Quality of Life by Country: A Clustering Analysis

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Abstract

BACKGROUND As economic globalization increases, it is important to understand how countries compare for key quality of life (QoL) measures when grouped by level of human development, and how these comparative results change by grouping approach. In the context of recent news reports about decreasing life expectancy in the United States, it is of particular interest to compare how the United States performs against other countries of a similar developmental level. METHODS Data for QoL measures of interest in calendar year 2016 was gathered and merged into a single country-level dataset. Each variable was examined via descriptive statistics and univariate visualizations, and continuous variables were compared pairwise with a correlation matrix. The top- and bottom-ranking 20 countries were determined for each QoL measure. For those variables for which the United States was not among the 20 highest performing countries, a series of pairwise k-means cluster analyses were run, with a sensitivity analysis performed for number of clusters. RESULTS The analytic dataset included 9 QoL variables. CONCLUSION

Background

The Centers for Disease Control and Prevention (CDC) has recently issued a report indicating that life expectancy in the United States has decreased in 2017 as compared to 2016, with the overwhelming majority of deaths caused by heart disease and cancer, arguably preventable illnesses (Murphy et al. (2018)). Given that the United States has the world's largest economy, this decline in life expectancy is particularly concerning, and indicates that national wealth may not be predictive of citizens' longevity (The World Bank (2018)).

As the world's economies trend toward globalism, there is increasing interest in understanding how these nations compare on key quality of life (QoL) factors, including but not limted to life expectancy. Several organizations report on QoL measures as they evolve, including among others the World Economic Forum (WEF), World Health Organization (WHO), and the United Nations Development Programme. The QoL measures reported by these bodies can be either unidimensional values or compound scores calculated from several factors of interest.

The objective of this analysis is to explore the relationships between key QoL indicators by country, with particular focus on how the United States ranks, through a series of visualizations and k-means clustering analyses.

Methods

This analysis included country-level QoL indicators as described in Table 1.

Table 1. Country-Level QoL measures.

Measure	Single or Compound	Description	Source
Gross Domestic Product (GDP)	Single	Valued in $US 2018	@worldbank_gdp
Infant mortality rate	Single	Number of infant deaths per 1,000 live births	@who_infantmort
Life expectancy at birth	Single	Expected life at birth, both genders	@who_life
Life expectancy at sixty	Single	Expected remaining life years at age 60, both genders	@who_life
Human Development Index (HDI)	Compound	Developmental level, scale of 0:1	@un_dvlpt_HDIdesc
Human Development Index (HDI)	Compound	Developmental category, four levels (low, medium, high, very high)	@un_dvlpt_HDIdesc
Social Progress Index	Compound	Social progress level, scaled from 0:100 and comprising three broad categories: basic human needs (e.g., nutrition, safety), foundations of wellbeing (e.g., basic knowledge, environmental quality), and opportunity (e.g., personal rights, freedoms)	@socialprog_desc
Global Gender Gap Index	Compound	Gender equality index, scaled from 0:1, based on measurements of gender-related gaps in such dimensions as economic participation, level of education, health and survival, and political offices held	@wef_gender_desc
World Happiness Score	Compound	Happiness score, scaled from 0:10, based on several factors including per-capita GDP, healthy life expectancy, social support, freedoms, and perception of corruption	@whr

Data for these measures was obtained for calendar year 2016 in `.csv` or `.xls(x)` formats. Additionally, dataframe containing country identifiers (full names and three-letter codes) was generated from the `countrycode` library to facilitate merging the datafiles into one dataframe.

Wrangling and Exploration

Each country-level datafile was imported, wrangled as needed, then tested against the dataframe containing country identifiers via `anti_join()` to identify mismatches. Mismatching country names were manually recoded for each datafile, then all datafiles were merged using serial `lef_join()` statements. Countries with wholly missing data were excluded. The resulting dataframe, titled `alldata`, is presented in Table 2.

Table 2. `alldata` dataframe contents.

Source	Variable Name	Description
Social Progress Imperative (2018)	SPI	Social Progress Index value (scale of 0:100)
The World Bank (2018)	GDP_USD_2018	2016 Gross Domestic Product (valued in $US 2018)
The United Nations Development Programme (2018)	HDIrank	Human Development Index ranking
The United Nations Development Programme (2018)	HDIindex	HDI index value (scale of 0:1)
The United Nations Development Programme (2018)	HDI_cat	HDI index category (5 levels)
Helliwell, Layard, and Sachs (2018)	happiness	World Happiness Score (scale of 0:10)
World Economic Forum (2016)	gendereq	Gender Equality Index (scale of 0:1)
World Health Organization (2018b)	infantmort	Infant mortality rate
World Health Organization (2018a)	birth_MF	Life expectancy at birth, males & females
World Health Organization (2018a)	sixty_MF	Life expectancy at 60 years, males & females

At least one univariate visualization was generated for each variable in `alldata` via `ggplot()`, and a correlation matrix was produced to investigate pairwise relationshps between continuous variables. Next, a series of ordered country-as-factor bivariate visualizations were created to explore the top and bottom 20 countries by ranking within each variable, with the United States denoted in red.

K-Means Clustering

For the variables for which the United States was not among the top 20 performing countries on country-level visualization, a series of k-means cluster analyses was performed. K-means clustering is described elsewhere; briefly, given bivariate data and a desired number k of groups, this classification algorithm classifies the points in the two-dimensional plane to minimize the total within-cluster variation for all clusters (James et al. (2013)). This is an iterative process that works by establishing k centroids, classifying each point by which centroid is closest, then moving the centroids to the center of their corrresponding clusters, and repeating the process. Iteration terminates when the centroids no longer move, and the classification established in this terminal iteraton is the clustering.

The Human Development Index categorizes the world's countries into four developmental levels (low, medium, high, and very high); thus k-means clustering analysis was performed assuming 4 clusters. Missing values were excluded to ensure the clustering algorithm would run, and a function was written to subset the clustering dataset (named `clusterdata`) to the variables of interest for each k-means analysis. On each output plot, the United States was identified by an enlarged `geom_point()`. A Shiny application was written to allow sensitivity analysis of the effect of varying k, with particular attention paid to any transitions between clusters for the United States with changing k.

Example Code

For brevity, example code for wrangling, plotting, and clustering is presented here; full code is available in the GitHub repository for this report (Prioli (2018)).

The libraries required for this analysis were loaded as shown below.

```r
library(tidyverse)
library(readxl)          # For importing .xls(x) datasets
library(lazyeval)        # For renaming columns in function
library(countrycode)     # For establishing uniform country identifiers
library(ggthemr)         # For prettifying output
library(gridExtra)       # For grid.arrange()
library(grid)            # For textGrob() to annotate grid.arrange() elements
library(kableExtra)      # For nicer output tables
library(GGally)          # For ggpairs() correlation matrix
library(wesanderson)     # For Wes Anderson palette

ggthemr("fresh")         # For prettifying plot framework
wes <- wes_palette("Darjeeling1", 5, type = "discrete")    # Establishing color scheme for cluster plots
```

Code for establishing a crosswalk for country names and 3-letter codes:

```r
countries_full <- codelist_panel %>%
  select(country.name.en, year, genc3c, iso3c, wb_api3c) %>%
  group_by(country.name.en) %>%
  mutate(maxyr = max(year)) %>%
  ungroup %>%
  mutate(maxyr = case_when(
    maxyr == year ~ 1,
    TRUE ~ 0
  )) %>%
  filter(maxyr == 1) %>%
  select(-maxyr) %>%
  distinct()

countries_full <- countries_full %>%
  mutate(country3 = case_when(
    iso3c == genc3c & iso3c == wb_api3c ~ iso3c,
    is.na(iso3c) == FALSE ~ iso3c,
    is.na(iso3c) == TRUE & is.na(genc3c) == FALSE ~ genc3c,
    is.na(iso3c) == TRUE & is.na(genc3c) == TRUE & is.na(wb_api3c) == FALSE ~ wb_api3c
  )) %>%
  rename(country = country.name.en) %>%
```

```r
  arrange(country)

countries <- countries_full %>%
  select(country, country3)
```

Code for importing and wrangling each data file, and standardizing country names (example shown for the Social Progress Index data):

```r
# Importing, subsetting, renaming

SPI_2016_raw <- read_xlsx("data/SPIdata.xlsx", sheet = 4)

SPIdata <- SPI_2016_raw %>%
  select(2:3) %>%
  rename(`SPI` = `Social Progress Index`,
         country3 = Code)

# Standardizing country names by using `anti_join()` to see which
# countries in `SPIdata` don't have a match in the `countries` dataframe

SPIanti <- SPIdata %>%
  anti_join(countries, by = "country3") %>%
  select(country3) %>%
  arrange(country3) %>%
  unique()
dim(SPIanti)
```

```
## [1] 5 1
```

```r
# Correcting for mismatches with `countries` using `mutate()`

SPIdata <- SPIdata %>%
  mutate(country3 = case_when(
    country3 == "CHI" ~ as.character(NA), # Nonstandard code for Chile; omitting (no data in these rows)
    country3 == "KSV" ~ "XKS",            # Nonstandard code for Kosovo
    country3 == "NCY" ~ as.character(NA), # Turk. Repub. of N. Cyprus; omitting (conflict w/Cyprus)
    country3 == "SML" ~ as.character(NA), # Unable to determine
    country3 == "WBG" ~ as.character(NA), # West Bank / Gaza Strip; omitting (conflict w/Palestine)
    TRUE ~ as.character(country3)
  )) %>%
  filter(!is.na(country3))

SPIanti <- SPIdata %>%
  anti_join(countries, by = "country3") %>%
  select(country3) %>%
  arrange(country3) %>%
  unique()
dim(SPIanti)
```

```
## [1] 0 1
```

```r
# Removing unneeded files

rm(list = c("SPI_2016_raw", "SPIanti"))
```

