Final Report - Group 01

HDI and Broadband - Data Analysis

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Abstract

This report analyzes the relationship between Human Development Index (HDI) and broadband access across various countries, highlighting trends and insights from the data. Lorem ipsum dolor sit amet, consectetur adipiscing elit. In egestas lobortis porta. Phasellus tincidunt metus sed mollis imperdiet. Aliquam blandit nibh in fermentum consequat. Fusce blandit magna quis nulla ornare, non mattis enim tempor. Nulla et odio dui. Nunc ut elit venenatis, porttitor dui et, placerat tortor. Sed aliquet sodales magna, sit amet porta odio tempor in. CHANGE THIS AT THE END

Contents

1. Motivation

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condimentum nisi. Sed at pellentesque mi. Vivamus id justo non elit lacinia efficitur. Sed commodo vehicula nisi, a tristique lectus cursus at. Nullam finibus elementum justo, a molestie augue iaculis sit amet. Praesent quis ante sit amet arcu condimentum commodo quis eu lectus. Curabitur pellentesque mattis enim, eu elementum lectus sollicitudin pellentesque. CHANGE THIS OF COURSE

2. Review of Similar Research

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3. Research Questions

3.1. Question 1

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3.2. Question 2

Lorem ipsum dolor sit amet, consectetur adipiscing elit. In egestas lobortis porta. Phasellus tincidunt metus sed mollis imperdiet. Aliquam blandit nibh in fermentum consequat. Fusce blandit magna quis nulla ornare, non mattis enim tempor. Nulla et odio dui. Nunc ut elit venenatis, porttitor dui et, placerat tortor. Sed aliquet sodales magna, sit amet porta odio tempor in. CHANGE THIS OF COURSE

3.3. Question 3

Lorem ipsum dolor sit amet, consectetur adipiscing elit. In egestas lobortis porta. Phasellus tincidunt metus sed mollis imperdiet. Aliquam blandit nibh in fermentum consequat. Fusce blandit magna quis nulla ornare, non mattis enim tempor. Nulla et odio dui. Nunc ut elit venenatis, porttitor dui et, placerat tortor. Sed aliquet sodales magna, sit amet porta odio tempor in. CHANGE THIS OF COURSE

4. Data

We are using three files from the Gapminder dataset:
HDI, Broadband, and GDP. (*Gapminder Datasets* 2023)

4.1 Loading the files

```
hdi <- read.csv("data/hdi_human_development_index.csv")
broadband <- read.csv("data/broadband_subscribers_per_100_people.csv")
gdp <- read.csv("data/gdp_pcap.csv")
```

4.2. Data Structure

In this section we will clean the header names of each dataset and explore and describe the datasets one by one.

1. Human Development Index (HDI):

Let's explore the shape of the dataset.

Rows x Columns

```
## [1] 193  35
```

Since there are 35 columns, let's only see the first and last five columns to see more detail of column names (after cleaning).

```
## [1] "country" "x1990"   "x1991"   "x1992"   "x1993"
```

```
## [1] "x2019" "x2020" "x2021" "x2022" "x2023"
```

The year range of this dataset is 1990 - 2023. We can also see that the column names have "x" characters that need to be cleaned further.

2. Broadband subscribers (per 100 people):

Rows x Columns

```
## [1] 206  27
```

And the first and last five column names:

```
## [1] "country" "x1998"   "x1999"   "x2000"   "x2001"
```

```
## [1] "x2019" "x2020" "x2021" "x2022" "x2023"
```

The year range of this dataset is 1998 - 2023. Again, the column names have "x"s that aren't helpful. Several columns have chr data type, which we will need to clean up.

3. Gross Domestic Product (GDP):

Rows x Columns

```
## [1] 193 303
```

And the first and last five column names:

```
## [1] "geo"   "name"  "x1800" "x1801" "x1802"
```

```
## [1] "x2096" "x2097" "x2098" "x2099" "x2100"
```

This dataset has the most number of years ranging from 1800 - 2100. The future year values might be predicted or empty which we can analyze further when standardizing and cleaning rows. The *geo* column is also interesting as after standardizing the country names, and merging the datasets, we can also map the data if needed.

4.3. Selecting the required columns

Since the dataset has values from 100+ years, we will narrow them down to the most recent decade starting from 2010 to 2023. Will also clean the years by removing the 'x' character before we select the columns of interest.

HDI

```
##       country  2011  2012  2013  2014  2015  2016  2017  2018  2019  2020  2021
## 1 Afghanistan 0.474 0.484 0.492 0.497 0.496 0.495 0.496 0.498 0.507 0.501 0.486
## 2      Angola 0.545 0.557 0.567 0.577 0.603 0.609 0.610 0.611 0.611 0.610 0.609
## 3     Albania 0.781 0.790 0.793 0.797 0.797 0.797 0.798 0.801 0.805 0.794 0.794
##    2022  2023
## 1 0.495 0.496
## 2 0.615 0.616
## 3 0.806 0.810
```

Need to talk about the values. WHAT DO THE VALUES MEAN

Broadband

```
##       country   2011    2012     2013     2014    2015   2016   2017   2018
## 1       Aruba     NA      NA 18.70000 18.60000 18.2000     NA     NA     NA
## 2 Afghanistan     NA 0.00491  0.00474  0.00457  0.0209 0.0254 0.0257 0.0435
## 3      Angola 0.0653 0.08150  0.08520  0.32300  0.5450 0.2900 0.3210 0.3500
##     2019   2020    2021    2022   2023
## 1 17.700 17.700 17.7000 17.5000     NA
## 2  0.052  0.068  0.0664  0.0796 0.0801
## 3  0.368  0.363  0.3910  0.3870 0.3740
```

Need to talk about the values. WHAT DO THE VALUES MEAN

GDP

```
##       country      2011      2012      2013      2014      2015      2016
## 1 Afghanistan  1962.057  2123.871  2166.402  2145.500  2109.747  2102.452
## 2      Angola  7663.286  8011.050  8099.679  8183.165  7966.886  7487.925
## 3     Albania 11052.778 11227.950 11361.252 11586.817 11878.438 12291.842
##        2017      2018      2019      2020      2021      2022      2023
## 1  2097.120  2061.709  2080.941  1969.306  1517.016  1386.755  1359.020
## 2  7216.061  6878.590  6602.269  6029.692  5911.836  5906.116  5778.834
## 3 12770.992 13317.119 13653.182 13278.370 14595.944 15491.992 16209.877
```

Need to talk about the values. WHAT DO THE VALUES MEAN

4.4. Standardizing country names - rows

Since the datasets might have countries that are not listed in the others, we need to make sure that we standardize all the country names to match one of the datasets as our source. We will take the HDI dataset as our source, and compare the names, and check for the difference in rows/country names. If we find any difference, we will make sure to either match those rows to the source dataset country names, and also remove territories and records that are not common amongst all.

```
## [1] "Number of rows in HDI, Broadband, and GDP datasets:"
```

```
## HDI:  193 , Broadband:  206 , GDP:  193
```

```
## [1] "Countries in Broadband but NOT in HDI:"
```

```
##  [1] "Aruba"                  "Bermuda"               "Cayman Islands"
##  [4] "Faeroe Islands"         "Gibraltar"             "Greenland"
##  [7] "Guam"                   "Macao, China"          "Monaco"
## [10] "New Caledonia"          "Curaçao"               "French Polynesia"
## [13] "British Virgin Islands"
```

```
## [1] "Countries in GDP but NOT in HDI:"
```

```
## [1] "Monaco"      "North Korea"
```

We can see some diffences in countries within each dataset. We will now standardized and filter the data to only focus on countries that are common amongst all three datasets.

After standardizing:

```
## Number of rows in HDI dataset: 191
```

```
## Number of rows in Broadband dataset: 191
```

```
## Number of rows in GDP dataset: 191
```

Now let's check for duplicates.

4.5. Handling duplicates (if any):

```
## 0 rows removed.
```

```
## 0 rows removed.
```

```
## 0 rows removed.
```

Now that we have standardized names, and checked for duplicates, let's explore the missing values.

4.6. Handling missing values - rows

```
## [1] "Empty values in HDI"

## [[1]]
## country    2011    2012    2013    2014    2015    2016    2017    2018    2019
##       0       1       1       1       1       1       1       1       1       1
##    2020    2021    2022    2023
##       1       1       1       0

## [1] "Empty values in Broadband"

## [[1]]
## country    2011    2012    2013    2014    2015    2016    2017    2018    2019
##       0      14       7       6       7       5       7       7      20       4
##    2020    2021    2022    2023
##       6       3       2      40

## [1] "Empty values in GDP"

## [[1]]
## country    2011    2012    2013    2014    2015    2016    2017    2018    2019
##       0       0       0       0       0       0       0       0       0       0
##    2020    2021    2022    2023
##       0       0       0       0
```

Not dropping any at this point

5. Methodology

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5.2. Data Distribution

5.2.1. Distribution of HDI

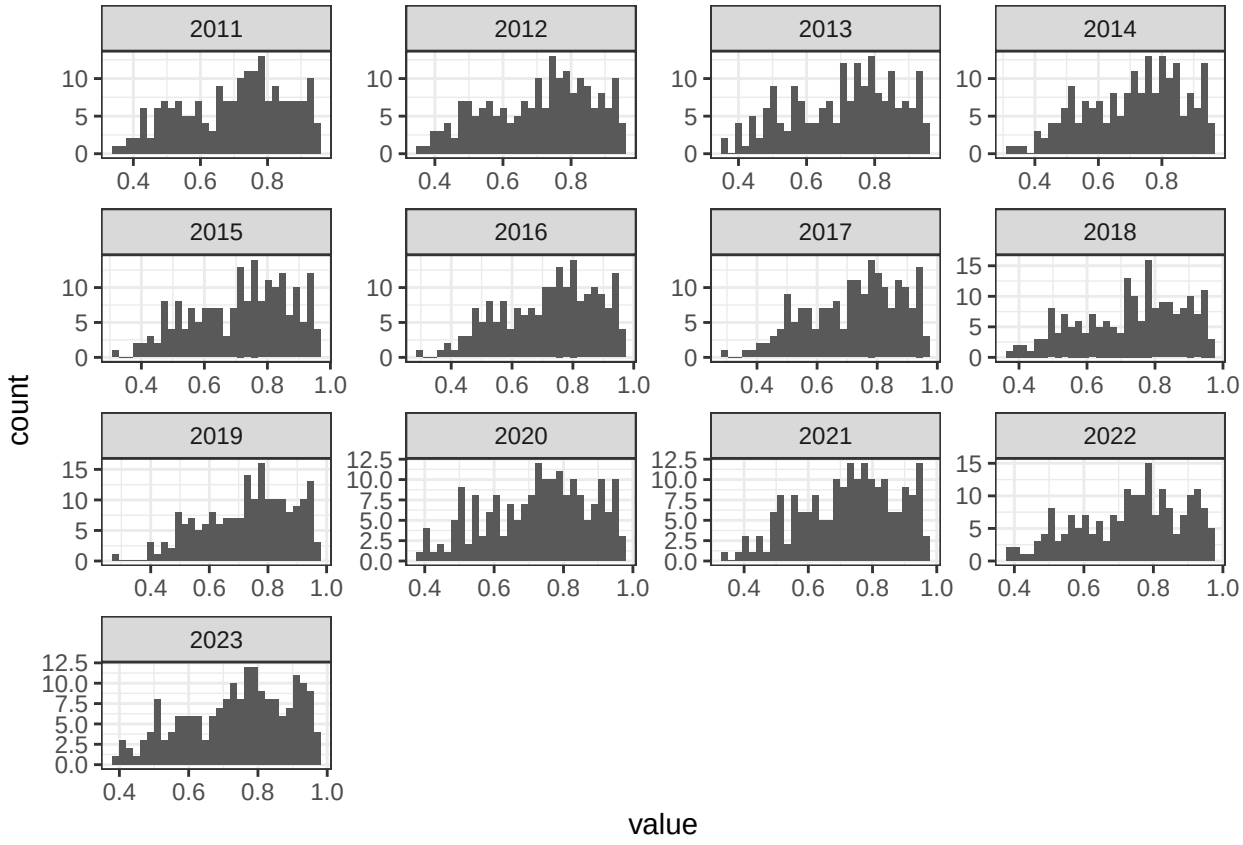


Table: Data summary

Name	hdi_clean
Number of rows	191
Number of columns	14
Column type frequency:	
character	1
numeric	13
Group variables	None

