Question 1 - Bash

 Using "echo", print your student number to the terminal. Additionally, print out your username from the operating system. Take a screenshot and include it in your submission

```
joshlegrice@Joshs-MacBook-Pro-2 ~ % echo "Student Number: 720017170"
[echo "Username: $(whoami)"
Student Number: 720017170
Username: joshlegrice
```

b) Move inside the directory DATE_FILES, which was provided along with unit 2 of the course, which you should store somewhere on your computer.

joshlegrice@Joshs-MacBook-Pro-2 ~ % cd /Users/joshlegrice/Desktop/University/3rd\ Year/Data\ Science\ in\ Economics/DATE_FILES joshlegrice@Joshs-MacBook-Pro-2 DATE_FILES %

cd = changes the current working directory to the file path given

c) Count the number of files in this directory.

ls -1 = Lists all files in the directory, one per line

| allows the output of the command before to be used as the input to the next command

wc -l = Counts the number of lines in the output of ls -1

#\$ = allow the code inside the brackets to be executed and not just echoed, like Python f string

```
joshlegrice@Joshs-MacBook-Pro-2 DATE_FILES % echo "Number of files: $(ls -1 | wc -1)"

Number of files: 3289
```

d) Print the names of the first 8 files in this directory, along with information about their ownership, date, and size.

```
joshlegrice@Joshs-MacBook-Pro-2 DATE_FILES % ls -lh | head -n 8
total 26312
                                                 2024 2015_01_01.txt
                           staff
                                   110B 25 Jan
rw-rw-r--0
              joshlegrice
                                                 2024 2015_01_02.txt
                                    110B 25 Jan
              joshlegrice
                           staff
              joshlegrice
                           staff
                                    110B
                                         25 Jan
                                                 2024 2015_01_03.txt
              joshlegrice
                                    110B 25 Jan
                                                 2024 2015_01_04.txt
              joshlegrice
                                    110B 25
                                            Jan
                                                 2024 2015_01_05.txt
              joshlegrice
                                    110B
                                         25
                                            Jan
                                                 2024 2015 01
                                            Jan
           1 joshlegrice
                           staff
                                   110B
                                         25
                                                 2024 2015 01 07.txt
```

ls -lh = lists the contents of the directory in long (l) format and human-readable (h).

| allows the output of the command before to be used as the input to the next command

head -n 8 = only displays the first 8 lines of the output

e) Move to the parent directory of this folder

```
[joshlegrice@Joshs-MacBook-Pro-2 DATE_FILES % cd ..
```

cd = change directory to the file path given

.. = indicates the parent directory of the current file

f) Create a new directory there, named second_10_days

```
joshlegrice@Joshs-MacBook-Pro-2 Data Science in Economics % mkdir -p second_10_days
```

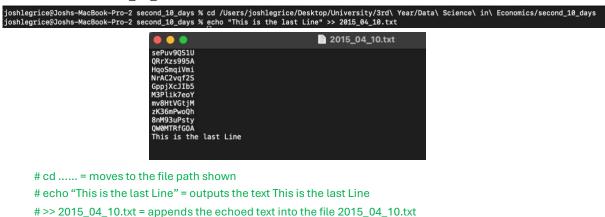
mkdir = command to make a new directory

#-p = ensures parent directories exist

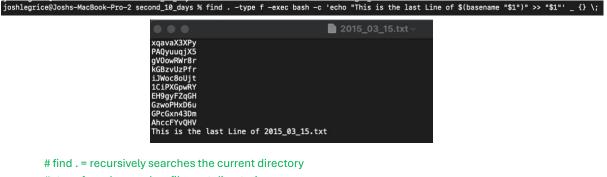
second_10_days = the name of the new directory

g) Copy from the DATE_FILES directory the files that are related to the days 10-19 of every month to the newly created directory.

h) Move inside second_10_days directory, and append the line "This is the last Line" to the end of file 2015_04_10



i) Write a one-line command to append the line "This is the last Line of X", where X is the name of the file, to the end of every file in the directory second_10_days

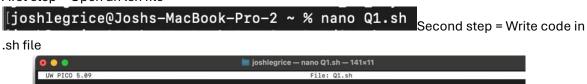


```
# Initial. = Tectursively searches the current directory
# -type f = only searches files not directories
# -exec bash - c = runs a bash command for each file found
# echo "This is the last Line of $(basename "$1") = outputs 'This is the last Line of (only the name of the file)'
# >> "$1""_{{}}; = appends the output of the echo into the file.
```

j) Using Bash: create a bash file Q1.sh. Write your code from (i) to it. Run the file Q1.sh including a screenshot showing how this runs on your system. Please explain any steps needed to run this file.

