Project 1

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Introduction

Economic mobility, or the ability of an individual to raise their economic status throughout their lifetime, is a marker of a healthy society. As economic mobility declines and income inequality rises throughout the United States, it is of increasing interest to determine which factors contribute to immobility. In this paper, we will investigate the correlation between economic, educational, and policy factors that contribute to economic mobility. We hypothesize that economic factors such as income inequality, will be most predictive of economic mobility.

Exploratory data analysis

```
# View NAs
nas <- colSums(is.na(mobility))
print(nas[nas > 0])
```

```
##              Mobility               Share01               Gini_99
##                    12                    32                    32
##          Middle_class       Local_tax_rate   Local_gov_spending
##                    32                     1                     2
##       School_spending Student_teacher_ratio          Test_scores
##                    10                    30                    36
##            HS_dropout              Colleges               Tuition
##                   148                   157                   161
##            Graduation      Chinese_imports        Teenage_labor
##                   160                    19                    32
##          Migration_in       Migration_out       Social_capital
##                    17                    17                    19
##         Violent_crime
##                    27
```

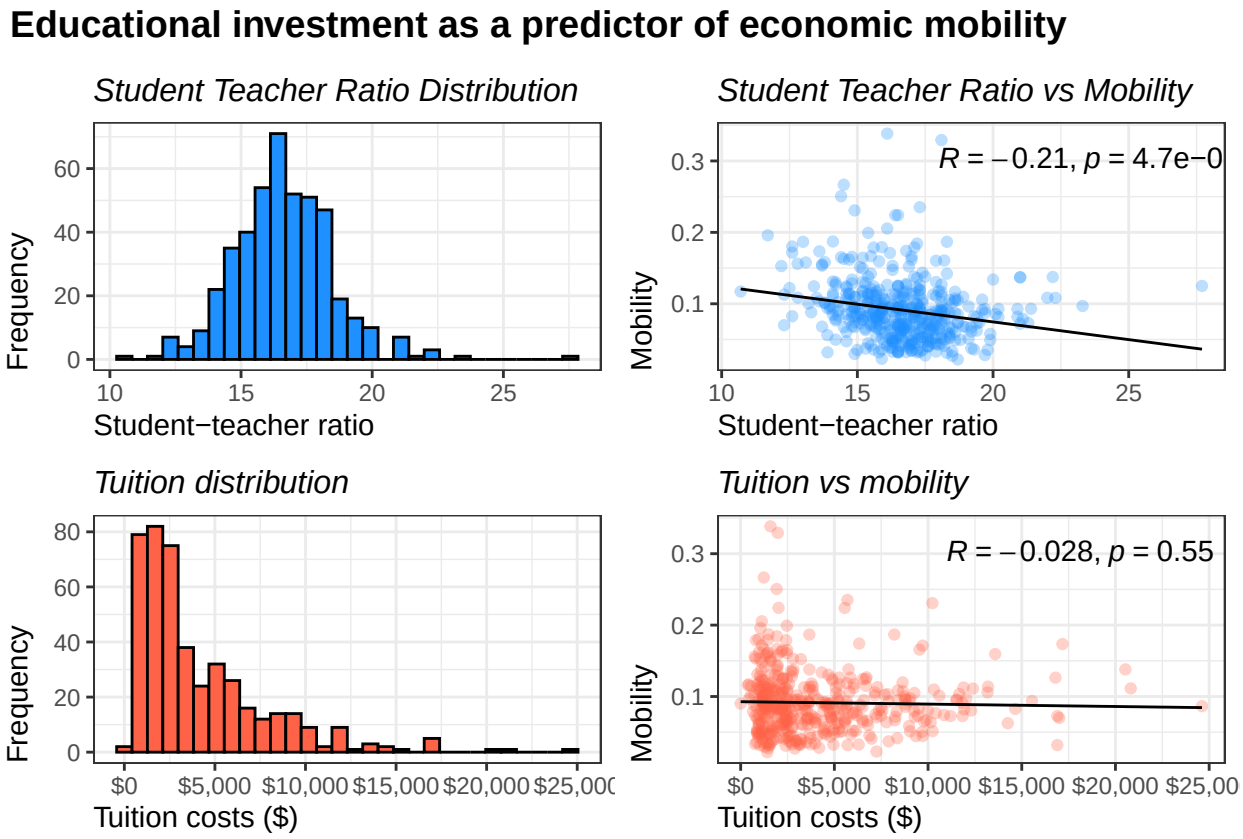
This dataset contains several rows for which one or more than one value is `NA`. Three steps were taken to eliminate `NA`s from the dataset while preserving its integrity.

1. *Drop the 12 rows that do not contain a value for* ***`Mobility`*** | These rows are useless for linear analysis because they do not contain the variable we are attempting to predict.
2. *Drop the features that contain a high incidence of* ***`NA`****s* | Any features that contained more than 100 NAs were designated as too poor in quality to be useful for the linear model. While some of these features were used for exploratory data analysis, they were removed from the dataset prior to modeling.
3. *Drop all remaining* ***`NA`*** *values* | After removing the most `NA` values, a small amount of rows with `NA`s remained. These rows were dropped.

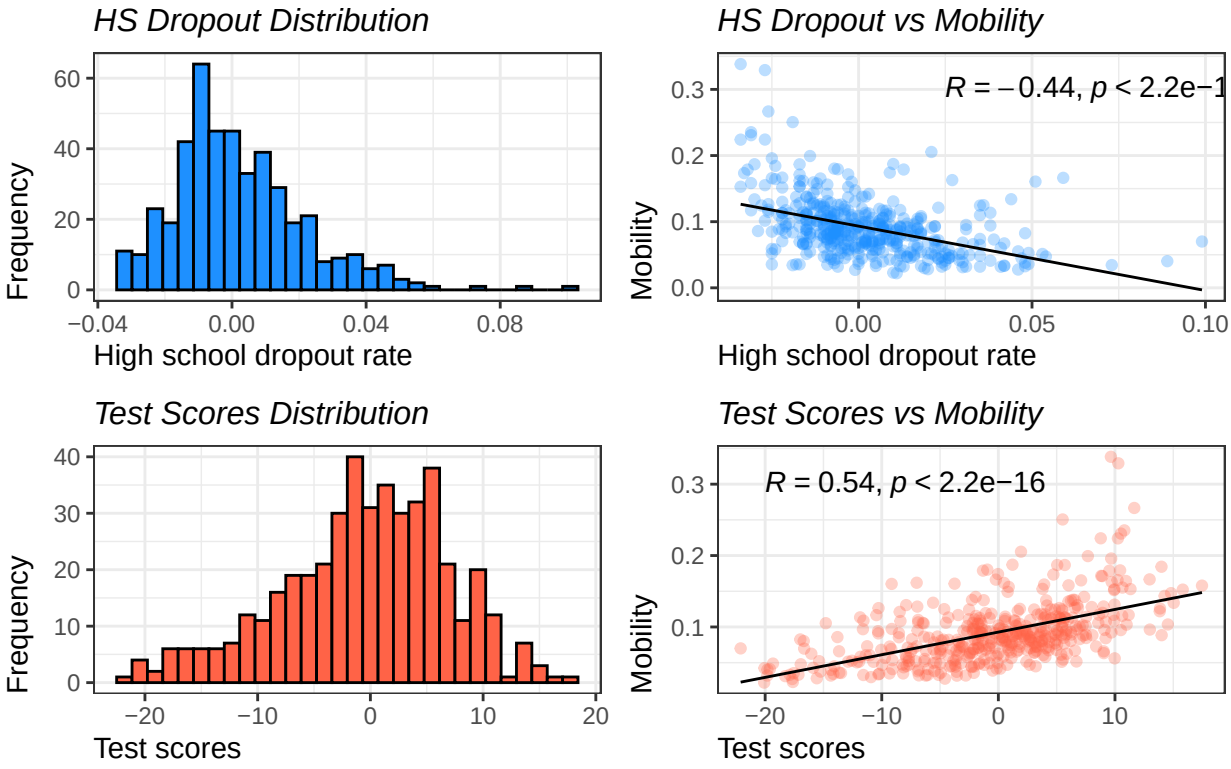
Simply dropping all rows with `NA`s would have resulted in a reduction of 39.4062078% of the data whereas our three-step procedure only resulted in a reduction of 14.5748988%.

Additionally, qualitative (non-numeric and non-quantitative) variables such as those representing latitude and longitude, state/region names, and the ID tag, were removed.

Education analysis



Educational outcomes as a predictor of economic mobility



Policy variables

When examining the mobility dataset, there seemed to be 2 main features that are directly impacted by government policies:

1. *Local tax rate* | Fraction of all income going to local taxes
2. *School expenditures* | Average spending per pupil in public schools
3. *Local government spending* | Local government spending per capita

Out of all the variables in the mobility dataset, the local tax rate and school expenditure are the most directly affected by government policy; that is, local tax rate and school spending are dependent on how the government chooses to raise and spend funds.

While `Chinese_imports` and `Manufacturing` were taken into consideration as policy-based predictors, both features were deemed to stem more from business practices that government policy. Chinese imports are impacted by US foreign policy, however, it would be difficult to untangle the competing market and regulatory factors,so it is difficult to say that these variables are linked to US government policy.

After examining the dataset to verify that `School_spending` and `Local_tax_rate` were valid, there was found to be very little missing values for these variables. In fact, it's less than mobility! This gives assurance that these two variables are valid enough within the dataset to be used as predicting variables.