Variable type: character

skim_variable	n_missing	complete_rate	min	max	empty	n_unique	whitespace
country	0	1	2	30	0	191	0

Variable type: numeric

skim_variable	n_missing	complete_rate	mean	sd	p0	p25	p50	p75	p100	hist
2011	1	0.99	0.70	0.15	0.35	0.57	0.72	0.82	0.95	
2012	1	0.99	0.71	0.15	0.36	0.58	0.73	0.82	0.95	
2013	1	0.99	0.71	0.15	0.36	0.58	0.74	0.83	0.95	
2014	1	0.99	0.71	0.15	0.32	0.59	0.74	0.83	0.96	
2015	1	0.99	0.72	0.15	0.32	0.60	0.74	0.84	0.96	
2016	1	0.99	0.72	0.15	0.30	0.61	0.75	0.84	0.96	
2017	1	0.99	0.72	0.15	0.29	0.61	0.75	0.84	0.96	
2018	1	0.99	0.73	0.15	0.37	0.61	0.75	0.85	0.97	
2019	1	0.99	0.73	0.15	0.28	0.61	0.75	0.85	0.97	
2020	1	0.99	0.73	0.15	0.39	0.61	0.74	0.84	0.97	
2021	1	0.99	0.73	0.15	0.34	0.61	0.74	0.84	0.97	
2022	1	0.99	0.74	0.15	0.38	0.62	0.76	0.85	0.97	
2023	0	1.00	0.74	0.15	0.39	0.62	0.76	0.86	0.97	

Comment on the distribution

5.2.2. Distribution of Broadband

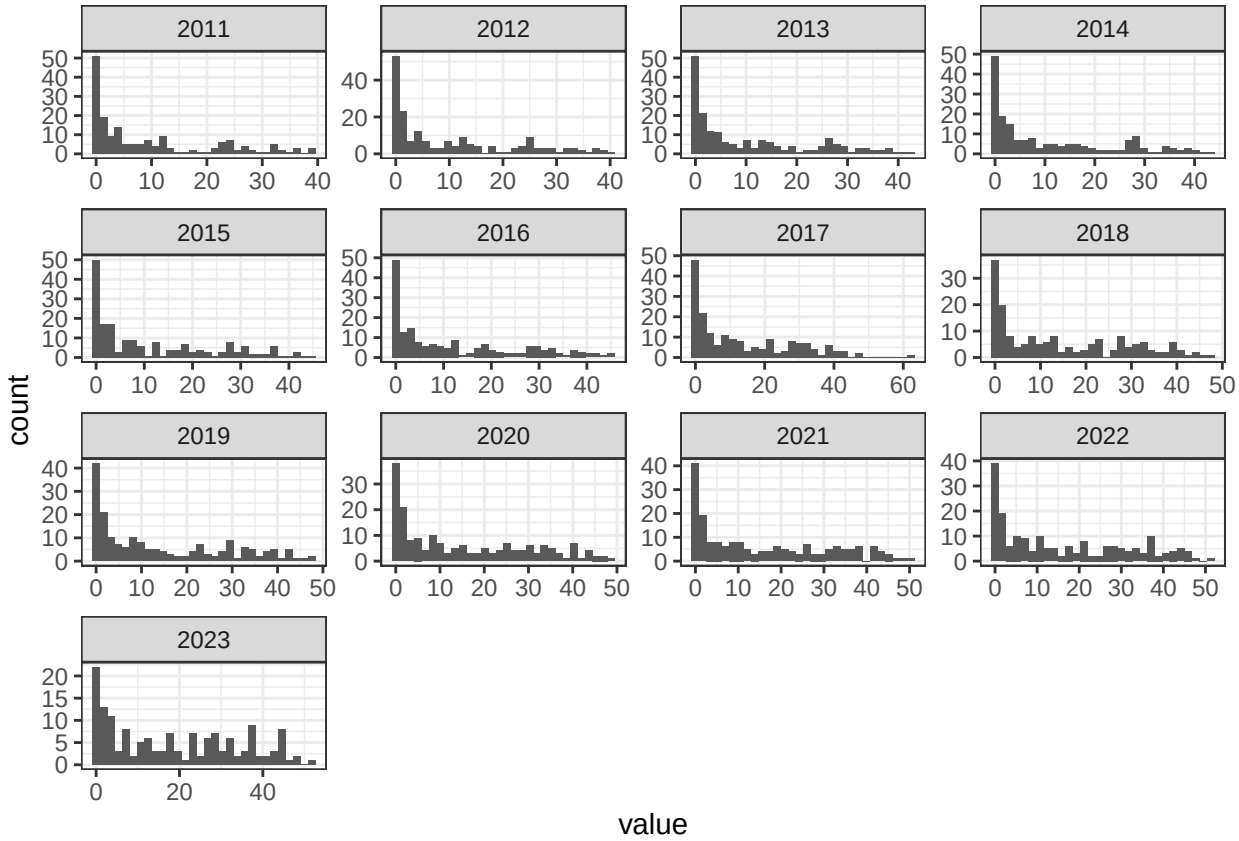


Table: Data summary

Name	broadband_clean
Number of rows	191
Number of columns	14

Column type frequency:	
character	1
numeric	13
Group variables	None

Variable type: character

skim_variable	n_missing	complete_rate	min	max	empty	n_unique	whitespace
country	0	1	2	30	0	191	0

Variable type: numeric

skim_variable	n_missing	complete_rate	mean	sd	p0	p25	p50	p75	p100	hist
2011	14	0.93	9.61	11.31	0	0.40	4.26	16.20	38.9	
2012	7	0.96	10.06	11.66	0	0.38	4.73	17.45	40.2	
2013	6	0.97	10.63	12.08	0	0.47	4.94	18.40	42.5	
2014	7	0.96	11.24	12.47	0	0.54	5.62	19.80	43.2	
2015	5	0.97	11.78	12.90	0	0.61	6.31	20.70	44.7	
2016	7	0.96	12.40	13.25	0	0.69	7.11	21.97	45.1	
2017	7	0.96	13.23	13.99	0	0.83	8.14	22.98	62.2	
2018	20	0.90	14.43	14.03	0	1.33	10.00	27.20	47.4	
2019	4	0.98	14.00	14.28	0	1.06	8.85	26.55	47.5	
2020	6	0.97	15.07	14.70	0	1.30	9.40	27.10	48.7	
2021	3	0.98	15.48	14.98	0	1.37	10.60	27.20	50.3	
2022	2	0.99	16.08	15.25	0	1.48	11.00	29.00	51.2	
2023	40	0.79	18.41	15.52	0	2.78	16.10	31.55	51.7	

Comment on the distribution

5.2.3. Distribution of GDP

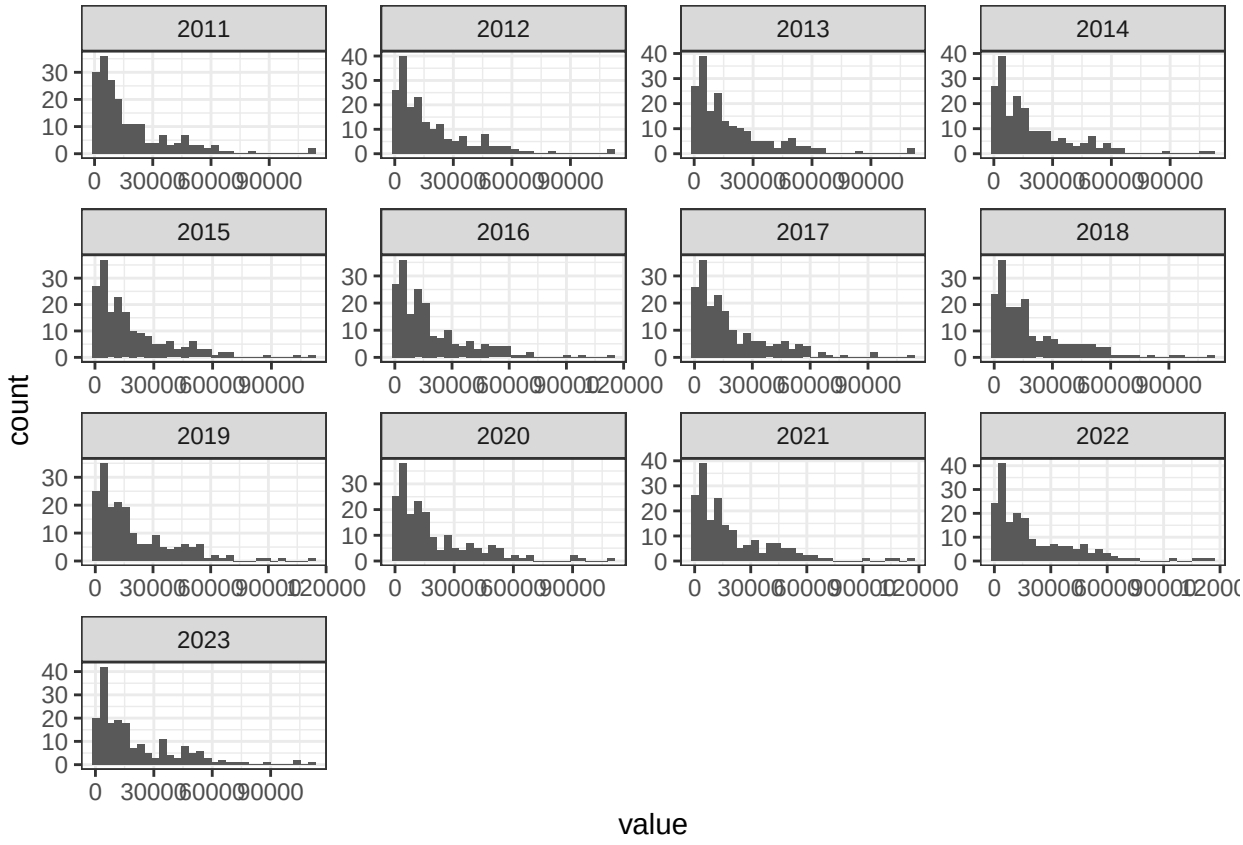


Table: Data summary

Name	gdp_clean
Number of rows	191
Number of columns	14
Column type frequency:	
character	1
numeric	13
Group variables	None