Code to combine individual data files into one dataframe and filter out countries with no data:

```r
joindata_1 <- full_join(countries, HDIdata, by = "country")
joindata_2 <- left_join(joindata_1, SPIdata, by = "country3")
joindata_3 <- left_join(joindata_2, WHRdata, by = "country")
joindata_4 <- left_join(joindata_3, genderdata, by = "country")
joindata_5 <- left_join(joindata_4, infantmortdata, by = "country")
joindata_6 <- left_join(joindata_5, lifeexpdata, by = "country")
```

```r
joindata_7 <- left_join(joindata_6, GDPdata, by = "country3")

joinsub <- joindata_7 %>%
  arrange(country) %>%
  mutate(exclude_flag = case_when(
    is.na(HDIrank) == TRUE &
      is.na(HDIindex) == TRUE &
      is.na(HDI_cat) == TRUE &
      is.na(SPI) == TRUE &
      is.na(happiness) == TRUE &
      is.na(gendereq) == TRUE &
      is.na(infantmort) == TRUE &
      is.na(birth_MF) == TRUE &
      is.na(sixty_MF) == TRUE &
      is.na(GDP_USD_2018) == TRUE             ~ TRUE,
    TRUE                                      ~ FALSE
  )) %>%
  filter(exclude_flag == FALSE) %>%
  select(-exclude_flag)

alldata <- joinsub %>%
  mutate(country = factor(country)) %>%
  mutate(country3 = factor(country3)) %>%
  mutate(US = case_when(
    country == "United States" ~ "US",
    TRUE                       ~ "Non US"
  )) %>%
  mutate(color = case_when(
    country == "United States" ~ "red",
    TRUE                       ~ "#545454"
  ))

alldata <- alldata[c(1:2, 13:14, 6, 12, 3:5, 7:11)]

len <- dim(alldata)[[1]]

# write_csv(alldata, paste0("data/alldata_", lubridate::today(),".csv"))  # Uncomment to export data
```

Example code for univariate explorations:

```r
SPI_hist <- ggplot(data = alldata, aes(x = SPI)) +
  geom_histogram(bins = ceiling(sqrt(len - sum(is.na(alldata$SPI))))) +
  xlab("Social Progress Index") +
  ylab("Count") +
  ggtitle("Figure 1.  Social Progress Index Distribution")

SPIsumm <- broom::tidy(round(summary(alldata$SPI), digits = 3))
sd <- round(sd(alldata$SPI, na.rm = TRUE), digits = 3)
SPIsumm <- cbind(SPIsumm, sd)
colnames(SPIsumm) <- c("Min", "Q1", "Median", "Mean", "Q3", "Max", "NA", "SD")
SPIsumm <- SPIsumm[c(1:6,8,7)]
SPIsumm_grob <- tableGrob(t(SPIsumm), theme = ttheme_minimal())

grid.arrange(SPI_hist, SPIsumm_grob, nrow = 1, widths = c(0.8, 0.2))
```

Example ordered country-level plot code:

```r
alldata_SPI <- alldata %>%
  filter(!is.na(SPI) == TRUE) %>%
  arrange(desc(SPI)) %>%
  select(SPI, country, US, color)
```

```r
alldata_SPI_top20 <- alldata_SPI %>% head(20)
alldata_SPI_bot20 <- alldata_SPI %>% tail(20)
alldata_SPI40 <- bind_rows(alldata_SPI_top20, alldata_SPI_bot20)

colors <- alldata_SPI40$color[order(alldata_SPI40$SPI)]

SPI_country_point <- ggplot(data = alldata_SPI40, aes(x = SPI,
                                                       y = fct_reorder(country, SPI), color = US)) +
  geom_point() +
  scale_color_manual(values = c("US" = "red", "Non US" = "#65ADC2")) +
  theme(axis.text.y = element_text(color = colors)) +
  guides(color = FALSE) +
  xlim(0, 100) +
  xlab("SPI") +
  ylab("Country") +
  ggtitle("Figure 9.  Social Progress Index by Country")
```

Example clustering code:

```r
kmdf <- function(data, x, y, z){
  kmdata <- data %>%
    select(x, y, z)
  kmdata <- return(kmdata)
}

kmdata <- kmdf(clusterdata, "country", "SPI", "logGDP")

set.seed(19811221)
km_SPI_GDP <- kmeans(kmdata[, 2:3], 4)
km_SPI_GDP_cluster <- as.factor(km_SPI_GDP$cluster)

clusterdata1 <- cbind(clusterdata, km_SPI_GDP_cluster)

km_SPI_GDP_plot <- ggplot(data = clusterdata1,
                          aes(x = logGDP, y = SPI,
                              color = km_SPI_GDP_cluster,
                              size = US,
                              shape = HDI_cat)) +
  geom_point() +
  ylim(0, 100) +
  scale_color_manual(values = wes) +
  scale_shape_manual(values = c(18, 17, 15, 16)) +
  scale_x_continuous(labels = scales::dollar_format(prefix = "$")) +
  guides(color = guide_legend(title = "Cluster"),
         size = FALSE,
         shape = guide_legend(reverse = TRUE, title = "HDI Category")) +
  xlab("log(GDP) ($US 2018)") +
  ylab("Social Progress Index") +
  ggtitle("Cluster Analysis, Social Progress Index vs. GDP")
km_SPI_GDP_plot
```

Results

Data Exploration and Visualizations

The Social Progress Index data ranges from 26.01to 89.62 and appears trimodal (Fig. 1).

Figure 1. Social Progress Index Distribution

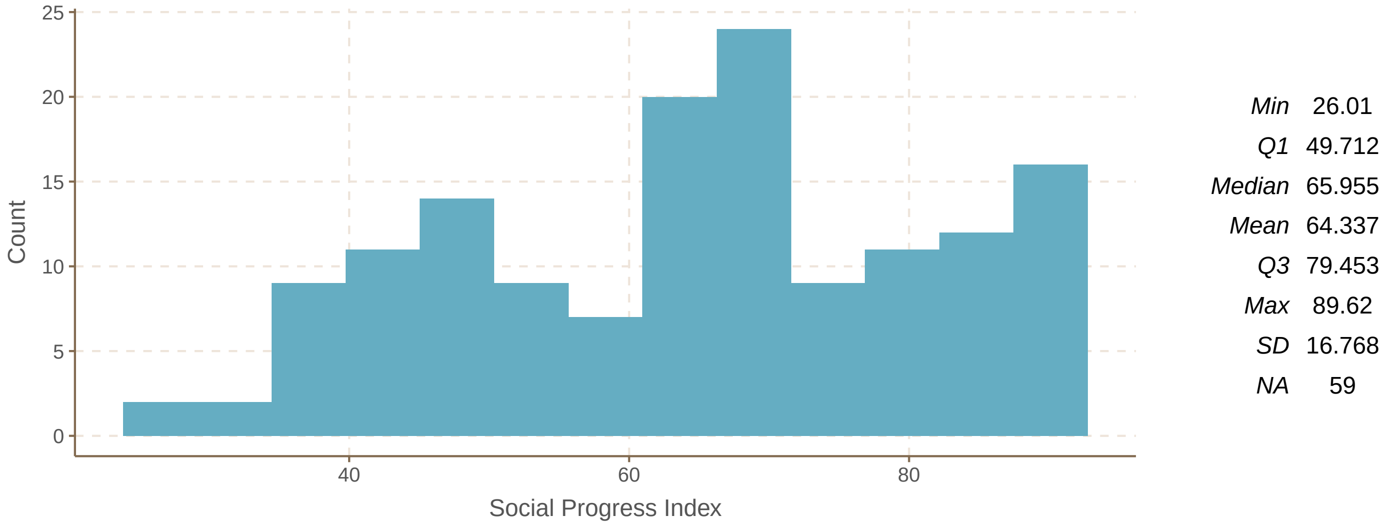


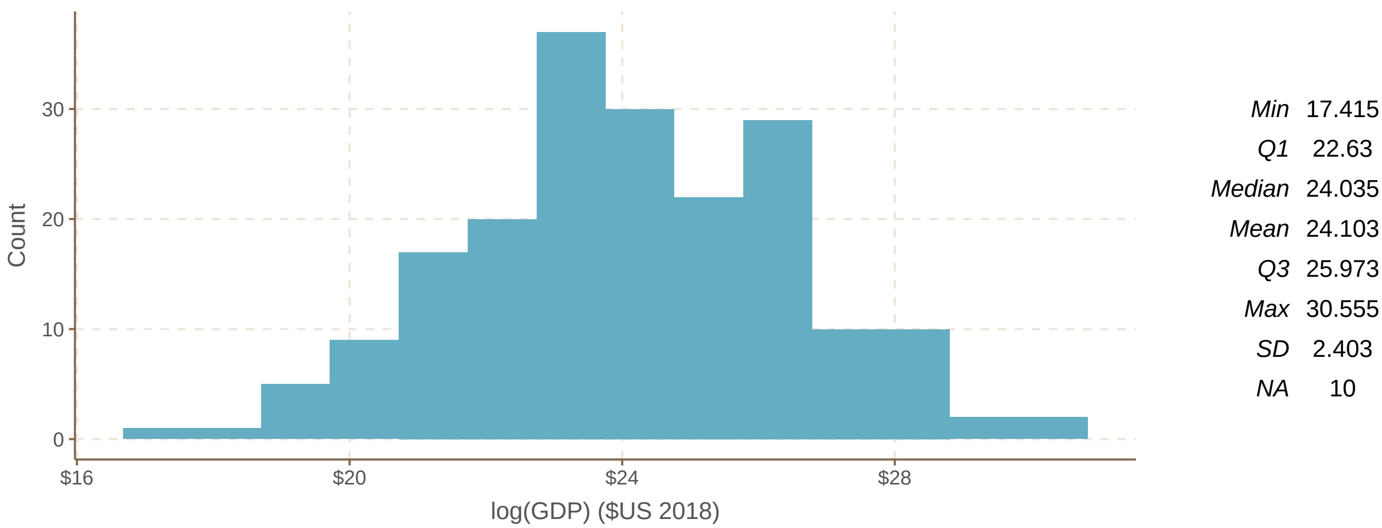
Table 3 shows summary statistics for the raw GDP values. These are unwieldy; however, after log transformation, the data is reasonably normally distributed, with mean 24.1 and standard deviation 2.4 (Fig. 2).

