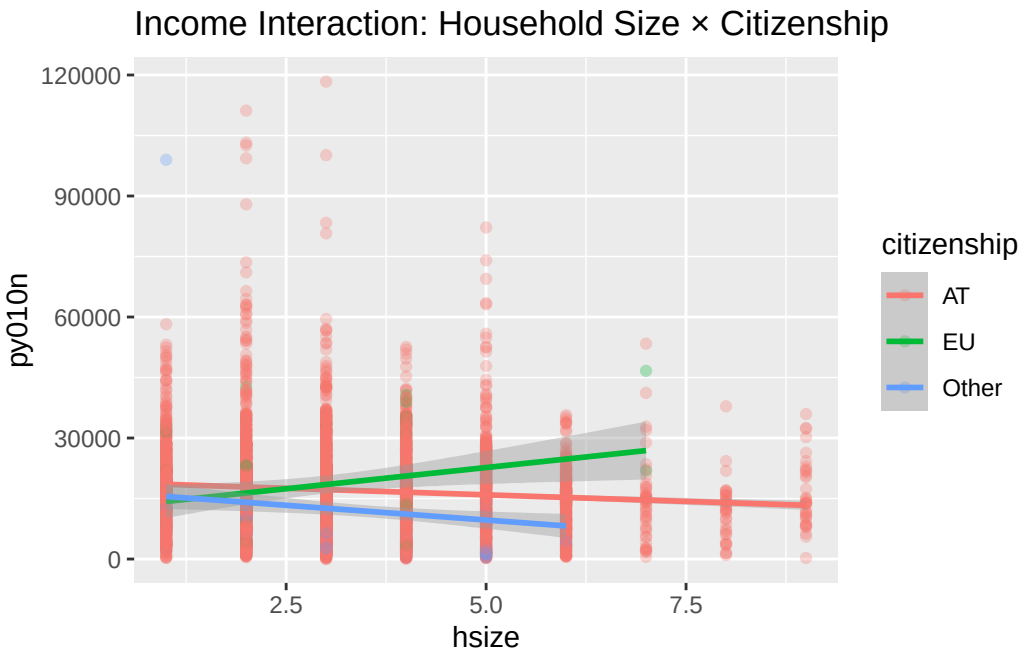

```
# Household Size × Gender
ggplot(dat, aes(x=hsize, y=py010n, color=gender)) + geom_point(alpha=0.3) + geom_smooth(metho
  labs(title="Income Interaction: Household Size × Gender")
```

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



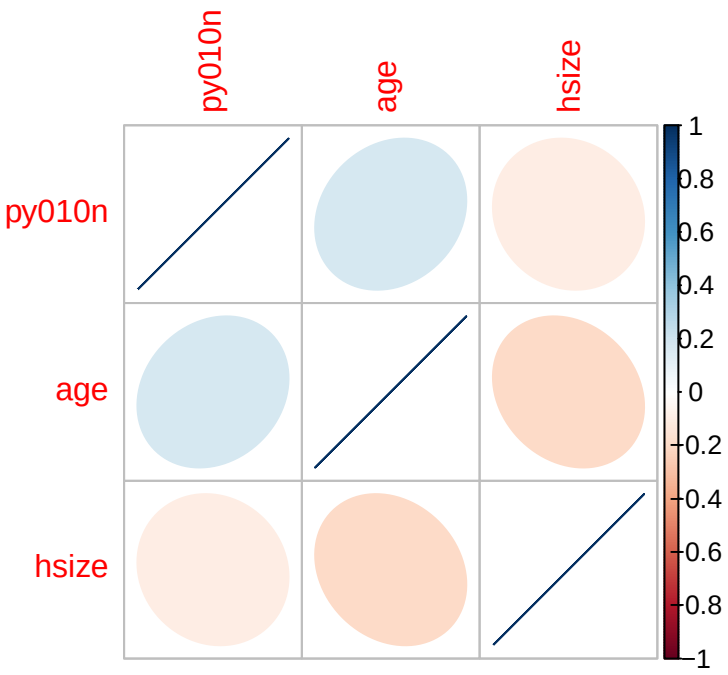

```
# Household Size × Citizenship
ggplot(dat, aes(x=hsize, y=py010n, color=citizenship)) + geom_point(alpha=0.3) + geom_smooth
  labs(title="Income Interaction: Household Size × Citizenship")
```