Variable type: character

skim_variable	n_missing	complete_rate	min	max	empty	n_unique	whitespace
country	0	1	2	30	0	191	0

Variable type: numeric

skim_variable	n_missing	complete_rate	mean	sd	p0	p25	p50	p75	p100	hist
2011	0	1	18175.43	19634.09	807.66	3705.53	10933.21	24937.33	111840.3	

skim_variable	n_missing	complete_rate	mean	sd	p0	p25	p50	p75	p100	hist
2012	0	1	18359.22	19518.19	506.72	3770.56	11098.89	25689.84	110892.4	
2013	0	1	18472.83	19488.91	624.18	3968.33	11361.25	25872.48	110354.4	
2014	0	1	18700.32	19561.46	614.46	4033.83	11767.16	26482.08	110611.0	
2015	0	1	18979.66	19815.30	594.92	4172.21	12030.38	27189.90	110483.3	
2016	0	1	19226.13	19995.38	501.11	4321.96	12336.90	27857.71	113510.3	
2017	0	1	19559.76	20168.35	458.77	4518.15	12497.82	28710.15	112243.4	
2018	0	1	19916.38	20450.98	435.41	4530.59	13218.92	29622.61	111441.6	
2019	0	1	20184.39	20670.50	425.94	4803.56	13215.57	30351.18	112461.8	
2020	0	1	19053.94	19977.86	386.68	4691.03	12407.79	26943.40	109597.0	
2021	0	1	20164.82	21367.89	395.80	4829.15	13045.93	30234.91	115683.5	
2022	0	1	20922.87	22044.01	364.70	4736.43	13148.07	33000.12	114938.7	
2023	0	1	21088.15	21712.32	354.18	4859.07	13416.93	33417.31	111043.4	

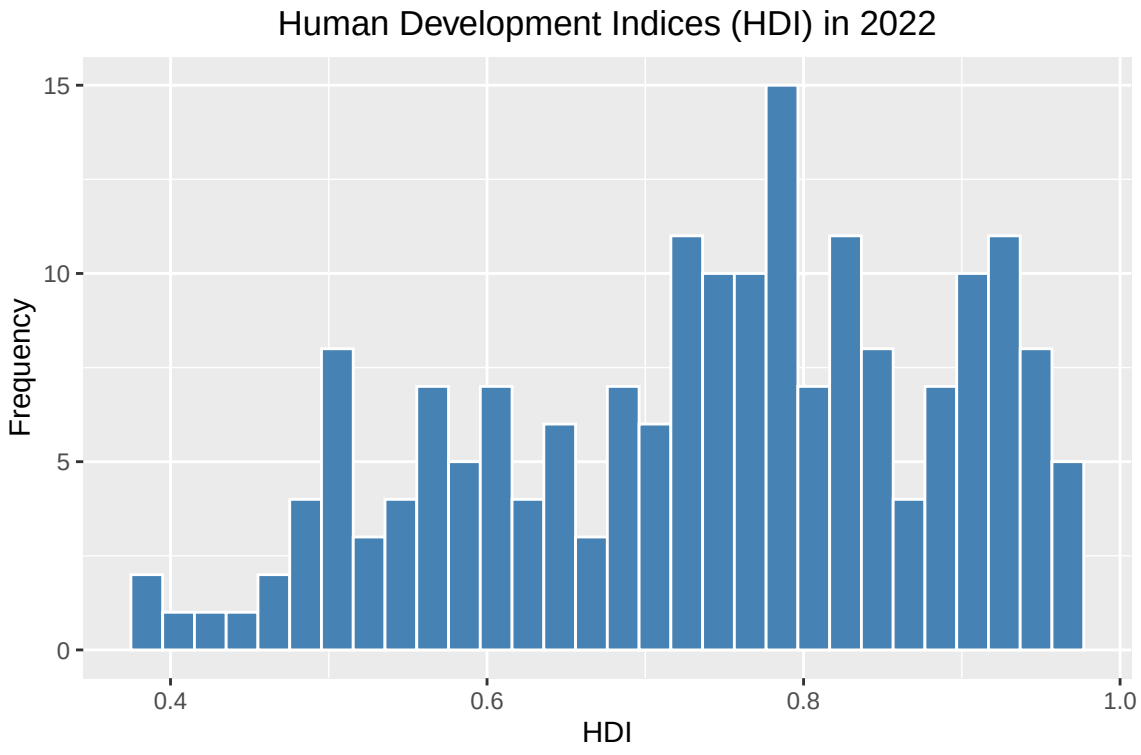
Comment on the distribution

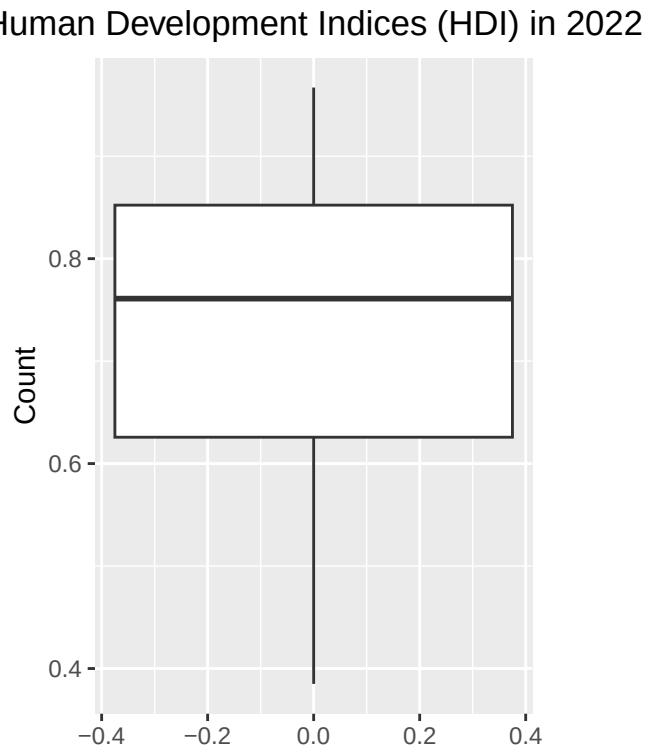
5.2.4. Reshape the data

Merge the data

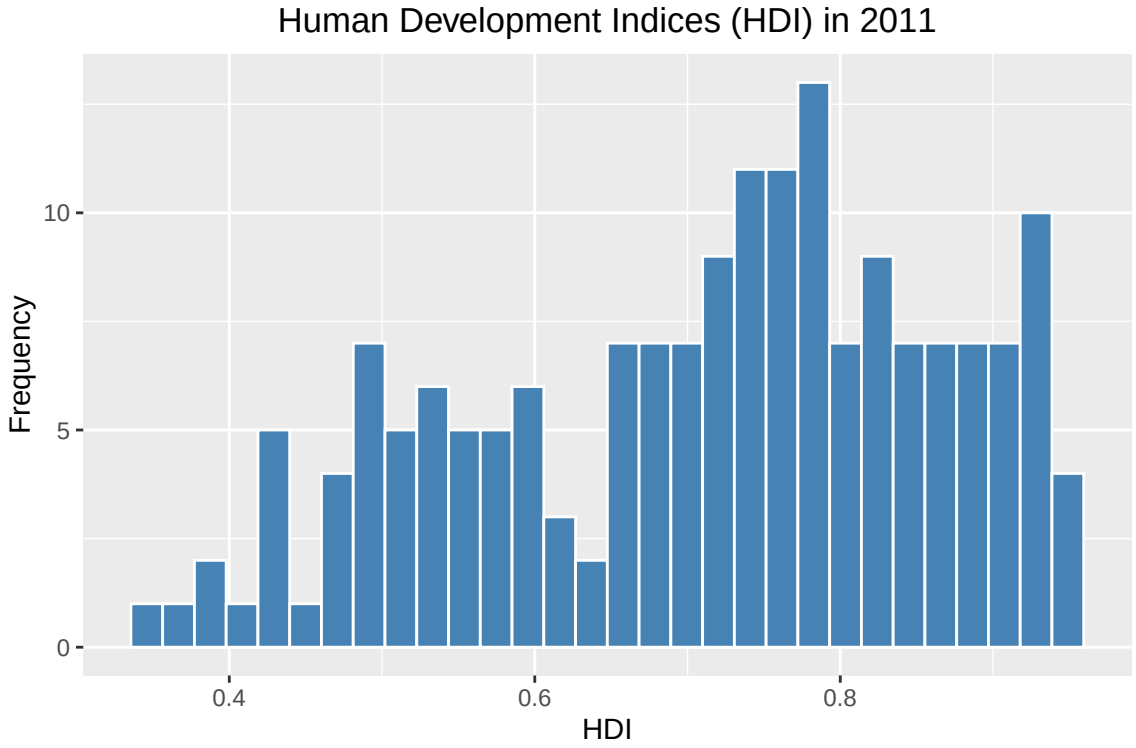
Skewness

Distribution of Human Development Index (2022)