**Table 3. Summary Statistics for `GDP_USD_2018`

Min	Q1	Median	Mean	Q3	Max	SD	NA
36572612	6734069913	27424071373	383069641832	1.90463e+11	1.86245e+13	1.640295e+12	10

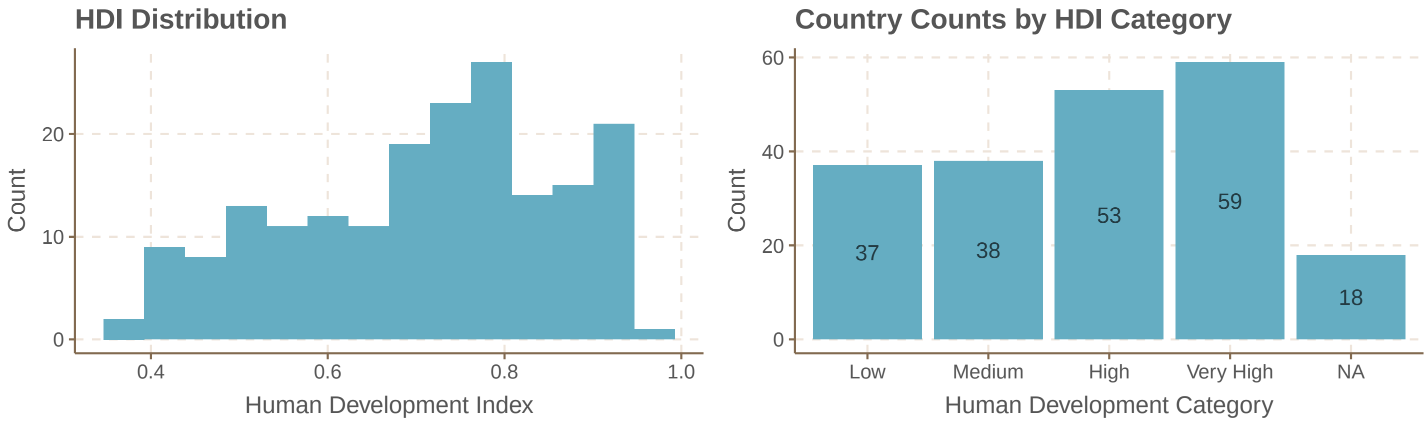
Taking the log transform and plotting:

Figure 2. Gross Domestic Product Distribution, Log Transform



The Human Development Index data (Fig. 3) appears multimodal, with the “very high” developmental category the most represented in the data.

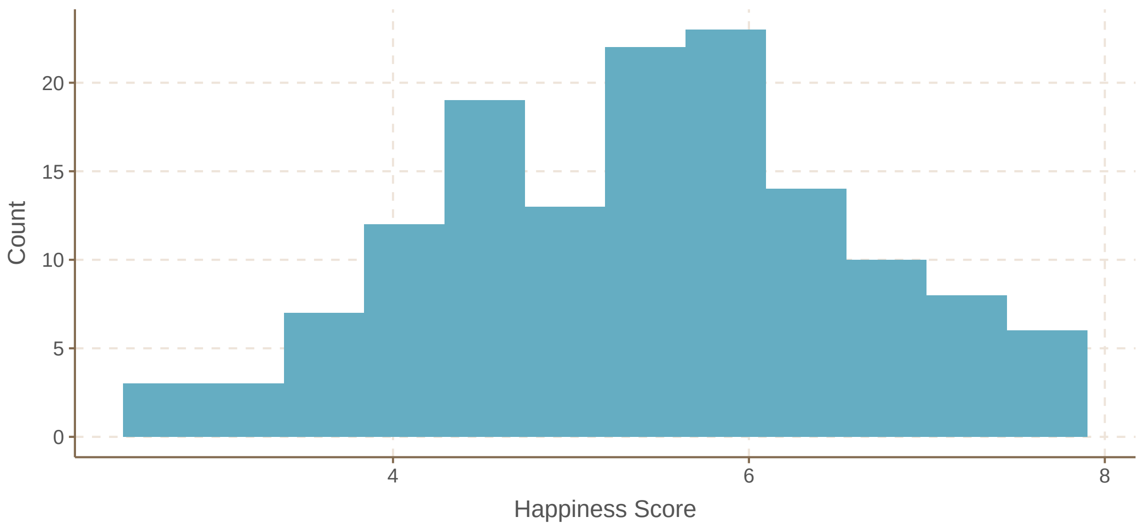
Figure 3. Human Development Index



Min	Q1	Median	Mean	Q3	Max	SD	NA
0.351	0.589	0.737	0.709	0.822	0.951	0.153	19

Figure 4 shows that the Happiness Score is reasonably normally distributed, having values ranging from 2.69 to 7.66.

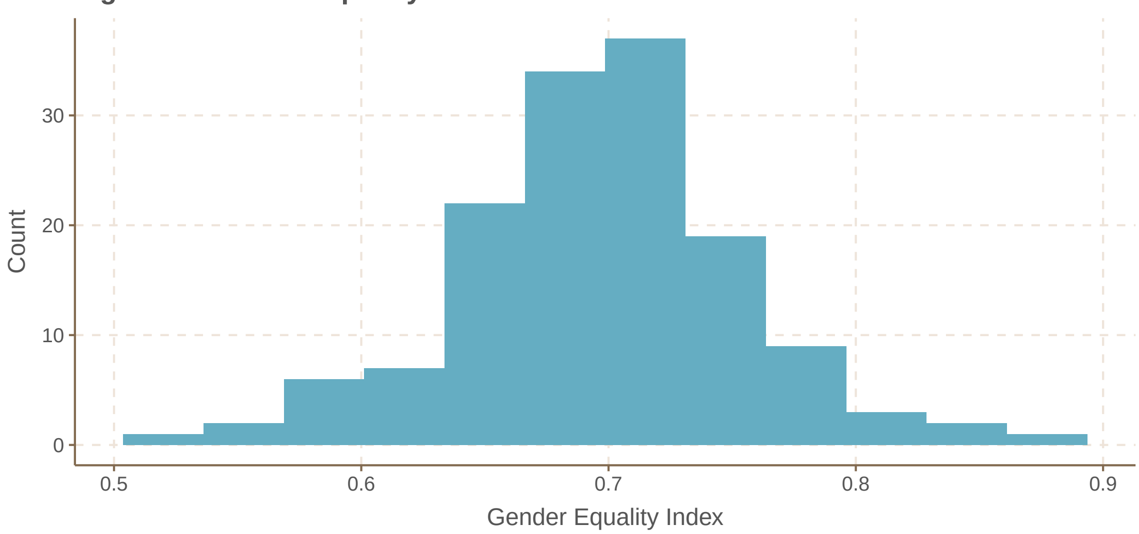
Figure 4. Happiness Score Distribution



Min	2.693
Q1	4.52
Median	5.424
Mean	5.402
Q3	6.145
Max	7.66
SD	1.146
NA	65

Figure 5 shows that the gender equality index is roughly symmetric in distribution, with mean and median quite close in value (0.6953 and 0.6983 respectively).

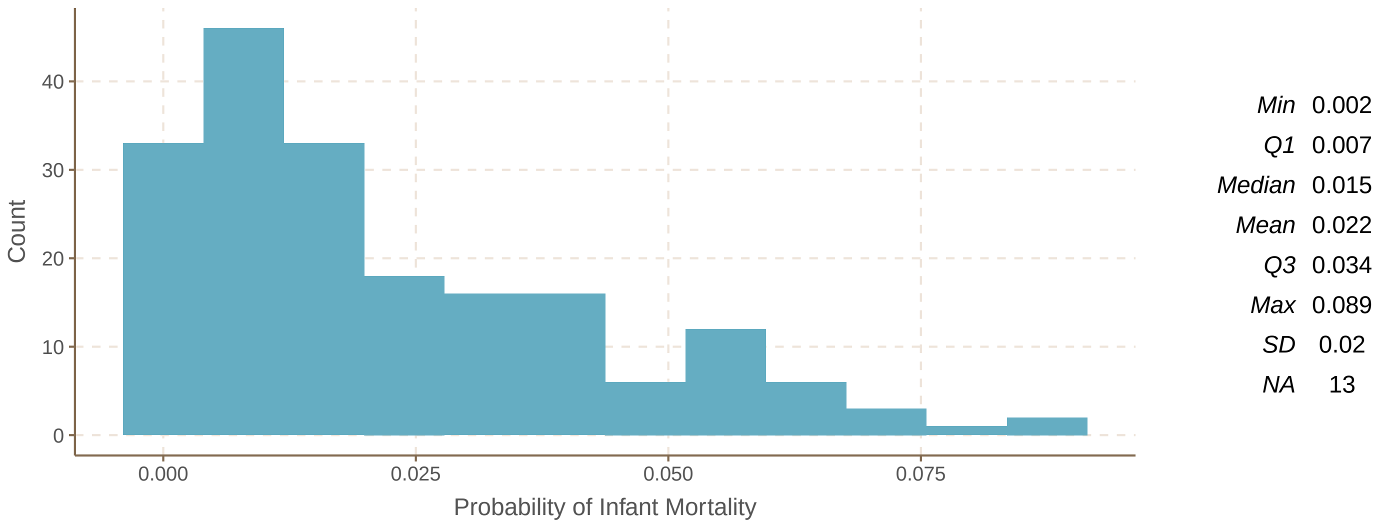
Figure 5. Gender Equality Index Distribution



Min	0.516
Q1	0.665
Median	0.698
Mean	0.695
Q3	0.729
Max	0.874
SD	0.057
NA	62

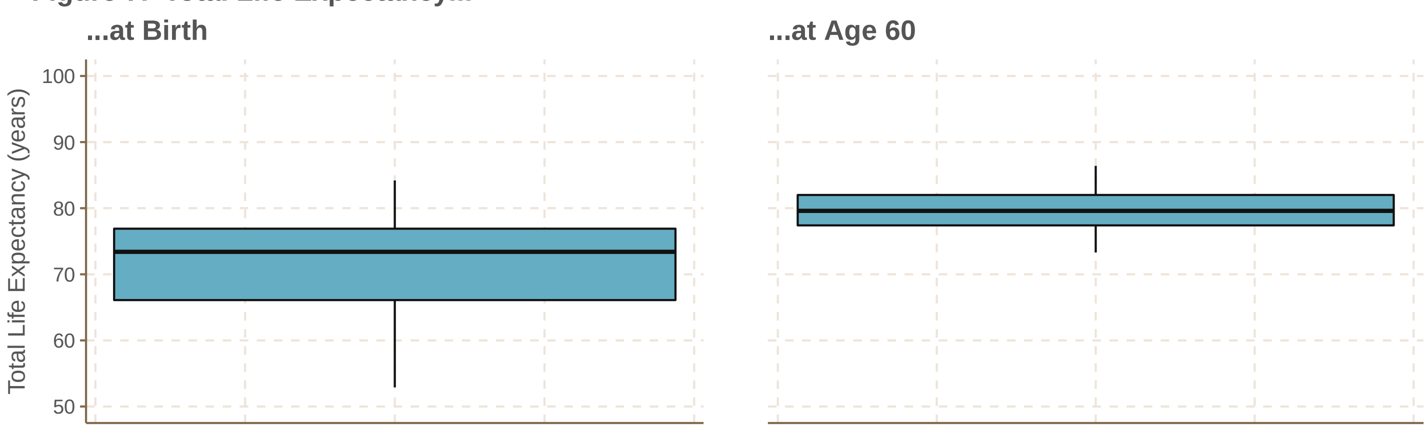
The infant mortality data (Fig. 6) is strongly right-skewed.