Had to place the .sh file into another directory as if placed in the second_10_days directory, it would write into the Q1.sh file with 'this is the last Line of Q1.sh'

First step = Open an .sh file



```
UW PICO 5.89

File: Q1.sh

#!/bin/bash
cd /Users/joshlegrice/Desktop/University/3rd\ Year/Data\ Science\ in\ Economics/second_10_days/
find . -type f -exec bash -c 'echo "This is the last line of $(basename "$1") " >> "$1"' _ {} \;

G Get Help

O WriteOut

R Read File

W Prev Pg

W Cut Text

O Cur Pos
X Exit

O Justify

W Where is
```

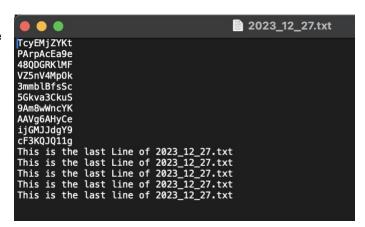
Final Step = Run .sh file

```
Last login: Thu Feb 20 11:29:33 on console
[joshlegrice@Joshs-MacBook-Pro-2 ~ % ./Q1.sh
joshlegrice@Joshs-MacBook-Pro-2 ~ % ■
```

example file – I ran it a

it worked

Output in an lot to make sure



Question 2 - SQL

a) Create a new database in SQLite named Q2.db

```
[joshlegrice@Joshs-MacBook-Pro-2 Assignment % sqlite3 Q2.db
SQLite version 3.43.2 2023-10-10 13:08:14
Enter ".help" for usage hints.
sqlite> ■
```

b) Create two tables named US_Code and US_Pop with column headings that match these two data frames

```
CREATE TABLE US_Pop (
ID INTEGER PRIMARY KEY AUTOINCREMENT,
Geo_ID VARCHAR(20),
Zip VARCHAR(10),
Gender VARCHAR(10),
AgeRange VARCHAR(20),
Population INTEGER,
FOREIGN KEY (Zip) REFERENCES US_Code(ZipCode)
);
```

c) Insert the data from the two files into the two tables. Make sure you don't insert the column heading from the file US_population.csv. Explain how you did this.

```
[sqlite> .mode tabs
[sqlite> .import US_codes.txt US_Code
US_codes.txt:41098: INSERT failed: UNIQUE constraint failed: US_Code.ZipCode
US_codes.txt:41439: INSERT failed: UNIQUE constraint failed: US_Code.ZipCode
US_codes.txt:41440: INSERT failed: UNIQUE constraint failed: US_Code.ZipCode
```

Had to remove duplicates before loading in the US_Code data due to the above error

```
joshlegrice@Joshs-MacBook-Pro-2 Assignment % awk -F'\t' '{print $2}' US_codes.txt | sort | uniq -d
09464
96860
96863
joshlegrice@Joshs-MacBook-Pro-2 Assignment % awk -F'\t' '!seen[$2]++' US_codes.txt > US_codes_cleaned.txt
```

awk -F'\t' '{print \$2}' US_codes.txt = Extracts the second column from the .txt file which is ZipCode # sort = sorts the values within the column

uniq -d = identifies and prints only the duplicate values = Used to visualise all duplicate values

awk -F'\t' '!seen[\$2]++' US_codes.txt = collects all the non-duplicates in the column into an array # > US_codes_cleaned.txt = saves the contents of the previous output into a new file

```
sqlite> .mode tabs
sqlite> .import US_codes_cleaned.txt US_Code
sqlite> select * from US_Code Limit 5;
```

CountryCode	ZipCode	City	StateFull	State2	CountyFull	FIPSCountyCode	MunicipalityFull	MunicipalityCode	Latitude	Longitude	Accuracy
US	99553	Akutan	Alaska	AK	Aleutians East	013			54.143	-165.7854	1
US	99571	Cold Bay	Alaska	AK	Aleutians East	013			55.1858	-162.7211	1
US	99583	False Pass	Alaska	AK	Aleutians East	013			54.841	-163.4368	1
US	99612	King Cove	Alaska	AK	Aleutians East	013			55.0628	-162.3056	1
US	99661	Sand Point	Alaska	AK	Aleutians East	013	l i		55.3192	-160.4914	1

.mode tabs to set the delimiter to tabs to distinguish columns

Remove headers from the US_populations.csv

```
joshlegrice@Joshs-MacBook-Pro-2 Assignment % tail -n +2 US_population.csv > US_population_cleaned.csv
joshlegrice@Joshs-MacBook-Pro-2 Assignment % ■
```

tail -n +2 = starts at line 2 and collects all rows

> US_population_cleaned.csv = moves the new data into the new file

I had trouble with importing the data straight into the US_Pop table due to this error

```
[sqlite> .mode csv
sqlite> .import US_Pop_Clean.csv US_Pop
```

```
US_Pop_Clean.csv:125718: expected 6 columns but found 5 - filling the rest with NULL US_Pop_Clean.csv:125718: INSERT failed: datatype mismatch US_Pop_Clean.csv:125719: expected 6 columns but found 5 - filling the rest with NULL US_Pop_Clean.csv:125719: INSERT failed: datatype mismatch
```