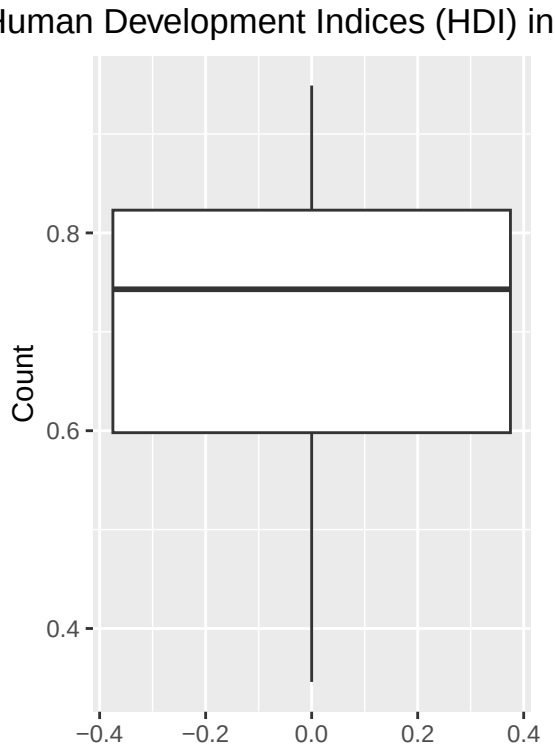




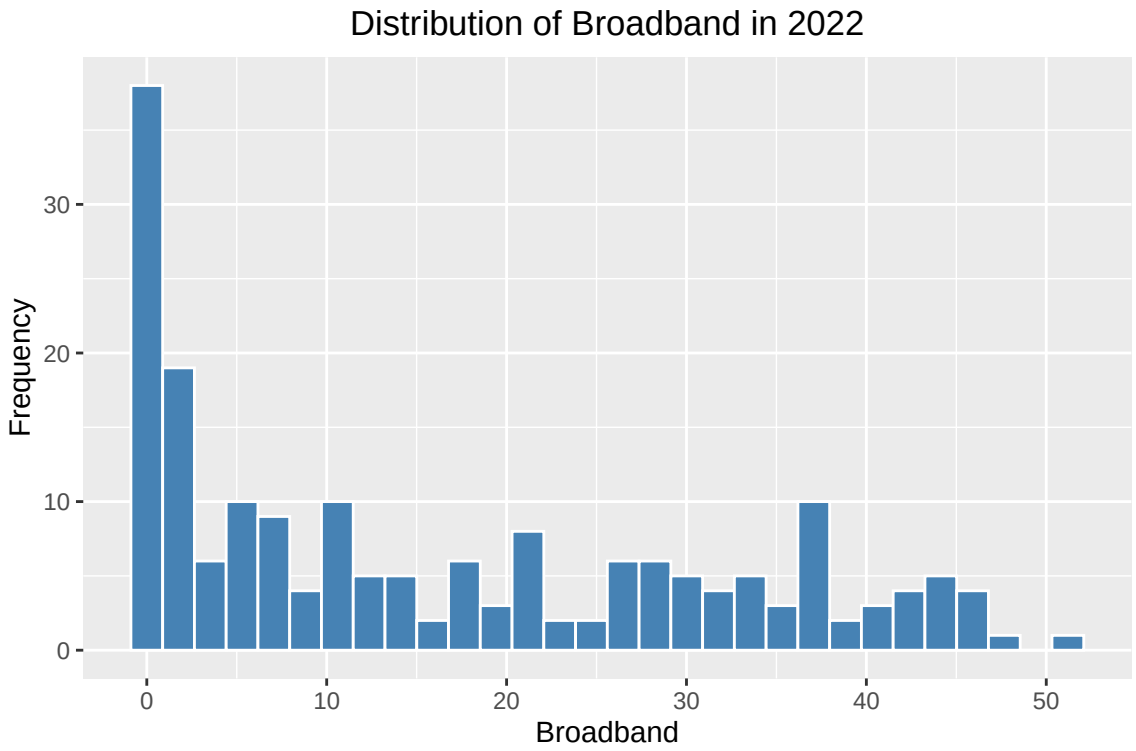
Distribution of Human Development Index (2011)



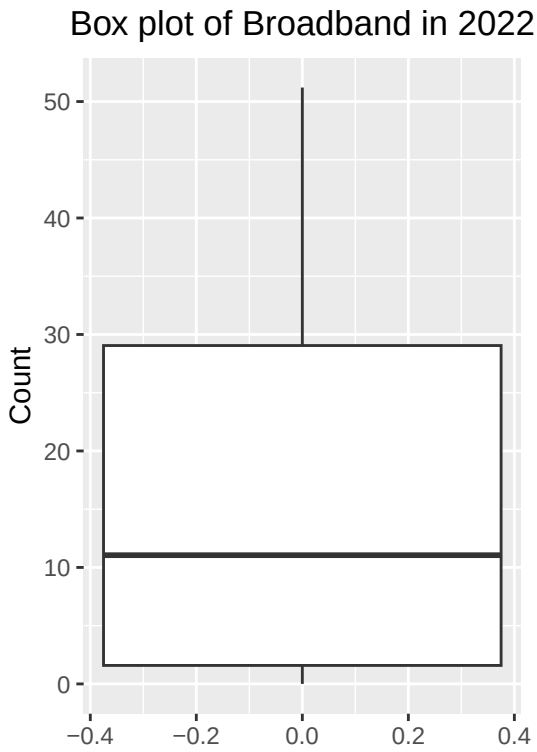
This histogram shows that the HDI of 2011 is mildy left skewed.



Distribution of Broadband (2022)

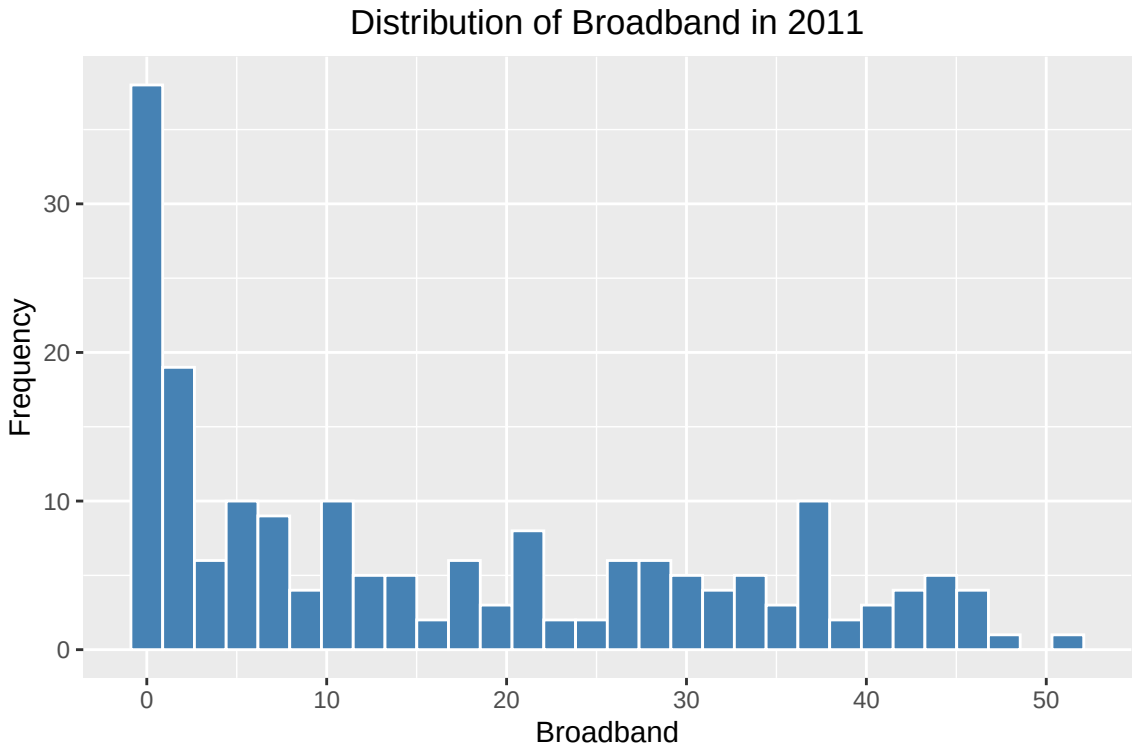


The histogram shows that the broadband data is right skewed.

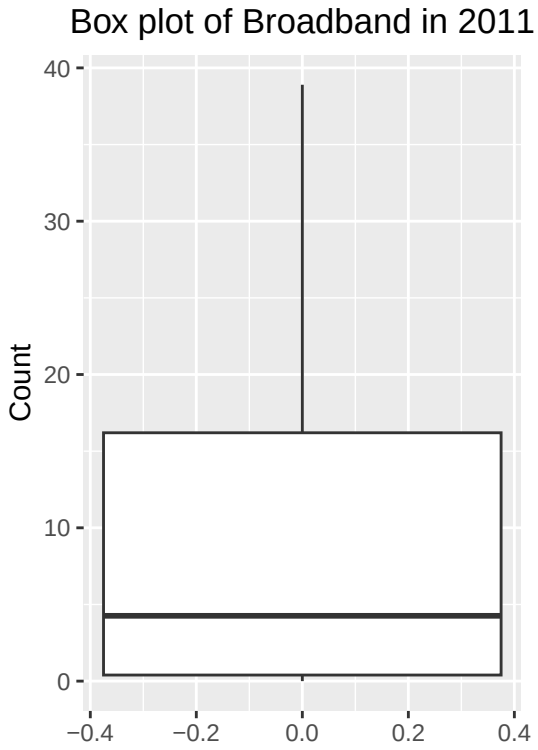


We need to transform the broadband dataset.

Distribution of Broadband (2011)

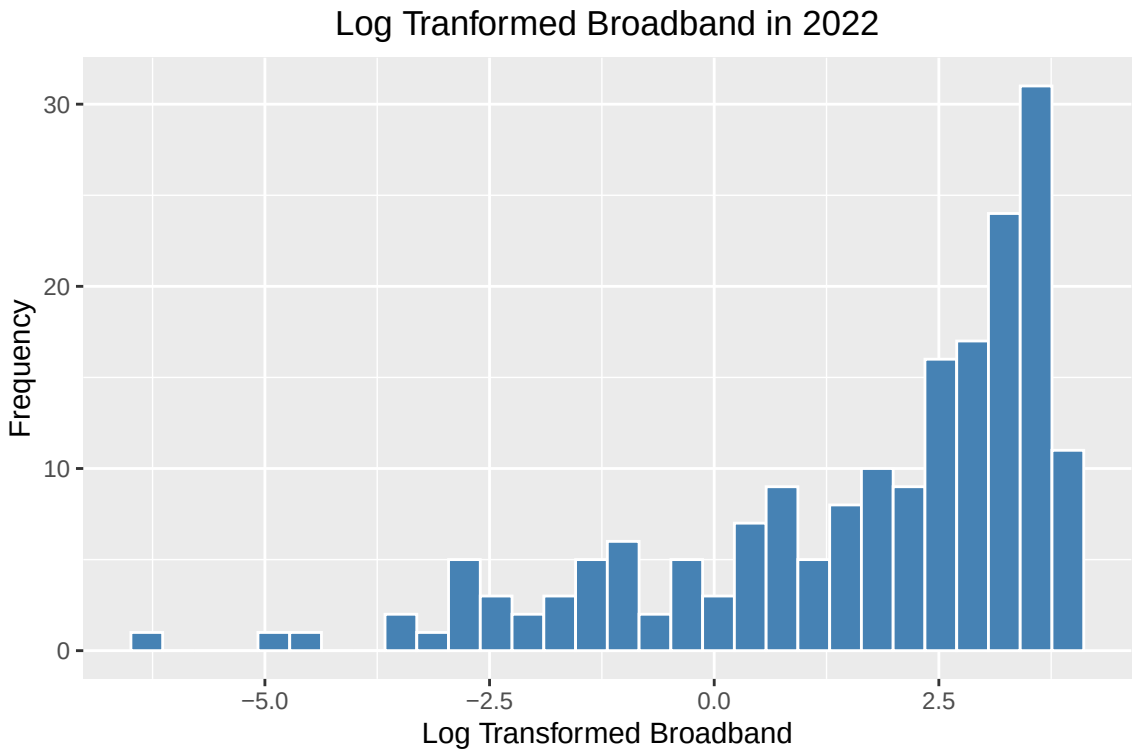


The histogram shows that the broadband data is right skewed.