Government policy is first examined by identifying the relationship between the three variables that are selected as predictors and verifying that these variables have a positive correlation between themselves. To verify these relations, a correlation matrix was created using pairwise relations. We highlight the policy-associated variables and display the top 5 variables that are correlated with each.

```
# Print strongest correlations
print(top_correlations$School_spending)
```

```
## # A tibble: 5 x 3
## # Rowwise:
##   Var1            Var2                Freq
##   <fct>           <fct>              <dbl>
## 1 School_spending Local_tax_rate      0.524
## 2 School_spending EITC                0.382
## 3 School_spending Local_gov_spending  0.367
## 4 Teenage_labor   School_spending     0.344
## 5 School_spending Gini_99            -0.325
```

```
print(top_correlations$Local_tax_rate)
```

```
## # A tibble: 5 x 3
## # Rowwise:
##   Var1               Var2             Freq
##   <fct>              <fct>           <dbl>
## 1 School_spending    Local_tax_rate  0.524
## 2 Local_gov_spending Local_tax_rate  0.450
## 3 Manufacturing      Local_tax_rate -0.373
## 4 Teenage_labor      Local_tax_rate  0.372
## 5 Local_tax_rate     Mobility        0.346
```

```
print(top_correlations$Local_gov_spending)
```

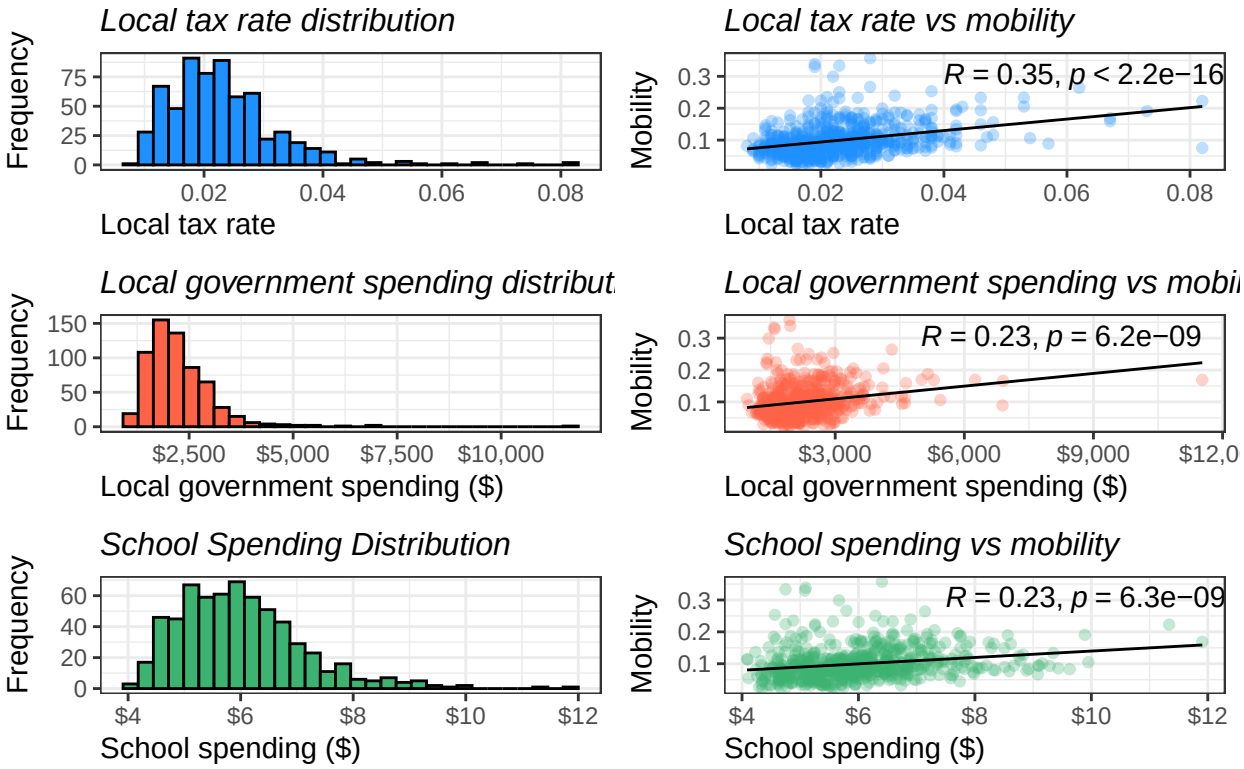
```
## # A tibble: 5 x 3
## # Rowwise:
##   Var1               Var2                Freq
##   <fct>              <fct>              <dbl>
## 1 Local_gov_spending Local_tax_rate     0.450
## 2 School_spending    Local_gov_spending 0.367
## 3 Local_gov_spending Income             0.301
## 4 Foreign_born       Local_gov_spending 0.295
## 5 Teenage_labor      Local_gov_spending 0.293
```

For the 3 predicting variables, all 3 are were correlated the highly with each other. `School_spending`, `Local_tax_rate`, and `Local_gov_spending` all have similar correlations, which verifies the covariate reliance on government policy.

From here, these 3 variables are used to examine the relations each has on demographic factors that directly affect an individual's economic mobility position. The demographic variables examined were `Seg_poverty`, `Gini`, `Gini_99`, `Middle_class`, `Single_mothers`, and `Test scores`. These were all used as sample variable measures because, based on previous findings, these variables all affect mobility. The sample variables are then used to generate scatter plots (see **Appendix A**) examining each specific predicting variable. A linear regression line and R and p values are displayed to elaborate on the linear trend lines.

`School_spending` seemed to be the only variable that has a linear relationship with the sample variables. While `Local_tax_rate` and `Local_gov_spending` did have linear relationships with the demographic variables, they were on the whole weak. Further, histograms and scatter plots that examine the distribution of each variable and its individual relationship to `Mobility` were generated to determine if the predictors have an initial linear regression relationship with mobility.

Policy predictors of mobility

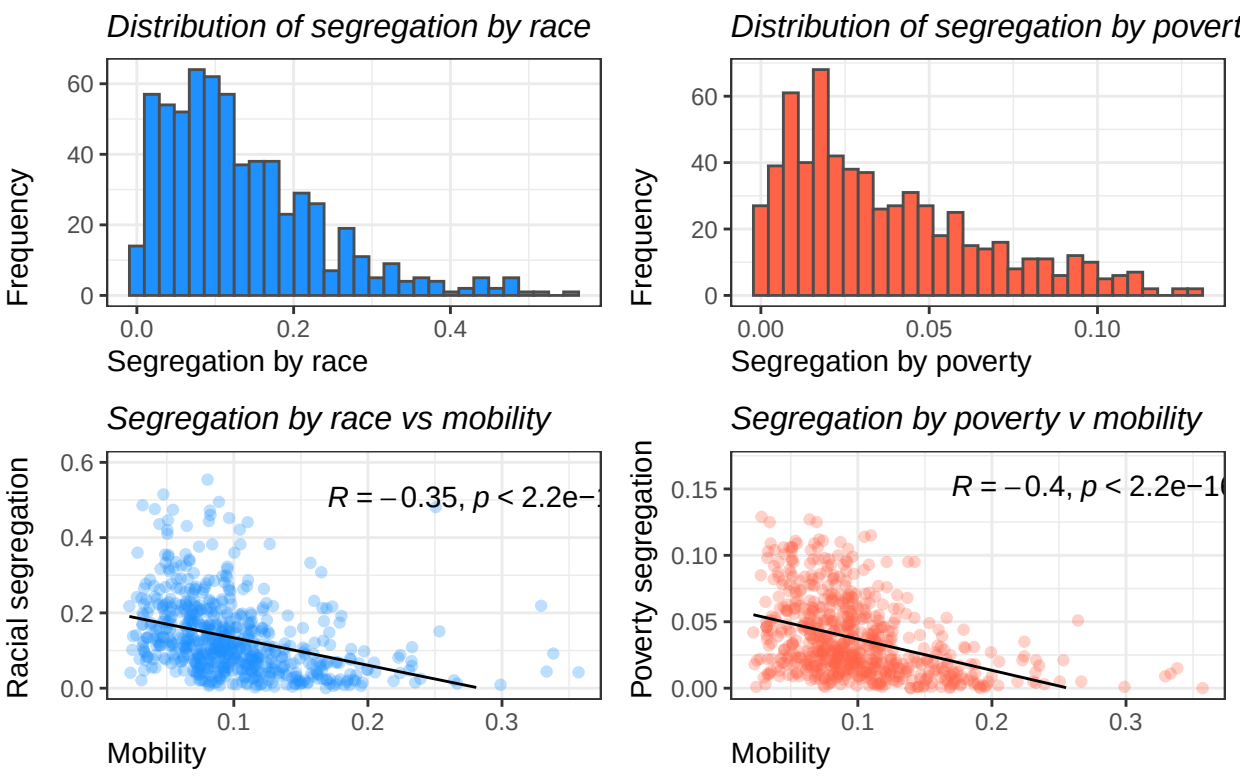


These results state to us that while there might be outlier data in all 3 relational graphs, there is still a somewhat linear relationship between mobility and tax rate. This is interesting because `School_spending` had was more highly correlated with `Mobility` than with demographic factors. `School_spending` and `Local_gov_spedning` do not seem to show the linear trends, but since `School_spending` had is so highly correlated with other demographic factors, it's inclusion in the model is justified.

Segregation factors

Covariate analysis of segregation factors (`Seg_racial`, `Seg_poverty`, `Seg_affluence` and `Seg_income`- see **Appendix B.4**) indicated that, while segregation on poverty lines is not particularly well correlated with segregation on racial lines, it is highly associated with segregation by affluence and segregation by income, which are also highly associated with each other. Since `Seg_poverty`, `Seg_affluence` and `Seg_income` are so strongly co-linear, `Seg_affluence` and `Seg_income` will be removed from the model.