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

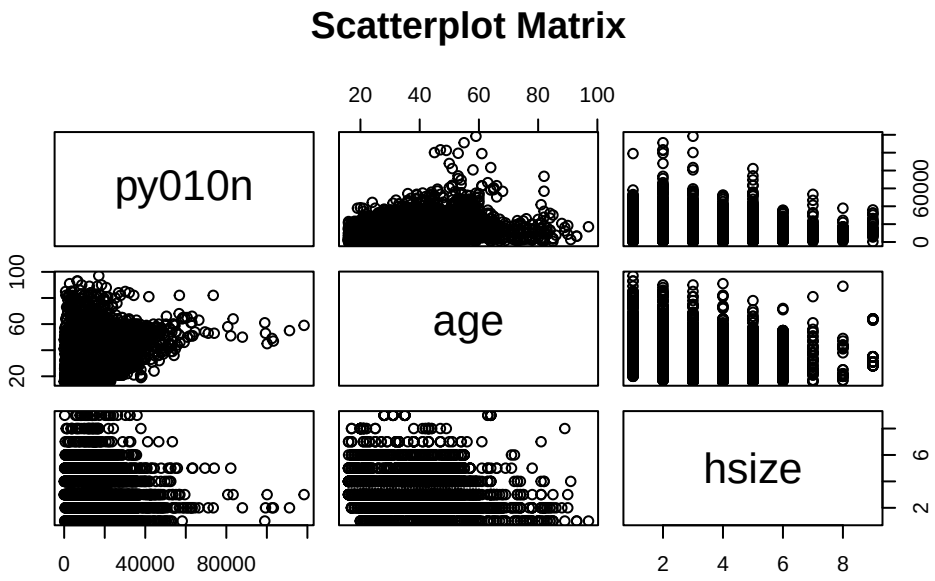


3.6 3.6 Correlation / Scatterplot Matrix

```
cor_mat <- cor(num_vars)
corrplot(cor_mat, method="ellipse")
```




```
pairs(num_vars, main="Scatterplot Matrix")
```



4 4. Regression Modeling

4.1 4.1 Linear Model

```
lm_model <- lm(py010n ~ gender + citizenship + hsize + age, data=dat)
summary(lm_model)
```

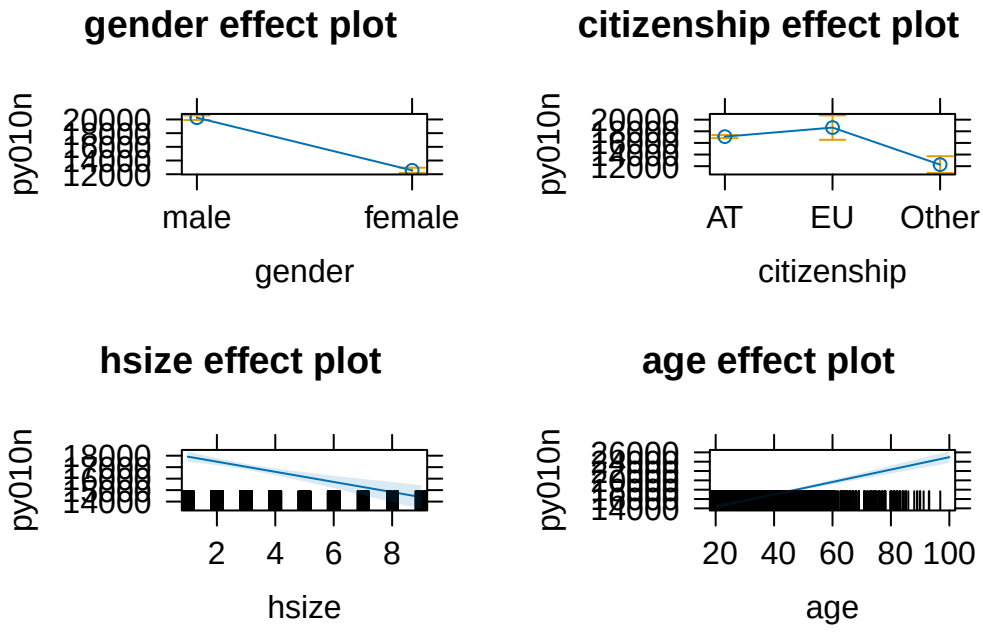
```
Call:
lm(formula = py010n ~ gender + citizenship + hsize + age, data = dat)

Residuals:
   Min     1Q Median     3Q    Max
-23585  -5909  -1124   4619  95330

Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
(Intercept)      16509.98     567.51  29.092  < 2e-16 ***
genderfemale     -7688.82     265.03 -29.012  < 2e-16 ***
citizenshipEU     1556.37    1079.80   1.441     0.15
citizenshipOther -4813.39     750.01  -6.418 1.50e-10 ***
hsize             -441.49      88.13  -5.009 5.64e-07 ***
age                133.00      10.29  12.923  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 9520 on 5261 degrees of freedom
Multiple R-squared:  0.1748,    Adjusted R-squared:  0.174
F-statistic: 222.8 on 5 and 5261 DF,  p-value: < 2.2e-16
```

```
Anova(lm_model)
```

```
Anova Table (Type II tests)

Response: py010n
                Sum Sq   Df F value    Pr(>F)
gender      7.6276e+10    1 841.667 < 2.2e-16 ***
citizenship 3.9581e+09    2  21.838 3.591e-10 ***
hsize       2.2740e+09    1  25.093 5.642e-07 ***
age         1.5135e+10    1 167.003 < 2.2e-16 ***
```

```
Residuals   4.7678e+11 5261
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
plot(allEffects(lm_model))
```