So, I imported the data into a temporary table and then copied the data into US_Pop

```
CREATE TABLE temp_US_Pop (
Geo_ID VARCHAR(20),
Zip VARCHAR(10),
Gender VARCHAR(10),
AgeRange VARCHAR(20),
Population INTEGER
);
```

sqlite> .mode csv sqlite> .import US_population_cleaned.csv temp_US_Pop sqlite> .mode box sqlite> Select * from temp_US_Pop limit 5;								
Geo_ID	Zip	Gender	AgeRange	Population				
8600000US61747	61747	female	3034	50				
8600000US64120	64120	male	85	5				
8600000US95117	95117	male	3034	1389				
8600000US74074	74074	female	6061	231				
8600000US58042	58042	female	04	56				

Inserting data from temp table to US_Pop

```
sqlite> INSERT INTO US_Pop (Geo_ID, Zip, Gender, AgeRange, Population)
...> SELECT Geo_ID, Zip, Gender, AgeRange, Population FROM temp_US_Pop;
sqlite> Select * from US_Pop Limit 5;
                   Geo_ID
                                           Zip
                                                        Gender
                                                                       AgeRange
                                                                                           Population
             8600000US61747
                                                        male
male
female
female
            8600000US64120
8600000US95117
                                         64120
95117
                                                                        85--
30--34
                                                                                           1389
231
56
            8600000US74074
                                          74074
58042
                                                                        60--61
             8600000US58042
```

d) Write an SQL query to print the total population per gender (using the US_Pop table only)

```
[sqlite> Select Gender, Sum(Population) as total
[ ...> From US_Pop
[ ...> GROUP BY Gender;

Gender total
female 158893428
male 153550999
```

e) Write an SQL query to print the total population per gender but join the two tables. If you see any difference in your results between this question and part (d), explain why this occurs.

```
sqlite> SELECT Gender, SUM(Population) AS Total_Population
...> FROM US_Pop
...> INNER JOIN US_Code ON US_Code.ZipCode = US_Pop.Zip
...> GROUP BY Gender;

Gender Total_Population

female 145020753
male 140467081
```

The difference is because INNER JOIN only includes records where zip codes exist in both US_Pop and US_Code, excluding unmatched zip codes from US_Pop. This results in a lower total population in part (e) compared to part (d).

f) Write an SQL query to print the total population per age group (use the US_Pop table only).

```
[sqlite> Select AgeRange, SUM(Population) as total
   ...> From US_Pop
   ...> Group by AgeRange;
  AgeRange
               total
              20424753
  9--4
  10--14
              20944112
  15--17
              13122942
  18--19
              9199406
  20--20
              4576820
  21--21
              4406896
  22--24
              12860695
  25--29
              21343672
  30--34
              20208179
  35--39
              20419129
  40--44
              21131371
  45--49
              22954730
  5--9
              20587220
  50--54
              22536142
  55--59
              19886767
              7200563
  60--61
              9834008
  62--64
  65--66
              5394788
  67--69
              7214846
  70--74
              9413691
  75--79
              7418022
  80--84
              5809980
  85-
              5555695
```

g) Write an SQL query to print the Top 10 largest states (full name) in terms of population size

```
sqlite> SELECT c.StateFull, SUM(p.Population) AS Total_Population
   ...> FROM US_Pop p
   ...> JOIN US_Code c ON p.Zip = c.ZipCode
   ...> GROUP BY c.StateFull
   ...> ORDER BY Total_Population DESC ...> LIMIT 10;
   StateFull
                   Total_Population
  California
                    37249464
                    25144800
  Texas
  New York
                    19377841
  Florida
                   18801226
  Illinois
                   12830581
  Pennsylvania
                    12702102
  Ohio
                   11535123
                   9883612
  Michigan
  Georgia
                    9687711
  North Carolina
                    9535477
```

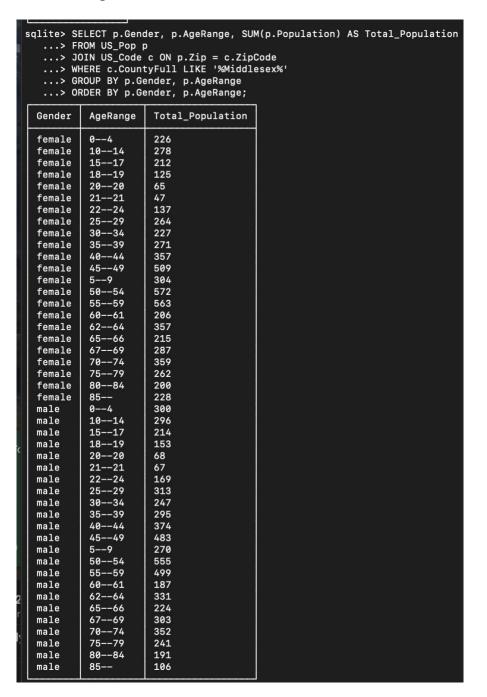
h) Write an SQL query to print the number of existing counties (not countries) in the database

```
sqlite> SELECT COUNT(DISTINCT CountyFull) AS Total_Counties
...> FROM US_Code;

Total_Counties

1853
```

i) Write an SQL query to print the total population per gender and age group for any counties containing "Middlesex" in their name.