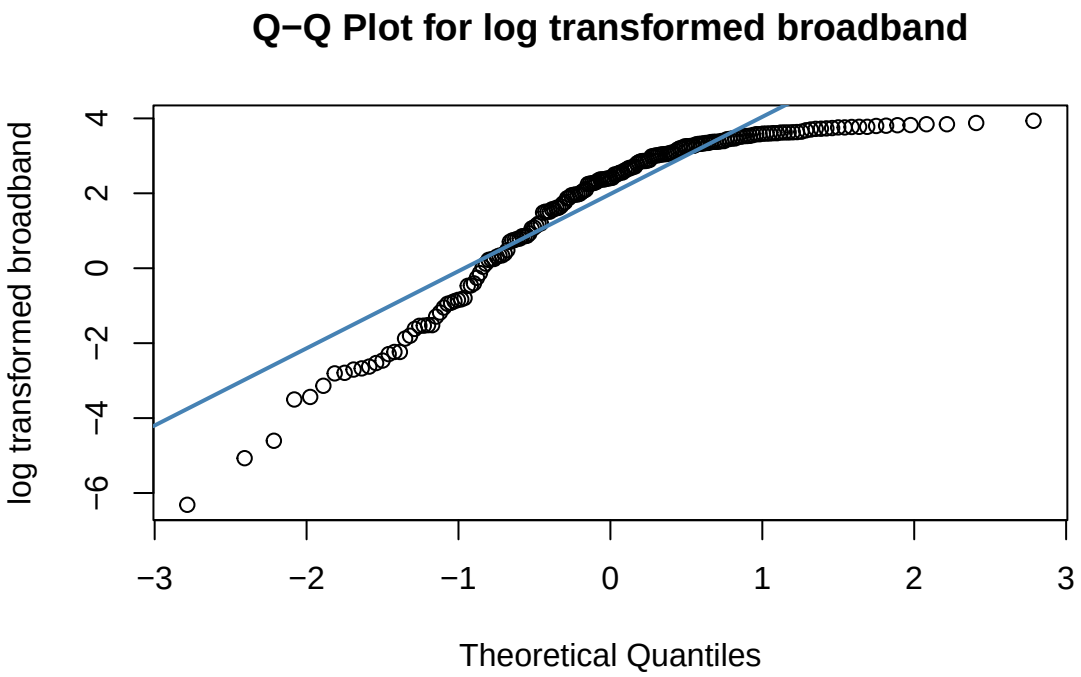


We need to transform the broadband dataset.

Option 1: Log Transform

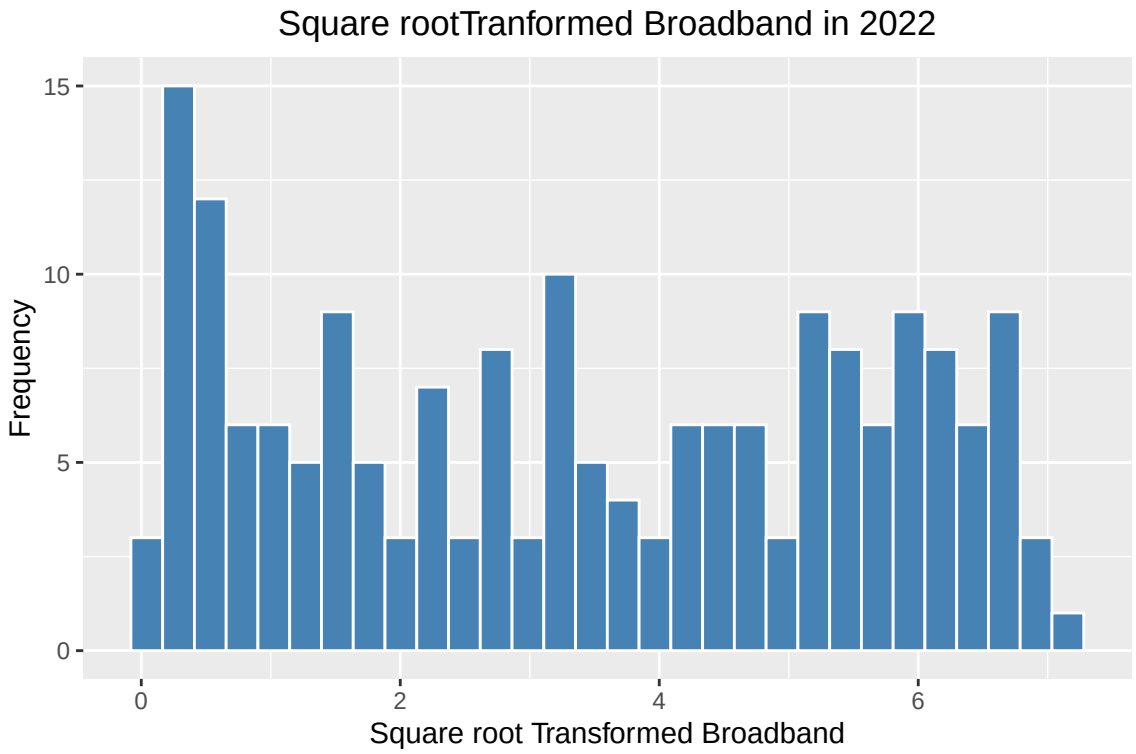



```
##
##  Shapiro-Wilk normality test
##
## data:  data_2022$log_broadband
## W = 0.85633, p-value = 2.711e-12
```

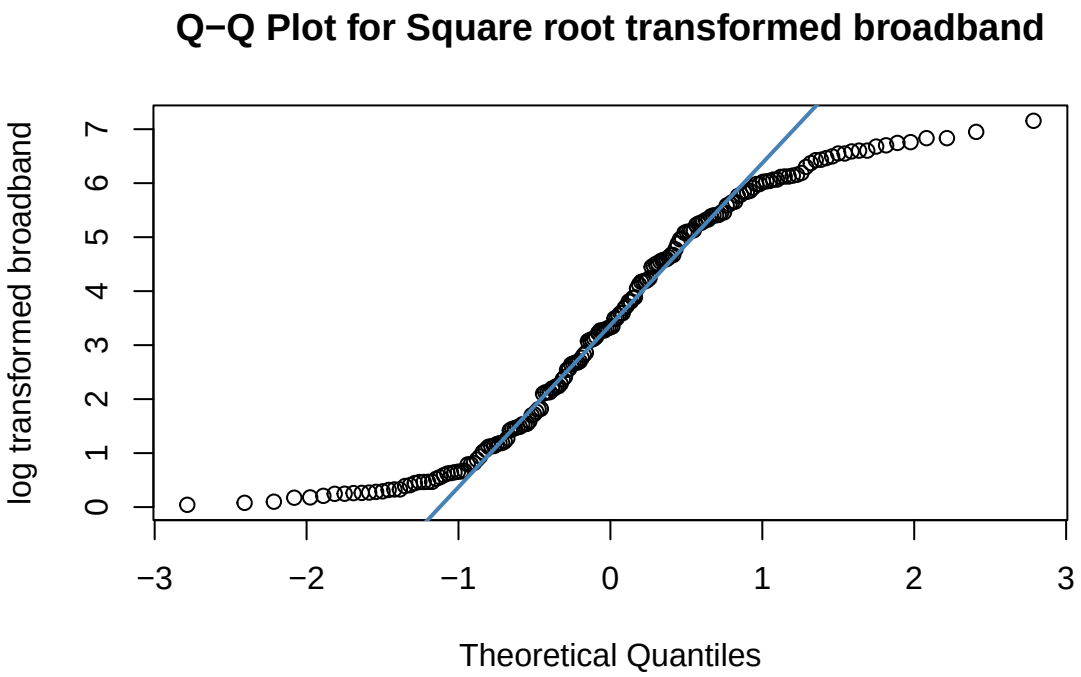


We see that the histogram of log transformed broadband values is also left skewed. We need to consider another transformed method

Option 2: Square root Transform



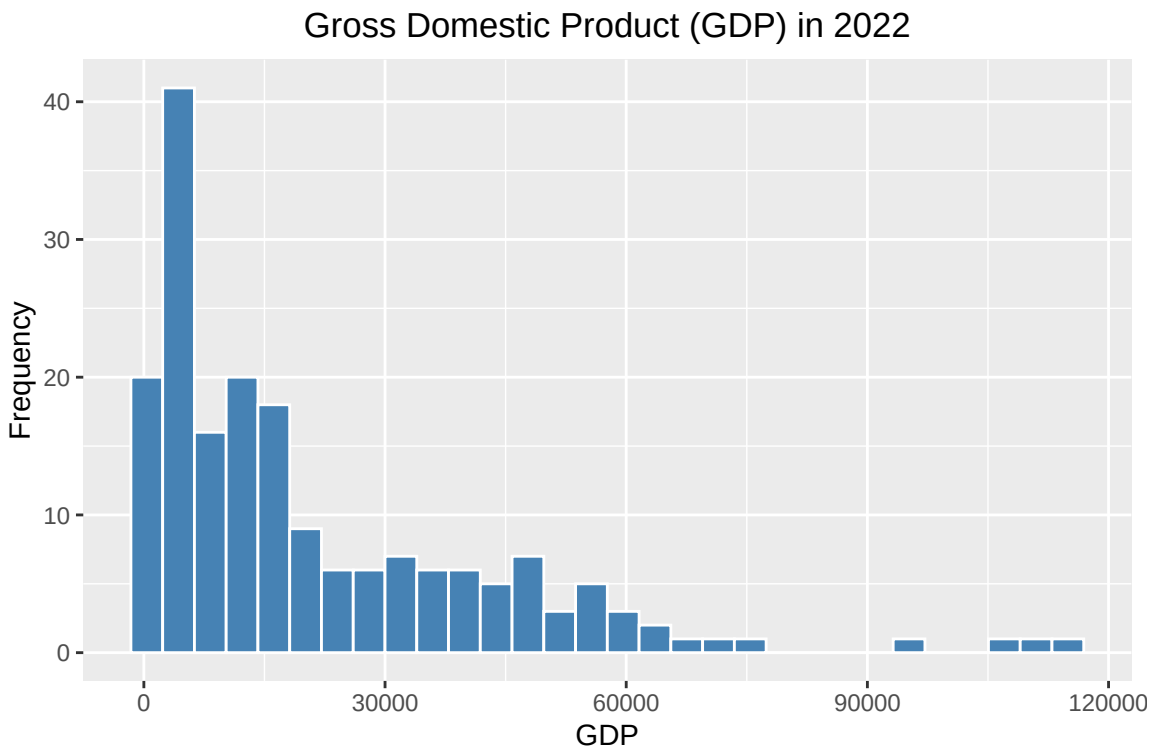

```
##
##  Shapiro-Wilk normality test
##
## data:  data_2022$sqrt_broadband
## W = 0.9293, p-value = 6.888e-08
```



The sqrt transform is preferable. Let's also apply this to 2011.