Additionally, other income related factors that are generally associated with integration were examined (see **Appendix B.3**). The `Middle_class` variable is colinear with `Gini` and `Gini_99`, while the `Share01` variable is co-linear with `Gini`. Additionally, `Gini` seems to be highly predictive of `Gini_99`. `Income` is not strongly associated with any of the other variables examined.



Exploring Key Perdictors in Mobility

Linear model

In our analysis of the factors associated with mobility, we employed both exploratory data analysis (EDA) and a multiple linear regression model, and a beta regression model to determine which variables exhibit a strong relationship with our outcome measure. Based on the regression output and correlation values from our EDA, we identified a subset of variables that appear particularly influential in explaining mobility.

```
lm.1 <- lm(formula = Mobility ~ .,
   data = mobility)

summary(lm.1)
```

```
##
## Call:
## lm(formula = Mobility ~ ., data = mobility)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.072790 -0.014110 -0.001634  0.011117  0.155600
##
## Coefficients:
##                              Estimate Std. Error t value Pr(>|t|)
## (Intercept)                 1.408e-01  5.642e-02   2.496  0.01284 *
## Population                  1.265e-09  1.485e-09   0.852  0.39463
```

```
## Urban                       1.523e-03  3.434e-03   0.444  0.65753
## Black                       6.422e-02  2.302e-02   2.790  0.00544 **
## Seg_racial                 -4.778e-02  1.475e-02  -3.238  0.00127 **
## Seg_income                 -2.523e-01  7.164e-01  -0.352  0.72481
## Seg_poverty                -6.192e-02  3.826e-01  -0.162  0.87148
## Seg_affluence               2.447e-01  3.649e-01   0.671  0.50269
## Commute                     5.881e-02  2.005e-02   2.933  0.00348 **
## Income                      4.698e-07  4.603e-07   1.021  0.30787
## Gini                        2.227e+00  2.734e+00   0.814  0.41574
## Share01                    -2.247e-02  2.735e-02  -0.822  0.41148
## Gini_99                    -2.341e+00  2.731e+00  -0.857  0.39158
## Middle_class                1.117e-01  3.488e-02   3.204  0.00143 **
## Local_tax_rate              2.019e-01  1.670e-01   1.209  0.22714
## Local_gov_spending          8.749e-07  1.665e-06   0.525  0.59945
## Progressivity               5.321e-03  8.745e-04   6.085 2.08e-09 ***
## EITC                       -3.454e-04  3.526e-04  -0.980  0.32773
## School_spending             1.299e-03  1.509e-03   0.861  0.38941
## Student_teacher_ratio       4.133e-04  7.256e-04   0.570  0.56918
## Test_scores                -8.006e-05  2.294e-04  -0.349  0.72726
## Labor_force_participation -3.130e-02  3.705e-02  -0.845  0.39854
## Manufacturing              -1.725e-01  2.094e-02  -8.237 1.11e-15 ***
## Chinese_imports            -8.960e-04  7.309e-04  -1.226  0.22072
## Teenage_labor              -1.819e+00  1.747e+00  -1.041  0.29819
## Migration_in               -5.001e-01  2.464e-01  -2.030  0.04281 *
## Migration_out               4.755e-02  2.990e-01   0.159  0.87369
## Foreign_born                1.930e-02  4.011e-02   0.481  0.63061
## Social_capital             -3.523e-03  1.985e-03  -1.775  0.07645 .
## Religious                   4.655e-02  9.886e-03   4.709 3.10e-06 ***
## Violent_crime              -4.199e+00  1.321e+00  -3.179  0.00156 **
## Single_mothers             -3.575e-01  6.966e-02  -5.132 3.89e-07 ***
## Divorced                   -1.735e-01  1.183e-01  -1.467  0.14282
## Married                     5.582e-04  5.074e-02   0.011  0.99123
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.02658 on 599 degrees of freedom
## Multiple R-squared:  0.7201, Adjusted R-squared:  0.7047
## F-statistic:  46.7 on 33 and 599 DF,  p-value: < 2.2e-16
```

Taking into account the exploratory data analysis and the linear model from above, we now have a list of possible predictors that we can use.

1. **Educational Spending**

- *School Spending* | Higher per-pupil expenditures can signal greater investment in educational resources, facilities, and student support programs, thereby fostering improved long-term mobility outcomes.
- *Test Scores* | These serve as a proxy for overall educational quality and student achievement, and they often correlate positively with economic and social mobility.
- *Colleges* | The presence and density of colleges in an area can enhance the availability of higher education and skill development opportunities, contributing to upward mobility.

2. **Social and Demographic Factors**

- `Black` & `Seg_racial` | The proportion of Black residents and the degree of racial segregation in a community are crucial indicators, reflecting underlying social structures and potential barriers or pathways to mobility. Areas with higher racial segregation often experience limited socioeconomic

opportunities.

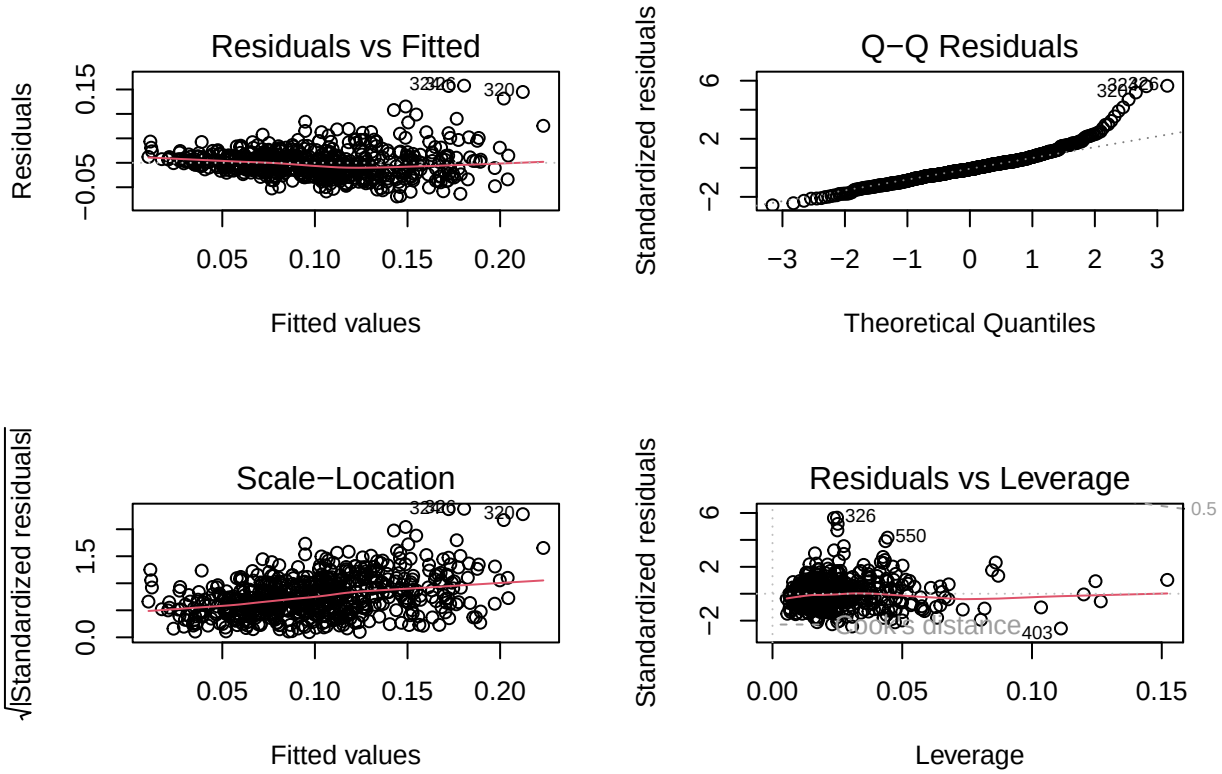
- `Commute` | Longer or more prevalent commutes could signal broader labor markets or suburban sprawl. Where commutes are feasible, individuals may have access to a wider range of job opportunities.
- `Gini` | Income inequality is often inversely related to mobility; higher inequality can concentrate disadvantage and limit pathways for advancement.
- `Middle_class` & `Progressivity` | Communities with a robust middle class or more progressive tax structures may provide support systems (e.g., social services, quality infrastructure) that encourage upward mobility.
- `Manufacturing` | A heavy reliance on manufacturing might limit economic diversification; in many cases, deindustrialization or technological shifts in manufacturing can hinder long-term mobility prospects.
- `Migration_in` | Areas experiencing inbound migration may be more economically dynamic, suggesting better job prospects and growth, which in turn can improve mobility opportunities.
- `Religious` | Higher religiosity can be associated with stronger community networks or social support, potentially facilitating resource sharing and stability that foster mobility.
- `Violent_crime` | High crime rates often correspond to reduced social cohesion and economic investment, negatively affecting people's prospects for advancement.
- `Single_mothers` & `Divorced` | Family structure measures can indicate economic vulnerability or instability, impacting children's outcomes and the intergenerational transmission of opportunity.

3. **Government Spending**

- `Local_tax_rate`: The percentage of local taxes levied on residents and businesses. While higher rates can reduce disposable income, they can also fund public services that may boost economic mobility.
- `Local_gov_spending`: Reflects how much local authorities invest in public services, infrastructure, and community programs. Effective spending can expand opportunities and resources, potentially promoting upward mobility.