Question 3 + 4

720017170

Question 3 - See .qmd for all code

(a) Import each dataset into memory as a separate data frame, keeping all countries as your sample.

```
plt.rcParams.update({'font.size': 14})

# Loading in the Data
Health_Data = pd.read_csv('Data/Health.csv', index_col=None)
Infant_Data = pd.read_csv("Data/Infant.csv",index_col=None)

# Replace .. with NA
Health_Data.replace("..", pd.NA, inplace=True)
Infant_Data.replace("..", pd.NA, inplace=True)

# Removing unnecessary columns
Health_Data = Health_Data.drop(columns=['Series Name', 'Series Code'])
Infant_Data = Infant_Data.drop(columns=['Series Name', 'Series Code'])

# Remove names in []
Health_Data.columns = Health_Data.columns.str.replace(r'\[.*\]', '', regex=True)
Infant_Data.columns = Infant_Data.columns.str.replace(r'\[.*\]', '', regex=True)
print(Infant_Data.head())
print(Health_Data.head())
```

```
Country Name Country Code 2000 2001 2002 2003 2004 2005
                                                              2006
0
                        AFG
                               92 89.3 86.6 83.7 80.9
     Afghanistan
                                                           78
                                                              75.1
1
         Albania
                        ALB
                               24 22.9 21.6 20.4
                                                   19.1
                                                        17.8
                                                               16.5
2
         Algeria
                        DZA 35.6 34.3
                                          33 31.6 30.3
                                                           29
                                                              27.8
                        ASM <NA> <NA> <NA> <NA> <NA> <NA>
3 American Samoa
                                                              <NA>
```

```
4
          Andorra
                             AND
                                    6.5
                                          6.3
                                                       5.8
                                                              5.6
                                                                    5.3
                                                                           5.1
                                              2019 2020
  2007
              2014
                    2015 2016
                                 2017
                                        2018
                                                            2021
                                                                  2022
                                                                         2023
  72.3
               56.2
                     54.6
                              53
                                  51.5
                                         50.1 48.8
                                                      47.4
                                                            46.1
                                                                   44.8
                                                                          <NA>
   15.3
                8.8
                      8.5
                             8.4
                                    8.3
                                          8.3
                                                 8.3
                                                       8.4
                                                              8.4
                                                                    8.4
                                                                          <NA>
1
2
   26.6
                 22
                     21.7
                            21.4
                                     21
                                         20.6
                                               20.1
                                                      19.7
                                                             19.2
                                                                   18.7
                                                                          <NA>
3
   <NA>
               <NA>
                      <NA>
                            <NA>
                                  <NA>
                                         <NA>
                                                <NA>
                                                      <NA>
                                                             <NA>
                                                                   <NA>
                                                                          <NA>
                                    3.1
                                                 2.9
4
    4.9
                3.5
                      3.4
                             3.2
                                            3
                                                       2.8
                                                              2.7
                                                                    2.6
                                                                          <NA>
[5 rows x 26 columns]
     Country Name Country Code
                                           2000
                                                            2001
                                                                          2002
                                                                                 \
0
      Afghanistan
                             AFG
                                                             <NA>
                                                                   17.00758553
                                            <NA>
1
                                                                   78.99478149
           Albania
                             ALB
                                      65.1501236
                                                     73.78884125
2
                                     62.11769485
                                                     67.33850098
                                                                   66.94760132
           Algeria
                             DZA
3
   American Samoa
                             ASM
                                            <NA>
                                                             <NA>
                                                                           <NA>
           Andorra
                             AND
                                  1287.00280762
                                                   1336.21142578
                                                                   1486.171875
            2003
                           2004
                                           2005
                                                            2006
                                                                            2007
                                                                                    \
0
     17.81492424
                    21.42946434
                                     25.10707283
                                                     28.91982269
                                                                     32.71720505
1
    106.29218292
                  138.11340332
                                    152.12762451
                                                    166.81382751
                                                                    212.61096191
     76.23547363
                                    101.30373383
                                                                    151.77920532
2
                    93.02433014
                                                    117.43313599
3
             <NA>
                            <NA>
                                            <NA>
                                                             <NA>
                                                                             <NA>
   1772.71337891
                   1990.0748291
                                  2214.64697266
                                                   2139.27539063
                                                                   2489.43115234
                 2014
                                 2015
                                                  2016
                                                                  2017
                                                                          \
   . . .
0
          60.18957901
                           60.05854034
                                           61.48645782
                                                            66.90921783
   . . .
         295.12359619
                          255.35635376
                                          277.04321289
                                                            297.4619751
1
2
                                          261.40023804
                                                           265.83843994
   . . .
         361.15942383
                            292.275177
3
                                                   <NA>
                  <NA>
                                   <NA>
                                                                   <NA>
4
        3089.84301758
                         2688.20629883
                                         2755.44848633
                                                         2873.29614258
                                                             2021
            2018
                            2019
                                            2020
                                                                   2022
                                                                          2023
0
     71.33430481
                                      80.28805542
                     74.23410797
                                                      81.31976318
                                                                    <NA>
                                                                           <NA>
1
     351.3012085
                    367.75839233
                                     396.88024902
                                                     464.74285889
                                                                    <NA>
                                                                           <NA>
2
    266.46469116
                    235.99041748
                                     206.03512573
                                                     204.56661987
                                                                           <NA>
                                                                    <NA>
3
             <NA>
                             <NA>
                                              <NA>
                                                              <NA>
                                                                    <NA>
                                                                           <NA>
   3164.38842773 3026.59741211 3269.29736328
                                                    3505.99145508
                                                                           <NA>
                                                                    <NA>
```