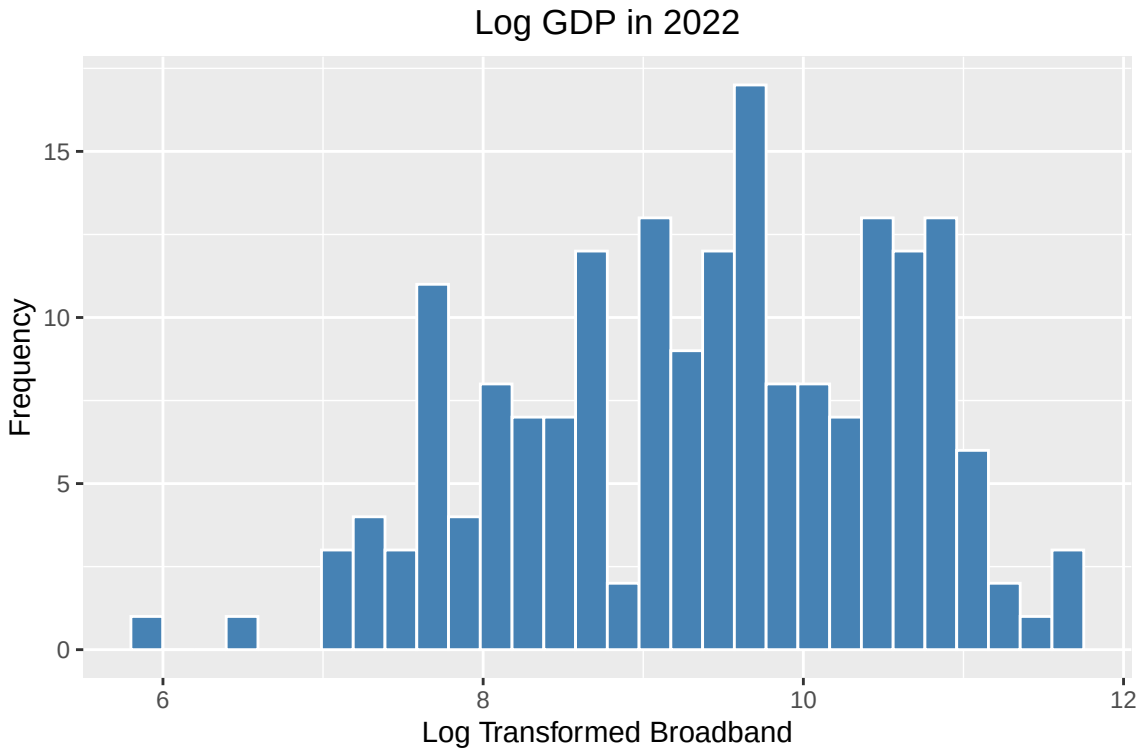
Square root Transform for 2011 broadband

Distribution of Gross Domestic Product (2022)

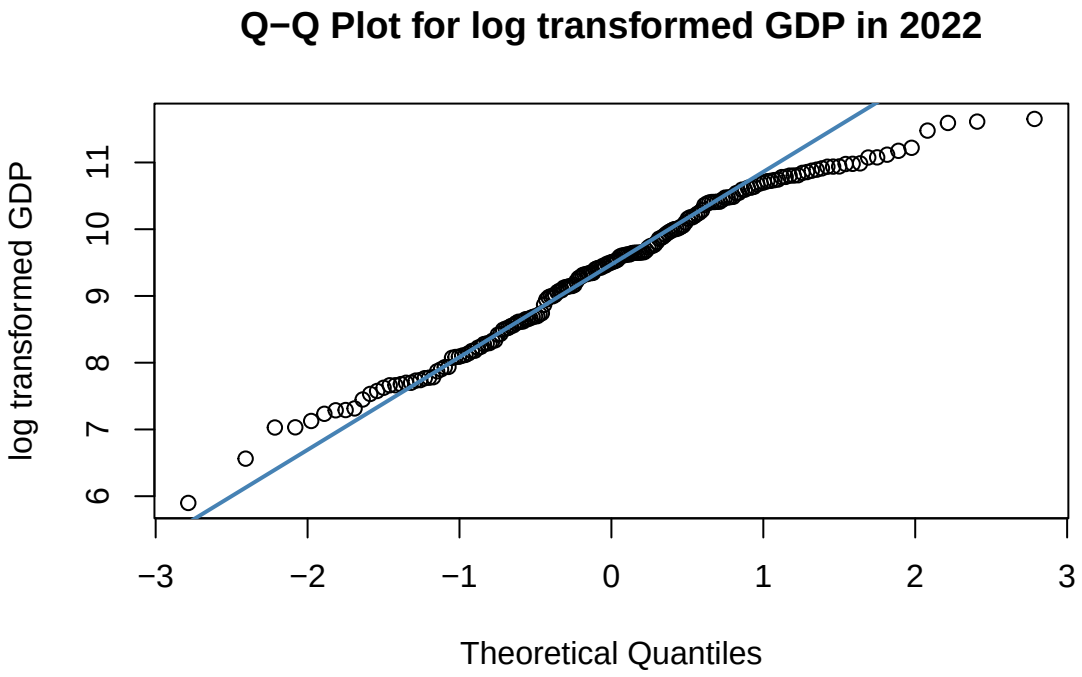


This data is right skewed

Log Transform for 2022 gdp



```
##
##  Shapiro-Wilk normality test
##
## data:  data_2022$log_gdp
## W = 0.97764, p-value = 0.004284
```



Standardization

To calculate z-scores, we need the mean and standard deviations. These values are joined to our long format table

Question 1

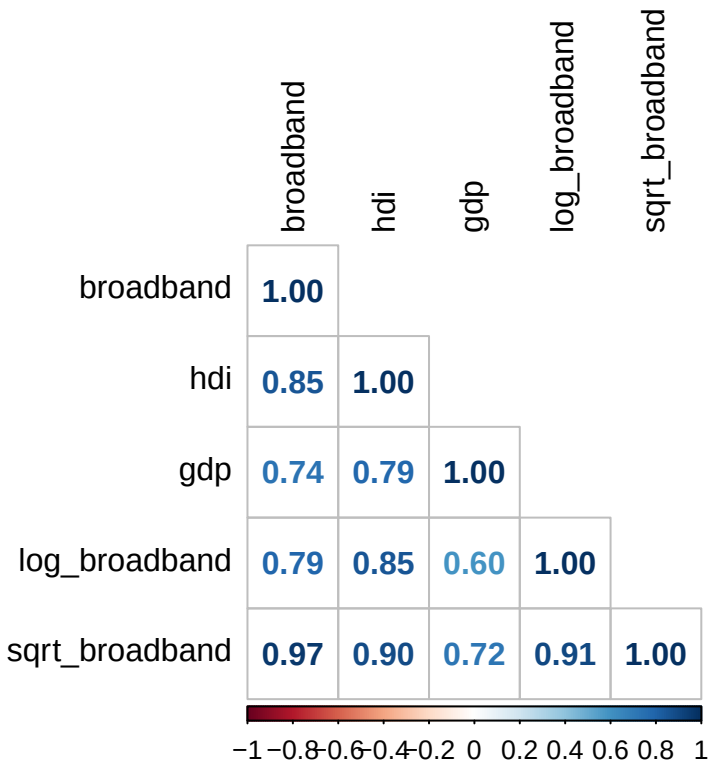
What is the relationship between HDI and broadband subscriptions, based on the latest available data, which is 2022.

Descriptives and EDA

Let's peek at means and standard deviations.

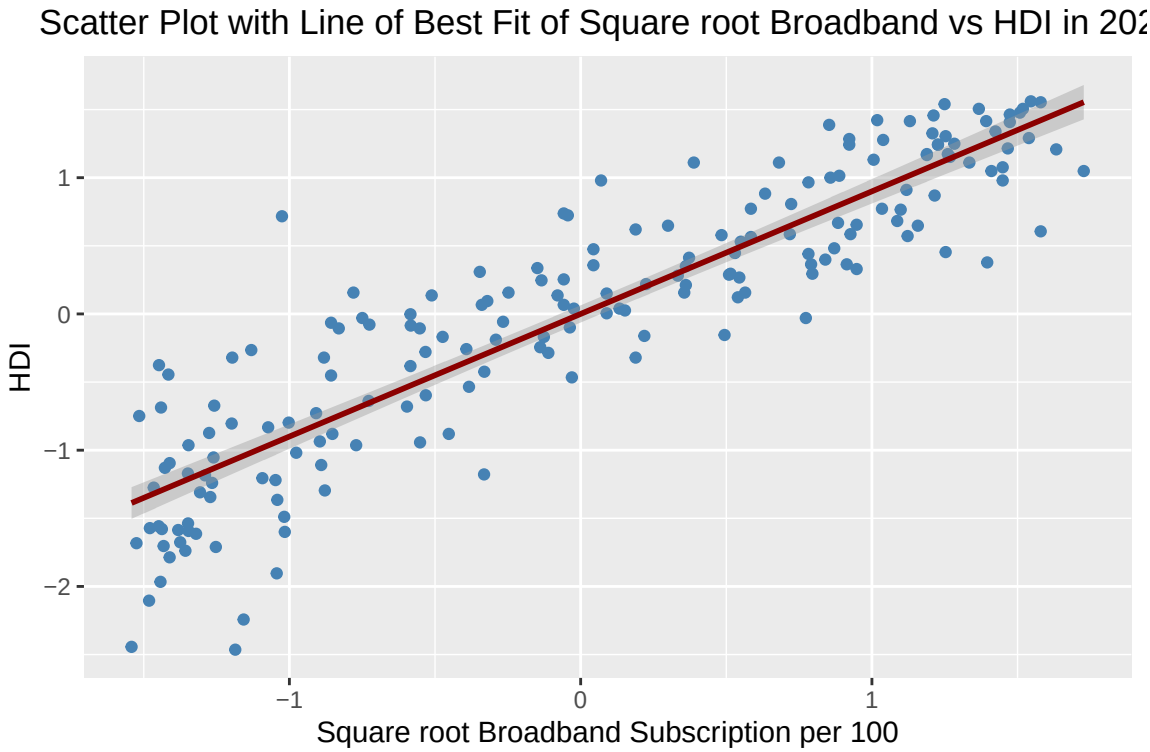
Correlation matrix

Let's look at the correlations between the independent variables. We want there to be low correlations for no multicollinerity.