4.2 4.2 Polynomial Model

```
poly_model <- lm(py010n ~ gender + citizenship + poly(age,2) + poly(hsize,2), data=dat)
summary(poly_model)
```

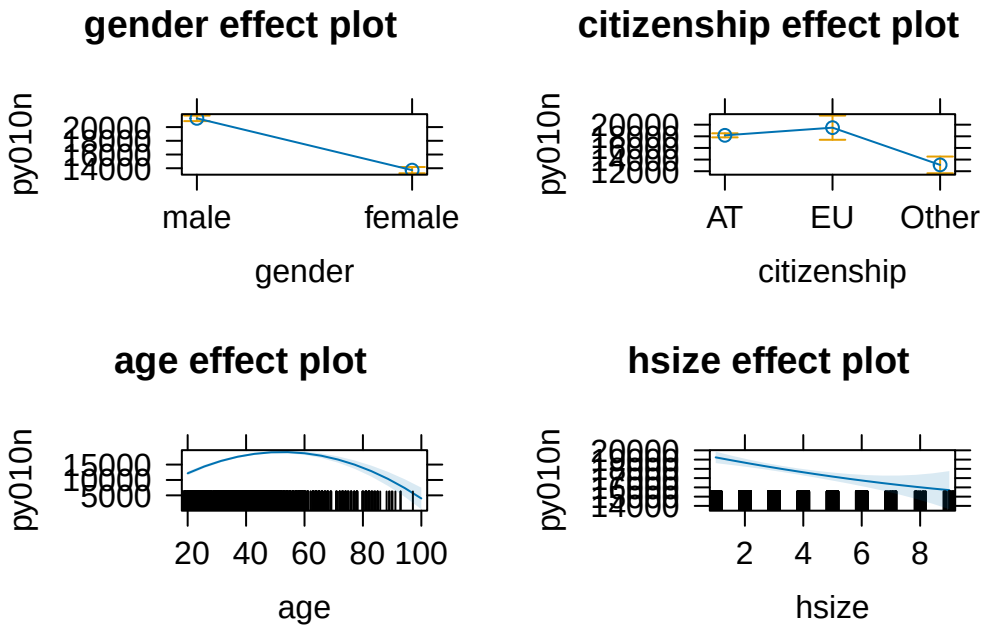
```
Call:
lm(formula = py010n ~ gender + citizenship + poly(age, 2) + poly(hsize,
    2), data = dat)

Residuals:
   Min     1Q Median     3Q    Max
-22110  -5804  -1103   4623  96100
```

```
Coefficients:
                  Estimate Std. Error t value Pr(>|t|)
(Intercept)        20337.7      173.5 117.236  < 2e-16 ***
genderfemale       -7549.7      261.4 -28.882  < 2e-16 ***
citizenshipEU       1313.6     1064.3   1.234    0.217
citizenshipOther   -5085.4      739.8  -6.874 6.95e-12 ***
poly(age, 2)1     124087.3     9589.4  12.940  < 2e-16 ***
poly(age, 2)2    -118841.7     9446.7 -12.580  < 2e-16 ***
poly(hsize, 2)1   -53916.1     9582.7  -5.626 1.94e-08 ***
poly(hsize, 2)2     4848.6     9445.8   0.513    0.608
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 9381 on 5259 degrees of freedom
Multiple R-squared:  0.1989,    Adjusted R-squared:  0.1979
F-statistic: 186.6 on 7 and 5259 DF,  p-value: < 2.2e-16
```

```
Anova(poly_model)
```

```
Anova Table (Type II tests)

Response: py010n
                   Sum Sq   Df F value    Pr(>F)
gender         7.3409e+10    1 834.159 < 2.2e-16 ***
citizenship    4.3277e+09    2  24.588 2.350e-11 ***
poly(age, 2)   2.9102e+10    2 165.348 < 2.2e-16 ***
poly(hsize, 2) 2.8014e+09    2  15.916 1.284e-07 ***
Residuals      4.6281e+11 5259
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
plot(allEffects(poly_model))
```