Figure 6. Infant Mortality Distribution



The total life expectancy data (Fig. 7) shows that total life expectancy for those who reach 60 years of age is greater than that for the general population at birth.

Figure 7. Total Life Expectancy...



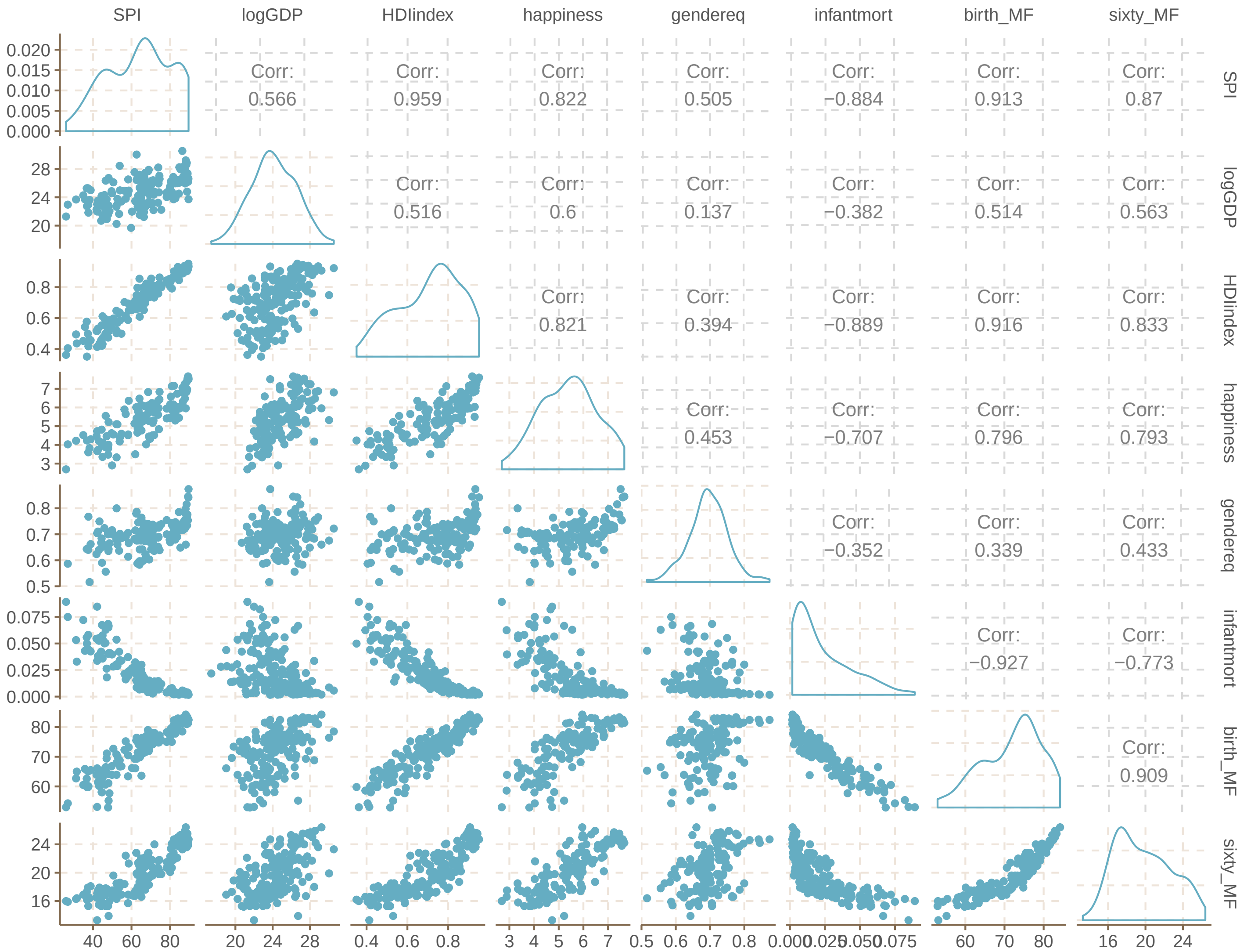
Min	Q1	Median	Mean	Q3	Max	SD	NA
52.9	66.1	73.4	71.9	76.9	84.2	7.564	24

Min	Q1	Median	Mean	Q3	Max	SD	NA
73.3	77.4	79.6	79.793	82	86.4	2.981	24

When investigating pairwise relationships between continuous variables (Fig. 8), strong positive linear relationships are seen between `HDIindex` and `SPI`, `happiness`, and `birth_MF`; between `SPI` and `happiness`, `birth_MF`, and `sixty_MF`; and between `happiness` and `sixty_MF`. Additionally, strong positive relationships that are possibly nonlinear are seen between `HDI_index` and `sixty_MF`, and between `birth_MF` and `sixty_MF`.

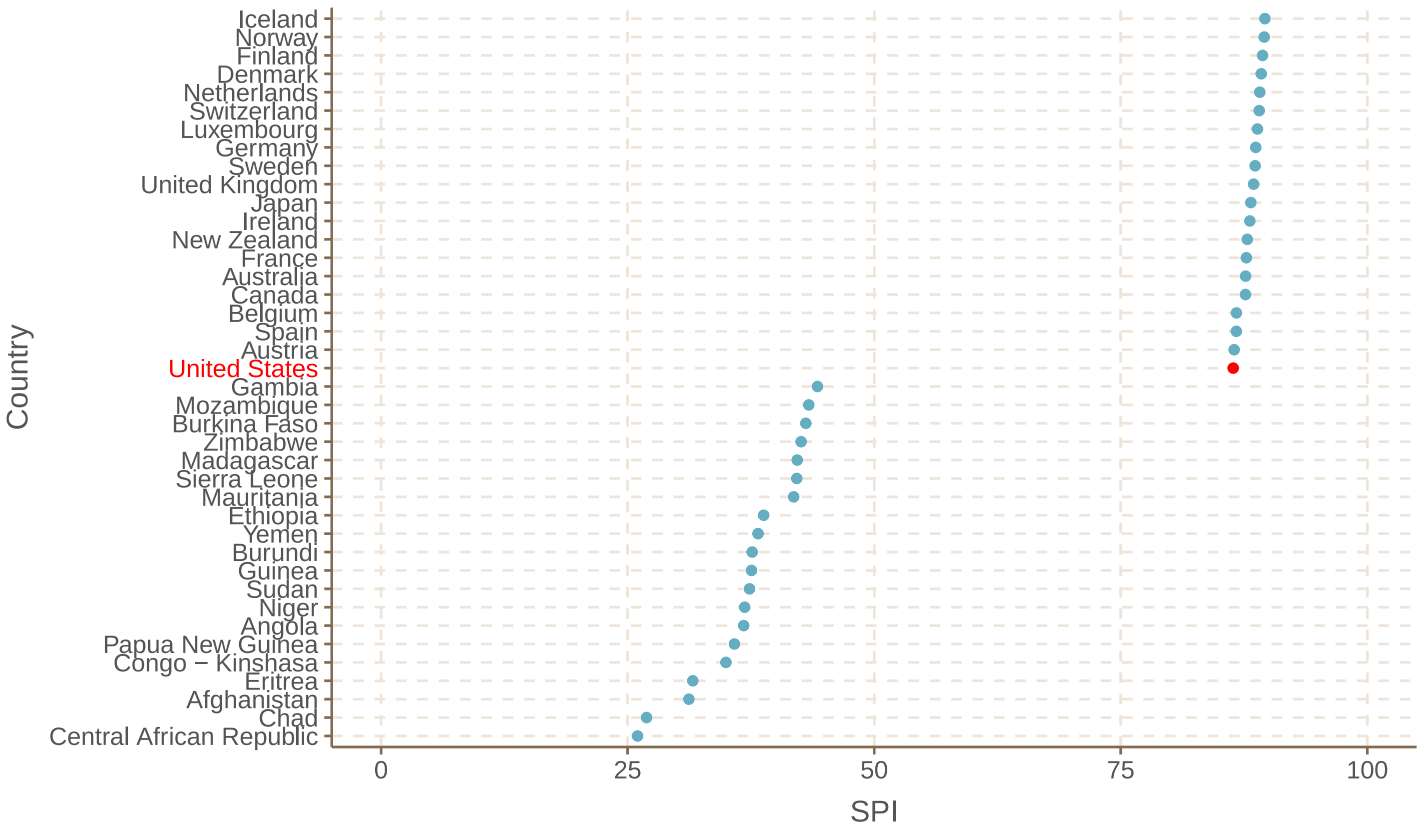
Strong negative relationships are seen between `infantmort` and `birth_MF`, between `HDIindex` and `infantmort`, and between `SPI` and `infantmort`, though the latter two of these may not necessarily be linear. A strong negative nonlinear relationship is seen between `infantmort` and `sixty_MF`.