From a methodological standpoint, these variables are significant predictors in our regression and/or showed string correlation in EDA phase. To refine this model, we plan to:

- Check for Multicollinearity using Variance Inflation Factors (VIFs) to ensure no subset of variables is overly redundant.
- Check for Heteroskedasticity see if any of the variable have varying variance
- How influential are outliers in the model and see if we need to remove them



We fitted the model, now let look for co-linearity between the variables then we can decide on how to deal with them.

```
vif(yikes)
```

```
##           Black      Seg_racial         Commute            Gini    Middle_class
##        2.394938        1.320021        2.932599        2.684005        4.097972
##  Local_tax_rate   Progressivity School_spending     Test_scores   Manufacturing
##        1.712259        1.229092        1.655802        2.264826        1.723279
##    Migration_in       Religious   Violent_crime        Divorced
##        1.389331        1.787569        1.613089        1.765527
```

Since the above factors are around 1-3, which suggest that colinearity isn't a huge concern. The highest VIF score is the "Middle_class" (about 4.097), which is borderline but still not extremely high. It's something to keep an eye on, but not a immediate concern.

```
coeftest(yikes, vcov = vcovHC(yikes, type = "HC3"))
```

```
##
## t test of coefficients:
##
##                    Estimate  Std. Error t value  Pr(>|t|)
## (Intercept)      0.05698998  0.03222521  1.7685 0.0774722 .
## Black           -0.04578197  0.01188349 -3.8526 0.0001291 ***
## Seg_racial      -0.08977309  0.01695497 -5.2948 1.658e-07 ***
## Commute          0.01104064  0.01722973  0.6408 0.5218967
## Gini            -0.01518672  0.02609392 -0.5820 0.5607773
## Middle_class     0.18999556  0.02912158  6.5242 1.424e-10 ***
## Local_tax_rate   0.56297971  0.24900925  2.2609 0.0241137 *
## Progressivity    0.00463411  0.00109617  4.2276 2.720e-05 ***
## School_spending -0.00063444  0.00158336 -0.4007 0.6887862
```

```
## Test_scores     -0.00019584  0.00022102 -0.8861 0.3759231
## Manufacturing   -0.16876108  0.02165467 -7.7933 2.777e-14 ***
## Migration_in    -0.34146670  0.12459017 -2.7407 0.0063077 **
## Religious        0.04806408  0.00958220  5.0160 6.905e-07 ***
## Violent_crime   -2.50481983  1.39186687 -1.7996 0.0724096 .
## Divorced        -0.52885532  0.08737476 -6.0527 2.471e-09 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The above result is a summary of each predictors estimated coefficient, its standard error, the t-statistic (coefficient / standard error), and the associated p-value. In short, there are variables like Black, Seg_Racial, Middle_class, Progressivity, Manufacturing, Religious, Divorced, and Local_tax_rate show significant relationships while some of the others do not reach conventional significance thresholds. And we in fact use the more significant variables when choosing our next model below.

```
yikes_refit <- lm(Mobility ~ Black +
                    Seg_racial +
                    Middle_class +
                    Progressivity +
                    Manufacturing +
                    Migration_in +
                    Religious +
                    Divorced +
                    Local_tax_rate,
                  data = high_cor)
coeftest(yikes_refit, vcov = vcovHC(yikes_refit, type = "HC3"))
```

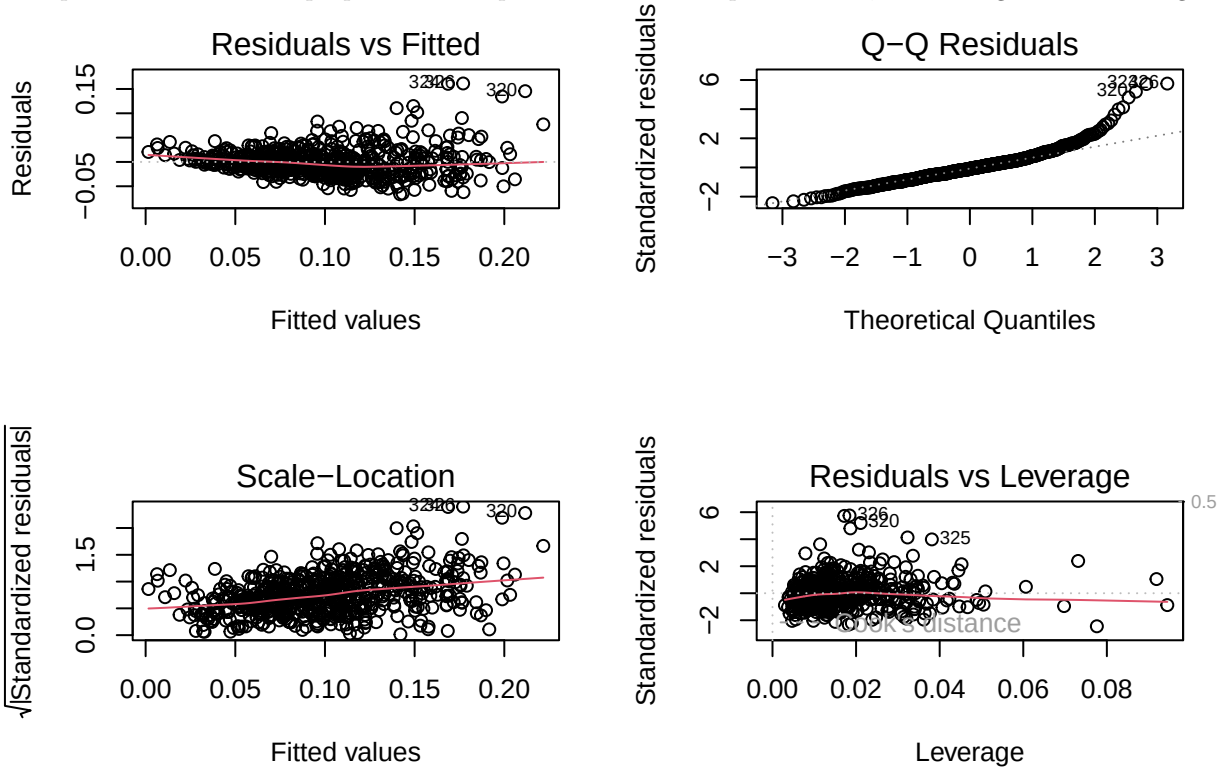
```
##
## t test of coefficients:
##
##                   Estimate  Std. Error t value  Pr(>|t|)
## (Intercept)     0.04179063  0.01956206  2.1363 0.0330432 *
## Black          -0.04962636  0.01073611 -4.6224 4.614e-06 ***
## Seg_racial     -0.09329019  0.01407567 -6.6278 7.386e-11 ***
## Middle_class    0.20544945  0.02397602  8.5690 < 2.2e-16 ***
## Progressivity   0.00425447  0.00088835  4.7892 2.095e-06 ***
## Manufacturing  -0.17453221  0.01996929 -8.7400 < 2.2e-16 ***
## Migration_in   -0.39467805  0.10803502 -3.6532 0.0002807 ***
## Religious       0.05151437  0.00954470  5.3972 9.634e-08 ***
## Divorced       -0.53260576  0.08454566 -6.2996 5.641e-10 ***
## Local_tax_rate  0.51959734  0.21268622  2.4430 0.0148414 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
summary(yikes_refit)
```

```
##
## Call:
## lm(formula = Mobility ~ Black + Seg_racial + Middle_class + Progressivity +
##     Manufacturing + Migration_in + Religious + Divorced + Local_tax_rate,
##     data = high_cor)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.066467 -0.016442 -0.002381  0.012039  0.161265
##
```