4.3 4.3 Spline Model

```
spline_model <- lm(py010n ~ gender + citizenship + ns(age, df=3) + ns(hsize, df=3), data=dat)
summary(spline_model)
```

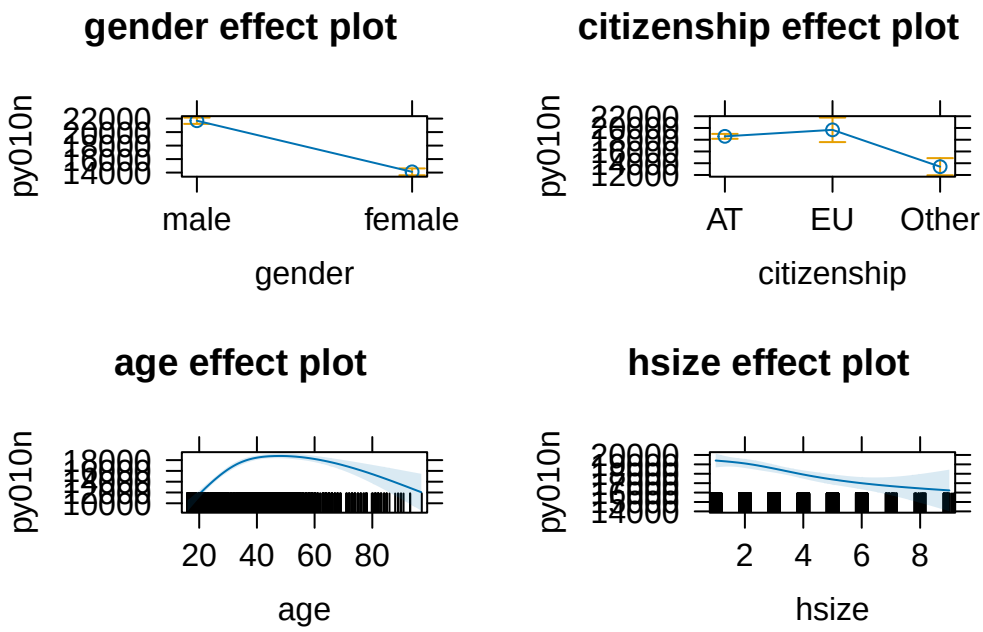
```
Call:
lm(formula = py010n ~ gender + citizenship + ns(age, df = 3) +
    ns(hsize, df = 3), data = dat)

Residuals:
   Min     1Q Median     3Q    Max
-21696  -5815  -1128   4546  96547

Coefficients:
                  Estimate Std. Error t value Pr(>|t|)
(Intercept)        13913.9      630.7  22.060  < 2e-16 ***
genderfemale       -7571.9      261.3 -28.980  < 2e-16 ***
citizenshipEU       1103.1     1065.2   1.036  0.30047
citizenshipOther   -5167.3      741.3  -6.971 3.54e-12 ***
ns(age, df = 3)1    7206.4      667.8  10.791  < 2e-16 ***
```

```
ns(age, df = 3)2    13315.5     1497.8   8.890  < 2e-16 ***
ns(age, df = 3)3    -1491.0     1724.2  -0.865  0.38721
ns(hsize, df = 3)1  -2217.2      678.4  -3.268  0.00109 **
ns(hsize, df = 3)2  -3115.8      979.8  -3.180  0.00148 **
ns(hsize, df = 3)3  -3011.2     1093.9  -2.753  0.00593 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 9375 on 5257 degrees of freedom
Multiple R-squared:  0.2003,    Adjusted R-squared:  0.1989
F-statistic: 146.3 on 9 and 5257 DF,  p-value: < 2.2e-16
```

```
Anova(spline_model)
```

```
Anova Table (Type II tests)

Response: py010n
                     Sum Sq   Df F value    Pr(>F)
gender            7.3816e+10    1 839.862 < 2.2e-16 ***
citizenship       4.3999e+09    2  25.031 1.516e-11 ***
ns(age, df = 3)   2.9832e+10    3 113.141 < 2.2e-16 ***
ns(hsize, df = 3) 2.8699e+09    3  10.884 3.996e-07 ***
Residuals         4.6204e+11 5257
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
plot(allEffects(spline_model, xlevels=50))
```