Figure 8. Correlation Matrix, Continuous Variables

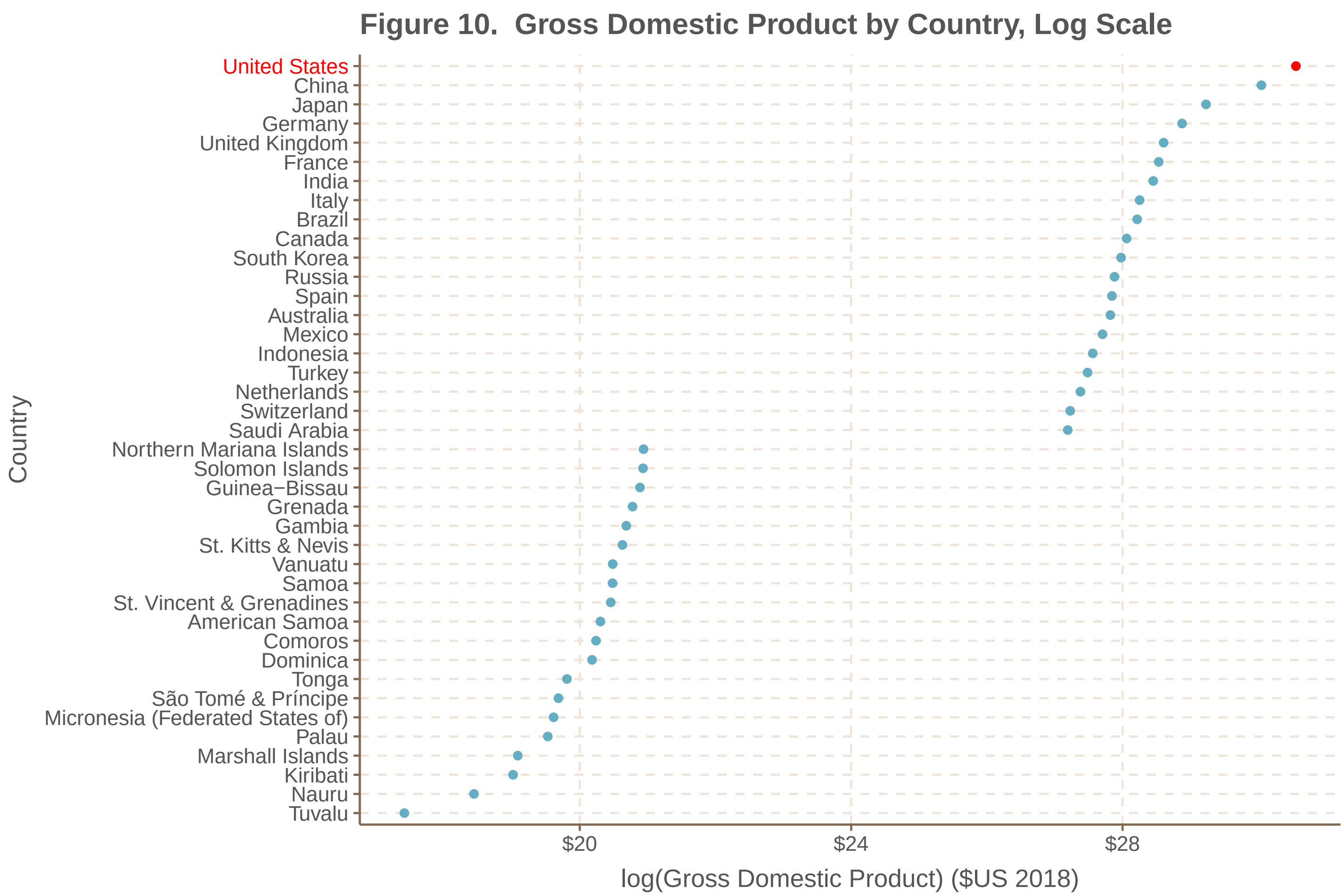


When assessing the top and bottom 20 countries by Social Progress Index, the United States was found to rank twentieth (Fig. 9).

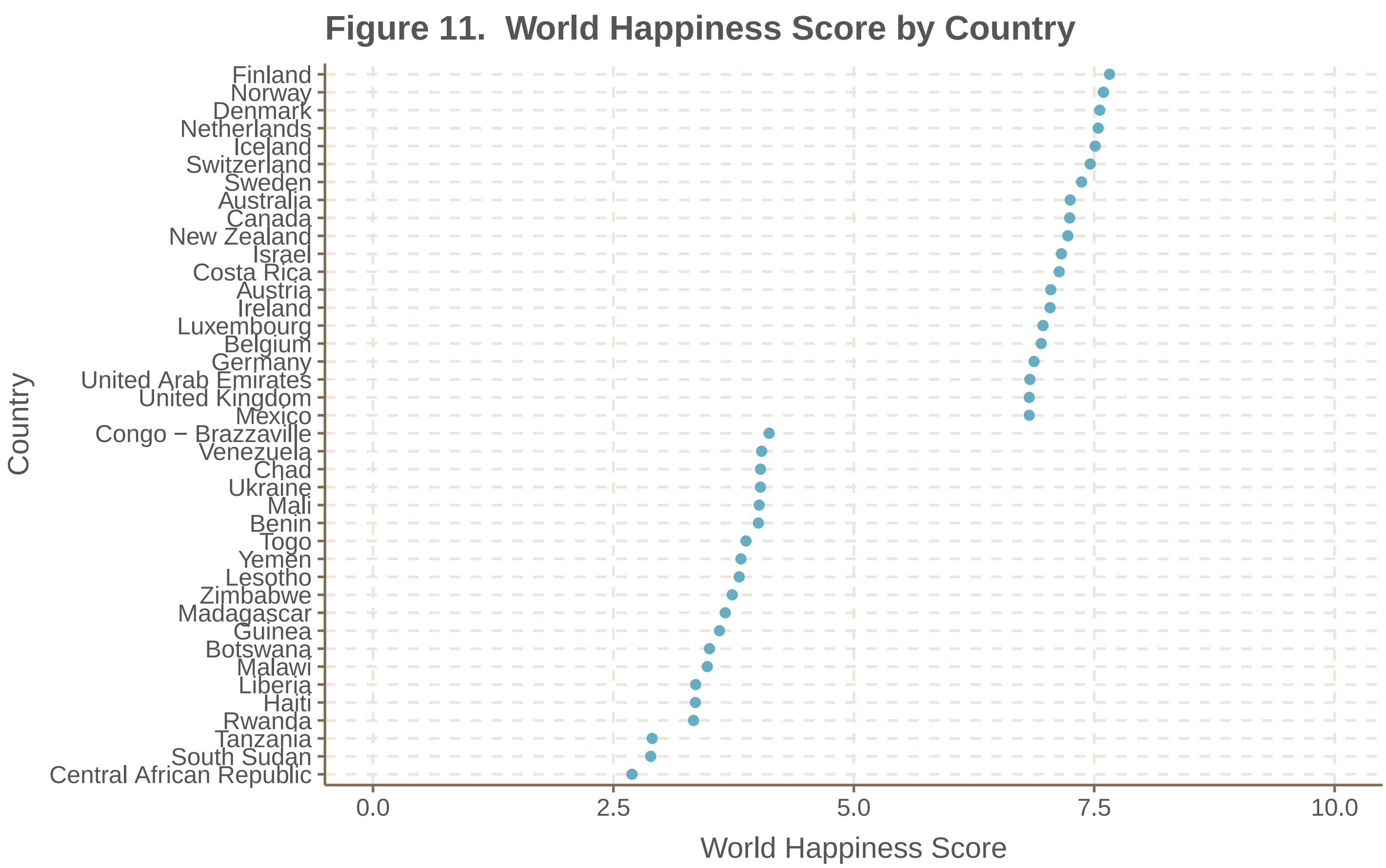
Figure 9. Social Progress Index by Country



The United States has the world's largest GDP (Fig. 10).



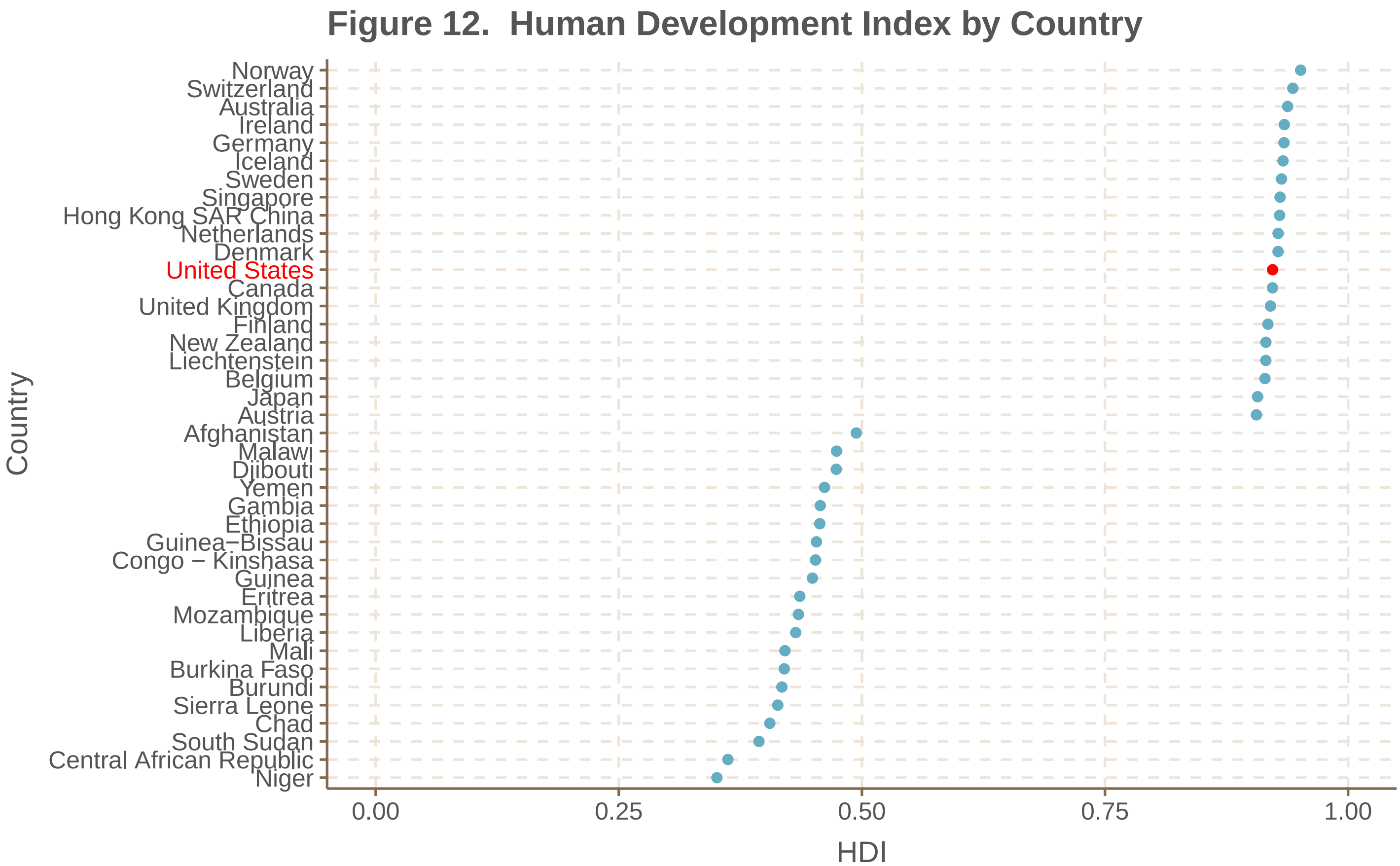
The United States is not among the top 20 countries in terms of happiness; it ranks 21st (Fig. 11).