[5 rows x 26 columns]

(b) If data are not already stored in this way, please reshape data so that they consist of a single line of data for each country and year.

	Country Name	Country Code	Year	Heathcare Expenditure (USD)
0	Afghanistan	AFG	2000	<na></na>
1	Albania	ALB	2000	65.1501236
2	Algeria	DZA	2000	62.11769485
3	American Samoa	ASM	2000	<na></na>
4	Andorra	AND	2000	1287.00280762

	Country Name	Country Code	Year	Infant Mortality Rates (per 1,000 live births)
0	Afghanistan	AFG	2000	92
1	Albania	ALB	2000	24
2	Algeria	DZA	2000	35.6
3	American Samoa	ASM	2000	<NA $>$
4	Andorra	AND	2000	6.5

(c) Calculate the total number of countries observed in each data frame Calculate the total number of years observed in each data frame.

```
# Counts the number of unique contries
num_countries_FDI = Health_Data_long["Country Name"].nunique()

# Outputs the number of unique countries using an f string
print(f"Total number of unique countries in Health_Data: {num_countries_FDI}")
num_years_FDI = Health_Data_long["Year"].nunique() # Counts the number of unique years
print(f"Total number of unique years observed in Health_Data: {num_years_FDI}")
```

```
num_countries_GDP = Infant_Data_long["Country Name"].nunique()
print(f"Total number of unique countries in Infant_Data: {num_countries_GDP}")
num_years_GDP = Infant_Data_long["Year"].nunique()
print(f"Total number of unique years observed in Infant_Data: {num_years_GDP}")

Total number of unique countries in Health_Data: 217
Total number of unique years observed in Health_Data: 24
Total number of unique countries in Infant_Data: 217
Total number of unique years observed in Infant_Data: 24
```

(d) Calculate the number of observations for which data is missing

```
# Sums the number of missing values in each dataset
missing_values_Health = Health_Data_long.isna().sum().sum()
print(f"Total missing observations in Health_Data: {missing_values_Health}")
missing_values_Infant = Infant_Data_long.isna().sum().sum()
print(f"Total missing observations in Infant_Data: {missing_values_Infant}")
```

```
Total missing observations in Health_Data: 1099 Total missing observations in Infant_Data: 700
```

(e) Join the two files by country and year so that you have single dataframe containing both variables. Explain clearly what type of join this is, and carefully check that the number of observations resulting from the join makes sense.

```
# Merge the data on Country Name, Country code and Year
merged_data = pd.merge(Health_Data_long, Infant_Data_long, on=['Country Name',
'Country Code', 'Year'])
print(merged_data.head())

# Print the number of rows in the DataFrame
num_rows = merged_data.shape[0]
print(f"Number of rows in the DataFrame: {num_rows}")
```

```
Country Name Country Code Year Heathcare Expenditure (USD) \
0 Afghanistan AFG 2000 <NA>
1 Albania ALB 2000 65.1501236
2 Algeria DZA 2000 62.11769485
```

3	American Samoa	ASM	2000		<na></na>
4	Andorra	AND	2000		1287.00280762
	Infant Mortality Rate	s (per 1	,000 live	births)	
0				92	
1				24	
2				35.6	
3				<na></na>	
4				6.5	
Νı	umber of rows in the D	ataFrame	5208		

The join completed in the above code chunk is an inner join and only keeps rows that exist in both Health_Data_long and Infant_Data_long. If a country or year exists in one dataset but not the other, it will be dropped.