4.4 4.4 Interaction Model

```
int_model <- lm(py010n ~ (gender + citizenship + ns(age,3) + ns(hsize,3))^2, data=dat)
summary(int_model)
```

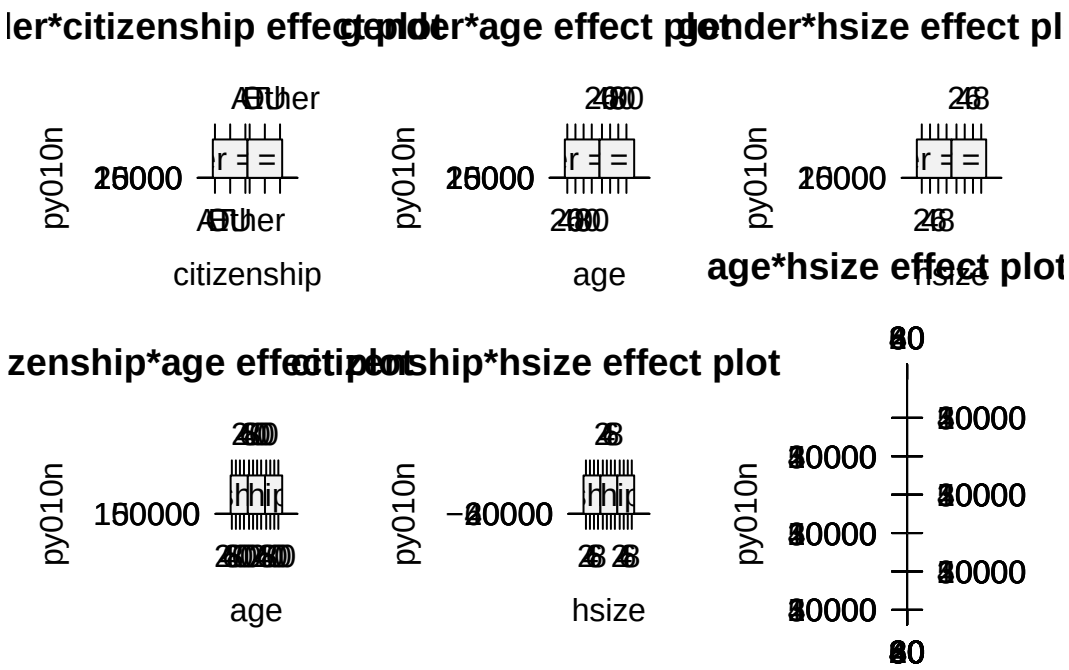
```
Call:
lm(formula = py010n ~ (gender + citizenship + ns(age, 3) + ns(hsize,
    3))^2, data = dat)

Residuals:
   Min     1Q Median     3Q    Max
-22493  -5814  -1051   4526  95508

Coefficients:
                            Estimate Std. Error t value Pr(>|t|)
(Intercept)                  13460.2     2193.4   6.137 9.05e-10 ***
genderfemale                 -3694.9     1266.9  -2.917 0.003555 **
citizenshipEU                -6592.6     7259.9  -0.908 0.363873
citizenshipOther              1020.4     4019.5   0.254 0.799603
ns(age, 3)1                   8509.7     1784.0   4.770 1.89e-06 ***
```

```
ns(age, 3)2                     15438.9     5186.9   2.977 0.002929 **
ns(age, 3)3                      2803.1     4155.8   0.675 0.500016
ns(hsize, 3)1                   -2041.1     2810.7  -0.726 0.467759
ns(hsize, 3)2                   -4369.1     5098.4  -0.857 0.391513
ns(hsize, 3)3                    -389.4     4311.8  -0.090 0.928045
genderfemale:citizenshipEU       1657.6     2257.6   0.734 0.462835
genderfemale:citizenshipOther     393.0     1497.5   0.262 0.792993
genderfemale:ns(age, 3)1        -6448.7     1381.4  -4.668 3.11e-06 ***
genderfemale:ns(age, 3)2        -9135.9     3149.9  -2.900 0.003743 **
genderfemale:ns(age, 3)3        -7029.8     3783.8  -1.858 0.063245 .
genderfemale:ns(hsize, 3)1      -3606.2     1394.3  -2.586 0.009723 **
genderfemale:ns(hsize, 3)2        430.2     2100.6   0.205 0.837740
genderfemale:ns(hsize, 3)3       2077.1     2373.4   0.875 0.381540
citizenshipEU:ns(age, 3)1       -1964.3     6024.1  -0.326 0.744376
citizenshipOther:ns(age, 3)1   -14492.4     5840.7  -2.481 0.013123 *
citizenshipEU:ns(age, 3)2       11401.6    14368.0   0.794 0.427499
citizenshipOther:ns(age, 3)2    59054.6    19794.1   2.983 0.002863 **
citizenshipEU:ns(age, 3)3        3107.6     9574.6   0.325 0.745518
citizenshipOther:ns(age, 3)3   111889.8    32948.7   3.396 0.000689 ***
citizenshipEU:ns(hsize, 3)1      8157.1     6825.6   1.195 0.232116
citizenshipOther:ns(hsize, 3)1   1033.3     5271.1   0.196 0.844590
citizenshipEU:ns(hsize, 3)2     14573.1    11094.8   1.314 0.189072