```
## Coefficients:
##                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)     0.0417906  0.0183809   2.274 0.023330 *
## Black          -0.0496264  0.0128633  -3.858 0.000126 ***
## Seg_racial     -0.0932902  0.0118153  -7.896 1.31e-14 ***
## Middle_class    0.2054495  0.0203783  10.082  < 2e-16 ***
## Progressivity   0.0042545  0.0007718   5.512 5.19e-08 ***
## Manufacturing  -0.1745322  0.0160459 -10.877  < 2e-16 ***
## Migration_in   -0.3946780  0.1261807  -3.128 0.001843 **
## Religious       0.0515144  0.0088718   5.807 1.02e-08 ***
## Divorced       -0.5326058  0.0834021  -6.386 3.33e-10 ***
## Local_tax_rate  0.5195973  0.1362840   3.813 0.000151 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.02829 on 623 degrees of freedom
## Multiple R-squared:  0.6702, Adjusted R-squared:  0.6654
## F-statistic: 140.6 on 9 and 623 DF,  p-value: < 2.2e-16
```

Having refined our model to include only statistically significant variables, we can now delve deeper into the data by identifying influential observations. The Q-Q plot below helps us pinpoint these observations, highlighting points that deviate from the expected distribution. These deviations may indicate outliers or data points that have a disproportionate impact on the model's performance, warranting further investigation.



After examining the diagnostic plots (Residuals vs. Fitted, Q-Q Plot, Scale-Location, and Residuals vs. Leverage), we identified observations 320, 325, 326, and others as potential outliers or influential points. These points appeared to deviate substantially from the overall trend, suggesting they might exert an undue influence on the regression results.

Why Remove Outliers?

1. *Influence on Parameter Estimates* | Outliers can disproportionately affect the estimated coefficients,

leading to skewed interpretations.

2. *Violation of Model Assumptions* | If extreme points violate assumptions of normality or homoscedasticity, they can compromise the validity of the model's inferences.
3. *Model Fit* | Removing influential points may improve the model fit and reveal a clearer relationship among the remaining data.

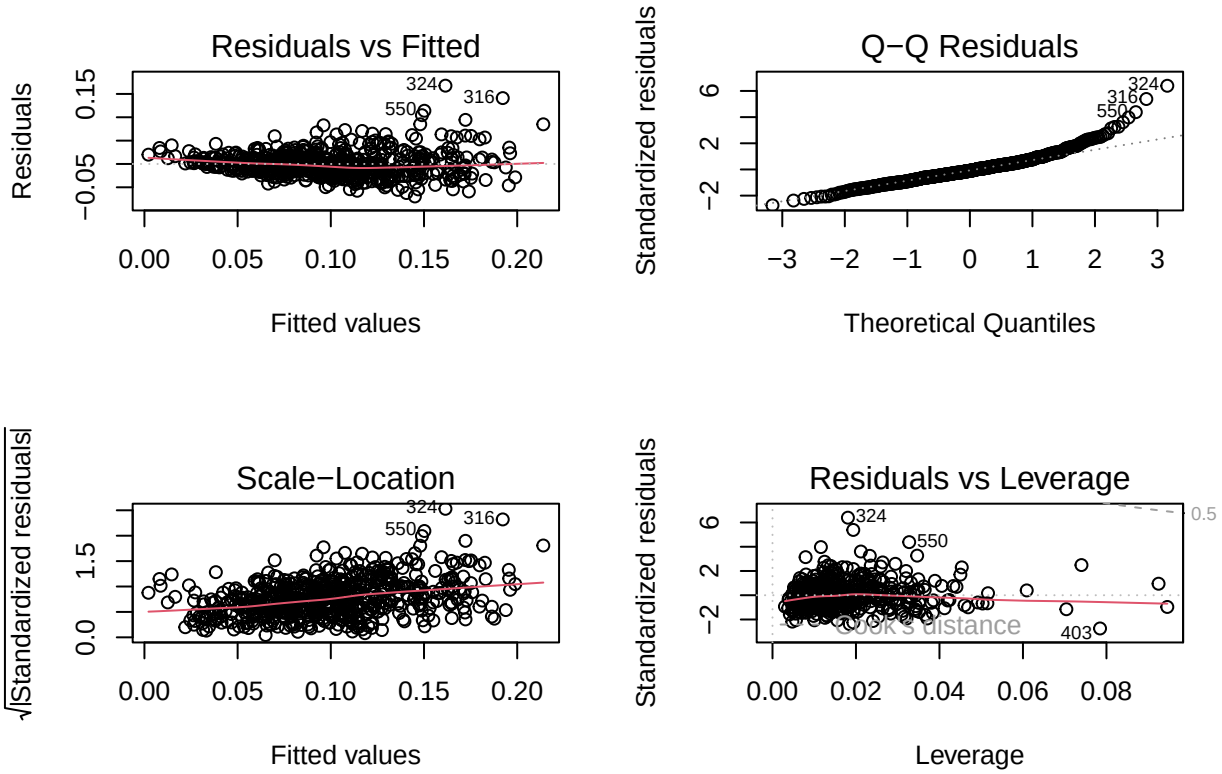
Now we just have to remove the outliers and refit the model.

```
high_cor_clean <- high_cor[-c(320, 325, 326, 385, 391, 393), ]
yikes_clean <- lm(Mobility ~ Black + Seg_racial + Middle_class + Progressivity + Manufacturing + Migrati

summary(yikes_clean)
```

```
##
## Call:
## lm(formula = Mobility ~ Black + Seg_racial + Middle_class + Progressivity +
##     Manufacturing + Migration_in + Religious + Divorced + Local_tax_rate,
##     data = high_cor_clean)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.069629 -0.015856 -0.002656  0.012126  0.167709
##
## Coefficients:
##                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)     0.0480667  0.0172375   2.789  0.00546 **
## Black          -0.0549853  0.0120468  -4.564 6.05e-06 ***
## Seg_racial     -0.0985409  0.0111992  -8.799  < 2e-16 ***
## Middle_class    0.1890656  0.0191673   9.864  < 2e-16 ***
## Progressivity   0.0036112  0.0007258   4.975 8.45e-07 ***
## Manufacturing  -0.1581657  0.0151367 -10.449  < 2e-16 ***
## Migration_in   -0.3455706  0.1183115  -2.921  0.00362 **
## Religious       0.0479549  0.0083284   5.758 1.34e-08 ***
## Divorced       -0.5178954  0.0782790  -6.616 8.01e-11 ***
## Local_tax_rate  0.5675728  0.1278860   4.438 1.07e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.02646 on 617 degrees of freedom
## Multiple R-squared:   0.68,  Adjusted R-squared:  0.6753
## F-statistic: 145.7 on 9 and 617 DF,  p-value: < 2.2e-16
```

```
par(mfrow = c(2, 2))
plot(yikes_clean)
```



This is likely the best we can achieve using a simple linear regression model, given that we're attempting to predict a probability (mobility). Because probabilities are bounded between 0 and 1, linear regression can struggle to provide accurate predictions or valid inferences in this context. As a result, we may need a more advanced modeling technique—such as logistic regression or another specialized method—to capture the probabilistic nature of mobility. This modeling mismatch is probably why we've encountered multiple issues when trying to predict mobility with a simple linear approach.

Beta regression

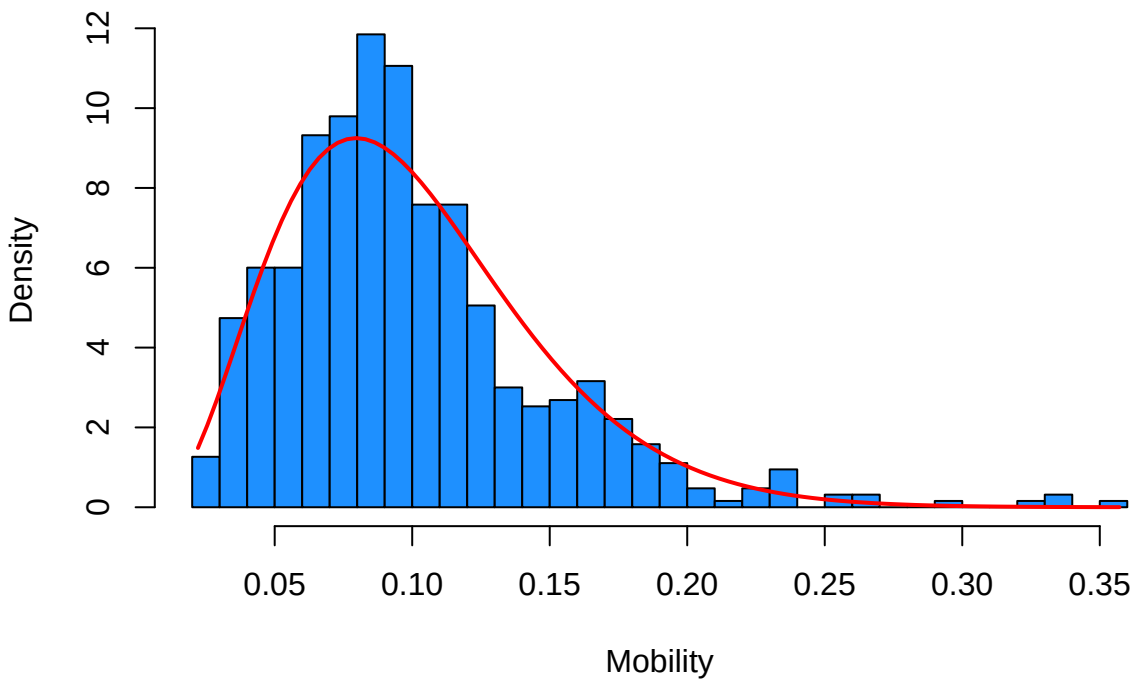
For the next model, I plan to use beta regression because it is specifically designed for response variables that lie between 0 and 1. However, before proceeding with beta regression, we need to verify that all values of our response variable lie strictly within the (0, 1) interval—a key assumption for beta regression.

We can confirm this in R with the following code:

```
## [1] TRUE
```

If this returns TRUE, it confirms that all values meet the (0, 1) requirement, and we can confidently move forward with the beta regression analysis.

While the histogram does not provide sufficient evidence that mobility follows a beta distribution, we can use the Kolmogorov-Smirnov (K-S), which essentially asks: 'How likely is it that we would observe these two samples if they were drawn from the same probability distribution?'



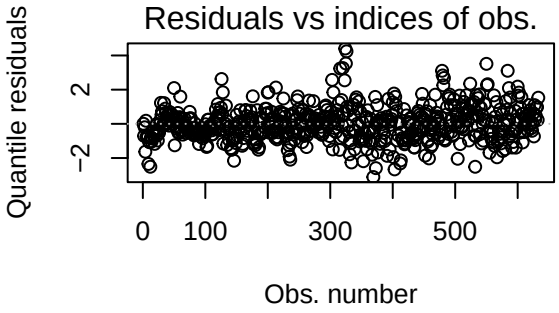