Plots

Scotterplot



```
##
## Call:
## lm(formula = hdi ~ sqrt_broadband, data = data_2022_standardized)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.39713 -0.27338  0.01689  0.26781  1.63966
##
## Coefficients:
##                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)    -3.281e-16  3.199e-02    0.00        1
## sqrt_broadband  8.998e-01  3.207e-02   28.06   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.4374 on 185 degrees of freedom
## Multiple R-squared:  0.8097, Adjusted R-squared:  0.8087
## F-statistic: 787.1 on 1 and 185 DF,  p-value: < 2.2e-16
```

Question 2

Are there countries that significantly deviate from this relationship between HDI and broadband subscription rate?

```
## # A tibble: 2 x 10
##   country broadband    hdi    gdp log_broadband sqrt_broadband log_gdp
##   <chr>       <dbl>  <dbl>  <dbl>         <dbl>          <dbl>   <dbl>
## 1 Kuwait     -0.977  0.717  1.22         -0.641          -1.03    1.18
## 2 Somalia    -1.02  -2.46  -0.915        -0.972          -1.19   -2.02
## # i 3 more variables: fitted_hdi <dbl>, residuals <dbl>, std_resid <dbl>
```

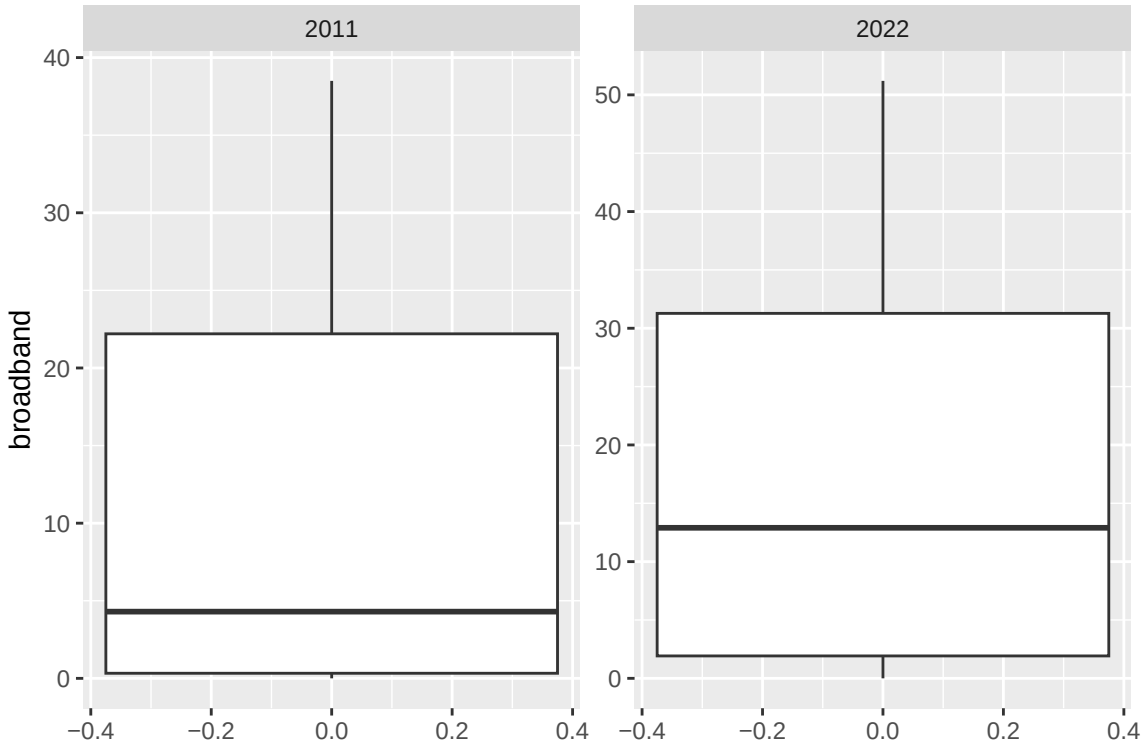
Our outliers in 2022 are Kuwait and Somalia

Question 3

How has broadband access by country changed between 2011, when the UN declaration was announced, and 2023?

Descriptives and EDA

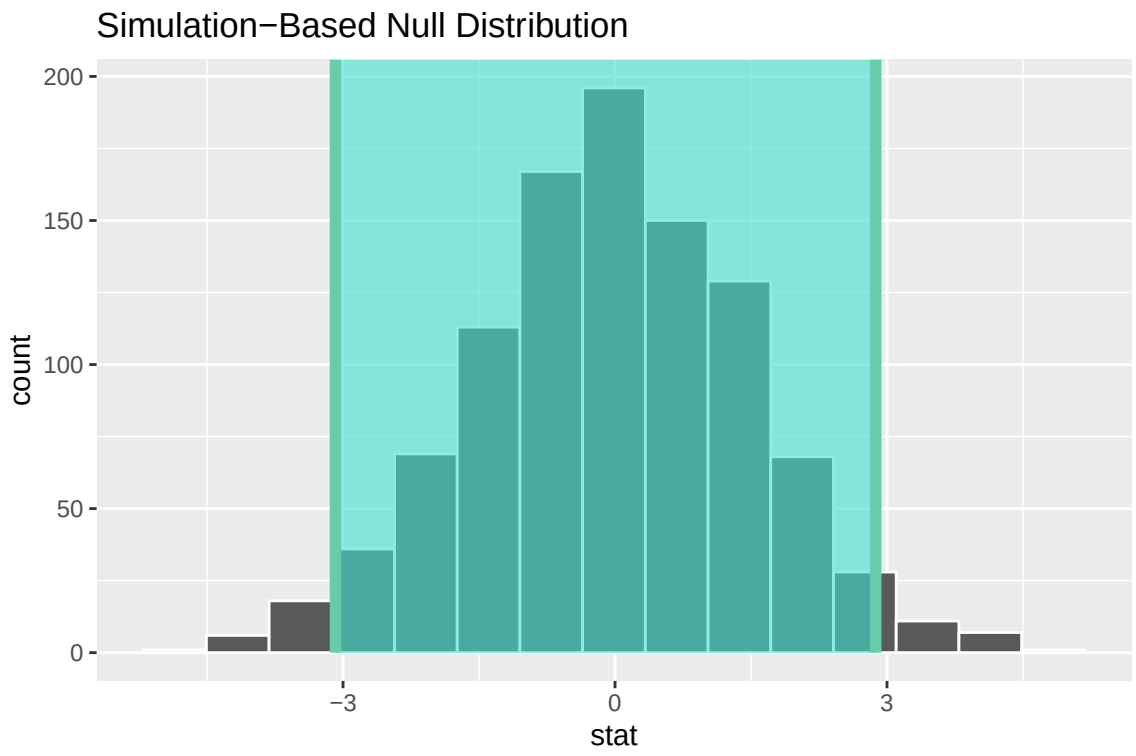
Plots



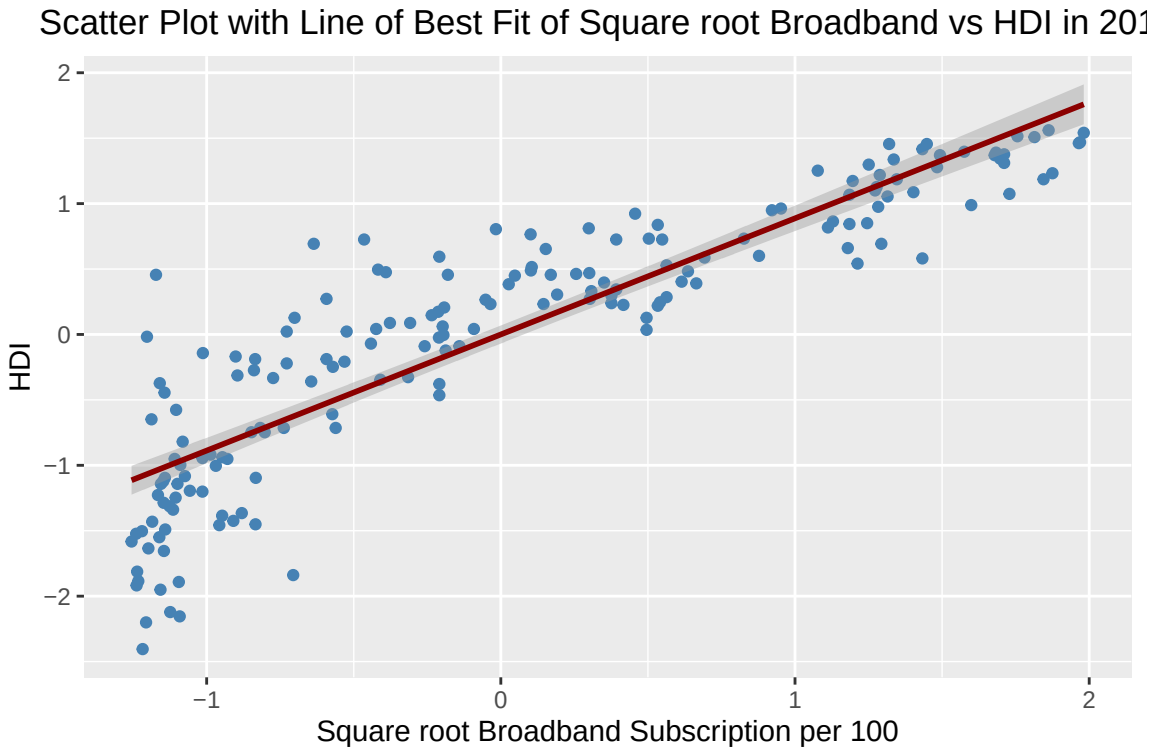
T-test

```
## [1] -9.393962 -3.880547
## attr(,"conf.level")
## [1] 0.95
```

```
## # A tibble: 1 x 2
##   lower_ci upper_ci
##      <dbl>    <dbl>
## 1    -3.08     2.88
```



Scatterplot



##

```
## Call:
## lm(formula = hdi ~ sqrt_broadband, data = data_2011_standardized)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.32383 -0.25418 -0.02857  0.29554  1.49645
##
## Coefficients:
##                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)    8.822e-17  3.473e-02    0.00        1
## sqrt_broadband 8.875e-01  3.483e-02   25.48   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.462 on 175 degrees of freedom
## Multiple R-squared:  0.7877, Adjusted R-squared:  0.7865
## F-statistic: 649.4 on 1 and 175 DF,  p-value: < 2.2e-16
```

##Outlier country in 2011

```
## # A tibble: 1 x 8
##   country broadband   hdi    gdp sqrt_broadband fitted_hdi residuals std_resid
##   <chr>       <dbl> <dbl>  <dbl>          <dbl>      <dbl>     <dbl>     <dbl>
## 1 Cuba       -0.846 0.456 -0.570          -1.17      -1.04      1.50      3.26
```

Our outlier is 2011 is Cuba

Question ??