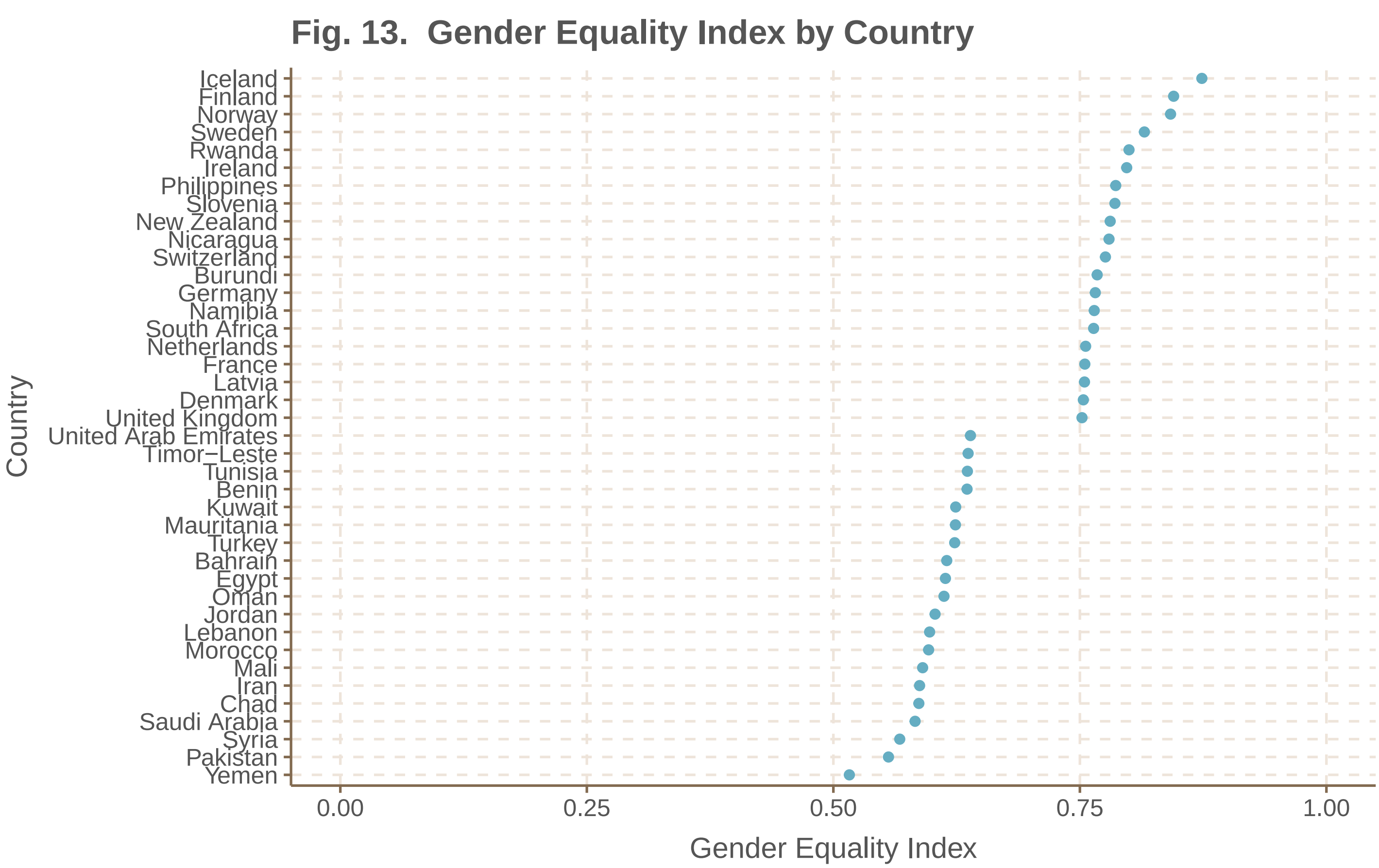

```r
which(alldata_WHR$country == "United States")
```

```
## [1] 21
```

Per Fig. 12, the United States ranks twelfth by HDI.



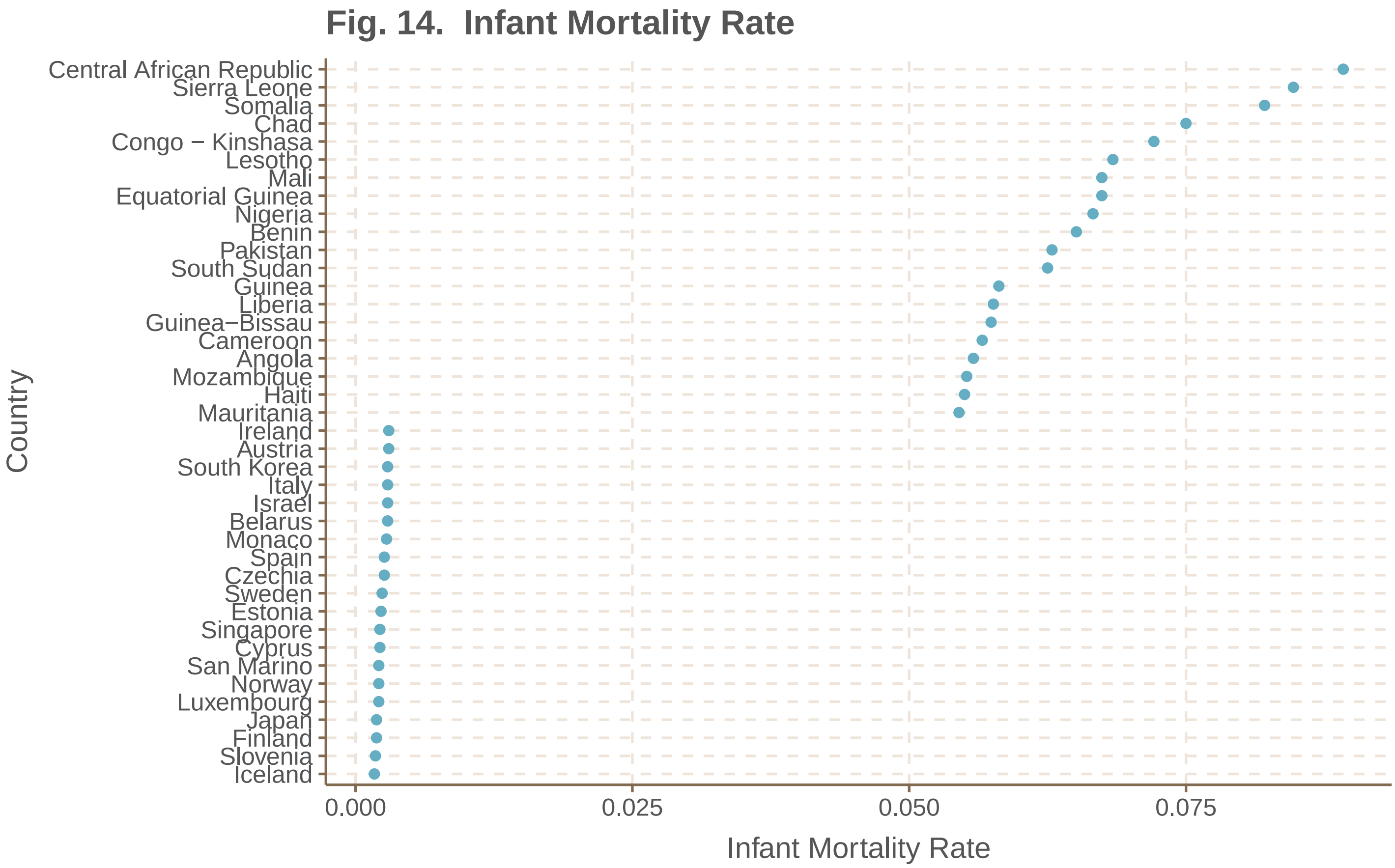
The United States is not among the top 20 countries in terms of gender equality; it ranks 45th (Fig. 13).



```r
which(alldata_gender$country == "United States")
```

```
## [1] 45
```