```
##
##  Asymptotic one-sample Kolmogorov-Smirnov test
##
## data:  high_cor$Mobility
## D = 0.052811, p-value = 0.05856
## alternative hypothesis: two-sided
```

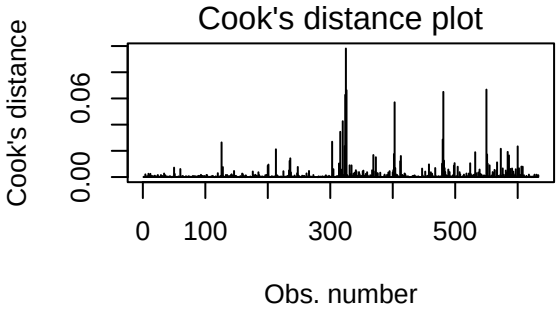
The p-value from the one-sample Kolmogorov-Smirnov test is 0.05856, which is slightly above the conventional 0.05 threshold. This suggests that we do not have strong evidence to reject the null hypothesis that our data follow a beta distribution.

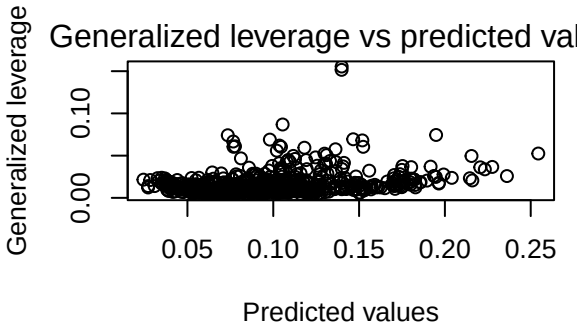
Beta regression

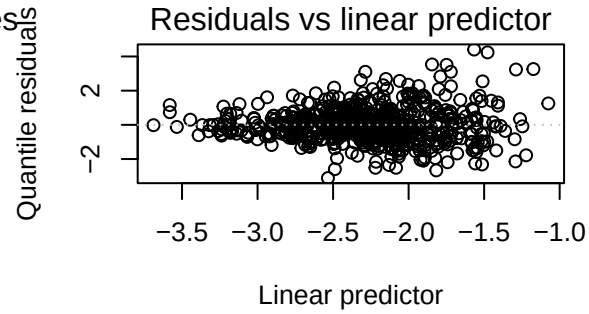
```
##
## Call:
## betareg(formula = Mobility ~ Black + Seg_racial + Middle_class + Progressivity +
##     Manufacturing + Migration_in + Religious + Divorced + Local_tax_rate,
##     data = high_cor)
##
## Quantile residuals:
##     Min      1Q  Median      3Q     Max
## -3.1124 -0.6053 -0.0501  0.5301  4.4049
##
## Coefficients (mean model with logit link):
##                Estimate Std. Error z value Pr(>|z|)
## (Intercept)    -2.80529    0.17635 -15.908  < 2e-16 ***
## Black          -1.26750    0.14661  -8.645  < 2e-16 ***
## Seg_racial     -0.90970    0.11543  -7.881 3.25e-15 ***
## Middle_class    1.93784    0.19057  10.169  < 2e-16 ***
## Progressivity   0.04289    0.00703   6.101 1.05e-09 ***
## Manufacturing  -1.66994    0.15308 -10.909  < 2e-16 ***
```

```
## Migration_in   -2.21954    1.20252  -1.846   0.0649 .
## Religious       0.50536    0.08251   6.125 9.09e-10 ***
## Divorced       -4.80191    0.78567  -6.112 9.85e-10 ***
## Local_tax_rate  4.68461    1.19788   3.911 9.20e-05 ***
##
## Phi coefficients (precision model with identity link):
##       Estimate Std. Error z value Pr(>|z|)
## (phi)  153.809      8.661   17.76   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Type of estimator: ML (maximum likelihood)
## Log-likelihood:  1497 on 11 Df
## Pseudo R-squared: 0.7531
## Number of iterations: 21 (BFGS) + 3 (Fisher scoring)
```









Overall, the beta regression model appears to be performing well based on several diagnostic indicators. First, the significance of the predictors in the mean model is high, with all coefficients (except Migration_in, which is still below the 0.05 threshold) showing very low p-values. This suggests that each variable contributes meaningfully to explaining the variability in Mobility. Furthermore, the pseudo R-squared value of approximately 0.75 indicates that the model accounts for a substantial portion of the variation in the data—quite high for a beta regression.

Looking at the diagnostic plots, the residuals versus observation indices and the residuals versus the linear predictor do not exhibit strong patterns, suggesting no obvious violations of model assumptions. The Cook's distance plot reveals that no single observation exerts undue influence on the model, and generalized leverage values are mostly low, indicating limited leverage points. Lastly, the estimated precision $\phi \approx 150$ is relatively large, pointing to a tightly clustered distribution around the fitted values. Taken together, these diagnostics imply that the beta regression model is a good fit, although you may want to confirm its predictive performance through additional fit metrics or cross-validation.