Question 4 - Investigating the Relationship Between Current Healthcare Expenditure per Capita and Infant Mortality Rates from 2000 - 2022

Missing Data

Table 1: Missing Observations of Variables

Varible	Total Missing Observations	Percentage of Missing Observations		
Health Expenditure	1099	21.1		
Infant Mortality Rate	700	13.4		

Both datasets contained a large amount of missing data, illustrated in Table 1. Potentially due to countries not collecting the data or collecting the data at different year intervals. Missing data can have an impact on data analysis if not handled properly and can lead to incorrect conclusions. The year 2023 contained no data; therefore, this column was dropped. To deal with the other missing data, I decided to drop all rows containing missing data, sometimes, this could result in a significant reduction of sample size; however, in this case with observational data, 1099 observations were removed (21.1% of the dataset) and only 27 countries were dropped, indicating this was an effective method to handling missing data as there were still 4109 observations. An alternative approach would've been mean, multiple or regression imputation if dropping rows with missing data caused a significant decrease in sample size.

Summary Statistics

Table 2: Summary Statistics of Variables

Variable	N	Mean	Median	SD	Min	Max
Heathcare Expenditure (USD)	4109.0	956.0	256.7	1685.7	4.0	12473.8
Infant Mortality Rates (per 1,000 live births)	4109.0	26.9	17.7	25.0	1.4	138.3

Table 2 displays the summary statistics for healthcare expenditure (USD) and infant mortality rates (per 1,000 live births) across 4109 observations, revealing significant differences between countries.

Healthcare expenditure per Capita showed a mean of \$956.0 but a lower median of \$256.7, indicating a negatively skewed distribution where only few countries spend more. The large standard deviation (\$1,685.7) and range (\$4.0–\$12,473.8) highlight large global and temporal differences in healthcare investment.

Infant mortality rates show similar variation, with a mean of 26.9 deaths per 1,000 live births and a median of 17.7. The high standard deviation (25.0) and range (1.4–138.3) may be attributed to major differences in healthcare investment and quality.

Distribution Analysis

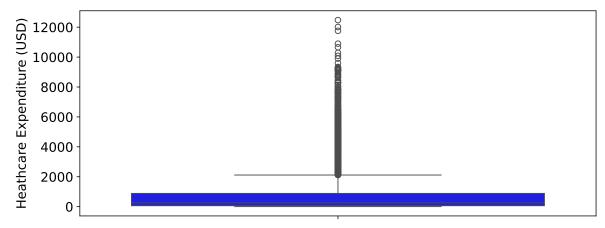


Figure 1: Box Plot of Healthcare expenditure Per Capita (USD)

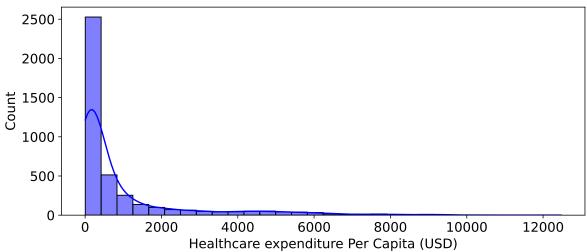


Figure 2: Histogram with Density of Healthcare expenditure Per Capita (USD)

Figures 1 and 2 show the distribution of healthcare expenditure per capita. Figure 1 shows that healthcare expenditure is highly negatively skewed, supporting the analysis from the summary statistics. The median expenditure is toward the lowers quartile, indicating that most countries have relatively little expenditure, while a few have significantly higher spending. The whiskers of the box plot are short, suggesting that a large proportion of the data is concentrated within a lower range, while the numerous outliers highlight extreme expenditure levels in some countries.

Figure 2 reiterates the negative skew of the data. Most countries have low healthcare expenditure, grouped toward the left of the axis, with just a handful having exceptionally high expenditures. The density curve (smooth blue line) shows the exponential drop in frequency as expenditure increases, emphasising that high-spending countries are exceptions rather than the rule.

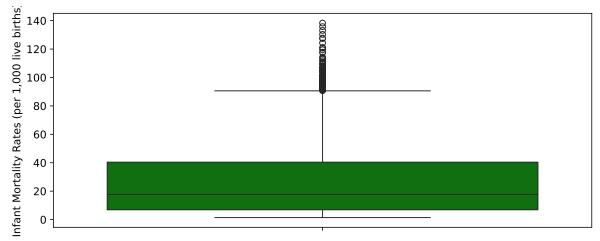


Figure 3: Box Plot of Infant Mortality Rate (per 1,000 live births)



Figure 4: Histogram with Density of Infant Mortality Rate (per 1,000 live births)

The distribution of infant mortality rate seen in Figures 3 and 4 is similar to that of healthcare expenditure per capita.

The variable is also negatively skewed, as seen by the median being significantly lower than the upper quartile. There are several outliers in Figure 3, with specific countries having abnormally high infant mortality rates.