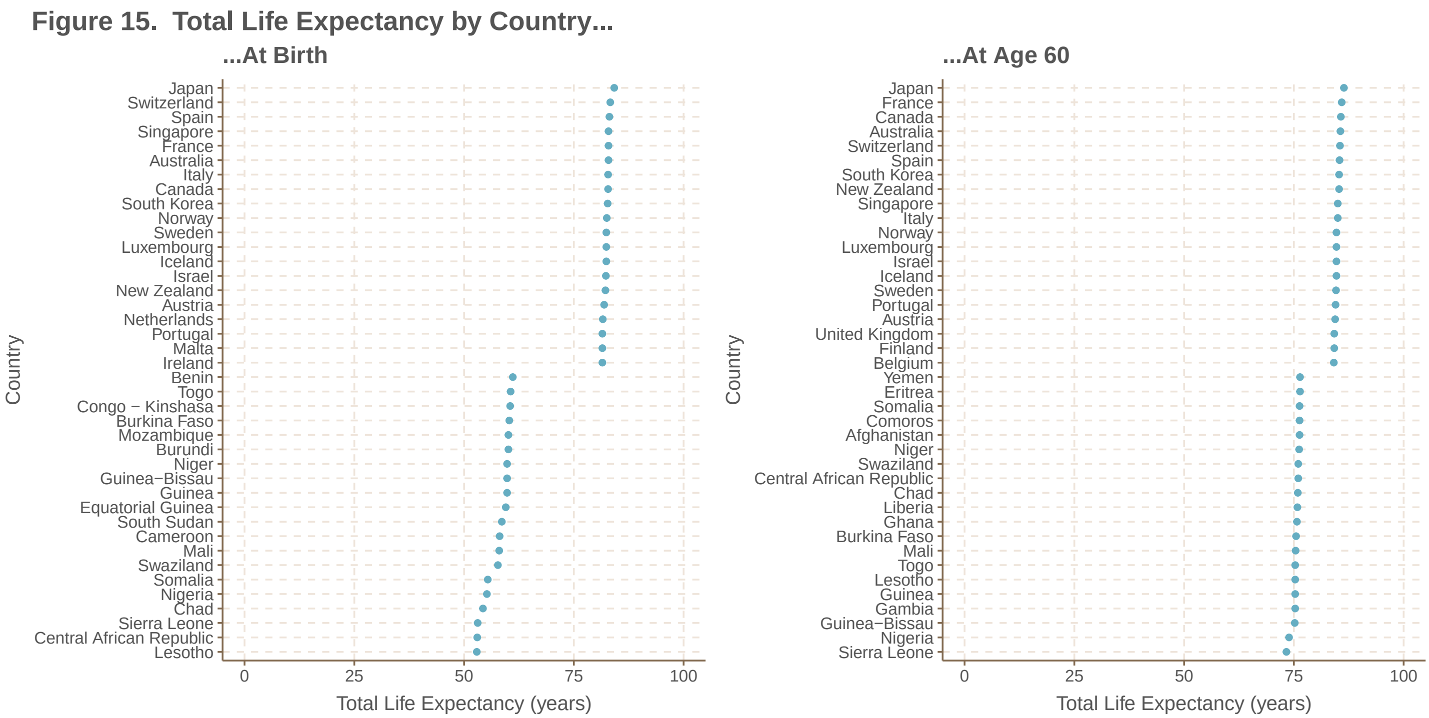
The United States has the world's 46th lowest infant mortality rate (Fig. 14).




```r
alldata_infantmort_asc <- alldata_infantmort %>% arrange(infantmort)
which(alldata_infantmort_asc$country == "United States")
```

```
## [1] 46
```

Finally, per Fig. 15, the United States is not among the top 20 countries for life expectancy, ranking 34th and 31st respectively for life expectancy at birth and at 60 years of age.




```r
which(alldata_lifeexp_birth$country == "United States")
```

```
## [1] 34
```

```r
which(alldata_lifeexp_sixty$country == "United States")
```

```
## [1] 31
```

Per the above country-level analyses, the United States was not among the top 20 performing countries for happiness, gender equality, infant mortality, and life expectancy at birth and at 60 years, thus these five fields were examined via clustering.

Clustering Analysis

Ten pairwise cluster analyses were performed assuming four clusters, shown in Table 4.

Table 4. Cluster Analyses Considered

Cluster Analysis	Variables
1	`happiness`, `gendereq`
2	`happiness`, `infantmort`
3	`happiness`, `birth_MF`
4	`happiness`, `sixty_MF`
5	`gendereq`, `infantmort`
6	`gendereq`, `birth_MF`
7	`gendereq`, `sixty_MF`
8	`infantmort`, `birth_MF`
9	`infantmort`, `sixty_MF`
10	`birth_MF`, `sixty_MF`

When clustering

Figure 16. Cluster Analysis, Gender Equality Index vs. Happiness Score

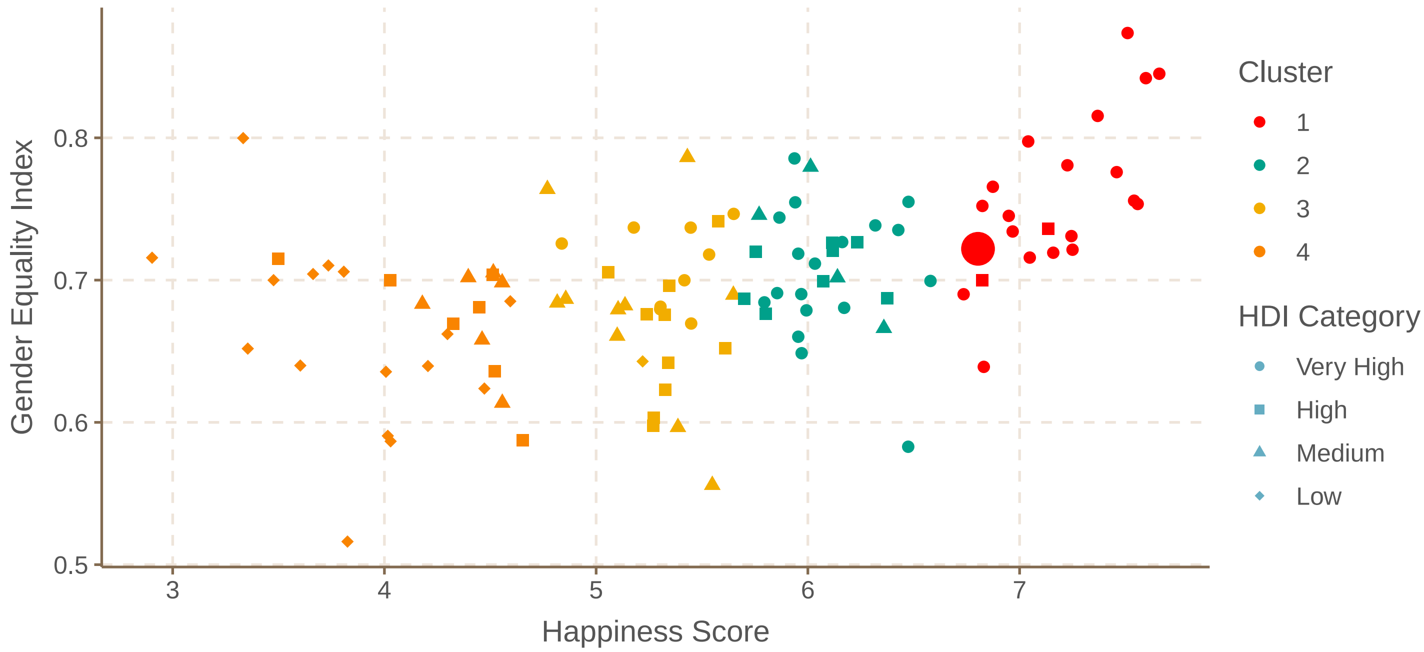


Figure 17. Cluster Analysis, Infant Mortality Rate vs. Happiness Score

Figure 18. Cluster Analysis, Happiness Score vs. Total Life Expectancy...

Figure 19. Cluster Analysis, Infant Mortality Rate vs. Gender Equality Index

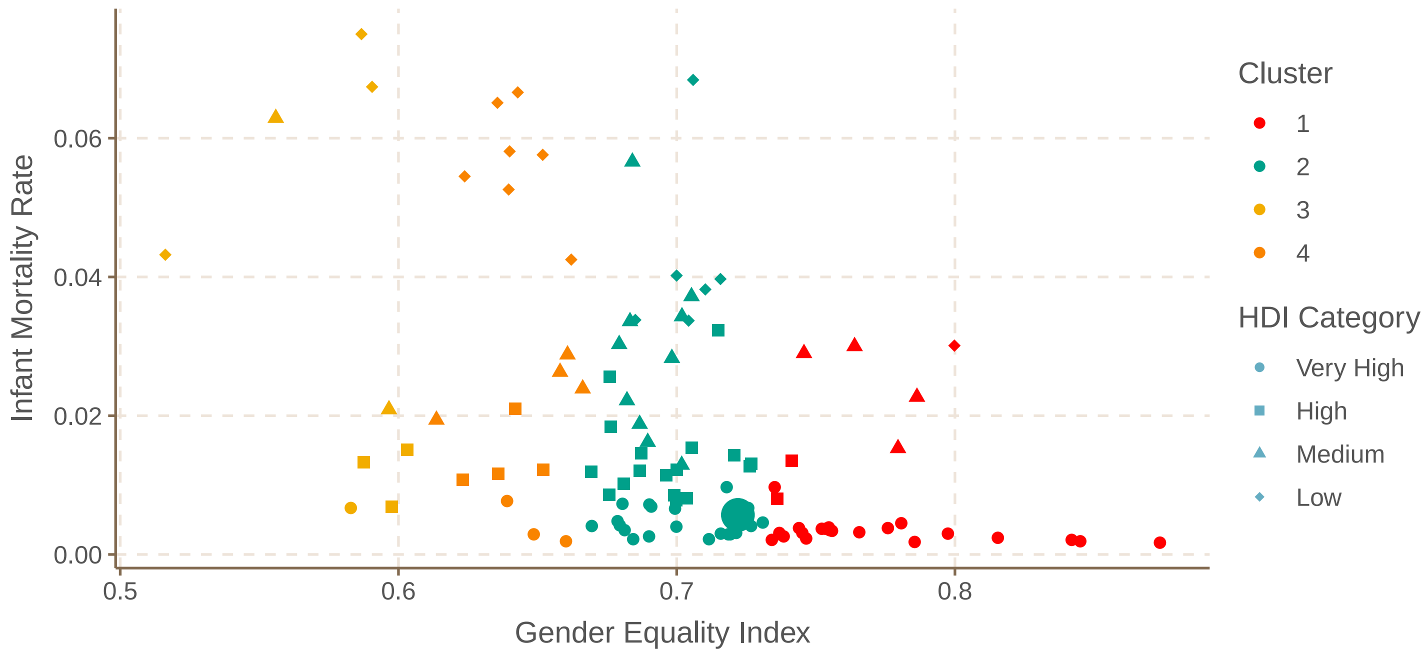


Figure 20. Cluster Analysis, Gender Equality Index vs. Total Life Expectancy...