Create a multi regression with gdp as the control variable

```
##
## Call:
## lm(formula = hdi ~ sqrt_broadband + log_gdp, data = data_2022_standardized)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.87118 -0.14524  0.02077  0.13574  0.79086
##
## Coefficients:
##                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)    -6.138e-16  1.926e-02    0.00        1
## sqrt_broadband  2.940e-01  3.869e-02    7.60 1.46e-12 ***
## log_gdp         6.991e-01  3.869e-02   18.07  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2633 on 184 degrees of freedom
## Multiple R-squared:  0.9314, Adjusted R-squared:  0.9307
## F-statistic:  1249 on 2 and 184 DF,  p-value: < 2.2e-16
```

Checking assumptions

Lack of Multicollinearity

```
## sqrt_broadband        log_gdp
##       4.015438       4.015438
```

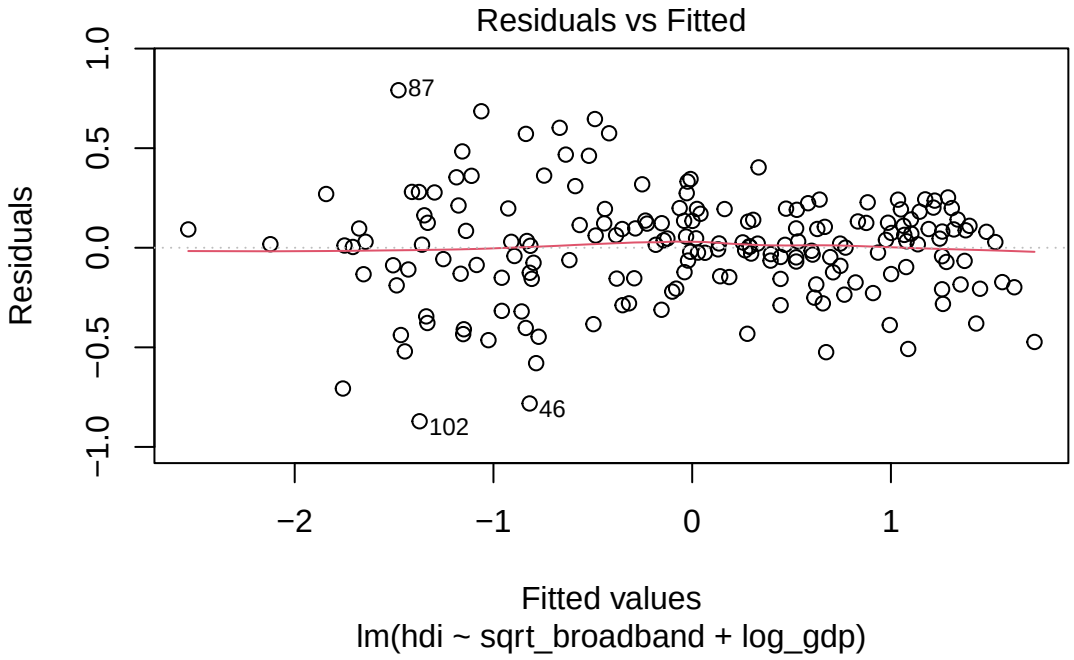
The variance inflation factors are 4.01 for sqrt_broadband and 4.01 for log_gdp. This indicates that there is not a strong linear relationship between these factors.

Independence

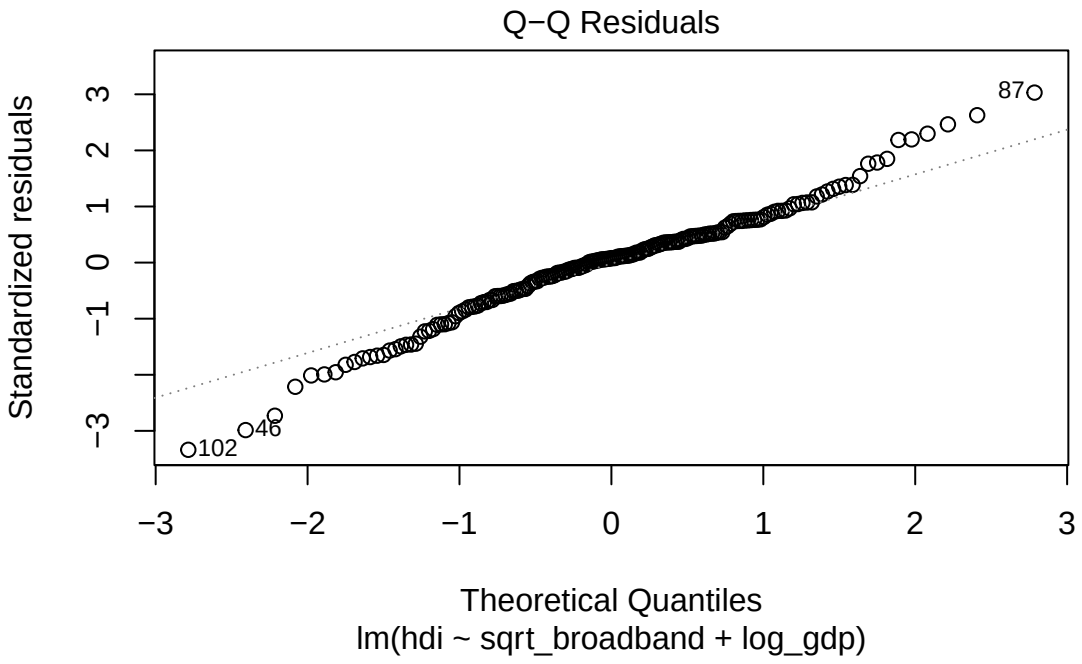
```
##
##  Durbin-Watson test
##
## data:  multi_reg
## DW = 1.9102, p-value = 0.2686
## alternative hypothesis: true autocorrelation is greater than 0
```

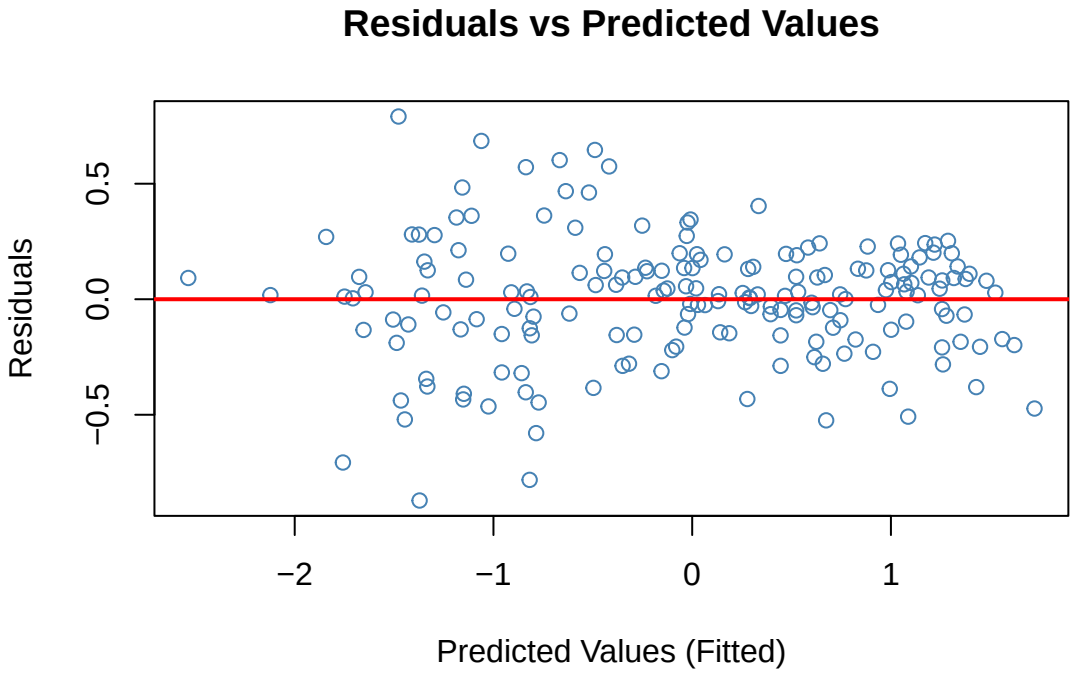
??

Normaility of residuals




```
##
##  Shapiro-Wilk normality test
##
## data:  res_model
## W = 0.98015, p-value = 0.009251
```

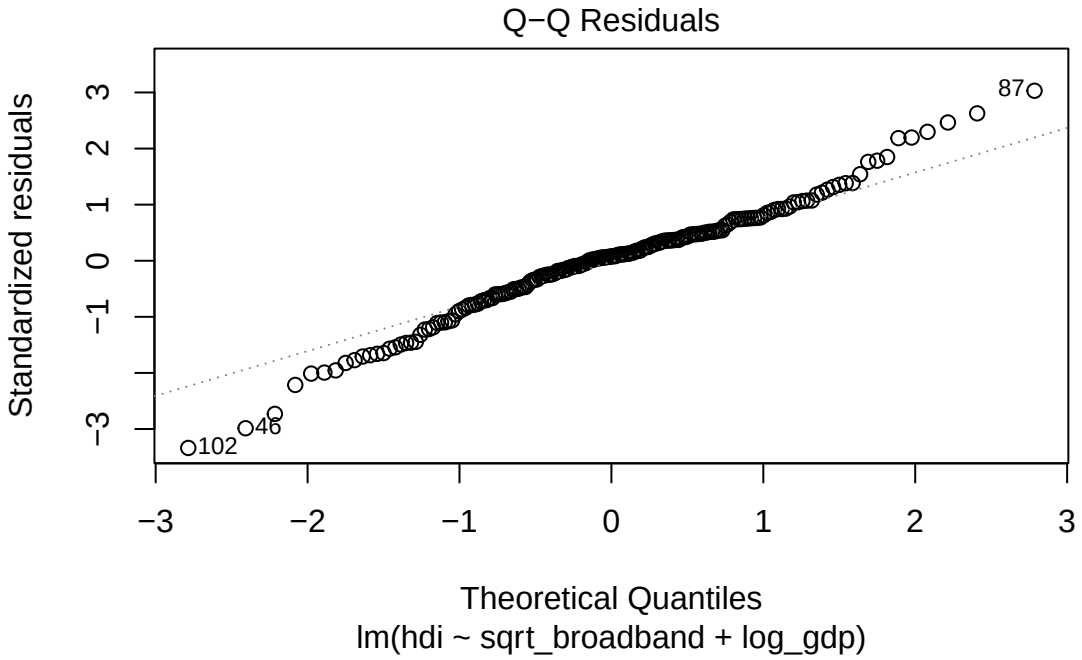





```
## integer(0)
```

Homoscedascity Next, let's look for the independence of the residuals.

```
##
##  Shapiro-Wilk normality test
##
## data:  res_model
## W = 0.98015, p-value = 0.009251
```



6. Results and Interpretation

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7. Discussions

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Appendix

Code

The report was created using *R* (R Core Team 2020) and *R Studio* (RStudio Team 2020) with *R Markdown* (RStudio, n.d.). The main library utilized for this purpose is *Tidyverse* (Wickham et al. 2019). Its used sub-packages include *dplyr* (Wickham et al. 2022) to enable query-like syntax, and *ggplot* (Wickham 2016) to create graphs and charts. Other packages and tools include *janitor* (Firke 2021), *knitr* (Xie 2022), *kableExtra* (Zhu 2021), and *scales* (Wickham and Seidel 2022).

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