This is supported by Figure 4, which displays that as rates rise frequency falls dramatically, the majority of observations being below 40 deaths per 1,000 live births. While infant mortality is low in many nations, it is much higher in others, most likely because of infrastructural constraints, economic considerations, and healthcare discrepancies. This may indicate a causal relationship between healthcare expenditure per capita and infant mortality rate needing investigation.

Due to the number of outliers within both variables, I decided to use the Interquartile Range (IQR) method to remove any outliers to ensure the regression analysis is more reliable and accurate. Outliers may skew the models fit and influence regression coefficients, inflating evaluation metrics such as mean absolute error (MAE). By applying the IQR method, the data represents a more consistent trend, reducing the impact of extreme values and improving the model's ability to capture the true relationship between healthcare expenditure and infant mortality rates.

Correlation Analysis

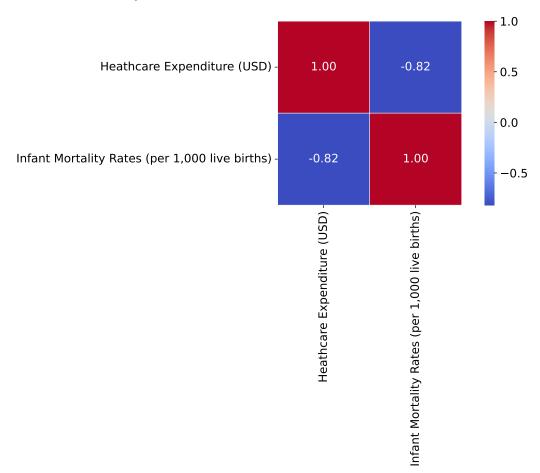


Figure 5: Spearman Rank Correlation Matrix of Healthcare Expenditure and Infant Mortality Rates

Figure 5 illustrates the relationship between healthcare expenditure per capita and infant mortality rates. The correlation coefficient of -0.82 indicates a strong negative correlation, suggesting that as healthcare expenditure increases, infant mortality rates to decrease. This aligns with economic and public health expectations, where greater investment in healthcare typically leads to better medical infrastructure, improved care, and reduced infant deaths. Spearman's rank correlation is used as it captures non-linear relationships, making it more robust. However, correlation does not imply causation, and additional factors such as healthcare efficiency, socioeconomic disparities, and government policies could be confounders in this relationship.

Regression Analysis

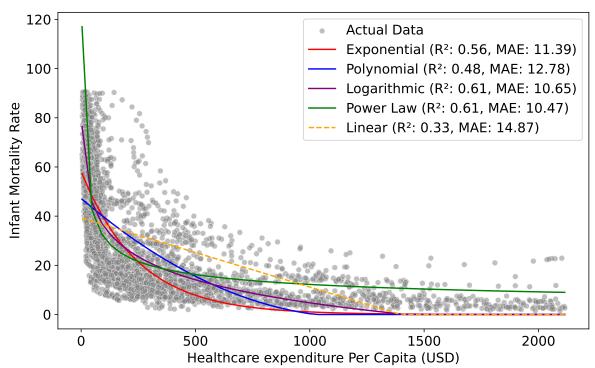


Figure 6: Comparison of Regression Models: Healthcare Spend vs Infant Mortality Rate

Figure 6 compares five regression models; exponential, polynomial, logarithmic, power law, and linear, in quantifying the relationship between healthcare expenditure per capita and infant mortality rates. All models are constrained to prevent infant mortality predictions below 0, ensuring a realistic representation. The linear model performs worst ($R^2 = 0.33$), not capturing the non-linearity of the data, indicating that non-linear regression methods may fit the relationship better.

Polynomial regression initially follows the relationship but overall performs poorly, shown by its lower R^2 of 0.48. Exponential and logarithmic regression perform well ($R^2 = 0.56$ and 0.61, respectively), capturing the steep initial decline in infant mortality rates before plateauing

at higher expenditure levels. The power law model achieves the best fit with an R² of 0.61, revealing that 61% of the variance in infant mortality rates is due to healthcare expenditure per capita, and the lowest mean absolute error (MAE) of 10.47.

This analysis proves that non-linear models, particularly power law and logarithmic regression, provide the most accurate representation of the data, reiterating the non-linearity of the relationship between healthcare expenditure per capita and infant mortality rates shown by Figure 5.

Regression Model Evaluation

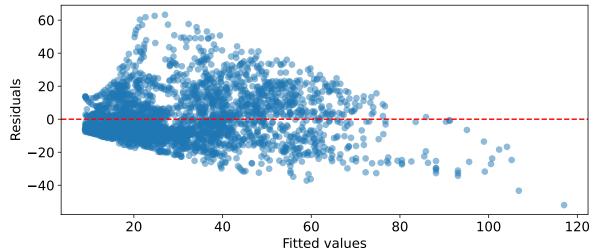


Figure 7: Residual Plot of Power Law Regression

The residuals, illustrated by Figure 7, for the power law regression model indicate some issues with fit of the model. The residuals display a clear pattern rather than being randomly scattered around 0, suggesting heteroscedasticity, where the variance of residuals increases as fitted values increase. This means that the model performs well at low levels of healthcare expenditure but struggles to maintain accuracy as expenditure increases. To address these issues, applying a log transformation to the dependent variable or using alternative regression techniques may help improve the model's fit.