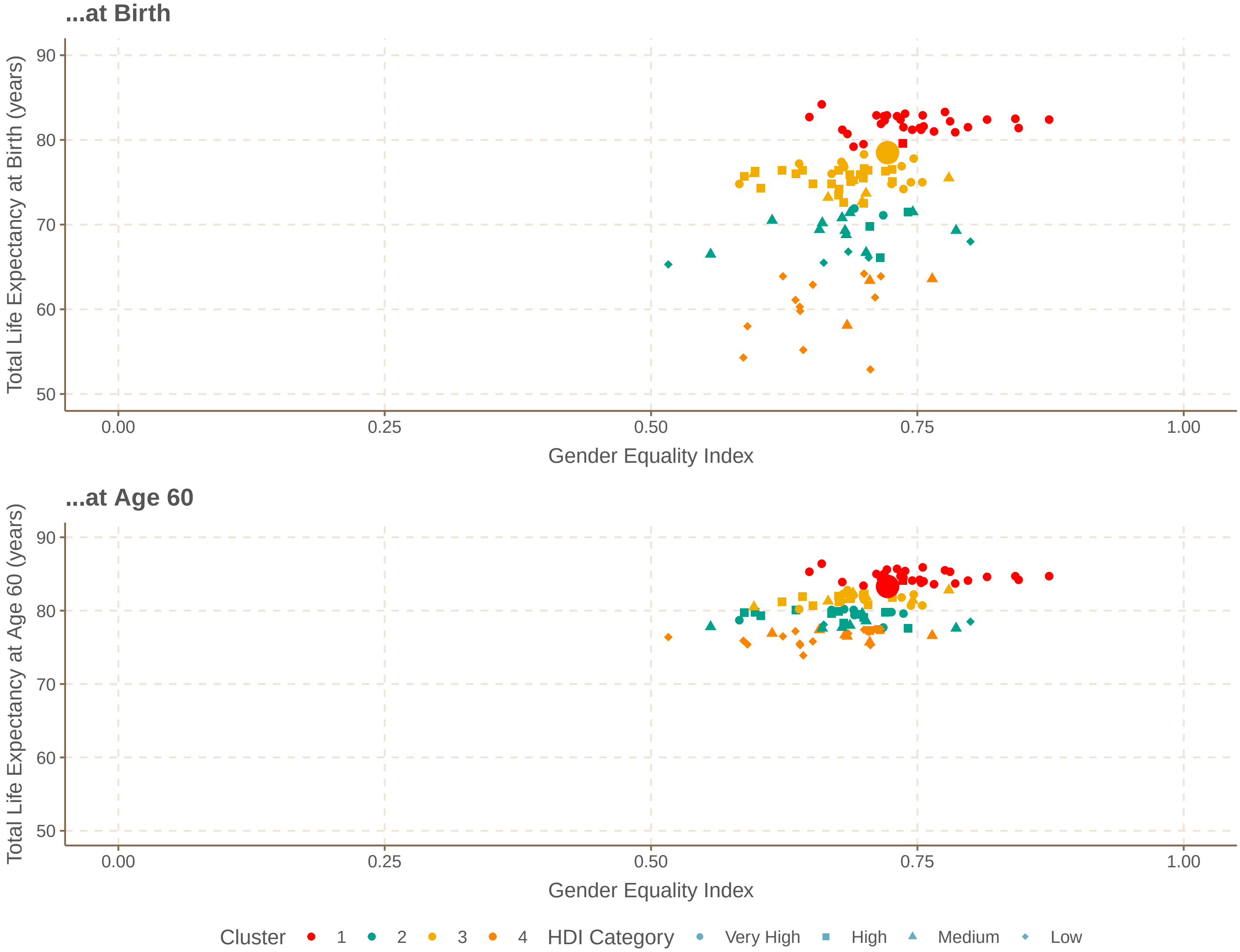


Figure 21. Cluster Analysis, Infant Mortality Rate vs. Total Life Expectancy...

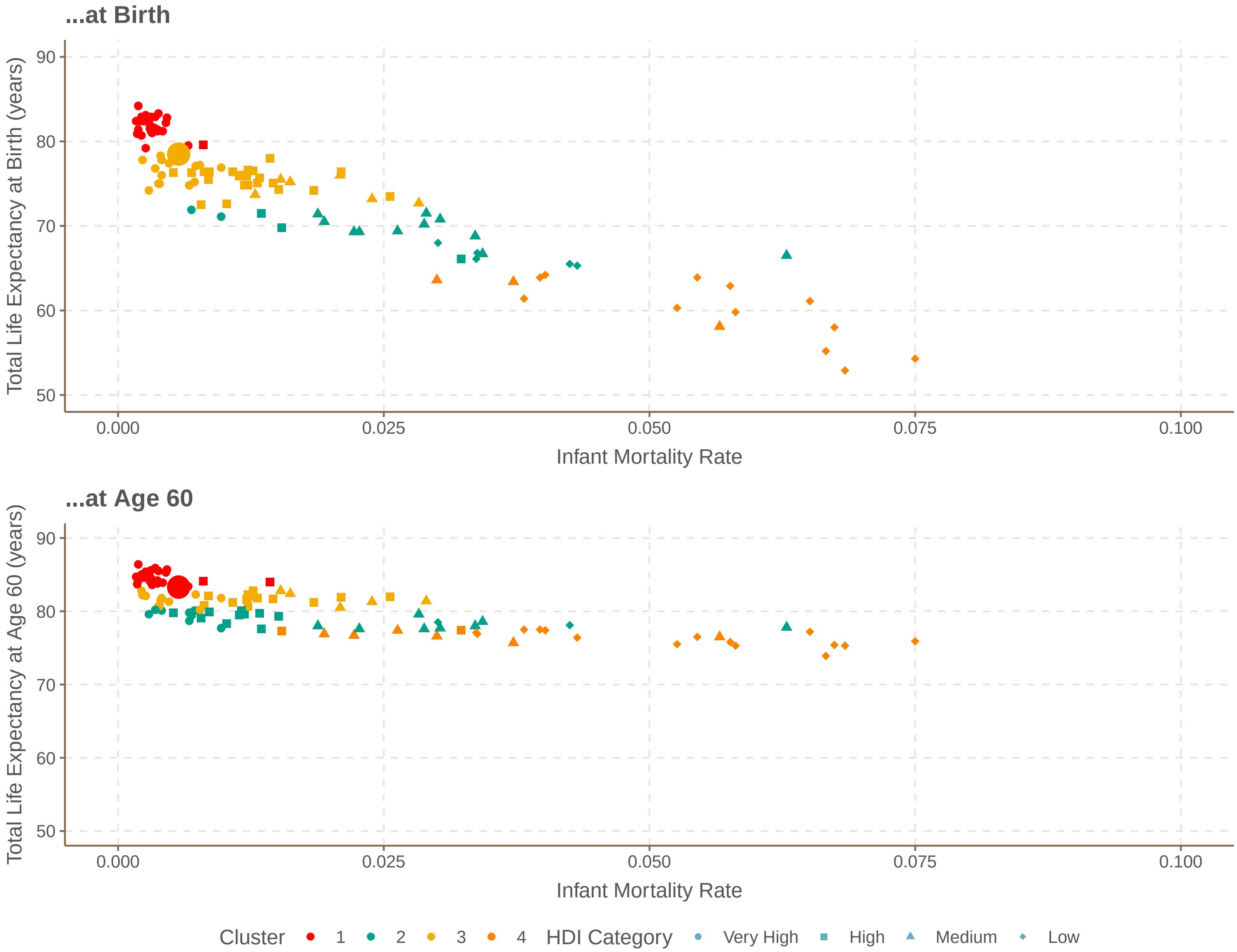
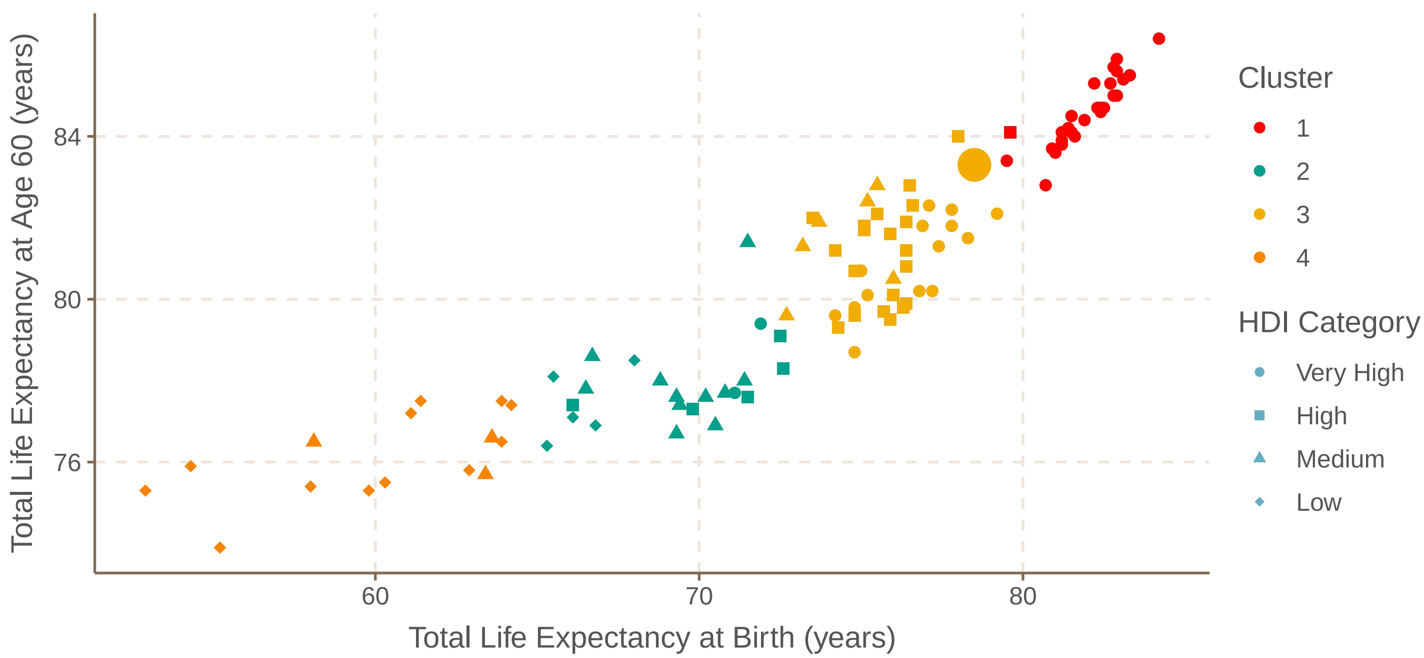


Figure 22. Cluster Analysis, Total Life Expectancy at Age 60 vs. at Birth



Discussion

Limitations

Conclusion

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