```
## AIC: -2972.293
```

```
## BIC: -2923.338
```

```
## Mean RMSE (5-fold CV): 0.02762679
```

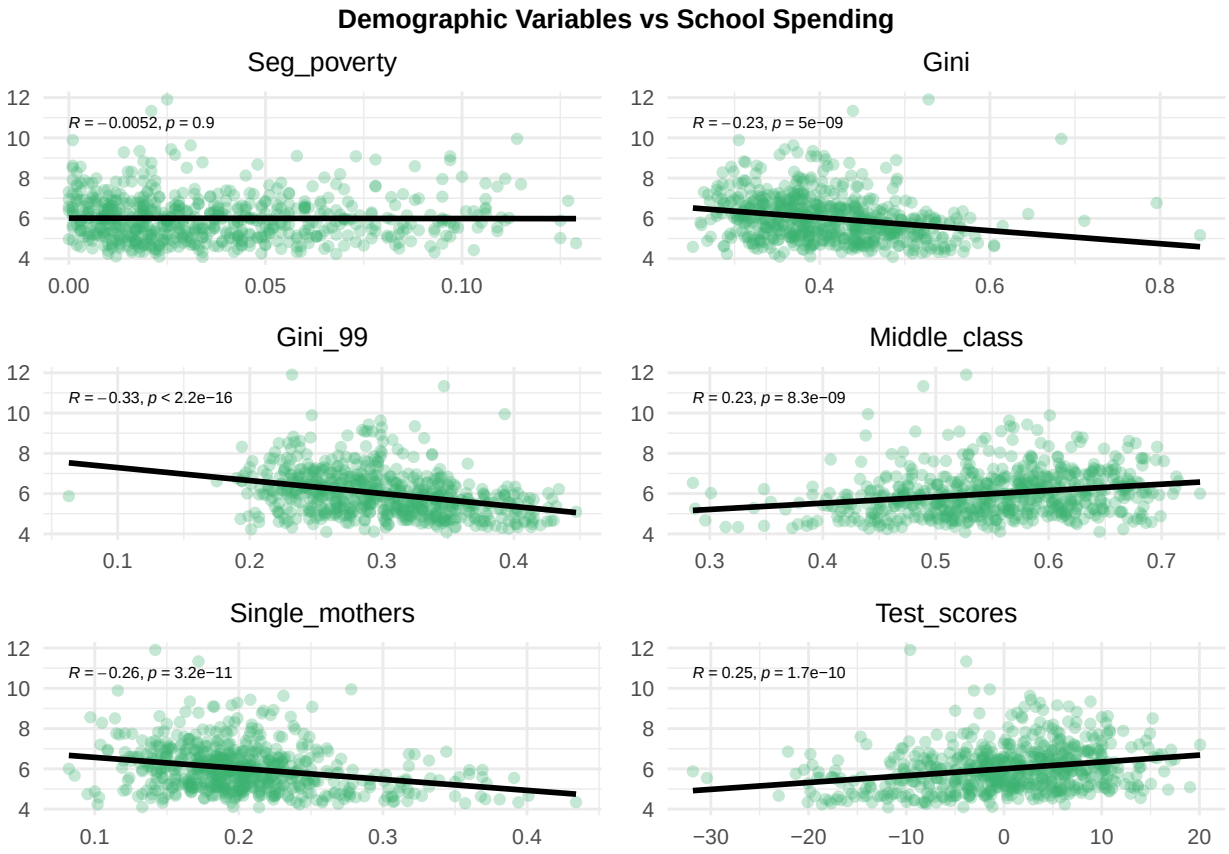
The model's fit is strong, as indicated by the AIC (-2972.293) and BIC (-2923.338), which suggest excellent in-sample fit, with lower values signifying a better model. The mean RMSE from the 5-fold cross-validation is 0.0276, meaning that, on average, the model's predictions are off by just 2.8 percentage points—indicating good predictive accuracy. Overall, these results suggest that your beta regression model is well-calibrated, performing well both in terms of fit and prediction. However, comparing these metrics across different models can provide additional insights into the relative performance.

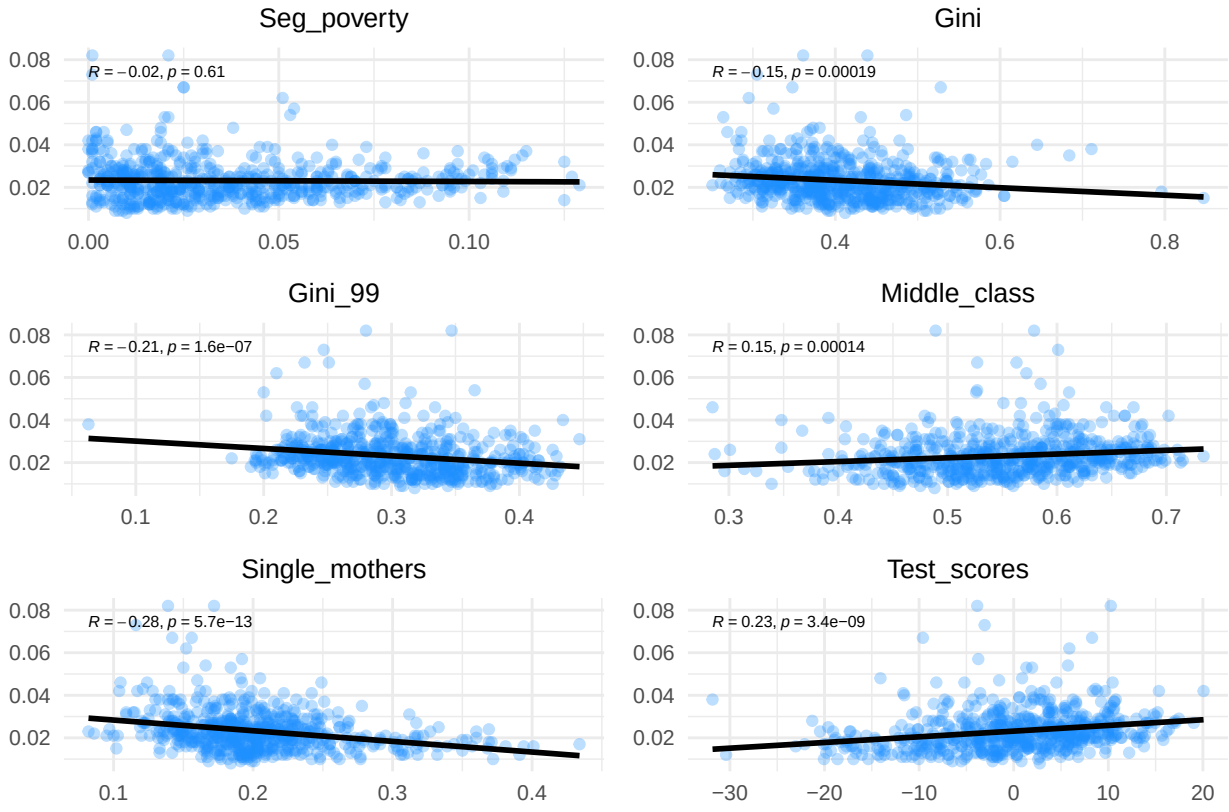
The negative AIC and BIC values indicate that the model has a high likelihood relative to its complexity, though these measures are most informative when comparing across multiple models. Meanwhile, the mean RMSE of approximately 0.028 suggests that, on average, the model's predictions deviate from the actual values by about 2.8 percentage points on the 0–1 scale, which is fairly small. Taken together, these results suggest that the beta regression model fits the data well, although further comparisons with alternative models or additional diagnostics would provide a more comprehensive assessment.

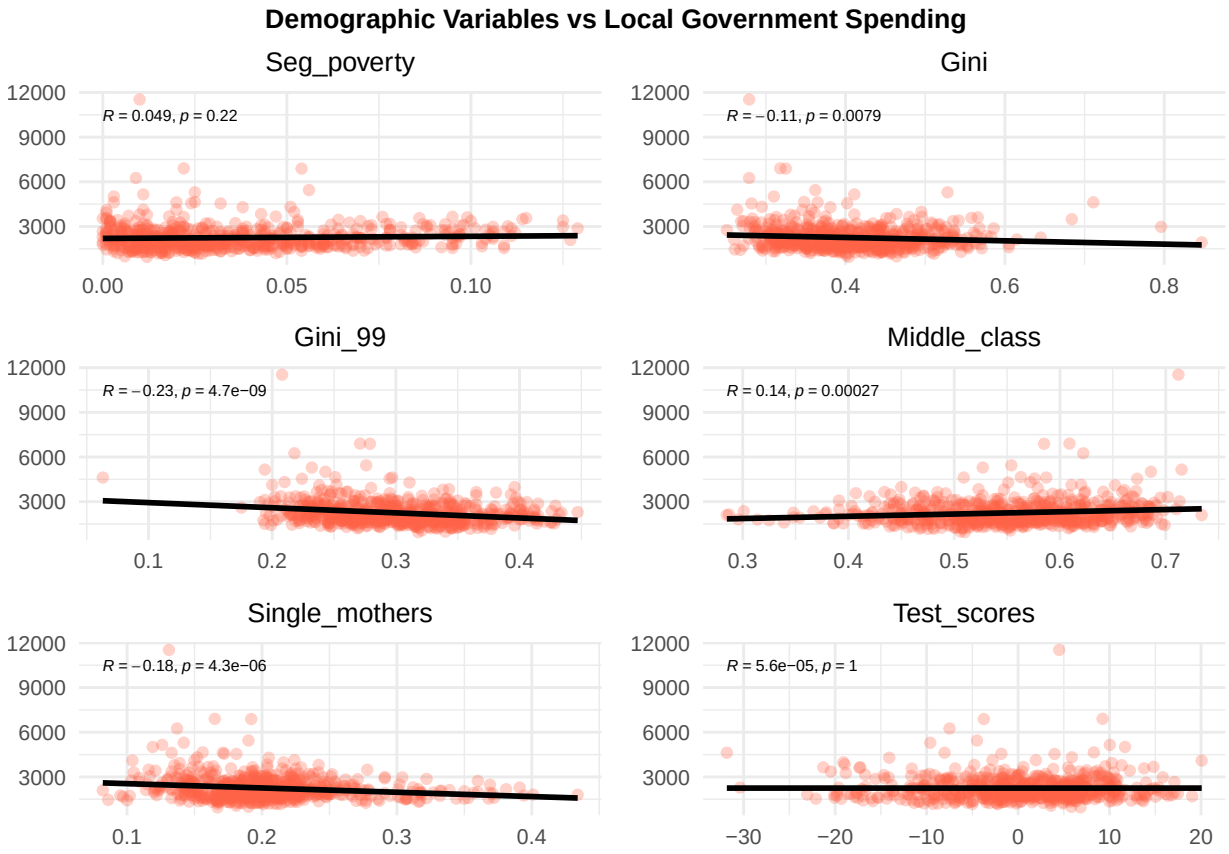
Appendices

Appendix A