citizenshipOther:ns(hsize, 3)2 -16978.8    11185.9  -1.518 0.129105
citizenshipEU:ns(hsize, 3)3     26088.3    15305.3   1.705 0.088342 .
citizenshipOther:ns(hsize, 3)3  -5405.8    16142.2  -0.335 0.737724
ns(age, 3)1:ns(hsize, 3)1        2636.3     3842.2   0.686 0.492659
ns(age, 3)2:ns(hsize, 3)1       -9483.7     9011.8  -1.052 0.292683
ns(age, 3)3:ns(hsize, 3)1      -23699.8    12037.9  -1.969 0.049032 *
ns(age, 3)1:ns(hsize, 3)2        2699.1     5119.5   0.527 0.598064
ns(age, 3)2:ns(hsize, 3)2        2817.2    11878.7   0.237 0.812540
ns(age, 3)3:ns(hsize, 3)2        2329.1    10580.4   0.220 0.825779
ns(age, 3)1:ns(hsize, 3)3        -183.0     6593.3  -0.028 0.977860
ns(age, 3)2:ns(hsize, 3)3       -2574.4    11412.4  -0.226 0.821536
ns(age, 3)3:ns(hsize, 3)3       10763.5    14573.6   0.739 0.460208
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 9316 on 5228 degrees of freedom
Multiple R-squared:  0.2147,    Adjusted R-squared:  0.209
F-statistic: 37.61 on 38 and 5228 DF,  p-value: < 2.2e-16
```

```
Anova(int_model)
```

```
Anova Table (Type II tests)

Response: py010n
                             Sum Sq   Df  F value    Pr(>F)
gender                     7.2912e+10    1 840.1387 < 2.2e-16 ***
citizenship                4.3629e+09    2  25.1364 1.366e-11 ***
ns(age, 3)                 2.9791e+10    3 114.4234 < 2.2e-16 ***
ns(hsize, 3)               2.7869e+09    3  10.7044 5.188e-07 ***
gender:citizenship         5.1964e+07    2   0.2994   0.74129
gender:ns(age, 3)          4.2695e+09    3  16.3985 1.324e-10 ***
gender:ns(hsize, 3)        6.0021e+08    3   2.3053   0.07475 .
citizenship:ns(age, 3)     1.2057e+09    6   2.3154   0.03101 *
citizenship:ns(hsize, 3)   1.3626e+09    6   2.6169   0.01556 *
ns(age, 3):ns(hsize, 3)    7.4561e+08    9   0.9546   0.47594
Residuals                  4.5371e+11 5228
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
plot(allEffects(int_model, xlevels=50))
```



5 5. Summary

This analysis shows skewed income with outliers, gender and citizenship differences, nonlinear relationships with age and household size, and relevant interactions. Polynomial and spline regressions provide flexible modeling of numeric predictors, and residual diagnostics suggest the models are adequate.