Time Series Analysis

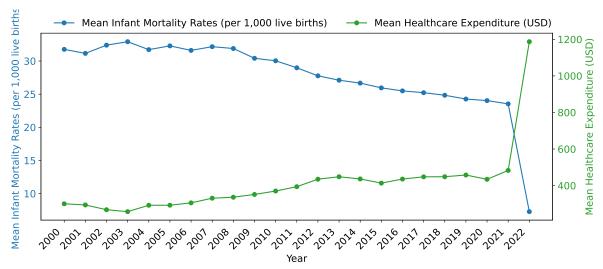


Figure 8: Time Series Analysis of Mean Infant Mortality Rates and Healthcare Expenditure

Figure 8 illustrates the non-linear negative association between mean infant mortality rates (IMR) and mean healthcare expenditure from 2000 to 2022. The trend indicates healthcare expenditure has steadily climbed, indicating greater investment in health infrastructure and services. Leading to a continual drop in IMR, reflecting these improvements in healthcare, economic development, and medical advances

An anomaly occurs in 2022 when healthcare expenditure increases disproportionately to other years and infant death rates significantly decrease. This large increases is likely due to pandemic-related expenditure, emergency health interventions, or data errors.

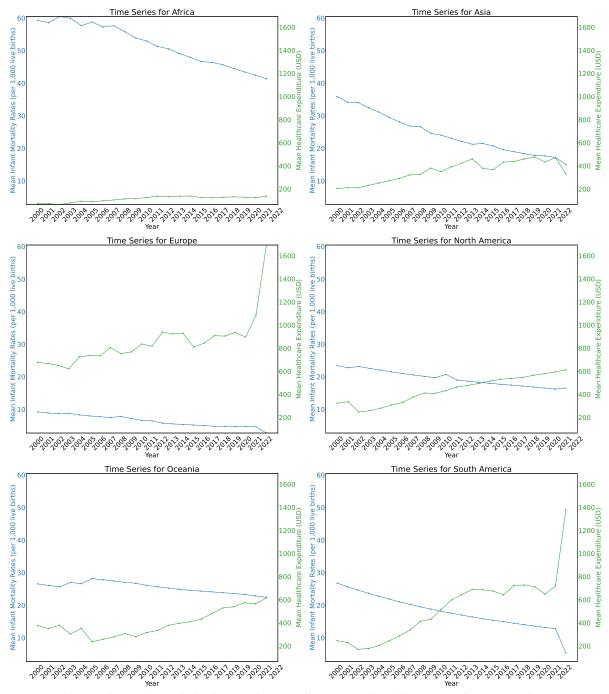


Figure 9: Time Series Analysis of Mean Infant Mortality Rates and Healthcare Expenditure By Continent

Figure 9 shows continent-specific relationships between mean IMR and mean healthcare expenditure from 2000 to 2022. The negative relationship across all continents reiterates that increasing healthcare investment has the potential to reduce infant mortality.

Asia and Africa have had considerable decreases in IMR, indicating substantial improvements in healthcare despite relatively small expenditure. Europe and North America, with larger starting expenditures, experienced lower IMR decreases, indicating diminishing returns on investment.

Healthcare expenditure rose significantly in 2022 in Europe and South America, potentially due to pandemic-related measures. This substantial rise in expenditure corresponds with an acceleration in IMR decreases, implying short-term healthcare gains.

Conclusion

In conclusion, there is a strong non-linear negative relationship between healthcare expenditure and infant mortality rates. Countries with higher healthcare investment generally experience lower infant mortality, though the impact varies based on economic and healthcare infrastructure factors.

The non-linear nature of this relationship indicates diminishing returns, where initial increases in spending lead to substantial improvements, but further investments yield smaller reductions in infant mortality. Regression and time-series analyses further reinforce this pattern, indicating long-term declines in infant mortality alongside growing healthcare expenditure.

Regional disparities are present, with high-income regions investing more per capita while achieving lower mortality rates, whereas lower-income regions show greater relative improvements despite lower absolute expenditure. The 2022 anomaly suggests short-term shifts in healthcare spending and outcomes, likely due to pandemic-driven policies.

While healthcare expenditure is an important driver of infant mortality rates, efficient allocation, accessibility, and policy effectiveness remain key determinants of long-term health improvements worldwide.

Link to Github Repository = BEE2041 Data Science in Economics Assignment