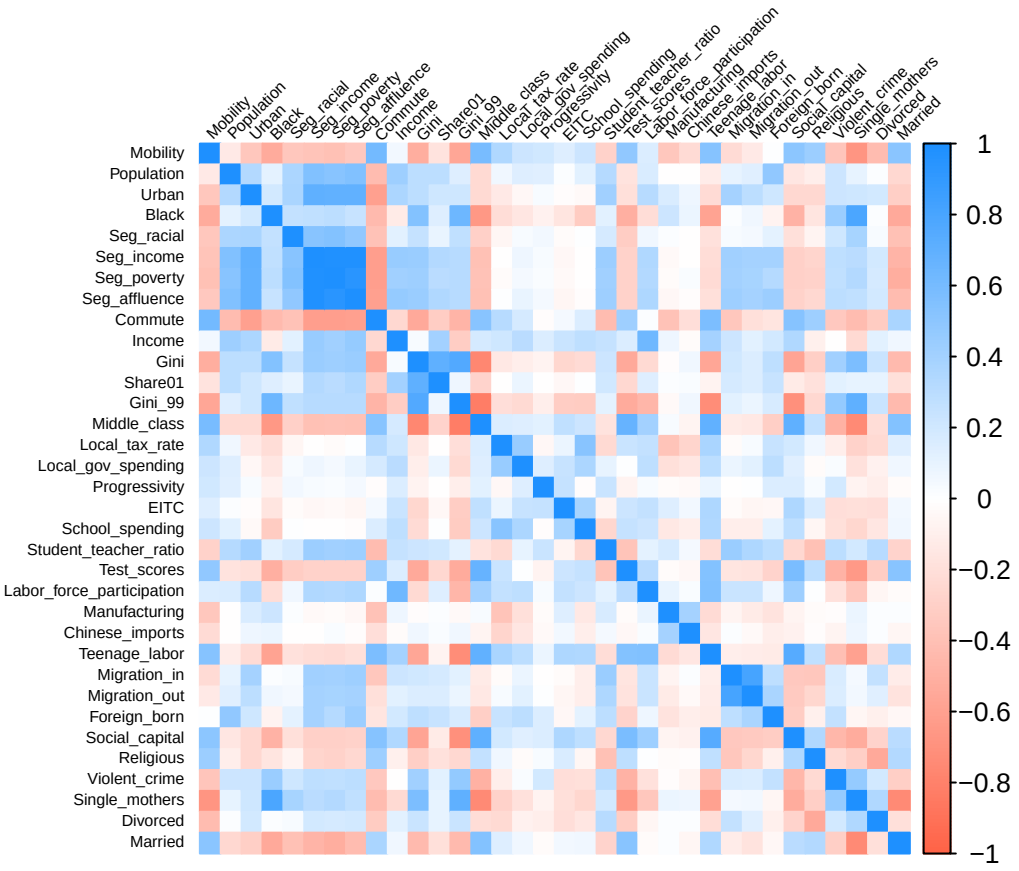
```
## `geom_smooth()` using formula = 'y ~ x'
## `geom_smooth()` using formula = 'y ~ x'
## `geom_smooth()` using formula = 'y ~ x'
## `geom_smooth()` using formula = 'y ~ x'
## `geom_smooth()` using formula = 'y ~ x'
## `geom_smooth()` using formula = 'y ~ x'
```


Demographic Variables vs School Spending
Seg_poverty
R = −0.0052, p = 0.9
Gini
R = −0.23, p = 5e−09
Gini_99
R = −0.33, p < 2.2e−16
Middle_class
R = 0.23, p = 8.3e−09
Single_mothers
R = −0.26, p = 3.2e−11
Test_scores
R = 0.25, p = 1.7e−10

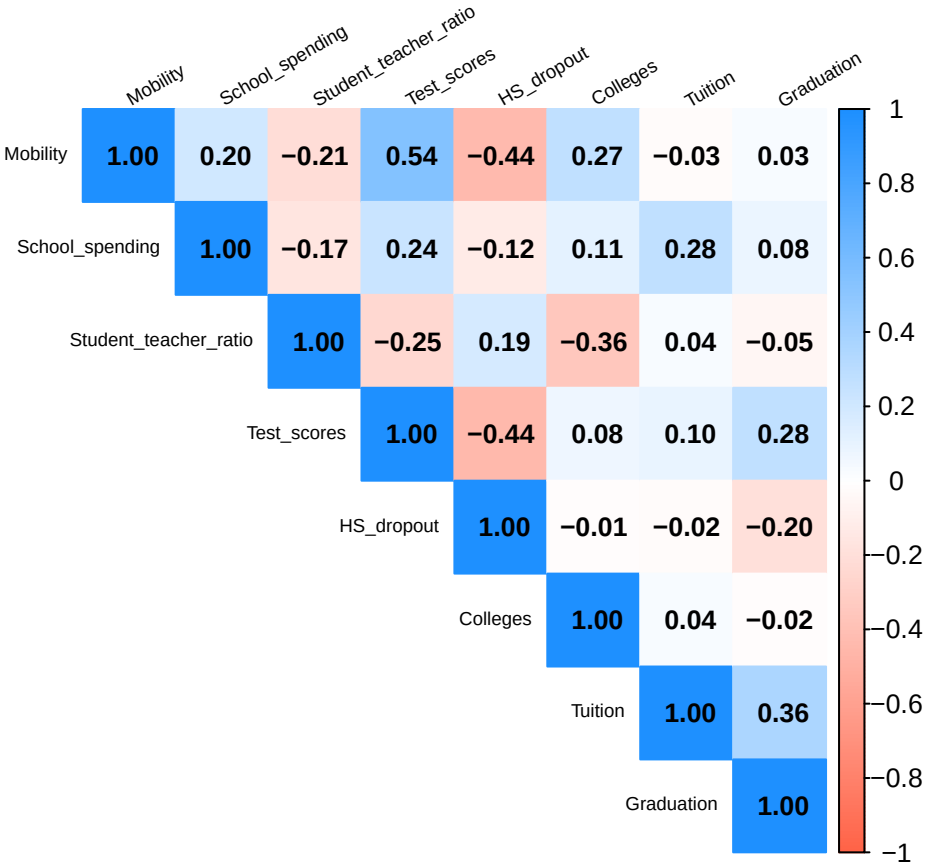

Demographic Variables vs Local Tax Rate
Seg_poverty
R = −0.02, p = 0.61
Gini
R = −0.15, p = 0.00019
Gini_99
R = −0.21, p = 1.6e−07
Middle_class
R = 0.15, p = 0.00014
Single_mothers
R = −0.28, p = 5.7e−13
Test_scores
R = 0.23, p = 3.4e−09


Demographic Variables vs Local Government Spending
Seg_poverty
R = 0.049, p = 0.22
Gini
R = −0.11, p = 0.0079
Gini_99
R = −0.23, p = 4.7e−09
Middle_class
R = 0.14, p = 0.00027
Single_mothers
R = −0.18, p = 4.3e−06
Test_scores
R = 5.6e−05, p = 1
12000
9000
6000
3000
0.00
0.05
0.10
0.4
0.6
0.8
0.1
0.2
0.3
0.4
0.5
0.7
−30
−20
−10
0
10
20

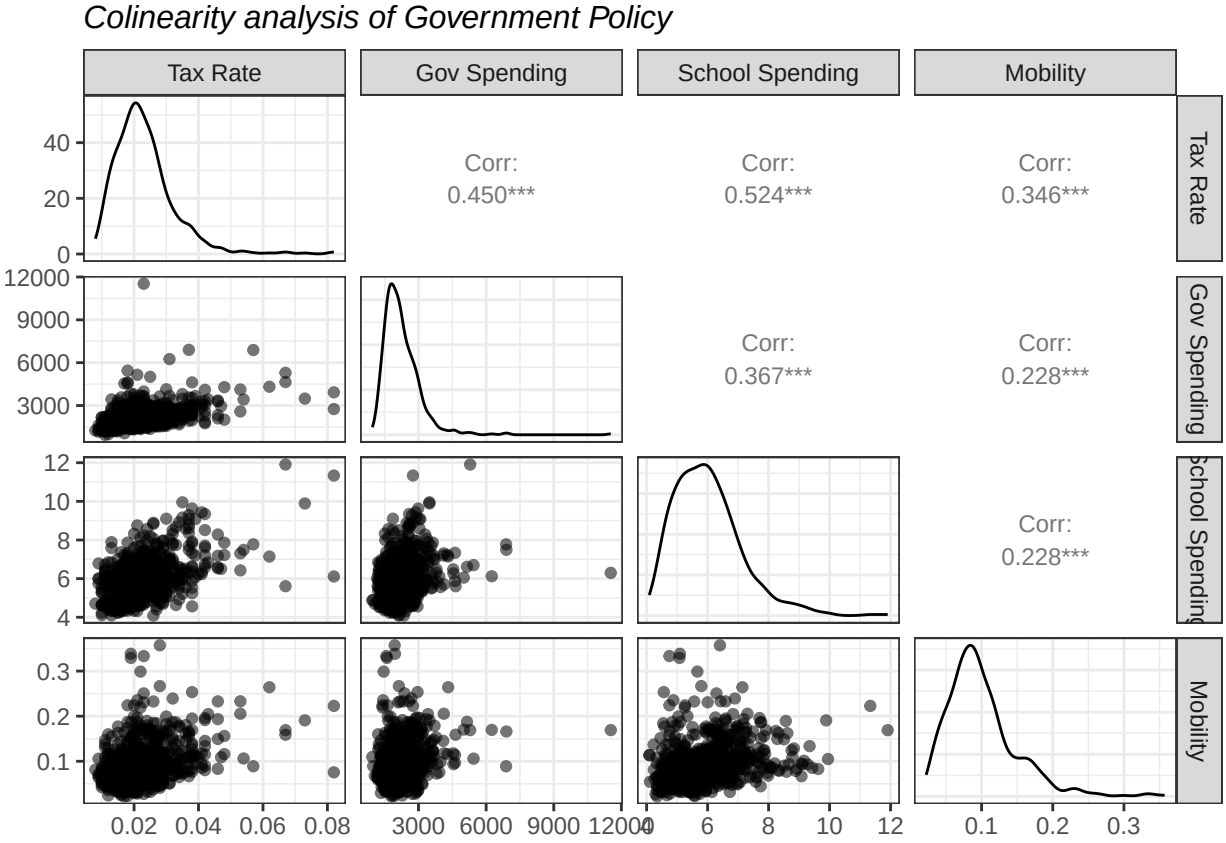
Appendix B - Colinearity Analysis



1 Education variables

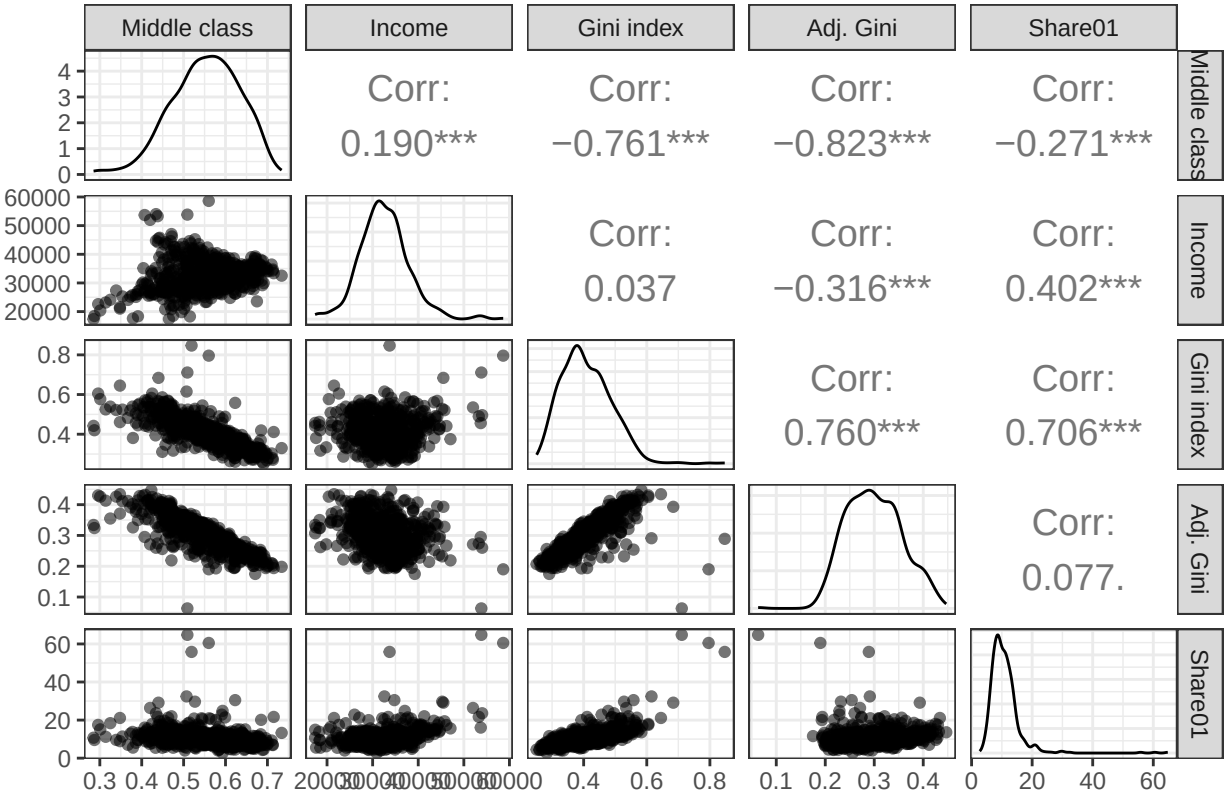


2 Government policy variables



3 Inequality variables

Colinearity analysis of income and income inequality



4 Segregation variables

Colinearity analysis of segregation